GOLDSMITHS COLLEGE, UNIVERSITY OF LONDON

Improving One-Handed Interaction with Touchscreen Smartphones

by

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degree of Doctor of Philosophy

in the

Department of Computing

Declaration of Authorship

I, Karsten Seipp, declare that this thesis titled "Improving One-Handed Interaction with Touchscreen Smartphones" and the work presented in it are my own.

Signed: ____

Date: ____

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Abstract

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One-handed operation of touchscreen smartphones presents challenges such as hard-to-reach targets and the thumb occluding the interface. There are two main approaches to address these challenges: Modification of the graphical user interface (GUI) and extension of the device's input modalities using its sensors. Previous work has presented techniques addressing a specific problem in isolation, but has failed to provide one solution which tackles all main challenges of thumb interaction together. This thesis examines whether this can be done.

To establish the background, the thesis finds that users prefer convenience over efficiency and confirms that they predominantly use one hand. To detect mode of operation, the thesis presents an approach to classify a user's finger with a high degree of accuracy using a single touch. Following the first research avenue, the thesis presents a thumb-optimised GUI that increases usability and efficiency of one-handed website operation. Following the second avenue of research, the thesis presents a novel one-handed input technique for smartphones, using a set of three off-screen gestures. Both approaches address the most common problems of one-handed smartphone operation via the thumb largely successfully, but fail to completely solve the problem of interface occlusion.

The thesis adds to the literature in the field of visual perception, input classification, GUI optimisation, and input techniques. Readers learn that visual search strategies of the desktop world may also apply to the mobile world and that eye gaze position may have a greater impact on target acquisition time than Fitts's law. The one-touch finger classification technique provides an additional layer of context and new opportunities for improving the human-machine dialogue. The thumb-optimised GUI presents practitioners with a potential blueprint for translating classical WIMP UI elements into thumb-friendly touch interfaces while the novel input technique provides a new layer of complexity for off-screen interaction.

Publications Derived from This Thesis

Seipp, K. and Devlin, K. (to appear), "A Client-Side Approach to Improving One-Handed Web Surfing on a Smartphone", Lecture Notes in Business Information Processing, Springer.

Seipp, K. and Devlin, K. (2014), "BackPat: One-Handed Off-Screen Patting Gestures", in *Proceedings of the 16th International Conference on Human–Computer Interaction with Mobile Devices and Services*, MobileHCI '14, New York, NY, USA: ACM, pp. 77–80.

Seipp, K. and Devlin, K. (2014), "The One Hand Wonder: A framework for Enhancing One-Handed Website Operation on Touchscreen Smartphones", in *Proceedings of the 10th International Conference on Web Information Systems and Technologies*, WEBIST'10, Lisbon, Portugal: SciTePress, pp. 5–18.

Seipp, K. and Devlin, K. (2014), "BackPat: Improving One-Handed Touchscreen Operation by Patting the Back of the Device", in *CHI 2014 Extended Abstracts on Human Factors in Computing Systems*, CHI EA '14, New York, NY, USA: ACM, pp. 555–558.

Seipp, K. and Devlin, K. (2013), "Enhancing One-Handed Website Operation on Touchscreen Mobile Phones", in *CHI 2013 Extended Abstracts on Human Factors in Computing Systems*, CHI EA '13, New York, NY, USA: ACM, pp. 3123–3126.

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Stewie (his voice getting progressively higher):

"How you uh, how you comin' on that novel you're working on? Huh? Gotta a big, uh, big stack of papers there? Gotta, gotta nice little story you're working on there? Your big novel you've been working on for three years? Huh? Gotta, gotta compelling protagonist? Yeah? Gotta obstacle for him to overcome? Huh? Little story brewing there? Working on, working on that for quite some time? Huh? Yeah, talking about that three years ago. Been working on that the whole time? Nice little narrative? Beginning, middle, and end? Some friends become enemies, some enemies become friends? At the end your main character is richer from the experience? Yeah? Yeah? No, no, you deserve some time off."

Stewie Griffin, *Family Guy*, series four, episode seven

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Abbreviations

AR	**A**ugmented **R**eality
CLI	**C**ommand **L**ine **I**nterface
cm	**C**enti**m**etres
CMC	**C**arpo**m**eta**c**arpal
CPU	**C**entral **P**rocessing **U**nit
CSS3	**C**ascading **S**tyle **S**heets **3**
DOM	**D**ocument **O**bject **M**odel
GOMS	**G**oals **O**perators **M**ethods and **S**election rules
GUI	**G**raphical **U**ser **I**nterface
HCI	**H**uman-**C**omputer **I**nteraction
HTTP	**H**yper**t**ext **T**ransfer **P**rotocol
IP	**I**nter**p**halangeal
IT	**I**nteraction **T**ime
IV	**I**ndependent **V**ariable
kB	**K**ilo**b**yte
MB	**M**ega**b**yte
MCP	**M**eta**c**arpo**p**halangeal
MHz	**M**ega**h**ert**z**
mm	**M**illi**m**etres
ms	**M**illi**s**econd
NN	**N**earest **N**eighbour
PNG	**P**ortable **N**etwork **G**raphics
OHW	**O**ne **H**and **W**onder
PCC	**P**earson **C**orrelation **C**oefficient
PPI	**P**oints **P**er **I**nch

px	**Pix**els
RAM	**R**andom **A**ccess **M**emory
RBI	**R**eality-**B**ased **I**nteraction
RSI	**R**epetitive **S**tress **I**njury
SD	**S**tandard **D**eviation
SDK	**S**oftware **D**evelopment **K**it
SVG	**S**calable **V**ector **G**raphics
UFOV	**U**seful **F**ield **o**f **V**iew
UI	**U**ser **I**nterface
W3C	**W**orld **W**ide **W**eb **C**onsortium
WIMP	**W**indows **I**cons **M**enus **P**ointer
WWW	**W**orld **W**ide **W**eb

Chapter 1

Introduction

This chapter will provide a brief overview of the challenges of one-handed mobile interaction and establish the research context of this thesis. Following this, it will provide an outline of the thesis and sum up its contributions to the field while highlighting limitations and constraints of the research conducted.

1.1 Introduction

If we follow Grudin's (2008) report on the development of the field of Human–Computer Interaction (HCI), the relationship between human and machine seems to have started off on the wrong foot somewhat. Rather than controlling the huge machines that most computers once were and elegantly feeding them questions to make them work in the service of humankind, early computer use could be likened to the image of an ant hill gone wild, with countless drones swarming around a large hill, catering for the beast's needs to keep it going and requiring a great deal of effort. Viewing such a scene may have inspired Shackel to define the relationship between these new gods of technology and their flock as that between master and slave (Shackel, cited in Grudin (2008, p. 4)).

The input method of feeding the huge machine a set of prepared punchcards was cumbersome, the processing of the task in an external computer "plant" was tedious, the machine's output on stacks of paper wasteful and long-winded, and the required separation of the people tending to the device's needs into various groups of specialists comprising managers, operators and programmers was rather stiff and archaic. Compared to today's standards the whole operation appears terribly inefficient.

Fast forward 50 years and computers have taken the shape of smartphones that fit in a hand and are used by a large part of society (Arthur, 2014). The former complex sets of instructions and procedures have been transformed into the most simple type of input there is: Pointing at things. This achievement is part of a long process of constantly improving the dialogue between human and computer, from the early punchcards over command line interfaces (CLIs) with keyboard input, to graphical user interfaces (GUIs) operated using a computer mouse, shifting computer use from the hands of professional operators to those of laymen, reducing the items required to interact with the device to a set of two: The screen of the device and the finger of the user.

Yet, this process has brought with it various challenges, manifested in a set of laws describing human difficulty of GUI operation. While these were originally derived from human interaction with stationary devices, the large amount of research attempting to tackle their challenges – as discussed in the literature review (Chapter 2, p. 33) – suggests that these may also apply to interaction with mobile devices. Therefore, evaluations of interfaces and techniques presented in this thesis are based on their ability to address the challenges described by these. In particular, the laws referenced most frequently throughout this thesis are:

- **Accot's law:** Prediction of the speed with which a user may follow a path in a tunnel. For example, this can be applied to controlling a slider (direct manipulation via the finger) or selecting an item from a drop-down menu (indirect manipulation via the computer mouse) (Accot and Zhai, 1997).
- **Fitts's law:** Predicts the speed with which a user can select a certain target, based on target size and distance to the pointing device. For example, the law would predict that a close, large target on the screen is faster to interact with than a distant, small target (Fitts, 1954).
- **Hick–Hyman law:** Predicts the time needed for a user to make a decision when confronted with a list of choices. The prediction follows a logarithmic scale, assuming that the user utilises techniques such as subdivision, allowing them to

locate information quicker than scanning the choices linearly one by one (Hyman, 1953).

The interaction challenges described by these laws are often accompanied by additional challenges intrinsic to thumb use, such as limited range of movement, interface occlusion by the thumb, and limited expressiveness of thumb input. A full listing of these can be found in Chapter 2, p. 40.

Although much innovative research has been carried out to develop new ways of conducting the dialogue between human and computers (Sutherland, 1968; Bolt, 1980; Baudel and Beaudouin-Lafon, 1993; Dourish, 2001; Feldman et al., 2005; Harrison et al., 2010; Vi and Subramanian, 2012; Solovey et al., 2012; Caramiaux et al., 2013; Loke and Robertson, 2013; Sakamoto et al., 2013), many issues and relics of the history of HCI appear to remain unresolved in the field of touch-based mobile HCI. This is particularly important, as users have a wide set of new input methods at their disposal, but seem slow to adapt these – be it for social reasons (Winston, 1998), potential inadequacy for a certain task (Cohen et al., 1989) or even embarrassment and lack of privacy (Wasinger et al., 2005; Ahlström et al., 2014).

Conducting a survey to determine users' preferred mode of phone operation, Karlson et al. (2006) found that users prefer to operate their devices with one hand via the thumb. Although slightly dated, the results are reconfirmed by the study presented in Chapter 3 (section 3.3.3, p. 115). Users appear to predominantly employ this mode of interaction despite its numerous challenges constituted by the limitations of the thumb's reach, its imprecision, interface occlusion, and low dexterity. With smartphones seemingly growing in size (Fingas, 2013), these challenges may have even greater impact on future smartphone generations. Research indicates that the thumb's representation in the brain and its sensory capacity are shaped by frequent one-handed smartphone use (Gindrat et al., 2015). Following the sensorimotor theory approach (O'Regan and Noë, 2001), this development observed by Gindrat et al. (2015) may ultimately lead to a perception of the thumb as the "natural" way to interact with handheld devices, suggesting research into improving smartphone operation via the thumb to be a worthwhile endeavour.

1.1.1 Problem

While a plethora of approaches exists for enhancing interaction with mobile devices in general – as indicated above – previous work for enhancing one-handed device operation via the thumb in particular has often attempted to address the challenges of this input mode by developing a specialised approach intending to **solve a single particular problem**, such as reaching a distant target or increasing selection precision. The literature review shows that solutions to the challenges of one-handed operation of touchscreen smartphones via the thumb are often devised by pursuing one of the following avenues:

- **1: Modifying the graphical user interface (GUI).** This presents the well-trodden (but not yet perfected) "standard" path of mobile Human–Computer Interaction.
- **2: Extending input modalities by utilising the device's sensors or additional hardware.** This follows a comparably new interaction paradigm, involving the actual device in the interaction, corresponding to the idea of an "embodied interface" (Fishkin et al., 1999, 2000).

However, a solution that addresses all the challenges of one-handed smartphone interaction – such as limited reach, limited precision, interface occlusion and the difficulty of steering a cursor (as identified in the literature review in Chapter 2, p. 41) – **together**, **using the same technique or interface**, has not yet been devised in either grouping.

Instead, should a developer wish to support a user in overcoming these challenges, the user must master a wide range of techniques and interfaces – within the same application – when following the contributions of previous research. Unfortunately, mastering multiple techniques requires much learning and practice and risks the problem of "command clash", should two or more techniques share the same set of gesture delimiters or input signals.

This prompts an exploration of whether the main challenges of one-handed smartphone interaction can be addressed successfully using just one technique or interface which follows either of the above two main research avenues for enhancing one-handed touch interaction, instead of using a dedicated technique or interface for each problem.

If this can be done, interaction may be simplified and the learning of multiple techniques may be reduced, providing a greater degree of usability and efficiency while simultaneously overcoming the main challenges of one-handed interaction via the thumb. In addition, designers and developers can learn whether a full solution to overcome these challenges can be produced using either of the identified main strategies so that they can make a decision for their utilisation. If not, they need to know whether it is necessary to accept a compromise when choosing either strategy and, if so, what that compromise may be.

1.2 Thesis Statement

To address this gap in the research, the thesis confirms the findings of Karlson et al. (2006) regarding users' preference for one-handed operation via the thumb and explores whether the main challenges of one-handed interaction – the challenges described by Fitts's law, Accot's law and the interface occlusion by the thumb (see Chapter 2, p. 41) – can be addressed together by devising a solution following either of the two main strategies for this mode of interaction, identified in the literature review:

- **1: Modifying the graphical user interface (GUI).**
- **2: Extending input modalities by utilising the device's sensors or additional hardware.**

If unsuccessful, the limitations of an approach following these strategies and aiming to address all challenges together need to be defined. Regarding the above, the following main research question can be formulated:

***Main RQ*:** Can an approach following either of the two main strategies to improve one-handed interaction (the modification of the GUI and the extension of the input modalities) address the challenges of Fitts's law, Accot's law and that of interface occlusion by the thumb (as defined in Chapter 2, p. 41) together, using a single interface or technique under a set of social and technical constraints, as formulated in Chapter 3, p. 126?

When aiming to answer the main research question, it is necessary to not only explore the capacity of an approach following either strategy to address the main challenges of one-handed smartphone operation, but also to take into account user preferences and habits and to explore the characteristics of a digitised touch. Gaining more knowledge in these areas may help to devise an approach that may not only tackle the challenges successfully, but also corresponds to user expectations and needs. Therefore, the following subordinate research questions emerge by means of which the answer to the main research question may be formed:

***RQ1*:** What is more important to users when operating a mobile device: Efficiency or comfort?

Exploring this research question will help to gain a better understanding of users' preferences and needs and therefore supports the creation of a successful interface and interaction technique with a potentially high degree of user acceptance.

***RQ2*:** Are the properties of a single "digitised" touch characteristic enough to distinguish between index finger and thumb of the left and right hand?

It is important to be able to distinguish between index finger and thumb input in as little interaction steps as possible to minimise the impact of unexpected interface changes on the user when aiming to provide a successful solution to the challenges of one-handed interaction using GUI modification. Exploring this research question will help to understand the feasibility of this prerequisite as well as inform the design of a thumb-adapted interface by further analysing the characteristics of one-handed touch operation.

***RQ3*:** Can an approach following the strategy of interface modification successfully address the main challenges of one-handed smartphone operation (as defined in Chapter 2, p. 41) together, using only a single interface?

Taking into account the insights gained from *RQ1* and *RQ2*, this research question will explore the potential of interface adaptation to improve one-handed smartphone operation with regards to the challenges described by Fitts's law, Accot's law and interface occlusion by the thumb. It thereby aims to directly inform the synthesis of an answer to the main research question.

***RQ4*:** Can an approach following the strategy of input modality extension using a device's sensors successfully address the main challenges of one-handed smartphone operation (as defined in Chapter 2, p. 41) together, using only a single technique?

By answering this research question, the potential of input modality extension to improve one-handed smartphone operation with regards to the challenges of Fitts's law, Accot's law and interface occlusion by the thumb will be elucidated. The insights gained from exploring this question serve as a direct prerequisite to answering the main research question.

Altogether, the thesis attempts to answer these questions by taking into account users' potential unwillingness to perform a certain effort or to change their habits if a sufficiently adequate approach is already available (Winston, 1998; Norman, 2002) and so focusses on implementing the solutions within the constraints of off-the-shelf smartphones and operation of these with only one hand.

1.3 Thesis Outline and Contribution

The thesis is structured as follows:

Chapter 2 defines the most common challenges of touch-based smartphone interaction and reviews existing approaches with regards to their potential to address these. The literature review is followed by exploring user habits and layout orientation performance to answer *RQ1* in Chapter 3, which is succeeded by the answering of *RQ2* in Chapter 4 by closely examining physical and digital properties of touches with index finger and thumb. Chapter 5 and Chapter 6 explore the potential of the strategies of GUI modification and input modality extension to tackle the main challenges of one-handed smartphone interaction using a single interface or technique and thereby address *RQ3* and *RQ4*. The thesis concludes with Chapter 7 by answering the main research question (*Main RQ*) and discusses the thesis's contribution to the mobile HCI literature, ending with a discussion of future work and some closing remarks.

By exploring the research questions, the thesis makes a number of contributions to the field of mobile HCI, comprising insights into user preferences and layout efficiency, the touch characteristics of index finger and thumb, as well as the provision of a powerful thumb-optimised interface and a novel interaction technique.

In particular, the main contributions are:

- Under the thesis's constraints, interface occlusion may only be reduced, but not eliminated completely, when aiming to develop an interface or interaction technique with a high degree of generalisability to address the main challenges of one-handed interaction together, using only a single-strategy approach (*RQ3*, *RQ4*, *Main RQ*). This way, the limitations of the paradigms of interface adaptation and input modality extension in providing a comprehensive solution to the challenges of one-handed interaction in a single-strategy approach is illustrated. As a result it is suggested that, under the thesis's constraints, a wholly successful approach for solving the main challenges of one-handed smartphone interaction may have to be multi-modal and that using solely touch input to solve the challenges of touch interaction may be inadequate. If only as single technique or interface is used, practitioners are likely to have to compromise on the aspect of interface occlusion.

- A touchscreen smartphone is faster to operate in landscape orientation than in portrait orientation using the index finger or both thumbs, but users prefer to operate these devices using only one hand and their thumb in portrait orientation and prefer comfort and ease over efficiency (*RQ1*). Further, the findings of Chapter 3 suggest that, at least within the conditions of the study, using solely Fitts's law for predicting interaction time for a given target on the mobile screen may be inadequate, but that initial point of gaze as well as scanning pattern seem to have a greater impact than distance of the target from the "pointer". This suggests that interface efficiency evaluation on mobile devices should consider the spatiotemporal arrangement of elements and point of gaze, corresponding to the suggestion of Welsh et al. (2008) and the work of Bailly et al. (2014) on desktop screens.

- The digital properties of a single touch are characteristic enough to differentiate between index finger and thumb with a high degree of accuracy (*RQ2*). This presents a major advance over the state-of-the-art approach provided by Goel et al. (2012), which requires up to five steps consisting of predefined actions in certain parts of the screen, yielding a similar degree of accuracy.

- A large array of desktop-centric interaction patterns can be translated into a semi-circular interface operated via a horizontal swipe and tap, increasing usability and efficiency of one-handed smartphone operation. Such an interface addresses most challenges of one-handed interaction successfully and may therefore serve as a blueprint for migrating other WIMP interaction patterns to the mobile realm (Chapter 5).

- Device movement, sound volume and sound profile can be synthesised into a set of three novel off-screen patting gestures to support one-handed smartphone operation. Performance and user preference for these gestures is highest for gestures performed with the index finger (followed by those performed with middle finger and thumb), but differs with application.

1.4 Limitations

It needs to be taken into account that the provided solutions are prototypes that require further development to be more robust. They are built for exploring the answers to the most common problems identified in the literature review, but may not address challenges not included in the review. In addition, it needs to be considered that the solutions are shaped by the constraints of this thesis, as defined in Chapter 3, p. 126. To increase acceptance and user adoption, the thesis suggests approaches should lead on from users' current interaction experiences, rather than impose changes onto their devices or behaviour. This attitude is derived from the user research within Chapter 3 and the finding that users appear to choose comfort, ease, and correspondence to habit over efficiency. With this in mind, the research is subject to the following limitations:

- All approaches are software-based.

- The approaches are to support devices following the average specifications defined in Chapter 3, section 3.3.1, p. 113, and therefore address the challenges of one-handed interaction with the means provided by off-the-shelf smartphones. However, approaches are transferable to other devices, beyond the constraints of this research.

- While the research demonstrates interesting effects which suggest further exploration of some areas, the thesis will only address the research questions as defined in Chapter 2, section 2.9, p. 68, and concentrate on answering these satisfactorily.

- The solutions focus on addressing the identified main challenges of one-handed interaction: The difficulty of reaching distant targets, interface occlusion, steering a cursor over a path, and limited selection precision. Therefore, text input – a research area in its own right as illustrated by the amount of work in its field (Silfverberg et al., 2000; Sazawal et al., 2002; Wigdor and Balakrishnan, 2004; McCallum et al., 2009; Yin et al., 2013) – is excluded from the research.

In addition to the above, the research in this thesis is limited in so far that it only examines one possible implementation of an approach attempting to simultaneously address all of the challenges of one-handed smartphone operation by following either of the two main research streams. As a result, explorations and conclusions may not be exhaustive and fully generalisable. However, these implementations are shaped by the requirements and constraints of this thesis, and provide the context under which its contributions are to be seen. Nonetheless, as the constraints are based on contemporary user behaviour and technological possibilities, the contributions are likely to be applicable to a wider body of current and future development and can be seen as a reference for mobile HCI practitioners and academics. Furthermore, the contributions this thesis makes to the dialogue between human and machine are not limited to the work undertaken in this thesis, but are transferable to other emerging technologies and developments, as described in Chapter 7, section 7.3, p. 325, and Chapter 7, section 7.7, p. 338. Finally, with the context and constraints of the research undertaken in this thesis established, you may now hopefully enjoy its reading!

Chapter 2

Literature Review

2.1 Introduction

The development of mobility in computing and communication has brought with it the need for new kinds of pointing devices and new interaction paradigms. The computer mouse was replaced with a wireless pen, which has now been superseded in many fields by the most natural pointing device of all: The human finger. While this has been accompanied by many positive aspects, this direct interaction also bears challenges that were better solved by indirect interaction. As a result, researchers aim to bridge the gap between direct and indirect input, hoping to combine the best of both worlds to support users in the rapidly growing field of mobile Human–Computer Interaction.

While other modalities, such as speech or gestures, have been developed to enhance interaction, the prevailing input method of mobile devices remains touch input, where the preferred mode of operation is to hold the device in one hand and operate it with the thumb of that hand, as reported by Karlson et al. (2006). This is despite the thumb being built for grasping rather than tapping (Bourbonnais et al., 1993). But as touch interaction still implies the use of a pointing device, some challenges of interaction with stationary devices and their mouse-operated GUIs may still apply. One of the fundamental challenges of HCI is described by Fitts's law: The impact of target size and distance from the pointing device on interaction time (Fitts, 1954). While the model has so far only been successfully applied to classic Windows Icons Menus Pointer (WIMP) interfaces and stylus-based input (Min Lin and Sears, 2005) and only partially successful to touch-based interaction (Bi et al., 2013), its core statement may be transferable to touch-based mobile interaction. Derived from Fitts's law is Accot's steering law (Accot and Zhai, 1997), which predicts the speed with which a cursor can be moved through a tunnel, such as when selecting an item from a drop-down menu or making a text selection. Although direct interaction has the benefit of being able to lift the "cursor" (finger) from the display and position it at the end of such a tunnel, drag and drop actions, text selection and slider control still require steering a cursor through a "tunnel" of surrounding elements. This is mostly due to the fact that the patterns of WIMP interaction seem to have been transferred to the domain of touch interaction, bringing with them the benefit of recognition at the cost of their inherent issues (such as selection precision) and possible inadequacies for touch interaction. The use of icons and buttons on a screen which simultaneously acts as the input and output device brings with it another challenge: Interface occlusion by the finger. While this may be less impactful when using a touchscreen smartphone with two hands (holding it in one hand and operating it with the index finger of the other), it is very prevalent in the domain of thumb-based interaction (Roudaut, 2009), where the user's thumb tends to rest on or hover above the screen.

With this in mind, this chapter reviews the literature contributed to overcoming these challenges when operating touchscreen smartphones one-handedly with the thumb. To do so, the chapter is divided into nine sections: Following the introduction, it will examine contributions made to improve direct pointing, target selection, cursor control and the problem of interface occlusion. While the boundaries between these are fluent and aspects of one often relate to another (as one often emerges from the other), they are listed separately to help structure the review. In addition, this chapter reviews literature regarding layout orientation and interaction speed as well as literature concerning the detection of handedness and input mode, as insights into both domains can be used in the process of enhancing touch interaction.

The chapter is concluded by a section identifying the gaps in the research that need addressing in order to overcome the above challenges, together with an agenda of how these are to be addressed.

2.2 Improving Direct Pointing

Probably the most straightforward way to support direct pointing is by adapting the interface. This approach largely consists of providing an interface that is designed to assist touch operation, or at least offering an improved display of information on small screens. It ranges from rather general recommendations such as greater button or font sizes to highly specialised, thumb-focussed GUIs. Whereas some of these approaches do not focus on the one-handed operation of the device in particular, but rather on accommodating the peculiarities of mobile interaction in general, they nonetheless present an essential part of improving thumb-based interaction and can be seen as a basis from which to further adapt and develop a thumb-optimised interface.

2.2.1 Improving Information Display

Regardless of whether one or two hands are used for device operation, Jones and Marsden (2006) give comprehensive advice on designing and evaluating mobile interfaces. Due to the small screen size of mobile devices, they recommend limiting the amount of information and interactive elements for best user performance. In addition, they suggest offering "focused, direct access" (Jones and Marsden, 2006, p. 259) to information and providing search functionality to minimise exploration of menus. These recommendations are also given by Fling (2009) and Kolko (2011), with the latter further recommending that permanent objects are placed in the same location as a clear point of reference and orientation. In addition, Fling emphasises the importance of considering the environmental context when designing mobile applications and reports that, as opposed to desktop users, mobile users are impacted by a large range of constraints and external distractions – all impeding their ability to focus on their goals. This may especially create challenges for resources that are consumed in both environments, mobile and desktop, such as the World Wide Web (WWW).

With the rising access of websites via mobile devices as reported by the Office for National Statistics (2013) and the intrinsic ability of the Web to be accessed via a large array of devices and sizes, much of the research into enhancing the display of information on mobile devices is based on adapting the layout of websites built for access via a desktop computer to the challenges of the mobile screen. In the past, users suffered from inadequate presentation, long pages, a small screen size and spread-out content, due to poor adaptation (Shrestha, 2007; Roto, 2005). Therefore, before the arrival of the touch-screen to the mobile Web experience, a common approach to address these challenges of mobile information display was to break down the large amounts of information of desktop-centric websites into amounts that are easier to consume on small-screen devices. One technique to achieve this is Web Page Segmentation, as used by Bandelloni et al. (2005), Gupta et al. (2007) and Hattori et al. (2007). In this approach, a proxy server analyses layout and content information, breaks down the page into segments from which to build separate pages, and serves a restructured website to the device on which the user can access theses segments through a table of contents menu (Fig. 2.1). In addition, Bandelloni et al. (2005) allow desktop users to "migrate" the current state of a website accessed from a desktop computer to their PDA, where the content will be presented using the Web Page Segmentation approach, but entered values such as form data will be preserved. In a similar approach, Mori and Paternò (2005) suggest the creation of abstract layout and functionality descriptions of websites, ensuring an optimised display of all components on all platforms. But although especially the latter presents an interesting idea of approaching Web design in general, the techniques only adapt the display of information, and not the interaction model, and not for one-handed thumb use. In addition, the requirement of a proxy server and the extra work incurred by using the TERESA tool presented by Mori and Paternò (2005) to prepare a website accordingly, limit the implementability of these approaches and demonstrate a need for further research into this area.

2.2.2 Adapting Interactive Elements

In addition to adapting the display of information, researchers have also focussed on adapting the interaction with it. To compensate for a larger, less accurate "pointer" and to reduce user effort, previous work has suggested increasing the minimum target size and spacing (Colle and Hiszem, 2004; Parhi et al., 2006; Park et al., 2008; LaVictoire and Everhart, 2009; Schildbach and Rukzio, 2010; Park and Han, 2010; Apple, n.d.*b*; Microsoft, n.d.) as well as locating targets in the centre of the screen, near the thumb's tip, for easy reachability (Parhi et al., 2006; Park et al., 2008) or at the opposite side of the hand holding the device, near the edge of the screen (Perry and Hourcade, 2008), following the recommendations of Fitts's law. A central location of interaction elements

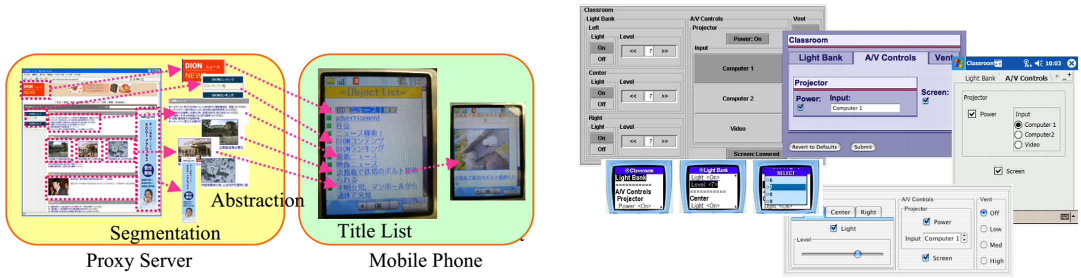

FIGURE 2.1: **Left:** An example of Web Page Segmentation re-portioning a website into smaller units, taken from Hattori, G., Hoashi, K., Matsumoto, K. and Sugaya, F. (2007), “Robust Web Page Segmentation for Mobile Terminal Using Content-Distances and Page Layout Information”, in *Proceedings of the 16th International Conference on World Wide Web*, WWW ’07, New York, NY, USA: ACM, pp. 361–370. Copyright 2007 IW3C2. **Right:** Device-specific representations of an interface generated by S.U.P.P.L.E., taken from Gajos, K. Z., Weld, D. S. and Wobbrock, J. O. (2008), “Decision-Theoretic User Interface Generation”, in *AAAI*, Vol. 8, pp. 1532–1536. Copyright 2008 AAAI. Please see Appendix B, section B.1, p. 342 for permission to include figures.

has the benefit of being usable by both left-handed and right-handed users, without the need for the detection of handedness and handedness-related interface adaptation. Findings supporting this view are presented by Karlson et al. (2006), who further report that for right-handed users movements of the thumb into the north-west or south-east area of the screen should be avoided (and vice versa for left-handed users), as these are ergonomically awkward to perform and thus impact user performance. In addition to changing the size of interactive elements to address the issues of direct touch, Henze et al. (2011) suggest improving the system’s evaluation of the touch event, showing that adaptations for improving touch operation can not only be made through adapting the GUI, but through adapting the input interpretation. But as this would require the application to “know” which hand and finger touches the device to apply the adequate corrections, the procedure has to be applied with caution.

Yet, if the mode of interaction is known to the system, carefully adapted interactive elements can greatly enhance usability and efficiency, as shown by Gajos et al.’s S.U.P.P.L.E. (Gajos et al., 2008). The system is capable of creating an interface that takes into account key factors such as device constraints, users’ motor abilities, usage patterns and personal preferences and as a result can support any style of interaction (Fig. 2.1). Similarly, Doulgeraki et al. (2009) present the E.A.G.E.R. toolkit which, following Trewin’s problematisation of the varying needs of Web users (Trewin, 2006), allows the generation of an ability-specific version of a website, taking into account degree of experience and motor skills. While presenting an interesting approach to not only support direct or indirect pointing, but also the user's abilities and needs, the approaches require the completion of a preference dialogue before use, which may lock the user to a certain interface once configured and do not cater for the change between one-handed and two-handed interaction nor changes in device orientation. Nonetheless, S.U.P.P.L.E.'s example of a dynamic, customisable space for organising frequently used functionality within the application's interface could be a promising approach for enhancing one-handed thumb input on mobile devices. This idea of a dynamic menu area has been partly utilised by Zhou et al. (2009) who populate the status bar of a desktop browser with shortcut buttons that provide links to pages or suggestions for possible form input based on the user's history and predicted behaviour, analysed by a dedicated Web server.

Another way to improve the mobile browsing experience is the creation of a specialised browser. The Read4Me browser by Yu and Miller (2011) dynamically converts a desktop site into a "mobile site", but also offers a text-to-speech service as well as a speech interface to reduce the amount of interactions with the GUI. This way, the approach addresses some of the challenges of direct pointing, target size and distance to the pointing device, and interface occlusion. Unfortunately, just as the proxy server-based approaches, this approach limits the presentation of the content and the interaction with it to a predefined form that does not adapt to orientation or mode of interaction. Most importantly, however, the approach requires the employment of proprietary software which is not available to all users by default and is therefore not compatible with the idea of an open and inclusive World Wide Web.

With an increase in technical capabilities and the arrival of the touchscreen to the mass smartphone market in the form of the Apple iPhone in 2007, the perception of the mobile Web as a nuisance rather than an experience may have undergone a profound change. Because of the bad user experience of websites on devices with relatively limited capabilities (Shrestha, 2007), Schmiedl et al. (2009) find that users can actually benefit from carefully adapted websites that do not rely on Web Page Segmentation or zooming, but instead maintain the original appearance and natively adapt the content following simple rules, enabled by a larger screen and a better browser engine. Therefore, a lot of advice is available on achieving this goal: Opera Software ASA (2007) recommend limiting the use of images to speed up loading time, avoiding frames to improve display and scrolling, and increasing the contrast to cope with changing light conditions. The W3C (2008) suggests reducing the number of navigation items, providing a consistent navigation mechanism and using a clear and simple language. This advice has been taken up by commercial companies, such as Akmin (2012), who offer the creation of mobile websites. However, with the arrival of the third version of the Cascading Style Sheets (CSS3) language and its Media Queries, some of this advice has been superseded by devices' improved technical capabilities, meaning Web designers finally have the ability to fully and seamlessly adapt the display of their websites to the properties of the device accessing it, without the need for server-side user agent detection, cutting down of content or proprietary software. This in turn has led to a great number of responsive themes and templates for popular Web publishing platforms (Envato, 2012, 2013).

While all of the above solutions allow an adapted display of information on mobile devices and improve some issues of direct pointing by altering the target size, they do not offer an adapted interaction model to the one-handed operation in particular, which, as mentioned above, exacerbates some of the problems of direct pointing, as the functional area of the thumb depends on the user's grip on the device as well as the finger and thumb size according to Bergstrom-Lehtovirta and Oulasvirta (2014), who extend the work of Otten et al. (2013) regarding variations in thumb reach with a mathematical model. Despite these varying factors, researchers have suggested that certain areas of the screen are generally easier to reach and interact with than others and that certain arrangements of layout elements are favourable when operating the device one-handedly: Wang and Shih (2009) propose a rounded device design and the positioning of buttons close to the thumb's tip to better cater for the limitations of the thumb concerning its movement range and to reduce muscle fatigue. This position would be comparable to the middle of the screen and so supports the findings of Park et al. (2008) and Parhi et al. (2006) discussed earlier. It further endorses the work of Wobbrock et al. (2008) who suggest a horizontal arrangement of elements when designing for thumb interaction, avoiding the hard-to-perform stretching of the thumb. However, to best cater for thumb-based input, it is essential to fully understand the limitations of this mode of interaction first. In her report on the state of her Ph.D., Roudaut (2009) addresses the problems related to interaction design on mobile devices when operating the device with only one hand.

She identifies the main limitations and challenges as:

- The lack of precision of the thumb.
- Possible interface occlusion through the thumb.
- The limited range of movement of the thumb, making it hard to reach distant targets near the borders of the screen.
- The “absence of a keyboard or of physical buttons” for input (Roudaut, 2009), especially for providing frequently used functionality such as copy and paste actions.
- A lack of the expressiveness the mouse offers (left click for activation, right click for contextual menus, hover states), resulting in a limited set of interactions for direct tap input.
- The potential confusion caused by either dragging the viewport, or its content, or a cursor.

In addition, Katre (2010) defines the following characteristics of thumb-based input:

- Ideal target sizes might be culturally biased, but in general targets for the thumb need to be larger than those for index finger or stylus input.
- Thumb contact size increases the closer it is to the top of the screen, but users with larger thumbs struggle to operate elements near the inside edge of the display, close to the interphalangeal (IP) joint situated at the root of the thumb, whereas users with smaller thumbs struggle to operate elements near the outer edge of the screen in the far corner of the device (compared to the position of the thumb), which indirectly supports the argument for a centrally positioned GUI.
- The contact shape of the thumb on the screen changes from an “elongated and narrow” shape at the bottom right corner to a “large and oval shape” in the top left corner (for right-handed users). Elements in these positions can be “stressful” to reach (Katre, 2010).
- The thumb has a limited dexterity.
- A raised frame impedes thumb-based operation near the edges of the screen.

- Users often hit a target off-centre and mostly to the right (if they are right-handed).
- A circular movement of the thumb (as opposed to stretching it vertically and horizontally) is most natural.
- User occupation and social background impact dexterity.

Following this, Katre suggests several important properties for interfaces that aim to support one-handed thumb use:

- A semicircular arrangement of buttons that follows the natural movement of the thumb.
- Horizontally enlarged buttons to match the shape of the thumb's tip.
- An adaptive button size to equally address the needs of small-handed and large-handed users.
- Adjusted interfaces for left-handed and right-handed users.
- The positioning of the device's screen at an angle of approximately 35 to 45 degrees to the IP joint. This in turn would reduce the need for a curved interface and could reduce the risk of repetitive stress injury (RSI).
- An appropriate screen size that allows easy reachability of all elements together with the omission of a raised frame.

In summary, the researchers suggest improving thumb-based interaction by altering target size to improve precision, changing the interface to accommodate the thumb's natural movement range and reducing interface occlusion by the thumb. This suggests that the main challenges of one-handed smartphone operation can be condensed to the following three:

The Main Challenges of One-Handed Smartphone Operation

- **The challenges to interaction time and selection precision as described by Fitts's law** (Fitts, 1954), likely to be exacerbated by the thumb's limited reach due to its confinement to the bottom/side of the device when holding the device with only one hand, depending on the grip.

- **The challenges of following a path or steering a cursor as described by Accot's law** (Accot and Zhai, 1997) due to the thumb's limited dexterity and range of movement, especially when holding and operating the device with one hand.
- **The challenges of interface occlusion by the thumb** due to the thumb hovering over the interface in its "resting" position or when selecting an object displayed on the screen.

While Roudaut also names the lack of expressiveness of direct pointing compared to indirect pointing as a problem of thumb-based interaction, this point may be considered a limitation rather than a challenge when compared to the list above. Nonetheless, a considerable amount of research has been conducted to tackle this limitation (see section 2.6, p. 56), as it can help to address some of the problems posed by Fitts's law, Accot's law and interface occlusion. It therefore presents an important part of previous work concerning the improvement of one-handed smartphone operation.

Taking the above points as a guide, previous work can be split into four main groups which will be addressed separately in this chapter:

- Research to reduce the impact of target distance and size on interaction time and precision.
- Research to limit interface occlusion.
- Research concerning the reduction of the impact of Accot's law.
- Research into extending the input vocabulary of direct touch.

In addition, this chapter will review work regarding user performance and layout orientation as well as work regarding the detection of handedness, both representing important areas of research when aiming to improve the one-handed operation of touchscreen smartphones.

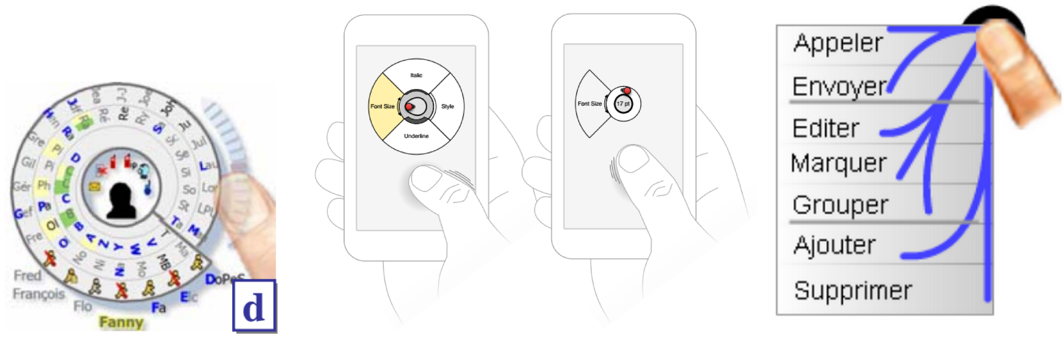

FIGURE 2.2: **Left:** The SpiraList interface, taken from Huot, S. and Lecolinet, E. (2006), "SpiraList: A Compact Visualization Technique for One-Handed Interaction with Large Lists on Mobile Devices", in *Proceedings of the 4th Nordic Conference on Human-Computer Interaction: Changing Roles*, NordiCHI '06, New York, NY, USA: ACM, pp. 445–448. Copyright 2006 Association for Computing Machinery, Inc. Reprinted by permission. http://doi.acm.org/10.1145/1182475.1182533. **Middle:** The Swiss Army Menu, taken from Bonnet, D. and Appert, C. (2011), "SAM: The Swiss Army Menu", in *23rd French Speaking Conference on Human-Computer Interaction*, IHM '11, New York, NY, USA: ACM, pp. 5:1–5:4. Copyright 2011 Association for Computing Machinery, Inc. Reprinted by permission. http://doi.acm.org/10.1145/2044354.2044361. **Right:** The Leaf menu, taken from Bailly, G., Roudaut, A., Lecolinet, E. and Nigay, L. (2008), "Menus Leaf: Enrichir les Menus Lineaires par des Gestes", in *Proceedings of the 20th International Conference of the Association Francophone D'Interaction Homme-Machine*, IHM '08, New York, NY, USA: ACM, pp. 169–172. Copyright 2008 Association for Computing Machinery, Inc. Reprinted by permission. http://doi.acm.org/10.1145/1512714.1512747. Please see Appendix B, section B.1, p. 342 for permission to include figures.

2.3 Reducing the Impact of Target Distance and Size on Interaction Time, Comfort and Precision

To reduce the impact of target distance and the thumb's limited reach on interaction time, researchers have devised a range of solutions. Huout and Lecolinet's SpiraList (Huot and Lecolinet, 2006) employs a circular interface, where information is organised alphabetically in a spiral to display large hierarchical lists and trees. The spiral can be spun via a dedicated interaction area and the "focus zone", a fixed and highlighted position in the outmost circle, shows the currently selected item (Fig. 2.2). This effectively solves the problem of target distance, but only partly that of interface occlusion, as the thumb may still obscure parts of the menu content while operating it. Unfortunately, no user studies are provided and SpiraList's potential to improve one-handed interaction on touchscreen smartphones remains unclear.

Francone et al. (2010) and Bonnet and Appert (2011) propose a concentric, circular menu, which can be operated from the middle outwards and makes all actions available by moving the thumb only a short distance, resembling the wheel button of the first version of the Apple iPod. While efficient to use, solving the problem of the thumb's limited reach and reducing interaction time by lowering the target distance, the menu occludes a large portion of the information it is meant to manipulate and its capacity for hosting menu items is limited by its radius. In this regard, Katre's and Roudaut's reported problem of interface occlusion is even exacerbated and, in the case of the Swiss Army Menu (SAM, (Bonnet and Appert, 2011)), the additional challenge of steering a cursor-like element into a given sector of the menu can increase interaction time, especially if the end of the "tunnel" is located in the north-west or south-east corner (Karlson et al., 2006) (Fig. 2.2). Although the menus can be navigated eyes-free by expert users, error rates are high (Francone et al., 2010) and novice users will still be impacted by the problem of interface occlusion.

Following the trend of circular interfaces, Apple (n.d. *a*) provides a built-in accessibility feature on a system level, called VoiceOver. The rotor module of this feature allows cycling through elements of a website or document and reads out the active item, reducing the problem of occlusion. However, this feature needs to be operated with two fingers and therefore has limited use for enhancing one-handed interaction.

Another approach to thumb-operated menus is Bailly et al.'s Leaf menu (Bailly et al., 2008), a linear menu that is opened by a tap or long tap on the screen. To reduce the required movement distance of the thumb to reach menu items outside of the thumb's reach, the menu is controllable via a set of "gesture shortcuts". This means that an item on the menu is mapped to a dedicated steering gesture of the thumb, allowing blind operation for expert users and successfully addressing some of the issues of Fitts's law by reducing target distance (Fig. 2.2). Yet, the amount of interactions possible and therefore the amount of menu content is limited, as the number of mapped gestures appears to be confined to seven. Furthermore, depending on the size of the vertical menu and the user's grip, the user could potentially struggle to perform the gesture to reach the last menu item if it requires stretching the thumb beyond its reach. Finally, the selection gesture requires the user to abide to Accot's law, potentially increasing interaction time depending on the difficulty of the path to be navigated with the thumb, and potentially reducing the positive effects of reduced target distance.

Instead of creating a specialised menu, an early technique by Karlson and Bederson (2007) to limit the impact of target distance on selection time proposed translating the position of the thumb. Here, the thumb's position within an easy-to-reach, minimised version of the screen is mapped to the interface via a cursor, allowing access of distant elements without moving the thumb outside its comfort zone. To define this zone, the user first "draws" a rectangle on the screen that then serves as the input area, making selection a two-step process. While the researchers report that this amalgamation of direct and indirect pointing improves interaction with distant and small targets and thus partly solves the problem of occlusion, the challenges arising from steering the cursor as well as the problem of interacting with close targets indicate that the technique's ability to address all challenges of thumb-based interaction is limited.

The idea of controlling a cursor from within an easy-to-reach screen area is also explored by Roudaut et al. (2008) who present MagStick. To activate it, the user taps the screen and pulls the thumb back towards the palm of their hand. This in turn creates a "telescopic stick" that the user can manipulate by moving their thumb (Fig. 2.3). By being able to control stick length and rotation angle, users can select targets outside of the reach of their thumb with high precision. A similar approach to MagStick is taken by BezelSpace and CornerSpace (Yu et al., 2013), where the user casts an offset cursor onto the screen by swiping towards the centre of the display, originating from the corner of the device. Subsequent movement of the thumb controls the position of the cursor, which can be used to select elements outside the thumb's reach. Building on MagStick and BezelSpace is ExtendedThumb (Lai and Zhang, 2014), where the user controls a virtual thumb on the display, combining the approaches of Offset Cursor (Potter et al., 1988) and ThumbSpace (Karlson and Bederson, 2007). Similar to MagStick, reaching distant targets takes longer than accessing them directly, but selection accuracy is increased, improving user satisfaction.

Combining the techniques of ThumbSpace and MagStick is Gesture Avatar by Lü and Li (2011). The researchers present a technique where the user draws a figure on the screen. The system then searches the surrounding GUI elements for objects with a similar shape and assigns control of the matching element to the shape-based avatar, making it easy to operate small interface controls (Fig. 2.3). This "draw to select" approach may improve the impact of target size on selection time, but this may be nullified by the time consumed for the drawing gesture. Furthermore, if multiple targets

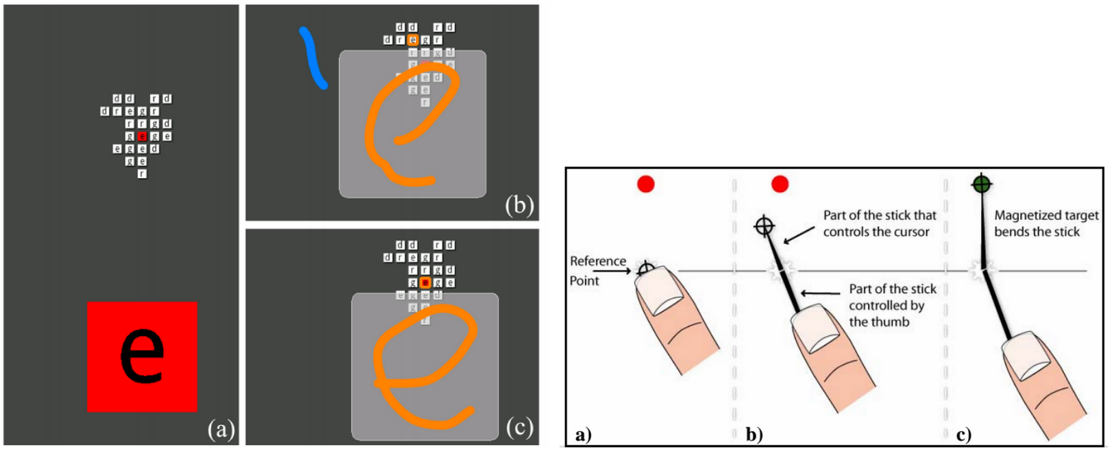

FIGURE 2.3: **Left:** The principle of Gesture Avatar, taken from Lü, H. and Li, Y. (2011), "Gesture Avatar: A Technique for Operating Mobile User Interfaces Using Gestures", in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '11, New York, NY, USA: ACM, pp. 207–216. Copyright 2011 Association for Computing Machinery, Inc. Reprinted by permission. http://doi.acm.org/10.1145/1978942.1978972. **Right:** Description of the MagStick principle, taken from Roudaut, A., Huot, S. and Lecolinet, E. (2008), "TapTap and MagStick: Improving One-Handed Target Acquisition on Small Touch-Screens", in *Proceedings of the Working Conference on Advanced Visual Interfaces*, AVI '08, New York, NY, USA: ACM, pp. 146–153. Copyright 2008 Association for Computing Machinery, Inc. Reprinted by permission. http://doi.acm.org/10.1145/1385569.1385594. Please see Appendix B, section B.1, p. 342 for permission to include figures.

match the drawn gesture, target ambiguity may affect the user experience negatively. However, the approach reduces the impact of Accot's steering law by allowing the user to control elements such as a video playhead from a "distance" using an avatar whose relative position is translated to the actual interface element.

A much simpler approach to reduce target distance is the implementation of gestures, as found in the Dolphin browser (Mobotap, 2012), where the user can perform a variety of simple swiping gestures to control the application. Although the need to enter a dedicated "gesture mode" prevents the gestures from clashing with existing input techniques, such as swipe, the additional interaction step as well as the motor skills to correctly perform the gestures might actually increase interaction time and make the approach unsuitable to improve the efficiency of thumb-based input, especially when considering the large number of possible interactions available on websites. However, some of these effects can be mitigated, as reported by Bragdon et al. (2011), who find that gestures initiated from the bezel can outperform direct tap input if the user is distracted, as these can be carried out eyes-free, without the need for selection precision.

Finally, Samsung present the implementation of a special one-handed operation mode for their range of large mobile devices (Petrovan, 2013). With this mode activated, the screen layout can be scaled down and moved closer to the thumb to provide better access to its elements. However, the downscaling of the content may amplify problems of selection precision. In addition, depending on the scale factor, some elements may still be outside of the thumb's reach.

In summary, approaches to reduce the impact of target distance and size on interaction time for one-handed operation often achieve their goal at the expense of other factors. While the effect of target distance on interaction time may be reduced due to either greater target proximity or the translation of location, as done by ThumbSpace (Karlson and Bederson, 2007) and Gesture Avatar (Lü and Li, 2011) respectively, the problem of occlusion either still partially remains or is amplified (as with the Wavelet menu (Francone et al., 2010)) and challenges may be added by requiring the user to navigate a "tunnel" for item selection (Leaf menus (Bailly et al., 2008), SAM (Bonnet and Appert, 2011)).

2.4 Improving Steering Tasks

As some approaches attempting to reduce the impact of target distance on interaction time, comfort and precision demonstrate, an issue that often accompanies the reviewed techniques is the need to control some kind of cursor or navigate a path with the thumb. Due to the limited mobility of the thumb, controlling a cursor, especially through a complicated "tunnel", can be challenging and time-consuming, as described by Accot's law. To reduce the need for navigating such a path with the thumb, researchers have explored tilting the device and translating the degree of tilt to the position of a virtual cursor or the manipulation of a value.

For example, Sazawal et al. (2002) examine the use of tilting a device for text input, by using the degree of tilt to select letters from different zones of the display. Oakley and O'Modhrain (2005) and Oakley and Park (2007) demonstrate the use of tilt gestures for list scrolling and the operation of marking menus, while Cho et al. (2007) explore tilt interaction for photo browsing. Crossan et al. (2008) show that wrist rotation – and therefore device tilt – can be used for target selection, employing additional hardware strapped to the user's wrist. Following this, Rahman et al. (2009) report that users can control up to 16 different tilt levels with their mobile device, illustrating the potential of tilt-based input. However, in comparison to keypad interaction, van Tonder and Wesson (2010) find that while tilt interaction is perceived as efficient for navigational tasks, such as the panning of a map, it is unsuitable for precise selection and users find it hard to control in various instances, as tilt interaction is inherently limited by the maximum angle by which the wrist and device can be rotated. Furthermore, despite researchers using vibrotactile feedback (Oakley and O'Modhrain, 2005; Cho et al., 2007), user experience can be hampered by the potentially flat viewing angle if the device is tilted beyond a certain degree. This suggests that in addition to vibrotactile feedback, auditory feedback should be given as a means of compensation for the loss of visual confirmation when using this technique. Finally, grip and view adjustment could cause inadvertent input and lead to user frustration, making it a challenge to use the technique efficiently. Therefore, the research indicates that tilting the device to control a cursor may not have the desired effect on reducing interaction time of steering tasks, despite being able to address the problem of occlusion and target distance. This in turn poses the question as to which other techniques could be employed to reduce the effect of Accot's law on selection processes for thumb-based interaction.

2.5 Limiting Interface Occlusion

The research into reducing interaction time and increasing comfort and precision for thumb-operated interfaces has primarily attempted to do so by reducing the distance between pointer and target (section 2.3, p. 43). However, as the analysis has shown, this is sometimes at the cost of interface or content visibility. To address this, researchers have explored a range of approaches that augment the interface and employ a cursor. In addition, back-of-device and side-of-device gestures have been explored to reduce the need for the finger to connect with and therefore occlude the interface. As a result, this section is divided into two subsections, addressing each of the strategies.

2.5.1 Interface Augmentation

Huot and Lecolinet's ArchMenu and ThumbMenu (Huot and Lecolinet, 2007) aim to address the problem of distance and interface occlusion by providing a curved interface close to the thumb. Here, users move their thumb over an arch of elements placed in the bottom right corner of the screen (Fig. 2.4). Interactions are not direct, but via a pointer which is directed by the user's right thumb. This way the content of each button is not concealed, but steering the pointer could be difficult when on the move, likely prolonging interaction time, as a result of steering such a cursor (Accot's law). However, the relatively close distance of the elements to the thumb represents a progression towards limiting the impact of target distance on interaction time as described by Fitts.

Another approach to reduce target occlusion of elements close to the thumb while increasing selection precision is presented by Vogel and Baudisch's Shift technique (Vogel and Baudisch, 2007). When the user touches the screen, Shift generates an enlarged view above the thumb, showing a section of the screen that is occluded by the thumb together with a cursor representing the thumb's current contact position (Fig. 2.4). Moving the cursor over a target and lifting the thumb allows precise selection of even small targets. This superimposed view of the area under the thumb is Shift's main difference to Potter et al.'s Offset Cursor (Potter et al., 1988), which only generates a cursor placed slightly above the pointing device, making it impossible to reach targets below the thumb, for example. Although Shift reduces the error rate for selecting small targets, task completion time is greatly increased in comparison to direct tap. This suggests that Shift should primarily be used for occasional, discrete selection tasks, but avoided for rapid, sequential selections, as the increased trade-off in task completion time might outweigh the benefits in error reduction, as identified by other researchers employing a proxy GUI element for target selection (Roudaut et al., 2008; Lai and Zhang, 2014).

Also attempting to improve selection of small targets close to each other is the Escape technique by Yatani et al. (2008). It requires targets to be assigned a "gesture direction": If the user taps into an area with a high target density, they can disambiguate their selection by sliding their thumb into the same direction the desired target is pointing in, indicating the gesture required for activation. This way, Yatani et al. could improve selection speed over Shift (Vogel and Baudisch, 2007), while maintaining a similar error

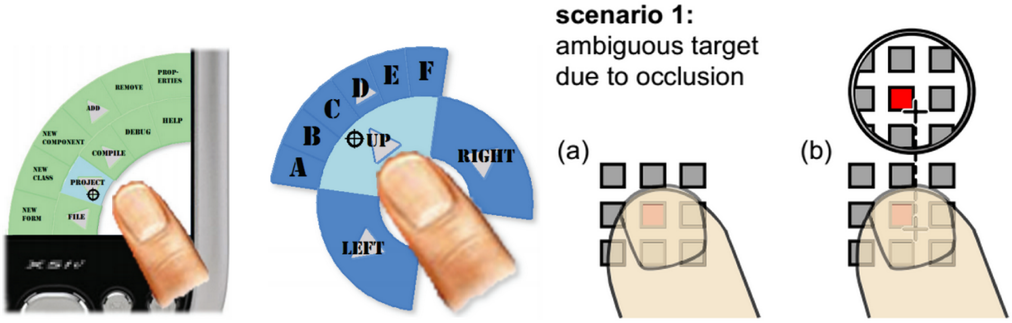

FIGURE 2.4: **Left:** The ArchMenu, taken from Huot, S. and Lecolinet, E. (2007), “ArchMenu et ThumbMenu: Contrôler son Dispositif Mobile ”sur le Pouce””, in *Proceedings of the 19th International Conference of the Association Francophone d'Interaction Homme-Machine*, IHM '07, New York, NY, USA: ACM, pp. 107–110. Copyright 2007 Association for Computing Machinery, Inc. Reprinted by permission. http://doi.acm.org/10.1145/1541436.1541457. **Right:** The Shift technique, taken from Vogel, D. and Baudisch, P. (2007), “Shift: a Technique for Operating Pen-Based Interfaces Using Touch”, in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '07, New York, NY, USA: ACM, pp. 657–666. Copyright 2007 Association for Computing Machinery, Inc. Reprinted by permission. http://doi.acm.org/10.1145/1240624.1240727. Please see Appendix B, section B.1, p. 342 for permission to include figures.

rate, successfully addressing the weak point of Shift. However, Escape has a range of limitations: Gestures can only be executed on-screen and can collide with existing gestures, such as swiping to drag the viewport when navigating a map – an issue of touch operation emphasised by Roudaut (2009). Furthermore, the amount of targets in a given area is limited to the amount of available gestures (eight), reducing Escape's applicability for interfaces with a very high target density.

A technique appearing to combine Escape and Shift is presented by Xu et al. (2011), named RegionalSliding. If the user taps into an area of high target density, a pop-up shows an enlarged representation of the contact area and its surrounding targets. Following this, the user can slide into the direction of the desired target and finalise their selection by lifting their thumb. This approach does not require the assignment of gestures to specific targets as Escape (Yatani et al., 2008) does, but might be hard to perform when the thumb is already stretched or in a corner of the display that would require sliding the thumb further than its maximum reach – or even off-screen – to make a selection. Furthermore, cancelling the selection process may be hard if the target density is too high and the thumb cannot be lifted above a “free” area. Therefore, a more successful technique for improving selection accuracy which is widely employed today is Roudaut et al.'s TapTap (Roudaut et al., 2008). Here, the user first taps onto the desired area of interest in which the target resides. Following this, a pop-up appears showing an enlarged version of the selected area, allowing the user to finalise their selection with another tap. This approach has the benefit that it neither needs a cursor, as found in Shift (Vogel and Baudisch, 2007), nor the assignment of target-specific gestures as in Escape (Yatani et al., 2008). In addition, cancellation is easy by simply tapping outside the pop-up – a great advantage over RegionalSliding (Xu et al., 2011). This way, Roudaut et al. show that selecting small targets otherwise occluded by the thumb can be greatly improved and the effect of target distance and size partly be mitigated by extracting information and presenting it in a dedicated screen area, without losing context. The impact of occlusion is reduced by enlarging the interface elements but, as the thumb still connects with the target, not removed completely.

While the approaches above all address the problem of occlusion, they do not solve it fully, due to the thumb still being on-screen and concealing parts of the interface. Yet, they may present an improvement in comfort and user experience and so the user may regard these as an enhancement of direct pointing, indicating that efficiency is not the all-important factor when enhancing direct interaction.

2.5.2 Back-of-Device and Side-of-Device Interaction

In addition to the on-screen techniques of the previous section, researchers have used the back of a device or its side to free the interface and support touch input. While this can help address the problem of occlusion, many of the presented techniques also help to reduce interaction time and therefore increase efficiency.

Wigdor and Balakrishnan (2004) as well as Scott et al. (2010) show that one-handed multi-tap text input can be improved by providing additional buttons on the back of the device – a simplified version of which can be found in the LG G2 phone, which has a volume button on its back. Similarly, Stienstra et al. (2011) attach a pressure-sensitive button to the back of a smartphone which can be operated to show a varying amount of context-related icons and information on the screen, depending on the pressure exerted. While all of these approaches are likely to have the potential to address issues such as target distance and occlusion, they require additional hardware and seem susceptible to inadvertent operation. The absence of an on or off state and the pressure-based control in Stienstra et al.'s technique limit it to being used for "displaying suggestive

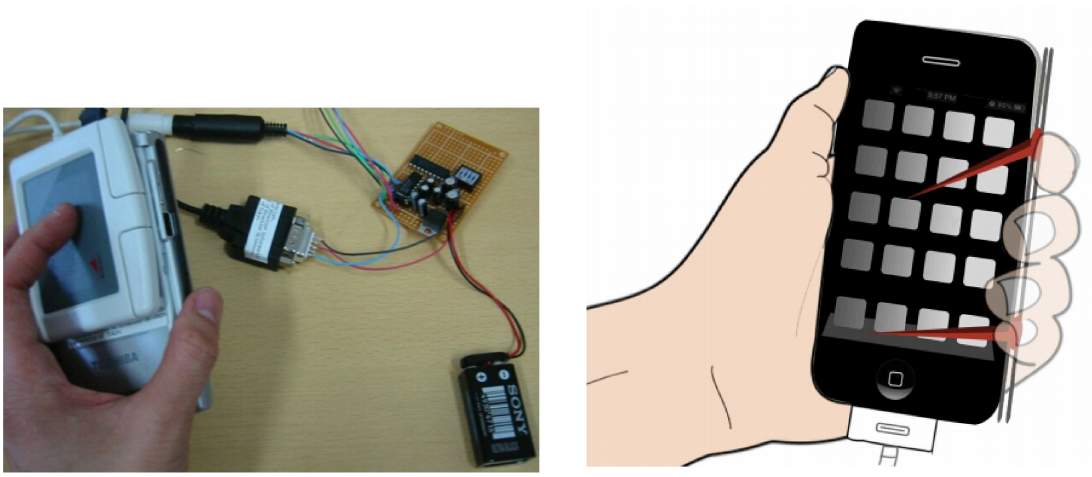

Figure 2.5: **Left:** HybridTouch using a touchpad on the back of a PDA, taken from Sugimoto, M. and Hiroki, K. (2006), "HybridTouch: An Intuitive Manipulation Technique for PDAs Using Their Front and Rear Surfaces", in *Proceedings of the 8th Conference on Human-Computer Interaction with Mobile Devices and Services*, MobileHCI '06, New York, NY, USA: ACM, pp. 137–140. Copyright 2006 Association for Computing Machinery, Inc. Reprinted by permission. http://doi.acm.org/10.1145/1152215.1152243. **Right:** Concept of the Unifone and its pressure sensor on the device's side, taken from Holman, D., Hollatz, A., Banerjee, A. and Vertegaal, R. (2013), "Unifone: Designing for Auxiliary Finger Input in One-Handed Mobile Interactions", in *Proceedings of the 7th International Conference on Tangible, Embedded and Embodied Interaction*, TEI '13, New York, NY, USA: ACM, pp. 177–184. Copyright 2013 Association for Computing Machinery, Inc. Reprinted by permission. http://doi.acm.org/10.1145/2460625.2460653. Please see Appendix B, section B.1, p. 342 for permission to include figures.

information" (2011) rather than the precise control of elements or values, for which this mode of input is unsuitable due to its slow interaction speed (Wilson et al., 2011) and users' limited ability to distinguish between more than three levels of applied force (Heo and Lee, 2011; Boring et al., 2012; Pedersen and Hornbæk, 2014).

For richer interaction, Sugimoto and Hiroki (2006) attach a touchpad to the back of a PDA that allows back-of-device input via the non-dominant hand holding the device, complementing pen input on the device's front (Fig. 2.5). Their studies show that assigning scrolling functionality to the index finger on the back of the device and drawing functionality to the pen on the front of the device improves task completion time compared to the base condition, where both tasks are performed via the pen only. In this, the researchers address the problem of occlusion and that of target distance from the pointing device. However, they also report that users rated precise control of the back-of-device input as hard. This matches the observations of Chau et al. (2006), who describe the index finger on the back of the device to be not as dexterous as the thumb on the front when holding the device in one hand. As a result, Wobbrock et al. (2008), who evaluate the performance of the index finger and the thumb in pointing tasks and path-drawing tasks on the front and back of the device while holding it in either one or two hands, suggest complementing thumb input on the front of the device with rather simple "one-dimensional" index finger input on the device's back.

Following the work of Sugimoto and Hiroki (2006) and Chau et al. (2006), Yang et al. (2009) attach a touchpad to the back of a touchscreen PDA to supplement thumb input with a cursor controlled via the index finger of the hand holding the device. Using their Dual-Surface Input technique, supplementing front-of-device thumb input with the agility of the index finger on the back of the device outperforms front-only and back-only input. This way, the study illustrates the benefits of back-of-device input to support and improve one-handed interaction when used together with touch. Yet, the study also shows problems with this approach when the index finger is used for motion-based tasks, as these often require a certain grip of the device: In order to operate either the thumb or the index finger with a greater degree of freedom, users have to frequently switch their grip, adding to the impact of Accot's law on interaction time when controlling the position of the finger. The resulting degree of user frustration and the potentially rapid tiring of the user's hand render the proposed implementation of Dual-Surface Input less suitable for continuous and frequent input, strengthening Wobbrock et al.'s (2008) suggestion to preferably employ the index finger on the back of the device for simple actions.

Other ways to capture the position of the finger on the back of a device include an additional touchscreen or camera mounted on the device's back, effectively removing interface occlusion from touch interaction. With LucidTouch, Wigdor et al. (2007) show the fingers' positions on the back of the device as a semi-transparent overlay on the screen. Although Baudisch and Chu (2009) show that this technique allows operation of very small displays, Wigdor et al. (2007) report user feedback regarding the usability of this input method on a tablet-sized device as "mixed", illustrating the potential but also the possible limitation of the approach.

As opposed to using finger position on the back of the device to perform direct tap input, Shen et al. (2009) and Wolf et al. (2012) use double-sided multi-touch input to explore a more natural, three-dimensional interaction with a mobile device. In this approach the simultaneous grip and movement on both sides of the device in various positions is interpreted as an expressive gesture. While this technique partly overcomes the problem of interface occlusion for some fingers, the technique requires coordinated grasping and movement interactions of fingers on both sides of the device, which limits its suitability for supporting one-handed interaction.

In addition to the above, approaches exist for back-of-device interaction realised without attaching additional hardware: With TimeTilt, Roudaut, Baglioni and Lecolinet (2009) illustrate how back-of-device input can be implemented by monitoring the accelerometer of a phone and use a tap on the back of the device to activate a mode that allows travelling through open applications by tilting the device. Similarly, Robinson et al. (2011) use a tap on a phone's back to control voice services eyes-free with the help of frequency analysis. Finally, Zhang et al. (2013) employ the accelerometer, gyroscope and microphone volume to detect taps on the four corners of the back case of a tablet when the device is in the user's pocket or held in two hands.

More targeted at enhancing thumb-based input in particular is Holman et al.'s Unifone (Holman et al., 2013), where pressure-sensitive strips are attached onto the side of a touchscreen smartphone (Fig. 2.5). This way, users can supplement one-handed input by exerting pressure in three different zones of the strip. The researchers explore the efficiency of the Unifone gestures in four different applications and find that when used for scrolling tasks, performance is 28% lower than when just using the thumb on the screen. However, tasks "that required displaced movement" of the thumb (Holman et al., 2013), such as formatting, application switching and map navigation, performed better with the Unifone gestures than just with the thumb. The authors conclude that this kind of "auxiliary" input is most efficient when used for tasks that otherwise would imply moving and stretching the thumb frequently over parts of the interface (Holman et al., 2013). In addition, they state that the nature of auxiliary input is "coarse" and that it should be brief, resembling the recommendations given by Wobbrock et al. (Wobbrock et al., 2008).

While Holman et al.'s approach illustrates the usefulness of additional input on the side of the device for one-handed interaction, it also shows its challenges: Being able to exert pressure onto the three predefined zones requires the user to hold the phone in a certain grasp with a degree of tension that limits thumb movement and could be tiring. This is further complicated by the observation of Stewart et al. (2012), that pressure exerted on the frame of a mobile phone increases when walking, implying that the Unifone would require dynamic adaptation of the pressure thresholds to compensate for this effect and avoid inadvertent operation, which in turn might challenge wider user acceptance. Finally, it is unclear how well pressure gestures can be executed in either of the three zones and how accurate the system performs with pressure sensors on both sides of the device to support left-handed and right-handed users alike. Technical limitations aside, the system successfully demonstrates how off-screen input can be employed to support thumb-based interaction and limit occlusion as well as reduce target acquisition time by mapping functionality to the fingers of the hand holding the device, depending on the context.

Another approach implementing additional hardware on the side of the device is Spelmezan et al.'s Power-Up Button (Spelmezan et al., 2013), where the researchers attach a proximity sensor to one side of the phone. Their approach allows a total of six gestures using pressure and proximity states that can be performed with the thumb of the hand holding the device. As with the Unifone (Holman et al., 2013), the researchers reduce occlusion by assigning functionality previously assigned to on-screen buttons to the device frame. But as no user study is provided, it remains unclear how well users can interact with the controller and how well input via the Power-Up Button compares to direct touch. Finally, with the omission of a gesture delimiter, the Power-Up Button's usability in a real-life situation and therefore its user acceptance are likely to be limited.

By following the recommendations given by Wobbrock et al. (2008), the work reviewed in this section demonstrates how simple back-of-device gestures can be used to enrich on-screen interaction with the potential to reduce the impact of occlusion and target distance on user experience. The presented techniques are predominantly of a supportive nature, extending direct touch and reducing the amount of on-screen interaction. Yet, despite Holman et al.'s consolidation of Wobbrock et al.'s characterisation of back-of-device gestures, it remains unclear to what extent one-handed input can benefit from these approaches and which fingers are most suitable to perform this kind of back-of-device interaction when the phone is operated with just one hand. Following this, it needs to be explored whether this kind of input can not only be used for occasional "auxiliary" input (Holman et al., 2013), but also for continuous input to further reduce interface occlusion by the thumb hovering over the display.

2.6 Extending the Input Vocabulary of Direct Touch

In addition to modifying the GUI to improve one-handed operation, researchers have explored extending the input vocabulary of the thumb using on-screen gestures to address the lack of right-click functionality and hot keys in direct interaction (Roudaut, 2009). Roudaut suggests adding a degree of expressiveness using a variety of sensors to make up for the missing tracking state of the mouse or to allow alternative interpretation of the touch event, multiplying the thumb's input capabilities. A good example of this is MicroRolls (Roudaut, Lecolinet and Guiard, 2009), where the researchers use minimal "rolls" of the thumb together with small-scale rubbing and swiping movements to create a set of 16 input gestures to either control GUI elements or offer hot-key-like shortcuts for often-used functionality, such as copy and paste (Fig. 2.6). Similarly, ThumbRock (Bonnet et al., 2013) interprets a backwards and forwards "rocking" motion of the thumb – a spatiotemporal shift in contact size and position – as input and the Glimpse technique (Forlines et al., 2005) allows two degrees of touch pressure to be used as input to simulate the hover state of a mouse pointer, for example. Building on this, researchers use pressure to support text entry (McCallum et al., 2009) or use contact size – often synonymous for pressure – to manipulate continuous values, such as the zoom factor of a map (Boring et al., 2012). Although these gesture sets allow the reduction of GUI elements on-screen and the need to access these – effectively reducing interaction time by eliminating the impact of target distance – and increase the expressiveness of touch input, they might be imprecise and difficult to control if performed when the thumb is stretched or bent outside its comfort zone or if the user is walking (Wilson et al., 2011). Furthermore, they add to the problem of interface occlusion by the thumb, as gestures are performed on-screen.

Instead of using changes in contact size to enrich the input vocabulary, Heo and Lee (2011) use the impact of the thumb when touching the device, measured via the phone's accelerometer, to differentiate between a normal tap and a "Force Tap", effectively adding a second state, such as hover, to the input vocabulary (Fig. 2.6). Hinckley and Song (2011) also combine touch and motion data obtained from a phone's internal sensors, describing a wide array of possible interactions. Their suggested set of gestures is predominantly activated by resting the thumb on the interface and performing a subsequent motion gesture of either the thumb or the whole device in order to manipulate

FIGURE 2.6: **Left:** The MicroRolls gestures, taken from Roudaut, A., Lecolinet, E. and Guiard, Y. (2009), "MicroRolls: Expanding Touch-Screen Input Vocabulary by Distinguishing Rolls Vs. Slides of the Thumb", in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '09, New York, NY, USA: ACM, pp. 927–936. Copyright 2009 Association for Computing Machinery, Inc. Reprinted by permission. http://doi.acm.org/10.1145/1518701.1518843. **Right:** The ForceTap technique, taken from Heo, S. and Lee, G. (2011), "ForceTap: Extending the Input Vocabulary of Mobile Touch Screens by Adding Tap Gestures", in *Proceedings of the 13th International Conference on Human–Computer Interaction with Mobile Devices and Services*, MobileHCI '11, New York, NY, USA: ACM, pp. 113–122. Copyright 2011 Association for Computing Machinery, Inc. Reprinted by permission. Please see Appendix B, section B.1, p. 342 for permission to include figures.

values, such as zoom levels. In this, the touch of the thumb works as an input delimiter, rather than for direct input. A user study shows that the gestures are deemed as easy to perform and intuitive, albeit not easy to discover. Yet, Hinckley and Song's research demonstrates the vast possibilities of enriching the thumb's input vocabulary using a combination of touch and motion, which has also been harnessed by various researchers discussed later in this chapter (p. 58).

Rather than using motion sensors for enriching input, Harrison and Hudson (2008) show with Scratch Input that scratching gestures on a variety of surfaces, such as cloth or wood, can be identified with an accuracy of up to 90% for simple gestures. Yet, it remains unclear whether these can be identified when performed on the screen and whether they can be employed to improve thumb-based operation. This idea is taken further by Lopes et al. (2011) who evaluate the sound frequency spectra of a tap, a knock, a slap and a punch onto a touchscreen's surface (Fig. 2.7). As these are clearly distinguishable, they propose mapping a variety of simple commands to be assigned to each sound and by doing so effectively address the lack of hot keys and a right-click functionality in the paradigm of direct pointing. In a similar approach, Harrison et al. (2011) suggest using sounds created by the fingernail, the knuckle, the fingertip and the finger pad to enrich touch input. However, the sets of gestures presented by Lopes et al. and Harrison et al. may be hard to perform with the thumb when holding the device in only one hand. Similar to ForceTap (Heo and Lee, 2011), Pedersen and Hornbæk (2014) differentiate between different levels of contact force by alysing the volume of the contact sound, but report users have difficulty distinguishing between more than two degrees of force – similar to Boring et al. (2012) – making it less flexible than Lopes et al.'s and Harrison et al.'s techniques (Lopes et al., 2011; Harrison et al., 2011). However, sound volume could be combined with pressure (and therefore contact size) on the display to improve differentiation and allow better control of force as an input method. While these techniques can be applied to reduce target distance by opening a submenu close to the pointing device, for example, the impact of target occlusion by the thumb is not addressed.

In contrast to extending direct pointing by using on-screen gestures in conjunction with the various properties of a touch event, researchers have further explored gestures performed with the whole device, rather than just the screen. Early research into this approach is presented by Harrison et al. (1998), who explore the design and use of tactile interfaces that are enhanced by a variety of sensors, "embedded or wrapped around the devices". Although embedded sensors are a standard in today's off-the-shelf smartphones, Harrison et al.'s work can be seen as pioneering and offers some valuable insights into the potential of this approach as well as its user acceptance. In their prototype, the researchers attempt to map real-world interactions, such as flicking a page, to gestures performed on the frame of the device using a network of pressure sensors. In addition, they explore the usability of these sensors to mimic a scroll bar using a set of "grasp gestures", extending the expressiveness of touch interaction. Furthermore, they explore how tilting of the entire device can be used to navigate through sequential lists – an idea proposed by Rekimoto (1996) and taken up by many researchers (Hinckley et al., 2000; Partridge et al., 2002; Oakley and O'Modhrain, 2005; Oakley and Park, 2007; Roudaut, Baglioni and Lecolinet, 2009). Last but not least, Harrison et al. also explore using pressure pads attached to the back of the device to detect user handedness which is used successfully to alter the interface accordingly.

User feedback shows that the proposed techniques are perceived as "cool" and well-suited for performing the mapped interactions. As a result, Harrison et al. suggest deeper exploration of more analogue or more natural input gestures to improve usability, and

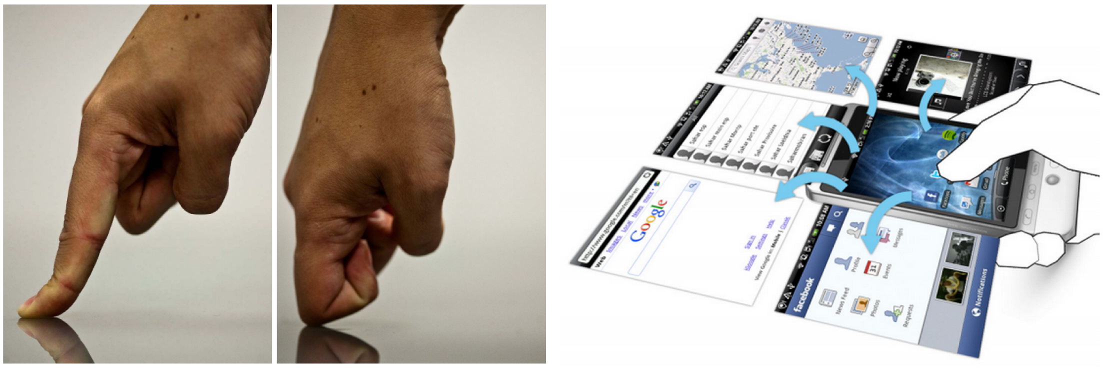

Figure 2.7: **Left:** A "Finger Touch" and "Knuckle Touch" gesture, taken from Lopes, P., Jota, R. and Jorge, J. A. (2011), "Augmenting Touch Interaction Through Acoustic Sensing", in *Proceedings of the ACM International Conference on Interactive Tabletops and Surfaces*, ITS '11, New York, NY, USA: ACM, pp. 53–56. Copyright 2011 Association for Computing Machinery, Inc. Reprinted by permission. http://doi.acm.org/10.1145/2076354.2076364. **Right:** The JerkTilts concept, taken from Baglioni, M., Lecolinet, E. and Guiard, Y. (2011), "JerkTilts: Using Accelerometers for Eight-Choice Selection on Mobile Devices", in *Proceedings of the 13th International Conference on Multimodal Interfaces*, ICMI '11, New York, NY, USA: ACM, pp. 121–128. Copyright 2011 Association for Computing Machinery, Inc. Reprinted by permission. http://doi.acm.org/10.1145/2070481.2070503. Please see Appendix B, section B.1, p. 342 for permission to include figures.

in fact, many gestures, such as flick, pinch, swipe, and tilt, have become the norm in today's mobile interaction design.

The users' response to the detection of handedness as "magical" (Harrison et al., 1998) shows how well received such a feature can be, especially as it not only impresses the user – and so potentially increases their admiration of the device and therefore their perception of increased usability as suggested by Tractinsky et al. (2000) – but also adds real additional value, such as the increase in writing space on a small display, as demonstrated by their user study. However, changing the interface depending on the user's handedness also highlights the importance of correct detection, as an error may cause user dissatisfaction and, if a high degree of correct detection cannot be ensured, may be better employed for non-critical and non-frequent tasks only.

The involvement of the whole device into the interaction – rather than just using the screen for input – is defined as an "embodied interface" by Fishkin et al. (1999, 2000). Linjama and Kaaresoja (2004) follow this idea and use taps against the side of the device to control elements on the screen. In this they free the display of occlusion by the thumb and improve the "naturalness" (Linjama and Kaaresoja, 2004) of interactions with the device by creating a more haptic experience. A "coarser" approach is taken by Ronkainen et al. (2007) and Hudson et al. (2010) who employ “whacking” gestures performed against the device when in a pocket or a bag to execute basic commands, such as cancelling a phone call.

By refraining from using the actual screen for input, the researchers successfully solve the problems described by Fitts’s law, Accot’s law and even the Hick–Hyman law, as in the case of the “whack gestures”, as decisions between interface items do not have to be made. Yet, all this comes at a price: These techniques are rather limited in expressiveness when compared to the work of Harrison et al. (1998), due to their unilateral and “rough” way of interaction. While they successfully address most problems of direct selection, they are not as flexible as the approaches that followed (see below) and combine device motion and touch. As such, the whacking gestures cannot be regarded as a successful solution to improving one-handed interaction as a whole, but rather as a stepping stone towards this goal by adding an alternative, complementary input technique for binary interactions.

Building on this work, researchers combine touch and device motion to further extend the thumb’s input vocabulary. With JerkTilts, Baglioni et al. (2011) present a set of gestures which consists of a distinctive back-and-forth jerk of the hand into eight directions (Fig. 2.7). To avoid inadvertent triggering of the gesture detector, the authors suggest using the touch-down state of the thumb on the display as a gesture delimiter. While this allows using tilts even for continuous input, frequent operation could be tiresome and negatively affect task completion time as users would need to refocus on the display after each tilt before deciding whether to perform the next interaction. Therefore, JerkTilts might be more suitable for simple, discrete input, such as flicking a page in a document or as a shortcut gesture for simple commands, such as undo and redo. This also applies to Ruiz and Li’s use of tilts for their DoubleFlip technique (Ruiz and Li, 2011), in which they employ a quick sideways roll of the device as either a robust gesture delimiter or a gesture itself.

By assigning gestures with the whole device to actions in an application, the researchers overcome the problems of target distance and limited precision of thumb-based interaction – while simultaneously extending the touch input vocabulary – and thus present an improvement over earlier work. But as the thumb is still required to touch the screen to delimit the gesture, they do not fully solve the problem of occlusion intrinsic to thumb-based interaction and the high degree of device movement further impacts interface visibility. Yet, by combining touch and motion, they add an interesting dimension to the paradigm of direct pointing.

The research reviewed so far, addressing the most common challenges of mobile touch interaction, seems to be divisable into two main approaches: Adapting the GUI and extending the input modalities. However, analysing the reviewed contributions made by following either of these approaches, we find that both hold a variety of approaches which address a given problem in isolation – be it the challenges of Fitts's law, Accot's law, interface occlusion or limited reach – but that none of the reviewed work offers a comprehensive solution to addressing these problems together, using a single approach or technique. It is therefore suggestive to explore whether a comprehensive solution to the challenges of thumb-based mobile interaction can be devised using either of the two approaches, rather than addressing just one of the challenges in isolation, as done in previous work.

2.7 User Performance and Layout Orientation

The previously discussed approaches to improve one-handed smartphone operation offer a variety of ways of overcoming the thumb's limitations, but do not offer insight into the users' rationale for preferring to operate the phone with only one hand (Karlson et al., 2006). Earlier research into users' reasons for choosing one interface over another suggests that aesthetic aspects (Tractinsky et al., 2000) or personal preference (Grudin and MacLean, 1985; Bailly et al., 2013) may outweigh efficiency. In addition, the shape of a mobile device follows the evolution of telephone handsets, manifesting in a vertically prolonged body connecting a user's ear and mouth, "affording" (Gibson, 1977; Norman, 1999) to be picked up and held with one hand, similar to a stick. But is this still applicable to devices which seem to be continually growing in size (Fingas, 2013) and where most of a device's front consists of a screen that simultaneously provides both input and output? In addition, is it suitable for a device where the orientation and therefore the interaction method – one or two hands – can be chosen freely and may change depending on the application?

In considering how to improve the one-handed operation of touchscreen smartphones, one has to understand why users operate a device the way they do. With the predominant mode of operation being one hand and the respective phone orientation therefore likely to be portrait mode, it has to be explored whether a phone is faster to operate in portrait or landscape orientation, and with one or two hands. This knowledge could be used to determine whether smartphone grasp and operation is either driven by efficiency or other factors and whether previous findings for stationary devices (Grudin and MacLean, 1985) also apply to mobile devices.

To investigate implications of layout and device orientation on user performance, and ultimately user habit and preference, a starting point might be the examination of the speed with which content presented in either orientation can be perceived and therefore interacted with. In this, a lot of research has focussed on eye movement and scanning strategies. Zusne (1970) reports that more eye movements are made on horizontally presented displays than on vertically presented displays and that the amount of horizontal excursions of the eye when searching for information is greater then the amount of vertical excursions. With regards to saccade speed, Bahill and Stark (1975) report that “vertical saccades are slower than horizontal saccades, with downward saccades being the slowest”. This might explain Dyson’s findings (Dyson, 2004), who reports that the reading speed of long lines of text (with 100 characters per line) is faster than that of shorter lines (with 25 characters per line). However, it might not necessarily mean that information is processed quicker when scanning a display horizontally, as Isys Information Architects Inc. (1999) report that users can “scan written material faster from top to bottom rather than left to right”. Their findings therefore might imply that a vertically presented layout is faster to digest than a horizontal one. This could be supported by Butler’s findings (Butler, 1965), who reports easier detection of symmetry in vertical layouts than in horizontal layouts, suggesting a higher visual salience of vertically presented information. A practical application of this is provided by Microsoft’s recommendation (Microsoft, 2012) to choose a vertical arrangement of radio buttons over a horizontal one when designing interfaces. However, it remains unclear whether this recommendation is meant to improve visibility or operability.

Another pointer regarding the impact of layout orientation on efficiency may be taken from the research of Wallace et al. (1998), who examine users’ search performance in horizontal and vertical lists. Although a “Goals, Operators, Methods and Selection rules”

(GOMS) model predicts a marginally better performance for search tasks in vertical lists, the differences in target selection time are not statistically significant. However, regarding the design of the study, it appears that Wallace et al.'s approach is slightly hampered by the fact that a "horizontal" list in their study is not a true horizontal arrangement of list items, but rather consists of three coherent vertical lists that are arranged next to each other. If a search task is performed on this list, the scanning pattern might still be predominantly vertical per list-division, making it not sufficiently different from scanning a single-column vertical list. Therefore their study provides only limited information regarding the perception and interaction speed of horizontally and vertically presented information.

Using a more robust study design, Chen and Carr (1926) report that the reading speed of horizontally and vertically presented information is largely culturally biased, which is demonstrated by the findings of Nakano (2005), who compare horizontal and vertical reading speed between people from Japan and the USA. Nakano finds that when counting numbers in either portrait or landscape orientation, Japanese participants are faster when the numbers are presented vertically, whereas participants from the USA perform better when these are presented horizontally, corresponding to the reading direction used in each country.

Finally, analysing eye-tracking-generated heat maps based on the desktop presentation of websites (Nielsen and Pernice, 2010) might lead to the assumption that a horizontal button layout will perform better due to user habit. However, Nielsen and Pernice's findings are based on the perception pattern of a large set of interrelated information on a desktop screen, not a single-file layout on a handheld device, and so may be of limited use. According to Fitts's law a vertical page navigation on a desktop interface is likely to be faster to use than a horizontal one based on the lower distance between the discrete items, yet it remains unclear whether the same holds true on a mobile device with equally sized and spaced items interacted with via direct touch. This suggests further examination of the impact of device orientation on mobile interaction performance.

2.8 Detection of Handedness

An approach to improve direct pointing that could be seen as a prerequisite for all GUI-based enhancements is the detection of the pointing "device" in mobile interaction. Depending on which finger is performing the interaction, certain changes to the layout, tailored to the characteristics of the operating finger and hand, have the potential to be more effective than the general approaches for improving direct pointing discussed earlier in this chapter (section 2.2, p. 35). Not only may the efficiency of interaction be increased, but also the user satisfaction, as demonstrated by the positive feedback Harrison et al. (1998) receive for adapting a PDA's interface to the user's grip with the help of pressure pads on the back of the device. Following the work of Harrison et al., Hinckley and Sinclair (1999) attach touch sensors to a computer mouse and trackball to either infer user intention and adjust the screen content accordingly or perform explicit commands in a desktop context. A similar approach is also taken by Kim et al. (2006), though in the mobile domain: The researchers use multiple capacitive touch sensors under the cover of a mobile device together with an accelerometer to determine the user's grip of the device and their possible intention, but report difficulties distinguishing between inadvertent and directed hand postures, highlighting the challenges of this technique when aiming to improve usability.

Another approach that uses additional hardware is presented by Wimmer and Boring (2009), who equip a PDA-shaped prototype with capacitive touch sensors (Fig. 2.8). Based on a user's grasp of the device and the resulting contact with the sensors, the researchers can infer a total of six different grasps. While the device does not provide a touchscreen and so does not allow potential input finger detection when touching it, the device allows the detection of handedness based on the user's grip, which can be employed for basic interface adaptation if a touch-enabled display was provided. Similarly, Taylor and Bove (2009) present two sensor-packed devices in the shape of a ball and in the shape of a soap bar, which can detect a user's grasp with up to 90% accuracy. Ono et al. (2013) vibrate objects and interpret the changes in the object's resonance caused by different grips to identify six hand postures with an accuracy ranging between 71.2% and 86.3%. As opposed to determining hand postures, Noor et al. (2014) use capacitive touch sensors on the back of a phone to predict which part of the screen the finger is likely to land on when shifts in the grip are detected. Rather than using this approach for sensing

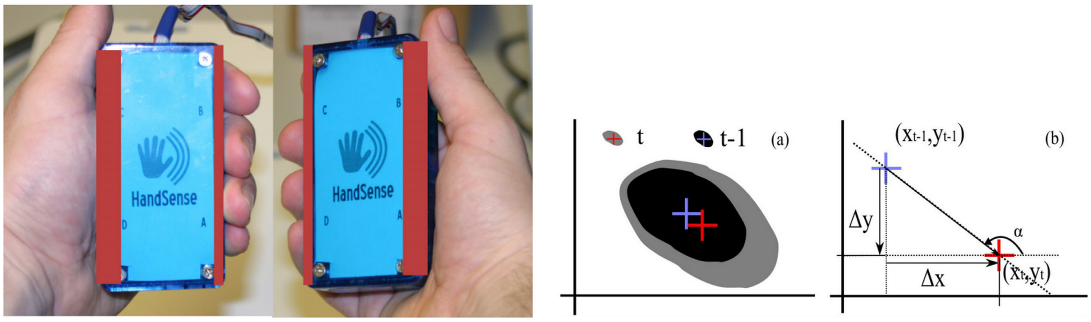

FIGURE 2.8: **Left:** HandSense, taken from Wimmer, R. and Boring, S. (2009), "HandSense: Discriminating Different Ways of Grasping and Holding a Tangible User Interface", in *Proceedings of the 3rd International Conference on Tangible and Embedded Interaction*, TEI '09, New York, NY, USA: ACM, pp. 359–362. Copyright 2009 Association for Computing Machinery, Inc. Reprinted by permission. http://doi.acm.org/10.1145/1517664.1517736. **Right:** Wang et al.'s technique to derive handedness from the finger's landing process, taken from Wang, F., Cao, X., Ren, X. and Irani, P. (2009), "Detecting and Leveraging Finger Orientation for Interaction with Direct-Touch Surfaces", in *Proceedings of the 22nd Annual ACM Symposium on User Interface Software and Technology*, UIST '09, New York, NY, USA: ACM, pp. 23–32. Copyright 2009 Association for Computing Machinery, Inc. Reprinted by permission. http://doi.acm.org/10.1145/1622176.1622182. Please see Appendix B, section B.1, p. 342 for permission to include figures.

handedness, it can be used for preloading content or animations of buttons the user is likely to interact with to improve interface responsiveness and user experience. Yet, the granularity of the possible landing zones is rather low, as in its current implementation the system only seems to be ble to differentiate between the finger likely to land in four zones of the display. In this, a more fine-grained sensor resolution might deliver more accurate predictions.

Rather than focussing on grip detection using additional hardware, Wang et al. (2009) interpret the data provided by a touchscreen controller of a tabletop device. They analyse a finger's landing process and use the directional development of the touch to detect hand orientation (Fig. 2.8). However, their algorithm requires the touch to be an "oblique" touch where two conditions are satisfied: Firstly that the contact area has to be larger than $120mm^2$ and secondly that the length of the touch point has to be larger than its width. Otherwise, the detection is aborted. Although the researchers show that the algorithm detects finger direction and handedness with up to 96.7% precision if the conditions are met, the approach bears problems when used with capacitive touchscreens prevalent in modern smartphones. The first problem is that many capacitive touchscreen controllers do not differentiate between the length and width of the touch point, but rather report the same value for both, forcing the developer to rely on other properties instead, such as the general touch size or touch pressure, both of which do not necessarily denote an oblique touch. The second problem is that users are likely not to perform the required touch gesture carefully, but rather simply touch the screen to pursue their goal, which limits the algorithm's accuracy to determine handedness when used on modern smartphones. Lastly, the authors state that when the thumb is used for input, correct detection of finger orientation is limited as users tend to touch the screen with the thumb's side and not its pad. This problem is exacerbated by the comparatively vertical angle with which the user touches a smartphone screen they are holding in their hand, reducing touch size and correct detection of handedness using Wang et al.'s approach. While the technique allows the detection of finger direction and thus handedness, it does not support detection of which finger is used for input. However, in a study evaluating finger input properties, Wang and Ren (2009) state that for a non-oblique touch, width and length of the registered touch area are between 30% and 40% of the physical size of the fingertip and for an oblique touch these are about 90%. Although not mentioned by the researchers, these observations could be used as a starting point for determining whether it is the thumb or index finger which has touched the screen.

Using contact size and form as a starting point, Guarneri et al. (2013) present an approach labelled ShapeTouch that allows shape recognition on a projected capacitive display. By evaluating directly the input capacitance map of the screen and limiting detection of certain shapes to certain screen regions, the researchers can differentiate between the shape of a cheek, ear, grip and finger. Other researchers (Cao et al., 2008) use the image of an infrared camera beneath a tabletop screen to differentiate shapes of objects on its surface. Yet, it is unclear to what extent the latter approach can be employed on touchscreen smartphones and whether either technique can be used to determined handedness and finger type on these.

Other approaches that could help to determine handedness are TapLogger (Xu et al., 2012) and TapPrints (Miluzzo et al., 2012). In these, the researchers monitor changes in the accelerometer and gyroscope created when touching the phone to infer the area of the screen in which the tap has occurred. Although not mentioned by the authors, whose aim is to determine touch location and therefore the touched GUI element – such as a letter on the soft keyboard – the distinctive patterns created by touches in different areas could potentially be used as a factor for determining handedness and finger type.

Rather than differentiating between different fingers, Harrison et al. (2012) measure the difference in impedance between various users and their environment, thus being able to differentiate touches of both users, even when using the same device simultaneously. Holz and Baudisch (2013) also focus on user classification, using a fibre-optic plate as a screen of a tabletop device. This way, the researchers can read a user's fingerprints through each touch event to verify their authorisation to perform a certain action. Of course, this technique could be extended to the realm of finger differentiation by training the system on the prints of each finger. Yet, the need for the interface to be projected challenge its degree of mobility. Furthermore, the different landing angles of a finger on different parts of a screen is likely to make correct detection difficult.

A more directed approach to determining handedness and input finger using digital touch properties is presented by Goel et al.'s (2012) GripSense. Monitoring the phone's accelerometer, gyroscope and touch events, the system can determine handedness and mode of operation within up to five interaction steps. The algorithm determines handedness and finger type by comparing the collected data of the interaction sequence to a set of properties that are characteristic of each hand and finger. This way, the system can differentiate between usage on a table or in a hand (99.7% accuracy), whether it is being used with the right or left thumb or the index finger (84.3% accuracy), or just grasped and not used. In addition, GripSense is able to distinguish between three levels of pressure with 95.1% accuracy.

The high degrees of accuracy come at a price, though. For the algorithm to make a correct decision, the user has to tap the screen in certain predefined areas and ideally perform a swipe as well. Yet, in a real-life situation this is not always possible. For example, thumb-based GUIs are predominantly located at the bottom of the screen and therefore some time may pass until the user taps the top of the screen as required by the algorithm in order to gain comparative data. Furthermore, users may change their grip depending on the task and GUI they are dealing with (Karlson et al., 2006), which can easily confuse the detection mechanism. In addition, should one decide to use the approach to dynamically adapt the interface to the user's mode of operation, an algorithm that requires up to five interaction steps to make a correct decision is not suitable, as by that point the user might have already finished their task. For this purpose, a mechanism with a maximum of two interaction steps, which can occur in any part of the screen and not only in specified areas, is the ideal.

Through this analysis of previous work on improving direct pointing through the detection of handedness and finger type, it is suggestive that this requires additional hardware or a prescribed interaction sequence to be effective. However, for reasons discussed above, this may not always be adequate. Therefore, the question arises as to what other methods may be developed to tackle this challenge and how efficient these may be in comparison to existing work.

2.9 Conclusion and Suggested Research

The above reviews of previous research have shown that extensive work in the field of mobile interaction design for one-handed touch operation has been done. As suggested earlier, many contributions made to address the problems of this mode of operation seem to fall into two main categories: GUI modification and extension of input modalities. While other modes of interaction exist, they each have their own set of challenges going beyond those of one-handed input: Speech input may have difficulties in referring to "spatial locations" (Hinckley, 2008, p. 169) or cause embarrassment (Wasinger et al., 2005; Feldman et al., 2005) or privacy issues (Hindus et al., 1995) while body gestures may be regarded as uncomfortable to perform in public (to a degree) (Ahlström et al., 2014).

It is therefore suggestive to focus on input via the hand – especially as this is users' main input method (Karlson et al., 2006) – which reduces complexity. However, the discussed approaches to support one-handed interaction often seem to only address a single factor of touch-based interaction in isolation – such as reaching distant targets or reducing occlusion, for example – but fail to address the other main challenges identified on page 41. Should a user wish to overcome all these challenges, they would have to master a variety of techniques and interfaces. However, this strategy requires a high degree of learning and may create further potential problems caused by changing contexts and clashing techniques.

2.9.1 Research questions

Regarding the above, there is a need to explore whether the **main challenges of one-handed smartphone interaction can be overcome together**, under the constraints of this thesis, built on an approach belonging to either of the two identified main research avenues of one-handed smartphone interaction and **only employing a single interface or technique**, thus reducing complexity and increasing learnability. To do so, this thesis will aim to answer the following main research question:

***Main RQ*:** Can an approach following either of the two main strategies to improve one-handed interaction (the modification of the GUI and the extension of the input modalities) address the challenges of Fitts's law, Accot's law and that of interface occlusion by the thumb (as defined in Chapter 2, p. 41) together, using a single interface or technique under a set of social and technical constraints, as formulated in Chapter 3, p. 126?

An answer to this question may not be derived from solely exploring the potential of the two main strategies to address these challenges. Instead, it is important to understand users' needs and preferences as well as the characteristics of index finger and thumb input to create a solution that may not only tackle the challenges successfully under the given constraints, but also corresponds to users' preferences and habits. Therefore, it is necessary to conduct research in a set of areas that will inform the design and development of adequate approaches and help synthesise an answer to the main research question. In particular, research into the following areas needs to be conducted:

- Device orientation performance and user habits
- The properties of touch and their applicability for determining handedness and mode of operation
- Thumb-optimised GUIs
- Extension of a phone's input modalities

To explore these areas, the following subordinate research questions emerge, each constituting a building block in answering the main research question:

***RQ1*:** What is more important to users when operating a mobile device: Efficiency or comfort?

Before beginning to conceive approaches for improving one-handed operation on touchscreen smartphones, it is essential to understand how users hold and operate their device and why they choose to do so. In particular, the relationship between mode of operation, orientation, interaction speed and user preference needs to be explored, and the social and technical constraints for the research in this thesis established. This research question will be explored in Chapter 3.

***RQ2*:** Are the properties of a single "digitised" touch characteristic enough to distinguish between index finger and thumb of the left and right hand?

Altogether, the available techniques for detecting handedness and input mode (finger or thumb) have several limitations. They either use additional hardware (Harrison et al., 1998; Kim et al., 2006; Wimmer and Boring, 2009), require multiple steps in predefined areas (Goel et al., 2012), or require the user's adherence to a certain way of touching the surface (Wang et al., 2009). While Guarneri et al.'s ShapeTouch technique seems to be the most promising approach (Guarneri et al., 2013), no data is available which examines its efficiency for differentiating between finger and thumb or the left hand and right hand. As discussed earlier, it would be desirable to perform input mode detection and the determination of handedness within only one interaction step, at the moment of a touch or just after it has occurred, as users can quickly change their way of operation. Therefore, it should be investigated whether the touch input properties as provided by a touchscreen controller and a device's sensors – such as touch size, pressure, duration, location, rotation and direction – are characteristic of each finger and hand and as a result can be used for a reliable detection of interaction mode and handedness. The investigation of this topic can be seen as a prerequisite to adapting the interface to thumb use with minimal disturbance of the user. This research question will be explored in Chapter 4.

***RQ3*:** Can an approach following the strategy of interface modification successfully address the main challenges of one-handed smartphone operation (as defined in Chapter 2, p. 41) together, using only a single interface?

The research reviewed illustrates how interfaces can be adapted for small screen display and how one-handed operation can be supported using additional GUI elements, graphical overlays, thumb-friendly menus or a combination of these. **However, none of the presented approaches successfully address all major issues of thumb-based touch operation together**. Regarding the reported promising performance of curved menus on thumb interaction, it is suggestive to examine whether an interface following Katre's and Roudaut's recommendations (Katre, 2010; Roudaut, 2009) can be constructed to unify the interaction model of a wide range of different elements to not only increase efficiency and comfort, but also to address all of the main challenges of one-handed interaction together in a single interface.

As the Web is increasingly accessed using mobile devices (Office for National Statistics, 2013), a worthwhile area of investigation and application for such an interface may be the one-handed operation of the Web's diverse and fluent layouts, which cannot be constrained to a static interface, as they are accessed via a plethora of devices and screen sizes. As previous research has predominantly focussed on adapting the presentation of websites rather than the interaction model for thumb use, it remains unclear whether interface adaptation that overcomes the limitations of previous work and addresses the main challenges of one-handed smartphone operation in so diverse and challenging an environment can be achieved. This research question will be explored in Chapter 5.

***RQ4*:** Can an approach following the strategy of input modality extension using a device's sensors successfully address the main challenges of one-handed smartphone operation (as defined in Chapter 2, p. 41) together, using only a single technique?

As the thumb's movement and precision are limited, researchers have explored approaches beyond the GUI. In particular, the research into back-of-device interaction has shown great creativity and results but it has also presented many challenges. To enrich touch interaction via this input mode, researchers use additional hardware (Sugimoto and Hiroki, 2006; Wigdor et al., 2007; Yang et al., 2009; Holman et al., 2013), built-in sensors (Roudaut, Baglioni and Lecolinet, 2009; Robinson et al., 2011; Zhang et al., 2013) and explore the utilisation of the index finger on the back of the device to support interactions of the thumb on the front of the device (Wobbrock et al., 2008). Yet, despite the large amount of previous work focussing on this area, it remains unclear whether an approach following the paradigm of input modality extension can address the main challenges of one-handed smartphone interaction together, using one technique. This research question will be explored in Chapter 6.

2.9.2 Conclusion

By exploring the above research questions, this thesis aims to establish whether thumb-based interaction can be improved with regards to the challenges of Fitts's law, Accot's law and interface occlusion by using either of the two main approaches: One based on the paradigm of modifying the GUI and one based on the paradigm of extending the hand's input modalities, using only a single interface or technique. Both approaches will draw on the insights into users gained from the work undertaken in Chapter 3 and work within a set of social and technical constraints (Chapter 3, p. 126). Chapter 7 will conclude the thesis and reflect the proposed approaches and findings, discussing their contribution to the field and suggesting future areas of research.

Chapter 3

Efficiency or Comfort: Why Do Users Hold Their Phones the Way They Do?

3.1 Introduction

This chapter conducts two quantitative studies to compare different modes of interaction and device orientation. It finds that interacting with a device is fastest when using two thumbs in landscape orientation. A user survey reveals that users prefer to operate their devices using one hand in portrait orientation, preferring comfort and habit over efficiency. Together with the average technical specifications gathered from users' devices, this chapter provides the foundation and constraints for the research conducted in the following chapters.

Regardless of the differences in perception speed between horizontally and vertically presented information (Chapter 2, section 2.7, p. 61), Wobbrock et al.'s 2008 studies that were discussed earlier show that the index finger performs better than the thumb in pointing tasks on the front and back of a device, suggesting that the prevalent thumb operation of mobile devices is not due to performance reasons, but to some other factor. As discussed in the previous chapter, the evolution of the smartphone from the telephone handset brings with it its affordance of being held in one hand. However, it remains unclear why users operate the device via the thumb of the same hand they hold it in (Karlson et al., 2006), especially as the researched detailed in the literature review clearly shows that operation via the thumb has many disadvantages, ranging from occlusion and imprecision to reach limitations and possible strain, especially when used for repetitive input. Even more so since data indicates that the majority of smartphones sold in recent years possess a touchscreen (GfK, 2012) and have lost the keypad that constituted the main input facility for the once widely used flip and candy-bar-style phones. This being the case, the interactive elements are extended across the height of the device, and no longer limited to an easy-to-reach area in the bottom half. With regards to the above, the following research question emerges:

***RQ1*:** What is more important to users when operating a mobile device: Efficiency or comfort?

To investigate, this chapter will explore efficiency aspects of phone orientation and mode of operation together with users' preferences relating to the operation of various applications. Understanding why users operate a phone the way they do and what impact phone orientation and mode of operation have on efficiency is important in order to design interfaces that aim to improve one-handed operation of touchscreen smartphones. To address these topics, this chapter pursues a set of research goals. The insights gained from these will help to answer the research question *RQ1*:

- ***G1*:** Establishing in which orientation (landscape or portrait) a phone is faster to use when using the index finger, one thumb, and two thumbs.
- ***G2*:** Determining which area of the display is fastest to interact with.
- ***G3*:** Defining the average technological specifications of today's smartphones.
- ***G4*:** Learning which applications users use the most and how users operate standard applications.
- ***G5*:** Learning users' subjective reasons for operating a device in the way they do.
- ***G6*:** Examining whether Karlson et al.'s (2006) findings about one-handed use of mobile phones are equally valid today, in a climate where the majority of sold smartphones are touchscreen-only devices (GfK, 2012).

To pursue these goals, this chapter is divided into four sections: Following the introduction, the chapter will examine the effects of phone orientation and mode of operation in two user studies, addressing the first two goals. This is followed by the results of a user survey which focusses on gaining further insight into users' devices and users' habits, expectations and preferences. Finally, a conclusion will be drawn and the research question *RQ1* answered, constituting a reference point for the research undertaken in the subsequent chapters.

3.2 The Impact of Phone Orientation and Mode of Operation on User Performance

This section will consider the impact of phone orientation and mode of operation on interaction speed. In particular, it will examine whether a touchscreen smartphone is faster to use in landscape or portrait orientation, with the index finger, the thumb, or both thumbs. It will explore whether certain areas of the display are faster to interact with in each orientation and mode of operation to inform interface design. To do so, this section is separated into two subsections: One presenting a user study to investigate the first two research questions by examining index finger input (Study One), and one presenting a user study to explore the same research questions by examining input with either one or two thumbs (Study Two).

3.2.1 Study One: Phone Orientation and User Performance with the Index Finger

This section is based on Seipp and Devlin (2013*b*), but is rewritten and provides a more comprehensive analysis than the paper.

Study One – Study Design

To investigate whether a phone is faster to use in landscape or portrait orientation using the index finger, a user study was conducted with 44 users (13 F, 20–35 years old). All users were British and right-handed, and 95% declared themselves to be regular smartphone users.

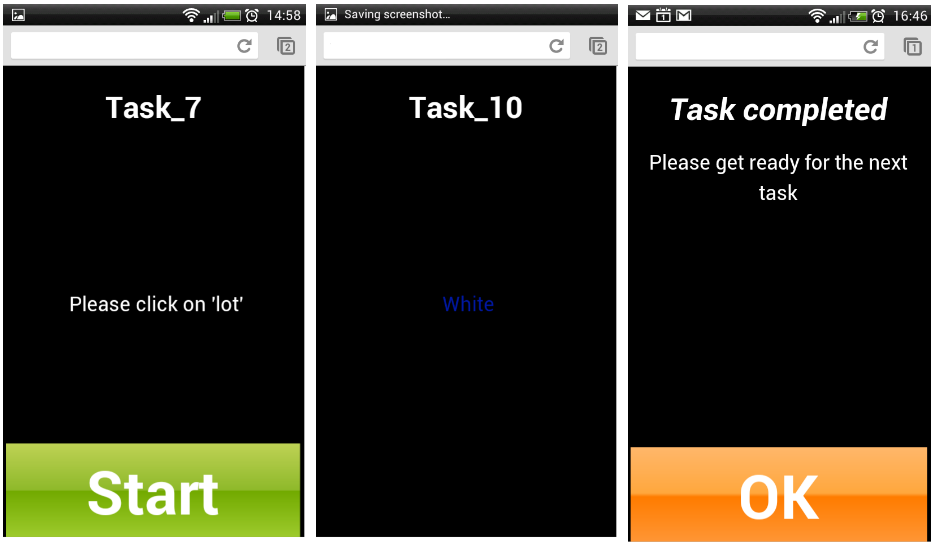

FIGURE 3.1: **Left:** The task screen of R1: Users had to tap on the button labelled "lot". **Middle:** The task screen of R2: Users had to tap on the button labelled "blue" (the font colour is the indicator). **Right:** The end screen displayed after task completion. Images taken from Seipp and Devlin (2013*b*).

The study was separated into two rounds: In the first round (R1), users were tasked with holding the phone in their right hand while operating it with their left index finger. The participants had to tap a target in layouts of three, five and eight buttons, once holding the phone in portrait orientation, once holding it in landscape orientation (Fig. 3.2). For each task, users were presented with an instruction screen, detailing the button to be found (Fig. 3.1). After tapping "Start", a layout was presented in which they had to identify the previously indicated button by tapping it. Following a successful tap, a confirmation was shown (Fig. 3.1) after which the next task screen was displayed. Recording started when the user tapped "Start" and ended when the correct target was tapped. Targets were placed in three predefined zones (Fig. 3.2) and had to be found twice in each layout and orientation, resulting in a total of 36 taps. Each target was a square of 8mm x 8mm, close to the recommended ideal button size given by Parhi et al. (2006), Park and Han (2010), Apple (n.d.*b*) and Microsoft (n.d.). To reduce visual salience impacting the results, all buttons had the same colour and were labelled with a three-letter word (Fig. 3.2).

In a second round (R2), an element of brief consideration was introduced to simulate a search task of an unknown element. For this, a Stroop-Effect-like method (Stroop, 1935) was employed: For each task, users were shown the name of a colour, displayed in a different font colour. The screen automatically vanished after one second, presenting

FIGURE 3.2: **Left:** A layout of eight buttons in portrait orientation in R1. **Right:** A layout of five buttons in landscape orientation in R2. The three target zones are superimposed in red. Images taken from Seipp and Devlin (2013*b*).

the layout of buttons in the same style as in R1, although with colour names replacing the three-letter button labels (Fig. 3.2), resulting in a slightly more complex feature set to process in the visual search. To complete the task, users had to tap the button that described the font colour in which the previously displayed word was written in (Fig. 3.2). Recording of the task completion time started as soon as the screen had vanished and ended once the user had tapped the correct target.

The study was counterbalanced by mode, button layout and orientation: Once the starting mode had been determined (normal or Stroop-like), users had to perform all tasks in one orientation first before moving to the other, with half of the participants beginning the tasks in portrait orientation. Within each orientation, half of participants performed the tasks by starting with a layout of three and ending with a layout of eight, while the other half started with a layout of eight, ending with a layout of three. This was done with the first 40 participants. The remaining four users started in Stroop-like mode in landscape orientation and a layout of five buttons, followed by three and then eight. Using scatter plots, any data points that had an interaction time (IT) in one of the three layouts that was larger than the limits listed below or where the user had tapped the screen more than once were identified as outliers and removed from the respective analysis.

- Three-button layout: Maximum IT 2.75 seconds
- Five-button layout: Maximum IT 3.25 seconds
- Eight-button layout: Maximum IT 3.75 seconds

The data sets and study information can be found in Appendix C, pp. 344–346. During the study it was observed that users retracted their index finger after tapping the "Start" and "OK" buttons shown on each task screen and end screen respectively, but let the finger hover near the bottom part of the display, both in landscape and portrait orientation.

Study One – Results R1

A three-way ANOVA showed an effect of target position ($F(2, 76) = 3.65$, $p = .031$), an effect of amount of buttons in a layout ($F(2, 76) = 123.65$; $p < .001$) and an interaction of orientation and amount ($F(2, 76) = 5.44$; $p = .008$). Please note: After closely reviewing the work, it was found that the ANOVA results were initially incorrectly reported in Seipp and Devlin (2013*b*), as outliers were included. As a result, this chapter provides the correct values for the ANOVAs without the outliers and two additional Wilcoxon tests. While these corrections extend the evaluation, they do not change the overall results reported in Seipp and Devlin (2013*b*).

TABLE 3.1: Mean and median IT for layouts with three (3), five (5) and eight (8) buttons in R1 of Study One.

Layout	**3**	**5**	**8**
Mean IT	1220.1	1380.9	1708.3
Median IT	1185.6	1388.3	1723.9
SD	199.3	227.7	303.9

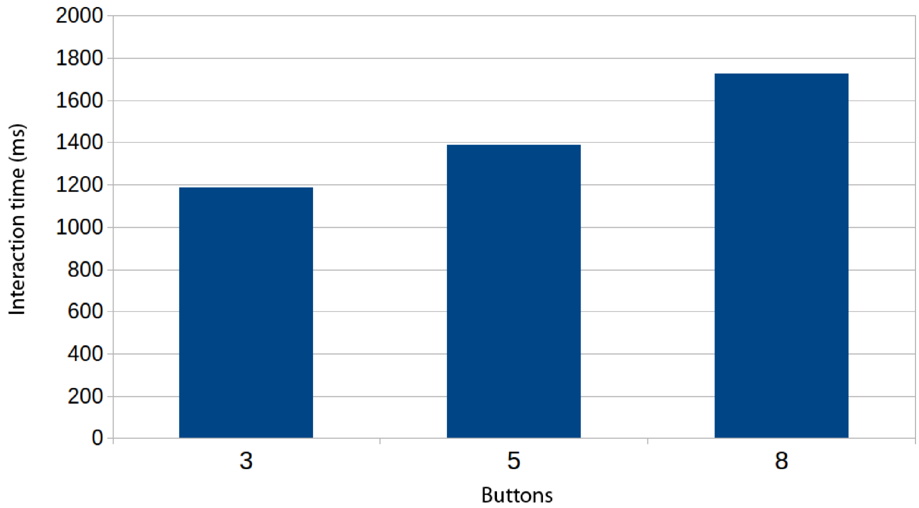

FIGURE 3.3: Visualisation of the median IT for layouts with three (3), five (5) and eight (8) buttons in R1 of Study One (taken from Table 3.1).

Effect of amount:

Breaking down the results using a Wilcoxon test revealed that the three-button layout was faster to interact with than both the five-button layout, $Z = 3.88$, $p < .001$, and the eight-button layout, $Z = 5.23$, $p < .001$. In addition, finding a target in the five-button layout was faster than finding a target in the eight-button layout, $Z = 5.32$, $p < .001$. See Table 3.1 and Figure 3.3. Results were Bonferroni-corrected (alpha: .05/3 = .017).

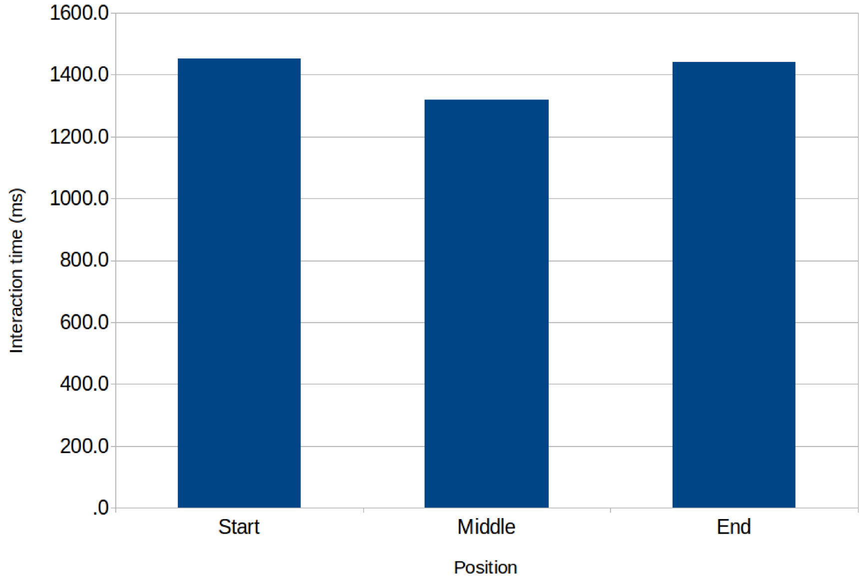

FIGURE 3.4: Visualisation of the median IT for positions *Start*, *Middle* and *End* in R1 of Study One (taken from Table 3.2).

TABLE 3.2: Mean and median IT for targets in positions *Start*, *Middle* and *End* in R1 of Study One.

Position	**Start**	**Middle**	**End**
Mean	1438.2	1318.8	1471.0
Median	1450.8	1318.5	1441.0
SD	244.4	237.0	245.0

Effect of position:

A set of Wilcoxon tests indicated that IT was lower for position *Middle* than for both position *Start* ($Z = 3.65$, $p < .001$) and position *End* ($Z = 3.6$, $p < .001$). Differences between positions *Start* and *End* were not observed. See Table 3.2 and Figure 3.4. The results were Bonferroni-corrected (alpha: $.05/3 = .017$).

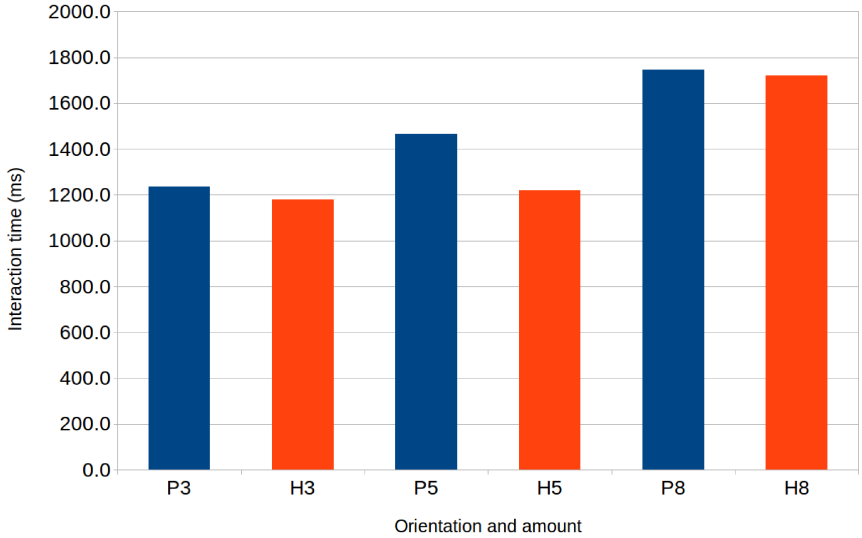

FIGURE 3.5: Visualisation median IT for layouts with three (3), five (5) and eight (8) in landscape (L) and portrait (P) orientation in R1 of Study One. (taken from Table 3.3).

TABLE 3.3: Mean and median IT for layouts with three (3), five (5) and eight (8) in landscape (L) and portrait (P) orientation in R1 of Study One.

Layout	**P3**	**L3**	**P5**	**L5**	**P8**	**L8**
Mean	1240.2	1251.0	1496.1	1279.3	1750.7	1698.0
Median	1235.8	1180.8	1466.8	1219.5	1747.3	1719.8
SD	188.7	307.6	261.4	248.1	320.9	365.6

Interaction of orientation and amount:

A set of Wilcoxon tests indicated that a five-button layout was faster to interact with in landscape than in portrait orientation ($Z = 4.55$, $p < .001$), but other differences were not statistically significant. See Table 3.3 and Figure 3.5. The results were Bonferroni-corrected (alpha: $.05/3 = .017$).

Study One – Discussion R1

The results show that IT increases with button count, which is to be expected and explainable with the Hick–Hyman law (Hick, 1952; Hyman, 1953).

The effect of target position shows that position *Middle* has the lowest IT in both orientations, but no statistically significant differences were found between positions

Start and *End*. The fastest interaction with targets in position *Middle* is likely due to the Simon effect (Simon and Wolf, 1963), which states that responses are fastest in the area of visual stimulation. As the user's gaze may have been fixed onto the middle of the screen to read the task instructions, it is likely to have remained in this position after the task screen had vanished and the button layouts were revealed.

The lack of statistically significant differences in IT for position *Start* and *End* suggests that either these had been learned by users, allowing them to quickly "jump" to these positions with their visual focus, or that the priming (Ware, 2012, p. 296) of the users with the target label allowed them to identify the target without employing a visual search strategy, making them equally fast to interact with in a potentially enlarged Useful Field of View (UFOV) (Ware, 2012, p. 173) due to a relatively low cognitive load.

In landscape orientation, this observation may be supported by an explanation following an informal prediction of Fitts's law: The users' index fingers hovered over the bottom middle of the screen, allowing a low IT for targets near this position and an equally high IT for targets to the left and right of it. However, in portrait orientation, Fitts's law would have predicted a lower IT for targets at the bottom of the screen (position *End*) and a higher IT for targets near the top (position *Start*), due to their differences in distance from the finger hovering over the bottom of the screen. As this is not the case, the results suggest that a different factor may have a greater impact on IT than Fitts's law. It is thinkable that the priming of the user with the target label greatly sped up the processing of visual information, potentially making differences in target distance neglectable within the constraints of this study.

A reason for this observation may be provided by Anderson et al. (1997), who discuss Shiffrin and Schneider's visual search study where users identify a letter among a set of numbers (Shiffrin and Schneider, 1977). Similar to Shiffrin and Schneider's study, the feature set of the targets in R1 was very simple, as they only differed in the first letter, allowing quick processing of the information by applying a "production pattern-match test" (Anderson et al., 1997) rather than a serial search task for target identification, resulting in a quick response time. Therefore Shiffrin and Schneider's study can help to interpret the similar IT for the target zones *Start* and *End*.

The observation that in a five-button layout the IT was lower when the phone was operated in landscape orientation, but that for the other layout configurations no statistically significant differences were observed between landscape and portrait orientation, suggests that there may be a light effect of orientation (with a trend of landscape being faster than portrait), but that target simplicity and priming the user with the target label have such a strong impact on IT, that the potential effect of orientation is cancelled in most situations.

All in all, the data suggests that under the study's conditions, visual aspects of a target may have a greater impact on IT than spatial aspects if the target name is known and if the feature set is rather simple. However, to elucidate this point, further research is necessary beyond the scope of this thesis.

Study One – Results R2

A three-way ANOVA of the data collected in the Stroop-like mode revealed an effect of orientation, $F(1, 28) = 38.66$, $p < .001$, an effect of target position, $F(2, 56) = 30.14$, $p < .001$, and an effect of button count, $F(2{,}41.38) = 70.85$, $p < .001$ (Greenhouse-Geisser-corrected). In addition, the ANOVA highlighted an interaction between target position and amount of buttons, $F(4, 112) = 25.6$, $p < .001$. Please note: After closely reviewing the work, it was found that the ANOVA results were initially incorrectly reported in Seipp and Devlin (2013*b*), as outliers were included. However, this chapter provides the correct values for the ANOVAs without outliers. The significance of the ANOVA results reported in the paper is not affected. The calculations of post-hoc tests, their significance and the findings are not affected either, as outliers were correctly excluded for these in the paper.

Table 3.4: Mean and median IT for landscape and portrait orientations in R2 of Study One.

Orientation	**Landscape**	**Portrait**
Mean IT	1314.4	1452.6
Median IT	1283.0	1437.0
SD	260.4	252.5

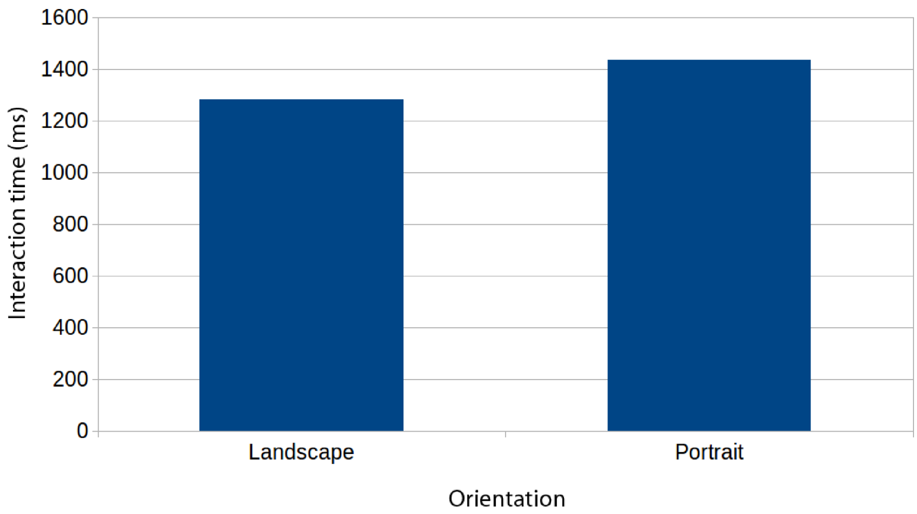

Figure 3.6: Visualisation of the median IT for landscape and portrait orientations in R2 of Study One (taken from Table 3.4).

Effect of orientation:

Breaking down the ANOVA results using a Wilcoxon test showed a statistically significant difference in IT between portrait and landscape orientations, $Z = 3.54$, $p < .001$. See Table 3.4 and Figure 3.6. Results were Bonferroni-corrected (alpha: $.05/2 = .025$).

TABLE 3.5: Mean and median IT for targets in positions *Start*, *Middle* and *End* in R2 of Study One.

Position	**Start**	**Middle**	**End**
Mean IT	1703.4	1272.9	1477.0
Median IT	1465.8	1224.3	1378.3
SD	756.3	313.0	324.0

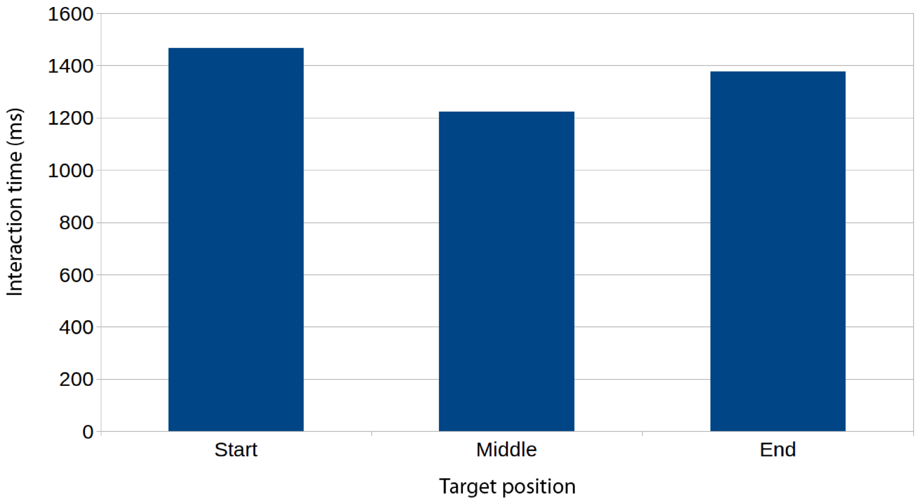

FIGURE 3.7: Visualisation of the median IT for targets in positions *Start*, *Middle* and *End* in R2 of Study One (taken from Table 3.5).

Effect of position:

Another Wilcoxon test showed that the difference in IT between the three target positions was statistically significant: Targets in position *Start* were slower to interact with than targets in both position *Middle*, $Z = 5.59$, $p < .001$, and *End*, $Z = 2.69$, $p = .007$. In addition, targets in position *Middle* were faster to interact with than those in position *End*, $Z = 4.91$, $p < .001$. See Table 3.5 and Figure 3.7. Results were Bonferroni-corrected (alpha: $.05/3 = .017$).

Table 3.6: Mean and median IT for layouts holding three (3), five (5) and eight (8) buttons in R2 of Study One.

Layout	**3**	**5**	**8**
Mean IT	1216.8	1352.7	1598.8
Median IT	1170.0	1302.9	1589.5
SD	208.4	238.1	306.7

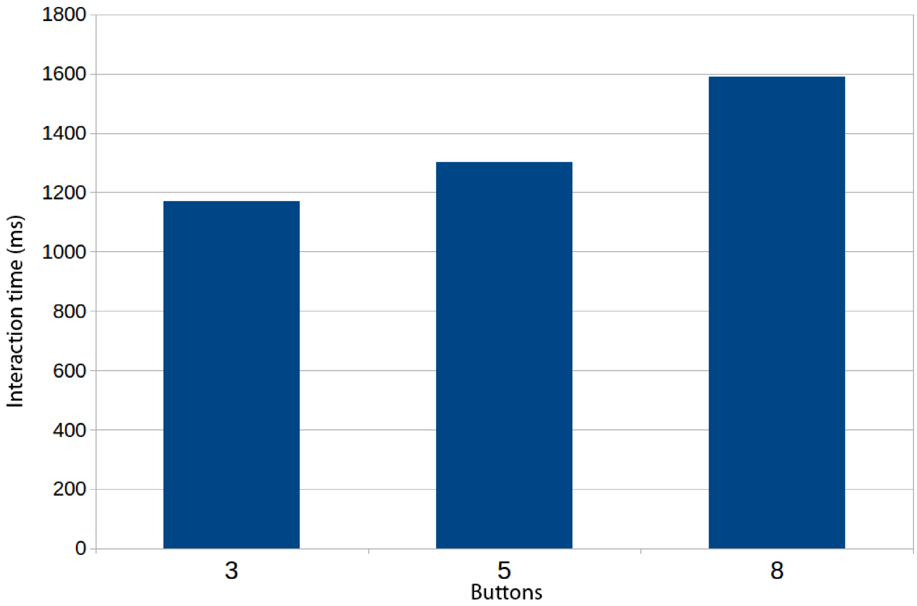

Figure 3.8: Visualisation of the median IT for layouts with three (3), five (5) and eight (8) buttons in R2 of Study One (taken from Table 3.6).

Effect of amount:

A Wilcoxon test revealed that users' IT was lower in layouts of three buttons than in layouts of both five buttons, $Z = 4.28$, $p < .001$, and eight buttons, $Z = 4.94$, $p < .001$. Furthermore, users' IT for targets in a layout with five buttons was lower than the IT for targets in a layout with eight buttons, $Z = 4.81$, $p < .001$. See Table 3.6 and Figure 3.8. Results were Bonferroni-corrected (alpha: .05/3 = .017).

TABLE 3.7: Mean and median IT for the positions *Start* (S), *Middle* (M) and *End* (E) in layouts of three (3), five (5) and eight (8) buttons in R2 of Study One.

Amount/pos.	**3 S**	**3 M**	**3 E**	**5 S**	**5 M**	**5 E**	**8 S**	**8 M**	**8 E**
Mean IT	1283.9	1311.2	1229.2	1520.7	1166.9	1454.2	1889.4	1415.0	1749.3
Median IT	1222.3	1299.5	1180.8	1458.3	1102.5	1392.5	1866.5	1285.4	1715.3
SD	270.1	300.7	266.4	321.0	264.9	291.1	436.2	407.5	385.6

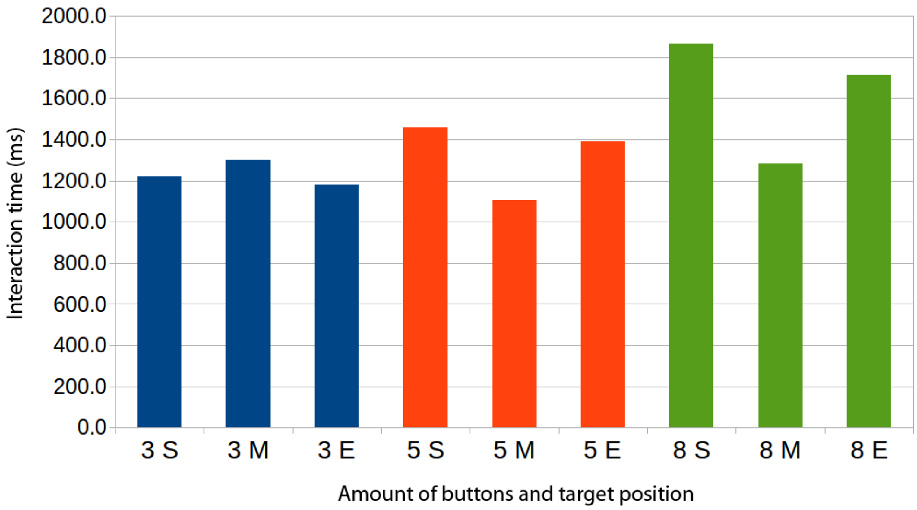

FIGURE 3.9: Visualisation of the median IT for the positions *Start* (S), *Middle* (M) and *End* (E) in layouts of three (3), five (5) and eight (8) buttons in R2 of Study One (taken from Table 3.7).

Interaction of amount and position:

Using further Wilcoxon tests to explore the interaction between amount of buttons and target position showed no statistically significant differences in IT between the three target positions in a three-button layout. However, in a layout with five buttons, targets in the position *Middle* were faster to interact with than those in both position *Start*, $Z = 5.36$, $p < .001$, and position *End*, $Z = 4.80$, $p < .001$. In the eight-button layout, targets in position *Middle* were faster to interact with than targets in both position *Start*, $Z = 4.34$, $p < .001$, and position *End*, $Z = 4.31$, $p < .001$. Targets in position *End* were faster to interact with than targets in position *Start*, $Z = 2.92$, $p = .003$. See Table 3.7 and Figure 3.9. All results were Bonferroni-corrected (alpha: $.05/9 = .006$).

Study One – Discussion R2

The breakdown of the three effects and one interaction indicates the following:

- If the user has not been primed with the target but has to perform a search task to find it, interaction with a device in landscape orientation is faster than interaction with a device in portrait orientation.
- The IT in both orientations increases with the amount of buttons in a layout, likely to be explainable with the Hick–Hyman law (Hick, 1952; Hyman, 1953) or the employment of a search strategy.
- Using the experimental set-up described earlier, both device orientations appear to hold zones in which a target is faster to interact with than in others. These are the same for both orientations. Although the effect was not visible in layouts with three buttons, layouts with five buttons showed that the position *Middle* is faster to interact with than positions *Start* and *End*. In a layout with eight buttons, this trend was stronger, revealing the lowest IT for targets in position *Middle*, followed by *End*, followed by *Start*, forming an efficiency rating for both orientations of *Middle* < *End* < *Start* in layouts with more than five buttons (Fig. 3.10).

The observed ranking of the three target positions is likely due to a combination of the Simon effect (Simon and Wolf, 1963) – which states that responses are fastest in the area of visual stimulation – reading order, and Fitts's law. As a user's gaze may have been fixed onto the middle of the screen to read the task instructions, it is likely to have remained in this position after the task screen had vanished and the button layouts were revealed. This allows quick perception of and interaction with targets in position *Middle*, similar to the observation made in R1 of Study One.

The second-fastest IT for targets in position *End* may be due to the employment of a serial search strategy, as reported by Megaw and Richardson (1979), which corresponds to the participants' practised reading pattern of top to bottom and left to right, starting in the middle of the screen, and is probably explainable by the ACT-R model, described by Anderson et al. (1997) and Nilsen and Evans (1999) and likely to be caused by the need to identify the more complex targets by reading and thinking, as opposed to R1 where targets had simpler labels and the user was primed with the target name.

FIGURE 3.10: The observed efficiency ranking of the three target zones in R2. *Middle* is fastest, followed by *End*, followed by *Start*. This applies to landscape and portrait orientation. In addition, interaction with a device in landscape orientation is faster than in portrait orientation.

In their ACT-R model, Anderson et al. suggest a time of 185ms for visual attention to switch to a different position. If this is applied to the IT for the three target zones in a layout of eight buttons where the observed effect is strongest, mean reaction times ought to be 185ms apart. If we assume that three elements are processed in one gaze (Kieras and Meyer, 1994), starting at position *Middle*, one shift in attention should suffice to identify the target at position *End*. However, mean IT for this position was 334ms higher than for position *Middle*, suggesting that either more than one shift of attention may be necessary in this potentially serial search or that the remaininG149ms may represent the target acquisition time. The shorter difference between position *End* and *Start* of 140ms suggests that the search method between these two is not serial, but directed, indicating that the user knows where to look for the next target after the search has reached the end of the list, resulting in a shorter time for switching attention and acquiring the target.

Another explanation attempt could be made by analysing the differences in IT using Fitts's law, as the distance between finger and target for position *End* was much lower than the distance between finger and position *Start* in portrait orientation. However, if this was the main factor, IT should have been the same for targets in position *Start* and

End in landscape orientation (as observed in R1), as these were equidistant to the index finger's starting point in the lower third of the horizontal middle of the screen. Yet, this does not apply to the measured IT for the respective positions, suggesting that the Simon effect and a search strategy based on a culture's reading pattern may have a larger impact on IT than target distance and size – a suggestion also made by Anderson et al. (1997, p.457), who ponder that if the target position is unknown, a visual search strategy may impact IT more than Fitts's law and vice versa. However, further exploration of this aspect would require eye tracking, which, if available, could help to model the selection time for linear menus (Bailly et al., 2014) and improve interpretation of these results.

Finally, the aforementioned possibility of users perceiving up to three items in one gaze (Kieras and Meyer, 1994) – probably depending on the distance between target and fovea – and a potentially enlarged Useful Field of View (Ware, 2012, p.173) in a low-density layout of three buttons may reduce the need for a search strategy and therefore helps to interpret the lack of statistical differences in IT in a three-button layout. In addition, differences in IT caused by distance from the pointing device may have been minimised due to the close proximity of the three targets.

The overall better performance of the landscape orientation over the portrait orientation may be due to a variety of factors: The slightly greater proximity of the index finger to the targets in the three positions when starting in the middle in landscape orientation compared to the bottom in portrait orientation (as observed during the study), the faster scanning of the horizontally presented information due to faster saccades (Bahill and Stark, 1975), and the possibility that horizontal movements of the hand and finger may be faster to execute than vertical ones. While the exploration of the impact of these factors goes beyond the scope of this chapter, future research could focus on examining the impact of scanning pattern, muscle groups and Fitt's law on IT by combining gaze tracking with electromyographical data and chronometric measurements. For answering the research questions, however, the finding that a device is faster to interact with in landscape orientation than in portrait orientation does suffice.

3.2.2 Study Two: Phone Orientation and User Performance with the Thumb

In order to avoid putting thumb input at a disadvantage by placing items in notoriously hard-to-reach areas of the screen for this mode (north-west and south-east, (Karlson et al., 2006)), a similar set-up to Study One (section 3.2.1, p. 75) was used to test user performance with the thumb. Ten participants (five F, mean age: 33.9, SD: 2.75, all right-handed, seven English, three German, all regular smartphone users) took part in a second study which explored the relation between phone orientation, number of buttons in a layout, number of thumbs used for input, and target position. The difference to Study One resides in the additional independent variable describing the mode of operation (one or two thumbs), but otherwise study design and procedure were unchanged, with tasks being repeated three times. The study was counterbalanced by mode (normal or Stroop-like) and number of buttons. Outliers were identified using scatter plots and a rule of thumb highlighting data points for removal that were significantly larger than twice the standard deviation. These were removed from the data set and treated as missing values by SPSS, the software used for the evaluation. The data sets and study information can be found in Appendix C, pp. 347–349.

During the study it was observed that for two-handed operation in portrait orientation, users tended to operate position *Middle* and *End* with their dominant thumb and position *Start* mostly with their non-dominant hand in layouts with more than three buttons. In layouts with three buttons, users mostly used their dominant hand for all target positions, with the non-dominant hand being mostly used for stabilising the phone. One user asked whether they had to use two thumbs in this mode of interaction or could use just one. In landscape orientation, users also tended to use the non-dominant thumb for targets in position *Start* (on the left of the display) and the dominant thumb in targets in position *Middle* and *End* (on the right of the display). It was observed that users struggled when operating the device with one hand in landscape orientation, especially when attempting to reach targets in position *Start*.

Study Two – Results R1

A four-way ANOVA showed an effect of number of thumbs, $F(1, 6) = 11$, $p = .016$, an effect of amount of buttons in a layout, $F(2, 12) = 112.95$, $p < .001$, and an effect of target position, $F(2, 12) = 11.9$, $p = .001$.

Further, the ANOVA showed an interaction between orientation and number of thumbs, $F(1, 6) = 15.4$, $p = .008$, an interaction between number of thumbs and amount of buttons, $F(2, 12) = 6.2$, $p = .014$, an interaction between orientation, number of thumbs and amount of buttons, $F(2, 12) = 6.7$, $p = .011$, an interaction between number of thumbs and target position, $F(2, 12) = 5.4$, $p = .22$, an interaction between orientation, number of thumbs and target position, $F(2, 12) = 8.4$, $p = .005$, and an interaction between amount of buttons and target position, $F(4, 24) = 6.3$, $p = .001$.

To analyse the effects and interactions, these were broken down one by one using a series of Wilcoxon tests.

Table 3.8: Mean and median IT for input using one and two thumbs in R1 of Study Two.

Thumbs	**One**	**Two**
Mean IT	1711.2	1397.9
Median IT	1620.5	1347.6
SD	315.9	207.9

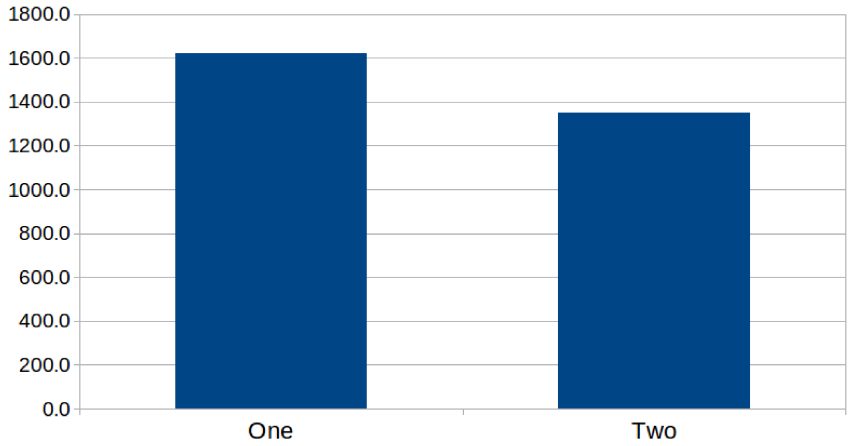

Figure 3.11: Visualisation of the median IT for input using one and two thumbs in R1 of Study Two (taken from Table 3.8).

Effect of number of thumbs:

A Wilcoxon tests showed that using two thumbs for input was faster than using one thumb for input, $Z = 2.8$, $p = .005$. See Table 3.8 and Figure 3.11.

TABLE 3.9: Mean and median IT for targets in layouts with three (3), five (5) and eight (8) buttons in R1 of Study Two.

Layout	3	5	8
Mean IT	1128.0	1557.2	1973.5
Median IT	1061.5	1489.5	1806.5
SD	135.8	304.9	339.7

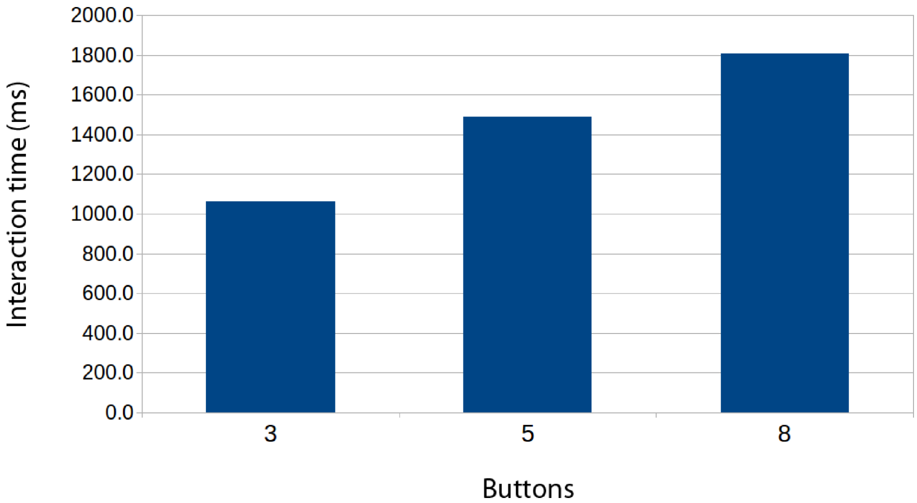

FIGURE 3.12: Visualisation of the median IT for targets in layouts with three (3), five (5) and eight (8) buttons in R1 of Study Two (taken from Table 3.9).

Effect of amount of buttons:

A Wilcoxon test revealed that interaction with a layout of three buttons was faster than interaction with layouts of both five buttons ($Z = 2.8$, $p = .005$) and eight buttons ($Z = 2.8$, $p = .005$). In addition, interaction with a layout of five buttons was faster than with a layout of eight buttons ($Z = 2.7$, $p = .007$). See Table 3.9 and Figure 3.12. Results were Bonferroni-Holm-corrected, starting with a divider of three.

TABLE 3.10: Mean and median IT for targets in positions *Start*, *Middle* and *End* in R1 of Study Two.

Position	Start	Middle	End
Mean IT	1603.9	1445.4	1622.4
Median IT	1512.2	1342.6	1501.4
SD	234.2	263.7	313.5

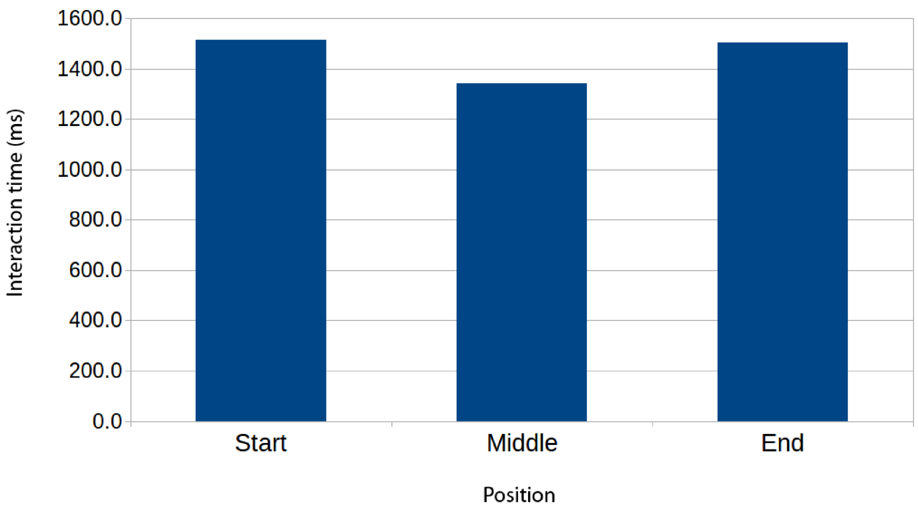

FIGURE 3.13: Visualisation of the median IT for targets in positions *Start*, *Middle* and *End* in R1 of Study Two (taken from Table 3.10).

Effect of target position:

A Wilcoxon test indicated that interacting with targets in position *Middle* was faster than interacting with targets in position *Start* and *End*, but the Bonferroni-Holm-corrected p values were not statistically significant (starting with a divider of three). See Table 3.10 and Figure 3.13. The interaction between position and number of thumbs suggests that the trend is only likely to exist when using the device with either one or two thumbs, but not in general for both modes of interaction.

Table 3.11: Mean and median IT for operation with one (1) and two (2) thumbs in landscape (L) and portrait (P) modes in R1 of Study Two.

Mode & orientation	**P1**	**P2**	**L1**	**L2**
Mean IT	1579.9	1469.4	1842.5	1327.9
Median IT	1468.3	1392.1	1804.5	1333.8
SD	305.2	218.5	357.7	229.6

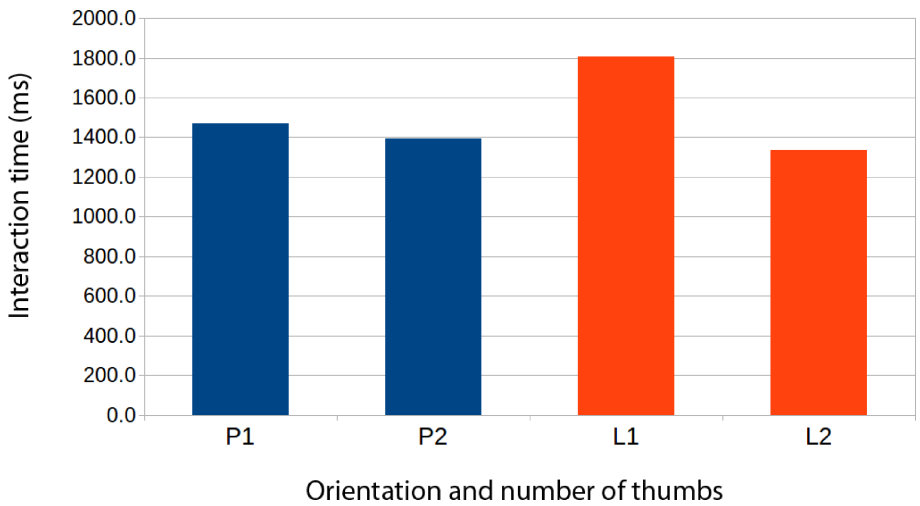

Figure 3.14: Visualisation of the median IT for operation with one (1) and two (2) thumbs in landscape (L) and portrait (P) modes in R1 of Study Two (taken from Table 3.11).

Interaction between orientation and number of thumbs:

Wilcoxon tests showed that using two thumbs in portrait orientation was faster than using one thumb in landscape orientation, $Z = 2.8$, $p = .005$, and that using one thumb in portrait orientation was faster than one thumb in landscape orientation, $Z = 2.6$, $p = .009$. In addition, using two thumbs in landscape orientation was faster than using only one, $Z = 2.7$, $p = .007$. The Wilcoxon tests also revealed a trend of two thumbs in landscape orientation to be faster than both one thumb in portrait orientation ($Z = 2.29$, $p = .022$) and two thumbs in portrait orientation ($Z = 2.19$, $p = .028$), but the Bonferroni-Holm-corrected results were not statistically significant when starting with a divider of six. See Table 3.11 and Figure 3.14.

TABLE 3.12: Mean and median IT for operation with one thumb (1T) and two thumbs (2T) in layouts of three (3), five (5) and eight (8) buttons in R1 of Study Two.

Mode & layout	**1T 3**	**1T 5**	**1T 8**	**2T 3**	**2T 5**	**2T 8**
Mean IT	1150.0	1735.9	2219.3	1103.6	1376.9	1735.4
Median IT	1113.1	1557.0	2035.1	1050.7	1366.6	1687.9
SD	121.5	372.5	458.5	164.3	295.5	266.6

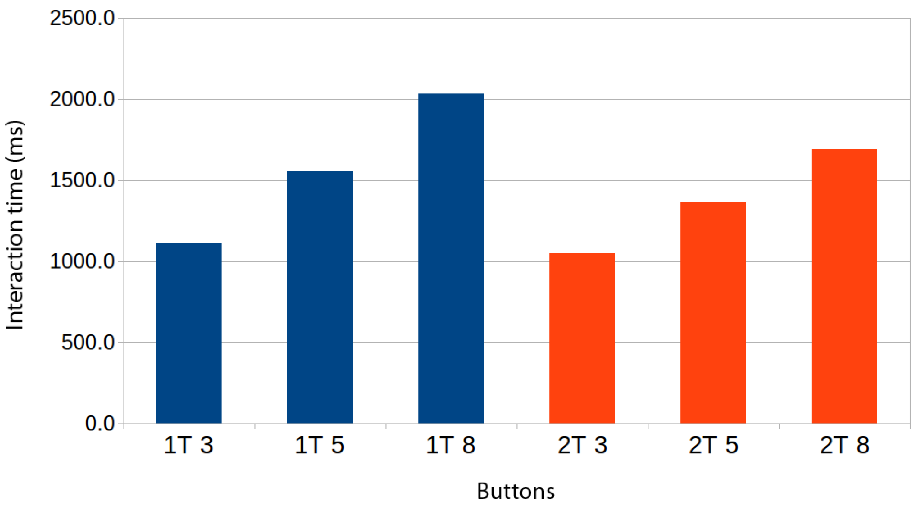

FIGURE 3.15: Visualisation of the median IT for operation with one thumb (1T) and two thumbs (2T) in layouts of three (3), five (5) and eight (8) buttons in R1 of Study Two (taken from Table 3.12).

Interaction between number of thumbs and amount of buttons:

A Wilcoxon test revealed that IT was lower when using two thumbs as opposed to one thumb in a five-button layout ($Z = 2.8$, $p = .005$) and in an eight-button layout ($Z = 2.8$, $p = .005$). There was no statistically significant difference between operating the device with one thumb and two thumbs in a layout with three buttons. Other constellations of number of thumbs and layout size were not compared. See Table 3.12 and Figure 3.15. A Bonferroni-Holm-correction was applied, starting with a divider of three.

Interaction between orientation, number of thumbs and target position:
A Wilcoxon test showed that the slowest mode of operation was using one thumb in landscape orientation, mirroring the difficulties of users with this mode of operation observed during the study. This mode of operation for position *Start* was slower than using two thumbs in landscape orientation, $Z = 2.8$, $p = .005$, and slower than using two thumbs in portrait orientation, $Z = 2.7$, $p = .007$. Furthermore, using one thumb in landscape orientation to interact with position *End* was slower than using two thumbs in landscape orientation, $Z = 2.8$, $p = .005$, and slower than using two thumbs in portrait orientation, $Z = 2.7$, $p = .007$. Finally, position *End* was fastest to interact with using two thumbs in landscape orientation, which was faster than using one thumb in portrait orientation, $Z = 2.7$, $p = .007$. Statistically significant differences in IT for position *Middle* were not found. In addition to the statistically significant differences, the Wilcoxon tests also revealed a series of trends, though these could not be regarded as statistically significant after applying a Bonferroni-Holm correction starting with a divider of 18:

- Using two thumbs in landscape orientation for interacting with position *Start* tended to be faster than using two thumbs in portrait orientation, $Z = 2.19$, $p = .028$, and faster than using one thumb in portrait orientation, $Z = 2.5$, $p = .013$.
- Using one thumb in portrait orientation to interact with position *End* tended to be faster than using one thumb in landscape orientation, $Z = 2.5$, $p = .013$.

For the respective interaction times, see Table 3.13, Table 3.14 and Figure 3.16.

TABLE 3.13: Mean and median IT for targets in positions *Start* (S), *Middle* (M) and *End* (E), using one (1) and two (2) thumbs, in portrait (P) orientation in R1 of Study Two.

Mode	**P1 S**	**P1 M**	**P1 E**	**P2 S**	**P2 M**	**P2 E**
Mean IT	1704.4	1498.6	1552.7	1516.8	1340.9	1564.4
Median IT	1600.3	1367.2	1537.6	1543.8	1317.6	1464.9
SD	473.7	340.8	246.7	236.3	200.6	364.1

TABLE 3.14: Mean and median IT for targets in positions *Start* (S), *Middle* (M) and *End* (E), using one (1) and two (2) thumbs, in landscape (L) orientation in R1 of Study Two.

Mode	**L1 S**	**L1 M**	**L1 E**	**L2 S**	**L2 M**	**L2 E**
Mean IT	1963.1	1539.2	2084.2	1255.3	1386.5	1341.9
Median IT	1898.9	1440.6	2038.6	1279.4	1348.4	1279.9
SD	391.2	425.0	668.6	267.0	287.7	255.1

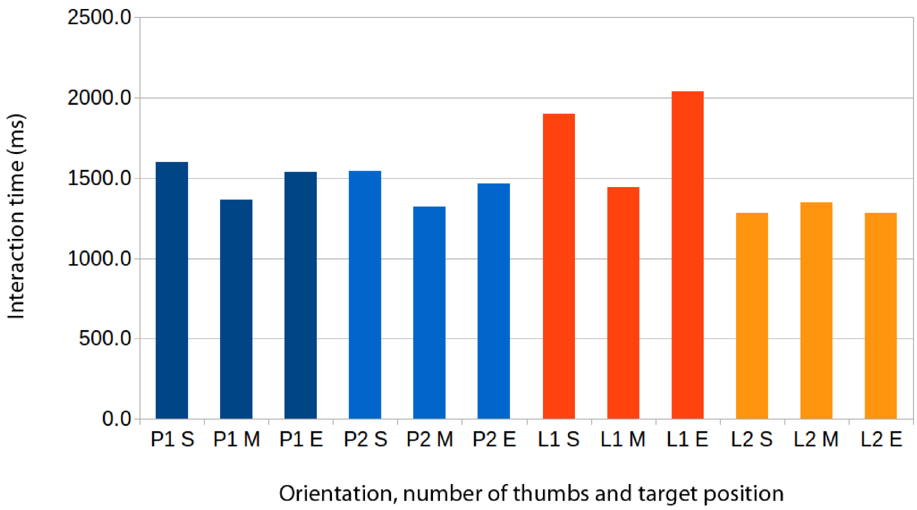

FIGURE 3.16: Visualisation of the median IT for targets in positions *Start* (S), *Middle* (M) and *End* (E), using one (1) and two (2) thumbs, in landscape (L) and portrait (P) orientations in R1 of Study Two (taken from Table 3.13 and 3.14).

Interaction between orientation, number of thumbs and amount of buttons: A set of Wilcoxon tests showed a layout of eight buttons was faster to interact with using two thumbs in landscape orientation than two thumbs in portrait orientation, $Z = 2.19$, $p = .028$, and showed a trend for a layout of eight buttons in landscape orientation to be faster to interact with using two thumbs than a layout of eight buttons in portrait orientation using one thumb, $Z = 2.1$, $p = .037$, but differences were not statistically

TABLE 3.15: Mean and median IT for operation with one thumb (1) and two thumbs (2) in layouts of three (3), five (5) and eight (8) buttons in landscape (L) and portrait (P) orientations in R1 of Study Two.

Mode	**P1 3**	**L2 3**	**P1 5**	**L2 5**	**P1 8**	**L2 8**	**P2 3**	**P2 5**	**P2 8**
Mean IT	1155.5	1094.4	1599.0	1324.6	1966.1	1578.8	1112.8	1429.3	1899.9
Median IT	1123.1	1047.9	1544.7	1248.3	1786.4	1547.6	1097.8	1371.9	1848.3
SD	140.9	189.3	351.3	317.5	487.2	321.0	167.9	316.3	328.0

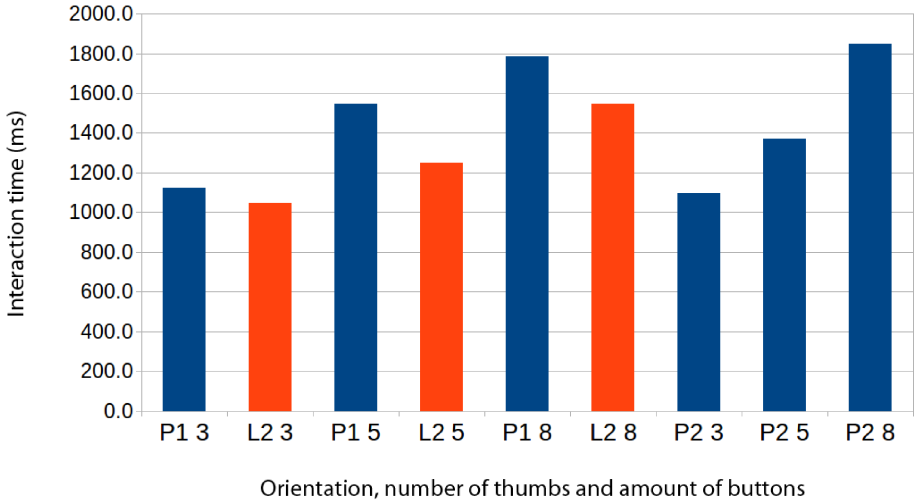

FIGURE 3.17: Visualisation of the median IT for operation with one thumb (1) and two thumbs (2) in layouts of three (3), five (5) and eight (8) buttons in landscape (L) and portrait (P) orientations in R1 of Study Two (taken from Table 3.15).

significant with an applied Bonferroni-Holm correction starting with a divider of nine. Other trends were not found. Due to the poor results for one-handed landscape operation indicated in the interaction between orientation and number of thumbs (Tab. 3.11), comparisons for this mode were not conducted. The results can be found in Table 3.15 and Figure 3.17.

TABLE 3.16: Mean and median IT for operation with one thumb (1) and two thumbs (2) for the target positions *Start*, *Middle* and *End* in R1 of Study Two.

Mode & position	**1 *Start***	**1 *Middle***	**1 *End***	**2 *Start***	**2 *Middle***	**2 *End***
Mean IT	1829.9	1524.8	1801.5	1386.0	1366.1	1453.1
Median IT	1762.7	1366.2	1725.2	1327.3	1334.6	1358.8
SD	337.0	370.2	403.5	195.2	229.8	266.5

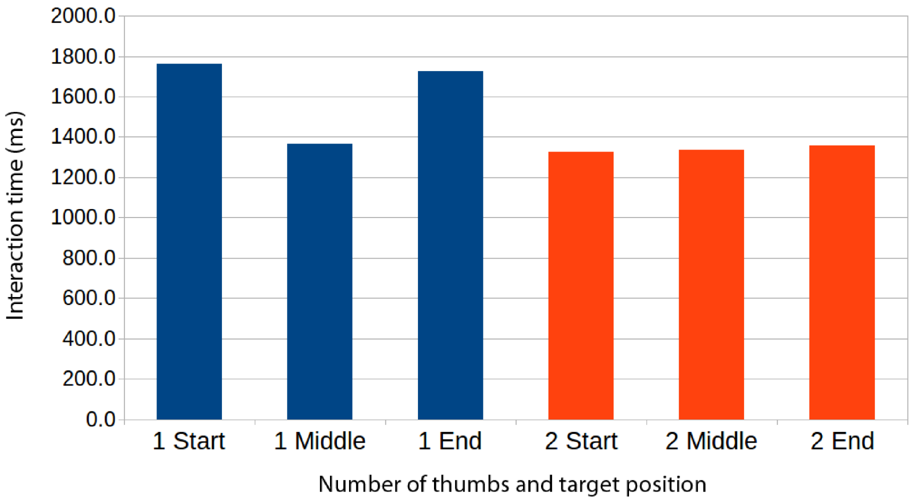

FIGURE 3.18: Visualisation of the median IT for operation with one thumb (1) and two thumbs (2) for the target positions *Start*, *Middle* and *End* in R1 of Study Two (taken from Table 3.16).

Interaction between number of thumbs and target position:

Comparing the IT for targets in the positions *Start*, *Middle* and *End* accessed with one thumb using a Wilcoxon test showed that the IT for targets in position *Middle* was lower than for targets in position *Start*, $Z = 2.29$, $p = .022$, and a light trend of IT for targets in position *Middle* to be lower than for targets in position *End*, $Z = 1.99$, $p = .047$. However, the result of the latter was not statistically significant with a Bonferroni-Holm correction starting with a divider of three. Comparing the IT for targets in the positions *Start*, *Middle* and *End* accessed with two thumbs using a Wilcoxon test showed no differences in IT between the three target positions. See Table 3.16 and Figure 3.18. When comparing the IT for targets in the three positions between one-thumb and two-thumb operation, the test revealed no statistically significant difference in IT for targets in position *Middle*, but showed a lower IT for targets in positions *Start* and *End*, when using two thumbs compared to one. For both target positions, the results were $Z = 2.8$, $p = .005$. All results were Bonferroni-Holm-corrected, starting with a divider of three.

Table 3.17: Mean and median IT for buttons in positions *Start* (S), *Middle* (M) and *End* (E), in layouts of three (3), five (5) and eight (8) buttons in R1 of Study Two.

Mode	**S3**	**M3**	**E3**	**S5**	**M5**	**E5**	**S8**	**M8**	**E8**
Mean IT	1145.0	1120.0	1129.6	1608.2	1487.5	1625.0	2041.0	1735.0	2170.0
Median IT	1090.8	1055.2	1049.2	1556.1	1407.2	1552.0	1924.6	1573.1	2056.2
SD	117.3	168.6	210.6	227.6	334.8	608.0	356.0	409.5	412.8

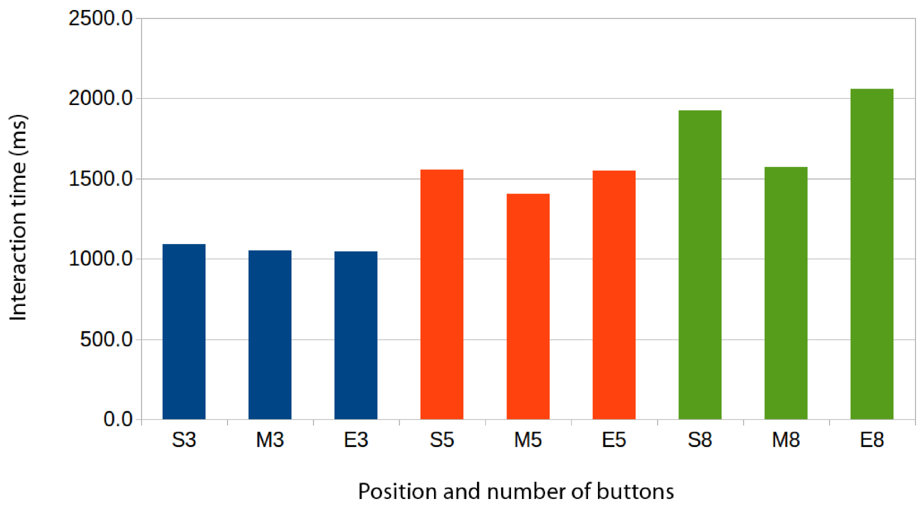

Figure 3.19: Visualisation of the median IT for buttons in positions *Start* (S), *Middle* (M) and *End* (E), in layouts of three (3), five (5) and eight (8) buttons in R1 of Study Two (taken from Table 3.17).

Interaction between amount of buttons and target position:

A Wilcoxon test did not show any statistically significant differences in IT between the three target positions in layouts of both three and five buttons. In a layout of eight buttons, targets in position *Middle* were faster to interact with than targets in position *End*, $Z = 2.5$, $p = .013$. In addition, this layout also showed a trend for targets in position *Middle* to be faster to interact with than those in position *Start*, $Z = 2.19$, $p = .028$, but an applied Bonferroni-Holm correction starting with a divider of three rendered the difference statistically insignificant. See Table 3.17 and Figure 3.19.

Study Two – Discussion R1

The breakdown of the effects and interactions revealed by the ANOVA indicates that in layouts with five or more buttons, operation with two thumbs is faster than with one thumb. In addition, the data suggests that operating a device in landscape orientation in a layout of eight buttons using two thumbs is faster than doing so in portrait orientation, indicating that this mode of operation may be the most efficient for interfaces with a high degree of target density. Although there seems to be a trend for one-handed operation where IT is ranked *Middle* < *End* < *Start*, as revealed in R2 of Study One for layouts with five or more targets, the results indicate that with two-thumb operation, all targets are equally fast to operate. In contrast, operating the device with only one thumb in landscape orientation clearly shows the effect of the thumb's limited reach, whose point of rest is the horizontal middle of the screen, resulting in a low IT for position *Middle*, but a high IT for the hard-to-reach positions of *Start* and *End*, corresponding to the observations made during the study.

Compared to the results of R1 in Study One, the observed effects do not seem to be affected by target simplicity and priming. R1 and R2 of Study One suggest that IT is not only influenced by the distance between target and pointer, but also by the point of gaze and the user's visual scanning pattern. This may explain the ranking observed for one-handed operation, where both Fitts's law and scanning pattern seem to impact IT more than the possible effect of priming. The priming may have led to a less diversified distribution of IT when operating the device with the flexible index finger in R1 of Study One, but its impact appears to be lowered, resulting in the IT ranking of *Middle* < *End* < *Start* in R1 of Study Two due to the stronger-weighting restrictions of movement bestowed upon the thumb. This suggests that a possible effect of priming may be more impactful on IT if no restrictions of movement apply to the input "device". However, exploring this relation further is beyond this chapter's scope and thus lends itself to future research. For the questions to be answered in this chapter, the insight that two-handed thumb operation tends to be more efficient than one-handed thumb operation of a touchscreen smartphone is sufficient.

Study Two – Results R2

An ANOVA revealed an effect of device orientation, $F(1, 5) = 8.31$, $p = .035$, an effect of number of thumbs, $F(1, 5) = 69.94$, $p < .001$, an effect of amount of buttons in a layout, $F(2, 10) = 40.23$, $p < .001$, an interaction between orientation and amount of buttons, $F(2, 10) = 4.1$, $p = .05$, an interaction between number of thumbs and amount

Table 3.18: Mean and median IT for targets in landscape (L) and portrait (P) orientations in R2 of Study Two.

Orientation	**L**	**P**
Mean IT	1354.8	1425.0
Median IT	1217.8	1324.1
SD	249.0	252.2

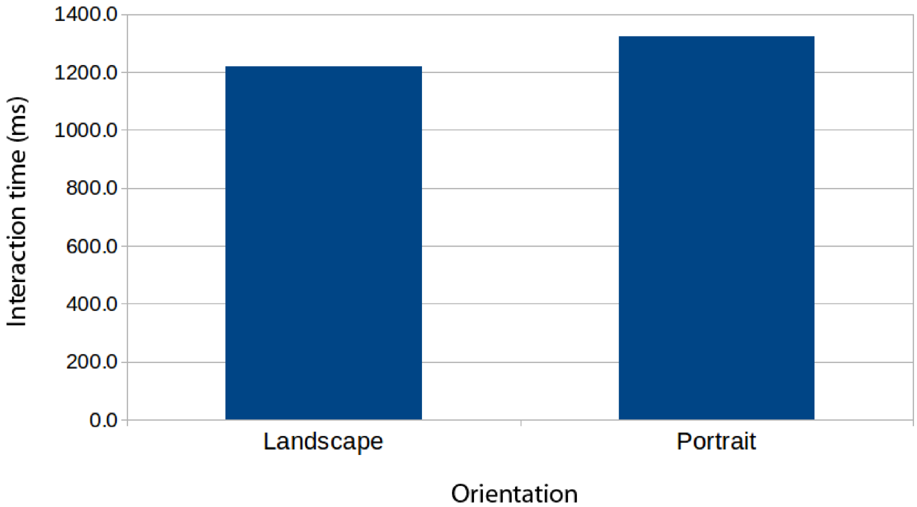

Figure 3.20: Visualisation of the median IT for targets in landscape and portrait orientations in R2 of Study Two (taken from Table 3.18).

of buttons, $F(2, 10) = 12.34$, $p = .002$, and an interaction between device orientation, target position and amount of buttons, $F(4, 20) = 3.47$, $p = .026$.

Effect of device orientation:

Breaking down the effect of orientation using a Wilcoxon test revealed that the device was faster to interact with in landscape orientation than in portrait orientation, $Z = 2.6$, $p = .009$. See Table 3.18 and Figure 3.20.

Table 3.19: Mean and median IT for device operation using one thumb (1) and two thumbs (2) in R2 of Study Two.

Thumbs	**1**	**2**
Mean IT	1478.7	1304.1
Median IT	1320.2	1223.7
SD	308.4	198.5

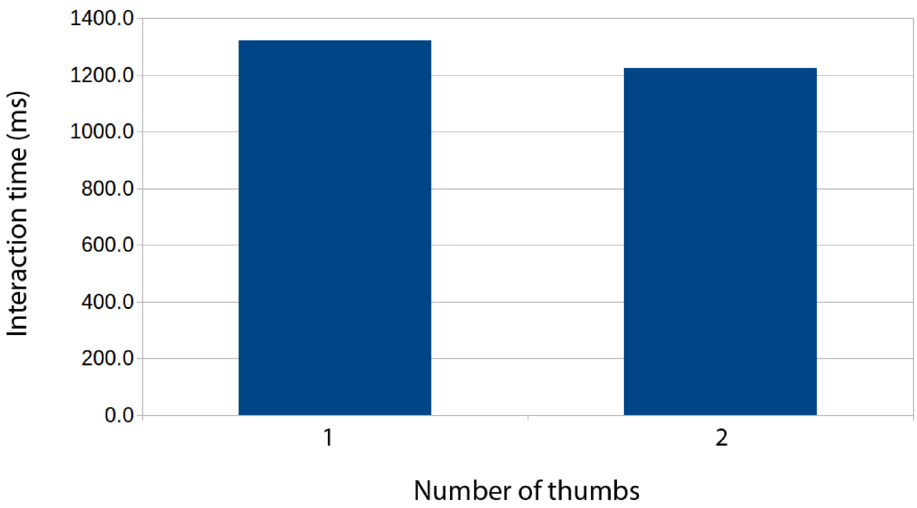

Figure 3.21: Visualisation of the median IT for device operation using one thumb (1) and two thumbs (2) in R2 of Study Two (taken from Table 3.19).

Effect of number of thumbs:

A Wilcoxon test showed that the device was faster to interact with using two thumbs rather than one, $Z = 2.8$, $p = .005$. See Table 3.19 and Figure 3.21.

TABLE 3.20: Mean and median IT for layouts with three (3), five (5) and eight (8) buttons in R2 of Study Two.

Amount of buttons	3	5	8
Mean IT	1090.7	1445.7	1623.3
Median IT	992.3	1364.4	1576.6
SD	189.5	257.9	312.8

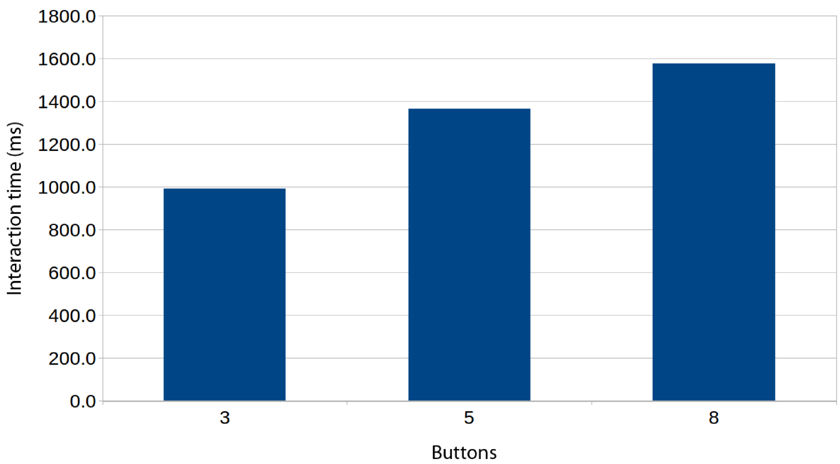

FIGURE 3.22: Visualisation of the median IT for layouts with three (3), five (5) and eight (8) buttons in R2 of Study Two (taken from Table 3.20).

Effect of amount of buttons:

A Wilcoxon test showed that a three-button layout was faster to interact with than both a five-button layout, $Z = 2.8$, $p = .005$, and an eight-button layout, $Z = 2.8$, $p = .005$. In addition, the test revealed that the five-button layout was faster to interact with than the eight-button layout, $Z = 2.09$, $p = .037$. A Bonferroni-Holm correction was applied to all results, starting with a divider of three. For the data, see Table 3.20 and Figure 3.22.

Table 3.21: Mean and median IT for layouts with three (3), five (5) and eight (8) buttons in landscape (L) and portrait (P) orientations in R2 of Study Two.

Mode	**L3**	**P3**	**L5**	**P5**	**L8**	**P8**
Mean IT	1107.4	1072.8	1304.3	1581.4	1643.8	1605.0
Median IT	983.8	1011.1	1228.9	1550.4	1553.4	1550.9
SD	255.2	125.5	190.4	330.8	312.3	331.5

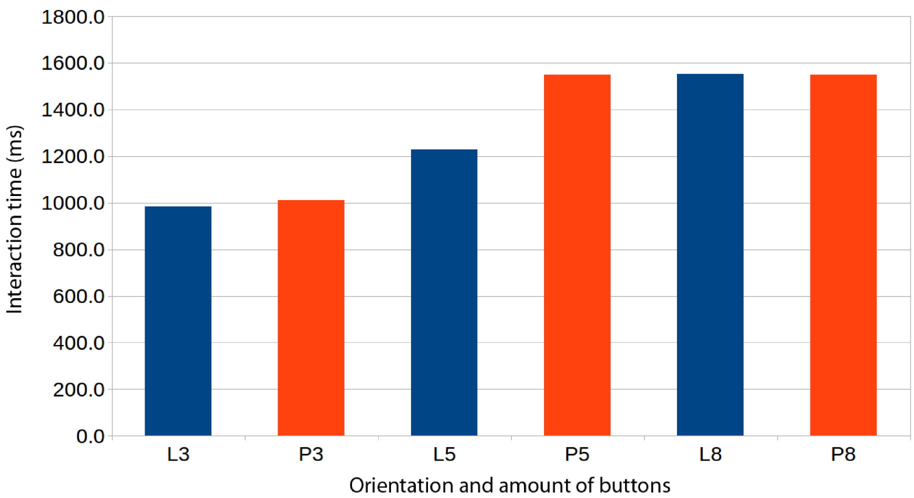

Figure 3.23: Visualisation of the median IT for layouts with three (3), five (5) and eight (8) buttons in landscape (L) and portrait (P) orientations in R2 of Study Two (taken from Table 3.21).

Interaction between orientation and amount of buttons:

A Wilcoxon test showed that a five-button layout in landscape orientation was faster to interact with than a five-button layout in portrait orientation, but there were no statistically significant differences for the other layouts. Results were Bonferroni-Holm-corrected, starting with a divider of three. See Table 3.21 and Figure 3.23.

TABLE 3.22: Mean and median IT for layouts of three (3), five (5) and eight (8) buttons, operated using one thumb (1T) and two thumbs (2T) in R2 of Study Two.

Mode	**1T 3**	**2T 3**	**1T 5**	**2T 5**	**1T 8**	**2T 8**
Mean	1086.0	1092.4	1619.1	1285.3	1730.6	1522.5
Median	980.0	1065.2	1510.5	1207.7	1618.7	1510.1
SD	226.5	159.9	343.9	200.6	398.0	248.5

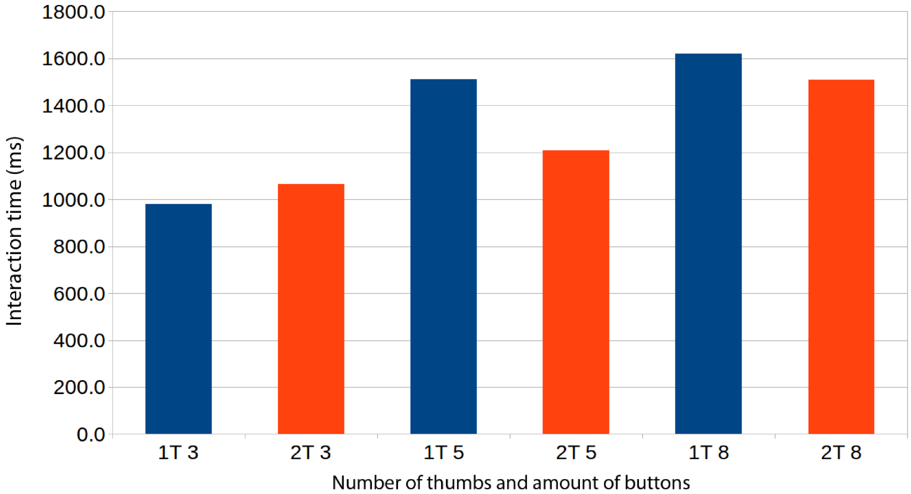

FIGURE 3.24: Visualisation of the median IT for layouts of three (3), five (5) and eight (8) buttons, operated using one thumb (1T) and two thumbs (2T) in R2 of Study Two (taken from Table 3.22).

Interaction between number of thumbs and amount of buttons:

A Wilcoxon test revealed that in both five-button and eight-button layouts, IT was lower when using two thumbs compared to one, $Z = 2.8$ $p = .005$ (in both comparisons). Results were Bonferroni-Holm-corrected, starting with a divider of three (Tab. 3.22, Fig. 3.24).

TABLE 3.23: Mean and median IT for layouts with three (3), five (5) and eight (8) buttons in landscape (L) orientation in positions *Start* (S), *Middle* (M) and *End* (E) in R2 of Study Two.

Mode	L3 S	L3 M	L3 E	L5 S	L5 M	L5 E	L8 S	L8 M	L8 E
Mean IT	1013.0	1140.8	1133.3	1440.6	1152.1	1313.8	1750.3	1563.2	1595.0
Median IT	942.2	1128.8	954.0	1450.2	1209.9	1240.4	1716.2	1536.1	1534.5
SD	171.6	210.1	433.6	268.5	195.7	227.8	412.6	380.9	337.4

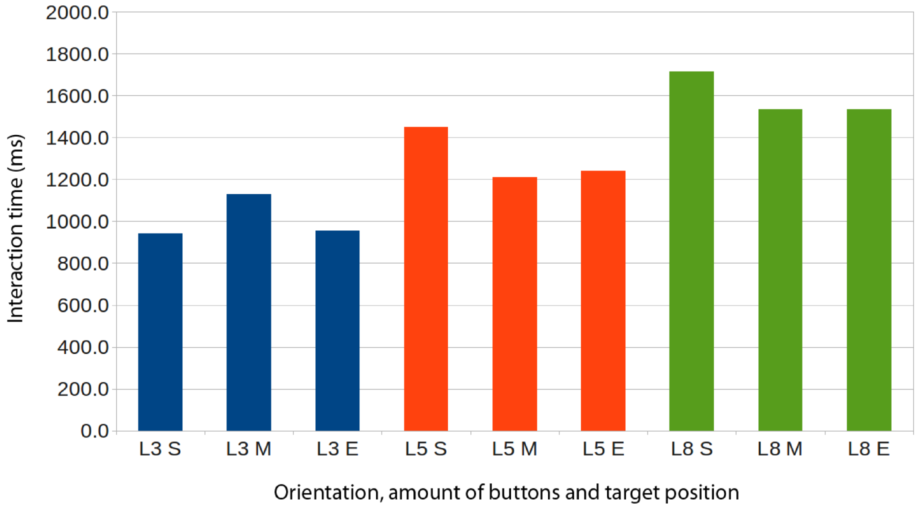

FIGURE 3.25: Visualisation of the median IT for layouts with three (3), five (5) and eight (8) buttons in landscape (L) orientation in positions *Start* (S), *Middle* (M) and *End* (E) in R2 of Study Two (taken from Table 3.23).

Interaction between device orientation, target position and amount of buttons:

For the landscape orientation, a Wilcoxon test showed no statistically significant difference in IT for layouts with three and eight buttons between the three target positions. However, in a layout with five buttons, IT for targets in position *Middle* was lowest and statistically significantly lower than IT for targets in position *Start*, $Z = 2.4$, $p = .017$. In addition, a trend of position *Middle* being faster to interact with than position *End* was visible, $Z = 2.19$, $p = .028$, albeit not statistically significant after applying a Bonferroni-Holm correction starting with a divider of three. See Table 3.23 and Figure 3.25.

TABLE 3.24: Mean and median IT for layouts with three (3), five (5) and eight (8) buttons in portrait (P) orientation in positions *Start* (S), *Middle* (M) and *End* (E) in R2 of Study Two.

Mode	P3 S	P3 M	P3 E	P5 S	P5 M	P5 E	P8 S	P8 M	P8 E
Mean IT	1082.8	1058.8	1042.3	1692.8	1314.7	1750.7	1575.6	1678.8	1589.9
Median IT	1037.2	1024.3	978.8	1713.2	1198.7	1655.1	1483.9	1643.0	1560.2
SD	169.4	162.4	156.9	367.6	294.8	473.8	415.5	486.6	222.1

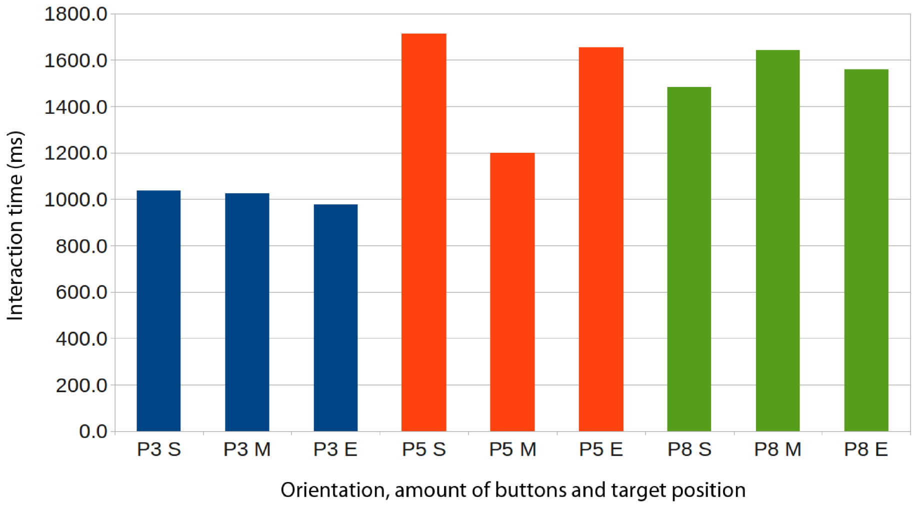

FIGURE 3.26: Visualisation of the median IT for layouts with three (3), five (5) and eight (8) buttons in portrait (P) orientation in positions *Start* (S), *Middle* (M) and *End* (E) in R2 of Study Two (taken from Table 3.24).

In portrait orientation, a Wilcoxon test showed that differences in IT between the three target positions only existed in the five-button layout. Here, position *Middle* was faster to interact with than both position *Start*, $Z = 2.5$, $p = .013$, and position *End*, $Z = 2.8$, $p = .005$. Results were Bonferroni-Holm-corrected starting with a divider of three. See Table 3.24 and Figure 3.26.

Study Two – Discussion R2

The Wilcoxon tests indicate that IT increases with the amount of buttons in a layout, either following the Hick–Hyman law (Hick, 1952; Hyman, 1953) or showing the effects of a possible linear search strategy (Megaw and Richardson, 1979; Anderson et al., 1997). The tests further suggest that a device is faster to operate in landscape orientation than in portrait orientation in a layout of five buttons, and that using two thumbs outperforms using only one thumb for interaction in layouts of five buttons or more. Furthermore, the tests suggest position *Middle* is fastest to interact with in a layout of five buttons, but that this effect is not visible in the three-button and eight-button layouts. In landscape orientation, position *Start* had the highest IT whereas position *Middle* and *End* have similar levels of IT (Fig. 3.25).

While the results of R2 partly seem to follow the results of R1, some results are unexpected and raise further questions. For example, why does, in a layout of five buttons in portrait orientation, the *Middle* position have the lowest IT, but this is not replicated in a layout of eight buttons? The observed scanning pattern of R2 in Study One together with a combination of Fitts's law and the Hick–Hyman law should suggest a similar distribution as in R1 of Study Two. Yet, this is not the case. A possible explanation may be that the scanning pattern could be different in an eight-button layout from that in a five-button layout when using one thumb, although the results of R2 in Study One and R1 in Study Two suggest that scanning patterns are the same for both layouts. Furthermore, this effect does not seem to apply to the landscape orientation, where the trend in the data is the same in both the five-button and eight-button layouts. This suggests further exploration using eye tracking to help explore possible reasons. However, as this is beyond the scope of the research questions, this exploration is a suggestion for future work. A simpler explanation would be the relatively small sample size of Study Two, which in comparison to the 44 participants of Study One is rather low, allowing a degree of sampling bias that may be not truly representative of the population. In this regard, the results of Study Two should be considered as trends, rather than definitive effects. Nonetheless, the results enable the answering of the general research question regarding the impact of layout orientation and mode of interaction on overall efficiency.

3.2.3 Comparison of Study One and Study Two

The results of Study One and Study Two showed differences in IT for devices operated in landscape and portrait mode, with one thumb, two thumbs, and the index finger, with targets located in three different locations. This section will compare the general performance of thumb-based and index-finger-based input to examine which one is more efficient. For this, a set of Mann-Whitney U tests was conducted, leaving out the one-handed operation of the device in landscape orientation which was observed to be

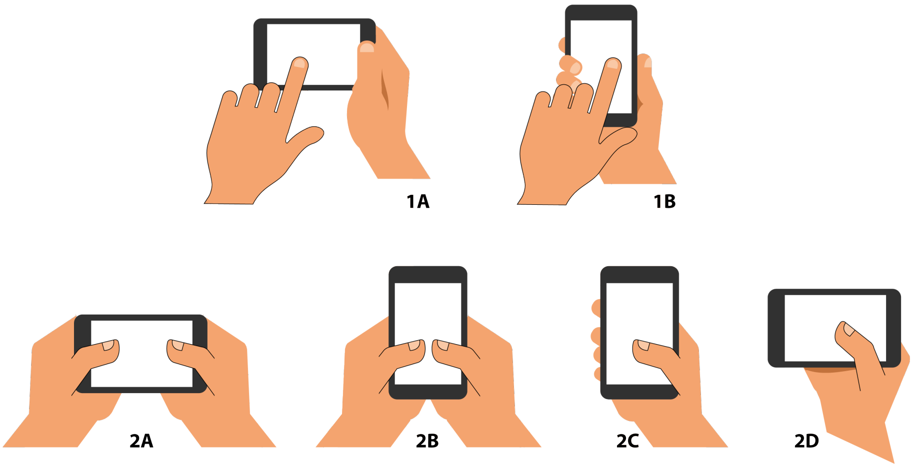

Figure 3.27: The hand postures and device orientations examined in Study One and Study Two ordered by input efficiency.

difficult to perform and, taking into account the results of Table 3.25, is not a mode of operation generally employed by users. The tests revealed that using two thumbs in landscape orientation was faster than using the index finger in portrait orientation, $Z = 2.07$, $p = .039$, but that otherwise no differences in IT between the various modes of operation and orientation were found using a Bonferroni-Holm correction, starting with a divider of six.

Nonetheless, it has to be considered that the studies were conducted on only one device size with targets not located in locations notoriously difficult to reach with the thumb (in the north-west or south-east area of the screen (Karlson et al., 2006)). While there is likely to be a statistical difference between the three target positions in the various modes of operation as indicated by the respective Wilcoxon tests in each study, this is not relevant in order to determine the most efficient mode overall. Within the two input mode groups (Fig. 3.27) the efficiency ranking seems to have the following trend:

Index finger input (from lowest to highest IT):

1. Index finger in landscape orientation
2. Index finger in portrait orientation

Thumb input (from lowest to highest IT):

1. Two thumbs in landscape orientation
2. Two thumbs in portrait orientation
3. One thumb in portrait orientation
4. One thumb in landscape orientation

3.3 User Survey

Sections 3.2.1 (p. 75) and 3.2.2 (p. 91) indicate that from an efficiency point of view, statistically significant differences between the input modes of the two groups do not exist, apart from the trend of two-thumb operation in landscape orientation to be more efficient than index finger operation in portrait orientation. Within the group of thumb operation, the results suggest two-thumb operation in landscape orientation is faster than any other thumb input mode. However, Karlson et al. (2006) found that 66% of users would prefer to only use one hand for most interactions. This indicates that factors other than input efficiency may be more important to users when operating a smartphone. To investigate, a survey was conducted with 31 participants, all third-year Computer Science students (mean age: 21, SD: 2.83, 26 right-handed, 3 left-handed, 2 ambidextrous), questioning their phone model, applications used, modes of interaction used for each application and subjective reasons for operating a device the way they do. One participant did not answer the questions regarding their most frequently used applications. The survey questions can be found in Appendix C, section C.5, p. 349.

3.3.1 Technological Constraints

This section lists technological constraints derived from the survey responses. Information about Central Processing Unit (CPU) speed, CPU cores, Random Access Memory

(RAM), and screen size was derived from the users' answers, taking technical specifications of each model provided by the respective vendor. The median values for these are:

- Screen size: 4.475 inches
- RAM: 1024 Megabyte (MB)
- CPU cores: 2
- CPU speed: 1350 megahertz (MHz)
- Devices with a touchscreen: 96.7%
- Devices possessing a gyroscope, accelerometer, microphone, camera and a proximity sensor: 96.7%

In terms of general network performance, the International Telecommunication Union (2011) reports a 45% population coverage worldwide for third-generation mobile telecommunications technology (3G), and a 90% coverage for second-generation mobile telecommunications technology (2G). However, more contemporary data suggests an even higher degree of coverage for 3G and later networks (International Telecommunication Union, 2014).

3.3.2 Most Frequently Used Applications

When asked which application they use the most, the users' first answer was:

- Messaging: 70%
- Browsing: 13.33%
- Social media: 10%
- E-books: 3.33%
- Calls: 3.33%

However, one user did not answer this question. Users often named multiple applications, but were asked to determine which one they used the most. The below list contains all secondary answers and onwards:

- Calls: 15.6%
- Social media: 15.6%
- Messaging: 15.6%
- Web browsing: 15.6%
- Gaming: 9.4%
- Taking notes: 3.1%
- Reading: 3.1%
- Video: 3.1%
- Calendar: 3.1%
- Organiser: 3.1%
- Calculator: 3.1%
- Music: 3.1%
- Camera: 3.1%
- Apps: 3.1%

3.3.3 Mode of Operation per Application

Users were asked how they operate the following applications: Web browsing, text writing, dialling, image gallery navigation (full screen), selection from a grid, calendar application, video watching, reading an E-book or PDF, and operating the camera. This choice of applications was guided by the list of examined applications by Karlson et al. (2006), but combined some of its subgroups and added a new "application" which resembled Karlson et al.'s calendar selection task: Selection from a grid – a view to comprise application grids and photo gallery overviews.

Table 3.25: Percentage of users operating the device one-handedly (Thumb and same hand), with one or two hands using their thumbs (a column combining the one-handed and two-handed thumb operation (Thumbs of either one or two hands)), and the index finger, and device orientation per application (landscape (L) orientation and portrait (P) orientation).

Task	**Thumb and same hand**	**Thumbs of either one or two hands**	**Index finger**	**P**	**L**
Web browsing	74.2	87.1	12.9	100	0
Text writing	38.7	90.3	9.7	100	0
Dialling	67.7	71	29	100	0
Image gallery	67.7	71	29	100	0
Grid selection	64.5	71	29	96.8	3.2
Calendar	61.5	65.4	34.6	100	0
Video	24.1	58.6	41.4	58.6	41.4
E-book/PDF	69	86.2	13.8	100	0
Camera	56.7	83.3	16.7	66.7	33.3

To respond, users were asked to show how they held and operated the device using their own phone while providing an oral description. For the evaluation, the answers were broken down into categories: Which hand was holding the device (left, right, both), which finger was used (index finger, one thumb, two thumbs), and which orientation the device was in (landscape or portrait). It was also noted whether users were operating the device with the same hand they were holding it in when they stated they used the thumb for input. Table 3.25 and Figure 3.28 show the results.

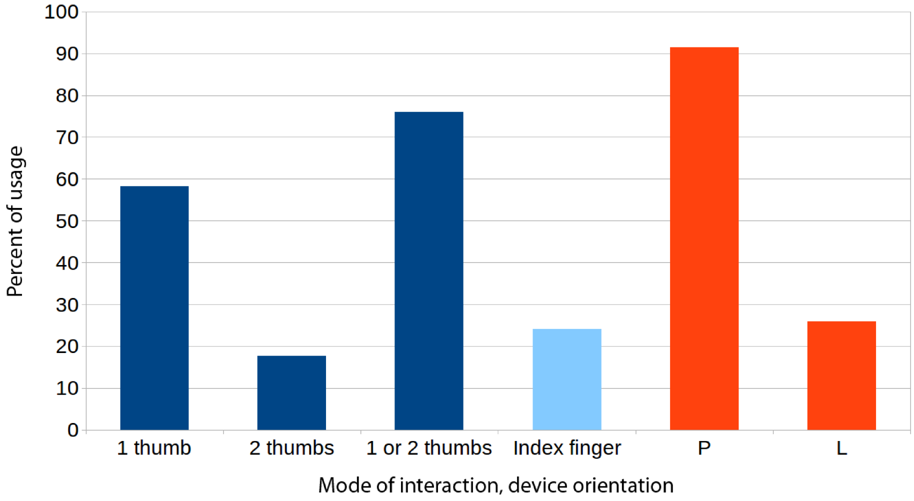

FIGURE 3.28: Visualisation of Table 3.25, showing mean percentage of users using one (1) thumb (holding the device in one hand and operating it with the thumb of the same hand), two (2) thumbs, one or two thumbs (the sum of users holding the device in either one or two hands and using either one or two thumbs), and the index finger for interaction. An additional column shows the mean percentage for two-thumb interaction in all applications to show the difference between one-thumb and two-thumb operation. The figure also shows the mean percentage of users holding device in portrait (P) and landscape (L) orientations.

3.3.4 Users' Reasons for Holding Their Phone the Way They Do

When asked why they hold their phones the way they do, participants gave a variety of reasons. Based on the responses shown in Table 3.26, the top five reasons are: It is more comfortable (17%), easier to hold (10.6%), easier to operate (10.6%), it feels natural (10.6%) and habit, based on other devices used or owned (8.5%). It is remarkable that efficiency was only given as a reason by one user (2.1%), but that comfort, ease of use, naturalness and habit appear most important to users when choosing a mode of operation.

Table 3.26: Users' reasons for holding the phone the way they do. Users were allowed to give multiple reasons. Each given reason was counted and is presented in the table.

Reason	**Responses**	**Responses %**
Comfortable	8	17.0
Easier to tap	5	10.6
Easier to hold	5	10.6
Feels natural	5	10.6
Habit	4	8.5
Lazy	3	6.4
Design of device	2	4.3
Convenience	2	4.3
More secure	2	4.3
Preference	2	4.3
Interface requires it	2	4.3
One hand busy	2	4.3
Don't know	2	4.3
Works best	1	2.1
Quickest way to perform a task	1	2.1
Interface allows it	1	2.1

3.4 Conclusion and Future Work

This section summarises the findings of each research goal and uses the insights gained from these to answer the research question *RQ1*. It finishes with suggestions for future work.

3.4.1 Findings of the Research Goals

***G1*: Establishing in which orientation (landscape or portrait) a phone is faster to use when using the index finger, one thumb, and two thumbs.**

Using the index finger, Study One indicates that interaction time is lower in landscape orientation than in portrait orientation. Using the thumbs for input, Study Two indicates the same. Within the group of thumb input (Study Two), a device is faster to operate using two thumbs than just one.

Comparing the studies with each other indicates no statistically significant difference in performance between thumb-based and index-finger-based operation other than the better performance of two-thumb operation in landscape orientation over index finger operation in portrait orientation. This suggests the most efficient mode of operation to be holding the device with two hands in landscape orientation and operating it with both thumbs, or holding it in landscape orientation with one hand and operating it with the index finger of the other hand (section 3.2.3, p. 111).

***G2*: Determining which area of the display is fastest to interact with.**

The studies indicate that the efficiency of target positions (and thus different parts of the display) is not fixed, in terms of making some more efficient than others by default, but appears to be strongly influenced by the gaze position determined by a previous dialogue or visual stimulus. The efficiency "rating" of a target position (or part of the display) then seems to follow a search pattern resembling the common reading pattern, rather than being based on target distance from the input "device". However, as R2 of Study Two showed, there may be exceptions. In addition, layouts of three buttons did not expose this efficiency pattern due to the possible absence of a search strategy likely to be caused by an enlarged Useful Field of View (UFOV) (Ware, 2012, p. 173) or high degree of target proximity, minimising possible effects of target distance from the input "device".

***G3*: Defining the average technological specifications of today's smartphones.**

As reported in section 3.3.1, the results indicate that the average smartphone has the following capabilities:

- Screen size: 4.475 inches
- RAM: 1024 megabyte (MB)
- CPU cores: 2
- CPU speed: 1350 megahertz (MHz)
- Devices with a touchscreen: 96.7%
- Devices possessing a gyroscope, accelerometer, microphone and a proximity sensor: 96.7%

$G4$: Learning which applications users use the most and how users operate standard applications.

According to the data in section 3.3.2, p. 114, two thirds of the most frequently used applications are text-input-based, and one third are a mixture of text- and pointing-based applications. As their most frequently used application, users named:

- Messaging: 70%
- Browsing: 13.33%
- Social media: 10%
- E-books: 3.33%
- Calls: 3.33%

However, users often named more than one application. The top five secondary answers and onwards were:

- Calls: 15.6%
- Social media: 15.6%
- Messaging: 15.6%
- Web browsing: 15.6%
- Gaming: 9.4%

This indicates that devices are primarily used for communication, with information consumption and entertainment use secondary to this.

In terms of operating standard applications applications, Table 3.25, p. 116, indicates that users predominantly hold the device in one hand and operate it with the thumb of the same hand (58.23%). In addition, users mostly use the portrait orientation (91.34%). Overall, usage of two thumbs appears to be low (17.76%), apart from when using applications that require high input frequencies (messaging) or a rotation of the device into landscape to extend the application options (video, camera). The results suggest that index finger usage is also low (24%), apart from in applications that require a higher degree of dexterity (calendar) or that are mostly operated in landscape orientation (video playback control). When combining one-thumb and two-thumb operation, the data indicates that in more than three quarters of the examined applications, users employ the thumb for interaction (76%), underlining the importance of supporting this input method.

***G5*: Learning users' subjective reasons for operating a device in the way they do.**

Users gave a range of reasons for holding a smartphone the way they do (Tab. 3.26, p. 118), but users responded most frequently that they choose a certain grip or mode of interaction for its comfort and ease of use and that this is further influenced by a feeling of naturalness – obviously implied by the device's affordance – and their habit, based on other devices they use or activities they perform.

***G6*: Examining whether Karlson et al.'s (2006) findings about one-handed use of mobile phones are equally valid today, in a climate where the majority of sold smartphones are touchscreen-only devices (GfK, 2012).**

Karlson et al. (2006) found that 45% of users used only one hand for device interaction. The results of the user survey in section 3.3, p. 113, were that one hand is used in 58.23% of the examined applications. The difference may be due to a variety of factors.

First, the sample size of the user study presented in this chapter is smaller than Karlson et al.'s and therefore more prone to sampling error, although its size should still provide sufficiently reliable data. Furthermore, Karlson et al. made a finer distinction between various application parts, as they broke down use of a calendar application into lookup and entry tasks, which could have impacted their findings. Lastly, of the participants of Karlson et al.'s study, only 42% had a touchscreen device and only 20% had a device without a keyboard, as opposed to 96.7% in this chapter's survey. This may suggest that users who have touchscreens and a keyboard might be inhibited from frequently using one hand to interact with on-screen target selection tasks, as they would have to stretch their thumb beyond the keyboard "barrier", resulting in a potentially lower usage of this interaction method.

With regards to text entry, Karlson et al. report that the majority of participants employed two hands for this task – a trend supported and amplified by the study in this chapter, likely due to the lack of multi-tap keyboards in users' modern devices, the high input frequency and the larger device size, making it harder to reach for and aim at the letters on a comparatively large touchscreen surface when holding and operating the phone in one hand.

This chapter's user survey suggests that camera operation is performed more frequently with two hands as opposed to one compared to Karlson et al's findings. This may be due to the larger device size, the potentially better support for landscape photographs in modern smartphones compared to flip phones and candy-bar-style phones, and the provision of buttons on a smartphone's side that support camera functionality. Similarly, media consumption (specifically, viewing a video) is more likely to be frequently performed with two hands, as modern devices support landscape orientation and have a larger screen, where the device is often held in one hand and operated with the other to facilitate steering tasks such as forwarding the playback position, illustrated by the responses given in Table 3.25, p. 116.

Web browsing seems to be also performed more frequently with one hand (as opposed to two) than reported by Karlson et al., suggesting that the omission of a hardware keyboard on the phones used by the participants in the user study facilitates one-handed pointing interaction with the thumb.

Trends that appear unchanged are photo browsing, reading, and dialling, which are all predominantly performed with one hand.

In summary, the general trends in phone operation Karlson et al. discovered are still valid today, with some appearing either slightly amplified or altered by the changes in devices' capabilities and dimensions. This in turn underlines the importance of supporting one-handed interaction as the prevalent mode of operation, especially since devices seem to be growing in size (Fingas, 2013), potentially intensifying the problem of the thumb's limited mobility (Karlson et al., 2006).

3.4.2 Answering Research Question 1

***RQ1*: What is more important to users when operating a mobile device: Efficiency or comfort?**

The findings of Study One and Study Two suggest that, if input efficiency is the most important factor, users should operate their phone using two thumbs in landscape orientation. Nonetheless, the insight gained from *G4* shows that when equally weighing all examined applications, the dominant form of input is one-handed operation via the thumb while holding the phone in portrait orientation. This is with the exceptions of entering text in portrait orientation and controlling a video in landscape orientation, where either a high input frequency is required or entertainment experience can be enhanced.

This suggests that, in general, users may be unwilling to dedicate both hands and therefore their full manual motor capabilities to the operation of their smartphone – unless required or if it is a less tiring option than their preferred mode of interaction. This indicates that convenience and the minimisation of effort may be more influential than efficiency when operating applications with a low input rate, where users can pull the device out of their pocket with one hand and operate it with the same, keeping their other hand free. This reconfirms Karlson et al.'s (2006) findings that users prefer one-handed operation whenever possible and only employ a second hand if the interface requires it. The users' subjective answers to why they hold and operate the phone the way they do may therefore be able to support this assumption (Tab 3.26, p. 118). Here users responded most frequently that they choose a certain grip or mode of interaction for its comfort and ease of use and that this is further influenced by a feeling of naturalness – obviously implied by the device's affordance – and their habit, based on other devices they use or activities they perform.

Regarding the above, the answer to *RQ1* is that, in general, comfort is more important to users than efficiency when operating a mobile device. The highest performing input modes are only chosen for input-heavy tasks or when an experience can be enhanced.

This indicates that a successful interface for improving one-handed operation is an interface that focusses on supporting convenience and ease of use in users' preferred interaction mode while at the same time improving efficiency, to reduce the need to use a second hand for input in difficult situations (such as access to a distant target).

3.4.3 Summary and Contribution

This chapter has examined the impact of device orientation, interaction mode and target position on target selection efficiency on touchscreen smartphones by presenting two quantitative studies. The results indicate that when used with the index finger, a device is fastest to interact with in landscape orientation, suggesting this device or layout orientation should be used on mounted touchscreens, such as those in time-critical environments (power plant controls rooms and plane cockpits, for example).

In addition, the chapter has illustrated that when operating the device with the thumb, using two thumbs tends to be more efficient than one thumb, and that operation in landscape orientation is faster than portrait orientation. However, little difference between either mode of interaction (thumb and index finger) seems to exist, aside from potential differences in input efficiency for discrete target positions in different modes of interaction. Yet, a light trend indicates two-thumb interaction in landscape orientation to be the most efficient mode of operation overall. The above studies have also shown that interaction speed of different parts of the layout varies in either orientation and that the reason for this may be the user's initial gaze followed by a search strategy corresponding to the direction of reading. The data suggests that this may be more influential on interaction time than the distance of the input "device" (finger or thumb) from the target, as targets closer to the pointer tended to have a higher interaction time than those further away but closer to the visual stimulus. This therefore contradicts predictions for interaction time following Fitts's law and suggests that, at least under the conditions of the study, predictions made using this law ought to consider the position of the visual stimulus and a user's search behaviour in addition to the target's distance from the pointer. The above was observed independently of mode of interaction or device orientation in three rounds of the user studies, apart from one showing the effect less pronounced (R2, Study Two).

As a result, these findings could be employed for designing dialogues which prioritise certain options over others, simply by placing them in close position to the main point of attention stemming from a preceding dialogue, or, if the target is to be harder to find than others in the same layout, to the left of the stimulus or above it, against the user's natural direction of reading. Combined with the reported tendency of interfaces to be faster to interact with in landscape than in portrait orientation, interaction with time-critical applications could further be improved by not only adapting the order of elements to the findings of this research, but also by presenting the layouts or devices in landscape orientation.

The chapter has also provided a contemporary report on device specifications as well as users' most frequent modes of interaction with a range of applications, suggesting that the findings reported by Karlson et al. (2006) still not only largely apply, but actually appear exacerbated by the characteristics of modern devices. This in turn has shown the need to support the prevalent way of interaction that is one-handed thumb-based interaction, especially as devices appear to have increased in size, making larger portions of the screen more difficult to reach with the thumb (Karlson et al., 2006).

Following this, the chapter has given deeper insight into users' rationales for holding and operating a touchscreen smartphone the way they do. Despite one-handed operation in portrait orientation performing rather poorly in terms of efficiency when compared to operating the device with two thumbs, in both portrait and landscape orientations (see section 3.2.2, p. 91), users predominantly employ this mode of interaction if the task does not require high-frequency input (as needed for messaging), or the interface was easier to interact with (controlling video playback in landscape orientation), or if a change in orientation would offer additional and required functionality (camera). This suggests that preference has a stronger impact on determining a user's choice of mobile interface and mode of operation than efficiency, and matches observations made by Grudin and MacLean (1985), who found that not all users automatically prefer the most efficient method when entering data, but sometimes choose a different and less efficient one, despite clear differences in performance.

As subjective reasons for a certain ways of holding and operating a device, users named comfort, ease of use, naturalness and habit. Therefore it seems advisable to correspond to these requirements when aiming to support interaction on touchscreen smartphones. The improvement of one-handed interaction should therefore focus on supporting and even increasing these factors while also considering aesthetics (Tractinsky et al., 2000), complying with "the user's information processing capabilities" (Welsh et al., 2008) and simultaneously offering improvements in speed of operation and functionality – a reason derived from the analysis of the application operation (section 3.3.3, p. 115) and named by Karlson et al. (2006) as a factor for changing the mode of interaction to a less-favoured one. To further accommodate the users in their habits, the findings suggest to avoid challenging the user with unexpected additional hardware or modifications to their device, but to focus on supporting one-handed interaction on off-the-shelf smartphones to assure user acceptance and learnability. Therefore, the following constraints for the research conducted in the following chapters can be formulated:

Constraints

- Solutions should be convenient and easy to use. They should not require a great effort to be made by the user, neither for interaction nor for modification of their device.
- Solutions should correspond to users' preferred mode of operation (one hand).
- With the user's preference for the known and to avoid effort – even if a performance gain can be achieved – solutions should work with off-the-shelf smartphones. Technical specifications for these are detailed in section 3.3.1, p. 113.
- Solutions should address the challenges of one-handed operation as defined in Chapter 2 (p. 33) to reduce the need for changing one's grip.
- Since these identified challenges consist of the difficulty of reaching distant targets, interface occlusion, steering a cursor over a path, and limited selection precision, solutions should focus on primarily addressing these. As a result, text input methods are excluded from the research.

With the insights gained from the research goals *G1* to *G5* and thus answering the research questions *RQ1*, this chapter provides the foundation for the research conducted in the following parts of this thesis. The knowledge about today's devices' technical capabilities supports the GUI-based approach presented in Chapter 5 as well as the off-screen input generation presented in Chapter 6. For both suggested ways of enhancing one-handed interaction on touchscreen smartphones, the insights gained into application operation and users' rationales for certain modes of interaction will act as a precondition and guide for developing and evaluating the presented techniques. Finally, this knowledge will be used in the conclusion of the thesis to contemplate further developments in the field of mobile HCI.

3.4.4 Future Work

While this chapter has provided insight into various aspects that inform the research undertaken in this thesis, it has also posed a set of questions that provide avenues for future work.

For example, the efficiency ranking of the three target zones observed in Study One and Study Two has introduced the question as to which factor is more decisive in mobile interaction: Target distance from the "pointer" or target distance from and spatial relation to the point of gaze. The contradictory results of the mean IT measured for the respective screen regions when compared to the informal predictions of Fitts's law suggest that a GUI should not solely be judged by isolating certain aspects – such as pointer-to-target distance – but rather as a whole, as part of a story and therefore as part of a chain of actions with a shifting visual focus, impacting user performance on manifold levels. This has also been found by Welsh et al., who state that "spatiotemporal arrangement of relevant and nonrelevant stimulus information will affect the manner in which actions are completed" (Welsh et al., 2008).

Although a model for predicting selection times in linear menus considering gaze and target position exists (Bailly et al., 2014), the weighting of the two factors in impacting the IT on touchscreen smartphones with the thumb remains an open question and thereby represents an important avenue for future work aiming at improving the dialogue between humans and their handheld devices. In this regard, future work will investigate how interaction can not only be made more comfortable by supporting a curved movement of the thumb and placing elements in easy-to-reach places as recommended by previous work (Roudaut, 2009; Katre, 2010; Park and Han, 2010), but also more efficient by considering the spatiotemporal arrangement of interactive elements in the thumb's comfort zone.

While this could help to further improve and understand one-handed interaction, this chapter's main contribution is the establishment that users appear to prefer comfort over efficiency when operating their mobile devices. However, it remains unclear whether this only applies to touchscreen smartphones, or whether this insight is transferable to other devices, such as smartwatches and tablets. For this, another important part of future work is the extension of the study to these form factors to examine whether their interaction design could also benefit from the insights gained into user preference and layout efficiency.

Altogether, this chapter has provided the foundation for the development of an adequate approach to improve one-handed interaction. The next chapter will provide insight into the characteristics of touches with index finger and thumb to further support the design and implementation of such an approach.

Chapter 4

The Properties of Touch and Their Applicability for Determining Handedness and Mode of Operation

4.1 Introduction

This chapter examines the expressiveness of digital touch. In particular, it discusses whether the information conveyed by the touchscreen controller and motion sensors of an off-the-shelf smartphone can allow the user's finger and hand to be identified with the first touch. It presents three approaches, the most accurate of which achieves finger type classification with an average accuracy of up to 83.1% and hand classification with an average accuracy of up to 62.2%. As such, the research can be utilised to dynamically adapt the interface to the detected mode of interaction – index finger or thumb – an example of which is given in Chapter 5.

Understanding users' rationale for holding a device the way they do, together with their preference of operation, are important first steps to improving the one-handed operation of mobile devices (see Chapter 3). However, making an assumption about the style of operation (using thumb or index finger) of a certain application solely based on user habit and preference for said application does not suffice as a basis for adapting an interface to a given context to improve usability.

Previous research – as detailed in Chapter 2, section 2.8, p. 64 – predominantly uses additional sensors on the device to infer a user's grip and mode of operation. However, some researchers (Goel et al., 2012) use the digital touch properties provided by a phone's Software Development Kit (SDK) with a high degree of success to achieve the same. Nonetheless, their approach requires up to five user interactions consisting of various swipes and taps that have to be performed in certain areas of the screen. As a premise for dynamic input mode detection this may seem inadequate, especially in situations where users only need to perform very few interactions in a limited area of the screen to achieve their goal – and even more so if designers want to follow Norman's advice of keeping the Gulf of Execution (the number of interactions necessary to achieve a goal) as narrow as possible (Norman, 2002). What is needed, therefore, is an approach that allows the detection of the mode of operation (finger type and hand) within a single interaction step – ideally by performing just one touch of the screen. Achieving this can be seen as a prerequisite to the implementation of a thumb-adapted interface.

A physical touch is very expressive: It consist of various phases, actions and stages and has a wide range of properties, such as strength, duration and even emotion, from which context can be derived. However, little is left of this complexity when expressed through the touchscreen of a mobile device, as it can only harness a limited amount of information. Because of this, the question arises as to whether the digital expression of touch is sufficient to infer the finger's physical properties and therefore deduct the mode of operation. In this regard, the following research question can be formed:

***RQ2*:** Are the properties of a single "digitised" touch characteristic enough to distinguish between index finger and thumb of the left and right hand?

To investigate, this chapter will examine digital touch properties such as size, pressure, duration, location, development, rotation and direction in all parts of a mobile display. It will then evaluate these properties' suitability for determining a user's hand and finger. As a result, the following set of research goals emerges:

- ***G1*:** Determining whether the digital touch properties of only one touch can be used to detect whether the index finger or thumb is being used for input.

- ***G2*:** Determining whether the digital touch properties of only one touch can be used to determine whether the left or right hand is being used for input.
- ***G3*:** Defining which input property is the most accurate for making these predictions.
- ***G4*:** Examining whether accuracy changes with target position – specifically, whether the data in certain areas of the screen is more characteristic for finger type or hand than in others.

The insights gained from these will allow *RQ2* to be answered.

This chapter is divided into two main parts. The first part comprises the initial data collection and evaluation of various digital and analogue touch properties (section 4.2, p. 131). This is done by visualising the values of the touch properties in all areas of the screen (section 4.3.1, p. 137), by examining the physical touch shape (section 4.3.2, p. 168) and by exploring the data in *Weka* (Holmes et al., 1994) (section 4.3.3, p. 174) using various classification methods.

The second part (section 4.4, p. 177) begins with an additional data collection and presents four approaches – *A*, *B1*, *B2* and *C* – to determine a user's finger and hand with a single touch of the display based on the findings described in the first part of the chapter. In a following evaluation, the four approaches are compared and the most accurate one determined. The chapter finishes with a conclusion (section 4.5, p. 215) to answer the research question and provides stimuli for future work.

4.2 Initial Data Collection

4.2.1 Study Design

To explore digital and analogue touch properties, a user study was conducted with 27 participants (8 F, mean age: 22.33 years, SD: 2.94). Using an HTC Sensation XE phone running Android 4.03, users were tasked with tapping 60 buttons highlighted at random (Fig. 4.1) in a specially created smartphone application. Users had to tap all 60 buttons with their left index finger, with their left thumb, with their right thumb and with their

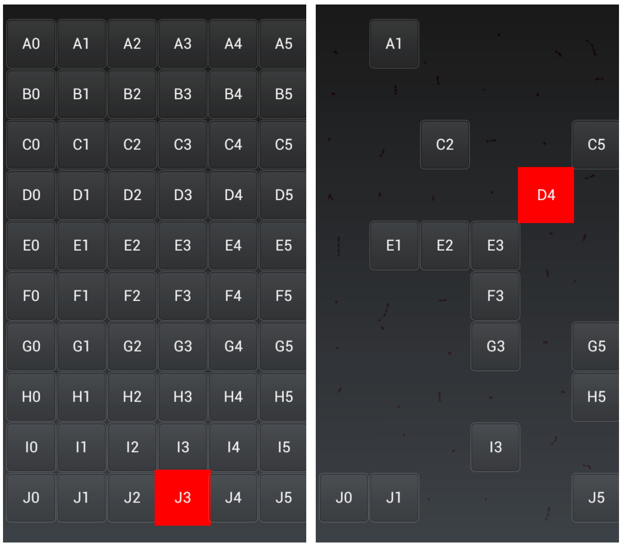

FIGURE 4.1: **Left:** The button grid as it appears at the start of each round with one random button highlighted. **Right:** The button grid “in-game” after several buttons have been pressed and removed.

right index finger. The tasks were performed in two conditions: While sitting in an office and while walking outside on the pavement of a quiet street. Each round started with 60 buttons on the screen and ended when all buttons had been pressed. The button the user had to press was highlighted in red and disappeared after it was hit (Fig. 4.1). One second after a successful touch, another button was highlighted at random. Errors, such as pressing the wrong button, had no effect as only the highlighted button was “active” and responded to being touched. Each button had a physical dimension of 9mm x 9mm, close to the size suggested by Parhi et al. (2006) and Microsoft (n.d.) who recommend 9.2mm x 9.2mm and 9mm x 9mm respectively as the optimum button size for discrete tasks on touchscreen smartphones. The buttons were laid out in a grid of six wide by ten tall on a screen with a resolution of 540px x 960px and the grid was horizontally and vertically centred on the screen. Altogether, users had to complete eight rounds, resulting in a total of 480 button presses per user. After users had finished these tasks, the physical properties of their fingers were recorded to examine the relationships between digital and physical characteristics. The recorded physical properties are described in section 4.2.3, p. 136. Two participants were asked to return on a later date to redo parts of the digital data collection due to a misconfiguration in the first collection.

4.2.2 Recorded Digital Values

Wang and Ren (2009) provide a summary of touch input properties that have been used in previous research to describe and improve input, such as motion, position and physical properties, but add touch shape and shape orientation to the list. The properties recorded in this study incorporated those listed by Wang and Ren (2009), but added several previously unused properties for classification: Duration of a touch, number of touch points created during the touch event and the distance between the first and last contact point of the finger on the screen. As previous research finds the data provided by the accelerometer to be of very little use when interpreting finger and hand type (Goel et al., 2012), this sensor was not used for the digital description of touch. Before detailing the recorded values, the terms used to describe various parts of the touch event should be clarified:

- *touchStart*: Describes the part of the touch event when the finger first touches down on the display.
- *touchMove*: Represents the part of the touch event when the finger slightly moves on the display during its contact.
- *touchEnd*: Describes the part of the touch event when the finger has been lifted from the display.

The following values were recorded:

- *Name:* Anonymised name of the user.
- *Handed:* The hand (left or right), input mode (index finger or thumb) and condition (sitting or walking) the taps were performed in. For example: "Right Thumb Walking" and "Left Finger". Sitting was considered the standard condition and was therefore not added to the description of a value.
- *Button Name:* The name of a button, such as "G4".
- *Button ID:* The ID of the button, ranging from 0 to 59.
- *Touchpoints:* A list of absolute and relative X/Y values for each *touchStart* and *touchMove* event registered per touch in px.

- *Detected Directions:* An array of directional changes during a touch, representing the directions into which the touch developed from start to end. For example, if a touch point that followed in the list of recorded touch events (touch history) after the first touch (*touchStart*) had an X value smaller than the first touch point, the value "Left" was recorded. If the subsequent point's value was greater than the first point's X value, the value "Right" was recorded.
- *Number of Touches:* The number of touch points created after the first touch.
- *Touch Size:* A list holding the contact sizes of a *touchStart* event and all subsequent *touchMove* events. The sizes ranged from 0 (no touch) to 1 (fully opaque touch).
- *Touch Size Mean:* The mean of the values recorded in the *Touch Size* array.
- *Touch Time:* The time the finger was left on the display in milliseconds (ms), effectively the time between *touchStart* and *touchEnd*.
- *Diff X:* The difference in the X value between the first and last touch point of the touch event in px.
- *Diff Y:* The difference in the Y value between the first and last touch point of the touch event in px.
- *X Offset:* The X Offset of the first touch point relative to the centre of the button in px.
- *Y Offset:* The Y Offset of the first touch point relative to the centre of the button in px.

The gyroscope values were recorded as a chain of values in different lists (arrays). One array recorded the gyroscope explicitly during the actual touch – from *touchStart* with every *touchMove* event until *touchEnd* – and another array recorded the gyroscope roughly every ms for the duration of the whole task, which spanned from the time the button was highlighted to the moment the button was touched and the finger lifted from the display (*touchEnd*). This way, two sets of gyroscope data were recorded. The values recorded during the touch only show changes in the gyroscope while the finger was on the display and moved whereas the other values document the changes in the gyroscope before and during the touch.

- *Gyro X:* An array of the rotation of the device over the X-axis on *touchStart* and *touchMove*. Each time a touch history point was created (Fig. 4.30), a value was recorded in Hz.
- *Gyro Y:* An array of the rotation of the device over the Y-axis on *touchStart* and *touchMove*. Each time a touch history point was created (Fig. 4.30), a value was recorded in Hz.
- *Gyro Z:* An array of the rotation of the device over the Z-axis on *touchStart* and *touchMove*. Each time a touch history point was created (Fig. 4.30), a value was recorded in Hz.
- *Gyro All X:* An array of the rotation of the device over the X-axis during the whole time of the task. The values were recorded in Hz with the frequency of the Android SDK's Sensor Manager constant *SENSOR_DELAY_GAME*, which equates to about 1 ms.
- *Gyro All Y:* An array of the rotation of the device over the Y-axis during the whole time of the task. The values were recorded as above.
- *Gyro All Z:* An array of the rotation of the device over the Z-axis during the whole time of the task. The values were recorded as above.
- *Gyro X Amplitude:* The difference between the lowest and highest recorded value in the *Gyro X* array.
- *Gyro Y Amplitude:* The difference between the lowest and highest recorded value in the *Gyro Y* array.
- *Gyro Z Amplitude:* The difference between the lowest and highest recorded value in the *Gyro Z* array.
- *Gyro X All Amplitude:* The difference between the lowest and highest recorded value in the *Gyro X All* array.
- *Gyro Y All Amplitude:* The difference between the lowest and highest recorded value in the *Gyro Y All* array.
- *Gyro Z All Amplitude:* The difference between the lowest and highest recorded value in the *Gyro Z All* array.

Other values were also recorded, but were not evaluated and therefore are not reported here. The data and study information can be found in Appendix D, pp. 351–353.

In addition to the above properties being recorded in an SQLite database, I recorded the graphical presentation of the discrete touch points of a touch on a hidden layer in the background. Each touch point was recorded as a dot which was connected via a thin line to the next point of the touch event, creating a "chain" between the touch points, from the *touchStart* event over the *touchMove* event(s) to *touchEnd*. This was done to visualise the spatiotemporal development of a touch on the screen (Fig. 4.30, 4.31, pp. 170–171).

4.2.3 Recorded Physical Values

In addition to the digital touch properties, various physical finger properties were also recorded. In particular, I recorded the length of the index finger and thumb of both hands, by measuring the distance from each finger's base (the bottom of the proximal phalanx) to its tip (the end of the distal phalanx, Fig. 4.2).

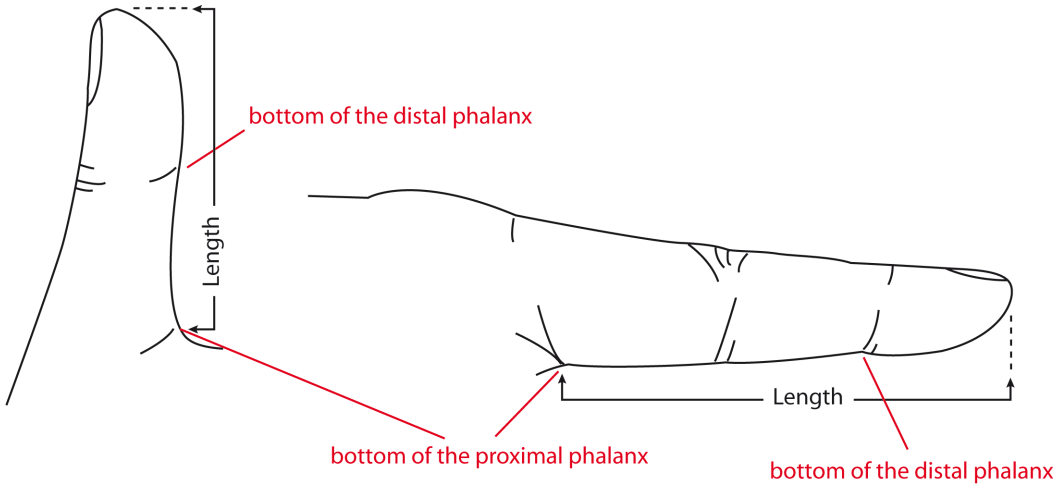

FIGURE 4.2: **Left:** Diagram of the thumb length measured. **Right:** Diagram of the index finger length measured.

In order to be able to ascertain the physical size of the area of the fingertip that might be used for a full-contact oblique touch, I measured the width and height of the participants' fingerprints. They were asked to press the top of their finger, ranging from the bottom of the distal phalanx right up to the nail bed (Fig. 4.2), onto an ink pad and roll their finger from left to right in order to cover all parts of the skin that could potentially come into contact with the display. Participants were then asked to position their finger on a parallel line to the tabletop and lower it onto a sheet of paper on the table, without rolling it to either side. The resulting width and height of the print on paper were measured in centimetres (cm) using a ruler.

In order to examine the shape of the physical touch area on different positions on the phone's screen, a sheet of paper was attached to the phone's display. The sheet replicated the layout of the button grid detailed in section 4.2.1, p. 131, but buttons were combined into groups of four which created 15 touch zones (Fig. 4.29). This procedure is similar to Katre's (2010) approach for measuring the shape of the thumb on different parts of the screen and is further described in section 4.3.2, p. 168.

4.3 Evaluation of the Digital Touch Properties

This section will evaluate the recorded digital touch properties with regards to their usefulness for answering the first two research questions of this chapter: Can they be used to differentiate between index finger and thumb within a single touch, and can they determine whether the right or left hand is being used?

4.3.1 Graphical Evaluation

To get an initial idea of the data and its potential for answering the research questions, I decided to visualise the mean values for each touch property per button, finger, hand and condition. For this I created a Web interface that represented the button grid of the app used for the data collection. Each "button" had a label with the original button name and a field for a property value. The SQLite database with the recorded values was made accessible via a local NodeJS server. For every recorded property, a query was created that provided its mean value for each button, finger, hand and condition. The mean value was written back into the respective field in the "button" representation and the background of each square was darkened according to the degree of the returned value to help visualise trends in the data (see Figure 4.3 for an example). If the value was beyond a certain threshold, the font colour was changed from black to white to improve readability.

The following pages show the resulting images for each recorded property and analyse trends in the data. In the captions of the following figures, the term “Left Finger” refers to the left index finger. The term “Right Finger” refers to the right index finger. If not specifically stated, all values and properties represent those in the sitting condition. Properties representing the walking condition have the term “walking” attached. Numbers have been shortened to four digits to fit into the grid and reported overall mean and standard deviation (SD) values in the captions have been rounded. Missing values from the data set were excluded from the mean calculation.

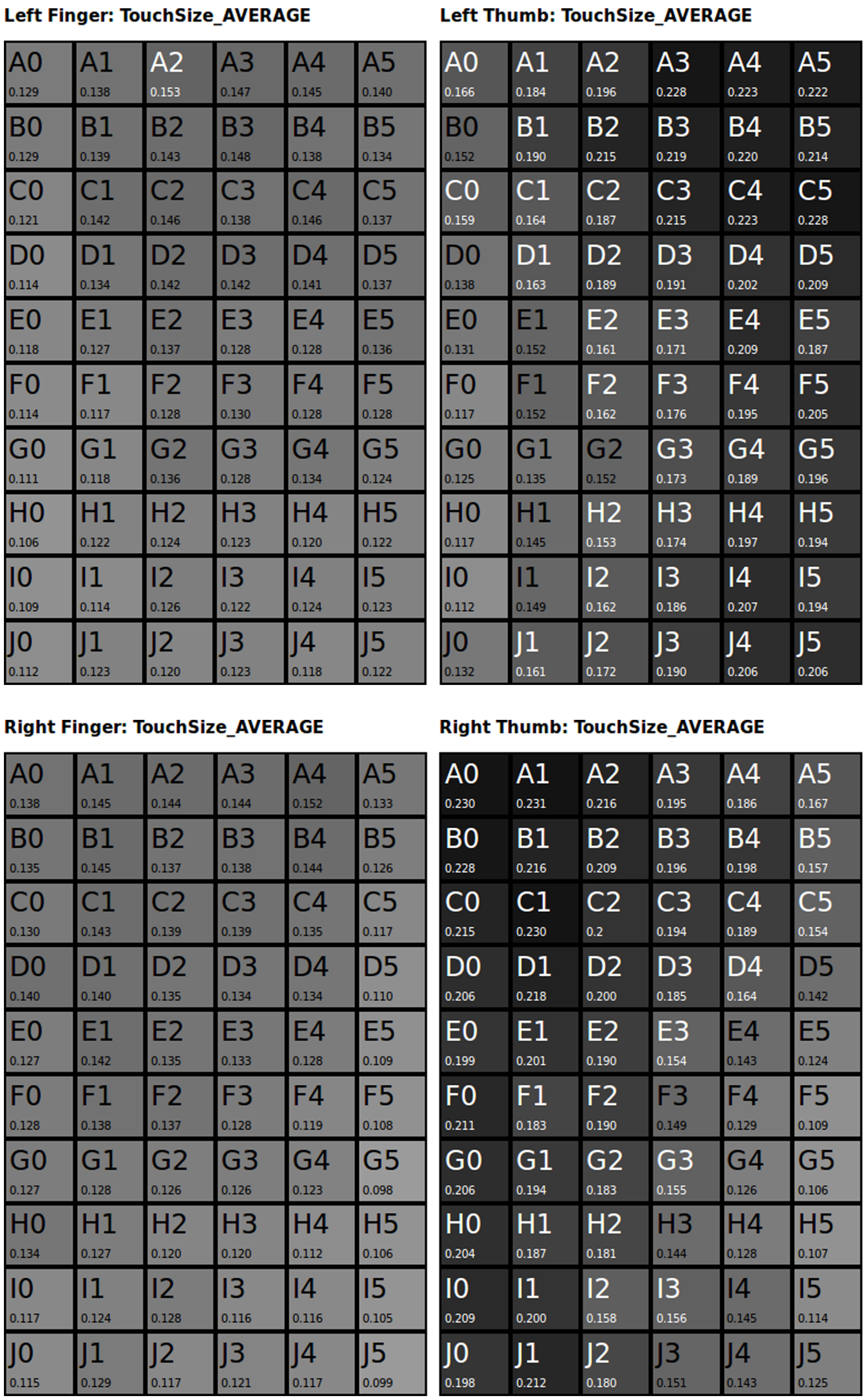

FIGURE 4.3: ***Touch Size Mean:*** Left Finger: Mean: .127, SD: .033; Left Thumb: Mean: .180, SD: .045; Right Finger: Mean .128, SD: .031; Right Thumb: Mean .178, SD: .038. Whereas *Touch Size Mean* increases from bottom to top – as found by Goel et al. (2012) – by an average of 32% for the index finger, there is no discernible differentiation between left and right hands. For the thumb, *Touch Size Mean* increases by an average of 18% from bottom to top, but the left and the right hand are clearly differentiable, as the *Touch Size Mean* also increases from side to side in a semicircular shape, representing the movement arc of the thumb. The data suggests that as the thumb is rather "fixed" in either corner when holding the phone, the touch becomes flatter and thus bigger the further the target is away from the thumb's base.

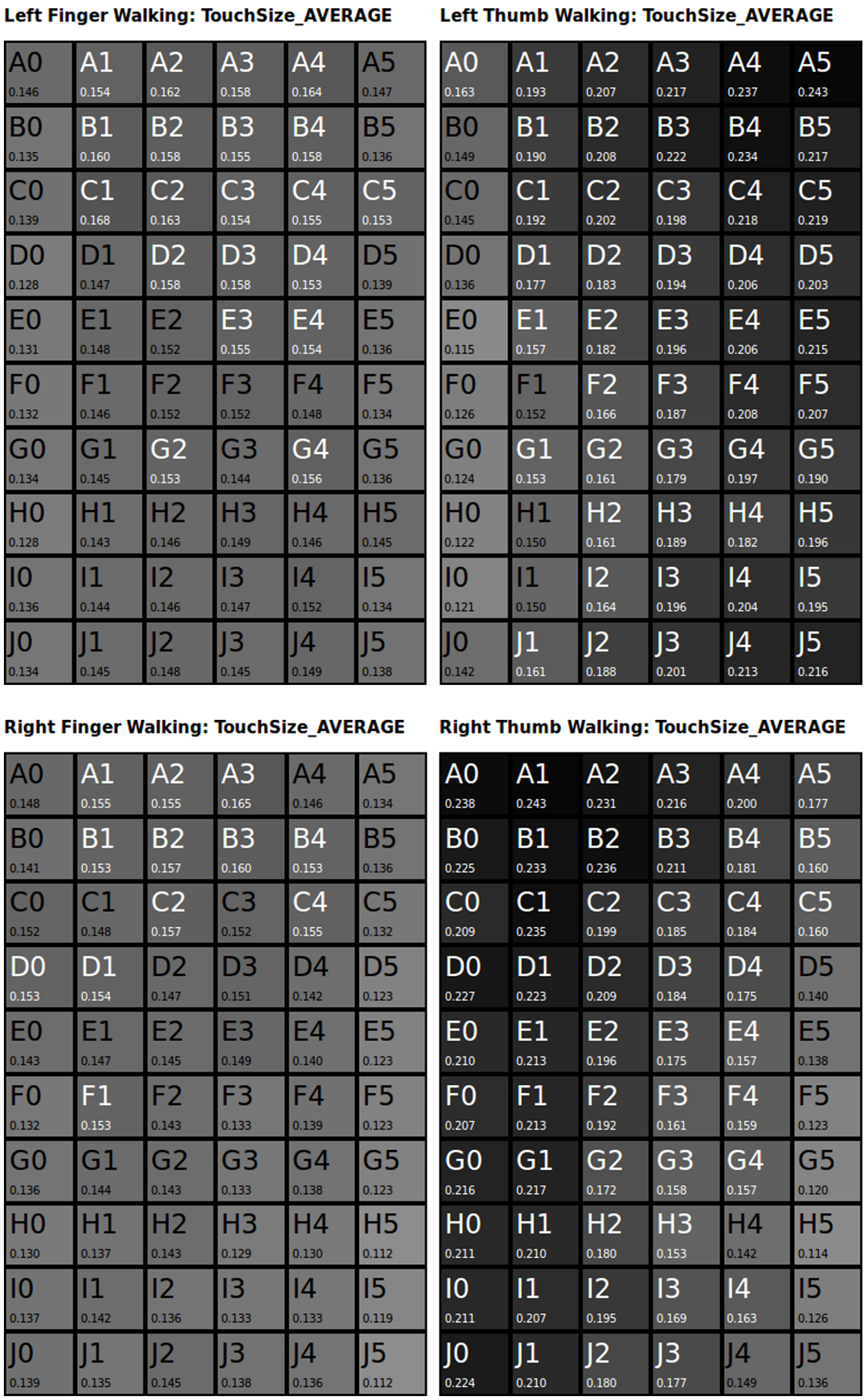

FIGURE 4.4: ***Touch Size Mean* walking:** Left Finger: Mean: .144, SD: .037; Left Thumb: Mean: .184, SD: .046; Right Finger: Mean .141, SD: .037; Right Thumb: Mean .188, SD: .038. The data follows the same trends as observed in the sitting condition (Fig. 4.3), but in general the values are slightly higher. For example, *Touch Size Mean* in the bottom row for both thumbs is an average of 6% greater and *Touch Size Mean* in the top row is an average of 5% greater. For both index fingers, *Touch Size Mean* in the bottom row is 17% greater and *Touch Size Mean* in the top row is 7% greater. This indicates that the effect of walking on *Touch Size Mean* is greater for index finger than thumb. It appears that, due to the movement, the finger is pressed "flatter" and less precisely onto the screen, whereas this effect is less strong for the thumb, which already has a rather "flat" touch.

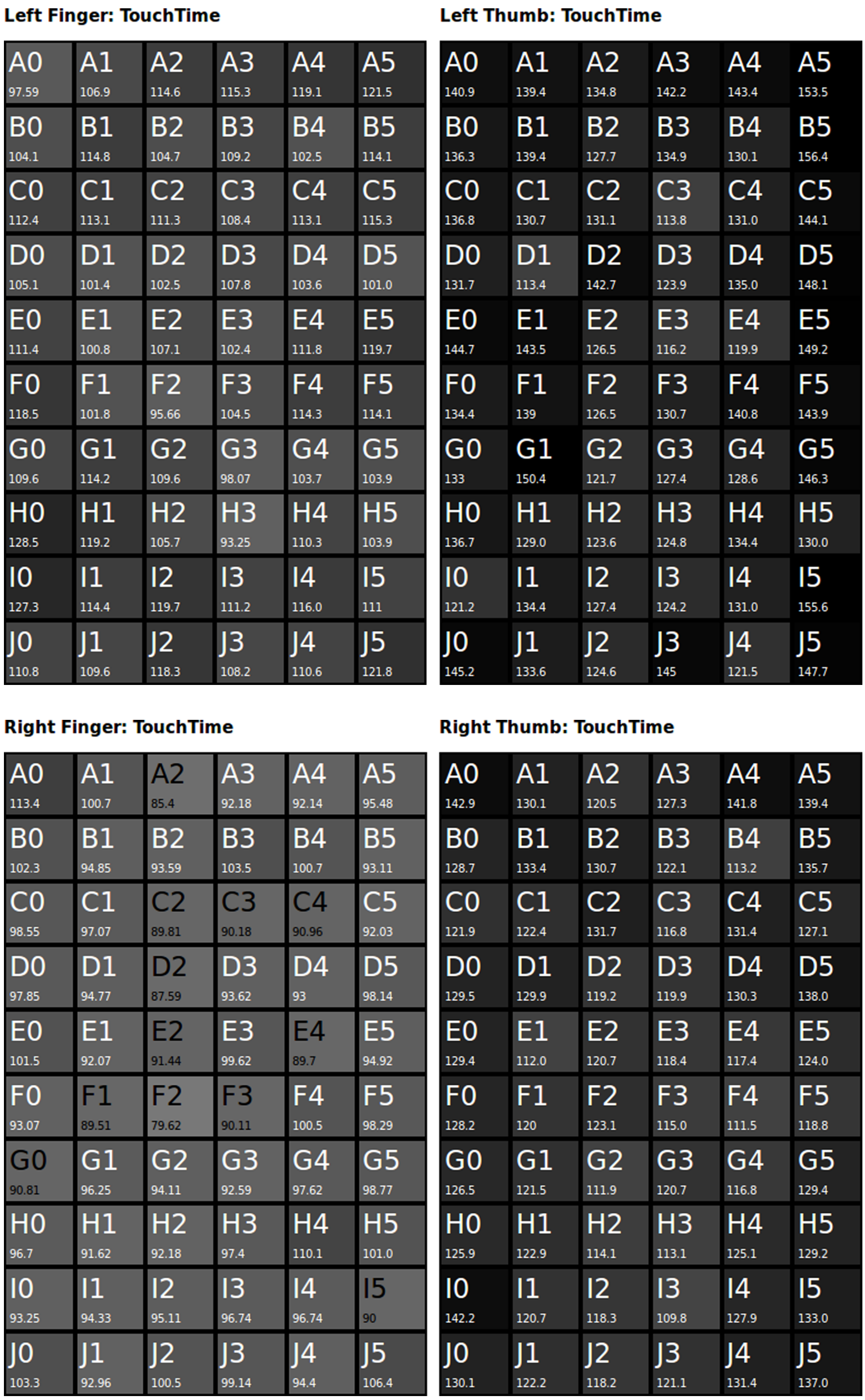

FIGURE 4.5: ***Touch Time*:** Left Finger: Mean: 110.12, SD: 54.75; Left Thumb: Mean: 134.62, SD: 50.75; Right Finger: Mean: 95.67, SD: 33.76; Right Thumb: Mean: 124.90, SD: 44.99. The differences in the mean values of the fingers suggest that thumb and index finger are likely to be distinguishable using this property and that there is a weak trend in the data for the *Touch Time* to increase from bottom to top for both thumbs (average of +5%), but not for the index fingers (average of -2%). In addition, *Touch Time* seems to be slightly higher for the left hand (average +10%), indicating that users may not be as secure and dexterous when selecting targets with their non-dominant hand.

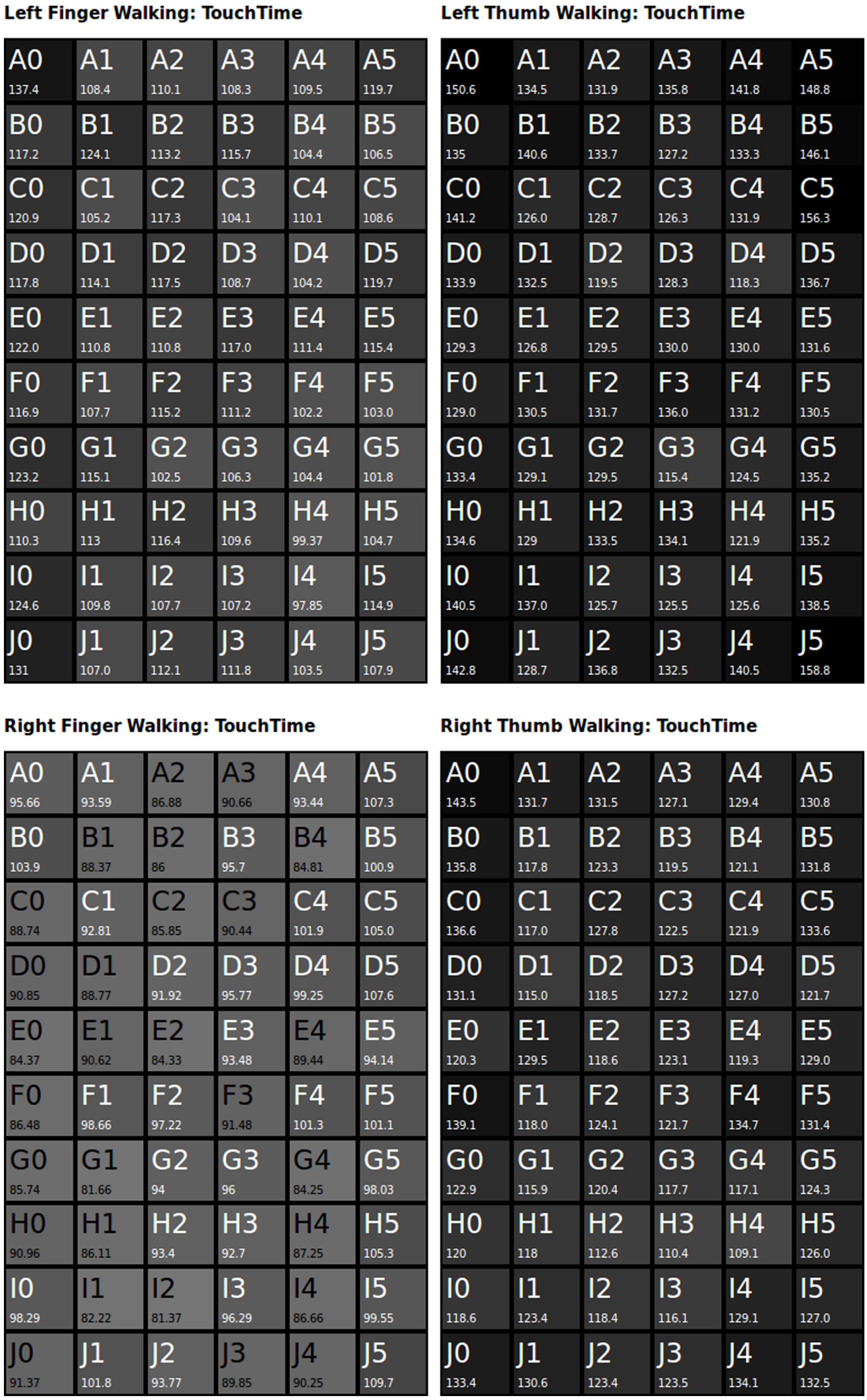

FIGURE 4.6: ***Touch Time* walking:** Left Finger: Mean: 111.86, SD: 50.32; Left Thumb: Mean: 133.27, SD: 59.51; Right Finger: Mean: 93.25, SD: 35.52; Right Thumb: Mean: 124.66, SD: 49.90. The data closely resembles that of the sitting condition (Fig. 4.5). It appears that walking does not impact *Touch Time*.

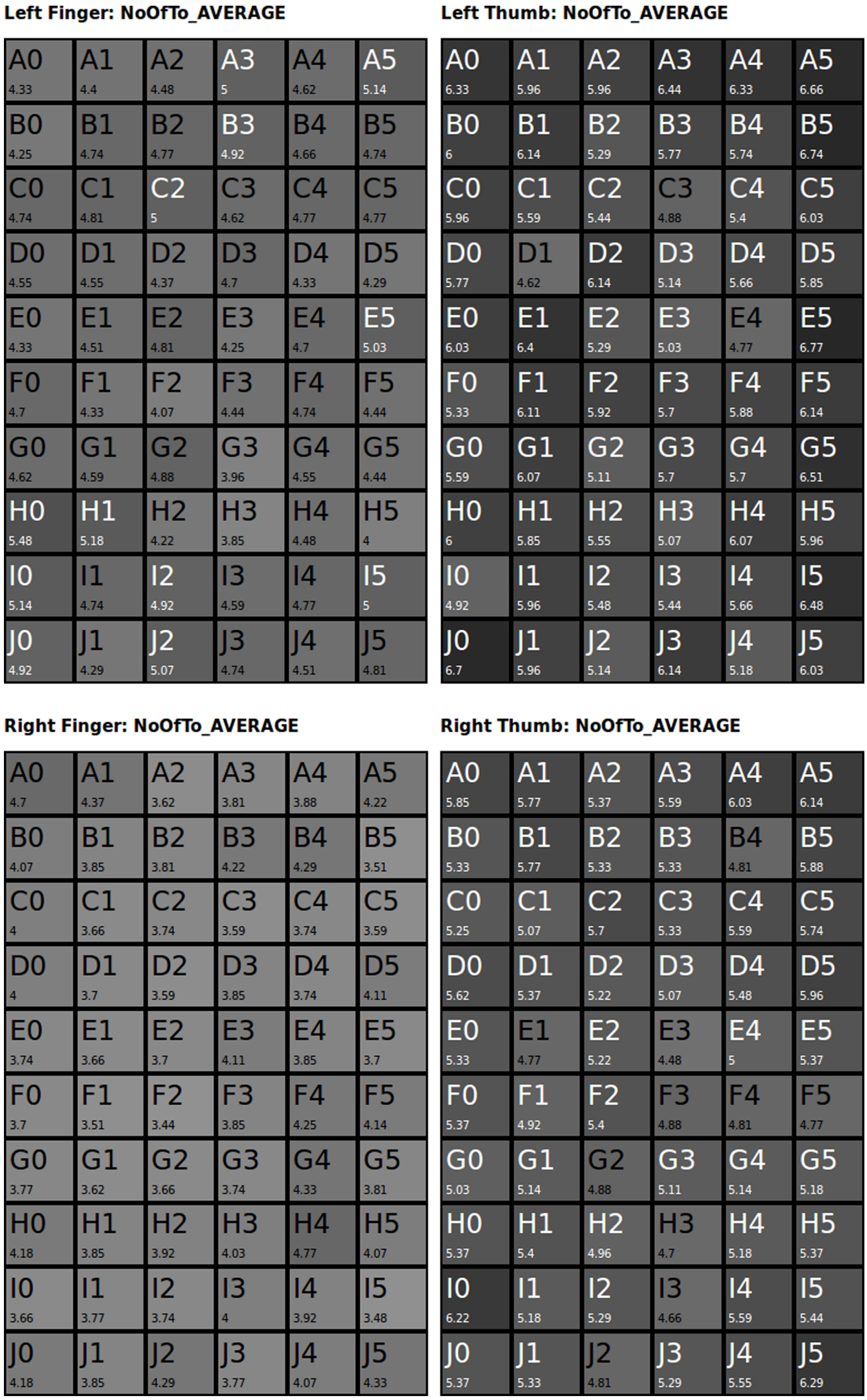

FIGURE 4.7: ***Number of Touches*:** Left Finger: Mean: 4.63, SD: 2.53; Left Thumb: Mean: 5.8, SD: 2.56; Right Finger: Mean: 3.91, SD: 1.55; Right Thumb: Mean: 5.33, SD: 2.14. The *Number of Touches* is rather equally distributed across the display for each finger. However, the colouring shows that the thumb creates more touch points on average than the index finger and that the left hand creates more touch points than the right hand. This may be due to the thumb being larger than the index finger and the left hand less dexterous than the right one, resulting in a less precise and less pointed touch.

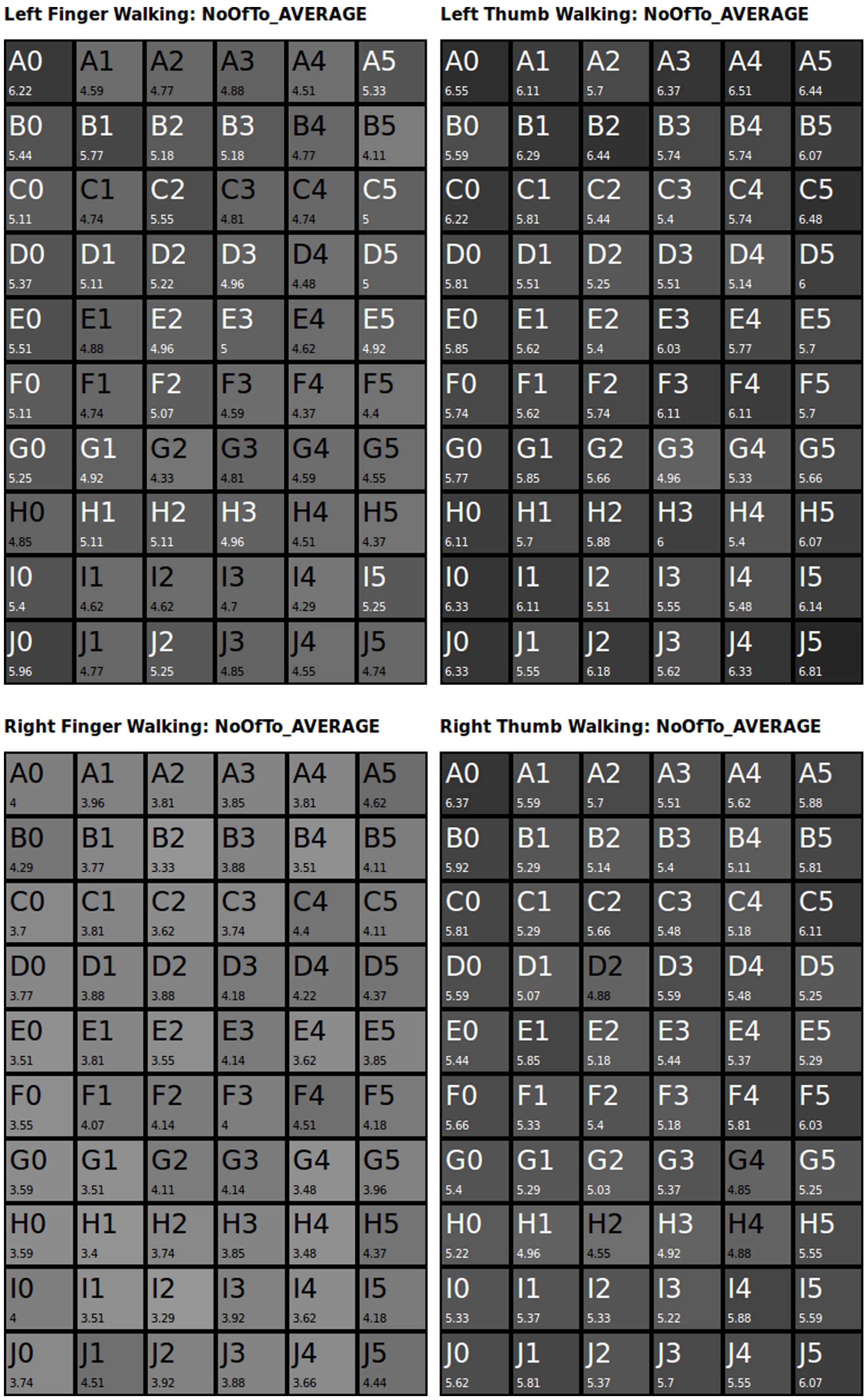

FIGURE 4.8: ***Number of Touches* walking:** Left Finger: Mean: 4.93, SD: 2.42; Left Thumb: Mean: 5.86, SD: 2.90; Right Finger: 3.90, SD: 1.85; Right Thumb: Mean: 5.45, SD: 2.42. The data shows the same trends as the sitting condition (Fig. 4.7), with the mean values being slightly higher, likely to be caused by small movements of the phone and finger during the touch while walking.

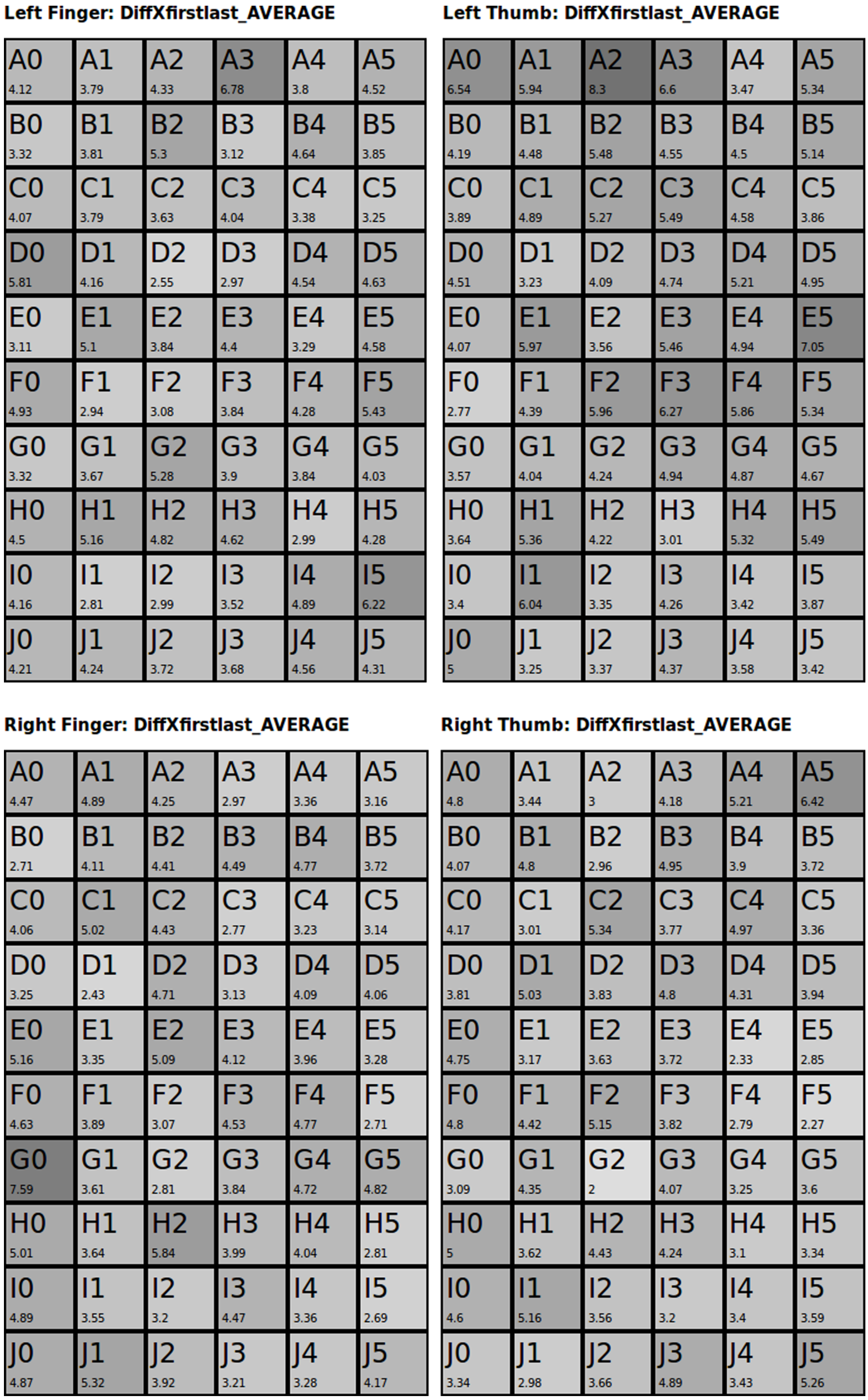

FIGURE 4.9: ***Diff X*:** Left Finger: Mean: 4.10, SD: 1.32; Left Thumb: Mean: 4.62, SD: 3.01; Right Finger: Mean: 3.97, SD: 1.43; Right Thumb: Mean: 3.92, SD: 1.41. Right and left thumb show a larger difference between first and last touch point on the X-axis in the first and last target positions of their "home" corner (columns 0 and 5), and a smaller value in most positions of the same column, where users tend to touch the screen with the thumb's side (Fig. 4.29). The left thumb shows larger differences at row A than at row J, likely to be caused by increased "slurring" due a lower degree of dexterity in this hard-to-reach area. Altogether, the fingers of the left hand possess a slightly higher mean difference between first and last touch points on the X-axis, probably due to a lower degree of dexterity of the non-dominant hand. This is also illustrated by Figures 4.7 and 4.5.

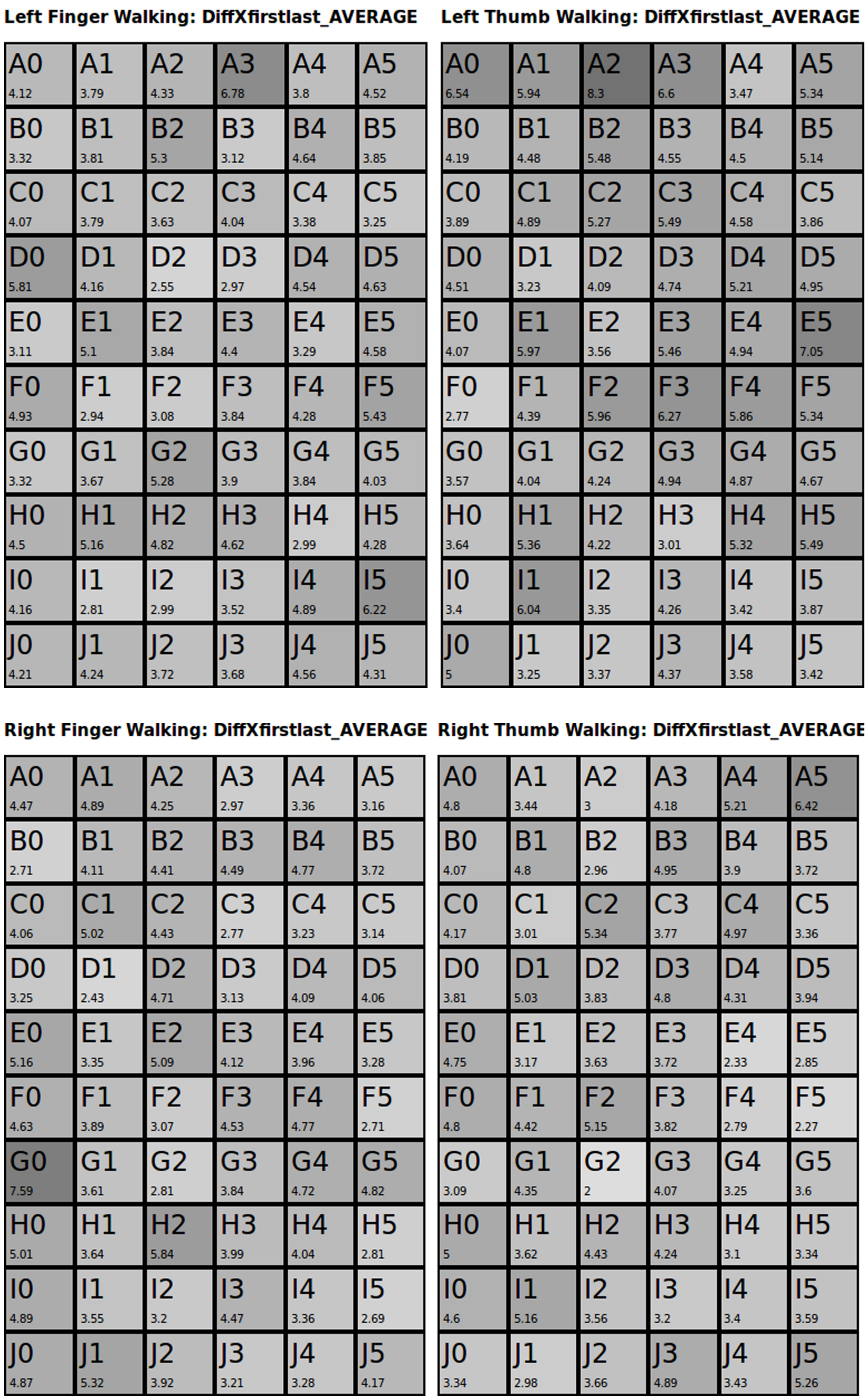

FIGURE 4.10: ***Diff X* walking:** Left Finger: Mean: 6.3, SD: 2.07; Left Thumb: Mean: 5.48, SD: 4.42; Right Finger: Mean: 5.65, SD: 2.2; Right Thumb: Mean: 4.72, SD: 2.33. The walking condition shows the same trends as the sitting condition (Fig. 4.9), but mean values are between 16% and 35% higher for the left hand, and between 20% and 42% higher for the right hand, likely to be caused by a less secure touch and slight movement of the phone while walking, as indicated by the increase in *Number of Touches* (Fig. 4.8).

Left Finger: DiffYfirstlast_AVERAGE

A0 4.54	A1 3.94	A2 6.38	A3 8.88	A4 3.38	A5 5.4
B0 3.68	B1 4.14	B2 5.13	B3 5.08	B4 5.09	B5 4.43
C0 4.62	C1 3.67	C2 4.59	C3 3.86	C4 3.5	C5 4.54
D0 4.05	D1 6.1	D2 3.63	D3 4.22	D4 4.19	D5 3.72
E0 3.82	E1 3.45	E2 4.71	E3 4.49	E4 4.48	E5 4.36
F0 3.12	F1 2.98	F2 3.52	F3 3.8	F4 5.08	F5 4.66
G0 3.86	G1 2.83	G2 3.57	G3 3.42	G4 3.45	G5 3.13
H0 4.37	H1 3.42	H2 3.38	H3 4.4	H4 4.24	H5 3.54
I0 4.46	I1 4.26	I2 4.64	I3 4.46	I4 5.24	I5 5.28
J0 3.61	J1 2.71	J2 4.42	J3 3.91	J4 4.4	J5 3.08

Left Thumb: DiffYfirstlast_AVERAGE

A0 5.26	A1 4.55	A2 7.35	A3 5.7	A4 3.86	A5 4.97
B0 3.49	B1 4.06	B2 3.68	B3 3.85	B4 4.62	B5 4.36
C0 5.21	C1 3.92	C2 3.55	C3 3.79	C4 4.43	C5 3.66
D0 3.03	D1 3.28	D2 3.91	D3 3.61	D4 5	D5 3.49
E0 3.74	E1 3.46	E2 3.59	E3 3.08	E4 3.12	E5 6.57
F0 3.78	F1 3.73	F2 4.3	F3 2.94	F4 3.37	F5 4.1
G0 4.76	G1 4.41	G2 3.12	G3 2.99	G4 3.12	G5 5.86
H0 3.53	H1 3.87	H2 3.08	H3 2.09	H4 4.73	H5 4.72
I0 5.13	I1 5.93	I2 3.59	I3 4.28	I4 4.06	I5 3.59
J0 4.77	J1 3.61	J2 4.98	J3 6.42	J4 3.76	J5 3.2

Right Finger: DiffYfirstlast_AVERAGE

A0 4.35	A1 4.24	A2 4.59	A3 3.48	A4 4.38	A5 4.79
B0 3.96	B1 3.96	B2 4.56	B3 4.82	B4 5.99	B5 2.72
C0 4.29	C1 5.34	C2 4.5	C3 4.2	C4 4.03	C5 3.53
D0 4.43	D1 4.35	D2 5.18	D3 3.59	D4 4.2	D5 4.64
E0 3.96	E1 3.17	E2 4.26	E3 4.2	E4 4.56	E5 4.92
F0 3.93	F1 5.73	F2 2.91	F3 3.42	F4 2.89	F5 3.51
G0 4.84	G1 3.45	G2 3.85	G3 3.28	G4 4.32	G5 3.36
H0 4.56	H1 4.51	H2 4.35	H3 3.08	H4 4.49	H5 3.59
I0 4.53	I1 3.57	I2 3.08	I3 2.94	I4 3.89	I5 2.6
J0 4.01	J1 2.97	J2 3.66	J3 2.15	J4 6.51	J5 3.72

Right Thumb: DiffYfirstlast_AVERAGE

A0 3.39	A1 5.94	A2 3.73	A3 4.55	A4 3.2	A5 4.23
B0 2.52	B1 4.84	B2 4.23	B3 5.46	B4 3.42	B5 3.83
C0 5.64	C1 3.59	C2 3.76	C3 3.4	C4 3.4	C5 3.76
D0 4.8	D1 3.94	D2 3.22	D3 4.2	D4 2.34	D5 4.64
E0 3.83	E1 4.48	E2 2.54	E3 2.86	E4 4.15	E5 4.1
F0 4.77	F1 4.1	F2 3.27	F3 3.95	F4 2.69	F5 3.54
G0 3.16	G1 2.9	G2 2.14	G3 4.05	G4 2.65	G5 1.94
H0 3.71	H1 3.72	H2 4.15	H3 3.45	H4 3.57	H5 2.76
I0 4.68	I1 3.3	I2 3.22	I3 4.32	I4 4.14	I5 2.83
J0 2.41	J1 4.06	J2 3.08	J3 3.74	J4 3.85	J5 4.53

FIGURE 4.11: ***Diff Y*:** Left Finger: Mean: 4.15, SD: 1.82; Left Thumb: Mean: 4.08, SD: 1.85; Right Finger: Mean: 3.99, SD: 1.35; Right Thumb: Mean: 3.66, SD: 1.36. As with the *Diff X* property, mean values of the vertical distance between the first touch point and the last touch point are slightly higher for the left hand. The trend for the left thumb and the right thumb to have lower values in columns 0 and 5 respectively continues for the *Diff Y* property, further illustrating the effect of touching the screen with the side of the thumb in these areas. In addition, the index fingers show a slightly larger distance on the Y-axis between the first touch point and the last touch point at the top of the screen compared to the bottom, probably due to the slight stretching of the finger to reach targets at the top, causing a flatter landing shape at a narrower angle and a small degree of sliding.

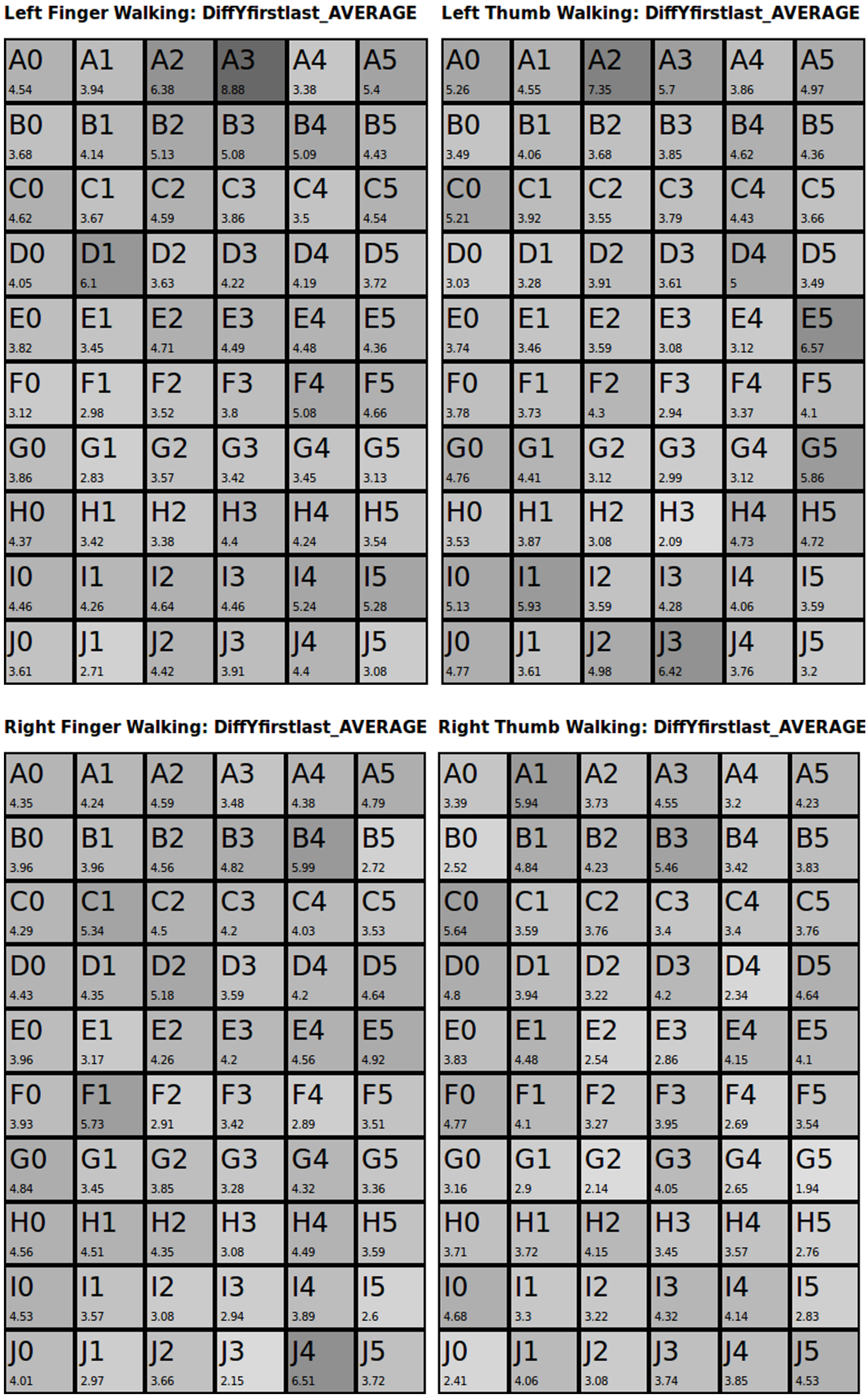

FIGURE 4.12: ***Diff Y* walking:** Left Finger: Mean: 6.35, SD: 2.23; Left Thumb: Mean: 4.77, SD: 2.57; Right Finger: Mean: 5.37, SD: 2.00; Right Thumb: Mean: 4.73, SD: 2.75. The walking condition shows the same trends as the sitting condition (Fig. 4.11), again with slightly higher values, possibly caused by an increase in phone movement and reduced focus on the task, likely to be caused by the increased cognitive load while walking (Wilson et al., 2011).

Left Finger: Xoffset_AVERAGE

A0 2.28	A1 -4.04	A2 -4.08	A3 -0.34	A4 -5.33	A5 -4
B0 -0.24	B1 -1.18	B2 -0.96	B3 -7.65	B4 -2.96	B5 -6.43
C0 -8.61	C1 0.56	C2 -3.76	C3 1.66	C4 -3.92	C5 0.88
D0 -1.4	D1 4.66	D2 2.42	D3 -2.54	D4 -4.56	D5 0.14
E0 -1.86	E1 0.3	E2 -3.78	E3 2.06	E4 0.6	E5 0.72
F0 0.08	F1 3.92	F2 -4.32	F3 0.62	F4 -1.78	F5 -1.3
G0 3.92	G1 -2.92	G2 -0.42	G3 1.2	G4 -2.66	G5 0.48
H0 -5.19	H1 3.68	H2 7.35	H3 2.1	H4 -3.2	H5 -3.66
I0 0.3	I1 -1.66	I2 -1.54	I3 1.24	I4 0.46	I5 1.62
J0 3.86	J1 4.42	J2 1.64	J3 1.26	J4 -0.2	J5 1.44

Left Thumb: Xoffset_AVERAGE

A0 -0.32	A1 -1.34	A2 4.1	A3 -2.88	A4 -8.03	A5 -12.7
B0 -4.48	B1 -0.6	B2 -0.62	B3 8.21	B4 -3.98	B5 -13.0
C0 -3.2	C1 -0.64	C2 -4.08	C3 2.24	C4 4.34	C5 -8.73
D0 -4.78	D1 -1.66	D2 -1.04	D3 1.78	D4 9.93	D5 -9.03
E0 -3.2	E1 -2.02	E2 -2.96	E3 -0.06	E4 7.01	E5 -1.66
F0 3.82	F1 -1.86	F2 -0.34	F3 6.21	F4 -1.28	F5 -8.37
G0 3.8	G1 1.94	G2 1.22	G3 -3.5	G4 6.07	G5 -0.6
H0 -0.04	H1 -2.48	H2 -0.8	H3 2.9	H4 5.79	H5 -5.61
I0 0.22	I1 4.46	I2 1.54	I3 4.44	I4 1.12	I5 -11.5
J0 -0.12	J1 -1.46	J2 -2.1	J3 -1.22	J4 -0.48	J5 -12.6

Right Finger: Xoffset_AVERAGE

A0 7.27	A1 -0.72	A2 -2.76	A3 -3.92	A4 1.72	A5 -5.55
B0 2.9	B1 -1.22	B2 2.82	B3 2.9	B4 -1.18	B5 0.18
C0 0	C1 5.61	C2 5.43	C3 -3.9	C4 -6.21	C5 1.54
D0 0.94	D1 1.84	D2 -3.08	D3 1.94	D4 -1.44	D5 -0.26
E0 0.7	E1 -1.6	E2 3.52	E3 0.24	E4 -0.36	E5 2.08
F0 4.96	F1 3.62	F2 -0.66	F3 2.6	F4 0.94	F5 1.24
G0 2.06	G1 2.48	G2 6.69	G3 -0.16	G4 3.82	G5 4.52
H0 5.05	H1 3.18	H2 8.77	H3 6.69	H4 3.84	H5 2
I0 1.5	I1 7.13	I2 5.85	I3 5.73	I4 -3.46	I5 1.24
J0 5.21	J1 2.64	J2 3.54	J3 1.44	J4 9.13	J5 -0.78

Right Thumb: Xoffset_AVERAGE

A0 10.94	A1 -0.5	A2 -5.51	A3 -5.87	A4 0.56	A5 1.62
B0 6.57	B1 -0.08	B2 -5.89	B3 -1.86	B4 -1.56	B5 2.16
C0 7.23	C1 0.26	C2 -2	C3 -1.06	C4 2.04	C5 0.92
D0 2.28	D1 -4.7	D2 -0.38	D3 -1.72	D4 6.07	D5 2.78
E0 1.36	E1 -0.66	E2 -0.42	E3 2.16	E4 2.72	E5 -0.08
F0 4	F1 -4.52	F2 0.2	F3 2.68	F4 1.34	F5 1.58
G0 8.35	G1 3.36	G2 6.39	G3 3.8	G4 -1.32	G5 -1.92
H0 7.77	H1 -1.22	H2 1.7	H3 2.66	H4 3.6	H5 -1
I0 4.72	I1 -0.2	I2 5.37	I3 1.94	I4 -0.62	I5 -1.58
J0 9.29	J1 8.23	J2 0.42	J3 4.18	J4 2.84	J5 -3.1

FIGURE 4.13: ***X Offset:*** Left Finger: Mean: -.68, SD: 4.39; Left Thumb: Mean: -1.07, SD: 5.64; Right Finger: Mean: 1.84, SD: 4.62; Right Thumb: Mean: 1.44, SD: 5.43. The visualisation indicates that the fingers of the left hand often tend to tap left of the horizontal centre of a target and that the fingers of the right hand often tend to tap right of a target's centre. For the left thumb and the right thumb, this effect is strongly visible in columns 5 and 0 respectively, probably caused by the thumbs' limited reach.

Left Finger Walking: Xoffset_AVERAGE

A0 -1.04	A1 1.18	A2 0.52	A3 -2.72	A4 0.6	A5 -3.84
B0 -5.15	B1 -1.9	B2 -1.42	B3 -2.62	B4 -0.18	B5 -1.42
C0 -3.58	C1 -0.68	C2 -0.74	C3 0.42	C4 1.56	C5 -0.82
D0 -2.62	D1 5.69	D2 2.8	D3 -2.46	D4 3.58	D5 0.4
E0 -3.96	E1 2.08	E2 5.19	E3 -0.82	E4 -0.18	E5 0.1
F0 -1.64	F1 3.6	F2 -0.92	F3 -4.98	F4 -1.04	F5 -2.76
G0 -0.14	G1 0	G2 -0.36	G3 4.44	G4 -0.48	G5 1.3
H0 0.18	H1 7.85	H2 1.16	H3 4.56	H4 -2.62	H5 -4.04
I0 3.1	I1 8.17	I2 1.96	I3 -0.56	I4 -4	I5 2.1
J0 6.33	J1 4.48	J2 6.67	J3 -0.28	J4 5.77	J5 -1.12

Left Thumb Walking: Xoffset_AVERAGE

A0 -1.66	A1 -2.34	A2 -7.29	A3 -1.5	A4 -4.14	A5 -15.9
B0 -6.65	B1 -10.4	B2 3.74	B3 4.6	B4 -0.58	B5 -12.2
C0 -5.83	C1 -5.87	C2 -3.06	C3 8.49	C4 4.92	C5 -9.73
D0 -5.99	D1 -4.1	D2 -3.9	D3 5.89	D4 0.18	D5 -4.3
E0 -5.17	E1 -8.99	E2 -1.16	E3 -5.39	E4 0.52	E5 -5.19
F0 -1.38	F1 -5.57	F2 -0.02	F3 -1.12	F4 -0.24	F5 -4.68
G0 -1.24	G1 -6.27	G2 -0.12	G3 2.6	G4 3.06	G5 0.12
H0 -2.78	H1 -3.04	H2 -0.2	H3 1.9	H4 4.7	H5 -4.38
I0 -2.28	I1 5.19	I2 0.58	I3 6.35	I4 7.19	I5 -6.03
J0 0	J1 0.26	J2 3.44	J3 2.18	J4 3.72	J5 -10.7

Right Finger Walking: Xoffset_AVERAGE

A0 8.03	A1 -1.2	A2 3.04	A3 -9.31	A4 -2.44	A5 0.2
B0 1.6	B1 1.9	B2 1.06	B3 -1.08	B4 -1.32	B5 -4.52
C0 5.21	C1 -2.46	C2 -1.46	C3 -1.38	C4 -2.46	C5 1.16
D0 4.88	D1 -3.14	D2 -8.63	D3 -1.94	D4 -4.28	D5 4.42
E0 3.9	E1 1.36	E2 -1.88	E3 4.2	E4 -0.04	E5 -2.02
F0 -1.52	F1 1.52	F2 6.53	F3 -8.83	F4 -3.68	F5 -0.68
G0 2.66	G1 -7.09	G2 3.36	G3 -1.26	G4 1.64	G5 0.4
H0 5.75	H1 4.46	H2 -4.92	H3 0.42	H4 2.72	H5 2.76
I0 3.3	I1 4.1	I2 8.39	I3 0.06	I4 -2.2	I5 -0.8
J0 5.51	J1 6.33	J2 11.98	J3 2.38	J4 6.79	J5 -1.3

Right Thumb Walking: Xoffset_AVERAGE

A0 13.68	A1 3.52	A2 -7.07	A3 -3.7	A4 5.31	A5 -4.66
B0 9.65	B1 3.68	B2 -3.92	B3 -3.66	B4 4.58	B5 1.9
C0 5.95	C1 -12.7	C2 -1.82	C3 5.07	C4 6.33	C5 0.82
D0 7.57	D1 0.22	D2 1.6	D3 -0.04	D4 2.7	D5 1.76
E0 4.54	E1 0.86	E2 5.39	E3 7.19	E4 3.44	E5 2.26
F0 0.82	F1 0.96	F2 5.35	F3 6.47	F4 5.29	F5 3.58
G0 3.1	G1 -3.68	G2 4.6	G3 2.86	G4 7.23	G5 1.94
H0 8.83	H1 -1.98	H2 5.57	H3 4.94	H4 9.57	H5 1.88
I0 6.73	I1 0.36	I2 1.46	I3 2.62	I4 5.55	I5 -2.68
J0 12.1	J1 9.83	J2 7.67	J3 4.44	J4 2.92	J5 3.48

FIGURE 4.14: ***X Offset* walking:** Left Finger: Mean: .41, SD: 4.16; Left Thumb: Mean: -1.87, SD: 4.6; Right Finger: Mean: .67, SD: 4.44; Right Thumb: Mean: 3.04, SD: 6.09. In the walking condition, the same trends apply as in the sitting condition (Fig. 4.13), although with higher values, with the exception of the right index finger which tends to hit targets to the left of its centre more frequently than in the sitting condition.

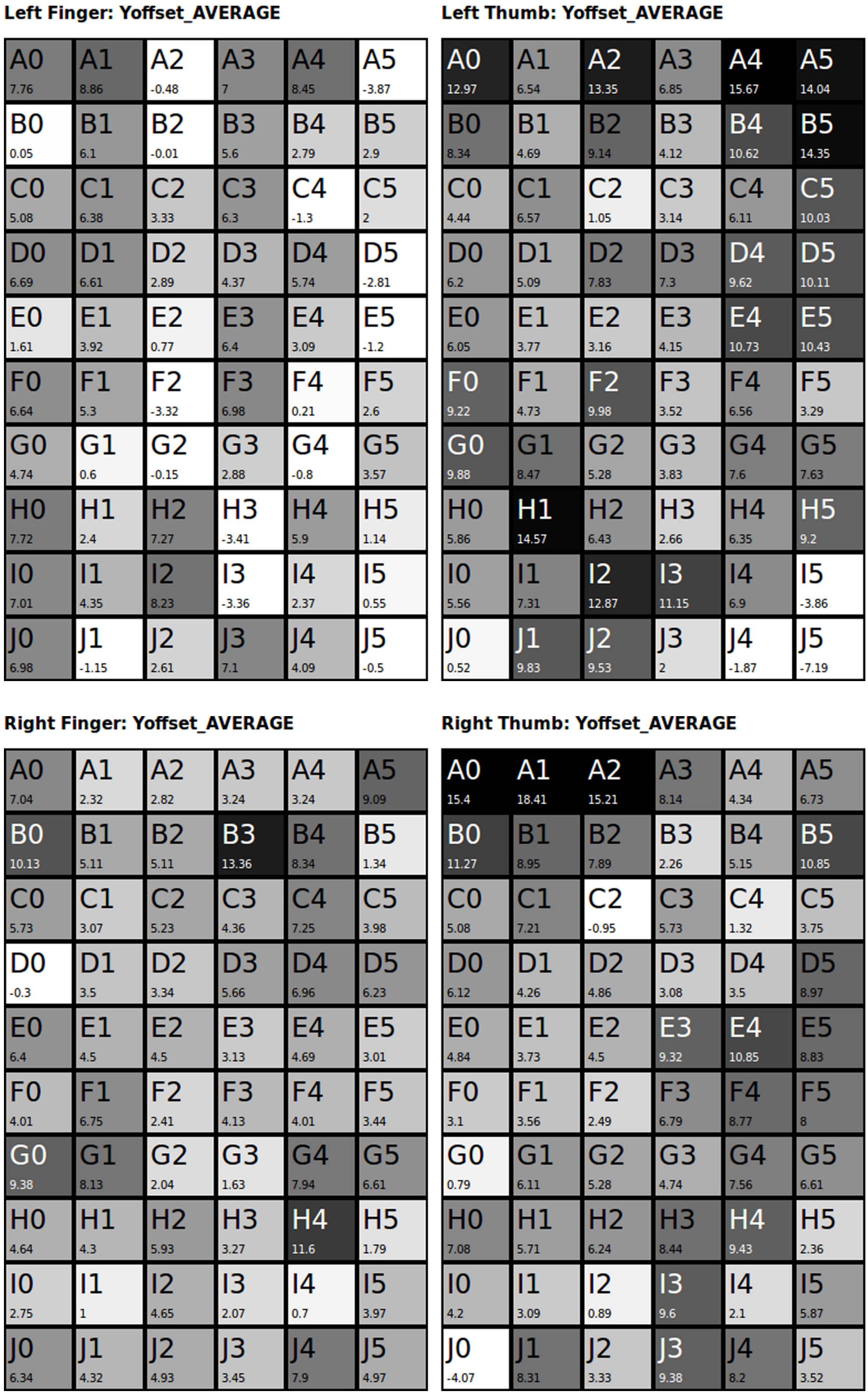

FIGURE 4.15: ***Y Offset*:** Left Finger: Mean: 3.23, SD: 5.25; Left Thumb: Mean: 6.9, SD: 4.60; Right Finger: Mean: 4.86, SD: 6.50; Right Thumb: Mean: 6.12, SD: 5.32. Left thumb and right thumb tend to hit targets below their centre, which is especially visible in the SW/NE and SE/NW corners of the display. Targets between these regions tend to be hit closer to the centre. The index fingers do not show a similarly characteristic profile, but the left index finger seems to hit targets more frequently above the centre. In contrast, the right index finger tends to hit targets more frequently below the centre.

Left Finger Walking: Yoffset_AVERAGE

A0 -0.44	A1 0.35	A2 1.9	A3 -0.33	A4 2.89	A5 2.82
B0 0.55	B1 5.68	B2 7.77	B3 0.17	B4 -1.5	B5 -3.25
C0 8.62	C1 0.18	C2 3.87	C3 2.95	C4 1.32	C5 -1.41
D0 1.1	D1 3	D2 9.05	D3 6.96	D4 -1.63	D5 -5.35
E0 -2.11	E1 0.88	E2 1.11	E3 4	E4 -1.35	E5 5.64
F0 -2.86	F1 -5.71	F2 3.86	F3 0.13	F4 2.41	F5 -6.32
G0 -4.68	G1 0.18	G2 -0.11	G3 7.37	G4 2.69	G5 5.89
H0 4.49	H1 -1.24	H2 -1.39	H3 -6.57	H4 -8.62	H5 3.65
I0 -3.89	I1 -2.11	I2 -7.47	I3 -3.13	I4 -4.08	I5 -2.33
J0 0.14	J1 0.9	J2 0.82	J3 4.55	J4 0.94	J5 3.41

Left Thumb Walking: Yoffset_AVERAGE

A0 4.11	A1 7	A2 9.85	A3 10.54	A4 3.46	A5 6.2
B0 5.34	B1 8.04	B2 5.3	B3 10.02	B4 11.42	B5 6.21
C0 3.49	C1 4.02	C2 3.98	C3 5.01	C4 3.6	C5 11.59
D0 1.18	D1 -2.43	D2 -0.33	D3 -1.48	D4 5.13	D5 6.35
E0 3.2	E1 1	E2 6.28	E3 8.64	E4 3.66	E5 -1.01
F0 7.59	F1 0.06	F2 2.53	F3 3.4	F4 0.09	F5 4.39
G0 6.38	G1 7.44	G2 -0.3	G3 5.81	G4 8.7	G5 9.12
H0 2.4	H1 4.03	H2 4.95	H3 6.58	H4 5.82	H5 6.12
I0 -0.13	I1 3.66	I2 1.57	I3 6.71	I4 6.93	I5 -0.55
J0 7.36	J1 2.72	J2 12.31	J3 2.19	J4 2.69	J5 -5.33

Right Finger Walking: Yoffset_AVERAGE

A0 -1.58	A1 3.84	A2 -2.76	A3 -5.8	A4 -2.31	A5 5.71
B0 0.77	B1 -1.99	B2 2.26	B3 5.68	B4 3.7	B5 -2.14
C0 0.44	C1 1.55	C2 3.79	C3 3.37	C4 6.91	C5 4.36
D0 0.83	D1 0.91	D2 -0.68	D3 0.61	D4 0.45	D5 -0.53
E0 2.21	E1 -0.06	E2 -1.58	E3 4.69	E4 1.87	E5 2.37
F0 4.51	F1 -3.43	F2 1.62	F3 1.01	F4 -2.1	F5 6.6
G0 -4.07	G1 4.17	G2 1.55	G3 2.92	G4 3.49	G5 1.93
H0 -3.83	H1 -2.88	H2 2.85	H3 -1.36	H4 -2.19	H5 2.13
I0 -1.76	I1 -4.92	I2 -0.47	I3 5.79	I4 2.83	I5 -1.04
J0 -1.91	J1 -0.88	J2 1.96	J3 -0.42	J4 0.56	J5 9.3

Right Thumb Walking: Yoffset_AVERAGE

A0 8.26	A1 12.36	A2 12.02	A3 7.15	A4 7.19	A5 3.31
B0 6.48	B1 2.52	B2 9.25	B3 3.44	B4 5.03	B5 7.35
C0 3.37	C1 2.53	C2 7.06	C3 2.46	C4 4.44	C5 2.04
D0 0.38	D1 0.72	D2 1.75	D3 4.26	D4 4.37	D5 6.31
E0 3.28	E1 1.68	E2 -3.78	E3 3.2	E4 0.5	E5 9.71
F0 10.21	F1 1.24	F2 0.32	F3 4.32	F4 0.44	F5 2.91
G0 -3.15	G1 3.57	G2 7.18	G3 11.02	G4 6.53	G5 1.44
H0 3.99	H1 8.71	H2 9.85	H3 10.73	H4 5.21	H5 10.12
I0 -3.4	I1 3.05	I2 7.39	I3 7.28	I4 7.85	I5 -0.66
J0 -11.8	J1 4.36	J2 0.97	J3 5.31	J4 2.57	J5 4.21

FIGURE 4.16: ***Y Offset* walking:** Left Finger: Mean: .57, SD: 4.72; Left Thumb: Mean: 4.58, SD: 5.13; Right Finger: Mean: .98, SD: 5.28; Right Thumb: Mean: 4.34, SD: 4.24. The walking condition shows the same characteristics for the thumbs as in the sitting condition (Fig. 4.15), although offsets tend to be lower. Both index fingers tend to hit targets above their centre more frequently. It appears that walking affects strongly the vertical targeting of the fingers, causing the fingers to connect with the target above their normal connection point. This results in a more frequent overshooting of the index fingers and a more precise targeting of the thumbs, whose rather high offset in the sitting condition is often mitigated by this effect to a value closer to the target centre.

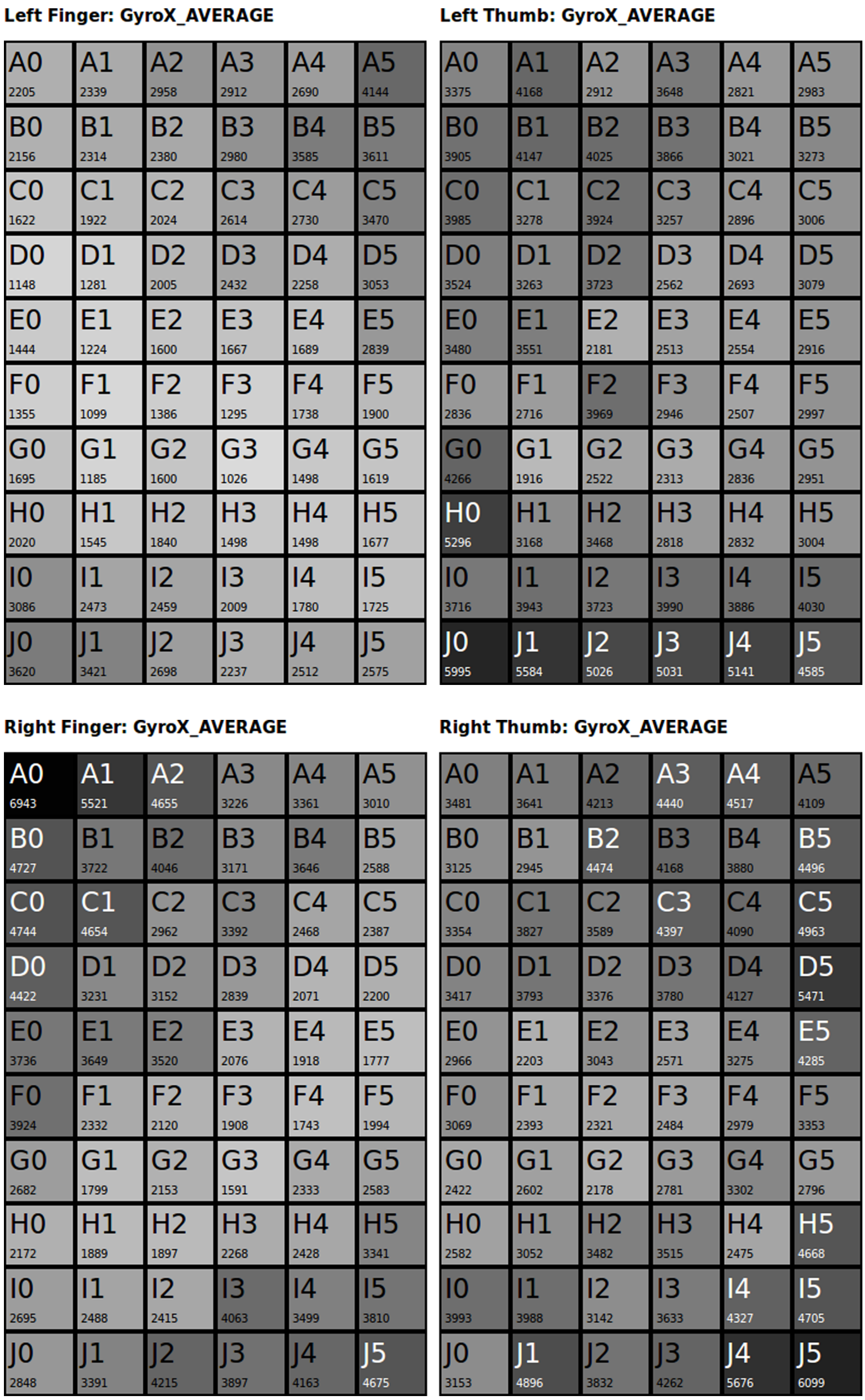

FIGURE 4.17: ***Gyro X Amplitude*:** Left Finger: Mean: 2195.41, SD: 926.91; Left Thumb: Mean: 3474.84, SD: 1007.03; Right Finger: Mean: 3100.34, SD: 1204.59; Right Thumb: Mean: 3636.96, SD: 926.66. The index fingers show characteristic device movement patterns around the X-axis in the SW/NE and SE/NW corners respectively. This indicates that users often move and tilt the device, even when being able to move their finger freely. Target selection with the thumbs shows strong device movement in each thumb's "home" corner and at the top of the left side and right side of the display respectively, indicating a tilt of the device over the X-axis to support selection. The least device movement on the X-axis for the thumbs can be observed in the display's middle.

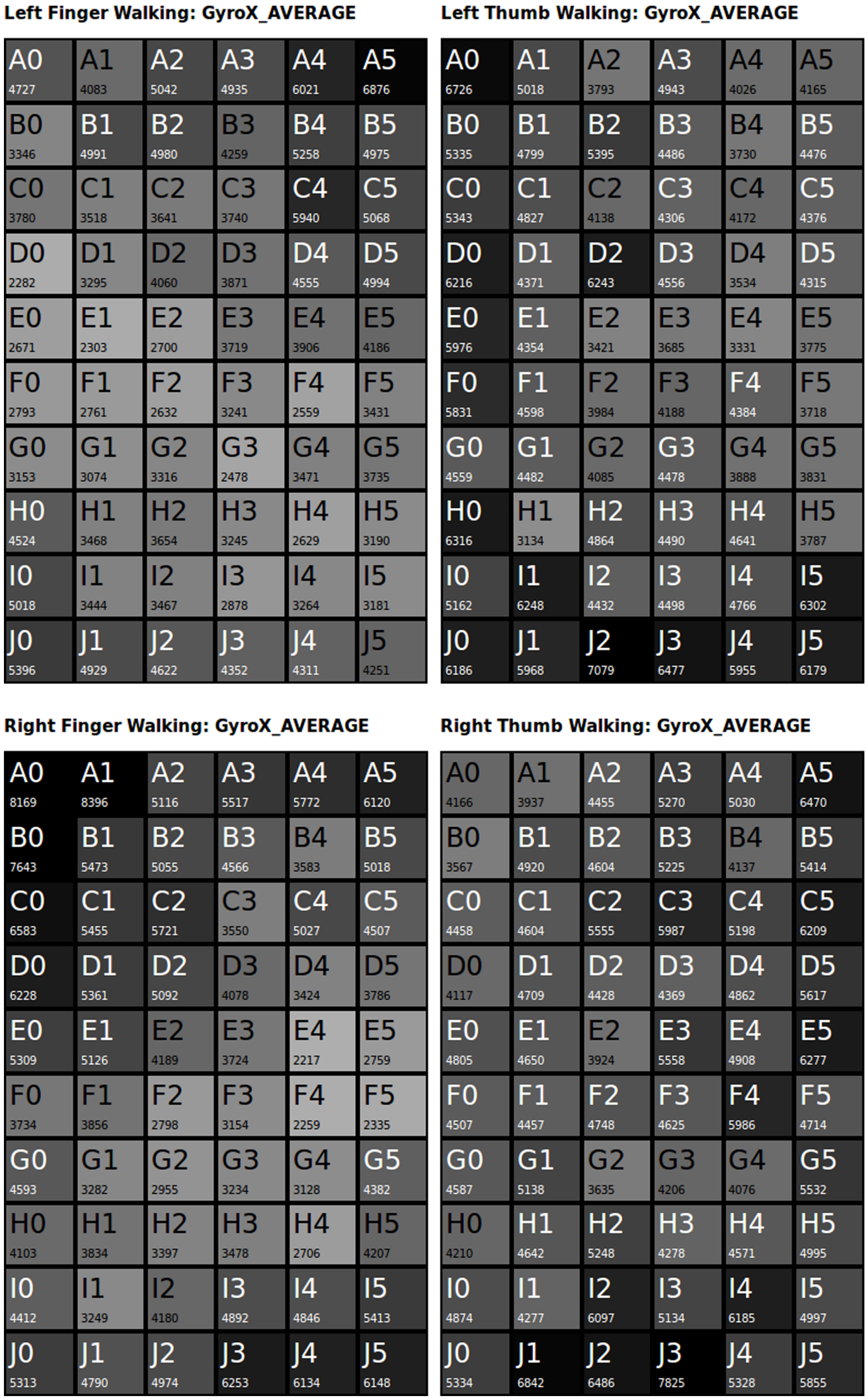

FIGURE 4.18: ***Gyro X Amplitude* walking:** Left Finger: Mean: 3856.72, SD: 1210.14; Left Thumb: Mean: 4768.96, SD: 1056.15; Right Finger: Mean: 4498.77, SD: 1500.44; Right Thumb: Mean: 4998.96, SD: 1254.68. The walking condition shows the same trends as the sitting condition (Fig. 4.17), but the values are higher and the effects clearer. This indicates that dexterity may be reduced while walking and that as a result users tend to move the device towards the finger more vigorously to help facilitate selection. In addition, a user's gait may cause the device to move.

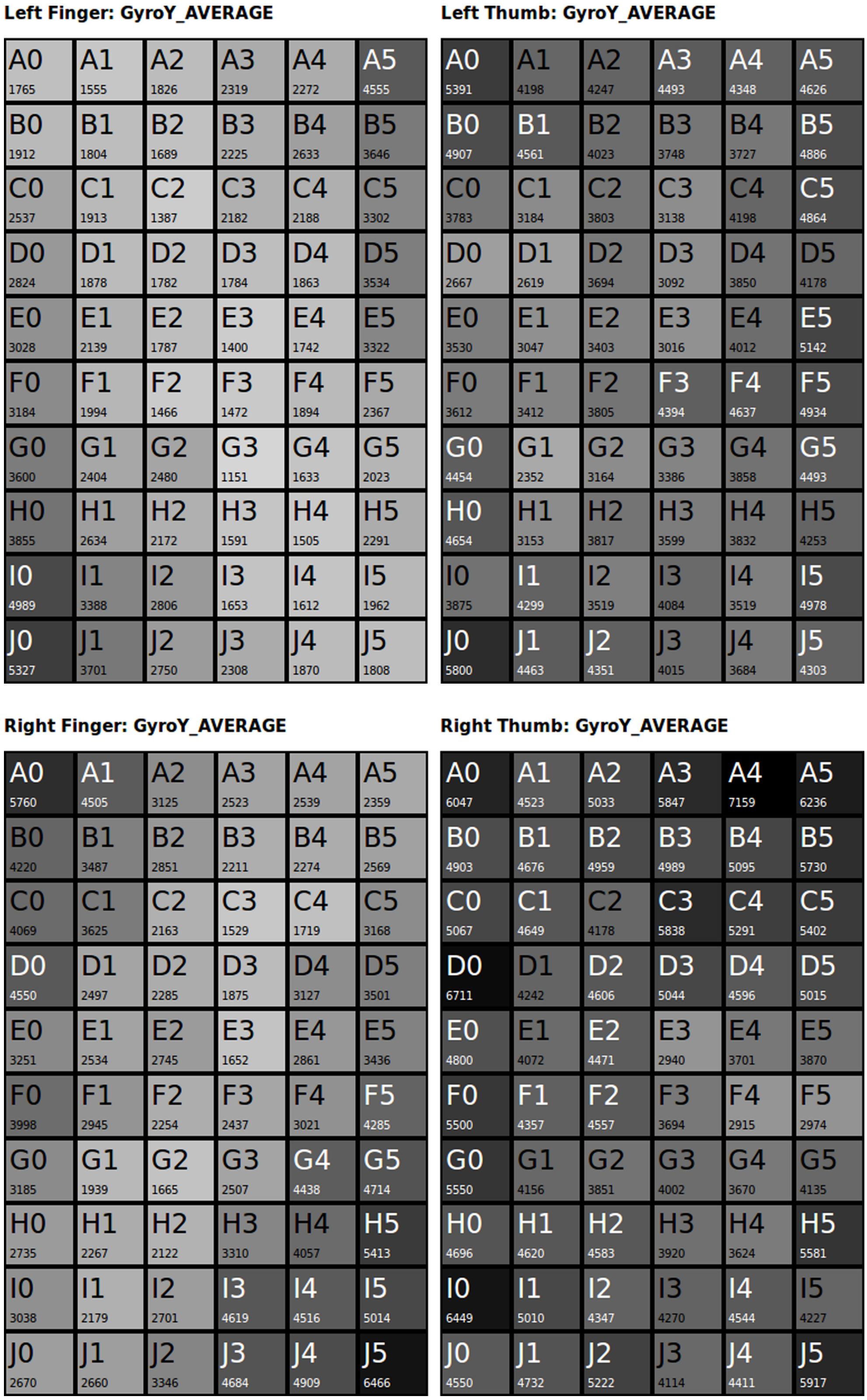

FIGURE 4.19: ***Gyro Y Amplitude*:** Left Finger: Mean: 2394.10, SD: 1008.29; Left Thumb: Mean: 3997.17, SD: 1200.65; Right Finger: Mean: 3209.53, SD: 1627.35; Right Thumb: Mean: 4744.73, SD: 1496.13. The left index finger and the right index finger show similar patterns as for the gyroscope's X amplitude (Fig. 4.17). The thumbs show high device movement around the Y-axis for most areas outside their natural movement arc, indicating a horizontal tilt of the phone during the touch, which is stronger than the vertical tilt over the X-axis (Fig. 4.17).

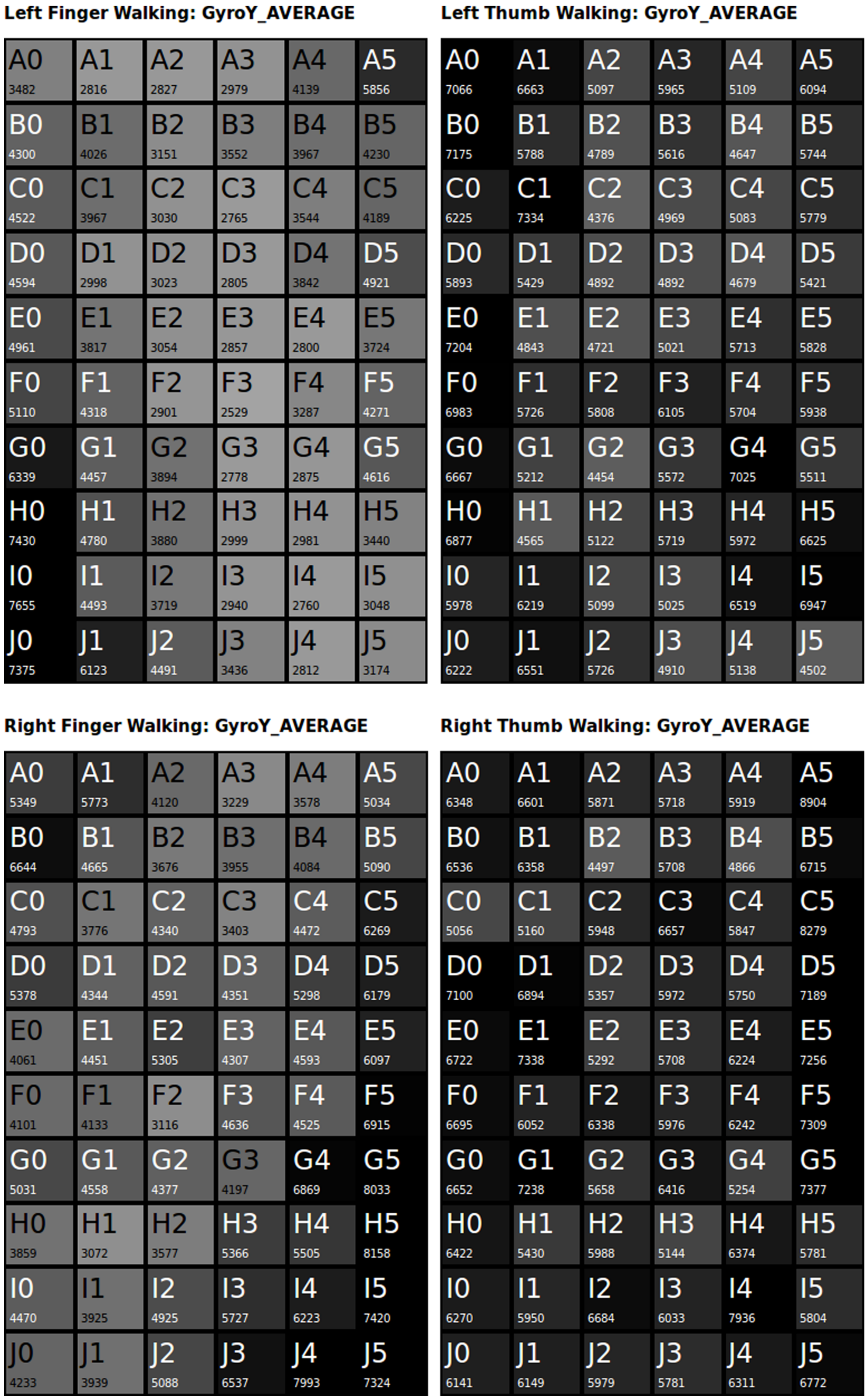

FIGURE 4.20: ***Gyro Y Amplitude* walking:** Left Finger: Mean: 3889.01, SD: 1151.32; Left Thumb: Mean: 5697.03, SD: 1122.00; Right Finger: Mean: 4841.36, SD: 2318.36; Right Thumb: Mean: 6277.26, SD: 1738.74. For the index fingers, the walking condition shows the same trends as the sitting condition (Fig. 4.19), again with higher values. Both thumbs show stronger device movement for all target positions with especially high Y-axis amplitudes for targets near the sides of the screen.

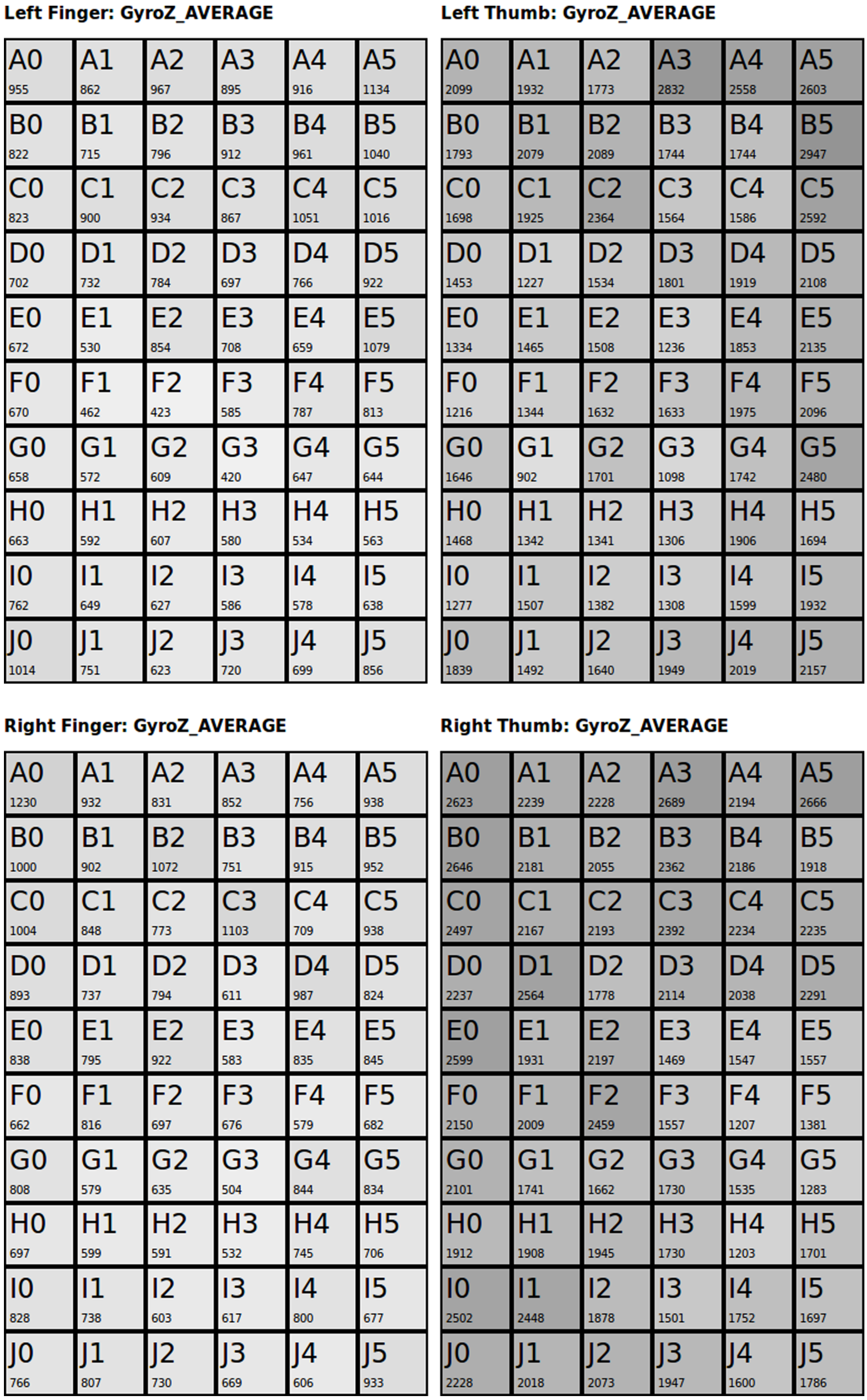

FIGURE 4.21: ***Gyro Z Amplitude*:** Left Finger: Mean: 733.56, SD: 388.71; Left Thumb: Mean: 1772.22, SD: 6093.85; Right Finger: Mean: 761.25, SD: 415.90; Right Thumb: Mean: 2016.72, SD: 669.46. The index fingers show a rather homogeneous distribution of Z-axis rotation when touching targets on the screen, with slightly higher values at the top and bottom. For the thumbs, the *Gyro Z Amplitude* is an average of 39% higher, with a light trend of higher values for targets outside of the thumbs' natural swiping arcs.

Left Finger Walking: GyroZ_AVERAGE

A0 2111	A1 1570	A2 1611	A3 1628	A4 1598	A5 2035
B0 2024	B1 1404	B2 1700	B3 1564	B4 1409	B5 1280
C0 1621	C1 1594	C2 1368	C3 1477	C4 1452	C5 1470
D0 1560	D1 1537	D2 1540	D3 1072	D4 1534	D5 1787
E0 1539	E1 1375	E2 1374	E3 1662	E4 1406	E5 1329
F0 1414	F1 1452	F2 1408	F3 1362	F4 1136	F5 1471
G0 1577	G1 1300	G2 1188	G3 1536	G4 1351	G5 1363
H0 1574	H1 1376	H2 1557	H3 1329	H4 1177	H5 1214
I0 2029	I1 1276	I2 1329	I3 1005	I4 1698	I5 1538
J0 1641	J1 1579	J2 1620	J3 1601	J4 1440	J5 1589

Left Thumb Walking: GyroZ_AVERAGE

A0 3954	A1 3791	A2 2953	A3 3488	A4 4013	A5 3701
B0 2541	B1 3316	B2 3467	B3 3550	B4 3614	B5 3373
C0 2903	C1 3270	C2 2923	C3 3161	C4 3489	C5 4654
D0 3298	D1 3283	D2 2912	D3 3263	D4 2828	D5 3688
E0 2676	E1 3304	E2 2500	E3 3247	E4 3300	E5 2904
F0 3246	F1 2688	F2 2670	F3 2682	F4 3929	F5 3853
G0 2531	G1 3150	G2 2573	G3 3059	G4 3129	G5 2775
H0 2834	H1 2057	H2 2562	H3 2655	H4 3125	H5 2725
I0 2237	I1 2336	I2 2982	I3 2784	I4 3612	I5 3977
J0 2628	J1 2371	J2 2534	J3 3074	J4 3406	J5 3540

Right Finger Walking: GyroZ_AVERAGE

A0 1366	A1 1426	A2 1710	A3 1850	A4 1567	A5 2005
B0 1754	B1 1408	B2 1403	B3 1292	B4 1394	B5 1600
C0 1542	C1 1760	C2 1510	C3 1116	C4 1422	C5 1933
D0 1103	D1 1414	D2 1207	D3 1406	D4 1486	D5 1937
E0 1093	E1 1323	E2 1073	E3 1444	E4 1193	E5 1558
F0 1263	F1 1268	F2 1505	F3 1437	F4 1491	F5 1676
G0 1518	G1 1684	G2 1380	G3 1387	G4 1236	G5 1566
H0 1493	H1 1689	H2 1339	H3 1457	H4 1581	H5 1624
I0 1595	I1 1245	I2 1561	I3 1215	I4 1394	I5 1550
J0 1452	J1 1553	J2 1596	J3 1686	J4 1575	J5 1930

Right Thumb Walking: GyroZ_AVERAGE

A0 4066	A1 3187	A2 3425	A3 3497	A4 3488	A5 4255
B0 3543	B1 2995	B2 2688	B3 3239	B4 3009	B5 3452
C0 3586	C1 3440	C2 4229	C3 3659	C4 3260	C5 3204
D0 3636	D1 3313	D2 3824	D3 3451	D4 3109	D5 3020
E0 3615	E1 3467	E2 3010	E3 3897	E4 2784	E5 3633
F0 4097	F1 2791	F2 3189	F3 3322	F4 3254	F5 2970
G0 4143	G1 2930	G2 2825	G3 3078	G4 2355	G5 3145
H0 3475	H1 3409	H2 3050	H3 2554	H4 2762	H5 2678
I0 3178	I1 3264	I2 3690	I3 2869	I4 3372	I5 2585
J0 3110	J1 3151	J2 3022	J3 2666	J4 2473	J5 2496

FIGURE 4.22: ***Gyro Z Amplitude* walking:** Left Finger: Mean: 1475.33, SD: 437.86; Left Thumb: Mean: 3113.81, SD: 743.64; Right Finger: Mean: 1458.16, SD: 441.49; Right Thumb: Mean: 3239.88, SD: 998.92. The walking condition shows the same trends as the sitting condition (Fig. 4.21), with values being an average of 96% higher for the index fingers and 67% higher for the thumbs.

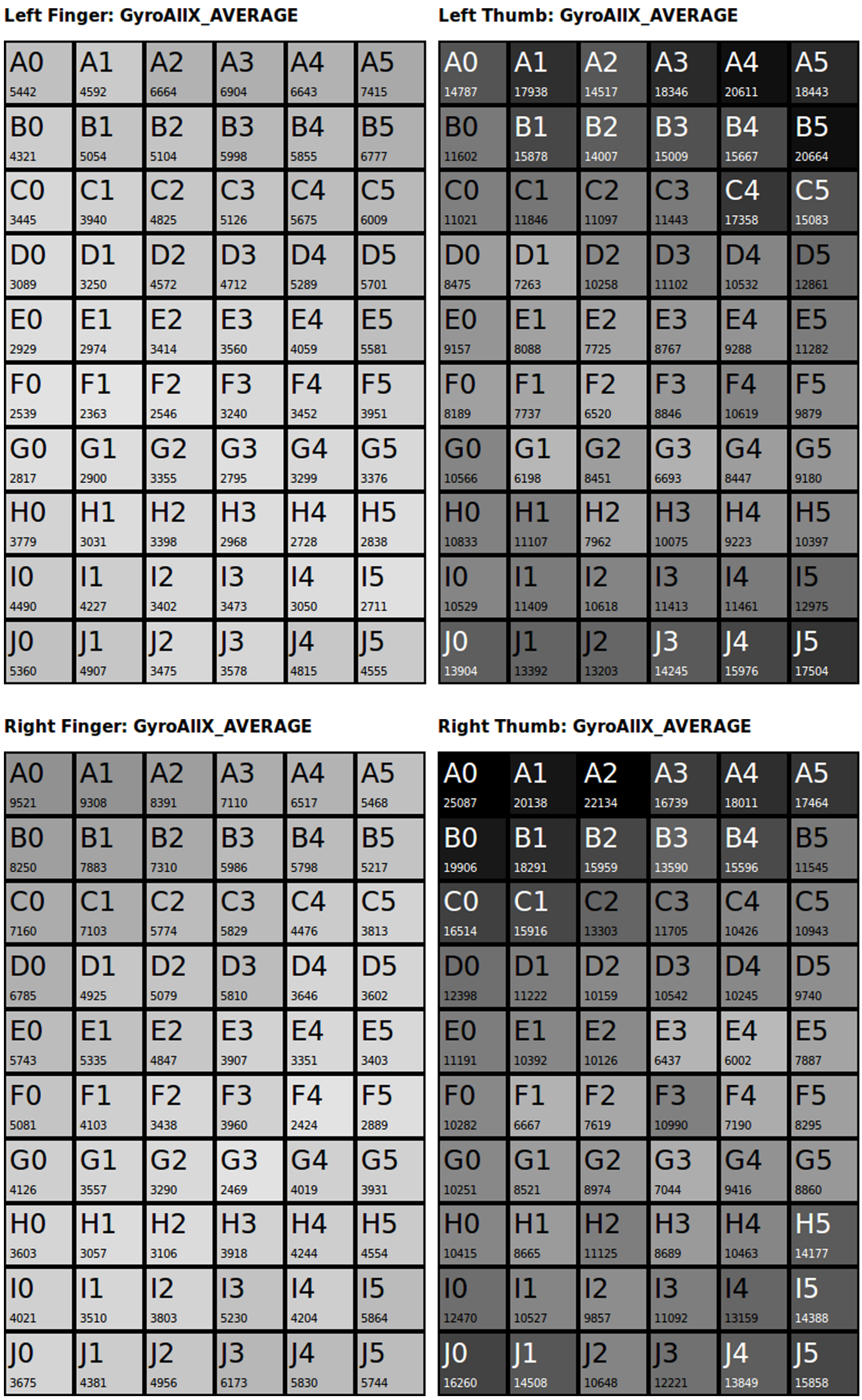

FIGURE 4.23: ***Gyro X All Amplitude:*** Left Finger: Mean: 4205.62, SD: 1381.80; Left Thumb: Mean: 11794.39, SD: 3353.21; Right Finger: Mean: 5008.40, SD: 1543.01; Right Thumb: Mean: 12201.48, SD: 4307.49. The gyroscope amplitude over the X-axis during the whole time of the task (from button highlight, through *touchStart* to *touchEnd*), shows the same characteristics for the index fingers and thumbs as the gyroscope amplitude over the X-axis during the touch (Fig 4.17), but with higher values, caused by tilting the phone towards the finger to facilitate selection. The especially high values at the top and bottom for the thumbs indicate a clear loss of grip stability when reaching for targets in these areas.

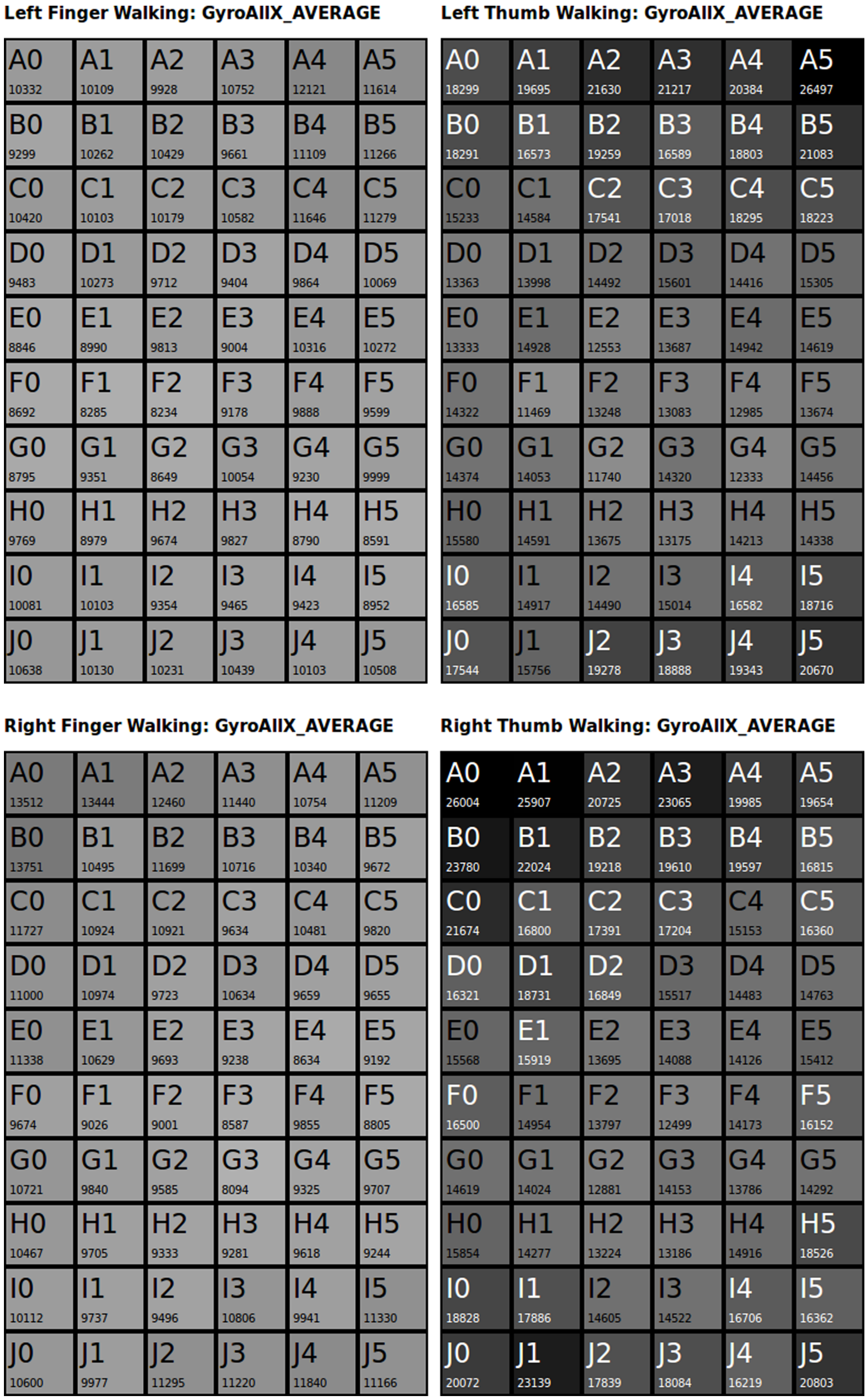

FIGURE 4.24: ***Gyro X All Amplitude* walking:** Left Finger: Mean: 9869.10, SD: 2543.42; Left Thumb: Mean: 16064.43, SD: 3476.81; Right Finger: Mean: 10345.96, SD: 2362.06; Right Thumb: Mean: 17055.24, SD: 4757.40. The walking condition shows the same characteristics as the sitting condition (Fig. 4.23), but with higher values.

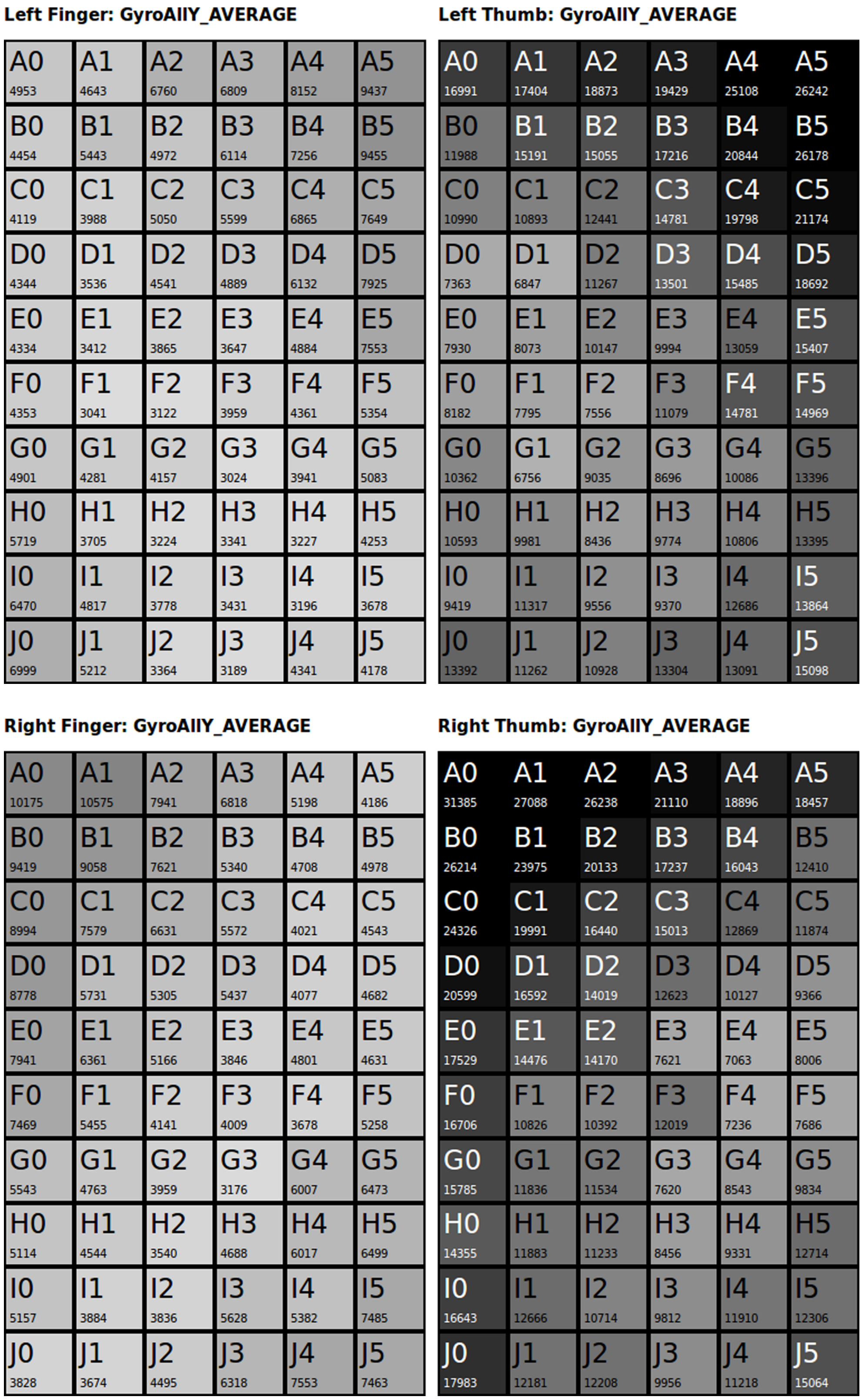

FIGURE 4.25: ***Gyro Y All Amplitude:*** Left Finger: Mean: 4941.28, SD: 1904.61; Left Thumb: Mean: 13122.09, SD: 3918.21; Right Finger: Mean: 5752.44, SD: 2292.00; Right Thumb: Mean: 14375.70, SD: 4410.10. The gyroscope amplitude over the Y-axis during the whole time of the task (from button highlight, through *touchStart* to *touchEnd*), shows the same characteristics for the index fingers and thumbs as the gyroscope amplitude over the Y-axis during the touch (Fig 4.19), but with higher values, since tilting of the device before the touch event is recorded too.

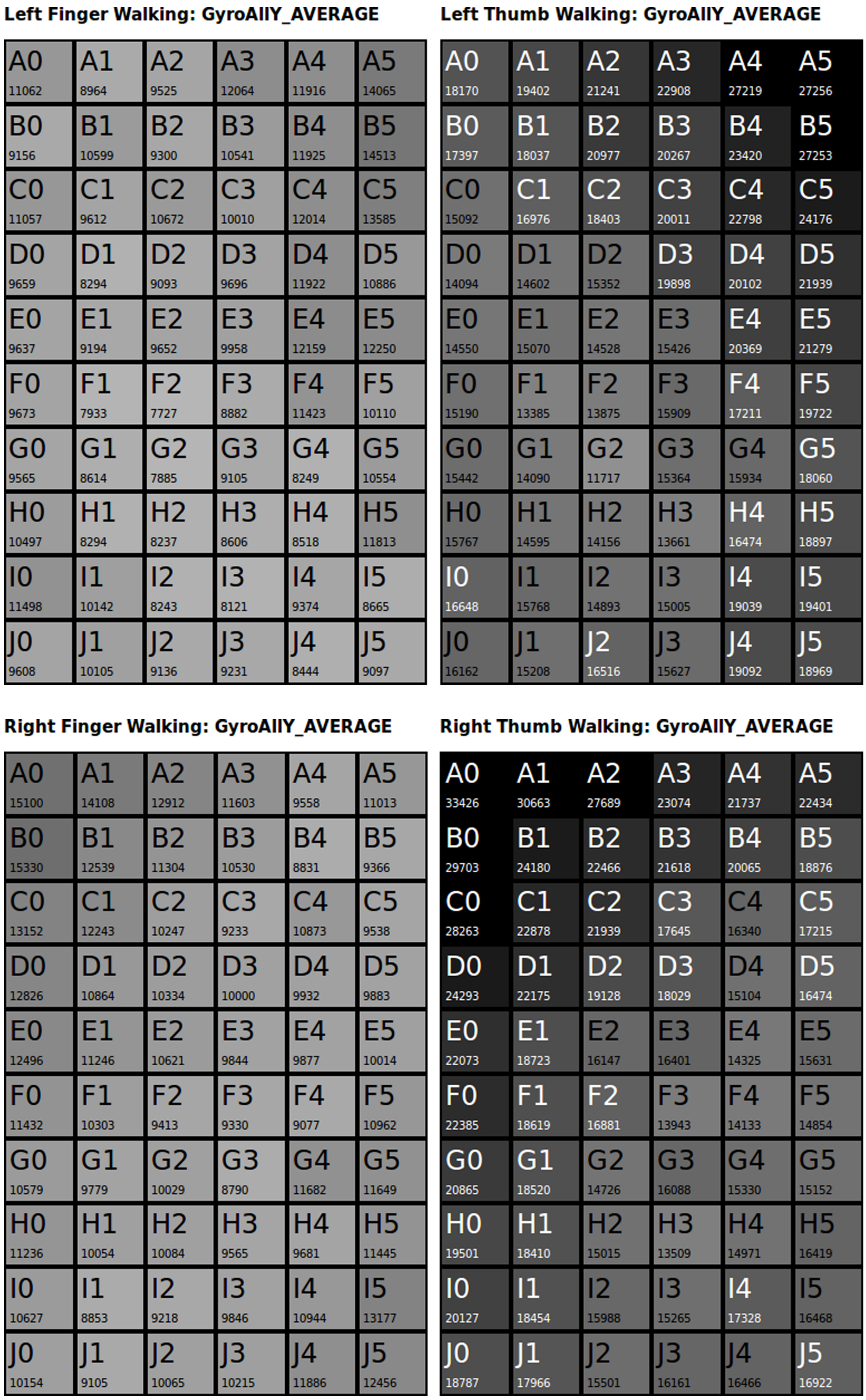

FIGURE 4.26: ***Gyro Y All Amplitude*** **walking:** Left Finger: Mean: 10005.47, SD: 3200.49; Left Thumb: Mean: 17833.14, SD: 4102.50; Right Finger: Mean: 10784.21, SD: 2899.25; Right Thumb: Mean: 19057.84, SD: 4855.97. The walking condition shows the same characteristics as the sitting condition (Fig 4.25), however with higher values.

Left Finger: GyroAllZ_AVERAGE

A0 3351	A1 3044	A2 3667	A3 4608	A4 4559	A5 4778
B0 2336	B1 3285	B2 2748	B3 3226	B4 3636	B5 4423
C0 1686	C1 2096	C2 3157	C3 3000	C4 3223	C5 3547
D0 1651	D1 1836	D2 2354	D3 2421	D4 2892	D5 3412
E0 1483	E1 1635	E2 1768	E3 1937	E4 2389	E5 3206
F0 1303	F1 1297	F2 1206	F3 1755	F4 2097	F5 2192
G0 1401	G1 1454	G2 1849	G3 1385	G4 1951	G5 2574
H0 1809	H1 2154	H2 1348	H3 1663	H4 1524	H5 1455
I0 1768	I1 1848	I2 1383	I3 1324	I4 1313	I5 1335
J0 2071	J1 2018	J2 1357	J3 1204	J4 2084	J5 1794

Left Thumb: GyroAllZ_AVERAGE

A0 9717	A1 8872	A2 9020	A3 10630	A4 13553	A5 13381
B0 6546	B1 8837	B2 7477	B3 9053	B4 10820	B5 14730
C0 6758	C1 6703	C2 6337	C3 7877	C4 10621	C5 10308
D0 3710	D1 3751	D2 5524	D3 7146	D4 6778	D5 9349
E0 4569	E1 6116	E2 5379	E3 5148	E4 6731	E5 7917
F0 4869	F1 4289	F2 4093	F3 5404	F4 5456	F5 7087
G0 5183	G1 3440	G2 4967	G3 3859	G4 5205	G5 6020
H0 6346	H1 6471	H2 4624	H3 5531	H4 6332	H5 7032
I0 6877	I1 7206	I2 6964	I3 7111	I4 6729	I5 7640
J0 9210	J1 8945	J2 8738	J3 10382	J4 9641	J5 9574

Right Finger: GyroAllZ_AVERAGE

A0 4098	A1 3743	A2 3383	A3 2932	A4 2862	A5 2283
B0 3473	B1 3434	B2 2939	B3 2492	B4 2346	B5 2598
C0 3162	C1 2780	C2 2781	C3 2579	C4 2511	C5 1833
D0 3045	D1 2099	D2 2121	D3 2649	D4 1847	D5 1753
E0 2468	E1 2096	E2 1910	E3 1648	E4 1825	E5 1857
F0 2124	F1 1882	F2 1511	F3 1821	F4 1238	F5 1236
G0 1624	G1 1571	G2 1393	G3 1229	G4 1796	G5 1595
H0 1689	H1 1474	H2 1490	H3 1648	H4 2339	H5 1515
I0 2007	I1 1291	I2 1362	I3 1945	I4 1485	I5 2325
J0 1739	J1 1393	J2 1481	J3 1831	J4 2352	J5 2044

Right Thumb: GyroAllZ_AVERAGE

A0 15739	A1 14100	A2 13130	A3 11050	A4 9521	A5 11888
B0 13143	B1 11346	B2 9486	B3 7252	B4 9219	B5 5647
C0 11037	C1 10443	C2 8846	C3 6821	C4 6517	C5 5808
D0 8125	D1 7265	D2 6724	D3 5820	D4 4923	D5 5520
E0 7800	E1 6762	E2 7411	E3 3892	E4 3273	E5 3480
F0 6293	F1 4693	F2 4908	F3 5524	F4 4196	F5 4793
G0 6548	G1 5600	G2 5647	G3 4763	G4 5252	G5 5080
H0 7596	H1 5364	H2 6019	H3 4961	H4 5888	H5 7495
I0 8700	I1 6334	I2 6163	I3 6746	I4 7620	I5 8123
J0 11190	J1 8294	J2 8292	J3 7327	J4 9212	J5 9562

FIGURE 4.27: ***Gyro Z All Amplitude:*** Left Finger: Mean: 2287.77, SD: 1110.62; Left Thumb: Mean: 7309.79, SD: 2786.87; Right Finger: Mean: 2132.96, SD: 905.18; Right Thumb: Mean: 7502.81, SD: 2718.95. The gyroscope amplitude over the Z-axis during the whole time of the task (from button highlight, through *touchStart* to *touchEnd*), shows the same characteristics for the index fingers and thumbs as the gyroscope amplitude over the Z-axis during the touch (Fig 4.21). However, since movements before the touch event are recorded too, these have higher values caused by tilting the phone towards the finger before the touch to facilitate selection.

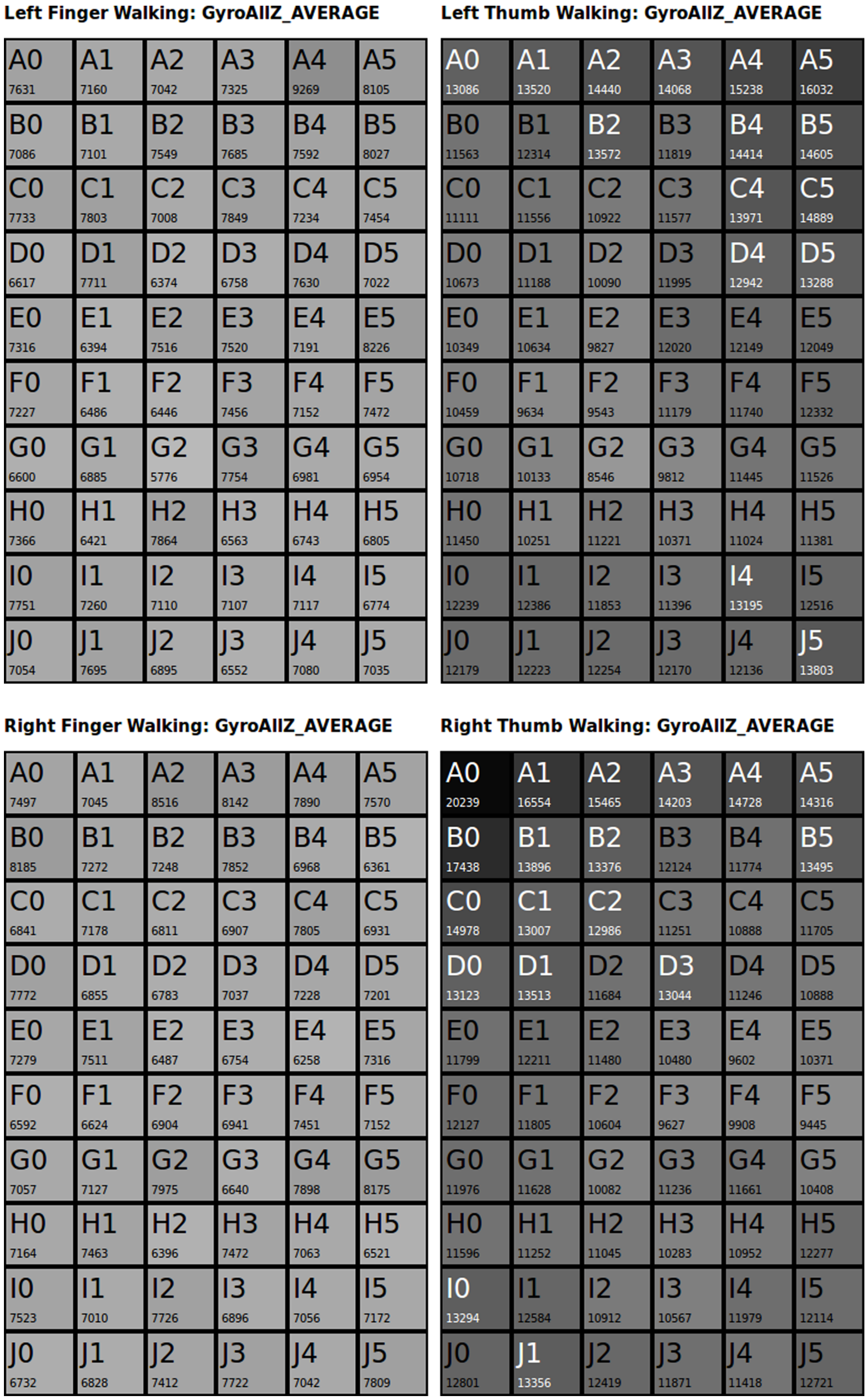

FIGURE 4.28: ***Gyro Z All Amplitude* walking:** Left Finger: Mean: 7221.78, SD: 1625.67; Left Thumb: Mean: 11950.31, SD: 2886.00; Right Finger: Mean: 7217.40, SD: 1650.60; Right Thumb: Mean: 12263.45, SD: 3134.88. The walking condition shows the same characteristics as the sitting condition (Fig 4.27), although with higher values.

Summary

The visualisation of the data shows characteristic trends for the properties *Touch Time, Touch Size Mean, Number of Touches, X Offset, Y Offset, Diff X, Diff Y* and *Gyroscope Amplitude* of the three rotational axes. In the walking condition, these trends are largely the same, but mean values are often higher (Tab. 4.1).

TABLE 4.1: The decrease and increase of the average values of the digital touch properties for index finger (Index) and thumb (Thumb) in % in the walking condition.

Property	**Index**	**Thumb**
Touch Size Mean	+11.8	+3.9
Touch Time	-0.3	-0.6
No. of Touches	+3.4	+1.9
Diff X	+48.1	+19.4
Diff Y	+44.0	+22.74
X Offset	-42.9	+95.6
Y Offset	-521.0	-46.0
Gyro X Amp.	+57.8	+37.4
Gyro Y Amp.	+55.8	+23.5
Gyro Z Amp.	+96.3	+67.7
Gyro X All Amp.	+119.4	+38.0
Gyro Y All Amp.	+94.4	+34.2
Gyro Z All Amp.	+226.6	+63.5

In general, the trends seem to be more finger-based than hand-based – apart from the characteristic patterns in each thumb's "home" and far corner. This also applies to the index fingers when examining the gyroscope amplitudes, albeit less strongly. A set of ANOVAs based on the mean values of the properties on the display with following Wilcoxon tests employing a Bonferroni-Holm correction starting with a divider of six for each examined property further revealed their potential for the detection of handedness and finger:

Touch Time: An ANOVA showed an effect of hand ($F(1, 26) = 9.28$, $p = .005$) and an effect of finger ($F(1,26) = 49.38$, $p < .001$), indicating that *Touch Time* differed between the hands and the different finger types. A Wilcoxon test showed a significant difference between the index finger and the thumb (left index finger vs. left thumb: $Z = 3.87$, $< .001$; right index finger vs. right thumb: $Z = 4.40$, p $< .001$) as well as a significant difference between the hands (left index finger vs. right index finger: $Z = 2.91$, $p = .004$; left thumb vs. right thumb: $Z = 3.2$, $p = .001$). This indicates that the duration of a touch can be used to identify finger type and hand.

Touch Size Mean: An ANOVA revealed an effect of finger ($F(1, 26) = 122.35$, $p < .001$) but no effect of hand. A Wilcoxon test showed that the difference in *Touch Size Mean* between the fingers of a hand was significant (left index finger vs. left thumb: $Z = 4.54$, $p < .001$; right index finger vs right thumb: $Z = 4.47$, $p < .001$), suggesting that *Touch Size Mean* can be used to distinguish between index finger and thumb.

Number of Touches: An ANOVA showed an effect of hand ($F(1, 26) = 9.41$, $p = .005$) and an effect of finger ($F(1, 26) = 49.71$, $p < .001$), indicating that fingers can be distinguished by the amount of touch points and that the left hand creates slightly more touch points during a touch event. A Wilcoxon test between the fingers of the left hand and the right hand showed significant differences between the fingers (left thumb vs. left finger: $Z = 3.87$, $p < .001$; right thumb vs. right index finger: $Z = 4.49$, $p < .001$) and between the hands (left thumb vs. right thumb: $Z = 2.93$, p = .003; left index finger vs. right index finger: $Z = 3.05$, $p = .002$).

Diff X, Diff Y: Performing an ANOVA on the mean values did not show a statistical difference between hands and fingers. While this may be different for discrete target positions, it indicates that these touch properties may be of limited use for finger and hand detection.

X Offset, Y Offset: An ANOVA showed no significant differences between finger and hand for the *X Offset*, but an effect of finger type on the *Y Offset* value ($F(1, 26) = 7.66$, $p = .010$). A Wilcoxon test showed a significant difference between the left index finger and left thumb ($Z = 3.58$, $p < .001$) and a significant difference between right index finger and right thumb ($Z = 3.34$, $p < .001$). This indicates that the *Y Offset* value of the touch may be useful for differentiating between index finger and thumb. Comparing the offset values to the ones reported by Park and Han (2010), the data does not reflect their findings that touches on elements in the upper part and on the left of the interface seem to generally have a positive *X Offset* and that elements at the bottom and the left part of the interface tend to have a negative one, when using the right thumb for input. While touches tended to have a positive *X Offset* in column A0 for the right thumb, no other patterns were clearly discernible. This may be due to the larger device size used in Park and Han's study together with the fact that they allowed users to support the device with the left hand when struggling to reach a target with their right thumb.

Gyro X Amplitude: An ANOVA of the gyroscope amplitude around the X-axis during the touch showed an effect of hand ($F(1,26) = 18.854$, $p < .001$) and an effect of finger ($F(1,26) = 27.1$, $p < .001$), as well as an interaction between hand and finger ($F(1,26) = 16.16$, $p < .001$). A Wilcoxon test revealed that the X amplitude differed significantly between the fingers (left index finger vs. left thumb: $Z = 4.3$, $p < .001$; right index finger vs. right thumb: 2.48, $p = .013$) and between the hands (left index finger vs. right index finger: $Z = 4.2$, $p < .001$), but not between the left thumb and the right thumb. This indicates that the gyroscope amplitude around the X-axis during the touch may be more useful for determining the mode of operation (finger or thumb), but not the hand.

Gyro Y Amplitude: An ANOVA of the gyroscope amplitude around the Y-axis during the touch showed an effect of hand ($F(1,26) = 24.64$, $p <.001$) and finger ($F(1,26) = 46.33$, $p < .001$). A following Wilcoxon test showed a significant difference between the fingers (left index finger vs. left thumb: $Z = 4.47$, $p < .001$; right index finger vs. right thumb: $Z = 3.51$, $p < .001$; left index finger vs. right index finger: $Z = 3.15$, $p = .002$; left thumb vs. right thumb: $Z = 2.84$, $p = .005$). This indicates this property's possible usefulness for determining finger and hand of the user during the touch.

Gyro Z Amplitude: An ANOVA of the gyroscope amplitude around the Z-axis during the touch showed an effect of finger type ($F(1, 26) = 152.07$, $p < .001$), but not of hand, and an interaction between finger and hand ($F(1, 26) = 4.76$, $p = .038$). A Wilcoxon test showed a significant difference between index finger and thumb (left index finger vs. left thumb: $Z = 4.52$, $p < .001$; right index finger vs. right thumb: $Z = 4.54$, $p < .001$). This indicates that the gyroscope amplitude around the Z-axis during the touch can be employed to detect whether the user touched the target with a finger or thumb.

Gyro X All Amplitude: An ANOVA of the gyroscope amplitude around the X-axis before and during the touch showed an effect of finger ($F(1, 26) = 117.94$, $p < .001$), but not of hand. A Wilcoxon test revealed a significant difference between the fingers of each hand (left index finger vs. left thumb: $Z = 4.30$, $p < .001$; right index finger vs. right thumb: $Z = 2.48$, $p = .013$) and a significant difference between the left index finger and the right index finger: $Z = 4.20$, $p < .001$. The results indicate that the property may be used to detect whether the index finger or thumb touched the target and, when the index finger is used, the hand too.

Gyro Y All Amplitude: An ANOVA of the gyroscope amplitude around the Y-axis before and during the touch showed an effect of finger ($F(1{,}26) = 134.37$, $p < .001$) as well as an effect of hand ($F(1{,}26) = 5.38$, $p = .028$). A following Wilcoxon test revealed that the differences between the fingers of a hand are significant (left index finger vs. left thumb: $Z = 4.54$, $p < .001$; right index finger vs. right thumb: $Z = 4.54$, $p < .001$), but that there were no significant differences between the fingers of both hands. This suggests that this property can be helpful for determining the mode of operation – index finger or thumb – but not the hand.

Gyro Z All Amplitude: An ANOVA of the gyroscope amplitude around the Z-axis before and during the touch showed an effect of finger ($F(1, 26) = 89.18$, $p <.001$), but no effect of hand. A Wilcoxon test showed a significant difference between the fingers of each hand (left index finger vs. right index finger: $Z = 4.45$, $p < .001$; left thumb vs. right thumb: $Z = 4.54$, $p <. 001$), which suggests that the gyroscope amplitude around the Z-axis before and during the touch is a useful property for determining mode of operation – finger or thumb.

The SPSS file used for the above calculations can be found in Appendix D, section D.2.1, p. 353.

4.3.2 Evaluation of the Physical Touch Properties

This section presents the physical finger and touch properties of the participants of the initial data collection. It explores the relationship between physical and digital touch properties and examines whether the physical properties provide any clues about the digital properties' ability to determine finger and hand of the user.

Examining the Physical Touch Shape

Figure 4.29 shows the shape of the four fingers when they touched the screen in 15 positions. Each square combined four targets of the test application (Fig. 4.1, p. 132). The touch shape of the thumb was often at an angle due to its limitation to a pivotal

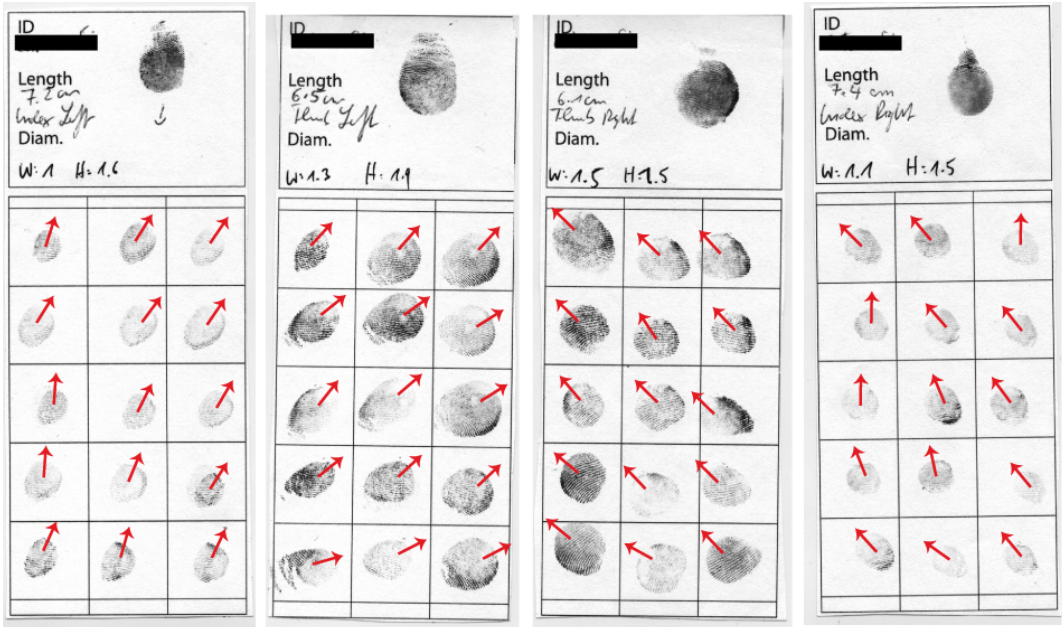

FIGURE 4.29: An example of the actual size of the finger and thumb of a user when touching the screen in 15 positions. **From left to right:** Left index finger, left thumb, right thumb, right index finger. To record the prints, a sheet of paper showing a grid combining four target positions of the application (Fig. 4.1, p. 132) into one square was attached to the phone's screen. Users pressed their fingers onto an ink pad and randomly tapped onto each square while holding the phone in the same way as they would when operating the application. Red arrows were superimposed to indicate the touch direction.

movement around its base, as presented by Katre (2010), with the same trend noticeable for the index finger, albeit less strongly due to its greater movement range. This suggests that Wang et al.'s (2009) technique to determine handedness based on the angle between the first touch point and the last touch point would work better for the thumb than the index finger.

In addition, touches of the left thumb and the right thumb showed a smaller profile in columns one and three respectively than in the same row at the opposite side of the screen. This indicates an increase in *Touch Size Mean* for the thumb when moving away from its origin. This was further visible by the slightly stronger colour profile on the side of each thumb's "home" corner in columns one and three, suggesting that in these areas the thumb primarily connects with the screen via its side, resulting in a reduced *Touch Size Mean* that grows in a semicircular fashion with increasing distance to the metacarpophalangeal joint (MCP) (Fig. 4.3, p. 139), as found by Katre (2010) and Goel et al. (2012).

Finally, touches of the left hand seemed to be slightly larger in size than those of the right, which confirms the assumptions made in section 4.3.1, p. 137 that touches with the non-dominant hand are less precise and dexterous than those performed with the dominant hand, resulting in a "sloppier" touch with increased *Touch Size Mean* and *Touch Time*, together with a larger number of touch points. However, it has to be noted that the described effects were not always as discernible as in the example shown in Figure 4.29. A full list of recorded shapes can be found in Appendix D, section D.4.2, p. 354.

Examining the Spatiotemporal Development

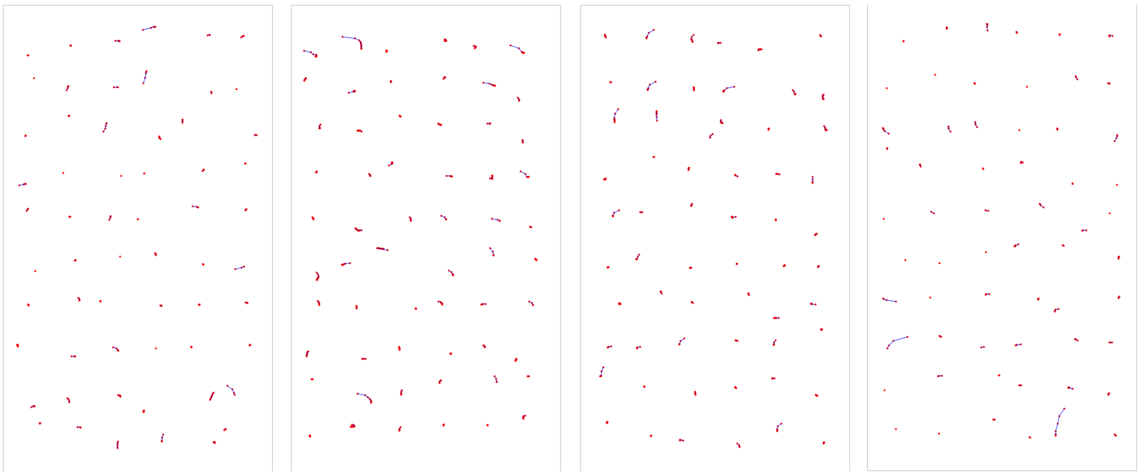

FIGURE 4.30: An example of the visualisation of the touch points created per touch by one user while sitting. **From left to right:** Left index finger, left thumb, right thumb, right index finger.

Figure 4.30 shows the spatiotemporal development of a touch for the index finger and the thumb of the left and right hands while sitting, based on the amount of touch points created during the contact with the screen. Although no clear distinction between index finger and thumb of each hand were noticeable, there was a trend for touches of the left hand to slightly veer to the left and for touches of the right hand to slightly veer to the right. This partially reflects the impression given by the touch shapes in Figure 4.29 and indicates that the spatiotemporal touch development could be utilised to determine handedness, as suggested by Wang et al. (2009).

The walking condition (Fig. 4.31) showed a similar trend, but with a slightly larger spatial expansion of some touches, caused by a "sloppier" contact with the device due

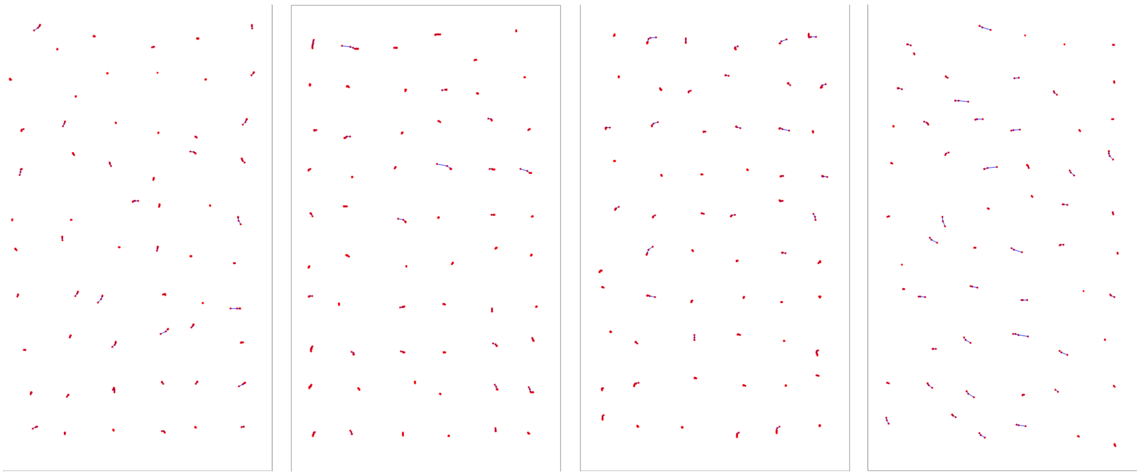

FIGURE 4.31: An example of the visualisation of the touch points created per touch by one user while walking . **From left to right:** Left index finger, left thumb, right thumb, right index finger.

to the user's and the device's movement, as described in section 4.3.1, p. 137. However, it has to be noted that the effects shown in Figure 4.30 and Figure 4.31 were not always as discernible as the examples in the presented graphics and therefore cannot be regarded as reliable indicators of handedness. The complete list of recorded images showing the spatiotemporal development of the touches can be found in Appendix D, section D.4.3, p. 354.

Physical and Digital Properties

Table 4.2 shows the mean values of the physical characteristics of shape width, shape height and limb length for each finger as well as the mean values of the most important touch properties, as determined by the ANOVAs on pages 165–168. The thumb's physical touch ellipse (Fig. 4.29) was an average of 26.2% wider and 17.5% higher than that of the index finger, which had a strong effect on the *Touch Size Mean* property, which was an average of 39.8% larger for the thumb.

The strongest physical factor impacting the digital touch properties seemed to be the limited dexterity and reach of the thumb, mainly caused by the thumb's total length, which was 16.6% shorter than that of the index finger. This resulted in a prolonged contact time with the display when touching (*Touch Time* +26.1% in comparison to the index finger), but found its strongest manifestation in the greatly increased gyroscope amplitudes, caused by the comparatively strong device movement when reaching for a

TABLE 4.2: The mean physical characteristics of the left index finger (L-I), the left thumb (L-T), the right index finger (R-I) and the right thumb (R-T) together with the mean values of the touch properties determined to be distinctive for the fingers, as provided by the ANOVAs on pages 165–168. The final column shows the mean percental relation of thumb to index finger (Thumb %). The full data set can be found in Appendix D, section D.4.1, p. 353.

Finger	**L-I**	**L-T**	**R-I**	**R-T**	**Thumb %**
Touch shape width	1.30	1.59	1.27	1.59	+26.2
Touch shape height	2.03	2.23	1.85	2.32	+17.5
Limb length	7.26	6.08	7.27	6.03	-16.6
Touch Size Mean	0.127	0.18	0.128	0.178	+39.8
Touch Time	110.12	134.62	95.67	124.9	+26.1
Number of Touches	4.63	5.80	3.91	5.33	+30.4
Gyro X Amp.	2195.41	3474.84	3100.34	3636.96	+34.3
Gyro Y Amp.	2394.10	3997.17	3209.53	4744.73	+56.0
Gyro Z Amp.	733.56	1772.22	761.25	2016.72	+153.5
Gyro All X Amp.	4205.62	11794.39	5008.40	12201.48	+160.4
Gyro All Y Amp.	4941.28	13122.09	5752.44	14375.70	+157.1
Gyro All Z Amp.	2287.77	7309.79	2132.96	7502.81	+235.1

target outside the thumb's natural movement arc (Fig. 4.27). This held true for all three gyroscope axes, but was especially visible for the rotation around the Z-axis before and during the touch, where the amplitude was an average of 235.1% higher for the thumb.

Exploring the correlation between the mean values of the physical and digital properties showed the following:

- No statistically significant correlations between the physical and digital properties for the index finger, apart from a correlation between the index finger's touch shape width and the *Number of Touches* (Spearman's *rho* = .423, p = .028).
- Correlation trends between the index finger's touch shape width and *Touch Time*.
- Correlation trends between the index finger's limb length and *Touch Time*.
- A statistically significant correlation between limb length of the thumb and the properties: *Gyro Y Amplitude* (Spearman's *rho* = .464 , p = .015), *Gyro Z Amplitude* (Spearman's *rho* = .533, p = .004), *Gyro X All Amplitude* (Spearman's *rho*

= .576, p = .002), *Gyro Y All Amplitude* (Spearman's *rho* = .644, $p <$ .001) and *Gyro Z All Amplitude* (Spearman's *rho* = .632, $p <$ .001).

- A statistically significant correlation between the thumb's touch shape width and the *Gyro X All Amplitude* (Spearman's *rho* = .479, p = .012).

Although correlation may not necessarily indicate causation, **the examination of the mean values suggests the ergonomic characteristics limb length and touch shape width of the thumb may be a cause of the patterns in the digital touch values**. The thumb's fixation to the hand holding the device and the resulting limited area of movement may cause a greater degree of movement of the device together with a flatter connection angle of thumb and screen to allow the former to reach all parts of the latter, as illustrated in the location-based visualisation of the gyroscope values shown in Figures 4.17 to 4.28, pp. 153–164.

Yet, the shortage of statistically significant correlations between the physical and digital properties for the index finger also indicates that distinctions between finger and thumb (based on correlations between their physical and digital properties) may not be made sweepingly for the whole screen, but rather require a subdivision of the screen into smaller areas to detect differences in the values of each with reference to a spatial location. This supports the approaches taken in section 4.4, p. 177, which evaluate the data separately for each grid unit. Nonetheless, the data in Table 4.2 highlights the gyroscope amplitudes to be the most distinctive touch properties for determining the user's finger, followed by *Touch Size Mean* and *Touch Time*.

Summary

This section has presented the physical shape of a touch, its spatiotemporal development using a visualisation of the digital touch points, and the mean physical length as well as touch shape width and height of the index fingers and thumbs of the left and right hands. Figure 4.29 has illustrated that some trends in the digital data, such as the larger *Touch Size Mean* of the thumbs, correspond to the physical shape of the touch and can help to differentiate between index finger and thumb. Furthermore, it has shown that touches, especially those of the thumb, often show a certain "direction", which has the potential to support the detection of handedness when touching the screen, further supported by the spatial development of the touch points in Figures 4.30 and 4.31. However, while these figures show some trends of the touches of the index fingers and thumbs, they do not fully represent the complete data set, in which the described observations are not always as clearly visible as in the included examples. As a result, the effects can only be seen as pointers for further investigation, but not as reliable indicators for finger and hand detection.

The last part of this section has listed physical properties of the fingers together with the mean values of the most important digital touch properties determined by the ANOVAs on pages 165–168. The data has shown that while index finger and thumb can be distinguished by *Touch Size Mean*, the most important difference between the two seems to be the device movement before and during the touch, likely to be caused by the difference in limb length and the thumb's limited mobility, suggesting that the gyroscope amplitudes are the most reliable factors for finger detection.

4.3.3 Evaluation Using Machine Learning

To further explore the data, it was divided into two sets, one for the sitting condition and one for the walking condition, and then loaded into the *Weka Explorer*. Visualising the data showed a weak correlation between hand type (index finger or thumb) and the properties *Touch Time*, *Gyro X Amplitude* and *Gyro Y Amplitude*, and a strong correlation between finger type and the properties *Touch Size Mean*, *Gyro Z Amplitude*, *Gyro X All Amplitude*, *Gyro Y All Amplitude* and *Gyro Z All Amplitude* (Fig. 4.32). However, correlation between the values and handedness was not visible, supporting the results of the ANOVAs in section 4.3.1, p. 137, which indicate that finger detection is more feasible than the detection of handedness using the data of a single touch.

Running machine-learning algorithms on the training data showed varying degrees of accuracy for determining the user's finger and hand (Tab. 4.3). For all algorithms, finger classification had the highest degree of accuracy, followed by hand classification. The best results were provided by the J48 classifier (J48, 82.6%) and the Random Forest algorithm usinG12 properties (RF12, 82.7%). Although results based on the tenfold cross-validated training data cannot be regarded as a reliable model without further validation, the results nonetheless indicate each algorithm's usefulness for classifying the data and suggest further pursuit of this approach.

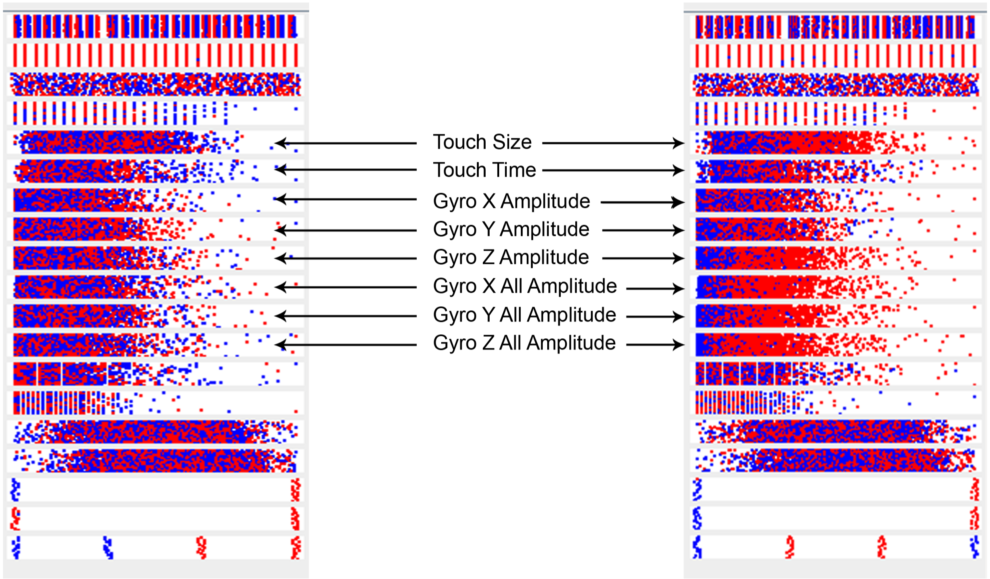

FIGURE 4.32: Visualisation of the data in the *Weka Explorer*. **Left:** Correlation between the highlighted touch properties and the left hand (blue) and the right (red) hand is not discernible. **Right:** Correlation between finger type (index finger (blue) and thumb (red)) and the highlighted touch properties is clearly visible.

TABLE 4.3: Correctly classified instances in % for the sitting (S) and walking (W) conditions when trying to determine the user's hand or finger using the recorded touch data. Rows show the accuracy of the *J48* classification (J48), the *Random Forest* classification usinG12 properties (RF12) as well as the accuracy of three *Nearest Neighbour* (NN) models using either one (K1), three (K3) or five (K5) neighbours. The models were built on the training set by leaving out the *Diff X* and *Diff Y* properties, whose inclusion in most cases produced less accurate results. Numbers are the result of the tenfold stratified cross-validation. The *Weka* output can be found in Appendix D, section D.3.1, p. 353.

Algorithm	**H**	**F**
S K1 NN	57.9	75.4
W K1 NN	56.6	72.6
S K3 NN	58.2	78.5
W K3 NN	57.5	75.5
S K5 NN	58.7	78.9
W K5 NN	58.4	76.3
S J48	58.2	82.6
W J48	57.9	80.6
S RF12	59.9	82.7
W RF12	59.1	78.4

Summary

The data visualisation in *Weka* highlights several properties that could be used in isolation for successful finger detection (Fig. 4.32) disregarding the screen area. However, the properties showed no clear correlation with handedness and suggests that hand detection may only be possible in certain screen areas, requiring a more precise breakdown of the data. This is emphasised by the machine-learning algorithms (Tab. 4.3) which indicate that finger detection is significantly more likely to be accurate than hand detection (Tab. 4.3), with the latter likely to require additional validation steps.

4.3.4 Discussion

The graphical evaluation in section 4.3.1, p. 137 showed distinctive trends in several properties for the fingers of each hand and that the characteristics were often amplified when walking. While some of this can certainly be attributed to a user's gait, such as the higher gyroscope values, it also suggests that users are less dexterous due to the higher cognitive load caused by the need for orientation (Schildbach and Rukzio, 2010), resulting in "sloppier" touches.

The results of the ANOVAs showed the varying potential of the touch properties for identifying the user's hand and finger. While the properties *Touch Time, Number of Touches, Gyro Y Amplitude*, and *Gyro Y All Amplitude* seem to be promising for both detection of finger and hand, the remaining properties seem to only be useful for determining the user's finger. This suggests that, overall, hand detection using the properties of only one touch is less feasible than finger detection when analysing the properties separately and that a more complex analysis of the data may be required in order to detect the user's hand. However, it has to be considered that the initial ANOVAs only used the overall mean value of each property, but that the effectiveness of each property for finger and hand detection may differ with target position, as the values can vary greatly between the screen regions, as shown with the *Touch Size Mean* property (Fig. 4.3) and the gyroscope properties (Fig. 4.23, 4.25, 4.27).

Analysing the physical touch shapes presented in section 4.3.2, p. 168, the fingerprints clearly indicate that a detection of the user's finger is highly likely based on the easily discernible differences in size. The development of the touch points during a touch event

(Fig. 4.30) suggests that the number of touch points created could be another helpful classifier. The frequently noticeable touch "direction" of the shapes (Fig. 4.29) and the corresponding development of the touch points (Fig. 4.30) also suggest that the detection of handedness is likely, albeit less easy to detect than the finger.

Finally, visualising the data in *Weka* (Fig. 4.32) has highlighted that the values of the properties *Touch Time*, *Touch Size Mean*, *Gyro X Amplitude*, *Gyro Y Amplitude*, *Gyro Z Amplitude*, *Gyro X All Amplitude*, *Gyro Y All Amplitude* and *Gyro Z All Amplitude* were largely different for index finger and thumb, but that no such clear distinction was observed between the left and right hands. This observation was largely supported by the results of the machine-learning algorithms (Fig. 4.3), which indicate that finger detection is possible, but hand detection less so, if a single touch is used for classification.

To determine how reliable finger and hand detection are using the recorded touch properties, a second user study was conducted. Section 4.4, p. 177 presents the mean values of the recorded properties for each target position and examines whether these properties are distinctive enough to allow finger and hand detection using a simple mean-based comparison, or whether classification using machine-learning algorithms allows better detection.

4.4 Determining the Input Mode Based on Touch Properties

The previous part of this chapter has shown trends in the data and highlighted various properties that may be suitable for determining the user's finger and hand when touching the screen. This second part of the chapter presents the mean values of each recorded property for all target positions when sitting and when walking and explores the accuracy of each touch property for predicting the mode of operation. It does so by using the recorded property values in a mean-based comparison against a new data point and by calculating the Pearson Correlation Coefficient (PCC) of certain properties of a new touch in relation to stored reference values (*Approach A*). In addition, this section shows the accuracy of predicting the user's mode of operation using five machine-learning algorithms employing a training set consisting of the data recorded in section 4.2, p. 131

and verifying the resulting models with newly recorded data (*Approach B*). The machine-learning approach is divided into two techniques: Classification of finger and hand using only the highest-ranking algorithm per target position (*Approach B1*) and classification of finger and hand using the three highest-ranking algorithms per target position in a voting process (*Approach B2*). Finally, the accuracy of all approaches will be compared to each other as well as to Wang et al.'s technique (2009) for hand detection (*Approach C*).

To explore the accuracy of the training data for predicting a user's finger and hand using the four approaches, a new set of data was collected from ten users (5 F, mean age: 33.8, SD: 3.97) using the same design as the initial data collection in section 4.2, p. 131, however without recording any physical properties.

4.4.1 *Approach A*: Finger and Hand Detection Accuracy Using Mean Comparison

To obtain the mean value of each property for each target position, finger and condition (sitting and walking), the data was structured in SPSS and exported as separate tables. It was then processed in a spreadsheet application and subsequently stored in an SQLite database. The data and study information can be found in Appendix D, pp. 355–356. For the visualisation, the data was extracted from the database and fed into a Web front end. The overview tables detailing the mean values for each property in both conditions for finger and thumb in each of the target positions can be found in Appendix D, section D.2.2, p. 353.

Inside the SQLite database, the mean property values for each position, finger and condition was held in a set of lookup tables. The following lookup tables were created:

- Left finger
- Right finger
- Left finger walking
- Right finger walking
- Left thumb
- Right thumb
- Left thumb walking
- Right thumb walking

These were then used to evaluate the new data points recorded in section 4.4, p. 177 and the results were saved in an evaluation table. The database with these lookup tables together with the initially recorded data (section 4.2, p. 131) as well as the second data collection (section 4.4, p. 177) can be found in Appendix D, section D.5.1, p. 356.

To classify the finger and hand of a new touch event, each property of the event was compared to the recorded mean value of this property in the respective screen region in all tables. If the value was within two standard deviations of the lookup value, the data and respective table name were extracted and added to a list. The list was then sorted and the entry with the value closest to the new data point was chosen to represent the current finger and hand of the user. The resulting string ("Right finger", for example) was then compared to the actual mode of operation, which was set in a dialogue before recording, and the result saved in an evaluation table, stating whether the user's finger and hand were correctly detected for the respective property and target location. The following figures show the possible accuracy of finger and hand classification using this approach:

Row	Column	Target	Time	Size	Touches	Off. X	Gyro X	Gyro Y	Gyro Z	Off. Y	Gyro X All	Gyro Y All	Gyro Z All
A	0	A0	75%	55.0%	70%	50%	45%	45%	57.4%	50%	72.5%	67.5%	72.5%
A	1	A1	70%	57.4%	65%	52.5%	45%	50%	50%	47.5%	62.5%	67.5%	77.5%
A	2	A2	80%	55.0%	72.5%	52.5%	57.4%	57.4%	67.5%	40%	60%	75%	82.5%
A	3	A3	70%	65%	67.5%	47.5%	40%	55.0%	57.4%	47.5%	67.5%	70%	70%
A	4	A4	70%	57.4%	75%	47.5%	37.5%	60%	65%	52.5%	67.5%	67.5%	80%
A	5	A5	77.5%	60%	77.5%	40%	60%	52.5%	70%	52.5%	60%	75%	70%
B	0	B0	80%	37.5%	75%	50%	40%	50%	55.0%	42.5%	65%	57.4%	80%
B	1	B1	82.5%	65%	75%	52.5%	27.5%	47.5%	57.4%	42.5%	65%	70%	85%
B	2	B2	60%	77.5%	65%	65%	37.5%	47.5%	62.5%	42.5%	75%	80%	75%
B	3	B3	72.5%	67.5%	77.5%	67.5%	32.5%	52.5%	67.5%	55.0%	80%	75%	87.5%
B	4	B4	75%	75%	70%	60%	47.5%	57.4%	65%	50%	75%	65%	72.5%
B	5	B5	75%	60%	75%	40%	37.5%	45%	70%	55.0%	80%	67.5%	85%
C	0	C0	77.5%	62.5%	82.5%	37.5%	40%	42.5%	45%	62.5%	72.5%	70%	77.5%
C	1	C1	70%	62.5%	77.5%	62.5%	40%	60%	50%	47.5%	60%	60%	75%
C	2	C2	75%	42.5%	62.5%	60%	52.5%	50%	70%	42.5%	70%	72.5%	70%
C	3	C3	72.5%	70%	75%	45%	42.5%	55.0%	60%	40%	72.5%	72.5%	72.5%
C	4	C4	65%	57.4%	80%	55.0%	37.5%	50%	62.5%	47.5%	80%	80%	85%
C	5	C5	77.5%	65%	77.5%	50%	52.5%	45%	57.4%	47.5%	65%	75%	70%
D	0	D0	65%	60%	67.5%	47.5%	52.5%	52.5%	75%	60%	65%	57.4%	65%
D	1	D1	67.5%	52.5%	67.5%	70%	42.5%	50%	57.4%	47.5%	75%	72.5%	77.5%
D	2	D2	65%	67.5%	62.5%	50%	52.5%	60%	67.5%	35%	72.5%	77.5%	75%
D	3	D3	75%	70%	67.5%	42.5%	47.5%	62.5%	65%	42.5%	72.5%	80%	80%
D	4	D4	75%	67.5%	67.5%	70%	47.5%	57.4%	57.4%	45%	65%	70%	67.5%
D	5	D5	67.5%	65%	65%	60%	42.5%	57.4%	60%	42.5%	70%	85%	87.5%
E	0	E0	72.5%	42.5%	82.5%	42.5%	47.5%	57.4%	52.5%	47.5%	72.5%	62.5%	72.5%
E	1	E1	60%	47.5%	70%	62.5%	35%	52.5%	57.4%	47.5%	55.0%	65%	65%
E	2	E2	70%	52.5%	67.5%	45%	47.5%	57.4%	52.5%	57.4%	62.5%	72.5%	70%
E	3	E3	65%	45%	70%	57.4%	47.5%	57.4%	52.5%	57.4%	70%	70%	70%
E	4	E4	77.5%	57.4%	75%	57.4%	62.5%	50%	52.5%	47.5%	65%	67.5%	72.5%
E	5	E5	77.5%	55.0%	70%	50%	50%	47.5%	60%	42.5%	65%	75%	80%
F	0	F0	67.5%	57.4%	70%	55.0%	42.5%	55.0%	50%	57.4%	60%	65%	77.5%
F	1	F1	65%	55.0%	75%	62.5%	50%	65%	67.5%	52.5%	75%	72.5%	77.5%
F	2	F2	75%	50%	67.5%	45%	67.5%	62.5%	52.5%	45%	72.5%	77.5%	85%
F	3	F3	70%	60%	65%	32.5%	50%	60%	60%	50%	65%	72.5%	70%
F	4	F4	77.5%	45%	77.5%	52.5%	42.5%	60%	62.5%	57.4%	65%	77.5%	82.5%
F	5	F5	67.5%	65%	80%	57.4%	50%	52.5%	65%	55.0%	72.5%	77.5%	80%
G	0	G0	75%	67.5%	75%	72.5%	50%	45%	60%	52.5%	70%	70%	82.5%
G	1	G1	75%	32.5%	62.5%	55.0%	45%	52.5%	60%	57.4%	67.5%	75%	85%
G	2	G2	60%	60%	60%	60%	52.5%	60%	72.5%	70%	85%	67.5%	75%
G	3	G3	72.5%	62.5%	75%	50%	65%	57.4%	70%	37.5%	77.5%	77.5%	80%
G	4	G4	67.5%	60%	67.5%	45%	60%	52.5%	60%	42.5%	77.5%	67.5%	72.5%
G	5	G5	72.5%	62.5%	72.5%	50%	50%	37.5%	65%	47.5%	77.5%	75%	77.5%
H	0	H0	75%	47.5%	70%	55.0%	57.4%	45%	55.0%	50%	75%	72.5%	77.5%
H	1	H1	60%	52.5%	62.5%	45%	67.5%	55.0%	67.5%	45%	80%	82.5%	85%
H	2	H2	72.5%	30%	75%	72.5%	62.5%	57.4%	62.5%	50%	72.5%	70%	77.5%
H	3	H3	75%	55.0%	70%	52.5%	52.5%	52.5%	57.4%	65%	80%	77.5%	82.5%
H	4	H4	62.5%	60%	70%	47.5%	37.5%	45%	67.5%	62.5%	72.5%	75%	80%
H	5	H5	65%	75%	72.5%	55.0%	55.0%	47.5%	67.5%	65%	77.5%	77.5%	80%
I	0	I0	67.5%	52.5%	72.5%	42.5%	52.5%	62.5%	70%	45%	77.5%	70%	72.5%
I	1	I1	57.4%	47.5%	55.0%	45%	57.4%	45%	67.5%	42.5%	77.5%	67.5%	90%
I	2	I2	70%	62.5%	62.5%	42.5%	50%	57.4%	57.4%	35%	77.5%	67.5%	80%
I	3	I3	62.5%	67.5%	67.5%	50%	47.5%	45%	60%	55.0%	75%	65%	80%
I	4	I4	70%	62.5%	67.5%	47.5%	67.5%	45%	50%	52.5%	85%	75%	77.5%
I	5	I5	87.5%	72.5%	70%	57.4%	60%	35%	57.4%	47.5%	62.5%	72.5%	67.5%
J	0	J0	55.0%	35%	57.4%	52.5%	37.5%	37.5%	55.0%	55.0%	80%	75%	92.5%
J	1	J1	75%	62.5%	77.5%	45%	62.5%	40%	67.5%	57.4%	75%	72.5%	82.5%
J	2	J2	72.5%	75%	67.5%	47.5%	50%	57.4%	55.0%	42.5%	82.5%	72.5%	80%
J	3	J3	70%	65%	77.5%	47.5%	67.5%	50%	60%	47.5%	77.5%	80%	85%
J	4	J4	72.5%	62.5%	75%	55.0%	57.4%	47.5%	60%	42.5%	80%	75%	72.5%
J	5	J5	67.5%	57.4%	72.5%	55.0%	45%	37.5%	65%	57.4%	75%	85%	75%

FIGURE 4.33: The detection accuracy of the properties *Touch Time, Touch Size Mean, Number of Touches, X Offset, Y Offset, Gyro X Amplitude, Gyro Y Amplitude, Gyro Z Amplitude, Gyro X All Amplitude, Gyro Y All Amplitude* and *Gyro Z All Amplitude* for the user's **finger** (index finger or thumb) in the 60 target locations A0 to J5 in the **sitting** condition, using the lookup tables holding the mean property values for each target position. The property with the highest accuracy per target is highlighted in black. If the highest accuracy in a target position is <75%, the highlight is red.

	0				1				2				3				4				5			
A	A0	Time 40%	Size 45%	Touches 47.5%	A1	Time 55.0%	Size 45%	Touches 57.4%	A2	Time 60%	Size 35%	Touches 62.5%	A3	Time 55.0%	Size 55.0%	Touches 55.0%	A4	Time 60%	Size 50%	Touches 60%	A5	Time 52.5%	Size 40%	Touches 57.4%
	Off. X 67.5%	Gyro X 55.0%	Gyro Y 47.5%	Gyro Z 55.0%	Off. X 47.5%	Gyro X 57.4%	Gyro Y 62.5%	Gyro Z 52.5%	Off. X 47.5%	Gyro X 40%	Gyro Y 35%	Gyro Z 40%	Off. X 52.5%	Gyro X 37.5%	Gyro Y 42.5%	Gyro Z 42.5%	Off. X 52.5%	Gyro X 32.5%	Gyro Y 45%	Gyro Z 47.5%	Off. X 27.5%	Gyro X 60%	Gyro Y 52.5%	Gyro Z 50%
	Off. Y 50%	Gyro X All 55.0%	Gyro Y All 52.5%	Gyro Z All 60%	Off. Y 62.5%	Gyro X All 55.0%	Gyro Y All 47.5%	Gyro Z All 47.5%	Off. Y 55.0%	Gyro X All 47.5%	Gyro Y All 42.5%	Gyro Z All 52.5%	Off. Y 50%	Gyro X All 47.5%	Gyro Y All 35%	Gyro Z All 50%	Off. Y 47.5%	Gyro X All 42.5%	Gyro Y All 67.5%	Gyro Z All 45%	Off. Y 45%	Gyro X All 42.5%	Gyro Y All 62.5%	Gyro Z All 45%
B	B0	Time 52.5%	Size 50%	Touches 60%	B1	Time 57.4%	Size 37.5%	Touches 55.0%	B2	Time 42.5%	Size 50%	Touches 50%	B3	Time 55.0%	Size 45%	Touches 55.0%	B4	Time 52.5%	Size 52.5%	Touches 52.5%	B5	Time 62.5%	Size 57.4%	Touches 62.5%
	Off. X 62.5%	Gyro X 52.5%	Gyro Y 52.5%	Gyro Z 47.5%	Off. X 50%	Gyro X 50%	Gyro Y 55.0%	Gyro Z 45%	Off. X 60%	Gyro X 50%	Gyro Y 52.5%	Gyro Z 52.5%	Off. X 52.5%	Gyro X 47.5%	Gyro Y 45%	Gyro Z 35%	Off. X 52.5%	Gyro X 45%	Gyro Y 55.0%	Gyro Z 47.5%	Off. X 42.5%	Gyro X 55.0%	Gyro Y 50%	Gyro Z 50%
	Off. Y 52.5%	Gyro X All 47.5%	Gyro Y All 55.0%	Gyro Z All 52.5%	Off. Y 42.5%	Gyro X All 50%	Gyro Y All 60%	Gyro Z All 47.5%	Off. Y 52.5%	Gyro X All 45%	Gyro Y All 57.4%	Gyro Z All 60%	Off. Y 42.5%	Gyro X All 52.5%	Gyro Y All 47.5%	Gyro Z All 45%	Off. Y 65%	Gyro X All 62.5%	Gyro Y All 50%	Gyro Z All 42.5%	Off. Y 57.4%	Gyro X All 55.0%	Gyro Y All 62.5%	Gyro Z All 57.4%
C	C0	Time 60%	Size 52.5%	Touches 52.5%	C1	Time 55.0%	Size 57.4%	Touches 52.5%	C2	Time 47.5%	Size 45%	Touches 45%	C3	Time 50%	Size 50%	Touches 52.5%	C4	Time 55.0%	Size 40%	Touches 57.4%	C5	Time 52.5%	Size 47.5%	Touches 57.4%
	Off. X 72.5%	Gyro X 55.0%	Gyro Y 47.5%	Gyro Z 52.5%	Off. X 50%	Gyro X 35%	Gyro Y 57.4%	Gyro Z 52.5%	Off. X 60%	Gyro X 50%	Gyro Y 47.5%	Gyro Z 45%	Off. X 70%	Gyro X 52.5%	Gyro Y 45%	Gyro Z 50%	Off. X 52.5%	Gyro X 45%	Gyro Y 52.5%	Gyro Z 47.5%	Off. X 50%	Gyro X 42.5%	Gyro Y 50%	Gyro Z 45%
	Off. Y 45%	Gyro X All 57.4%	Gyro Y All 47.5%	Gyro Z All 55.0%	Off. Y 62.5%	Gyro X All 52.5%	Gyro Y All 57.4%	Gyro Z All 52.5%	Off. Y 45%	Gyro X All 40%	Gyro Y All 45%	Gyro Z All 50%	Off. Y 55.0%	Gyro X All 45%	Gyro Y All 55.0%	Gyro Z All 40%	Off. Y 42.5%	Gyro X All 50%	Gyro Y All 52.5%	Gyro Z All 37.5%	Off. Y 45%	Gyro X All 57.4%	Gyro Y All 52.5%	Gyro Z All 42.5%
D	D0	Time 62.5%	Size 40%	Touches 60%	D1	Time 57.4%	Size 42.5%	Touches 50%	D2	Time 52.5%	Size 52.5%	Touches 52.5%	D3	Time 57.4%	Size 47.5%	Touches 57.4%	D4	Time 57.4%	Size 57.4%	Touches 50%	D5	Time 52.5%	Size 60%	Touches 55.0%
	Off. X 55.0%	Gyro X 42.5%	Gyro Y 47.5%	Gyro Z 62.5%	Off. X 40%	Gyro X 55.0%	Gyro Y 57.4%	Gyro Z 60%	Off. X 55.0%	Gyro X 50%	Gyro Y 50%	Gyro Z 52.5%	Off. X 47.5%	Gyro X 60%	Gyro Y 35%	Gyro Z 47.5%	Off. X 55.0%	Gyro X 57.4%	Gyro Y 45%	Gyro Z 50%	Off. X 52.5%	Gyro X 60%	Gyro Y 55.0%	Gyro Z 55.0%
	Off. Y 55.0%	Gyro X All 47.5%	Gyro Y All 60%	Gyro Z All 55.0%	Off. Y 45%	Gyro X All 57.4%	Gyro Y All 47.5%	Gyro Z All 52.5%	Off. Y 52.5%	Gyro X All 50%	Gyro Y All 45%	Gyro Z All 57.4%	Off. Y 57.4%	Gyro X All 45%	Gyro Y All 55.0%	Gyro Z All 55.0%	Off. Y 50%	Gyro X All 52.5%	Gyro Y All 57.4%	Gyro Z All 62.5%	Off. Y 55.0%	Gyro X All 55.0%	Gyro Y All 42.5%	Gyro Z All 70%
E	E0	Time 55.0%	Size 47.5%	Touches 57.4%	E1	Time 52.5%	Size 47.5%	Touches 55.0%	E2	Time 47.5%	Size 40%	Touches 52.5%	E3	Time 42.5%	Size 45%	Touches 57.4%	E4	Time 55.0%	Size 47.5%	Touches 47.5%	E5	Time 65%	Size 62.5%	Touches 57.4%
	Off. X 55.0%	Gyro X 55.0%	Gyro Y 50%	Gyro Z 37.5%	Off. X 47.5%	Gyro X 37.5%	Gyro Y 50%	Gyro Z 45%	Off. X 47.5%	Gyro X 42.5%	Gyro Y 47.5%	Gyro Z 50%	Off. X 37.5%	Gyro X 35%	Gyro Y 50%	Gyro Z 50%	Off. X 52.5%	Gyro X 47.5%	Gyro Y 45%	Gyro Z 60%	Off. X 52.5%	Gyro X 40%	Gyro Y 57.4%	Gyro Z 50%
	Off. Y 40%	Gyro X All 80%	Gyro Y All 57.4%	Gyro Z All 47.5%	Off. Y 52.5%	Gyro X All 62.5%	Gyro Y All 57.4%	Gyro Z All 55.0%	Off. Y 40%	Gyro X All 45%	Gyro Y All 47.5%	Gyro Z All 40%	Off. Y 60%	Gyro X All 47.5%	Gyro Y All 52.5%	Gyro Z All 62.5%	Off. Y 57.4%	Gyro X All 52.5%	Gyro Y All 47.5%	Gyro Z All 52.5%	Off. Y 55.0%	Gyro X All 45%	Gyro Y All 52.5%	Gyro Z All 50%
F	F0	Time 60%	Size 30%	Touches 55.0%	F1	Time 52.5%	Size 47.5%	Touches 47.5%	F2	Time 62.5%	Size 42.5%	Touches 57.4%	F3	Time 57.4%	Size 50%	Touches 55.0%	F4	Time 52.5%	Size 60%	Touches 55.0%	F5	Time 57.4%	Size 60%	Touches 60%
	Off. X 62.5%	Gyro X 52.5%	Gyro Y 52.5%	Gyro Z 37.5%	Off. X 42.5%	Gyro X 55.0%	Gyro Y 32.5%	Gyro Z 60%	Off. X 47.5%	Gyro X 47.5%	Gyro Y 50%	Gyro Z 47.5%	Off. X 47.5%	Gyro X 42.5%	Gyro Y 62.5%	Gyro Z 42.5%	Off. X 50%	Gyro X 47.5%	Gyro Y 47.5%	Gyro Z 45%	Off. X 55.0%	Gyro X 42.5%	Gyro Y 55.0%	Gyro Z 57.4%
	Off. Y 47.5%	Gyro X All 47.5%	Gyro Y All 55.0%	Gyro Z All 57.4%	Off. Y 52.5%	Gyro X All 55.0%	Gyro Y All 40%	Gyro Z All 47.5%	Off. Y 45%	Gyro X All 55.0%	Gyro Y All 52.5%	Gyro Z All 62.5%	Off. Y 47.5%	Gyro X All 50%	Gyro Y All 55.0%	Gyro Z All 45%	Off. Y 65%	Gyro X All 50%	Gyro Y All 47.5%	Gyro Z All 57.4%	Off. Y 55.0%	Gyro X All 52.5%	Gyro Y All 52.5%	Gyro Z All 52.5%
G	G0	Time 62.5%	Size 52.5%	Touches 55.0%	G1	Time 65%	Size 40%	Touches 57.4%	G2	Time 55.0%	Size 55.0%	Touches 55.0%	G3	Time 52.5%	Size 55.0%	Touches 70%	G4	Time 57.4%	Size 65%	Touches 55.0%	G5	Time 57.4%	Size 62.5%	Touches 57.4%
	Off. X 57.4%	Gyro X 52.5%	Gyro Y 42.5%	Gyro Z 57.4%	Off. X 55.0%	Gyro X 42.5%	Gyro Y 50%	Gyro Z 42.5%	Off. X 55.0%	Gyro X 55.0%	Gyro Y 45%	Gyro Z 65%	Off. X 55.0%	Gyro X 57.4%	Gyro Y 52.5%	Gyro Z 52.5%	Off. X 45%	Gyro X 37.5%	Gyro Y 62.5%	Gyro Z 50%	Off. X 55.0%	Gyro X 45%	Gyro Y 60%	Gyro Z 55.0%
	Off. Y 65%	Gyro X All 55.0%	Gyro Y All 47.5%	Gyro Z All 55.0%	Off. Y 57.4%	Gyro X All 45%	Gyro Y All 40%	Gyro Z All 50%	Off. Y 55.0%	Gyro X All 47.5%	Gyro Y All 57.4%	Gyro Z All 47.5%	Off. Y 47.5%	Gyro X All 45%	Gyro Y All 60%	Gyro Z All 47.5%	Off. Y 42.5%	Gyro X All 42.5%	Gyro Y All 55.0%	Gyro Z All 47.5%	Off. Y 52.5%	Gyro X All 52.5%	Gyro Y All 55.0%	Gyro Z All 57.4%
H	H0	Time 65%	Size 35%	Touches 65%	H1	Time 60%	Size 65%	Touches 57.4%	H2	Time 55.0%	Size 47.5%	Touches 57.4%	H3	Time 45%	Size 57.4%	Touches 40%	H4	Time 47.5%	Size 57.4%	Touches 47.5%	H5	Time 65%	Size 62.5%	Touches 35%
	Off. X 55.0%	Gyro X 45%	Gyro Y 50%	Gyro Z 42.5%	Off. X 45%	Gyro X 55.0%	Gyro Y 52.5%	Gyro Z 60%	Off. X 57.4%	Gyro X 50%	Gyro Y 45%	Gyro Z 50%	Off. X 60%	Gyro X 42.5%	Gyro Y 55.0%	Gyro Z 45%	Off. X 50%	Gyro X 42.5%	Gyro Y 60%	Gyro Z 52.5%	Off. X 57.4%	Gyro X 47.5%	Gyro Y 50%	Gyro Z 55.0%
	Off. Y 55.0%	Gyro X All 52.5%	Gyro Y All 42.5%	Gyro Z All 50%	Off. Y 35%	Gyro X All 47.5%	Gyro Y All 45%	Gyro Z All 60%	Off. Y 52.5%	Gyro X All 50%	Gyro Y All 45%	Gyro Z All 42.5%	Off. Y 47.5%	Gyro X All 65%	Gyro Y All 50%	Gyro Z All 55.0%	Off. Y 45%	Gyro X All 50%	Gyro Y All 50%	Gyro Z All 45%	Off. Y 50%	Gyro X All 47.5%	Gyro Y All 55.0%	Gyro Z All 42.5%
I	I0	Time 45%	Size 37.5%	Touches 57.4%	I1	Time 62.5%	Size 47.5%	Touches 60%	I2	Time 60%	Size 47.5%	Touches 50%	I3	Time 62.5%	Size 50%	Touches 55.0%	I4	Time 52.5%	Size 50%	Touches 57.4%	I5	Time 57.4%	Size 62.5%	Touches 57.4%
	Off. X 67.5%	Gyro X 47.5%	Gyro Y 42.5%	Gyro Z 50%	Off. X 52.5%	Gyro X 37.5%	Gyro Y 47.5%	Gyro Z 45%	Off. X 62.5%	Gyro X 47.5%	Gyro Y 52.5%	Gyro Z 45%	Off. X 70%	Gyro X 52.5%	Gyro Y 42.5%	Gyro Z 65%	Off. X 45%	Gyro X 50%	Gyro Y 57.4%	Gyro Z 45%	Off. X 55.0%	Gyro X 50%	Gyro Y 50%	Gyro Z 45%
	Off. Y 47.5%	Gyro X All 45%	Gyro Y All 42.5%	Gyro Z All 52.5%	Off. Y 52.5%	Gyro X All 52.5%	Gyro Y All 55.0%	Gyro Z All 55.0%	Off. Y 57.4%	Gyro X All 55.0%	Gyro Y All 42.5%	Gyro Z All 50%	Off. Y 47.5%	Gyro X All 57.4%	Gyro Y All 45%	Gyro Z All 52.5%	Off. Y 52.5%	Gyro X All 47.5%	Gyro Y All 37.5%	Gyro Z All 40%	Off. Y 60%	Gyro X All 55.0%	Gyro Y All 57.4%	Gyro Z All 62.5%
J	J0	Time 70%	Size 32.5%	Touches 60%	J1	Time 47.5%	Size 45%	Touches 57.4%	J2	Time 57.4%	Size 52.5%	Touches 52.5%	J3	Time 60%	Size 50%	Touches 57.4%	J4	Time 45%	Size 50%	Touches 65%	J5	Time 47.5%	Size 55.0%	Touches 52.5%
	Off. X 77.5%	Gyro X 55.0%	Gyro Y 57.4%	Gyro Z 47.5%	Off. X 42.5%	Gyro X 60%	Gyro Y 47.5%	Gyro Z 50%	Off. X 42.5%	Gyro X 52.5%	Gyro Y 42.5%	Gyro Z 45%	Off. X 60%	Gyro X 55.0%	Gyro Y 60%	Gyro Z 37.5%	Off. X 57.4%	Gyro X 52.5%	Gyro Y 55.0%	Gyro Z 37.5%	Off. X 25%	Gyro X 55.0%	Gyro Y 60%	Gyro Z 47.5%
	Off. Y 57.4%	Gyro X All 42.5%	Gyro Y All 57.4%	Gyro Z All 62.5%	Off. Y 47.5%	Gyro X All 47.5%	Gyro Y All 57.4%	Gyro Z All 52.5%	Off. Y 50%	Gyro X All 45%	Gyro Y All 42.5%	Gyro Z All 40%	Off. Y 65%	Gyro X All 50%	Gyro Y All 55.0%	Gyro Z All 47.5%	Off. Y 45%	Gyro X All 50%	Gyro Y All 47.5%	Gyro Z All 37.5%	Off. Y 65%	Gyro X All 50%	Gyro Y All 40%	Gyro Z All 42.5%

FIGURE 4.34: The detection accuracy of the properties *Touch Time, Touch Size Mean, Number of Touches, X Offset, Y Offset, Gyro X Amplitude, Gyro Y Amplitude, Gyro Z Amplitude, Gyro X All Amplitude, Gyro Y All Amplitude* and *Gyro Z All Amplitude* for the user's **hand** (left or right) in the 60 target locations A0 to J5 in the **sitting** condition, using the lookup tables holding the mean property values for each target position. The property with the highest accuracy per target is highlighted in black. If the highest accuracy in a target position is <75%, the highlight is red.

A	A0	A1	A2	A3	A4	A5
Time	75%	62.5%	62.5%	72.5%	72.5%	60%
Size	35%	50%	57.4%	62.5%	70%	62.5%
Touches	65%	70%	62.5%	65%	67.5%	70%
Off. X	50%	55.0%	55.0%	50%	50%	45%
Gyro X	67.5%	57.4%	60%	42.5%	65%	57.4%
Gyro Y	52.5%	50%	67.5%	62.5%	62.5%	52.5%
Gyro Z	62.5%	60%	55.0%	52.5%	67.5%	55.0%
Off. Y	42.5%	47.5%	30%	50%	45%	47.5%
Gyro X All	70%	60%	62.5%	62.5%	62.5%	72.5%
Gyro Y All	57.4%	70%	72.5%	67.5%	87.5%	75%
Gyro Z All	75%	67.5%	70%	67.5%	67.5%	77.5%

B	B0	B1	B2	B3	B4	B5
Time	75%	65%	65%	65%	70%	70%
Size	42.5%	47.5%	67.5%	57.4%	65%	57.4%
Touches	72.5%	67.5%	70%	55.0%	60%	57.4%
Off. X	42.5%	50%	57.4%	47.5%	45%	45%
Gyro X	40%	57.4%	50%	27.5%	57.4%	50%
Gyro Y	47.5%	50%	62.5%	62.5%	55.0%	55.0%
Gyro Z	62.5%	45%	57.4%	57.4%	57.4%	57.4%
Off. Y	35%	47.5%	55.0%	50%	52.5%	47.5%
Gyro X All	52.5%	75%	62.5%	60%	60%	75%
Gyro Y All	65%	62.5%	62.5%	65%	70%	72.5%
Gyro Z All	67.5%	65%	60%	60%	67.5%	72.5%

C	C0	C1	C2	C3	C4	C5
Time	77.5%	70%	67.5%	67.5%	60%	62.5%
Size	40%	52.5%	62.5%	60%	55.0%	52.5%
Touches	75%	60%	60%	60%	60%	57.4%
Off. X	37.5%	55.0%	45%	47.5%	55.0%	55.0%
Gyro X	55.0%	40%	35%	32.5%	60%	52.5%
Gyro Y	47.5%	47.5%	62.5%	67.5%	57.4%	52.5%
Gyro Z	60%	57.4%	55.0%	57.4%	67.5%	62.5%
Off. Y	50%	47.5%	40%	52.5%	42.5%	47.5%
Gyro X All	50%	62.5%	62.5%	52.5%	45%	45%
Gyro Y All	65%	70%	67.5%	72.5%	70%	65%
Gyro Z All	75%	60%	65%	62.5%	60%	67.5%

D	D0	D1	D2	D3	D4	D5
Time	75%	60%	60%	67.5%	60%	65%
Size	47.5%	37.5%	47.5%	50%	57.4%	37.5%
Touches	62.5%	62.5%	75%	65%	52.5%	65%
Off. X	45%	47.5%	55.0%	52.5%	37.5%	50%
Gyro X	50%	40%	57.4%	47.5%	47.5%	50%
Gyro Y	35%	47.5%	55.0%	42.5%	50%	40%
Gyro Z	52.5%	60%	52.5%	62.5%	62.5%	55.0%
Off. Y	60%	62.5%	42.5%	55.0%	37.5%	42.5%
Gyro X All	52.5%	57.4%	65%	52.5%	70%	67.5%
Gyro Y All	70%	65%	67.5%	60%	67.5%	65%
Gyro Z All	70%	57.4%	60%	62.5%	70%	60%

E	E0	E1	E2	E3	E4	E5
Time	77.5%	70%	72.5%	70%	62.5%	57.4%
Size	57.4%	40%	57.4%	62.5%	62.5%	52.5%
Touches	55.0%	62.5%	62.5%	67.5%	57.4%	52.5%
Off. X	47.5%	60%	62.5%	37.5%	70%	45%
Gyro X	40%	60%	52.5%	45%	50%	52.5%
Gyro Y	42.5%	52.5%	57.4%	65%	50%	52.5%
Gyro Z	47.5%	65%	65%	57.4%	52.5%	47.5%
Off. Y	45%	50%	57.4%	57.4%	47.5%	60%
Gyro X All	52.5%	57.4%	55.0%	57.4%	65%	50%
Gyro Y All	65%	67.5%	70%	72.5%	72.5%	72.5%
Gyro Z All	67.5%	65%	57.4%	55.0%	75%	57.4%

F	F0	F1	F2	F3	F4	F5
Time	70%	57.4%	67.5%	70%	62.5%	72.5%
Size	50%	55.0%	52.5%	57.4%	47.5%	57.4%
Touches	67.5%	62.5%	70%	62.5%	55.0%	65%
Off. X	57.4%	62.5%	45%	52.5%	40%	57.4%
Gyro X	55.0%	55.0%	60%	45%	55.0%	50%
Gyro Y	52.5%	57.4%	62.5%	65%	60%	60%
Gyro Z	67.5%	60%	65%	70%	62.5%	50%
Off. Y	52.5%	55.0%	45%	50%	52.5%	47.5%
Gyro X All	55.0%	57.4%	55.0%	57.4%	65%	70%
Gyro Y All	62.5%	67.5%	80%	65%	65%	67.5%
Gyro Z All	52.5%	62.5%	65%	45%	62.5%	52.5%

G	G0	G1	G2	G3	G4	G5
Time	65%	55.0%	57.4%	55.0%	60%	62.5%
Size	42.5%	52.5%	42.5%	47.5%	55.0%	57.4%
Touches	65%	57.4%	55.0%	57.4%	62.5%	67.5%
Off. X	50%	52.5%	35%	42.5%	57.4%	55.0%
Gyro X	52.5%	55.0%	55.0%	65%	60%	50%
Gyro Y	37.5%	65%	42.5%	55.0%	52.5%	52.5%
Gyro Z	47.5%	52.5%	70%	52.5%	47.5%	75%
Off. Y	50%	42.5%	47.5%	50%	45%	47.5%
Gyro X All	60%	55.0%	57.4%	45%	52.5%	52.5%
Gyro Y All	60%	52.5%	57.4%	70%	62.5%	60%
Gyro Z All	55.0%	62.5%	50%	57.4%	47.5%	62.5%

H	H0	H1	H2	H3	H4	H5
Time	62.5%	70%	60%	60%	65%	65%
Size	72.5%	42.5%	35%	60%	50%	47.5%
Touches	55.0%	72.5%	60%	52.5%	65%	62.5%
Off. X	47.5%	47.5%	57.4%	47.5%	52.5%	55.0%
Gyro X	52.5%	52.5%	60%	52.5%	62.5%	52.5%
Gyro Y	42.5%	45%	47.5%	45%	60%	50%
Gyro Z	72.5%	52.5%	60%	65%	60%	67.5%
Off. Y	52.5%	60%	57.4%	65%	40%	50%
Gyro X All	47.5%	72.5%	67.5%	62.5%	62.5%	72.5%
Gyro Y All	67.5%	47.5%	67.5%	65%	52.5%	70%
Gyro Z All	62.5%	47.5%	65%	57.4%	65%	60%

I	I0	I1	I2	I3	I4	I5
Time	60%	67.5%	52.5%	50%	60%	57.4%
Size	60%	30%	60%	60%	62.5%	52.5%
Touches	65%	60%	52.5%	55.0%	57.4%	55.0%
Off. X	40%	55.0%	47.5%	47.5%	52.5%	55.0%
Gyro X	50%	55.0%	52.5%	40%	60%	55.0%
Gyro Y	37.5%	45%	47.5%	62.5%	47.5%	45%
Gyro Z	47.5%	55.0%	60%	57.4%	57.4%	57.4%
Off. Y	50%	57.4%	55.0%	57.4%	67.5%	55.0%
Gyro X All	62.5%	57.4%	70%	60%	70%	70%
Gyro Y All	55.0%	62.5%	55.0%	62.5%	65%	62.5%
Gyro Z All	62.5%	50%	77.5%	60%	77.5%	62.5%

J	J0	J1	J2	J3	J4	J5
Time	67.5%	57.4%	55.0%	62.5%	70%	72.5%
Size	30%	40%	57.4%	62.5%	67.5%	65%
Touches	65%	65%	62.5%	52.5%	67.5%	72.5%
Off. X	47.5%	52.5%	42.5%	45%	60%	40%
Gyro X	47.5%	40%	55.0%	70%	52.5%	50%
Gyro Y	42.5%	52.5%	42.5%	60%	42.5%	37.5%
Gyro Z	52.5%	45%	52.5%	55.0%	52.5%	62.5%
Off. Y	47.5%	40%	52.5%	37.5%	55.0%	57.4%
Gyro X All	67.5%	62.5%	67.5%	70%	65%	57.4%
Gyro Y All	70%	62.5%	70%	67.5%	50%	52.5%
Gyro Z All	70%	57.4%	62.5%	72.5%	62.5%	57.4%

FIGURE 4.35: The detection accuracy of the properties *Touch Time*, *Touch Size Mean*, *Number of Touches*, *X Offset*, *Y Offset*, *Gyro X Amplitude*, *Gyro Y Amplitude*, *Gyro Z Amplitude*, *Gyro X All Amplitude*, *Gyro Y All Amplitude* and *Gyro Z All Amplitude* for the user's **finger** (index finger or thumb) in the 60 target locations A0 to J5 in the **walking** condition, using the lookup tables holding the mean property values for each target position. The property with the highest accuracy per target is highlighted in black. If the highest accuracy in a target position is <75%, the highlight is red.

Target	Time	Size	Touches	Off. X	Gyro X	Gyro Y	Gyro Z	Off. Y	Gyro X All	Gyro Y All	Gyro Z All
A0	50%	30%	57.4%	67.5%	55.0%	50%	47.5%	40%	60%	50%	55.0%
A1	52.5%	52.5%	50%	55.0%	65%	57.4%	52.5%	47.5%	67.5%	57.4%	50%
A2	57.4%	47.5%	67.5%	57.4%	45%	45%	37.5%	60%	55.0%	42.5%	52.5%
A3	55.0%	45%	60%	50%	45%	45%	47.5%	47.5%	42.5%	52.5%	40%
A4	60%	55.0%	62.5%	55.0%	47.5%	50%	45%	60%	45%	52.5%	65%
A5	60%	55.0%	65%	42.5%	42.5%	55.0%	45%	52.5%	55.0%	55.0%	67.5%
B0	45%	42.5%	45%	60%	45%	50%	50%	47.5%	62.5%	57.4%	42.5%
B1	67.5%	47.5%	65%	35%	45%	52.5%	45%	57.4%	72.5%	57.4%	45%
B2	60%	55.0%	55.0%	40%	40%	55.0%	50%	57.4%	45%	57.4%	47.5%
B3	60%	45%	62.5%	40%	40%	50%	50%	62.5%	57.4%	42.5%	45%
B4	52.5%	55.0%	45%	42.5%	55.0%	45%	50%	57.4%	60%	50%	60%
B5	75%	57.4%	47.5%	42.5%	55.0%	47.5%	32.5%	60%	52.5%	65%	47.5%
C0	70%	35%	72.5%	67.5%	52.5%	57.4%	45%	52.5%	65%	57.4%	50%
C1	57.4%	50%	65%	50%	50%	42.5%	45%	50%	60%	50%	42.5%
C2	62.5%	55.0%	52.5%	50%	50%	52.5%	45%	55.0%	42.5%	42.5%	52.5%
C3	62.5%	52.5%	65%	50%	42.5%	42.5%	50%	50%	50%	52.5%	35%
C4	57.4%	65%	52.5%	52.5%	52.5%	50%	57.4%	52.5%	52.5%	47.5%	52.5%
C5	55.0%	57.4%	65%	50%	35%	47.5%	42.5%	55.0%	52.5%	52.5%	60%
D0	52.5%	30%	62.5%	57.4%	62.5%	50%	40%	55.0%	50%	57.4%	50%
D1	55.0%	45%	62.5%	60%	47.5%	55.0%	45%	57.4%	45%	57.4%	55.0%
D2	55.0%	40%	57.4%	37.5%	50%	47.5%	55.0%	55.0%	52.5%	55.0%	50%
D3	60%	50%	42.5%	52.5%	45%	50%	45%	42.5%	32.5%	50%	30%
D4	52.5%	45%	47.5%	45%	35%	37.5%	60%	40%	62.5%	60%	55.0%
D5	65%	62.5%	67.5%	47.5%	57.4%	50%	40%	60%	65%	52.5%	50%
E0	55.0%	52.5%	62.5%	62.5%	52.5%	50%	27.5%	45%	65%	57.4%	40%
E1	52.5%	50%	57.4%	42.5%	50%	47.5%	47.5%	50%	57.4%	47.5%	47.5%
E2	65%	42.5%	70%	52.5%	47.5%	50%	45%	60%	52.5%	52.5%	45%
E3	72.5%	62.5%	70%	67.5%	50%	52.5%	57.4%	67.5%	37.5%	42.5%	42.5%
E4	65%	55.0%	62.5%	50%	55.0%	52.5%	57.4%	47.5%	62.5%	55.0%	62.5%
E5	55.0%	77.5%	70%	60%	52.5%	55.0%	47.5%	55.0%	52.5%	50%	52.5%
F0	42.5%	57.4%	65%	50%	47.5%	47.5%	40%	50%	42.5%	55.0%	42.5%
F1	67.5%	50%	72.5%	52.5%	62.5%	50%	57.4%	45%	55.0%	57.4%	55.0%
F2	72.5%	47.5%	72.5%	52.5%	50%	52.5%	55.0%	62.5%	62.5%	52.5%	45%
F3	52.5%	45%	57.4%	37.5%	45%	62.5%	52.5%	52.5%	47.5%	65%	57.4%
F4	47.5%	57.4%	52.5%	47.5%	62.5%	55.0%	42.5%	45%	42.5%	42.5%	52.5%
F5	42.5%	65%	57.4%	62.5%	45%	62.5%	40%	50%	50%	45%	67.5%
G0	60%	57.4%	55.0%	60%	55.0%	52.5%	55.0%	47.5%	47.5%	50%	52.5%
G1	67.5%	57.4%	67.5%	50%	47.5%	60%	45%	47.5%	57.4%	47.5%	50%
G2	67.5%	40%	60%	62.5%	47.5%	50%	55.0%	52.5%	52.5%	55.0%	37.5%
G3	50%	52.5%	42.5%	45%	37.5%	47.5%	52.5%	50%	45%	57.4%	60%
G4	62.5%	57.4%	55.0%	52.5%	47.5%	57.4%	45%	55.0%	37.5%	47.5%	42.5%
G5	62.5%	60%	52.5%	50%	45%	50%	37.5%	65%	47.5%	50%	50%
H0	72.5%	47.5%	72.5%	65%	62.5%	37.5%	50%	65%	45%	50%	57.4%
H1	55.0%	45%	57.4%	45%	57.4%	42.5%	42.5%	50%	47.5%	57.4%	47.5%
H2	65%	35%	67.5%	55.0%	47.5%	50%	50%	62.5%	47.5%	42.5%	52.5%
H3	47.5%	60%	60%	52.5%	57.4%	47.5%	62.5%	52.5%	55.0%	55.0%	52.5%
H4	60%	67.5%	67.5%	55.0%	50%	52.5%	52.5%	52.5%	50%	52.5%	50%
H5	45%	65%	42.5%	55.0%	50%	65%	50%	50%	60%	42.5%	47.5%
I0	57.4%	52.5%	65%	55.0%	62.5%	72.5%	42.5%	45%	50%	62.5%	45%
I1	57.4%	42.5%	70%	45%	52.5%	52.5%	50%	42.5%	42.5%	45%	52.5%
I2	42.5%	45%	67.5%	60%	55.0%	55.0%	55.0%	55.0%	50%	50%	50%
I3	47.5%	52.5%	62.5%	52.5%	50%	50%	45%	45%	47.5%	50%	55.0%
I4	52.5%	65%	65%	60%	57.4%	65%	45%	55.0%	50%	62.5%	50%
I5	55.0%	67.5%	57.4%	62.5%	45%	52.5%	62.5%	50%	60%	62.5%	67.5%
J0	52.5%	30%	52.5%	60%	40%	60%	47.5%	42.5%	67.5%	42.5%	50%
J1	42.5%	45%	42.5%	57.4%	50%	60%	47.5%	52.5%	67.5%	62.5%	47.5%
J2	62.5%	47.5%	62.5%	52.5%	52.5%	50%	52.5%	50%	47.5%	27.5%	47.5%
J3	52.5%	55.0%	50%	57.4%	47.5%	65%	52.5%	37.5%	50%	50%	42.5%
J4	62.5%	70%	67.5%	52.5%	57.4%	70%	52.5%	55.0%	45%	57.4%	52.5%
J5	57.4%	67.5%	50%	60%	55.0%	52.5%	55.0%	45%	45%	57.4%	50%

FIGURE 4.36: The detection accuracy of the properties *Touch Time, Touch Size Mean, Number of Touches, X Offset, Y Offset, Gyro X Amplitude, Gyro Y Amplitude, Gyro Z Amplitude, Gyro X All Amplitude, Gyro Y All Amplitude* and *Gyro Z All Amplitude* for the user's **hand** (left or right) in the 60 target locations A0 to J5 in the **walking** condition, using the lookup tables holding the mean property values for each target position. The property with the highest accuracy per target is highlighted in black. If the highest accuracy in a target position is <75%, the highlight is red.

In addition to comparing the touch properties of a new touch event against a stored mean value, the gyroscope data as well as the *Touch Size* were also evaluated, based on the temporal development of the values. For this, the mean development of the X, Y and Z axes rotation during the touch (*Gyro X, Gyro Y, Gyro Z*) as well as before and during the touch (*Gyro All X, Gyro All Y, Gyro All Z*) and the mean development of the *Touch Size* array were calculated for each position and mode. The temporal development of each of these properties coming from a new touch event was then compared against the respective averaged arrays by determining the PCC. The lookup table holding the array with the highest PCC was then selected as the "winner" and the resulting table name compared to the actual input mode as with the mean value comparison. The following Figures 4.37 to 4.40 show the results:

Target	Size	Gyro X	Gyro Y	Gyro Z	Gyro X All	Gyro Y All	Gyro Z All
A0	60%	80%	62.5%	47.5%	42.5%	52.5%	55.0%
A1	50%	70%	55.0%	45%	40%	52.5%	62.5%
A2	45%	67.5%	45%	47.5%	20%	50%	45%
A3	72.5%	80%	62.5%	55.0%	45%	57.4%	47.5%
A4	55.0%	67.5%	42.5%	55.0%	37.5%	50%	47.5%
A5	50%	70%	70%	40%	32.5%	47.5%	52.5%
B0	67.5%	67.5%	65%	47.5%	37.5%	52.5%	55.0%
B1	62.5%	82.5%	55.0%	60%	65%	47.5%	45%
B2	47.5%	75%	55.0%	30%	50%	47.5%	57.4%
B3	40%	75%	45%	47.5%	47.5%	62.5%	55.0%
B4	65%	70%	65%	55.0%	52.5%	60%	40%
B5	55.0%	70%	42.5%	62.5%	35%	42.5%	50%
C0	67.5%	67.5%	60%	52.5%	47.5%	60%	40%
C1	65%	67.5%	57.4%	55.0%	60%	30%	55.0%
C2	42.5%	62.5%	50%	50%	62.5%	50%	40%
C3	47.5%	75%	60%	65%	52.5%	37.5%	40%
C4	47.5%	60%	57.4%	37.5%	57.4%	60%	45%
C5	50%	65%	45%	40%	52.5%	55.0%	55.0%
D0	32.5%	47.5%	62.5%	45%	50%	55.0%	40%
D1	75%	57.4%	50%	37.5%	52.5%	37.5%	42.5%
D2	50%	57.4%	62.5%	57.4%	50%	50%	40%
D3	47.5%	72.5%	47.5%	60%	62.5%	40%	47.5%
D4	40%	57.4%	47.5%	40%	62.5%	35%	55.0%
D5	47.5%	50%	52.5%	55.0%	50%	35%	42.5%
E0	57.4%	62.5%	80%	50%	67.5%	40%	40%
E1	47.5%	50%	57.4%	55.0%	55.0%	50%	62.5%
E2	47.5%	45%	45%	62.5%	40%	47.5%	47.5%
E3	60%	72.5%	50%	47.5%	32.5%	55.0%	52.5%
E4	35%	50%	62.5%	47.5%	40%	57.4%	52.5%
E5	47.5%	65%	57.4%	60%	57.4%	40%	35%
F0	55.0%	62.5%	70%	57.4%	30%	52.5%	37.5%
F1	57.4%	60%	55.0%	52.5%	42.5%	42.5%	57.4%
F2	47.5%	45%	57.4%	67.5%	60%	55.0%	42.5%
F3	42.5%	55.0%	60%	37.5%	55.0%	37.5%	45%
F4	57.4%	52.5%	70%	67.5%	52.5%	40%	55.0%
F5	57.4%	40%	65%	57.4%	57.4%	67.5%	40%
G0	45%	62.5%	65%	35%	35%	35%	55.0%
G1	62.5%	42.5%	57.4%	50%	42.5%	30%	40%
G2	50%	52.5%	57.4%	62.5%	40%	40%	55.0%
G3	60%	47.5%	45%	60%	25%	40%	52.5%
G4	60%	52.5%	45%	60%	55.0%	55.0%	60%
G5	65%	47.5%	62.5%	50%	37.5%	47.5%	10%
H0	60%	60%	55.0%	55.0%	42.5%	50%	20%
H1	50%	50%	65%	50%	40%	45%	37.5%
H2	67.5%	62.5%	47.5%	47.5%	45%	62.5%	57.4%
H3	50%	62.5%	57.4%	55.0%	47.5%	47.5%	42.5%
H4	42.5%	55.0%	67.5%	47.5%	40%	55.0%	72.5%
H5	65%	60%	52.5%	60%	40%	22.5%	37.5%
I0	65%	55.0%	52.5%	55.0%	45%	27.5%	50%
I1	55.0%	55.0%	67.5%	52.5%	55.0%	60%	42.5%
I2	52.5%	62.5%	47.5%	60%	42.5%	50%	42.5%
I3	60%	65%	57.4%	52.5%	40%	60%	57.4%
I4	42.5%	52.5%	45%	40%	45%	32.5%	60%
I5	62.5%	52.5%	60%	62.5%	47.5%	30%	30%
J0	57.4%	42.5%	40%	52.5%	50%	40%	55.0%
J1	57.4%	50%	65%	60%	50%	52.5%	40%
J2	37.5%	57.4%	65%	50%	37.5%	57.4%	42.5%
J3	52.5%	57.4%	60%	62.5%	47.5%	52.5%	60%
J4	60%	57.4%	50%	45%	50%	55.0%	62.5%
J5	65%	60%	62.5%	47.5%	40%	60%	42.5%

FIGURE 4.37: The detection accuracy of the properties *Touch Size, Gyro X, Gyro Y, Gyro Z, Gyro X All, Gyro Y All* and *Gyro Z All* for the user's **finger** (index finger or thumb) in the 60 target locations A0 to J5 in the **sitting** condition, using a PCC calculation based on averaged arrays stored in the lookup tables for each target position. The property with the highest accuracy per target is highlighted in black. If the highest accuracy for a target position is <75%, the highlight is red.

Target	Size	Gyro X	Gyro Y	Gyro Z	Gyro X All	Gyro Y All	Gyro Z All
A0	47.5%	52.5%	65%	50%	47.5%	35%	37.5%
A1	60%	47.5%	60%	50%	50%	37.5%	37.5%
A2	52.5%	52.5%	52.5%	50%	57.4%	37.5%	40%
A3	57.4%	50%	57.4%	60%	55.0%	40%	50%
A4	45%	40%	60%	55.0%	57.4%	30%	37.5%
A5	47.5%	52.5%	65%	47.5%	27.5%	32.5%	42.5%
B0	42.5%	57.4%	50%	65%	45%	50%	55.0%
B1	35%	55.0%	57.4%	67.5%	57.4%	40%	47.5%
B2	37.5%	37.5%	57.4%	50%	52.5%	45%	47.5%
B3	50%	57.4%	57.4%	57.4%	40%	35%	35%
B4	37.5%	42.5%	62.5%	50%	47.5%	42.5%	70%
B5	45%	60%	75%	55.0%	47.5%	32.5%	45%
C0	45%	70%	57.4%	55.0%	47.5%	35%	45%
C1	45%	62.5%	52.5%	62.5%	60%	50%	50%
C2	40%	40%	55.0%	57.4%	52.5%	30%	47.5%
C3	55.0%	55.0%	67.5%	50%	57.4%	42.5%	65%
C4	60%	35%	52.5%	50%	52.5%	37.5%	42.5%
C5	57.4%	65%	57.4%	35%	55.0%	45%	55.0%
D0	55.0%	45%	60%	57.4%	60%	47.5%	55.0%
D1	37.5%	55.0%	50%	42.5%	47.5%	42.5%	60%
D2	30%	37.5%	60%	72.5%	45%	37.5%	45%
D3	40%	45%	45%	65%	47.5%	62.5%	55.0%
D4	42.5%	40%	60%	52.5%	50%	55.0%	50%
D5	47.5%	45%	57.4%	47.5%	47.5%	55.0%	47.5%
E0	40%	52.5%	62.5%	57.4%	60%	52.5%	57.4%
E1	42.5%	62.5%	45%	57.4%	65%	52.5%	50%
E2	45%	45%	45%	52.5%	45%	55.0%	32.5%
E3	52.5%	52.5%	62.5%	55.0%	57.4%	67.5%	52.5%
E4	52.5%	62.5%	62.5%	70%	52.5%	55.0%	52.5%
E5	42.5%	55.0%	62.5%	67.5%	47.5%	57.4%	42.5%
F0	52.5%	62.5%	55.0%	52.5%	50%	65%	40%
F1	35%	52.5%	42.5%	60%	65%	70%	67.5%
F2	42.5%	52.5%	55.0%	62.5%	62.5%	50%	47.5%
F3	40%	50%	52.5%	52.5%	47.5%	52.5%	47.5%
F4	37.5%	37.5%	52.5%	50%	52.5%	67.5%	52.5%
F5	50%	30%	62.5%	42.5%	50%	37.5%	45%
G0	52.5%	50%	52.5%	32.5%	55.0%	70%	40%
G1	42.5%	40%	47.5%	52.5%	42.5%	57.4%	55.0%
G2	42.5%	50%	52.5%	55.0%	60%	80%	42.5%
G3	40%	57.4%	40%	42.5%	62.5%	60%	42.5%
G4	40%	45%	50%	50%	60%	62.5%	52.5%
G5	55.0%	47.5%	67.5%	45%	50%	40%	57.4%
H0	52.5%	52.5%	55.0%	45%	35%	55.0%	60%
H1	50%	55.0%	65%	50%	40%	42.5%	35%
H2	35%	52.5%	50%	37.5%	45%	75%	37.5%
H3	42.5%	52.5%	55.0%	45%	47.5%	50%	55.0%
H4	50%	55.0%	57.4%	65%	47.5%	42.5%	40%
H5	42.5%	55.0%	70%	55.0%	47.5%	52.5%	40%
I0	37.5%	52.5%	57.4%	57.4%	50%	60%	67.5%
I1	45%	47.5%	65%	37.5%	40%	37.5%	35%
I2	50%	47.5%	62.5%	52.5%	45%	57.4%	40%
I3	50%	50%	70%	55.0%	52.5%	22.5%	45%
I4	50%	47.5%	70%	50%	62.5%	35%	45%
I5	55.0%	52.5%	52.5%	45%	52.5%	52.5%	52.5%
J0	45%	55.0%	67.5%	37.5%	42.5%	50%	32.5%
J1	55.0%	52.5%	70%	55.0%	42.5%	65%	42.5%
J2	45%	42.5%	75%	47.5%	65%	32.5%	42.5%
J3	50%	52.5%	65%	65%	32.5%	52.5%	52.5%
J4	45%	45%	82.5%	30%	60%	75%	30%
J5	35%	57.4%	50%	40%	42.5%	67.5%	42.5%

FIGURE 4.38: The detection accuracy of the properties *Touch Size, Gyro X, Gyro Y, Gyro Z, Gyro X All, Gyro Y All* and *Gyro Z All* for the user's **hand** (left or right) in the 60 target locations A0 to J5 in the **sitting** condition, using a PCC calculation based on averaged arrays stored in the lookup tables for each target position. The property with the highest accuracy per target is highlighted in black. If the highest accuracy for a target position is <75%, the highlight is red.

Target	Size	Gyro X	Gyro Y	Gyro Z	Gyro X All	Gyro Y All	Gyro Z All
A0	60%	**62.5%**	55.0%	50%	37.5%	35%	60%
A1	47.5%	**67.5%**	50%	57.4%	52.5%	55.0%	35%
A2	52.5%	**70%**	55.0%	55.0%	55.0%	52.5%	47.5%
A3	57.4%	**75%**	50%	47.5%	57.4%	42.5%	50%
A4	60%	67.5%	67.5%	**72.5%**	40%	52.5%	47.5%
A5	55.0%	**67.5%**	40%	42.5%	62.5%	50%	37.5%
B0	52.5%	**70%**	62.5%	57.4%	52.5%	55.0%	45%
B1	42.5%	**77.5%**	50%	52.5%	72.5%	42.5%	52.5%
B2	37.5%	50%	**60%**	32.5%	50%	52.5%	**60%**
B3	55.0%	**72.5%**	35%	52.5%	70%	40%	62.5%
B4	60%	52.5%	50%	**65%**	52.5%	60%	50%
B5	55.0%	**65%**	47.5%	62.5%	55.0%	45%	**65%**
C0	57.4%	50%	57.4%	55.0%	47.5%	47.5%	**60%**
C1	60%	**67.5%**	62.5%	57.4%	42.5%	47.5%	47.5%
C2	57.4%	50%	42.5%	47.5%	45%	**60%**	37.5%
C3	60%	**67.5%**	50%	42.5%	57.4%	50%	**67.5%**
C4	42.5%	**65%**	60%	50%	**65%**	40%	47.5%
C5	47.5%	**62.5%**	52.5%	52.5%	47.5%	57.4%	55.0%
D0	55.0%	60%	**65%**	42.5%	47.5%	50%	52.5%
D1	45%	60%	65%	50%	45%	**67.5%**	45%
D2	42.5%	57.4%	57.4%	37.5%	57.4%	**60%**	45%
D3	**52.5%**	47.5%	45%	47.5%	47.5%	32.5%	50%
D4	55.0%	57.4%	55.0%	47.5%	**62.5%**	37.5%	57.4%
D5	60%	**62.5%**	40%	**62.5%**	40%	47.5%	30%
E0	45%	37.5%	**62.5%**	42.5%	40%	57.4%	57.4%
E1	52.5%	42.5%	**55.0%**	42.5%	35%	**55.0%**	52.5%
E2	50%	60%	57.4%	55.0%	42.5%	35%	**65%**
E3	45%	52.5%	42.5%	37.5%	**57.4%**	47.5%	45%
E4	50%	55.0%	57.4%	35%	**60%**	57.4%	45%
E5	52.5%	50%	50%	40%	45%	**57.4%**	**57.4%**
F0	55.0%	**65%**	52.5%	50%	47.5%	35%	32.5%
F1	**62.5%**	32.5%	52.5%	50%	45%	35%	45%
F2	52.5%	42.5%	52.5%	**55.0%**	47.5%	**55.0%**	45%
F3	50%	42.5%	**65%**	55.0%	55.0%	42.5%	55.0%
F4	52.5%	42.5%	45%	60%	55.0%	**62.5%**	60%
F5	50%	35%	52.5%	45%	50%	**55.0%**	37.5%
G0	47.5%	60%	**72.5%**	62.5%	62.5%	65%	40%
G1	45%	47.5%	50%	55.0%	45%	**60%**	52.5%
G2	52.5%	55.0%	42.5%	**62.5%**	50%	50%	37.5%
G3	42.5%	**67.5%**	55.0%	60%	45%	62.5%	45%
G4	**60%**	52.5%	55.0%	55.0%	47.5%	50%	42.5%
G5	57.4%	**65%**	60%	55.0%	47.5%	62.5%	57.4%
H0	52.5%	40%	55.0%	52.5%	35%	40%	**57.4%**
H1	65%	45%	57.4%	55.0%	**67.5%**	65%	55.0%
H2	37.5%	45%	**60%**	45%	37.5%	55.0%	42.5%
H3	47.5%	**70%**	57.4%	42.5%	52.5%	60%	62.5%
H4	**65%**	50%	55.0%	50%	**65%**	50%	42.5%
H5	57.4%	52.5%	52.5%	52.5%	40%	**60%**	55.0%
I0	42.5%	**62.5%**	57.4%	55.0%	42.5%	55.0%	40%
I1	47.5%	57.4%	**72.5%**	60%	65%	55.0%	55.0%
I2	52.5%	**62.5%**	47.5%	45%	57.4%	**62.5%**	55.0%
I3	62.5%	62.5%	**67.5%**	57.4%	60%	62.5%	55.0%
I4	47.5%	47.5%	45%	40%	52.5%	**60%**	42.5%
I5	52.5%	50%	**57.4%**	45%	40%	50%	42.5%
J0	**57.4%**	47.5%	55.0%	50%	52.5%	42.5%	40%
J1	**67.5%**	57.4%	42.5%	47.5%	60%	50%	50%
J2	45%	47.5%	**57.4%**	50%	**57.4%**	55.0%	47.5%
J3	50%	45%	**67.5%**	62.5%	47.5%	50%	52.5%
J4	57.4%	55.0%	50%	52.5%	42.5%	**62.5%**	52.5%
J5	47.5%	35%	62.5%	67.5%	37.5%	55.0%	**70%**

FIGURE 4.39: The detection accuracy of the properties *Touch Size, Gyro X, Gyro Y, Gyro Z, Gyro X All, Gyro Y All* and *Gyro Z All* for the user's **finger** (index finger or thumb) in the 60 target locations A0 to J5 in the **walking** condition, using a PCC calculation based on averaged arrays stored in the lookup tables for each target position. The property with the highest accuracy per target is highlighted in black. If the highest accuracy for a target position is <75%, the highlight is red.

Target	Size	Gyro X	Gyro Y	Gyro Z	Gyro X All	Gyro Y All	Gyro Z All
A0	47.5%	47.5%	75%	65%	52.5%	37.5%	32.5%
A1	35%	37.5%	62.5%	42.5%	37.5%	50%	45%
A2	55.0%	47.5%	57.4%	50%	57.4%	42.5%	45%
A3	52.5%	42.5%	55.0%	50%	60%	37.5%	52.5%
A4	47.5%	57.4%	67.5%	52.5%	70%	32.5%	57.4%
A5	45%	50%	72.5%	47.5%	65%	32.5%	50%
B0	47.5%	60%	57.4%	62.5%	45%	42.5%	62.5%
B1	47.5%	57.4%	50%	52.5%	40%	45%	50%
B2	30%	52.5%	55.0%	32.5%	42.5%	62.5%	42.5%
B3	45%	55.0%	52.5%	35%	47.5%	45%	52.5%
B4	37.5%	50%	55.0%	45%	42.5%	45%	55.0%
B5	47.5%	55.0%	67.5%	67.5%	60%	50%	52.5%
C0	50%	40%	62.5%	60%	42.5%	35%	47.5%
C1	45%	52.5%	57.4%	52.5%	60%	50%	52.5%
C2	42.5%	57.4%	55.0%	50%	42.5%	35%	57.4%
C3	45%	55.0%	57.4%	45%	60%	57.4%	47.5%
C4	62.5%	57.4%	50%	35%	55.0%	40%	70%
C5	60%	62.5%	57.4%	60%	37.5%	47.5%	52.5%
D0	40%	55.0%	65%	47.5%	62.5%	52.5%	50%
D1	52.5%	62.5%	55.0%	47.5%	55.0%	45%	32.5%
D2	37.5%	50%	55.0%	55.0%	52.5%	57.4%	55.0%
D3	40%	50%	52.5%	57.4%	57.4%	50%	32.5%
D4	57.4%	47.5%	57.4%	62.5%	52.5%	57.4%	40%
D5	57.4%	47.5%	60%	47.5%	50%	50%	45%
E0	27.5%	32.5%	52.5%	47.5%	57.4%	40%	67.5%
E1	47.5%	55.0%	62.5%	57.4%	40%	52.5%	50%
E2	37.5%	40%	57.4%	45%	47.5%	62.5%	50%
E3	50%	55.0%	47.5%	57.4%	52.5%	50%	55.0%
E4	42.5%	62.5%	72.5%	65%	55.0%	47.5%	47.5%
E5	60%	57.4%	60%	47.5%	50%	65%	55.0%
F0	47.5%	45%	75%	27.5%	40%	50%	67.5%
F1	42.5%	47.5%	52.5%	65%	42.5%	40%	62.5%
F2	35%	55.0%	45%	77.5%	57.4%	27.5%	47.5%
F3	52.5%	40%	55.0%	52.5%	45%	57.4%	62.5%
F4	42.5%	52.5%	57.4%	62.5%	40%	55.0%	45%
F5	57.4%	42.5%	65%	52.5%	40%	42.5%	50%
G0	50%	60%	57.4%	62.5%	50%	57.4%	60%
G1	45%	50%	55.0%	57.4%	52.5%	67.5%	32.5%
G2	55.0%	52.5%	60%	50%	47.5%	60%	42.5%
G3	47.5%	52.5%	55.0%	37.5%	62.5%	35%	35%
G4	45%	42.5%	72.5%	57.4%	52.5%	75%	42.5%
G5	47.5%	55.0%	72.5%	45%	47.5%	60%	57.4%
H0	37.5%	55.0%	65%	62.5%	57.4%	50%	47.5%
H1	50%	57.4%	55.0%	55.0%	57.4%	50%	47.5%
H2	52.5%	37.5%	65%	67.5%	55.0%	55.0%	52.5%
H3	45%	47.5%	62.5%	55.0%	50%	55.0%	52.5%
H4	37.5%	40%	60%	57.4%	45%	50%	45%
H5	47.5%	42.5%	52.5%	35%	50%	50%	52.5%
I0	50%	47.5%	65%	67.5%	35%	52.5%	50%
I1	45%	37.5%	52.5%	62.5%	47.5%	70%	50%
I2	55.0%	42.5%	72.5%	55.0%	37.5%	60%	45%
I3	50%	52.5%	77.5%	52.5%	52.5%	50%	60%
I4	50%	47.5%	67.5%	47.5%	47.5%	52.5%	57.4%
I5	52.5%	40%	47.5%	50%	52.5%	30%	60%
J0	42.5%	42.5%	72.5%	55.0%	42.5%	62.5%	52.5%
J1	42.5%	42.5%	80%	57.4%	60%	47.5%	52.5%
J2	32.5%	45%	70%	50%	37.5%	35%	57.4%
J3	40%	42.5%	65%	50%	42.5%	50%	40%
J4	45%	62.5%	65%	52.5%	40%	55.0%	42.5%
J5	37.5%	55.0%	80%	60%	60%	35%	45%

FIGURE 4.40: The detection accuracy of the properties *Touch Size, Gyro X, Gyro Y, Gyro Z, Gyro X All, Gyro Y All* and *Gyro Z All* for the user's **hand** (left or right) in the 60 target locations A0 to J5 in the **walking** condition, using a PCC calculation based on averaged arrays stored in the lookup tables for each target position. The property with the highest accuracy per target is highlighted in black. If the highest accuracy for a target position is <75%, the highlight is red.

Table 4.4: Mean detection accuracy combined for all target positions in % per property for each detection category (finger (F), hand (H) and condition (sitting, walking (W)) using lookup table-based single-value mean comparisons. The final row shows mean accuracy for all target positions if only the property with the highest detection accuracy (HA) per target is considered. The most accurate properties in each column are **bold**.

Property	**F**	**H**	**FW**	**HW**
Touch Time	70.8	**55.3**	64.8	57.5
Touch Size Mean	58.2	49.5	53.0	52..0
Number of Touches	70.7	55.1	62.3	**59.6**
X Offset	52.4	53.0	50.0	52.8
Y Offset	49.7	51.7	49.8	52.2
Gyro X Amplitude	49.3	48.7	52.0	50.2
Gyro Y Amplitude	51.8	50.4	52.0	52.3
Gyro Z Amplitude	60.7	49.3	58.0	48.3
Gyro All X Amplitude	71.8	50.9	61.0	52.5
Gyro All Y Amplitude	72.2	51.00	**65.5**	52.2
Gyro All Z Amplitude	**77.5**	51.0	62.8	50.3
HA	**80.1**	**63.2**	**71.0**	**65.8**

Tables 4.4 and 4.5 summarise the overall accuracy per property using a lookup table-based single-value mean comparison and a PCC calculation. In the single-value comparison, the *Gyro All Z Amplitude* property was the most reliable finger classifier in the sitting condition with an average detection accuracy of 77.5%. For hand detection the *Touch Time* property provided the highest detection accuracy with a success rate of 55.3%.

Calculating the PCC of the gyroscope and *Touch Size* arrays of a new touch event with regards to the averaged array data for each button position highlighted the *Gyro X* array as the most accurate classifier for the user's finger with an accuracy of 60%. For hand detection, PCC-based comparison using the *Gyro Y* array was the most accurate (58.4%).

In the walking condition, overall finger classification accuracy was highest using the *Gyro All Y Amplitude* property with a degree of 65.5%, whereas hand classification accuracy was highest for the *Number of Touches* property at 59.6%. Using PCC calculation, the *Gyro X* array provided the highest resemblance to the stored averaged arrays with a

Table 4.5: Mean detection accuracy combined for all target positions in % per property for each classification category (finger (F) and hand (H)) and condition (sitting, walking (W)) using a lookup table-based PCC calculation for the array of each property. The final row shows the mean accuracy for all target positions if only the property with the highest detection accuracy (HA) per target is considered. The most accurate properties in each column are **bold**.

Property	**F-PCC**	**H-PCC**	**FW PCC**	**HW PCC**
Size	54.0	45.8	52.5	46.2
Gyro X	**60.0**	50.5	**55.7**	49.7
Gyro Y	56.6	**58.4**	54.6	**61.0**
Gyro Z	52.0	52.2	51.5	53.0
Gyro All X	46.6	50.7	50.9	50.3
Gyro All Y	47.7	49.6	51.9	49.2
Gyro All Z	47.5	47.3	50.0	50.3
HA	**66.5**	**64.9**	**63.9**	**65.0**

classification accuracy of 55.7%. For hand detection, the *Gyro Y* array performed best with an average of 61% accuracy.

Summary

Figures 4.33 to 4.40, pp. 180–188, have shown the varying accuracy for each touch property to detect the user's finger and hand for each of the 60 target positions. The figures together with Table 4.4 and Table 4.5 show that "finger" was the most reliable classifier for both single-value mean comparison and PCC calculation, whereas hand detection did not appear to be reliable with the proposed approach. In the walking condition, finger detection accuracy was often greatly reduced, whereas the already rather low accuracy for hand detection was not much affected by the walking condition.

The above suggests that to improve classification accuracy, it is necessary not to use the same property for each target position, but rather to determine the most accurate property for each target location and use only this property to classify new input data. For finger classification, accuracy can then be increased to up to over 90% in some cases (Fig. 4.33). With this approach, the potential overall finger classification accuracy averaged at 80.1%, and hand classification accuracy increased to 63.2% in the sitting condition. For the PCC-based approach, classification accuracy could be increased to 66.5% for finger and 64.9% for hand.

The results indicate that using the lookup-approach, finger classification with only one touch evaluated on the highest-scoring property in each target location may be possible with a reasonable degree of accuracy in the sitting condition (average 80.1%). In this condition, the most accurate properties for finger classification were *Gyro All Z, Gyro All Y, Gyro All X, Number of Touches* and *Touch Time*. In the walking condition, these were *Gyro All Y, Touch Time, Gyro All Z, Number of Touches* and *Gyro All X*. Classification using the PCC seems unreliable, with the highest property accuracy being 61% for *Gyro Y* on average.

While the potential accuracy for finger classification using the highest-scoring property in each target location is reasonable (an average of 80.1%), it is not ideal and poses the question as to whether this approach should be pursued further. Instead, it may be more fruitful to explore other techniques for classification. Therefore, the next section will examine the effectiveness of a range of machine-learning algorithms to perform the classification tasks.

4.4.2 *Approach B*: Finger and Hand Detection Accuracy Using Machine Learning

To explore the classification accuracy for finger and hand using standard machine-learning algorithms, the data for each target location and condition was evaluated using the following set of algorithms:

- *K1 (Nearest Neighbour):* weka.classifiers.lazy.IBk -K 1 -W 0 -A weka.core.neighboursearch.LinearNNSearch -A weka.core.EuclideanDistance -R first-last
- *K3 (Nearest Neighbour):* weka.classifiers.lazy.IBk -K 3 -W 0 -A weka.core.neighboursearch.LinearNNSearch -A weka.core.EuclideanDistance -R first-last
- *K5 (Nearest Neighbour):* weka.classifiers.lazy.IBk -K 5 -W 0 -A weka.core.neighboursearch.LinearNNSearch -A weka.core.EuclideanDistance -R first-last
- *J48:* weka.classifiers.trees.J48 -C 0.25 -M 2

- *RF12:* weka.classifiers.trees.RandomForest -I 10 -K 12 -S 1 -num-slots 1

The performance of each algorithm configuration in each position and mode was determined by performing a tenfold cross-validation on the respective data. The accuracy of the cross-validated models for classifying the user's finger and hand in each target position for the sitting and walking conditions is illustrated in Figures 4.41 to 4.44.

Target	K1	K3	K5	J48	RF
A0	85.2%	86.1%	87.1%	80.6%	82.4%
A1	81.5%	86.1%	84.3%	76.9%	83.3%
A2	85.2%	88.9%	86.1%	85.2%	87%
A3	89.8%	88.9%	87%	87.9%	88.9%
A4	91.7%	88.9%	89.8%	84.3%	89.8%
A5	78.7%	79.6%	80.6%	82.4%	87%
B0	76.9%	78.7%	79.6%	81.5%	80.6%
B1	78.7%	84.3%	88%	83.3%	86.1%
B2	82.4%	84.3%	86.1%	82.4%	86.1%
B3	83.33%	87%	86.1%	86.1%	85.2%
B4	87%	90.7%	91.7%	90.7%	90.7%
B5	78.7%	81.5%	76.9%	79.6%	80.6%
C0	74%	76.9%	75.9%	72.2%	75%
C1	72.2%	76.9%	78.7%	78.7%	82.4%
C2	83.3%	79.6%	80.6%	70.4%	83.3%
C3	79.6%	85.2%	87%	73%	79.6%
C4	82.4%	87%	88.9%	78.7%	82.4%
C5	64.8%	76.9%	78.7%	79.6%	75.9%
D0	71.3%	73.1%	73.1%	66.7%	67.6%
D1	71.3%	81.5%	78.7%	70.4%	71.3%
D2	76.9%	83.3%	81.5%	84.3%	88.9%
D3	76.9%	77.8%	80.6%	75%	77.8%
D4	67.6%	70.4%	74.1%	73.1%	75.9%
D5	82.4%	81.5%	82.4%	75%	81.5%
E0	75.9%	79.6%	78.7%	69.4%	75.9%
E1	66.7%	70.4%	65.7%	68.5%	74%
E2	76.9%	77.8%	75%	77.8%	80.6%
E3	68.5%	64.8%	71.3%	67.6%	71.3%
E4	66.7%	72.2%	74.1%	66.7%	79.6%
E5	67.6%	69.4%	75%	72.2%	74.1%
F0	75.9%	75%	75%	83.3%	83.3%
F1	69.4%	75.9%	76.9%	75%	75.9%
F2	82.4%	78.7%	75.9%	77.8%	77.8%
F3	65.7%	71.3%	68.5%	70.4%	75%
F4	76.9%	79.6%	75%	80.6%	82.4%
F5	68.5%	75%	76.9%	85.2%	82.4%
G0	66.7%	78.7%	77.8%	81.5%	82.4%
G1	71.3%	77.8%	76.9%	75.9%	80.6%
G2	68.5%	73.1%	71.3%	74%	78.7%
G3	68.5%	74.1%	75.9%	83.3%	83.3%
G4	74.1%	76.85%	75.9%	77.8%	79.6%
G5	74.1%	75.9%	80.6%	80.6%	84.3%
H0	71.3%	76.85%	75%	75%	78.7%
H1	77.8%	80.6%	81.5%	85.2%	87.1%
H2	82.4%	84.3%	85.2%	88.9%	87.9%
H3	77.8%	78.7%	77.8%	78.7%	74.1%
H4	75.9%	75%	70.4%	75.9%	86.1%
H5	88.9%	84.3%	86.1%	87.9%	91.7%
I0	80.6%	82.4%	86.1%	78.7%	81.5%
I1	70.4%	77.8%	80.6%	82.4%	83.3%
I2	76.9%	87.9%	88.9%	83.3%	90.7%
I3	83.3%	81.5%	81.5%	84.3%	85.18%
I4	83.3%	86.1%	88.9%	92.6%	92.6%
I5	83.3%	81.5%	85.2%	87.1%	88.9%
J0	88.9%	85.2%	89.8%	89.8%	94.4%
J1	80.6%	87.1%	87.9%	87.9%	93.5%
J2	85.2%	86.1%	85.2%	96.3%	93.5%
J3	76.9%	82.5%	78.7%	88.9%	88.9%
J4	80.6%	85.2%	84.3%	79.6%	87.1%
J5	85.2%	83.3%	85.2%	80.6%	86.1%

FIGURE 4.41: The **finger** classification accuracy of the *Nearest Neighbour* algorithms (K1, K3, K5), the *J48* classifier (J48) and the *Random Forest* classifier usinG12 attributes (RF) for each target position in the **sitting** condition provided by the tenfold cross-validation. The three highest-scoring algorithm configurations per target are highlighted in black. If the highest accuracy for a target position is <75%, the highlight is red.

	0			1			2			3			4			5		
A	A0	K3 79.6%	K5 81.5%	A1	K3 64.8%	K5 69.4%	A2	K3 55.6%	K5 50.1%	A3	K3 40.7%	K5 39.8%	A4	K3 68.5%	K5 65.7%	A5	K3 59.3%	K5 58.3%
	K1 75%	J48 73.1%	RF 80.6%	K1 59.3%	J48 59.3%	RF 55.6%	K1 54.6%	J48 52.8%	RF 52.8%	K1 47.2%	J48 52.8%	RF 50%	K1 60.2%	J48 57.4%	RF 63.9%	K1 61.1%	J48 50%	RF 68.5%
B	B0	K3 71.3%	K5 76.9%	B1	K3 59.3%	K5 53.7%	B2	K3 45.4%	K5 42.6%	B3	K3 40.7%	K5 46.3%	B4	K3 55.6%	K5 50.9%	B5	K3 67.6%	K5 71.3%
	K1 66.7%	J48 66.7%	RF 70.4%	K1 62.9%	J48 64.8%	RF 56.48%	K1 56.5%	J48 52.8%	RF 55.6%	K1 46.3%	J48 46.3%	RF 53.7%	K1 54.6%	J48 44.4%	RF 51.9%	K1 63.9%	J48 66.7%	RF 64.8%
C	C0	K3 71.3%	K5 69.4%	C1	K3 67.6%	K5 71.3%	C2	K3 48.2%	K5 50.9%	C3	K3 54.6%	K5 56.5%	C4	K3 57.4%	K5 59.3%	C5	K3 59.3%	K5 66.7%
	K1 69.4%	J48 66.7%	RF 73.15%	K1 62.1%	J48 62.9%	RF 68.5%	K1 58.3%	J48 56.5%	RF 56.5%	K1 50%	J48 43.5%	RF 54.6%	K1 62.9%	J48 60.2%	RF 61.1%	K1 58.3%	J48 60.2%	RF 58.33%
D	D0	K3 73.1%	K5 68.5%	D1	K3 66.7%	K5 68.5%	D2	K3 57.4%	K5 48.1%	D3	K3 39.8%	K5 43.5%	D4	K3 69.4%	K5 68.5%	D5	K3 67.6%	K5 70.4%
	K1 73.1%	J48 73.1%	RF 77.8%	K1 60.2%	J48 62.1%	RF 67.6%	K1 57.4%	J48 47.2%	RF 49.1%	K1 48.1%	J48 45.4%	RF 50.9%	K1 61.1%	J48 60.2%	RF 55.6%	K1 69.4%	J48 62.9%	RF 69.4%
E	E0	K3 76.9%	K5 74.1%	E1	K3 63.9%	K5 62.1%	E2	K3 61.1%	K5 61.1%	E3	K3 43.5%	K5 43.5%	E4	K3 61.1%	K5 61.1%	E5	K3 62.9%	K5 67.6%
	K1 71.3%	J48 62.9%	RF 69.4%	K1 67.6%	J48 68.5%	RF 69.4%	K1 55.6%	J48 47.2%	RF 56.5%	K1 43.5%	J48 44.4%	RF 42.6%	K1 58.3%	J48 56.5%	RF 63%	K1 67.6%	J48 57.4%	RF 65.7%
F	F0	K3 66.7%	K5 62.1%	F1	K3 55.6%	K5 62.1%	F2	K3 53.7%	K5 53.7%	F3	K3 56.5%	K5 56.5%	F4	K3 52.8%	K5 59.3%	F5	K3 71.3%	K5 71.3%
	K1 62.1%	J48 68.5%	RF 71.3%	K1 56.5%	J48 50%	RF 51.8%	K1 50.9%	J48 49.1%	RF 62.1%	K1 55.6%	J48 45.4%	RF 56.5%	K1 48.1%	J48 56.5%	RF 49.1%	K1 59.3%	J48 67.6%	RF 63.9%
G	G0	K3 59.3%	K5 62.1%	G1	K3 55.6%	K5 60.2%	G2	K3 55.6%	K5 55.6%	G3	K3 53.7%	K5 55.6%	G4	K3 54.6%	K5 56.5%	G5	K3 62.1%	K5 63.9%
	K1 53.7%	J48 53.7%	RF 57.4%	K1 52.8%	J48 62.9%	RF 61%	K1 54.6%	J48 52.8%	RF 53.7%	K1 53.7%	J48 46.3%	RF 58.3%	K1 59.3%	J48 57.4%	RF 61.1%	K1 65.7%	J48 70.4%	RF 74%
H	H0	K3 64.8%	K5 67.6%	H1	K3 58.3%	K5 60.2%	H2	K3 47.2%	K5 50%	H3	K3 47.2%	K5 52.8%	H4	K3 49.1%	K5 50.1%	H5	K3 68.5%	K5 67.6%
	K1 64.8%	J48 64.8%	RF 67.6%	K1 49.1%	J48 53.7%	RF 56.5%	K1 49.1%	J48 45.4%	RF 50.9%	K1 52.8%	J48 50.9%	RF 62.1%	K1 54.6%	J48 64.8%	RF 59.3%	K1 69.4%	J48 65.7%	RF 77.8%
I	I0	K3 56.5%	K5 63.9%	I1	K3 62.1%	K5 58.3%	I2	K3 54.6%	K5 60.2%	I3	K3 46.3%	K5 55.6%	I4	K3 61.1%	K5 65.7%	I5	K3 65.7%	K5 68.5%
	K1 60.2%	J48 62.1%	RF 64.8%	K1 57.4%	J48 48.1%	RF 62.9%	K1 51.9%	J48 48.1%	RF 48.1%	K1 48.1%	J48 53.7%	RF 59.3%	K1 62.1%	J48 59.3%	RF 66.7%	K1 63.9%	J48 72.2%	RF 76.9%
J	J0	K3 66.7%	K5 68.5%	J1	K3 58.3%	K5 58.3%	J2	K3 48.1%	K5 54.6%	J3	K3 46.3%	K5 42.6%	J4	K3 68.5%	K5 72.2%	J5	K3 75%	K5 74%
	K1 60.2%	J48 67.6%	RF 68.5%	K1 52.8%	J48 62.1%	RF 68.5%	K1 50.9%	J48 46.3%	RF 51.9%	K1 50%	J48 50.9%	RF 57.4%	K1 66.7%	J48 61.1%	RF 65.7%	K1 66.7%	J48 76.9%	RF 73.1%

FIGURE 4.42: The **hand** classification accuracy of the Nearest Neighbour algorithms (K1, K3, K5), the *J48* classifier (J48) and the *Random Forest* classifier usinG12 attributes (RF) for each target position in the **sitting** condition provided by the tenfold cross-validation. The three highest-scoring algorithm configurations per target are highlighted in black. If the highest accuracy for a target position is <75%, the highlight is red.

Target	K3	K5	K1	J48	RF
A0	84.3%	83.3%	80.6%	85.2%	90.7%
A1	94.4%	94.4%	90.7%	85.2%	89.8%
A2	87.9%	87.9%	89.8%	89.8%	91.6%
A3	82.4%	85.2%	77.8%	77.8%	87.9%
A4	90.7%	92.6%	82.4%	81.5%	91.7%
A5	80.6%	83.3%	79.6%	85.2%	84.3%
B0	70.4%	76.9%	68.5%	78.7%	83.3%
B1	87.1%	89.8%	82.4%	78.7%	84.3%
B2	84.3%	85.2%	84.3%	88.9%	89.8%
B3	81.5%	81.5%	76.9%	81.5%	79.6%
B4	80.6%	80.6%	75.9%	75%	78.7%
B5	87%	87.9%	84.3%	75.9%	86.1%
C0	78.7%	75.9%	77.8%	75%	78.7%
C1	75.9%	77.8%	72.2%	77.8%	86.1%
C2	84.3%	80.6%	82.4%	79.6%	82.4%
C3	79.6%	83.3%	72.2%	73.1%	76.9%
C4	76.9%	78.7%	66.7%	76.9%	81.5%
C5	74.1%	75%	74.1%	71.3%	80.6%
D0	79.6%	78.7%	77.8%	73.1%	75%
D1	77.8%	77.8%	77.8%	80.6%	87%
D2	78.7%	75.9%	77.8%	76.9%	79.6%
D3	81.5%	79.6%	75%	69.4%	79.6%
D4	75%	75%	63.9%	68.5%	77.8%
D5	78.7%	75%	68.5%	76.9%	79.6%
E0	71.3%	72.2%	65.7%	67.6%	76.9%
E1	70.4%	75.9%	71.3%	77.8%	80.6%
E2	75%	75.9%	72.2%	77.8%	75%
E3	72.2%	72.2%	75.9%	73.2%	75.9%
E4	75%	76.9%	71.3%	75.9%	75.9%
E5	70.4%	75%	66.7%	75%	76.9%
F0	79.6%	82.4%	75%	86.1%	84.3%
F1	79.6%	76.9%	75.9%	75.9%	79.6%
F2	78.7%	82.4%	73.1%	78.7%	80.6%
F3	75%	77.8%	74.1%	72.2%	72.2%
F4	74%	75.9%	75%	66.7%	84.3%
F5	74.1%	79.6%	75.9%	66.7%	75%
G0	77.8%	74.1%	75%	77.8%	80.6%
G1	74.1%	75.9%	69.4%	67.6%	75.9%
G2	65.7%	63.9%	57.4%	66.7%	68.5%
G3	75.9%	76.9%	67.6%	63.9%	75.9%
G4	73.1%	75%	73.1%	70.4%	72.2%
G5	66.7%	73.1%	65.7%	77.8%	74.1%
H0	81.5%	75.9%	71.3%	68.5%	75.9%
H1	64.8%	71.3%	58.3%	66.7%	67.6%
H2	70.4%	75%	70.4%	75%	73.1%
H3	73.1%	74.1%	70.4%	67.6%	74.1%
H4	75%	70.4%	69.4%	71.3%	76.9%
H5	72.2%	75%	66.7%	73.1%	75.9%
I0	75.9%	76.9%	71.3%	75%	74.1%
I1	75%	77.8%	70.4%	73.1%	81.5%
I2	73.1%	76.9%	71.3%	64.8%	71.3%
I3	78.7%	79.6%	75%	69.4%	74.1%
I4	75%	78.7%	68.5%	72.2%	78.7%
I5	70.4%	72.2%	65.7%	71.3%	75.9%
J0	74.1%	70.4%	73.1%	74.1%	81.5%
J1	81.5%	86.1%	80.6%	87.1%	82.4%
J2	75%	75%	65.7%	70.4%	80.6%
J3	74.1%	76.9%	71.3%	71.3%	74.1%
J4	73.1%	75.9%	73.1%	73.1%	75.9%
J5	73.1%	76.9%	75.9%	78.7%	76.9%

FIGURE 4.43: The **finger** classification accuracy of the *Nearest Neighbour* algorithms (K1, K3, K5), the *J48* classifier (J48) and the *Random Forest* classifier usinG12 attributes (RF) for each target position in the **walking** condition provided by the tenfold cross-validation. The three highest-scoring algorithm configurations per target are highlighted in black. If the highest accuracy for a target position is <75%, the highlight is red.

	0			1			2			3			4			5		
A	A0	K3 64.8%	K5 66.7%	A1	K3 57.4%	K5 63.9%	A2	K3 45.4%	K5 49.1%	A3	K3 39.8%	K5 50.1%	A4	K3 55.6%	K5 60.2%	A5	K3 64.8%	K5 57.4%
	K1 68.5%	J48 63.9%	RF 69.4%	K1 58.3%	J48 55.6%	RF 60.2%	K1 45.4%	J48 49.1%	RF 52.8%	K1 38.9%	J48 47.2%	RF 48.1%	K1 53.7%	J48 48.1%	RF 59.3%	K1 65.7%	J48 59.3%	RF 59.3%
B	B0	K3 63.9%	K5 65.7%	B1	K3 56.5%	K5 62.9%	B2	K3 45.4%	K5 50.9%	B3	K3 47.22%	K5 42.6%	B4	K3 50.9%	K5 48.1%	B5	K3 65.7%	K5 60.2%
	K1 63.9%	J48 66.7%	RF 71.3%	K1 59.3%	J48 55.6%	RF 61.1%	K1 46.3%	J48 57.4%	RF 53.7%	K1 43.5%	J48 48.1%	RF 42.6%	K1 49.1%	J48 59.3%	RF 60.2%	K1 65.7%	J48 55.6%	RF 62.9%
C	C0	K3 69.4%	K5 69.4%	C1	K3 68.5%	K5 69.4%	C2	K3 65.7%	K5 57.4%	C3	K3 46.3%	K5 55.6%	C4	K3 62.9%	K5 56.5%	C5	K3 65.7%	K5 64.8%
	K1 62%	J48 68.5%	RF 75%	K1 66.7%	J48 59.3%	RF 62%	K1 59.3%	J48 62%	RF 62.9%	K1 51.9%	J48 43.5%	RF 54.6%	K1 60.9%	J48 46.8%	RF 51.9%	K1 63.9%	J48 67.6%	RF 63.9%
D	D0	K3 74.1%	K5 74.1%	D1	K3 56.5%	K5 63.9%	D2	K3 51.9%	K5 48.1%	D3	K3 52.8%	K5 58.3%	D4	K3 59.3%	K5 60.2%	D5	K3 61%	K5 68.5%
	K1 62.9%	J48 76.9%	RF 78.7%	K1 56.5%	J48 54.6%	RF 55.6%	K1 42.6%	J48 53.7%	RF 57.4%	K1 50.9%	J48 50.9%	RF 47.2%	K1 55.6%	J48 50.9%	RF 59.3%	K1 58.3%	J48 58.3%	RF 63.9%
E	E0	K3 63.9%	K5 65.7%	E1	K3 61.1%	K5 62%	E2	K3 54.6%	K5 53.7%	E3	K3 55.6%	K5 55.6%	E4	K3 52.8%	K5 51.9%	E5	K3 68.5%	K5 70.4%
	K1 67.6%	J48 76.9%	RF 78.7%	K1 51.9%	J48 47.2%	RF 62.9%	K1 50.9%	J48 43.5%	RF 50.9%	K1 50.9%	J48 40.7%	RF 44.4%	K1 54.6%	J48 48%	RF 57.4%	K1 65.7%	J48 54.6%	RF 60.2%
F	F0	K3 70.4%	K5 74.1%	F1	K3 50%	K5 51.9%	F2	K3 51.8%	K5 43.5%	F3	K3 51.9%	K5 51.9%	F4	K3 51.9%	K5 55.6%	F5	K3 67.6%	K5 62.9%
	K1 72.2%	J48 66.7%	RF 59.3%	K1 49.1%	J48 56.5%	RF 58.3%	K1 54.6%	J48 44.4%	RF 60.2%	K1 48.1%	J48 44.4%	RF 51.9%	K1 50.9%	J48 51.9%	RF 56.5%	K1 69.4%	J48 61.1%	RF 66.7%
G	G0	K3 58.3%	K5 62.1%	G1	K3 58.3%	K5 57.4%	G2	K3 49.1%	K5 52.8%	G3	K3 58.3%	K5 55.6%	G4	K3 53.7%	K5 48.4%	G5	K3 67.6%	K5 63.9%
	K1 53.7%	J48 64.8%	RF 68.5%	K1 62.9%	J48 54.6%	RF 62%	K1 50.9%	J48 55.6%	RF 58.3%	K1 50.9%	J48 44.4%	RF 51.9%	K1 62.9%	J48 69.4%	RF 64.8%	K1 62%	J48 57.4%	RF 60.2%
H	H0	K3 70.4%	K5 68.5%	H1	K3 59.3%	K5 63.9%	H2	K3 50%	K5 55.6%	H3	K3 49.1%	K5 51.9%	H4	K3 50.9%	K5 61.1%	H5	K3 71.3%	K5 72.2%
	K1 75.9%	J48 69.4%	RF 66.7%	K1 61.1%	J48 62%	RF 64.8%	K1 50%	J48 48.1%	RF 60.2%	K1 48.1%	J48 50%	RF 47.2%	K1 50.9%	J48 57.4%	RF 54.6%	K1 66.7%	J48 70.4%	RF 74.1%
I	I0	K3 69.4%	K5 67.6%	I1	K3 56.5%	K5 61.1%	I2	K3 60.2%	K5 54.6%	I3	K3 52.8%	K5 53.7%	I4	K3 56.5%	K5 60.2%	I5	K3 63.9%	K5 68.5%
	K1 59.3%	J48 62.9%	RF 68.5%	K1 60.2%	J48 68.5%	RF 56.5%	K1 64.8%	J48 50%	RF 47.2%	K1 52.8%	J48 50%	RF 56.5%	K1 55.6%	J48 60.2%	RF 64.8%	K1 69.4%	J48 64.8%	RF 70.4%
J	J0	K3 64.8%	K5 71.3%	J1	K3 54.6%	K5 58.3%	J2	K3 51.9%	K5 50.9%	J3	K3 53.7%	K5 56.5%	J4	K3 62.9%	K5 57.4%	J5	K3 70.4%	K5 75.9%
	K1 63.9%	J48 67.6%	RF 70.4%	K1 52.8%	J48 53.7%	RF 58.3%	K1 42.6%	J48 46.3%	RF 52.8%	K1 61.1%	J48 48.1%	RF 49.1%	K1 61.1%	J48 73.1%	RF 67.6%	K1 65.7%	J48 67.6%	RF 68.5%

FIGURE 4.44: The **hand** classification accuracy of the *Nearest Neighbour* algorithms (K1, K3, K5), the *J48* classifier (J48) and the *Random Forest* classifier usinG12 attributes (RF) for each target position in the **walking** condition provided by the tenfold cross-validation. The three highest-scoring algorithm configurations per target are highlighted in black. If the highest accuracy for a target position is <75%, the highlight is red.

TABLE 4.6: Mean classification accuracy in % derived from the cross-validation for finger type (F) and hand (H) when using *Approach B1* (the highest ranking algorithm per target position) and *Approach B2* (the three highest-ranking algorithms per target position in a voting process), when sitting and walking (W).

Mode	***Approach B1***	***Approach B2***
F	84.1	82.1
F (W)	78.7	80.8
H	61.8	64.5
H (W)	60.9	63.7

Figures 4.41 to 4.44, pp. 193–196, show that the performance of each algorithm varied with target position in both conditions. Similar to *Approach A*, these suggest not to use just one algorithm for all target locations, but to choose the most accurate one in each screen area. However, as algorithm performance may change depending on the quality of new data, I decided to evaluate *Approach B* using two sub-approaches. This way, the reliability of the algorithm configurations can be explored:

- ***Approach B1*:** Only used the highest-scoring algorithm per screen area.
- ***Approach B2*:** Used the three highest-scoring algorithms per screen area in a voting process. For this, the three highest-scoring algorithms per screen area were used, with preference given to higher *K* configurations over lower ones. If all three highest-scoring algorithms were *K Nearest Neighbour* algorithms, the one with the lowest accuracy was replaced by the next-highest decision tree algorithm. This was done to make the approach more robust to possible fluctuations in the data, allowing a better adaptation to such fluctuations by offering a more varied interpretation.

According to the results of the stratified tenfold cross-validation in Figures 4.41 to 4.44, pp. 193–196, the predicted classification accuracy of each approach is presented in Table 4.6. The data in the table indicates that *Approach B1* may be more suitable for finger classification in the sitting condition, but that *Approach B2* may be more accurate when walking in classifying finger and hand.

Altogether, the classification of the touch properties using machine-learning algorithms appears promising. Five algorithm configurations were applied to the data of each target location and the potential performance indicated by a tenfold cross-validation. As the cross-validated models provided a reasonable degree of classification accuracy, this suggests exploration of their performance on additional data in order to verify their accuracy. For the verification I used the data provided by the ten participants of the second data collection, as the data was independent of the training data. The data was evaluated once by classifying it with the highest-scoring algorithm in each location determined by the cross-validation (*Approach B1*) and once using the three highest-scoring algorithms for each location determined by the cross-validation in a majority voting process (*Approach B2*).

Figures 4.45 to 4.48, pp. 199–202, show the performance of *Approach B1* and Figures 4.49 to 4.52 show the performance of *Approach B2* on the validation data:

	0			1			2			3			4			5		
A	A0	K3 80%	**K5 85%**	A1	**K3 80%**	K5 77.5%	A2	**K3 85%**	K5 85%	A3	K3 87.5%	K5 87.5%	A4	K3 75%	K5 72.5%	A5	K3 82.5%	K5 82.5%
	K1 80%	J48 85%	RF 87.5%	K1 67.5%	J48 75%	RF 72.5%	K1 85%	J48 75%	RF 87.5%	**K1 77.5%**	J48 75%	RF 72.5%	**K1 75%**	J48 80%	RF 80%	K1 77.5%	J48 77.5%	**RF 87.5%**
B	B0	K3 90%	K5 85%	B1	K3 77.5%	**K5 75%**	B2	K3 82.5%	K5 75%	B3	**K3 82.5%**	K5 90%	B4	K3 82.5%	**K5 82.5%**	B5	**K3 82.5%**	K5 80%
	K1 85%	**J48 72.5%**	RF 85%	K1 75%	J48 72.5%	RF 82.5%	K1 80%	J48 85%	**RF 82.5%**	K1 82.5%	J48 92.5%	RF 87.5%	K1 85%	J48 92.5%	RF 92.5%	K1 72.5%	J48 82.5%	RF 82.5%
C	C0	**K3 77.5%**	K5 75%	C1	K3 75%	K5 80%	C2	K3 80%	K5 82.5%	C3	K3 77.5%	**K5 75%**	C4	K3 80%	**K5 77.5%**	C5	K3 80%	K5 77.5%
	K1 75%	J48 80%	RF 82.5%	K1 82.5%	J48 77.5%	**RF 72.5%**	**K1 80%**	J48 70%	RF 77.5%	K1 77.5%	J48 82.5%	RF 85%	K1 80%	J48 90%	RF 80%	K1 65%	**J48 87.5%**	RF 87.5%
D	D0	K3 67.5%	**K5 80%**	D1	**K3 80%**	K5 82.5%	D2	K3 82.5%	K5 77.5%	D3	K3 82.5%	**K5 85%**	D4	K3 80%	K5 75%	D5	K3 82.5%	**K5 82.5%**
	K1 80%	J48 67.5%	RF 77.5%	K1 65%	J48 82.5%	RF 72.5%	K1 82.5%	J48 77.5%	**RF 77.5%**	K1 82.5%	J48 82.5%	RF 82.5%	K1 62.5%	J48 77.5%	**RF 92.5%**	K1 80%	J48 82.5%	RF 80%
E	E0	**K3 77.5%**	K5 80%	E1	K3 62.5%	K5 70%	E2	K3 70%	K5 77.5%	E3	K3 75%	K5 77.5%	E4	K3 72.5%	K5 77.5%	E5	K3 67.5%	**K5 72.5%**
	K1 80%	J48 85%	RF 82.5%	K1 60%	J48 60%	**RF 72.5%**	K1 65%	J48 85%	**RF 70%**	K1 62.5%	J48 70%	**RF 75%**	K1 70%	J48 67.5%	**RF 72.5%**	K1 70%	J48 67.5%	RF 67.5%
F	F0	K3 70%	K5 70%	F1	K3 70%	**K5 70%**	F2	K3 75%	K5 72.5%	F3	K3 75%	K5 72.5%	F4	K3 65%	K5 70%	F5	K3 77.5%	K5 75%
	K1 75%	J48 72.5%	**RF 77.5%**	K1 77.5%	J48 87.5%	RF 82.5%	**K1 72.5%**	J48 85%	RF 77.5%	K1 65%	J48 72.5%	**RF 75%**	K1 75%	J48 77.5%	**RF 82.5%**	K1 70%	**J48 85%**	RF 82.5%
G	G0	K3 90%	K5 87.5%	G1	K3 75%	K5 80%	G2	K3 67.5%	K5 70%	G3	K3 82.5%	K5 85%	G4	K3 77.5%	K5 80%	G5	K3 77.5%	K5 75%
	K1 85%	J48 85%	**RF 90%**	K1 72.5%	J48 87.5%	**RF 82.5%**	K1 70%	J48 82.5%	**RF 90%**	K1 70%	J48 85%	**RF 87.5%**	K1 70%	J48 75%	**RF 75%**	K1 72.5%	J48 77.5%	**RF 80%**
H	H0	K3 77.5%	K5 82.5%	H1	K3 82.5%	K5 82.5%	H2	K3 80%	K5 85%	H3	K3 72.5%	K5 77.5%	H4	K3 80%	K5 77.5%	H5	K3 75%	K5 82.5%
	K1 65%	J48 85%	**RF 87.5%**	K1 72.5%	J48 87.5%	**RF 90%**	K1 80%	**J48 92.5%**	RF 90%	K1 65%	**J48 92.5%**	RF 82.5%	K1 82.5%	J48 85%	**RF 87.5%**	K1 80%	J48 87.5%	**RF 82.5%**
I	I0	K3 85%	**K5 85%**	I1	K3 75%	K5 80%	I2	K3 67.5%	K5 75%	I3	K3 67.5%	K5 70%	I4	K3 75%	K5 80%	I5	K3 77.5%	K5 82.5%
	K1 80%	J48 85%	RF 92.5%	K1 67.5%	J48 87.5%	**RF 85%**	K1 62.5%	J48 87.5%	**RF 85%**	K1 72.5%	J48 92.5%	**RF 87.5%**	K1 67.5%	J48 82.5%	**RF 90%**	K1 75%	J48 82.5%	**RF 82.5%**
J	J0	K3 95%	K5 92.5%	J1	K3 87.5%	K5 82.5%	J2	K3 82.5%	K5 87.5%	J3	K3 82.5%	K5 82.5%	J4	K3 85%	K5 85%	J5	K3 90%	K5 92.5%
	K1 97.5%	J48 95%	**RF 95%**	K1 85%	J48 90%	**RF 87.5%**	K1 85%	**J48 90%**	RF 90%	K1 77.5%	J48 77.5%	**RF 87.5%**	K1 82.5%	J48 90%	**RF 92.5%**	K1 85%	J48 95%	**RF 90%**

FIGURE 4.45: The **finger** classification accuracy for the 60 targets positions while **sitting** using ***Approach B1***. The highest-scoring algorithm from the previous cross-validation is highlighted in each position.

	0			1			2			3			4			5		
A	A0	K3 70%	**K5 75%**	A1	K3 60%	**K5 57.5%**	A2	**K3 42.5%**	K5 57.5%	A3	K3 45%	K5 57.5%	A4	**K3 42.5%**	K5 47.5%	A5	K3 67.5%	K5 72.5%
	K1 60%	J48 72.5%	RF 72.5%	K1 55%	J48 65.5%	RF 62.5%	K1 57.5%	J48 45%	RF 65%	K1 45%	**J48 45%**	RF 57.5%	K1 45%	J48 57.5%	RF 52.5%	K1 70%	J48 75%	**RF 67.5%**
B	B0	K3 67.5%	**K5 67.5%**	B1	K3 57.5%	K5 62.5%	B2	K3 47.5%	K5 57.5%	B3	K3 57.5%	K5 62.5%	B4	**K3 50%**	K5 47.5%	B5	K3 60%	**K5 50%**
	K1 77.5%	J48 57.5%	RF 67.5%	K1 60%	**J48 45%**	RF 50%	**K1 57.5%**	J48 55%	RF 60%	K1 50%	J48 55%	**RF 55%**	K1 62.5%	J48 35%	RF 50%	K1 60%	J48 45%	RF 52.5%
C	C0	K3 80%	K5 77.5%	C1	K3 60%	**K5 62.5%**	C2	K3 52.5%	K5 45%	C3	K3 57.5%	**K5 40%**	C4	K3 60%	K5 50%	C5	K3 55%	**K5 65%**
	K1 87.5%	J48 55%	**RF 70%**	K1 57.5%	J48 52.5%	RF 52.5%	**K1 52.5%**	J48 50%	RF 55%	K1 55%	J48 57.5%	RF 67.5%	**K1 57.5%**	J48 57.5%	RF 70%	K1 65%	J48 65%	RF 67.5%
D	D0	K3 57.5%	K5 65%	D1	K3 60%	**K5 52.5%**	D2	**K3 57.5%**	K5 50%	D3	K3 62.5%	K5 60%	D4	**K3 57.5%**	K5 65%	D5	K3 65%	**K5 67.5%**
	K1 60%	J48 67.5%	**RF 70%**	K1 65%	J48 70%	RF 75%	K1 57.5%	J48 47.5%	RF 57.5%	K1 60%	J48 50%	**RF 52.5%**	K1 52.5%	J48 50%	RF 57.5%	K1 52.5%	J48 45%	RF 52.5%
E	E0	**K3 75%**	K5 70%	E1	K3 62.5%	K5 67.5%	E2	K3 45%	**K5 37.5%**	E3	K3 60%	K5 60%	E4	K3 40%	K5 42.5%	E5	K3 55%	**K5 60%**
	K1 77.5%	J48 60%	RF 80%	K1 52.5%	J48 57.5%	**RF 65%**	K1 60%	J48 40%	RF 40%	K1 60%	**J48 40%**	RF 57.5%	K1 50%	J48 50%	**RF 60%**	K1 62.5%	J48 57.5%	RF 55%
F	F0	K3 60%	K5 62.5%	F1	K3 65%	**K5 60%**	F2	K3 55%	K5 75%	F3	K3 60%	K5 62.5%	F4	K3 55%	**K5 52.5%**	F5	K3 62.5%	**K5 60%**
	K1 62.5%	J48 72.5%	**RF 57.5%**	K1 60%	J48 57.5%	RF 62.5%	K1 52.5%	J48 65%	**RF 50%**	K1 62.5%	J48 47.5%	**RF 42.5%**	K1 52.5%	J48 50%	RF 62.5%	K1 60%	J48 72.5%	RF 65%
G	G0	K3 52.5%	**K5 62.5%**	G1	K3 52.5%	K5 60%	G2	K3 52.5%	**K5 47.5%**	G3	K3 40%	K5 35%	G4	K3 62.5%	K5 62.5%	G5	K3 57.5%	K5 62.5%
	K1 60%	J48 60%	RF 72.5%	K1 50%	**J48 52.5%**	RF 80%	K1 45%	J48 50%	RF 55%	K1 60%	J48 60%	**RF 47.5%**	K1 60%	J48 62.5%	**RF 70%**	K1 55%	J48 67.5%	**RF 75%**
H	H0	K3 62.5%	K5 62.5%	H1	**K3 55%**	K5 62.5%	H2	K3 60%	K5 57.5%	H3	K3 57.5%	K5 65%	H4	K3 62.5%	K5 67.5%	H5	K3 72.5%	K5 72.5%
	K1 55%	J48 70%	**RF 65%**	K1 65%	J48 60%	RF 60%	K1 52.5%	J48 62.5%	**RF 57.5%**	K1 55%	J48 57.5%	**RF 60%**	K1 60%	**J48 57.5%**	RF 65%	K1 72.5%	J48 57.5%	**RF 67.5%**
I	I0	K3 60%	K5 65%	I1	K3 47.5%	K5 57.5%	I2	K3 60%	**K5 62.5%**	I3	K3 70%	K5 62.5%	I4	K3 57.5%	K5 62.5%	I5	K3 60%	K5 70%
	K1 62.5%	J48 62.5%	**RF 72.5%**	K1 55%	J48 60%	**RF 52.5%**	K1 65%	J48 60%	RF 57.5%	K1 75%	J48 62.5%	**RF 70%**	K1 60%	J48 57.5%	**RF 60%**	K1 62.5%	J48 62.5%	**RF 70%**
J	J0	K3 80%	K5 77.5%	J1	K3 65%	K5 65%	J2	K3 50%	**K5 52.5%**	J3	K3 67.5%	K5 72.5%	J4	K3 50%	**K5 70%**	J5	K3 80%	K5 82.5%
	K1 70%	J48 52.5%	**RF 77.5%**	K1 62.5%	J48 67.5%	**RF 65%**	K1 55%	J48 50%	RF 42.5%	K1 70%	J48 75%	**RF 67.5%**	K1 65%	J48 62.8%	RF 72.5%	K1 77.5%	**J48 60%**	RF 77.5%

FIGURE 4.46: The **hand** classification accuracy for the 60 targets positions while **sitting** using ***Approach B1***. The highest-scoring algorithm from the previous cross-validation is highlighted in each position.

Row	Column	Position	K3	K5	K1	J48	RF
A	0	A0	75%	77.5%	80%	77.5%	**85%**
A	1	A1	75%	**80%**	75%	80%	82.5%
A	2	A2	80%	75%	72.5%	85%	**87.5%**
A	3	A3	77.5%	77.5%	75%	82.5%	**82.5%**
A	4	A4	87.5%	**92.5%**	82.5%	90%	90%
A	5	A5	85%	80%	75%	**77.5%**	72.5%
B	0	B0	80%	72.5%	80%	77.5%	**85%**
B	1	B1	77.5%	**82.5%**	75%	80%	70%
B	2	B2	82.5%	80%	67.5%	80%	**80%**
B	3	B3	77.5%	80%	77.5%	**70%**	82.5%
B	4	B4	90%	**90%**	90%	77.5%	80%
B	5	B5	77.5%	**77.5%**	82.5%	80%	87.5%
C	0	C0	70%	77.5%	70%	75%	**72.5%**
C	1	C1	65%	70%	60%	82.5%	**75%**
C	2	C2	**77.5%**	75%	70%	77.5%	85%
C	3	C3	70%	**77.5%**	70%	82.5%	82.5%
C	4	C4	75%	77.5%	72.5%	75%	**75%**
C	5	C5	70%	72.5%	67.5%	77.5%	**77.5%**
D	0	D0	**65%**	67.5%	70%	82.5%	70%
D	1	D1	72.5%	72.5%	70%	72.5%	**72.5%**
D	2	D2	80%	77.5%	70%	75%	**85%**
D	3	D3	**75%**	80%	75%	72.5%	72.5%
D	4	D4	67.5%	65%	65%	77.5%	**65%**
D	5	D5	75%	60%	67.5%	67.5%	**67.5%**
E	0	E0	70%	67.5%	72.5%	72.5%	**70%**
E	1	E1	75%	65%	70%	72.5%	**70%**
E	2	E2	77.5%	77.5%	77.5%	**72.5%**	75%
E	3	E3	80%	77.5%	80%	75%	**70%**
E	4	E4	67.5%	**70%**	55%	62.5%	75%
E	5	E5	57.5%	65%	75%	70%	**65%**
F	0	F0	75%	77.5%	85%	**72.5%**	77.5%
F	1	F1	60%	57.5%	62.5%	67.5%	**65%**
F	2	F2	75%	**75%**	75%	62.5%	77.5%
F	3	F3	70%	**72.5%**	70%	70%	75%
F	4	F4	67.5%	67.5%	65%	72.5%	**75%**
F	5	F5	70%	**70%**	70%	72.5%	70%
G	0	G0	57.5%	52.5%	65%	62.5%	**62.5%**
G	1	G1	72.5%	65%	77.5%	67.5%	**62.5%**
G	2	G2	57.5%	60%	52.5%	55%	**72.5%**
G	3	G3	67.5%	**75%**	62.5%	65%	70%
G	4	G4	72.5%	**75%**	70%	65%	57.5%
G	5	G5	75%	75%	65%	**77.5%**	72.5%
H	0	H0	**75%**	70%	55%	72.5%	67.5%
H	1	H1	65%	**67.5%**	65%	67.5%	60%
H	2	H2	77.5%	75%	75%	**75%**	67.5%
H	3	H3	72.5%	82.5%	60%	72.5%	**62.5%**
H	4	H4	57.5%	70%	62.5%	70%	**70%**
H	5	H5	77.5%	77.5%	70%	80%	**77.5%**
I	0	I0	67.5%	**70%**	57.5%	77.5%	67.5%
I	1	I1	67.5%	67.5%	67.5%	75%	**57.5%**
I	2	I2	67.5%	**67.5%**	67.5%	75%	75%
I	3	I3	50%	**57.5%**	52.5%	65%	70%
I	4	I4	80%	77.5%	77.5%	70%	**77.5%**
I	5	I5	70%	77.5%	72.5%	77.5%	**67.5%**
J	0	J0	77.5%	70%	62.5%	80%	**85%**
J	1	J1	70%	72.5%	62.5%	**77.5%**	75%
J	2	J2	65%	70%	57.5%	75%	**65%**
J	3	J3	77.5%	**80%**	72.5%	77.5%	80%
J	4	J4	72.5%	75%	57.5%	82.5%	**75%**
J	5	J5	57.5%	65%	65%	**75%**	67.5%

FIGURE 4.47: The **finger** classification accuracy for the 60 targets positions while **walking** using ***Approach B1***. The highest-scoring algorithm from the previous cross-validation is highlighted in each position.

	0			1			2			3			4			5		
A	**A0**	K3 85%	K5 87.5%	**A1**	K3 65%	**K5 65%**	**A2**	K3 50%	K5 57.5%	**A3**	K3 50%	**K5 55%**	**A4**	K3 50%	**K5 55%**	**A5**	K3 57.5%	K5 60%
	K1 77.5%	J48 55%	**RF 67.5%**	K1 57.5%	J48 57.5%	RF 67.5%	K1 57.5%	J48 47.5%	**RF 57.5%**	K1 60%	J48 57.5%	RF 42.5%	K1 55%	J48 50%	RF 60%	**K1 55%**	J48 57.5%	RF 57.5%
B	**B0**	K3 62.5%	K5 70%	**B1**	K3 60%	**K5 55%**	**B2**	K3 67.5%	K5 62.5%	**B3**	K3 67.5%	K5 62.5%	**B4**	K3 65%	K5 72.5%	**B5**	**K3 72.5%**	K5 67.5%
	K1 67.5%	J48 47.5%	**RF 62.5%**	K1 62.5%	J48 70%	RF 72.5%	K1 62.5%	**J48 42.5%**	RF 65%	K1 62.5%	**J48 52.5%**	RF 65%	K1 57.5%	J48 57.5%	**RF 52.5%**	K1 70%	J48 50%	RF 62.5%
C	**C0**	K3 85%	K5 85%	**C1**	K3 60%	**K5 60%**	**C2**	**K3 50%**	K5 45%	**C3**	K3 65%	**K5 62.5%**	**C4**	**K3 52.5%**	K5 55%	**C5**	K3 65%	K5 67.5%
	K1 87.5%	J48 80%	**RF 87.5%**	K1 70%	J48 57.5%	RF 55%	K1 45%	J48 50%	RF 55%	K1 60%	J48 72.5%	RF 70%	K1 55%	J48 47.5%	RF 60%	K1 70%	**J48 60%**	RF 60%
D	**D0**	K3 70%	K5 77.5%	**D1**	K3 60%	**K5 50%**	**D2**	K3 62.5%	K5 55%	**D3**	K3 32.5%	**K5 42.5%**	**D4**	K3 62.5%	**K5 60%**	**D5**	K3 77.5%	**K5 72.5%**
	K1 60%	J48 65%	**RF 65%**	K1 57.5%	J48 67.5%	RF 65%	K1 60%	J48 52.5%	**RF 57.5%**	K1 45%	J48 57.5%	RF 35%	K1 67.5%	J48 65%	RF 67.5%	K1 62.5%	J48 52.5%	RF 65%
E	**E0**	K3 65%	K5 72.5%	**E1**	K3 62.5%	**K5 62.5%**	**E2**	K3 50%	K5 57.5%	**E3**	K3 57.5%	**K5 57.5%**	**E4**	K3 55%	**K5 60%**	**E5**	K3 67.5%	**K5 62.5%**
	K1 72.5%	J48 57.5%	**RF 65%**	K1 57.5%	J48 47.5%	RF 52.5%	K1 45%	J48 55%	**RF 50%**	K1 55%	J48 57.5%	RF 70%	K1 50%	J48 55%	RF 55%	K1 67.5%	J48 57.5%	RF 65%
F	**F0**	K3 75%	**K5 62.5%**	**F1**	K3 57.5%	K5 57.5%	**F2**	K3 62.5%	K5 62.5%	**F3**	K3 57.5%	K5 52.5%	**F4**	K3 52.5%	K5 60%	**F5**	K3 52.5%	K5 65%
	K1 72.5%	J48 52.5%	RF 62.5%	K1 57.5%	J48 65%	**RF 72.5%**	K1 70%	J48 40%	**RF 60%**	K1 42.5%	J48 65%	**RF 60%**	K1 45%	J48 50%	**RF 57.5%**	**K1 60%**	J48 62.5%	RF 75%
G	**G0**	K3 67.5%	K5 65%	**G1**	K3 57.5%	K5 62.5%	**G2**	K3 30%	K5 40%	**G3**	**K3 50%**	K5 55%	**G4**	K3 60%	K5 65%	**G5**	**K3 65%**	K5 67.5%
	K1 55%	J48 60%	**RF 70%**	**K1 52.5%**	J48 55%	RF 55%	K1 57.5%	J48 50%	**RF 65%**	K1 37.5%	J48 47.5%	RF 50%	K1 67.5%	**J48 70%**	RF 72.5%	K1 65%	J48 57.5%	RF 65%
H	**H0**	K3 67.5%	K5 62.5%	**H1**	K3 62.5%	K5 62.5%	**H2**	K3 67.5%	K5 62.5%	**H3**	K3 62.5%	**K5 62.5%**	**H4**	K3 60%	**K5 50%**	**H5**	K3 72.5%	K5 67.5%
	K1 67.5%	J48 55%	RF 57.5%	K1 55%	J48 52.5%	**RF 62.5%**	K1 60%	J48 55%	**RF 57.5%**	K1 52.5%	J48 52.5%	RF 62.5%	K1 67.5%	J48 57.5%	RF 62.5%	K1 72.5%	J48 70%	**RF 70%**
I	**I0**	**K3 57.5%**	K5 57.5%	**I1**	K3 55%	K5 55%	**I2**	K3 57.5%	K5 52.5%	**I3**	K3 57.5%	K5 52.5%	**I4**	K3 70%	K5 75%	**I5**	K3 70%	K5 72.5%
	K1 55%	J48 65%	RF 55%	K1 50%	**J48 52.5%**	RF 62.5%	**K1 67.5%**	J48 60%	RF 50%	K1 52.5%	J48 52.5%	**RF 52.5%**	K1 77.5%	J48 57.5%	**RF 72.5%**	K1 80%	J48 67.5%	**RF 77.5%**
J	**J0**	K3 70%	**K5 82.5%**	**J1**	K3 55%	K5 67.5%	**J2**	K3 47.5%	K5 42.5%	**J3**	K3 60%	K5 65%	**J4**	K3 67.5%	K5 70%	**J5**	K3 77.5%	**K5 80%**
	K1 67.5%	J48 50%	RF 77.5%	K1 65%	J48 67.5%	**RF 57.5%**	K1 42.5%	J48 47.5%	**RF 45%**	**K1 47.5%**	J48 52.5%	RF 67.5%	K1 57.5%	**J48 72.5%**	RF 70%	K1 75%	J48 75%	RF 60%

FIGURE 4.48: The **hand** classification accuracy for the 60 targets positions while **walking** using ***Approach B1***. The highest-scoring algorithm from the previous cross-validation is highlighted in each position.

	0		1		2		3		4		5	
A	A0	85%	A1	82.5%	A2	87.5%	A3	80%	A4	75%	A5	85%
B	B0	85%	B1	77.5%	B2	77.5%	B3	87.5%	B4	90%	B5	87.5%
C	C0	77.5%	C1	77.5%	C2	80%	C3	85%	C4	80%	C5	80%
D	D0	75%	D1	85%	D2	80%	D3	82.5%	D4	90%	D5	82.5%
E	E0	80%	E1	65%	E2	80%	E3	75%	E4	75%	E5	72.5%
F	F0	77.5%	F1	70%	F2	80%	F3	80%	F4	77.5%	F5	85%
G	G0	90%	G1	77.5%	G2	85%	G3	90%	G4	77.5%	G5	77.5%
H	H0	85%	H1	92.5%	H2	90%	H3	80%	H4	87.5%	H5	87.5%
I	I0	87.5%	I1	87.5%	I2	72.5%	I3	85%	I4	87.5%	I5	82.5%
J	J0	95%	J1	90%	J2	90%	J3	82.5%	J4	87.5%	J5	90%

FIGURE 4.49: The **finger** classification accuracy for the 60 targets positions while **sitting** using ***Approach B2***. The three highest-scoring algorithms of each position from the cross-validation classify the finger using a majority voting system.

	0		1		2		3		4		5	
A	A0	72.5%	A1	62.5%	A2	50%	A3	45%	A4	42.5%	A5	67.5%
B	B0	67.5%	B1	57.5%	B2	60%	B3	65%	B4	62.5%	B5	52.5%
C	C0	77.5%	C1	62.5%	C2	60%	C3	55%	C4	62.5%	C5	65%
D	D0	65%	D1	67.5%	D2	60%	D3	57.5%	D4	60%	D5	62.5%
E	E0	72.5%	E1	62.5%	E2	42.5%	E3	62.5%	E4	45%	E5	62.5%
F	F0	70%	F1	65%	F2	67.5%	F3	60%	F4	52.5%	F5	65%
G	G0	60%	G1	65%	G2	50%	G3	40%	G4	70%	G5	70%
H	H0	62.5%	H1	60%	H2	57.5%	H3	62.5%	H4	62.5%	H5	70%
I	I0	70%	I1	57.5%	I2	62.5%	I3	70%	I4	62.5%	I5	80%
J	J0	80%	J1	70%	J2	50%	J3	75%	J4	60%	J5	80%

FIGURE 4.50: The **hand** classification accuracy for the 60 targets positions while **sitting** using ***Approach B2***. The three highest-scoring algorithms of each position from the cross-validation classify the hand using a majority voting system.

	0		1		2		3		4		5	
A	A0	82.5%	A1	75%	A2	87.5%	A3	85%	A4	92.5%	A5	80%
B	B0	82.5%	B1	80%	B2	80%	B3	80%	B4	90%	B5	80%
C	C0	75%	C1	75%	C2	80%	C3	80%	C4	75%	C5	72.5%
D	D0	70%	D1	75%	D2	85%	D3	77.5%	D4	65%	D5	70%
E	E0	72.5%	E1	75%	E2	80%	E3	77.5%	E4	72.5%	E5	62.5%
F	F0	75%	F1	60%	F2	75%	F3	70%	F4	75%	F5	72.5%
G	G0	60%	G1	65%	G2	5%	G3	70%	G4	70%	G5	77.5%
H	H0	75%	H1	70%	H2	75%	H3	77.5%	H4	70%	H5	77.5%
I	I0	72.5%	I1	67.5%	I2	70%	I3	57.5%	I4	80%	I5	80%
J	J0	82.5%	J1	77.5%	J2	65%	J3	80%	J4	77.5%	J5	70%

FIGURE 4.51: The **finger** classification accuracy for the 60 targets positions while **walking** using ***Approach B2***. The three highest-scoring algorithms of each position from the cross-validation classify the finger using a majority voting system.

	0		1		2		3		4		5	
A	A0	80%	A1	67.5%	A2	57.5%	A3	52.5%	A4	57.5%	A5	55%
B	B0	62.5%	B1	67.5%	B2	67.5%	B3	65%	B4	60%	B5	70%
C	C0	87.5%	C1	60%	C2	52.5%	C3	67.5%	C4	60%	C5	65%
D	D0	70%	D1	52.5%	D2	57.5%	D3	47.5%	D4	62.5%	D5	77.5%
E	E0	72.5%	E1	60%	E2	60%	E3	57.5%	E4	52.5%	E5	65%
F	F0	62.5%	F1	62.5%	F2	67.5%	F3	45%	F4	57.5%	F5	57.5%
G	G0	65%	G1	57.5%	G2	52.5%	G3	52.5%	G4	72.5%	G5	62.5%
H	H0	62.5%	H1	67.5%	H2	52.5%	H3	67.5%	H4	67.5%	H5	70%
I	I0	65%	I1	47.5%	I2	62.5%	I3	57.5%	I4	77.5%	I5	77.5%
J	J0	82.5%	J1	60%	J2	47.5%	J3	60%	J4	72.5%	J5	72.5%

FIGURE 4.52: The **hand** classification accuracy for the 60 targets positions while **walking** using ***Approach B2***. The three highest-scoring algorithms of each position from the cross-validation classify the hand using a majority voting system.

The overall mean results of the two approaches are presented in Table 4.7.

TABLE 4.7: Mean classification accuracy for finger type and hand in % when using *Approach B1* and *Approach B2* on the verification data set provided by the second data collection, when sitting (S) and walking (W).

Mode	***Approach B1***	***Approach B2***
Finger (S)	82.2	82.5
Finger (W)	73.8	73.9
Hand (S)	58.6	62.5
Hand (W)	60.8	62.9

Table 4.7 indicates that the cross-validated models were rather stable under the conditions examined, as classification accuracy on the verification data set for both approaches differed only between 0–5%. I therefore decided to derive the accuracy of each approach from the mean accuracy of the cross-validation and the verification performance. Table 4.8 shows the results.

TABLE 4.8: Mean classification accuracy for finger type and hand in % when taking the mean performance from the cross-validation and verification, when sitting and walking (W).

Mode	**Mean *Approach B1***	**Mean *Approach B2***
Finger	83.1	82.3
Finger (W)	77.3	75.2
Hand	61.6	62.2
Hand (W)	62.3	61.9

Summary

Figures 4.41 to 4.52, pp. 193–204, have shown the varying accuracy of each algorithm to classify the user's finger and hand correctly for each of the 60 target positions in the sitting condition and walking condition. The figures, together with Table 4.3, showed that "finger" was classified correctly most frequently, whereas hand classification was not reliable. In the walking condition, classification accuracy was reduced for finger, whereas the already rather low accuracy rate for hand detection was not much affected and even showed a small increase. This suggests that the models use patterns in the data that are relatively distinctive for either hand, disregarding the change in magnitude caused by the user's and the device's motion, which seemed to have a much stronger impact on the distinction between index finger and thumb.

The varying accuracy of each algorithm in each target position showed that in order to improve classification accuracy, it is necessary to not use the same algorithm for each target position, but rather to decide which algorithm to employ depending on the target position. Using a tenfold cross-validation of the training data, algorithm accuracy for each target position and mode was established. Based on the results, two approaches for classifying data were presented:

Approach B1 used the highest-scoring algorithm determined by the cross-validation for each target position. This resulted in a predicted average accuracy of 84.1% (see Tab. 4.6) and an actual accuracy of 82.2% for finger detection while sitting using the verification data (see Tab. 4.7). This indicates that the model is relatively stable under the study conditions and thereby suggests the accuracy should be derived from the mean results of cross-validation and verification, which results in 83.1% for classifying finger type while sitting, and 77.3% while walking (Tab. 4.8). Average hand classification accuracy is 61.6% while sitting and 62.3% while walking, suggesting that detection of handedness is not possible with a single touch using this approach.

Approach B2 used the three highest-scoring algorithms per target position in a majority voting process determined by the cross-validation. The predicted average accuracy for finger detection while sitting was 82.1% (see Tab. 4.6) and 82.5% when using the verification data set (see Tab. 4.7). As with *Approach B1*, this indicates a reasonable degree of stability of the models under the study conditions, suggesting the model accuracy should be derived from the mean values of cross-validation and verification, resulting in an average classification accuracy for finger type of 82.3% when sitting and 75.2% when walking, and an average classification accuracy for hand classification of 62.2% and 61.9% when sitting and walking (Tab. 4.8). Similar to *Approach B1*, this suggests that hand detection is not possible with a single touch.

Both approaches showed reduced accuracy for finger and hand classification when walking. However, the decrease was less evident when using *Approach B2*. This suggests that this mixture of *K Nearest Neighbour* and decision tree algorithms per screen position is more stable than relying on a single algorithm per screen position. As new data may be likely to differ from the data provided by the training and validation set, it is suggestive to employ *Approach B2* in favour of *Approach B1*, as the former appears to be more flexible in handling fluctuations in the data, indicating it may have a higher degree of reliability in a real-world application.

To identify which properties are most influential for classifying finger and hand using the above techniques, *Weka*'s attribute selector using the *BestFirst* search method (*weka.attributeSelection.BestFirst -D 1 -N 5*) and the *CfsSubsetEval* evaluator (*weka.attributeSelection.CfsSubsetEval -P 1 -E 1*) were run on the data. Tables 4.9 and 4.10 show the results.

Table 4.9: *Weka*'s ranking of the most influential properties for finger classification.

Rank	**Finger, sitting**	**Finger, walking**
1	*Touch Size Mean*	*Touch Size Mean*
2	*Gyro Z Amplitude*	*Gyro Z Amplitude*
3	*Gyro All X Amplitude*	*Gyro All X Amplitude*
4	*Gyro All Y Amplitude*	*Gyro All Y Amplitude*
5	*Gyro All Z Amplitude*	*Gyro All Z Amplitude*
6		*Offset X*
7		*Offset Y*

Table 4.10: *Weka*'s ranking of the most influential properties for hand classification.

Rank	**Hand, sitting**	**Hand, walking**
1	*Number of Touches*	*Number of Touches*
2	*Touch Time*	*Touch Size*
3	*Gyro X Amplitude*	*Touch Time*
4	*Gyro Y Amplitude*	*Gyro Y Amplitude*
5	*Gyro All X Amplitude*	Offset X
6	Offset X	

4.4.3 *Approach C*: The Accuracy of Wang et al.'s Approach

The evaluation of *Approach A* and *Approach B* has shown that finger classification is possible with a reasonable degree of accuracy when using the data of only one touch and comparing it to a set of training data. However, the presented approaches were unsuitable to reliably detect handedness with a potential mean classification accuracy of 63.2% for the lookup table and a mean 62.2% for the machine-learning approach

(*Approach B2*) in the sitting condition. Therefore, it needs to be determined whether a different approach can yield better results.

Wang et al. (2009) present a technique to determine a user's handedness on tabletop surfaces. Here, the researchers measured the angle between the first touch point and the last touch point as well as the diameter of the touch shape to determine whether the user touched the surface with a finger of either the left or right hand. As indicated by the often angular orientation of the recorded physical touch shapes (Fig. 4.29), this approach seems to be rather promising. However, as the researchers only used tabletop surfaces for their study, it remains unclear whether the technique can also be applied to touchscreen smartphones, where the display is often held at a steep angle compared to the input finger and is frequently moved towards the pointing device to support input.

To investigate the accuracy of Wang et al.'s (2009) approach on a touchscreen smartphone, I implemented a simplified version into the evaluation of the data set recorded in section 4.2, p. 131. As a touch often consists of more than one touch point created during the landing and lifting process of the finger on the screen, it was determined that the very first touch be the origin of the touch against which all subsequent touch points were evaluated. For each touch point, the X coordinates of both points were evaluated. If the X coordinate of the current touch point was lower than that of the origin, the system registered the directional development as “Left”, and, if the X coordinate was greater than that of the origin, it registered as “Right”. When the coordinates were the same or if there was only one touch point, nothing was registered. The registered direction was then collected in an array and saved together with the other touch properties. As the touch developed between the *touchStart* and *touchEnd* event, multiple values were added to the array, each indicating a touch point's relative position to the origin, resulting in data structure in the exemplary form of “[Left, Left, Right, Left]” (Fig. 4.53). This particular array describes the development of a touch that had created four touch points following the first touch, where the first two touch points were to the left of the origin with the third being to its right and finally with a fourth touch point being positioned left of the origin again.

The resulting arrays of detected directions were then evaluated in three ways:

1. By frequency: Which word was most frequent in the list?

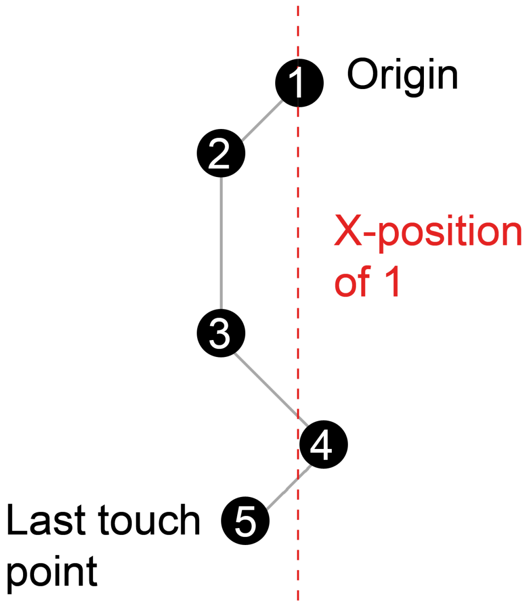

FIGURE 4.53: An enlarged exemplary visualisation of the touch points created during a touch (see Fig. 4.30 for actual size). The touch point created at the touch origin (1) is followed by two touch points to its left (2, 3), a touch point to its right (4), and a last touch point to its left (5). The resulting touch point development would be recorded as "[Left, Left, Right, Left]".

2. By relation of the first subsequent touch point to the origin: Was it to the left or right of the origin?

3. By relation of the last touch point to the origin: Was the last subsequent touch point to the left or right of the origin? This type of evaluation strongly resembles Wang et al.'s approach (2009).

Each result was then compared to the actual hand operating the device and a value of 1 registered for each correct classification.

Results and Evaluation

The evaluation showed the following results:

- For the detection by frequency, the overall classification accuracy was 39.1% in the sitting condition and 39.2% in the walking condition.

- For the classification based on the relation between origin and first subsequent touch point, the overall accuracy was 56.5% for the sitting condition and 54.6% for the walking condition.

- For the classification based on the relation between origin and last subsequent touch point, the overall accuracy was 68.8% for the sitting condition and 69% for the walking condition.

This indicates that evaluating the relation between first touch point and last touch point is the most accurate way of classifying a user's hand. Figure 4.54 presents the accuracy per target position and condition for this technique:

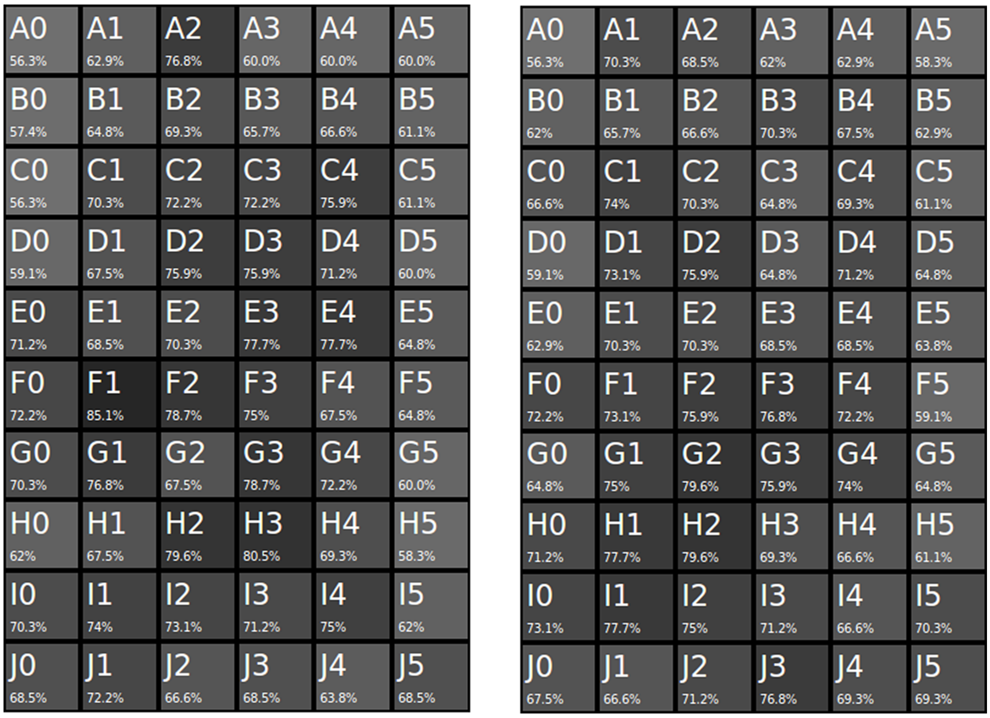

FIGURE 4.54: The classification accuracy for handedness using the difference between the first touch point and last touch point on the X-axis. **Left:** Sitting condition. **Right:** Walking condition. Numbers have been truncated to fit into the graphic. Mean accuracy for all target positions is 68.8% for the sitting condition and 69% for the walking condition.

Figure 4.54 shows that the most accurate classifications were registered for targets in the horizontal centre of the screen. This is likely due to the comparatively unusual landing of the thumb in columns 0 and 5 where the left thumb and right thumb respectively tended to touch the screen with their side (Fig. 4.29, p. 169). Figure 4.55 defines this more precisely by splitting the hand classification accuracy for each finger:

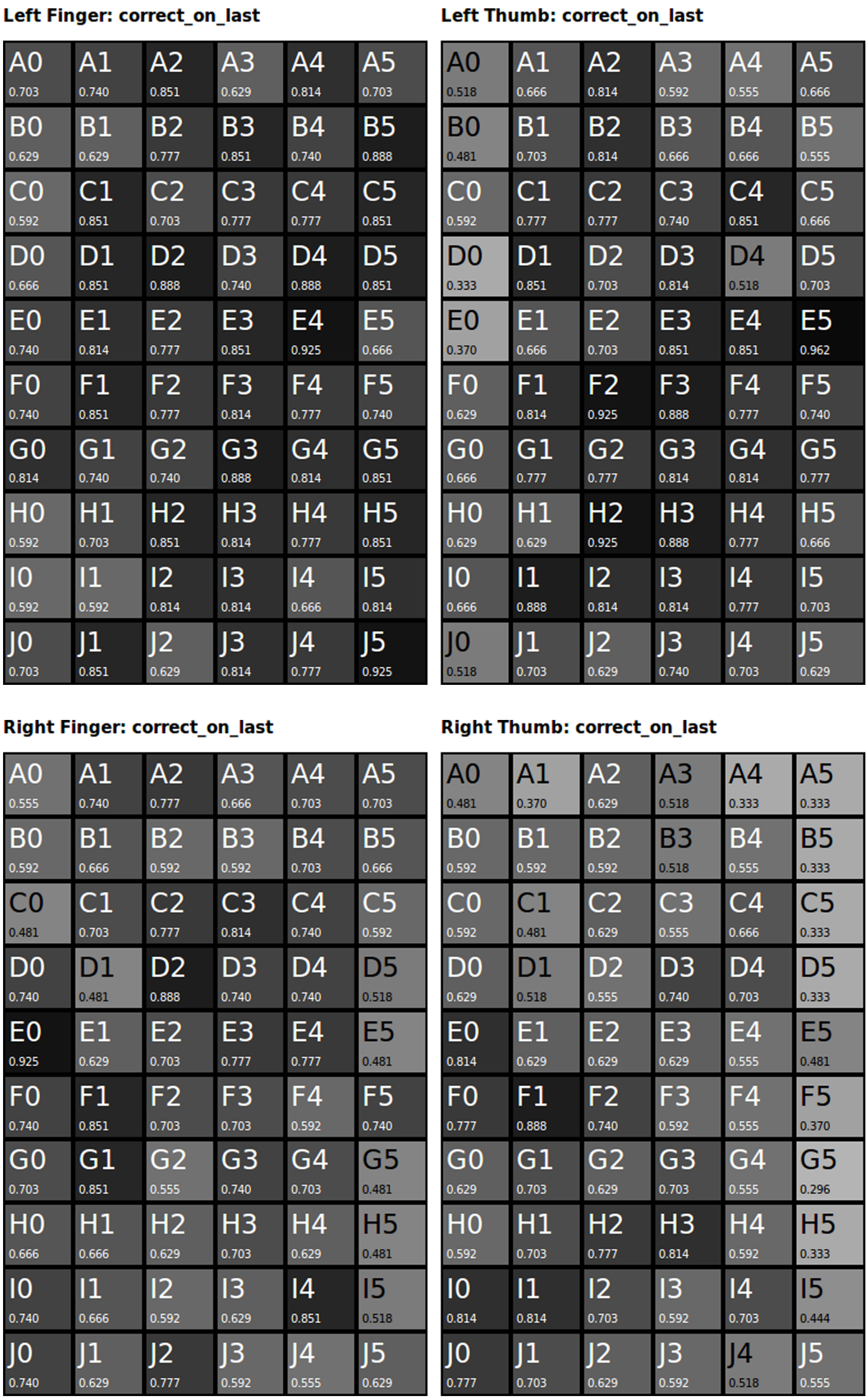

FIGURE 4.55: The classification accuracy for handedness using the difference between first touch point and last touch point on the X-axis for each finger in the **sitting** condition. Classification of handedness is most accurate for touches of the left index finger and is notably poor for targets in column 0 for the left thumb and for targets in column 5 for the right thumb, where the thumbs tend to land slightly sideways (Fig. 4.29).

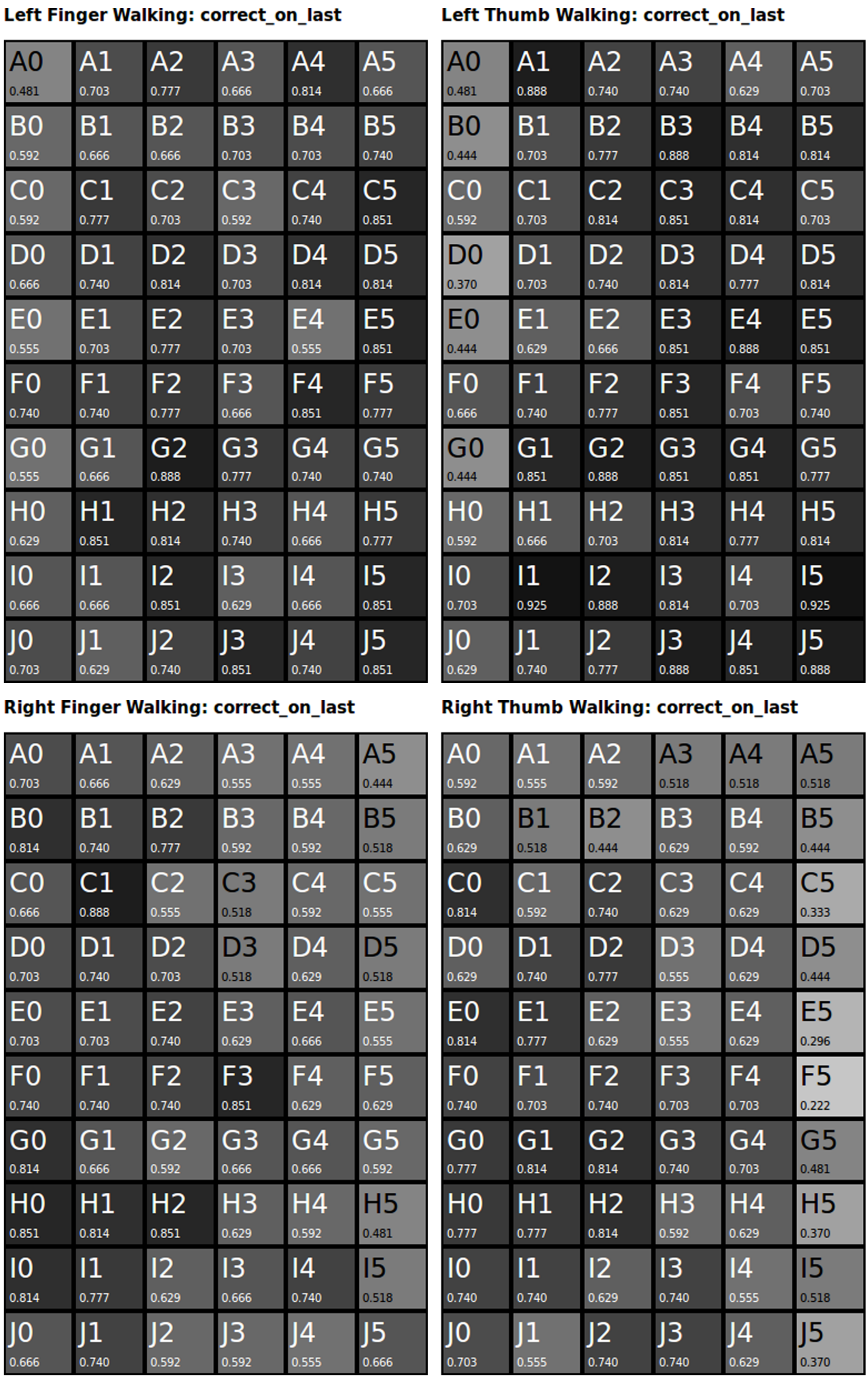

FIGURE 4.56: The classification accuracy for handedness using the difference between first touch point and last touch point on the X-axis for each finger in the **walking** condition. Classification is notably poor for targets in column 0 for the left thumb and for targets in column 5 for the right thumb, where the thumbs tend to land slightly sideways (Fig. 4.29). For both index finger and thumb, classification is most accurate on the opposite half of the display.

The splitting of the data showed that accuracy of hand classification using *Approach C* (section 3) differed not only for screen region but also for the finger used. Overall hand classification accuracy was highest for the left index finger and lowest for the right thumb (Tab. 4.11), which was probably due to the index finger's comparatively homogeneous landing process in most screen areas, caused by its greater freedom of movement. One trend in the data was that, especially in the walking condition, the classification accuracy was most accurate on the opposite half of the display for index finger and thumb. This is likely due to a stretching of the finger and a subsequent "drifting" of the last touch point towards the direction of input when retracting the finger from the far side of the screen.

TABLE 4.11: The overall hand classification accuracy in % for the left index finger (LF), left thumb (LT), right index finger (RF) and right thumb (RT) in the sitting (S) and walking (W) conditions.

Condition	**LF**	**LT**	**RF**	**RT**
S	77.1	71.5	67.5	59.0
W	72.3	74.8	66.0	62.5

Summary

This section has shown that an approach to classify the user's hand using the horizontal relation between first touch point and last touch point, similar to Wan et al.'s technique for tabletops (Wang et al., 2009), provided an overall accuracy of 68.8% in the sitting condition and 69% in the walking condition. The rather low degree of accuracy may be due to various factors: As opposed to Wang et al.'s use of a "flat" tabletop touchscreen mounted at 0° horizontally, the study presented here used a touchscreen smartphone, which was held at a steeper angle towards the input finger, resulting in a less oblique touch. In addition, the phone often seems to have been moved towards the input finger (Fig. 4.23, p. 159), further changing the touch shape and angle at which the finger had landed. Wang et al. point out that their technique only works for "oblique" touches where the user consciously presses the finger pad onto the screen, and that accuracy for non-oblique touches is greatly reduced. However, with the touch shape peculiarities of the thumb (Fig. 4.29), the changing context of use (Jones and Marsden, 2006; Fling, 2009) and its impact on user attention and precision (Schildbach and Rukzio, 2010), an oblique touch can not always be performed or might even be forgotten or rejected by the user of a smartphone for the fear of activating the wrong target by mistake (Siek et al., 2005). These issues therefore render Wang et al.'s approach unsuitable for the mobile environment and suggest further research to increase hand classification accuracy.

4.4.4 Discussion

This section has presented the collection of a second data set (section 4.4, p. 177) and its evaluation regarding the initial research questions using three approaches. First, a mean-based comparison which employed a set of lookup tables using either a single-value comparison for each property, or calculated the PCC of a property's value development against the respective averaged property arrays for each target position (*Approach A*). The second approach used five machine-learning algorithms per target position to evaluate the new data against the initial training set (*Approach B*), separated into two strategies (*Approach B1*, *Approach B2*). Thirdly, an approach similar to Wang et al.'s (2009) technique for finger orientation was used to analyse the original data collected in section 4.2, p. 131 (*Approach C*).

Approach A has shown that the accuracy of each property for finger and hand classification varies with target position, but that, overall, the most accurate properties appear to be *Gyro All Z Amplitude* for finger detection and *Touch Time* for hand detection. It has further shown that in the walking condition, the potential finger classification accuracy when using only the highest-scoring property in each target location was reduced by about 2.4–9.1%, depending on whether a single-value comparison or a PCC calculation was used. In contrast, hand classification was slightly improved by the walking condition with an average increase of about 1%. Altogether, *Approach A* suggests a reasonable degree of accuracy for finger classification, but proves unreliable for hand classification.

Approach B has illustrated that the five employed algorithms provided varying degrees of classification accuracy for each target position, but that the *RF12* algorithm proved most reliable in most cases. Due to the varying performance of the algorithms in different target positions, the approach was divided into two strategies: *Approach B1* and *Approach B2*. As with *Approach A*, the average finger classification accuracy in the walking condition was reduced by 6–7%, whereas hand classification accuracy was hardly affected (0.3–1.3%). In summary, *Approach B1* and *Approach B2* allowed finger classification with a good degree of accuracy overall, but were unreliable for hand classification, with

Approach B2 appearing to be more reliable for dealing with fluctuations in the data caused by movement.

Similar to *Approach A* and *Approach B*, *Approach C* has shown that classification accuracy varies with target position, but in contrast to the other approaches, *Approach C* only used a single property: The difference on the X-axis between the first and last touch point. Finger classification was not possible using *Approach C*, and hand classification was not reliable as its accuracy was only slightly higher than *Approach B*. Walking did not appear to affect the technique's accuracy.

The results of both *Approach A* and *Approach B* suggest breaking down the screen into multiple squares and applying different evaluation configurations for each screen area for better accuracy, with *Approach B* being between 2–3% more accurate overall when classifying a user's hand (depending on the strategy) and therefore the preferred approach of the two, consolidated by cross-validation and verification steps. The graphical evaluation allowed the derivation of trends in the accuracy of certain properties, which – to an extent – is likely to scale to other device sizes to support finger classification. For best accuracy, however, both approaches require the producer of a device to supply a set of training data for each screen area. In comparison to *Approach C*, both approaches were slightly less suitable for hand detection by 5–6% while sitting. Yet, with all approaches being less than 70% accurate in determining a user's hand, none can be deemed reliably suitable for the task through a single touch of the display.

In summary, despite the low degree of success for hand classification using the three approaches, finger classification using only a single touch seems possible with a good degree of accuracy.

4.5 Conclusion and Future Work

This chapter has analysed the characteristics of touchscreen operation using the left and right index fingers and thumbs while walking and sitting. It has shown how digital and physical properties change based on the user's finger, hand, the target position on screen and, in the case of digital properties, the amplification of trends observed in the sitting condition when walking.

In particular, the graphical evaluation has shown clear trends for various properties that help understand the implication of finger and hand on factors such as grip stability and device movement. Changes in the *Gyro All X Amplitude, Gyro All Y Amplitude* and *Gyro All Z Amplitude* properties (Fig. 4.23 to 4.28) especially emphasise screen areas which require the user to move the phone when interacting with them, even when operating the device with two hands. The movement patterns that develop in a line following the direction of the finger diagonally across the display (Fig. 4.57) illustrate how selection with the index finger is not a single-handed process, but rather a two-handed task where the hand holding the device supports the hand used for the pointing task by tilting the phone towards the finger for targets which require the user to stretch or contract their finger. This corresponds to Guiard's kinematic chain theory (Guiard, 1987), where one hand prepares and supports an interaction which is then finished by the other.

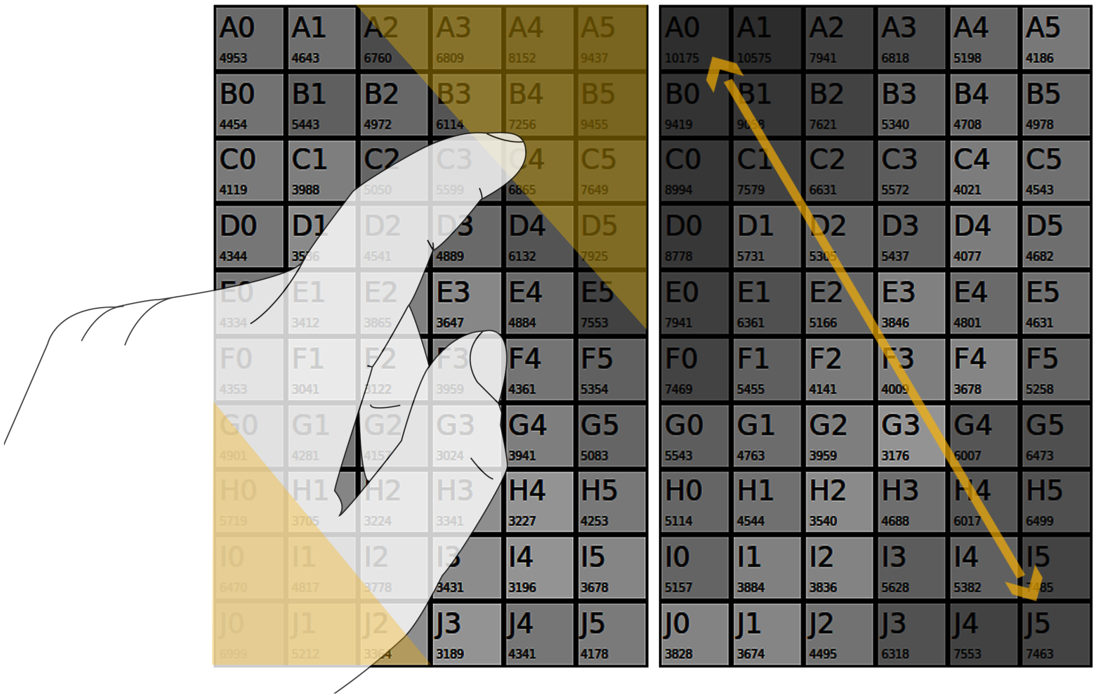

FIGURE 4.57: **Left:** For interactions with the left index finger, targets in the SW and NE corner of the display (yellow) have a high *Gyro Y Amplitude* value, indicating a tilting of the device towards the finger to support interaction in these regions. **Right:** The *Gyro Y Amplitude* values for interactions with the right index finger show a mirrored effect. Graphics were darkened for emphasis.

The concentric changes of the *Touch Size Mean* property for the thumb (Fig. 4.3) have illustrated its limited reach and precision, accompanied by a loss in dexterity in these areas expressed by an increase in *Touch Time*. This in turn has emphasised the middle of the screen as the optimum target area, as suggested by various researchers (Parhi et al., 2006; Park et al., 2008; Wang and Shih, 2009). In particular the low movement profile in the area of the thumb's natural swiping arc (Fig. 4.23 to 4.28) suggests a high grip stability when interacting with elements in these areas and thus supports the utilisation of a semicircular interface for improving one-handed smartphone operation in Chapter 5.

The above trends have highlighted the gyroscope amplitudes on all three axes together with the *Touch Time* and *Touch Size Mean* properties as the most influential ones for finger detection, which was largely confirmed by the results of the second data collection (section 4.4, p. 177) using the mean-based lookup table approach (*Approach A*), as well as by the results of the machine-learning evaluation (*Approach B*). However, it has to be noted that in *Approach A* the *Touch Size Mean* property seems to play a much smaller role than in *Approach B*.

A juxtaposition of the digital and physical touch properties (section 4.3.2, p. 168) has shown the effect of finger type, length, and physical touch shape on the *Touch Time* and *Touch Size Mean* properties as well as the gyroscope values, which further underlines the usefulness of these properties for finger classification. By illustrating the relation between physical and digital properties, this chapter extends the work of Wang and Ren (2009), who compare the physical width and length of the fingers to the contact size of these on a tabletop screen.

An evaluation of the physical touch shapes of index finger and thumb on 15 areas of the screen (Fig. 4.29, p. 169) has shown a touch "direction", especially for touches of the thumb, which could be linked to the temporal development of the touch history points (Fig. 4.31, p. 171). This in turn suggests that Wang et al.'s (2009) technique for the detection of handedness on tabletop surfaces based on the angle between the first touch point and the last touch point could be applied to touchscreen smartphones. However, despite a definite effect, the approach proved unreliable with an average accuracy of only 68.8% per target for the sitting condition and 69% for the walking condition, due to the unfulfillable prerequisite of users performing an oblique touch (Wang et al., 2009)

Finally, a comparison between *Approach A* and *Approach B* (section 4.4.4, p. 214) has evaluated the appropriateness of both techniques for answering the research question in this chapter with the following results:

4.5.1 Findings of the Research Goals

***G1*: Determining whether the digital touch properties of only one touch can be used to detect whether the index finger or thumb is being used for input.**

Section 4.4, p. 177, has shown that finger classification is possible with a potential average accuracy of 80.1% in the sitting condition and 71% in the walking condition when using *Approach A*.

Utilising *Approach B* suggests an average maximum of 83.1% classification accuracy for the sitting condition and 77.3% for the walking condition (if strategy *B1* is used), making *Approach B* the preferred classification method. While this degree of accuracy means that in the vast majority of cases the index finger and thumb can be classified correctly with only one touch, the accuracy is slightly too low to be considered fully reliable. It is therefore suggestive that system designers should utilise the results of two touches for a wholly reliable analysis.

***G2*: Determining whether the digital touch properties of only one touch can be used to determine whether the left or right hand is being used for input.**

The results in section 4.4, p. 177, indicate that hand classification on average is not sufficiently reliable with a potential mean accuracy of 63.2% for *Approach A* and a mean accuracy of 62.2% for *Approach B* in the sitting condition (using strategy *B2*), and a potential mean accuracy of 65.8% for *Approach A* and a mean accuracy of 61.9% for *Approach B* in the walking condition. This suggests at least three touches should be analysed before an assumption is made regarding the user's handedness. Therefore, it can be concluded that when using the methods employed, a single touch cannot be used to determine whether the left or right hand is being used for input.

***G3:* Defining which input property is the most accurate for making these predictions.**

The graphical evaluation and the results of *Approach A* have shown that average classification accuracy for finger as well as hand differs by condition. In the sitting condition, the most accurate property for finger classification was *Gyro All Z Amplitude* (77.5% potential average accuracy) whereas for hand classification it was *Touch Time* (55.3% potential average accuracy).

In the walking condition, the most accurate property for finger classification was *Gyro All Y Amplitude* (65.5% potential average accuracy) and for hand classification, it was *Number of Touches* (with a potential average accuracy of 59.6%).

Using *Approach B*, the most influential property for finger classification was *Touch Size Mean* in both sitting and walking conditions. For hand classification, the *Number of Touches* property was rated strongest in both conditions.

***G4*: Examining whether accuracy changes with target position – specifically, whether the data in certain areas of the screen is more characteristic for finger type or hand than in others.**

Classification accuracy does appear to change with property and target position: For *Approach A*, the potential finger classification accuracy differed greatly between target position and property and ranged from 32.5% to 92.5% in the sitting condition (Fig. 4.33, p. 180) and from 27.5% to 87.5% in the walking condition when considering all properties, not just the highest-scoring ones (Fig. 4.35, p. 182).

For hand classification using *Approach A*, the potential accuracy ranged from 30% to 80% in the sitting condition (Fig. 4.34, p. 181) and 27.5% to 75% in the walking condition (Fig. 4.36, p. 183) when considering all properties.

For *Approach B*, algorithm accuracy predicted by the cross-validation for finger classification ranged from 64.8% to 96.3% in the sitting condition (Fig. 4.41, p. 193) and from 57.4% to 92.5% in the walking condition (Fig. 4.43, p. 195). The hand classification accuracy in turn varied between 39.8% and 81.5% when sitting (Fig. 4.42, p. 194) and between 38.9% to 78.7% when walking (Fig. 4.44, p. 196).

This shows that classification accuracy varies for each property with target position and underlines the necessity for taking a grid-based approach which considers each property's and algorithm's accuracy in each area of the screen for an improved classification.

4.5.2 Answering Research Question 2

***RQ2*: Are the properties of a single "digitised" touch characteristic enough to distinguish between index finger and thumb of the left and right hand?**

With a mean accuracy of 62.2% for hand classification using *Approach B*, the properties of a single "digitised" touch are not characteristic enough for detecting the user's hand.

With a mean accuracy of 83.2% for finger classification using *Approach B*, the properties of a single "digitised" touch cannot be regarded as quite characteristic enough for detecting the user's finger reliably. Instead, a second touch may be required for a wholly accurate classification.

However, due to the varying performance of each property and algorithm per target location, the answer to this research question is as follows:

The properties of a single "digitised" touch are characteristic enough for finger and hand classification using a single touch, depending on where the user touches the screen and depending on which property and algorithm is used.

It is therefore suggestive to take a location-based approach to finger and hand classification: In screen areas where any touch property or algorithm has an accuracy greater or equal to 90%, single-touch classification can be considered reliable using that property or algorithm. For target areas with lower accuracy ratings, a decision should be made on two or three touches, allowing the system to strike a balance between prediction speed and reliability.

4.5.3 Comparison to Previous Work

The often clearly discernible patterns in the data across the display for fingers and hands have illustrated the rationale of Goel et al.'s approach to use touches in predefined areas of the screen to identify finger and hand. However, comparing the approaches discussed in this chapter to Goel et al.'s GripSense (2012) reveals advantages as well as disadvantages: The fact that finger classification is possible with a single touch – or two touches in low-confidence screen areas – anywhere on the screen is a great advancement over Goel et al.'s technique requiring a set of up to five interactions (tap and swipe) in predefined screen areas to make a decision. Here, *Approach B1* provided an average accuracy of 83.1% compared to Goel et al.'s 84.3% accuracy for finger classification, however, *Approach B1* has the great advantage of using up to only a fifth of the required interactions without spatial and procedural constraints, and therefore successfully addressed a major problem of Goel et al.'s approach. In contrast, GripSense allows the detection of handedness when the device is used with the thumb with an average accuracy of 85.4%, meaning it performs better than *Approach B2* which achieves 62.2%. Yet, *Approach B* allowed hand classification for touches with either index finger or thumb performed by both hands, whereas GripSense only allows this for thumb operation, making the results not exactly comparable. In addition, the accuracy of *Approach B* could be raised to a reliable level by making a decision after three touches, which may still provide an advantage over GripSense's five steps and its procedural constraints. Finally, the performance of GripSense has not been evaluated in a walking condition and as a result the overall performance of this technique in comparison to the approaches presented in this chapter cannot be evaluated completely.

Compared to Wang et al.'s (2009) technique for hand classification (*Approach C*), *Approach B* performed slightly worse with 62.2% accuracy in the sitting condition and 61.9% accuracy in the walking condition compared to Wang et al.'s 68.8% and 69% respectively. However, *Approach C*'s lower requirement of computational power – the gyroscope does not have to be continuously monitored – clearly makes it the preferred choice. But, as both *Approach B* and *Approach C* provide a rather low accuracy, neither of them can be used to detect handedness with one touch reliably and should be employed only with a minimum set of three touches.

The above evaluations and the data presented in section 4.4, p. 177, have shown that a software-based classification of input finger using a single touch is possible with a promising degree of accuracy, which therefore presents a possible advantage over the existing solution provided by GripSense. Yet, *Approach B*'s performance has yet to be evaluated in a real-world application in order to better compare it to GripSense. To use the approach to classify a user's finger in a given application on a given device, one could implement it as follows: By subdividing the surface of the device into a virtual grid of 9mm x 9mm-sized squares, training data must be collected for each grid unit and saved as done in section 4.2, p. 131. A device can then process new data in this way: When a touch occurs on the screen, its XY coordinate is matched to a position in the grid in whose dimensions and coordinates it fits. Once the corresponding grid unit has been determined, the incoming touch data is evaluated against the previously collected reference data for this unit. Here, it is important to understand that grid units do not have to be actual buttons. Rather, they are invisible, laid over the interface to serve

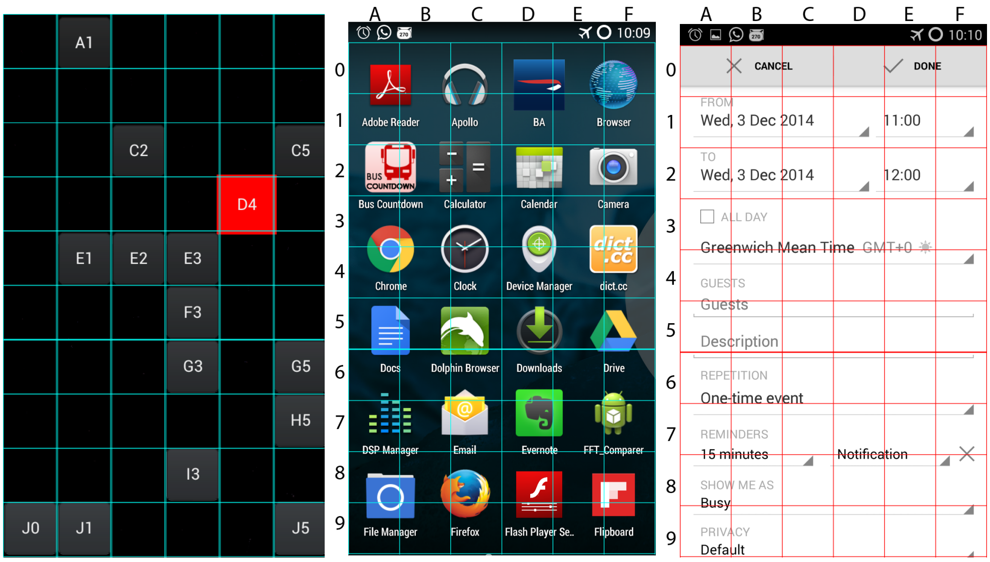

FIGURE 4.58: **Left:** The collection of the touch data for each of the 60 grid units. Buttons are located in each grid unit to facilitate collection. **Middle:** An invisible grid is laid over an application interface. Incoming touches are attributed to a grid unit and evaluated based on the previously collected data. **Right:** More complicated layouts could employ the technique, as hitting a unit off-centre is of little relevance due to the unimportance of the *X Offset* property for finger classification.

solely as points of reference from which to draw the comparison data and algorithm configuration (Fig. 4.58). Hitting a unit off-centre is of little relevance, as the offset property is not important for finger classification. Figure 4.58 illustrates this principle.

However, the presented techniques require a minimum of three touches to provide reliable hand detection. In contrast, hardware-supported detection mechanisms for handedness (see Chapter 2, section 2.8, p. 64) have provided high degrees of classification accuracy. It is therefore suggestive to employ the presented techniques not alone, but in tandem with a hardware solution. This way, sensors on the back or the side of a device can provide hand classification information, whereas finger detection is performed "as-you-tap" using *Approach B*. In addition, the low-accuracy hand classification provided by the software approach can support hand classification via the hardware and vice versa, for an even higher degree of accuracy for both finger and hand detection.

4.5.4 Future Work

Although the work in this chapter has shown promising potential for classifying a user's finger with a single touch of the display and thus represents a prerequisite for deploying a thumb-adapted interface, some pathways emerge for improving the classification accuracy and improving the scalability of its main contribution:

Increasing Classification Accuracy

In addition to the preconfigured property or algorithm "map" provided by *Approach A* and *Approach B*, accuracy could potentially be increased using per-user calibration. This could be achieved in a dedicated calibration application or over time by continuously evaluating new user data against the existing data points, even on a per-app basis. Future work will investigate the benefit of both strategies compared to the current "one-size-fits-all" approach to establish the degree by which these can improve finger and hand classification. If successful, classification accuracy may be particularly improved for users with "irregular" finger or hand dimensions or for those who purchase a device with a configuration created for a different market. Furthermore, it will be investigated how the reduction of accuracy for finger classification in the walking condition can be compensated with a set of filters to stabilise or normalise the values provided by the sensors.

Beyond the use of user-calibrated profiles, future work will examine a set of different algorithms to further improve classification accuracy. While the widely utilised standard algorithms employed in this study have shown a promising performance on a set of absolute values, algorithms used in other domains that utilise the temporal change of a set of values, such as gesture or speech recognition (Caramiaux et al., 2013; Selouani and O'Shaughnessy, 2003), might yield better results.

Scalability

The presented approach for finger detection is likely to be transferable to a wide range of smartphones following the procedure described in Figure 4.58. However, for better flexibility and our further understanding of touch, the definition of trends and patterns in the data relating to device size, device weight, orientation and target position present a very valuable field of study, especially as previous research shows that touch properties (for example the offset on the X and Y axes), even those of the same user, change with different devices (Buschek et al., 2013). Therefore, future work will consider developing a set of functions modelling the development of each property based on typical device characteristics. This could make the presented research more valuable for future developments as well as allow the transfer of the approach to different device sizes without their prior configuration.

Overall, the research and evaluations in this chapter have provided thorough insight into the digital and physical characteristics of touches of the index finger and thumb. This chapter's main contribution – the detection of the user's input finger using the information of only one touch – can easily be applied to support one-handed interaction using a thumb-optimised interface (when the thumb is detected). This way, the findings present a direct prerequisite for dynamically adapting the interface to support one-handed operation. Further, the analysis of the device movement profiles for thumb interaction (Fig. 4.23 to 4.28) shows that the grip is most stable when accessing targets in the region corresponding to the thumb's natural swiping arc and therefore suggests placing interactive elements in this area. As a result, the following chapter will provide an example of a thumb-optimised interface that employs these insights. Such an interface could be used as a dynamically adapted GUI in response to detection of the thumb on application start or during use.

Chapter 5

Improving One-Handed Interaction Through Interface Adaptation

5.1 Introduction

This chapter presents the design and development of a thumb-optimised interface that attempts to tackle all of the main issues of mobile touch interaction as defined in the literature review together by following the paradigm of GUI modification. It is largely successful in doing so, though it does not completely solve the issue of interface occlusion. See Seipp (2014) for a video demonstration of the interface.

The previous chapter examined the properties of digital touch and demonstrated that these can be used to differentiate between the index finger and thumb on a smartphone's screen. In addition, the research has revealed areas of the screen which can be reached with minimal device movement, suggesting that these should be preferred when placing interactive elements. If the strategy of interface modification is used to improve one-handed operation of touchscreen smartphones, classifying the user's finger upon the first touch can be seen as a prerequisite for modifying the interface to correspond to the characteristics of the finger operating it. With the insights gained from Chapter 3, it is suggestive to focus on comfort and ease when doing so, while attempting to achieve at least satisfactory efficiency. This chapter presents the design and evaluation of a thumb-optimised interface that intends to correspond to these requirements. Although requiring manual activation in its current state, the interface can be seen as an example of a dynamically adapted interface supporting users changing between one- and two-handed input, offering the "standard" interface for index finger input and an enhanced interface for one-handed thumb operation, addressing the identified challenges of this.

The World Wide Web (WWW) is an example of an environment where users may frequently change between one- and two-handed interaction due to a high content type diversity and layout adaptability to different screen sizes and orientations, changing between video control, text input and simple selection tasks, for example. The general increase of global mobile Web access (Fling, 2009) – which has grown by more than 50% in the UK alone between 2010 and 2013 (Office for National Statistics, 2013) – suggests directing attention towards improving operability for this environment on mobile devices. This may be especially important as the comparatively poor UX of some websites, as opposed to their app counterparts, has been named as a reason why apps are so successful (Anderson, 2010; Gassée, 2014). Research indicates that the majority of users prefer to operate their devices with the thumb (Karlson et al., 2006) and the survey evaluated in Chapter 3, section 3.3, p. 113, suggests that the WWW environment is part of this trend. In addition, Chapter 3 has shown that most touchscreen smartphones now house a powerful CPU, a large screen, large amounts of RAM (see Chapter 3, section 3.3.1, p. 113) and a browser capable of supporting the latest Web standards as well as hardware acceleration (Fig. 5.1).

Yet, an increase in the screen size of mobile phones makes a larger portion of the screen harder (Karlson et al., 2006) and less precise (Park and Han, 2010) to reach, by requiring the thumb to be stretched or contracted. Due to the fluent layouts of websites and the high diversity of elements, users can often be confronted with challenges arising from varying degrees of target size and distance from their thumb, steering a cursor in difficult positions, interface occlusion and the ability to only see a small portion of the site at a time. This is accentuated by the fact that one change of the scroll position can create a very different situation, bringing with it new challenges to the user. However, existing approaches to enhance mobile Web usability appear to focus on the presentation of information on small screens rather than on the operation of a website's diverse content with the thumb (see Chapter 2, section 2.2, p. 35). Therefore, with regards to the

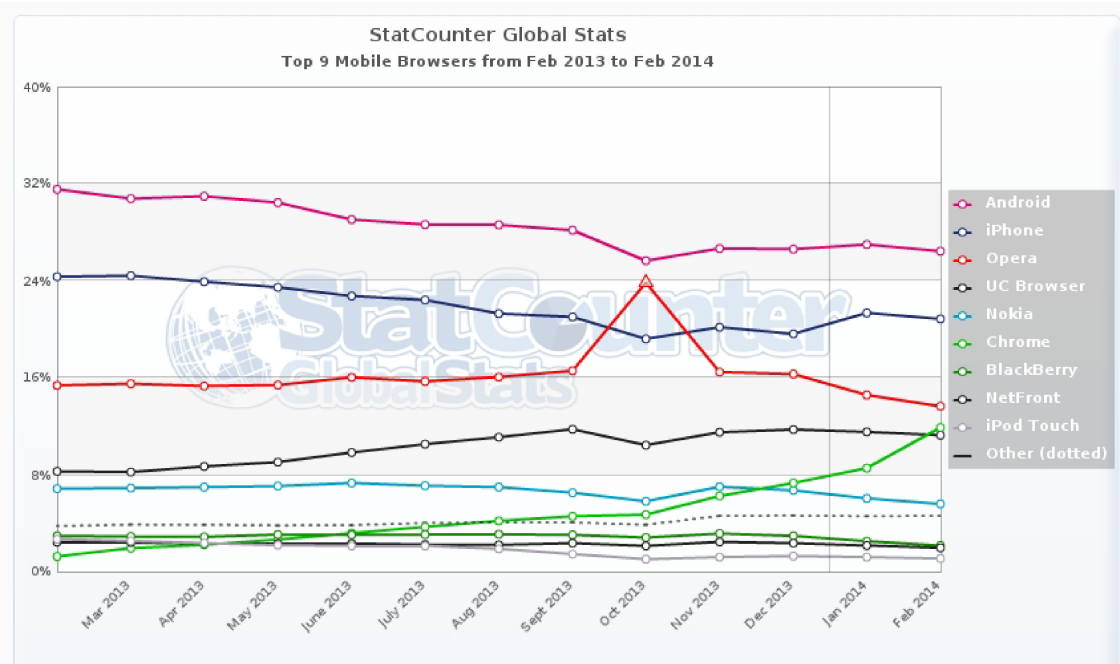

FIGURE 5.1: Mobile browser statistics from February 2013 to February 2014 provided by Statcounter.com (StatCounter, 2014). Webkit-based browsers (Android, iPhone, Chrome, UC Browser) dominate the market.

increase in mobile Web access, the diversity of interactive elements, and the insufficient adaptation to one-handed operation, the Web appears to be a worthwhile area in which to investigate the effectiveness of the paradigm of interface modification in addressing all of the most common challenges of one-handed smartphone operation in one combined approach.

5.2 Requirements

Based on the results of the user survey in Chapter 3, section 3.3, comfort, the support of naturalness and ease of use seem to be important factors to consider in order to enhance one-handed operation of touchscreen smartphones. In addition to these, information and interactive elements ought to be presented in a way that does not make two-handed input appear a better choice of operation in order to avoid frustration (Karlson et al., 2006).

To support mobile Web browsing in particular, Shrestha (2007) recommends using a Web interface "which should support easy and flexible control". The W3C suggest to "provide a consistent navigation mechanism" (W3C, 2008) and Jones and Marsden (2006) name "focused, direct access" to information a key feature of a successful Web interface, where the interactive elements are ideally located at the thumb's tip, as Wang and Shih (2009) suggest. In addition, the following properties are suggested for thumb-optimised design:

- A curved arrangement of elements, following the natural swipe arch of the thumb (Katre, 2010).
- The reduction or avoidance of occlusion (Roudaut, 2009).
- The minimisation of thumb movements in the north-west and south-east direction for right-handed users and vice versa for left-handed users (Karlson et al., 2006).
- Horizontally widened GUI elements to match the wider contact shape of the thumb (Katre, 2010).
- Larger interactive elements to cope with the imprecision of the thumb (Park and Han, 2010).
- The support of "horizontal motion whenever possible" (Wobbrock et al., 2008).

Furthermore, a successful approach should address the shortcomings of previous work, as elaborated in Chapter 2, section 2.2, p. 35, and be possible within the technical and social constraints established in Chapter 3, section 3.3, p. 113. Therefore, the approach should:

- Not need a special browser or require an installation or modification effort by the user.
- Use standard Web technologies.
- Preserve the intended presentation and the page structure.
- Not only adapt to display size, but also to mode of operation.
- Be optional and be activated or deactivated easily.
- Be easy to implement by novice developers and be compatible with popular Web publishing platforms.
- Not require configuration by the user.

- Be responsive to changes of device orientation and mode of operation.

When aiming to provide an approach for improving one-handed operation of websites on touchscreen smartphones, it needs to be accepted and embraced by webmasters as well as users. For this, two informal interviews with Web developers were conducted, in order to ascertain which aspects are important. Their feedback indicated that the approach:

- Needs to be unobtrusive.
- Should be operable by both left-handed and right-handed users.
- Should not collide with existing features and should inherit functionality from existing elements.
- Should not collide with any JavaScript frameworks used on a website.
- Must be freely configurable.
- Must be easy to implement and the design and functionality of the website must stay intact.
- Should have a small file size.
- Should work on all smartphones with a large screen.

The transcripts of the interviews can be found in Appendix E, section E.1, p. 357.

Taking into account the above, I chose a wheel menu as the main part of the interface, as Francone et al. (2010) demonstrate that such an interface is easy to understand and operate. By locating the interface in the bottom left or right corner (depending on handedness), the visible quarter section of the wheel corresponds to Katre's proposed circular arrangement of GUI elements (Katre, 2010), where all interactions can be performed within the thumb's comfort zone, without having to stretch or contract the thumb frequently. In addition, users are provided with a central point of reference in which interactive objects are placed in the same location, which is suggested as good practice by Kolko (2011) and which means that occlusion is reduced. Taking this design as the foundation of a thumb-optimised interface, the following research question can be formulated:

***RQ3*:** Can an approach following the strategy of interface modification successfully address the main challenges of one-handed smartphone operation (as defined in Chapter 2, p. 41) together, using only a single interface?

To answer this question, it is necessary to explore a set of research goals to gain deeper insight into the potential of the curved interface and its suitability for addressing the main challenges of one-handed smartphone operation in the context of this thesis. As a result, the research in this chapter pursues the following set of goals:

- ***G1*:** Confirming that a curved interface is a suitable basis for exploring the potential of the strategy of interface modification to address the main challenges of one-handed smartphone interaction.
- ***G2*:** Examining whether the enhancements made by such an interface can be implemented using client-side technologies at runtime, allowing the user to freely move between one- and two-handed interaction.
- ***G3*:** Determining whether the wheel menu design and the reduction of all interactions (excluding text input) to a set of swipe and tap actions, which are administered through the interface in a dedicated area of the screen, is an effective approach for controlling the diverse elements of a website.

As a result and to inform the answer to *RQ3*, the remainder of this chapter presents the design and evaluation of an interface, which I have termed the *One Hand Wonder* (*OHW*). In particular, the development, implementation, effectiveness in comparison to non-enhanced one-handed operation and general system performance will be reported. This part of the chapter has been published in two conference proceedings (Seipp and Devlin, 2013*a*, 2014*c*) and a book of selected papers (Seipp and Devlin, to appear). While this chapter builds on these papers, the content that has been published earlier has been rewritten and significant amounts of information have been added. Most figures have been taken from Seipp and Devlin (2014*c*) and, where applicable, this is acknowledged in each figure's caption. The permission to include these figures has been granted by the WEBIST secretariat and can be found in Appendix E, section E.3, p. 360.

Following this, a discussion regarding the approach's effectiveness in answering the research question will be presented. The chapter concludes with the identification of possible improvements and directions for future research.

5.3 Development

To validate Katre's suggestion that a curved interface will match the natural swipe arch of the thumb (Katre, 2010), a user study was conducted with seven users (3 F, mean age 31.43 years, SD 4.65), all of whom were regular users of mobile devices with touchscreens. All users were right-handed and tasks were performed using a HTC sensation XE running Android 4.03 with a custom application which recorded the touch and swipe gestures for each user.

Users were instructed to take their eyes off the screen and look at a wall while moving their thumb ten times from right to left and back over the screen while touching it, focussing on letting the thumb move naturally and with minimum effort. Users were asked to do this once with their right hand and once with their left hand. No visual feedback was given, but swipe coordinates were recorded in the background.

The visualisation of the data showed that when asked to move their thumb from right to left and back naturally, without effort, the users' thumbs indeed described a curve (Fig. 5.2) – a shape expected when considering the movement range of the carpometacarpal (CMC) and metacarpophalangeal (MP) joints. The visualisation of the swipe data corresponds to observations made by Hürst and Merkle (2008), who report that users deem this type of movement to be "intuitive and natural", as well as to the findings of Otten et al. (2013), who report similar shapes for areas which are easy to reach by the thumb on a smartphone screen. This is further supported by the findings of Chapter 4, which indicate that the device movement is comparatively low for targets placed on the thumb's natural swiping arc (Fig. 4.23 to 4.28, pp. 159–164), providing a high degree of grip stability. The data therefore supports the decision for a curved arrangement of elements using a wheel menu design as a basis for a comfortable interface for one-handed operation. This form of interface also minimises the need to stretch the thumb, allowing a reduction of necessary movements to just two: A sideways swipe and a simple tap. With this in mind a series of paper prototypes was developed and iteratively tested with users. From these the design of the interface was derived (Fig. 5.3).

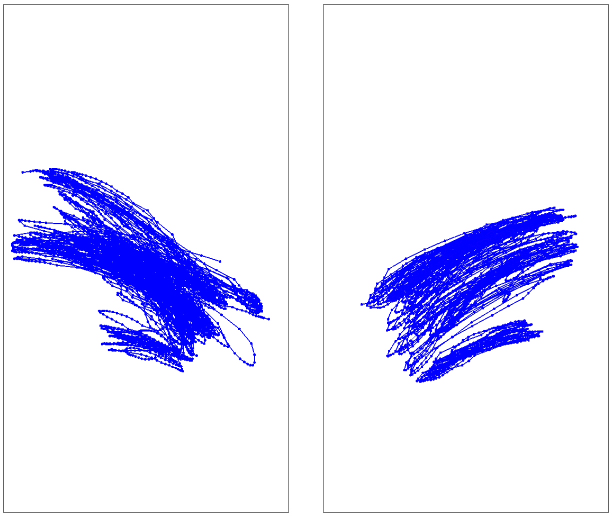

FIGURE 5.2: Visualisation of the movement data. **Left:** The sideways thumb movement of the left hand. **Right:** The sideways thumb movement of the right hand. Right image taken from Seipp and Devlin (2014*c*) with permission from WEBIST.

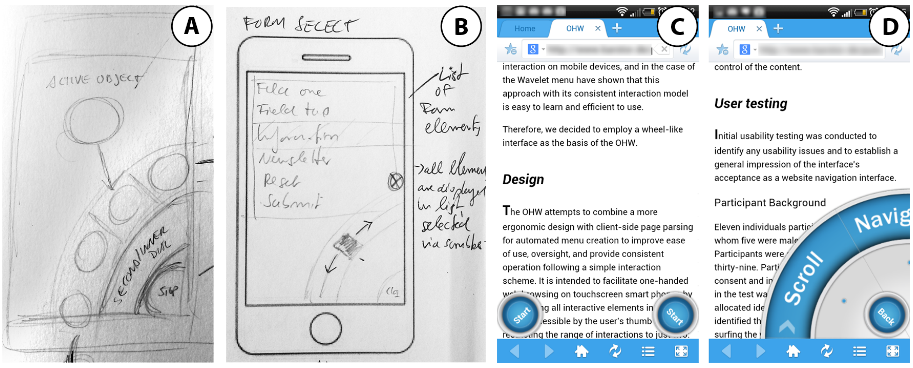

FIGURE 5.3: **A:** An early sketch of the interface. **B:** An annotated paper prototype. **C:** The final interface at start-up. **D:** The final interface launched. Images C and D taken from Seipp and Devlin (2014*c*) with permission from WEBIST.

5.4 Functionality

The interface consists of three main parts:

- A *display zone* (Fig. 5.4, red) showing menu content or the currently active element, such as a video or a form element. When in scrolling mode or when selecting an item from the wheel menu, this zone displays the Web page.
- An *interaction zone* (Fig. 5.4, green) on which the user swipes and taps to manipulate items in the *display zone*. Confirmation actions are triggered by tapping

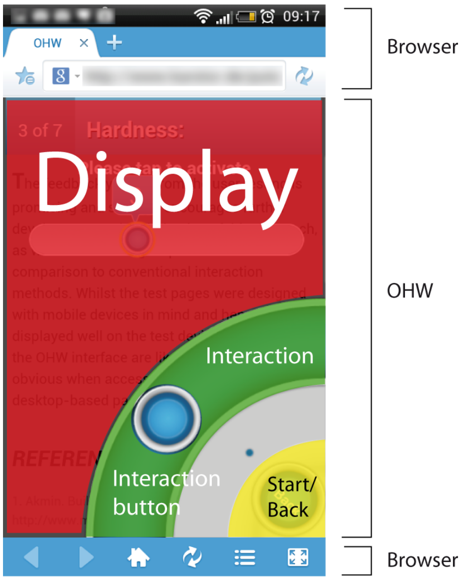

FIGURE 5.4: The three zones of the *OHW* interface. Colours were superimposed for easier differentiation by the reader. **Red:** The *display zone*. **Green:** The *interaction zone*. **Yellow:** The *Start/Back* button. As the *OHW* is part of the Web page it enhances, the browser elements (URL bar and navigation buttons) surround the interface at the top and bottom of the screen.

the round *interaction button* in the *interaction zone* which represents properties of elements in the *display zone*, such as scroll or playback position.

- A *highlight zone* at the top of the *display zone* in List views, made visible by a blue border and highlighting the currently selected item (Fig. 5.7).
- A *Start/Back* button (Fig. 5.4, yellow) which is used for navigating backwards through different states of the interface and for showing and hiding the wheel menu.

Once the page has loaded the user can activate the interface by tapping the *Start* button on either side of the screen – depending on their handedness (Fig. 5.3, C). The interface is launched and moves up into the visible area of the screen (Fig. 5.5). Swiping over the interface rotates the wheel and provides access to content and functionality by tapping the respective wedge (Fig. 5.3, D; Fig. 5.5). Once the interface has been launched, the *Start* button is replaced by a *Back* button, which can either be used to hide the interface or to navigate one level backwards when inside a submenu of the *OHW*. No changes to the design of the website are made and branding and layout stay intact. Only the operation of the website is altered when the user decides to use the interface.

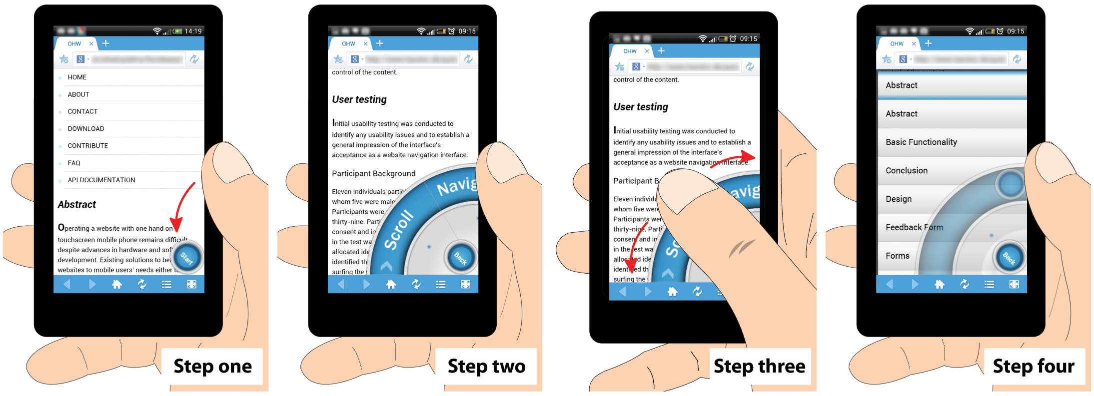

FIGURE 5.5: Typical interaction sequence of the *OHW*: **Step one:** The user wants to operate the website with one hand and chooses to launch the interface by pressing the *Start* button. **Step two:** The interface starts up with the wheel menu. **Step three:** The user spins the wheel menu to select an option. **Step four:** The user has opened the *Headlines* menu and can choose to select a headline to jump to by swiping over the interface as in step three. To jump to the headline currently in the blue *highlight zone* (Abstract), the user taps the interface on the *interaction button* without the need to stretch the thumb to reach the target. To return to the wheel menu, they hit the *Back* button. For a video demonstration of the interface, see Seipp (2014).

To accommodate changing input modes, such as the switch from one-handed to two-handed operation, the *OHW* can be toggled on or off at any time. For example: The user is holding an item in one hand while operating the phone with the other and so decides to press the *Start* button and operate the website via the *OHW* interface (Fig. 5.6). Then the user puts the object in their other hand down and so has both hands available for interaction and decides to hide the interface and use the website normally (Fig. 5.6). In addition to switching the enhancement on and off via the *Start/Back* button, the *OHW* offers users the option of directly launching the interface for any interactive object on the page by double-tapping the respective element. Finally, the *OHW* can be used in either orientation, portrait or landscape (Fig. 5.6), to accommodate changes in a device's orientation.

5.4.1 Views

The *OHW* attempts to combine a thumb-friendly design with client-side page parsing for automated menu creation to improve ease of use, oversight, and to provide consistent operation following a simple interaction scheme. In its standard configuration, the *OHW* offers a variety of views which are used to either show the content of a menu belonging to a wedge in the wheel or to show and operate an interactive element, such as a video

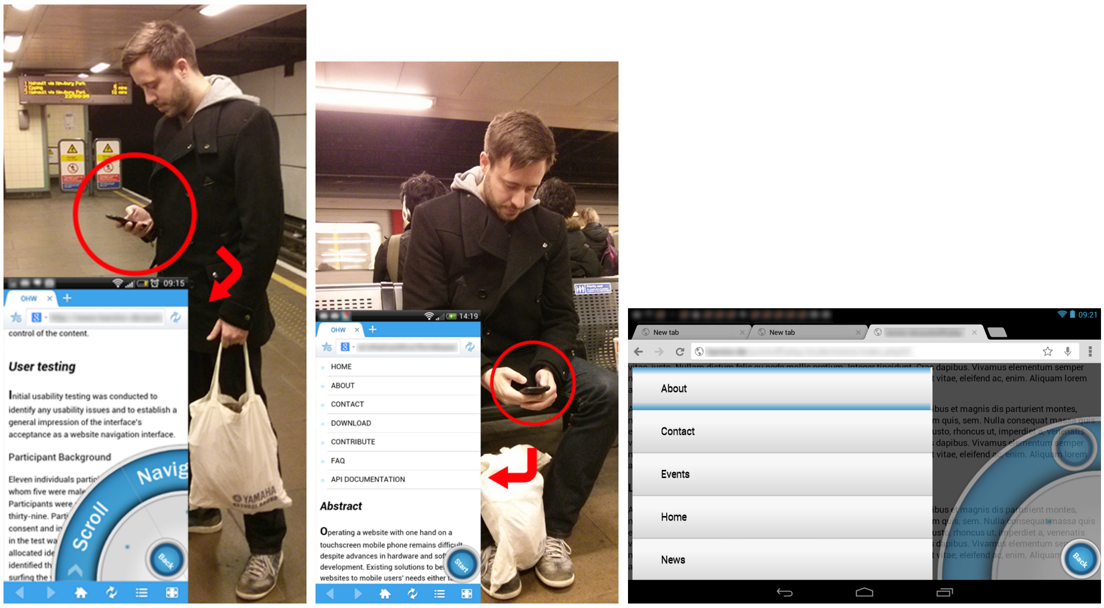

FIGURE 5.6: **Left:** With only one hand available for input, the user operates the website via the *OHW* interface. **Middle:** After freeing the other hand, the user hides the *OHW* interface and operates the website normally. **Right:** The *OHW* can also be used in horizontal orientation for either one- or two-handed input on tablets, as all elements are optionally accessible via direct tap. Right image taken from Seipp and Devlin (2014*c*) with permission from WEBIST.

or a checkbox, via the interface. When the interface is launched, swiping and tapping actions in the *interaction zone* are used to manipulate the views in the *display zone*. A variety of views are employed by default to visualise different element types, but can be altered and combined by the webmaster to extend the *OHW*'s functionality. These include the following:

List View

This is employed whenever items are presented in a list and can hold text or images with text, depending on the content (Fig. 5.7). It is used for the *Headlines*, *Navigation*, *Links* and *Media* menus, as well as drop-down lists. By sliding their thumb over the *interaction zone*, the user can move the list content up or down. The circular button inside the *interaction zone* indicates the scroll position and confirms the selection within the blue *highlight zone* at the top of the screen upon tapping. Tapping on the *interaction zone* (but not on the *interaction button*) will scroll the list view to the respective position, a function that was added after the first usability study (section 5.6, p. 241).

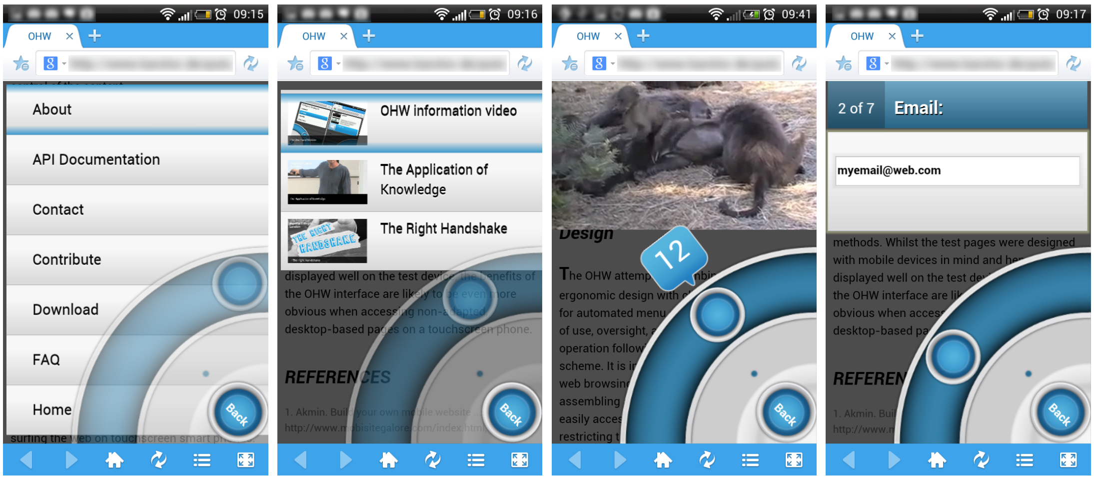

FIGURE 5.7: **Far left:** The standard list view. The blue *highlight zone* at the top of the screen indicates the currently selected element. **Left:** The list view with images. **Right:** The media player view. **Far right:** A text input field in the form view. All images but image "Right" taken from Seipp and Devlin (2014*c*) with permission from WEBIST.

Media Player

If a media element is double-tapped directly or selected via a list view, it is played back in the media player. Swiping over the *interaction zone* controls the playback position (Fig. 5.7, right) of the media item which is shown in an element above the *interaction button*, indicating the playback progress.

Form View

All elements of a form are analysed and displayed in a horizontal arrangement which the user can navigate between using the semicircular scroll pane in the *interaction zone*. By swiping the thumb over the *interaction zone*, the form elements scroll into view from right to left or vice versa. Each element consists of a counter to express the current position within the view, a description, and a content field to hold any input (Fig. 5.7, far right).

Text Input

For text input (Fig. 5.8), the basic OS interface is used. The first prototype used a dedicated concentric keyboard within the OHW interface, built in JavaScript and CSS,

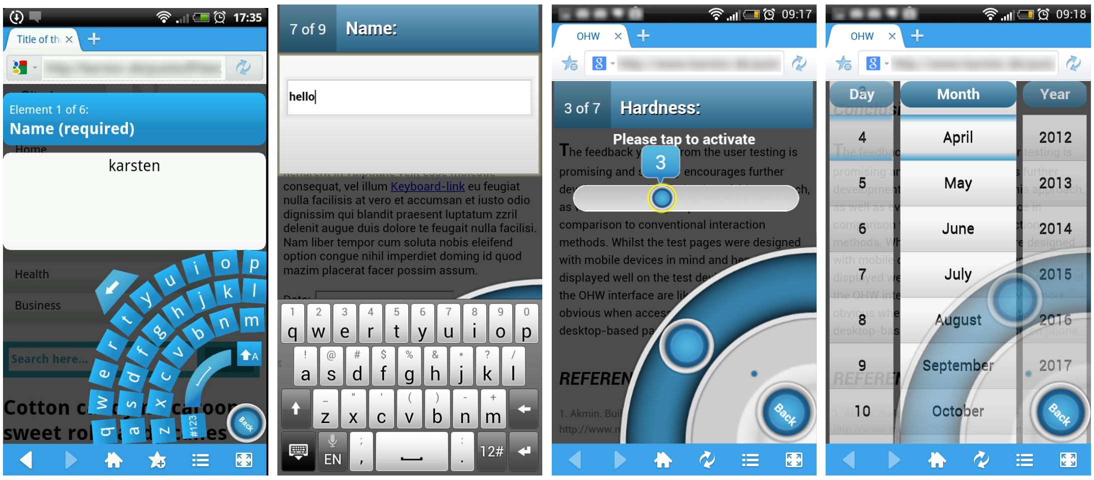

FIGURE 5.8: **Far left:** Text input via the deprecated concentric *OHW* keyboard. **Left:** Text input using the system standard keyboard. **Right:** The slider input view. **Far right:** The date input view. Right and far right image taken from Seipp and Devlin (2014*c*) with permission from WEBIST.

but user testing showed that this approach under-performs in comparison to existing solutions and that users prefer the standard keyboard.

Slider

An input field of the type *range* (a field where users can enter a number within a certain range) is represented by a slider consisting of a background, a slider-head, and a text field expressing the position of the slider as a numeric value (Fig. 5.8, right). Swiping in the *interaction zone* moves the slider head in the *display zone*.

Date Selector

Activating an element of the type *datetime* (a field where users can enter a date) will transform the content area in the form element overview into three lists: Day, month and year (Fig. 5.8). Swiping over the *interaction zone* will jump between the three lists. A tap activates the highlighted list which can then be scrolled by swiping again. A tap on the round *interaction button* sets the value and activates the next list.

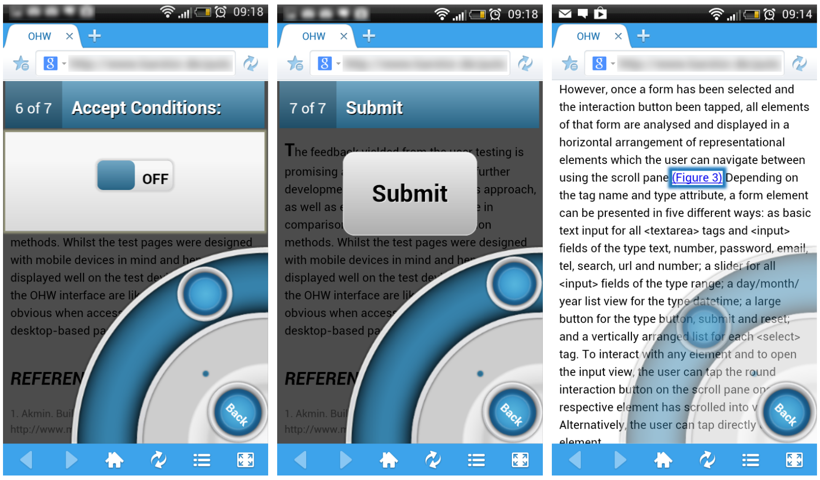

FIGURE 5.9: **Left:** The checkbox and radio button view. **Middle:** The button view. **Right:** The scroll view. All images taken from Seipp and Devlin (2014*c*) with permission from WEBIST.

On/Off Switches

Checkboxes and radio buttons (Fig. 5.9) are displayed as on/off switches that can be operated by tapping on the *interaction button* in the *interaction zone*. Groupings are supported.

Buttons

Buttons are represented by large buttons operated via the *interaction zone* or with a direct tap, as requested by users in the usability study (section 5.6, p. 241).

5.4.2 Scrolling

The *OHW* also provides scroll functionality similar to that found in the Opera Mini browser (ASA, 2012*a*). Tapping the *Scroll* wedge allows the user to scroll the page by swiping their thumb over the *interaction zone*. While scrolling, interactive elements closest to the current scroll position are outlined one at a time (Fig. 5.9, right) and can be activated by tapping the interface's *interaction button*.

For a video demonstration of the interface, see Seipp (2014).

5.5 Implementation

The approach consists of several JavaScript modules with application logic and display templates, a configuration file consisting of JavaScript objects (Fig. 5.10), a CSS file for object styling and transition properties, and a set of graphics for the wedges in the wheel as well as the *interaction button*. PNG graphics were chosen over a more flexible Scalable Vector Graphics (SVG) implementation due to varying browser support. To facilitate cross-browser compatibility and implementation by webmasters, most script modules were developed using jQuery, a popular JavaScript library (Pingdom, 2010). All calls to the jQuery library explicitly address the jQuery namespace, allowing simultaneous implementation alongside other poplar libraries, such as MooTools. To improve the speed of the interface, 3D CSS translations and transitions were applied to all elements, which showed to be significantly faster than updating the display by manipulating the margin or position properties of elements.

To implement the *OHW* into a website, the webmaster must link to the main JavaScript file and CSS in the <head> element of their website. In addition, the jQuery JavaScript library must be available. Once the page has loaded, the main application file parses the DOM for a set of elements and initialises the respective modules necessary for their control, assembling all corresponding wedges into a wheel interface. The default element selectors, for which the page is searched, are the anchors in the <nav> tag for the content of the *Navigation* menu and the poster attribute and <source> tags belonging to the <video> tag as well as the <source> tags of the <audio> tag to build the *Media* menu. The <h1>, <h2> and <h3> tags inform the content of the *Headlines* menu, all <a> tags apart from those found in <nav>, <aside> and <footer> provide the content of the *Links* menu, and all <form> tags build the content of the *Forms* menu. The *Scroll* wedge is available in any case. Altogether, the *OHW* uses six wedges by default to construct the wheel menu: *Scroll*, *Navigation*, *Headlines*, *Forms*, *Media*, *Links*.

The webmaster can adapt this standard configuration by editing a JavaScript file to extend or restrict the scope of each module and to customise the wedge names and their functionality (Fig. 5.10). A module consists of the following properties:

- *name*: The internal name of the wedge.

```
Navigation :
{
    name: 'Nav',
    id: 'ohw_bt_nav',
    source: OHW_resourcePrefix + 'img/wheel_navi_'+ OHW_theme +'.png',
    alt: 'Navigation',
    cssClass: 'OHWwedge',
    rotFactor:60,
    view: 'ListView',
    selector: 'nav a, #navigation a',
    selectorParts: {link:'self'},
    onTap: OHW_tapNav,
    swipeModes: ["isScrubber", "isList", "isLinks"],
    modeToAdd:'',
    cache:true,
    cacheContent:''
},
```

FIGURE 5.10: An example configuration of the *Navigation* wedge which is to show the content of the page navigation in the *OHW*.

- *id*: The ID of the wedge in the DOM for control via JavaScript.
- *source*: The graphic to be used for the wedge.
- *alt*: Alt text for the wedge graphic.
- *CSSClass*: CSS class to be used for the wedge styling.
- *rotFactor*: Standard rotation of the wedge.
- *view*: View to be used upon tapping the wedge. See section 5.4.1, p. 234.
- *selector*: CSS selectors of content to appear in the view.
- *selectorParts*: Optional description of selectors for extracting information of possible children.
- *onTap*: Function to be used when an element in the view is interacted with. The *OHW* offers a range of predefined functions, but these can be edited and swapped for custom functions.
- *swipeModes*: Global modes to activate for signalling the interface state to the controller.
- *modesToAdd*: Optional modes to add for customised controls.
- *cache*: Whether or not the generated view should be cached for faster display.
- *cacheContent*: The cached HTML.

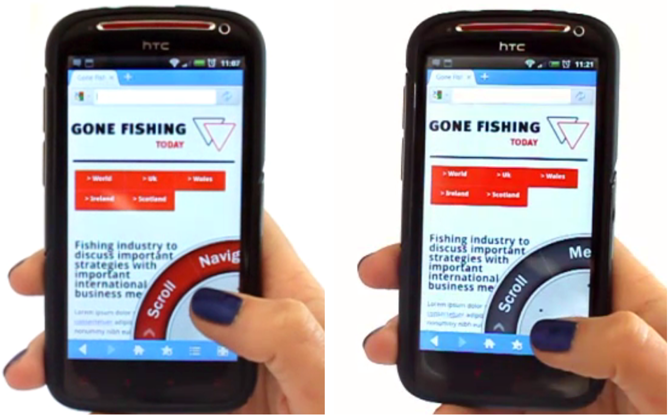

FIGURE 5.11: **Left:** The red theme of the *OHW*. **Right:** The black theme of the *OHW*. All aspects of the interface can be customised via CSS.

While all of the above can be edited for extensive customisation, changing the value of *selector* and optionally *source* is enough to configure the *OHW* according to the content of a page and should suffice in most cases when implementing it.

Depending on the configuration and the elements found on the page, the wheel menu is constructed and events are bound to interactive elements, such as form elements and media elements, to allow their operation through the interface. Existing jQuery behaviours are retained and will either be triggered through interaction with the *OHW* or directly, without the interface. To adjust the look, two colour themes (Fig. 5.11) are provided in addition to the standard blue theme and can be activated in the configuration file. Through editing the CSS, the look can further be adapted to blend in with the visual style of the page.

The *OHW* can work with websites using HTML4 Transitional or Strict Doctypes as well as HTML5 Doctypes and can optionally detect incorrect mark-up by reporting unusual content lengths for the tags supported by default. This can be adjusted in the configuration file. The *OHW* source code can be found in Appendix E, section E.2, p. 358.

5.6 Study One – Usability

Initial usability testing was conducted to identify any usability problems and to establish a general impression of the interface's acceptance as a website navigation interface.

5.6.1 Participant Background

There were 11 participants in the test (6 F), aged between 26 and 39 years. Participants gave their consent and their test data was stored under a randomly allocated identifier. The majority of participants identified themselves as well-experienced in surfing the Web on touchscreen smartphones. Overall, users judged their experience as: Extensive (two), good (six), basic (two) and very limited (one). About 45% stated they regularly use non-touch smartphones such as the Blackberry Bold 9000, Blackberry Curve 8900 and Nokia E35 whereas the rest stated that they regularly use touchscreen smartphones such as the Samsung Galaxy S, HTC Desire and Apple iPhone. One participant stated that they regularly use both types and another stated they surf the Web with an iPod touch.

5.6.2 Testing Procedure

For the test, each participant used a HTC Sensation XE mobile phone running Maxthon Mobile Browser version 2.4.5 on Android 2.3.4. The standard zoom setting of the browser was set to “far”. Each participant watched a ten-minute video tutorial followed by a five-minute self-directed exploration of the interface on a very basic website, to better understand its mode of operation. Following this, a think-aloud protocol was undertaken with users given a task sheet with a variety of tasks to perform on two different websites. The tasks comprised: Finding a certain video; finding a link; finding a form; entering data into various form fields; navigating to a second page; and finding sections of information on both pages. Both of the test pages were enhanced by the *OHW* interface but used a different theme (blue for the first website, red for the second). The self-directed exploration of the interface was performed by all but one participant who preferred to skip this section and move on to the actual usability test as they deemed the functional principle of the *OHW* interface to be very simple.

Two videos were recorded simultaneously: One filming each participant’s face and one filming their hand operating the phone. The participant’s voice was recorded on both. In case of technical problems a supervisor was available to offer help. Having finished the tasks, participants were asked to complete a questionnaire rating their experience relating to each task and some more general questions concerning their overall impression of the *OHW* interface on a five-point Likert scale. One participant failed to complete the

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I like that I can control the website with one hand	–	–	✔✔	✔✔	✔✔✔✔✔✔✔
The functionality of the interface was easy to use	–	–	–	✔✔✔✔✔	✔✔✔✔✔✔
The interface was easy to operate	–	–	–	✔✔✔✔✔✔	✔✔✔✔✔
If this interface was widely used for many websites it would help me feel more confident navigating these sites and locating the information I need	–	–	✔✔✔	✔	✔✔✔✔✔✔✔
Completing tasks 1-5 gave me confidence to complete task 6 on a completely different website	–	–	✔✔	✔✔✔	✔✔✔✔✔✔
Using the interface when operating the phone one-handed helped in finding the desired information quickly/easily	–	–	–	✔✔✔✔✔✔	✔✔✔✔✔
Finding the section about feeding fish was quick/easy when using the interface to operate the phone with one hand	–	–	–	✔✔✔	✔✔✔✔✔✔✔
Navigating to the fishing page was quick/easy when using the interface to operate the phone with one hand	–	✔	–	✔✔	✔✔✔✔✔✔✔✔
Choosing between the discrete elements of the form was quick/easy when using the interface to operate the phone with one hand	–	✔	✔✔	✔✔✔✔	✔✔✔
Entering text using only one thumb was quick/easy when using the interface to operate the phone with one hand	–	✔✔✔✔	✔	✔✔✔	✔✔
Finding the comment form was quick/easy when using the interface to operate the phone with one hand	–	–	✔	✔✔✔	✔✔✔✔✔✔✔
Finding the link with the help of the interface was quick/easy when using the interface to operate the phone with one hand	–	–	–	✔✔✔	✔✔✔✔✔✔✔✔
The interface helped me gain an overview of the page	–	–	✔✔✔✔	✔✔✔	✔✔✔✔
Finding the section about the popularity of raspberries was quick/easy when using the interface to operate the phone with one hand	–	–	–	✔✔✔✔✔✔	✔✔✔✔✔
Finding the video was quick/easy when using the interface to operate the phone with one hand	–	–	✔	✔	✔✔✔✔✔✔✔✔✔

FIGURE 5.12: The Likert results of the usability study.

form input tasks due to technical problems and another one aborted the task of locating a section of information on the second page. In both cases, no answer was provided to the relevant question in the questionnaire and thus no data collected. The study tasks and study information can be found in Appendix E, pp. 361–364.

5.6.3 Results

Figure 5.12 shows that users rated the functionality of the interface easy to understand and apply and liked the idea of being able to control the whole website with just one hand. Furthermore, the data revealed that finding the video, the link, the comment form, the various sections of the website and navigating to the other page as requested in the task sheet were considered to be quick and easy using the *OHW* when operating the phone one-handedly.

In particular the retrieval of the video and the link were perceived to be very straightforward and efficient and that these tasks were performed easily by all participants.

Furthermore, ten of the eleven participants located the comment form straight away by using the *Forms* menu and so could proceed swiftly to filling in the form data. As mentioned above, one person encountered technical difficulties and therefore could not complete this task.

The *Navigation* menu was used efficiently to jump from the first to the second page, though one participant tried to use the search form on the page instead. The video recordings also revealed that users, even those with iPhones, very quickly learnt how to navigate the page using the interface. This suggests that the *OHW* has a promising degree of learnability. In addition, users found the interface to be visually appealing and remarked on its logical structure and smooth operation. Users also pointed out that the interactive elements were easy to reach with the thumb and could envision the usefulness of this interface when only having one hand available to operate their smartphone.

The study also revealed several areas that required improvement before the final implementation of the interface. The most frequently mentioned issue was the sensitivity of the interface when scrolling a list or navigating between the horizontally ordered form elements. Long lists were deemed rather difficult to control precisely. Another problem was identified regarding text input. Whereas many people liked the quarter circular Qwerty-like layout, some had difficulties reading letters that were too strongly rotated. In addition, touch events onto the keys were not always precisely recognised. It was also observed that the iPhone and iPod touch users sometimes tried to directly tap onto list elements rather than using the *interaction button* in the interface's *interaction zone*. Suggestions made by the users for improving the interface included:

- An alphabetic order of the items in the *Links* view.
- Potentially using more screen space for lists.
- The possibility to quickly jump to a position on the page by tapping anywhere onto the scroll bar background.
- The inclusion of the URL when displaying links.

Following this, the approach was improved by incorporating most user suggestions and addressing the identified usability issues, resulting in these changes:

- Enabling direct interaction with all elements in the *display zone*.
- Stretching List views over the whole height of the display.
- Sorting items alphabetically in the List view, not by order of occurrence.
- Adapting dynamically the sensitivity of the interface to the length of the list being scrolled.
- Removing the *OHW* keyboard and replacing it with the system standard keyboard.
- Allowing users to tap the scroll interface background to quickly jump to the respective scroll position on the page.

It must be noted that in favour of readability and screen space, URLs were not added to the display of link items in lists.

5.7 Study Two – Application

Taking a new version of the *One Hand Wonder*, improved by the findings of the usability study (Study One), a second study was conducted to measure the interface's efficiency and usefulness in a variety of tasks. The data and study information can be found in Appendix E, pp. 365–367.

5.7.1 Participant Background

In total, 22 users (7 F) with an age between 20 and 34 years participated in the study. Of these, 19 were undergraduate Computing students in their final year, and three were young professionals. All users were right-handed and stated they used touchscreen mobile devices regularly.

An informal exploration session of the *OHW* was held with the 19 Computing students, where students could access a website enhanced by the *OHW* and examine its functionality and operation on their own device. Experiments started a week after the session and users were given a second introduction to the interface before commencing with the first task of the study.

5.7.2 Study Design

A website presenting the *OHW* was created to serve as the basis of the user study. The website was designed using relative measures, CSS media queries and good practice methods (W3C, 2008; Opera Software ASA, 2007) to allow optimum presentation across devices, making it easy to read and use on desktop computers and mobile devices alike.

The website itself used the HTML5 Doctype and consisted of a variety of HTML tags that can be regarded as standard elements: The page navigation consisted of a list of seven links (<a>) encompassed by a <nav> tag. Different sections of the page were headed by different degrees of headlines for which the <h1>, <h2> and <h3> tags were used, resulting in 11 headlines and sub-headlines. All text was wrapped in discrete <p> tags and enriched by images (<img>) to visualise the figures. Three video elements were embedded using the <video> tag, including a poster image for each. The website also contained a feedback form, consisting of two input fields of the type *text*, one input field of the type *datetime*, one input field of the type *range*, one input field of the type *checkbox*, one <select> element with 14 <option> elements and one input field of the type *submit*, displayed as a button. To support document flow and layout, <div> tags were used. The page had a white background and used a black font colour for all text, rendering at the standard font-size of 16px, referenced as 1em. Links in the text had the browser default colour blue.

In the first part of the study, users had to perform ten discrete tasks directly on the website. Before each task, the scroll position and values of the website were reset so that each task started at the beginning of the page. To present the task, a screen with the instructions was laid over the website (Fig. 5.13), with a nearby computer screen showing a copy of the task instructions in case users forgot them during the study. As soon as the user pressed “Start”, recording started and it stopped only once the task condition was fulfilled, including errors. For example, recording only stopped once a certain element was clicked or a specific video was forwarded to a certain playback position.

The ten discrete tasks were:

1. Retrieving and selecting a menu item from the page navigation.
2. Locating a video on the page and moving the playhead to a defined time.

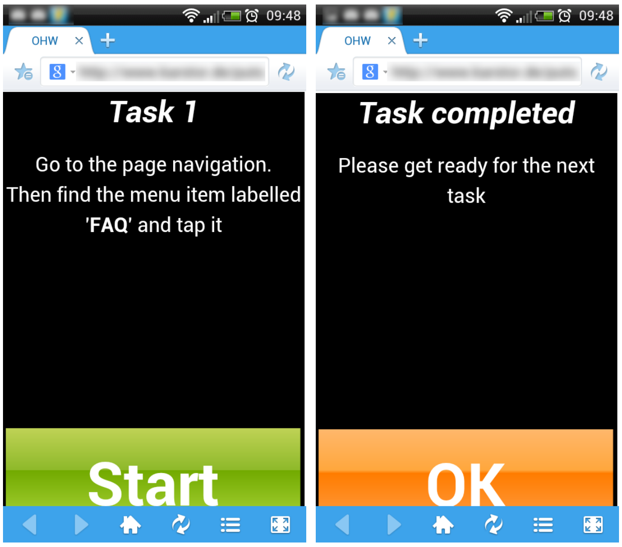

FIGURE 5.13: **Left:** The task start screen. Tapping "Start" will remove the screen, expose the underlying website and start the recording. **Right:** The end screen shown after task completion.

3. Locating the comment form and enabling a checkbox.
4. Locating a second video and invoking playback.
5. Locating the comment form and entering a date into the date field.
6. Locating a certain link in the body page.
7. Locating the comment form and adjusting the range input to a defined value.
8. Locating a section in the website with a certain heading.
9. Locating the submit button in the comment form and activating it.
10. Scrolling the page to a defined point and clicking a link.

Dillon et al. (1990) suggest that interaction techniques cannot be evaluated in isolation by only exploring the final phase of task execution, but rather that the complete chain of decisions and actions leading up to the task and executing it need to be considered to gauge a technique's true cost. Similarly, Hinckley (2008, Chapter 9) collates the findings of previous work and reports that interactions are often "compound" tasks, consisting of a list of sub-tasks working together as one. Based on this I decided to include steps such as finding the target, activating the interface, and executing the final part of the task in the study design.

In addition, while the ten tasks listed above allowed determining the *OHW*'s performance for solving a certain problem, they were unsuitable for predicting the approach's performance on a website which may contain any combination of these elements. The tasks measured the *OHW*'s performance in single, isolated instances, but neglected to account for the spatial proximity and relations of page elements. To compensate for this and to allow ascertaining the *OHW*'s performance in a situation that resembles "real-life" more closely, a second set of tasks was created. In contrast to the first round, this second set of tasks was performed as one large use case, consisting of the ten sub-tasks 1c to 10c. Instead of resetting the website after each task, as was done in round one, the website (scrolling position, values and states) remained unchanged after completing a part of the use case and recording was merely paused to display the instructions for the next part. After all ten coherent parts were completed, the use case was finished and recording stopped. This use case consisted of the following parts:

1c. Locating a certain section on the page headed by a particular headline.

2c. Scrolling the page to retrieve a link.

3c. Returning to the page navigation and selecting a specific item.

4c. Locating a video and manipulating the playback position to a specified value.

5c. Locating a second headline in the text.

6c. Scrolling the page again to retrieve another link.

7c. Locating the comment form and filling in a particular name.

8c. Locating and activating a checkbox in the comment form.

9c. Entering a date into a date field in the comment form.

10c. Locating and activating the submit button in the comment form.

All tasks were performed on a HTC Sensation XE smartphone running the Android 4.03 operating system and the Maxthon Mobile browser. For each task, the amount of interactions needed to complete the task as well as the completion time were recorded using a JavaScript framework that captured, recorded and propagated all events on the website and saved these in a localStorage object with later upload to a MySQL database.

A within-subjects design was chosen where participants performed the tasks of the study in two modes: Once with the *OHW* interface and once without it, the latter representing the non-enhanced base condition of the website (normal mode). To counterbalance the study, half the participants performed the tasks first with the *OHW* whereas the other half of participants began the study in normal mode, without an enhanced interface.

5.7.3 Results

The results showed a varying performance of the users in the different parts of the study. As this is representative of the difficulty of the different tasks, possible outliers were not removed, as they are an important part of the data. This resulted in a data set which did not meet parametric assumptions, meaning that the recorded values did not follow a normal distribution. In addition, the data was drawn from a rather small sample size of 22 participants and some of the tasks differed strongly from each other – for example the control of the video playback position and the activation of a checkbox. Therefore, the tasks had to be treated separately, leading me to choose a series of Wilcoxon signed-rank tests over an ANOVA. To get a better idea of the performance of the *OHW*, the results for amount of interactions and task completion time are reported separately. The data can be found in Appendix E, section E.9, p. 367.

Results: Amount of Interactions Needed

The data revealed that using the *OHW* allowed users to perform several tasks with less interactions than the normal, non-enhanced way of operation (Tab. 5.1, Fig. 5.14):

- Task 1 (Retrieving and selecting a menu item from the page navigation): 32% of interactions needed.
- Task 3 (Locating the comment form and enabling a checkbox): 62% of interactions needed.
- Task 4 (Locating a certain video and invoking playback): 72% of interactions needed.
- Task 6 (Locating a certain link in the body page): 47% of interactions needed.
- Task 8 (Locating a section in the website with a certain heading): 74% of interactions needed.

TABLE 5.1: Median interactions per task and the use case (C) with and without the *OHW*, including Z and p values from the Wilcoxon tests as well as the percentage of interactions (I) needed with the *OHW* when compared to user performance in normal mode (performance in normal mode = 100%). Table taken from Seipp and Devlin (2014*c*) with permission from WEBIST.

Task	**OHW**	**Normal**	Z	p	**%I OHW**
1	6	19	3.49	$< .001$	32%
2	14	13.5	0.63	.526	104%
3	14	22.5	2.93	.003	62%
4	9	12.5	2.1	.036	72%
5	26.5	27	0.15	.884	98%
6	7.5	16	3.9	$< .001$	47%
7	12	12.5	0.06	.952	96%
8	14	19	1.97	.049	74%
9	13.5	9.5	2.95	.003	142%
10	51.5	26	3.98	$< .001$	198%
C	104	127	2.18	.029	82%

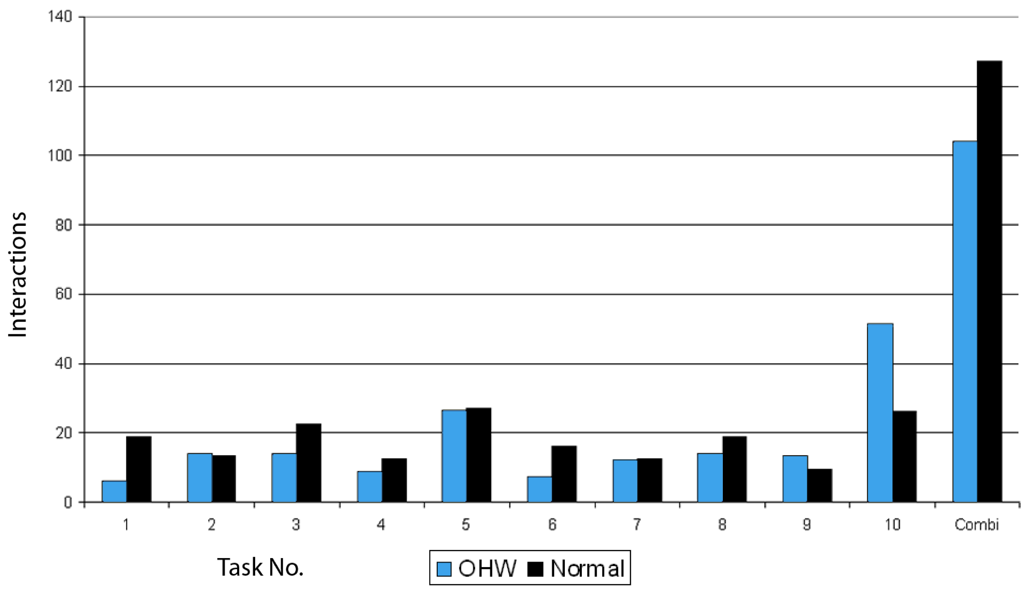

FIGURE 5.14: Visualisation of the data displayed in Table 5.1: Median taps per task for *OHW*-enhanced mode and normal mode of interaction.

However, there were two tasks which required more interactions to complete with the *OHW* than in normal mode:

- Task 9 (Locating a second video and invoking playback): 142%.
- Task 10 (Scrolling the page to a defined point and clicking a link): 198%.

The results for the completion of the use case (C) show that when using the *OHW*, users were able to complete the ten additional, coherent tasks with 82% of the interactions needed compared to normal mode.

Results: Amount of Time Needed

Performing a Wilcoxon signed-rank test on the completion time for each task showed that users were able to perform nine of the ten tasks in less time when using the *OHW* (Tab. 5.2, Fig. 5.15):

- Task 1 (Retrieving and selecting a menu item from the page navigation): 33% of time needed.
- Task 2 (Locating a video on the page and moving the playhead to a defined time): 57% of time needed.
- Task 3 (Locating the comment form and enabling a checkbox): 47% of time needed.
- Task 4 (Locating a second video and invoking playback): 36% of time needed.
- Task 5 (Locating the comment form and entering a date into the date field): 73% of time needed.
- Task 6 (Locating a certain link in the body page): 33% of time needed.
- Task 7 (Locating the comment form and adjusting the range input to a defined value): 72% of time needed.
- Task 8 (Locating a section in the website with a certain heading): 46% of time needed.
- Task 9 (Locating the submit button in the comment form and activating it): 70% of time needed.

However, scrolling the page with the *OHW* to a defined point and clicking a link (Task 10) took 147% of the time needed for using the website in normal mode with one hand.

TABLE 5.2: Median completion time (T) in seconds needed per task (1 to 10) and the use case (C) with and without enhancement by the *OHW*, including Z and p values as well as % of time needed with the *OHW* in comparison to non-enhanced interaction in normal mode (performance in normal mode = 100%). Table taken from Seipp and Devlin (2014*c*) with permission from WEBIST.

Task	OHW	Normal	Z	p	%T OHW
1	11.40	34.30	4.11	<.001	33%
2	25.90	45.10	4.07	<.001	57%
3	20.50	43.90	4.11	<.001	47%
4	10.20	28.60	4.11	<.001	36%
5	33.90	46.60	3.98	<.001	73%
6	9.50	29.10	4.11	<.001	33%
7	18.80	26.30	3.85	<.001	72%
8	14.80	31.90	4.07	<.001	46%
9	15.50	22.10	3.17	.002	70%
10	65.40	44.50	3.56	<.001	147%
C	153.20	255.10	4.11	<.001	60%

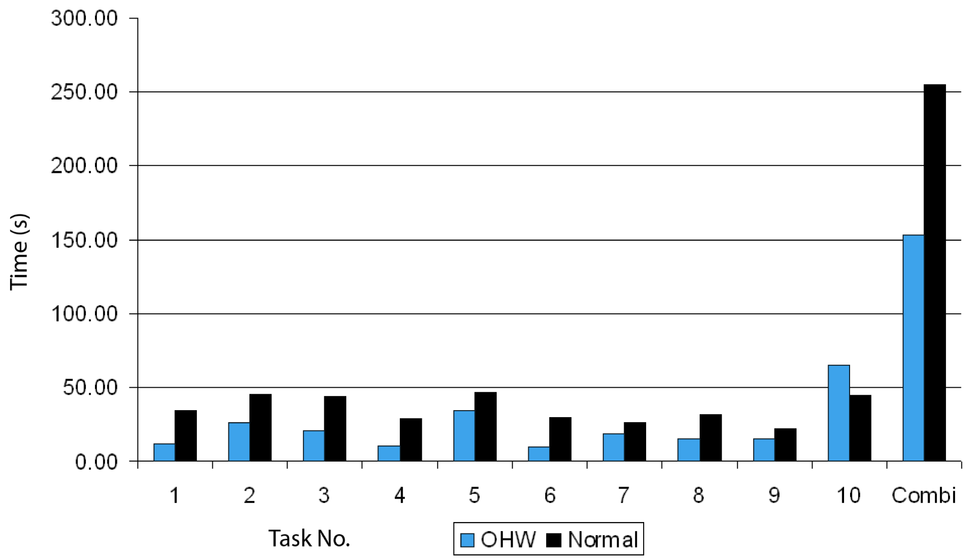

FIGURE 5.15: Visualisation of the data displayed in Table 5.2: Median time needed per task for *OHW*-enhanced mode and normal mode of interaction.

5.7.4 Performance

To evaluate the *OHW*'s applicability and versatility, it was implemented into seven websites via a proxy script, as access to these sites to implement the *OHW* directly into the source code of each site was not possible. The PHP-based script was configured to use request headers that are typical of mobile devices to allow access to the mobile version of each site. The obtained code was then injected with the necessary <script> tag for the *OHW* and subsequently served to the browser. The structure of each site was studied in advance and an adapted configuration file was used for each site, detailing CSS selectors, tap functions and views (see section 5.5). This way, the *OHW* was implemented into the following pages: Wikipedia (2013), BBC (2013), W3C (2013), Google (2013), WordPress (2013) and YouTube (2013). Implementation into Flickr (2013) failed, as the script could not retrieve the site. The implementation required the wedge names to be changed to better match each site's content. Performance of the interface on all sites was good, but hampered in two cases: The links menu felt unresponsive on the Wikipedia article, as it contained 538 items. In addition, the interface occasionally "stuttered" in the desktop version of the BBC website (BBC, 2013), due to concurrent fading animations and tracking scripts, and videos could not be played back in the YouTube implementation, as videos were served as 3GP files, which were not natively supported by the browser.

To better gauge the *OHW*'s technical performance, start-up time on the above websites and rendering time for list views were measured (Tab. 5.3). This was done by measuring three times the time needed for the interface to appear on the screen and be ready for interaction after the page had loaded from a clear browser cache and the Load event of the Window object had fired. To assess the time required by the *OHW* to build a list view of various lengths, the time between a tap on a wedge in the wheel and the display of the list view in the *display zone* was measured three times. This was done by loading the mark-up of a WordPress blog (WordPress, 2013) via the proxy script and dynamically injecting varying amounts of items into the DOM before the page was served to the browser. All tests were performed on a HTC Sensation XE running the Android 4.03 standard browser and again on an iPhone 3GS with iOS 6.1 running the Safari browser.

The results (Tab. 5.3) show an overall acceptable performance and start-up time of the *OHW* on the Android device and a good performance and start-up time on the iPhone. Whereas the time to create a view increased with the amount of elements to display on the Android device, the rendering time on the iPhone was not impacted by an increase in items. On comparatively complex websites, such as the BBC page and Wikipedia, start-up time on the iPhone was 39% and 36% faster than on the Android device, whereas the comparatively simple sites, such as Google and W3c, were parsed more rapidly on

Table 5.3: The mean time needed for creating a list view (Fig. 5.7) of varying length and for the interface to be ready for interaction after the page had loaded (system start-up time (SU)) for the HTC Sensation XE (S. XE) and iPhone 3GS (3GS). All measurements in seconds. Table taken from Seipp and Devlin (2014*c*) with permission from WEBIST.

Task	**S. XE**	**3GS**
List view, 30 items	1.1	0.6
List view, 60 items	1.5	0.7
List view, 120 items	1.9	0.7
List view, 480 items	2.4	0.6
SU Wikipedia	1.4	0.9
SU BBC News	2.3	1.4
SU W3C	0.3	0.8
SU Google	0.3	1.0
SU WordPress	1.5	1.4
SU YouTube	0.9	0.9

the Android device. Start-up on the YouTube and WordPress sites was similar on both devices.

5.8 Discussion

The discussion evaluates the *OHW* with regards to its contribution compared to previous work, Roudaut's and Katre's recommendations for thumb-optimised interfaces (see Chapter 2, p. 41), Nielsen's heuristics for interface design (Nielsen, 1995) and the research goals of this chapter.

5.8.1 Benefits Over Previous Research

Compared to previous research, the presented approach is unique in so far that it attempts to address all identified challenges of thumb-based interaction together in one interface, rather than singling out one aspect in isolation. In doing so, it also largely overcomes the limitations of previous research, but this is not without some problems that should be acknowledged.

As opposed to Web Page Segmentation (Hattori et al., 2007; Gupta et al., 2007) and the Read4Me browser (Yu and Miller, 2011), the *OHW* leaves the layout of the page intact, preserving design, branding and spatial context. However, although spatial context of elements on the page is maintained, it is not transported to the temporary list view or item view overlay in the *display zone.*

In terms of its advantages in implementation, the *OHW* can be deployed by novice webmasters without the need for a proxy server and a complex configuration. In addition, it is compatible with popular Web-publishing platforms, such as WordPress. It is not bound to bespoke or proprietary software (as in Yu and Miller (2011)), as it can be implemented in any modern browser due to its use of standard, client-side technologies. This way, the *OHW* is more congruent with the idea of an open and inclusive Web. The reliance on standard client-side technologies supports the approach's longevity, as no installation of specific software is necessary.

In comparison to S.U.P.P.L.E. (Gajos et al., 2008) and E.A.G.E.R. (Doulgeraki et al., 2009), the *OHW* provides a flexible interface that can quickly adjust to a changing input modality without reconfiguration, be it in landscape or portrait mode, with one hand or two hands. However, the *OHW* is more specific than these approaches, limiting its advantages over these systems, but making it unique in its core domain, as it addresses and improves a so-far neglected aspect of mobile website interaction: The one-handed operation. Rather than just adjusting the display of the website as in Web Page Segmentation, the *OHW* adjusts the interaction with the page to the common one-handed operation. In addition, the *OHW* does not require the user to undergo a configuration process, but can be used shortly after the page has loaded.

Compared to the Wavelet menu (Francone et al., 2010) and the Swiss Army Menu (Bonnet and Appert, 2011), the *OHW* occludes less screen content through its positioning in the bottom left or right corner. In addition, its operation requires less careful aiming at GUI elements due to its simplified interaction model and large buttons. Furthermore, it offers a curved interface that follows the natural movement arch of the thumb (Fig. 5.2) for all interactive elements and not just a circular menu to access the content. In comparison to the ArchMenu and ThumbMenu (Huot and Lecolinet, 2007), its direct-touch approach and the inclusion of a static *highlight zone* for operating list views (Fig. 5.7) allow operation without a movable cursor, which could be hard to operate when "on the move" in addition to the challenges stated by Accot's law. Last but not least, the interface allows control over website elements rather than an offline application and the menu content is fully controllable by the webmaster via a configuration file.

5.8.2 Evaluation with Regards to Roudaut's and Katre's Requirements for Thumb-Optimised Interfaces

The *OHW* interface successfully implements the main requirements of a thumb-optimised interface as outlined in Chapter 2, p. 41, but does not fully solve the problem of interface occlusion nor allows adaptation to the user's hand size:

- It supports the thumb's lack of precision by utilising large interactive elements that do not require precise targeting.
- It reduces the effect of occlusion by the thumb by separating the display into an *interaction zone* and a *display zone*. This works well for operating all interactive elements, apart from the wheel menu, where the thumb can occlude the text on the wedges, depending on the thumb's degree of extension onto the screen.
- The location of the interface in the thumb's "comfort zone" allows operation of all elements without having to stretch the thumb and thereby losing precision. When in scroll mode, elements on the page can be selected through swiping over the interface, successfully addressing the problem of the thumb's limited movement range.
- Operating a website through the interface can reduce possible confusion, as it clearly separates interaction with page elements from interaction with the viewport.
- The lack of expressiveness of the thumb is mostly successfully addressed by reducing the operation of all elements to swipe and tap through the interface, eliminating the need for expressive input. However, zooming the page is not supported.
- The *OHW* uses a semicircular interface for all interactive elements and allows their operation within the natural movement arch of the thumb. However, the position of the *Start/Back* button requires contracting the thumb. While the button's position frees screen real estate, its frequent operation could induce muscle fatigue as stated by Karlson et al. (2006).

- The *OHW*'s interface elements are horizontally and vertically enlarged to fit the shape of the thumb's tip.
- The interface can be used by left-handed and right-handed users alike.
- The *OHW* cannot be configured by the user to adjust the interface to their hand size. Furthermore, its *interaction zone* is located in the bottom third of the display when operating the device in portrait orientation, requiring the user to grip the phone in a certain way.

5.8.3 Evaluation Using Nielsen's Usability Heuristics

When compared to Nielsen's usability heuristics (Nielsen, 1995), the *OHW* could be considered a usable interface, for it addresses most points successfully:

Visibility of system status: The status of the interface is always clearly visible to the user and the system provides a generally high responsiveness on mobile-adapted pages. On non-mobile adapted pages (as explored in the BBC implementation, section 5.7.4, p. 252) or without considerate configuration (as shown with the Wikipedia implementation, also section 5.7.4, p. 252), the responsiveness can be reduced. However, this is in the control of the webmaster and can be addressed in the interface's configuration.

Match between system and the real world: By default, the interface uses plain words (for example: *Headlines, Navigation, Forms, Media, Scroll, Links, Start, Back*) and is therefore easily understandable. With configuration by the webmaster, this can be adjusted to match the page content more specifically. The utilisation of lists, sliders, buttons, text fields and switches complies with generally established interface standards.

User control and freedom: In the event of inadvertent operation of the interface, the consistently placed *Back* button allows easy cancellation of a selection process or menu navigation, for example. The ability to switch the enhancements on and off and the adaptation to different phone orientations together with optional direct-touch operation of elements in the *OHW*'s *display zone* provide user freedom. However, undo and redo functionality is not implemented into the interface.

Consistency and standards: The reduction of all interactions to two gestures – swipe and tap – administered through the interface's *interaction zone* provides a high degree of consistency. The employment of a simple and clearly labelled *Back* button with a consistent location to allow cancellation, navigating back within the menu hierarchy or ultimately hiding the interface when no further backwards steps are possible, corresponds to the common functionality of a browser's back button.

Error prevention: Upon implementation, the framework can alert the webmaster when detecting an irregularity while parsing the DOM. For users, the *OHW* does not provide any error feedback. However, as the behaviour of the website elements is preserved when implementing the *OHW*, existing error handling methods provided by the webmaster, such as form validation, are kept and will be displayed as intended by the designer. However, for proper implementation of existing error handling into the *OHW* interface, the webmaster would have to add custom functionality.

Recognition rather than recall: The current system status and options are visible in the *display zone* and *interaction zone*. The use of only semicircular swipe and basic tap gestures reduces the user's memory load regarding the operation of each element. The curved "lane" resembling a scroll bar invites a swiping interaction and the rounded button suggests a tapping interaction, following Norman's concept of perceived affordances (Norman, 2002) . In addition, the employed views are based on established interaction patterns, facilitating recognition and ultimately operation. However, instructions on how to use the interface are not available by default. Yet, the consistent operation allows a high degree of learnability and recognition, as the user will be able to interact with the content of any website implementing the *OHW* once they have used it, even if they collected their experience while using a different website.

Flexibility and efficiency of use: With the previously mentioned ability to switch the interface on and off at any time, its adaptation to portrait orientation and landscape orientation, and its reliance on standardised client-side technologies, the interface can be considered flexible. The reported reduction in the number of required interactions and task completion time highlight its efficiency. This is supplemented by the inclusion of direct-tap interaction in the *display zone* and an "expert-mode", allowing users to quickly activate the enhanced interface by double-tapping an interactive element without the need for pressing the *Start* button and selecting the desired option from the menu. However, Study Two has shown that scrolling long parts of a page using the *OHW*'s scroll functionality is inefficient. This has since been addressed by combining native scrolling and *OHW* scrolling, but its performance still requires verification.

Aesthetic and minimalist design: By default, the *OHW* only shows information that is absolutely necessary, strictly extracting element content from the page and not adding any descriptions or additional information, apart from a counter in the form overview to indicate the position in the form. The design of its elements aims to be simple and functional, but can be adjusted via CSS. However, the operation of simple elements, such as buttons, through the interface might appear over-engineered considering that the button can be interacted with directly without mediation through the *OHW* interface. Yet, the ability to toggle the interface on and off together with the provision of direct interaction with all elements mitigates this aspect.

Help users recognise, diagnose, and recover from errors: As described earlier, the *OHW* does not provide error handling methods for the user. These are part of the website's application logic and not part of the interface. However, the webmaster can extend the *OHW* to support these.

Help and documentation: For the end user, the *OHW* does not provide documentation by default. This can be supplied by the webmaster, but the easy operability of the interface – as found in Study One – and its simplified interaction model might not require this to be extensive.

Overall, the general compliance with the above points matches the positive feedback given in Study One as well as the positive feedback received when presenting the improved version of the *OHW* in a hands-on environment to a diverse audience at the CHI 2013 conference (Seipp and Devlin, 2013*a*).

With regards to the greater aim of HCI to support users in their tasks and make interactions with computers more convenient, less error prone and more approachable, the OHW fits well into the idea of the graphical user interface that allows easy access to a program's functionality to novice users. As such, the *OHW* can be regarded as some kind of minuscule evolution of the GUI, albeit in a rather small and niche aspect. It caters for an issue that has occurred as a result of the spread of graphical user interfaces and their use on handheld devices: The ergonomic peculiarities of one-handed touch interaction. As discussed in Chapter 1 and Chapter 2, GUIs have (although greatly simplifying the interaction between humans and computers) unveiled a new set of issues and challenges intrinsic to the limitations (and capabilities) of human motor abilities. While these have been addressed with optimised layouts following the WIMP principle and different interaction techniques, the arrival of the mobile device, its form factor and users' preference for convenience and comfort over efficiency (as indicated in Chapter 3) have created a new way of interaction: Holding the device with one hand and using it with the thumb of the same hand. While this is generally being addressed by following a set of design guidelines (Apple, n.d.*b*; Microsoft, n.d.), the support for horizontal and vertical device operation with both one and two hands, together with the fluid and adaptive layout of modern Web pages, have created a situation where task-tailored interfaces (as used for specialist desktop applications) are hard to provide. Here, the *OHW* and its optional activation offers situative enhancements to support the user in an environment with changing contexts. It extends the idea of the GUI from being a static gateway to the computer to being a changing, adaptive mediator between the user's needs and the device's functions that is not just optimised for a task or general operation but also optimised for a situation and the relating interaction style.

5.8.4 Findings of the Research Goals

This section presents the findings of the research goals defined earlier in this chapter.

***G1*: Confirming that a curved interface is a suitable basis for exploring the potential of the strategy of interface modification to address the main challenges of one-handed smartphone interaction.**

The findings of the initial user study in section 5.3, p. 231, have confirmed the suggestions of Katre (2010) that a curved interface is a suitable basis for exploring the potential of the strategy of interface modification to address the main challenges of one-handed smartphone interaction. It corresponds to the shape described by the thumb's natural swiping arc (Fig. 5.2, p. 232) and thus allows comfortable operation, supporting the findings of Hürst and Merkle (2008) and Otten et al. (2013). Further, the research in Chapter 4 has shown that device movement is low when reaching for targets in this area, allowing a high degree of grip stability (Fig. 4.23 to 4.28, pp. 159–164) when using this kind of interface.

***G2*: Examining whether the enhancements made by such an interface can be implemented using client-side technologies at runtime, allowing the user to freely move between one- and two-handed interaction.**

The interface's ability to be toggled on and off when needed, together with the provision of an "expert-mode" that transforms the input controls of an interactive element via a double-tap gesture, even when the interface is hidden, shows that the framework is flexible enough to support changes in the user's mode of operation. This is further aided by the *OHW*'s ability to work on landscape-oriented devices as well as allowing users to direct-tap elements in the *display zone*, should they wish to do so.

From a technical perspective, the research has shown that thumb-based operation of websites can be improved using standard client-side Web technologies to create a thumb-optimised interface at runtime. The framework can be implemented into a variety of pages by adjusting the wedges and configuring the CSS selectors for each to match the wheel menu titles to the page content, as the standard configuration may not allow sufficiently precise representation. Custom functionality can be added by extending or chaining the framework's tap handlers. Start-up times of the interface and rendering performance ranged between "acceptable" (2.3 seconds) and "good" (0.3 seconds), even on large pages, if the content of a view was not too extensive. However, the disadvantage of this client-side approach is that the interface has to share the browser resources with the page content. As discovered on the BBC implementation, concurrent CPU-heavy processes, such as fading animations and frequent DOM updates, can directly impact the performance of the *OHW*. Therefore, websites that are badly prepared for mobile devices in terms of resource consumption will not necessarily benefit from implementing the *OHW*. However, already mobile-adapted pages that have been developed with care can benefit greatly from the enhanced interface by providing a higher degree of usability and comfort over non-enhanced, one-handed thumb operation.

Another limitation is the dependency on the browser for displaying media formats. The YouTube implementation (section 5.7.4, p. 252) has shown that the *OHW* can only enhance operation of media files that are supported natively by the browser. Should the browser need to open the files in an external player, the user would have to use the system standard controls, losing any enhancements provided by the *OHW*. Another limiting aspect of this client-side approach is the requirement of JavaScript to be enabled.

Whereas many modern Web services rely on this technology, a report by Yahoo (Zakas, 2010) indicates that, depending on the country of origin, up to 2% of visitors to their pages had JavaScript disabled, potentially excluding these groups from the improvements for one-handed operation provided by the *OHW*.

Judging the *OHW* against the requirements set forth by Web developers, the framework fulfils nearly all requirements: It is unobtrusive, can be operated by left- and right-handed users, leaves design and functionality of the website intact, transfers existing behaviour, such as click functions of specific elements, into the interface, can co-exist with other JavaScript frameworks on the page, can be freely configured and extended, is straightforward to implement by including its main code file in the header of the page, and has an acceptable start-up time (Tab. 5.3). However, with its current dependence on the jQuery framework and the use of PNG files for the wedges of the wheel, the bandwidth footprint of the framework can augment to a total of 352 kB if uncompressed, depending on the content of the website. Although 250 kB are consumed by the jQuery framework and might be considered as neglectable due to the framework's popularity (Pingdom, 2010) and therefore the likelihood of it being either already in the browser cache or part of the website, the *OHW*'s current use of graphic files for the wheel components means that the requirement for a small file size is not yet fully achieved and could be an area for improvement in future work, by replacing the wedge graphics with SVG elements where supported.

***G3*: Determining whether the wheel menu design and the reduction of all interactions (excluding text input) to a set of swipe and tap actions, which are administered through the interface in a dedicated area of the screen, is an effective approach for controlling the diverse elements of a website.**

The findings of this research goal are double-edged: On the one hand, the research indicates that elements as diverse as a date field, a checkbox and a video file can all be successfully controlled through the same interface using only a sideways swipe and a tap requiring little targeting for input. The reduction of the required set of interactions to these two together with the provision of an easy-to-access menu system resulted in a general increase in efficiency and effectiveness when operating a website with only one thumb.

On the other hand, the quantitative results have shown that this mode of interaction did not improve scrolling in the tested implementation, but actually reduced efficiency for this task. This shows that one-handed scrolling is already very effective and may not necessarily benefit from the proposed interface. To address this, the scrolling function has since been improved to allow combined use of device scrolling and *OHW* scrolling. This way users can scroll large amounts of the page quickly by swiping over the screen outside of the *interaction zone*, but can use the *OHW* to fine-tune the scroll position and select highlighted page elements outside the reach of their thumb.

The feedback provided in the initial usability study (Study One, Tab. 5.12, p. 243) showed that 82% of users liked being able to control a website with just one hand using the interface and 100% deemed the interface easy to operate, corresponding to Kolko's suggestion of a consistent set of interactions to increase usability (Kolko, 2011). Taking into account the improvements implemented after this initial study, the *OHW* can be seen as a promising solution from both a usability perspective and an efficiency perspective. The positive user feedback was reconfirmed during a demonstration session at the CHI 2013 conference (Seipp and Devlin, 2013*a*), where users could explore the *OHW* implemented in the websites mentioned in section 5.7.4, p. 252, as well as the *OHW* project website used for the user study (Study Two, section 5.7, p. 245).

Based on the results of Study Two, the types of pages that might benefit the most from the *OHW* are pages with large amounts of structured content, such as news sites, blogs, forums and wikis. Here the wheel menu can provide an alternative way of navigation – as suggested by Trewin as best practice (Trewin, 2006) – and offers quick access to the content with relatively little search time, if wedge names and selectors are paired efficiently. Other pages that may benefit are pages that heavily rely on form input, especially with high numbers of checkboxes or radio buttons. Due to their small size, these can be difficult to control precisely when operating the website via the thumb on a non-enhanced page. Control of these elements benefits from the *OHW* interface, as users do not have to aim or reach, but can control them from within their thumb's comfort zone via an adapted interface. Pages displaying large amounts of audio and video may benefit from the categorised access via the wheel menu as well as the curved interface, whose presentation in line with the natural movement arc of the thumb has the potential to allow more comfortable control of the media files and possibly reduces fatigue of the thumb when compared to the standard, non-curved interface of the browser, as steering tasks are simplified. Yet, it remains unclear to what extent image-based websites, such as a photographer's portfolio, may benefit from the *OHW*, as the system does not provide controls for image galleries as standard. This functionality could be developed by the webmaster using the *OHW*'s plugin model and a dedicated view, but shows that in such cases, more work than simple "plug and play" is needed for a successful implementation.

5.8.5 Answering Research Question 3

***RQ3*: Can an approach following the strategy of interface modification successfully address the main challenges of one-handed smartphone operation (as defined in Chapter 2, p. 41) together, using only a single interface?**

Reviewing the design and efficiency of the *OHW* suggests that the interface addresses most of the challenges of direct interaction via the thumb successfully, but that it does not manage to solve the problem of interface occlusion completely. In particular, these challenges are addressed as follows:

Fitts's law: As outlined in Chapter 1 and Chapter 2, one of the great challenges of GUI design is the effect of target size and distance from the pointing device on interaction time, as described by Fitts's law. Although based on classical WIMP interfaces on stationary screens, the amount of research reviewed in Chapter 2 to minimise the impact of these factors on interaction with mobile devices suggests that the law's core statement may also apply to mobile interaction and may even be exacerbated by the limited movement range of the thumb, especially when using the device one-handedly. On websites with a fluent layout, elements can often be placed outside the thumb's natural swiping arc, making interaction with them harder and potentially more time-consuming. This may apply especially to larger handsets or to situations when the top of the page has been reached and scrolling cannot be used to move the content closer to the thumb. Here, the *OHW* can mitigate the effects of target distance and size in various ways, as detailed below.

With the interface's approach to control the whole site via swipe and tap actions inside the thumb's comfort zone, pointing at targets is not necessary as these can be selected via the list views with their static *highlight zone*, form element overview or the select/scroll view. This can be done without bending or stretching the thumb, effectively reducing interaction time in most cases (Tab. 5.2) and the need for precision. This is further supported by translating vertical target distance into a curved, horizontal swipe of the thumb – a movement easier to perform with the thumb than a pointing or vertical movement (Wobbrock et al., 2008).

By allowing users to toggle the interface on and off, dividing the screen into an *interaction zone* and *display zone* as well as enabling optional direct selection of items in said *display zone*, the *OHW* combines the paradigms of direct and indirect pointing and as a result can increase interaction speed and comfort. By limiting direct pointing to the *interaction zone*, where the thumb can perform the required actions with minimal effort, selections in the wheel menu are made or a "cursor" (the *highlight zone*) is controlled in the *display zone*, allowing interaction with targets whose distance from the thumb would otherwise require stretching it and thus potentially cause a greater interaction time, especially when the device is operated with only one hand. This way, direct pointing is used to prepare and control indirect pointing or perform only simple actions within a small range of the screen, better suited to this mode of interaction and thereby playing to the strong points of both input methods.

Accot's law: Similarly, controlling media playback position and slider values in the *display zone* using the translation of the swiping position inside the *interaction zone* mitigates the effect of Accot's steering law by simplifying the path the finger needs to follow. Here, the thumb can follow its natural curved movement arc (Fig. 5.2) to control the items in the *display zone* and does not need to bend or stretch to achieve exact horizontal movement for slider and media playback control (Fig. 5.7).

Occlusion: Despite the separation of *display zone* and *interaction zone*, the thumb can still partially occlude some interactive elements, such as when operating the wheel menu or when scrolling a list view, whose items in the bottom third may be partially hidden by the thumb. While the impact of the last point could be explored with the help of gaze tracking, this chapter's evaluation of the interface shows the limitations of the paradigm of interface modification to support one-handed interaction on touch-screen smartphones: **Although addressing the identified main issues of GUI interaction largely successfully, the *OHW* cannot fully solve the problem of interface occlusion**. While other graphical interfaces beyond my knowledge may exist that are more successful, neither the reviewed previous work nor the *OHW* could present a completely successful solution to the problems of one-handed smartphone interaction within the constraints of this thesis.

5.9 Conclusion and Future Work

This chapter has examined whether all of the most common challenges of one-handed smartphone interaction can successfully be addressed together via the approach of interface modification, using a single interface. It has shown that a thumb-adapted GUI implementing a simple interaction approach based on a semicircular swipe and a tap can be successfully applied to a variety of elements, allowing operation of these within the natural movement arch of the thumb. This is supported by a wheel menu which allows quick access to a page's content using a set of list views. This way, the amount of interactions as well as task completion time can be reduced when compared to non-enhanced interaction, overcoming the usability problem of long "tunnel" pages as identified by Roto et al. (Roto, 2005). However, the gained improvements over the normal operation of a website do not apply to page scrolling, which is already easy to perform with just one hand as shown by the results of the user study.

As a response to *RQ3*, the chapter has found that a curved interface that corresponds to the thumb's natural swiping arc, supported by a wheel menu, can address the problems stipulated by Fitts's law and Accot's law successfully, but that occlusion by the thumb cannot be fully overcome. Yet, by implementing the approach as an interface for one-handed website operation, the presented work has successfully addressed a major omission of previous research in the domain of mobile website operation and introduced a framework that allows the adaptation of the operation of a website to one-handed use, rather than just the adaptation of the display.

As opposed to earlier approaches, the described framework has illustrated that an adaptation of all elements to a specified interaction mode is possible to achieve at runtime using standards-based client-side technologies, if the website has been designed for operation on mobile devices and resource consumption is not too extensive. Rather than requiring a proxy server or proprietary software for the modifications, the approach provides a solution that is in line with the idea of an open Web and the implementation on different websites has shown that the approach is flexible and straightforward to employ.

Nonetheless, challenges may arise from keeping the system up to date and adapting it to new browser versions and engines.

Most importantly, though, the research in this chapter has shown that a wide range of desktop-centric interaction patterns can successfully be “translated” into a semicircular swipe and tap performed in the comfort zone of the thumb. This raises the question as to whether this approach proves flexible and robust enough as a blueprint for converting any mouse-based or finger-based interaction pattern into a thumb-friendly version, offering a versatile solution to the challenges of one-handed thumb interaction with touchscreen smartphones.

Future work will therefore extend the range of interactive elements and examine whether these may be successfully adapted to one-handed operation using the presented interface. Furthermore, it will be explored whether the interface may also improve usability and efficiency on larger devices, such as tablets, by allowing users to operate these primarily with their thumbs, instead of the index finger (Fig. 5.6, right, p. 235). For this, a study will be conducted on a range of tablet sizes comparing the operation of various interactive elements via the index finger to the operation of these via the thumb and the *OHW*. By further exploring the scalability of this approach to larger device sizes, usability of these may be enhanced when the user holds them with two hands (thus requiring operation via the thumb) due to lacking a place for resting the device on when walking, for example.

Finally, to improve interface performance, future work will investigate how the thumb-optimised representation of each interactive element may be directly implemented into the browser. Here, the extension of the WAI-ARIA accessibility standard with additional roles and descriptors will be explored. This could allow the browser to re-model the interface for a given control using its core layout engine, taking the *OHW* design as a guide, addressing the technical challenges arising from a JavaScript and CSS implementation as identified in this chapter.

Altogether, despite demonstrating that all of the main issues of one-handed smartphone operation can be tackled together via the same interface, the presented interface cannot completely solve the issue of interface occlusion through the thumb. **This suggests that, under the constraints of this thesis, the potential of the approach of interface modification to solve the most common challenges of one-handed**

operation simultaneously may be limited or even insufficient. It is therefore suggestive to examine whether an approach following the paradigm of input modality extension may be more successful than GUI modification in addressing these challenges together. As such, the following chapter will explore the improvement of one-handed device operation through the avenue of input modality extension by using a set of sensor-based off-screen gestures.

Chapter 6

Improving One-Handed Interaction Through Extending the Input Modalities

6.1 Introduction

Following the paradigm of input modality extension using sensors, this chapter presents a set of novel off-screen gestures to improve one-handed interaction and address the challenges identified in the literature review. It presents an examination of the potential of this approach to solve all of the main challenges of one-handed smartphone operation together, using one technique. Although successful in addressing the main issues, the problem of interface occlusion cannot be eliminated, as the thumb still touches the screen as part of the interaction chain. See Seipp (2014) for a video demonstration of the technique.

The previous chapter introduced a system that improves one-handed operation by adapting the interface for thumb use, making all functionality available via simple swipe and tap motions within the natural swipe arc of the thumb. While this system has shown a high degree of usability and efficiency, it could not completely solve all challenges of one-handed operation of touchscreen smartphones together using one interface. This leads to the question of whether an approach following the paradigm of input modality extension using sensors can be employed to tackle this problem instead.

To investigate the performance of sensor-enhanced input, researchers have explored a range of approaches that utilise the front, back, or sides of the device, and even the device as a whole (see Chapter 2, section 2.6, p. 56 and section 2.5.2, p. 51), enriching the thumb's input vocabulary with different actions. The related previous work can be divided into three main categories: Motion as input (Oakley and O'Modhrain, 2005; Baglioni et al., 2011; Ruiz and Li, 2011; Yu et al., 2013; Heo and Lee, 2011), sound as input (Lopes et al., 2011; Harrison and Hudson, 2008; Harrison et al., 2011) and back-of-device or side-of-device interaction (Wobbrock et al., 2008; Baudisch and Chu, 2009; Roudaut, Baglioni and Lecolinet, 2009; Holman et al., 2013; Zhang et al., 2013). However, this previous work has a range of limitations, including needing additional hardware to be attached to the device, not being suitable for continuous input and not exhausting the sensors' potential. Most importantly, though, previous work often addresses a single issue of one-handed operation in isolation, failing to provide an approach suitable for addressing all of the main challenges of this mode of smartphone operation together. With this in mind, the following research question emerges:

***RQ4*:** Can an approach following the strategy of input modality extension successfully address the main challenges of one-handed smartphone operation (as defined in Chapter 2, p. 41) together, using only a single technique?

To explore the answer to this research question, it is necessary to examine how such an approach could be implemented on an off-the-shelf smartphone, which finger may be best for supporting thumb input using this technique, and what kind of applications and tasks can benefit. Therefore, the studies in this chapter are designed to achieve the following research goals, which together will answer the research question *RQ4*. These goals can be defined as follows:

- ***G1*:** Exploring whether it is feasible to combine sound volume, sound profile and device motion to enrich one-handed input using the capabilities of an off-the-shelf smartphone.
- ***G2*:** Learning which finger is most suitable for a technique using these properties, performed on either the back or side of the device.

- ***G3*: ** Determining which applications, operated with one hand, can benefit from this technique.

To pursue these goals and answer the research question, this chapter will explore the usability and effectiveness of a technique that introduces a set of off-screen patting gestures to support one-handed interaction. It will introduce a novel way of detecting whether the index finger or middle finger has performed the gesture against the back of the device, or whether the gesture was performed with the thumb against the side of the device. Further, this chapter will examine the performance of these gestures in three applications which represent the common challenges of one-handed smartphone operation (target distance from the pointer, steering tasks, limited dexterity and occlusion) and evaluate user feedback for each to gauge the gestures' potential. In addition, the presented input technique will be formally evaluated using GOMS models, a list of heuristics and its success in addressing the research question. Finally, the technique's impact on a range of conceptual frameworks and common issues in HCI is assessed while comparing it to previous work. The chapter will be concluded by answering the research question *RQ4* and giving a discussion of future work.

Parts of this chapter have been published in two conference proceedings (Seipp and Devlin, 2014*a*,*b*), but their content has been rewritten for this thesis including additional, unpublished material as well as an extensive evaluation.

6.2 Method

Holding a phone in one hand allows the thumb to be moved across the display for direct interaction. However, if the thumb is rested on the frame of the device, it becomes possible to move either the index or middle finger in order to perform a simple "patting" gesture against the back of the device. In addition, rather than tapping targets on the screen, the thumb can tap against the device's side. Figure 6.1 shows a description of the three gestures.

Analysing each of the gestures, it is discernible that they cause the device to move slightly following the direction of impact, and are accompanied with a flat, pat-like sound created by the finger connecting with the device, if performed with sufficient

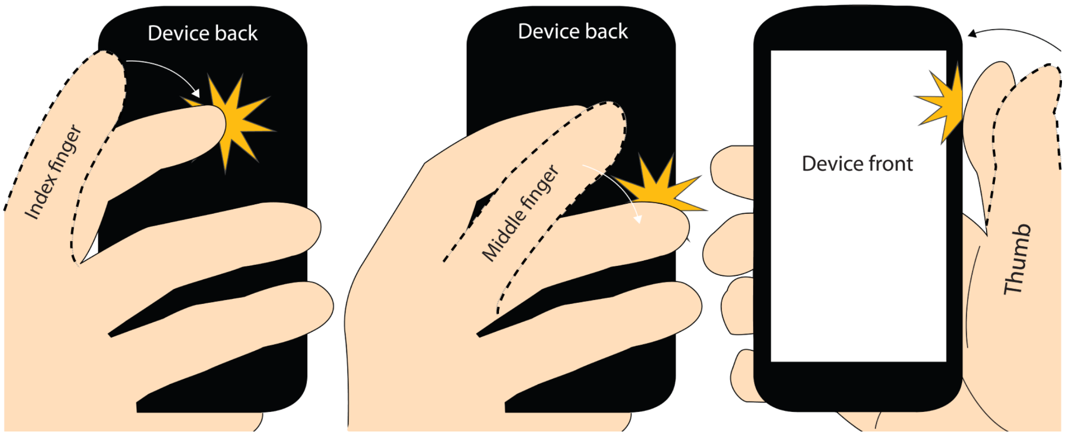

FIGURE 6.1: The three *BackPat* gestures: *BP-index*, *BP-middle* and *BP-thumb*. Image taken from (Seipp and Devlin, 2014*b*).

force. The presented technique is termed *BackPat*, and for brevity, I will refer to each *BackPat* gesture using the following descriptors:

- *BP-index*: Where the index finger is used to pat the upper part of the device's back.
- *BP-middle*: Where the middle finger is used to pat the middle outer part of the device's back.
- *BP-thumb*: Where the thumb is used to pat the device's side.

Each pat can be used on its own as a distinctive input signal performing the gesture only once, or, if executed twice in quick succession, as a double-pat. This depends on the gesture events a developer may subscribe to when using the technique in an application.

Despite the three gestures performing essentially the same action – that of a "pat" – they should be different enough to avoid the trap of Norman's "description error", which highlights the danger of two similar interaction possibilities located close to each other (Norman, 2002), especially when supplemented by distinctive graphical feedback. Nonetheless, performing these gestures in a more pronounced fashion can further ensure this problem is avoided and provide additional benefits: The more distinctive a gesture, the easier it is for the gesture interpreter to analyse and read the user's action correctly.

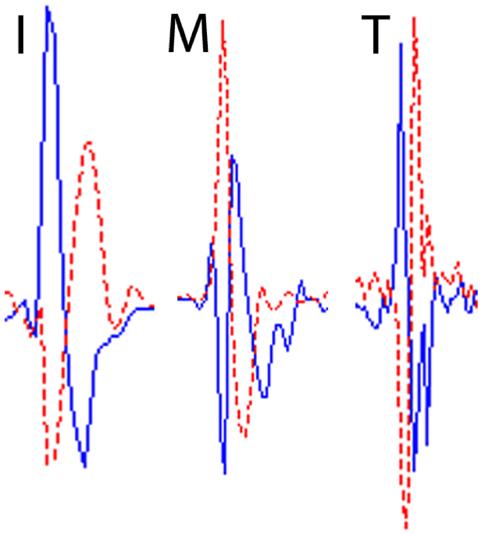

Figure 6.2: Examples of gyroscope patterns for the middle finger (M), index finger (I) and thumb (T) when executing the three *BackPat* gestures. The full (blue) line represents the angular velocity around the X-axis, the dashed (red) line the angular velocity around the Y-axis. For *BP-index* and *BP-middle* the angular velocity around the Z-axis is not noteworthy, but is very high for *BP-thumb* on the side of the device, supporting correct pat detection of the otherwise rather similar patterns of T and I. Figure taken from Seipp and Devlin (2014*b*).

6.2.1 Functional Principle

In order to learn what degree of gesture explicitness is convenient for users, a preliminary user study was conducted with six participants (3 F, mean age: 32, SD: 3.74), using a HTC Sensation XE phone running Android 4.03 and a custom sensor recording application. Users were asked to pick up the device and long-touch the screen to initiate recording. The long-touch serves as a suggested gesture initiator, but others are conceivable. Users were asked to perform two rounds: One for the index finger and one for the middle finger. For each, they executed the gesture ten times while the device's rotation over the X, Y and Z axes was recorded using its gyroscope sensor as well as the sound properties made by each pat. This was done once with the right hand and once with the left. An analysis of the data showed clear patterns in the gyroscope data and high peaks in the sound level whenever a pat was performed. Using these values in a set of heuristics, a basic gesture detector was built as an Android application and the thresholds for gesture recognition were adjusted in a second study with the same users. Here, the patting with the thumb against the side of the device was introduced as a third gesture, for which thresholds were also defined. Figure 6.2 shows the characteristic

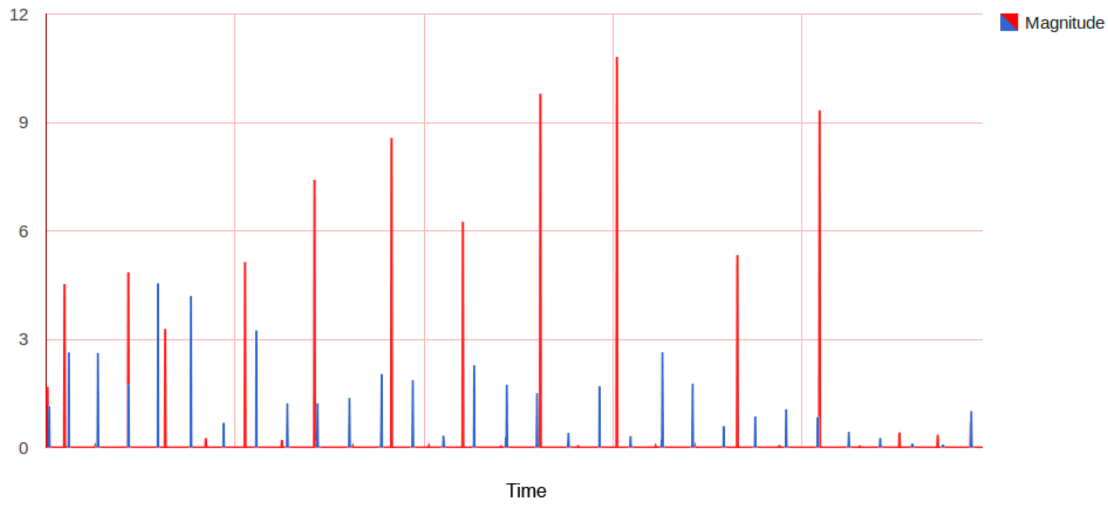

Figure 6.3: The volume of pats (red) and speech (blue) on a scale from 0–12. Pats were performed on the back of the device using *BP-index*. Speech was recorded 30cm from the device. Sentence recorded: "Weil du so gerne Pflaumenmus magst, habe ich fuer dich heut' Pflaumenmus gekauft", part of Juergen Theobaldy's poem "Speziell fuer dich".

gyroscope patterns of each patting gesture. The information sheet and consent form of the study can be found in Appendix F, section F.1, p. 369.

Combining the gyroscope data with the sound volume created by each pat allowed a more stable recognition of the gestures. In the volume development of a typical pat, each was marked by a sharp rise and fall (Fig 6.3) and these were even discernible while talking in about 30cm proximity to the phone while performing the pats. The peak detection works as follows: The sound level of the incoming audio is continuously monitored. If the sound rises above a certain threshold, the buffered volume is compared in a short window before and after the peak has been detected. If the peak's volume is 30% higher than that of the surrounding data, a pat sound is registered.

This windowing approach bears two advantages: First, the sound of a pat can be distinguished from the background noise due to the characteristic changes in volume, providing a relatively reliable gesture delimiter, as described by Zhang et al. (2013). Second, the short delay provides sufficient time for the gyroscope patterns to occur and be interpreted.

While this approach provided a good starting point for performing the gestures as well as differentiating between them, I decided to improve gesture detection by analysing the

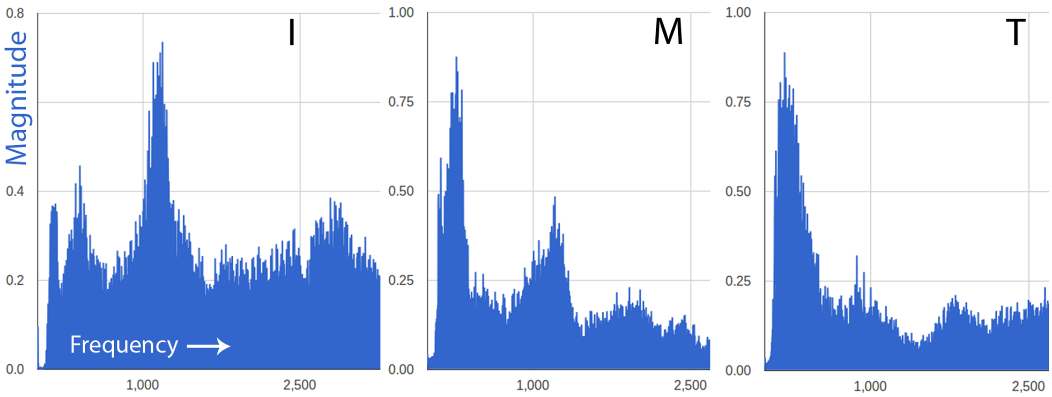

FIGURE 6.4: Averaged frequency (X-axis) magnitudes (Y-axis) of each pat between 0–2500Hz. A pat of the thumb (T) shows a characteristic profile between 0–1200 Hz, the middle finger (M) between 0 and 2300 Hz – partially resembling the thumb – and the index finger (I) between 400 and 2700 Hz. Figure taken from Seipp and Devlin (2014*b*).

profile of each pat sound in addition to its volume and the gyroscope data. For this, the patting sounds of all gestures were recorded from three users (1 F, mean age: 30.3, SD 4.1). Performing a Fast Fourier Transform (FFT) of the averaged data and visualising the magnitudes of the frequencies showed a distinctive image for each pat (Fig. 6.4).

The averaged data of each pat was then used in a detection algorithm which extracts three frequency ranges that were defined to be characteristic of each pat (Fig. 6.4) from the device's microphone and calculates the Pearson Correlation Coefficient (PCC) of these extracts and the reference data. Which finger had performed the pat was then determined by the PCC with the highest value, if found to be above or equal to 0.5. Comparing the pat sounds of six users (2 F, mean age: 31.8, SD: 3.7) to the reference data as well as to speech and music (Tab. 6.1) illustrates that classification between the discrete fingers is possible due to the varying audio profiles created by the pats' differing location and connection angles with the device surface. However, performing a PCC between the reference data and an incoming pat sound while talking within 30cm distance of the device reduced the PCC to an average of 0.32 for the three pats. This was deemed unsuitable for gesture interpretation as the value was close to the PCC measured between music or speech and the reference data (Tab. 6.1).

For an online video of the technique, please see Seipp (2014). The *BackPat* source code can be found in Appendix F, page 371.

Table 6.1: PCC range for the pat sounds compared to a recorded parliamentary speech (Speech) and to a Jungle tune (Music). For the resource URLs, please see Appendix F, section F.3, p. 371. The measurements were taken twice per pat sound and sound source. The PCC range for speech and music comparison is based on the rounded average values of the lowest and highest PCC measured during 60 seconds of playback. The right part of the table presents the mean PCC of pats performed by six users (2 F, mean age: 31.8, SD:3.7) in comparison to the reference data (ref.). Table taken from Seipp and Devlin (2014*b*).

Pat sound	**Speech**	**Music**	**Thumb ref.**	**Index ref.**	**Middle ref.**
Thumb	0.00 – 0.14	-0.10 – 0.20	0.58	0.37	0.44
Index	0.10 – 0.30	0.00 – 0.31	0.37	0.48	0.35
Middle	0.10 – 0.30	0.10 – 0.30	0.44	0.35	0.56

6.2.2 Gesture Detection Accuracy

The comparison of the reference data against different sound sources (Tab. 6.1) suggested a minimum PCC value of 0.38 to be enough for detection. It was therefore decided to set the thresholds as follows to improve pat classification under non-lab conditions:

- Thumb: PCC >= 0.45.
- Index and middle finger: PCC >= 0.38.

The minimum PCC for thumb classification was adjusted to 0.45 due to its high similarity with the middle finger sound spectrum (Fig. 6.4), which might easily generate false positives. An accuracy test of the modules was then conducted under various conditions with six users (1 F, mean age: 33.2, SD: 4.5). Before the accuracy test users were given five minutes of exploration to familiarise themselves with the three gestures. The study data and study information can be found in Appendix F, pp. 369–373. The results of the test are shown in Tab. 6.2.

The data in Table 6.2 showed that peak analysis and gyroscope interpretation were the most reliable modules. However, the accuracy of the gyroscope interpretation was impacted by walking. Gesture detection via frequency analysis (FA) was possible under lab conditions with users taking care to perform the correct sound, but its reliability was reduced by background noise, which had less of an effect on peak detection. Although the FA results might be improved using directional microphones (as suggested by Lopes et al. (2011)), a larger sample size, frequency filtering or per-user calibration, the data

Table 6.2: Percentage of correctly interpreted pats by six users performing ten pats per module. Results shown for each module (Gyro (G), Peak (Pk) and Frequency Analysis (FA), separately in % under lab conditions (L = sitting, low noise level), with recorded talking (T) at -0.6 to -0.3 db in the background (see Appendix F, section F.3.1, p. 371), while walking (W), and all modules active (All) with equal weighting. Column All illustrates the importance of a tiered approach over an equally weighted one, as the overall accuracy can be lowered if all modules are equally considered. The data can be found in Appendix F, section F.4.1, p. 373. Table taken from Seipp and Devlin (2014*b*).

Finger	**Pk (L)**	**Pk (T)**	**G (L)**	**G (W)**	**FA (L)**	**FA (T)**	**All (L)**
T	87%	87%	85%	75%	77%	35%	91%
I	98%	98%	83%	70%	78%	63%	73%
M	97%	85%	87%	68%	78%	73%	80%

suggests it is not sufficiently reliable in a “real-life” situation, especially not when used as the sole classifier.

To address this, only a minor role was allocated to the FA in a tiered gesture detection approach: If the peak detection signals that a pat has occurred, the gyroscope data is examined for each pat’s characteristic pattern. From this, if a finger cannot reliably be determined, the FA module is queried and used for classification if the PCC is high enough. This three-step analysis allows gesture detection in situations where one model may be prone to failing. For example, when walking, the FA may provide more accurate results than the gyroscope. In turn, the gyroscope module is more reliable in a noisy environment, compensating for potential false positives of the FA. This way, gestures can be detected with a good degree of confidence (Tab. 6.2), without extra hardware or per-user calibration. However, it has to be noted that the gesture detector is likely to require calibration on different device ranges, due to different materials being used for the casings, different ergonomic user characteristics and varying degrees of gyroscope sensitivity.

6.2.3 Configuration

The gesture detector provides the following algorithm configurations per module, each with their own advantages and disadvantages:

Peak Module (P)

Configuration A: The sound volume is continuously measured. If it breaks through a certain threshold, it is registered as a potential peak. After a delay between 50 and 150ms the volume levels aggregated before and after the estimated peak event are analysed. If the recorded levels in the list following the position earmarked as a peak are 20% lower, the peak detection is confirmed and the event sent to the controller. The length of windowing delay can be adjusted, depending on the hardware of the device. While set in an options dialogue in the current implementation, it is suggested to adjust the required difference between peak and non-peak volume dynamically to the level of environmental noise.

Configuration B: The sound volume is continuously measured. If it breaks through a certain threshold, it is registered as a peak. This is faster than configuration A, but more prone to error in a noisy environment.

Gyroscope Module (G)

Configuration A: The gyroscope values are continuously measured. If a peak in volume is detected (using the **P**.A configuration), the values accumulated in the array of each axis since the peak detection are analysed after a brief delay. If the amplitude measured for the X-axis is greater than a certain threshold, as well as larger than the amplitude of the Y-axis, and the amplitude on the Y-axis is below a certain threshold, a *BP-index* gesture is registered. If the amplitude measured for the Y-axis is greater than a certain threshold, as well as larger than the amplitude of the X-axis, and the amplitude on the X-axis is below a certain threshold, a *BP-middle* gesture is registered. If the amplitude of the Z-axis is larger than a certain threshold while X and Y are below their thresholds, a *BP-thumb* gesture against the side of the device is registered.

Configuration B: The gyroscope values are continuously measured. If a peak in volume is detected (using the **P**.B configuration), the last positions in each gyroscope array are examined and the values of them compared. If the X-value is above a certain threshold and higher than the Y-value which has to be below a certain threshold, a *BP-index* gesture is registered for the module. If the Y-value is above a certain threshold and higher than the X-value which has to be below a certain threshold, a *BP-middle* gesture is registered for the module. For the thumb, the value of the angular rotation around the Z-axis is queried and a *BP-thumb* gesture registered if this is above a certain threshold, with X and Y values having to be below their predetermined detection values. Analysing the gyroscope values immediately after a volume peak is detected (rather than their amplitudes over short period of time) is faster than configuration A, but more prone to error when shaking the device or walking. To address this, a pat is only registered if the value is below a maximum value defined for each axis. These values depend on the gyroscope's sensitivity.

Frequency Analysis Module (FA):

Configuration A: The microphone input is recorded with a sample rate of 8000 Hz. After the buffer has been filled with 8000 samples, an FFT is performed and the result compared against each reference array using a PCC calculation. For this, only the relevant portions of the input and reference arrays are compared:

- Thumb: Positions 0–1200
- Index finger: Positions 400–2700
- Middle finger: Positions 0–2300

The calculation with the highest PCC determines the "winner", which is then fed back to the controller.

Configuration B: This is the same as configuration A, but with a buffer length of 3000, allowing nearly three times as many calculations in the same time, albeit with less accurate results. In both cases, the evaluation of the FA is always slightly "stale" in comparison to the other modules (**P** and **G**), due to the greater amount of time needed to collect the data, which confirms its role as a fall-back module in favour of sound volume and gyroscope movement.

Which of the above configurations should be used can either be determined when initialising the gesture controller or at runtime via an options dialogue. In any case, it should be adapted to the application in use and the degree of responsiveness and precision needed. Applications which require only one pat, such as the *Pat-Into-Place* technique introduced later in this chapter (p. 282), should be configured using the slower configuration of [**P**.A, **G**.A, **FA**.A], whereas applications where a quick succession of pats is needed – such as text selection, list item selection and when using a double-pat gesture – should use a configuration of [**P**.B, **G**.B, **FA**.B].

The gesture controller collects the recommendations of the above approaches and makes a decision. It then emits the following events to the hosting application, where the detection thresholds and timers can each be configured:

- *tapTop* event: Triggered when a patting gesture with the index finger at the upper third of the device occurs (*BP-index*).
- *tapMiddle* event: Triggered when a patting gesture with the middle finger, slightly at the side of the device occurs (*BP-middle*).
- *tapSideRight* event: Triggered when a patting gesture with the thumb against the side of the device occurs (*BP-thumb*).
- *onAbortPatternCheck*: Triggered when the pattern check is aborted due to insufficient or inconclusive data.

By subscribing to these events, developers can build a variety of applications, four of which will be presented in section 6.3.

6.3 Application

6.3.1 Study One

To gauge user acceptance and performance of *BackPat* together with users' ability to perform the gestures, a small study of six users was conducted (3 F, mean age: 32, SD: 3.74) with three applications: Text selection, multiple selection of items in a list, and reaching targets outside the thumb's reach. The study data and study information can be found in Appendix F, pp. 374–376.

FIGURE 6.5: The three applications tested with users. **Left**: Text selection. The text selection tasks are highlighted in red. To allow beginning the selection tasks from the middle of the line, three "words" were broken down into "xxx" and an "i" was appended to one. **Middle**: A list selection task where the user has to select the grey list elements, starting at "List item 5" (the bottom one highlighted). **Right**: The target positions of the *Pat-Into-Place* study where targets at the bottom or top of the screen can be moved towards the thumb using either *BP-index* or *BP-middle*. Figure taken from Seipp and Devlin (2014*b*).

Study One – Text Selection

Users were tasked to select three words starting in the middle of a text field which was horizontally and vertically centred on the screen, with each line holding six words in the form of "xxxxx" (Fig. 6.5). The fields the user had to select were coloured red. The field was 24 lines high, with a font size of 27 pixels (px) and line height of 32px. For the content, the Roboto Regular font was used, displayed on a HTC Sensation XE with a screen resolution of 540px x 960px at 256 points per inch (PPI) running Android 4.03. User had to select the highlighted text in three ways: Once in the system "standard" way of dragging a selection bracket to encompass the words, once by performing several *BP-middle* gestures in quick succession to extend the selection one word per pat to the left, and once by performing several *BP-index* gestures to extend the selection one word per pat to the right. Each round had to be performed three times with the mean task time saved for each user and technique.

Although *BackPat* allows adjusting the text selection if it overshoots by performing a tap with the other finger to move the selection bracket into the opposite direction, users had to restart a test round if such an error was made to ensure only the results of one action were recorded. To start recording, users were tasked to long-tap the screen (a tap with an average duration of about 500ms) on a highlighted word and subsequently perform

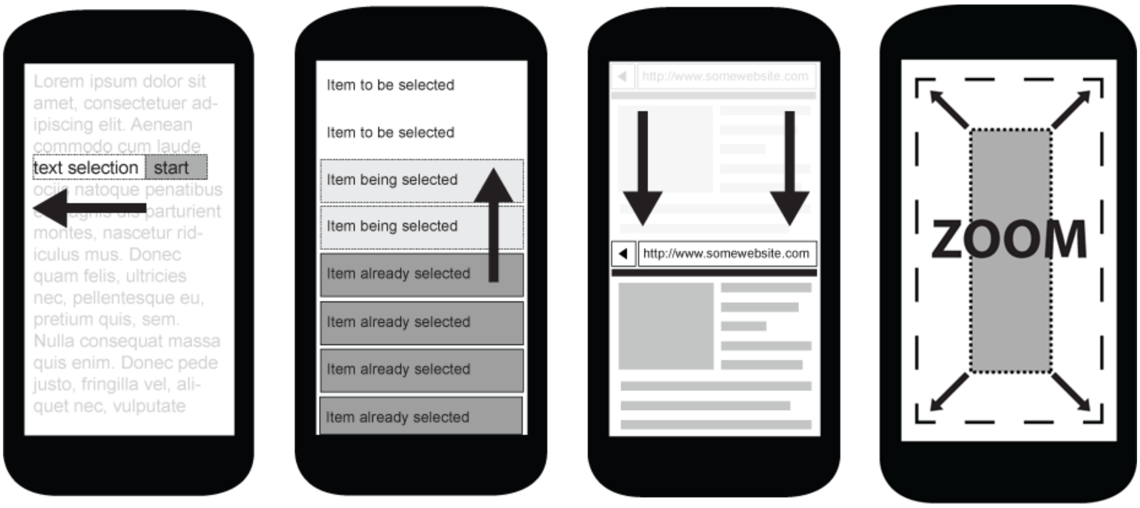

FIGURE 6.6: Description of the effect of a *BackPat* gesture in four example applications. **From left to right**: Extending a text selection, selecting items in a list, moving targets that are outside the thumb's reach to the level of the thumb, and map and image zoom. Images taken from Seipp and Devlin (2014*a*).

the *BackPat* gestures or front-of-device thumb movements to complete the selection. Recording finished when the selection was held for 500ms. After recording was finished, users gave feedback on a five-pointer Likert scale regarding ease of use and logic of the application's gesture configuration.

Study One – Reaching Distant Targets

In the second part of the study, users were asked to explore the use of *BackPat* for reaching targets outside the thumb's reach. To do so, a user first taps the screen with their thumb in an easy-to-reach place. This tells the system which vertical location on the screen is easy to reach for the user's thumb. Performing a subsequent *BP-index* gesture moves targets at the top of the screen down towards the position of the thumb determined in the first step, allowing easy access of previously hard-to-reach elements (Fig. 6.5). This can be useful in order to move the URL bar in a browser down to the thumb so that the user can interact with it easily, for example (Fig. 6.6). In contrast, targets at the bottom of the screen can be moved upwards by performing a *BP-middle* gesture. For ease, this gesture is termed *Pat-Into-Place* (*PIP*) in the rest of this thesis. Of course, touching the screen with the thumb to set the coordinates for targets to be moved to is not mandatory. Instead, targets can just be moved to a fixed (but generally easy-to-reach location) by simply performing a *BP-index* gesture or double-pat gesture.

Table 6.3: Mean interaction time in ms for participants 1–6 (ID) when extending a text selection to the left (L-N) and right (R-N) in normal mode (using the system default procedure of dragging the selection brackets with a thumb) and using *BP-index* (BP-I) and *BP-middle* (BP-M).

ID	**L-N**	**BP-M**	**R-N**	**BP-I**
1	2704	2630	1829	2117
2	4260	2722	3165	1933
3	3654	2265	2845	1812
4	3227	1852	2600	2714
5	5952	1676	2498	2777
6	4626	3191	6631	2143

However, in the study, the preliminary touch on the screen helped to define the "landing" coordinates of the targets and also served as a gesture delimiter. Once implemented into an application, this should ideally be a long-touch to avoid the initial tap inadvertently activating a button. After some self-guided exploring and a comparison against the "normal" way of stretching or contracting the thumb to reach a target, users provided feedback on a five-point Likert scale. As opposed to the text selection study, quantitative data was not recorded.

Study One – Multiple Selection

In the third part of the study, users were asked to explore *BackPat*'s usability for multiple selection of list items. As in the text selection study (p. 281), a selection was initialised with a long-tap. To extend the selection upwards, users could perform a *BP-index* gesture. To reduce the selection or extend it downwards, users performed a *BP-middle* selection. Users were asked to explore the application with minimal guidance and compare it to the "standard" way of selecting items one by one using their thumb. Once finished, users gave feedback on a five-point Likert scale. As opposed to the text selection study, quantitative data was not recorded.

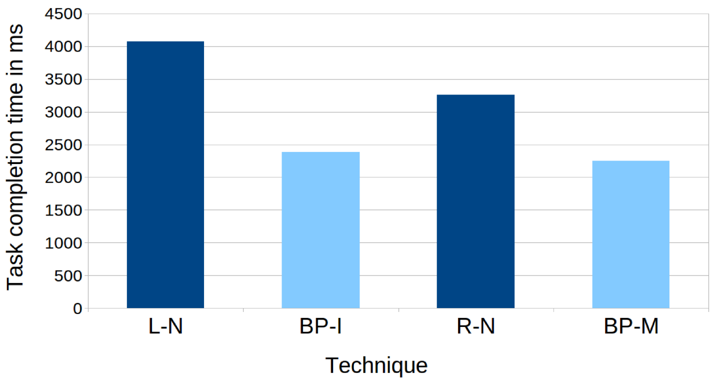

FIGURE 6.7: The mean task times for text selection using the thumb stretched to the left in normal mode (L-N), *BP-middle* extending the selection to the left (BP-M), the thumb stretched to the right in normal mode (R-N) and *BP-index* extending the selection to the right (BP-I). The data can be found in Appendix F, section F.5.1, p. 376.

Evaluation Study One

Text Selection

Table 6.3 shows the mean task times for selecting three words of text using *BP-index*, *BP-middle* and moving the thumb left and right across the display. Although predictions on data based on such a small sample size cannot be wholly reliable, an ANOVA indicated a significant effect of mode ($p = .001$). A following paired samples t-test revealed that the mean completion time for the text selection tasks using *BackPat* (2319.30, SD: 206.20) was lower than using the standard selection mode (3665.90, SD: 1171.70). The difference was statistically significant, $t(5) = 3.10$, $p = .027$, suggesting the possible usefulness of *BackPat* for enhancing small text selections.

Evaluating the Likert scale feedback showed a light trend for users to judge *BP-middle* to be easier to use than *BP-index*, but a Wilcoxon test on the data showed no statistically significant difference. The data can be found in Appendix F, section F.5.1, p. 376.

Reaching Distant Targets (*PIP*)

The analysis of the user feedback showed a light trend of judging *BP-middle* to be easier to perform than *BP-index* and *BP-index* to make selection faster than *BP-middle* when compared against the normal mode of operation, but differences were not statistically

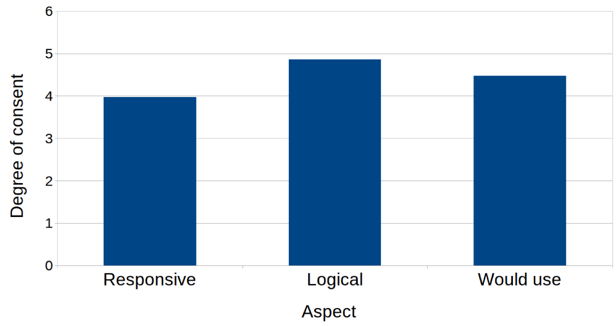

FIGURE 6.8: The mean feedback values given by six users on a Likert scale from 1 (totally disagree) to 5 (totally agree). Users judged whether the system was responsive (Responsive), the gesture configuration logical (Logical), and whether they would use the technique if it was available (Would use). The data can be found in Appendix F, section F.5.1, p. 376.

significant. However, users agreed that *BackPat* made selection of hard-to-reach targets easier than selecting them directly. The data can be found in Appendix F, section F.5.1, p. 376.

Multiple Selection

The user feedback suggested that users preferred *BP-middle* over *BP-index*, but differences were not statistically significant. Users agreed that *BP-middle* made multiple selection of items easier. The data can be found in Appendix F, section F.5.1, p. 376.

Summary

Three different applications have shown the possible potential of *BackPat* for enriching one-handed smartphone operation. The quantitative data of the text selection study (Tab. 6.7) suggests a high degree of effectiveness for short text selection. The qualitative user feedback indicates user acceptance of the technique with a preference for *BP-middle* over *BP-index*. Altogether, *BackPat* appears to be a promising technique: The configuration of the gestures and applications was judged as logical while the technique was found to be responsive, with users indicating that they would use the technique if it was available in an application (Fig. 6.8).

6.3.2 Study Two

To gain a clearer picture of the usability and efficiency of *BackPat*, this section will present the results of three larger user studies. While the applications examined are the same as in Study One (section 6.3.1, p. 280), the task scope was extended, and quantitative as well as qualitative data was collected for each application. As the goal of this chapter is to examine whether the approach of input modality extension can be used to address all of the main challenges of one-handed smartphone operation – as defined in the literature review – together, using a single technique, the applications cover these as follows:

- **Text selection:** Accot's law (steering law), interface occlusion.
- **Multiple selection:** Limited dexterity, interface occlusion.
- ***Pat-Into-Place*:** Fitts's law (increasing precision and reducing interaction time when selecting distant targets).

By evaluating *BackPat* in these applications, its potential (and that of the approach of input modality extension via sensors in general) for offering a solution that addresses all of these challenges using a single technique can be examined. The study data and study information can be found in Appendix F, pp. 377–379.

Study Two – Text Selection

Using a text field with the same configuration as in Study One (section 6.3.1, p. 281), users were tasked to select 0.5 lines, 1 line, 1.5 lines and 2 lines of text (Fig. 6.5). This had to be done three times for each amount of text using the following techniques: Stretching the thumb to the left and up (normal mode), stretching the thumb to the right and down (normal mode), *BP-index*, *BP-middle*, and *BP-thumb*. *BackPat* was configured as follows:

- *BP-index*: Extends the selection to the right by one word per pat.
- *BP-middle*: Extends the selection to the left by one word per pat.

- *BP-thumb*: Extends the selection to the right by one word per pat.

If users overshot, they were asked to restart the round. Recording started once the initial selection had been created using a long-tap and stopped once the selection had been completed and held for 500ms. The study was counterbalanced by mode, task and finger. Altogether, 20 users took part in the study (5 F, mean age: 25.4, SD: 4.57, 18 right-handed, 2 left-handed). Scatter plots and a rule of thumb highlighting values significantly larger than twice the SD were used to examine the data for outliers. Two sets were removed due to missing data. One set was removed due to the user not being able to hold the device, leaving a total of 17 cases. After the tasks had all been completed, users provided feedback on a five-point Likert scale.

Study Two – Multiple Selection

In a list view with 11 items, spanning the whole width and height of the screen of a HTC Sensation XE running Android 4.03 with a resolution of 540px x 960px at 256 PPI, users were tasked to select three, six and eleven consecutive items. This had to be done three times using each of the following techniques: Moving the thumb up (normal mode), moving the thumb down (normal mode), using *BP-index*, *BP-middle*, and *BP-thumb*. *BackPat* was configured as follows:

- *BP-index*: Extends the selection upwards, one item per pat.
- *BP-middle*: Extends the selection downwards, one item per pat.
- *BP-thumb*: Extends the selection upwards, one item per pat.

Selection tasks always had to begin mid-list (at “List item 5”) when selecting three or six items, or at the top (“List item 0”) and bottom (“List item 10”), when selecting all 11 items (Fig. 6.5). Recording started by tapping the first item and ended when the last item of the task had been selected. There were 24 users in the study (6 F, 21 right-handed, 2 left-handed, 1 ambidextrous), which was counterbalanced by task and mode. No outliers were found in the data. After the tasks had been completed, users provided feedback on a five-point Likert scale.

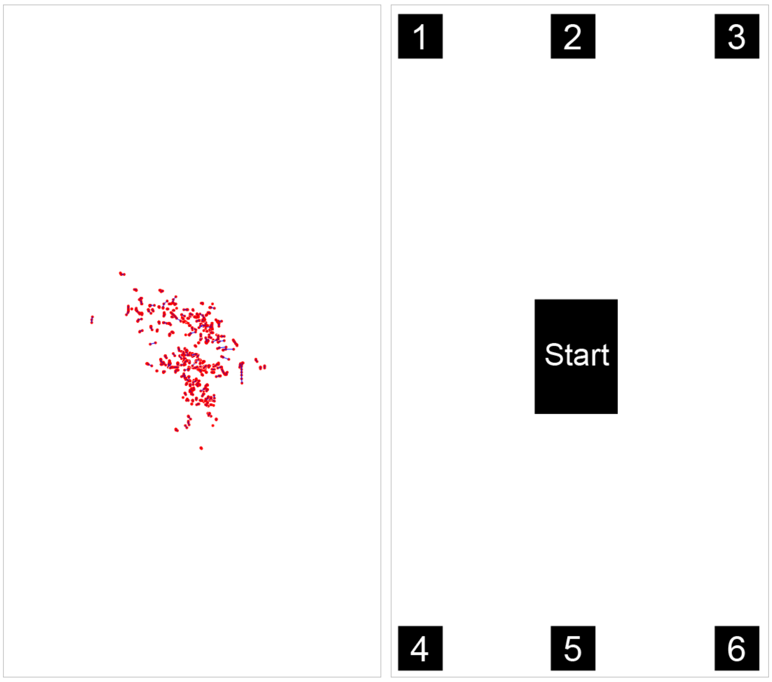

FIGURE 6.9: **Left:** The touch points created by the users tapping the screen in what they considered the thumb's resting position. **Right:** An illustration of the six target locations users had to interact with in the *PIP* study. Targets can be grouped as follows: Group left = 1 and 4, group middle = 2 and 5, group right = 3 and 6.

Study Two – Reaching Distant Targets (*PIP*)

In a third study, users were tasked to use *BackPat* to "*pat*" distant targets *into* a *place* (*PIP*) that would be easily reachable by the thumb and then interact with them. As outlined in section 6.3.1, p. 282, users had to interact with six targets in each corner of the screen (Fig. 6.5, 6.9). Specifically, users had to perform the following tasks three times: Reach for the targets at the top of the screen by stretching the thumb (normal mode), reach for the targets at the bottom of the screen by contracting the thumb (normal mode), use *BP-index* to move targets at the top of the screen down to the level of the thumb, and *BP-middle* to move targets at the bottom of the screen up to the level of the thumb. In each task, the interaction time, amount of taps (errors) and the tap offset to the target centre were recorded.

Targets were a size of 4mm x 4mm, a size rated as hard-to-interact-with by Park and Han (2010). Each round ended, once a target had been tapped successfully. To start each round and the recording, users had to tap a button in the middle of the screen to ensure the same starting point for all interactions. This point was determined by having seven users (3 F, mean age: 31.43, SD: 4.65) hold the phone in one hand while tapping the screen ten times in a position they regarded as the thumb's resting point over the screen, without any degree of thumb extension or contraction (Fig. 6.9). This was done once with the left hand and once with the right hand. The centre was deducted from the mean X and Y coordinates of the touches and width and height were based on the standard deviation of each coordinate. Recording stopped once the user had tapped the respective target. There were 18 users (4 F, 15 right-handed, 1 ambidextrous, 2 left-handed, mean age: 26.6, SD: 4.57) in the *PIP* study. One case was identified as an outlier while another had incomplete data, leaving 16 cases. After the tasks had all been completed, users gave feedback on a five-point Likert scale.

Study Two – Results and Evaluation

Text Selection

An ANOVA showed a main effect of amount of text to select, $F(1.81, 28.95) = 16$, $p < .001$, a main effect of technique, $F(1.83, 29.24) = 6.19$, $p = .007$, and an interaction of technique and amount, $F(4.23, 67.66) = 10.78$, $p < .001$. The results were Greenhouse-Geisser-corrected. As the data did not match parametric assumptions, I referred to the median task times when analysing the data, for it presented the data more adequately than the mean. In addition, a Wilcoxon test was employed over the t-test to break down the effects. The data can be found in Appendix F, section F.6.1, p. 379.

A Wilcoxon test indicated that selecting 0.5 lines of text beginning in the centre of the screen and ending at the screen's edge (Fig. 6.5) was faster using any *BackPat* method than using the thumb in normal mode. *BP-index* was the fastest technique (Tab. 6.4) – significantly faster than moving the thumb left, $Z = 3.62$, $p < .001$, or to the right, $Z = 2.68$, $p = .007$, in normal mode. *BP-index* was also faster than *BP-thumb*, $Z = 2.86$, $p = .004$, and *BP-middle* was faster than moving the thumb left in normal mode, $Z = 3.39$, $p = .001$. See Table 6.4 and Figure 6.10.

SelectinG1 line of text that starts in the middle of a line and ends in the middle of the following line (Fig. 6.5) was fastest moving the thumb towards the right and down in normal mode, which was significantly faster than *BP-thumb*, $Z = 3.15$, $p = .002$, the slowest technique. In second place was *BP-index*, which was also faster than *BP-thumb*,

Table 6.4: Rounded median (Med) and mean (M) task times and SD of the text selection user study for each mode (*BP-index* (BP-I), *BP-middle* (BP-M), *BP-thumb* (BP-T) and normal left and right (N-L, N-R)) in ms for 0.5, 1 and 1.5 lines. Due to the clearly visible trends in the data for 1 and 1.5 lines of text selection, the results for 2 lines of text selection are omitted for brevity. Figure taken from Seipp and Devlin (2014*b*)

Mode	**0.5 Med**	**0.5 M**	*SD*	**1 Med**	**1 M**	*SD*	**1.5 Med**	**1.5 M**	*SD*
BP-T	3535	3356	*818*	5395	5392	*1643*	5702	6569	*2448*
BP-I	2669	2670	*366*	3521	3561	*583*	4642	4669	*642*
BP-M	2971	2959	*649*	3775	3866	*710*	4495	4126	*1400*
N-R	3663	3853	*1384*	3406	3849	*1575*	3273	3656	*1048*
N-L	4059	5141	*2548*	3622	4132	*1479*	3474	4126	*1894*

$Z = 3.43$, $p = .001$. Using *BP-middle* was also faster than using *BP-thumb*, $Z = 3.15$, $p = .002$. See Table 6.4 and Figure 6.10.

SelectinG1.5 lines of text (Fig. 6.5) with the start point in the middle of a line and the end point at the screen edge was fastest using the thumb in normal mode (Tab. 6.4). Moving the thumb to the right was faster than using *BP-middle*, $Z = 2.96$, $p = .003$, *BP-index*, $Z = 3.24$, $p = .001$, and *BP-thumb*, $Z = 3.62$, $p < .001$. The fastest BP technique was *BP-index*, with it being faster than *BP-thumb*, $Z = 2.81$, $p = .005$. See Table 6.4 and Figure 6.10.

The p values in each Wilcoxon test were Bonferroni-Holm-corrected, starting with a divider of ten. Due to the clearly discernible trend of reduced efficiency for longer text selection (>= 1 line of text) using the *BackPat* technique, the selection times for 2 lines of text were not evaluated.

The results indicate that *BackPat* improves short text selections (0.5 lines), as already suggested by the data evaluated in Study One (section 6.3.1, p. 280). For larger amounts of text (1 line), *BackPat* was less efficient (Fig. 6.10). Finally, the results for selectinG1.5 lines of text show that the *BackPat* technique is inferior to stretching or contracting the thumb, which allows users to easily jump between lines which otherwise would have to be “patted down” word by word. The data therefore suggests that *BackPat* would be best used as a complementary method to direct tap: Users can cover large vertical differences by moving the thumb over the display, but can fine-adjust their selection with a few pats, especially in hard-to-reach areas. Regarding the efficiency of the *BackPat*

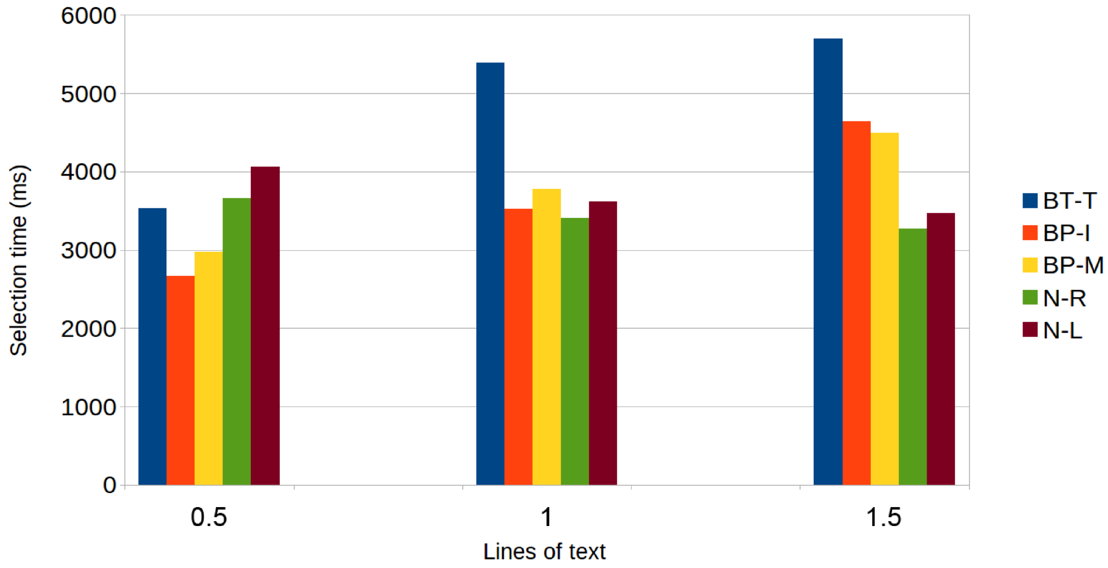

FIGURE 6.10: Visualisation of the median task completion times of the text selection user study presented in Table 6.4, grouped by amount of lines of text to select (0.5, 1, 1.5).

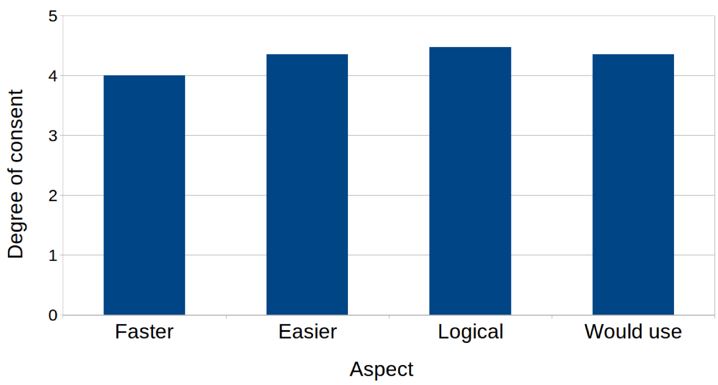

FIGURE 6.11: User feedback given on a five-point Likert scale after using *BackPat* for selecting various amounts of text. Users were asked whether they felt that *BackPat* made selection faster (Faster, SD: .94), easier (Easier, SD: .7), if the gesture input mapping was logical (Logical, SD: .62), and whether they would use it, if available (Would use, SD: .86).

gestures to support text selection, the fastest *BackPat* technique was *BP-index*, followed by *BP-middle*, followed by *BP-thumb* (according to the mean task completion times).

A Wilcoxon test of the feedback given showed that users judged *BP-index* (mean: 4.82, SD: .39) to be easier to use than *BP-middle* (mean: 4, SD: 1.06), $Z = 2.51$, $p = .012$, and *BP-thumb* (mean: 3, SD: 1), $Z = 3.69$, $p < .001$, and *BP-middle* to be easier to use than *BP-thumb*, $Z = 2.36$, $p = .018$. A Bonferroni-Holm correction was applied with a divider of three. In terms of whether a *BackPat* technique made selection faster, users agreed that *BP-index* and *BP-middle* improved selection speed, with *BP-index* being judged as slightly faster, albeit not statistically significant. Users felt both made selection faster than when using *BP-thumb*, though, with a result of $Z = 2.86$, $p = .004$ for *BP-index* (mean: 4.29, SD: .92) over *BP-thumb* (mean: 3.12, SD: 1.11), and a result of $Z = 2.29$, $p = .022$ for *BP-middle* (mean: 4, SD: .87) over *BP-thumb*. A Bonferroni-Holm correction was applied with a divider of three. This subjective user feedback thus matches the quantitative performance of the three gestures, highlighting *BP-index* as the most effective and usable. The data can be found in Appendix F, section F.6.1, p. 379.

Judging *BackPat* as a whole, users felt that *BackPat* made selection faster, easier, that the gesture configuration was logical and that they would use it, if available (Fig. 6.11).

Multiple Selection

A Greenhouse-Geisser-corrected ANOVA showed a main effect of amount, $F(1.28, 29.52) = 353.21$, $p < .001$, a main effect of mode, $F(1.96, 45.18) = 8.10$, $p = .001$, and an interaction of amount and mode, $F(4.54, 104.51) = 10.40$, $p < .001$. As the data did not match parametric assumptions, I chose the median over the mean for my analysis, as well as the Wilcoxon signed-ranks test over the t-test. The data can be found in Appendix F, section F.6.1, p. 379.

A Wilcoxon test showed that when selecting three items (Tab. 6.5), normal mode outperformed *BackPat* mode. Here, moving the thumb downwards was faster than *BP-middle*, $Z = 3.71$, $p < .001$. *BP-middle* was also slower than moving the thumb upwards, $Z = 3.63$, $p < .001$. The fastest *BackPat* method was *BP-index*, which was significantly faster than *BP-middle*, $Z = 3.26$, $p = .001$. *BP-middle* was the slowest selection method, being significantly slower than *BP-thumb*, $Z = 3.20$, $p = .001$. See Table 6.5 and Figure 6.12.

When selecting six items, using *BP-index* was the fastest technique (Tab. 6.5), being significantly faster than moving the thumb in a downwards motion in normal mode, $Z = 3.34$, $p = .001$, faster than moving the thumb in an upwards motion in normal mode, $Z = 3.26$, $p = .001$, faster than using *BP-middle*, $Z = 4.09$, $p < .001$, and faster than

TABLE 6.5: Rounded median (Med) and mean (M) task times and SD for each mode (*BP-index* (BP-I), *BP-middle* (BP-M), *BP-thumb* (BP-T) and normal up and down (N-U, N-D)) in ms for selectinG3, 6 and 11 items in a list.

Mode	**3 Med**	**3 M**	*SD*	**6 Med**	**6 M**	*SD*	**11 Med**	**11 M**	*SD*
BP-T	1236	1374	*646*	2436	2674	*1466*	3680	4372	*1975*
BP-I	1073	1254	*548*	1837	1927	*534*	3071	3256	*991*
BP-M	1728	2612	*2071*	2764	3295	*1732*	4352	5765	*3147*
N-U	939	1014	*482*	2544	3037	*1276*	5704	5796	*1139*
N-D	920	1008	*393*	2439	2633	*815*	5660	6040	*1520*

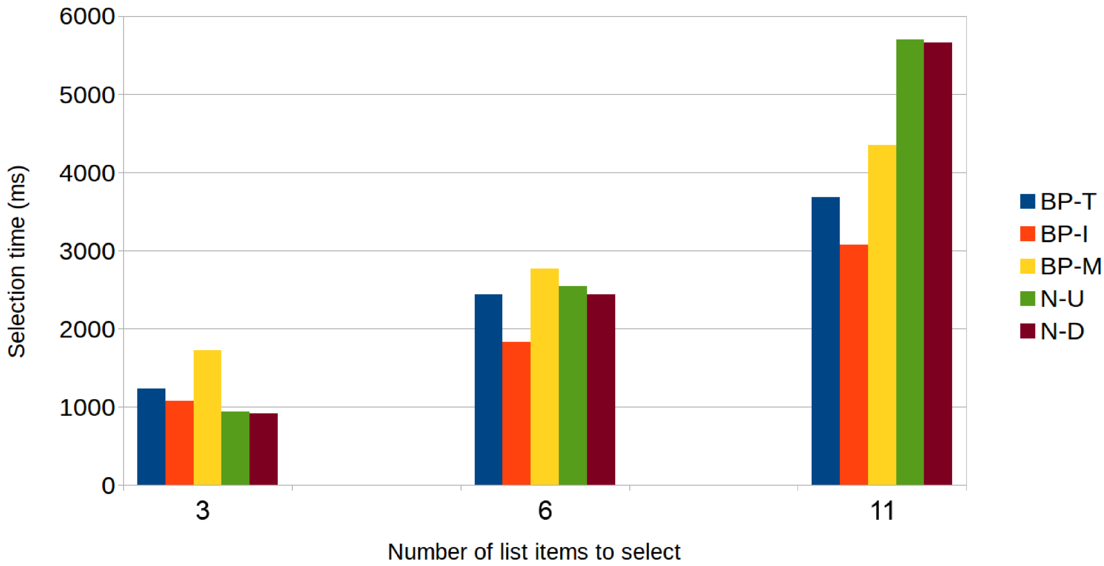

FIGURE 6.12: Visualisation of the task completion times of the multiple selection user study presented in Table 6.5, grouped by amount of list items to select (3, 6, 11).

using *BP-thumb*, $Z = 3.26$, $p = .001$. *BP-thumb* was also faster than moving the thumb up in normal mode, $Z = 3.97$, $p < .001$. See Table 6.5 and Figure 6.12.

For the selection of 11 items in a list, *BP-index* was again the fastest approach, being faster than *BP-thumb*, $Z = 3.11$, $p = .002$, and *BP-middle*, $Z = 3.51$, $p < .001$, and faster than moving the thumb up, $Z = 4.09$, $p < .001$, and down, $Z = 3.97$, $p < .001$. *BP-thumb* was also faster than moving the thumb up, $Z = 3.11$, $p = .002$, and down, $Z = 3.11$, $p = .002$. All Wilcoxon tests were Bonferroni-Holm-corrected, starting with a divider of ten. See Table 6.5 and Figure 6.12.

With regards to the *BackPat* gestures only, the data showed that, altogether, *BP-index* was faster than *BP-thumb*, which in turn was faster than *BP-middle*. A Wilcoxon test

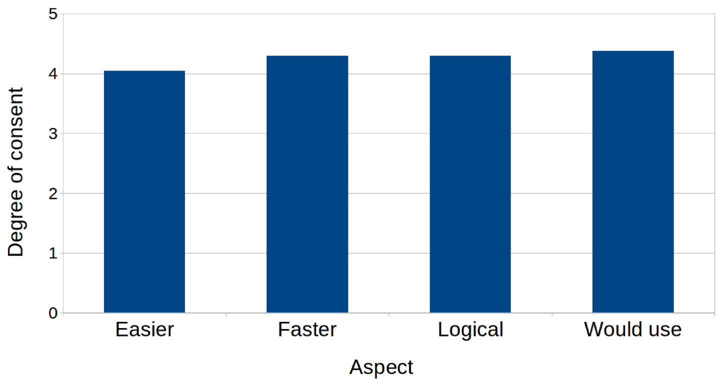

FIGURE 6.13: User feedback given on a five-point Likert scale after using *BackPat* for selecting multiple items in a list. Users were asked whether they felt that *BackPat* made selection faster (Faster, SD: .87), easier (Easier, SD: .94), if the gesture input mapping was logical (Logical, SD: 1), and whether they would use it, if available (Would use, SD: .98).

of the user feedback (Fig. 6.13, p. 294) showed that users found *BP-index* (mean: 4.37, SD: .92) made selection easier than *BP-middle* (mean: 2.67, SD: 1.17), $Z = 3.77$, $p < .001$, and BP-thumb (mean: 3.79, SD: 1.18) also made selection easier than *BP-middle*, $Z = 2.54$, $p = .011$. The comparisons were Bonferroni-Holm-corrected, starting with a divider of three. The data can be found in Appendix F, section F.6.1, p. 379. In summary, *BackPat* shows great potential for reducing selection time when selecting six items or more in a list. This suggests using *BackPat* as a complementary method: Small selections with up to three items should be performed using direct tap, as the change of grip necessary to perform the *BackPat* gestures outweighs potential benefits. For larger selections, however, efficiency can be improved by using the *BackPat* technique over direct tap.

The average task completion times (Tab. 6.5, Fig. 6.12) illustrate that *BP-middle* was the slowest *BackPat* technique for multiple selection. This is mirrored by user preference, as they preferred *BP-index* over *BP-thumb*, and *BP-thumb* over *BP-middle*. This suggests *BP-index* should be used for extending a selection upwards and *BP-thumb* for extending a selection downwards. Less frequent actions – such as the opening of a context menu after the selection – could be assigned to *BP-middle*.

Overall, users' feedback was that *BackPat* made selection faster, easier, that the gesture configuration was logical and that they would use it, if available (Fig 6.13).

Reaching Distant Targets Using *PIP*

When using *PIP*, error rates tended to be lower (Tab. 6.7, Fig. 6.14), but differences were not statistically significant. With regards to task completion time, an ANOVA revealed an effect of mode, $F(3, 45) = 20.46$, $p < .001$, but none of target position. As with the text and list selection studies, the data did not meet parametric assumptions. Therefore, I referred to the median in my analysis as it offered a better representation of the data, together with a Wilcoxon test instead of a t-test. The data can be found in Appendix F, section F.6.1, p. 379.

A Wilcoxon test showed that reaching targets with a downwards movement of the thumb in normal mode was fastest (Tab. 6.6, Fig. 6.14) – faster than reaching distant targets "patted into place" using *BP-index*, $Z = 3.46$, $p = .001$, and faster than accessing targets "patted into place" using *BP-middle*, $Z = 3.26$, $p = .001$. Accessing distant targets directly using an upwards movement of the thumb was also faster than using *BP-index*, $Z = 3.46$, $p = .001$. Considering only the *BackPat* techniques, *PIP* via *BP-middle* was faster than *BP-index*, $Z = 3.15$, $p = .002$. A Bonferroni-Holm correction was applied to all Wilcoxon tests, starting with a divider of six. See Table 6.6 and Figure 6.14).

Regarding X offset and Y offset on targets in the three positions of left, middle and right (Fig. 6.9, p. 288), an ANOVA showed an effect of target position on the X offset, ($F(2, 30) = 24.8$, $p < .001$, but none of interaction technique. A Wilcoxon test showed that the X offset was greatest for targets on the left of the screen (mean: 13.1px, SD: 2.14). It was greater than the offset for targets in the middle (mean: 7.4px, SD: 2.45), $Z = 3.2$, $p =.001$, and greater than the offset for targets on the right of the screen (mean: 7.3px, SD: 2.48), $Z = 3.72$, $p < .001$.

This indicates that target selection accuracy is neither influenced by stretching or contracting the thumb vertically nor by using a *BackPat* gesture to move targets towards the thumb and then tap them. Instead, a target's position on screen on the X-axis and therefore its horizontal distance from the thumb seems to be the decisive factor.

A Wilcoxon test on the user feedback showed that users found using *BP-middle* (mean: 4.06, SD: .77) made selecting distant targets slightly easier than *BP-index* (mean: 3.75, SD: 1.18), but the difference was not statistically significant. The same was observed for

TABLE 6.6: Rounded median (Med) and mean (M) task times (T) and SD in ms for each mode (*BP-index* (BP-I), *BP-middle* (BP-M), and moving the thumb up and down in normal mode (N-U, N-D)) to reach distant targets. Values show task times for the target positions left (L), middle (M) and right (R).

Mode	Med T-L	M T-L	*SD*	Med T-M	M T-M	*SD*	Med T-R	M T-R	*SD*
N-D	1669	1853	*1221*	979	1343	*848*	974	1275	*874*
N-U	1980	3147	*970*	1376	1451	*684*	1174	1462	*684*
BP-M	2144	2524	*1124*	2139	2480	*1007*	1968	1992	*658*
BP-I	2671	3147	*1573*	2967	3055	*852*	2424	3014	*1611*

TABLE 6.7: Rounded mean error rates (E) and SD for each mode (*BP-index* (BP-I), *BP-middle* (BP-M) and moving the thumb up and down in normal mode (N-U, N-D)) to reach distant targets. Values show mean error rates for the target positions left (L), middle (M) and right (R).

Mode	E-L	*SD*	E-M	*SD*	E-R	*SD*
N-D	1	*1.86*	0.67	*1*	0.33	*0.67*
N-U	0.5	*0.9*	0.83	*1.45*	0.67	*1.07*
BP-M	0.83	*1.98*	0.67	*0.68*	0.17	*0.4*
BP-I	0.5	*0.68*	0.67	*1.4*	0.33	*0.68*

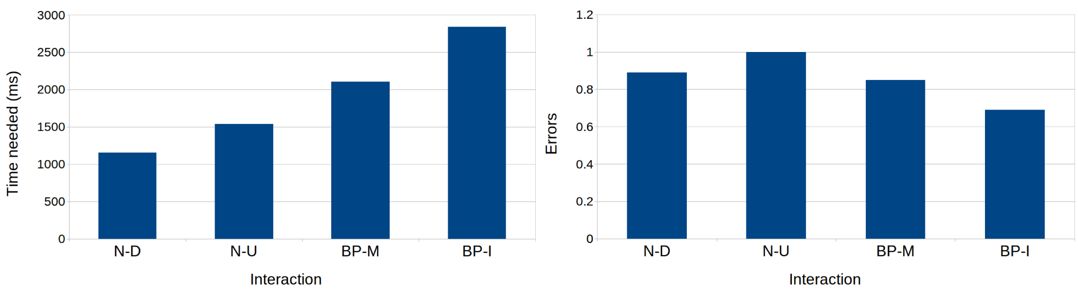

FIGURE 6.14: Visualisation of the task completion times (left) and error rates (right) of the *PIP* user study presented in Tables 6.6 and 6.7, grouped by mode.

users' feedback on whether a *BackPat* technique made selection faster, indicating that users felt that the *BP-middle* gesture (mean: 4, SD: .089) made reaching these targets faster than the *BP-index* gesture (mean: 3.88, SD: .96), but again without statistical significance. The data can be found in Appendix F, section F.6.1, p. 379.

The user feedback on *PIP* as a whole (Fig. 6.15) showed that users found *PIP* made targets easier and faster to reach than stretching or bending the thumb – despite a longer task completion time – and that they would use the technique, if available. Furthermore,

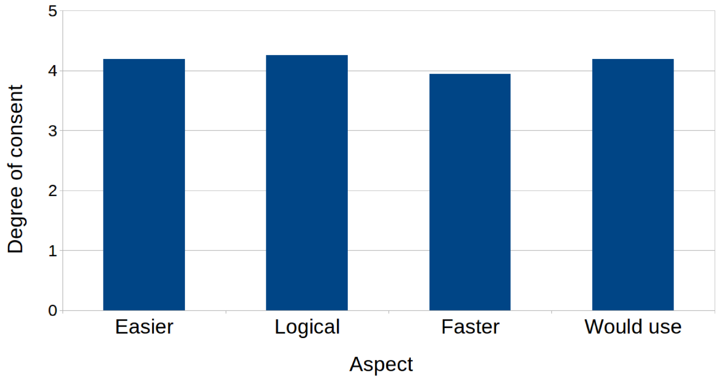

Figure 6.15: User feedback given on a five-point Likert scale after using *BackPat* to reach distant targets by *patting* them *into place*. Users were asked whether they felt that *BackPat* made reaching these targets easier (Easier, SD: .91), faster (Faster, SD: .91), whether the gesture input mapping was logical (Logical, SD: .93), and whether they would use *PIP*, if available (Would use, SD: .75).

the recent implementation of the *PIP* gesture's effect of moving the top of the interface towards the thumb in order to interact with distant targets upon a press of a button in the Apple iPhone 6 indicates the gesture's potential and possible high degree of user adoption.

6.4 Evaluation

Analysing task completion times and user feedback in three applications has highlighted use cases that can both benefit and suffer from the employment of *BackPat*. For example: Whereas short text selection near the edges of the screen benefitted from *BackPat* in terms of task completion times, short multiple selection in a list in the centre of the screen was slowed down by the technique. Therefore I decided to compare a simplified GOMS (Goals, Operators, Methods and Selection rules) model of the tasks involved in all three studies to the task completion times to help understand the reasons for these differences.

6.4.1 GOMS Models

Text Selection

The user study showed that for short selections, *BackPat* improved selection time. However, as the amount of words to be selected increased, performance deteriorated, up to the point where the technique proved rather inadequate (selectinG1.5 lines of text). The GOMS model for 0.5 lines of text selection (Fig. 6.16) shows that *BackPat* requires two additional steps compared to normal mode. Yet, performance using *BackPat* was faster than using the thumb and direct tap. This suggests that the adjustment phase is very time-consuming when using the thumb, causing a comparatively poor performance of direct tap interaction in this case. This is likely due to the fact that in this task the cursor had to be positioned near the edge of the display with a rather stretched or contracted thumb, which can be relatively hard to achieve.

For 1 line of text selection the GOMS-predicted better task completion for direct selection is likely to be caused by three factors: First, the large number of patting gestures needed for *BackPat* selection. Second, the thumb's adjustment phase may be less difficult as the selection ends in the centre of the screen. Third, the thumb is not stretched and has to travel a very short distance (about one line in height).

For 1.5 lines of text, *BackPat* is clearly inferior with regards to task completion time, as it requires three times as many actions due to the user having to "pat down" each line word by word. In contrast, the ability to vertically jump between the lines allows quick selection via the thumb directly.

List Selection

For the selection of three items in a list, using *BackPat* requires one interaction step more than selecting the items using direct tap (Fig. 6.17). However, in contrast to the text selection study, this consumed more time than direct selection. This suggests that adjusting the grip for *BackPat* is a rather expensive action, resulting in more time needed to complete a task. The problem of grip adjustment time has also been reported by Holman et al. (2013) when evaluating the Unifone as well as by Spelmezan et al. (2013), who present the Power-Up button on the side of a device. However, the task

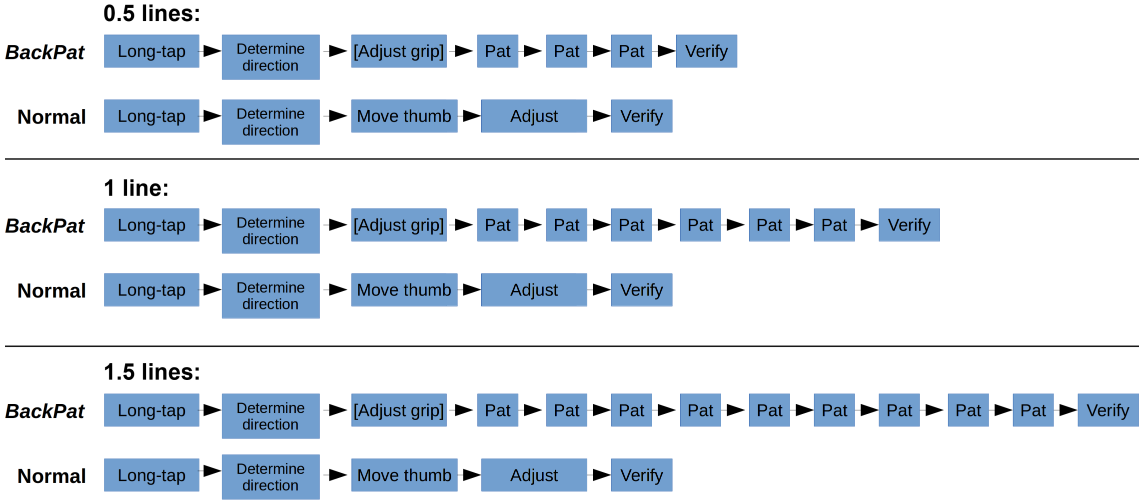

FIGURE 6.16: Simplified GOMS models of the text selection tasks using the thumb with direct tap (normal) and *BackPat*, selecting 0.5 lines (top), 1 line (middle) and 1.5 lines of text (bottom). For *BackPat*, the [Adjust Grip] method is optional, as it is not required for the technique to be performed. However, during the study it was observed that users frequently performed this action.

time for selecting six or more items in the list indicates that the cost of grip adjustment can be compensated for, if the amount of direct tap actions is six or more and equal to the amount of pats. This suggests that a *BackPat* gesture can be executed faster than a stretch and tap task and that it benefits from being comparatively stationary and executable in a high frequency with little effort. In addition, the amount of time a “stretch & tap ” action requires is likely to increase with the degree of thumb extension and distance from the thumb’s resting point, which needs to be considered if the GOMS model were to be evaluated in more detail.

Reaching Distant Targets

The simplified GOMS model of the *PIP* technique indicates longer task completion times in comparison to stretching or contracting the thumb to reach a target due to a higher number of interaction steps (Fig. 6.18), which correlates with the time measurements taken (Tab. 6.6). This suggests that *BackPat* using the *PIP* technique is an inadequate interaction technique. However, users felt that the technique not only facilitated the target acquisition task, but was also faster than when accessing the target directly.

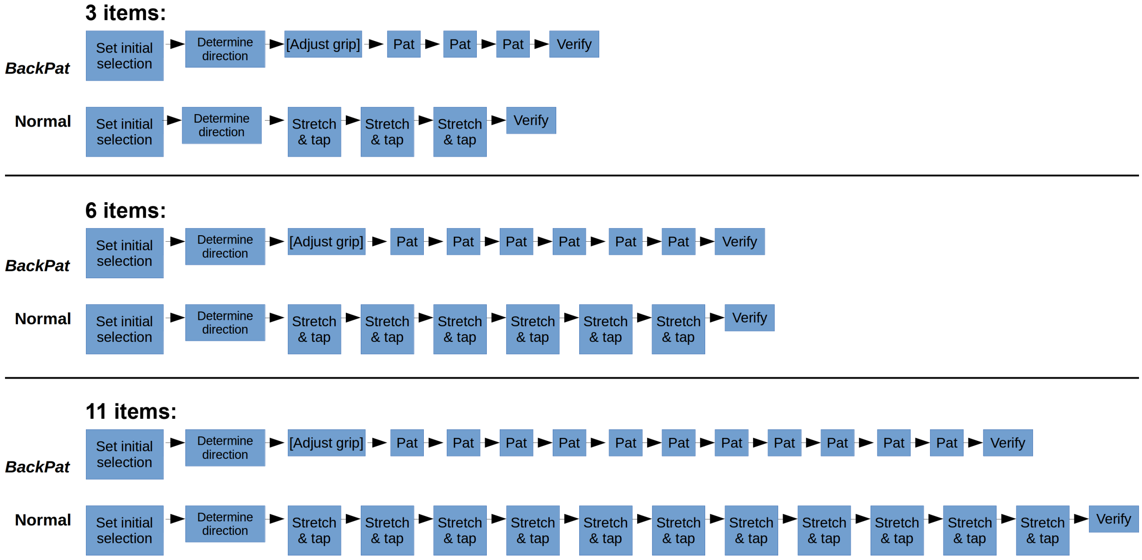

FIGURE 6.17: Simplified GOMS models of the multiple selection tasks using the thumb with direct (normal) tap and *BackPat*, selectinG3 items (top), 6 items (middle) and 11 items of text (bottom). For *BackPat*, the [Adjust grip] method is optional, as it is not required for the technique to be performed. However, during the study it was observed that users frequently performed this action.

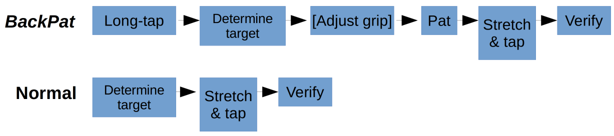

FIGURE 6.18: Simplified GOMS model for one-handed interaction with hard-to-reach targets, using the thumb with direct tap (normal) and *BackPat* and the *Pat-Into-Place* technique. For *BackPat*, the [Adjust grip] method is optional, as it is not required for the technique to be performed. However, during the study it was observed that users frequently performed this action.

Summary

The simplified GOMS models have illustrated the use of *BackPat* as a "compound" interaction technique (Hinckley, 2008, Chapter 9), listing the actions necessary to prepare and execute the gestures, as recommended by Dillon et al. (1990). Together with the performance of the technique in the three discussed applications, this suggests that *BackPat* can improve one-handed interaction when:

- The thumb is stretched near the edge of the screen and needs to perform fine adjustments of a cursor.

- The amount of tap interactions necessary matches the amount of pat interactions to perform the same task.
- A target is outside of the thumb's reach. Despite longer task completion time, using *PIP* is considered an improvement in user experience (Fig. 6.15).

While not representing the full range of possible enhancements for thumb-based interaction, this list can be helpful for identifying further applications of *BackPat* beyond the scope of this chapter.

6.4.2 Heuristic Evaluation

To identify the problems and potential of the *BackPat* technique, it is necessary to examine how well it complies with a set of commonly accepted standards. While the evaluation of Study Two and the GOMS models have illustrated general efficiency and usability of the *BackPat* technique, various other aspects need to be examined to better judge its potential as a means of supporting one-handed interaction. To evaluate the usability of user interfaces, Nielsen (1995) provides a checklist of ten heuristics. However, similar heuristics for evaluating an interaction technique do not appear to exist. Smutz et al. (1994) focus on evaluating a technique's effectiveness and examine ergonomic aspects, ease of use and productivity. Bowman and Hodges (1999) advise the consideration of external factors and application type to evaluate an interaction technique. Mackay (2002) suggests that interaction techniques need to be evaluated using different tasks and user goals, as user behaviour changes based on the "cognitive context" and the task ahead, drawing on Norman's analysis of the rationale of design decisions in HCI (Norman, 1983). Similarly, Blackwell and Green (2003) advise evaluating usability of an artefact with regards to the activity to be performed and supply a list of "cognitive dimensions", such as cognitive demand and flexibility of operation, with which to evaluate a system. The notion of context is also considered by Appert's CIS model (Appert et al., 2005; Appert, 2006), which adds a context factor to a GOMS-like evaluation, named an "interaction graph", as well as aspects such as persistence, fusion and development. However, these characteristics have only been attributed to a classic WIMP interface and are reliant on this paradigm, suggesting further research of the CIS model's applicability to touch and back-of-device interaction. Other researchers (Moran, 1981; Norman,

2002) name clarity of mapping, simplicity and the ease with which a user can discover the functionality as measures to evaluate usability. Gesture interpretation accuracy and therefore reliability together with task completion times offer another objective measure for evaluation. Finally, it may be helpful to evaluate an interaction technique based on the design principles established in its domain. With the inclusion of the physical device into the interaction, it is suggestive to evaluate the technique according to the design principles defined by Fishkin et al.'s definition for an "embodied user interface" (Fishkin et al., 1999). Bringing these aspects together and taking Nielsen's usability heuristics as a guide (Nielsen, 1995), I have evaluated the *BackPat* interaction technique using the following twelve-point list of heuristics:

Visibility of system status: In *BackPat*'s current implementation, the context of the system's state is not always clearly visible. Whereas the user may know that they are using *BackPat* for text selection because a context menu may pop up which holds actions for copy and paste, a similar indicator is not given in the multiple selection task and the target acquisition task. To prevent mode errors (Norman, 2002), a short flashing of the screen accompanied by a sound and the visibility of an icon in a status area are thinkable. However, the employment of such indicators requires careful examination and further study, as they add to the technique's cognitive load.

Flexibility and efficiency of use: The three applications indicate that the technique is flexible and can be used for selection tasks, value manipulation (such as the degree of zoom on a map application and the volume level of a music track) and interface alteration (*PIP*). Other possible applications include controlling a voicemail service and even user identification by performing a pat pattern on the back or side of the device. With *BackPat* being an optional gesture set, the user is free to use direct tap if they wish, or even combine the two input modes. However, the actual input is limited to performing a rather coarse patting gesture – a characteristic attributed to back-of-device gestures by Holman et al. (2013) – and cannot be customised by the user, but rather requires them to hold the device and execute a gesture in a preconfigured way on a predefined point on the device. The support of a double-pat gesture allows extending the input vocabulary, but does not allow continuous input. Rather, it might be employed as a shortcut for the *PIP* gesture, which would avoid the need for a long-tap for activation.

With regards to efficiency, the task completion times and simplified GOMS models have shown a high degree of efficiency when moving a cursor in hard-to-reach areas and performing a repetitive task, but a low efficiency for the facilitation of target selection, despite positive user feedback. Here, utilising the double-pat gesture to combine the long-tap gesture delimiter and the subsequent pat could improve efficiency, but requires validation in a separate user study.

Gesture complexity: Depending on context and implementation, the technique has a low to medium complexity. Whereas the gesture itself is rather simple, it needs to be activated via a gesture delimiter, such as a long-tap, and then may require users to change their grip to perform the actual input action. In addition, users have to execute the gestures in predefined areas on the device for maximum accuracy, slightly increasing the complexity. In contrast, complexity of the double-pat gesture is relatively low, as gesture and gesture delimiter are combined in one technique, simplifying execution but limiting input to a single action.

Discoverability: Without instruction, the gesture set appears hard to discover due to both its difference to front-of-device tap input and its novelty. Without an instruction screen interfering with a user's interaction with the device to bring the technique to a user's attention once they have started a text selection, for example, users are unlikely to discover the technique for themselves, as "culturally" they may be used to simply holding the device and tapping the screen. Once they have discovered it, though, they can explore its functionality in every application they use without additional hints.

Adherence to design principles: The *BackPat* technique is evaluated following the design principles defined by Fishkin et al. (1999):

- *Embodiment Principle:* The technique corresponds well to the "Embodiment Principle", as the input gestures are performed on and with the device, with the result of a task being displayed on the device's screen.
- *Physical Effects Principle:* The evaluation of the qualitative feedback indicates that the current input/output mapping is logical, but alternative configurations have not been examined and could provide different results. Using *BP-index* against the top of the device extends list selection towards the top of the screen or makes objects in this area move towards the thumb, reflecting the act of shaking a tree or, following the kinematic energy of the pat tilting the device towards

the user, the notion of moving something towards oneself – in this case towards one's input "device", the thumb. In this regard, the technique's "kinesthetic connectivity" reinforces the "conceptual connectivity of the task", corresponding to Buxton's description of "well-structured manual input" (1986).

Using the *BP-middle* for the *PIP* action moves targets from the bottom upwards or – when a user has previously moved them downwards using *BP-index* – back up to their original position. Here the gesture mapping seems to rely on the existence of the respective "counter-gesture", which allows the user to induce the exact opposite action, to be regarded as logical: With the mapping of the *BP-index* gesture against the top of the device to move targets at the top of the screen, it is suggestive that to move them up again, the other, lower finger can be used. It is also thinkable that the same gesture to move targets down can be used to undo the effect and move the targets back up again. Although implemented in a prototype, data regarding this configuration is not available and suggests further research.

In the text selection study, a *BP-index* gesture extended the selection to the right towards the bottom of the screen, which may seem illogical regarding the previously discussed mapping of interaction near the top of the device to cause a reaction of the GUI in the same area or at least towards the same direction. Rather, the mapping in this application was based on horizontal orientation: Using *BP-middle*, the user pats the left side of the device (when holding the device in the right hand), extending selection to the left. The "counter-gesture" of using the index finger moves the selection to the right. While in itself logical, the behaviour might be unexpected for users who have used *BackPat* with a different application first.

With regards to the thumb, the mapping in the text selection application appears logical by extending the text selection to the right, towards the direction of input. In the list item selection application, the selection was extended to the top, which could be attributed to the thumb connecting with the device in the top half. Yet, following the kinetic energy of the thumb hitting against the side of the device may suggest an options dialogue or sidebar moving in from the respective direction rather than manipulation of a selection. Here, more research and data are necessary to explore such a configuration. The changing mappings of horizontal and vertical manipulation between the applications as well as the potential mapping issues for left-handed users highlight the difficulty of designing a coherent gesture set that can be used across multiple applications and contexts. Whereas the current configuration and user feedback have provided an example of a possible implementation, more research is necessary to optimise this aspect.

- *Metaphor:* With the aim of creating one technique that can be used for a variety of tasks, definition of an adequate metaphor is hard, as a user's understanding and expectation of a gesture may change with each application. However, the common metaphor of patting and thereby tilting the device may be understood as gestures inducing change in the readout of a display or affecting the movement of materials in a container, for example the controlling of the flow of salt from a salt pot. Therefore the basic metaphor of influencing something comparatively delicate using a fine motor movement seems adequate for allowing users to understand possible effects of the technique on the state of an application, although with different results depending on the context. For a more detailed evaluation, see "Physical Effects Principle", p. 303.

- *Kinaesthetic Manipulation Principles:*
  - *Comfort:* The task completion times have shown that *BackPat* can be used by novice users to a satisfactory degree if given prior instruction. While practice is likely to improve performance, it was observed that some users struggled to perform the patting gestures with sufficient force to trigger the gesture detector or even lacked the finger length and strength to clasp the device with only one hand. This suggests that the technique is not suitable for everybody and that its feasibility strongly depends on device size and weight as well as hand size and dexterity.
  - *Appropriate Modifiers:* The small patting gestures seem to be appropriate for inducing a small degree of change on a small handheld device. However, as the change of the display caused by the *PIP* technique (such as moving targets from the top of the screen down towards the thumb, Fig. 6.6, p. 282) may be rather stark, assigning this effect to the more expressive double-pat gesture may appear more appropriate than using just a single pat which otherwise has a much smaller impact on the application state.
  - *Roles of the Hands:* The technique is operated with just one hand and therefore does not require the user to delegate a certain functionality to a different hand. Instead, they use the hand that is already holding the device for further engagement with it, corresponding well to this principle. By doing so, the technique also fulfils users' preference of operating their device with only one hand (see Karlson et al. (2006) and Chapter 3, section 3.3.3, p. 115).
  - *Socio-Cultural Factors:* The technique seems to suitable for the socio-cultural context in which it was tested: It complements users' preferred mode of smartphone operation and seems to be well received with regards to users' feedback on whether they would use the technique if it was available (Fig. 6.11, Fig. 6.13, Fig. 6.15, pp. 291–297). Movements are of a small and discrete nature, allowing a reasonable degree of privacy and, as the gesture is similar to a very basic manipulative gesture of "standard" items (see "Metaphor", p. 305), it appears to possess a high degree of social acceptability. However, the sound caused by the patting of the device may be regarded as unacceptable in a particularly quiet environment, such as a library. In this case users

may have to relinquish using the technique and revert to non-enhanced touch interaction, limiting *BackPat*'s applicability.

- *Sensing Principles:* The sensors used to detect the gesture are subject to a number of limitations of which user should be aware if they want to employ the technique. This in turn may reduce the feeling of naturalness of the gesture, indicating that more research is required regarding the detection accuracy and resilience to improve the technique. For a detailed description of the challenges of correctly sensing a user's gesture, see "Gesture detection accuracy", p. 308 and "Impact of external factors", p. 308.

- *Communication Principles:*

  - *Start/Stop Signal: BackPat* can be configured to use a long-tap as a gesture delimiter, giving it the potential to be a "Start" or "Stop" signal. However, this is not necessary, as the gestures are rather simple and binary. Yet, employing such a signal may reduce inadvertent operation and therefore may be desirable to implement.
  - *Appropriate Linguistic Units: BackPat* allows conceptualising the technique as a very basic direct command or sentence when communicating with the device. Depending on the context of use, these could mean "select next/previous list item", "extend/reduce text selection", "move target up/down" or "zoom in/out", with other meanings and commands possible. Yet, the equivocation of a gesture and its dynamic meaning may complicate mastering the technique, as it requires the user to know which mode the system is currently in (e.g. text selection mode or *PIP*).
  - *Gestural Sequencing: BackPat* allows gestural sequencing by performing a gesture multiple times. However, this does not change the meaning of the command, it simply repeats it until the user is happy with the application state. As shown by the GOMS analysis (section 6.4.1, p. 298), this may work well for short tasks, but may be inadequate for longer ones. While single-pat and double-pat gestures could be combined to create sequences, this seems inadequate when compared to the possibilities provided by the thumb to perform certain tasks much quicker. One area where a certain sequence of pats performed with different fingers may be useful, though, may be device

authentication. Here, a sequence could be attributed the role of a password or sentence in order to unlock a device, and the abstract gesture given a very precise meaning, making it potentially superior to alternatives – such as pin entry and basic swipe gestures – with regards to repeatability by third parties.

Mapping of gesture to effect: Please see "Physical Effects Principle" (p. 303).

Ergonomic feasibility: Please see point "Comfort" (p. 306).

Error prevention and recovery: Errors are largely prevented by the gesture delimiter. However, if an input is generated by mistake, performing the respective counter gesture can undo a selection or state. If text or a list item selection or even a *PIP* action is accidentally triggered via *BP-index*, a *BP-middle* gesture can be used to undo the last selection or action. If a double-pat is used where a counter gesture existing of a double-pat with another finger has not been defined, performing the same action again might be used as an undo function. While this appears to be a promising approach, further research is required to establish user acceptance and performance.

Cognitive load: With *BackPat*'s current implementation, cognitive load may be high, suggesting a reduction to only two or even just one gesture – depending on the context of use. Reducing the current implementation to only two gestures – *BP-index* and *BP-middle* – the load seems acceptable, as the configuration has been judged as logical and easy to use (Fig. 6.11, Fig. 6.13, Fig. 6.15, pp. 291–297). However, as described earlier, the main challenge is gesture continuity across applications. If this can be achieved, cognitive and mental load can be greatly reduced.

Gesture detection accuracy: The measurements in Table 6.2, p. 277, indicate a reasonable gesture detection accuracy for the current state of development. As interaction and result are rather coarse, this may be sufficient for the examined applications and context, but gesture detection accuracy is reduced by walking and noise. If both are present, the technique may be unusable and therefore requires improvements in this aspect.

Impact of external factors: As indicated in the last point, external factors can influence the technique's accuracy, presenting a major weak point and recommending further research to improve the technique for widespread use. Due to the coarse nature of the gestures and their output, it is suggestive that if a user's cognitive load is increased

– such as by walking (Wilson et al., 2011) – and if gesture detection accuracy is not too greatly hampered by its effects, *BackPat* could present an advantage over direct tap as it does not require careful aiming. For example, rather than carefully manipulating a vertical slider to increase track volume, users could adjust it with a few pats. Yet, the extent of this possible benefit is still to be researched.

As the display is needed for feedback, changing light conditions may also impact usability, which suggests researching additional feedback options to improve the technique's reliability and versatility. Another factor is the user's grip of the phone, which could be inadequate for performing a gesture just after the device has been picked up – though the same may apply to direct tap input. Therefore, the user would have to consider context and task to determine the most appropriate technique.

Versatility: The explored techniques indicate a high degree of versatility when using *BackPat* for simple actions. This is further extended by the support for single-pat and double-pat gestures. But despite its implementability into numerous applications, *BackPat* is limited to relatively coarse interactions that do not require too many repetitions. For example, while *BackPat* could be used for adjusting values using a slider, the results of the text selection study suggest that for great leaps on the slider scale, direct touch is the more efficient technique, with minor adjustments then to be made by *BackPat* in areas that are hard to reach for the thumb. Therefore, *BackPat* appears more applicable to simpler interactions such as one-handed zoom, voicemail control, short selections and target acquisition, and so not replacing but supporting direct tap interaction.

Summary

The above heuristic evaluation has shown that the *BackPat* input technique has potential, but also faces challenges which have not been fully addressed and explored within the constraints of this thesis. In particular, the issues identified regarding gesture detection accuracy and cross-application input mapping indicate that further research is required to make the technique a viable option for supporting one-handed interaction, especially in day-to-day use. Nonetheless, the evaluation of its versatility and efficiency highlights that it is a promising technique for addressing common problems of single-handed, thumb-based interaction and indicates that user acceptance would be high, suggesting further research to be a worthwhile endeavour.

6.4.3 Theoretical Evaluation

This section will evaluate the *BackPat* technique regarding its potential to address the most common problems of GUI operation introduced in Chapters 1 and 2, focussing on the problems described by Fitts's law and Accot's law together with the issue of interface occlusion and the technique's role in bridging the gap between direct and indirect pointing.

As stipulated by Fitts's law, target size and distance influence the interaction time and precision. When holding the device in only one hand and operating it with the thumb, these factors can become even more of an issue as the thumb's reach is limited and its precision rather low. Here, the user studies and the GOMS models have illustrated that *BackPat* can mitigate the challenges the law describes and as a result can be regarded as a promising contribution to address these in a novel way: In the multiple selection study, target selection was facilitated by the *BackPat* gestures. Rather than having to select targets one by one with a likelihood of longer interaction times caused by an increase in distance and thumb extension, the fast and coarse *BackPat* gestures allowed quick selection of six or more items, despite the high cost for grip adjustment, reducing the effects of target distance and size on interaction time described by Fitts's law.

The *PIP* technique (p. 288) helped to reduce the impact of target distance by moving the target to the same level as the thumb, therefore only requiring a horizontal movement of the thumb for selection, as recommended by Wobbrock et al. (2008). Yet, utilising *PIP* took longer than reaching for the targets and so did not present a gain in efficiency over non-enhanced direct-tap interaction. However, users found the technique made selection faster than normal selection, indicating an advance in addressing target reachability issues from a user perspective and supporting the findings of Chapter 3, section 3.4.2, p. 123, in terms of users preferring comfort over efficiency and speed. With *PIP*, *BackPat* allows users to use the thumb for all interactions on the screen, reducing the need for two-handed interaction, even if the interface suggests this with out-of-reach elements (users' main reason for abandoning the preferred mode of one-handed interaction, as reported by Karlson et al. (2006)). Instead, the thumb can stay in its comfort zone, reducing strain and fatigue on the thumb.

Compared to other techniques, which implement a cursor to reach distant targets (Karlson and Bederson (2007); Roudaut et al. (2008); Yu et al. (2013); Roudaut et al. (2008); Lai and Zhang (2014)), *PIP* has the potential to reduce interaction time over indirect interaction, as it allows direct selection of the target, albeit at the cost of precision (Albert, 1982). In conclusion, *BackPat*'s success in addressing the issue of slow interaction with distant targets is two-fold: If multiple targets in a row are to be selected, the effect of target distance and size is successfully mitigated by the comparatively quick executability of the technique. If a single target is to be selected, interaction time increases and accuracy may only be improved minimally, but ease of use is likely to be greater than accessing the target normally.

With regards to Accot's law – which describes the speed with which users can follow a path in a tunnel – the utilisation of the *BackPat* technique in the text selection study (p. 286) highlighted the advantage that the user no longer had to steer the selection cursor with their finger, but could instead control it using the patting gestures, reducing the need for accuracy and dexterity when operating the phone single-handedly with the thumb. This can be a particular issue when the thumb is stretched, which was shown in the reduction of task completion time for selecting 0.5 lines of text ending near the frame of the device when using *BackPat* (Tab. 6.4). Yet, the positive effect was reduced when selecting one line of text or more, where the selection could quickly be extended by multiple words using short vertical movements of the thumb, rather than selecting each word using a *BackPat* gesture. Therefore, *BackPat* reduces the need for a high degree of dexterity when steering a cursor through a narrow tunnel with the thumb, but its efficiency depends on the cursor position and tunnel characteristics.

In terms of the problem of interface occlusion intrinsic to touch-based smartphone operation – especially via the thumb (Roudaut, 2009) – *BackPat* provides a good approach, albeit not a perfect one: Whereas operation via the back or side of the phone means that the interface is not obstructed by the thumb or finger, the current initial gesture delimiter (a long-tap on the screen) still impacts interface visibility. Although this effect is reduced by the user only having to touch the screen at the beginning and end of an interaction sequence when selecting text or list items and therefore freeing the screen for manipulation of the selection, the benefit of the approach with regards to interface occlusion is only evident if the user's goal requires more than two touch interactions.

Overall, the fundamental challenges of touch-based mobile HCI listed above are addressed by the *BackPat* technique with a reasonable degree of success by combining basic touch interactions with physical actions including the body of the device, corresponding to the idea of "embodied interaction" proposed by Fishkin et al. (1999, 2000), and matching the description of a "full" embodiment (Fishkin, 2004). Yet, the improvements and advantages in overcoming these challenges are not comprehensive. Rather, the degree of the technique's success is determined by the context of use and the user's goals, following Hinckley and Wigdor's citation of Bill Buxton: "Everything, including touch, is best for something and worst for something else" (Hinkley and Wigdor, 2011). With this in mind, the strength of *BackPat* is its optional use: If a problem can benefit from utilising the technique, the user can activate it, even when only using it for parts of the problem – such as the final adjustment of a text selection. In other situations where direct-touch interaction seems a better or "good enough" choice (Norman, 2002), users are free to ignore it, allowing a high degree of flexibility and emphasising *BackPat*'s use as a supportive technique. This nicely illustrates *BackPat*'s role with relation to the fundamental categorisation of direct and indirect input techniques, as it adds an interesting dimension: Similar to the *OHW* presented in Chapter 5, *BackPat* combines the two interaction paradigms of direct and indirect pointing and ultimately uses the strength of both to enhance one-handed interaction in two ways. Whereas the initiation of an interaction sequence is always done by direct pointing, such as the creation of an initial text selection using a long-tap, the following interactions are indirect by controlling a cursor using the back-of-device and side-of-device gestures. The technique's optional use and its cooperation with direct-touch interaction allow the user to use the technique they deem the most promising and convenient for the task at hand, blurring the lines between the two paradigms and illustrating the benefits of multi-modal input in a division of labour (Hinkley and Wigdor, 2011, p. 4): The thumb works to the best of its abilities for direct input, but can be supported by the indirect input of *BackPat* in difficult situations for greater comfort and efficiency.

6.4.4 Comparison to Related Work

Compared to related work, *BackPat* has introduced various advances. With regards to the Unifone (Holman et al., 2013), *BackPat* has shown that back-of-device and side-of-device gestures can be used for continuous input and cursor control, rather than comparatively crude actions such as mode switching and zooming. It has further shown that different interactions can be mapped to the fingers of the hand holding the device, allowing rapid change of the cursor position and even undoing an action – all without additional hardware.

Compared to the tilt-based techniques (Oakley and O'Modhrain, 2005; Baglioni et al., 2011; Ruiz and Li, 2011; Yu et al., 2013), *BackPat* enables users to interact with the device using minimal motion, allowing them to continuously monitor the screen for feedback when performing multiple gestures, without the need for refocussing their eyes on the interface after an input gesture. In addition, *BackPat* largely successfully addresses the problem of interface occlusion by the thumb and is therefore an advancement over the ForceTap and Fat Thumb approaches (Heo and Lee, 2011; Boring et al., 2012). Compared to techniques harnessing sound as input (Lopes et al., 2011; Harrison et al., 2011; Harrison and Hudson, 2008), *BackPat* illustrates that this also can be implemented using the back or side of the device and is not limited to on-screen gestures.

BackPat has followed the vision of Hinckley and Song (2011) and further explored the potential of the built-in sensors of a phone. It has shown that these can be used for back-of-device gestures performed by the hand holding the device and that the sound profile created by the different contact angles and locations on the back of the device can be used to support gesture differentiation in a tiered approach in conjunction with device movement to enhance reliability – an advancement over the BackTap gesture (Zhang et al., 2013), which uses only the gyroscope data and sound volume to interpret gestures performed with two hands on the corners of a device. This way, *BackPat* presents another step towards a richer interaction model for one-handed device interaction. While various aspects may require improvement, its implementation in the presented applications suggests a large degree of versatility and potential for improving one-handed interaction.

6.5 Conclusion and Future Work

This section list the findings of the research goals and answers the research question posed at the beginning of this chapter followed by the conclusion and the discussion of future work.

6.5.1 Findings of the research goals

***G1*: Exploring whether it is feasible to combine sound volume, sound profile and device motion to enrich one-handed input using the capabilities of an off-the-shelf smartphone.**

The gesture detection accuracy tests (section 6.2.2, p. 276) together with the user studies conducted in this chapter (section 6.3, p. 280) have illustrated that sound volume, sound profile and device movement can be utilised to create a set of three novel input gestures consisting of "pats" with the index finger and middle finger against the back of the device, and with the thumb against the side of the device. In contrast to some on-screen gestures, these are rather "coarse", as described by Holman et al. (2013). The gesture detection accuracy varied and was affected by the user walking or being in a noisy environment. To compensate for this, a tiered approach for the gesture detection was suggested, championing volume peak and gyroscope patterns, supplemented by frequency analysis when the gyroscope analysis fails. While the effectiveness of this tiered approach has been illustrated by the accuracy test performed for each module (Tab. 6.2, p. 277), its "real-life" reliability and usability under these conditions remain unverified, as the user studies reported in section 6.3.2, p. 286, were performed under lab conditions. Under these conditions, however, the approach has shown to be sufficiently reliable for users to perform selection and manipulation tasks, often with an increase in efficiency and usability over normal direct-touch interaction.

***G2*: Learning which finger is most suitable for a technique using these properties, performed on either the back or side of the device.**

The quantitative and qualitative results indicate that, in general, gestures with the index finger against the back of the device are the fastest to execute and also have the highest user acceptance. This supports Wobbrock et al.'s (2008) findings that users prefer the index finger over the thumb for back-of-device input. Furthermore, the data suggests that the middle finger and thumb gestures are equally suitable for input. However, due to its higher detection accuracy and more stable grip on the device, the middle finger gesture may ultimately be more suitable for frequent input than the thumb gesture. The differing performance of the gestures in the three applications indicates that each gesture's performance and perceived usefulness varies with task and context – as suggested by previous work (Mackay, 2002; Blackwell and Green, 2003) – and that more research is required for a clearer picture.

***G3*: Determining which applications, operated with one hand, can benefit from this technique.**

This chapter has provided quantitative and qualitative data for *BackPat*'s performance in text selection, multiple selection in lists and target acquisition as well as suggested *BackPat*'s use for zooming maps and images. The quantitative data indicates that text selection and list item selection can benefit, but this depends on the scope of the task – as further illustrated by the GOMS analysis. From a user experience point of view, the interaction with hard-to-reach targets can also benefit, despite an increase in task completion time compared to non-enhanced interaction. Further applications, such as the control of a voicemail service or basic media player control, are thinkable, but require validation. The conclusion drawn from the GOMS analysis (p. 300) can be used as a guide for determining further applications, suggesting *BackPat* may improve one-handed interaction in applications which require frequent tapping and access to targets outside the thumb's reach, as indicated by Holman et al. (2013).

6.5.2 Answering Research Question 4

***RQ4*:** Can an approach following the strategy of input modality extension successfully address the main challenges of one-handed smartphone operation (as defined in Chapter 2, p. 41) together, using only a single technique?

The results indicate that the *BackPat* technique can be used for single input as well as continuous input and that this is more efficient than "normal" interaction if the amount of pats matches the amount of tap interactions required and targets are located in different positions. By doing so, the technique addresses the challenges of the thumb's limited dexterity and selection precision. However, continuous property modification via *BackPat* is likely to cause fatigue of the hand. The problem of limited mobility of the thumb is overcome by using the *PIP* technique to move distant targets closer to the thumb before tapping them, and so tackles the challenges described by Fitts's law. Furthermore, the technique can be used to steer a cursor over the screen (as in the text selection task) – albeit with some limitations – and can therefore address the challenges posed by Accot's law. As discussed in section 6.4.3, p. 310, the problem of interface occlusion is overcome only in cases where otherwise multiple tap interactions are required, as the initial long-tap still requires the thumb to move over the display.

In summary, the research indicates that the paradigm of input modality extension using a phone's sensors may not be able to comprehensively solve all of the most common challenge of one-handed interaction together through a single technique, as the problem of interface occlusion cannot be completely eliminated, only reduced.

6.5.3 Conclusion

This chapter has examined the potential of the approach of input modality extension to address all of the main challenges of one-handed smartphone interaction together (as defined in Chapter 2, p. 41), using a single technique. To do so, the chapter has introduced three novel off-screen patting gestures, which can be interpreted with a reasonable degree of accuracy using a tiered approach combining sound volume, sound profile and device movement. User studies based on applications representing the most common challenges of mobile HCI defined in the literature review have shown efficiency and usability of the technique. A formal analysis has highlighted strengths and weaknesses as well as indicated that – in contrast to previous work (Holman et al., 2013) – the gestures can be used for continuous input, albeit with some limitations. All in all, the *BackPat* technique improves one-handed interaction on touchscreen smartphones and addresses the main problems of one-handed smartphone operation, such as the limited reach of the thumb, lack of accuracy, dexterity and interface occlusion, largely successfully, depending on task scope.

In contrast to a GUI-based approach, as presented in Chapter 5, the *BackPat* technique does not temporarily augment the application interface, but simply offers an additional mode of input and in this way presents a promising alternative to users to support their preferred interaction style, be it touch, speech, or in-air gestures, which can all be combined with *BackPat*. However, as with the approach in Chapter 5, the issue of interface occlusion could not be solved completely. By supporting touch interaction and not replacing it, *BackPat* in its current implementation still requires the user to touch the screen to initiate the gesture or perform a follow-up interaction. **While this improves one-handed interaction from an efficiency point of view in some areas, it does**

not fully solve the issue of occlusion of touch-based interaction, but rather renders it a less important factor by reducing the need for the thumb to be above the display.

In summary, the potential of the approach of input modality extension to address all of the main challenges of one-handed smartphone interaction under the thesis's constraints (Chapter 3, p. 126) using just one technique seems limited. Yet, although neither previous work nor *BackPat* could provide a fully successful solution to the problem, it is thinkable that other approaches may be developed that are more successful. However, within the thesis's constraints, the presented technique has satisfactorily answered the research question. In conclusion, to fully overcome the main challenges of one-handed smartphone operation, it seems suggestive that a successful strategy for addressing these may not be feasible using solely one of the two main approaches of either GUI modification or input modality extension, but rather a multi-modal approach, playing to the strong points of each.

6.5.4 Future Work

The research conducted in this chapter has introduced a novel set of off-screen gestures and evaluated their ability for addressing the main challenges of one-handed interaction. Yet, by doing so it has also defined areas that need further exploration. In this regard, future work can be separated into three main areas: Exploring *BackPat*'s versatility, defining an overarching gesture configuration for a wide set of applications, and improving gesture detection accuracy.

Versatility

As Mackay once asked: "Which Interaction Technique Works When?" (Mackay, 2002), the full impact of *BackPat* on enhancing one-handed interaction on touchscreen smartphones can only be judged if further comparisons to existing techniques in numerous contexts and use cases are made. Therefore, future work will methodologically test the performance of the techniques in a variety of tasks and situations, to better determine its applicability. Similarly, research needs to be conducted to improve the "discoverability" of the gestures, so that novice users can find them without prior instruction.

Configuration

In the studies conducted in this chapters, users performed the *BackPat* gestures in an isolated context (such as only controlling a cursor or only moving a target) with a single, fixed configuration. Future work regarding the gesture configuration will examine how users can cope with a changing application context and mode, such as when the *BackPat* input interpretation changes between *PIP* and text selection in the same interaction sequence, and how these modes are made visible to the user, as discussed in section 6.4.2, p. 301. This also raises the question of what a unified set of *BackPat* gestures might look like, where they are consistent across applications. The research in this chapter has indicated that efficiency and user preference differ depending on the application, which further complicates the definition of such a gesture set. This may be due to varying user preferences and abilities, but for a high degree of usability and user acceptance, consistency is absolutely essential if *BackPat* is to be used for more than one type of input. Here, future research will be directed towards determining whether such an overarching set can be defined and what the most logical configuration may be.

Furthermore, future work will explore the use of the double-pat gesture as a shortcut for the *PIP* gesture or as a more general function, such as a copy or paste command. While the double-pat gesture has been informally presented to users (Seipp and Devlin, 2014*a*), no data has yet been collected as to its efficiency.

Gesture Detection Accuracy

The final part of future work will examine whether the gesture detection accuracy can be improved with directional microphones attached to the back of the device as well as with different algorithms for evaluating the sound and movement profiles. Here, algorithms similar to those used in speech or gesture recognition (Selouani and O'Shaughnessy, 2003; Caramiaux et al., 2013) might provide a more reliable gesture interpreter that is less sensitive to changes in the intensity of the signals, but it has to be investigated whether these provide a sufficiently high response rate for continuous manual input on a mobile device.

With the potential of the strategies of interface adaptation and input modality extension to address the main challenges of one-handed smartphone interaction established, the following chapter will conclude the thesis and answer the main research question as well as discuss the impact of the thesis's findings on the field of mobile HCI.

Chapter 7

Conclusion

7.1 Introduction

This chapter will critically reflect on the work presented in the thesis and its contribution to the field. It presents the conclusion of the potential of the two main avenues for improving one-handed smartphone operation – as defined in the literature review – and discusses contributions to the literature as well as practical and academic implications of the thesis's findings in addition to its limitations.

Using two example implementations, this thesis has examined whether the two main approaches used for addressing the identified common problems of touch-based mobile HCI – GUI adaptation and extension of the input modalities – have the potential to address the main challenges of one-handed smartphone operation together (as defined in Chapter 2, p. 41) using only a single interface or technique. This stands in contrast to previous approaches, which often only devise a specialised solution to an isolated problem, failing to provide a comprehensive solution following either research avenue.

To explore the answer to this main research question, this thesis has pursued a set of subordinate research questions to provide insight into users' preference for one-handed interaction over more efficient modes of operation, the properties of touches with index finger and thumb and the resulting implications for adapting the interface to a given mode of operation, as well as the potential of either approach to address the above challenges together using only a single interface or technique.

Taking into account the findings of the subordinate research questions, this chapter answers the main research question and finds that, under the thesis's constraints, neither strategy can address all of the main challenges of one-handed interaction together using only a single interface or technique. Both examined implementations fail to completely overcome the problem of interface occlusion and only manage to reduce it. It is therefore concluded that **a successful approach to overcoming these challenges together may have to be multi-modal**, combining the strong points of each strategy and thereby sacrificing the avoidance of complexity for increased usability.

To summarise and conclude the research, this chapter is separated into seven parts: Following the introduction, the answers to the subordinate research questions *RQ1* to *RQ4* will be presented separately for each topic (section 7.2, p. 321), cumulating in the synthesis of the answer to the main research question (*Main RQ*). Subsequently, the thesis's contributions to the literature will be discussed (section 7.3, p. 325). Following this, the implications of the findings on current and future theory and practice will be presented (section 7.4, p. 331) together with the thesis's limitations (section 7.5, p. 333). Finally, the chapter is concluded with a section discussing future work (section 7.6, p. 335), and finalised by some closing remarks (section 7.7, p. 338).

7.2 Answering the Research Questions

In order explore the capacity of the improvement of one-handed interaction on touch-screen smartphones using the two main research avenues of interface modification and input extension, this thesis has set out to answer a set of subordinate research questions, each representing a building block of the answer to the main research question. The below section shows the summarised responses to these questions and ends with the answer to the main research question.

7.2.1 Answers to the Subordinate Research Questions

***RQ1*: What is more important to users when operating a mobile device: Efficiency or comfort?**

Based on the findings of Chapter 3, it seems that, in general, comfort is more important to users than efficiency when operating a mobile device. The most efficient input modes are only chosen for input-heavy tasks or when an experience can be enhanced. For a more detailed response see Chapter 3, section 3.4.2, p. 123.

***RQ2*: Are the properties of a single "digitised" touch characteristic enough to distinguish between index finger and thumb of the left and right hand?**

Single-touch finger classification of the index finger and thumb is possible with an average accuracy of 83.1% across the whole display of a phone. In screen areas where any touch property or algorithm has an accuracy greater or equal to 90%, single-touch classification can be considered reliable using that property or algorithm. For target areas with lower accuracy ratings, a decision should be made on two or three touches, allowing the system to strike a balance between prediction speed and reliability. However, hand detection using a single touch is not reliable, with a mean accuracy of 62.2%. See Chapter 4, section 4.5.2, p. 219, for a more detailed response.

***RQ3*: Can an approach following the strategy of interface modification successfully address the main challenges of one-handed smartphone operation (as defined in Chapter 2, p. 41) together, using only a single interface?**

In brief, the results of the studies conducted in Chapter 5 indicate that an approach following the recommendations of previous work (Katre, 2010; Roudaut, 2009) addresses most of the challenges of one-handed thumb operation of touchscreen smartphones successfully, but does not fully solve the problem of interface occlusion when aiming to solve these challenges together, using a single interface. For a more detailed response, see Chapter 5, section 5.8.5, p. 264.

***RQ4*: Can an approach following the strategy of input modality extension using a device's sensors successfully address the main challenges of one-handed smartphone operation (as defined in Chapter 2, p. 41) together, using only a single technique?**

The research conducted in Chapter 6 indicates that an approach following the strategy of input modality extension to address the main challenges of one-handed smartphone interaction together, using a single technique, may only partly overcome the problem of occlusion, as the thumb may still be involved in the interaction chain – whether it is used to activate the gesture controls with an initial touch or to finalise the sequence, such as when tapping on a "copy" button after defining a text selection. For a more detailed response, see Chapter 6, section 6.5.2, p. 315.

7.2.2 Answering the Main Research Question

This section will list the individual contributions of each chapter to synthesise the answer to the main research question (*Main RQ*).

Chapter 3 has provided insights into layout performance and user preference and established that users prefer comfort over efficiency when operating mobile applications, providing the foundations for the approaches developed in Chapter 5 and Chapter 6.

In preparation for the interface developed in Chapter 5, Chapter 4 has investigated the characteristics of touches with index finger and thumb and provided support for the design of the curved interface in Chapter 5, as well as a method to detect the user's mode of operation with a single touch to allow the device to quickly adapt the interface if the thumb is detected.

Based on the findings of Chapter 3 and Chapter 4, Chapter 5 has explored the potential of the approach of GUI modification to address the main challenges together using a single interface and found that, despite increasing input efficiency and comfort, the problem of interface occlusion could only partially be solved.

Using the insights into users and their devices gained in Chapter 3 as a guide, Chapter 6 has examined the potential of the approach of input modality extension using a device's sensors to address the main challenges of one-handed interaction together, using only a single technique. Despite being able to address the challenges described by Fitts's law and Accot's law, the approach was unable to completely solve the problem of interface occlusion.

Combining the insights gained into one-handed smartphone interaction via the thumb from answering the subordinate research questions *RQ1* to *RQ4*, the main research question may now be answered:

***Main RQ*: Can an approach following either of the two main strategies to improve one-handed interaction (the modification of the GUI and the extension of the input modalities) address the challenges of Fitts's law, Accot's law and that of interface occlusion by the thumb (as defined in Chapter 2, p. 41) together, using a single interface or technique under a set of social and technical constraints, as formulated in Chapter 3, p. 126?**

Both approaches have considered insights into user preference and touch characteristics. While doing so, they have addressed most identified challenges successfully and indicated a high degree of generality and applicability, which corresponds to Buxton's (1986) idea of good practice for manual input techniques. Yet, neither of these was able to fully solve the problem of interface occlusion under the constraints outlined in Chapter 3, p. 126, although they did reduce it.

While not exhaustive and each only representing *one* possible way of developing a comprehensive approach to address the challenges of one-handed interaction following either strategy, **the results suggest that the problem of interface occlusion may not be fully solvable on devices using the same surface for input and output with a single-strategy approach addressing the three main challenges together, as long as the thumb touches the screen during any part of the interaction chain**, which ultimately makes the possible solution a prisoner of its constraints. The research has shown that an approach that may be effective for supporting one-handed interaction in one area may not be so in others and that the trade-off in a single-strategy approach may be the only partial solving of the problem of interface occlusion in favour of addressing the challenges of target distance, limited dexterity and imprecision.

The answer to the main research question is therefore that it seems not possible to use touch to overcome all the challenges of one-handed touch interaction in a single-strategy approach. Rather, a successful approach may require the fusion of the two paradigms. **In this regard, a successful solution would be built on the strong points of each strategy, improving one-handed interaction with touchscreen smartphones using a multi-modal implementation:** Whereas problems of reachability, speed and cursor control could be addressed using the *BackPat* technique, problems of interface occlusion and limited selection accuracy could be addressed using an increased button size in combination with a method similar to Shift (Vogel and Baudisch, 2007). This way, users only have to learn one technique (*BackPat*) and could combine it with the light but effective visual enhancements of Shift, addressing the most common problems of one-handed touchscreen operation successfully and thereby improving the human-machine dialogue via the thumb.

When comparing the potential of both strategies in a single-strategy implementation, the approach developed following the strategy of GUI adaptation appears to provide a higher degree of overall efficiency when compared to the non-enhanced base condition of one-handed interaction in the respective studies (Chapter 5 and Chapter 6), as the data indicates that task completion time using the *OHW* was shorter in all tasks but one. In contrast, while effective, the advantages of the *BackPat* technique only applied in certain conditions. This suggest that when only using a single strategy to improve one-handed operation of touchscreen smartphones, GUI adaptation may provide the better results overall and is therefore suggested as the preferred strategy for improving one-handed interaction, if multi-modal enhancement is not an option.

7.3 Contributions to the Literature

Whereas previous work has often focussed on solving a single problem in isolation – such as occlusion or selection precision – the thesis contributes to the literature by providing the first implementation and evaluation of an approach following either the strategy of GUI adaptation or that of input modality extension to address the identified main challenges of one-handed smartphone operation via the thumb (Chapter 2, p. 41) together, using only a single interface or technique under a set of social and technical constraints, as defined in Chapter 3, p. 126.

Compared to previous work, the evaluation of the potential of the two approaches in a single-strategy implementation may be seen as part of a resume of the work contributed to these strategies to date: The findings suggest that without a multi-modal approach the necessary degree of generality required for a single-strategy approach may not be achievable using either of the main strategies and therefore suggests that, ultimately, both strategies are inadequate to comprehensively solve the challenges of one-handed smartphone interaction on their own.

Therefore, although other more successful implementations may be developed than those presented in this thesis, it is suggestive that to fully overcome the challenges of one-handed touch interaction via the thumb using a single-strategy approach on devices that share the same surface for input and output, touch may not be used. Instead, new input methods need to be developed that can replace or extend this mode of interaction, such as brain-to-computer interfaces (Vi and Subramanian, 2012; Solovey et al., 2012) or input via a set of body sensors (Bolt, 1980; Baudel and Beaudouin-Lafon, 1993), allowing a more natural and direct way of interaction (Dourish, 2001), without mediation through a consciously operated transducer.

The main finding of this thesis may present an important means of orientation and reference for researchers aiming to further explore the potential of GUI modification and input modality extension for this interaction method. Beyond that, the thesis provides numerous contributions derived from the research leading up to the above conclusion, each relating to a certain aspect of the literature. To help present these, the contributions are described separately for each research topic and chapter.

7.3.1 Research into Device Orientation Performance and User Habits

Chapter 3 has addressed a gap in the research regarding input efficiency of mobile devices by providing evidence that a touchscreen smartphone may be faster to operate in landscape than in portrait orientation. The data indicates that this is the case when operated with the index finger or two thumbs, with a slight trend of two-thumb operation in landscape orientation to be the fastest mode of operation. In addition, it indicates that beyond this trend, no statistically significant difference in interaction time seems to exist between index-finger operation and one-handed thumb operation in the analysed layout configurations and device size. Yet, this finding does not rule out that certain areas of the screen may be faster to operate with the thumb, while others may be operated quicker using the index finger.

The chapter builds on earlier work regarding visual perception and combines the observations of earlier studies about saccades (Zusne, 1970; Bahill and Stark, 1975) and perception speed (Chen and Carr, 1926; Nakano, 2005) with chronometric measurements of target acquisition time (Fitts, 1954) on mobile devices. It indicates that search strategies as they are applied to larger screens or desktop environments (Megaw and

Richardson, 1979; Anderson et al., 1997) also seem to apply to mobile devices under certain conditions.

In addition, the chapter has shown that – as suggested by Welsh et al. (2008) for stationary displays – the arrangements of elements on a mobile device's screen and their relation to a previous stimulus (Simon and Wolf, 1963) appear to have a higher impact on interaction time (IT) than Fitts's law alone, which seems to be of rather secondary importance. This may have strong implications for researchers exploring the law's applicability to mobile devices. Yet, to fully clarify this point, eye tracking data would be required. If so, it is suggestive that Bailly et al.'s model could be utilised to make predictions about the selection time in certain screen areas (Bailly et al., 2014). This supports the view of Dillon et al. (1990), who point out that selection tasks cannot be evaluated in isolation, but must be regarded as part of a greater story. Therefore, factors such as gaze position and target position in a spatiotemporal sequence should be taken into account, in addition to size and distance from the pointer, when evaluating GUI efficiency. This in turn suggests the enrichment of formal mobile UI evaluation frameworks by these factors, as these frameworks may commit the mistake of singling out only one aspect for their analysis (Barrera et al., 2014; Kluth et al., 2014), and therefore may neglect the above multi-dimensionality of the task of target selection.

With regards to improving our understanding of users, the chapter has added to the findings of Grudin and MacLean (1985) and Tractinsky et al. (2000), who suggest that users' preference for a given interface may be based on personal preference and aesthetics rather than efficiency (though the latter is often a goal in HCI research according to Grudin (2008) and Dourish (2001, Chapter 1)), by presenting users' reasons for choosing one touch interaction style over another, where they named comfort, ease of use, and naturalness as their most important reasons. These findings can offer a means of orientation for future interfaces and interaction techniques (Jacob et al., 2007), or an additional means for evaluating their possible acceptance and perceived usability among the target population. The findings may also be employed as another set of aspects under which to describe or develop interaction techniques and may extend such systems that aim to support designers in making decisions regarding which technique to use in a given context, as proposed by Roudaut (2009).

7.3.2 Research into the Properties of Touch and Their Applicability for Determining Handedness and Mode of Operation

The research into this aspect of touch interaction indicates that the comparatively limited characteristics of a digital touch event are expressive and distinctive enough for differentiating between index finger and thumb with an average accuracy of 83.1%. Properties like gyroscope amplitude, touch duration, and touch size seem to directly relate to a finger type and its physical characteristics, such as mobility, width and length, indicating that touch input can be richer than we think or currently implement (Forlines et al., 2005; McCallum et al., 2009; Roudaut, Lecolinet and Guiard, 2009; Heo and Lee, 2011; Hinckley and Song, 2011; Lopes et al., 2011; Boring et al., 2012; Pedersen and Hornbæk, 2014). In addition, the hand belonging to the finger performing the touch was determined with an average accuracy of 62.2% upon the first touch, further providing an additional layer of meaning to the dialogue between human and machine.

Compared to earlier work regarding finger detection (Goel et al., 2012), the presented approach demonstrates a major advance, as it suggests that finger detection can be achieved with a single touch on off-the-shelf smartphones, rather than requiring the user to perform a predefined sequence consisting up to five interaction steps. In addition, it successfully illustrates how the information created by a touch can be classified with a high degree of confidence without additional hardware (as in Harrison et al. (1998); Hinckley and Sinclair (1999); Wimmer and Boring (2009); Taylor and Bove (2009)), assisting the user without their knowledge by quickly adapting the interface and supporting their way of interaction with an adapted GUI (Seipp and Devlin, 2013*a*, 2014*c*) or input interpretation (Henze et al., 2011), thereby potentially increasing the user's admiration of the device (Harrison et al., 1998), which in turn may help to develop emotional bonding between human and computer, and further reduces the gap between human intent and the computer's provision for it.

Compared to the work of Wang et al. (2009) regarding the detection of handedness, the presented machine-learning approach provided a slightly smaller degree of accuracy, but the different nature of the two techniques (Wang et al.'s finger landing process on the X-axis versus analysing a wide array of touch properties using machine-learning algorithms) suggest a possible combination of these to improve hand classification. Furthermore, existing hardware-based approaches (Wimmer and Boring, 2009; Taylor and Bove, 2009) could be combined with this software technique to improve their reliability and vice versa. In addition, techniques such as TapPrints and TapSense (Harrison et al., 2011; Miluzzo et al., 2012) could potentially refine their predictions for GUI element location if they "know" which finger has touched the device. Altogether, the contributions of Chapter 4 may have wide implications and applications for and in the field of mobile HCI.

7.3.3 Research into Thumb-Optimised GUIs

Chapter 5 has addressed a major omission in the field of mobile Web browsing – the support of users' preferred mode of operation: One-handed operation via the thumb. Whereas previous work predominantly focusses on improving the display of information (Bandelloni et al., 2005; Gupta et al., 2007; Hattori et al., 2007), the work in this thesis has focussed on the interaction with the same, keeping the layout intact and working independently of browser and platform, as opposed to Yu and Miller (2011). In addition, the presented approach can be flexibly turned on and off, works in both landscape and portrait orientations and therefore can allow greater freedom than S.U.P.P.L.E. (Gajos et al., 2008) and E.A.G.E.R. (Doulgeraki et al., 2009), which in addition do not cater for one-handed thumb interaction, but could be extended for this context using the *OHW* interface. Yet, it has to be acknowledged that these two approaches cover a wide range of user needs which are not covered by the *OHW*, making it a less versatile approach overall, but a promising solution in the domain of one-handed touch interaction.

Whereas previous research attempts to address a certain problem of one-handed interaction in isolation – such as the thumb's limited reach (Huot and Lecolinet, 2007; Karlson and Bederson, 2007), target distance to the pointer (Lai and Zhang, 2014), lack of precision (Vogel and Baudisch, 2007; Yatani et al., 2008), target occlusion (Roudaut et al., 2008; Lü and Li, 2011) or interaction time (Bailly et al., 2008) – the GUI-based approach presented in Chapter 5 has addressed all of these together with a promising degree of success by combining a specialised interface with a simplified set of interactions. In addition, Chapter 5 has shown that these enhancements can be made at runtime in the browser and do not require a proxy server to pre-process the page, unlike Bandelloni et al. (2005), Gupta et al. (2007) and Hattori et al. (2007), or specialised proprietary software (Yu and Miller, 2011; ASA, 2012*b*).

Finally, the work conducted in Chapter 5 illustrated how classic WIMP elements – such as sliders, checkboxes, and pulldown menus – can be translated into a thumb-friendly interface. This way, the chapter suggests how recognisability can be combined with operability and an increase in efficiency when migrating interface elements between the domains of indirect and direct pointing and may act as a guide for future work aiming to adapt approaches established in the desktop world to that of one-handed touch interaction.

7.3.4 Research into Extending a Phone's Input Modalities

As opposed to using a GUI approach (as in Chapter 5), Chapter 6 has presented a novel method for combining sound volume, sound profile and device movement into a new input method, created by "patting" the back or side of an off-the-shelf smartphone. It has successfully extended previous work in this area which uses additional hardware in the form of side-mounted pressure sensors (Holman et al., 2013), device tilt (Oakley and O'Modhrain, 2005; Baglioni et al., 2011; Ruiz and Li, 2011; Yu et al., 2013), device movement (Heo and Lee, 2011), sound (Robinson et al., 2011; Lopes et al., 2011; Harrison et al., 2011) or sound volume and device movement (Zhang et al., 2013), adding a new dimension to back-of-device input (Baudisch and Chu, 2009).

The combination of sound volume, sound profile and device movement allows the differentiation between index finger, middle finger, and thumb pats and so can support a richer interpretation of the input compared to previous work, totalling in six input gestures, if double-pat gestures are included. The examination of the performance of the three fingers of the same hand for off-screen input extends the work of Wobbrock et al. (2008) by adding the middle finger to the performance evaluation of back-of-device input, rather than just thumb and index finger. The studies support Wobbrock et al.'s finding that the index finger appears to allow the most efficient input and is preferred by users, but that finger preference and performance seem to vary by application, corresponding to the findings of Mackay (2002) and Blackwell and Green (2003) about a technique's perceived usefulness. In addition, the method of finger differentiation on the back of the device can advance the vocabulary of this specific form of input and add another layer of expressiveness to existing techniques (De Luca et al., 2013; Leiva and Català, 2014).

The user studies in Chapter 6 have shown that input may still be "coarse" (Holman et al., 2013), but that it is not limited to simple, discreet gestures, as suggested by the researchers. Instead it demonstrated this input method's employability for continuous input with the potential to outperform front-of-device input via the thumb, extending our knowledge about this "auxiliary" (Holman et al., 2013) interaction method and the dexterity of index finger and middle finger while holding a device in the same hand. This form of input not only extends the input vocabulary of the hand, it also has the potential to make interaction with mobile devices more natural and realistic (Jacob et al., 2007, 2008), and therefore increase expressiveness, meaning and usability by including the actual device and a wider set of the user's motor skills into the dialogue, corresponding to the idea of an "embodied interface" (Fishkin et al., 1999, 2000). The *BackPat* technique potentially offers a wide range of meaningful and more natural interactions, that do not require moving the whole device (as in Baglioni et al. (2011)), but allow the user to keep their focus on the display to observe the effects of their input: Patting the back or side of the device may be seen as similar to tapping a mechanical display to induce change of the readings or – following the direction of movement of the finger against the back of the device and tipping the device slightly towards the user – to bringing content closer to the user using a zoom function.

Finally, by enhancing basic touch interaction and complementing it with physical interaction, the work undertaken in Chapter 6 may be seen as another example of combining GUI interaction and physical action to help transition users "softly" to this "new" (although in its essence very old) method of interaction that is embodied interaction (Dourish, 2001) in the domain of digitised dialogues between human and computer.

7.4 Implications

The main implication of the thesis is the insight for researchers and practitioners that a single-strategy approach following either of the two main research streams may be unsuitable for addressing the main challenges of one-handed smartphone operation together. The knowledge that they may have to compromise on solving the problem of interface occlusion by the thumb and that the presented approach of GUI modification may be more efficient overall when compared to non-enhanced interaction, can help practitioners choose between the approaches when aiming to improve the one-handed operation of a smartphone application. In addition, this knowledge may be used as a basis for future research aiming to further explore the potential of both strategies, or as a means of comparison to costs and benefits of other single-strategy approaches, such as voice control or whole-body gestures.

In addition to the implications of the findings of the main research question on the field of contact-based mobile HCI, the following implications can be derived from the exploration of the subordinate research questions:

- Practitioners can improve the usability and efficiency of time-critical touchscreen applications by implementing the findings of performance differences of different layout orientations, together with the insight into potential search patterns and the resulting target location efficiency rating on mobile devices.
- The finding that users of mobile applications seem to favour comfort over efficiency may guide developers of new interaction methods, interfaces and techniques and could serve as a measure to gauge user acceptance and the potential success of these.
- The detailed evaluation of touch characteristics and especially the definition of a device movement profile for various target positions, as shown in Figure 4.23, page 159, to Figure 4.28, page 164, can be employed by designers to evaluate the grip stability of their GUIs and therefore the comfort and usability for index finger or thumb-based operation.
- The demonstrated profiling of sensor input to classify a user's finger (index finger or thumb) upon the first touch of the screen will allow designers to adapt and optimise the interface (as in Seipp and Devlin (2013*a*, 2014*c*)) or input interpretation (as in Henze et al. (2011)) upon application start, and therefore can improve usability without disruption or notion of the user (as in Gajos et al. (2008) and Doulgeraki et al. (2009)) and as a result further reduce the friction of the human-computer dialogue, making interaction more seamless and providing the mobile device with another layer of context.
- The demonstration that a wide range of desktop-centric interaction patterns can be transformed into a semicircular, thumb-friendly interface may inspire practitioners to migrate other interaction patterns to the domain of one-handed smartphone

interaction. Here the approach provided by the *OHW* may be seen as a blueprint for further translations, improving the one-handed operability of these. As this can be performed with standard web technologies, this approach may be implemented by practitioners today at no cost.

- The insight that sound volume, sound profile and device movement can be combined to differentiate between different fingers on the back of the device may support the development of new back-of-device authentication methods, making the unlocking of devices more secure by avoiding visual hints, as shown by De Luca et al. (2013). In addition, a large set of applications on off-the-shelf smartphones can be enhanced today by providing additional functionality or supporting the thumb using the *BackPat* technique. This may establish a new concept of how we operate our smartphones with only one hand: Not just with the thumb on the screen, but also using the index finger, middle finger and thumb on the back or side of the device. The inclusion of the whole device into the interaction (following the definition of an embodied interface by Fishkin (1999)) will allow practitioners to make Human-Computer Interaction more natural while at the same time supporting users' favourite mode of operation, by allowing them to closer integrate the device into the human motor-perceptual apparatus, without the need for additional hardware, thus further smoothing the human-computer dialogue.

7.5 Limitations

Despite the contributions to the literature and despite providing a wide range of practical applications, the research conducted in this thesis does have several shortcomings, the main one of which may be the technological and social constraints under which the research was conducted (Chapter 3, p. 126). Without these, more successful approaches may have been developed. Yet, the findings are valuable, as they illustrate what can be achieved within these parameters. Beyond this, the limitations of the research are as follows:

Chapter 3

In Chapter 3, the comparatively small sample size of Study Two led to some unexpected or unexplainable results, suggesting that potential sampling error could lower the impact of the findings of this part of the study, and that these should be regarded as trends rather than definitive effects. In addition, only one form factor was examined – that of a 4.7 inch smartphone – but it remains unclear whether the observed effects also apply to different device types and sizes, and even tablets. The inclusion of gaze tracking data could have been helpful to better interpret some of the findings, but this, however, goes beyond the scope of this chapter. Finally, the studies in Chapter 3 were only conducted while sitting and not also while walking. Therefore, the findings potentially lack generalisability, which suggests further research to extend their validity.

Chapter 4

While illustrating the potential of machine-learning algorithms to classify a user's finger and hand based on a phone's touch and motion sensor input, the validity of the results could further be improved by a larger-scale study or by testing the performance of the approaches in different applications. While the test application used a grid of buttons simulating an application grid or calendar grid, using a different type of GUI, such as text input or a people list, could further extend the validity of the findings. Also, it remains to be examined how well the approach scales to different form factors and display orientations.

Chapter 5

The shortcoming of the *OHW*'s approach to support one-handed smartphone operation via an adapted GUI is the lack of end-user customisation of the interface. Due to it being a Web-based solution with no access to a device's local data, potential system-wide calibration of thumb length can not be utilised for adjusting the interface size. However, I decided to trade off deployability against customisability for the current implementation to avoid user effort and the need of specialised software, as is the case in previous work, but rather provide a flexible solution that corresponds to the idea of an open Web. Similarly, the restriction of the interface's position to the bottom third of the display was chosen as a compromise between avoidance of content occlusion and user customisation. Yet, both limitations could be addressed by changing the approach's constraints, if desired, but their consideration may contribute little to the already sufficiently answered research questions.

Chapter 6

The chapter presents a variety of applications for the *BackPat* technique, but does not provide a comprehensive overview of further applications, nor the technique's performance in comparison to other interaction techniques supporting one-handed operation. In order to fully gauge its potential, such a comparison is advisable to help practitioners in selecting the right interaction method for a problem. Furthermore, the discoverability of this form of input and its effect may be rather low, as it requires the user to perform an action they may not consider, with their focus being the front of the device for all input and output. In this case, an active effort would be required to introduce the technique to the user via a demonstration video or similar – despite the technique being based on a real-world action.

Lastly, the thesis only explores the performance of two example implementations, one for each identified main research stream (GUI modification and input modality extension). While this provides insight into each paradigm's potential to provide an approach that addresses all of the main challenges of one-handed smartphone operation via the thumb together, the insight gained may not be exhaustive. However, the finding that interface occlusion is unlikely to be fully solvable on devices with the same surface for input and output indicates that potential future developments following either paradigm using a single interface or technique may not be more successful than the approaches presented in this thesis.

7.6 Future Work

This section provides a set of suggestions for future work, stemming from questions and opportunities identified during the research conducted.

Chapter 3

The work undertaken in Chapter 3 suggests to combine gaze tracking, electromyographical data of the muscle groups involved, and target position in relation to the visual stimulus, in order to model interaction time for menu items on mobile devices in both landscape and portrait orientations. From this, the impact of each factor could be deducted and their role in direct pointing and selection tasks be better determined to support the development of future high-performance touch or gesture interfaces. In addition, it is suggestive to explore the scalability of the findings to different form factors to examine whether the observed effects are limited to a single device class, or can be seen as general trends in the field of touch-based mobile HCI.

Chapter 4

Future work emerging from the findings of the studies conducted in Chapter 4 will concentrate on improving the finger detection accuracy as well as examining the scalability of the approach to other device sizes. To increase accuracy for finger and hand detection, it will examine the performance of user-specific models as well as the applicability of different types of algorithms, such as those used for gesture or speech recognition (Caramiaux et al., 2013; Selouani and O'Shaughnessy, 2003).

To investigate the scalability of the grid-based classification, it is suggestive to examine its performance on different screen sizes and orientations. This will allow the detection of trends in the data which may be universal and therefore may be used for classification without the use of machine-learning algorithms.

Chapter 5

As the chapter has illustrated that a wide variety of desktop-centric interaction patterns can be "translated" into a semicircular interface for one-handed interaction via the thumb, future work will investigate whether this method can also be used for other interactive elements that have not been considered in the study. This way, the approach's utility as a blueprint for migrating interactive elements from the WIMP era to the domain of one-handed smartphone interaction could be evaluated further.

Similarly, the question of whether interfaces could be further optimised for index-finger operation also arises. Assuming that horizontal movement of the index finger across a mobile device's display is less strenuous and faster than vertical movement (based on the findings of Chapter 3), what could an interface look like that supported this behaviour in particular? Could, as with the *OHW*, different interaction patterns be combined into one unified interface?

To investigate the versatility of the presented interface, future work will further examine whether the *OHW* may also be used to support thumb-based operation for larger devices in landscape orientation. This mode of operation may be employed when a user is operating a tablet when walking, holding it in both hands due to the lack of a resting place. In combination with the migration of other interactive elements, this avenue may help to further explore the *OHW*'s potential as a universal interface for thumb-based operation.

Future work will also focus on a closer integration of the *OHW* interface into the browser combined with the technique for finger classification presented in Chapter 4 to allow a more dynamic interface adaptation and address performance issues.

Chapter 6

Apart from extending the *BackPat* input method to a wide range of applications, the observations of the user studies presented in Chapter 6 suggest further research should be undertaken regarding a *BackPat* configuration that is seen as logical across all applications. As the studies indicate, preference for each gesture may change with application. Exploring the reasons for this could contribute towards the definition of this comprehensive configuration or, if multiple configurations are required, towards finding the most suitable one for each application. This research could also feed into the exploration of changing context and input configuration: How can users cope with changing *BackPat* configurations when they quickly change between a *PIP* action (where a *BP-index* gesture moves targets down, towards the thumb) and a text selection task (where a *BP-index* gesture moves a selection cursor to the right)? How can the current mode and configuration be made visible to the user to prevent possible mode errors?

Following the paradigm of Reality-Based Interaction (RBI) (Jacob et al., 2007), it is suggestive to investigate which application the technique would lend itself to best. If users see it as a similar action as tapping weighing scales to adjust the weight, for example, would its best use be in order to cycle through applications, as in TimeTilt (Roudaut, Baglioni and Lecolinet, 2009)? Or would it be used best as a binary answer in simple dialogues, responding either yes or no? Could blind users employ it to respond to a screen reader or to “tab” through website elements?

Chapter 6 has presented only one possible way of interpreting these patting gestures. Therefore, future work will explore the consolidation of the gesture interpretation using different algorithms, signal filtering, and additional hardware. This way, gesture reliability could be increased to foster more widespread use of the technique.

Regarding the findings of the main research question that the identified main problems of one-handed smartphone interaction – the problems described by Fitts's law, Accot's law and interface occlusion by the thumb – may not be completely overcome using a single-strategy approach following the paradigms of GUI adaptation and input modality extension, it is suggestive to explore whether a symbiosis of the *OHW* and the *BackPat* technique may be more successful. Future work will examine whether such an approach could simplify the definition of an overarching gesture set, as outlined above. Here, the addition of a curved interface may reduce the amount of gesture effects and contexts to consider, since part of the functionality may be mapped to this, rather than solely to the *BackPat* gestures.

7.7 Closing Remarks

If the computer (in this case a touchscreen smartphone) is to be the extension of our senses, always ready to hand as a repository of knowledge and assistance (Bush, 1945), "augmenting [hu]man's intellect" (Engelbart, 1963), it is essential that its operation supports users' habits and preferences, minimising effort and maximising efficiency by designing interfaces in accordance with these aspects as well as anatomical limitations, giving users more convenient control of this new "part" of the body. Therefore, this thesis has tackled the problem of improving one-handed interaction of touchscreen smartphones from various angles: Better understanding users' rationales for operating the phone the way they do, classifying the finger from a single touch, presenting a thumb-optimised GUI and proposing a set of off-screen gestures to supplement touch interaction. Each of the contributions made can help to reduce the friction between human intent and a computer's provision for it, making a mobile device more aware and responsive to the varying interaction contexts of touch input and further supporting the user in the pursuit of their goals. While only on a small scale, this subtle progress can help to support the ongoing harmonisation between human and computer and the perception of a mobile device as something whose functionality and operation requires so little effort and prescriptive behaviour that the resulting freedom and comfort allows a change of perception of the device towards something that is second nature, rather than second best.

While the presented methods for enhancing this human-machine dialogue may have been applied to the current state of technological development, the concepts behind them may continue into the future, even one in which HCI advances further and moves to a set of interconnected, specialised devices, rather than a handheld unit. For example, should wearables such as smart watches, activity trackers and Google Glasses work in unison to replace smartphones, the knowledge of this thesis's contributions could be transferred as follows:

- The synthesis of sound volume, sound profile and device movement could be used to enrich taps on smart watches, which often have very small displays, and assign meanings to taps with the index finger and middle finger. The same could be applied to tapping the frame of a pair of Google Glass glasses, to either provide menu navigation shortcuts or work as a means of authorising access to a given data source.
- The insight into efficiency of landscape and portrait layouts is likely to be transferable to Google Glass devices and humans' interaction with public displays, such as interactive information terminals, and can improve interaction efficiency with these devices. In addition, it could even be transferred to the design of mid-air gestures to optimise their executability and ergonomics by focussing on horizontal rather than vertical gestures.
- The insight that users prefer comfort over efficiency may be used as a criteria for making design decisions when developing new interaction methods and interfaces.
- The preference of users for one-handed touch interaction, its comparatively high degree of "privacy" in comparison to larger gestures and speech input (Wasinger et al., 2005; Ahlström et al., 2014) and its dis-ambiguity for selecting targets may lead to mobile devices and touch interaction being the preferred mode of communication for the foreseeable future. But even if these devices change in shape and structure (Roudaut et al., 2013; Dimitriadis and Alexander, 2014; Pedersen et al., 2014), the contributions made to the optimisation of thumb-based GUIs can be valid and useful, as it is thinkable that users may still operate these new, flexibly shaped devices with their thumb.
- In the future, one-tap finger classification may still be applied to provide new forms of devices with context to either adapt interfaces or otherwise attribute meaning to a user's mode of operation.

Whatever developments occur, future research is likely to continue to focus on bridging the communication gap between humans and computers. In the process, sociocultural forces as well as technological inventions will shape progress. What will and will not be is therefore hard to predict, but it can be assumed that the ultimate outcome of the strive towards improved communication will be the symbiosis of human and machine (Licklider, 1960), finally replacing translation with integration.

Appendix A

Chapter 1

There is no content in Appendix A. As each appendix (A–F) relates to a certain chapter (1–6), it is merely included in order to begin with A, however there is no appendix material relating to Chapter 1 to include.

Appendix B

Chapter 2

B.1 Permission to Include Figures

The various permissions to include the figures referenced in the literature review can be found on the DVD-ROM in the folder "Chapter2/licenses". These can be opened with a PDF reader.

Appendix C

Chapter 3

C.1 Study One Information Sheet and Consent Form

Information sheet for "Operating vertical and horizontal button layouts"

This study is to investigate the perception speed of the user with regards to horizontal and vertical button layouts on mobile devices. In this study the participant will be asked to tap on a certain button presented on the screen of the mobile device while holding it in "portrait mode" or "landscape mode". This is to be repeated several times with varying amounts of buttons. Which button the user is to press will be shown on the screen in form of an instruction screen before each task. Once you are ready, please press the OK button to start the task.

In a second round, the experiment will be amended slightly. Instead of being asked to press button "X" on the following screen, participants will be seeing the name of a colour instead (e.g GREEN, BLUE, RED, YELLOW). Participants are to interpret the **colour** the **name is written in** and then press the respective button in the following screen. For example, if you see the word **RED** [written in green] you are supposed to click the green button.
Again, the task are to be performed first by holding the device in "portrait mode" and "landscape mode"

Both rounds are to be performed while holding the device in one hand and operating it with the index finger of the other. The study begins with a brief explanation followed by some self-directed experimentation with some practice tasks. After this initial phase, the device is handed back to the researcher and the experiment begins

All interactions will be recorded in a (text-)list together with the task completion time for each task.

The collected data will be stored with no identifier other than the participant ID that is assigned on an incremental basis. Participation in this research is voluntary. Volunteers are under no obligation to complete the study and can cease participation at any time. If you have any questions regarding the purpose, procedure, or other aspects of the experiment, or if you would like to know more about the research, please feel free to send an e-mail message to the investigator at k.seipp@gold.ac.uk.

You may keep a copy of this sheet for your reference.

Figure C.1: Information sheet for Study One.

CONSENT FORM

Operating vertical and horizontal button layouts.

Karsten Seipp, PhD candidate at the Department of Computing at Goldsmiths College.
Email: k.seipp@gold.ac.uk

	Please write initials into box
1. I confirm that I have read and understand the information sheet provided for the above study and have had the opportunity to ask questions.	☐
2. I understand that my participation is voluntary and that I am free to withdraw at any time, without giving reason.	☐
3. I agree to take part in the above study.	☐

Please tick box

	Yes	No
6. I agree to the use of anonymised quotes in publications	☐	☐
7. I agree that my data gathered in this study may be stored (after it has been anonymised) in a specialist data centre and may be used for future research.	☐	☐

Name of Participant	Date	Signature
Karsten Seipp		
Name of Researcher	Date	Signature

Figure C.2: Consent form for Study One.

C.2 Study One Data

The data of R1 can be found on the attached DVD in the folder “Chapter 3”. The file name is “S1 ANOVA normal.sav”. The file can be opened with SPSS 21.
The data of R2 can be found on the attached DVD in the folder “Chapter 3”. The file name is “S1 ANOVA stroop.sav”. The file can be opened with SPSS 21.

C.3 Study Two Information Sheet and Consent Form

Information sheet for "Operating vertical and horizontal button layouts" -- Study Two

This study is to investigate the perception speed of the user with regards to horizontal and vertical button layouts on mobile devices. In this study the participant will be asked to tap on a certain button presented on the screen of the mobile device while holding it in "portrait mode" or "landscape mode". This is to be repeated several times with varying amounts of buttons. Which button the user is to press will be shown on the screen in form of an instruction screen before each task. Once you are ready, please press the OK button to start the task.

In a second round, the experiment will be amended slightly. Instead of being asked to press button "X" on the following screen, participants will be seeing the name of a colour instead (e.g GREEN, BLUE, RED, YELLOW). Participants are to interpret the **colour** the **name is written in** and then press the respective button in the following screen. For example, if you see the word **RED** [written in green] you are supposed to click the green button.
Again, the task are to be performed first by holding the device in "portrait mode" and "landscape mode"

Both rounds are to be performed as follows:

In "portrait mode"

- Holding the device in one hand, operating it with the thumb of the same hand
- Holding the device in two hands, operating it with both thumbs

In "landscape mode"

- Holding the device in one hand, operating it with the thumb of the same hand
- Holding the device in two hands, operating it with both thumbs

The study begins with a brief explanation followed by some self-directed experimentation with some practice tasks. After this initial phase, the device is handed back to the researcher and the experiment begins.

All interactions will be recorded in a (text-)list together with the task completion time for each task.

The collected data will be stored with no identifier other than the participant ID that is assigned on an incremental basis. Participation in this research is voluntary. Volunteers are under no obligation to complete the study and can cease participation at any time. If you have any questions regarding the purpose, procedure, or other aspects of the experiment, or if you would like to know more about the research, please feel free to send an e-mail message to the investigator at k.seipp@gold.ac.uk. You may keep a copy of this sheet for your reference.

Figure C.3: Information sheet for Study Two.

CONSENT FORM

Operating vertical and horizontal button layouts – Study Two.

Karsten Seipp, PhD candidate at the Department of Computing at Goldsmiths College.
Email: k.seipp@gold.ac.uk

Please write initials into box

1. I confirm that I have read and understand the information sheet provided for the above study and have had the opportunity to ask questions. ☐
2. I understand that my participation is voluntary and that I am free to withdraw at any time, without giving reason. ☐
3. I agree to take part in the above study. ☐

Please tick box

	Yes	No
6. I agree to the use of anonymised quotes in publications	☐	☐
7. I agree that my data gathered in this study may be stored (after it has been anonymised) in a specialist data centre and may be used for future research.	☐	☐

Name of Participant	Date	Signature
Karsten Seipp		
Name of Researcher	Date	Signature

Figure C.4: Consent form for Study Two.

C.4 Study Two Data

The data of R1 can be found on the attached DVD in the folder "Chapter 3". The file name is "S2 thumbs-Normal.sav". The file can be opened with SPSS 21.
The data of R2 can be found on the attached DVD in the folder "Chapter 3". The file name is "S2 thumbs-Stroop.sav". The file can be opened with SPSS 21.

C.5 User Survey Questions

- How do you browse the Web?
- How do you write a text?
- How do you dial?
- How do you navigate an image gallery?
- How do you hold your phone when selecting a file from a grid?
- How do you operate the calendar application?
- How do you watch a video?
- How do you read an E-book?
- How do you operate it when using the camera?
- What do you do most with your phone?
- Why do you hold it the way you hold it?
- Are you left- or right-handed?
- Which phone do you use?
- What is your age?

Appendix D

Chapter 4

D.1 Study One Information Sheet and Consent Form

Information sheet for "Mapping Touch Input Characteristics"

This study is to investigate the touch properties of thumb and index finger in different parts of a touchscreen smartphone while walking and sitting. In the experiment you will be asked to tap a certain button on the screen. The button you are to tap will be highlighted in red. This will have to be done for all buttons, using the left index finger, the right index finger, the left thumb and the right thumb, once while sitting, once while walking. All interactions will be recorded in a database.

The study begins with a brief explanation. Following the completion of the study, you will be asked to have your thumb diameter and length measured. This will be followed by a short task where you will be asked to apply some water colour to your thumb and index finger and subsequently tap certain areas on a piece of paper mounted onto a smartphone, in order to record the different touch shapes of index finger and thumb. Sanitary wipes to clean your hands afterwards will be provided. The recorded shapes will be used for interpreting the recorded digital data.

Time permitting, the participant will be asked to perform another short experiment. Here, the participant will be asked to perform a series of taps and swipes while holding a phone in different ways. The touch-information created will be saved anonymously and used to understand the characteristics of different fingers and actions.

The collected data will be stored with the participant ID that is assigned on an incremental basis. Participation in this research is voluntary. Volunteers are under no obligation to complete the study and can cease participation at any time. If you have any questions regarding the purpose, procedure, or other aspects of the experiment, or if you would like to know more about the research, please feel free to send an e-mail message to the investigator at k.seipp@gold.ac.uk.

You may keep a copy of this sheet for your reference.

Figure D.1: Information sheet for Study One.

CONSENT FORM

Mapping Touch Input Characteristics

Karsten Seipp, PhD candidate at the Department of Computing at Goldsmiths College.
Email: k.seipp@gold.ac.uk

	Please tick box
1. I confirm that I have read and understand the information sheet provided for the above study and have had the opportunity to ask questions.	yes ☐
2. I understand that my participation is voluntary and that I am free to withdraw at any time, without giving reason.	yes ☐
3. I agree to take part in the above study.	yes ☐

	Please tick box
6. I agree to the use of anonymised quotes in publications	yes ☐
7. I agree that my data gathered in this study may be stored (after it has been anonymised) in a specialist data centre and may be used for future research.	yes ☐

Name of Participant	Date	Signature
Karsten Seipp		
Name of Researcher	Date	Signature

Figure D.2: Consent form for Study One.

D.2 Study One Data

The data can be found on the attached DVD-ROM in the folder “Chapter4/Study 1 DB”. The file name is “directional-touches.db”. This file is a SQLite database. The touch values were recorded in the table “buttontouchdata”.

D.2.1 SPSS Files

The data can be found on the attached DVD-ROM in the folder “Chapter4/SPSS”.

D.2.2 Mean Property Values in Each Target Location

Figures showing the mean value and SD of each property and target location used in the mean-based comparison can be found on the attached DVD-ROM in the folder “Chapter4/Touch property values”.

D.3 Weka

D.3.1 Initial Classification Results

The initial Weka classification output can be found on the attached DVD-ROM in the folder “Initial Classification Output”.

D.4 Physical Attributes

D.4.1 Physical and Digital Finger Attributes

The full table showing each participant’s physical finger properties can be found on the attached DVD-ROM in the folder “Chapter4”. The file name is “Physical and digital means.ods”.

D.4.2 Touch Shapes

Scans of the physical touch shapes can be found in the folder "Chapter4/Touch shapes".

D.4.3 Touch History Images

The recorded touch history images can be found in the folder "Chapter4/Touch history".

D.5 Study Two Information Sheet and Consent Form

Information sheet for “Mapping Touch Input Characteristics” – Study Two

This study is to investigate the touch properties of thumb and index finger in different parts of a touchscreen smartphone while walking and sitting. In the experiment you will be asked to tap a certain button on the screen. The button you are to tap will be highlighted in red. This will have to be done for all buttons, using the left index finger, the right index finger, the left thumb and the right thumb, once while sitting, once while walking. All interactions will be recorded in a database.

The collected data will be stored with the participant ID that is assigned on an incremental basis. Participation in this research is voluntary. Volunteers are under no obligation to complete the study and can cease participation at any time. If you have any questions regarding the purpose, procedure, or other aspects of the experiment, or if you would like to know more about the research, please feel free to send an e-mail message to the investigator at k.seipp@gold.ac.uk.

You may keep a copy of this sheet for your reference.

Figure D.3: Information sheet for Study Two.

CONSENT FORM

Mapping Touch Input Characteristics -- Study Two

Karsten Seipp, PhD candidate at the Department of Computing at Goldsmiths College.
Email: k.seipp@gold.ac.uk

Please tick box

1. I confirm that I have read and understand the information sheet provided for the above study and have had the opportunity to ask questions. yes ☐
2. I understand that my participation is voluntary and that I am free to withdraw at any time, without giving reason. yes ☐
3. I agree to take part in the above study. yes ☐

Please tick box

6. I agree to the use of anonymised quotes in publications yes ☐
7. I agree that my data gathered in this study may be stored (after it has been anonymised) in a specialist data centre and may be used for future research. yes ☐

Name of Participant	Date	Signature
Karsten Seipp		
Name of Researcher	Date	Signature

Figure D.4: Consent form for Study Two.

D.5.1 Study Two: Recorded Data and Lookup Tables

The data can be found on the attached DVD-ROM in the folder "Study 2 DB".

Appendix E

Chapter 5

E.1 Interview Transcripts

E.1.1 Interview One

Interview with Stephen Coe, freelance Web designer and developer.

Question: What should an interface consider that supports one-handed operation on websites using client-side technologies?
The interface:

- Should not change the page design.
- Should not be obtrusive.
- Should be fast and work well.
- Should work with (and should not clash with) JavaScript libraries on the page, such as MooTools, jQuery etc.).
- Should have an on/off switch.
- Should be extendible via plugins and easy to configure.

E.1.2 Interview Two

Interview with Daniel O'Donnell, former Web designer and developer at Imperial College London.

Question: What should an interface consider that supports one-handed operation on websites using client-side technologies?
The interface:

- Should work for left- and right-handed users.
- Should not interfere with JavaScript libraries.
- Should maintain the functionality of the original website and support events bound to its elements.
- Should have a small file size.
- Should not remove the page design.
- Could be a jQuery plugin.
- Should be easy to add and easy to maintain.
- Should be fast.
- Should work on all modern smartphones that have a large touchscreen.

E.2 *The One Hand Wonder*: Source Code

The code of the *OHW* can be found on the attached DVD-ROM in the folder "Chapter5/OHWsource".
An example implementation can be found in the file "formtest.htm" in the same folder.
The *OHW* uses the jQuery library (v. 1.8) and the following jQuery plugins:

touchSwipe – jQuery Plugin

http://plugins.jquery.com/project/touchSwipe

http://labs.skinkers.com/touchSwipe/

Copyright (c) 2010 Matt Bryson (www.skinkers.com)

Version: 1.2.5

FastClick

Author: Rowan Beentje (rowan@assanka.net), Matt Caruana Galizia (matt@assanka.net).

jQuery-CSS-transform

Author: Zachary Johnson www.zachstronaut.com

jQuery.UI.iPad plugin

Date: 27.08.2010

Project home: http://code.google.com/p/jquery-ui-for-ipad-and-iphone/

jQuery Waypoints

Author: Caleb Troughton

URL: https://github.com/imakewebthings/waypoints

E.3 *The One Hand Wonder*: Permission to Include Figures

RE: Publication permissions - Karsten Seipp https://pod51048.outlook.com/owa/#viewmodel=...

RE: Publication permissions

webist.secretariat@insticc.org

Mon 19/05/2014 18:17

To:Karsten Seipp <k.seipp@gold.ac.uk>;

Dear Karsten Seipp,

Thank you for your email and my sincere apologies for the delay.
Regarding your question, as long as you mention in the references the paper that was published in the WEBIST 2014 you are allowed to use some figures in your PhD thesis.

Best Regards,
Carla Mota

From: Karsten Seipp [mailto:k.seipp@gold.ac.uk]
Sent: sexta-feira, 16 de Maio de 2014 10:30
To: webist.secretariat@insticc.org
Cc: comm@insticc.org
Subject: Publication permissions

Dear Mrs Mota,

I hope you are well. I am writing to you to enquire whether you may have yet had the time to deal wiht my email below. I would like to use some of the figures of my paper mentioned below in my PhD thesis and would like to request permission from Scitepress to do so. Could you possibly provide me with this permission or suggest how to obtain it?

Kind Regards,
Karsten Seipp

From: Karsten Seipp
Sent: 01 May 2014 17:34
To: WEBIST Secretariat
Subject: Re: WEBIST 2014 - Photos available

Dear Mrs Mota, I hope you are well.

1 of 3 26/05/14 14:21

Figure E.1: Permission to include figures published in Seipp and Devlin (2014*c*)

E.4 Study One Information Sheet and Consent Form

E.4.1 Information Sheet

Information sheet for "Navigating websites with the OHW interface"

This study is to set up to obtain a general impression of the usability of the OHW (One Hand Wonder) interface for websites viewed on touchscreen phones. In this study the participant will be asked to perform several tasks on a website via a special software interface, using a mobile phone provided by the researcher. The study begins with watching a video tutorial followed by some self-directed experimentation with the interface. After this initial phase, the user will be asked to perform various tasks (see task sheet) and finally answer a short questionnaire.

Both, the self-directed experimentation with the interface and the performance of the set tasks will be recorded on video and audio. The user is expected to constantly comment on her actions and utter any concerns or positive aspects found with the interface in this think-aloud-study

The video and audio recordings, together with the completed questionnaire, will be anonymised and are stored with no identifier other than the participant ID that is assigned randomly. Participation in this research is voluntary. Volunteers are under no obligation to complete the study and can cease participation at any time. If you have any questions regarding the purpose, procedure, or other aspects of the experiment, or if you would like to know more about the research, please feel free to send an e-mail message to the investigator at k.seipp@gold.ac.uk.

You may keep a copy of this sheet for your reference.

Figure E.2: Information sheet for participants of Study One.

E.4.2 Consent Form

CONSENT FORM

Navigating websites with the OHW interface

Karsten Seipp, PhD candidate at the Department of Computing at Goldsmiths College.
Email: k.seipp@gold.ac.uk

Please write initials into box

1. I confirm that I have read and understand the information sheet provided for the above study and have had the opportunity to ask questions. ☐
2. I understand that my participation is voluntary and that I am free to withdraw at any time, without giving reason. ☐
3. I agree to take part in the above study. ☐

Please tick box

	Yes	No
6. I agree to the use of anonymised quotes in publications	☐	☐
7. I agree that my data gathered in this study may be stored (after it has been anonymised) in a specialist data centre and may be used for future research.	☐	☐

Name of Participant	Date	Signature
Karsten Seipp		
Name of Researcher	Date	Signature

Figure E.3: Consent form for participants of Study One.

E.5 Study One Tasks

<u>OHW tasks:</u>

**Please perform these tasks in order. Please comment on everything you think and do as you perform the tasks.
Should you not be able to complete the task, please say so and feel free to abort it.
In this case please proceed with the next task.**

1 Find the video about the opening of Exhibition Road. Start it. Once the video starts loading or has started playing, return to the page.

2 Find the section about the popularity of raspberries.

3 Find a link named “Funding”.

4 Find the comment form and fill in your first NAME, today’s DATE, and the AMOUNT 7.

5 Navigate to the “Fishing” page.

6 On the fishing page find the section about feeding fish.

Please note that any links other than the ones named above do not work in this user test. In case you activate such a link, you will get a short alert. Just press “OK” to close the alert.

Figure E.4: Tasks for participants of Study One.

E.6 Study One Questionnaire

The questionnaire can be found on the attached DVD-ROM in the folder "Chapter5". The file name is "OHW_study1_questionnaire.pdf".

E.7 Study Two Information Sheet and Consent Form

Information sheet for "Navigating websites with the OHW interface – Study Two

This study is to determine the efficiency of the OHW (One Hand Wonder) interface for websites viewed on touchscreen phones in comparison to using the website without it. In this study the participant will be asked to perform several tasks on a website via a special software interface, using a mobile phone provided by the researcher. The study begins with a brief explanation followed by some self-directed experimentation with the interface if needed. After this initial phase, the user will be asked to perform various tasks displayed on the phone while sitting. This is to be done once with the interface and once without the interface (the "normal" way). Both modes of operation have to be undertaken by holding the phone in only one hand.

All interactions will be recorded in a (text-)list together with the task completion time for each task.

The collected data will be stored with no identifier other than the participant ID that is assigned on an incremental basis. Participation in this research is voluntary. Volunteers are under no obligation to complete the study and can cease participation at any time. If you have any questions regarding the purpose, procedure, or other aspects of the experiment, or if you would like to know more about the research, please feel free to send an e-mail message to the investigator at k.seipp@gold.ac.uk.

You may keep a copy of this sheet for your reference.

Figure E.5: Information sheet for participants of Study Two.

CONSENT FORM

Navigating websites with the OHW interface – Study Two

Karsten Seipp, PhD candidate at the Department of Computing at Goldsmiths College.
Email: k.seipp@gold.ac.uk

Please write initials into box

1. I confirm that I have read and understand the information sheet provided for the above study and have had the opportunity to ask questions. ☐
2. I understand that my participation is voluntary and that I am free to withdraw at any time, without giving reason. ☐
3. I agree to take part in the above study. ☐

Please tick box

	Yes	No
6. I agree to the use of anonymised quotes in publications	☐	☐
7. I agree that my data gathered in this study may be stored (after it has been anonymised) in a specialist data centre and may be used for future research.	☐	☐

Name of Participant	Date	Signature
Karsten Seipp		
Name of Researcher	Date	Signature

Figure E.6: Consent form for participants of Study Two.

E.8 Study Two Tasks

The tasks can be found on the attached DVD-ROM in the folder "Chapter5". The file name is "OHW_study2_tasks.pdf".

E.9 Study Two Quantitative Data

The data can be found on the attached DVD-ROM in the folder "Chapter5". The file name is "OHW_Normal_quant.sav". This file can be opened with SPSS V21.

Appendix F

Chapter 6

F.1 Gesture Recording Information Sheet and Consent Form

Information sheet for “Gesture recording”

The aim of this study is analyse the sound and movement characteristics of a set of gestures. For this the user will be asked to hold the phone in one hand and perform a “patting” gesture with the index finger of the hand holding the device against the device's back ten times. After that, the user will be asked to perform the same gesture using the middle finger.

The data will be stored in a database and will be used to explore the characteristics of the gestures.

The data will be stored with the participant ID that is assigned on an incremental basis. Participation in this research is voluntary. Volunteers are under no obligation to complete the study and can cease participation at any time. If you have any questions regarding the purpose, procedure, or other aspects of the experiment, or if you would like to know more about the research, please ask the investigator or send an email to k.seipp@gold.ac.uk.

You may keep a copy of this sheet for your reference.

FIGURE F.1: Information sheet for the initial gesture recording.

CONSENT FORM

Gesture recording

Karsten Seipp, PhD candidate at the Department of Computing at Goldsmiths College.
Email: k.seipp@gold.ac.uk

Please tick box

1. I confirm that I have read and understand the information sheet provided for the above study and have had the opportunity to ask questions. yes ☐
2. I understand that my participation is voluntary and that I am free to withdraw at any time, without giving reason. yes ☐
3. I agree to take part in the above study. yes ☐

Please tick box

6. I agree to the use of anonymised quotes in publications yes ☐
7. I agree that my data gathered in this study may be stored (after it has been anonymised) and may be used for future research. yes ☐

Name of Participant　　Date　　Signature

Karsten Seipp
Name of Researcher　　Date　　Signature

Figure F.2: Sample consent form for the initial gesture recording.

F.2 *BackPat* Source Code

The source code of *BackPat* can be found on the attached DVD-ROM in the folder "Chapter6/BackPatSource". The technique is defined by the library "BT_Controller", which uses the dependencies "GyroscopeTest" and "FFT_comp_lib". In addition, the folder contains the implementation of *BackPat* into various example applications: "BP_List_CHI" (multiple selection in lists), "BT_ImageZoom" (image zooming), "BT_MapAgain" (map zooming using index finger and middle finger double-pat gestures), "BT_tx" (text selection), "BT_wintop_web" (*Pat-Into-Place* demonstration using a double-pat gesture of the index finger in a Web browser example). *BackPat* uses the library "Apache Commons Math" (https://commons.apache.org/proper/commons-math/download_math.cgi) for calculating the Pearson Correlation Coefficient (PCC), and the library "JTransforms" (https://sites.google.com/site/piotrwendykier/software/jtransforms) for creating Fast Fourier Transforms (FFT) of audio data.

F.3 Resource URLs

F.3.1 Speech and Music

The parliamentary speech used in the study can be found at
https://www.youtube.com/watch?v=eL5hqvTWkYg
Title: "Lord James of Blackheath $ 15,OOO,OOO,OOO,OOO FRAUD EXPOSED February 16 2012"
Last accessed: 25.01.2015

The music used in the study can be found at
https://www.youtube.com/watch?v=O7TklQTeuSE
Title: "M Beat feat. General Levy: Incredible"
Last accessed: 25.01.2015

F.4 Accuracy Test Information Sheet and Consent Form

Information sheet for "Accuracy test"

The aim of this study is to measure the reliability of the gesture detector of the *BackPat* technique. To do so, the user will be asked to perform the three *BackPat* gestures under a variety of conditions, such as when sitting and walking, and with pre-recorded talking in the background. The user will be shown the gestures and asked to familiarise themselves with these. Following this exploration, the recording begins where the gestures will have to be performed 10 times each under various conditions. The recorded data will be stored in a database.

The data will be stored with the participant ID that is assigned on an incremental basis. Participation in this research is voluntary. Volunteers are under no obligation to complete the study and can cease participation at any time. If you have any questions regarding the purpose, procedure, or other aspects of the experiment, or if you would like to know more about the research, please ask the investigator or send an email to k.seipp@gold.ac.uk.

You may keep a copy of this sheet for your reference.

FIGURE F.3: Information sheet for the accuracy test.

CONSENT FORM

Accuracy test

Karsten Seipp, PhD candidate at the Department of Computing at Goldsmiths College.
Email: k.seipp@gold.ac.uk

	Please tick box
1. I confirm that I have read and understand the information sheet provided for the above study and have had the opportunity to ask questions.	yes ☐
2. I understand that my participation is voluntary and that I am free to withdraw at any time, without giving reason.	yes ☐
3. I agree to take part in the above study.	yes ☐

	Please tick box
6. I agree to the use of anonymised quotes in publications	yes ☐
7. I agree that my data gathered in this study may be stored (after it has been anonymised) and may be used for future research.	yes ☐

Name of Participant	Date	Signature
Karsten Seipp		
Name of Researcher	Date	Signature

Figure F.4: Consent form for the accuracy test.

F.4.1 Accuracy Test Data

The data of the accuracy test can be found on the attached DVD-ROM in the folder "Chapter6/AccuracyTest".

F.5 Study One Information Sheet and Consent Form

Information sheet for "*BackPat* User Studies" – Study One

This study is to investigate the usability of a novel set of back-of-device interaction to aid one-handed use of touchscreen smartphones. In a series of three applications, the user will be asked to perform various tasks, ranging from selecting items in a list to reaching targets outside the thumb's reach and selecting various amounts of text.

In the text selection study, the user will be asked to select text using the text "normally" using the thumb and with the *BackPat* technique. Tasks completion times will be recorded anonymously. After this, users will be asked to provide feedback on a five-point Likert scale.

Following the above, users are asked to explore two more applications: Reaching distant targets and selecting items in a list. After this, users will be asked to provide feedback on a five-point Likert scale.

The collected data will be stored with the participant ID that is assigned on an incremental basis. Participation in this research is voluntary. Volunteers are under no obligation to complete the study and can cease participation at any time. If you have any questions regarding the purpose, procedure, or other aspects of the experiment, or if you would like to know more about the research, please feel free to send an e-mail message to the investigator at k.seipp@gold.ac.uk.

You may keep a copy of this sheet for your reference.

FIGURE F.5: Information sheet for Study One.

CONSENT FORM

***BackPat* User Studies – Study One**

Karsten Seipp, PhD candidate at the Department of Computing at Goldsmiths College.
Email: k.seipp@gold.ac.uk

	Please tick box
1. I confirm that I have read and understand the information sheet provided for the above study and have had the opportunity to ask questions.	yes ☐
2. I understand that my participation is voluntary and that I am free to withdraw at any time, without giving reason.	yes ☐
3. I agree to take part in the above study.	yes ☐

	Please tick box
6. I agree to the use of anonymised quotes in publications	yes ☐
7. I agree that my data gathered in this study may be stored (after it has been anonymised) in a specialist data centre and may be used for future research.	yes ☐

Name of Participant Date Signature

Karsten Seipp
Name of Researcher Date Signature

Figure F.6: Consent form for Study One.

F.5.1 Study One Data

The Likert scale feedback can be found on the attached DVD-ROM in the folder "Chapter6/StudyOne".

The recorded task times can be found on the attached DVD-ROM in the folder "Chapter6/StudyOne".

F.6 Study Two Information Sheet and Consent Form

Information sheet for "*BackPat* User Studies" – Study Two

This study is to investigate the performance of a range of back-of-device interactions to aid one-handed use of touchscreen smartphones. The user will be asked to use the technique to perform tasks such as selecting items in a list, reaching targets outside the thumb's reach or selecting various amounts of text. Which of these tasks is to be performed will be determined by the researcher. The tasks will have to be performed once using the thumb and once using the *BackPat* technique.

The study begins with an explanation of the technique and the participant will be instructed how to use use it. After a brief period of training, the recording of the participant's actions will begin. All interactions will be recorded in a database. After this, users will be asked to provide feedback on a five-point Likert scale.

Time permitting, the participant will be asked to perform another short experiment. Here, the participant will be asked to perform a series of taps and swipes while holding a phone in different ways. The touch-information created will be saved anonymously and used to understand the characteristics of different fingers and actions.

The collected data will be stored with the participant ID that is assigned on an incremental basis. Participation in this research is voluntary. Volunteers are under no obligation to complete the study and can cease participation at any time. If you have any questions regarding the purpose, procedure, or other aspects of the experiment, or if you would like to know more about the research, please feel free to send an e-mail message to the investigator at k.seipp@gold.ac.uk.

You may keep a copy of this sheet for your reference.

Figure F.7: Information sheet for Study Two.

CONSENT FORM

***BackPat* User Studies – Study Two**

Karsten Seipp, PhD candidate at the Department of Computing at Goldsmiths College.
Email: k.seipp@gold.ac.uk

	Please tick box
1. I confirm that I have read and understand the information sheet provided for the above study and have had the opportunity to ask questions.	yes ☐
2. I understand that my participation is voluntary and that I am free to withdraw at any time, without giving reason.	yes ☐
3. I agree to take part in the above study.	yes ☐

	Please tick box
6. I agree to the use of anonymised quotes in publications	yes ☐
7. I agree that my data gathered in this study may be stored (after it has been anonymised) in a specialist data centre and may be used for future research.	yes ☐

____

Name of Participant Date Signature

Karsten Seipp ____________________ ____ _______________ _______________________
Name of Researcher Date Signature

Figure F.8: Consent form for Study Two.

F.6.1 Study Two Data

The Likert scale feedback can be found on the attached DVD-ROM in the folder "Chapter6/StudyTwo".

The recorded task times can be found on the attached DVD-ROM in the folder "Chapter6/StudyTwo".

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