Tailoring Interaction.
Sensing Social Signals with Textiles.

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PhD thesis

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January 2021

Abstract

Nonverbal behaviour is an important part of conversation and can reveal much about the nature of an interaction. It includes phenomena ranging from large-scale posture shifts to small scale nods. Capturing these often spontaneous phenomena requires unobtrusive sensing techniques that do not interfere with the interaction. We propose an underexploited sensing modality for sensing nonverbal behaviours: textiles. As a material in close contact with the body, they provide ubiquitous, large surfaces that make them a suitable soft interface.

Although the literature on nonverbal communication focuses on upper body movements such as gestures, observations of multi-party, seated conversations suggest that sitting postures, leg and foot movements are also systematically related to patterns of social interaction. This thesis addressees the following questions: Can the textiles surrounding us measure social engagement? Can they tell who is speaking, and who, if anyone, is listening? Furthermore, how should wearable textile sensing systems be designed and what behavioural signals could textiles reveal?

To address these questions, we have designed and manufactured bespoke chairs and trousers with integrated textile pressure sensors, that are introduced here. The designs are evaluated in three user studies that produce multi-modal datasets for the exploration of fine-grained interactional signals. Two approaches to using these bespoke textile sensors are explored. First, hand crafted sensor patches in chair covers serve to distinguish speakers and listeners. Second, a pressure sensitive matrix in custom-made smart trousers is developed to detect static sitting postures, dynamic bodily movement, as well as basic conversational states.

Statistical analyses, machine learning approaches, and ethnographic methods show that by monitoring patterns of pressure change alone it is possible to not only classify postures with high accuracy, but also to identify a wide range of behaviours reliably in individuals and groups. These findings establish textiles as a novel, wearable sensing system for applications in social sciences, and contribute towards a better understanding of nonverbal communication, especially the significance of posture shifts when seated. If chairs know who is speaking, if our trousers can capture our social engagement, what role can smart textiles have in the future of human interaction? How can we build new ways to map social ecologies and tailor interactions?

Acknowledgements

This journey has started with Pat Healey and Becky Stewart accepting me into their world, teaching me how to conduct research, how to ask the right questions, how to work across disciplines, and how to sneak the word ‘arse’ into academic publications. Thank you for inspiring me, encouraging and trusting me, challenging me and supporting me, letting me *tailor* my own research world, and for doing so much more than I would have ever dared to expect from supervision.

Pursuing a PhD would have only been half the fun if it wasn’t for the community in the Cognitive Science group and the Media & Arts Technology (MAT) programme, and the friendships that have been found at the department. Special Thanks goes to *miei amici* Adan Benito Temprano and Giulio Moro, the best possible life coaches. They have been patient, supportive, understanding, necessarily sarcastic, and always on call.

I’m thankful to colleagues, academics, technicians, admin and other members of staff who have made my life easier, more amusing, entertaining, and who have been generous and warm hearted in their multidimensional support and companionship - no matter whether that was programming advice, anxiety relief, or catching the wrong note in a Karaoke song. Amongst the many names that have formed this experience, and to whom I would like to express my gratitude, there are some I’d like to highlight. Thank you to my fellow PhD students Liang An, Betul, Angela, Vanessa, Rishi, James, Tom, Rosella, Alexandra, Hazar, and Leshao. Thank you to the coolest office gang Soomi, Lida, Daniel, Lucia and Moh. I would like to thank the academics turned friends, too. Many Thanks to Karen Shoop, Paul Curzon, Lorenzo Jamone, and Arman Khouzani. Another big Thanks goes to programme manager Jonathan Winfield and director Nick Bryan-Kinns for nurturing my research ambitions and supporting me in all my endeavours. Thank you also to Edward, Hayley, as well as Geetha and Ho, and the entire EECS team for carrying all of us PhD students through our journey.

I am also lucky to have received the support, love and care from my family and friends outside of the Engineering and Computer Science world - in Vienna. I am infinitely grateful to my mother Gabriele, my brother Clemens and my grandparents Alfred and Hermine, who always strengthen me, who have made me more than I am, and without whom I would never have been able to get as far as to pursuing a PhD. It is to them I dedicate this thesis to. The family that has always been there for me, no matter what, also includes my father Alexander, my aunts Sabine and Kathi, my other grandmother Anna, and my loving cousin Lukas. Thank you. Special Thanks also goes to my chosen knitted family Natalie, Maria and Lisa for being my heart companions, for growing and dancing with me. Other companions of the heart, as well as all participants who were willing to exchange Austrian wafers for their time, sceptically putting on trousers equipped with sensors in the crotch and sitting on ‘electric’ chairs, are also thanked here.

Finally, I would like to thank the EPSRC and AHRC Centre for Doctoral Training in Media and Arts Technology (EP/L01632X/1) for funding this research journey.

Statement of Originality

I, Sophie Skach, confirm that the research included within this thesis is my own work or that where it has been carried out in collaboration with, or supported by others, that this is duly acknowledged and my contribution indicated. Previously published material is also acknowledged. I attest that I have exercised reasonable care to ensure that the work is original, and does not to the best of my knowledge break any UK law, infringe any third party's copyright or other Intellectual Property Right, or contain any confidential material. I accept that the College has the right to use plagiarism detection software to check the electronic version of the thesis. I confirm that this thesis has not been previously submitted for the award of a degree by this or any other university. The copyright of this thesis rests with the author and no quotation from it or information derived from it may be published without the prior written consent of the author.

Signature:

Date: 24 December 2020

Declaration

The work in this thesis has been undertaken entirely by me, Sophie Skach. All drawings, illustrations and figures included have been produced by me, as are the presented developments in pattern construction and fabrication, as well as all other design work. In the context of this research, this concerns the development of textile sensing systems in chairs and trousers. The processes of the development of these designs is documented in the corresponding chapters.

The electronic hardware, in particular the design of circuit boards, was developed by me and milled in the Electronics Lab at Queen Mary University of London under the supervision of the responsible technician. Here, I received support in the form of inductions to machinery and advise offered by my supervisor Becky Stewart, Giulio Moro, and Adan Benito Temprano.

The software scripts used in the presented research, used for data collection, pre-processing and analysis, were written by me. Guidance and advice for *Python* (in the form of tutorials and open source learning materials) has been provided by my supervisor Becky Stewart, my colleagues Tom Gurion and Adan Benito Temprano, by Arman Khouzani, and for SPSS by my supervisor Pat Healey.

The experimental studies presented in this thesis have also been designed, organised, and conducted by me, and were approved by and discussed with my supervisors and the Ethics Committee at Queen Mary University of London.

I would like to express my sincere thanks to my supervisors, colleagues and friends for this guidance, advice and support in these areas.

I would further like to express my thanks to all co-authors of the publications mentioned in this thesis. They are listed in a separate section in Chapter 1 and pointed to in relevant sections in the thesis. All papers are peer reviewed and written by me. Some text parts and analysis methods were obtained and edited collaboratively with my supervisors.

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Chapter 1

Introduction

1.1 Personal Statement

A good designer is a good observer. This is what is taught in many fashion design courses - what I was taught as a fashion design student for more than a decade. A skill that I have developed for the purpose of identifying, translating and processing trends for the design of textile structures, pattern constructions, and collections of menswear and womenswear, and a skill that I have come to apply for conversation analysis, identifying patterns of human behaviour. Previously, I used tools and methods of fashion design to bridge to other disciplines, too. In my design work, knitting structures resembled prime number or Fibonacci rows, mathematical formula were applied to the geometric construction of a garment pattern to create volume, or the concept of a mathematical proof was presented as a performative concept of a garment collection.

My personal motivation to undertake this research journey comes from an interest in multiple disciplines and the challenge to connect them where possible, exploring whether one field of study or design practice can inform another. This interest has also guided me through my academic and industry endeavours, working as a tailoring manager before starting this PhD, studying mathematics prior to that, and studying and working in fashion prior to that. This motivation and appeal to interdisciplinary approaches stems, amongst other influences, from the Renaissance and Baroque era, when natural sciences, humanities and design was intertwined in fundamental ways, enabling a golden era of technical and philosophical innovations that still shape our societies today.

Here, I am a fashion designer in a computer science department, part of a cognitive science research lab, investigating social interaction. In the past, I had the role of a mathematician doing fashion, and a knitwear technologist studying mathematics. Therefore, the hands and mind authoring this thesis, that has been submitted as part of the Media & Arts Technology programme within a School of Computer Science and Engineering, bring a variety of disciplines with them. I have pursued this PhD to explore the potential of these disciplines informing, challenging and benefiting from each other, and aiming to use the knowledge acquired from textile and garment construction and design to eventually dissect the embodiment of social behaviour.

On the notion of dissection, the drawing below illustrates a metaphor that I have created during the observations and analyses on the display of postural body movements during social interactions, and the display of (wearable) technology and its components in designs for ubiquitous computing. The drawing shows a simplified tailored suit jacket - one of the most complex items of clothing to construct and make, but with a desire to appear effortlessly ever since its 'invention'. The left side of the drawing shows how a suit jacket looks when completed and worn, while the right side shows the pattern construction and inner lining (not including all parts actually needed), concealing what is the fundamental part of the system for it to achieve its desired form. Translated to the study of human behaviour: the left side, a glance at a conversation, a social encounter; and the right side, the collaborating components of verbal and nonverbal, not always visible signals determining the nature of the encounter, its form.

In that sense, another statement echoing from the lessons of my design and technology courses, and that can be transformed into a metaphorical statement on dissecting social interaction: *A good designer is a good pattern cutter.*

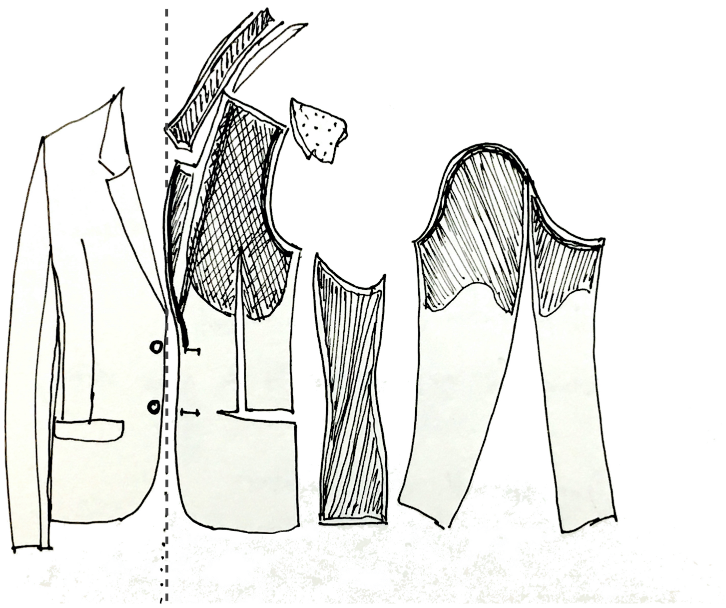

Figure 1.1: The visible (left) and concealed (right) parts of a tailored suit jacket.

1.2 Research Motivation

Textiles are an interface we have been familiar with for thousands of years, often in the form of, but not bound to clothing. Seen as an extension of our skin, they are used to culturally and socially express ourselves. The fabrics we wear on our body already function as tools of nonverbal communication. Together with biomechanical cues like gestures, gaze and posture, nonverbal signals make up a large part of human interaction and contain detailed information about the nature of a conversation. From signals elicited through clothing, economical, political, cultural information can be retrieved, while from nonverbal bodily signals, we can tell, whether an interaction is friendly or confrontational, what the social relation between interactants is, whether people are interested or bored and often who or what they are talking about.

We use spatial orientation, gestures and postural shifts to manage speaker turns, mark topic shifts, and to signal attitude and affect (Kendon, 1990b; Schegloff, 1998; Bull, 2016; D'Mello et al., 2007a), while head movement provide listener feedback (Bavelas et al., 1992). Many of these signals derive from the upper body, which has been studied extensively in the last decades. However, the lower body is potentially rich in social cues, too (Schegloff, 1998). Postures such as leg crossing or stretching can be signals of perceived behaviours and emotions (Bull, 2016), and can contribute to affect detection (Cassell et al., 2001). In comparison to identified embodied social signals, the lower body is rarely attended.

Sensing sometimes subtle nonverbal cues can be challenging. These signals are often analysed using computer vision based technologies (Kleinsmith and Bianchi-Berthouze, 2013; Karg et al., 2013). The reliance on visual cues can be vulnerable to problems with occlusion and can provoke privacy concerns, since sometimes, more dimensions of data are captured than needed. Most obviously, the presence of a camera is always to some degree intrusive. Consent may be difficult to obtain and even when it is obtained people's awareness of being videoed can affect the naturalness of their behaviour. Optical motion capture markers in particular are cumbersome, visually intrusive, require special clothing different to the clothing materials we naturally engage with, and reinforce the potentially distorting effects of being in a laboratory. In recent years, more wearable solutions have been introduced, such as deploying accelerometers (Hung et al., 2013), sEMG (Wang et al., 2019), or pressure sensors (Gaus et al., 2015) on the body. These are sometimes designed as accessories or are mounted on a person's piece of clothing.

The first concepts of wearable technologies deployed on and integrated in clothing included the use of cameras (Ryan, 2014). On-body sensing has the advantage of being more selective about what data is collected. Ubiquitous approaches have been used to sense affective states with pressure sensors (D'Mello et al., 2007a) and inertial measurement units (IMU) (Olugbade et al., 2019), group dynamics with accelerometers (Varni et al., 2010; Hung et al., 2013), and actively promote interactional behaviour using radio frequency tags (Khaorapapong and Purver, 2012). The limitations of many of such sensors and recording systems are their conspicuous forms of industrial design e.g., encapsulated in plastic or integrated in other rigid gadget-like devices, such as wristbands, smart watches or belts (Patel et al., 2012).

A material that has the ability to circumvent these issues are textiles. Fabrics provide promising properties to capture bodily data and present advantages compared to other, often intrusive to wear sensors: they are soft, flexible, and comfortable to wear on the body. They are materials we are in close contact with: from book covers to car seats to our underpants, textiles are omnipresent in our environment and can act as an interface to connect our analog and digital worlds. Textiles as a sensing surface and a fundamental part of wearable computing have been explored for several decades (Post and Orth, 1997), and has been used for a variety of applications including health care, sports and performing arts. They enable body movement to be captured in continuous, unintrusive ways, and are used to identify gestures (Strohmeier et al., 2018; Li et al., 2020), torso movement (Mattmann et al., 2007), sitting postures (Meyer et al., 2010a), even micromovements like shoulder lifts or breathing (Dunne et al., 2006a).

Amongst a variety of textile sensors, measuring piezo-resistive signals like pressure have proven to be particularly useful when recording posture, gesture and other bodily movement. These explorations in 'posture-aware' smart clothing mostly focus on tracking movement of the upper body, assuming that the torso, including the arms, is most relevant to identify these bodily signals. There is relatively little work on placing textile sensors on the legs and feet. Examples of research utilising the lower body for textile sensor measurements do so in a context of assessing sports performance or for gait recognition. They furthermore involve deploying sensors on a finished garment with sometimes improvised techniques, rather than embedding them in the fabric less intrusively. This distribution of signals being measured on the upper versus the lower body parallels the literature on studying behavioural cues. Only few have tested lower body garments, e.g. trousers as a measuring tool for bodily cues (Dunne et al., 2011; Yu et al., 2021).

Figure 1.2: A seated social encounter: ink sketch capturing seated conversation in a room surrounded by fabric surfaces.

In general, smart textiles are broadly represented in Human-Computer-Interaction, but are less investigated as a methodology for capturing interaction between humans. With clothes as an integral part of embodied social interaction, it is surprising they have not been exploited to a larger extent to capture nonverbal behaviour. This thesis explores the potential of smart textiles embedded as a sensing system for social interaction through two prototype technologies: chairs and trousers (highlighted in Figure 1.2).

1.3 Aims and Objectives

The first aim of this thesis is to challenge the assumption that the upper body is the best or only source of significant non-verbal social cues (e.g. Ekman and Friesen (1969a)). The working hypothesis is that we should examine nonverbal behaviour elicited by salient postural movements involving all of the body, before special attention is given to the signals the lower body conveys. Although legs and feet have previously been described as "worst" when it comes to assessing the signalling capacity of the human body, it has also been claimed that legs perform the most "honest" nonverbal signals (Ekman and Friesen, 1969a). Observing legs as transmitters of social cues, we extend a small corpus of work in which the lower body is at the centre of interest. Most studies on nonverbal behaviours mention leg movements only in passing (Bull, 2016; Scheflen, 1964), while studies measuring leg or feet movement usually have an individual or egocentric focus but do not address social interaction. We investigate whether it is possible to deduce information about social interaction from tracking bodily movements on the lower body in naturalistic conversation, and explore whether there is so far overlooked potential in signals deriving from the lower body, too.

Second, I focus on unstaged social encounters, rather than single-user settings. Postural movements in particular are often detected from acted procedures rather than in spontaneous interaction (Kleinsmith and Bianchi-Berthouze, 2013). This naturally leads to a concern with methods of data collection. While camera based techniques can capture changes in overall body configuration, they do not sense the shifting weights and forces that movements induce. Even though depth-camera systems like Kinect can detect some shifts in pressure as well, they are still limited by occlusion. We critique the intrusiveness of such systems capturing nonverbal bodily cues, whether for upper or lower body, and propose sensing systems that make use of everyday materials and objects, to embed sensing technology into elements of our everyday life. This aims at reducing the potential impact on our actions and behaviours when interacting with others.

Third, I explore textile surfaces as a sensing technology for detecting embodied social behaviour. The general awareness of the omnipresence of textile materials is often little, because they are so interlocked with everyday experiences and tactile sensations. People often don't think of textiles beyond the purpose of clothing. In the field of wearable technology, textiles have not been broadly established as an unintrusive, on-body sensing method, although their potential to replace more rigid, hard electronics has been noted (Swallow and Thompson, 2001). Textiles have exciting potential to "make technology invisible", especially in the context of social computing and behavioural studies where "invisibility", or ambience in smart sensing networks is desired. One of the goals of this research is to design and evaluate textiles that can capture movement and touch interaction in social encounters. We explore whether we can reliably identify behavioural cues and social states from textiles in different forms: for example, chairs that assess conversational engagement, and trousers that detect fidgeting. Soft, wearable textile interfaces that are able to detect signals of social behaviour could unlock new aspects of nonverbal communication.

1.4 Research Questions

Our research merges questions from two areas - social science and smart textile design. Both accumulate a set of research questions this thesis addresses.

1.4.1 Conversational Investigations and Nonverbal Cues

1. What are the principal lower body posture shifts that can be observed in unscripted social interaction? What information on conversational behaviour can we infer from these movements? In particular, what social signals can we extract from sensing movement on legs and buttocks alone? What do leg postures reveal about interpersonal and egocentric behaviour? What possible interactional functions of the lower body movements might there be?

2. When sensing body movement and posture on the lower body, what other nonverbal behaviours can be detected from this? What specific types of social signals can be detected from the lower body? Are the movements we can detect with the lower body partially or wholy independent of torso movements or do they derive from secondary upper body movements?

3. What computational methods are most appropriate for discriminating social behaviours? Are sensors placed on the lower body sufficient to capture information about conversational behaviours? Is it possible to make statements about conversational engagement and interactional dynamics overall from sensors on the lower body alone?

1.4.2 Designing Textile Sensing Systems

1. How can we design and engineer sensors for on-body computing integrated in textile structures? Furthermore, can these designs be optimised to be able to capture social behaviour? How should textile interfaces be constructed to function as social behaviour sensing systems? What are the most suitable techniques as well as sensing capacities for integration into clothing? What

	Study 1 (Chairs)	**Study 2 (Trousers)**	**Study 3 (Trousers)**	**Study 4 (Trousers)**
Study Type	multi-user	single user	multi-user	single user
Setting	spontaneous conversation	instructed tasks	spontaneous conversation	instructed tasks
Participant Number	27 (9 groups of 3)	10	42 (14 groups of 3)	10
Analysis Software	SPSS	WEKA	Python	n/a
Statistical Method	Multivariate GLM	Random Forest Model	Random Forest Model	n/a
Classes to Distinguish	4 (conversational cues)	19 (sitting postures)	2 - 5 (conversational cues)	n/a

Table 1.1: Overview and comparison on the studies that have been carried out during this PhD

approaches are suitable to process sensor data extracted from textiles that are to detect social behaviour?

2. What is the potential of textile sensing systems as a new modality for capturing social behaviour? Are textiles suitable for detecting interactional signals? Is it possible to distinguish basic conversational states with textile sensors, for example, identify listeners and speakers? What are the limits of textile sensors capturing social interaction?

3. If our garments can understand, analyse and predict the nonverbal cues we emit, what are the implications for garment designers? How might we exploit this possibility in fashion design? What challenges does it comprise in the process of constructing such garment? What are the practical use cases such garments might have?

1.5 Methodologies: an Overview

Many social interactions happen when seated, for example in meetings, coffee houses and even on public transport. Consequently, chairs are objects on which much postural movement is performed, that is also crucial to decoding conversations. They have the potential for collecting data without any audio or visual recordings of the participant, securing their privacy and anonymity, and presenting an unintrusive method to do so. Clothing presents similar possibilities. The same sensing systems can be integrated in textile surfaces for both, ”on-body” (clothes) and ”off-body” (furniture) applications. We explore the use of conductive pressure sensitive fabrics to measure posture changes as signals of social interaction. To test our hypotheses , we have designed and evaluated 'smart' chairs and trousers, each incorporating different designs of embedded sensing systems.

Ethnographic Observations

Ethnographic studies provide the starting point for this research. They informed the choices of sensor design, fabrication techniques, sensing objects, as well as hypotheses on key non-verbal behaviours, e.g. identifying conversational states and their correlation with bodily movement or posture. With an initial interest in the potential of objects and surfaces, in particular fabric surfaces, in our everyday surroundings, a variety of indoor scenarios were identified as appropriate observation targets. The primary approach to capturing features of posture in interaction is through the use of hand drawings.

	Chair Covers	**Trousers**
Conductive Material	silver	coated nylon
Non-conductive Material	cotton and elastane	viscose and cotton
Textile Sensor Structure	woven	knitted
Sensor Shape	round patches	sensor matrix
Sensor Size	ca 5x10cm	1x1cm
Sensor Number	8 (4+4)	200 (100+100)
Sensor Placement	seat & back rest	thighs & buttocks
Amount Produced	3	3

Table 1.2: Comparison of the sensor designs for both, chair covers and trousers

The process of drawing, like verbal transcriptions, forces the analysts attention on to the details of body posture and posture shifts (Heath, 2014). They also preserve the anonymity of the observees and facilitate exploratory approaches to design development. A report on how the observations were conducted, and what hypotheses were extracted from their findings can be found in Chapter 3. Expansions of those observations are documented in Chapters 4, 5 and 6.

Design Prototypes

The performance of textile sensing systems in social interaction is approached through designing two different objects that are transformed into sensing surfaces: chairs and trousers. The chairs we introduce in Chapter 3 present a sensing system that takes advantage of the static nature of the object in regards to deployment of electronic components. The trousers are first introduced in Chapter 4 refine the design engineering and data evaluation of the chairs and extend them to a wearable on-body sensing system.

The choice of materials for the sensors is informed by the use cases. When designing for clothing integrated systems, we aim for stretchable and yet robust fabrics, whereas for static objects it may differ. These properties are achieved by the quality of the fibre itself (percentage of elastane), but also by the way it is manufactured into a textile surface (knitted or woven). An overview of the different sensor designs can bee seen in Table 1.2.

User Studies

A series of user studies are presented that test the hypotheses formed through the ethnographic studies, and to validate the design of the textile sensors and their integration in chairs and trousers. Two different approaches are taken. First, single user studies in controlled environments are conducted that evaluate the textile sensing systems, and to prepare for further in situ evaluation. Second, multi-user studies in an unstaged, naturalistic interactional scenario are conducted. Here, the focus is on three-way conversations around a table in order to detect spontaneous behavioural states and social signals. These studies are described in detail in Chapter 3 and 5. A comparison and overview of all studies and their parameters can be found in Table 1.1.

Quantitative Analysis

The data collected in the user studies was analysed with different analysis methods. In our approaches, we focus on exploring instantaneous data.

- **Statistical Analysis:** We present a variety of statistical analysis in the scope of this research that serve as first explorations, as well as later expansions of the machine learning approaches. The different analyses occurring in this work are a MANOVA in Chapter 3, and a non parametric Friedmanss two-way analysis of variance by ranks for analysing behaviour types is used in Chapter 6.

- **Machine Learning Approaches:** Chapters 4 and 5 explore techniques for classifications of different sitting postures and conversational behaviours. We explore machine learning methods to analyse our sensor data. After testing Support Vector Machines, Nearest Neighbour and Gaussian Naive Bayes algorithms, the results we present in detail stem from an analysis using Random Forest models.

- **Data Driven Approaches:** Lastly, we use a peak detection analysis to explore further patterns of sensor data. Here, local peaks are identified, representing major shifts in pressure distribution

The different methods, as well as the softwares we used to implement these analyses are listed as an overview in Table 1.1.

1.6 Contributions

This work contributes to an expanded understanding of small and large scale signals the body transmits in social interaction, extending existing work on upper body cues. We draw attention to an often underestimated set of postural movements in the lower body. This thesis demonstrates the relevance of these movements for communication. Capturing bodily signals on the lower body, however, also reveals information about other salient body movement deriving from the torso. We are able to capture such conversational cues with sensors around the legs and buttocks alone, which pick up a large range of postural shifts and touch interaction. This is achieved by developing a bespoke system of fabric pressure sensors. Smart chairs and trousers present the first design using textiles to capture social interaction.

Another contribution of this research is the exploration towards unintrusive sensing methods to analyse social behaviour and conversation. With the approach taken and the studies presented in the following chapters, we contribute findings to a wider research area on ubiquitous social computing and multimodal approaches to such. Therefore, the sensing system we propose in this work can be introduced as a way to collect data unintrusively and without augmenting people's natural habitat, which arguably benefits the data that is collected as less distorted or affected by the measuring process.

Our design of textile pressure sensors adds to the potential use cases for wearable, smart textiles in general, reimagining the role of textiles and garments in particular in the context of social interaction and communication. Using sensors made entirely of fabric to detect nonverbal social signals is a novel application area in the field that goes beyond the more traditional egocentric approaches. This work thereby shows the potentials and limitations of textiles as a measuring tool for human behaviour, evaluating different data processing and analysis methods. With the development of the presented prototypes we furthermore contribute to the concept of bespoke textile and garment making, discussing the benefits of this approach. The suggested design and its application area invite to discuss optimisations and novel manufacturing and integration techniques for electronic textiles.

Moreover, we challenge traditional forms of ubiquitous computing by adding this new modality to the field.

In summary, the novelty presented here is the exploration, as well as the design of textiles as a "socially aware" sensing system. I propose they have the capacity to detect behavioural cues in social interaction, and can even find new, sometimes subtle body movements not yet part of the topology of nonverbal cues.

1.7 Thesis structure

The thesis is structured around 8 chapters that are structured as follows:

Chapter 2 presents an in depth literature review of the core themes of the thesis and divided into three sections: nonverbal behaviours, wearable technologies, textile sensing systems.

Chapter 3 presents the design and evaluation of a textile sensing system capturing social signals. Smart chair covers are introduced, and the design process documented. The performance is tested in a user study that seeks to distinguish speakers from listeners and to detect other nonverbal signals using textile pressure sensors in chairs.

Chapter 4 introduces a wearable pressure sensing system embedded in custom-made trousers. A benchmark study of posture classification validating the new design is presented and further analysis methods are determined.

Chapter 5 Explores the wider potential of smart trousers for capturing nonverbal signals. A comprehensive data collection is reported in which participants' lower body movements in unstaged seated conversations are tracked. Basic conversational states are classified using a variety of machine learning approaches.

Chapter 6 Explores an extended set of nonverbal cues and postural movements that are evaluated based on the previous chapter's user study data. The data driven analysis focuses on the significance of large postural shifts in conversation.

Chapter 7 Considers the design engineering processes and issues for the sensing trousers that were observed during the user studies. Improvements, challenges, and applications in relation to manufacturing techniques, clothing and sensor design are discussed and a new prototype as an iterative trouser design is introduced and evaluated.

Chapter 8 Highlights and summarises contributions, discusses findings of the conducted studies, and gives prospects on future research directions.

1.8 Associated Publications

Portions of the work detailed in this thesis have been presented in national and international scholarly publications, as follows:

1.8.1 Publications directly relating to thesis chapters:

- **Chapter 3:**

  Skach, S., Healey, P. G.T., & Stewart, R. (2017, July). Talking Through Your Arse: Sensing Conversation with Seat Covers. In Proceedings of the 39th Annual Conference of the Cognitive Science Society. London, UK. Cognitive Science Society. pages 3186-3190

- **Chapter 4:**

  Skach, S., Stewart, R., & Healey, P. G.T. (2018, October). Smart Arse: Posture Classification with Textile Sensors in Trousers. In Proceedings of the 20th ACM International Conference on Multimodal Interaction (ICMI '18). Boulder, Colorado. ACM. (pp. 116-124). DOI:https://doi.org/10.1145/3242969.3242977

  Skach, S., Stewart, R., & Healey, P. G.T. (2019). Smarty Pants: Exploring Textile Pressure Sensors in Trousers for Posture and Behaviour Classification. In Multidisciplinary Digital Publishing Institute Proceedings (Vol. 32, No. 1, p.19).

- **Chapter 5:**

  Skach, S., Stewart, R., & Healey, P. G.T. (2021). Sensing Social Behavior With Smart Trousers. In IEEE Pervasive Computing, Vol. 20, No.3, pp.30-40, doi: 10.1109/MPRV.2021.3088153.

- **Chapter 6:**

  Skach, S., & Healey, P. G.T. (2019, September). Posture Shifts in Conversation: An Exploratory Study with Textile Sensors. In Proceedings of the 23rd Workshop on the Semantics and Pragmatics of Dialogue. London, UK. SemDial (10 pages)

- **Chapter 7:**

  Skach, S., & Stewart, R. (2019). One Leg at a Time: Towards Optimised Design Engineering of Textile Sensors in Trousers. In Adjunct Proceedings of the 2019 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2019 ACM International Symposium on Wearable Computers (UbiComp/ISWC '19 Adjunct). London, UK. ACM (pp.206209). DOI: 10.1145/3341162.3343775

1.8.2 Publications outside of the thesis layout, but related

- **Journal Papers:**
  Albert, S., Heath, C., Skach, S., Harris, M. T., Miller, M., & Healey, P. G.T. (2019). Drawing as transcription: how do graphical techniques inform interaction analysis? In Social Interaction. Video-Based Studies of Human Sociality, 2(1). DOI: 10.7146/si.v2i1.113145.

Greinke, B., Skach, S., Wood, E. (2021). Folded Electronic Textiles: Weaving, Knitting, Pleating and Coating Three-dimensional Sensor Structures. Leonardo, MIT Press. (9 pages)

- **Conference Papers:**

  Stewart, R., Skach, S., & Bin, A. (2018, June). Making Grooves with Needles: Using e-textiles to Encourage Gender Diversity in Embedded Audio Systems Design. In Proceedings of the 2018 Designing Interactive Systems Conference (DIS '18). Hong Kong. ACM. (pp. 163-172). DOI: 10.1145/3196709.3196716

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Chapter 2

Literature Review

Chapter Overview

The literature reviewed here centres around three themes that form the basis of this work's research. The first section focuses on assessing what embodied behaviour has been identified in previous work, summarising what nonverbal signals we know of and when they are used. The questions of interest in this chapter are what signals are transmitted by whom, in what situation and how they are addressed. Special attention is paid to the distinction between speakers and listeners, posture shifts, as well as lower body movements as a proposed underinvestigated body part for interactional signals.

Second, methods to capture such behaviours are examined. Measuring and analysing bodily signals has traditionally relied on ethnography and vision based data, but new methods and tools have been emerging. Ubiquitous and wearable technologies are increasingly used in the field of social computing for a wide range of applications, including posture and behaviour recognition.

The third part looks at smart textile sensing systems and their potential to detect body movement and followingly different embodied activities and social behaviours. Amongst a large variety of textile sensors, piezo-resistive sensors and smart clothing developments are highlighted and put in relation with social computing.

2.1 Non-Verbal Behaviour in Conversation: Touching, Twisting and Twinkling Interactants

2.1.1 Introduction and Overview

Vinciarelli et al. (2008) discriminate between social signals and behaviours. A social signal is described as a "set of temporal changes in neuromuscular and physiological activity that last for short intervals of time in contrast to behaviours that last on average longer". Muscular movement in the human body may provide overt social cues, as well as causing physiological changes in temperature, pulse or heart beat. Overtly visible nonverbal cues include gross body position and orientation. For example, Schegloff (1998) coined the term *body torque* to describes the relation between the upper and lower body as a signal of level of engagement and side activities within a social encounter. Also Kendon highlighted overall physical arrangements, called F-Formation (Kendon, 1990b) in which the direction of the lower body provides a cue for social groupings, or the *main track* of a conversation, while the upper body can open and close side tracks. These orientations also give information about conversational “rights” for all participants of the encounter, and signal these also to outside observers. The spaces in between participants can signal the interpersonal relationship, and the nature of the interaction. Vinciarelli et al. (2008), for example, divide the space between conversation partners into different categories, identifying the level of intimacy and other relational properties. Additionally, the orientation of participants’ bodies can give indications about who is intending to enter or leave such a conversational formation (Kendon, 1990b).

In addition to gross body position, smaller body movements provide cues including gaze, gestures, and fidgeting (Witchel et al., 2016; Schegloff, 1998; Chalkley et al., 2017b; Healey et al., 2015). For example, nodding and other nonverbal signals provide continuous feedback, often to indicate repair, a change of turn, or to respond to a speaker. It is striking how subtle some of these cues are. It has been shown, for example, that blinking functions as listener feedback (Hömke et al., 2017), or that it doesn’t take more than a few seconds to identify the quality of a lecture (Ambady and Rosenthal, 1992), based on a variety of social signals. Minimal shifts in muscular movement can signal whether a laughter is genuine or faked (Ekman et al., 1990; Scott et al., 2014; Griffin et al., 2013).

Posture alone is a good indicator for different levels of engagement in a conversation and in interpersonal relationships, too, and has been studied as a monomodal feature for affect detection (Kleinsmith and Bianchi-Berthouze, 2013). It ranges from posture being associated with trust (Shmueli et al., 2014), dominance, social hierarchy (Huang et al., 2011), or stress and attention level (Arnrich et al., 2010; Chalkley et al., 2017b) to detecting fatigue in drivers (Furugori et al., 2003). Also learning interest (Mota and Picard, 2003) and boredom (D’Mello et al., 2007a; Kroes, 2005) have been measured through posture monitoring. Often, these postural signals are small movements like fidgeting (Chalkley et al., 2017b; Witchel et al., 2016) and are evaluated in relation to other nonverbal cues like gestures. It has been suggested, that with a multimodal approach like this, it is possible to discriminate a large range of emotions (Scherer and Ellgring, 2007; Gunes and Piccardi, 2007; Kleinsmith et al., 2011; D’Mello and Graesser, 2010).

In this section, literature on these categories of social cues is reviewed, first identifying nonverbal signals of communication transmitted by the mere spatial formation and choreographic collaboration interactants perform, considering them as one cohesive group. Next, I look at interpersonal signals, consciously or unconsciously sent behavioural cues by one interactant to their conversation partner, revealing basic conversational states as well as more complex affective states and emotions. Lastly, I pay attention to changes in body posture as one of the tools of communication used by all interactants. The here reviewed works are summarised in Table 2.1 at the end of this section.

2.1.2 Interaction in Shared Space

Situating Ourselves

There are many factors that affect the quality of an interaction. The space we are surrounded by, for example the walls that define a room, the objects that are placed near us, all constrain how we use space for interaction. Ekman and Friesen (1969a) note that furniture occludes some body parts and also determines the space between interactants. In general, the distance between people not only reveals the social relationship, but also plays a role in the perception of social cues. For example, when participants of a conversation are too close to each other, it becomes difficult to observe leg movement, and when they are too far from each other, it is hard to see micromovements in the face. The communicative signals our bodies send can vary depending on whether our encounter happens seated or free standing. This determines the movement and positions the lower body can perform

(Kendon, 1990b), and seating arrangements affect participation. It is claimed that, for example, extrovert people tend to privilege seating arrangements that minimise interpersonal distances, while introvert ones do the opposite (Burgoon and Jones, 1976). The behavioural cues that accompany verbal communication can have a major impact on the perception of verbal communication. It has been claimed that verbal messages account for only 7% of an overall social perception and that the dominant source of information in a communication are non-verbal social signals (Mehrabian, 1968a).

The number of interactants influences each participant's behaviour and the social setting allows or restricts individual's abilities of nonverbal signals. Conversational states in a dyad differ, in part, from those in triads (Tannen et al., 2015). Before examining the fine-grained structure of conversation, we consider the premises of it, including the spatial settings.

In addition to the physical space we need to consider the type of institutional setting in which interaction takes place. One common setting of interest are clinician - patient scenarios (McCabe and Healey, 2018; Tarn et al., 2006), often psychotherapy sessions, see e.g. Scheflen (1973b, 1964), who examines interactions of a group of four people, as well as Ekman and Friesen (1969a), Hall et al. (1995) and Ben-Sira (1980), looking at dialogues. More casual conversations between two or more people have been studied by Schegloff (1998, 2004), Healey et al. (2015); Healey and Battersby (2009), Goodwin (2000), who recorded a group of archeologists as well as children playing, Heath and Healey (2011), who recorded seated conversations of a group of architects, or Luff et al. (2000) who observed a series of workplace studies. Nonverbal behaviour has also been investigated for interaction in large groups including audience during a performance (Theodorou et al., 2016; Theodorou and Healey, 2017) or in classroom settings, e.g. in D'Mello et al. (2007b). The last, however, is also an example of a more recent scenario in which nonverbal behaviour is studied: interaction between humans and a device or a screen (Witchel et al., 2016; D'Mello and Graesser, 2009; Chalkley et al., 2017b), which reduces the number of human interactants to one.

Spatial Formations

In conversations between two or more people, certain spatial formations are created and maintained, can reveal the level of intimacy and relationship between them (Kendon, 1990a; Vinciarelli et al., 2008). These arrangements are termed as F-Formations a term coined by Kendon (1990a), who was one of the first to consider spacing in social behaviour from the viewpoint of groups and not just individuals, acknowledging the collaborative signals that are produced within interactional spaces, as well as for outsiders and bystanders. F-Formations are determined by the orientation of the lower body. These F-Formations depend not only on the number of people participating in the interaction, but also their ability to cooperate in order to maintain their formation. What Kendon termed as formation, Scheflen (1973b) described as relation and has established his own taxonomy of behavioural segments (Scheflen, 1973b). Others, however, have since stuck to Kendon's convention (Ekman et al., 1990; Marshall et al., 2011; Hung and Kröse, 2011) and so this work continues to use of F-Formations, too.

F-formations are built from individual transactional segments: the space we look into when we are speaking. When transaction segments overlap it creates three distinct spaces: the O-space (the inner, overlapping circle), P-space (peripheral circle) and R-space (reference space) that make up the F-Formation (Kendon, 1990a), see the diagram in Figure 2.1. Kendon argues that the orientation of the lower body (more specifically: feet) defines the basic spatial and orientational relationship, while the upper body allows for additional "layers within a conversation, such as side conversations or

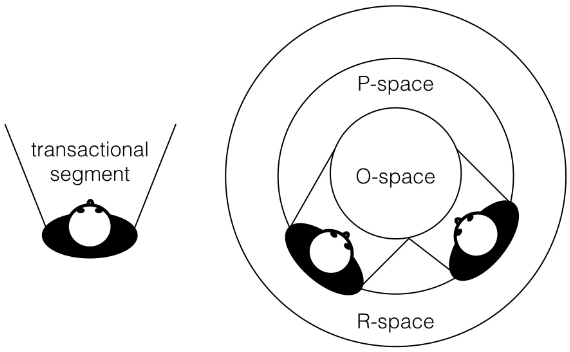


Figure 2.1: Diagram of the different transactional spaces as described by Kendon: the O-space, the P-space and the R-space.

temporary lack of attention or other short distractions. This, however, results in losing equal access to the O-space, the most inner zone of the joint transactional space (Healey and Battersby, 2009).

So while the feet are what initially implies our orientation, the head is still free to move - as is the upper body in general. These findings from observations seem to mostly describe conversations in which all participants are standing. The number of participants influences the postural behaviour and spatial arrangement, too. There are certain arrangements that are only possible with two subjects, and some that can only be formed with at least three subjects. While two participants can form a vis-a-vis, L or side-by-side arrangements easily, this becomes more difficult or even unnatural for three or more participants. Any group larger than two can be in a circular, semicircular, rectangular or linear arrangement. The higher number of participants, the more spatially complex arrangements emerge (Kendon, 1990b,a). Most commonly, these spatial arrangements are formed in an angle, and not directly face to face (in Western society), as argued by Ekman and Friesen (1969a).

Joining or leaving such formations as well as adjusting them can signal things about the intentions of participants and even something about the content of conversations. F-Formations also encourage and discourage certain types of interaction (Marshall et al., 2011), and show that a group can be seen as a complex system that conveys global properties not necessarily possible to retrieve from individual properties (Varni et al., 2010). The organisation of basic spatial arrangements, for example whether an interaction is seated or free standing, can also lead to different patterns and occurrences of social behaviours (Ingham, 1974). In addition to the formations of participants, we need to consider how bodies are configured and move within them.

Body Orientation

The interactional space participants share is defined by the orientation of the upper and lower body parts. Scheflen (1972); Kendon (1970); Schegloff (1998) separate the body into torso and leg orientations when describing twists, torques and other movements. Harrigan and Rosenthal (1983) distinguish 3 trunk angles (forward, backward, straight), 2 arm positions (on lap, crossed), 2 leg positions (open, crossed) and nodding. Schegloff (1998) has coined the term “body torque” to describe differences in a participants upper and lower body orientation, for example by leaning towards some event or a person with the torso, but having the hip bones and feet rotated towards another event or person and thereby creating a twist between the upper and lower body. In combination with head and gesture orientation, three different basic spatial possibilities emerge: 1) the speaker orients to the third-party with a gesture while continuing to orient to the addressee with their head; 2) the speaker orients to the addressee with a gesture and orients to the third party with their head or 3) the speaker uses a combination of head and gesture orientation to the third party. This again allows for multi-"layered conversations, also helping participants to manage turns and visually distinct such sub-dialogues Healey and Battersby (2009).

It is suggested that the correlation of bodily orientation and social signals also works the other way around, resulting in postural synchronies across participants (Bernieri, 1988; Bernieri and Rosenthal, 1991). Barsalou et al. (2003) argues that the perception of social signals also produces embodiment, sometimes intentionally, leading to bodily mimicry, and conclude that "embodiment in others elicits embodiment in the self", which is also suggested by Chartrand and Bargh (1999). That accounts for intentionally as well as unintentionally transmitted cues, as Ekman and Friesen (1969a) suggest with their observation that when unconsciously performed cues are caught, it causes discomfort and sometimes embarrassment not only to the one transmitting the cues, but to both, the observer and observee.

2.1.3 Interpersonal Signals: of Speakers and Listeners

A natural consequence of collaboration is that nonverbal behaviour is heavily influenced by interaction partners and their behaviour (Butzen et al., 2005). In multiparty conversation, whether in dyads or large groups, we can easily distinguish between speakers and listeners. Often, these distinctions can be made at an instant and from looking at visual, nonverbal cues alone (Schegloff, 1984). Bodily signals reveal even more than such basic conversational states, too. They let us decode affective states and other social behaviours that tone conversations and show details on interpersonal relationships (Ambady and Rosenthal, 1992). Most research on fine-grained non-verbal cues has been directed towards activities of the upper body, focusing on gestures and facial expressions. It is interesting to look at lower body and leg movements as social cues too. A large part of what follows focuses on identifying and distinguishing between speakers and listeners, presented in increasing levels of granularity. The richness of nonverbal cues, however, reaches of course beyond characteristics of basic conversational states.

Speakers and Speaker Gaps

The most distinct, and most obvious to spot characteristics that are associated with speakers are hand gestures. Tracking and measuring hand and arm movement is often used as the main parameter for identifying speakers (Schegloff, 1984; Healey et al., 2015), alongside verbal recording techniques (Efron, 1941). But there are more subtle, as distinct cues that allow us to differentiate between speakers and listeners. Overall, body posture is a good indicator for these conversational states. Scheflen (1973a, 1972) describes held posture and changes as part of speech units, and Bull and Connelly (1985) evaluated different body movements in relation to different types of speech. Scheflen was one of the first to link these movements so directly to speech, including nonverbal signals transmitted by the head. Gaze, for example can be used as a marker (or *transfix*, as Scheflen (1973b) calls it) to accompany, emphasise and tone a syntactic sentence, and can contribute to a conversational and behavioural hierarchy and structure (Scheflen, 1964). The most commonly studied of the varieties of people's movements are the gestures that speakers produce while talking. These include gestures that contribute to the content of what is said, such as iconics, metaphorics and pantomimes (McNeill, 1992; de Ruiter, 2010), as well as gestures that help to orchestrate the interaction such as beat gestures and gestures that can hold or hand over the turn to someone else (Bavelas et al., 1992; Healey and Battersby, 2009). Even micro-movements like facial expressions, e.g. raising an eyebrow, can be in line with changes in tonality, e.g. lowering voice Condon and Ogston (1966); Bavelas et al. (2000).

The moments surroundings speech units are filled with nonverbal signals, too. This applies to moments before and after a speaker's turn, but also to gaps and short pauses of a speaker (Hepburn and Bolden, 2014). Hadar et al. (1984) note that there is more body movement just before or at the start of a speaking turn; and Scheflen (1973b) observed that indicating the wish to speak is often done through sitting erect and forward leaning, moving more rapidly, and through head turns. Such movements, whether small or large scale, help to maintain the communicative flow (Ekman and Friesen, 1969a). Next speaker can be selected through hand gestures that can become as explicit as a finger point (Scheflen, 1973a), or by touching other interactants. Routinised actions like lighting a pipe and always performing a certain movement while doing so (Scheflen, 1973b), can also contribute to these dynamics and are often important elements of successful conversations.

Active and Passive Listeners

Listener's body movements are also organised in characteristic ways and together with speakers' nonverbal behaviour are observed to contribute to overall rapport (Harrigan et al., 1985; De Silva and Bianchi-Berthouze, 2004). Most obviously through the production of concurrent feedback or 'backchannels' (Yngve, 1970). Although these are often produced as non-interruptive verbal acknowledgements such as a brief "aha" or "mmhm" people also frequently backchannel by nodding in response to an ongoing turn. Listeners are also distinguished from speakers by their relative lack of hand movement although they move their hands more when a speaker requests clarification or makes repairs to their turn (Healey et al., 2015).

In general, listeners are often observed to perform different movements than speakers. With fewer gesturing activities, hands are sometimes used to perform other nonverbal cues. Face rubbing, head scratches and other self touch interactions, for example, are learned responses and are often performed unconsciously (Butzen et al., 2005). Actions like these are mostly performed unaware of their communicative function, such that "one can be oblivious to the clues they provide to interact" (Ekman and Friesen, 1969a). These behaviours are sometimes claimed to be most revealing because of their "honest" nature (Mehrabian, 1969; Scheflen, 1973b). Signals are of course also sent intentionally, communicating their established meaning which may include deception. It has been claimed that specific body movements, mostly facial and gestural cues are associated with deception Ekman and Friesen (1969a).

Active listeners may also display congruence in body movement (Bavelas et al., 2000), for example, signalling "readiness for alliance" (Scheflen, 1973b), while backing or leaning away from interaction partners can indicate dossociation from them, especially when paired with folding arms and crossing legs, averting the body from the relation (Scheflen, 1973b). Movement can therefore not only be seen as a listener response to an event during interaction, but also as something that triggers a response, or as Barsalou et al. (2003) puts it "constitutes a stimulus". Such stimulus, so the argument, can also be of affective nature.

2.1.4 The Significance of Posture in Interaction

As early as in the late 19$^{\text{th}}$ Century the significance of posture as a nonverbal signal was pointed out linked to emotions (Darwin, 1872; James, 1884). Vinciarelli et al. (2008); Kendon (1970); Scheflen (1964) and others have all argued that posture as a gross bodily position is the most reliable social signal. We can extract conversational as well as affective states by examining the body language of people.

Postures in Conversation

Body posture contributes to the order and structure of an interaction, forming its "program", as Scheflen (1964) calls it. Further, Scheflen (1964, 1972) describes the movement of different body parts as syntactic units that can occur on their own or while other activities or behaviours are performed. Both postural movement or static posture can indicate the duration of an utterance (Scheflen, 1973b), or can tone up or tone down verbal messages (Wiemann and Knapp, 1975).

Posture also defines individual behaviour and the contribution of each participant to the conversation. It can determine how individuals relate to one another and the way posture is maintained or changed differs depending on the level of intimacy between interactants. It is suggested that the more familiar we are with each other, the more subtle postural signals become (Wiemann and Knapp, 1975). Riskind and Gotay (1982) suggest that posture not only communicates, but affects emotional state as well as behaviour and performance of participants' skills. For example, solving puzzles upright or slumped makes a difference in the performance - people doing better when asked to maintain an upright position than when slouched (Riskind and Gotay, 1982).

In a series of studies, Bull (2016) looked at postural signals of boredom and interest, agreement and disagreement signals (Bull, 1978). Embodying boredom is typically done by dropping the head, leaning backwards and supporting the head with hands, while interest is signalled with leaning forward and drawing back legs. In a conversational context, signals of boredom are mostly seen in listeners, while interest applies to both, listeners and speakers. Disagreement is associated with a straightened head, folded arms and head supported by hands. Interest, on the other hand, is associated with the obvious head nod, but also leaning sidewards and raising a foot or leg. In conclusion, Bull (2016) argues that boredom and interest are better identifiable from posture than agreement and disagreement. It is often noted that disagreement and other negative notations in interaction are easier to identify than positive signals (de Gelder, 2006; Bernhardt and Robinson, 2007; Camurri et al., 2003). Even from head movement alone, positive and negative emotions can be discriminated (Behnke et al., 2021). Nevertheless, posture has also been used to detect types of laughter (Griffin et al., 2015a, 2013), as well as agreement, warmth and interest when the torso leans sidewards or towards a congruent posture with its interactants (Bull, 2016; Haase and Tepper, 1972). Synchrony in postures during interactions has been found a signal for a deep social connection (Vinciarelli et al., 2008; Delaherche et al., 2012)

There are others who have explored links between postural behaviours and verbal behvaviours (Winters, 2005; Ekman and Friesen, 1969a), as well as with rapport (Lafrance and Broadbent, 1976; De Silva and Bianchi-Berthouze, 2004; Müller et al., 2018), which can often be predicted more accurately with nonverbal signals than with vocal messages (Ambady and Rosenthal, 1992). Posture can be used to convey other messages in interaction, including dominance, social status, and can also serve to regulate and coordinate conversation (Vinciarelli et al., 2014).

Embodiment and Affect

In addition to conversational behaviours, posture has been used as a measure to detect affective states and emotions both in interactional and isolated scenarios. Many works have explored the embodiment of a range of basic emotions (Vinciarelli et al., 2008; Kleinsmith and Bianchi-Berthouze, 2013; Karg et al., 2013; Noroozi et al., 2021; Camurri et al., 2003). Similar to extracting conversational behaviours, affect and emotion is often detected from upper body signals, face and hand gestures presenting a dominant part of the literature. An overview with common associations is given in Table 2.1.

In general, however, it can be difficult to assign specific distinctive body movements to emotions (Ekman, 1999). There is large variation amongst people's behaviours and embodied conversational states. This occurs in displaying them consciously, unintentionally, and also in deception Ekman and Friesen (1969a). Eventually, everyone acts in "their own" way and also in response to other interactants' behaviour (Scheflen, 1973b; Vinciarelli et al., 2008). This is important to acknowledge when collecting, processing and interpreting such data (Aigrain et al., 2015). Additionally, behavioural as emotional states are not always bound to static body postures, but can be described with motion features as well, such as speed and acceleration of a movement(Camurri et al., 2003), or spatial direction and amount of movement (Behnke et al., 2021).

While the focus of this work is on signals elicited during human interaction, many of the studies on affective and emotional cues often rely on human-computer interaction scenarios, or third party judgements of participants watching videos of people (Harrigan and Rosenthal, 1983; Butzen et al., 2005), there are few who consider non-acted settings (Kleinsmith et al., 2011).

In summary, although full body posture has been acknowledged as an important signifier for affective and behavioural cues (Griffin et al., 2013; Niewiadomski et al., 2019; Camurri et al., 2003), especially when signalling at a distance (Walk and Walters, 1988), it has been understudied compared to research on facial and hand gestural expressions (Karg et al., 2013; Kleinsmith and Bianchi-Berthouze, 2013; Noroozi et al., 2021; Poppe, 2007). Moreover, when studying posture in relation to affect, the upper body is usually examined in more detail. The lower body receives less attention in behavioural studies and conversation analysis, mostly being absent from analysis or only mentioned marginally. There are also few specific and consistent descriptions about postural movement that includes both, the upper and lower body in relation to each other. Nevertheless, there is some evidence for the importance of lower body signals in interaction.

2.1.5 Lower Body Movements

In between the dominating literature on upper body cues, there are also indications that the lower body may be rich in social cues (Kendon, 1990a; Burgoon et al., 1990; Duncan, 1972; Schegloff, 1998; De Meijer, 1989). It is noted that the orientation of the lower body, especially the feet signals the 'main track' of a conversation, while the upper body can be used to manage side tracks. This applies to both, seated and standing conversations. There are some leg movements that predominantly occur in seated interactions - such as leg crossing, bouncing feet and also, for example, rubbing hands on thighs. These movements are rarely discussed in studies of nonverbal communication and embodied social interaction. We know very little about the meaning of, for example, leg crossing, bouncing, fidgeting, feet tapping, rubbing thighs, other touch interaction on legs, nor of movement around the hips and buttocks. Where leg movements are discussed it is primarily for gait recognition (Niazmand et al., 2011; Dunne et al., 2011), or in relation to the upper body, mostly gestures and trunk movements (Bull and Connelly, 1985; Mehrabian, 1968a; De Meijer, 1989). Similarly, when buttocks are a mean of measure, it is mostly to detect sitting postures in single users rather than behaviour in a conversational setting (Tan et al., 2001; D'Mello et al., 2007a; Meyer et al., 2007). In comparison, isolated parts of the upper body, including facial expressions, are often described without correlating to other body parts. It is only occasionally acknowledged, e.g. in Cassell et al. (2001), that the lower body may contribute to affect detection in its own right; or that leg movement can indicate and mark turn taking (Duncan, 1972).

When dividing postural movement into the upper and the lower body, the torso usually gets more attention in research as well as from other interactants, whether conversations are seated or standing. It may be because the lower body is thought to convey social signals in a less subtle way (Mehrabian, 1968b; Knapp and Hall, 2009). This depends in part on the assumption that leg related social cues are largely unconsious or unintentional (Wiemann and Knapp, 1975). For example, when speakers draw legs back and lean forward, they indicate interest and attention, while stretched out legs are observed more in boredom (Bull, 2016). These movements might happen without being consciously directed at interaction partners.

Leg Positions

Conscious social cues can be transmitted with legs, too, such as revealing a thigh, or sitting with open closed legs to indicate "openness" for interaction Mehrabian (1968b). The terminology of *open* and *closed* postures is applied to leg positions as well, describing the two states of crossed (closed) and uncrossed (open) legs, which are generally perceived as more friendly (Harrigan and Rosenthal, 1983). Additionally, legs are linked to play a role in detecting dominance (Shibata et al., 2013), and slightly bent knees can contribute to discriminate contempt as well as fear and disgust (De Meijer, 1989). Leg movement was further examined in studies about postural synchrony between interactants (Schmidt et al., 1990). They are mostly described in combination with other cues, though, like orientation, gaze, and leaning forward. In relation to rapport, for example, these leg postures are mentioned only marginally and as not significant on their own (Harrigan et al., 1985).

When looking at leg crossings, Bull (2016) determines four categories: leg crossing above knee, at knee, ankle over thigh, and at ankle, also dividing these into open and closed postures. When legs are crossed above the knee, with the lower knee visible, they are in their most closed position. Leg crossings are also thought to be associated with disagreement (Bull, 2016), most clearly where legs crossed are most tightly - as "closed" as possible. The knees

Micromovement on the Lower Body

Small scale movement on the lower body is also interactionally relevant and provide cues to social behaviours. There is evidence that fidgeting and thigh movement play a significant role in detecting attention levels (Chalkley et al., 2017b; Witchel et al., 2016). Tracking feet movement alone has also proven to be a good indicator for detecting overt postures as well as movements correlated with gestures and nodding (Cheng et al., 2013), showing that even when performing relatively small scale gestures, the entire body is in motion. Patterns of bodily movement therefore always affect both, the upper and lower body, although in seated conversations, more commonly, only the upper body fully visible to all interactants when seated, while the legs and feet are least monitored by both, performer and observer (Ekman and Friesen, 1969a; Mehrabian, 1972). In free standing conversations, feet are described to signal engagement and participation in F-Formations, too (Kendon, 1990a).

2.1.6 Summary: Dissecting Embodiment

In summary, the bodily signals we send and receive during conversation are multilayered and can be of complex nature. Table 2.1 gives an overview of such signals, listing well established and known

Body Part	**Body Movement**	**Associated Behaviour**	Reference
Whole Body	large movement	'hilarious' laughter	Griffin et al. (2015b)
	posture change	stress	Aigrain et al. (2015)
		topic change	Scheflen (1964)
	synchronisation	empathy, dominance	Varni et al. (2009)
	movement	intensify emotions	Kret et al. (2013)
	shift	disgust	Gunes and Piccardi (2007)
Torso	turning away	disgust	Ekman and Friesen (1969a)
	leaning away	dislike	Mehrabian (1972)
	leaned forwards	warmth, empathy, attention	Ekman (1999)
			Mehrabian (1969)
		attention, interest	Bull (2016)
	erect and forward	wish to speak	Scheflen (1973b)
	sidewards movement	nervousness	Arnrich et al. (2010)
	slumped, slouched	lower performance	Riskind and Gotay (1982)
	congruence	'deep psychological meaning'	Vinciarelli et al. (2008)
	shoulder shrug	uncertainty	Gunes and Piccardi (2007)
	contract, backing	fear, disgust	Gunes and Piccardi (2007)
	spine bending	laughter	Griffin et al. (2013)
	torso flexion	chronic pain	Olugbade et al. (2019)
Arms & Hands	touch	appoint addressee	Scheflen (1973b)
	index finger	silence	Scheflen (1973b)
	arm folding	dissociation from partner	Scheflen (1973b)
	arms crossing	anger, fear	Gunes and Piccardi (2007)
	various hand gestures	induce feedback	Ekman and Friesen (1969a)
	self touch	comfort, internal conflict	Butzen et al. (2005)
	finger & palm movement	anxiety, uncertainty	Gunes and Piccardi (2007)
	increased gesturing	detect laughter	Griffin et al. (2015a)
	gesture movement	emotions	Bernhardt and Robinson (2007)
	hand velocity	discriminate emotions	Glowinski et al. (2008)
	self touch	stress	Aigrain et al. (2015)
Head	head turn	elicit addressee status	Scheflen (1973a,b)
			Healey and Battersby (2009)
	head slump	emotional distress	Olugbade et al. (2019)
	nodding	agreement, knowledge	Bourai et al. (2017)
		backchannels, feedback	
	various facial expressions	affect, emotion	Ekman (1999)
		interest	Kapoor et al. (2004)
	close to hands	fear	Foo et al. (2021)
		disgust	Gunes and Piccardi (2007)
Legs	stretched	boredom	Bull and Connelly (1985)
	tucked back	interest	Bull and Connelly (1985)
	fidgeting, thighs move	attention level	Chalkley et al. (2017b)
	slightly bent knees	fear, disgust	De Meijer (1989)
	"open" legs	open/ready for interaction	Mehrabian (1969)
	uncrossed	friendly	Harrigan and Rosenthal (1983)
	while seated	dominance	Shibata et al. (2013)
Feet	orientation	conversational involvement	Kendon (1990a)
			Schegloff (1998)
	movement	speaker turn marker	Duncan (1972)

Table 2.1: This table is only a selection of a wide range of nonverbal cues, but serves as an overview of some of the important cues mentioned in the above section.

bodily movements and their associated social behaviour, dividing them into different body parts that were discussed in this section.

Gaps in Current Literature

While the upper body has received much attention in research on non-verbal communication, the lower body has been largely ignored. Nonetheless there are good reasons to think that the lower body may be a valuable source of information during interaction. The range of movements and their relation both to other body movements and interactional states indicates that they are a promising but underexploited target for social sensing. Independent of the body part being examined, taking measurements from one part is commonly the focus of studies on nonverbal behaviour and assigning affective states to body postures, although there are of course exceptions (Niewiadomski et al., 2016, 2018). The appeal to work towards a more multimodal and multi-part approach has been made by Vinciarelli et al. (2008) and others. Another appeal deriving from examining the settings under which data from body signals is analysed and collected, is that there is a need for data sets of more naturalistic, non-acted body movements, as well as more "real life" context (Kleinsmith and Bianchi-Berthouze, 2013; Karg et al., 2013; Vinciarelli et al., 2008).

2.2 Methods for Capturing Social Signals

2.2.1 Introduction: An Overview of Different Approaches

Vision Based Approaches

Much of the early research on nonverbal communication was driven by the increasing availability of video cameras (Goffman, 1959; Edward and Hall, 1959), as well as ethnographic studies (including hand drawings and sketches), often analysing detailed case studies of psychotherapy sessions (e.g. Scheflen (1964); Condon and Ogston (1966); Kagan et al. (1969)). Camera based systems are still the most commonly used to capture bodily behaviour and engagement in human interaction. Sophisticated computer vision developments like face recognition and eye tracking are established methods in the field and have been proven successful for many explorations in activity recognition (Khurana et al., 2018), as well as identifying attention and anxiety (Kret et al., 2013). Camera and other vision based technologies can also detect dominance behaviour in group interactions (Hortensius et al., 2014; Jayagopi et al., 2009; Hung et al., 2007), mimicry and laughter (Griffin et al., 2015a), interest (Kapoor et al., 2004), as well as a variety of other emotions (Glowinski et al., 2008) and interactional cues (Stergiou and Poppe, 2019), including the use of webcams (Griffin et al., 2015a; Gaffary et al., 2015). Advanced techniques like *OpenPose* can recover whole skeletons from video images (Cao et al., 2019), and in depth camera systems like *Kinect* have been a popular tool to capture body movement for a wide range of applications, including engagement activities in stroke recovery (Galindo Esparza et al., 2019), or capturing dance movement (Alexiadis et al., 2011), amongst various other human-computer-interaction applications (Stergiou and Poppe, 2019). Another development that extracts postural, gestural and affective features from video, amongst other inputs, is the *EyesWeb* platform by Camurri et al. (2000). This allows for real-time analysis of body movement, for example demonstrated in use cases capturing dance (Camurri et al., 2016) and sport performances (Niewiadomski et al., 2019), or detecting emotions in music listening (Varni et al., 2009), as well as music performing (Castellano et al., 2008) tasks.

When other modalities are explored, vision based approaches are often used alongside them and build the largest corpus in automatically processing nonverbal postural cues (e.g. Gunes and Piccardi (2009); Giraud et al. (2013); Lavelle et al. (2013); Melzer et al. (2019)).

Motion Capture Techniques

Other than videos, motion capture systems have become a widely used technique for detecting nonverbal behaviour (Noroozi et al., 2021). Markers are attached to a body suit to outline a skeletal structure. The details that can be captures depend on the amount of markers used, e.g. for more fine grained hand movement is recorded, or more coarse grained full body movement.

Optical motion capture systems have been used to analyse multiparty conversation, including gestural cues and head movement (Healey et al., 2015), to extract affect from hand gestures (Bernhardt and Robinson, 2007; Kapur et al., 2005), and even to explore nonverbal behaviour in mental disorders (Lavelle et al., 2013) or chronic pain and stress levels (Olugbade et al., 2019). There are different systems of motion capture technologies that are used in research on nonverbal behaviour. A system named *Xsens*, for example has been used to automatically detect laughter from full body postures (Niewiadomski et al., 2016), and another one named *Vicon* has been shown successful in identifying a set of basic emotions from postural cues (Kleinsmith et al., 2009).

Another motion capture system that deploys wearable sensors in addition to visual body markers, *Animazoo*, has been used to capture instrument playing for educational purposes (Linden et al., 2011). In the example of the *EyesWeb* platform, motion capture data is processed together with accelereomter data, supporting the detection of synchrony, dominance, social interaction in music performance, and other affective states, for example from dance movements (Camurri et al., 2000; Varni et al., 2009; Niewiadomski et al., 2019; Varni et al., 2010; Kapur et al., 2005). Overall non-optical techniques, for example magnetic motion capture systems (Shockley et al., 2003), are less common and typically do not include whole body movements or leg postures, or are not used in an interactional context to capture behavioural or emotional states (O'Brien et al., 2000).

There are, however, downsides to motion capture techniques. Most of them are costly and it is not always feasible to deploy these systems (Jakubowski et al., 2017). This can be a disadvantage in experimental settings due to issues such as the practicalities of setting up cameras, or participants wearing tight, relatively intrusive velcro body suits. Optical motion capture systems further rely on visual cues, face occlusion and privacy concerns, and are therefore limited in their application.

Multimodality

More recently, other multimodal systems have been introduced to develop classification models based on nonverbal cues and affective states. A network of sensors relying both visual and physiological measures and featuring off- and on-body sensing can gather rich information about bodily movement, and has often been argued to achieve higher accuracy than monomodal approaches in automatic recognition of social behaviour (Baltrušaitis et al., 2019). Complex sensor networks include sensors in the environment, interior and exterior, sensors on the body, and, in between the two, sensors in devices that can be either close to or on the body, but also be put aside, e.g. mobile phones (Wang et al., 2014; Lazer et al., 2009).

Amongst wearable sensors, in combination with motion capture systems, accelerometers, IMUs and EMG sensors are common and can be integrated in accessories, body suits or digital devices and objects we interact with. For example, accelerometers have helped to detect the quality of interactions in group scenarios (Hung and Kröse, 2011), but also feed back to such (Damian et al., 2015) and to track hand movement in relation to anxiety (Cosma et al., 2017), or fidgeting in screen based tasks (Chalkley et al., 2017a). IMUs and EMGs can help to discriminate stress levels and pain (Wang et al., 2021; Olugbade et al., 2019), and are used in many other health and sport related applications (Fernández-Caramés and Fraga-Lamas, 2018).

But there are also other sensors that have been proven to reliably detect embodied behaviour and social cues. In particular when focusing on capturing sitting postures and body movement, pressure sensors have the potential of replacing more complex data collection (Tan et al., 2001; Nathan-Roberts et al., 2008; Arnrich et al., 2010; Cheng et al., 2013). Studies using piezoresistive sensors have proven reliable for determining a large number of different body postures as well as behavioural cues with high accuracy (Tan et al., 2001; Meyer et al., 2007; Shibata et al., 2013; Gaus et al., 2015; Bibbo et al., 2019). It is also worth noticing that, when using more simple methods like pressure measurements, the sensors are commonly deployed on the chair (Tan et al., 2001; Shibata et al., 2013; D'Mello and Graesser, 2010; Karg et al., 2013; Bibbo et al., 2019). There are also opportunities for integrating pressure sensors into clothing and for exploiting the potential of ubiquitous materials like fabrics (Meyer et al., 2010a), or on other surfaces to measure 'social touch' (Gaus et al., 2015).

Nevertheless, when nonverbal signals are recorded in a multimodal setting, wearable sensors like accelerometers and IMUs are still outnumbered by vision dependant channels (Karg et al., 2013). Especially when looking at human interaction in natural settings, also audio data are dominant co-measures of collected visual information (Nihei et al., 2016; Scherer and Ellgring, 2007; Hough et al., 2016; Cummins et al., 2013; Stewart et al., 2018; Murray and Lai, 2018; Kapur et al., 2005). With posture having been identified as an important signifier for social and affective behaviour, however, biometric data collection has become popular, too (Vinciarelli et al., 2008). The developments of multimodal sensor networks, including solutions for wearable technology, encourage the discussion on a ubiquitous deployment of such (Poslad, 2011). In particular with a focus on exploring unstaged, natural social interaction.

In this section, the examined literature focuses around modalities other than video and audio recordings, looking at ubiquitous sensing environments, sensor networks worn on the body, and different approaches to capture postural behaviour in particular.

2.2.2 Ubiquitous Social Computing

When capturing signals of social interaction, the technologies used aim ideally preserve a natural environment for subjects, not interfering with their performed, spontaneous behaviour and movements. Under this aspect, large and 'boxy' systems like cameras and audio recording devices can be intrusive but have been successfully used to investigate social behavioural cues, such as for example laughter (Griffin et al., 2013). But also motion tracking is a common sensing system that is used to investigate human interaction (Healey et al., 2015). Sensing methods have been suggested that use objects and attributes integrated in everyday situations, fulfilling the aim of an unobtrusive, pervasive sensing. This can be ceiling light capturing physical presence and body movement (Venkatnarayan and Shahzad, 2018), conductive surfaces like doorknobs to detect touch (Sato et al., 2012), floor mats (Sundholm et al., 2014) or the surface of seats to track postural movement (Tan et al., 2001; Slivovsky and Tan, 2000). Chairs have been established as successful ubiquitous sensing objects to not only track postural, but also behavioural cues and cognitive states, and will be given more attention in this thesis later on. In recent works, for example, it has been shown that sensors embedded in a chair cover could reliably detect stress levels (Arnrich et al., 2010; D'Mello et al., 2007a), fatigue in drivers (Furugori et al., 2003), or cultural differences (Shibata et al., 2013), to name only a few examples. More will be explored in Chapter 3.

In- and Outdoors

The surroundings of interior spaces, too, can be transformed into sensing surfaces. Wall papers can be turned into touch sensitive surfaces that could be used to control light (Buechley et al., 2010), and light itself functions as a sensing tool to track and identify postures and gestures (Venkatnarayan and Shahzad, 2018; Li et al., 2015). Motion sensors on the ceiling, as well as indirect sensing from tracking the use of household objects can indicate people's behaviours and social dynamics (Singla et al., 2010). The floor, too, can serve as a large sensing surface, for example through analog sensors and circuits concealed in carpets (Kim et al., 2016). These recording technologies are all relatively far away from the body - the target to collect data from, and can yet capture great details of bodily action. However, more fine grained movement and refined social and affective cues can be detected with objects in more direct touch with our body, such as furniture, interior objects, and accessories. Especially with the upper body to serve as the major body part to extract these social signals from, objects we engage with more directly have been utilised to capture nonverbal signals. Pillows (Vogl et al., 2017; Park et al., 2003), table tops (Gaver et al., 2006), door knobs (Sato et al., 2012), cabinets and wardrobes (Kang et al., 2010), for example, have been transformed into smart devices and sensing surfaces. Together with sensor networks in walls and floors, this allows for entire interior facilities like a kitchen (Olivier et al., 2009) to act as a smart room that can track their users' actions, movements and behaviours.

Ambient sensing is imagined outside the home, too. There can be outdoor augmentations for smart environments, such as ambient woods to enhance learning experiences (Rogers et al., 2004). Through shared surfaces in communal spaces, interaction between people can be encouraged and facilitated, for example through the use of screen and audio elements (Brignull et al., 2004). Also interactional configurations like F-Formations can be mediated through interactive surfaces embedded in furniture (Marshall et al., 2011). Engaging with such designed artefacts arguably also affects the embodied behaviour we exercise (Candy, 2007), so the aim for ubiquitous sensing when capturing natural behaviour are often intertwined (Poslad, 2011; Pentland, 2000).

Sensing Networks

Both scenarios, indoor and outdoor, public and private are most effective with a network of different modalities cross-validating their data and capturing detailed information about people from multiple angles. A mix of active and passive sensors can contribute to an uninterrupted "Internet of Things" for a large variety of applications (Wilson, 2004; Poslad, 2011). Also when focusing on one specific signal that is aimed to be detected, measuring it with multimodal techniques improves the outcomes (Morency et al., 2008, 2010). Especially when investigating rich and multilayered behavioural cues in social interaction, or when trying to identify affective states and emotions (Kapoor and Picard, 2005; Kleinsmith and Bianchi-Berthouze, 2013; Karg et al., 2013; Noroozi et al., 2021), and 'new' modalities are being establish to widen the opportunities for applications and unobtrusiveness (for example Di Lascio et al. (2018); Jin et al. (2018)). Nevertheless, it has been acknowledged that extracting social interaction features is often challenging, also with a multimodal approach (Varni et al., 2010).

In conversation analysis, audio input is generally one of the main contributors of sensor data because special attention is given to vocal and verbal cues, though linked with visual, nonverbal behaviours. For this, facial expressions and hand gestures are typically examined in great detail, sometimes even dividing upper and lower facial expressions (Kapoor and Picard, 2005). In comparison, body posture is analysed without as much detailed specification, despite gross movements being acknowledged to be as relevant as micromovements in the face (D'Mello and Graesser, 2010). Sometimes, information on body posture is made from facial cues, too (Kapoor and Picard, 2005), while screen based interaction tend to focus on gaze tracking and other computer vision technologies to closely monitor head movements (Subburaj et al., 2020; D'Mello et al., 2007b; D'Mello and Graesser, 2009). Mutlimodal processing of audiovisual data has been shown to improve the automatic detection of backchannels (Morency et al., 2010), as well as task performances of individuals (Murray and Lai, 2018). Exceptions to these conventions of course exist, but form a margin - an example is the work by (Antonio Gómez Jáuregui et al., 2021), using force plates in addition to video recordings to track postural shifting.

2.2.3 Capturing Interaction with Wearable Technologies

One part of multimodal and ubiquitous sensing systems are wearable technologies, with an ever growing range to take measuresments directly from the body. Compared to the previously discussed camera systems, often installed at a fixed location, wearable technologies come to the advantage that they are independent of the location and environment of the people. Through wearable sensing, it became possible to track someone's actions wherever they go - far wider reaching than, for example, CCTV. That applies for the individual as well as for group related behaviours and actions. While this can sound like an dystopian, surveillance heavy vision, its proposed and promoted use cases are often healthcare, rehabilitation and other medical uses, as well as for sports (Patel et al., 2012; Sharma et al., 2017), and more recently also gaming industries (Fernández-Caramés and Fraga-Lamas, 2018).

Tracking body movement continuously and automatically process its signals can be done in different ways: through sensors integrated in our mobile phones, accessories of other form carried or worn on the body, such as jewellery, and sensors directly deployed on the body as embedded systems, for example in clothing (Gonçalves et al., 2018; Fernández-Caramés and Fraga-Lamas, 2018). While mobile phones present a 'wearable' device that is carried rather than worn, not attached in some form to the body, accessories and gadget like objects function as a state in between on-body sensing and carried mobile devices, as they are being worn, but are in their early forms exterior, intrusive objects (Choudhury and Pentland, 2003), different to more recent designs that resemble conventionally worn accessories (Kettley, 2008). Lastly, sensors embedded or deployed onto the body directly, even on the skin, are reviewed, and commonly used modalities are summarised.

Mobile Sensing

A mobile phone, or smart phone, is one of the sensing devices that are best adapted and woven into our daily life (Lane et al., 2010). In relation to connected smart sensing networks, they often serve as a base on which data streams can be connected and evaluated through apps (Patel et al., 2012). But they also bear a variety of sensors themselves, including bluetooth, GPS, accelerometers (Katevas et al., 2014), cameras and microphones, that have been explored for social sensing, human interaction in small and large groups, and individual behavioural patterns (Lane et al., 2010; Shmueli et al., 2014). For example, Hao et al. (2013) monitor sleep in individuals, Katevas et al. (2015) investigate gait synchronisation in groups, and Wang et al. (2014) investigate group members' attitudes in meetings. In some cases, mobile phones are used as feedback devices strapped onto the body, too (Singh et al., 2014).

Nevertheless, smart phones are small computers that often gather far more data variables than are needed (and wanted), so the concerns around maintaining personal privacy remain, although there are attempts to improve this issue (Malekzadeh et al., 2018). Mobile phones' sensing networks can be intrusive, and phones can easily be put aside so that it is no longer possible to collect a continuous data stream.

Accessories

Other wearable technology devices that present alternatives to mobile phones are smart accessories that can be worn on the body, e.g. like jewellery (Kettley, 2008; Groeger and Steimle, 2018). So while the mobile phone itself has become a substantial part of our basic equipment we take with us everywhere, other designs of sensor networks are integrated more ubiquitously by resembling already familiar products and objects, such as wristbands, watches, necklaces or belts (Fernández-Caramés and Fraga-Lamas, 2018; Patel et al., 2012). These devices, too, can collect data on individual nonverbal behaviour, for example tracking hand gestures and arm movements with capacitive touch sensing in a wristband (Rekimoto, 2001), or utilising conductive objects in the environment (like doorknobs and handles) with a sensing board designed as a wristband in order to sense gestures and other activities and interactions with these objects (Sato et al., 2012; Vogl et al., 2017; Groeger and Steimle, 2018).

Interpersonal relationships and group patterns can also be investigated with this wearable approach, as was shown with the 'Sociometer' by (Choudhury and Pentland, 2002, 2003), a device worn around the neck and used to analyse conversations over a longer period of time, or detect when people are in close proximity. This has made it possible to approach questions on social behaviour and dynamics, such as who we interact with, what conversational details there are and how engaged we are in different situations (Choudhury and Pentland, 2003) with wearable devices that was previously only possible with traditional recording devices.

Common sensor that such accessory-like devices embed are accelerometers, pressure sensors, IMUs, EEG or EMGs, as well as capacitive sensors. Acceleration has been used to interpret different kinds of body movement, for example to detect fall and other activities like walking, dancing, jumping, or running (Wilson, 2004; Attal et al., 2015). Social interaction between humans has been explored with the use of accelerometers, too (Hung et al., 2013). Often, joints are used as a measure point, for example wrists equipped with accelerometers and IMU sensors to determine attention level in screen based tasks (Witchel et al., 2016; Chalkley et al., 2017b), to assess audience behaviour during performances (Theodorou and Healey, 2017), or to generally identify gestures (Rekimoto, 2001). Here, too, sometimes multimodal approaches, such as a combination of armband and smart glasses are used to support social interaction, e.g. in Damian et al. (2016). Capacitance and pressure have demonstrated versatile in their use cases, too, recognising gestures in sleeves (Schneegass and Voit, 2016), or in wrist bands (Rekimoto, 2001). EMG and EEG sensors were successfully used for exploring social and affective behaviours, too (Damian et al., 2016; Soleymani et al., 2016). A summary of some commonly used wearable sensors can be found in Table 2.2.

Reference	Modality	Placement	Use Case
Damian et al. (2016)	IMU, EMG, audio	wrist, head phones, glasses	assessing social interaction
Soleymani et al. (2016)	EEG	face	emotion recognition
Theodorou and Healey (2017)	IMU	wrist band	gesture movement, audience engagement
Rekimoto (2001)	capacitive sensor, accelerometer	wrist band	gesture recognition
Chalkley et al. (2017a)	IMU, accelerometer	wrist, ankles	detect fidgeting in screen based task
Groeger and Steimle (2018)	capacitive touch	jewellery	various applications, interaction design
Kettley (2008)	distance sensing, LEDs	jewellery	social relationships
Choudhury and Pentland (2003)	audio, accelerometer, infrared sensor	around the neck	social relationships
Hung et al. (2013)	accelerometer	around the neck	social formations
Attal et al. (2015)	accelerometer, IMU	strapped on various body parts	activity recognition
Schneegass and Voit (2016)	pressure sensors	under-arm sleeve	interface for smart watches

Table 2.2: An overview of a selection of wearable sensing systems, featuring commonly used sensors worn as accessories or gadget-like devices.

On Body Sensing

The concept to use on-body sensors to determine affective states, social interaction and group dynamics, as well as simple presence sensing has been explored with a variety of recording devices and sensor technologies. Sensors deployed directly on the body can replace other systems without reducing the quality and quantity of data they collect. These wearable sensors are often used in combination with body suits for motion tracking (Drapeaux and Carlson, 2020; Olugbade et al., 2019; Camurri et al., 2003). And while such motion capture suits have the advantage to sense full body movement with one modality alone, wearing the body suits with attached markers to be detected by the installed camera systems is intrusive and does not foster spontaneous behaviour in natural settings. Nevertheless, it has been used to explore unstaged conversation, for example investigating listener behaviour in seated multiparty interaction (Healey et al., 2013), and also exploring nonverbal communication in patients with schizophrenia (Lavelle et al., 2013).

Additional sensors contribute towards a multimodal network capturing a wide range of bodily signals. Embedded in the surface of clothing (Gioberto et al., 2013; Dunne et al., 2006a), or even directly on the skin (Weigel et al., 2015; Charry et al., 2011), commonly used modalities for on-body sensing are, similarly to accessory designs, accelerometers (Varni et al., 2010; Camurri et al., 2003; Niewiadomski et al., 2019), gyroscopes(Charry et al., 2011; Drapeaux and Carlson, 2020), IMU (Chalkley et al., 2017b), RFID (Jin et al., 2018; Ukkonen et al., 2012; Khaorapapong and Purver, 2012), EEG (Rayatdoost and Soleymani, 2018; Soleymani et al., 2016), as well as EMG sensors (Wang et al., 2019; Olugbade et al., 2019). Such sensors have been used to extract information on emotional stress and pain levels of full body movement (Olugbade et al., 2019), as well as of parts of it (Charry et al., 2011), including nonverbal behaviour of chronic pain (Wang et al., 2019). In general, many works involving detecting affective states or recognising emotion use physiological on-body sensor data (Soleymani et al., 2012; Rayatdoost and Soleymani, 2018), whether it is in performative contexts (Camurri et al., 2003, 2000; Mahmoud et al., 2013; Volpe et al., 2016), or in health care related applications (Wang et al., 2015; Haladjian et al., 2018; Bisio et al., 2019), including sports (Niewiadomski et al., 2019; Ribas Manero et al., 2016), all commonly investigated (Noroozi et al., 2021).

When deploying sensors on the human body in motion, wearability comfort and ubiquitousness for the wearer is generally desired, aiming not to compromise body movements as well as sensor designs. Hereby, the importance of sensors' flexibility is often emphasised (Patel et al., 2012) - they should be soft, bendable and be incorporated without causing any disruption or augmentation of natural human behaviour. These criteria can pose challenges when it comes to designing sensing systems for the body (Sharma et al., 2017), however the increasing popularity of integrating wearable sensors in garments has offered solutions to some of these challenges.

2.2.4 Detecting Postures

With all the different wearable sensor designs, placements and types mentioned above, many are used to detect nonverbal cues such as gestures, gaze, body orientation and posture, and deduct affective states and social engagement levels from it (Kleinsmith and Bianchi-Berthouze, 2013; Karg et al., 2013), in addition to measuring such physiological signals for rehabilitation, performance, or sport purposes (Helmer et al., 2008; Jakubowski et al., 2017; Patel et al., 2012; Niewiadomski et al., 2019). Postures have been identified as a reliable indicator for a variety of social and affective behaviours in screen based (Gunes and Piccardi, 2009, 2007) or face to face interaction (Bernhardt and Robinson, 2007; Griffin et al., 2015a), as well as in single user scenarios (Behnke et al., 2021; Varni et al., 2010). Some postural movements, however, have been associated with social cues in either of those scenarios. For example, a slumped posture may suggest boredom, while an upright posture can indicate interest, and also arousal and valence can be indicated through postural cues (Kleinsmith et al., 2011; Kapoor and Picard, 2005; Kapoor et al., 2007; Chalkley et al., 2017a; D'Mello et al., 2007a; Kapur et al., 2005). Here, again, multimodal approaches have been praised for high accuracy levels in classifying such bodily cues automatically (Kleinsmith et al., 2011; Kapoor and Picard, 2005; D'Mello and Graesser, 2010). Mostly, postural cues are measured with a combination of camera based systems like video recordings or motion capture suits, and one measure of physiological data, such as acceleration or EMG sensors (Kleinsmith et al., 2011; Healey et al., 2015; Olugbade et al., 2019; Jakubowski et al., 2017). Many of the social or affective postural behaviours have been identified through methods using acted postures, though, not detected in natural settings (Kleinsmith and Bianchi-Berthouze, 2013; Karg et al., 2013; Noroozi et al., 2021), and sometimes even from avatars (Buisine et al., 2014). Other commonly posture associated behavioural cues have been extracted from data sets of dance or music performances (Volpe et al., 2016; Camurri et al., 2003, 2000; Varni et al., 2009).

Sitting Postures

While in settings involving rehabilitation, performance or sport related tasks, the deployed on-body sensors collect postural information from single users in motion, for example during running or other physical exercising (Ribas Manero et al., 2016; Schneegass and Voit, 2016), interactional engagement is frequently assessed in seated individuals (Kapoor et al., 2007; D'Mello et al., 2007b; D'Mello and Graesser, 2009; Kleinsmith et al., 2011; Witchel et al., 2016). Afterall, "sitting is one of the natural actions in our daily life" (Kamiya et al., 2008), whether that is in front of the screen for educational

(D'Mello et al., 2007b), work related tasks (Chalkley et al., 2017a; Nathan-Roberts et al., 2008), including interview settings (Antonio Gómez Jáuregui et al., 2021), social or cognitive engagements (Stewart et al., 2018; Bibbo et al., 2019), or even when in a car (Furugori et al., 2003; Riener and Ferscha, 2008). Seated postures have further been used to explore cultural differences (Shibata et al., 2013; Kleinsmith et al., 2006), or to correct ergonomic (Kim et al., 2018).

Aiming to capture sitting postures also lends itself to using sensors on the seating surface, e.g. the chair, or on the body itself, e.g. along the back (spine). Also the combination with recording devices in a smart environment are effective to capture postural cues, creating a multimodal sensing network. Sitting posture can be sensed in direct ways with sensors on the body parts in motion, measuring acceleration (Chalkley et al., 2017b), EMGs (Olugbade et al., 2019), capacitive sensors (Singh et al., 2015), or using motion capture body suits (Healey et al., 2013, 2015; Lavelle et al., 2013; Kapur et al., 2005); but also in indirect ways, for example retrieving postural information through EMG sensors measuring forehead tension (Strack and Neumann, 2000), or force plates integrated in the floor (Giraud et al., 2013). Most commonly, sitting postures assessed for interactional, affective and behavioural studies, are captured by instrumentalising chairs (Kapoor et al., 2004, 2007; Shibata et al., 2013; D'Mello et al., 2007a), as will be elaborated further in Chapter 3, too. With the nature of shifting weight across the surface of a seat, pressure sensors have emerged as one of the most popular modalities to detect sitting postures (Meyer et al., 2010a; D'Mello et al., 2007a; Tan et al., 2001; Kapoor et al., 2004; Shibata et al., 2013).

The Use of Pressure Sensors

A large number of sitting postures and behavioural cues can be identified with this approach (Kleinsmith and Bianchi-Berthouze, 2013; Karg et al., 2013). However, pressure sensors are also used beyond sitting posture detection alone. D'Mello et al. (2007a), for example, found that frequent changes in pressure refer to boredom and restlessness of learners, and Kapoor et al. (2007) associated frustration with different postures captured with pressure sensors in a seat. Together with pressure, other modalities have been explored and combined with information of postural shifts, such as facial cues (D'Mello and Graesser, 2010; Strack and Neumann, 2000). Encapsulated as a grid in plastic sheets[1], or deployed manually as patches or self made sensing surfaces, pressure sensors achieve high accuracies identifying small scale changes of postural movement (Tan et al., 2001; Cheng et al., 2013; Riener and Ferscha, 2008). Additionally, when comparing different resolutions of pressure sensing grids in these works, in other words the amount of sensors used to identify postures, the best results were not always achieved with the highest number of sensors. A more detailed comparison of pressure sensors in chairs can be found in a separate literature review section in Chapter 3.

2.2.5 Automatic Detection of Behavioural Cues

Sensor driven approaches to detecting human behaviour requires suitable processing and analysis methods. In recent years, algorithms and classification models have been used to validate sensing systems and to identify signals of bodily movement and social behaviour. Machine Learning and Deep Learning methods have replaced traditional statistical methods (Noroozi et al., 2021), with some models being more frequently used than others, as surveys show (Kleinsmith and Bianchi-Berthouze, 2013; Noroozi et al., 2021). Overall, many different approaches have been used to detect nonverbal, embodied affective states from the whole body, as well as from individual body parts (sometimes

[1] as is commercially available e.g. via *Tekscan*

the face alone), and using various modalities to measure these (Kleinsmith and Bianchi-Berthouze, 2013).

Processing Sensor Data

As mentioned above, many signals still stem from visual data, dominantly recorded video, which also led to developments in computer vision have achieved high recognition accuracies with all vision dependant data, such as cameras (Vinciarelli et al., 2008; Karg et al., 2013). Often in combination with multimodal networks, it is possible to predict fine grained behaviours like listener backchannels (Morency et al., 2010, 2008) as well as to recognise emotions (Kleinsmith and Bianchi-Berthouze, 2013), affect from gestures (Kapur et al., 2005), head movement (Behnke et al., 2021), as well as from full body movement (Bernhardt and Robinson, 2007). To do so, different types of on-body sensors have been used, gathering physiological data, such as IMUs, EMGs, EEGs, piezo-resistive sensors, and others mentioned above and compared in Table 2.3.

In some studies, it is argued that machines and algorithms have performed better in detecting such signals than humans (Morency et al., 2008; Bourai et al., 2017; Subburaj et al., 2020; Klein et al., 2004). This applies even when it comes to measuring affective states, automatically detecting arousal and valence through postural cues (Kleinsmith et al., 2011). This is not just a central topic in social sciences but also in computer vision research (Pentland, 2000) and HCI in general.

Machine Learning for Social Interaction

Automatic detection of postures or postural activities and behaviours (Tan et al., 2001; Slivovsky and Tan, 2000) have been developed with Hidden Markov Models (HMM) (Kapoor and Picard, 2005; Delaherche et al., 2012), LSTM (Wang et al., 2019; Bello et al., 2021), Naive Bayes (Meyer et al., 2010a), Nearest Neighbour (NN) algorithms (Singh et al., 2015), Conditional Random Fields (CRF) (Soleymani et al., 2016; Delaherche et al., 2012), or decision tree based approaches (Gunes and Piccardi, 2009; Gaus et al., 2015; Griffin et al., 2015a), to name only a few. Table 2.3 shows an overview of some of the works mentioned in this review chapter, representing commonly used approaches to automatically detect postural cues.

Machine learning approaches can be applied to extract and detect patterns for behavioural discrimination (Atallah and Yang, 2009), as well as for classifying and identifying social signals. Social touch (Gaus et al., 2015) and laughter in interaction (Scherer et al., 2012; Griffin et al., 2013, 2015a) can be measured, too, in addition to social engagement and head nods (Foster et al., 2013; Behnke et al., 2021) is detected with these methods. HMM models have proven successful when detecting backchannels (Morency et al., 2010) and recognising head nods in natural conversation (Fujie et al., 2004). Also Gaussian models and Conditional Random Fields (CRF) have been explored in the detection of signals of social interaction (Kapoor and Picard, 2005). HMM and CRF have specifically been shown useful for extracting dynamic features and temporal structures of postural behaviour (Delaherche et al., 2012). Finally, models based on decision trees, like Random Forests, present an alternative to more complex neural networks and are an approach and have been used in many works assessing on-body sensors (Olugbade et al., 2019; Gaus et al., 2015; Griffin et al., 2015b). Gunes and Piccardi (2009) for example, found that this approach is suitable to analyse full body movement, while models like SVMs have been more successful with classification accuracies for facial cues.

An overview of the different algorithms for the detection of social cues from body movement can be found in Table 2.3, though there are more detailed surveys discussing the different approaches

Reference	Signal Input	Analysis Method	Use Case
Gunes and Piccardi (2009)	visual cues of whole body	RF (Random Forest)	affect detection
	face	SVM	affect detection
Gunes and Piccardi (2007)	video, mocap of face and body motion	Bayes Net	affective behaviour
Bernhardt and Robinson (2007)	visual cues of hand gestures	SVM	affect detection
Varni et al. (2010)	multimodal (video, mocap)	Recurrence Analysis	leadership, dynamic
Delaherche et al. (2012)	video	HMM, CRF	conversation dynamics, interpersonal synchrony
Gaus et al. (2015)	pressure sensor	RF	social touch
Kapoor and Picard (2005)	pressure sensor, video	HMM	interest detection through posture
Griffin et al. (2013)	torso	RF	laughter type
Griffin et al. (2015a)	vision based system (Kinect)	RF	laughter detection
Olugbade et al. (2019)	multimodal (IMU, EMG, Mocap)	RF, SVM	stress, pain level, posture
Behnke et al. (2021)	head movement images, video films	Bayesian models	emotion detection in head movement
Soleymani et al. (2016)	EEG	LSTM, CRF	emotion recognition

Table 2.3: A comparison of different, commonly used algorithms used to automatically detect social signals

in connection of affective states by Kleinsmith and Bianchi-Berthouze (2013), Karg et al. (2013), or Noroozi et al. (2021).

2.2.6 Summary

With the richness of nonverbal cues, the tools to detect them are just as wide in range. Generally, an unobtrusive approach is desired, distracting the natural actions as little as possible. A combination of smart environments, devices and on-body sensors is used to monitor people's actions and presence, movements and behaviours in an increasingly connected world (Poslad, 2011).

On-body sensors that capture physiological data have been used alongside more 'traditional', vision based methods (Karg et al., 2013), and contribute to a multimodal network of sensor input, enabling additional insights to nonverbal signals. The methods to detect such actions and behaviours vary depending on the signal input, or modality, as well as the data quantity and features to distinguish (Noroozi et al., 2021). As will be elaborated more in Chapter 5, Ensemble Trees like Random Forest algorithms show to be an appropriate approach for the type of data this thesis will collect and work with.

Gaps in Current Literature

The recommendations that can can be taken from the reviewed works in regards to analysis method, choice of sensors when gathering bodily signals, and placement of sensors, are accompanied by drawbacks, too.

One limitation are the settings in which embodied social behaviour is analysed. Most examples here of research analysing body movement and behavioural cues use postural information assessed by observers that are not part of the scenario in which the postures are performed. While there is a large corpus using acted postures, and sometimes even avatars to form a data base that is later judged by observers, there is a smaller corpus deriving from data captured in natural settings and group interaction (Kleinsmith and Bianchi-Berthouze, 2013).

Moreover, the objective to detect affective behaviour is widely addressed in the field of wearable computing. What is less studied are, whether the postural movements and signals associated with affect and an individual's perception and transmission of a social signal can be validated in a conversational setting, in multi-party interaction in unstaged scenarios and socially natural environments. These limitations resonate with the ones identified in the previous section of this chapter, 2.1.

Furthermore, the wearability and comfort of some of the sensing systems deployed on the human body does not always comply with the idea of a truly ubiquitous, unintrusive approach. This is, amongst other things, an issue of materiality, with many sensors consisting of rigid, in plastic encapsulated components that are not in alignment with smooth, bodily movements. This factor is something that is given more attention in the next section and in this thesis in general, working towards establishing a solution for a soft interface that does not interfere with natural behaviours and bodily actions when investigating social interaction.

2.3 Textile Sensing

2.3.1 A Soft Interface to Our World

A Historical Overview

Fabrics, or more generically, textiles are a material we have been familiar with for thousands of years, mostly in the form of, but not bound to, clothing. Seen as an extension of our skin, it is used to protect as well as to culturally and socially express ourselves (Ryan, 2014). Raw materials to manufacture yarns and fabrics have been sourced from animals and plants of all sorts, allowing for a wide range of properties when turned into a fabric surface and product. And it was not until the early 20$^{\text{th}}$ Century that the very first artificially created textile was introduced. Nylon, the first synthetic fibre was established as a commercially available material in the 1930s by DuPont (Koch-Mertens, 2000b; Pailes-Friedman, 2016). It is still a popular material for both the clothing industry and the field of smart textiles, where it often serves as a base fabric for conductive coatings or similar (for a product sample, see companies such as Eeonyx, Statex, etc). When looking for textiles with conductive properties that allow for sensor and soft circuit developments, we don't have to focus on modern day technologies and synthetic innovations, however, but can find such properties in early clothing that dates back to Ancient Egypt, where metal threads were woven into fabrics and metal accessories were used for closings and embellishments (Ryan, 2014). Metal threads were a widely used material for embroidery, and even comparatively large scale metal plates along the front torso as parts of corsets in clothing in 16$^{\text{th}}$ Century in Europe (Koch-Mertens, 2000a).

We can see that throughout costume history, intentionally and unintentionally, conductive materials have been integrated with different techniques and have been worn closely to and on the human body[2]. Making use of these properties, turning textiles into a sensing surface and making it a fundamental part of wearable computing has developed over the last 30 years (Post and Orth,

[2]even in the human body, when including piercings

1997). It has since been used for a variety of applications including medicine (López et al., 2010), sports (Helmer et al., 2008; Coyle et al., 2009), and the arts (Sicchio et al., 2016), as well as in the lifestyle (Poupyrev et al., 2016) and gaming industries (Chu et al., 2012). Sensing and actuating fabrics, as well as their nonconductive relatives technical fabrics, have travelled to space to serve as a more flexible and unintrusive alternative to gadgets and other hard shell devices worn on the body, and are also designed as smart skin for robots, in particular for humanoids (Vallett et al., 2016). Textile innovations have always derived from needs or desires related to the human body, or, in other words, have always been created in direct connection to the human body, serving as a layer between our physical and cultural self, a layer between us and the world. Textiles can therefore also act as an interface to connect this analog world and digital spaces through tactile experience. Under these premises, electronic components and microcontrollers like the *LilyPad* (Buechley et al., 2008) have been developed and have contributed to integrate textiles to digital design.

A Textile Material Overview

Combining textiles with electronics comes in various forms and techniques, creating different desired sensing characteristics through a wide range of materials and structres. Soft textile systems can act as three different components in a circuit: as sensors, actuators or batteries (Castano and Flatau, 2014). They can also form the circuit itself that connects these components, replacing wires. The numerous fabrication techniques to create fabric sensors, or fabric based circuitry all show different advantages and disadvantages. They are assessed by their flexibility level and are evaluated against their possibilities for connection and bonding to other electronics (Castano and Flatau, 2014).

To equip textiles with electronic properties, conductive elements are integrated on a fibre, yarn or fabric based level. Metal particles can be combined with wool fibres, e.g. in a steel wool (Satomi and Perner-Wilson, 2007; Nonnis and Bryan-Kinns, 2019), or pure metal strings are treated as filaments and twisted into yarns, either as the core of a twisted yarn (Huang et al., 2008), the coating elements (Fernando et al., 2020), or alongside non-conductive mixed yarns (Poupyrev et al., 2016). A more recently developed and more complex method is to integrate electronic components such as temperature sensors or LEDs into the fibres of twisted yarn using nanotechnology, so that further manufacturing processes can be conducted on industrial machines and the electronic parts become invisible (Hardy et al., 2019, 2020; Dias, 2015; Lugoda and Morris, 2015). With this technique to miniature electronics, the electronic yarn can still be used on common knitting machines or weaving looms and has the potential to be manufactured on an industrial level.

The next step in the textile process is creating a fabric surface. To do so, conductive yarn or yarn with integrated electronics is mostly knitted or woven into surface structures, as are many of the textiles we come in touch with in everyday environments. This structural familiarity is also why fabrics entail so many advantages as an ubiquitous interface (Swallow and Thompson, 2001). While with commercially conductive yarn[3], it is possible to create conductive fabrics on domestic machines or by hand, there are also commercially available fabrics of different suppliers[4], possible to acquire in large quantities. Additionally, fabrics that are initially produced as non-conductive textiles can later be coated with conductive films, often based on carbon (Jost et al., 2013; Fernando et al., 2020) or silver. With these different ways of producing conductive textile surfaces, there is interest in comparing their performance as reliable fabric based sensors (e.g. Liang et al. (2019a)). As such, they can be used for a wide range of applications, including capturing movements by measuring stretch

[3]e.g. through companies like *Statex*, *Karl Grimm*, *Barts & Francis*, and others

[4]e.g. through distributers like *Hitek*, or companies like *Eeonyx*, *Statex*, *Medtex*, or *Plug & Wear*, to name a few.

(Liang et al., 2019b), but also for generating and storing electricity themselves (Weng et al., 2016). Similar to yarn based developments, the properties of the textile structure define the optimal use case for a textile based sensor, as well as determine their behaviour in regards to resistive characteristics.

Together with conductive yarns and fabrics, other techniques are used to create circuits, actuators or sensors. For example, printing a circuit has the advantage to enable a flexible, soft circuit board that can be employed onto a finished garment (Catchpole, 2019; Jost et al., 2013). Here, nonconductive fabrics operate as a substrate for conductive ink such as copper or silver. This technique has been used to design antennas and temperature sensing fabrics for various on-body applications (Ibanez Labiano and Alomainy, 2019).

Another technique is embroidery and sewing (Gioberto et al., 2013; Milo and Reiss, 2017). This way, hard electronic components can be attached to fabrics in a robust, yet flexible way. An example can be seen in Trindade et al. (2014), where EKG sensors are embroidered, or in the work of Ukkonen et al. (2012), where RFID tags are sewn onto fabrics. Embroidery has also been used to manufacture textile antennas (Dias, 2015), as well as entire textile computer systems (Posch and Kurbak, 2016).

Overall the field of textile sensing, including material innovation, is developing rapidly and the examples mentioned here present a small selection of common designs, techniques and use cases. More detailed reviews on the state of the art of electronic textiles in general can be found in Castano and Flatau (2014); Weng et al. (2016), and Gonçalves et al. (2018).

2.3.2 Textiles for Social Computing

There are many application areas smart textiles have been introduced to, ranging from solutions for the medical sector (Yang et al., 2019) including rehabilitation (Patel et al., 2012; Gioberto, 2014), to performance art (Sicchio et al., 2016; Greinke et al., 2021a) to sports (Yu et al., 2021; Coyle et al., 2009) to games (Chu et al., 2012) or other leisure activities (Poupyrev et al., 2016). For this section, the focus of reviewed works lies on use cases of textile sensing in social contexts. While this can be a similarly broad field to look into, I examine the role of textiles in scenarios including unstaged, multiparty social interaction and scenarios where textiles support the communication of social behaviours, or measure such.

Textiles, smart or not, have always played a significant part in human interaction. This close relation between textiles and humans makes all products and surfaces made of and covered by textiles a convenient, natural sensing material when it comes to capturing social signals. Unintrusively close to our skin, following our bodily actions in the form of clothing, or designed as a soft interface with familiar surface qualities in smart environments, textile sensing systems can be used to monitor and log everyday activities when incorporated in e.g. table cloths (Gaver et al., 2006), or pillows (Vogl et al., 2017). They can also function as materials encouraging interaction between people (Giles and van der Linden, 2015; Kettley et al., 2016), as well as interaction with objects (Buechley et al., 2010; Nonnis and Bryan-Kinns, 2019).

One advantage of using textiles lies in its unobtrusiveness and ubiquity in the context of collecting data, as well as in its material properties as a soft, flexible, and easily modifiable surface that can mould around the body effortlessly, and can even be treated like other, ‘everyday’ fabrics (Niazmand et al., 2010; Ju and Lee, 2020). For use cases in social computing, especially in regards to wearable smart textiles, these advancements ease the deployment in everyday scenarios as well as a more and more accurate data processing and interpretation.

Social Smart Textiles in Healthcare

Under these premises, social smart textiles have been explored for use cases in health care and in the medical sector. Many have mentioned e-textiles as a possibility for rehabilitation applications (Patel et al., 2012; Haladjian et al., 2018), describing them as ‘medical wearables’ (Griffin and Dunne, 2016) or ‘wearable health technology’ (Møller and Kettley, 2017). Pressure sensing mats on seat covers and beds detect pressure points in patients, e.g. in (Sundholm et al., 2014; Arnrich et al., 2010), textile activity recognition systems monitor elderlies’ movements, and exoskeletal body suits even actively support muscle activity (Béhar, 2017; Yang et al., 2019). But also for humans at the other end of the age spectrum, smart textiles prove to be convenient. Textile sensors have been emdedded in baby suits to track their movement (Jakubas et al., 2017) for unintrusive and comfortable health monitoring.

There are numerous examples of textile sensors, presented in different structural techniques, being used as wearable health monitoring systems, e.g. in Paradiso et al. (2005), to measure physiological and biomechanical elements (Pacelli et al., 2006), monitoring a patient’s activities, movements, or also measures like heart rate, pulse, blood pressure, etc (Weng et al., 2016; Fernández-Caramés and Fraga-Lamas, 2018; Yang et al., 2019; Hughes-Riley et al., 2018). Many of these are proposed for rehabilitation purposes (Wang et al., 2015), as well as for wheelchair users (Ma et al., 2017)

Also when in interactional scenarios in a healthcare context, most fabric sensors are designed to be embedded in an interaction between humans and computers, or to be centred around the body for health applications. Very few address social interactions, e.g. Dunne et al. (2006a,b). There is, however a need to integrate textiles in social scenarios, too, for example to reduce barriers in assistive technology (Yang et al., 2019; Blumenkranz et al., 2018).

Improving digital technology through textiles, is a pledge that not only suits the application in healthcare, but in general the field of wearables (Kettley et al., 2011, 2017).

Social Smart Textiles for Collaboration

Another social computing application area in which textiles find use is in education. Here, tangible interfaces are used to engage in collaborative play (Nonnis and Bryan-Kinns, 2019). Textile interfaces have found particular popular use in educational settings for autistic children, providing a soft, and therefore safe material property (Nonnis and Bryan-Kinns, 2019; Zhiglova, 2018). In general, using smart textiles fosters collaborative and participatory design practices, as shown in a variety of workshops, also in marginalised communities (Giles and van der Linden, 2015; Meissner et al., 2018, 2017; Kettley et al., 2016). Giles and van der Linden (2015), for example, has used e-textile design practices to enhance tactile experiences for visually impaired people through workshops and co-design approaches.

In other social contexts, textile interfaces are used in education to facilitate workshops and group activities for visually impaired people (Giles and van der Linden, 2015), people with disabilities (Meissner et al., 2018; Blumenkranz et al., 2018), with mental health conditions (Kettley et al., 2016; Cosma et al., 2017), and children with autism (Nonnis and Bryan-Kinns, 2019; Zhiglova, 2018). In the context of participatory and collaborative design, textiles are often mentioned as an interface through which accessibility to technology can be secured (Giles and van der Linden, 2015; Meissner et al., 2018; Kettley et al., 2016), presenting a tangible experience in comparison to screen based activities. The idea of tangible representation of digital interfaces is something that has received a wide research community’s interest, and plays an important role in social computing as well (Foo

Reference	Textile Design	Sensor Type	Suggested Use Case
Cosma et al. (2017)	portable small objects	accelerometers	anxiety reduction
Gaver et al. (2006)	table cloth	pressure	track social movement, object placements
Khaorapapong and Purver (2012)	jacket	RFID	meetings between strangers / anxiety reduction
Nonnis and Bryan-Kinns (2019)	soft floor sculpture	capacitive	collaborative for autistic children
Blumenkranz et al. (2018)	various textile interfaces	various (capacitive, piezo-resistive)	people with disabilities

Table 2.4: Examples of smart textile use for applications for social interaction

et al., 2021; Petreca et al., 2013).

Textiles have also been shown to be a suitable sensing surface when tracking social dynamics of group interactions, for example tracking activities around a table (Gaver et al., 2006), or when mingling and meeting with others (Khaorapapong and Purver, 2012), but also to comfort people with anxieties in such scenarios (Cosma et al., 2017).

A brief summary of some examples of textiles used for social computing applications involving human interaction is presented in Table 2.4, also listing the textile sensor types being used for different designs. Although I recognise there are more examples of smart textiles being designed for a social context, the proportion of such in comparison to smart textiles designed for an ego-centric application, including human-computer-interaction and healthcare, is small. This is also acknowledged in recent surveys, projecting significant developments of smart textiles in this area (Ju and Lee, 2020), forming a growing part of an ambient sensor environment (Cosma et al., 2017).

2.3.3 Smart Clothing

The term 'smart wear' was something circulated as early as 1995 by Pentland (Ryan, 2014), describing business clothes with integrated wearable technology. Soft sensors with material properties that are a familiar sensation on our skin have many advantages when it comes to measuring bodily signals, and have been used for a large variety of other applications. In performing arts like dance (Sicchio et al., 2016), as musical interfaces or for optical, aesthetic purposes in fashion (Seymour, 2008, 2019), smart clothing has become a well integrated part of tangible interfaces for wearable technologies. Depending on the application, different electronic components and textile sensors are integrated through different methods in the garments. Accelerometers and physiological sensors like IMUs, EMG, EEG sensors are amongst common sensors to deploy on pieces in smart clothing (Acar et al., 2019).

Replacing rigid sensing materials with softer, more flexible textile materials has allowed research to focus on positioning these new fabric interfaces on the body. 'Smart Clothing' now sits alongside mobile phones and other wearable gadgets in the field of ubiquitous computing and offers a novel modality to conventional sensing techniques. It serves as interfaces in human-computer interaction (HCI), e.g. (Poupyrev et al., 2016; Schneegass et al., 2014), but also in communication between humans, e.g. (Khaorapapong and Purver, 2012).

In parallel to health care applications, the same body measurement systems can be used to inform fitness performance for sports applications. Textile techniques are used to measure muscle activities of runners (Ribas Manero et al., 2016), and to provide practical solutions for cycling gear, for example by LEDs integrated in electronic yarn woven into joint areas of a jacket, or LEDs in gloves that light up when forming a fist (Posch, 2011).

Textile sensing design has also been adapted for non-humans. Robots have been equipped with textile 'skin' to react to outer stimuli like touch (Vallett et al., 2016), and studies on the interaction between robots and humans has shown that dressed robots appeared more approachable for people than 'naked' robots revealing their metal shell (Trovato et al., 2016). And even in outer space, e-textiles are used to replace more rigid wearables, offering an on-body sensing system to monitor astronauts' health status with fully integrated textile circuits, e.g. in Lee et al. (2018).

Application areas that are often proposed and explored with textile sensing techniques are health care, sports, community engagement, education and interaction design, including games and other screen based activities (Fernández-Caramés and Fraga-Lamas, 2018; **?**). More recently, also robotics and space design engineering have adapted techniques and benefits of textiles as soft sensing systems.

Social Smart Clothing?

Although textiles have been praised for their beneficial material properties in relation to social scenarios and interaction, the designs presented for different applications are mostly based on objects or accessories rather than integrated in clothing. Given the communicative nature of the textile we wear on our body (Schmelzer-Ziringer, 2015; Barthes, 2006; Berzowska, 2005), however, comparatively few items of clothing are instrumented to contribute to social interaction in a non-egocentric manner. There are, however, numerous examples of smart clothing that react to outer stimuli, including those initiated by interaction partners or other humans, see e.g. Seymour (2008); Pailes-Friedman (2016); Kettley (2016).

Examples show, that mostly upper body garments are used when measuring postural and gestural movement through textile sensing on the body. Even capturing sitting postures has been explored with stretch sensors in T-shirts (Mattmann et al., 2007), focusing on the changes in posture of the torso only. Recognising gestural movement enables clothing to act as a remote control for digital devices, for example smart watches (Schneegass and Voit, 2016), whose interface can be replaced by a smart sleeve, or mobile phones that can be controlled with small hand gestures on a jacket (Poupyrev et al., 2016). There are also designs of wearable textile sensing intended to be worn as a separate layer underneath clothes (Rekimoto, 2001), whereby the electronics are detachable from any fabric that requires washing. Integrated in smart clothes, textiles have been suggested to be capable of measuring aspects beyond posture detection, too, assessing social compatibility (Khaorapapong and Purver, 2012). Sensing systems in clothing are also suggested to act as technologies encouraging group activities like going running together (Mauriello et al., 2014).

Smart Trousers

While the upper body is typically the focus of design investigations on smart clothing, also the lower body provides useful cues to capture in certain application areas. In use cases where the legs are in more movement than the torso, for example in running, or cycling, sensors in trousers can be used to measure muscle activity to assess the athlete's performance. This can be achieved by deploying EMG and EKG sensors on the garment (Ribas Manero et al., 2016). Pressure sensors play a role in monitoring leg activity for various gym exercises, too (Zhou et al., 2016). The advantage of sport outfits is that they are mostly cut very tightly to the body for a slim fit, so that the electrical bio signal sensors are in direct contact with the skin without further manipulation. There are examples of cycling trousers, however, where sensors are attached to the body in a conventional way via straps, and trousers are used to conceal and protect the sensing area (Liu et al., 2019). 'Smart' trousers are also used for gait recognition and other movement detection, for example with accelerometers placed above the knee (Van Laerhoven and Cakmakci, 2000), or reflective markers attached on trousers, captured by camera systems (Dunne et al., 2011).

Reference	Sensors Used	Sensor Placement	Suggested Use Case
Ribas Manero et al. (2016)	EMG, EKG	on top thighs	Measure muscle activity for runners
Niazmand et al. (2011)	accelerometers	along side seam	gait recognition for Parkinsons Disease
Van Laerhoven and Cakmakci (2000)	accelerometers	above knee	gait recognition
Zhou et al. (2016)	pressure sensors		leg activity monitoring for exercise
Singh et al. (2015)	capacitive sensors	on thighs	gesture recognition
Cha et al. (2018)	piezo-electric sensors	knees and hips	gait recognition
Honnet et al. (2020)	piezo-resistive sensors	all over leggings	leg movement recognition
Yu et al. (2021)	pressure sensors	around knee	measure knee movement, prevent injuries
Gioberto et al. (2014)	goniometer	knee and hip	measure joint flexion
Bisio et al. (2019)	IMU, pressure	knee, thigh, foot	home rehabilitation

Table 2.5: A comparison of smart trousers.

An interesting observation when comparing upper and lower body smart textile designs is, that for trousers, the sensor integration appears impoverished. For example, in (Cha et al., 2018), sensors are simply attached with copper tape, and Bisio et al. (2019) uses relatively rigid wires to connect the circuit. Singh et al. (2015) straps a sensor array on trousers, and while Ribas Manero et al. (2016) and Yu et al. (2021) use a more refined approach for textile integration, the design features commercially available trousers that requires the sensor design to be adapted. In comparison, many upper body garments are designed and fabricated "from scratch" to incorporate textile sensors. Moreover, trousers are never used to capture movement from body parts other than legs. For example, we find T-shirts measuring whole body movements including the legs (Mattmann et al., 2007), but no trousers or other legwear measuring movements of the torso.

2.3.4 Tailoring Electronic Integration

Embedding sensors in clothing has to fulfil slightly different requirements than when embedding sensors in other textile surfaces. Clothing as a wearable dynamic, flexible surface bears challenges that static objects don't, but they also provide solutions that are unique to clothes. There are examples of sensing clothes that present all of these techniques: areas of conductive yarn woven into a garment and transformed into a capacitive touch area (Poupyrev et al., 2016) or nano-electonics in yarns as light signals in cycling jackets (Hardy et al., 2019); sewn in areas of conductive and resistive fabric bonded onto base fabric as part of a suit jacket (Stewart, 2016) or dance costume (Liang et al., 2019b); embroidered speakers and circuits on dresses and other upper body garments (Satomi and Perner-Wilson, 2007).

Garment Engineering

The pattern construction and tailoring techniques of garments also afford an unintrusive, concealing way of integrating rigid, less flexible sensors and hard electronic components such as RFID tags in sleeves (Khaorapapong and Purver, 2012), interactive touch pads interwoven in denim jackets (Poupyrev et al., 2016), or batteries and microcontrollers in buttons (Stewart, 2016), where all electronic components were integrated with techniques borrowed from traditional tailoring. The notion of tailored suits has been used in relation to the development and design of textile sensing in clothing, too (Catrysse et al., 2003; Wicaksono et al., 2020), and the handcraft of bespoke garment making, which offers technical solutions beneficial for a precise and ubiquitous integration of electronic components.

Nevertheless, there are examples in which on-body sensing is conducted in ways that do not account for these factors of design engineering that garment manufacturing crafts offer. In many projects, ready made garments are acquired and later equipped with electronic components (Liu et al., 2019; Khaorapapong and Purver, 2012; Chalkley et al., 2017b; Ribas Manero et al., 2016), etc., rather than designing a garment accounting for textile sensing parameters.

Hard-Soft Connections

Connecting circuit boards, wires and sensors that are textile based with hard electronic components can be done by soldering, though these connections present the risk of breaking. Instead, snap buttons, safety pins and other conductive supplies used in clothing and textile related products can be used. Satomi and Perner-Wilson (2007) document an ever growing design archive of solutions related to these design and engineering challenges. These developments contribute to the improvement of the compatibility between electronic components and textiles. Designers and researchers have worked on more robust connections between them and have designed microcontrollers and boards that allow for a textile friendly handling (Buechley and Perner-Wilson, 2012). Examples of outcomes of such developments are toolkits (Posch and Fitzpatrick, 2018) that contribute towards appropriate handling of smart textiles.

There are, of course, combinations of the above mentioned techniques, too, for example in the Integrated Circuit Button Jacket by Stewart (2016) that embeds a fabric designed circuit, uses embroidery to connect hard and soft electronic components, and is powered by a battery housed in a 3D printed button to close the jacket (and circuit).

Textile and Non-Textile Sensors

Although a wide range of sensors can be designed and crafted from textile materials, in many works on smart textiles, commercial sensors made of more rigid materials are acquired and attached to base fabrics where the textile properties are not taken into account. Accelerometers, identification tags, EEG and EMG sensors and other hard, non-textile materials are deployed on fabrics or finished products for on-body applications (Liu et al., 2019; Witchel et al., 2016; Catrysse et al., 2003; Colyer and McGuigan, 2018). In some of these cases, fabrics, whether in the form of clothing or interior object surfaces fulfil the purpose of concealing the operating technology, still contributing to the idea of ubiquitous, 'invisible' computing.

Some of them in use can be replaced by fabrics, too, others however are without 'soft', textile alternative. This poses one of the main challenges in wearable technology and is often discussed (Catrysse et al., 2003; Buechley et al., 2008; Stewart, 2019). Solutions to this challenge haven been approached from different angles. Some, e.g. Rekimoto (2001) suggest modular designs in which problematic, not washable components can be removed from the garment (or other textile interface) as a separate layer. Others, e.g. Molla et al. (2018), suggest various insulation designs to conceal the components so they are under less risk of being damaged. Insulation, as well as the concealing and revealing of the technology and electronic components linked with a textile is another ongoing design engineering challenge in the field that is discussed (Berglund et al., 2014). Part of the rigid components that disrupt softness and flexibility are batteries. Powering smart clothes or other textile products usually includes detachable, rechargable batteries. A method to overcome this is by integrating solar cells in yarn or to use flexible solar panels that can be embedded in textile surfaces (Smelik et al., 2016; Satharasinghe et al., 2020).

2.3.5 Textile Pressure Sensors

Looking at the different sensors that can be made from textile materials, piezo-resistive (e.g. pressure and stretch) and capacitive sensors are amongst the most commonly used. With different coatings and through other methods that induce conductive properties varying in resistance, some raw materials themselves can be utilised as piezoresistive sensors. For example, yarn with a small percentage of stainless steel twisted with synthetic fibres can be sensitive to pressure and strain due to its high resistance, while yarn with a high density of conductive areas, e.g. silver coated yarn, better works as a textile wire due to its low resistance (Castano and Flatau, 2014; Chen et al., 2020). To build a pressure sensor consisting of textile elements only, both characteristics are needed to integrate a resistive layer to a circuit with two conductive elements - one connecting to Ground, one to Power and a corresponding pin on the microcontroller for reading sensor measurements, see Satomi and Perner-Wilson (2007). When turning a textile, piezo-resistive surface into a pressure sensor, the deformation of the textile is measured, the applied pressure input changes the touch point and affects the electrical resistance, which then varies (decreases when pressed, increases when released). This is measured and translated into an analog sensor signal (Satomi and Perner-Wilson, 2007; Castano and Flatau, 2014). Layering different types of fabric - conductive fabrics and a spacer fabric in between (Meyer et al., 2010a) - enables an entirely textile based design of the sensors and is relatively easy to accomplish, as well as cost effective.

The application areas of textile pressure sensors can be compared with the wide range of applications for more conventional pressure sensors. Integrated in chairs and garments, they are used to capture body postures in various contexts (Romano, 2019; Strohmeier et al., 2018; Meyer et al., 2010a), but also act as soft, interactive interfaces (Donneaud and Strohmeier, 2017a). A selection of textile pressure sensors in different designs and for different applications is shown in Table 2.6.

Measuring Body Movement and Posture

As already mentioned in section 2.2, pressure is a common modality to monitor bodily movement and capture postural behaviour, and can therefore be used to explore other nonverbal behaviour and affective states. Also from Table 2.6, it can be seen that many examples of textile pressure sensors are used to capture body posture. Textile pressure sensors have been used on chairs for posture classification (Romano, 2019; Ishac and Suzuki, 2018; Meyer et al., 2010a; Xu et al., 2013) or for other postural activity recognition (Zhou et al., 2014), as well as on garments to evaluate different body movement tasks, such as on arms (Dunne et al., 2006b), as well as micromovements like breathing.

Reference	Sensor Design	Placement	Application
Meyer et al. (2010a)	matrix	seat surface	sitting posture classification
Pizarro et al. (2018)	square patch	glove	gesture recognition
Donneaud and Strohmeier (2017b)	matrix	flat surface interface / table top	musical interface
Romano (2019)	matrix	seat surface	sitting postures / personalised seat design
Nachtigall (2016)	small sensor patches	shoe	foot ergonomics
Sundholm et al. (2014)	matrix	floor mat	activity recognition (gym exercises)
Parzer et al. (2018)	woven surfaces	various	interface for remote control
Li et al. (2019)	woven square patch	various	movement detection
Xu et al. (2013)	in cushion	in seat	sitting posture detection
Ishac and Suzuki (2018)	in cushion	in chair	posture detection
Kim et al. (2018)	large woven squares	on chair (seat and back)	posture detection for correction
Romano (2019)	woven into seat surface	chair surface	posture detection for personalised design
Zhou et al. (2014)	matrix	various (table cloth, chair)	various
Blumenkranz et al. (2018)	patches of various shapes	various	soft interface design / communication tool
Dunne et al. (2006b)	foam sensor patches	upper body garment	arm movement, breathing
Bisio et al. (2019)	small sensor patches	foot sole	exercise recognition / home rehabilitation
Yu et al. (2021)	sensor patches	around knee	knee movement detection

Table 2.6: A comparison of different textile pressure sensors designs and their use cases.

While most posture classification systems measure pressure using in plastic encapsulated, industrially produced force sensing resistors (FSRs) (Tan et al., 2001; Slivovsky and Tan, 2000; Riener and Ferscha, 2008; D'Mello et al., 2007a), it has been shown that textile pressure sensors can compete with them (Meyer et al., 2010a). Moreover, they are easier to integrate in products where plastic and less flexible materials reduce movement, for example when measuring gestures in gloves (Pizarro et al., 2018), or small scale movement in the torso (Dunne et al., 2006b).

The example of Dunne et al. (2006b) also illustrates that 'posture-aware' smart clothing often tracks the movements of the upper body, being integrated in a T-shirt, shirt or also jacket (Enokibori et al., 2013; Mattmann et al., 2007; Greinke et al., 2021a), reflecting the common findings in social sciences in relation to nonverbal, postural behaviour.

Textile Pressure Matrices

Another observation when examining different works of textile pressure sensors, in particular in relation to posture sensing as well, is, that many sensors are configurated as a matrix. Again, this is also a common design in non-textile pressure sensors in similar contexts, using pressure sensitive matrices in sheets with a fine grid for a high resolution, mounted on chairs (Tan et al., 2001). A prominent textile sensor matrix is the design adaption by Donneaud and Strohmeier (2017a), which will be mentioned in more detail in Chapter 4, too. This design has initially not been used to capture sitting postures, but to act as a musical interface (Donneaud and Strohmeier, 2017b). Since these and other early developments of pressure sensor matrices, many different designs have been explored for on-body interfaces like gestural controls, e.g. touch pads (Perner-Wilson and Satomi, 2019b), table surfaces (Zhou et al., 2014), or parts of furniture surfaces (Parzer et al., 2018; Li et al., 2019). Embedded in seat surfaces, pressure sensors have also contributed to customised, ergonomic chair design, accounting for customers' pressure points on the seat (Romano, 2019) and contributing to improving sitting postures (Kim et al., 2018).

With a textile based engineering solution, it has also become possible to transfer these measuring systems on the human body for a wearable pressure and posture sensing network, i.e. the clothing presented in this thesis.

2.3.6 Summary: Gaps and Limitations

The growing field of textile sensing has already seen many design explorations and suggested use cases. In some areas, smart textile sensors have the ability to replace their rigid equivalents, enabling an overall softer circuitry and system design.

Despite the many advantages textiles promise, textile sensing designs are still a niche and not established as alternatives to rigid components. This may be linked to pending solutions to challenges around the integration, scalability and contextualisation of textile sensors.

While some avenues are frequently explored, mostly in relation to single user focused tasks for rehabilitation, sports, or health monitoring, applications where textiles enrich social encounters between people, or fostering collaboration, is explored only marginally. The way in which other wearable sensors are exploited to capture human conversation and behavioural cues, textiles are yet to catch up with other systems.

Additionally, when examining smart clothing, the previously mentioned focus on upper body movement and social signals is reflected here as well. The design engineering of upper body garments seems to be more advanced than works involving trousers, both in garment design as well as in sensor design.

In summary, there is a wide range of use cases for textile sensing systems, and not all of them are mentioned here. The way in which smart textiles are embedded in our everyday life is growing as well, reaching different sectors and disciplines. However, there is little work on the utilisation of textile sensing systems in behavioural studies and interaction analysis.While individualistic sensing approaches are explored for a variety of applications in HCI, applications to human-human interaction are rare.

In this research, I investigate this gap and will introduce different approaches of using textile sensing systems in the context of conversation analysis, starting with exploiting chairs as tools to measure conversational engagement in group interactions. This research seeks to further explore the potential of clothes for measuring cues of social (multiparty) interaction through the nature of postural behaviour.

2.4 Conclusion

The three sections and themes reviewed above have helped to identify gaps and limitations in the research fields this thesis aims to contribute to. In summary, the key observations deriving from this chapter that determine the research presented further, are as follows.

- The review of studies on nonverbal behaviour in section 2.1 have shown the dominance of the upper body and the lack of attention on the lower body as an active part of a transmitter of social signals. While there are mentions of it in some works, the potential relevance in an extended understanding of embodied behaviour in social encounters is rarely discussed. Furthermore, despite much work on full body movement in recent years, the role of postural shifts and overt bodily movement is underinvestigated when compared to the large corpus of studies on hand gestures or facial expressions.
- After examining technologies capturing social signals, in section 2.2, it was found that the neglect of the lower body is recurring. Most technologies are centred around the upper body, including face and hands. Additionally, the methods of investigating body movement and postural behaviour are mostly dependant on vision based technologies, although multimodal approaches adding physiological sensor input gain popularity, after some works showed that accuracies in automatic detection can be increased.
- Lastly, the use of textiles and smart garments is explored in section 2.3, summarising the advantages and potential use cases of this fast growing domain. Examples show that conductive textiles have the capability to replace rigid materials with comparable sensor performance. There, I also note the gaps of smart textile deployments in social, interactional, face-to-face contexts, not only exploring single user events and actions, but taking social dynamics into account when gathering data with textiles and wearables.

In all reviewed areas, the lower body and legs receive less interest than the upper body. Furthermore, all three areas showed how the use of acted, or staged data of embodied behaviour like postural movement, is outweighing the processed and analysed data from more natural, unstaged settings and face-to-face interactions. These aspects are found both in textile sensing literature, as well as in conversation analysis works and wearable computing. In the chapters to follow, I address the here identified gaps in relation to my research goals and objectives.

Chapter 3

On The Edge of Our Seat: Sensing Conversation with Textile Chair Covers

Chapter Overview

The benefits and potentials of textile sensors for an application in behavioural studies have been laid out in the previous chapter. Here, this modality is exploited in the context of social interaction, exploring questions about nonverbal conversational behaviours. I ask whether it is possible to sense participatory movements in conversation in a natural environment with a comparatively simplistic approach: pressure sensors in chair seat covers. Using custom built fabric sensors I test whether it is possible to detect people's involvement in a conversation using only pressure changes on the seats they are sitting in.

This chapter is structured as follows. First, I review existing sensing chair covers that have been developed for different use cases, from static sitting posture classification to measuring affect. Based on existing literature and ethnographic observations that are reported here, a sensing chair cover, and a study evaluating it, is designed. The development of sensing chair covers is introduced, explaining the fabrication process and the methods used to evaluate these textile sensors. I present the data collection of this textile sensing system, and conduct a statistical analysis to test the performance of the system. The results from Multivariate Tests show that even from this 'minimal' data particles of talking, backchanneling and laughter can be distinguished. Each state is associated with distinctive patterns of pressure change across the surface of the chair, in particular drawing attention to the role of the buttocks - the sensors on the seat surface of the chair cover introduced here. The chapter closes with discussing these findings and speculating on the possible applications of this new, unintrusive form of social sensing.

A compressed form of the design, evaluation and key results reported in this chapter has been published as: *Skach, S., Healey, P. G.T., & Stewart, R. (2017, July). Talking Through Your Arse: Sensing Conversation with Seat Covers. In Proceedings of the 39th Annual Conference of the Cognitive Science Society. London, UK. Cognitive Science Society. pages 3186-3190.*

3.1 Introduction

The significance of nonverbal cues during a conversation alongside verbal and vocal cues has been emphasised since early studies of conversation, and is illustrated by how much we can infer about an interaction from the observation of body movements alone. These bodily signals correlate with people's levels of participation. We can often tell just by looking at who is talking to whom, who -if anyone- is listening, who is likely to speak next, whether the interaction is hostile or friendly and so on (Kendon, 1990b). These inferences from non-verbal performances can be striking; people appear to be able to make reliable estimates of the quality of someone's teaching over a whole semester from a single 5 second video of body movements alone (Ambady and Rosenthal, 1992). Research on non-verbal communication has tended to focus on relatively large scale overt body movements, they are the easiest signals for participants to perceive and respond to and the most tractable for analysis. For example, speakers normally gesture significantly more than listeners, and listeners frequently produce concurrent feedback or backchannels, by nodding in response to an ongoing turn. Furthermore, overt movements like body torques explained by Schegloff can signal multi-layered participation in conversation. Typically, research in this field takes advantage of video and, more recently, motion capture equipment to capture and analyse these movements, e.g. (Healey and Battersby, 2009; Gunes and Piccardi, 2009; Varni et al., 2010). The rapid development of new sensor technologies and their application to social signal processing has opened an intriguing new space of possibilities for detecting patterns of interaction (Vinciarelli et al., 2009). For example, it is possible to detect people's levels of interest, stress and intoxication in conversation using the speech signal alone i.e. without knowing anything about the content of what is said (Schuller and Rigoll, 2009; Schuller et al., 2013). Most of these technologies, however, require the augmentation of our natural (interior) environment, installing intrusive sensing systems or even deploying parts of sensor networks on people themselves. Moreover, and as elaborated in the previous chapter, many of these technologies, such as video or automatic speech recognition, often collect more data than arguably necessary for the purpose. Challenging these relatively intrusive technologies, this chapter introduces an approach that makes it possible to create anonymised 'minimal' forms of social sensing by using electronic textiles.

In this work, I explore the potential of this modality for one of the most commonly used parts of the physical environment for seated social interaction: chairs. Even the shape and position of unoccupied, uninstrumented chairs can indicate a great deal about interaction; chairs around a small table suggest something very different from chairs in rows (see also Anderson (1996)). These arrangements, just like Kendon's F-Formations, can apply constraints and affordances to interaction and predetermine conversational hierarchies. Moreover, chair covers are often made of stretch and soft fabric, that as such is unintrusively embedded in interior environments. This alone makes textiles a promising sensing material. Conductive properties in fabrics therefore allow for chair covers to be turned into sensing surfaces without changing their appearance or textile properties.

Different possibilities of using seat covers as sensing surfaces have been explored in recent years, for example to determine sitting postures of computer users Tan et al. (2001); Slivovsky and Tan (2000). The most common type of sensing in chair covers therefore is pressure sensing, which I follow to use in this design, too. In most works, however, the postural behaviours and states that are measured come from single users and human-device interaction rather than human-human communication. The design of a sensing fabric chair cover I introduce here is built with the objective to pick up social behaviours and conversational states, going beyond an egocentric sensing approach and proposing textiles as a modality for social sensing. For this purpose, and based on observational findings, I decided on a configuration of eight sensors distributed across the chair cover, taking continuous pressure readings.

With a chair as the starting point and instrument of measurement, the studies of nonverbal behaviour focuses on the parts of the body that come in touch with the chair, but overall raises the research questions as to what elements of a conversation a simple sensing system in a chair can pick up. Even more generally, I ask, whether it is possible to make any statements about the quality and levels of engagement of a conversation by taking information from the chair people sit on alone. Could a chair tell who is speaking, who is listening, who is most or least active during a seated conversation?

3.2 Background

In this chapter, I draw attention to review sensing devices that are not necessarily wearable, but that fulfil the premise of being part of our natural surroundings, objects commonly present during social interaction. A summary of existing research in this domain is given, and a focus on social sensing networks in domestic spaces is created, elaborating on the social performance of objects, in particular furniture in our environment, before focusing on chairs as sensing devices for the purpose of posture detection. With a chair being used as a sensing device, the situations in which data can be collected focus on environments involving people sitting down. In examples of related literature, sensors on seat surfaces are deployed in domestic environments (Vogl et al., 2017), work and education related (D'Mello et al., 2007a), and public spaces, as well as vehicles (Riener and Ferscha, 2008). Also in screen based scenarios (Griffiths et al., 2014) and Human-Computer-Interaction (Witchel et al., 2016). Sometimes, these seat surfaces are part of a larger network of sensors in smart environments in multimodal sensing approaches, or function as individual, stand-alone sensing systems for specific use cases. This section gives a brief summary on other works in which chairs have been utilised as a sensing system, and identifies them as a commonly used object for social sensing in smart environments.

3.2.1 Social Sensing in Ambient Environments

Connected homes and IoT devices have become a familiar idea in our society and are used to track our activities, to monitor our movements for the suggested purpose of safety, comfort and often health. This happens outdoors and indoors, in public as well as in domestic spaces. Monitoring and assessing social dynamics of spaces that are built for interactional gatherings can furthermore inform future design, since it reveals how space is used, and by whom.

This 'social performance' of environments is traditionally captured with camera systems, especially in public spaces like gyms (Khurana et al., 2018) or market places (Gardair et al., 2011). Advanced computer vision methods and wireless communication technologies like bluetooth (Clark et al., 2018) have improved the performance of this approach, but other modalities have been popularised, too. Especially interior spaces offer a versatile use of different pervasive sensing methods, both in domestic and public settings like theatres (Theodorou and Healey, 2017) or office environments (Milenkovic and Amft, 2013). In domestic environments, including care homes, ubiquitous computing is used for activity recognition to track individual's movements (Wilson et al., 2015), but also to track interaction between residents (Singla et al., 2010). Many ubiquitous sensing systems are suggested for applications surround elderly care and health monitoring, but also communal spaces for students, equipped with different media have been explored (Brignull et al., 2004).

Soft Sensing Objects

Deploying sensing systems in these environments ubiquitously to not distract from and affect the subject's actions and intentions is key to this idea. Therefore, objects that are already in this environment have been utilised as sensing areas by either equipping existing objects with new sensors (Poslad, 2011), utilising existing properties of objects as sensing surfaces (Sato et al., 2012; Vogl et al., 2017), or replicating objects with embedded sensors (Gaver et al., 2006). Here, the materiality of the sensing object is key for ubiquitous integration into the environment. Especially in domestic homes, many interior objects we interact with or come in contact with consist of a soft surface - ranging from carpets (Kim et al., 2016) to table cloths (Gaver et al., 2006) to pillows (Schelle et al., 2015). What most of them have in common is the material they are made of: textiles. The sensor types used in these objects vary. Pressure sensors are common and easy to deploy, for example to detect the weight of objects (Gaver et al., 2006). But also accelerometers and vibrotactile feedback were used for posture detection in carpets (Kim et al., 2016) and seat cushions (Ishac and Suzuki, 2018), and temperature as well as humidity sensors are deployed in pillows (Li and Chiu, 2018). While some of these sensors are possible to be produced of textile materials, the latter examples include deploying of more rigid components into soft, textile objects.

The Social Performance of Furniture

In domestic smart environments, in addition to soft surfaces, furniture plays an important role when utilising everyday objects as sensing surfaces (Park et al., 2003). They present the objects people are most commonly in contact with and are therefore appropriate surfaces to capture activities, movements or postures. They also allow for a relatively easy integration even of bulky sensing equipment and can house larger sensing systems than wearable or on-body designs. Early prototypes like the ambient kitchen by Olivier et al. (2009) demonstrates how multimodal sensing approaches, including cameras, RFID sensing and accelerometers mounted on furniture, allows for continuous and accurate monitoring of people's activities and movements.

3.2.2 Smart Chairs and Pressure Sensors

With chairs being one of the most used objects when measuring people's sitting postures, are chairs. This has a good reason, and has been proven successfully in multiple studies, as well as commercial products[1]. People frequently change the position of the torso, lower body, and feet during seated conversations. These movements necessarily cause pressure changes on the surface of the chair and are detectable by measuring changes in resistance. Previous work has investigated the use of chairs to not only classify postures through pressure sensors, but to detect affective states as well, creating pressure maps of both, static and dynamic postures - posture identification versus continuous tracking (Tan et al., 2001; Slivovsky and Tan, 2000; Arnrich et al., 2010). The number of pressure sensors and postures, their arrangement, and study context in these works varies.

An overview of the work discussed here can be seen in Table 3.1, showing number, position, and type of sensing systems.

[1] see Tekscan BPMS https://www.tekscan.com/, and BodiTrak https://www.boditrak.com/

Number and Position of Pressure Sensors

Commercially available pressure measurement systems, such as BPMS (Body Pressure Measurement System) by Tekscan[2] have been used in many of these works (see for example D'Mello et al. (2007a) and Arnrich et al. (2010)), which consists of a plastic mat with up to 2000 integrated pressure sensors that allow for the creation of detailed pressure maps. But also lower resolutions as presented in (Meyer et al., 2007) are able to detect movement and classify postures. The number of sensors on the chair has decreased over time, earlier works using over 4000 pressure units (Tan et al., 2001), and more recent works deploying only 4-12 sensors on a chair (Griffiths et al., 2014; Kim et al., 2018; Shibata et al., 2013; Bibbo et al., 2019), as is listed in Table 3.1. The amount of sensors additionally affects the arrangement of the sensors, being configures as a matrix, or as sensor patches.

These varying number of sensors is distributed across the entire chair surface, and occasionally on the floor, too (Shibata et al., 2013). Almost all works place sensors on the seat surface as well as back rest of the chair, only Griffiths et al. (2014) places pressure sensors on the back alone. In comparison, using only the seat and not the back is a more popular solution, as demonstrated by Meyer et al. (2010a) and Kamiya et al. (2008).

Contexts of Posture Measurement

Applications for these sensing systems have been in the analysis of posture to improve seating comfort (e.g. Milivojevich et al. (2000)), designs for objects involved in rehabilitation (e.g. for wheelchairs) and Human-Computer-Interaction. For example, presenting chairs as novel haptic interfaces for computer games (Tan et al., 2001; Soave et al., 2020), or as a system to measure people's cognitive states in various situations (Arnrich et al., 2010; Bibbo et al., 2019). This includes measuring a car driver's fatigue (Furugori et al., 2003) or identifying individuals (Riener and Ferscha, 2008). Affective states are measured with pressure sensors in chairs, too. Shibata et al. (2013) detects states of arousal, while (D'Mello et al., 2007a) measures boredom, and Arnrich et al. (2010) stress levels.

These studies showed the large range of information a chair can reveal about its occupier, although the study settings of these works are often similar. The data is mostly collected in single users, being confronted with a screen based task. While results of single participants engaging with a screen can say a lot about their behaviour and engagement in a different setting, too, our bodily movements when in the same physical space with our interactants may be different.

Additional Modalities

In some works mentioned in Table 3.1 use other modalities in addition to pressure sensors on the chair. Capacitive sensing is used for detection of seat occupancy (George et al., 2009), or EMG sensors,also deployed on the chair's back, help to combine sitting posture detection with heart rate measures (Griffiths et al., 2014). Shibata et al. (2013) adds accelerometers to detect states of arousal, and Mota and Picard (2003) uses five different modalities for their data collection. In few studies focusing on sitting posture detection, no chairs are used at all, but approaches to wearable sensing are explored, for example optical markers (Nathan-Roberts et al., 2008) or accelerometers (Chalkley et al., 2017b; Witchel et al., 2016).

Chairs can be equipped with feedback technologies, too. For example, a chair detecting sitting postures can actively support posture correction (Ishac and Suzuki, 2018) through tactile feedback.

[2] see https://www.tekscan.com/

Author	no. of sensors	sensor system	placement	study context	no. of postures
Tan et al. (2001)	42x48(x2) = 4032	Tekscan BPMS	seat & back	sitting postures in office environment	14 (static & dynamic)
Mota and Picard (2003)	42x48	Tekscan BPMS	seat & back	screen based game / learning	9
D'Mello et al. (2007a)	38x41	Tekscan BPMS	seat & back	screen based, detect boredom, engagement	n/a (postural features)
Kamiya et al. (2008)	64	"Flexiforce" sensor sheets	seat	single user sitting postures	9
Meyer et al. (2010a)	240	textile based sensor matrix	seat	single user sitting posture classification	16
Arnrich et al. (2010)	1024	Tekscan	seat & back	measuring stress level (single user)	n/a
Shibata et al. (2013)	12	Nintendo balance wii board	floor(4), seat(4), back(4)	measure arousal from sitting postures	n/a
Griffiths et al. (2014)	4	square force sensors	back rest	screen based, single user	7
Kim et al. (2018)	10	textile based sensor array	4 in back, 6 on seat	screen based single user	7
Bibbo et al. (2019)	8	pressure sensors on office chair	4 on seat, 4 on back	measure cognitive engagement	8

Table 3.1: An overview and comparison of selected works using pressure sensing chairs for capturing postural movement.

In the domain of virtual reality and gaming, haptic feedback in chairs is used to enhance users' experience (Soave et al., 2020).

Conclusion

In the works reviewed here, several use the same commercial pressure sensing system, while others deploy individually commercially available sensors, see Table 3.1. Despite it has been shown that fabric based pressure sensors can detect sitting postures with high accuracies, too (Meyer et al., 2010a), only few others use textile solutions that can be integrated in the chair's surface. In this thesis, one aim is to establish textile based pressure sensors further as a reliable sensing system in detecting postures and social signals, which is why in this chapter, textile pressure sensors are designed and tested.

Additionally, the settings of many works include single users and are missing a comparison with multi-user scenarios, though testing features that occur in social contexts. In this thesis, I try to counterbalance this and look at the use of smart chair covers in multi-user settings of social encounters, not isolating individuals but examining postures of conversation partners.

3.3 Ethnographic Observations

The objectives laid out in this chapter are (1) to design and test a sensing chair cover, for which the appropriate parameters like size, amount, shape and type of sensor, as well as materiality need to be determined, and (2) to investigate nonverbal patterns of conversational behaviours that the proposed chair covers look to discriminate. The starting point for both are a series of ethnographic observations that formed the base of hypotheses on body movements and postures that co-occur with conversational states, as well as to establish a ground truth to build design and experimental settings on. The findings of these observations inform the settings for future user studies extending this chapter, and also supported the further specification of this research overall.

3.3.1 Methods

The observations focused around seated conversations in non-domestic, interior environments: an educational environment and an office and work space. The focus of the observations were multi-party informal face-to-face meetings between two and four interactants. Within these informal meetings and casual conversations, the observations focused on capturing postural states that correlate with conversational behaviours. Special attention was paid to patterns of movement between speakers and listeners (determine eventual “typical” speaker and listener postures), forming hypotheses about these patterns I could later compare the data with that is collected, and presented in the next sections of this chapter.

Observation Spaces

The interior spaces in which the observations were carried out were a common room at the School of Electronig Engineering at Queen Mary University of London, and the Digital Catapult Centre[3] at Kings Cross in central London. Both spaces have multiple tables deployed and are used for casual social interactions, as well as informal meetings and discussions. Permission to conduct my ethnographic observations was given by administrative and managing staff of both places[4].

Observer & Observation Tools

The ethnographic studies were conducted by one single observer, the author of this thesis. The tool to capture them were analog sketching tools - a paper notebook and an ink pen. Capturing observations with drawings was done to retain anonymity of the subjects. No cameras, audio or other sensing technologies were used to record the observed scenarios. All drawings (throughout this and the next chapters) were produced by the observer. The amount of detail captured in these scenarios varied, and was subject to available visibility, as well as available time to produce the drawings. Figures 3.2 and 3.3 present a selection of these figurative sketches. Facial details or other elements revealing the observee’s identity were not captured. Instead, chairs and tables were included, as also seen in the Figures.

3.3.2 Observation Subjects

The before mentioned environments these observations were conducted in determined what types of relationships, and to a degree, what demographics of people would be present. At the university,

[3] https://www.digicatapult.org.uk/
[4] in verbal form only.

research students were studied, while at the Digital Catapult Centre, people from different backgrounds, academics and other staff members were subject of observations. The observees interacted in dyads, groups of three, and groups of four. Larger settings were excluded from this ethnographic analysis because it exceeded the focus of this research.

The relationship between subjects was amicable, but within a work environment. The observed groups were colleagues that appeared to have different levels of knowledge of each other, but were no strangers. That also determined the atmosphere of the conversations as well, which was casual and relaxed. The age or identity was not revealed, as the observer did not interact with observees. The compositions of the observed groups were mixed-gendered, as well as single-gendered.

The duration of the captured interactions were in a range between brief encounters over a coffee break that lasted a few minutes and group meetings that could last for 2 hours. All observations were conducted from a distance of a few metres from the conversation, and the content of what was discussed in these encounters was not captured in any form. With the interactions being observed in common areas, often other people passed by or were present in the rooms, but only observations were documented that were not interrupted by external individuals, since this would have affected postural behaviour and would have changed spatial formations.

3.3.3 The Role of Furniture in Seated Conversations

Pieces of furniture like a table can change the dynamics of an interaction, restrict or enable certain social hierarchies, formations, as well as numbers of possible interactants. But they can also affect individual's movement as such and afford the range of possible postures within the conversation.[5] This is suggested in existing literature, for example in the works of Kendon (1970), Bull and Connelly (1985), Schegloff (1998) and Scheflen (1964), and is supported by my observations reported here. The findings here describe the effect on conversational movement and maintained sitting postures when a table was present.

Table Shapes and Social Hierarchies

Different roles within a conversation are often embodied through spatial formations, or F-Formations (Kendon, 1990b) between participants. For this, the my observations looked at potential differences in social as well as postural dynamics of a conversation around a rectangular and a circular table, like the ones sketched in Figure 3.1. These shapes and designs of pieces of furniture in our everyday environment predetermine such F-Formations. Observations of meetings around a rectangular table had the interesting effect of putting the person at the head or end of the table in a position that facilitated more marked and frequent postural movement in addition to associated rights to speak reported in literature. Interactants at the head position had different postural patterns overall, appearing more vivid and posturally more in motion, also having longer and more frequent periods of talking. On the other hand, round tables distributed those rights both for speech and postural movement more equally across all conversation partners. This finding backs suggestions of existing work, e.g. (Kendon, 1990b)

Followingly, using a round table in further research I would conduct was a decision not only suggested by literature, but reinforced and confirmed by the ethnographic findings.

[5]This, by the way, is also what our clothing allows, in a far more direct way than furniture. But this is elaborated on and discussed in Chapter 7 of this thesis.

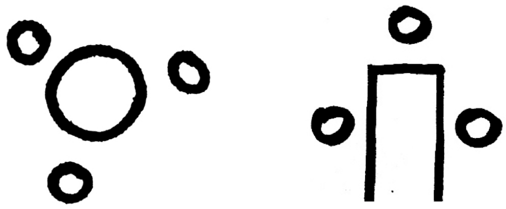


Figure 3.1: Sketches of round and rectangular table shapes affecting seating arrangements and social hierarchies.

Upper and Lower Body Movements

The presence or absence of a table makes an overall significant difference to the dynamics of postural movement of participants. These differences were notable both in upper and lower body postures, but eventually have drawn the attention to movements in the latter. In particular, a table can support a variety of postures in relation to leaning forward, resting arms, elbows and hands on the table's surface, which sometimes supports exaggeration or emphasising of postures, which furthermore help to demonstrate behavioural cues (e.g. it is often suggested attentive listeners lean forward, see (Bull, 2016)). When observing seated conversations without a table present, these postures were naturally less overt. In this sense, a table can be seen as an actively used artefact to perform postures and support conversational cues. This applied to gestural movement itself, too. While speakers knowingly move their hands significantly more than listeners, I observed that the presence of a table allowed listeners to move their hands more frequently, too - though not as rapidly and vivid as speakers do. While in "un-tabled" scenarios, hands tended to rest more quietly on the lap, or are being crossed in front of the chest, a table allowed for gestural fidgeting, moving objects on the table around, resting the hands on the table instead of on the lap, or even performing more discreet hand-lap interactions that are concealed from other conversation partners (e.g. tucking hands between thighs, or rubbing their thighs and tapping their knee with one or more fingers).

Regarding lower body postures, observational findings suggest that whenever a table was present, there was also more frequent movement of the feet that exceeded the action of crossing legs. Although not necessarily visible to other interactants, orientation of lower legs and feet sometimes followed and emphasised torso orientation, or contradicted it to form a body torque (Schegloff, 1998). This is particularly interesting when considering again that the legs are not directly visible and therefore not an obvious interactional signal. Actions like leg bouncing, tip-toeing, fidgeting or leg-hand touch interactions are more frequently performed than initially anticipated and seem to be a potential channel of compensation of the more consciously performed torso and gestural movements. On the other hand, marked leg crossing postures appeared to occur less frequently with a table present than without. No table resulted in more "closed" (Mehrabian, 1968a) and seemingly interlocked leg crossing postures, while a table appeared to allow for more relaxed and comfortable leg postures. Other leg related sitting postures, however, were performed more overtly when not on display. One explanation of this could be that participants felt more secure to perform postures hidden from others, as if a table provided a layer of protection to some, enabling more improvised, non-directed movement. I observed that a table can therefore act as an important instrument dividing the more incidental and the more intended postural cues of individuals.

In summary, these observations suggest, that, while the torso is the most visible body part in a seated conversation, the legs and lower body in general can reveal a great deal about subconscious social behaviours, too and appear to be an under-examined parameter in the studies of nonverbal communication.

3.3.4 Speaker and Listener Postures

The most distinct conversational states are those of speakers and listeners. As mentioned before, gestures and facial expressions have been studied in great detail to distinguish speakers and listeners, establishing patterns of movement and postures that are associated with either states. Here, my observations focus on overt bodily movement of both, the lower and the upper body, as well as changes of maintained postures as well as between conversational states. In particular, I draw attention to leg crossing and leaning forwards or backwards. A brief overview of the key postural characteristics for each of these conversational states described here can be seen in Table 3.2.

Table 3.2: Observational Hypotheses of Speaker and Listener Postures as well as the transitional state between the two.

Conversational State	Observed Postural Behaviour
Speaker	sitting straight, no leg crossing or very marked torso movement
Listener	more overt movement in torso and legs
Transition	common changes in overall posture

Speakers

Generally, speakers were sitting mostly straight up and moved their torso only in subtle ways and did not perform any marked movements during a turn (gesturing excluded). However, when the torso was moved, it was found that forward moving postures were more common than backward leaning postures. The lower body seemed to move even less in any marked way, and it was also observed that crossing legs was not commonly performed by speakers either. It was only towards the end of a turn or a speaker pause that small shifts and postural adjustments occurred, including leg crossing postures.

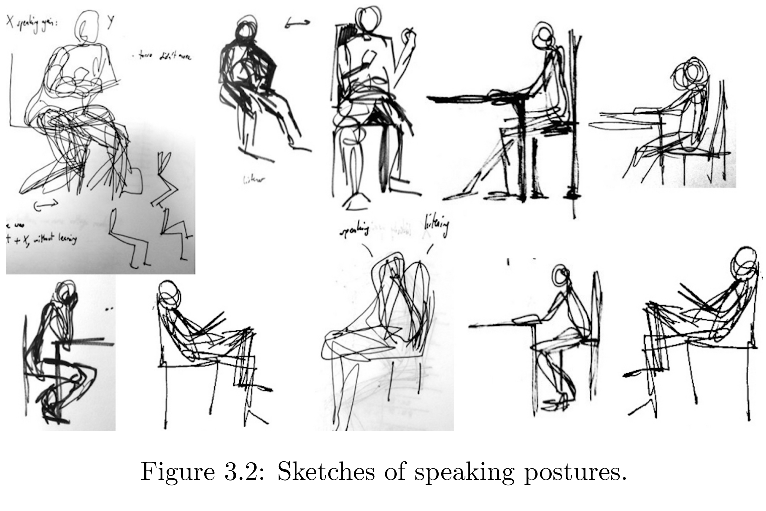


Figure 3.2: Sketches of speaking postures.

Listeners

In contrary, listeners appeared to be far more active. They were more likely to execute more obviously noticeable and marked movements in both their upper and lower body. This includes overt leg crossing, moving the torso back or forwards, and performing an overall change in the so far held sitting posture. One possible explanation for this could be that these changes in posture are believed to be less disruptive to the conversation when carried out while listening, rather than during a speaker's turn. The observations also suggested that there was also a postural difference between first and second addressees. In the case studies here, it appeared as if second addressees leaned towards the speaker more often than the directly addressed interactants.

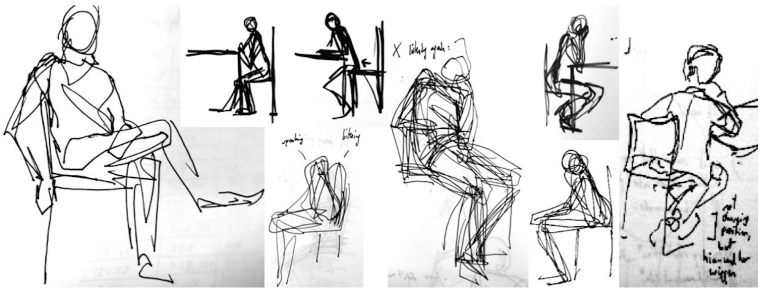


Figure 3.3: Sketches of listener postures.

Transition Between States

When changing from speaking to listening mode, or vice versa, I observed that participants often signalled their intention to do so through postural adjustments. For example, a listener and second addressee who was leaning back, leaned forward and straightened their back just before taking a turn. Additionally, when they had their legs crossed, they were likely to "uncross" their legs at the start of a speaking turn. Vice versa, when ending their turn, speakers sometimes leaned back and /or crossed their legs. Both of these postural changes often seemed to act as signifiers of the participants' intention or as visual emphasis of this conversational state. This phenomenon of observed preparatory movements is something that will be elaborated on in Chapter 6, while for now, I focus on the movements within a speaking turn and listening mode.

3.3.5 Conclusion and Further Implications

In the beginning of this section, it was mentioned that these observational findings would help to inform further procedures in regards to the design engineering and the methods of evaluation for a textile based sensing system measuring nonverbal behaviour.

Summary

In general, the observations back up findings of literature in regards to how the shape of objects, such as a table, affects the social structure of an interaction (Kendon, 1990b, 2010). Also the findings with regard to postural movements and postural states correlating to conversational events and behaviours, also confirm previous findings of Scheflen (1964, 1972) and Schegloff (1998). In some regards, however, my findings expand already established and well known embodied social behaviours, especially in regards to lower body movement, that was noticed and observed with more attention than most past works have.

Based on these observations and the review of related studies, it was decided to place sensors on a chair's seat surface and backrest, as this arrangement would be able to cover both, lower and upper body movement.

Implications for Further Steps

Firstly, the observations of different behavioural states in correspondence to postures supports an approach for investigating postural differences between gross conversational states further, like distinguishing between speakers and listeners before exploring more fine grained nonverbal behaviours and micro-movements. These more overt states will be the centre of the following exploratory study because at this stage, it is not known yet how successful the self-made textile sensing system will be.

Secondly, after observing the shifts of postural movement in listeners and speakers, and noticing marked differences between these behaviours, the type of sensors suitable to capture such postural behaviours are pressure sensing systems, which have also been proven a successful modality in previous related work (D'Mello et al., 2007a; Tan et al., 2001). This allows to collect the changes of pressure applied on the seat and back of the chair to identify different postural states. The number of sensors I will use is drawn from the symmetric arrangement of the human body in combination with the different body parts that are moved at the same time during a postural change, for example, in leg crossings. Indications of the areas in which sensors should be placed was also drawn from the observations. These conclusions are in line with existing literature, where either a large amount of sensors has been places all over the surface of a chair (Arnrich et al., 2010; Tan et al., 2001; D'Mello et al., 2007a) or a minimal amount positioned across the seat and backrest of a chair (Shibata et al., 2013; Griffiths et al., 2014).

Another decision based on the observational findings of different arrangements of interactants were the settings and groupings for the user studies. Here, I examine groups of three people to be able to collect data about speakers and two types of listeners: first and second addressees, and will use a setting with a round table to conduct the studies.

3.4 Chair Cover Design

Here, I introduce the design of a custom made sensing chair cover. Simple textile pressure sensors that are embedded in a fabric chair cover are developed to capture postures of chair occupiers during conversation, and to explore nonverbal behavioural patterns of speakers and listeners. This is achieved with sensor patches of conductive fabric and resistive foam, sewn onto the back of the chair cover, marking significant areas where the upper and lower body come in touch with a seat. The sensing system consists of eight such sensor patches per cover, each assembled by hand, and connected to a circuit board to collect the data from pressure changes.

First, I present the design process and prototyping of the textile sensors, centering around the material properties of electronic textiles. For the development of the textile sensors, a variety of conductive materials was experimented with to select the best performing textile for the intended use. Secondly, the process of integrating these sensors into a custom made chair cover is described, determining placement and number of sensors, as well as other factors relevant to the engineering of the final sensing system, including the choice of chair type that would be used for future studies. In

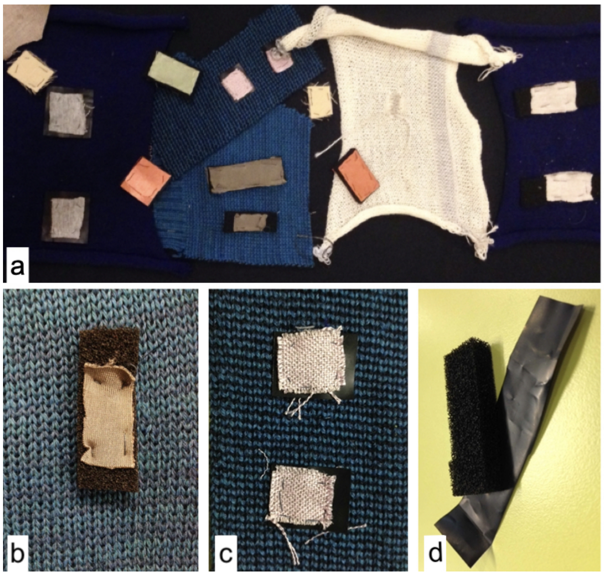


Figure 3.4: A variety of conductive materials: a) first design of sensors and chair cover: sensor patches are too big and chair has rolling legs - both was adapted for final design. b) testing of different sizes and shapes of sensors. c) and d) testing of different conductive materials. d) two different resistive materials: foam and velostat.

this section, the iterative design process to approximate the final prototype is summarised, illustrated in Figures 3.4, 3.6 and 3.7, showing different materials, sensor shapes, chair cover designs and the circuit board.

3.4.1 Textile Pressure Sensors: Design and Development

The pressure sensors were made from two types of material: conductive woven fabric and resistive foam, hand cut and sewn into soft sensor patches that were then manually attached to the fabric chair cover; and hard electronic components. The sensor patches consist of three layers: the bottom and top layer of conductive fabric, and the middle layer of the resistive foam. The choice of materials and the manufacturing techniques had to meet the requirements of the use case. The sensors had to be soft, unintrusive, comfortable to sit on, yet robust, stable and reliable. These soft textile materials were linked to rigid electronic components and connect to the circuit board that held the battery and microcontroller to collect data from the sensors.

Conductive Textile Materials

An important aspect of the design was the choice of material, since this affected the behaviour of the sensor, its deployment possibilities and measurement sensitivity. Two different materials are needed to build a piezo-resistive textile pressure sensor: a highly conductive fabric and a resistive material. While the chair cover as such required to be a flexible, stretchable sensing system, the pressure sensors themselves did not need to be stretchable. In fact, the more robust they would be, the more stable would the sensor readings be. Therefore, I experimented with woven fabrics, since this textile structure, in comparison with knitted fabrics, is less elastic and while still soft, provides more support in maintaining its shape over time.

The conductive materials experimented with are displayed in Figure 3.4a-c. For this stage of

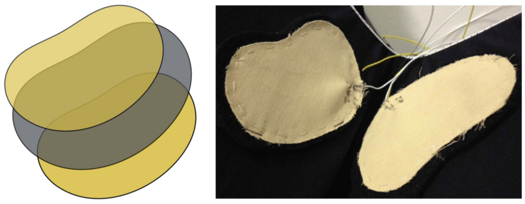


Figure 3.5: Close-ups of sensor design: **Left:** the schematics of the piezo-resistive sensor with 2 conductive layers on the outside, and a resistive layer in between. **Right:** two hand stitched textile pressure sensors in three layers. The non conductive cotton layer of the silver fabric faces up, the conductive side faces the resistive foam. The layers are stitched together with a non elastic synthetic sewing thread in lose stitches.

prototyping, small sensor samples were produced that were examined for their conductivity (and resistance), touch, and robustness. For robustness, different densities of weaves, e.g. a tightly woven copper taffeta, as well as more a more losely woven twill were sampled. Conductivity was tested of different silver coated, copper, and carbon fabrics The touch and feel of the fabrics was determined by the softness of the material and textile structure. All fabrics examined, and shown in Figure 3.4 are commercially available.

After testing various woven conductive fabrics with similar properties in regards to their performance and behaviour as a pressure sensor (Fig. 3.4), the fabric chosen for the layers connecting the resistive material was SaniSilver, a 164g/m^2 weave, purchased from LessEMF[6]. It is woven as a double-face, a reversible fabric with silver yarn showing on one side of the fabric, creating a highly conductive surface (<1 Ohm per square), and a (non-conductive) cotton yarn visible on the other, so that the fabric as a whole is conductive on only one side. This allows for additional shielding from direct touch with human skin and other conductive surfaces (for example metal parts in chairs), that could affect the conductivity of the sensor materials and affect the circuitry. The washability of the fabric is limited due to the properties of the silver yarn. It is possible, however, to hand wash the fabric and use distilled water to not damage or affect its conductivity. A close-up of this fabric is seen in Figure 3.5.

The resistive material I used was an antistatic, ESD foam, see Figure 3.4d). It is made of polyurethane impregnated with carbon and is commonly used as packaging material for electronic parts. Its consistency is soft with a height of ca. 5mm and it is easily compressible due to its relatively low density, which makes it appropriate for pressure sensing and comfortable to sit on.[7]

The piezo-resistive pressure sensors are then constructed so that two swatches of the conductive fabric, using the layer showing the silver yarn, are facing the resistive foam on both sides, as is shown in Figure 3.5. When pressure is applied to the sensor patch on either side, the foam compresses and reduces the resistance between the two fabric swatches. This change in resistance is measured by a microcontroller.

Preliminary Testing

All materials sampled were examined for their reliability as a sensor. By this, I mean the behaviour of the sensor over time. The range of values, the deformation of the material when pressed, and its recovery into original state are measured and visualised, see Figure 3.6d. The fabrics used for

[6] https://www.lessemf.com/

[7] Such ESD foams come in different densities and foam heights, see e.g. https://uk.farnell.com/w/c/static-control-site-safety-clean-room-products/esd-protection-products/esd-anti-static-foam/prl/results?st=foam

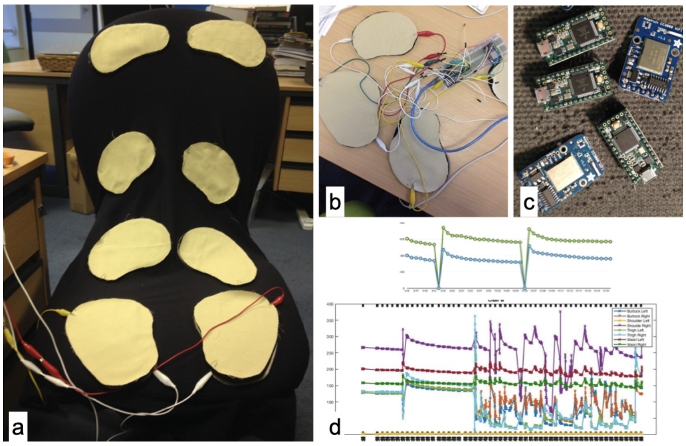


Figure 3.6: Early prototyping stages: a) first design of sensors and chair cover: sensor patches are too big and chair has rolling legs - both was adapted for final design. b) testing of different sizes and shapes of sensors. c) microcontrollers (Teensy 3.2, HuzzahFeather). d) simple data visualisation of pressure sensor patches.

the final chair cover had to measure a large range of pressure, that would vary widely from one measurement to the next, and over a period of up to 30 minutes.

The sensors were connected with detachable wires (using corcodile clips, as can be seen in Fig.3.6a-b) to an Arduino, plugged into the computer with a wire. Analog readings were taken and displayed in real time. Observing the sensors' behaviour when different pressure was applied informed the choice of material, as well as the final design of a circuit board. Each sensor was individually observed and tested to identify the range of reading values it would provide and to find a suitable resistor that was integrated in the circuit board.

Electronic Components

Although sensors can be made out of soft and flexible materials, there are still some components made of rigid, hard and inflexible materials, that are a necessary part of the circuitry and hardware setup. These components are: the power supply, the microcontroller, and connectors between hard and soft elements. I used a Teensy 3.2. microcontroller, taking advantage of its small size, depicted in Figure 3.6c and compatibility with the software used here, Arduino. To power the circuit board, I used a USB battery that was plugged into the Teensy.

The circuit board was designed as a voltage divider circuit the sensors were put into. To link the sensors to the circuit board, I used thin, insulated wires that were embroidered onto the conductive layer of the woven fabric with conductive thread (a twisted silver thread purchased from Statex[8]). The end of these wires was first stripped off, punched through the fabric to connect with the conductive silver threads of it, and sewn on in a coiled form, see Figure3.5(right). Each sensor was equipped with two of those embroidered on wires, connecting the sensor to an analog pin on the microcontroller, and to connect to Power (3.3.V) and Ground.

The circuit was soldered onto a strip board that housed the microcontroller, the datalogger (with an SD card), the battery and the sensor connections, too. The front and back of the final design is shown in Figure 3.7a-c. This small board was later placed underneath the chair, taped onto the floor. For easier prototyping and debugging, the circuit board was made so that the microcontroller

[8]https://statex.de/en/fibres-and-yarns/

and the datalogger could be simply removed and plugged back in, as seen in Figure 3.7d.

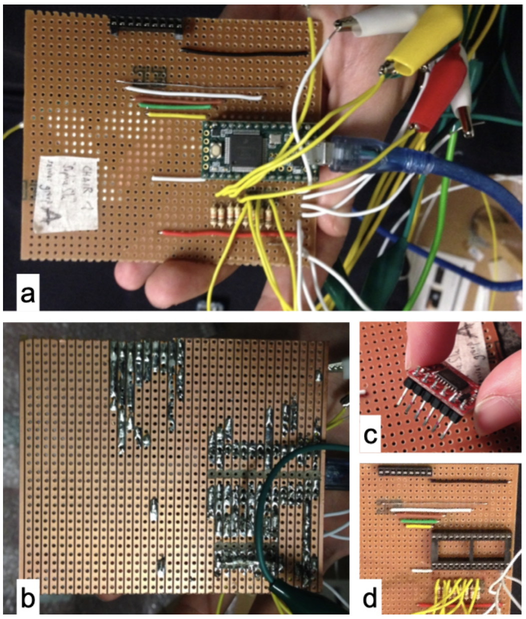


Figure 3.7: The chair's circuit soldered onto a strip board: a) the final board with the microcontroller, resistors and connection cables attached; b) the backside of the board, showing the soldering points; c) the datalogger with a micro SD card, where the data was stored; d) the circuit board without the electronic components attached: header pins with black framing.

3.4.2 The Chair Cover

The shape and size of the chair cover itself was determined according to available chairs at the research lab at the Computer Science department at Queen Mary University of London[9]. For all future experimental settings, I used four legged chairs without wheels that had a back rest, but no arm rest, as is shown in the chair in Figure 3.8. As the base material of the chair cover served a knitted light weight interlock fabric made of a cotton and elastane mix. An elastic ribbon (textile rubber band) was sewn along the edges, so that the fabric could easily be mounted onto the chair. The elastic ribbon, similar to a rubber band, would hold it in place. Additionally, the fabric band stitched onto the sides of the chair cover allowed it to tied it closer to the chair between the seating and the back rest surface.

After the sensor layers were hand stitched together to form the final sensor patch, the patches were attached to the layer of the jersey fabric of the chair cover with the same technique: using a cotton sewing thread and a loose hand stitch to not compress the foam, but to secure the exact position of the sensors on the chair cover.

Sensor Placement

The sensing system was designed so that eight sensor patches were deployed in one chair cover, distributed symmetrically as shown in Figure 3.8, and in Figure 3.9 (left) for a schematic illustration. I divided the areas to be sensed into four key areas, two on the backrest, and two on the seat of the chair. The distance between the sensors and the edges of the fabric cover were measured (Fig.3.9,

[9]since these chairs would be used for future user studies.

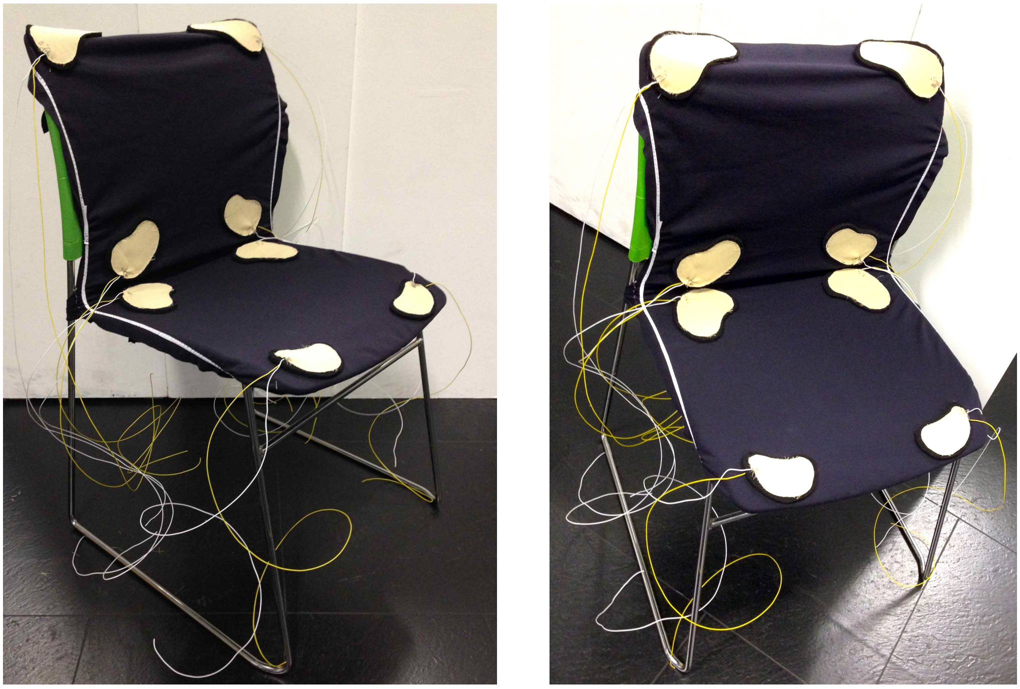


Figure 3.8: The final prototype of the chair cover, facing inside out

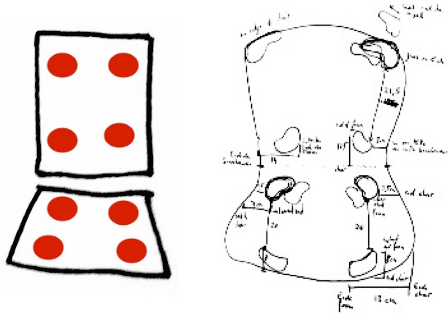


Figure 3.9: Schematics and sketch of the distribution of textile pressure sensors across the fabric chair cover.

right) for symmetric positioning. . While in some other works, the number of sensors deployed on a chair, is up to 2000 pressure sensing elements (Tan et al., 2001), I intended to use a small amount of sensors as has been proven sufficient in more recent works (Shibata et al., 2013). Moreover, since a goal was not to identify fine grained sitting postures alone, but to explore social behaviours through such, I started with a 'bottom-up' approach, identifying the most basic and fundamental areas in which key postural movements were observed: shoulders, lower back, buttocks, and upper legs (thighs). These are the areas that were defined on the chair cover and into which the sensors were placed.

This was also approximated in earlier prototypes and informed by observations. The size of the seating and back rest surface, for example, prompts the sensors to be positioned towards the edges of the areas because of the overall relatively small surface area the available chairs provided compared to, for example, desk chairs with larger back rests. The body therefore came in touch with the entire surface of the planes on back and seat.

3.5 Evaluation

The final design of the chair cover presented above now needs to be tested for its suitability as a social sensing platform. With the aim of the design to be deployed in an interactional context, measuring postural behaviour in conversation, a user study has been conducted.

This section describes the design and settings of this study, that was also approved by the university's ethics committee[10].

3.5.1 Spatial Arrangement

In this work, seated social interactions of small groups are examined. Assessing different roles within a conversation, arrangements of three-way interactions were established. To ensure equal social and conversational rights in such constellation (Kendon, 1990b), a round table was chosen and the three interactants were seated around it equally distributed, such as shown in Figure 3.10, with the schematic illustration on the right, and a still image of the real life scenario on the left.

The chairs used in this experiment are the same chairs that were used when adjusting the chair covers' size and sensor positioning - plastic and metal chairs as seen in Figure 3.8 and 3.10 (left), too. The goal is to capture the movements of each participant in these triads, so different relations between conversation partners can be assessed. For this purpose, multiple identical chair covers were produced.

Figure 3.10: Arrangement of how participants were seated on a round table - in equal distance and distribution, the sensing chair covers highlighted in red (right).

3.5.2 Participants

Participants were recruited within the department as well as externally, of different academic and non-academic educational degrees. They were allocated into groups of three friends or colleagues to ensure they all had some initial level of familiarity with each other. As mentioned in earlier works on nonverbal behaviour, familiarity is a factor that supports potentially more subtle postural movement and can support the display of other social signals, too (Wiemann and Knapp, 1975; Riskind and Gotay, 1982). In total, 9 trials were conducted, collecting data from 27 participants, of which were 11 female and 16 male and between the age of 20 and 40. The grouping of the participants followed all possible configurations: male only (2 trials) and female only groups (1 trial), as well as mixed groups with either two females, one male (2 trials); or one female, two males (4 trials).

[10]reference QMREC1778a, see Appendix A

3.5.3 Procedure

All sessions of the experiment were carried out in the Human Interaction Lab at Queen Mary University of London. The groups of three were seated around a circular table on chairs equipped with the sensing fabric covers. The chair covers were mounted on the chairs with the integrated sensors on the backside, facing he chair's surface and not coming in direct touch with the chair occupier. Because the sensors were integrated on this back side of the cover, they were concealed from the participants' view. Due to their materiality and soft properties, their presence was not noticed when sat on the chair, which was later commented on by participants. The sensor elements, with the foam as the thickest material, are thin enough to not create a difference in height or feel like an uneven cushion. The surface is flat and unintrusive.

Once seated, the participants were asked to resolve a moral dilemma: the balloon task[11]. This is a fictional scenario describing three people in a hot air balloon that is about to crash, if one of the passengers does not jump to their certain death. The participants' task was to discuss options and come to an agreement on how to resolve this dilemma and who to throw off. I aimed to record 15 to 20 minutes of conversation, so if not having come to an agreement after this time, participants were given the option to stop the conversation or carry on (vice versa, if they came to an agreement faster, alternative scenarios were provided to encourage further discussion). The exact instruction can be found in Appendix A.

Prior starting the experiment, participants were given a consent form and an information sheet stating that this research explores the relationship of postural states and social behaviour in group discussions such as this collaborative task. At this point of the experiment (prior and during the recording), it was not revealed to the participants what sensor type was deployed in the chair covers, or where the exact position of the sensors were. They were fully debriefed after the session had finished. Research ethics approval was obtained and consent forms were signed by all participants before any video, audio and pressure sensor data was collected. Appendix A documents the details of this procedure, including consent forms and information sheets participants were handed.

After signing the consent form and being explained the collaborative task, the sensing chair covers were switched on just before participants sat down around the table, and the recording of video and audio started.

3.5.4 Data Collection

Sensor Data

A circuit board with the microcontroller (a Teensy 3.2), the micro SD card and the battery all mounted on one strip board, was placed underneath each chair. The wires were also gathered there and laid from the sensors to the circuit board along the legs of the chair (2 wires per sensor). Pressure readings were recorded with a sampling frequency of 4Hz (4 readings per second), the unit of measure using these piezoresistive sensors is Ohm (Ω). Each sensor was assigned to an analog pin on the microcontroller providing 3.3. volts to run the programme, which read analog output values from the sensors. Moreover, each sensor was individually observed and tested to identify the range of reading values it would provide and to find a suitable resistor that was integrated in the circuit board.

[11] Other comparable dilemmas and tasks commonly used in interaction studies and conversation analysis research are, for example, the Apartment task (e.g. Hough et al. (2016)) and the winter survival task (e.g. Murray and Oertel (2018))

During the experiment, the raw and unfiltered sensor data from the pressure patches was collected. The data was then stored locally on the micro SD cards as simple text files, documenting a time stamp, the name and numeric value of the analog sensor, its corresponding pin and sensor name (number between 1 and 8, identifying its position on the chair cover as well). The decisions to use the raw sensor data and to store it locally without real-time access and data monitoring was made after experimenting with other approaches. In earlier prototypes, filtering and calibration techniques were tested, as well as data collection through wireless communication to a server. These preliminary tests suggested that collecting the raw sensor data was most reliable, and sufficient for the final analysis (reported below), where, amongst other aspects, the relative changes between the participants were calculated. Therefore, also the differences in weight had no effect on the outcome of the analysis and the validity of the sensor data. Moreover, it was useful to examine the data for errors in a raw state, and still enabled normalisation and filtering methods in a further stage of data processing. As for the data storage, tests with WiFi boards were made, sending the data to a server, where each sensor could be monitored in real-time[12]. Slow wifi connections and general network problems caused gaps in data streams and prompted us to collect the data independent from such factors.

Video Data

Additionally, the interactions were captured on two cameras placed in different corners in the room, placed on a tripod. Each participant was wearing a lapel microphone to facilitate speaker-specific analysis of the audio for transcription. Additionally, the audio was captured with microphones mounted on the cameras.

3.5.5 Data Processing and Annotation

The data from the video recordings was annotated using the software package Elan (Brugman and Russel, 2004). This open source annotation tool allows for multiple data streams to be imported and synchronised with one interface, and to be annotated in a merged timeline. An example of the software's user interface can be seen in Appendix A.

Coding Scheme

With the aim of identifying different conversational states from the sensor data alone, I focused on three distinct key behaviours that were hand coded for each participant: talk, laughter and backchannels. When determining speaking modes, periods of overt speech were coded, regardless of postural and gestural changes, or nodding. But exploring postural movement in interaction overall, it was noticed that often, a postural or gestural change was performed immediately prior to speaking. This can make the start of an utterance ambiguous. For the purposes of this study, the beginning of utterances was defined as the onset of speaking, and finished with the offset of it. For laughter, responsive as well as speakers concurrent laughter was noted. Therefore, laughter is annotated for both, speakers and listeners. Backchannels were coded for all continuous verbal particles of response, as well as repair initiations. Common examples of such listener particles are “hmm”, “yeh”, “aha”, etc. An overview of the coding scheme for these behavioural cues can be seen in Table 3.3.

[12] Adafruit IO servers were used (see https://io.adafruit.com/), providing simple visualisations of the incoming data. Also the WiFi module, a Huzzah Feather, came from Adafruit

For further analysis, pairwise comparisons between speakers and listeners were made, too. The elements for listener behaviours were divided into active and passive listeners. While active listeners were defined by the sum of the annotations for backchannels and laughter, “passive” listeners were created from the gaps of all annotations. The same was done with the other coded behaviours, too. This means that within the listening mode, any gross and subtle body movement, as well as nodding or any other conversational action is included. With the aim of distinguishing speakers from listeners, this level of detail in annotations appeared sufficient, although the sensitivity of the sensors allows for richer and more fine-grained distinctions.

Table 3.3: Coding scheme used in Elan.

Tiers per participant	Social behaviour
speaking	verbal utterance
laughter	responsive and concurrent
backchannel	responsive, repair initiation
active listener	laughter & backchannel
passive listener	gaps of all coded tiers

These annotations were marked in the video timeline with an annotation value of 1, while their gaps were assigned values of 0. This created a binary coding scheme for each behaviour, assigning these annotation values to the sensor data as well when the different timelines were aligned.

Timeline synchronisation

To align the annotations with the recordings from the sensing chair covers, the sensor data was imported to Elan as small annotation units of 250ms (4Hz) each, synchronised with the time stamps of the video annotations, and with an annotation value of the pressure reading.

The video was imported to Elan first, and served as a baseline for the merged timeline, onto which the sensor data’s timestamp was fitted. This was achieved by creating a synchronisation aid at the start of each session’s recording. With the chair covers in sight of the cameras, the sensors were pressed to create a marked spike in pressure change - captured by both video cameras as well as the microcontroller printing the pressure values into a txt file. This synchronisation event served as a clapperboard throughout the experiment. Each txt file contained the information of one chair with its 8 pressure sensors, so all sensors of a chair shared the same timestamp. Later, these spikes in sensor data readings were used to import the sensor data files to Elan to match the timeline of the videos showing the pressure spike being performed.

Lastly, the sensor data was recorded at a constant frequency of 4Hz, which made it easy to split it into equal annotation units, with the sensor value documented as the annotation text. This procedure of aligning the different timelines was done in Elan.

Final Data Sets

The merged annotated data was then exported from Elan so that a statistical analysis could be conducted. For this analysis, the first and last 5 minutes of the recorded conversation were excluded to account for eventual postural adjustments and initial biased behaviours due to the study settings (assuming that participants would adjust to a more natural behavioural pattern once familiarised with the setting and once feeling more comfortable in the recording environment). This was also

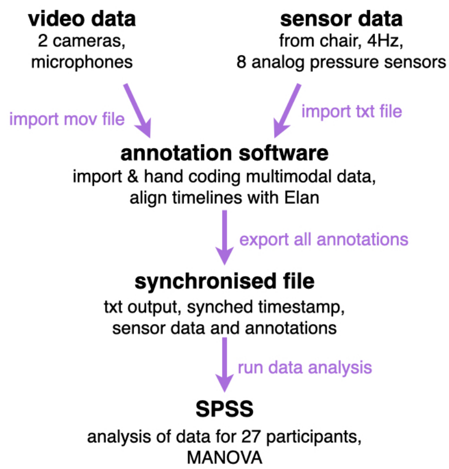


Figure 3.11: A simplified diagram of the different steps for the processing and analysing of the multimodal data from the chair experiment.

done because, even though participants were grouped so that there was a level of familiarity, some had only know each other briefly.

These cropped data files determined the final data set that was used for analysis, which consisted of 82963 data points (instances) in total, 10656 for talk annotations, 1001 for laughter and 459 for backchannels, and the rest classified as passive listener behaviour, including all other behaviours and movements that were not annotated for this study. This means, there are 81962 non-laughter data points, 82504 non-backchannels, and 10656 non-talk data points. The big differences in the numbers between speech and the other two behaviours can be explained with the total duration of these different behaviours. The total time of talking instances is summed up to 87.95 minutes, while the total time for backchannels is 3.79, and for laughter 8.26 minutes. The remaining data points account for the gaps of these coded behaviours, which were used as passive listener data. On average, participants provided data sets of 4880 coded instances, or ca. 20 minutes with a maximum of 26.4 min (6338 instances) and a minimum of 11.8 min (2832 instances).

A diagram summarising the steps of the data collection and further processing, as well as analysis is shown in Figure 3.11.

3.6 Results

The data from all eight sensors were analysed in a General Linear Model Multivariate Regression using SPSS v.24. Talking, Laughing and Backchanneling were included as binary predictors coded as 1 or 0 for presence / absence of each behaviour. All two and three-way interactions of these three factors were included in the model. Participants were also included as a main effect to ensure individual variation was accounted for.

3.6.1 Multivariate Tests

Multivariate Tests (Pillai's Trace, Wilk's Lambda, Hotelling's Trace, Roy's Largest Root) show all three dialogue factors reliably predict the outputs of the pressure sensors. Here, I focus on reporting the results of Pillai's Trace test statistics, a generally robust test for a small sample size like this.

The F statistics for Talk is $F_{(8,82933)} = 9.68$, for Backchannel $F_{(8,82933)} = 10.2$ and for Laughter $F_{(8,82933)} = 6.95$ (all with Degrees of Freedom $df = 8$). The p values of all three behaviours are $p < 0.00$ with Alpha $= \alpha = 0.05$. The effects are very small with Partial Eta Squared, the proportion of variance associated with the effect, of 0.001. This is different when looking at participants as the main effect, where the contribution of individual variation is, in contrast, much larger. Pillai's Trace shows an F statistic of $F_{(8,82933)} = 6.95$, a p-value $p < 0.00$ ($\alpha = 0.05$) and the percentage of variance with the effect, Partial Eta Squared $\eta_p^2 = 0.71$. Results of the other tests are almost identical, with the exception of small variations in F statistics and Partial Eta Squared, which can be viewed in Appendix A, and an overview of the results of the Pillai's Trace are summarised in Table 3.4.

Table 3.4: Multivariate Tests (Pillai's Trace) with Alpha $\alpha = 0.05$ for all three coded behaviours: Talk, Laughter, Backchannel. From left to right, p-value, F statistic, Degrees of Freedom, and Partial Eta Squared are reported.

Behaviours	$p < \alpha$	$F_{(8,82933)}$	df	η_p^2
Talk	.000	9.679	8.000	.001
Laughter	.000	6.946	8.000	.001
Backchannel	.000	10.210	8.000	.001

3.6.2 Between-Subject Effects

Tests of Between-Subjects Effects and pairwise comparisons analyse the contribution of each of the eight sensors to talk, backchannel and laughter. The results of these tests show that different patterns of pressure changes across the chair are associated with the different conversational states, with different effects on different sensors.

The overview of these Between-Subject Effects in Table 3.5 shows that the lower body (thigh and leg sensors) provides overall more significant clues for each coded behaviour than the upper body does (waist and shoulder sensors). Here we can see that all behaviours rely on the sensors on the seat, the area around thighs and buttocks, to be discriminated. The p-values of Talk and Laughter show that both thighs are significant, and the sensor on the left buttocks is significant for all three behaviours. The sensors most sensitive to talking were in the seat of the chair, in particular in both thighs and the left buttocks, while the shoulders were least significant for it, which can be deduced from Table 3.5. In general, the left side appears more important in these tests than the right side, in particular for buttocks, waist and shoulders, as Table 3.5 lists. The waist appears only significant for backchannels, here also the left side more than the right. The Partial Eta Squared for all behaviours is $\eta_p^2 = 0.000$. A more illustrative overview of the results of the tests conducted here is also shown in Figure 3.13. Additionally, examining the estimated marginal means of the sensors reveal the patterns of pressure changes for each behaviour.

3.6.3 Estimated Marginal Means

Talking

For mode of talking, estimated means show that the sensors correspond to increased pressure from the thighs and reduced pressure from the buttocks, which is illustrated in Figure 3.12c. The standard error SE of the 8 different sensors for Talk are listed in Table 3.6 and range from $SE = 2.83$ (right waist) to $SE = 9.44$ (left thigh).

Table 3.5: P-values of Tests Between Subjects with Alpha = $\alpha = 0.05$ for all three coded behaviours: Talk, Laughter, Backchannel. Results smaller than α are highlighted in **bold**.

Sensors	Talk	Laughter	Backchannel
Thigh Left (L)	**.000**	**.009**	.063
Thigh Right (R)	**.000**	**.006**	**.001**
Butt L	**.017**	**.000**	**.000**
Butt R	.356	.383	.173
Waist L	.092	.351	**.000**
Waist R	.145	.656	**.004**
Shoulder L	**.000**	.086	**.000**
Shoulder R	.611	.739	.370

Table 3.6: Standard Error of the Mean of each sensor in relation to Talk, Laughter and Backchannel

	Thigh L	Th. R	Butt L	B. R	Waist L	W. R	Shoulder L	Sh. R
Talk	9.447	7.546	4.749	5.291	3.925	2.831	5.334	7.032
Laughter	13.482	10.769	6.777	7.550	5.601	4.040	7.612	10.035
Backchannel	13.644	10.899	6.859	7.641	5.669	4.088	7.704	10.156

These means of all sensors during speech describe a body posture that can be interpreted as 'keying up' and sitting straight, shifting the weight slightly forward (as opposed to slouching or leaning back), also illustrated in Figure 3.15 below. Furthermore, the sensor pair for the buttocks seemed to be the one mostly relevant for identifying speech than identifying the other behaviours. Table 3.8 summarises the deduced postures from the different patterns in pressure across all coded behaviours.

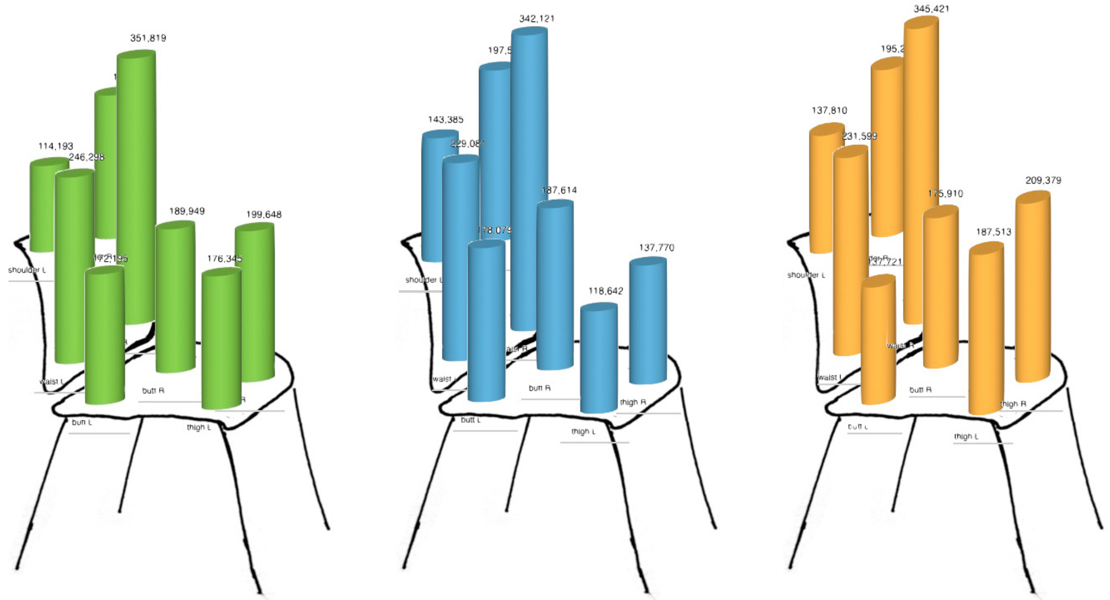
Laughter

In contrast to this, laughter corresponded to reduced pressure in the thighs and increased pressure in the buttocks with no significant changes detected in the seat back, see Figure 3.12b. The most significant sensors for laughter are the ones for the thighs, placed close to the edge of the seat placed where the back mid thigh touches the chair cover, also illustrated in Figure 3.13. This strong focus on the thighs compared to all other sensors is what distinguishes laughter from the other two behaviours most. Additionally, estimated means show a very small decrease of pressure in the waist and in the shoulders. These results don't make it easy to deduce a static sitting posture, but may suggest more movement around the legs and the torso. This also corresponds to laughter being a dynamic movement rather than a static posture.

The Standard Error SE for laughter is reported in Table 3.6.

Table 3.7: Contribution of different sensing areas to coded behaviours and conversational state

Social Behaviour	Significant Sensors	Least Significant Sensors
speaking	both thighs, left buttocks, left shoulder	right shoulder
laughter	both thighs, left buttocks	both waist sensors
backchannel	left thigh, buttock and waist	right buttocks and shoulder



(a) BACKCHANNELS:
thighs: L(176.345), R(199.648);
butt: L(172.195), R(189.949);
waist: L(246.298), R(351.819);
shoulders: L(114.193), R(189.709)

(b) LAUGHTER:
thighs: L(118.642), R(137.770);
butt: L(178.079), R(187.614);
waist: L(229.081), R(342.121);
shoulders: L(143.385), R(179.532)

(c) TALK:
thighs: L(187.513), R(209.379);
butt: L(137.721), R(175.910);
waist: L(231.599), R(345.421);
shoulders: L(137.810), R(195.288)

Figure 3.12: Estimated means of all participants for backchannels, laughter and talk. (L = left, R = right)

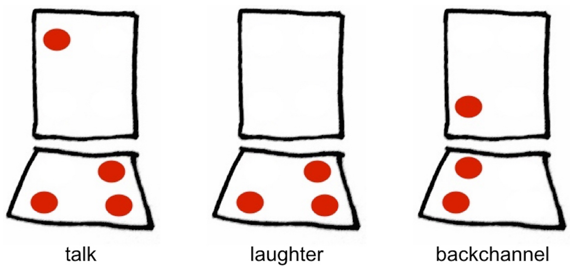


Figure 3.13: Illustration of significant sensors for detecting talk, laughter and backchannel.

Table 3.8: Different patterns of pressure changes across all eight sensors for each coded behaviour, and the derived sitting posture from these.

Social Behaviour	Pressure Changes in Sensors	Deduced Posture
speaking	more pressure in thighs, less pressure in buttocks	sitting up straight, slightly leaning forward
laughter	less pressure in thighs, more pressure in buttocks little less pressure in waist little more pressure in shoulders	no distinct posture, more dynamic posture shifts, probable leg movement
backchannel	more pressure in thighs, more pressure in buttocks, more pressure in waist	sitting straight, no tendency to lean forward, leaning more towards left

Figure 3.14: Typical speaker and listener postures illustrating the distribution in pressure across the chair cover. Left: a speaker is leaning forward, applying most pressure on the back thighs and reducing pressure in buttocks. Right: a listener leaning back and shifting the weight from the thighs to the buttocks and lower waist.

Backchannels

A noticeable outcome for backchannels that distinguished it from the other behaviours was the slight asymmetry of the sensors that contribute most to identify this state. It appears that the left side of the body is more significant than the right side. Table 3.7 and Figure 3.13 show that while the sensors on the left thigh, buttock and lower waist are most significant, the sensors on the right buttock and shoulder are least relevant for backchannels. Table 3.6 reports the Standard Error SE for backchannels. Compared to the other two behavioural states, backchannels also show more significance in the upper part of the lower body (or: the lower end of the upper body) up until the waist, while laughter and talk are focused more around the seat surface alone.

3.6.4 Summary of Results

In summary, we can look at this correspondence between sensors and behaviours in a way that suggests each of them has a unique pattern of pressure distribution to identify them. Laughter seems most distinguishable from movement on the mid legs, talking from movement around the upper legs and buttocks, and backchannels from pressure changes broadly from mid legs to buttocks to lower waist. Figure 3.12 illustrates these outcomes with the displayed estimated means for each sensor, showing the shifts in pressure distribution for each behaviour. The Figure also shows that, for example, the transition from talking to backchannelling occurs through a shift in pressure distribution from increased pressure in legs for talking to increased pressure across the entire surface of the seat for backchannelling - a seemingly slightly more backwards leaning, minimally slouching, or 'resting' posture. This also gives us a clue for general distinctions between general speaker and listener postures, see e.g. Figure 3.14 and Figure 3.15, that show modes of talking in more up-right postures and participants leaning forward, while when returning to listener states, their posture becomes more relaxed and leaned backwards. These findings are also backed from the Between-Subject Effects reported above and summarised in Table 3.5.

An overview of how each sensor contributes to identifying the coded behaviours is shown in Table 3.7 and Table 3.8, and visually summarised in Figure 3.13.

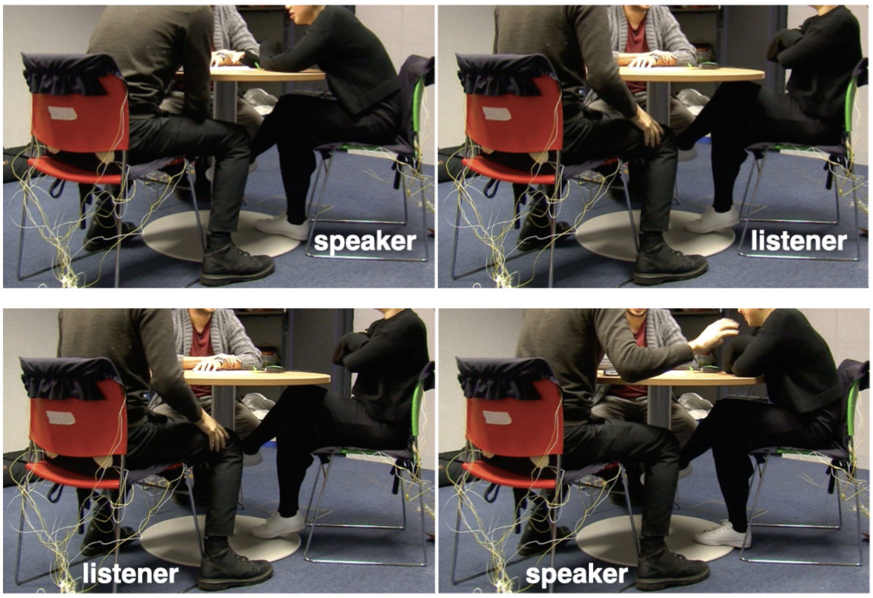


Figure 3.15: Two stills of a video displaying the findings of pressure distribution of listener and speakers in a marked posture. **Top row:** participant on the right (dressed in black) leaning forward while speaking, visibly applying less pressure on the back, and leaning back once finished their utterance, shifting the pressure on the seat surface towards the back. **Bottom row:** Participant on the left (in khaki jumper) sitting straight while listening, being addressed, and moving their torso forward when starting to gesture and speak.

3.7 Discussion

These results show that it is possible, in principle, to detect significant aspects of social interaction from quite limited, indirect and noisy data of self made textile sensors. The small movements detected by these pressure sensors embedded in chair seats are small-scale and almost completely invisible correlates of the gross body movements that typically distinguish speakers from listeners and laughter from silence. Interestingly, even the relatively small movements associated with listener responses such as backchannels appear to create a distinguishable pressure signature on a chair. The ability to extract such patterns of social interaction from sensing pressure changes could replace other, more complex motion detection systems and mitigate privacy concerns, since the data collection is anonymous, involves no audio or video data and does not capture any of the content of the conversation.

3.7.1 A Social Textile Chair Cover

A contribution of this chapter is to be seen from a textile perspective in regard to having shown that textile sensing - even in a simple form as presented here - is capable of identifying cues that are not restricted to single user scenarios, but also cues that derive from face to face interaction.

The literature reviewed here has shown good results for chair covers detecting affective states and a variety of sitting postures using a very high number of sensors (Mota and Picard, 2003; Tan et al., 2001; Arnrich et al., 2010). In more recent years, the number of sensors has been scaled down, which has also been my approach when building the sensing chair cover. Here I show that as little as 8 sensors are sufficient to dinstinguish basic conversational states. The simplicity of this approach provides an enticing factor in design engineering and multimodal research and could encourage a wider use of textiles as a sensing material. Besides, this modality of using fabric sensors also prompted participants to comment that "it felt comfortable and not different than sitting on a 'normal', common chair", adding value to the usability comfort textiles provide for a ubiquitous computing approach to smart environments.

3.7.2 Gathering from the Buttocks

The finding of the relevance of the lower body in detecting conversational states is something that has not been brought into focus and discussed to much extent before. There are indications in previous works that the buttocks are relevant in detecting postural movement as well as social behaviours. Mota and Picard (2003) for example identified four significant areas on the seat through feature engineering, two on the buttocks, and two on thighs. Also Shibata et al. (2013) mention that legs are relevant for perceiving dominance, and D'Mello et al. (2007a) notes that the back rest of the chair was not significant when distinguishing affective states.

Further, my results link listener behaviour to increased back pressure, and speaker behaviour to a decrease in pressure towards the back, which links to findings of D'Mello et al. (2007a), who describe a "heightened" posture distinct to interest, as opposed to a posture applying more pressure in the back distinct to boredom.

The sensing chair cover of this work revealed that movements on the seat surface, initiated by the buttocks and legs, potentially provide social signals that add to a more complete understanding of participants' body language in social interaction. While there is a vast amount of literature analysing facial and gestural signal in great detail, the lower body is mentioned, if at all, only very marginally. This might be due to its rather small scale movements that do not appear to be intentional and as directional as other signals. (Kleinsmith and Bianchi-Berthouze, 2013) pointed out works mentioning legs and lower body postures relevant to some affective states and behaviour. However, the buttocks as a large muscle contributing to such corpus has not been discussed to this extent.

The results of this study suggest, however, that legs and the lower body in general are worth investigating further as a social signal in the scope of this research, and will draw attention to small scale as well as large scale shifts in posture of the lower body further.

From another viewpoint, it is arguably also the movements deriving from the upper body that are picked up from the sensors underneath the buttocks. Gestures, leaning into different directions, and even shoulder shrugging are not only local movements, but affect the entire body. The buttocks could therefore be where these movements oscillate to. In this case, we could speculate about how well in general the simple sensors can pick up such upper body movement, so that it may be sufficient to place sensors underneath the buttocks to capture both, torso and leg postures.

Both perspectives enable to envision a potential new set of unidentified lower body postures as social signals, and propose for the legs to be put into more spotlight in the analysis of nonverbal communication.

3.7.3 Future Work and Improvement

Further development to optimise the design and engineering of the sensors would doubtlessly improve the quality of the sensing and data collection. Reevaluating the design in regards to size, shape and amount of sensors could refine their performance and improve the results, too. As it can be seen in the timeline of developments in sensing chairs, the amount of sensors has been reduced, and with the results suggesting that the buttocks sensors may be sufficient to detect gross movement, it may be possible to scale down the required numbers of sensors even further.

The demonstration that even relatively crude sensors can detect minimal changes in posture, suggests that future work should explore the possibility of capturing more complex social behaviour, too, especially relational questions such as whether interactions are, for example: convivial or combative; autocratic or egalitarian, or whether it is possible to characterise regularities in multiparty interaction (see e.g. Abney et al. (2014)).

We have seen that in this fairly small data set, individual variation is large. With a data set of a higher number of participants, this could potentially be reduced and patterns of postural movement would show more clearly across the data population. Another take on this, however, would be to use the characteristics of individual variation and exploit other analysis methods, for example machine learning approaches, to train person specific classifiers. These (admittedly more "timely") mechanisms in general would also improve the accuracy and robustness of this basic analysis, although it would at the same time undermine the advantage of anonymity.

3.7.4 Potential Applications & Further Questions

What could this form of sensing be used for? Where could such chairs be deployed? The principle opportunities for application are in any situations where there is value in the ability to unintrusively gather information about general patterns of social interaction including levels of interest and engagement. One example is architecture where the ability to sense a building's energy performance and patterns of air flow is highly valued but currently has no social counterpart. I speculate that the ability to make simple, systematic assessments of a building's 'social performance' by instrumenting the chairs in a building could also have a significant positive impact on domestic and workplace design. For example, the chair covers could assess the engagement of group meetings, providing data that could inform interior arrangements of furniture to facilitate social encounters.

A second example is in the evaluation of audience responses, for example continuous audience response measure, CARM, which is used by broadcast hosts to evaluate their programs. The deployment of such a sensor network in an auditorium, meeting room or a classroom could help to assess levels of engagement of students and other audiences. A significant advantage of using chairs, as opposed to wearable devices in such context is that the identity individuals does not need to be revealed, and yet detailed information about social engagement can be retrieved. In addition, there are possibly applications to augmented human interaction where, for example, live feedback about how much people are dominating (or not) a conversation can have significant effects on the conduct of the interaction (Donath, 2002).

Other questions that arose were, whether it is easier to detect emotional cues than it is to detect turn taking. Is it more obvious - from a perspective of a chair - if a person is speaking or listening than it is if a person is confident or shy? And what is more important for such detection: maintaining or changing a postural state?

Furthermore, focusing on the dynamics of continuous postural behaviour, the act of leg crossing, for example, could be of interest in exploring social interaction, as well as general movement of feet, that was mentioned in observational studies before, but hasnt been carried further for this project.

If nothing else these results shed some light on Stephen Fry's (1984) advice that when delivering

Shakespeare one should "always gather from the buttocks"[13].

3.7.5 Summary

In this chapter, the design and evaluation of a textile based pressure sensing chair cover has been introduced. With a design of 8 woven pressure sensing patches, basic conversational states are distinguished. My work confirms findings of previous works in related areas, and strengthens the approach to use only a small number of sensors to detect postural movement from which social behaviour can be deduced. My work furthermore includes multi-user settings, which in many works is unattended.

Contributions

The findings deriving from this study contribute to the understanding of the relevance of lower body movement in social interaction. They draw attention to the role of the buttocks and thereby extend the currently established taxonomy of nonverbal cues . It is suggested, that basic conversational states can be detected with measuring the change of pressure distribution around the buttocks and thighs. With this, the here presented results demonstrate the power of simple pressure sensors on a chair in detecting nonverbal behaviour, such as discriminating speakers from listeners in seated interactions.

Based on these results, this study is a first step towards my aim to establish textiles as a sensing technique to capture social behaviour and becoming an integral part of multimodal sensing networks in the context of behavioural studies.

Limitations

The chair introduced here promotes the use of fabric sensor, but is one of many established sensing seat systems using pressure sensors made of other materials. While I have focused on testing the performance of the textile based systems for basic conversational states, focusing on the distinction between speakers, listeners, as well as cues of laughter and backchanneling, other works have assessed far more complex behaviour and affective states with chairs.

Furthermore, the effects of the results are small and there is a large individual variation, which could derive from the small data set processed here, as well as from the unstaged, spontaneous execution of postures. The methods used to analyse this postural data do not take dynamic postures into account, which may affect the reliability of the results, too. In the scope of the next chapters, these challenges will be addressed.

The limitations of this work can help to identify objectives and goals of next steps of this research. At the same time, the results extracted from this exploratory study provide a basis for hypotheses to build on. So it is in the chapter to follow where I explore textile sensing in social interaction further, aiming to address some of the challenges faced with chairs u developing and presenting a new design.

[13]See https://www.youtube.com/watch?v=eOBV7DS65S8 at 03:45

Chapter 4

Smart Trousers: Designing and Validating A Wearable Textile Sensor System

Chapter Overview

The last study has shown that just from measuring the changes of pressure being applied on the seat, it is possible to distinguish basic conversational states. Here I introduce a novel design further exploiting textile pressure sensing: bespoke 'smart' trousers with an embedded sensor matrix. The design process and construction of this wearable sensing system, based on further observations, are described and its use to detect a variety of postures validated by conducting a user study with data gathered from 6 participants. With simple machine learning techniques, I further demonstrate its ability to discriminate between 19 different basic sitting posture types with high accuracy.

The publication derived from the work in this chapter, presenting the design and user study, is: *Skach, S., Stewart, R., & Healey, P. G.T. (2018, October). Smart Arse: Posture Classification with Textile Sensors in Trousers. In Proceedings of the 20th ACM International Conference on Multimodal Interaction (ICMI '18). Boulder, Colorado. ACM. (pp. 116-124).*
DOI:https://doi.org/10.1145/3242969.3242977

4.1 Introduction

In the last study, fabric sensors in chairs were used to identify speakers and listeners, pick up laughter and backchannels. Using textile pressure sensors on the seating surface has revealed the relevance of the lower body in detecting such conversational states. This so far underinvestigated part of the body implies the existence of other potentially valuable cues and patterns of movement that contribute to a more holistic understanding of nonverbal behaviour. Subtle movements, including those from from legs and buttocks, that are not necessarily as directed and intentional as gestures or mimicry, can still give clues about interactional behaviour, on their own or in combination with upper body signals. In seated conversations, which are the situational focus of this research, people continually adjust their posture and re-arrange their hands and legs. For example: hands resting on laps; elbows on thighs; a forward leaning posture; hands that are tucked between thighs; hands on knees and many other variations, that have been mentioned in literature on nonverbal behaviour in social interaction, but not analysed in detail, compared to the rich corpus of work on gaze and gesture.

In this chapter, I look at postures of the lower body in seated situations and the positions of hands on upper legs. The overarching question is what can these different postural states tell us about conversational engagement and potentially even about more complex, affective states? This will be explored step-wise in the next three chapters. For this part of the thesis, the more specified questions addressed are, whether the same type of sensor design used in the previous chapter can also measure sitting postures. More specifically, the previous findings raise the question, whether ore lower body postures can be identified through this modality. Based on this, further research objectives in regard to design engineering of the sensing system emerge: what is the best textile sensing system to explore lower body movement further?

Chapter 3 tested a static sensing system deployed in fabric chair covers, suggesting the changes of pressure on the surface of a seat are sufficient to identify different conversational states. The sensors were relatively coarse grained and intrinsically limited by the fact that seat chair covers are in contact with only a relatively small proportion of the body. Behaviours such as resting the hands in our laps or between the knees are difficult to detect in this way. So, while the chairs could pick up changes across the surface of the seat, they could not do that with body parts not directly in contact with it.

Here, I progress to developing and validating the same type of textile sensors in a wearable system for the lower body: trousers. Moving from stationary to wearable sensing systems comes with advantages as well as challenges. Rather obviously, chairs only work when someone is in contact with them, which limits the sensing capability to the specific situation and environment. A wearable sensing system is not restricted to a specific environment and follows and moves with the body. On the other hand, the hardware set up, the robustness of hard-soft connections, or reliability of the data collection run more risks to fail or break in designs of wearable solutions, since the components are exposed to spontaneous movement of the participant. In the following chapter, I address some of these challenges of the design engineering and exploit the advantages of wearable textile sensors in the case study of 'smart' trousers. I introduce the new design of textile sensors and their circuitry that are adapted to a wearable system. This influences the choice of materials used and the design engineering of other hardware components such as the robustness and unobtrusiveness in regards to the circuitry.

The basic question of concern in this work is whether we can reliably detect different seated postures by detecting pressure changes on the surface of a pair of trousers. To do this, an unobtrusive on-body textile motion capture system that uses a matrix of fabric pressure sensors around the thighs and buttocks was developed. These trousers allow for a more fine grained tracking of pressure changes and, compared to chair covers, have the potential to capture hand and elbow contact as well as more distinct movement involving the thighs. The selected postures for testing derive from video-based observations of naturalistic seated multi-party interactions that are taken from the last study's data collection. I collect a data set of a total of 19 posed postures in a controlled environment to benchmark the sensing capabilities using automatic classification techniques.

4.2 Background

Based on the findings in Chapter 3, it is indicated that sensing the seat surface alone - the area the lower body is in contact with, may be enough to identify a variety of postures. This varies from other common approaches, like using a high resolution array of sensors on the seat (Tan et al., 2001; Meyer et al., 2010b; Mota and Picard, 2003; Arnrich et al., 2010), or recording video data. In this section, the review on how sitting postures are detected, and what role textile sensors and in particular trousers play when doing so.

4.2.1 Sitting Posture Classification

Being able to detect sitting postures has been a task in HCI for various applications, as elaborated in Chapter 2. Operating a computer, whether for educational purposes or as part of office work, has an impact on our posture, and vice versa, posture can affect the quality of tasks we carry out (Jaimes and Liu, 2005). People slouch and slump when sitting down. Detecting such unhealthy postures can help to intervene and encourage people to improve their posture, or to stand up for a moment (Xu et al., 2013). But also without feedback or interference, detecting a person's sitting posture while they are performing a screen based task is a useful way to obtain information on their interest and attention level, boredom and other behavioural and affective states (D'Mello et al., 2007a; Witchel et al., 2016; Kapoor and Picard, 2005). While these examples deploy the sensors on a chair, also floor mats have been designed to detect different body postures, for example during gym exercises (Sundholm et al., 2014; Zhou et al., 2016).

In the last Chapter, sitting posture detection in social contexts and face-to-face interaction was examined. Here, I focus on more controlled studies involving single users, expanding the existing large corpus of research in this area. When focusing on capturing sitting postures in that regard, it has been shown that pressure sensors on chairs have the potential of replacing more complex data collection, like from accelerometers, IMU sensors (Intertial Measurement Units) or motion capture markers Nathan-Roberts et al. (2008); Arnrich et al. (2010); Cheng et al. (2013).

4.2.2 Classification Specifications

Posture detection studies accumulate a variety of classification and other analysis approaches. Their performance varies depending on the amount of postures that are to be distinguished, the amount of sensors used to capture them, the number of participants as well as number of repetitions of each posture per participant (size of data set), and lastly the type of classification algorithm used to identify the postures.

In a study distinguishing 16 different postures related to leg crossing and upper body movements with 9 participants (Meyer et al., 2007) using textile pressure sensors, a Naive Bayes model has shown a success rate with only 5% error. Similarly, Tan et al. (2001) achieved a 96% accuracy with 20 participants when testing pressure maps created from 64 pressure sensors in the commercially available "Tekscan" system. In a study classifying 9 different sitting postures with 10 participants, using a Support Vector Machine (SVM) learning model, accuracies between 93.9% and 98.9% were achieved (Kamiya et al., 2008). Cheng et al. (2013) reported an accuracy of 0.88 for a Linear Discriminant Analysis (LDA) with sample data of 5 subjects, 7 postures and only 4 different sensors. Less accurate classification is reported in (Riener and Ferscha, 2008). With a multitude of parameters yielding different results, it is difficult to determine one parameter that is responsible for improving classification accuracy. Reviewing existing literature, it is implied that not necessarily the amount of sensors used is key for better posture detection, but the combination of the quality of the data set prior analysis, as well as the data processing methods contribute to good results. Moreover, these parameters are also determined by the use cases these sensing networks are designed for. A high resolution of pressure sensors is not always necessary, as shown in the works of Shibata et al. (2013);

Reference	no. of sensors	no. of postures	no. of participants
(Meyer et al., 2007)	240	16	9
(Kamiya et al., 2008)	64	9	10
(Shu et al., 2015)	100	3	-
(Cheng et al., 2013)	4	7	5
(Sundholm et al., 2014)	6400	10	7
(Romano, 2019)	48	-	-
(Donneaud and Strohmeier, 2017a)	265	-	-
(Zhou et al., 2016)	128	-	6
(Strohmeier et al., 2019)	16	-	-
my work presented here	200	19	10

Table 4.1: A selection of existing pressure sensor matrices showing the amount of sensors, and, where applicable, the number of postures and participants used for evaluation; compared with the design introduced in this chapter.

Bibbo et al. (2019); Griffiths et al. (2014), and as was indicated with the pressure sensor patches on the chair cover in the last Chapter.

In this chapter, I identify 19 different sitting postures that derive from the information of existing literature, as well as from observations conducted and described below; 10 participants; and 200 sensors (for an overview, see Table 4.1).

4.2.3 Textile Pressure Sensor Matrices

The pressure sensors used to capture sitting postures are often presented as a matrix configuration. The previously mentioned, commercially available pressure mat by "Tekscan", that is often used in related research (Tan et al., 2001; D'Mello et al., 2007a), houses a 42x48 matrix with a total of 2016 sensors with each sensor forming a 1x1cm square, equally distributed across a plastic sheet that can be mounted on a seat. Also self made pressure sensor matrices are used for sitting posture detection, for example in (Meyer et al., 2007; Shu et al., 2015; Cheng et al., 2013). They are often manufactured with a lower resolution, such as an 8x8 matrix (64 sensors in total) (Kamiya et al., 2008), or a 10x10 matrix (Shu et al., 2015). There are, however, also textile pressure mats consisting of a 80x80 matrix (6400 sensors) for a high resolution image to detect a variety of body postures and pressure points of different body parts (Sundholm et al., 2014). While the commercially available pressure matrix sheet consists of plastic layers, selfmade solutions of fabric sensors offer a softer and more flexible surface, and can be as fine grained and small scale as the unit size and measurement of a yarn, as is demonstrated in (Parzer et al., 2018). Using single strands of yarn to create a sensor matrix is afforded by the process of weaving. With piezoresistive yarn, a pressure sensor matrix can be woven in one layer and is fully integrated in the textile surface (Romano, 2019). In most designs, however, strips of conductive fabrics are used and arranged in a layout of rows and columns to sandwich a middle layer of a resistive fabric, as explained in (Meyer et al., 2007) and (Donneaud and Strohmeier, 2017a,b). Amongst a large range of textile sensors matrix designs, made of textile and non-textile materials, deployed in chairs, used as touch pads, or utilised as wearable interfaces, the design I will refer to most in this thesis in regards to hard- and software configuration is the matrix by Donneaud and Strohmeier (2017a). This, as well as a selection of pressure sensor matrix designs mentioned here is summarised in Table 4.1.

Manufacturing techniques for textile pressure matrices have been optimised in recent years (Perner-Wilson and Satomi, 2019b,a; Strohmeier et al., 2019), since the characteristics of sensor matrices are desirable for many research areas.

4.2.4 Sensing Trousers

Other textile sensing designs that have been explored for classifying sitting postures are garments. Most examples demonstrate use cases for upper body garments. Only few have focused on the potential of trousers for capturing postures. This can be explained with the upper body being considered to contain more information about body movement and its social implications, e.g. through gestures that are captured with tilt sensors and accelerometers, or heart rate being measured with sensors around the chest. There are, however, works that have discovered trousers as an equally informative interface for sensors. For example, Dunne et al. (2011) used motion capture markers on trousers to track leg movement, and prototypes where conductive thread is stitched on trouser fabric to detect joint movement and bending (Gioberto et al., 2013). Ribas Manero et al. (2016) measured muscle activity with ECG sensors in running trousers with embroidered conductive threads. Similar methods are used in (Colyer and McGuigan, 2018), deploying EMG sensors in shorts[1]. In other works, accelerometers were mounted on trousers (Niazmand et al., 2010). Finally, also textile sensors have been embedded in trousers - for example patches on front thighs to recognize touch and envision new input formats for device interaction Heller et al. (2014). What else trousers can be used for in the context of smart, interactive clothing is discussed by Van Laerhoven and Cakmakci (2000), who ask what trousers should and could be taught by humans.

Only a few have tested trousers as a measuring tool for bodily cues. Mostly, these tests are directed towards sports applications, sensing muscle activity in legs (Zhou et al., 2016; Bieber et al., 2011; Ribas Manero et al., 2016). However, touch (Heller et al., 2014) and gait recognition (Gafurov and Snekkenes, 2009) have been explored with fabric sensors, too. In the healthcare sector, such measurements are useful to monitor patients' movements (Niazmand et al., 2010). In some of these examples, the sensors are often accelerometers attached to a finished garment (Van Laerhoven and Cakmakci, 2000) rather than integrated into the garment (Dunne et al., 2011). In designs where electronics are detachable from 'smart' trousers, it is argued that this provides solutions to washability and powering challenges (Niazmand et al., 2010).

Compared to the range of designs of 'smart' upper body garments, trousers are rarely the focus of embedded textile sensors. The examples given above often present ad hoc solutions of mounting sensors on legs, and use purchased garments to attach rather than embed textile circuitry and rigid electronic components. To my awareness, a fine grained, carefully developed sensing network for lower body garments has not been established for the purpose of detecting postures (and consequently, nonverbal social cues).

4.3 Designing Sensing Trousers

Wearable textile sensing systems, especially when deployed as close to the human body as clothing, need to meet certain requirements that distinguish them from static textile sensors. For example, the connections between hard electronic components and soft conductive textiles must be robust enough to allow for bodily movements like bending, stretching, or squeezing. Furthermore, the placement of such "hard" components needs to fulfil standards of wearability comfort, and the size of these parts should be reduced to a minimum to not interfere with natural dynamics of body movement. Lastly,

[1] https://www.myontec.com/

also powering of a wearable, in a garment embedded sensing system with a battery that needs to be replaces or recharged and in addition presents another rigid component, can be more challenging than in other, more static systems.

Deploying fabric sensors in garments has the benefit of having an unobtrusive, non-distracting and therefore less distorting sensing interface that is comfortable to wear and does not modify our common surroundings. It can be independent of the environment and can be in itself sustainable and autonomous, embedding all components necessary to collect and store data, process it and power itself all through wearable engineering solutions. These properties have led this research to focus on textile sensors in clothing, and the choice of materials as well as the pattern cutting design was guided by this approach on ubiquitous technology.

In this section, I introduce the sensing trousers used in all future studies. The step-wise design and evaluation process in chronological order are described. I start by conducting ethnographic observations of multiparty interaction that inform the goals of the final product and provide guidance for evaluation methods. Next, I translate the findings of these observations into designing and prototyping for the textile sensors and style of trousers. Moreover, these observations determine that detecting pressure is a reasonable means to sense postural behaviours on the lower body. The sensing system thus needs to detect both the amount of pressure and the location where it occurs - a task suited to a two-dimensional matrix of pressure sensors (Donneaud and Strohmeier, 2017b,a).

4.3.1 Observations Continued: Additional Findings

Methods

The goal of additional observations is to inform the development of the sensing trousers, and to identify a series of sitting postures focusing on the lower body that will be used in the next user study. The basis of ethnographic studies carried out was the corpus of videos of the last study (Chapter 3). Including a previous pilot study, that corpus consisted of 12 videos with a total of 36 participants. The videos showed seated three-way conversations lasting between 15 and 30 minutes, a setting continued to be used to assess the trousers further. To continue to preserve anonymity of participants when displaying postures, the observations were captured via drawings. All drawings were created by the author of this thesis, using black ink on paper. Different to the observations carried out for the chair study informing the design of the sensing chair covers, where the postural movement of the entire body as an overt movement was examined, I now focus on lower body postural movement.Special attention is given to leg crossing and touch interaction with the hand on the upper legs during social interaction. The findings of this second round of observations are reported below, and summarised through hand drawings in Figures 4.1, 4.2, and 4.3. The details of what would be captured in these observations were guided by the idea of pressure sensitive textile surfaces on the lower body - for example the bodily surface covered by trousers.

In addition to the video corpus, which was used to identify a series of postures, three volunteers were later asked to wear mock-up trousers and were engaged in informal, brief interactions, during which the touch interactions on the lower body were traced with a marker on the mock-up trousers. An example of this scenario is later shown in Figure 4.6 when describing the design of sensors and trousers. This was done to confirm the identified sitting postures and to determine the resolution and position of sensors.

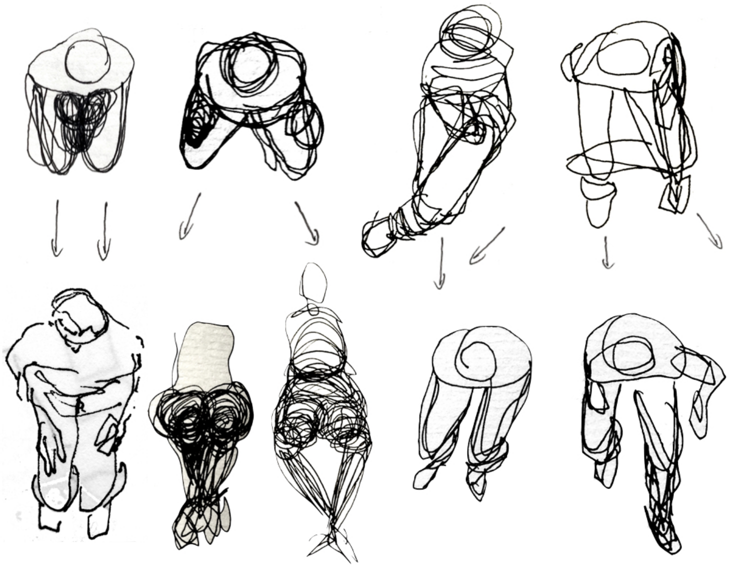


Figure 4.1: Drawings of different leg positions and orientations during sitting postures.

Legs and Feet

Identifying which parts of our legs and feet are positioned and moved in which ways to afford a certain sitting posture is one of the aims of this collection of observations. For example, I examine in how many different ways legs are crossed, and what common sitting postures are held in a scenario with a table. While eventually, the objective is to determine the social context of when people cross their legs, for this first step of validating the sensor system design, the investigation her concentrates of the recurrent movement on the lower body in conversation - how we cross and touch our legs, and in how many different ways. Hereby, the combination of postures in lower legs, upper legs, torso and hands were observed, resulting in a variety of overall sitting postures. For lower legs, the positions determined were either stretched or with knee bent, while for upper legs or thighs, I observed left and right leg crossing positions, as well as a change in posture when hands were tucked between thighs, positioning the legs slightly more spread or with thighs touching. Changes in torso were categorised as leaning forwards or backwards postures (movements along the sagittal axis), including details about hand postures during those changes, and sitting straight. A summary of what postures and movements of which body parts were observed is given in Table 4.2. Additionally, Figure 4.1 shows a collection of such different leg postures including leg crossings, stretching, and leg spreading that were observed in seated conversations.

Traces of Touch

To inform the trouser design, it is also important to determine which areas of the legs are most commonly touched by either the other leg in leg crossing postures, or by the hand of the subject. This additional parameter that was not paid attention to in previous observation, and that now plays an important role in the data I aim to collect, is the touch interaction between the hands and the legs. With the trousers, the aim is to be able to track the traces of touch of the hands on the lower body. So, for example, a question in the observations was, where the hand palms come in touch with the thigh, or whether both hands are placed on the lap. This is of particular interest when looking to detect listeners who don't use their hands to gesture as speakers do, but still perform movements

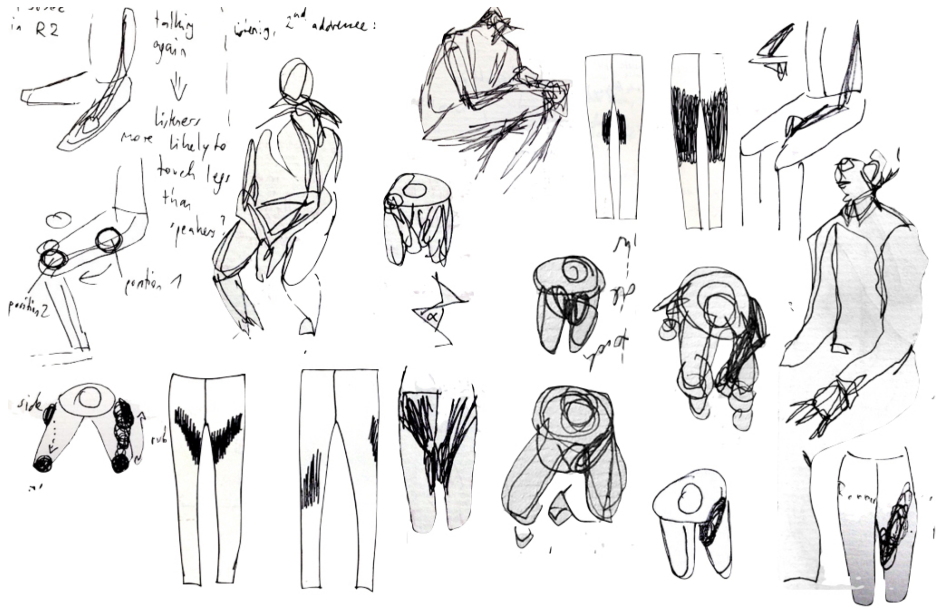


Figure 4.2: Sketches of observations of touch interactions between the hands and legs. Shaded or hatched areas represent the surface on which hands or arms are placed on the thighs.

body part	**observed sitting positions**
torso	movement along sagittal axis, leaning forwards & backwards; slouching, sitting straight up
arms & hands	hands on lap, between thighs, on knees ; under arm and elbow touching thighs; or arms and hands not in touch with lower body at all
upper legs	distance between thighs: touching or spread; crossed in narrow posture (thighs crossing), crossed with lower leg (or ankle) on other thigh
lower legs & feet	stretched out, away from chair, knees bent, lower legs and feet underneath chair, tucked back

Table 4.2: Sitting postures observed, divided into different body parts.

Figure 4.3: Traces of touch on legs - most common areas where hands touch on thighs, points of touch for leg crossing postures, and the defined area of sensor placement.

that involve the hands. For example, I observed hands rubbing thighs frequently, or hands being tucked between thighs that are pressed against each other. For speakers, it is generally assumed that more gestural actions are performed where hands are not in touch with the legs much. Observed postures and behaviours were most often displayed as touch between the hands and thighs, the two thighs coming into contact with each other, and the shifting of weight when in a seated position. But also postures in which hands were used to support a leaning forward movement, or to hold feet in place while crossing legs appeared frequently, which was observed both in speakers and listeners, as well as transitions between these states. Other touch points on legs are between the different legs themselves, when knees or thighs are touching. Findings of these traces of touch are illustrated in Figure 4.3, marking the areas on thighs where touch happened commonly in the observations.

In Figure 4.2, drawings of different touch interactions of the hands on the legs - mostly thighs - can be seen. Areas where hand touch was most commonly observed are marked (in red), as well as the pressure and touch areas of leg crossing postures (in green). Later, the combined area of these most observed touch interactions were used to identify the area on the legs for sensor placement and density, as Figure 4.2 suggests, too.

Summary

The aspects these additional observations focused on relate to leg crossing and the effect of upper body movements on the lower body, such as gestural movement and shifts in the torso. The goal was to determine a set of sitting postures that can be classified with the sensing trousers, as well as to specify the positioning and types of sensors that are to be designed around the lower body. The findings of the observations resulted in a collection of 19 different sitting postures combining positions of different body parts (see Table 4.2, that formed the base for the followed evaluation. Together with the additional informal tests with volunteers to trace touch interactions on legs directly, they contribute to the further design process of the trousers, informing choice of material, sensor type and positioning, as well as the pattern construction to accommodate for the sensor design.

4.3.2 Materials

The trousers consist of three different types of materials: non conductive base fabric that would be the material in direct contact with the wearers' skin; conductive fabrics that are concealed on the inside of the trousers and are turned into sensors; and the electronic components that collect the data. All conductive material was integrated into the trousers so that it would not come in direct contact with the skin when being worn.

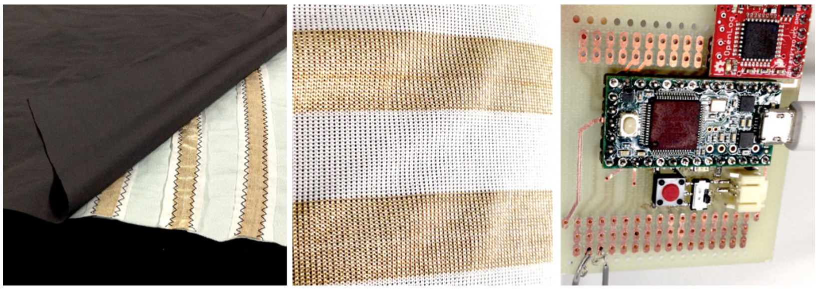


Figure 4.4: Materials used to manufacture the textile sensor matrix and the trousers. Right: grey resistive layer on top of conductive silver stripes stitched on cotton jersey. Black viscose jersey as bottom layer. Middle: conductive zebra fabric. Right: microcontroller and datalogger for micro SD card on prototype circuit board.

Conductive fabrics

Piezo-resistive pressure sensors usually consist of a combination of 3 layers: 2 highly conductive layers, and a piezo-resistive layer in between, preventing the two layers from touching directly and short the circuit. The resistive layer (see Figure 4.4 top left) is also conductive, but with a much lower conductance than the other layers, that changes when the material is deformed. For this piezo-resistive layer, a stretch jersey from Eeonyx[2], EeonTex LTT-SLPA was used, which has a surface resistance of 10-20 kΩ per square. It is made of a nylon (72%) and spandex (28%) mix that has been tested for machine washability by the manufacturer, and weighs 163g/m^2. The two highly conductive outer layers are a single jersey 'Zebra' fabric, purchased from Hitek[3], knitted in stripes of 1cm conductive and 1cm non-conductive yarn, depicted in Figure 4.4 (middle). The fabric is light weight with 129g/m^2, and is made of silver-plated nylon yarn and textured polyester (for the non conductive parts). The stripes are later cut and sewn onto non-conductive jersey, arranged into stripes and columns of the matrix. All fabrics used to make this sensor matrix can be commercially purchased per meter. And just as conventional, non-conductive jersey knits, these fabrics can be produced on machines common in the textile industry, in this case an industrial knitting machine in a fine gauge.

Non-conductive fabrics

The outer layer, the shell of the trousers, consists of a black viscose-cotton single jersey knit in a fine gauge (see black fabric in Figure 4.8), which ensures a high wearing comfort, elasticity and good washability. It is also a fabric that is commonly used in leggings and T-shirts. The pattern parts on the inside of the trousers, acting as lining fabric, cover the thighs and buttocks up from the knees,

[2] https://eeonyx.com
[3] https://www.hitek-ltd.co.uk

and are made of a light cotton elastane mix single jersey knit (pale blue fabric in Figure 4.4 and 4.5). This fabric also forms the base on which strips of conductive fabric are sewn on to create the matrix of sensors. It conceals all conductive layers of the textile sensors integrated between them. This layering of non-conductive and conductive fabrics make the trousers thicker on some parts: around the thighs and buttocks. However, since all fabrics are light weight and single jersey knits, participants and prior fitting models reported the trousers to be comfortable and only a bit 'warmer' around the upper legs.

Up until this point only textile materials are used in the trousers, but rigid materials are introduced in order to record the change in pressure from each crossing point of the matrix, as well as to power the system.

Electronic components

All materials that are not made of fabric are placed on a solid, custom built circuit board that houses a microcontroller, a Teensy 3.2, a USB battery and a datalogger with a micro SD card on which the data was locally stored (see Figure 4.4, right). The individual rows and columns of the matrix, each forming one layer of fabric, were linked to the input pins of the micro controller through thin and flexible insulated wires, embroidered to the fabric, as shown in Figure 4.5, and soldered to the circuit board. The band of connected insulated wires was used to reduce thickness of all wiring from the stripes of the matrix to the board. A textile solution with insulated yarns was too labour intensive for the production of a first prototype, but is introduced later in Chapter 7.

One layer of the matrix is connected to analog pins on a microcontroller and the other layer to digital pins through the wires embroidered onto the conductive fabric stripes. The other end of each wire is soldered to connectors attached to the printed circuit board (PCB). The PCB design and microcontroller code is adapted from (Donneaud and Strohmeier, 2017b,a). A small USB battery is attached and both the PCB and battery are placed in the hem of the trousers near the ankle, as shown in Figure 4.8 (on bottom right).

Figure 4.5: Wiring of the sensor matrix: encapsulated thin wires are embroidered to the conductive fabric stripes of the rows (left) and columns (right) to connect to the microcontroller, concealed through a fabric tubular panel on the inside leg (left).

4.3.3 Sensor Matrix

Pressure Sensors

Informed by the observations of lower body movement, two pressure sensor matrices are constructed to be integrated in the trousers - one on each leg. The sensing area is defined around the knees, thighs and buttocks of the trousers, covering most of the front, side and back leg. The matrix consists of a 10x10 grid resulting in 100 crossing points on each leg of the trousers. This is made of the cut up silver coated stripes of the 'Zebra' fabric described above, and is designed in the exact shape of trouser patterns, so that it can be later accurately mapped around the upper legs. The width of the conductive stripes is 1cm, so that all 100 pressure points are the same size of 1x1cm. Each layer is arranged perpendicular to the other - i.e. if the top layer is arranged in stripes running left to right, the bottom layer is arranged in stripes running up and down. These stripes are not in direct contact with each other but separated by the layer of the resisitve fabric. Therefore, the crossing points of the matrix touch this in-between layer on each side to measure its change of resistance when being compressed. Donneaud and Strohmeier (2017b) use the same principle, also adapted from preceding work and open-source designs for pressure sensor matrices (Roh et al., 2011; Zhou et al., 2014), while the size and selection of conductive and piezo-resistive materials varies in all these examples.

This design of a pressure sensitive matrix presents an effective method to enable measuring a high number of sensors simultaneously and with one connected system, rather than encapsulating each sensor and process them separately, as earlier examples of pressure matrices showed (Tan et al., 2001; Mota and Picard, 2003).

Array and Circuit Design

The arrangement of the grid is not symmetric or distributed equally as it is in most other sensor matrix designs, but designed to be more dense (or fine grained) with sensors closer to each other in areas where hand touch occurred more commonly, in this case on the inner and top thigh, and less dense at the outer leg, along the side of the thigh and across the back thigh and buttocks, which is displayed in Figure 4.9. This applied to the vertical stripes of the matrix, while the ten horizontal stripes are distributed equally across the length of the matrix, from the knee to the hip. This arrangement derives from the observations that both in leg crossing postures, as well as in postures involving hand touch on legs, the sides of legs are touched less frequently, and little change in pressure distribution occurs because of this. On the other hand, the top leg present a surface on which both hands and other leg parts touch each other, sometimes only on a small part of the surface (hands). This is why a higher sensing resolution is needed, also shown in Figure 4.9, which is based on the identified areas in Figure 4.3. Lastly, the back of the leg is in touch with the chair with a large part of its surface, where the pressure matrix doesn't require a high resolution for this purpose.

Each leg has its own sensor matrix, micro controller and circuit board, so each leg collects data independently from the other. This has practical reasons, such as the limited number of input possibilities on the micro controller or the design of the cabling integration not interfering with wearability comfort, but also reduces the risk of error, when one leg fails to collect data, the other one still functions without interruption. A drawback of this, however, is certainly the increased cost with two micro controllers per pair of trousers[4]. Each leg has therefore a separate timestamp, that later needs to be synchronised and aligned with other recording modalities - an additional step when preprocessing the data for analysis.

[4]though a small cost of appr. 20 GBP

Figure 4.6: Prototyping with mock-up trousers to test fit and validate observations of hand touch interactions on legs, marking most common touch areas.

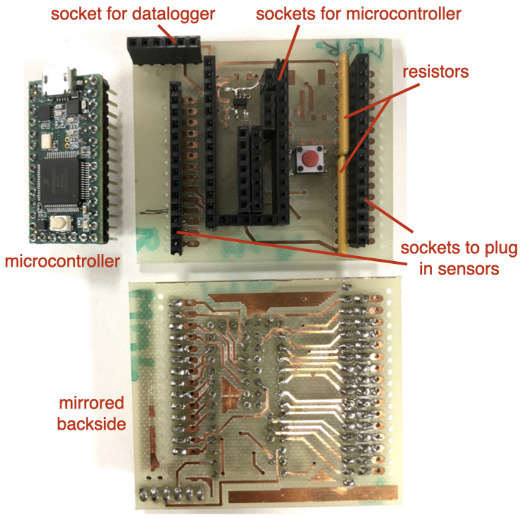


Figure 4.7: The final milled circuit board with sockets to plug in the electronic components, front and back side (mirrored, showing the soldered connections)

Hardware

While the schematic of the sensor matrix as well as of the printed circuit board (PCB) follows in principle the work of Donneaud and Strohmeier (2017a)[5], the size, PCB design and data processing was altered and modified to fit this new use case. The connections to the pins and the placement of the microcontroller on the breakout board is adopted, but the amount of sensors that need to be connected to the pins differs from Donneaud and Strohmeier (2017a), the arrangement is redesigned. While the matrix in their example consists of 16x16 (256) data points in total, the design here features 10x10 for one matrix. The circuit was drawn so that the board could be as small as possible, including the additional datalogger for local data storage on a micro SD card.

The custom milled circuit board has detachable pin sockets so that the board can be removed from the trousers, and the wires that are embroidered to the matrix can be simply unplugged. This was useful for debugging processes while prototyping and enabled us to easily replace faulty components.

The stepwise fabrication of the circuit board is documented in Appendix B, and the final design that was multiplied for the trousers is seen in Figure 4.7.

[5]https://matrix.etextile.org

Integration in Trousers

The fabric pattern pieces forming the sensor matrix were attached to the trousers along the inside leg seam and the crotch seam. The top end of the sensing fabric layers was stitched onto the non-conductive fabric of the outside layer of the trousers for additional stability and for holding the sensor matrix in place. The bottom hem of the matrix fabrics was hanging loose. The wires that are embroidered onto the rows and columns of the matrix were attached on that bottom hem for the columns, and along the inside leg and crotch seam for the rows. A detailed view of these specifications can be seen in Figure 4.8. All components of the matrix were embedded into the trousers' pattern construction and manufacturing process, rather than deployed retrospectively.

The exact placement and density of sensors around the legs of the trousers was determined by preliminary wearability tests. The findings of the observations conducted beforehand determined the area in which sensors are relevant to be deployed. To optimise the location of each sensor and to construct the matrix with the best possible distribution, the *toile*[6] of the trousers was worn by three volunteers that were prompted to perform a series of sitting postures involving hand touch and engaged in a conversation. The touch points were then traced on the trousers, as shown in Figure 4.6 and transferred to the sensor matrix design, informing the resolution of sensors in different areas across the legs.

4.3.4 Pattern Construction

Trousers that are to be tested with a large number of different people need to fit each person and fulfill standards of wearing comfort. Both are requirements for the pattern construction of the trousers and are supported by the choice of fabrics that are used. Additionally, the 'seamless' and unintrusive integration of the sensors influences the engineering of a basic trouser pattern block, a template of the final construction from which all pattern pieces can be cut, and further developed from.

Tailoring Leggings

The aim is to have a pair of trousers that sits close to the body, enabling more precise data collection and posture tracking. I decided to make leggings because they are both, elastic and tight, and are a piece of clothing that most people are familiar with and use. A standard pattern block for trousers made of stretch fabric and without a side seam can be seen in Figure 4.9. This block was created by the author of this thesis, applying standard pattern construction rules used in tailoring and clothing design development. The side seam is eliminated to enable an easier integration of the sensor matrix around the outer thighs, for which a continuous flat surface without the interruption of seam allowances creating an uneven area is preferable. Using a stretch fabric, the shaping of the trousers without a side seam is easy to achieve, while with woven unelastic fabrics, e.g. in suit trousers, that would be more challenging. Housing the microcontroller and the 20 wires per leg that link the rows and columns of the pressure sensor matrix with the circuit board unintrusively adds certain requirements to the construction of the trousers. On the inside of the legs, a tubular fabric panel of 5cm width was inserted, so that all wiring could be pulled through it down to the hem, where it could easily be attached and detached to the microcontroller, as shown in Figure 4.8. This tubular panel, sewn in a technique similar to a 'french seam', where seam allowance is sewn together in two steps to conceal the raw edge of a fabric. The panel prevents the electronic components from

[6] or mock-up, prototype

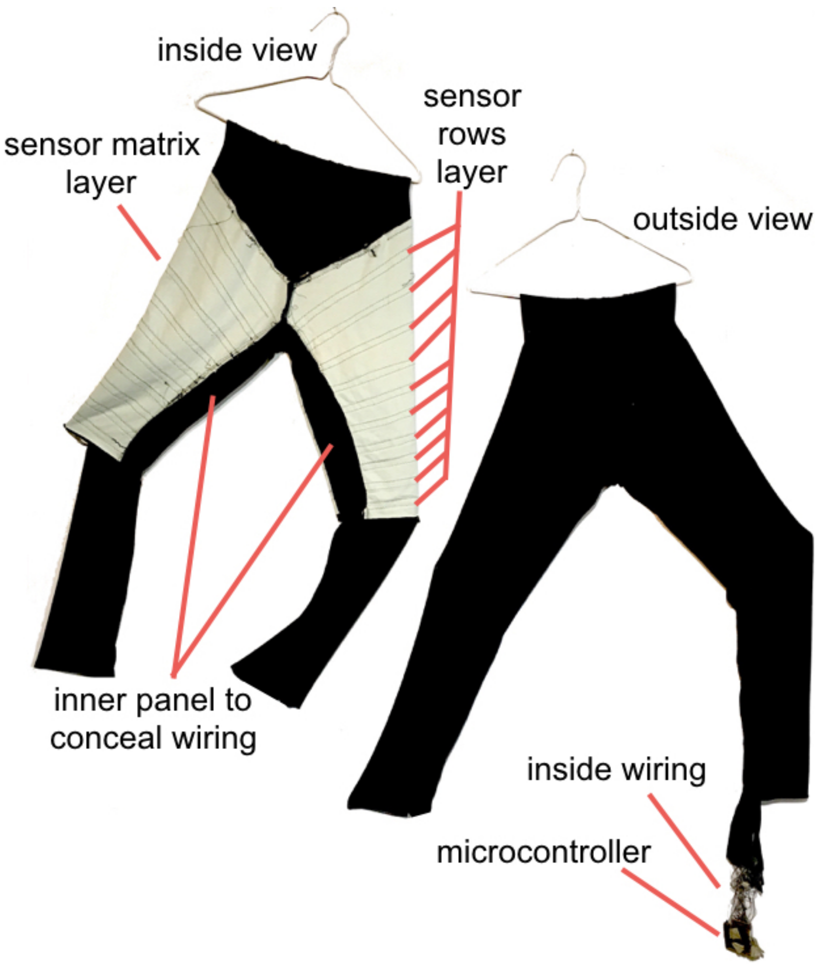


Figure 4.8: Inside and outside view of sensing trousers. Left: layer of sensor matrix embedded on the inside from crotch to knees stitched onto seams of tubular panel on inside leg. Right: ‘shell’ of trousers, fabric bands on hem with microcontroller

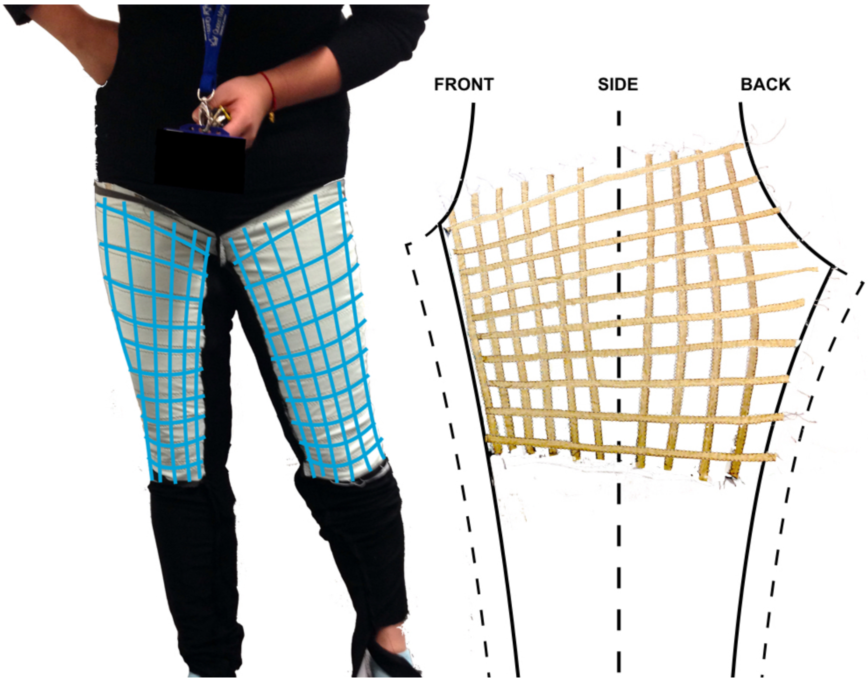


Figure 4.9: Left: the 'smart' trousers being worn inside out. Right: the flat pattern of the trousers, with no side seam, and the placement and mapping of the sensor matrix across the thighs and buttocks

coming into direct contact with the skin as it is concealed between layers of the soft non-conductive fabric. A work-in-progress image of integrating the wiring in the tubular panel can be seen in Figure 4.5. The hem of the trousers could be rolled up, so that the PCB could be tucked in and concealed. Additional fabric bands at the hem served to tie the PCB and battery closer to the leg if needed.

Grading System

Differences in body shape also entail that the sensor points of the matrix are not always in the very same position. With the choice of material and pattern system, however, this variation can be minimised. The stretch knit fabric used accommodates multiple clothing sizes and body shapes with one pattern cut, and can still sit tightly (e.g. as is worn in Figure 4.9). To allow for a wide range of sizes, however, a grading system was developed, and three different sizes of trousers were manufactured. The system was determined through the measurement data of 11 different subjects (volunteers), 7 male and 4 female. Average measurements of these volunteers, as well as standard clothing size tables formed the base for the sizes Small, Medium and Large.

This did not affect the resolution or positioning of the sensor matrix, but only the overall width of the trousers, allowing for more fabric around the thighs and crotch area. The development of this grading system followed a process common in the tailoring industry. This means that by increasing one size, the crotch point is lowered by 0.5cm and widened by 1cm, in addition to inserting 2cm along the initial side seam across the entire length of the pattern. This is repeated to increase by another size.

4.4 Evaluation: Posture Classification

To assess the reliability and overall performance of the sensing trousers, I conducted a user study[7]. I tested 19 different postures that were identified through ethnographic observations described above, drawing from a video corpus of 12 seated three-way conversations (36 different subjects). The postures tested here are considered to be often reoccurring static sitting postures and are, in part, also tested in other works, for example in (Meyer et al., 2010a; Kamiya et al., 2008; Xu et al., 2013), amongst others.

The design for this experiment follows settings of some of those user studies with similar research objectives, in particular orientating towards the work of Meyer et al. (2010a), who identified 16 similar sitting postures and tested these with 9 subjects in three rounds for classification purposes. Other works evaluated gesture classification with even fewer subjects (e.g. Junker et al. (2008); Cheng et al. (2013)). Examples like this show that even with collecting posture data of only one person (Tan et al., 2001), but having multiple recordings per posture, results are accurate enough for classification models.

4.4.1 Participants

The data was collected from 10 participants, aged between 19 (2) and 42 (1) years (the rest between 26 and 36years). Five female and Five male subjects of different clothes sizes were recruited. This will provide a data set that allows us to test all three sizes of trousers that were manufactured, compare their performance and ensure the same quality and sensor behavioural characteristics across the different models and across different physiques of participants. Later the data of 4 participants had to be discarded due to an error with the formatting of the data files, and the data of the remaining 6 participants was analysed.

4.4.2 Procedure

The study consisted of single user actions, in which participants were asked to perform the series of sitting postures when instructed to do so. The study took place in the Materials Lab of the School of Electronic Engineering and Computer Science at Queen Mary University of London, where a chair was placed in front of a camera. Participants were putting on the trousers themselves or were assisted to do so if needed, then asked to take a standing position in front of the chair, facing the camera. They were briefed on the procedure and then asked to follow verbal instructions performing a variety of sitting postures and gestures. After this instruction, while still standing, the recording started and the instructor, positioned next to or behind the camera, read out the sequence of postures the participant should perform. The 19 posture types are:

1. standing up (hands to the side, natural standing position)
2. sitting down, up straight = “home position” (first “natural” position taken when sitting down, without hands, knees or lower feet touching each other)
3. sitting straight with knees touching
4. leaning back
5. leaning forward (without hands touching thighs or knees)

[7] Ethics Approval Reference: QMREC2133a

6. slouching
7. leg crossing: left over right leg
8. right leg crossed over left leg
9. leg crossing: left on right leg with ankle touching knee
10. right on left leg with ankle touching knee
11. sitting up straight, hands touching knees
12. leaning forward with hands on knees
13. hands rested in crotch / on lap
14. hands tucked between thighs, knees touching (thighs pressing on hands, hands touching each other)
15. hands on mid thighs
16. elbow on thighs, leaning forward
17. lower feet postures: both lower feet stretched out
18. lower feet bent in
19. lower feet crossed.

Here, the postures involving events around the thighs were performed twice - once on each side (posture 7 - 10). The postures involving only movement in the lower legs were not divided into separate instructions accounting for left and right sides(postures 17-19), since there were no sensors covering the lower legs and the overall focus remains on upper leg movement.

Each posture was held for 5 seconds and returning to the "home position" for 2-3 seconds in between. This was timed by the instructor. As the home position, I determine the default sitting posture that was first taken when sitting down onto the chair, a position that felt "natural" to the participant and can be described as sitting up straight with uncrossed and untouched legs and feet, and with arms handing straight down on the side. The instantaneous pressure readings from the 200 sensor points for the duration of one posture are defined as an instance (this accounts for 4 instances per second). Each participant repeated this sequence of instances three times, which results in approximately 60 instances per participant per posture.

4.4.3 Data Collection and Processing

Sensor Data

The raw sensor data was collected with the rows of conductive fabric of the matrix forming the digital inputs and the columns the analog inputs on the corresponding microcontroller, a Teensy 3.2. Pulling the digital pins high and reading analog input values from the column one by one creates a sensor reading for all data points across the matrix. The pressure sensor data was collected in a format in which each sensor is stored in a separate column, with each row accounting for the readings over time, starting the recording at the onset of the microcontroller, in other words: as soon as the trousers are 'switched on'. A time stamp was included for later synchronisation between the two legs of the trousers, as well as with a video recording. A detailed documentation of the method of how the sensor data is collected from each data point of the matrix can be found in (Donneaud and Strohmeier, 2017a,b). Unlike in their work, however, here the data is not processed and visualised immediately in real-time, but stored as a txt file on a micro SD card (plugged into the datalogger) for off-line analysis. After the completion of the postures by each participant, the data is normalized so that the minimum sensor value is 0.0, and the maximum sensor value is 1.0. The data was then visualised and mapped to the corresponding location on the sensor grid using the open source software platform Processing[8], as seen in Figure 4.11. The Figure shows each data point on the matrix as a circle of varying size, correlating to the applied pressure over time. This was used to informally and preliminarily inspect the sensor data, gaining a first understanding of the sensors' behaviour and trousers' performance. This visual representation of the sensor data was also useful to detect any errors in the data, e.g. malfunctioning or disconnected sensors.

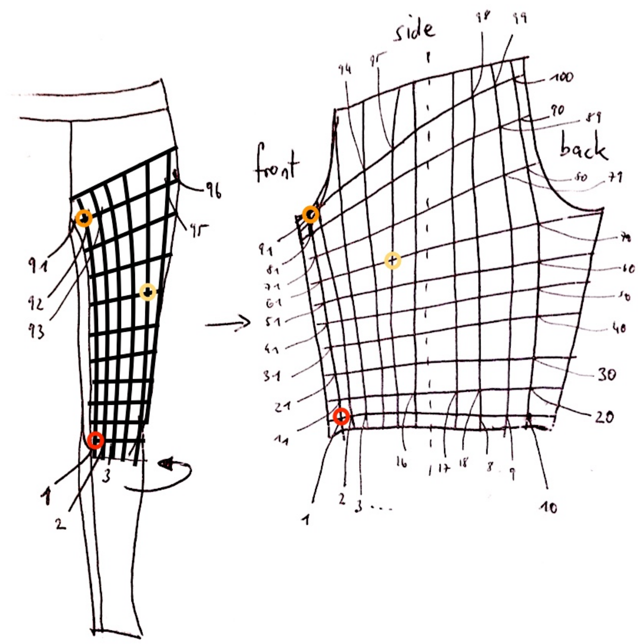


Figure 4.10: A draft sketch of how the sensors on the flat pattern block on the right map around the leg when the trousers are assembled (left). The sensor numeration across the matrix on the leg is arranged as follows: sensor 1 on front inner leg on knee, sensor 100 on back inner leg on buttocks, 10 sensors per rows.

Mapping of Sensors on the Trousers

The mapping of the data visualisation and sensor numeration is arranged as shown in Figure 4.10, where the first sensor sits on the front inside leg and the last sensor on the top of the back pattern. The sensors are counted row by row, starting on the inside front leg counted horizontally towards the back leg (so row 1 counts sensor 1 - 10, row 2 sensors 11 - 20, etc.). A screenshot of the animation with the same mapping can be found in Figure 4.11, showing each data point as a circle increasing in size when the pressure on the sensor increases, e.g. bigger circles on the top end mean more pressure on the buttocks, which would indicate a sitting position. Note that one grid depicts the data of one leg only, so it is not representative for the whole pair of trousers.

[8]https://processing.org

Figure 4.11: Visualisation of two different leg crossing postures. Each circle represents on data point of the sensor matrix, mapped around the participant's left leg (the observer's right leg). Bigger circles indicate increased pressure.

Video annotation and synchronisation

Alongside the sensor data, a video recording documents the session capturing the verbal instructions and postures of the participant. One camera was placed in front of the chair, so that the participant would be captured from a front view when performing the postures.

To generate a ground-truth data set of the 19 different postures, annotations for each of the postures were added to the video recordings using the software package Elan (Brugman and Russel, 2004). All postures were hand coded as static positions, discarding any transition periods between them. For example, the movement between crossing a leg and returning to the home position was not included in the posture, but treated as noise and removed. The sensor data was time-aligned with the video annotations and exported into ARFF format for further analysis. This file format is created for further processing in the machine learning software Weka (Holmes et al., 1994; Hall Eibe Frank et al., 2009), and organises the labels of the data and different postures into a specific order and format. While the raw sensor data was collected during the study, the normalized pressure readings were used as the input for the classification algorithm.

4.5 Results

The aim for the trouser sensing system is for it to automatically recognize the posture of the wearer. The first steps towards achieving this is to generate ground-truth data to train a machine learning model performing a classification task in order to provide a baseline indication of the system's performance.

The 200 sensor data points were captured at 4 Hz resulting in over 9000 total postural instances across six participants. Of these 1327 were instances of the standing posture with 325 to 626 instances of each of the remaining seated postures. The higher number of standing postures is due to longer standing periods in between the cycles of posturing, which were also taken into account for analysis. Instances where the participant was not clearly displaying one of the postures were discarded from the data set.

The open source software Weka (Holmes et al., 1994; Hall Eibe Frank et al., 2009) was used to train and evaluate a Random Forest model with bagging with 100 iterations. It was first evaluated with individual participants, then as a population-level model with all participants, and finally with individual participants withheld from training.

4.5.1 Individual Model

When training a Random Forest model and evaluating using 10 fold cross validation with stratified data on a single participant, it showed excellent results in classifying postures with an average of 99.31% of postures classified correctly. The percentage of correct classifications for each participant can be seen in Table 4.3, ranging from 98.80% to 99.75% average accuracy across all postures. The models showed particularly good performance when classifying between standing and seated postures, with only misclassifying one posture for two participants as seated with leaning back or the home position instead of standing (participants C and D). Proportionally, this only occurred once in a data set of 1264 (participant C) and 1649 (participant D) instances, of which were 163 (C) and 263 (D) standing position instances, and significantly fewer for the postures they were misclassified as. The confusion matrices of these two participants are attached in Appendix B. The success in the classification between seated and standing is likely because of the significant difference in sensor values on the underside of the trousers, however the imbalanced data captured may also play a role. For each participant there was up to four times as many instances of standing than any other posture in the data set due to the sequence of positions recorded. For example, participant A with the highest overall accuracy of correct classifications has 202 standing posture instances, and between 47 and 152 instances for all other postures (most others counting around 100 instances - half the size of the standing posture data).

Misclassifications between the remaining 18 sitting postures were equally rare in the individual model overall, with maximum one instance being incorrectly classified. In most of these cases, the postures that were mixed up are similar postures, for example both relating to hands touch on legs (thighs and knees), leg crossing or movements in lower feet. Participants showed 0 - 3 misclassifications in total, for example confusing one instance of a posture involving lower legs and feet with a similar posture involving lower legs, too. Similarly, mostly postures were confused for which pressure is applied on the same body parts - e.g. postures of hands touching the thighs.

When examining the F-measures, four of the six participants had the best classification performance with standing (all except participants C and D) and worst with the feet crossing and hand-dependent postures. This can be seen in Table 4.4. The Table also shows that the lowest

Participant	Individual	Leave-One-Out
A	99.75%	64.26%
B	99.58%	42.71%
C	**99.68%**	**27.93%**
D	**99.21%**	**10.97%**
E	98.80%	32.20%
F	98.84%	50.10%

Table 4.3: Percentage of correct classifications for each participant when trained on a single participants and evaluated using cross-validation, and when that participant was withheld from the training set then used as the test set. Participants C and D in bold are the two participants who misclassified standing postures.

Postures	A	B	C	D	E	F	Community
standing up	1.000	1.000	0.997	0.996	1.000	1.000	0.999
sitting down, home position	1.000	0.978	0.989	0.982	0.991	0.986	0.987
sitting, knees touch	1.000	0.992	0.982	0.983	0.979	0.986	0.984
leaning back	1.000	1.000	1.000	0.992	0.977	0.991	0.995
leaning forward	1.000	0.993	1.000	1.000	0.977	0.992	0.995
slouching	1.000	0.986	1.000	1.000	0.994	0.982	0.990
leg cross L over R	1.000	0.995	1.000	1.000	1.000	1.000	0.995
leg cross R over L	0.994	1.000	1.000	1.000	0.985	0.979	0.992
leg cross L on R, ankle on knee	0.988	0.994	1.000	1.000	1.000	0.991	0.996
leg cross R on L, ankle on knee	0.993	0.993	1.000	0.993	0.963	0.984	0.986
sitting up, hands on knees	0.994	1.000	1.000	0.987	0.986	0.981	0.987
leaning forward, hands on knees	0.989	1.000	1.000	0.990	0.986	0.980	0.988
hands rest on lap	1.000	1.000	1.000	0.995	0.967	0.996	0.994
hands tight between legs	1.000	1.000	1.000	0.983	0.993	0.987	0.987
hands on mid thighs	0.992	1.000	1.000	0.987	0.976	0.973	0.986
elbows on thighs, leaning forward	1.000	1.000	1.000	0.995	0.994	0.993	0.996
lower feet stretched	1.000	1.000	0.988	1.000	1.000	0.984	0.995
lower feet bent	1.000	0.991	0.990	0.976	1.000	0.984	0.990
lower feet crossed	1.000	0.992	1.000	0.981	0.990	0.984	0.992

Table 4.4: F-Measures of all 6 individual participants and as community for all 19 postures, in the order they were performed as instructed.

F-Measure overall, 0.963 (participant E) is from a leg crossing posture. For the two participants C and D with misclassified standing postures, their leg crossing postures performed better than other postures. Weighted average F-Measures for all individuals are 0.993, for Recall and Precision as well, with the best participant having average F-Measures of 0.997 for all postures, and the poorest performing participant 0.988. Again, Recall and Precision results are identical, and can be checked in Table 4.5. Details of F-Measures of all 19 postures for each participant are listed in Table 4.4 in the order they were performed in the study.

4.5.2 Community Model

General Community

The next step was to examine the potential of building a generic, population-level model with a total of 9128 instances. I started by training a Random Forest model on the aggregate collection of postures from all six participants and then evaluating it using 10 fold cross validation with stratified data. This had excellent results with 99.18% of postures classified correctly, with F-Measures, Recall

Results	Community	Individual (Avg.)	Leave-One-Out (Avg.)
Accuracy	99.18%	99.31%	38.03%
F-Measures	0.992	0.993	0.375
Recall	0.992	0.993	0.380
Precision	0.992	0.993	0.388

Table 4.5: Overview of Random Forest classification results for community, individual and leave-one-out models. Results are averaged across all 6 participants for the last two models.

and Precision results of 0.992, summarised in Table 4.5. A detailed list of all F-Measures per posture for this general community model are also shown in Table 4.4. Here, the best result is for the standing posture with F-Measures of 0.999. The lowest F-Measure in the community model is for the sitting posture without hands involved and the knees touching, which is 0.984. Leaning backwards and forwards, as well as having the lower legs stretched were amongst the best performing postures when looking at F-Measures.

Similar patterns occurred as when building individual models for each participant. Again, standing performed well when compared to non-standing positions, though it still has up to 4 times as many posture instances than other postures. It had one more misclassification when compared to the individual models - along with being confused by knees touching and the home position, it misclassified a slouching posture. However, in perspective, these are a total of only 2 misclassified postures across 1327 instances for standing. Similarly, between sitting postures, the maximum of misclassifications was on 4 occasions when slouching was falsely identified as the home position, as well as 3 times when a leg crossing posture was incorrectly classified as the posture when hands were tucked between the thighs. Twice out of 389 instances, a leg crossing posture was confused with a posture with hands resting on the thigh. The community model's confusion matrix and detailed numbers of misclassifications are reported in Appendix B.

Leaving One Participant Out

The ideal trouser sensing system would be able to train from data sets of lab-based postures, and then correctly classify the postures of a new wearer who had not previously gone through an individual training phase. To evaluate the feasibility of this application, I generated six Random Forest models withholding a single participant from the set, and then tested that model with the withheld participant data. As was expected, all participants performed much worse than when their data was included in the training set, but all performed better than random chance.

The two participants that performed the worst here were the same that performed the worst at classifying between standing and seated postures, participant C and D in Table 4.3. Those whose individual models could better distinguish between standing and non-standing also performed better when their data was not included in the training data with the best performance being 64.26% from participant A. The average results of all tested participants when left out from the training data are lower, with 38.03% correct classifications, and F-Measures of 0.375, shown in Table 4.5.

The classifications from the model built without participant A can be seen in the confusion matrix in Figure 4.12. The matrix compares which postures were confused with which other postures. For example, "hands tucked between thighs", "hands in crotch / on the lap" and "hands on mid thighs" were often misclassified as "hands on knees". This can be explained with the similarity of the postures as well as the variations of hand positioning per participant and posture repetition. For example, participants were observed performing the same posture in a variety of ways in different cycles, but

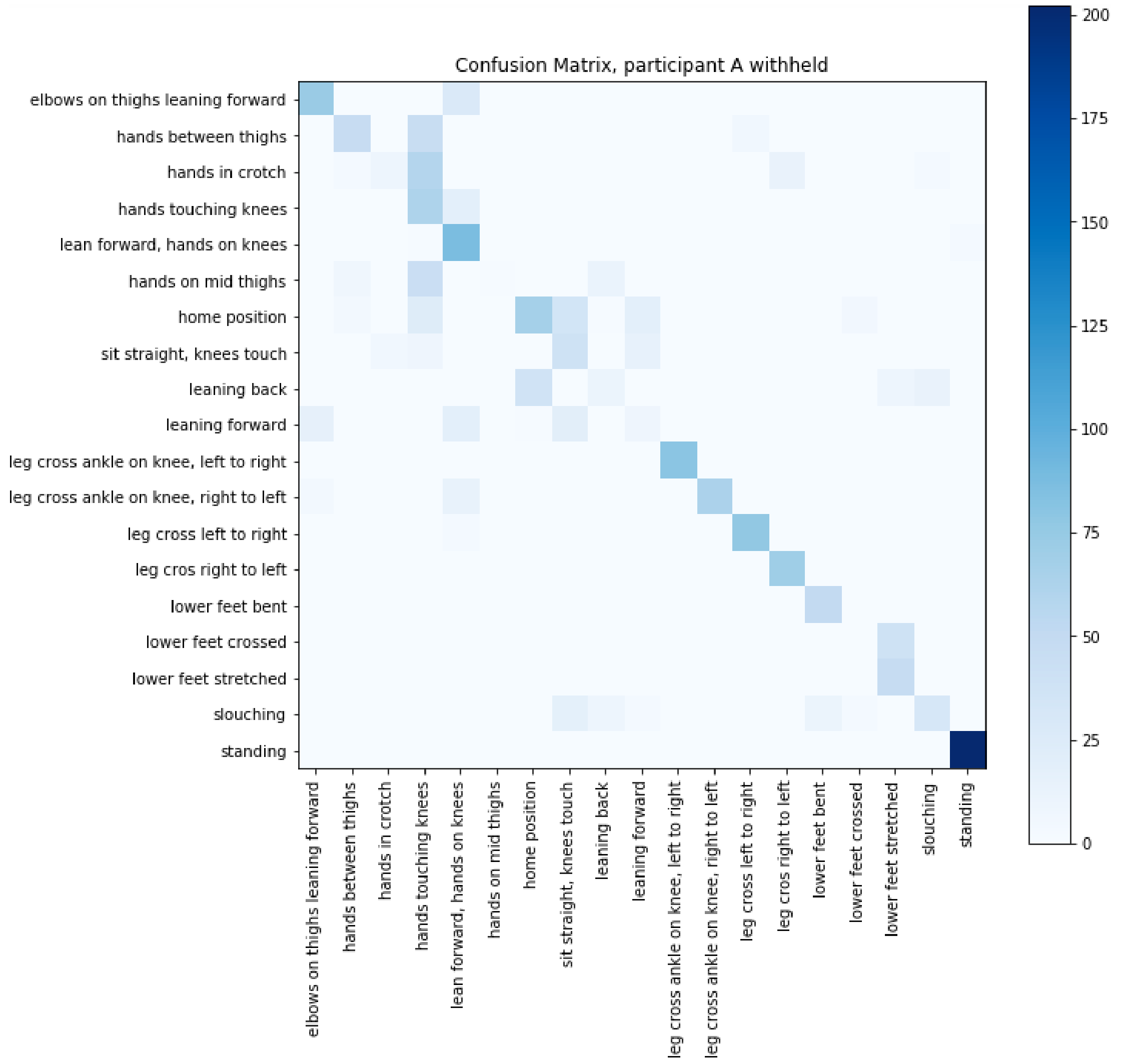


Figure 4.12: Confusion Matrix, participant A withheld. Number of instances are colour coded as shown on side bar (0-202 instances, white to dark blue).

also that different participants interpreted the verbal instructions, though as precisely instructed as possible, in different ways - for example when asked to lay their hands on the lap or crotch, each participant would place their hands on another exact position. Other postures that were confused with each other are “leaning back” and “home position”, both only performing movement of the upper body and only slightly shifting the pressure distribution amongst the legs. Lastly, the postures referring to lower leg movement were the third category of misclassifications. Lower legs being bent, crossed or stretched did also not implicate movement of the upper legs and buttocks as much, the area where the sensor matrix was placed. Other, less common misclassifications of the best performing participant in the community model can be deducted from Figure 4.12.

Other tested participants, when withheld from the training set, still performed very well and with no misclassifications distinguishing the standing posture from others, but showed frequent incorrect classifications between similar sitting postures. For example, postures in which the torso was leaning forward were confused with each other, such as leaning forward with elbows on thighs with hands on knees while leaning forward. Furthermore, the home position was sometimes classified as leaning back, while all different leg crossing positions performed well and were only rarely classified as another posture. Other examples of common mismatches were slouching with leaning back or lower feet stretched, or hands on thighs with hands on knees - all postures that share some key characteristics (e.g. when slouching, some participants also leaned back and stretched their legs). More confusion matrices are added to Appendix B.

In summary, these different participant tests were able to recognize standing better than any other posture. This indicates that may be a potential application in recognizing the postures of a wearer who has not gone through a training phase, but more data needs to be collected to better inform the machine learning model.

4.6 Discussion

This user study served the purpose to validate 'smart' trousers as a wearable, textile sensing system to be carried further and tested in an interactional context to investigate nonverbal behaviour. Given the small number of sample data used here, there is much room for improvement for this classification model. Yet, the implications for use cases that emerge from the results of these sensing trousers are promising, and encourage to continue to work towards establishing textile sensors as a novel modality in the field of behavioural studies.

4.6.1 Classification Improvements

The machine learning model shows good performance when building a general population-level model, as long as the participant being tested is represented in the training of that model. It has significantly worse performance when testing a model with a participant who is not represented within the training set. This indicates that the sensors could be effectively used to automatically identify postures of individuals, as well as potentially individuals themselves, if that participant goes through a data collection phase. Without more data and model refinement, this is not yet ready for generic use where an unknown participant could have their postures detected without training. In addition to a larger data set, multiple sessions of performing the postures to be classified would also help to compensate for the variation a single participant shows when performing the same posture. Moreover, a more balanced data set, with the same number of instances for each class, would help to achieve more accurate and realistic results. In particular, this would imply to reduce the number of instances used for the standing posture, or to separate this posture from all other siting postures altogether and focus on more similar categories of postures to explore more fine grained differences in the classification accuracies.

Another aspect of the study set up that may affect the results is the controlled data collection with static postures in a repeating order. The trousers were worn once by each participant and have not been tested with variations in order and duration of postures, or for consistency in multiple wearing sessions, which could lead to minimal changes in sensor positions. In other words, clothes as sensing systems are per se dependant on the user, layers of fabric are not always at the very same position when being worn on different occasions, and also wrinkles, twists and other parameters come into play in a soft, flexible sensing surface placed directly on the human body in motion. Even though the same person performs the same, precisely instructed posture multiple times, there are individual differences not only in the posture itself, but, in perspective to more spontaneous, not instructed situations. Differences in the duration of such postures varies, too, given different scenarios. Moreover, in social interaction, dynamic postures are more common, and occur in different order and with different transitional movements that potentially add noise to the data. I have accounted for that potential noise regarding repetition and order effects, and plan to dedicate future work to investigate these points further by testing the trouser design in conversational scenarios.

4.6.2 New Social Postures

The evaluation in this chapter has shown that there may be a much richer collection of postural cues on the lower body yet to explore that has so far been invisible to other sensing technologies, or has simply not been the centre of examination. If thighs and buttocks can provide such details about behavioral cues with their shifts in movement and touch interactions, as I have shown with the sensing chair covers, there are potentially additional and complimentary cues to be collected from lower legs, feet movement or other areas of the lower body that have not been explored in detail and that go beyond gesturing and apparent twists in posture. In comparison to the chair covers, this wearable sensing system has the potential to pick up these more fine grained differences in these postures, and detect additional interactional movements choreographed by upper and lower body interacting.

Translating the classified postural movements to affective states and a measure for conversational engagement, trousers have the potential of identifying a “smart arse”, or could detect if someone is listening, interested, bored or restless. For example, future work is directed towards specific questions as to whether leg crossing correlates with gaze and determining addressees; whether the position of hands on legs bears information about levels of arousal and valence to detect stress, comfort, anxiety, etc.; or elaborate further on findings of existing work (Witchel et al., 2016) that suggest that thigh movement implies user attention level, or that lower legs when bent in a sharp angle (tucked towards the chair) signal attention in listeners, too (Bull, 2016). This also leads to questions that expand on the sensing capacities of this sensor design. Having trousers that can not only capture leg movement, but that also pick up touch of the hands, it is intriguing to explore how well, or if at all, trousers can also pick up upper body movement, like nodding, head turns or conversational states like speaking and listening; and, if not, how an equivalent design would look like for garments for the upper body.

Given the lack of literature on the lower body as a behavioural social signal, these trousers could contribute to add to this body of work and evaluate the significance, as well as richness of leg movement in conversation. This can concern overt postures like the ones that were tested here, but also investigate micromovements like small scale shifts and fidgeting, leg bouncing or general orientation of feet. Overall, the evolving research question determining this research’s work to follow, is: if trousers can detect postures, can they also detect behaviours?

4.6.3 Directions for Potential Applications

The contribution this work can make towards affect detection and understanding different modalities of human communication could benefit applications in the medical sector for the design of therapies, like physiological rehabilitation, as well as cognitive therapies. Furthermore, such trousers could be designed to feed back this information to participators of social encounters and thereby help to improve human interaction scenarios. Such “socially aware trousers” are not only potentially enriching for interaction between humans, but also for applications in Human-Computer-Interaction - even if that is only by replacing rigid interfaces with soft, flexible textile sensing surfaces that can be worn unobtrusively on the body.

Textiles that feel like everyday clothing items, electronically enhanced or not, are a material we already engage with traditionally, and clothes are something omnipresent. This is their foremost advantage compared to other modalities with similar sensing capacities, for example Kinect v2, which may be able to sense muscular force, but is vision dependent and requires special spatial settings to take bodily measures. The material aspect of sensors made from fabrics are an important aspect when evaluated against other technology.

The ability to monitor postural shifts and pressure applications has also the potential to inform garment construction and pattern cutting in direct dependency with the intended use case. This could range from applications for fashion retail, e.g. clothes that take size measurements[9], to the simple objective to develop more comfortable trousers for professions that require a lot of sitting (e.g. in offices). More speculatively, systems like these trousers can be made to identify their wearer with application scenarios in health and safety, and could also be a gateway for an even less intrusive, embedded contactless payment option. Such implications to the design of trousers would give the saying "you are what you wear" yet another notion and would make our clothing not only subject of personal expression, but also of identification and a more active part of our everyday actions. In the future, clothes may not only be objects that project communication, but potentially be aware of how we communicate with others.

4.6.4 Summary

In this paper, I have presented an unobtrusive method of capturing different sitting postures that is integrated in stretch trousers. Using a textile pressure matrix around the thighs and buttocks, it is possible to detect different leg movements as well as gestures on the lower body. I demonstrate that shifts in pressure on the upper leg are enough to train machine learning models to identify leg crossing, positions of hands on thighs and knees, lower leg postures, as well as more subtle weight shifts with high accuracy. Automatic classification models using standard machine learning tools were tested to distinguish between 19 posture types, and have shown promising results towards this research's goal to establish textiles as a suitable wearable sensing design to capture body-centric data, and eventually make garments "socially aware" - and posturally aware for a start.

Contributions

In summary, the contributions of this chapter are to the design adaptations to sensing trousers and the pressure sensor matrix embedded in them. The benchmark study of this chapter showed that textile pressure sensors as a wearable on-body system can compete with previously used sensors on a chair surface.

The trousers present a design that integrates the sensing system from an early design stage onward, advancing most sensing trousers presented in literature. The design and engineering process of the trousers is further an addition to smart garment developments, providing solutions to circuit and sensor integration for lower body garments. The focus on trousers is also a contribution towards the proposed attention for lower body garments in general, standing alongside the more elaborated works on textile sensor design for upper body garments.

[9] https://zozo.com/

Limitations

The presented study comes with limitations, too. The success of the classification results is drawn from a small data set of only 6 participants, and the performed postures and evaluated postures are performed in an isolated, not interactional context, participants being prompted to perform them in an instructed manner. Aiming to deploy the sensing trousers in a 'real world' scenario, the here achieved results are not realistic to hold for unstaged, spontaneous postural movements. These restrictions apply also to the machine learning model, risking to be overfitted. To overcome these challenges and restrictions, the trousers will further be tested in different experimental set ups, introduced in the next two chapters.

By exploring fabrics as an interface so close to our body, I anticipate that it will be possible to identify additional postures as relevant cues in social interaction. This is what will be explored further in the next chapter: placing the trousers in an unstaged environment, worn by participants engaging in spontaneous conversation. After validating the design of the trousers here, I will also elaborate on additional classification techniques and further explore the potential of trousers as a sensing system in the work to follow.

Chapter 5

Posturing in Conversation: Detecting Social Behaviour with Sensing Trousers

Chapter Overview

With a successful benchmark study that has validated the trousers as a sensing system for bodily data, the work in this chapter proceeds to explore their potentials further in a social context. Here, investigating behavioural and postural aspects in multi-user interaction with trousers are investigated. Where I previously validated the sensing trousers with instructed static postures, I now seek to test them in a context allowing for spontaneous movement in an interactional setting, paralleling the objectives and study structure in Chapter 3 used to evaluate the chair covers. By doing so, I conduct a user study in a similar format, looking at seated three-way conversations.

The data set I present here forms the basis for a large range of explorations spanning into the following two chapters. In this chapter, I take on the objective of distinguishing basic conversational behaviours, firstly focusing on the differences between speakers and listeners, and secondly testing the trouser based wearable sensing system for additional listener behaviours, too. I explore how far the modality of fabric pressure sensors in trousers can be explored as an instrument to analyse social interaction, and what approaches are most suitable to achieve this. Different classification methods are tested before a Random Forest model is used to evaluate this data set against the objectives set out here.

The chapter is structured into first presenting a recap of relevant literature as well as the key aspects of the design of the sensing trousers. Then, the study procedure and data collection is reported, followed by explaining the results of classification for a Random Forest model, and a discussion to contextualise this chapter's findings.

The publication accompanying this chapter is: *Skach, S., Stewart, R., & Healey, P. G.T. (2021). Sensing Social Behavior With Smart Trousers. In IEEE Pervasive Computing, Vol. 20, No.3, pp.30-40, doi: 10.1109/MPRV.2021.3088153.*

5.1 Introduction

The intentional signals we perform for people we interact with are well and unambiguously on display and carried out as overt, marked movements. They are also mostly focused around three defined areas: the expressions of the face, the movement of arms and the overall orientation of the torso. We use these body parts to emphasise and support our verbal and vocal communication. Movements in the lower body, however, are often overlooked as conversational cues, though they regularly serve as measures to detect sitting postures in similar scenarios, not accounting for social context. Based on the findings and observations described in the previous two chapters, I propose that these less explored cues deriving from movements in the lower body are interactionally relevant, too, and make a significant contribution to nonverbal communication.

As mentioned previously as well (Chapter 2), all nonverbal social signals, lower or upper body related, have the potential to contribute information about a large part of human interaction and contain detailed information about people's social behaviours e.g., whether a conversation is friendly or confrontational, whether people are interested or bored and often who or what they are talking about. At a glance, we can identify speakers, listeners, make inferences about their relationship to each other and the level of their engagement in the encounter. What social signals does the lower body provide? Can leg movement identify speakers in a conversation? Can leg movement say as much about interactional dynamics as hand movement does? And, more generically, are social behaviours revealed through legs as much as they are through the torso? Might legs enhance or confirm what hands and face are able to communicate? Or do we reveal additional cues with our lower body that have so far not been deduced from the upper body?

Sensing these sometimes subtle cues can be challenging. Even more so when focusing on the lower body, which in seated conversations often involving a table, is difficult to capture. Traditional, vision dependant technologies can easily reach their limit in such scenarios. In addition to problems of requiring the physical space to be instrumented, and sensitive issues around surveillance and data protection, they risk failing to capture the body parts of interest because of occlusion, hidden by tables or other objects in an environment. To overcome obstacles like these, on body sensing systems have become increasingly popular, although wearable sensors often employ conspicuous forms of industrial design e.g., encapsulated in plastic or integrated in other rigid devices, such as wristbands (Rekimoto, 2001), smart watches or belts (Trindade et al., 2014). These forms of wearable computing are usually multi-functional and designed for conscious and reflective use which can, and often explicitly aims to, alter a wearer's behaviour. The on-body sensing system presented here, pressure sensitive trousers, addresses many of the above issues and present the first textile sensing design to capture social behaviours; a new potential filed of application for e-textiles.

In this chapter, I draw the attention back to the research questions set out in Chapter 3, asking and elaborating on whether it is possible to detect overt conversational behaviours in a naturalistic setting from textile pressure sensors, with the difference that now I use the sensing trousers rather than sensing chair covers to investigate these questions. I look at the distinction between speakers and listeners, and furthermore divide listeners into active and passive interactants, carrying out responsive rhythmic movements such as nods and laughs but also verbal responses defined as backchannels (Schober and Clark, 1989; Goodwin, 1979); or behaving more passively, unengaged, which will be called "incidental" listeners. The basic research question here is whether this method of textile pressure sensing can detect such refined behavioural states and deduce valuable information about social interaction.

Using trousers enables us to detect how well lower body movements signal social behaviours, and also how effectively lower body sensors are to pick up signals the upper body provides or. Where the four sensor patches on the chair covers provided basic information on shifts of pressure of both, the upper and lower body, the trousers are able to pick up a larger variety of fine grained movements and potentially detect gestural actions that previously remained undetected. In summary, the aim is to address the objectives around behavioural studies and conversation analysis on a more detailed, specified level with the on-body pressure sensors than may have been possible with the ones deployed on a chair. I investigate how much of the large set of conversational behaviours and states the trousers are able to inform us about.

The additional sensors on the trousers may help to pick up the identified cues and behaviours more clearly than the sparse amount of sensors used before. However, the additional sensors also run the risk of creating more noise in the collected data that the minimalist chair-based approaches avoided. To address these questions and assess the trousers as a sensing system for capturing social interaction, machine learning approaches and feature engineering methods are explored.

5.2 Background

5.2.1 Recap: The Lower Body in Conversation

The sitting postures that were determined in the previous Chapter derived from observations of unstaged multiparty conversation. Some of these postures have been linked to social signals, that are mentioned in Chapter 2. In summary, leg postures in their own rights have rarely been associated with social behaviours, and have mostly been mentioned marginally. Most commonly, leg postures are set in relation with gestural movement and upper body postures, which are reported to be of clearer correlation in regards to perceived behaviours and emotions (Bull and Connelly, 1985; Mehrabian, 1968a). In particular self touch, for example hands touching legs, has been found to indicate comfort or internal conflict (Butzen et al., 2005).

The meaning of posture changes in the lower body have been linked to boredom and interest, signalling attention when legs and feet are tucked in, and boredom when legs and feet are stretched out (Bull, 2016). Leg movement in general, whether that is a change of posture on a large scale, or some small movements like fidgeting, has been associated with different attention levels (Chalkley et al., 2017b). From looking at movement of feet, indications of speaker turns can be drawn (Duncan, 1972). The observation of static lower body postures, in particular leg crossing, has been found to be perceived as friendly or unfriendly (Harrigan and Rosenthal, 1983), with uncrossed or crossed legs reportedly signalling ‘openness’ or readiness for interaction (Mehrabian, 1969). The orientation of feet in multiparty interaction can reveal the involvement of a participant in the encounter (Kendon, 1990a).

5.2.2 Evaluation of Smart Garments

Using selfmade textile sensors for classification tasks can be challenging. Their behaviour is not as linear as from “off-the-shelf” sensors and sometimes requires more pre-processing steps before being modeled for classification (Dunne et al., 2006a). This applies even more so when such sensors are embedded as wearable systems in clothing, since there are additional factors to be considered, such as washability, electrical interference through the human body and individual sensor calibration. In many studies that introduce smart clothing for sensing postural movement, the electromechanical properties of the sensor design are assessed in a controlled environment (Molla et al., 2018; Metcalf et al., 2009; Gioberto et al., 2013). The proposed application areas for smart garments measuring body movement are commonly in sports (Schneegass and Voit, 2016), rehabilitation or other health-care related scenarios (Wang, 2016; López et al., 2010), as well as performance art (Liang et al., 2019b; Sicchio et al., 2016), there are few in-situ studies when testing the garments. For most of these use cases, immediate feedback is desired, which is achieved by processing and classifying the sensor data in real time (Helmer et al., 2008).

To detect a variety of touch interactions or body movement with textile sensors, often a network of multiple sensors (for example in form of a sensor matrix) is used. In garments, stretch sensors are common to detect joint movement (Mattmann et al., 2007; Gioberto et al., 2013; Metcalf et al., 2009), and capacitive sensors to capture touch interaction and proximity (Poupyrev et al., 2016; Vallett et al., 2016).

The methods to process this sensor data and identify different bodily actions vary, too. Techniques from computer vision research have been applied, such as blob detection (Donneaud and Strohmeier, 2017a) or creating heat maps of sensor data. Machine learning approaches have been tested in relation to upper body garments, too. For example, Naive Bayes classifiers with cross fold validation have been used for posture detection through T-Shirts (Mattmann et al., 2007), and also neural networks (e.g. LSTM) have been proposed for activity recognition (Guan and Ploetz, 2017). For recent developments of textile pressure matrices, a variety of algorithms are tested to explore the best performance of selfmade sensors (Strohmeier et al., 2019).

5.2.3 Classifications of Interactional Cues

While in Chapter 4, some common machine learning algorithms for sitting posture detection with (textile) pressure sensors were briefly reviewed, the classification task encountered in this Chapter is for social cues that can be less distinct than instructed, performed postures. Sitting postures are often detected with pressure sensors as the only or main sensing modality. The detection of social signals has been achieved with multimodal approaches, traditionally with video and audio techniques. Gaussian Mixture Models or Hidden Markov Models were successful approaches to detect behaviour in group interaction, such as the dominant person in a meeting (Hung et al., 2007). In other studies, statistical analyses (ANOVA) and supervised learning models like k-Neirest Neighbour (KNN) have been used, for example to detect laughter from body movement (Griffin et al., 2013). Gaus et al. (2015), Murray and Lai (2018) and Subburaj et al. (2020) have used a Random Forest classifier for the detection of gesture and touch in social contexts (Gaus et al., 2015), and to assess social behaviour in group meetings (Murray and Lai, 2018; Subburaj et al., 2020). Wang et al. (2019) and Krishna et al. (2018) propose LSTM when analysing behaviour with motion capture systems and EMG sensors and for predicting human activity. Using neural networks for the detection of nonverbal social signals can derive from, and can be combined with language processing methods in multimodal sensing approaches (Murray and Lai, 2018). In summary, the combination of features, modalities, and the classification task lead to an exploration of a wide range of analysis approaches. The parameters in this work have led to an exploration of different classification models, too, whose selection is based on the reports of some of the examples mentioned here and in Chapter 2.

5.3 Study Design

In order to test whether different conversational states correlate with different postural movements, it must be assured that the sensing system in use is able to distinguish between a variety of such movements. In this work, it is desirable to capture the richness of micromovements and potentially 'invisible' shifts and changes of pressure, that may be important indicators for social behaviours. To investigate this further, I have conducted a user study to evaluate whether the changes in pressure detected by the trousers can be correlated with social behaviours exhibited during a seated conversation.

The data set created here is used for analyses investigating conversational states in this chapter, but also serves as the base for further explorations introduced in Chapter 6. The data set consists of 14 three-way conversations that are recorded with video cameras and with the sensing trousers, capturing the change of pressure of each participant's lower body movement. I investigate four key conversational states that are hand coded from videos and synchronised with the trousers' sensor data. In further pre-processing stages the data is formatted so that it can be analysed with different machine learning approaches.

5.3.1 Trouser Design Recap

The sensor data collected for this user study stems from the 'smart' trousers introduced in the previous chapter (Chapter 4). Here is a brief overview to remind ourselves of the key characteristics of the design of the sensing trousers.

- Textile pressure sensors are arranged in a matrix design with a 10x10 grid, resulting in 100 sensors per matrix and leg, therefore 200 sensors in each pair of trousers. The sensor matrix covers the area around the buttocks and thighs, from the crotch to the knee around the upper leg.
- The changes in pressure are collected as analog readings at 4Hz, stored locally on a micro SD card placed in the hem of the trousers. The raw sensor data is collected as a txt file, each leg with a unique time stamp, and normalised in a later processing stage.
- Three pairs were made in different sizes to accommodate a wide range of clothing sizes and body shapes. Additionally, the trousers are stretchy and resemble conventional leggings with an elastic waistband.

A schematic illustration of the trousers can also be viewed in Figure 5.1, showing the position of the sensor matrix on front and back legs.

5.3.2 Participants

I recruited a total of 42 participants to record 14 sessions of three-way conversations. The recruitment was done via email lists and in person approaches within the university department, as well as in outside networks. The participants were aged between 20 and 45 years and represented a broad range of clothing sizes. The grouping of the conversations was organised in accordance with the available sizes of the trousers so that in each session all three pairs of trousers could be worn (sized Small, Medium and Large) and the pressure data of all three interactants could be recorded. Furthermore, where possible, it was attempted to allocate people into groups where a basic level of acquaintance

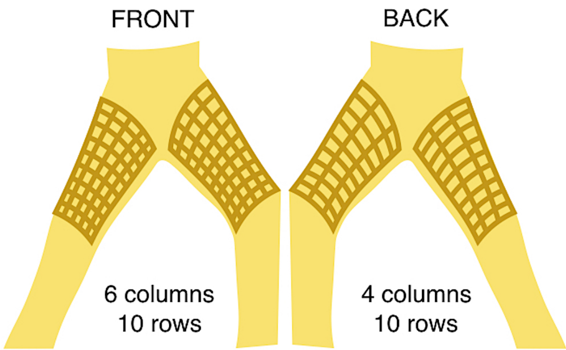


Figure 5.1: Recap of the sensing system used for this study: a 10x10 pressure sensor matrix is mapped around the upper legs and buttocks of stretch trousers: 60 sensors are placed on the front leg (left), 40 sensors on the back leg (right)

or amicable relationship was given, and it was avoided to bring together a group of people that have never met before. Aiming for familiarity between interactants has already been a factor in the chair study, enabling a more relaxed and casual behaviour.

Participants were grouped into triplets of different gendered arrangements: 1 group of males only, 4 groups of females only, 6 groups with 2 females and 1 male, and 3 groups with 1 female and 2 male subjects. The data evaluated here comes from a subset of 20 of those participants, 13 females and 7 males, representing all different grouping arrangements. Of these, 4 participants were part of only female groups, one of only male groups, 6 of mixed groups with one female and two males, and 9 of mixed groups with two females and one male. 9 participants present ‘isolated cases’, by which is meant that noone else from their group is included in the data set. The remaining 11 participants come from 5 different groups, so that pairs of participants share the same conversation and recorded study session. Two sessions of mixed groups (one with 2 females and 1 male, and the other one with 2 males and 1 female) are included in the data with all participants.

This subset was determined through technical issues that occurred during the experiment. Out of the 42 participants, for 3, the video camera recordings were faulty, and the others showed technical faults related to either the hardware (e.g. a ripped wire that would eliminate the recording of a group of sensors) or the software of the trousers (e.g. gaps in data collection, corrupted files). A more detailed evaluation of the hardware performance of the sensing trousers is discussed in a separate section in Chapter 7, addressing the errors noted here.

5.3.3 Procedure

The settings of this study follows the same guidelines that were used in the study presented in Chapter 3 when I evaluated the sensing chair covers. The groups of three were sat around a circular table with equal distance to each other, as pictured in Figure 5.2. The round table was used to encourage equal rights to participate Kendon (1970, 2010), see Chapter 3. All participants sat on plastic, non-movable office chairs without arm rests, but with a back rest. The chairs were identical to the ones used in the study evaluating the sensing chair covers. Each group was given the same conversational task - a moral dilemma - to discuss and resolve between themselves. Enabling an ongoing conversation for around 20 minutes in which each interactant has the same ground to participate in the conversation. In case a conclusion was reached early, an alternative dilemma was provided (revealed to them in advance, so no interruption during the recording took place). Overall, all conversations lasted between

Figure 5.2: Two examples of recorded conversation, viewing the two different angles of the video cameras used. All participants are wearing the sensing trousers.

15 and 25 minutes. During the interaction, participants were alone in the room and the facilitator only reentered after they gave a sign that the conversation had finished or after 25 minutes.

Participants were encouraged to put on the trousers themselves, and also take them off themselves, but were offered assistance where needed. The trousers started to record data once they were put on and adjusted for a comfortable fit, and were switched off before they were taken off, as soon as the conversation ended and the facilitator reentered the room. Before any recording started, everyone was briefed on the conversation task and the overall aim of the research. They were told the scope of the study was to look into social behaviour through exploring the relationship of postural states in group discussions, and that the trousers they were asked to wear are used for additional data collection. It was not revealed until after the sessions had finished that the mode of sensing was pressure information. Consent forms were signed to allow video and on-body data collection, and approval by the university's Ethics Committee was granted (see Appendix C).

5.3.4 Data Collection

Throughout the duration of the conversation, the raw data from the 200 sensor points of each pair of trousers was recorded with 10 bits of resolution at 4Hz. This results in 800 measurements (or 400 per leg) per second, which is referred to as one reading or one instance. The sensor data was stored as a txt file on a micro SD card and was integrated to the circuit board in the hem of each leg, powered by a USB battery. The format and frequency the data was collected for this study are identical to the previous study investigating sitting postures.

In addition to collecting the pressure sensor data from each of the three pairs of trousers, the 14 sessions were recorded with two video cameras that were placed in different corners of the room to capture each participant from various angles, as seen in Figure 5.2. An LED light on the micro-controller flashed on as soon as the trousers were 'switched on' by plugging in the battery once the trousers were worn and the participant set up and ready to start the seated conversation. This was captured by the video cameras and was the visual reference point for synchronising the sensor of each leg and the video data. The timestamp of the sensor data starts at that onset and is later merged with the annotations of the video data by approximating the different timelines. Additionally, and similar to the procedure of the chair study, a reference points for the sensor data was recorded: after the recording of trouser and video data started, a visible pressure on each leg was applied either by the participants by pressing their hand onto a leg, or by the instructor when asked for assistance. This would make it easier to correctly align all data streams.

5.3.5 Coding Behavioural Cues

Annotations

The video recordings of the conversations were annotated for the four different behavioural states this work focuses on: talking, backchanneling, laughing, and nodding. This expands the analysis of Chapter 3 to nods, another rhythmic movement and element of listener responses that potentially affects the overall postural behaviour.

For modes of talking, I focused on overt speech. The start and end of a verbal utterance was determined through the on and offset of speech. Talk was split into separate annotations when speaker pauses were longer than 400ms. This time window threshold was determined through observations, as well as other speech transcription conventions (see e.g. Hepburn and Bolden (2014)). Talk was also distinguished from backchannels, which were coded separately.

Backchannels are identified as verbal responses to the speaker and initiated repair, not considered as particles of speech, and that were already examined in the chair study, too. Nonverbal signals such as gestures or shoulder shrugs were not included in this annotation scheme. Backchannels and all other conversational states distinguished from speech are determined as different attentive, or active, listener behaviours.

When coding for laughter, I distinguish between smiling and laughing, based on shifts in muscular movement, differentiating between 'social' (can be subtle, staged) and Duchenne laughter (spontaneous, embodied, entails more muscle movement) (Ekman et al., 1990). For the purpose of this work, smiling was not included in the coding scheme and only concurrent, 'embodied' laughter was accounted for.

Listeners' head movements were divided into nods and other movements. As nods, I define distinct up- and downwards movements of the head of a listener. While distinct nods as nonverbal responses to the speaker were coded for, other movements like single head turns or adjustments in relation to postural shifts were not included for this study. These would count towards other, unspecified non-verbal behaviours and incidental movements that occurred, and were only indirectly included in a fifth mode that I determine as incidental listener movement. This is movement that cannot be directly attributed to displays of recipiency. Modes of incidental listeners who are not considered recipients therefore includes all postural changes and adjustments, gestures, coughs or harrumphs, scratching or other ostensibly incidental verbal and nonverbal signals, but also participants' least active postures. The annotations for this mode as a class to analyse later was created by the absence of all others. A summary and overview of the definitions of these behaviours can be seen in Table 5.1.

Annotators

In total, a set of 5 different annotators hand coded the videos, and each video was processed by 2 annotators for cross validation using the open source software package Elan (Brugman and Russel, 2004). Annotators were recruited from the Cognitive Science research group at Queen Mary University of London. The hand coding was conducted with a binary approach, "1" for presence and "0" for absence of the behaviour. The annotations were coded to a precision of 10 milliseconds (in comparison, the sensor data is recorded at a 250 milliseconds frequency). Inconsistencies between annotators were discussed and resolved in group sessions examining the data together. These were formed by the author of this thesis and one of the annotators. Furthermore, a set of annotation

Class	Subclasses	Description
Speaker		Verbal utterance; onset of speaking; overt speech
Active Listener	Backchannels	Verbal response to speaker; repair initiation, e.g. “uuhhm”, “yeah”, “aah”, etc.
	Laughter	Verbal or ”embodied” laughter; Duchenne smile rather than ‘social smile’
	Nodding	Distinct up- and downwards movement of head; no separate head turns
Incidental Listener		“Silence”; no distinct listener behaviour; includes shoulder shrugging, coughs; listener and other head turns; posture adjustments; posture changes; scratching; other “inattentive”, unspecified listener movement

Table 5.1: Overview of the coding scheme for the annotated behavioural cues.

rules was established to help clarify a behaviour and to identify an annotation as well as to find their correct starting and end points. The annotations are arranged into a hierarchical taxonomy with *active listener*, *incidental listener*, and *speaker* as the top three classes. The *active listener* class encapsulates a further three subclasses which were also annotated: *backchannels*, *laughter*, and *nodding*. A description of the behaviours exhibited for each annotation type can be seen in Table 5.1.

5.3.6 Data Pre-Processing

Sensor Data

The raw sensor data from the pressure sensor matrix was first normalised before any further processing. For this, the range of values from the analog readings of pressure were mapped onto a scale between 0 and 1. This was done for each leg (each file of data) separately. The time stamp of each leg's sensor data was recreated to be merged with the annotations' timeline. Approximating three different timelines resulted in a lag over time of a maximum of ca. 350 milliseconds. To compensate for this inaccuracy, annotations that were shorter than 400 milliseconds were removed.

Furthermore, overlapping annotations were removed to allow for a discrete labelling for the classification algorithms to be tested. Co-occurrences of two behaviours within the same participant were coded separately but ultimately discarded for analysis purposes (e.g. simultaneous presence of laughter and nodding, or nodding and backchanneling), since this would have affected the models trained to classify the individual modes. Were only a short overlap occurred in proportion to the remaining annotation, the annotation was split and only the overlapping part was removed. For example, if a speaker started laughing at the end of their turn, laughter and speech were coded separately and the transition between them was treated as separate events.

Merging Timelines

After the coding was completed, the annotations were merged and time-aligned with the sensor data of both legs and a new overall timeline was created. The baseline of the video annotations served as the timestamps the sensor data would be approximated towards, being the most accurate. To synchronise the different data files, a new timeline with merged information was computed. This was done by extracting each leg's data and annotations and find a time frame into which the three different data points fit into. Any data that was not assigned to one of the classes described above were discarded for analysis. This mostly related to the beginning and the end of the conversation, when participants were still briefed, or stood up when finishing the session.

Broken Sensors

Any sensor data from malfunctioning sensors was also removed before further analysis. In order to evaluate the same set of sensors for each participant, any sensors that broke for one participant, were removed from all other participants' data. Participants with more than $\frac{1}{5}$ (or 40 sensors) of the sensors broken were discarded. Most commonly, when sensors were faulty, it was 10 - 20 sensors per participant, translating into one or two wires either ripped or pulled out of the circuitry and cutting it short, or having another contact error at some point during the recorded session. It was observed that when sensors broke, often the same set of sensors broke, e.g. the wire of the same row or column was pulled out. When a set of broken sensors had no overlap with other participants, this data was discarded as well. This resulted in a sample size of 20 participants, for most of which the same set of sensors was broken to avoid removal of functioning and well performing sensors where possible. Most frequently when errors occurred, it was because the electrical connection to one row or column was broken, which equals 10 sensors. However, since different participants had different subsets of sensors broken, I removed a total of 64 out of 200 sensors for each participant. Distributed across both legs of the trousers, 28 sensors on the right and 36 sensors on the left legs were removed for analysis. In both legs, the very first two (bottom row around the front and back knee) and the very last row (top row from the crotch around the hips to the buttocks) were the most common ones to break.

Imbalanced Data Sets

The sensor data sets for each coded behaviour was of a different size because these behaviours occur more or less frequently in relation to each other. Durations of talk are naturally longer than the more brief, verbal listener responses, or backchannels. Durations of laughter and nodding vary. Recording the pressure changes of a session of an average of 20 minutes therefore resulted in a large variety of data sets, e.g. talking containing more data than backchanneling. (Exact numbers are reported in the results section below.)

Processing of imbalanced data sets can be handled in different ways. One approach I tested is to delete a part of the data to balance the different data sets. This is usually done by a randomised removal of a percentage of the largest data set to make it equal to, for example, the second largest set. This has the advantage of processing the data faster, but comes at the cost of removing potentially valuable sensor data, since it is not known (yet) how important or biased the removed instances are. The results reported below stem from an analysis maintaining all of the collected data without modifying the size of data sets and without removing data of any class. Issues that derive from this approach are accounted for in the classifying methods and address potential problems of imbalanced data sets.

5.4 Results

The analysis first explores whether the trousers' pressure sensors can discriminate between the two most basic conversational states: speaking and listening. It then explores whether it can discriminate between all three basic states of speaking, active listening, and incidental listening of participants who are not overtly displaying recipiency (Heath, 1982). The second stage explores whether the trousers' pressure sensors could discriminate between the non-verbal response directed movements characteristic of active listeners (i.e. backchannels, nods and laughter), first without including incidental movements and then taking incidental movements into account, too. This resulted in testing for the ability to automatically discriminate between the following behaviours:

1. 2 classes: Speaker and Active Listener cues;
2. 3 classes: Speaker, Active Listener, and Incidental Listener cues;
3. 4 classes: Speaker, Backchannels, Laughter, and Nodding cues;
4. 5 classes: Speaker, Backchannels, Laughter, Nodding, and Incidental Listener cues.

Furthermore, the ability to discriminate between these classes was examined at the individual level for each of the 20 participants and at the community level for a generalised model representative of all participants. Additionally, each participant's data was tested against the remaining participants' data by withholding them from the training set.

In total, the data set consists of 22870 instances of talking gathered from all 20 participants and 12095 instances of active listener behaviours (backchannels + nods + laughter). Amongst the active listener behaviours, backchannels had the fewest instances (2380), followed by laughter (4383) and nods (5062). With defining incidental listening as a fifth class, presenting the entire data set of all further unidentified listener and speaker behaviour, this forms the largest class with a total of 36828 instances. The relative distribution of cues derives from the duration and frequency of occurrence of each of the behaviours. The number of talk instances correlate with an average duration of 3.21 minutes across all participants, while backchannels last approximately 0.68 seconds, laughter annotations 1.90 seconds and nodding 1.45 seconds on average. Hence the number of occurrences does not result in an initially balanced data set, since the responsive, active listener classes are mostly shorter than speech utterances. For comparison, during a conversation of 15-25 minutes talk occurred 112 times on average, backchannels 56 times, laughter 34 times and nodding 53 times.

These are average measurements, and relative proportions of each behavioural class can vary across individuals. Backchannels appeared to form the smallest data set in most cases, sometimes accounting for only $\frac{1}{10}$ of the larger set of talk instances. Nevertheless, for models of individual as well as of general community all data sets were kept in its original size and proportion for the analysis reported here. For preliminary tests, however, the models were adjusted to a balanced distribution of instances by removing randomly selected data. In all four discrimination scenarios, the number of instances was downsampled to the size of the smallest data set by randomly discarding a percentage of the larger data set. That means, that in the case of comparing different active listener behaviours (4 and 5 classes), all classes were fitted to the size of the backchannel data, and in the 2 and 3 class discrimination case, speaker and incidental listener samples were reduced to the size of the active listener set. While initially, this was done to avoid overfitting a model, for the final analysis other measures were taken to compensate for the imbalanced number of instances. In the classifier selection reported below, parameters were set to weight the data sets differently, applying more 'weight' to smaller data sets, so they are eventually treated similarly in the classification training model. The reason for not modifying the data sets is to have a realistic proportion of empirically collected data, and to avoid biases by removing potentially valuable information. Balancing data by removing a random part of it would assume a balanced occurrence of these instances in spontaneous conversation as well, which has been shown is not the case.

5.4.1 Classifier Model Selection

There is a variety of classification algorithms that can be used. Here, I focus on some that are common in the field of ubiquitous computing and social sciences. For preliminary testing and exploring some of these standard and established models, the open source machine learning software Weka (Holmes et al., 1994) was used to train and evaluate classification models, following the approach and methodology of the previous posture classification study reported in Chapter 4. This was done with a sample data set of the annotated and pre-processed data of the first 6 participants. Drawing from these early test results, all models were then refined and tested again with the programming language Python (Raschka and Mirjalili, 2019), using the data analysis package *pandas*.

Four types of models to distinguish between the behaviours were initially investigated on all or parts of the data sets: Random Forest, Support Vector Machines (SVMs), K-Nearest Neighbour algorithm, and Gaussian Naive Bayes. Each of them bears different advantages and disadvantages in regards to the type of data processed here, and by testing the different models, these characteristics were explored. Based on the performance of these classifiers, a Random Forest classification was selected as the model to carry further and analyse my data with. I will therefore elaborate on Random Forest in detail below, and give a brief summary of the results of the other classifiers here. For all tests, the data was kept in its original, imbalanced format and split into a training (60%) and test set (40%).

SVMs have commonly been used to detect affective states or social behaviours (Di Lascio et al., 2018), and are a popular approach for ubiquitous computing applications (Hammerla and Plötz, 2015). Two different SVMs (one of them a linear SVM) were evaluated, and both performed poorly in comparison to other models, though the linear SVM showed better results than the non linear one. However, both individual and general community models showed Recall and F-Measure results close to 0.00 for mostly all classes. Even though stratified data was used during training, the test sets of withheld participant data with sometimes imbalanced distribution of instances caused overfitting towards the class with the largest number of instances. Overall accuracies for the different multiclass discrimations of the linear SVM were: 0.67 for 2 class discrimination, 0.60 for 3 classes, 0.66 for 4 classes, and 0.60 for distinguishing between 5 different classes. These scores are the mean average overall accuracy.

The Gaussian Naive Bayes (GNB) classifier performed similarly poorly. Again, the lowest overall accuracy is reported for the 5 class discrimination with only 0.25 and the 4 class discrimination with 0.33 for the community model. Slightly better performance show the 2 and 3 class discrimination with 0.59 (2 classes) and 0.45 (3 classes) average overall scores.

Much better results were achieved by a K-Nearest Neighbour classifier. The test set of the community model achieves an overall average accuracy of 0.81 (5 classes) and 0.83 (3 classes) for the test with the biggest imbalanced data included - the incidental listener set. For the discrimination between the identified speaker and listener classes only, the model's mean average score is 0.89 for 2 classes, and 0.85 for 4 classes.

The poor performance of the SVMs and the GNB, is probably due to the relatively large test set and small training set. For the SVMs, this was later adjusted to 30% test set, but did not achieve significantly better outcomes.

Random Forest Classifier

In comparison, a Random Forest model outperformed all other classifiers that were tested for both, individual and community models and for all different social behaviour analyses when initially evaluated with 10 fold cross validation. Therefore, this analysis focuses on reporting only the performance of Random Forest classification (Breiman, 2001). The particular model I evaluate here uses a 5 fold cross validation[1] with stratified data and bagging with 100 iterations. The trees are built with unlimited depth, a minimum of 1 instance per leaf and a random number of seeds. A schematic of how such trees are built is illustrated in Figure 5.3, showing the top of a tree for an individual participant of depth 3 (Figure 5.3a) and furthermore of depth 6, too (Figure 5.3b). The tree shown here serves as an example to illustrate the schematic of how the trees are built, and does not imply that the sensor numbers shown in the figure (e.g. R93 stands for right leg, sensor number 93, which maps to the top row around the buttocks) are of more significance than others. In fact, individual trees usually show a very high variance and risk of overfitting, which is compensated through the high number of trees, each of them presenting a model of the fit, whose average is computed for the final model fit. When building the decision trees, the quality of the split[2], so called gini impurity, is taken into account for each tree (the higher the number, the 'better' is the split), as well as the number of instances at this point to form a decision for the classifier (Raschka and Mirjalili, 2019).

Considering the imbalanced data sets that are evaluated against each other here, I modify the classifier so that the different classes are weighted inversely proportional to how frequently they appear in the overall data set. In the following sections, I report both, the accuracies when balancing the weight of the data sets, and when each data set is assigned the same weight(Pedregosa et al., 2011).

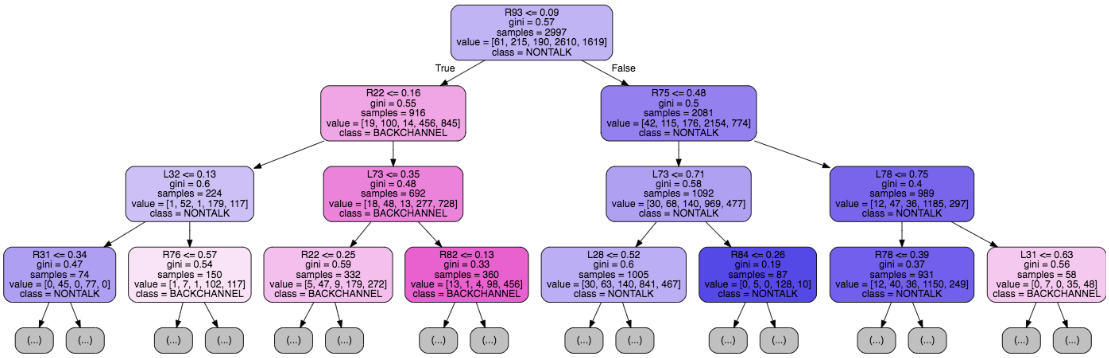
Feature Importance

In addition to the predictions the Random Forest classifier provides, the importance of each feature is evaluated - each sensor across the pressure matrices in both of the trousers' legs. The goal of this feature extraction is to gain a better understanding of the classifier, eventually improving the model, and interpretation of the data I work with (Strobl et al., 2008). Additionally, this may help to discover clusters of sensor groups that would allow to reduce the high dimensionality of the 200 sensors for future iterations of the trousers. Consequently, reducing the number of sensors in the classification algorithm would also reduce the running time (Strobl et al., 2008)

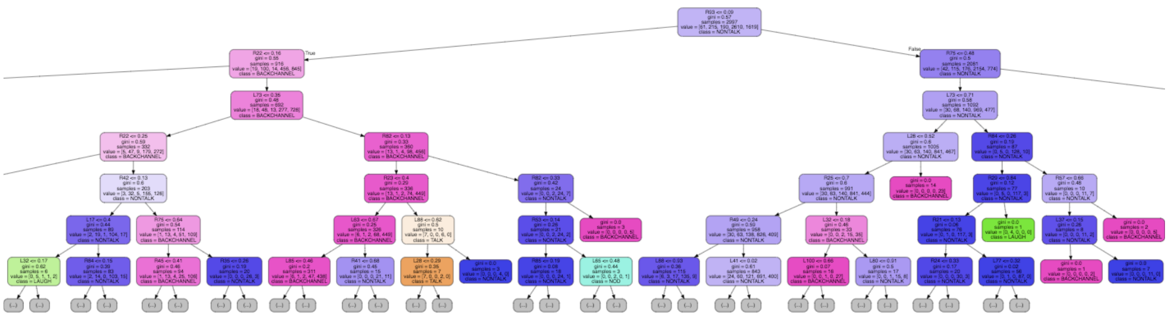
To evaluate the importance of each sensor across the sensor matrices, the gini impurity is computed as the reduction of the criterion by that feature (Pedregosa et al., 2011), determining the quality of a split, and the gini value is normalised (Raschka and Mirjalili, 2019). A higher value indicates higher importance of the given feature. These gini impurity values also play an important role when building the decision trees of the Random Forest classifier, as seen in Figure 5.3, and are the basis upon which the results for the feature importance are extracted. This impurity based feature importance is a property of the Random Forest classification algorithm that is generated and reported on in the following section.

[1]I tested data on 10 fold cross validation (CV), too, but report the results from a 5 fold CV to improve running time, since it did not change the results.

[2]a split is defined as the minimum number of samples required to split an internal node.



(a) A random decision tree for participant A of depth 3



(b) The same tree showing 6 layers (of same participant)

Figure 5.3: An example of how a decision tree of the Random Forest classifier is built for one participant with 5 classes to discriminate. The figure shows the top and starting point of a tree of depth 3 and a fraction of the same tree of depth 6. For each node, it can be seen which sensor (R93, R22, R75 etc) was taken to determine the following branches of the tree, the gini impurity value, the number of samples, the corresponding values and the class of the instance.

	2 classes	3 classes	4 classes	5 classes
Talk	0.958	0.856	0.976	0.865
Incidental Listener	-	0.940	-	0.946
Active Listener	0.865	0.628	-	-
Backchannels	-	-	0.519	0.263
Nodding	-	-	0.812	0.549
Laughter	-	-	0.788	0.667

Table 5.2: F1 Measures of the Random Forest classification per class, averaged across individuals.

	2 classes	3 classes	4 classes	5 classes
Accuracy	0.932	0.879	0.904	0.872
Balanced Accuracy	0.912	0.810	0.770	0.660
Precision	0.933	0.866	0.868	0.808
Recall	0.912	0.810	0.770	0.660
F1 Measure	0.919	0.830	0.798	0.701

Table 5.3: Overview of Random Forest classification results for individual models across all classes. All results present the average results across participants.

5.4.2 Speakers and Listeners

A set of models was trained to discriminate between the two classes of speaker and active listener with no instances of incidental listening included. First each participant was treated as an independent data set and an individual model was trained and evaluated using 5 fold cross validation. Then the aggregate data set of all 20 participants was used to train a model also evaluated using 5 fold cross validation. Last, 20 models trained with 19 of the participants were evaluated against the withheld participant.

A second set of models were then trained and evaluated using the same procedure, but with the addition of a third class - incidental listening. These are the instances where neither active listening nor speaking behaviours are exhibited.

Individual Models

The mean accuracy for discriminating between 2 classes is 93.2% for equally weighted classes, or 91.2% for a balanced weight assignment based on the size of data sets, the best across the other three individual model approaches. Even the worst overall percentage of correctly classified instances, 86.5%, is better than the average performance of the 5 class discrimination, which is elaborated on below. Also Precision, Recall and F1 Scores (F-Measures) are high, averaging at 0.93 (Precision), 0.91 (Recall) and 0.92 (F1 Scores). The F1 Measures are 0.86 for listeners and 0.96 for speakers, averaged across all participants, see Table 5.2, and Table 5.4 for details on each participant's F1 Measures.

When the third class for incidental listener behaviour is included, the overall performance has a lower of mean accuracy of 87.9% with equally weighted data sets, or 81.0% with balanced weighted data sets, see Table 5.3. This is also reflected in the average Recall, Precision and F-Measure results across all 20 participants, that show slightly lower results, as can be observed in Table 5.3, too. When taking incidental listening into account, there is also more variation between speakers and listeners in the results than before in the 2 classes discrimination scenario: 0.86 speakers' and 0.63 active listeners' F-Measures. Comparing this with incidental listeners, showing an F-Measure result of 0.94 averaged across all participants (Table 5.2), the results for all three behaviours are relative to later multi-class discrimination still considerably balanced and only show slight variations in their overall performance. An overview of the average results of Recall, F1 Measures, Precision and the two accuracy measures are listed in Table 5.3. Additionally, Table 5.4 lists all average F1 Measures per participant and per class.

Looking at misclassifications, the 2 and 3 class discriminations show similar results that reinforce each other. In both occasions, speakers and listeners are rarely mixed up, but if they are, speakers are more likely misclassified as listeners, than listeners as speakers. Expectedly, incidental listener movement behaves the same and is mostly misclassified as listeners than as speakers. Only in 4 out of 20 cases, it is more often confused with speakers. We can also see that adding this additional class doesn't necessarily decrease the performance of the model. The confusion matrices for the 2 and 3 class evaluation illustrate the above described results, and one participant's normalised confusion matrix can be seen in Figure 5.5a, in the top row (coloured in green). Note the confusion matrices show the results of the classifier weighting each class equally, not balancing the weights to account for smaller data set classes.

Participant	2 classes	3 classes	4 classes	5 classes
A	0.925	0.838	0.795	0.707
B	0.936	0.814	0.785	0.673
C	0.925	0.850	0.830	0.748
D	0.931	0.807	0.832	0.751
E	0.938	0.808	0.878	0.684
F	0.942	0.899	0.834	0.787
G	0.918	0.787	0.744	0.633
H	0.916	0.839	0.889	0.687
I	0.914	0.769	0.775	0.660
J	0.912	0.889	0.772	0.767
K	0.945	0.782	0.858	0.671
L	0.934	0.784	0.831	0.668
M	0.929	0.850	0.765	0.673
N	0.909	0.772	0.804	0.603
O	0.881	0.808	0.694	0.676
P	0.841	0.841	0.662	0.662
Q	0.934	0.859	0.808	0.727
R	0.858	0.804	0.729	0.642
S	0.919	0.886	0.768	0.753
T	0.971	0.907	0.910	0.836

Table 5.4: (Macro-)Average of F1 Score (F-Measures) on Test Data per Participant and per class.

To understand the distribution of the data better, boxplots in Figure 5.4 show the F1 Scores for all 20 participants for the 2 and 3 class discrimination. In the 2-class scenario (left in the Figure), in which only annotated speakers and listeners are included, speakers perform visibly better. Their F1 Scores have a narrower interquartile range with a median of 0.95. The listeners' median of F1 Scores is at 0.90, with two outliers at 0.775 and 0.800. Overall, the range of active listener results is wider spread and significantly lower than the speakers' results. This remains true in the 3 class scenario, too. A difference in sample sets affects the F1 Scores, as can be seen in Figure 5.4, right. The active listener class (laughter, backchannels and nods) shows the largest variance across all participants with the lowest results. The larger sample sets perform much better, with narrower interquartile ranges and higher overall scores.

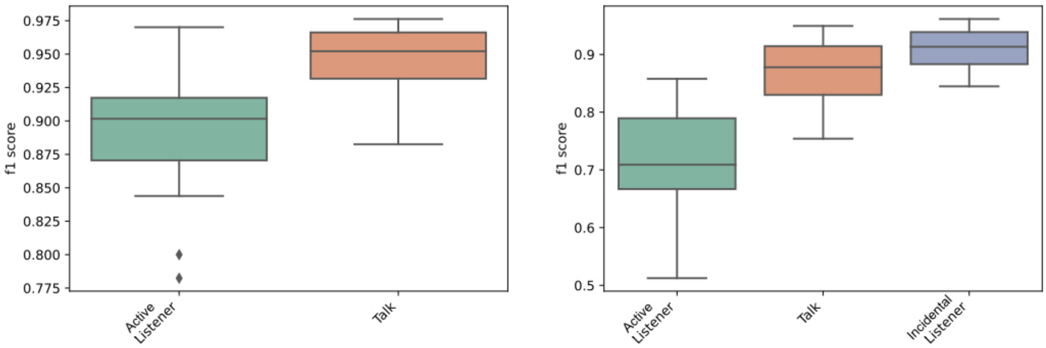


Figure 5.4: Boxplots showing the distribution of F1 Scores across all 20 participants in the 2-class (left) and 3-class (right) discrimination.

Community Models

Applying the same cross validation with 100 trees to a general community model, the results are of similarly high accuracies, with 93.1% correctly classified instances for the 2 class discrimination, and a lower 87.7% when including the incidental listeners, and similarly when balancing the weight so that smaller data sets are assigned more weight, with a 92.0% accuracy for 2 classes, and 82.5% for 3 classes, see Table 5.5. Examining the confusion matrices of these community models, we can see that speaking always performs slightly better than active listening, which yet shows good average Precision(0.93 for 2 classes, 0.87 for 3), Recall (0.92 for 2 classes, 0.83 for 3) and F-Measure (0.93 for 2, 0.84 for 3 classes) results. In both cases, talk is proportionally rarely misclassified. The confusion matrix of the 3 class discrimination reveals that the third class is slightly more often classified as active listening than as talk, whereas talk, just like for the individual models, is, if at all, misclassified as listening rather than speaking. Both community model confusion matrices are illustrated in Figure 5.5b with plotted normalised results.

Each participant was tested against a community level when being withheld from the training set, which consisted of the data of the remaining 19 participants. Here, the average percentage of correct classification is 52.1% when comparing speakers with active listeners (which is just above chance), and 46.3% when including incidental listeners' data. Modifying the weight of the differently sized data sets, the mean balanced accuracy is slightly better for the 2 class discrimination of 53.4%, but slightly worse with 33.7% correct classification when including the third class of incidental listening. The average results for Precision, Recall and F1 Measures can be seen in Table 5.6. While Precision and Recall show almost identical results, indicating the classification success for both, 2 and 3 class discrimination, is just above or equal to chance, the F1 Measures show even weaker outcomes with an average of 0.488 for 2 classes, and 0.284 for 3 classes. All results can be compared in Table 5.6, and present a notable decrease in overall performance compared to a general community model.

The withheld participant's performance can also be compared with the individual model, as is presented through the normalised confusion matrices in Figure 5.5a. This shows that even the participant with the best results in the individual model does not keep up when tested against the community model, but shows results around the average. Other participants that performed among the best in the individual models did not have better results when being withheld from the training set. Conclusively, there are no correlations found between participants' performance in the individual and the community model.

One could argue that the number of instances of the test set could be responsible for the variety of results and the overall weak performance of withheld participants. In cases of larger test sets (max. 3008 instances for the 2 class discrimination, and 4900 for 3 classes), the performance overall was better (above average).

	2 classes	3 classes	4 classes	5 classes
Accuracy	0.931	0.877	0.898	0.867
Balanced Accuracy	0.920	0.825	0.783	0.677
Precision	0.931	0.868	0.878	0.832
Recall	0.920	0.825	0.783	0.677
F1 Measure	0.925	0.843	0.821	0.729

Table 5.5: Results overview for community models across all classes. All results are average outputs of the Random Forest classifier

	2 classes	3 classes	4 classes	5 classes
Accuracy	0.521	0.463	0.615	0.457
Balanced Accuracy	0.534	0.337	0.251	0.197
Precision	0.534	0.337	0.237	0.186
Recall	0.534	0.332	0.251	0.196
F1 Measure	0.488	0.284	0.200	0.164

Table 5.6: Random Forest classification results for withheld participants (exlcuded from the training set).

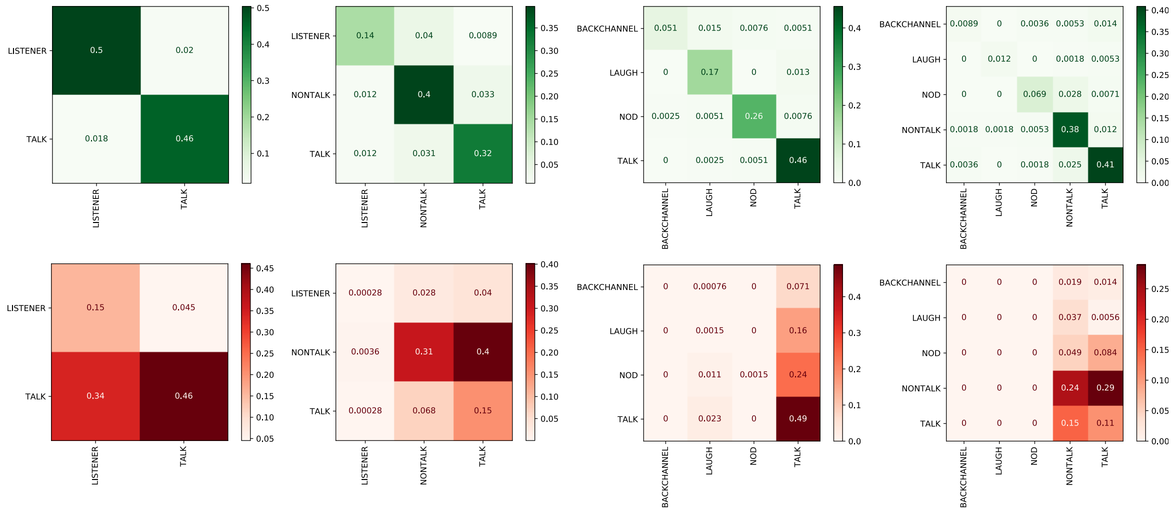
5.4.3 Backchanneling, Laughing, and Nodding

Next I explore whether the textile pressure sensors can not only distinguish listeners from speakers, but also more fine-grained conversational states. The same training and evaluation procedure used to evaluate the discrimination between speakers and active listeners is now applied to (1) discriminating between the subclasses of laughter, nods and backchannels, summarised as active listeners and then to (2) discriminating between speakers, the subclasses of active listeners, and incidental listeners through the addition of the unspecified sensor data, determined by the gaps of all other coded behaviours.

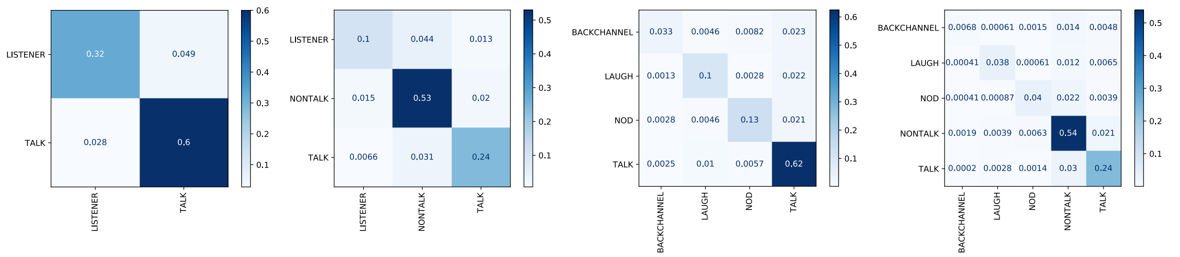
Individual Models

For the 4 class individual model, the overall average percentage of correct classifications is 90.4%, and 77.0% when balancing the weight distribution across the different subsets of data, while for the 5 class model, it is 87.2%, but only 66.0% for a balanced accuracy, compare Table 5.3. Like in the previous groupings of behaviours with 2 and 3 class distinction, this drop in the results was expected given that the fifth class that was included, incidental listening, entails all unspecified movement and nonverbal signals, whether accidental and intentional. Looking at the results of the participants separately, the average accuracy ranges between 50.65% and 85.31% for 4 classes (talk, backchannels, laughter, nods), and between 49.10% and 77.23% when including incidental listeners. These variations are bigger than the ones in the previous model for individuals with 2 and 3 classes.

Both, for the 4 and 5 behaviour discrimination, Precision, Recall and F-Measure results demonstrate that amongst the differentiated active listener behaviours, laughter performs best, followed by nodding. The F1-Measures for laughter are 0.788 for 4 classes, and 0.667 for 5 classes, see Table 5.2.



(a) Overview of confusion matrices with the individual model confusion matrices of the same participant who performed well across all 4 classification tasks on the top row, and the same participant's performance when withheld from the training set on the bottom row. The scale for all matrices is the proportion of all instances.



(b) Confusion Matrices of the community models for 2, 3, 4 and 5 class discrimination. The scale for all matrices is the proportion of all instances.

Figure 5.5: Confusion matrices of the Random Forest classification for individual, withheld and community model (from top to bottom).

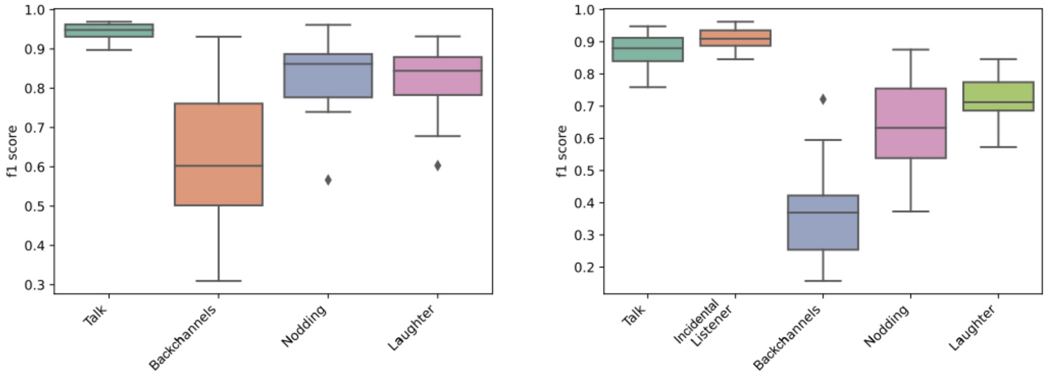


Figure 5.6: Boxplots showing the distribution of F1 Scores across all 20 participants in the 4-class (left) and 5-class (right) discrimination.

And while nodding shows slightly better F1-Measures of 0.812 for 4 classes, the 5 class discrimination yields a result of only 0.549. Backchannels, in comparison perform worst with F1 Measures of 0.519 (4 classes) and 0.263 (5 classes). These results are averaged across all participants and are listed in Table 5.2. A detailed view of average F1-Measures for all 20 participants can be reviewed in Table 5.4, and an average across all participants and classes in Table 5.3 (last two columns). In comparison, however, talk outperforms the active listener behaviours by far with an average of 0.976 F1 Score in the 4 class discrimination scenario, and 0.865 in the 5 class discrimination. Being the largest data set and including the most diverse signals and movements, the fifth class of incidental listening scores highest, with F1 Measures of 0.946. And yet, this outcome could be an indicator for the ability of the system to detect fine grained differences of behaviour, while it struggles more to compare those against a more generic state like talk.

Examining confusion matrices of the 4 class model, as well as the Recall and F-Measure results for each class in more detail, we see that while 'talk' performs best, nodding and laughing also show good results and rarely misclassify each other. Most participants with high Recall and F-Measure results for laughter and nods, also have above average results for backchannels. Common misclassification of the weakest of the 4 classes for the individual model happen towards talk, and vice versa talk instances being classified as backchannels. An argument for this could be that these verbal backchannels in their characteristics could be seen as particles of talk. This is illustrated with the confusion matrix of one participant in Figure 5.5a for both, and can be observed in the 4 and 5 class discrimination scenario.

When the class for incidental listeners is included, the confusion matrices suggest similar patterns with talk as the strongest and best performing category. In most cases of incorrectly classified instances, talk gets confused with either backchannel or incidental listener, and rarely with laughter or nods. This additional behavioural category shows a wider spread of misclassifications across the remaining four, but has overall fewest confusions with speaking. This raises the question of whether a backchannel could be considered as talk in general, as well as to how fine grained the listener behaviours can be defined for further system evaluation.

Summarising the results for individual models, the distribution of F1 Scores for each participant and each class, both for 4 and 5 class discrimination is shown in Figure 5.6. Classes with smaller data sets, such as backchannels and nods have a more scattered distribution of F1 Scores than speakers and incidental listeners, who both have a narrow interquartile range with minimum scores still better than the best scores of the smaller classes. In general, there seems to be a correlation between high

F1 Scores and data set size: the larger the data set, the better the performance. Backchannels, the smallest data set for both, 4 and 5 class scenarios, show the largest variation of F1 Scores and the lowest median, while the largest data sets, speakers (for 4 classes) and incidental listeners (for 5 classes), demonstrate the highest values and most dense distribution of scores.

Community Models

The general community model for the discrimination between the specified 4 behaviours shows an overall performance of 89.8%, or 78.3% for balanced weighting of classes, with average results of 0.878 for Precision, 0.783 for Recall and 0.821 for F1 Measures, see Table 5.5. With Recall results of 0.777 for backchannels, 0.833 for laughter, 0.809 for nods, and 0.706 for talk, this reflects the results of the individual models. Looking at misclassifications of the 4 class model in Figure 5.5b, the correct classifications still outweigh the incorrect ones, despite showing lower overall results compared to the individual models. Both rhythmic listener movements, laughing and nodding, are only on rare occasions confused with each other, but most commonly with talk, and least commonly with backchannels. The same misclassification trend is true for backchannels, being mostly misclassified as talk. Morevoer, the confusion matrix for the 4 class discrimination in Figure 5.5b shows that talk seems to be more distinct to nods than to laughter with fewer misclassifications towards this class.

Similar patterns can be observed when adding the fifth class, although the general accuracy drops to 86.7% and the balanced accuracy to 67.7%. Including this class of incidental listener movement also yields the lowest results for Precision, Recall and F1 Measures, as can be seen in Table 5.5. The confusion matrix in Figure 5.5b reveals that backchanneling, as the smallest data set and poorest performing class, is now more often classified as the fifth incidental listening class than as itself. Moreover, also the performance of the class of talk drops similarly to the 3 class discrimination that includes the large class of incidental listening, which becomes the strongest amongst all classes (and presents the largest data set).

When training the community model for 19 participants and testing it on the withheld one, the results show poor precision in both occasions, as Table 5.6 reveals. Here, the biggest difference in accuracies when applying the different weighing of data sets to the classifier. While the general average accuracy is 61.5% for 4 classes and 45.7% for 5 classes, the results of the balanced average accuracy drop to 25.1% for 4 classes and to 19.7% for 5 classes. This is also reflected in the low results for Precision, Recall and F1 Measures, also shown in Table 5.6. For the withheld participants, the misclassification results for the different behaviours vary a lot with variations of the data size. The number of instances ranges from 795 to 2992 for the 4 class discrimination, and from 1034 to 4887 for the 5 classes. In the 4 class discrimination, the best Recall results are 0.875 for backchannels, 0.544 for laughter and 0.124 for nods, while talk performs much better with up to 0.988. Backchannels and nods present mostly the smallest sample sets among all behavioural cues, both resulting in the lowest F1 Measures. The number of instances for talk is always larger than for the remaining three active listener behaviours, which are most often confused with talk, but less so with each other (except occasionally with laughter, as can be seen in the corresponding confusion matrix in Figure 5.5a).

For the 5 class discrimination, the results are even worse. Average F1 Measures are as low as 0.164. The confusion matrix in Figure 5.5a displays the results of a single participant that performed well when only observing the average classification accuracy. We can see almost all misclassifications towards the biggest data sets - the class of talking and incidental listening. Moreover, there are more incorrect assignments than correct ones for the small data sets of the three active listener behaviours.

The relatively good average F1 Measures in Table 5.4 are mostly due to the performance of the two large data sets, and are not representative when it comes to backchannels, nods and laughter.

5.4.4 Feature Importance

The results of the Random Forest classification describe how well the sensing trousers perform overall and for specific interactional behaviours. It is also useful to ask, which sensors or sensor groups are significant in the process of building the model. When running the Random Forest classifier, the information on the gini impurity and therefore the values for determining the sensor importance are computed already (Raschka and Mirjalili, 2019). Here, I look at this impurity based feature importance and visualise it mapped on the sensor matrices embedded in the trousers with each sensor as a crossing point of the matrices' rows and columns. The sensors that were removed from the analysis are also removed here (illustrated in grey in Figure 5.7), and the remaining sensors are coloured in a range of red tones, visualising the sensors with higher importance in darker colours, and the ones with low importance in light tones of the same colour.

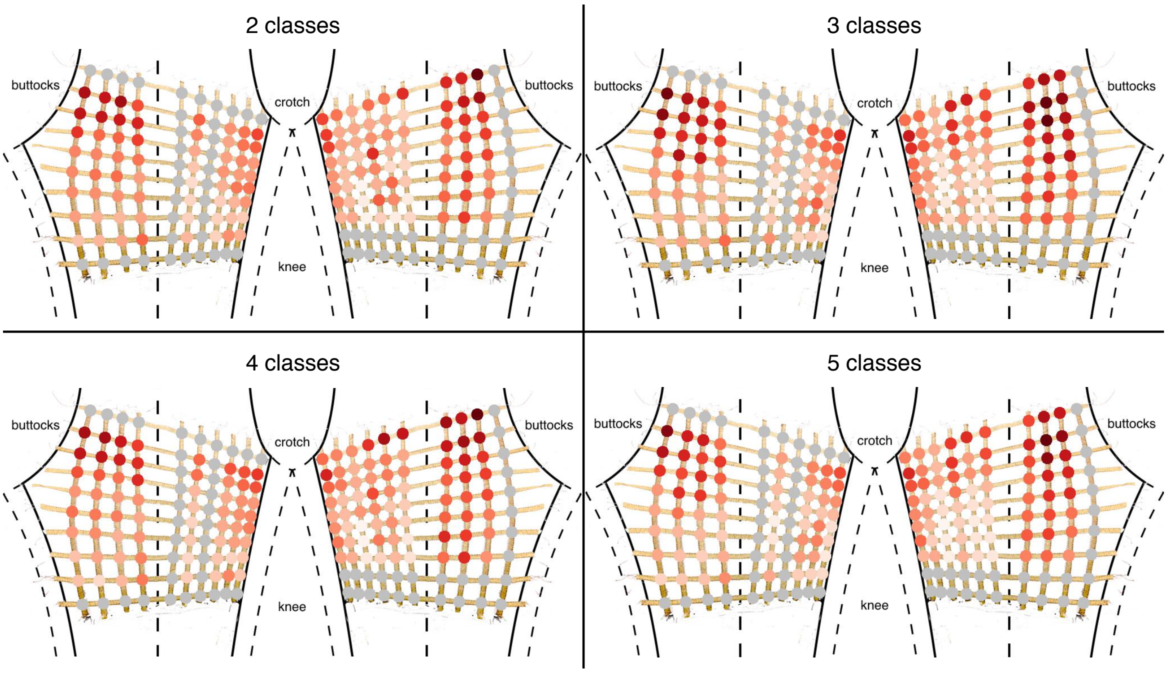
Community Model

First, I examine the important features for the community models, based on the data set of all 20 participants. This is depicted in Figure 5.7a for all classes. In general, across all different discriminations, the visualisation of sensor importance shows that the area around the upper buttocks is most significant for all classes. This confirms the findings in Chapter 3. The different legs of the trousers appear to be of slightly asymmetric importance, and the front outer thighs of lowest importance overall. Moreover, a small area on the inner thigh close to the crotch holds relevant features and the mid right thigh appears slightly more significant than the left one. The very bottom row of the sensor matrix (greyed out) can not be analysed due to faulty senor data in this area, which would map to the knee.

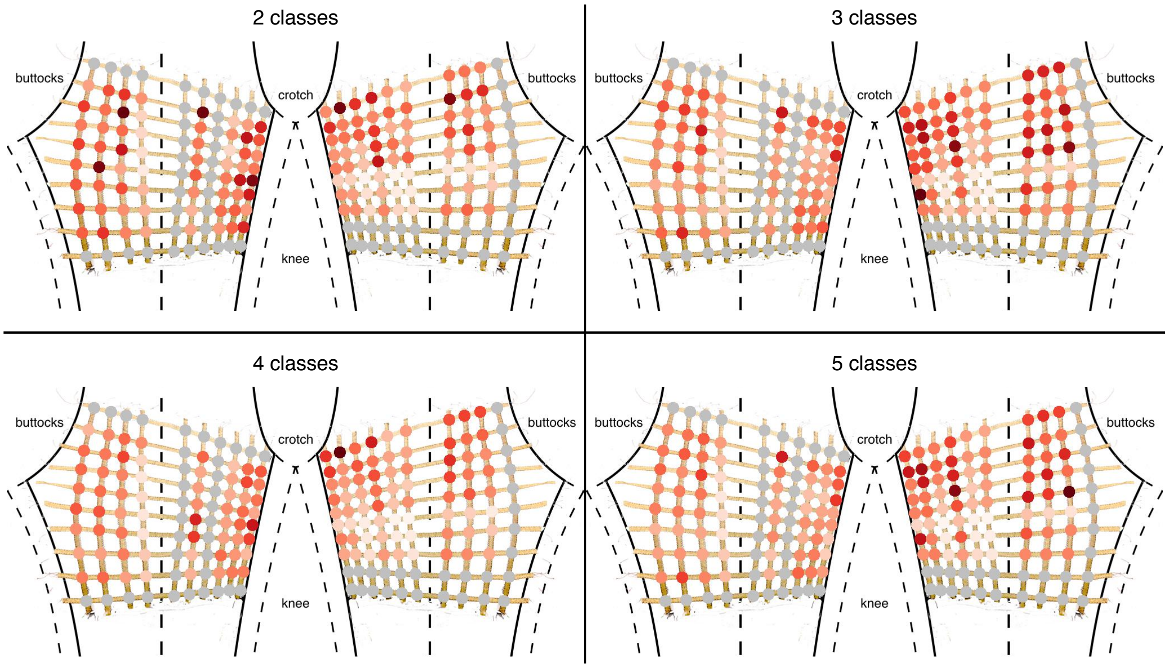
On this first glance, there is a major overlap of sensor importance across all four classification models. When examining the results in detail, however, fine grained differences between the four scenarios can be found. In particular, there seems to be a shift in significant sensors when including the class of incidental listening (3 and 5 class discrimination, see top and bottom right in Figure 5.7a), compared to the classifications only including the data of active listener behaviours and speakers (2 and 4 classes, see top and bottom left of Figure 5.7a). Looking at the importance of the sensors around the buttocks, the very upper buttocks area appears more relevant for the 2 and 4 classes only distinguishing between speakers and listeners, while the mid or central buttocks are more relevant when incidental listening is included in the classification. The most significant sensors for the 2 and 4 classes are also more concentrated in the buttocks area, while for the 3 and 5 classes the more significant sensors in the buttocks area cover a larger surface.

Moving on to the sensors covering the thighs, similar differences for the incidental listening data can be observed. The sensors of low importance in the 3 and 5 class discrimination are slightly wider spread across a larger area on the front thighs than in the 2 and 4 class scenarios, for which the very bottom front thigh seems least important and the mid thigh slightly more important in general. In all four cases, the back mid thigh of the right leg also appears more significant than the equivalent of the left leg.

Lastly, the sensors in the crotch area of the trousers do not seem to follow the 2 and 4, and 3 and 5 class discrimination pattern, but rather only distinguish between the 2 class scenario and the



(a) Sensor importance of **community** models from all 20 participants for all 2-5 class discrimination variations.



(b) An example of an **individual**'s sensor importance visualisation for all class discrimination variations. The participant illustrated here is amongst the best performing for the classifier's individual model.

Figure 5.7: Comparison of the sensor importance for community (top) and individual (bottom) models for all class discriminations across both legs of the trousers. The colours of the circles for each data point are mapped from pale (not important) to dark red (most important), representing the importance of the individual data point (sensor). The grey circles on the data points represent the broken sensors that are not included in the analysis.

rest, see the top left of Figure 5.7a. When looking at the differences between speakers and active listeners, the inner top thigh close to the crotch area is of slightly lower importance than for all other multi-class models.

Individual Model

Extracting the important features for each participant reveals a relatively large individual variation across all multi-class discriminations. In Figure 5.7b, one participant is depicted that performed well in the Random Forest classification (see participant "T" in Table 5.4) in all different scenarios. While in some core characteristics, this example is representative for the other 19 participants' feature importance, other sensors and sensor groups of seemingly high or low importance are specific to this participant. Therefore, the feature extraction for this individual model is only described in detail briefly. Rather, I point out some general differences between the results for individuals and the community model. Examples of other participants' feature importance for all different class discrimination is illustrated in Appendix C.

Something that varies strongly from the feature importance for the community data that was also one of the most clear patterns, is the importance of the buttocks. Across most individuals, sensor groups around the buttocks area are not yielded as highly significant, but rather single sensors are very concentrated around one point or very small surface area. This implies that high pressure has been applied on very small surface areas in patterns varying from participant to participant. Additionally, the asymmetry in results between the right and left leg becomes more visible when examining the important sensors for individual participants - another indication for a large variation across people.

If anything, one can observe a minor trend towards slightly higher sensor importance on the inner leg, as well as on the outer, towards the side seam leaning buttocks area, rather than on mid or inner buttocks, and the top thigh in general.

5.5 Discussion

Overall, the results show that distinct conversational states can be readily discriminated using only information from pressure changes on the thighs and buttocks. While we are used to thinking of upper body movements, especially of the head and hands, as natural signals of communicative engagement, the idea that similar information can be signalled by lower body movements is less familiar. The simplest explanation is that these systematic patterns of lower body movement are simply translations of upper body movements. For example, vigorous gesticulation or laughter inevitably causes movements in other parts of the body including the legs. This does not detract from their potential interest as a target for sensing. However, observations suggest that these are not solely secondary movements. Some movements, such as leg crossing or 'bouncing' would appear to be both potentially significant signals and ones in which causation works in the opposite direction with lower body movements having secondary effects on upper body movement. Nevertheless, these oscillations of one body part to another can help to identify different roles in a conversation.

5.5.1 Individual Variation

Both, in the confusion matrices as well as the visualisations of the feature importance, a large individual variation can be observed. While general community models that average the data set of all 20 participants used in this analysis, show good performances, the F1 Measures, Precision and recall values drop significantly when withholding one participants from the training set and testing the model on the individual. The good performance of the individual models across all classes, however, indicates the existence of distinct patterns of nuances of nonverbal behaviour and bodily movement. What could be concluded with these results, is, that people show repetitive nonverbal patterns, but everyone does so differently, which has already been acknowledged by Ekman (1992); Scheflen (1973b). This outcome is not unexpected, since each of us has developed specific signals of embodied social behaviour that we perform consistently, but that can be very different from our conversation partners. We are, in this sense, more similar to ourselves than to others. And while this leads to poor results in the testing model reported here, it also bears advantages in regards to personalised, social computing applications.

The visualisation of the feature importance shows where these individual differences lie. We can observe, which sensors determine the classified social signals in each person differ. This explains the results from the classifier, in particular the poor performance of individuals when tested against the remaining participants. So, while for general community models, areas of importance can be identified, it is difficult to identify in more detail which single sensors are most important, given the variation of individuals. So, for future iterations of the sensor design, the number of overall sensors can be reduced and the areas of sensing refined, e.g. placing more sensors in the buttocks area, and fewer on the top thigh, or also modifying the required size of sensors in specific areas.

The visualisation of feature importance also showed the asymmetry of the importance of the sensors in the different legs. Overall, the right leg seems to be slightly more important for the Random Forest classifier than the left leg. Reasons for such asymmetry, at this point, can only be speculations. Leaning more towards one side than the other might correlate with spatial orientations towards speakers, but could also be linked to right or left handedness. Another speculative explanation, however, are also the broken sensors in the trousers. While on both sides, similar amounts of sensors were removed, they are not fully symmetric, as can be seen in the sensors marked in grey in Figure 5.7. Further explorations towards postural shifts and a more fine grained dissection of bodily movements may help to explain this phenomenon better.

5.5.2 Additional Conversational Cues

Individuals do not only display distinct movement patterns of pressure application, speakers and listeners also move differently. For example, they produce different gesture types (Bavelas et al., 1992) and quantitative data from motion capture shows that their hand movements are both faster and more frequent (Healey et al., 2015). The fact that this difference can be picked up using lower body pressure sensors reinforces how marked it is. More interestingly, the sensors can also discriminate between people's listening behaviour depending on how actively they are signalling their attention to the speaker. I speculate that this is a combination of two factors: one is the motion signature of the active signals themselves (nods, backchannels, laughter) and the other is the suppression of incidental movements that can be interpreted as a sign of distraction or inattention. This is consistent with the finding that direct addressees appear to suppress their hand movements relative to ratified but unaddressed participants (Healey et al., 2015; Battersby and Healey, 2010).

This work serves as an investigation towards potentially yet unexplored nonverbal cues in conversation. I identified three active listener signals for the scope of this study, but acknowledge that there may be a range of other signals not specified, that are conflated within the category of incidental listeners. The variety of its subcategories, such as shoulder shrugging, fidgeting, coughing or more overt movements like slouching, leaning back or performing a gross postural change, could affect the classification accuracy. The misclassifications of the 3 and 5 class discrimination that include the unspecified class of incidental listener movement could be interpreted as indicators of additional conversational cues. Therefore, splitting this class into further subcategories may reveal interesting correlations between different postural patterns, and might also reduce the problem of noise for the samples of incidental listener movement. The sensors around the upper legs or buttocks have therefore given way to a more fine grained exploration towards such cues. This comparatively simple modality of pressure sensors could help to detect interactionally significant behaviour and movement that conventional technologies have so far overlooked. With the methods introduced here, we can furthermore draw attention to areas of the body that have not been considered as contributing parts to nonverbal communication, as was already indicated with the work on chair covers. The buttocks, for example, seems to bear conversational information and picks up both movement from the torso as well as from the legs. So, instead of focusing on hand gestures or facial cues, I have explored a technique to expand on these measures to analyse human interaction.

But even within the already identified cues in this work, there is more to exploit. Nodding, for example, is a movement mainly performed by first addressees, while laughing can be more ambiguous. Detecting different addressees in a conversation with more than 2 participants could give additional insights that help to assess overall dynamics in a conversation. Moreover, nodding and laughing appear to be events that are distinct to other behaviours in a conversation including unclassified gross posture shifts (see Chapter 6). Looking for further correlations between these behaviours and conversational roles could be a task textile sensors could approach, and that will be explored further in the next chapter.

5.5.3 Tweaking Algorithms

So far, the detected behaviours were predetermined and annotated. However, looking for correlations in speaker and listener behaviours, this is not always the case and as mentioned above, additional signals may be hidden in unspecified data and not be coded for. Also, the goal is to eventually be able to find behavioural patterns without involving a camera.

Temporal Structure

The mention of nods and laughter as two rhythmic movements opens the discussion for another aspect not addressed in this analysis: temporal structure. With different methods, like extracting features over time using the Fourier Transformation (FFT) or sequence analysis (LSTM), dynamic shifts within one behaviour could be detected and be used to identify yet more fine grained and versatile movement. Also exploring other classifiers further might yield different results, taking temporal structure into consideration. Alternatively, Conditional Random Fields (CRF) may be useful to specify the window size of the data. Another option would be to observe the sensor data through a rolling window and moving average, possibly reducing the dimensionality of the data for that.

However, even without a classification model that takes temporal relationships into account, the two rhythmic active listener classes show interesting and distinct behaviours. Examining the confusion matrices of both, individual and community levels with all participants present in the training set, the number of their pairwise misclassifications is low, and they are typcially confused with speaking. This could be due to the sample size of the speaking class, or due to the variety of movement that happens within speaking, different speaker movements were not discriminated.

Data Balancing

Preprocessing the data is key to the outcome of classification algorithms. This data showed extremely imbalanced sets of different identified behaviours - backchannels forming the smallest data set and talking, as well as incidental listening the largest. Addressing this imbalance with different methods potentially yields different results. I have decided to not downsample the data as such, but to balance the weighting of the classes when testing the classifier. With this approach, smaller classes were treated as more 'important' or significant while the weight of larger classes was reduced. An alternative approach to balancing is adaptive boosting (Freund and Schapire, 1995; Hastie et al., 2009) which involves weighting different classes in different ways. Depending on the goal of a classification, the question as to which set of data is to be treated more importantly than another becomes more relevant. Only wanting to detect speech, for example, would not require to increase the weight of laughter and nods, but rather 'tune' those down to achieve better results.

Another way to balance the different data sets is to downsample the large ones. A downside to this is, however that potentially valuable data is removed and could lead to further biasing of the results. Other methods can also upsample smaller data sets, creating synthetic data points with a variety of methods. This, too, however, bears the risk of overfitting towards a specific group of data points and not considering others enough, which would be a less useful approach to the data set. In this case here, therefore, manipulating the data sets themselves, would affect the results of the classifier and not provide a true representative outcome.

In summary, there are many parameters to experiment with, especially when taking this approach further and evaluating the trousers in an even less controlled environment, or "the wild", which may lead to even more imbalanced data sets of different categories of behaviours and movements. Therefore, the goal of such data balancing approaches is always to reduce the risk of overfitting, and improve the accuracy and stability of the classifier that is applied - something that should be considered prior to acquiring data.

Further Feature Reduction

In addition to balancing the differently sized data sets, other feature engineering methods that are supported by the classification algorithms can be explored. Here, I have reported on the feature importance across both sensor matrices in the trousers. This shows us which areas of the matrices are more or less relevant for the classifier. By being able to cluster certain sensors into differently significant areas eventually also leads to the question as to how many sensors are needed to detect the determined behavioural cues in total. Even though the trousers were designed with initially a matrix of 100 sensors per leg, almost $\frac{1}{3}$rd of the data points was discarded for analysis - effectively removing sensors. However, the goal is to identify the most significant sensor points and reduce the overall number of sensors without compromising on the ability of behaviour detection. The initial intended oversampling of data points serves to later investigate feature importance and, for future iterations of such custom-made 'smart' trousers, optimise the required and reduced number of features. Another approach to address these aspects and reduce the number of features is to use a principal component analysis (PCA), or linear discriminative analysis (LDA) (Pedregosa et al., 2011). They are both methods to check for and to prevent overfitting. LDA, in contrast to PCA, takes the class labels - the behaviours in this case - into account and uses the variance of data points to find so called 'super' attributes.

5.5.4 Potential Applications

When identifying signals for different behaviours in the past, we relied on the postural information from technologies based on visual recording systems - these are also where familiar nonverbal cues are drawn from. Being able to distinguish small muscular movements, invisible to an observer's eye, may reveal a new layer of patterns of movement that correlate with social behaviours and that are distinct to other known signals. Understanding nonverbal behaviour in human communication is key to many applications in health care, but also in HCI and even robotic research, for example when designing humanoids. E-textiles play an increasingly important role in these disciplines and are often used to capture bodily data, although only rarely in relation to behavioural cues.

The ability of textile sensors to pick up such social behaviours in all their subtlety makes them a promising method for unintrusive, ubiquitous computing. In contrast to many works that suggest a network of multiple sensors of different modalities is needed to capture complex collaborative behaviours in social interaction, this design presents a simple, "easy-to-make" approach to the field. In proportion to the entire body, a relatively small area around upper legs is used that functions as the sensing surface. It could be shown that with trousers, it is possible to identify individuals' behavioural states with high accuracy. These results only hold as long as the participant is already included in the training set. Withheld, this classification task becomes much more challenging, yet pursuable. A data set of 20 participants is comparatively small, and a larger corpus may be able to improve the performance of a community model. This aims at being able to detect such behaviours of participants whose sample data has nor previously been recorded. Depending on the application, this may or may not be needed. Trousers that are to identify their wearers, for example, require their own sample data, and not that of others.

5.6 Summary

The sensing trousers can reliably distinguish conversational states: speaking vs listening and explicit active listener behaviours: laughter, backchannels and nodding. Simple machine learning approaches can automatically discriminate between speaking and listening with high accuracy. For individual participants, the different groupings of behaviours are clear, and when testing the models on a general community level, the performance is good. It is only when withholding a participant in the training set, that the boundaries of my sensing system show and the behaviours are confused with each other. Backchannels perform worst; laughter and nods, even though both rhythmic movements, seem to be distinct to each other and only rarely confused; and talk performs best, also forming the largest data set. One conclusion drawn from these results is that we all as individuals move differently, but in characteristic ways.

Contributions

While the previous chapter has validated the design of the smart trousers through a benchmark study in a controlled environment, in this chapter, it was possible to show the performance of the trousers in a naturalistic setting, evaluating spontaneous postures in multiparty face to face interaction. This work is a contribution to the yet sparse corpus of bodily data captured in such settings.

Further, the findings of Chapter 3 could be confirmed and strengthened, spotlighting the interactional relevance of the buttocks area when discriminating embodied social signals and basic conversational states. These findings expand the existing, limited knowledge of lower body behaviours.

The methods these findings were gained also contribute to the field of smart textile developments, exploring classification methods for smart lower body garments. With the here used parameters, including the contextual setting and type of smart garment used, this work presents a novelty and introduces the first pair of trousers used for conversation analysis.

Limitations

Something that the approach here has not covered so far, are the movements that occur surrounding the identified conversational states. While I have looked at overt speech, I have not accounted for other significant nonverbal cues in relation to speech, such as preparatory postural adjustment. These more overtly embodied signals have so far been summarised in the category (or class) of 'incidental' listening and are not further identified or distinguished. That includes small scale movements such as fidgeting, as well as large scale movement like a change in sitting posture or leaning a body part forwards or backwards. These types of movement may have interactional relevance.

Further work in the next Chapter (Ch 6) will explore these, and dissect posture shifts and other movements of different body parts in their own rights, widening the angle of inspection into this data set that forms the core body of this research.

The work to follow is directed at exploring potential correlations between other listener behaviours and postural micromovements, as well as between participants, for example by analysing statuses of different addressees in a conversation. My goal is to uncover yet concealed behavioural cues that may be significant signals in social interaction. So that eventually, we might be able to teach our trousers to 'listen' to our conversations.

Chapter 6

Sifting Through Shifts: Explorations on Posture Shifts

Chapter Overview

In the last chapter, I focused on capturing overt conversational behaviours that speakers and listeners perform, and have classified these with supervised machine learning techniques. This approach required to identify and annotate and predetermine the behaviours to explore. Something that has not been accounted for so far, is an unsupervised data driven approach to take into account all movement that happens outside of the previously determined categories. In particular, these could be postural adjustments in relation to a speaker's utterance, or marked changes of sitting postures while listening.

Here, a more detailed exploratory assessment of previously unclassified movements is presented, examining them for additional distinctive features. Furthermore, rather than using supervised learning classification algorithms, a new approach is introduced: analysing interactional and behavioural events based on distinctive features in the sensor data.

This divides the chapter into two analyses exploring the same data set from different perspectives. The data used for these explorations presented here comes from a subset of the data set introduced in the previous Chapter 5: seated three-way conversations captured with video and pressure sensing trousers. The results reported in this chapter also mark the final steps of the explorations towards detecting cues of social interaction with the 'smart' trousers.

The first study reported in this chapter is also available as a conference paper: *Skach, S., & Healey, P. G.T. (2019, September). Posture Shifts in Conversation: An Exploratory Study with Textile Sensors. In Proceedings of the 23rd Workshop on the Semantics and Pragmatics of Dialogue. London, UK. SemDial*

6.1 Introduction

One of the most salient body movements people make in natural conversation is a general posture shift in which most or all of the body goes through a momentary adjustment. While these movements could, of course, be explained by fatigue or physical discomfort there is also evidence suggesting they have communicative significance (Scheflen, 1964; Bull and Connelly, 1985; Hadar et al., 1984). Unlike, say, iconic gestures or nods that accompany each utterance these are relatively global, infrequent movements that seem to mark larger conversational units or signal something about participant's stance towards an issue. Scheflen (1964) was one of the first to document these moments in detailed case studies of psychotherapy sessions. He defined posture shifts as movements involving at least half the body and proposed that they are organised around changes in *position* or point of view. Others have since elaborated on Scheflen's findings, suggesting different interpretations of posture shifts and associating a variety of conversational meanings to them (Condon and Ogston, 1966; Bull and Brown, 1977; Kendon, 1970; Ekman and Friesen, 1969b; Mehrabian, 1969).

In this chapter, I explore posture shifts further and make use of the modality the pressure sensing trousers to detect these gross bodily shifts. I ask, what these salient movements mean and how they contribute to conversation, and expand the exploration of the potential of pressure sensors in trousers to detect changes of conversational states and discuss the qualitative characteristics of some of these events. With the common judgement that posture shifts appear mainly in speakers (Wiemann and Knapp, 1975; Hadar et al., 1984; Condon and Ogston, 1966), but findings of listeners generally performing more movement than listeners, it is worth questioning whether posture shifts really appear predominantly in relation to speech, or whether with more research investigating this type of movement, the view on posture shifts should be reframed. Further, changes in pressure that are not necessarily visible to other interactants, as well as audible conversational cues are examined. The research questions addressed in this chapter are concerned with additional features and social cues that the sensing trousers are able to pick up in human interaction with a focus on posture shifts of the full body.

The approach to analyse these explorations is driven by the characteristics of the sensor data. Instead of taking the annotations as a starting point to analyse the corresponding sensor data, I look at significant characteristics and interesting patterns in the unlabelled sensor data first, establishing local peaks and the largest changes in pressure across both legs' sensor matrices. The overall aim is to reveal potentially hidden data structures beyond the labels previously identified and investigated, assessing what conversational and bodily signals those pressure changes correlate with. By looking at the data first, attention was drawn to a new set of social cues so far not accounted for. For example, identifying not only who is speaking, but is holding the floor within the conversation (Edelsky, 1981; Dielmann et al., 2010; Dommel and Garcia-Luna-Aceves, 1997) - who is in the centre of attention amongst the participants, will be part of this analysis. Furthermore, the dissection of the different body parts in motion may provide a more systematic view on nonverbal communication, expanding on previous categorisation systems (Harrigan and Rosenthal, 1983; Buisine et al., 2014; Cappella, 1997; Birdwhistell, 1970; Jolly, 2000).

In the scope of this approach, an extended annotation scheme that derives from the data centred investigations is introduced. It is divided into categories such as types of movements, visibility of movements or postural shifts causing the peak in pressue data - or, in other words, that cause the major change of pressure distribution across the sensing area in the trousers. Further categories for the new annotation scheme concern directions of movement, but also additional conversational states like the status of addressees, as well as giving more prominence to the lower body and full body posture shifts. With these approaches and explorations, my research also seeks to expand on the existing categorisation when describing body movement in social context by suggesting an additional scheme for annotation. I further aim to test the limits and additional potentials of the wearable textile sensing system for applications in social behavioural studies, but also to shed light on conversational social signals that have yet been underinvestigated or only mentioned marginally.

6.2 Background

6.2.1 Categorising Postural Movement

Scheflen (1964) has described posture shifts mostly in relation to speech and has defined them as a movement involving at least half of the body. Cassell et al. (2001) adds by defining a posture shift as a motion or a "position shift for a part of the human body, excluding hands and eyes". According to this, nodding accounts for a posture shift, too. Harrigan and Rosenthal (1983), too, discuss nodding as a postural movement. Others have assigned nodding to verbal backchannels (Delaherche et al., 2012).

These examples show that it can become complex to divide the body into different segments to analyse nonverbal behaviour. Harrigan and Rosenthal (1983) have analysed body movement under the following factors: 3 trunk angles (forward, backward, straight), 2 arm positions (on lap, crossed), 2 leg positions (open, crossed) and nodding as distinct head movement. Bull and Connelly (1985), on the other hand, identified 3 postures related to the upper body and 5 related to the lower body, evaluating them in relation to 6 different categories of speech. Several systems describing full body postures have been introduced, both based on movements of different body parts, as well as affective associations of postures. For example, Buisine et al. (2014) categorises *idle*, *still*, and *congruent* postural movement, while Dael et al. (2011, 2012) categorises movement on three levels, according to their social context (*function*), the body parts in use (*anatomical*), and the body's orientation in space (*form*). In the research of Cappella (1997), nonverbal behaviour is analysed dividing body parts into micro-units, annotating movement separately for e.g. eyes, mouth, head, elbows, wrists, fingers, etc. Describing postural behaviour through small grouped body movement has already been done by Birdwhistell (1970), too, naming smallest units *kine*, that can be grouped into *kineme*, implying social meanings of small unit movement, as well as more complex *kinemorphs*, which include gestures. These categorisations to define behavioural actions, Birdwhistell's theory of *kinesics* were based on muscular tension, as well as the duration of the movement. They have not been established as a universally used system, though, and have been criticised as not suitable to explain bodily actions (Jolly, 2000).

These examples illustrate the amount of detail that is commonly given to the lower body compared to the upper body, the latter divided into more fine grained patterns of movement. Observations of the posture shifts in the lower body only document two overt leg crossing positions.

6.2.2 Posture Shifts and Conversational Roles

Posture Shifting Speakers

There are several suggestions as to what postural shifts mean and what role they play in punctuating communication between interactants, between speakers and addressees, and also when in conversation they are most likely to appear. Generally, posture shifts have been associated with changes in topics, so called *locution cluster*, coined by Kendon (1970), or *situations* (Gumperz, 1982). Often, they are also reported in connection to speaker behaviours, or listeners' perception of speakers. Hadar et al. (1984) reports that they appear primarily at the start of a speaking turn, when the interactant changes their state from listener to speaker, or after a long speaker pause. They can accentuate speaker behaviours in fine grained ways (Ekman and Friesen, 1969b), and the change of speech categories is also accompanied by changing postures (Bull and Brown, 1977).

Speakers are said to punctuate the end of their turn and maintain a more upright posture overall, leaning rather forward than backwards (Wiemann and Knapp, 1975), or emphasise words and phrases. Duncan (1972) suggests foot movement as a potential turn unit marker. Micro-movements like facial expressions, e.g. raising an eyebrow, can be in line with changes in tonality, such as lowering one's voice (Condon and Ogston, 1966). The speaker's role also determines the status of listener addressees. By turning their body towards a recipient, or in some cases touching them, the speaker selects that recipient as the first addressee (Scheflen, 1973b).

Shifts Beyond Speech

Posture shifts can also appear outside of speech, although listeners' postures are examined less often. It is suggested that the status of an addressee can be interpreted by the openness of their legs and arms (Mehrabian, 1968b), and that listeners synchronise with speakers (Condon and Ogston, 1966) and shared postures between them are linked to a high rapport (Lafrance and Broadbent, 1976). Also pauses between speech as listener turns are associated with postural adjustments by (Hadar et al., 1984).

Posture shifts are interesting signals in interaction in their own right. For example Bull has considered frequent posture changes as a marker of boredom (Bull, 2016). Condon and Ogston (1966); Lafrance and Broadbent (1976) also reported on postural synchrony, leading to higher rapport, or if incongruent, are indicators for negative relations between people Lafrance and Broadbent (1976). Posture shifts are also self synchronised movements to speaker turns , as signals for different levels of engagement in a conversation (Schegloff, 1998) or to correlate with tonic stress (Bull and Connelly, 1985). Furthermore, the exposure and intensity of such movement may present cues to interpersonal relationships. For example, Wiemann and Knapp (1975) suggested that the more familiar interactants are with each other, the more subtle the postural shifts and bodily movement, moving parts of limbs (fingers) rather than entire body parts. This can be linked to Kendon (1972)'s observation that generally, those body parts are in more motion than the torso and the legs.

Although posture shifts are important non-verbal signals (Kleinsmith and Bianchi-Berthouze, 2013), not least because of their relative scale, there is not an extensive body of literature on them compared to other non-verbal signals such as the small movements that don't affect larger body parts (gaze or gestures). More attention has been given to posture as a static feature of participation in conversation, especially in relation to posture matching as indication of affiliation or attraction (Beattie and Beattie, 1981; Bianchi-Berthouze et al., 2006; Mehrabian, 1969; Lafrance and Broadbent, 1976), in their spatial formation (Kendon, 1990b).

6.3 Methodology

In this chapter, the data set presented in the previously is evaluated against a broader range of postural movements and nonverbal behaviours. Instead of focusing on sitting postures and basic conversational states alone, I extend the numbers of features by more dynamic postures, focusing on shifts in postural movements in an interactional context, analysing individual body parts, and also extend the conversational states introduced previously, now looking at different statuses of addressees, amongst other aspects.

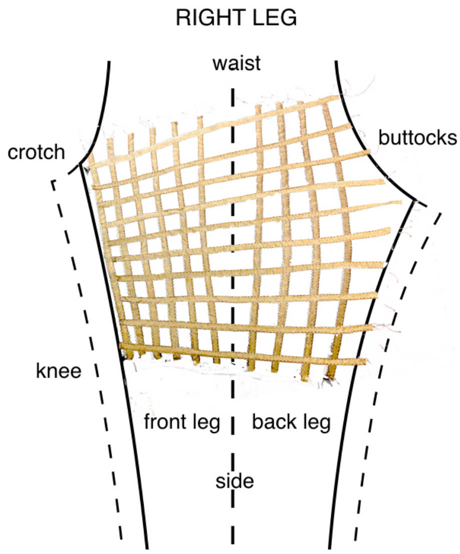


Figure 6.1: A reminder of the distribution of the 10x10 textile pressure sensors across one leg of the designed and manufactured 'smart' trousers: 60 sensors on the front leg, 40 sensors on the back leg.

6.3.1 A Brief Trouser Data Recap

The multimodal data used for this chapter's investigations consists of the pressure sensor data of the trousers and the video data of the 14 sessions of three-way seated conversations.

Trouser Design

The matrix is deployed around the upper leg, covering the area from the knee upwards to the buttocks in the back and the crotch in the front, see illustration and schematic in Figure 6.1. With a sensor matrix mapped around each leg, a total of 200 sensors is embedded in one pair of trousers, 100 on each leg, of which 60 are mapped on the upper or front leg, and 40 on the back leg (back thighs and buttocks). (A detailed documentation of the design and manufacturing process of this wearable sensing system is also reported in Chapter 4.)

Participant Subsets

I select two subsets of the collected data to hand code for the additional features. One set of 5 participants serves to analyse postural shifts, as well as pre and post speech movement. A second set of 10 participants serves to detect major changes in pressure across the sensor matrix, that is further annotated for an extended set of nonverbal cues. The subsets of data come from the previously analysed 20 participants and were selected by the performance for individual and community based classification tasks. The 5 participants used for the first analysis is represented as a subset in the second analysis.

Procedure

Later, the sensor data of both legs was synchronised with the coded annotations. Before this synchronisation process, the broken sensors mentioned above were removed, which resulted in a total of 165 sensors used for further processing and analysis. For each participant, the same sets of sensors were removed to retain consistency.

Figure 6.2: The sensing trousers worn by the participants are highlighted in yellow

6.3.2 Data Analysis Approaches

There are two different approaches to assessing the data sets presented here. While the sensor data and video recordings are identical to what I was already working with in the last chapter, as well as the preprocessing of the data, the analysis to examine the aspects I focus on now deviates from the ones previously reported.

Factor Analysis

The procedure in the first exploration presented below (section 6.5) uses a factor analysis aiming to reduce the complexity of the 200 pressure sensors in the matrix when identifying posture shifts in relation to speakers and listeners. The approach follows the previous methods of annotating the recorded conversations and comparing these with the synchronised sensor data that is collected from the trousers. Hence, the sections or sets of sensor data looked at for certain behaviours and postures is predetermined by the annotations that are coded.

Peak Detection

For the second exploration documented in section 6.6, the basis of investigation was not to predetermine the types of movements and behaviours, but to first extract interesting characteristics of the sensor data before annotating the correlating events. These events were therefore only identified through the findings in the sensor data, yielding major changes in pressure. This approach resulted in a much larger set of annotation tiers that is described in the next section.

Observations

Additionally, for both explorations with different takes on the same data set, observational findings are reported. They focus on evaluating the annotated behaviours and movement types and were conducted using the video recordings of the subset of conversations.

6.4 Extended Annotation Scheme

Elan (Brugman and Russel, 2004) was used to annotate the video recordings for all behavioural and postural cues investigated here. At least two annotators were used for the behavioural states examined and coded for all participants in the last chapter - overt speech, backchannels, laughter and nods, as well as for annotations used for the data subset for analysing posture shifts: pre-speech, post-speech and posture shifts (elaborated on below). The two annotators were the author and an

Class	Tier Name	Description
Behaviours	**Talk**	on- and offset of overt speech
	Pre-Speech	2sec immediately before talk
	Post-Speech	2sec immediately after talk
	Laughter	overt, 'embodied' laughter
	Backchannel	verbal listener responses
	Nods	Head nodding
	Floor Holder	centre of attention of conversation
	First Addressee	Listener primarily addressed by speaker
	Second Addressee	Listener not addressed by speaker
Body Parts	Torso	trunk movement (incl. shoulders), twists, leaning
	Buttocks	movement in hips, buttocks (e.g. adjustments, wiggles)
	Legs	any large & small scale leg and feet movement
	Arms	gesturing, touch interaction with other body parts
	Head	all significant head movement beyond nodding
Visibility	Concealed	underneath the table surface
	Revealed	above the table surface
Movement Type	**Posture Shift**	gross movement of torso & legs
	Fidgeting	rhythmic small scale movement
Movement Axis	YZ axis	Coronal plane, leaning sidewards movement
	XY axis	Transverse plane, up and down movement
	XZ axis	Sagittal plane, back and forwards leaning movement
Intention	Intentional	directed, interactionally relevant movement
	Incidental	accidental, reactional movement

Table 6.1: Overview of the hand coded annotations in Elan for a set of 10 participants. The annotations highlighted in bold are used for the first exploration presented in this chapter, while the remaining annotations were conducted following the second exploration of peak detection.

additional paid research assistant. As described in Chapter 5, annotation rules were established and discrepancies were resolved in data sessions examining the videos together. Criteria regarding hand coding accuracy was applied here, too, marking events with an accuracy of a 10 milliseconds time frame in the Elan timeline interface. For all additional cues that are presented in the following section, including identifying types and visibility of movement, as well as individual body parts in use, that are identified through detected peaks in the sensor data, one annotator was used (the author).

In total, 23 different parameters were used to create an annotation matrix that served for further analysis. Below, these parameters are described and divided into annotation clusters, distinguishing between behavioural cues, types of postural changes and finally details of bodily movement. Naturally, some of these parameters would co-occur. For example, head movement and nodding are expected to overlap largely, and in any type of coded movement, mentions of which body part was in motion can be found in the annotation matrix. A summary and overview of all hand coded annotations used for analysis in this chapter can be seen in Table 6.1.

6.4.1 Conversational Context

Expanding on the annotations that were conducted in the previous chapter, I focus on basic conversational behaviours that occur in three-way conversations: speakers and listeners. The annotations for speakers are described as overt speech with starts and ends of annotations defined by onset and offset of audible speech. Other first pass coding focused on active listener behaviours, in particular on nodding, laughing and backchannelling, determined as reported in Chapter 3 and 5.

Preparatory Movement

Second pass annotation then coded the moments immediately before and after speaking arbitrarily defined as 2 seconds just before, and 2 seconds just after speech. These were coded regardless of other non-verbal behaviours or marked bodily movement and are included in the analysis to investigate preparatory movement in relation to speech.

Addressees

Third pass coding was used to identify first and second addressees. This is to determine the status and level of engagement of listeners and distinguishes, who of the non-speakers is addressed by the speaker. While the first addressee is identified through orientational and directional cues from the speaker, emphasised by gaze, gesture or torso posture, the second addressee is determined indirectly, through the absence of a speaker and first addressee annotation mark.

Centre of Attention / Floor

Lastly, participants who present the centre of attention within the conversation were coded for, for the purposes here named *floor holders*. This category is largely determined by the gaze of interactants - coding for who is being looked at by the others. While this mostly overlaps with speakers' turns, there are rare cases in which participants draw the attention of others outside of their speaking turn just before or just after speech (within a 2 second window in both directions), and were yet identified as the floor holders. In these instances, the centre of attention was reached through marked laughter and a posture change, while noone else was talking either.

In summary, the annotations in relation to conversational context are: Speech; Pre- and Post Speech; First or Second Addressee; "Active Listener" Behaviours divided into Backchannels, Laughter and Nods; and Floor Holders.

6.4.2 Type of Movement

Here, the overarching question is, which type of movement, if any, is performed. For the scope of this work, posture shifts and fidgeting was observed.

Posture Shifts

Posture shifts are defined as gross body movement involving either or both, the upper and the lower body, describing a positional movement of these body body parts. This includes leaning forwards, backwards, and sidewards, but also performing leg crossing and adjusting sitting position with thighs and hips (shifting the weight within a seated counterpose). Both, speaker and listener posture shifts were included. In the scope of this work, I exclude gaze and gestures from identifying as posture shifts, but treat those as separate annotations.

Fidgeting

Fidgeting accounts for bouncing, wiggling, rubbing hands on thighs, and generally small scale movement that implies a certain rhythm and repetition. Both, leg and arm movement, as well as the interaction between them is included. One-off movements or head nods are not included in this annotation category.

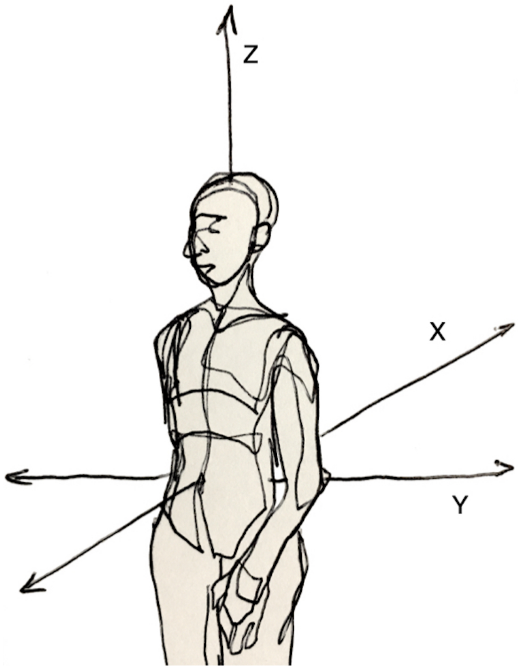


Figure 6.3: Different axes of movements the annotations correlate with: XY axis presents the Transverse plane, YZ axis the Coronal plane, and XZ axis the Sagittal plane.

6.4.3 Movement Axis

Furthermore, the nature of bodily movement was divided into directional facets. Three dimensions of movement are coded: back- and forward leaning (longitudinal) movement along the Sagittal plane in coordinates on the Z and X axis in Figure 6.3; sidewards movement along the Coronal plane in Y and Z axis in Fig.6.3; and up- and downward movement along the Y and X axis in Fig.6.3, the Transverse plane. Where combinations of directions along these planes and axes appeared, only the dominant movement was annotated for. Diagonal forwards and backwards leaning was annotated as Sagittal movement rather than coronal movement.

6.4.4 Visibility of Movement

The relevance of a nonverbal conversational cue relates, amongst other factors, to the visibility of such movement, whether it is concealed or revealed from interaction partners. In this work, with a table present in the seated interaction, the visibility of postural behaviour can be described in regards to movement below or above the table - assuming this correlates to general visibility and invisibility of the movement for others. Furthermore, determining whether a movement is concealed or revealed is dependant on the other interactants. Therefore, this annotation category is always in reference to others, to the conversational set up and relates to visibility of the subject's movements to their recipients. For example, leg movement or hand touch carried out underneath the table would be coded as concealed, where the body parts above the table surface are not markedly affected by the movement. Leaning forward or moving heads and arms would be coded as revealed movement, clearly visible to others and performed mostly above the table surface.

In cases where the performed movement contains both, revealed and concealed elements, which also results in having different body parts in action, the event was either split in two separate events with all according annotations following, or the significantly dominant movement performance was accounted, while the minor or side event was dropped from annotation. This was allowed only, however, when the allocation was unambiguous.

6.4.5 Different Body Parts

As indicated above, for each movement type and behaviour, different parts of the body are in motion. Here, I observe and note them as isolated events to obtain a holistic and precise decomposition of interactional movement during the detected peak of pressure change. The coding of the different body parts is not binary, since more than one identified part could be moved simultaneously. Thereby, I divide the human body into the following parts, that are also illustrated in Figure 6.4 below:

Torso annotations include all overt upper body movement and accounts for marked twists like body torques the torso is involved in, as well as smaller scale adjustments and posture changes in the torso. The defined area of the torso is the trunk, between hip bones and shoulders (collar bones).

Buttocks are defined as the area around the hip bones and the crotch, presenting a link between the thighs and the torso. The buttocks are separated from torso annotations because it was observed that some postural adjustments and shifts seem to be executed with marked movements in this area rather than significant other upper or lower body movement. An example for this is wiggling and weight shifting from one butt cheek to the other. Annotations in which the buttocks are highlighted can also include overall posture adjustments, fidgeting and sidewards wiggling.

Legs involve any large and small scale movement of the upper and / or lower legs and feet are annotated here. Leg crossings, leg bouncing, tip-toeing, and other marked movement possibly responsible for a peak of pressure change in the sensor data are accounted for.

Arms annotations account for any significant movement of arms, but don't include hand movement only. For example, marked gesturing would be included here, while subtle finger movement without at least the underarm in motion would be ignored. In cases of touch interactions between the arms and legs, both categories would receive an annotation.

Head movement annotations are largely in co-occurrence with nodding. The difference to the nodding annotations, however, are, that here, I also include head shakes and arhythmic, "one-off" movement of the head such as shrugs, changing the direction of gaze in a marked, noticeable way.

The last two categories, arms and legs, have been included in the annotation scheme despite being in no obvious relation to the sensing system, which is placed on the lower body only, because it was observed that in some cases, overt movements of these body parts affect the overall position and dynamics of the body and therefore the distribution of pressure across the sensing area in the trousers. Especially in combination with other body parts performing marked movement, a more significant peak in the sensor data could be observed.

6.4.6 Incidental and Intentional Movement

Lastly, I analyse and code the performed movement for its interactional intention. These events are divided into accidental, or incidental movement and intended, more directed or orchestrated

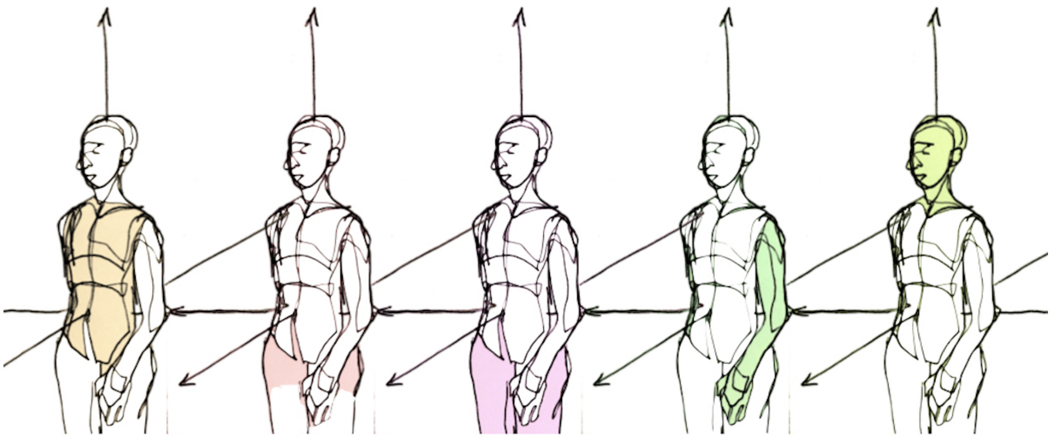


Figure 6.4: The five different body parts accounted for in the movement annotations: torso, buttocks, legs (including feet, not shown here), arms, and head.

movement. By accidental movement, I mean any non intended movement that does not align with any other behaviour introduced above. This is something that is not interactional and is, if anything, at most in correlation with a behaviour or other movement, such as an action like scratching, as well as unrelated postural adjustment (e.g. when adjusting the chair rather than being related to conversational topics). Other events that were coded as incidental or accidental, are postural reactions to a cough, sneeze or hiccough, some hand to face or head movements (e.g. scratching, twirling, stroking one's hair), occasional stretching of the back, and in general seemingly uncontrolled movement in an unrepetitive, arhythmic manner. Intentional movement was only coded indirectly as absence of incidental movement.

6.5 Exploration One: Posture Shifts

6.5.1 Data Subset One

The first explorations towards posture shifts are done with a small subset of 5 of the 20 participants: 4 female, 1 male. The participants were selected randomly from a predetermined subset of participants. Two participants of this subset were part of the same conversation, so that 4 different conversations are presented here.

6.5.2 Annotation Driven Approach for Data Processing

First, I explore posture shifts as gross bodily events during a conversation with the annotation and analysis methods we are already familiar with, aiming to evaluate the relevance of these bodily adjustments in an interactional sense. The highlighted annotations summarised in Table 6.1 are used to look at movement in relation to speakers and listeners, focusing on postural adjustments in preparation to and immediately after speech. The data synchronisation consists of time aligning the video annotations and pressure sensor data of 4Hz sampling frequency - this process is explained in further detail in Chapter 5, where the same principle has been applied.

In summary, these explorations on posture shifts in relation to speakers and listeners included the following annotations:

Comp.	Total	% of Variance	Cumulative in %
1	55.151	34.255	34.255
2	36.034	22.381	56.637
3	23.190	14.404	71.041
4	11.958	7.427	78.468
5	8.823	5.480	83.947
6	6.055	3.761	87.709
7	3.444	2.139	89.848
8	2.613	1.623	91.470
9	2.408	1.495	92.966
10	1.352	0.840	93.806

Table 6.2: Variance Explained (Extraction Sums of Squares Loadings) for first 10 components

- Speech
- 2 seconds immediately before and immediately after speech
- Posture Shifts

The first part of the data analysis explores posture shifts in relation to speakers and listeners and approaches questions, as to how and if marked bodily movements relate to these basic conversational states. Here, I look at the small data set of five randomly selected participants. The results are reported in two steps: a) an investigation of the pressure sensor data with a factor analysis and b) observations of the interactional context of the posture shifts.

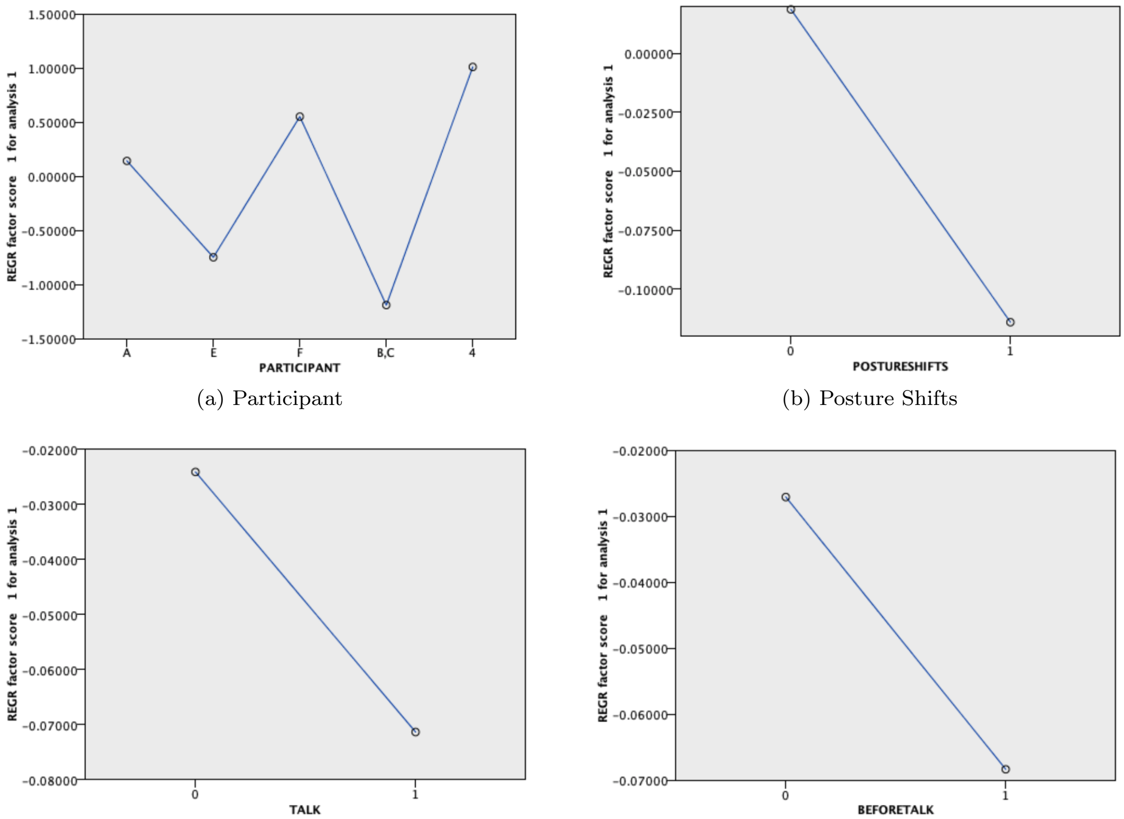
Across the 5 participants in the videos, posture shifts occurred on a regular basis. In a time window of 15 minutes, an average of 37 posture shifts were annotated per participant, which equates to 2-3 posture shifts each minute. By posture shift, I define the positional movement of the torso and / or the lower body including the legs. In the scope of this work, gaze and gestures are excluded from postural shifts, but acknowledge that gestures in particular are often described as part of a postural shift that affects the dynamics of at least the entire torso (Cassell et al., 2001).

6.5.3 Factor Analysis

The 200 pressure sensors on each participant (100 right leg, 100 left leg) produce a relatively complex array of pressure measurements with a significant amount of redundancy between sensors. Hardware failures reduced this to 165. If a sensor failed on one participant the data were deleted for all participants to ensure equivalent sensor arrays were used for each person. The sensors yielded a total of 6278 pressure measurements across the whole sample. In order to reduce the complexity of the sensor data a factor analysis was calculated using SPSS (v.25). This yielded 10 components that account for 94% of the variance, see Table 6.2. Appendix D lists further outputs up to component 31, which cumulatively covers 98% of the variance, although components 11 - 31 account for less than 0.6% of the variance individually (component 11 for 0.6%, component 31 for 0.078%).

The influence of the four coded behaviours (also listed in Table 6.1) on pressure changes was analysed using Automatic Linear Modelling with forward stepwise model selection. Talk (1/0) Beforetalk (1/0) Aftertalk (1/0) and Participant (1-5) were used as predictors and the regression factor score for each component from the factor analysis for each pressure observation as the target.

For Component 1 the model fit is 88%, Information Criterion -10,438. The analysis shows that 'Participant' ($p < 0.000$), 'Postureshift', (Coefficient = -0.133 $p = 0.003$) 'Talk' (Coefficient = -



(a) Participant

(b) Posture Shifts

(c) POSTURE

(d) Participant

Figure 6.5: Estimated Means of the first factor for the top ten significant effects ($p < 0.05$) are displayed

0.047, $p < 0.000$) and 'Beforetalk' (Coefficient = -0.041 $p < 0.004$) predict changes in first factor (component) of the pressure data. The estimated means of these effects for Factor 1 are illustrated in Figure 6.5. Components 2-8 are primarily predicted by Participant with different Components picking out different subgroups of participants. There are two exceptions: Component 3 is also marginally predicted by 'Aftertalk' (Coefficient -0.031, $p < 0.000$) and Component 6 is also predicted by 'Postureshift'. Component 9 which has a relatively poor model fit (4.5% accuracy, and Information Criterion -216.0) is predicted by 'Postureshift' (Coefficient = -0.204, $p < 0.000$), 'Aftertalk' (Coefficient = 0.125, $p = 0.001$) and 'Beforetalk' (Coefficient = 0.101 $p < 0.005$).

The effect of the individual sensors for Component 1 from the computed component matrix are visualised in Figure 6.6, showing which sensors have positive and negative associations. The colours in the Figure are mapped so that the dark tones represent positive association, and the light ones negative associations. The two sensors with the highest positive values are on the mid front leg (L64=0.914 and R61=0.909), and the sensors with the most negative associations are on the right back leg (R87=-0.763) and the left lower front thigh (L32=-0.777). A full component matrix with all values is attached in Appendix D. From this, we see that the front mid thigh on the left leg, and the mid buttocks of the right leg affect the predictions most positively, while the sensors in crotch proximity, on the upper buttocks, as well as on lower mid thighs have negative associations. Interestingly, these patterns are not symmetrical.

The raw pressure data changes corresponding to the predictors found for Component 1 are il-

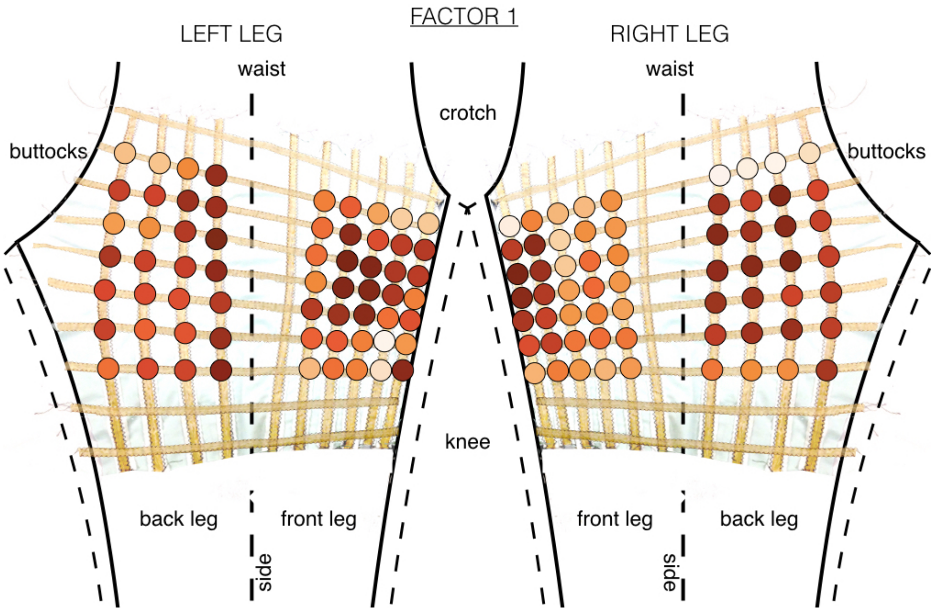


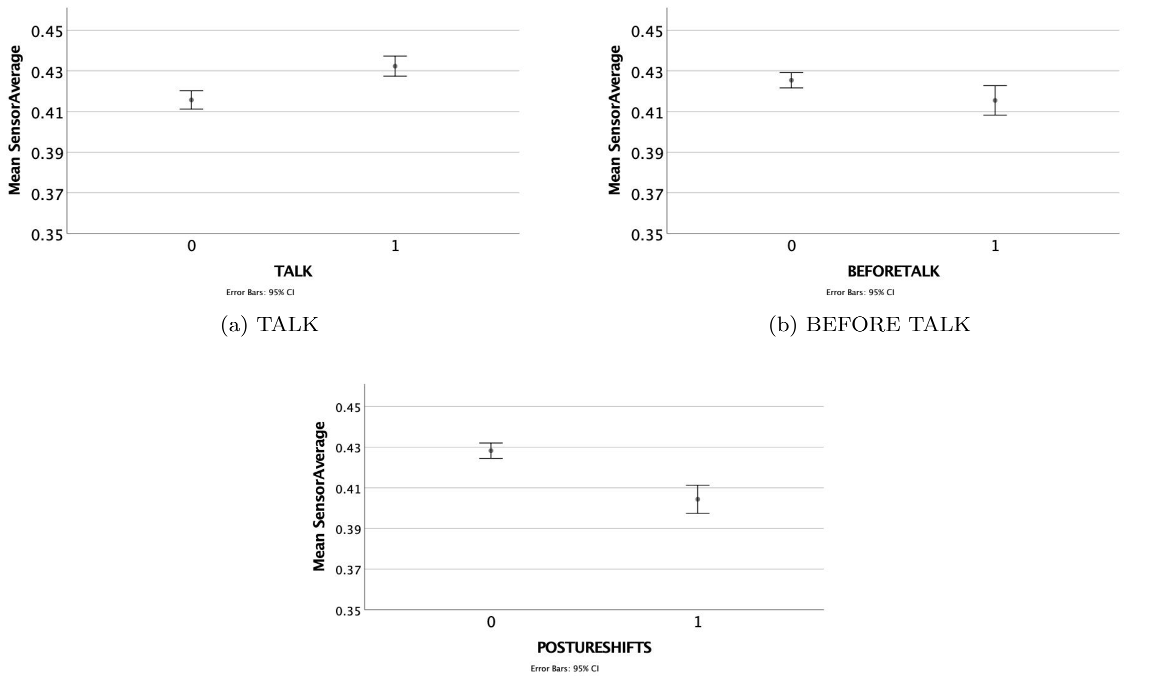
Figure 6.6: Component Matrix: visualisation of component 1 for each sensor, mainly discriminating posture shifts, talk, and pre-speech movement. Dark colours show positive associations, bright tones negatives (similar to a heat map).

lustrated in Figures 6.7c, 6.7a and 6.7b. Note that, in effect 'Beforetalk' is the inverse of Talk but sampled over a smaller data set. Together they show that talking is associated with an overall increase in lower body pressure (when seated) and that the shift takes place in a two second window prior to speaking. Conversely, large scale posture shifts are associated with an overall decrease in lower body pressure.

Overall, these preliminary results suggest that the array of pressure sensors can be used to discriminate between global posture shifts and also the smaller movements people make immediately before and after speaking. This replicates the earlier analysis of the pressure data comparing talking vs. listening using machine learning techniques (Chapter 5). The results also highlight the substantial individual variation in the pattern of the pressure data. Individual identities form the largest and most consistent predictor of pressure patterns across all the analyses.

6.5.4 Observational Findings

The posture shifts coded from the videos were explored to develop hypotheses about the possible functions of the large scale posture shits in this corpus. For a better overview, the types of posture shifts are divided according to the time of their appearance in relation to overt speech: before, during, after and between speakers' turns. The findings reported here emerge from observations of the video data (2 cameras capturing each participant's movement from different angles). Additional notes from these observations per participant are attached in Appendix D. Other than the factor analysis reported above, the findings here do not take the pressure sensor data into account and focus on the visual inspections of the videos alone.



(a) TALK

(b) BEFORE TALK

(c) POSTURE

Figure 6.7: Pressure change when talking, before talking and with posture shifts, from left to right. Average Normalised Sensor Data

Preparatory Movement

Listed below are the four categories of posture shifts before a speaker's turn, and are also illustrated in Figure 6.8:

1. Start and end of movement several seconds before utterance (end of movement ≥2sec before talk), however still close enough to be seen as preparatory.

2. Start of movement before speech, outside of 2sec window, but completion within this time window, up to the very start (onset) of speech.

3. Occurrence of posture shift precisely within 2 seconds before speech, ending at the very start of utterance.

4. Posture shift starts within 2sec just before, and is executed and completed during speech

The evaluation of the sample set of 5 participants indicates that, considering the frequency of these categories, 80% of preparatory postural movements happens in part or as a whole within a time window of the 2 second annotations. The remaining preparatory posture shifts happen largely between 4 and 3 seconds before speech. This describes the most common types of preparatory posture shifts: 2) and 4) in Figure 6.8 and the list above - the completion of a posture shift just before or during a speaking turn. These findings support hypothesis on posture as preparation for speech, and also align with previous suggestions that posture indicates turn taking and interactants signal their next speaking turn through these movements.

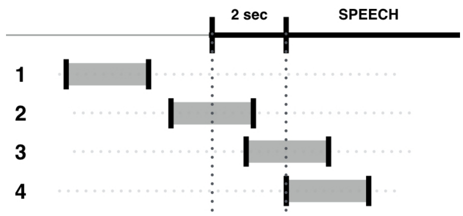


Figure 6.8: Preparatory Movement Types: 1) performed several seconds before utterance; 2) completion within 2 sec before talk; 3) start & end within 2 sec window;, completion often precisely at start of talk; 4) start within 2 sec window, overlap with talk.

Delayed Post-Speech Shifts

It was observed that postural shifts that are not classified as preparatory movement, but rather as post-speech movement, follow a different pattern. Overall, they occur slightly less frequent and are only rarely performed in the immediate aftermath of talking utterances (inside the 2seconds time frame). This is not to say they don't exist, but more commonly, they seem to be performed with a short delay. This delay can be categorised in similar ways as the preparatory movement (mirroring Figure 6.8), segmenting the post-speech movement with 2 second windows:

1. overlap with speech: posture adjustment performed towards the end of speech and beyond: start of movement within speech, completion after speech has ended.
2. no delay: start of postural movement immediately after offset of speech
3. short delay: after utterance ends, postural shift is performed with a delay of $\leq$ 2 seconds (within the specified time window)
4. long delay: considered as a movement being performed more than 2 seconds after speech has ended (outside specified time window)

I have found that only rarely, post-speech movements are performed immediately at the offset of speech. Most postural shifts that are associated with the end of an utterance are performed with a delay between 1 and 4 seconds after talking (with rare outliers up to 5 seconds after, everything later than this was not linked as a post-speech postural adjustment) - yet 49% of them falling into the specified time window of 2 seconds post talk. In fact, most movements of this category started within this time window, but at the same time, a much higher percentage (28%) of posture shifts started only clearly after 2 seconds post speech. Again, this means that categories 3) and 4) are the most common amongst post-talk postural movement - with a short or long delay.

Active Listener Postures

Postural adjustments that do not appear to be closely associated with speaking are also observed. These postural movements often co-occur with other conversational behaviours and appear to signal something about a participant's relation to what is happening in the interaction. I observed that in most cases where not linked to speaker behaviour, posture shifts are related to specific 'active' listener signals, such as nodding, backchannelling or laughing but that go somewhat beyond these specific forms of concurrent feedback. Two examples are depicted in Figure 6.9, and a summary of co-occurrencs between posture shifts and previously coded conversational behaviour is listed in Table 6.3. From the table, it can be seen that just over 40% of the coded posture shifts are associated

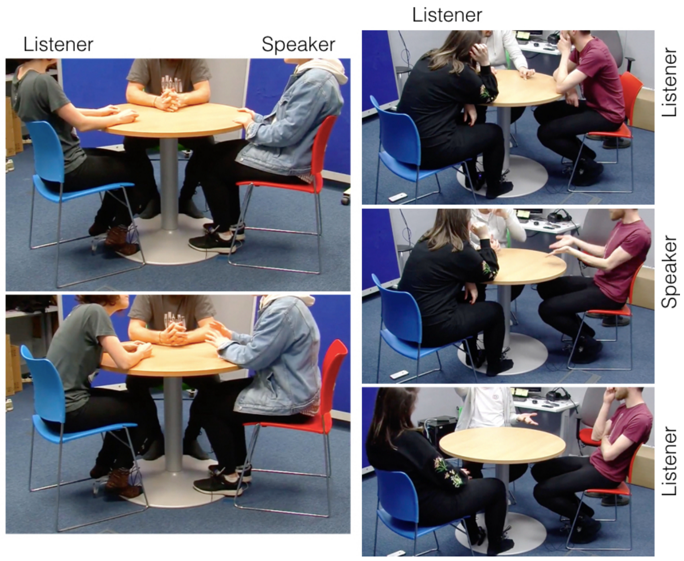


Figure 6.9: Examples of postural shifts, to be read from top to bottom: Left: Listener leans towards speaker, responds to their posture change (leaning forward). Right: Listener posture shifts on the left; postural transitions from listener to speaker and back, on the right.

with speech, while 42.4% are assigned to 'active listener' behaviours, divided into laughter(28.8%), nods(6.5%), and backchannels(7.1%).

In some cases, shifts in postures seem to predict these behaviours, too, similar to the patterns of preparatory movement for talk. From the preliminary observations and the small data set here, the movement patterns for backchannels were most similar to the ones for talk. This seems plausible if considering backchannels as a subset, or subcategory of speech. During nodding, the movement of both torso and legs appeared visibly more subtle and was observed to only become more embodied when close (within 5 seconds) to a speaking turn. This could be discussed as another extended preparation for speech, too. When looking at laughter, postural movement was expectedly the most marked and obvious. It is to note, that with laughter, smiling was not included.

Additionally, the observations suggest that not only during these active listener behaviours, but also for the transition from inattentive to attentive listeners, postural shifts play a role in embodying these shifts, expanding on the findings of Kendon (1972), Scheflen (1964), Gumperz (1982) and others. Posture shifts in between these identified listener and speaker behaviours make up 17.4% of the annotated, observed movements, shown in Table 6.3.

Participant	Speech	Laughter	Nods	Backchannel	Rest ('Non-Talk')
P1	16	16	2	0	2
P2	10	18	4	5	6
P3	17	3	1	3	8
P4	17	7	4	3	9
P5	14	9	1	2	7
total	74	53	12	13	32
in %	40.2	28.8	6.5	7.1	17.4
avg.	14.8	10.6	2.4	2.6	6.4

Table 6.3: Overview of all observed postural shifts for all 5 participants, and

6.5.5 Discussion

The results of this exploratory study suggest that posture shifts are a significant and rich interactional phenomenon. It is furthermore suggested that this type of nonverbal behaviour can be detected with sensors around the thighs and buttocks. Nonetheless, it is important to acknowledge that the data sets presented here are small and the observations made here can only be considered preliminary. The following themes emerging in relation to the study of posture shifts are a general discussion of what my preliminary findings may imply in the context of the wider literature on posture shifts.

Topic Changes in Speech

Kendon (1972) has discussed posture shifts in relation to changes in topics, and Bull and Connelly (1985) have also noted different postural patterns in different categories of speech (e.g. drawing back legs or raising a foot during a statement). In this work, I have not considered differences in what is being said, but have treated it like a broad, overt event. Posture shifts that were performed during speech were coded and included in the analysis, but were not further divided into more fine grained categories of nuanced speech. Therefore, I did not examine whether postural movement during a speaker turn correlates with topic changes. From observation, however, it is suggested that in some occasions, there is evidence to confirm the works of Kendon, Cassell et al. (2001), Schulman and Bickmore (2011), and others. For example, the participants of this sample set that have embodied such topics in a marked way, have moved both their torso and lower body significantly. Following this, it would be interesting to explore whether different markedness of posture shifts correlate with different conversational events not only in individual cases, but in a general conversational structure.

Individual Variation

The most obvious point about the data presented here is the large levels of individual variation. Individual participants showed patterns of movement that seemed distinct to them, and may be a starting point towards an approach to identify individuals through postural movement. Nonetheless, the analysis suggests that there are still commonalities in the patterns of posture change that may generalise across indivduals.

Familiarity and Synchrony

The idea that interactants move in different ways depending on how familiar they are with each other comes from Wiemann and Knapp (Wiemann and Knapp, 1975), and suggests more subtle movement when participants know each other. This aligns with the works of Kendon (1990b), discussing spatial organisation as a signifier for interpersonal relationships. This pehenomenon was noted in individual cases and have not gathered enough evidence to support Wiemann and Knapp's suggestion in full, but have observed that the number of gross body movements decreased after the first 5 minutes into the conversation. After that, movements became more subtle. In this context, it is to note that the participants grouped together, were in different personal relationships: some knew each other briefly (e.g. same workplace), some were not familiar with each other at all.

Bouncing, Swinging and Fidgeting

In consideration of individual variation, there were some nuances postural movements I observed that were more or less distinct in different participants. Rhythmic, continuous events were leg bouncing and back- and forwards swinging with the torso. These events occurred alongside other, previously mentioned behaviours that present more specified social signals and are to find for each participant: nodding and laughter. In some cases, they also appeared to correlate with affective states. One participant, for example, bounced their leg in supposedly uncomfortable moments. Another participant, when listening and not giving any other cues to speakers, continuously moved his torso back and forth, lightly swinging. Others have performed smaller movements like fidgeting more frequently than gross postural shifts.

Handedness and 'Footedness'?

One additional suggestion emerging from this study is that the pressure sensors of the left leg appear to be more discriminative of posture shifts than the right leg. This might have two reasons: the variation of the sensor performance, considering self made sensors as difficult to calibrate; or a potential correlation with handedness. There are some indications that people gesture differently with their dominant hand - this might influence the pressure distribution of legs, too. If, for example, one leg would prove more dominant and relevant to detect a range of postural movements, would it be possible to collect data from that half of the body only to achieve similar results and explore the same research questions? To elaborate on these ideas, more information about the participants is required, that was not asked for in the studies.

6.5.6 Summary

The findings of this exploratory study are summarised as the following key points:

- Preparatory (pre-speech) posture shifts happen within a 2 seconds window before the start of an utterance, so immediately before the onset of speech.
- Post-speech shifts are performed with a delay from speaking turn (after a few seconds pause after the end of a turn).
- In total, more posture shifts were associated with listener behaviours than within speech.
- Additionally, some findings already mentioned in Chapter 5 were confirmed in this study, especially in regard to a large individual variation, the relevance of buttocks (compare feature importance and factor analysis), and a slight asymmetry in pressure distribution for the relevant features.

6.6 Exploration Two: Peak Detection

6.6.1 Data Subset Two

A second subset for a more detailed analysis going beyond posture shifts consists of 10 participants, 7 female and 3 male. This set of participants includes the 5 selected above for their good performance in individual models for different classifications analysed in the previous section, and additional 5 that were selected based on similarly good performance from a ranking of all participants.

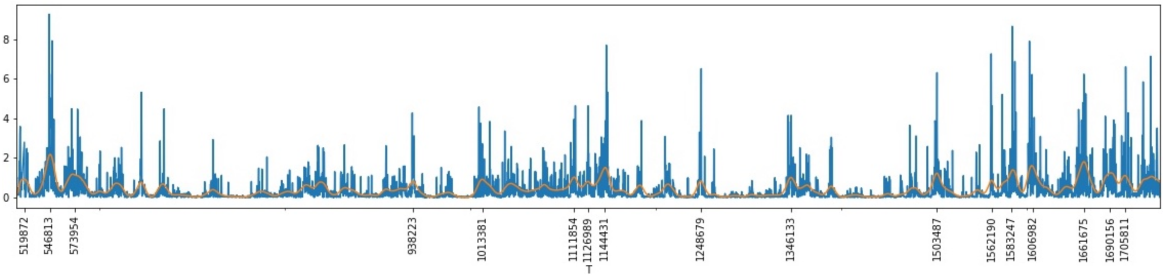


Figure 6.10: Sensor data reduced to one dimension: Shown in blue is the normalised sensor data, and in comparison in orange the filtered data. The ticks on the time axis (x axis) mark the most significant peaks.

6.6.2 Data Driven Analysis Approach

Peak Detection

Instead of starting with labelling the data for posture shifts observed in videos, now the reverse, a data driven approach is taken. The sensor data is visualised and inspected for large changes in pressure, described as local peaks in sensor readings, without predetermined conversational context. I define such peak as the highest local amplitude. The aim here is to detect data structures potentially ignored from previous analysis, based on the most significant shifts in pressure distribution across the 200 sensors of the sensor matrix. This approach therefore does not take observable (visible) posture shifts as the starting point for investigation, but discusses a larger range of conversational verbal and nonverbal behaviours based on these data structures.

To do so, first the dimension of the sensors is reduced to create one linear representation (one dimension) of the data, as can be seen in Figure 6.10. The normalised pressure readings of each instance and sensor is compared to its previous[1], and the difference between each element is calculated. In other words: two instances of each sensor are compared, and the sum of all 200 sensors is created. The absolute value of this sum forms the entry for this instance, reducing the readings of all sensors to one reading. An example of one participant's data of this computation is the blue graph in Figure 6.10. The Figure shows a range of small and large peaks in the data, that is now dissected. Here, I look at the largest, local changes of pressure by applying a filter on the data first to reduce the magnitude of the peaks - see the orange, smoothed graph in the same Figure. A second order low pass *Butterworth* filter is used with a cutoff frequency of 0.06Hz. This means that peaks within a determined time frame of around 16 seconds are detected. Additionally, to coarsen the grain of these local peaks further, I only consider the peaks for further analysis, that are one standard deviation above the mean.

The final set of filtered peaks was then assigned the timestamps of the video data (after synchronising the sensor and video data as done before), so that the large shifts in pressure could be synchronised with the corresponding videos and annotated for an extended set of social behaviour and movement. Figure 6.11 visualises this processing step with the examples of speech and listening annotations of one participant.

[1]in terms of the spreadsheet format the data is put in with each row presenting a new reading or instance, and each column being assigned to one of the 200 sensors.

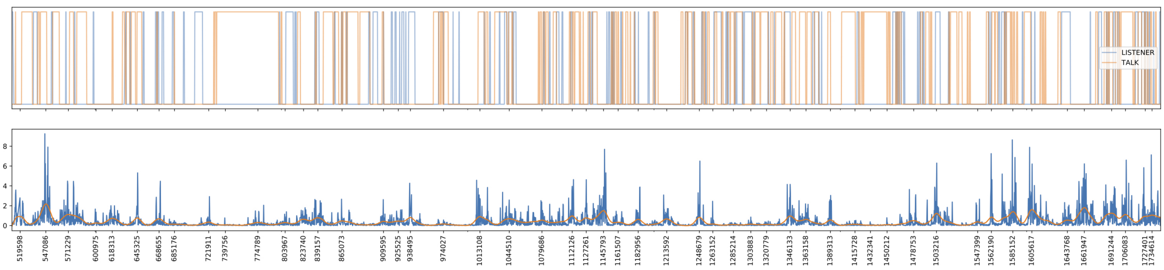


Figure 6.11: Alignment of detected peaks in pressure data (bottom) and corresponding annotations of ’talk’ and ’listener’ (top).

Further Ethnographic Observations

The data subset that is analysed here comes from ten participants, whose sensor data was processed and filtered to detect local peaks of pressure change with the method described above. Applying the low pass filter and selecting only the local maxima one standard deviation above the mean yielded between 11 and 28 peaks per participant, with a total of 187 peaks across all ten participants.

These peaks were time aligned with the video data, so that the social context to the detected major changes in pressure recordings could be examined. This also served as a base for the extended annotation scheme introduced above. In the event of a detected peak, the corresponding video clip was extracted including 10 seconds before and after the peak. This seemingly large time window was selected to be able to analyse the peaks appropriately in a conversational context and annotate for the correct social and bodily cues. This process happened in two steps: first, conducting multiple data sessions in which the videos were observed, the “peak clips” selected, discussed and analysed and in which the annotation scheme was established. Secondly, the videos displaying the detected peaks were annotated while in parallel inspecting the sensor data visualisation. This direct comparison of video and sensor data was useful to eradicate any errors, and to examine potential clusters or patterns of types of peaks.

Considering the large set of signals considered here, it is worth remembering that the sensing surface this information is extracted from stems from the lower body alone. So, given that it is trousers used to detect not only leg movement here, but a variety of upper and lower body signals, as well as conversational behaviours, the observations address questions on what happens - bodily and socially - when our body goes through such significant shift in pressure distribution in seated conversation; what the expectations towards the movements are this analysis exposes, whether they will be obvious to an observer or reveal something that is generally concealed.

Statistical Analysis

After the identified peaks of pressure data are annotated and categorised following the coding scheme of Table 6.1, an ANOVA is performed, a non-parametric Friedmans two-way analysis of variance by ranks to explore differences or co-occurrences across the additionally identified behaviour types and movements. With this additional analysis, the observations annotated could be examined for correlations.

Annotations	Labels				
Behaviour	Speech	Pre-Speech	Post-Speech	Floor Holder	
	55	26	27	66	
	Laughter	Nod	Backch.	1st Addr.	2nd Addr.
	42	15	28	75	55
Movement Type	Posture Shift	Fidgeting			
	97	64			
Axis	Sidewards	Forth/Back	Up/Down		
	33	100	32		
Visibility	Concealed	Revealed			
	53	134			
Intention	intentional	incidental			
		26			
Body Parts	Torso	Buttocks	Legs	Arms	Head
	133	68	79	86	17

Table 6.4: Overview of labels assigned to the 187 peaks for 10 different participants, grouped into 6 categories with a total of 23 labels.

6.6.3 Observational Findings

The video clips showcasing 187 peaks are analysed following the 23 annotations describing six different categories. In the previous section presenting results of a preliminary analysis focusing on posture shifts, these movements are now presented from a data driven perspective of detected peaks. An overview of the different annotations reported here, and their definition, can be seen in Table 6.1. The following observations are presented according to the grouping of the coding scheme.

It should be noted that the reported observations and statistics do not derive from discrete annotating. Detected peaks had between 3 and 11 labels, for which e.g. behavioural cues and body movement was both coded and general co-occurrences between annotation categories were allowed. This resulted in a total of 1311 annotations for the 187 peaks. An overview of these annotations is shown in Table 6.4.

Behaviours

Of all detected peaks, only 30% are assigned to speakers. The rest is listeners' movement, divided into primary and secondary addressees. 75 times (40%) when a major change in pressure is detected, the participant is classified as the primary addressee. The remaining 30% comes from secondary addressees (55 annotations). Amongst these possible conversational states in a three-way interaction, first addressees seem to display most overt bodily movement. But also the previously discussed pre-speech and post-speech movements are included in the listener categories.It appears, that in the 2 seconds time window immediately before and after speech, major bodily movement is rare (26 annotations for pre-, 27 for post-speech, both equivalent of around 14%).

Dissecting the other behavioural cues further, I divide the state of listeners into more detailed listener responses: backchannels, laughter and nods. Amongst them, laughter shows expectedly the most peaks and corresponding marked movements - yet only forming less than a quarter (22,5%) of all movement peaks. Backchannelling and nodding occur similarly rarely as preparatory movement. Nods yield the fewest peaks, which was expected.

Lastly, the observations on participants representing the centre of attention in the conversation, here described as floor holders, link 35,3% of peaks to this state. This is slightly more than speakers, and slightly less than first addressees, confirming previous observations and the definition of this category.

Body Parts

The majority of peaks measured by the trousers is assigned to torso movement - 71,1%. Bearing in mind that the annotations for different body parts can overlap in the annotation scheme, or in other words, are not coded binary to each other, the leg movement responsible for pressure changes accounts for 41,7% of all peaks, and buttocks for 36,4%. Together, this makes up slightly more than torso movement, implying that major changes and shifts in pressure application when seated are caused by both, the upper and lower body movements equally. A summary of the annotations for the different body parts including the results for head and arm movement can be seen in Table 6.5.

Body Parts	Torso	Legs	Buttocks	Arms	Head
annotations of 187 peaks	133	79	68	86	17
annotations in %	71,12	41,71	36,36	45,99	9,09

Table 6.5: Summary showing which body parts have been associated with major changes in pressure (detected peaks). The annotations for these categories are not binary coded and can therefore overlap.

Movement Type

When examining significant shifts in pressure distribution across a large sensing surface, we could expect to see a marked posture shift. Here, I add fidgeting to such nonverbal signals movement, that I distinguish from posture shifts. Both describe overt bodily changes and adjustments of at least half the body.In the analysis here, more than half of the major peaks in pressure changes are assigned to posture shifts (51,87%, equals 97 detected peaks), and 34,22% (64 annotations) are associated with fidgeting movement. Such postural movement can further be described through its movement axes, which I annotated separately, too.

Movement Axis

The majority of axis related movement is a forwards and backwards movement (alongside the Sagittal plane). 53,48% (or 100 events) of all annotated peaks is related to XZ-axis movement, while both, up and downwards and sidewards movement alongside the Coronal plane makes up 17% each. These are torso movements and are annotated independent of other social behaviours or bodily events, so can co-occur with, for example laughter, which would often be associated with a back and forwards leaning shift in posture, but also other behavioural cues, such as signalling attention through leaning forward, or signalling the end of a turn by leaning backwards.

Visibility

With these results of body shifts and back and forwards movement, as well as torso movement presenting the majority of the analysed data peaks, it is not surprising that most of these movements are visible to the other interactants, and revealed rather than concealed. In fact, only 53 of the 187 events of significant pressure changes are categorised as concealed movement.

Intention of Movement

Lastly, I determine whether the movement surrounding the detected peak in the sensor data is performed intentionally or incidentally. As stated when introducing the annotation scheme, however, I have found that only around 14% of the movement seen in the data peaks would be described as incidental, including actions like correcting one's posture, movement occurring while unintentionally coughing, or scratching. This means, that the majority of movement that is performed during interaction is in fact interactionally relevant and contributes to the conversation.

6.6.4 Results: Nonparametric Analysis

In addition to, and to confirm some of my observational findings, a statistical analysis was carried out. To analyse this relatively small data set with many annotation variables as well as large individual variation, non-parametric statistical tests based on comparison of ranks across conditions were used and run in SPSS v.24. I report the results of a Friedmans two-way analysis of variance by ranks for analysing behaviour types. First, I focus on correlations between the different roles within a three-way conversation, before I examine the type and direction of movement more closely.

Participant Role

The counts of peaks that were summed and compared here are from speaker, primary addressee and secondary addressee. This was to investigate, whether speakers move more (show more peaks) than listeners. The results of the Friedmans Related Samples Two-Way Analysis show that there is no overall difference ($N = 10$, $FriedmansStatistic = 3.00$, $p = 0.223$ with $df = 2$ Degree of Freedom, and with Alpha $= \alpha = 0.05$). No evidence is found that large movements are specially associated with dialogue role and, in particular no evidence is provided that they are specially associated with speaking. Furthermore, there is no suggestion that primary recipients shift posture less than secondary recipients (there is evidence though that, e.g. primary recipients tend to suppress hand movements, which suggests posture shifts may have an independent function).

We can now break down the participant roles a little more by looking at the relative contribution of arm and leg movements to the detected local peaks of movement. Within-subjects comparison of the count of peoples arm movements in each participant role test, whether peoples movement peaks are associated with the hands and arms more common when they are speakers than primary or secondary addressees ($N = 10$, $FriedmansStatistic = 7.70$, $p = 0.021$). Pairwise comparisons for these roles yielded the following results (all with $N = 10$ and Alpha $= \alpha = 0.05$): Secondary vs. Primary Addressee: $TestStatistic = 2.12$, $p = 0.034$; Secondary Addressee vs. Speaker: $TestStatistic = 2.24$, $p = 0.025$; and Primary Addressee vs. Speaker: $TestStatistic = 0.91$, $p = 0.911$. This suggests that the speaker and primary addressee are equally likely to have movement peaks associated with arm movements, while secondary addressees have reliably fewer peaks associated with arm movements. The same question can be applied to leg movement. However, here, the Friedman Statistic ($= 0.39$) of the Related Samples Two-Way Analysis shows no reliable difference ($p = 0.823$). In summary, we can say that peaks driven by hand movements are more likely to occur in speakers than in recipients, while for peaks driven by leg movement, no such conclusion and clear distinction can be made.

Movement Axes

The same tests were carried out to examine the correlation of different movement axes along the Sagittal (front-back movement) and the Coronal plane (sidewards movement), as well as up and downwards movement along the Y axis. The counts of shifts on each axis were summed for each participants and a within-subjects comparison using Friedmans Related Samples Two-Way Analysis of Variance by Ranks. Here I investigate, whether one of the axis movements is more frequent than others in major changes of pressure (peaks). Overall, the difference in the use of the three axes suggests that large movements are normally oriented with respect to the O-space (Kendon, 1990a), the overlapping transactional space between participants ($N = 10$, $FriedmansStatistic = 9.89$, $p = 0.007$ with Alpha $\alpha = 0.05$). When comparing the axes pairwise with each other, the overall preponderance of front-back (Sagittal) movement becomes clear. However, it is worth noting that for one participant, up-down movements were more frequent than sagittal movements. The results of these pairwise comparisons are: Up-down vs. Sides: ($N = 10$, $TestStatistic = 0.1$, $p = 0.823$) ; Up-down vs. Front-Back ($N = 10$, $TestStatistic = 1.25$, $p = 0.005$) ; and Sides vs. Front-Back ($N = 10$, $TestStatistic = 1.15$, $p = 0.010$).

Next, I investigate whether the peaks of movement can be linked to preparation to speech. Here, the comparison of counts of peak movements 2 seconds before and 2 seconds after speaking (pre- and post-speech) for each participant were tested by applying another non-parametric test: Related Samples Wilcoxon Signed Rank Test. No reliable difference was found ($N = 10$, $TestStatistic = 23.0$, $p = 0.95$ with Alpha $\alpha = 0.05$), which suggests that the major changes in pressure distribution are not especially associated with preparatory movement for speech. This is consistent with the finding above that they are also not associated with participant role (speaker, primary or secondary addressee).

6.6.5 Discussion

Speaker and Listener Peaks

Scheflen (1964); Hadar et al. (1984); Condon and Ogston (1966) and others have linked posture shifts mostly to speech utterances, to emphasise, prepare or contrast verbal content. Listener movements, in comparison, have not been studied to the same amount of detail. The peak detection here, however shows that the most overt movement comes from primary addressees, and only around a third of major movement shifts is associated to speakers. No clear evidence was found that preparatory movement to speech is performed as a large posture shift, either. These results of the nonparametric analysis confirm the observational findings. Why do listeners move so significantly more than speakers? Does that indicate that attention is being embodied most obviously? Do addressed participants in a conversation feel as if they have to showcase attention level? Or does being addressed unconsciously bring more tension and quite literally, pressure changes with it? The findings show that it may be worth investigating these movements further, exploring posture shifts in relation to social behaviour and affective states from a listener's perspective.

The peaks analysed here, however, do not only cover large scale posture shifts, but also smaller movements that within the chosen rolling window have yielded as local major peaks. This raises the question how visible overt movements are to observers and interaction partners. For example, some of the detected peaks are associated to laughter rather than explicit posture shifts, and just under a third of peaks stems from secondary addressees, who are given least attention by the other interactants in a constellation of three-way conversations.

Independent of participant role, laughter was expected to yield the most overt peaks of postural movement, but has shown to form only 22,5% of the major peaks. This may be because the laughter recorded here is not always very overt or as embodied as we may imagine. A possible future study could look into different types of laughter (e.g. social vs Duchenne laughter, fake vs. genuine laughter) to explore how different movements correlate with it.

In this work, I have focused on comparing only a few annotated behaviours and movement types that were observed during the recorded conversations. With the extended annotation scheme presented here, further potential correlations can be explored, that may yield unexpected nonverbal behavioural patterns contributing to social interaction.

Upper and Lower Body Peaks

The observational finding that most peaks of movement derive from the torso can be seen as a confirmation with the finding of the nonparametric analysis that the principle axis of movement is found towards and away from the O-space, along the Sagittal plane. The reason for this could be biomechanical constraints on ease of movement, speculating that the seating arrangement used in the studies affords back and forwards movement better than sidewards movement or rotation. Another explanation could be the sensitivity to the O-space and shared gesture space as the 'centre of the conversation and therefore centre of movements. Furthermore, this could be linked with the embodiment of laughter, often moving along this axis.

Dividing the body halfs into upper and lower body movements has further shown that speakers and primary addressees have more marked arm movements than secondary addressees, while no such distinction could was found for leg movements.

6.6.6 Summary

In summary, the results of both analyses indicate, that the sensors in trousers are able to pick up overt postural changes in the upper body, too. And vice versa, that marked movement in the upper body seemingly oscillates down to the lower body. The ability of trousers to pick up movement from the upper body, and that even through small scale movement, one body half measures movement of the other, can lead to new research questions. For example, whether a head nod can be monitored by sensors in the buttocks, or similarly, whether a head shake also makes the buttocks shake. In regards to the trousers as a sensing surface capable of detecting these interactional correlations, we can ask, how listeners' trousers look like, or how trousers need to be designed to comfort certain speaker postures, allow for specific axis movement more than for other, or afford laughter better, engaging their wearer in a directed fashion.

These preliminary explorations can form the foundation of further research into postural shifts in conversation, which would require to collect a larger data set to validate and expand on the findings reported here.

The summarised findings deriving from the observations and nonparametric analysis presented here are listed in the following key points:

- Speakers do not move more overtly than listeners. More posture shifts were labelled as primary addressees than as speakers.
- The annotated posture shifts do not necessarily correlate with the largest shifts in pressure distribution across the trousers. Local pressure peaks have been observed to present small

scale movement, too.

- Both, the upper body (torso) and the lower body (buttocks and legs) cause posture and pressure shifts. These findings indicate, that the sensing trousers are able to pick up upper body movement, too.
- Movement along the Sagittal plane is the dominant posture shift causing peaks in pressure distribution.

6.7 Conclusion

These exploratory analyses contribute to the discourse on the meaning of posture shifts and other marked bodily movement and their role in conversation. In the first part of the analysis, it was shown that it is possible to identify different types of posture shifts related to and surrounding speech utterances. I have further expanded on these findings, evaluating different types and occurrences of movement against their conversational context, examining correlations between behaviours and movement axes. Although posture shifts have traditionally been associated with turn markers or cues for emphasising verbal content, this work indicates that these salient movements are interactional signals in their own rights, and used by both, speakers and listeners.

The two preliminary analyses presented here combine ethnographic studies and statistical methods that support each other's findings. They serve as explorations to test the potential and limitations of the sensing trousers as a "socially aware" piece of smart clothing and give us an idea of future application areas, too. Finding the appropriate analysis methods is as important as providing a well designed, reliable sensing system. With this chapter, I close the series of studies investigating conversational cues and will proceed with reflecting on the engineering aspects of the prototype used for these studies, assessing it for their performance as a wearable soft computing system design.

Chapter 7

Design Investigations

Overview

When developing wearable textile sensing systems, there are many design variables that can be explored that lead to different solutions for final products. In the chapters 3 and 4, I introduced designs for sensing chairs and trousers, custom made for the purpose of capturing nonverbal behaviour in seated social encounters. All parameters of these prototypes were developed in consideration of this particular use case and have served as first iterations of prototypes for a concept proof. This chapter leaves space to discuss design and engineering related topics of the textile sensors that were developed in the scope of this research. I revisit the designs and suggest refinements in regards to sensor and manufacturing techniques. The principles of these improvements are then carried further into the development and presentation of a new iteration of the sensing trousers, whose mechanical features are tested in a preliminary user study.

Further, I reflect on the potential of smart clothing as a sensing modality in social interaction, for behavioural studies, and conclude with thoughts on the impact of the engineering details of garment construction, like the importance of pattern cutting, as well as on the role of specific items of clothing in a cultural context.

The new iteration of the sensing trousers presented here can also be found in the conference proceedings: *Skach, S., & Stewart, R. (2019). One Leg at a Time: Towards Optimised Design Engineering of Textile Sensors in Trousers. In Adjunct Proceedings of the 2019 ACM International Joint Conference on Pervasive and Ubiquitous Computing and International Symposium on Wearable Computers (UbiComp/ISWC '19 Adjunct).*

7.1 Introduction

Custom made textile sensors encounter design and manufacturing challenges that differ from conventional printed circuit board based sensors. The field of e-textiles commonly deploys such sensors on the human body, overcoming these challenges is crucial for reliable sensor performance and usability. This means working towards wearability, comfort, robustness, and ubiquitousness for a user-centred design approach is important, as well as achieving sensor reliability to capture natural human movement, that is often subtle, unpredictable and shows large individual variation. These parameters for the design of textile sensors is relevant given the prognosis of the predicted growth of the sector of smart clothing (Ju and Lee, 2020; Fernández-Caramés and Fraga-Lamas, 2018). The investigations carried out in Chapters 5 and 6 explore the performance of the developed trousers in the context of unstaged, spontaneous interaction, examining conversational cues and interactional bodily movement. The participants in these studies moved in a non-choreographed or instructed fashion. Here, robustness, comfort and other design engineering aspects of the presented trouser design are evaluated as a step of an iterative design process for optimised sensing trousers and textile sensors embedded in smart clothing. Based on these findings, I introduce a second prototype that integrates these improvements, and that is evaluated against these factors in the form of a single user pilot study.

Before closing this exploratory chapter on design investigations, the importance of tailoring, or pattern cutting in the design process and engineering of wearable, soft sensing systems, as well as the aspect of fashion design in the same process and its impact on human behaviour are discussed. This is presented as a continuous design process following the developments of smart sensing trousers, proposing ideas for further design iterations.

7.2 Even Smarter Trousers: Towards Optimised Design Engineering for Embedded Textile Sensors

7.2.1 Introduction

What makes a good, wearable textile sensor for an article of "smart clothing" from an engineering perspective? In the field of wearable technology, pushing forward the state of the art for electronic textiles is often shown through self-made sensors and Open Source libraries (Perner-Wilson and Buechley, 2010; Stewart, 2019; Satomi and Perner-Wilson, 2007).

More conventional products using printed circuit boards bear the risk of being intrusive when collecting data. Knitted or woven fabrics consist of a material we are very familiar with that augments our everyday environment, and which follows our movements more organically. As such they are particularly relevant to the wider field of ubiquitous and unobtrusive computing. A common surface to integrate textile sensors is naturally the human body itself, in the form of utilising clothing.

Handcrafted sensor designs can be evaluated against technical requirements like any other sensor system, but they are likely to have more sensor-to-sensor variability than sensors that can be purchased "off the shelf". There are several challenges that come with making your own textile sensors. One is the connection between flexible and rigid components which occurs when linking fabric sensors with batteries, microcontrollers or other electronics that textiles cannot yet replace (Buechley and Perner-Wilson, 2012; Buechley and Eisenberg, 2009). This is an obstacle to the wider task of creating soft, wearable technology that is as physically robust as more rigid counterparts.

There is a large corpus of work assessing the performance, durability and washability (Molla et al., 2018; Berglund et al., 2014) of textile sensing systems. These considerations add to the more general questions of how the sensors perform in regards to continuously reliable data collection, or linearity of sensor behaviour (Acar et al., 2019). Depending on the intended application of a design, different test methodologies are followed. Usually, they can be divided into two approaches: testing a textile sensor's performance with a machine or with users. A systematic investigation of self-made sensors often happens on machines specifically built for these purposes (Stewart and Skach, 2017; Liang et al., 2019a; Atalay et al., 2013), and can extensively test the sensors' behaviour over time and other material related characteristics, like piezo-resistance for stretch or pressure sensors. Other experiments address this aspect and further explore textile sensors in more natural settings, such as directly on the human body during a specific task (Pizarro et al., 2018). These aspects are all crucial in the process of designing and manufacturing a good sensor, and it is important for these components not to be overlooked for the assessment of a wearable, textile sensor capturing bodily data: interactive settings in which body movement is not created in isolation, but within a more natural context.

7.2.2 Mechanical Evaluation of the Sensing Trousers

A Brief Recap

The design of the sensing trousers, referred to here as prototype 1, has been sufficiently introduced in Chapter 4. Therefore, I summarise only the details of the manufacturing process relevant for the mechanical and design engineering evaluation:

- The pattern of the trousers is constructed so there is no side seam, but only a seam along the inside of the leg (an inseam). This was done to allow a smooth transition from sensor connections from the front to the back leg.
- Each layer of the matrix forms a separate sheet of fabric to allow for easier debugging and to conceal all conductive material from the skin. The trousers consist of a total of 4 layers: 3 matrix layers (1 for rows, 1 for columns, 1 for resistive fabric sheet) connected to the trousers' shell through the crotch and inseam.
- Hard-soft connections of the matrix are embroidered, fabric stripes are connected to the circuit board through insulated ribbon wire. All wiring runs along the inside of the leg, concealed with a 5cm wide tubular fabric panel, 20 connected wires per leg.

The assessment of the mechanical performance of the trousers considered here stems from the second user study that was reported in Chapter 5, where a total of 42 participants wore the trousers over a period of 20 minutes each, engaged in a conversation. The details of the data collection and study setting are found in Chapter 5.

Findings from Examining the Hardware Design

Exposing the trousers to this quantity and type of use allows to examine their mechanical performance in addition to their sensor performance explored in previous chapters. From this available data set, here the data of 26 participants is used to evaluate the hardware design (the remaining were discarded for this part due to software related issues).

number of ripped wires	0	1	2	3 or more
participants	4	12	5	5

Table 7.1: Overview of number of wires pulled out of sensor embroidery during first user study.

In particular, the robustness of the hard-soft connections is reviewed, as this presented the most vulnerable element in the design. Amongst the 26 participants, up to 4 wires were pulled out from the embroidered connection to the pressure matrix in a single wearing. With each wire connecting to a column or row of the matrix, 10 sensors were lost. An inspection of the sensor data showed 4 participants with no faulty data, 12 with only one wire pulled, and 5 participants with either 2,

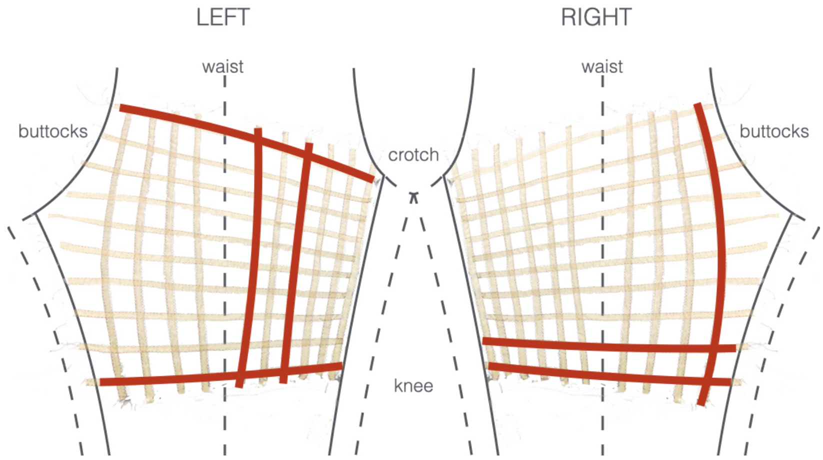


Figure 7.1: Summary of all commonly broken sensors across all participants are highlighted in red. These sensors were removed for analysis.

3 or 4 disconnected wires. A summary of the commonness of the occurrence of pulled or ripped wires is given in Table 7.1, showing 4 participants with no faulty data, 12 with only one wire pulled, and 5 participants with either 2, 3 or 4 wires disconnecting sensors. Now looking at the position of these disconnected sensors in Figure 7.1, it could be seen that for both, the connections to rows and columns, wires connected closest to the knee and crotch were most prone to breaking., also coinciding with the areas where body creases or garment folds are most common (knee bent and hip bent).

In all cases where only one wire was pulled off a column - connected around the knee, it was the wire furthest away to the inside right leg where all wires were gathered, highlighted in Figure 7.1. The Figure also illustrates the two columns for which the embroidered wire broke on the front leg, which can be found closely to the outer side of the left leg - in a position where a fold can appear when seated. It was similar to the rows of the matrix, where all embroidered connections were at the front inner leg. Here, the wire positions around the body folds or joints were most likely to be disconnected - that is the first row around the knee on both legs, the second row on the right leg as well as the top (last) row on the left leg. An overview of these sensor rows and columns is shown in Figure 7.1. Comparing the front and back leg, more wires were ripped on the front leg, and only one wire was disconnected on the back.

Therefore, while it was considered best for the design of the sensor matrix to have no side seam and only have a narrow panel along the inner leg to house the wiring, the tests showed that this position may increase the risk of the wires alongside the inner leg to be pulled off their embroidery.

Additionally, participants were informally asked about comfort after a recording session had finished and the trousers were taken off again. The list of questions is attached in Appendix E. Some participants reported feelings of restriction when putting the trousers on and moving their legs freely (e.g. leg crossing), being conscious about the wiring. Some also mentioned that while the trousers were comfortable to wear, the additional layers on the top thigh would make them warm after a while.

7.2.3 An Improved Iteration of Sensing Trousers

The findings derived from the interactions with the participants were used to design a new iteration of the sensing trousers. With a new design, I refer to the previous trousers as "prototype 1" and to the

Figure 7.2: Comparison of different wiring solutions and hard-soft connections. Prototype 1 (top) depicts the thin ribbon wires embroidered onto the conductive fabric. Prototype 2 shows fabric wires made of conductive yarn and sewn onto the conductive stripes, insulated with braided paracord.

new ones as "prototype 2" from now on. With suggestions for another iteration of the trouser design, the above identified difficulties in the user study with the trousers' hardware can be addressed. In this section, the development of design related improvements towards a more robust, durable, and comfortable pair of pressure sensing trousers is presented. Significant changes of this new iteration of the trousers concern the connections between textile and electronic components, as well as the overall wearing comfort. In summary, to improve this, the pattern construction was slightly adapted through adding a side seam, the fabric layers were reduced, and instead of metal wires, conductive threads were embedded.

Hard-Soft Connections: Textile Wires

Instead of using ribbon wire, highly conductive copper yarn[1] was insulated with textile paracord, following the techniques introduced by Posch and Fitzpatrick (2018), where conventional tailoring and garment manufacturing equipment is utilised to provide suitable e-textile tools as an alternative to their rigid and less flexible counterparts. These textile wires are hand made by twisting 3-4 strands of highly conductive yarn together to form the core of the wire, and pulling them through a tube like braided paracord that forms the insulation layer. The paracord used is 3mm in diameter and consists of synthetic yarn. To prevent its ends from fraying, they were singed. Using yarn instead of wire has the advantage of being more soft, flexible, and being sewable with a conventional (domestic) sewing machine (the stitches can be seen in Fig.7.3b), while the wires used before had to be hand stitched onto the conductive fabric. A comparison of how the different wire designs are attached to fabric is depicted in Figure 7.2.

In prototype 1, a total of 20 wires all run along the inner leg down to the ankle. Although the string of wires were attached together through a connection in the insulation layer to keep the wires untangled and running in parallel down the leg to the circuit board, see Figure 7.2, the more

[1] Purchased from Karl Grimm, `http://www.karl-grimm.com/`

rigid materiality added to bulkiness of the design. In prototype 2, the less bulky fabric wires were distributed to run alongside the inner and outer side of the leg - ten on each side. The 'wires' for the matrix columns ran along the inside leg, with the rows of the matrix running along the outer side seam, see Figure 7.2 and 7.3b. This design has the advantage that the fabric wires are independent from each other, unlike the ribbon wires that were connected in a band, and don't pull each other out under strain. Therefore, the new wires can withstand more strain overall. A disadvantage of the separated wires, however, is the risk of getting tangled.

(a) Construction steps for tailoring Prototype 2: reducing layers of fabric by attaching conductive 'rows' and 'columns' of the sensor matrix onto the resistive fabric layer and the shell of the trousers directly; and adapting the pattern construction with added side seam. Construction steps from left to right.

(b) Left and Centre: Close-ups of textile wires consisting of 4-strand copper yarn insulated with singed paracord. These new wires are machine sewn onto the conductive fabric strips forming the rows and columns of the matrix. Right: new placement of groups of wires running alongside both, the inner and outer leg for a balanced distribution.

Figure 7.3: Details of the second trouser prototype with improved wiring, and fabric layering design, as well as adapted pattern construction.

Reducing Layers

Following comments from the first study's participants regarding the noticed thickness of the trousers around the sensing area, which made the trousers warmer, the aim for a new iteration was to reduce the layering of the fabrics. Although it is useful to be able to separate the matrix' layers for early stage prototyping, for a future, higher tier prototype, this is not needed. The first prototype features 4 layers, arranged as shown in Figure 7.4 (left). In that design, in the case of any material related flaw, the rows, columns and resistive layer could easily be replaced. This was useful since it was the first prototype produced. After sufficient testing, however, such precautions become redundant and a higher fidelity design can be developed, reducing the amount of layers needed by merging them were possible and saving material. Now, the layers for the second prototype were reduced by half, see Fig.7.4 (right). This was achieved by using thermal bonding to attach the conductive fabric stripes forming the outer layers of the sensor matrix directly onto the other fabric layers. The thermal bonding used here is appropriate to maintain flexibility of the fabrics. Figure 7.3 shows the steps of manufacturing the new prototype and of creating the overall thinner trousers, showing the reduced layering. The columns of the sensor matrix were bonded onto the non-conductive fabric of the outer layer or shell of the trousers. This can be done with a domestic iron as well as with a heat press. For additional robustness, the stripes attached to the non-conductive fabric layer can also be sewn on with a sewing machine, or affixed by hand as done in Figure 7.3a (yellow lines). The rows of the matrix were bonded onto the resistive layer that forms the lining of the new trouser design and determines the size of the sensing area (from upper buttocks to knee), see Figure 7.3a. A schematic illustration of both prototypes' layering system is shown in Figure 7.4.

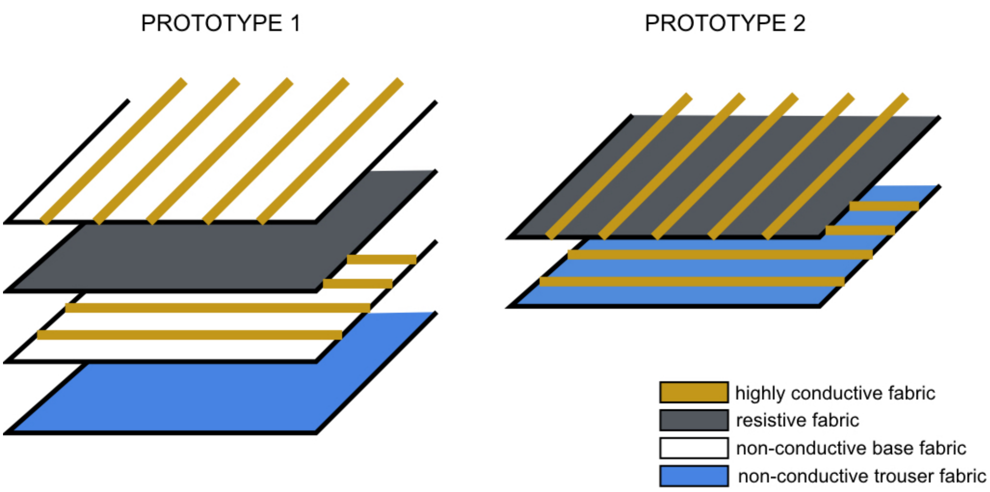


Figure 7.4: Comparison of the layering of the two trouser prototypes. Left: Prototype 1 with a total of 4 layers that can be separated. Right: new Prototype 2 with a reduced 2 layer matrix design.

Modified Pattern Construction

In relation to the distribution of wires, the pattern of the trousers was adapted for the new prototype, too. Having found that with some wires regularly being disconnected at the same position (see Figure 7.1, one approach to address this issue was to distribute the wires so not all are gathered in one area and the connection from wires farther away from the circuit board are not put under increased strain. At the same time, the trouser seams acted as a useful concealing element for wires in prototype 1,

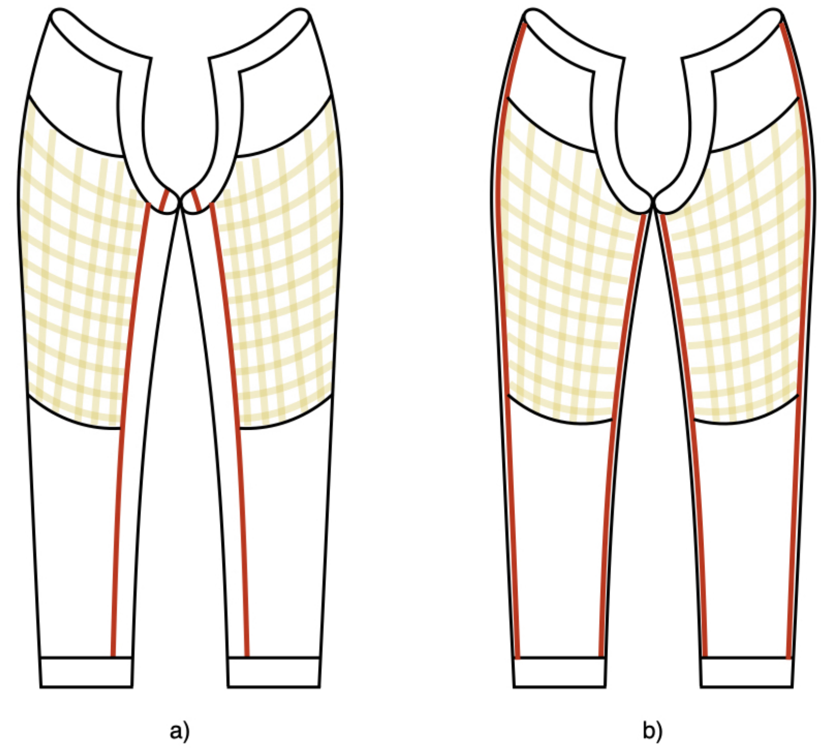


Figure 7.5: Comparison of the pattern construction of a) the previous design (prototype 1) and b) the new iteration (prototype 2)

which is a desirable design goal for prototype 2, too.

To address this, the approach for the new iteration of the trousers was to introduce a side seam in addition to the inseam, as seen in Figure 7.5, where the seams for both prototypes are highlighted in red. Using the seam allowance on the inside of the trousers as a support to loosely stitch the fabric wires to, having two seams now allowed to distribute wires to both the inseam and the side seam, creating less bulk. In this solution, all wires sewn onto the rows of the matrix could be stitched along the side seam (see Fig.7.3b), and all wires of the matrix' columns could be run along the inseam.

With the observations that the side of the upper legs is not touched or in touch with other surfaces regularly in sitting postures, the area around the position of the side seam does not feature sensors. Only the rows of the sensors and the resistive fabric layer are connecting the front and back leg along the side seam. Therefore, the risk of this (in an 'unused' area on the trousers) added seam of disrupting the performance of a sensor or sensor group is minimal. Another 'side effect' of adding a side seam is the possibility to tailor a more refined silhouette of trousers. While this is not as relevant for jersey knit trousers as these, it is a construction detail relevant to style and fit of trousers in general. The result of this adapted pattern design is illustrated in Figure 7.5, and shown as a fabric cut in Figure 7.3a.

7.2.4 Piloting Prototype 2

The second prototype was evaluated in a small single user pilot study. While in the previous user studies tested the trouser design as well as the sensor performance, this pilot study reported here does not collect sensor data or does not seek to detect postural cues. The sensor matrix was not connected to a microcontroller. Instead, this last study focuses on mechanical aspects only, drawing attention to the elements shown to be risk and error prone in the previous prototype. In particular, the carried out examinations can be summarised into the following two aspects:

- The wearing comfort in regard to change in wiring (material and distribution) and reduced layering;
- The robustness of hard-soft connection with machine sewn wires and their feasibility in regard to their fabrication technique (use of bonding tape).

Participants

10 participants, 8 female and 2 male, tested the new trousers. All participants, with the exception of 1 male, took part in the evaluation involving multiparty seated conversations and were therefore familiar with the concept of sensing trousers, having worn prototype 1. They were between 25 and 36 years. Other than in the previous study, however, participants here were not offered assistance when putting on and off the new prototype - this was to examine potential usability issues at an early stage.

Procedure

The goal of this pilot study was to imitate the type of postural movements and strain applied during the study of the previous trouser design, so the two prototypes can be compared. Participants put on the trousers by themselves and were asked to perform a series of sitting postures that were identified and selected as common in the previous data set. This sequence of postures was performed twice by each participant. To further imitate the amount of uses of the first prototype, participants were asked to take the new trousers off and put them on again after each cycle. The postures performed were (in the same order for each participant):

- putting trousers on;
- standing position;
- sitting down ('home position' as in Chapter 4);
- crossing legs in both directions (one after the other: first left over right; then right over left leg);
- stretching lower legs and feet;
- stretching out lower legs;
- leaning forward with elbows resting on thighs;
- rubbing thighs with hands;
- hands resting on knees;
- fidgeting, which was described as a combination of bouncing legs, rubbing legs with hands or tucking hands between or under legs;
- taking trousers off.

After each session, but not between the cycles, the trousers were inspected for any errors or broken elements, with special attention given to the performance of the new yarn-based wiring regarding connection technique and distribution of wires. Participants were also asked to comment on the comfort and wearability of the trousers. Since these tests were intended as an informal study, the sessions were not recorded and only notes were taken by the instructor and in some cases an assistant volunteer.

7.2.5 Preliminary Findings

The outcome of the pilot study evaluating the new trousers is divided into the received participant feedback on wearing comfort regarding the design changes undertaken, as well as the mechanical performance of the fabric based wiring.

Participant Feedback

All (10) participants mentioned improved comfort and reduced thickness of the second prototype. Participants pointed out an overall 'softer' touch of the new trousers compared to the first prototype and said they felt "lighter to wear". It was also reported that movement could be performed more comfortably and without concerns of damaging the sensors in the trousers or wires. The one participant who had not taken part in the previous study said although he had been told of the presence of a sensor matrix, this was not something they could feel when wearing the trousers. It was pointed out that through the thin outer fabric, the trousers felt more like sport leggings than the previous prototype. In summary, the received feedback was positive. The notes taken during participant interactions are attached to Appendix E (for each participant).

Robustness of Wires

While the participant feedback is mostly concerned with the implications of the reduced layering of fabrics in the trousers and change of wiring materials, a quantitative inspection of the adapted design and its mechanical properties looked promising as well. None of the yarn-based wire connections were ripped from the pressure matrices. Although not as much worn as the first prototype, there were no signs of the machine sewn connection being loosened, being torn or put under mechanical pressure from the 10 trials with 2 cycles each. This is, as expected, a significant improvement compared to the first prototype, and is summarised in Table 7.2, along other compared features with the first prototype.

7.2.6 Comparing the Two Prototypes

After this preliminary testing of the new iteration of the trousers, the performance of the two prototypes can now be compared following the above specified parameters of the wearing comfort that includes assessing all design elements relating to the new layering and fabrication techniques; and the mechanical robustness of the new wiring technique and distribution.

Hard vs. Soft Wiring

When comparing the number of wires damaged, ripped or pulled in detail, prototype 2 clearly outperforms the first pair of trousers, with no damage being done to the wire connections whatsoever, as the comparison Table 7.2 shows. Sewing conductive thread instead of embroidering wires adds to

	Prototype 1	Prototype 2
Number of layers	4	2
Fabric layer connection	machine sewn	thermal bonding
Connection type	wire	thread
Connection method	hand embroidered	machine sewn
Connection path	all on inseam	distributed (inseam + side seam)
Side seam	no	yes
Number of trials	26	10
Number of ripped 'wires'	22	0
Number of seams on leg	2	2

Table 7.2: Overview of Prototypes 1 and 2 of the sensing trousers, comparing different aspects of design engineering.

the trousers' robustness and also allows for more flexibility in the placement of the yarn-based 'wires' (see Figure 7.3b). This means they can be attached in areas that are subject to higher pressure, strain or abrasion without increasing the risk of breaking or being damaged. In comparison, the embroidered wires of the first prototype easily pulled out of the hand embroidered stitches, or the thin, untwisted core of the wire broke when being pulled too much. The conductive yarn, in contrast, is twisted and difficult to break without tools. While both techniques - embroidering and machine sewing have been used in the field (Satomi and Perner-Wilson, 2007), the latter has become more popular in recent year not least through the availability of conductive yarn thin and flexible enough to be used with conventional domestic sewing machines[2].

One disadvantage the hand-made fabric wires pose in comparison to the ribbon wires is the labour-intensive threading of the conductive thread through the hollowed paracords. It requires more steps than the already insulated wires. With advancing textile technologies, however, insulated textile yarns are being developed as well, as already sampled in Briot et al. (2020), for example.

Fabrication Feasibility

This evaluation focuses on the mechanical aspects of the design engineering, which is only one factor to consider for smart garments. The next step would be to assess the performance of the textile sensor matrix in the new iteration of trousers. In addition to the feasibility of the time-consuming making of textile wires, a factor to examine here is, whether the technique of thermal bonding when connecting the different layers of conductive and non-conductive fabric compromises the measurement capability by restricting the natural properties of the stretch fabrics. A risk this design presents in comparison to the first prototype is the over-stretching of the bonding material, for example through use over time, resulting in detachment of conductive fabric stripes from their base fabric. For prototype 1, all conductive stripes were machine stitched onto their base fabric, listed amongst other compared factors in Table 7.2. Although the bonding process is more time-efficient, it is less robust and needs to be further tested for this design. In other designs, e.g. in Liang et al. (2019a) and Freire et al. (2018), this technique has provided promising results for textile stretch sensors made from similar conductive fabrics.

[2]Manufactured and purchasable by *Statex*, *Karl Grimm*, *Plug & Wear*, or *Barts & Francis*, amongst others

Suggestions for Further Improvement

For further prototypes that could not be implemented int the scope of this research, additional technical improvements for embedding sensors in a textile surface are proposed and sampled, building on the findings from the evaluation of the first two, as well as on other recent developments in the field of smart textiles, for example suggested by Satomi and Perner-Wilson (2007); Posch and Fitzpatrick (2018); Freire et al. (2018, 2017). As securely routing the electrical connections with less bulk improves wearability and robustness of the trousers, for a higher tier prototype, the electrical 'wires' can be integrated directly to the fabric of the garment to further improve performance. Instead of manually insulating them with paracord and creating separate strands of wires that risk being tangled, these elements of a circuitry can be integrated into the creation of a textile surface, using methods like multi-layered weaving or knitting. Figure 7.6 shows a developed swatch of a knitted fabric seamlessly creating insulating tubes (rows) which can hold conductive yarn. By knitting tubular elements into the fabric, the copper yarn is insulated without further post-manufacturing processes, as used in the earlier prototypes described here. This suggestion of a third iteration has not been developed into a fully functioning garment, but serves as a proof of concept for a technique that could enable even more concealed technologies. The technique used here is an adaptation of a knit structure named *Milano Rib* (see e.g. Greinke et al. (2021b).

Figure 7.6: Exploration of integrated wiring system in a knitted surface.

Depending on the use case and pattern design, an integrated circuit with all its components could be produced with this technique, varying in trouser design, style, pattern construction and also matrix design. Industrial, computerised knitting machines are able to manufacture these on large scale, and with metal yarns like the ones used here, or also other textile techniques like polymerized dying (Honnet et al., 2020). Adding developments of integrating sensors and other electronic components into the fibre core through nanotechnology (Dias, 2015) could help to eradicate all rigid components of a circuit. Additionally, pattern construction can be used to integrate these components in desired ways, appropriate for different use cases (Kettley et al., 2010).

Possibilities and requirements of component integration are, lastly, determined by the way a piece of clothing is used and how it is worn. For example, sensing systems integrated in a tailored suit don't have the same washability requirements, care instructions or abrasion appearances as when integrated in casual wear stretch trousers, and could therefore pose an advantage when using fragile electronics (Stewart, 2016; Greinke et al., 2021a). Additionally, 'second layer' or outerwear garments are often lined, which offers another possibility to conceal electronic components altogether, other than single layered shirts (e.g. Harms et al. (2008)). This may also be an advantage if dry cleaning is required, so that chemicals don't come in direct contact with sensors and circuitry.

7.3 Exploratory Design Adaptations

The concept of embedding soft, flexible sensors in casual wear trousers like the ones I propose prompts ideas on further use cases of such garments, and also on variations of the design of the trousers and of the sensor matrix. To conclude the report and documentation of the various studies of the smart trousers, I present a selection of additional designs and engineering solutions that aim to expand the spectrum of how textile sensors in trousers can be envisioned in the future. The aspects these additional design explorations concentrate on are the textile sensor matrix, it's arrangement and integration to trousers; the extension of sensor types; and the consideration of trousers as a product of our everyday wardrobe. The following suggestions are based on the experience of the handling and reception of the trousers throughout the conducted experiments, and are motivated by other current developments in smart textiles and clothing as well as the gaps deriving from them.

7.3.1 Matrices Refined

Matrices have been a desirable sensor network design in the field of e-textiles for some years as a potentially high resolution sensing surface, and have been envisioned in various designs, materials and techniques, for example by Perner-Wilson and Satomi (2019a,b), Donneaud and Strohmeier (2017b,a), Romano (2019), Roh et al. (2011), Zhou et al. (2014), and Strohmeier et al. (2019).

Customised Mapping

The sensor matrix presented in prototype 1 and 2 is designed so that the data points are relatively equally distributed across the upper legs, with a slightly higher concentration (60 data points) on the front thigh than on the back thigh (40 data points). This was determined by observations of touch interactions and variations of sitting postures around the leg area. However, also other distributions and placements of these elements of a matrix are possible. Figure 7.7a and 7.7c present preliminary ideas of such variations utilising the rows and columns of the matrix as design aspects in different ways contributing to the aesthetics of a sensing garment. All elements of such sensor networks, the different fabrics, yarns, the components of the sensors - rows, columns, can be revealed or concealed - can be placed on the top side of the garment or in the lining. Combinations and layering of the revealed and hidden rows and columns can be used to create check patterns, as suggested in sketches in Figure 7.7c, as well as pinstripe like patterns, often found in formal wear, e.g. tailored suits. The exact areas of the body that are to be measured can be defined on a fine grained basis, as noted in previous chapters with a factor analysis (Chapter 6) or yielding sensor importance with a Random Forest classifier (Chapter 5). The exact number of sensors needed can be increased or decreased in my matrix design, following the results of the previous analyses. Detecting speakers may require a different number of sensors than detecting listeners or laughter. Additionally, the buttocks were found to be important sensing areas, but have used fewer sensors in this area compared to the front top thigh. Sensing postural shifts may be possible with sensors on the backside of trousers alone. Vice versa, if only hand touch on the legs were to be captured, sensors on the top inner leg may be sufficient.

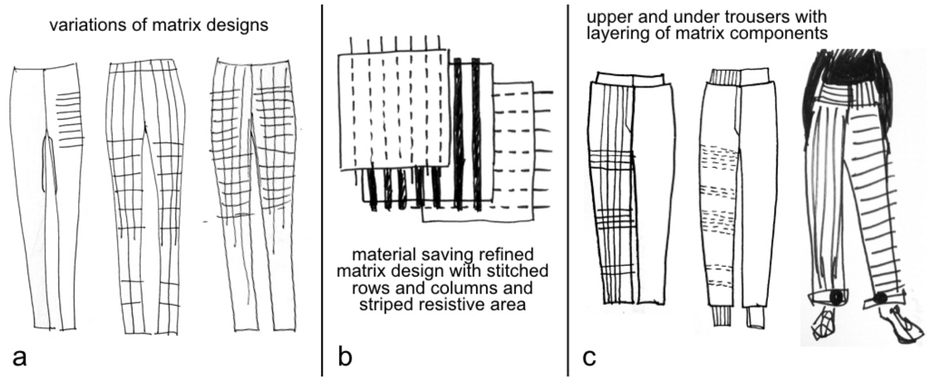


Figure 7.7: Different matrix designs: a) matrices adapted to concentrate around certain leg areas on the same fit and pattern of the trousers as prototypes 1 & 2 ; b) alternative design to a matrix design, resulting in smaller sensor points and reduced use of conductive materials; c) variations of different trouser designs and styles incorporating sensor matrices.

Material Integration

The number of materials used to manufacture the trousers can be varied, too. While in this work's smart trousers, 1cm wide stripes of highly conductive fabric were cut to create $1cm^2$ sensors, the size of the data points can be decreased to the size of a stitch, as indicated in Figure 7.7b and shown by Perner-Wilson and Satomi (2019c). This also leads to a more efficient and cost-effective use of the resistive layer between the conductive rows and columns, that can be cut as stripes (see also Figure 7.7b and run alongside one direction of the conductive stripes. Moreover, the trousers cover the entire upper leg, having mapped sensors from the front inner thigh to the backside, and from the knees to the crotch and upper buttocks area. With more efficient use of materials, the rows and columns of the sensor matrix can be reduced, or the material that is not forming a data point of the matrix, can be cut to be reduced in width. Optimisations in regards to material waste are important for working towards a final product able to be scaled for manufacturing.

7.3.2 Beyond Matrices

An overall accompanying question when designing sensor networks in trousers has been, what designs other than matrices could be useful and interesting to explore. While matrices have great advantages in providing a high resolution of data points, some applications and scenarios may not require this level of complexity and would allow for a reduced, simplified, as well as more specifically located sensor design. Moreover, additional modalities of sensing may be required for different applications. We have already seen trousers with integrated EMG sensors (Liu et al., 2019) or ECG sensors to measure muscle activity, for example in running exercises (Ribas Manero et al., 2016). Also haptic feedback is possible to deploy in trousers, for example in yoga pants[3]. But even focusing on the piezoresistive sensing networks used in my prototypes, there is a large variety in leg signals that can be picked up and accompanying placements of pressure and stretch sensors, as indicated in Figure 7.8. Instead of matrices, patches, stripes or larger pattern areas can be used as sensors, capturing specific touch or pressure points or leg movement. The sketches in Figure 7.8a-f show examples of combinations of such, and are all based on observations of leg movement and touch interactions in recorded conversations. The pattern cutting and fit of the trousers depicted there resembles the

[3]https://www.wearablex.com

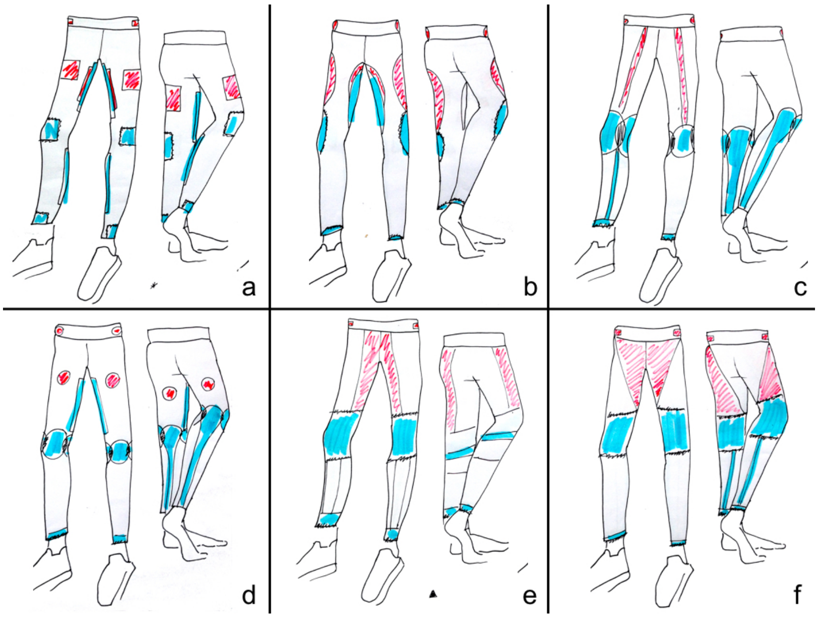


Figure 7.8: A variation of sensor placements in 'smart' trousers as constructed for prototype 1 and 2. The areas coloured in red represent pressure sensor suggestions, while the blue coloured areas suggest stretch sensing.

prototypes introduced earlier, but is also based on research of sportswear, e.g. leggings used for running.

Varying in sensor placement, size and type can further specify the exact postures we can capture with different designs. Stretch sensors on knee patches, such as drafted in Figure 7.8 a and d can focus on measuring leg postures like stretching out the lower legs and feet or tucking them back, behind a chair. The red sensing areas on the upper thigh in the same Figure present pressure sensors that can detect hand touch, either on a specific point (Figure 7.8a or along and within a determined area (Figure 7.8 c and e). These additional sensing suggestions could also be combined with the existing prototype of a pressure sensor matrix, providing additional information and cross-validation amongst sensors with the same principle of piezoresistive sensing.

7.3.3 Alternative Design Pathways

While optimisation methods affect the components of sensor matrices, matrix designs are not limiting on the overall design of the trousers they are to be embedded in. In this work, stretch trousers close to the body have been introduced, imagining legging like trouser styles or also stretch, skinny jeans. A question that emerges is, how close to the skin do sensing trousers really have to be in order to still capture bodily actions accurately. Or, in other words, can body movement also be captured with loose garments, such as jogging or sweat pants? Some works have explored this question with unbuttoned jackets (Bello et al., 2021), or other upper body garments (Harms et al., 2008).

The objective to move towards more 'casual' fitting trousers is also based in potential use cases for such. Unbiased, unstaged, and natural social and postural behaviour is mostly performed in familiar and private environments, for example at home. The nature of interactions that we encounter at home are different to the ones in professional or more formal environments (Vinciarelli et al., 2008). This affects the expressiveness, and potentially other parameters of nonverbal behaviour that we aim to capture, too. But even when not in social exchange with other humans, sensing body movement

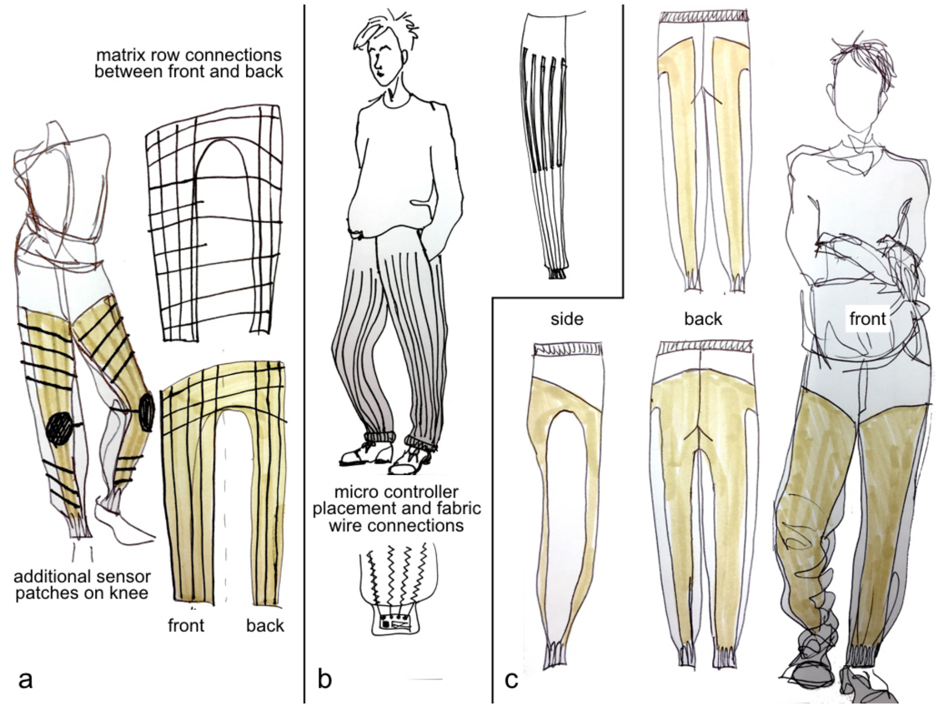


Figure 7.9: Variations of sensing trouser styles, sensor matrices suggested on more casual, loose fitted jogging pants rather than legging slim fit designs.

at home can be relevant. Simple activity recognition or presence sensing in smart environments could be done less intrusively with clothing people naturally wear in those environments, than deploying gadget like devices on or off the body. Also in the fast evolving research in gaming technologies, 'smart casual pants' could be used for control and for device interaction mechanisms, and also sensing postures of gamers for both ergonomic and game-play purposes.

Figure 7.9 sketches out initial design variations of loosely cut trousers with consideration for integrated sensor matrices and additional sensor patches on the knee (as in Figure 7.9a, unintrusive placements of the microcontroller and other electronic hardware (Figure 7.9b, and suggestions for pattern constructions of sensing areas to spare the side parts but include the lower legs in Figure 7.9c. These sketches also address the concern raised above in regards of material efficiency, sparing out the side area of the legs and focusing on the precise sensing areas only.

7.4 Design for Human Interaction: Clothes and Their Role in Wearable Technology

7.4.1 On the Role of Pattern Cutting

The Relationship Between (Smart) Textiles and Pattern Cutting

The evolution of smart textiles can be compared to the evolution of textiles in general, their history, cultural and societal status and technological enhancement. This includes the processing of textiles, too. Since their early developments, textiles have played an important role in the history of human culture. Methods to manufacture fabric surfaces, from spinning yarn to mechanical knitting techniques, have been developed not long after the first stone tools were invented and before the time when agriculture began to spread. This dates back approximately 30,000 years (Hirst, 2019). These felted, knitted and woven surfaces had a functional purpose, as well as a cultural and social meaning. Felts, probably the first textiles in history, were traditionally given less worth than weaves, which, in comparison, require a thread to be spun prior to creating the textile surface. The latter were treated (and traded) as valuable goods. So it was not until the 11^{th} Century that the idea of cutting into such preciously woven fabric became popular (Koch-Mertens, 2000a). Only then, the craft (or art, as it is often referred to, see e.g. Sprenger (2009)) of pattern cutting and tailoring was developed, but quickly led to extravagant, close to the body fashions, peaking with tights-like trousers or very narrow sleeves in the Medieval ages (in the Gothic period). This new possibility to emphasise body shapes instead of draping around them had great impact on the fashions of the time, even so that at one point, finely cut, detachable sleeves were given to women by their admirers the same way in more recent centuries flowers have been (Koch-Mertens, 2000a).

Jumping ca. 600 years from the Middle Ages into the future marks the era when textiles, and in particular clothing was first considered as an appropriate material for on-body sensing. The discovery of this material property and the possible textile manipulation (e.g. through conductive coating) fits well into an age in which ubiquitous computing has been established and seems to become an increasing fundamental part of an ambient, 'smart' environment (compare e.g. Kettley et al. (2010)). In recent years, we have seen many examples of how electronic textiles can be integrated in clothing for various applications (Kettley, 2016; Seymour, 2019). For example, being able to capture postures with upper body garments (Dunne et al., 2006a) has proven useful for patient monitoring, rehabilitation (Wang et al., 2015), affect detection, but also in playful approaches for performance art (Greinke et al., 2021a) or as interfaces for virtual games. Developments of smart garments can already be found in commercially available products, too (Poupyrev et al., 2016; Gonçalves et al., 2018; Fernández-Caramés and Fraga-Lamas, 2018). Examples like Poupyrev et al. (2016), Greinke et al. (2021a), Griffin and Dunne (2016), Capineri (2014), and the documented works of Perner-Wilson and Buechley (2010), Buechley and Perner-Wilson (2012), Kettley et al. (2010), or Posch and Fitzpatrick (2018), demonstrate how each step of the manufacturing process of a garment, including the 2D layout of fabric patterns, can be taken into account when aiming to integrate electronic components in a "tailor-friendly" way.

Trouser Patterns

In this work, too, pattern cutting and the consideration of textile specific knowledge forms a substantial part in the development of a well performing wearable sensing system, as indicated in previous chapters. This concerns the optimisation of circuitry embedding, as well as sensor placements and the construction of the garment in consideration of the material choices, as different materials accommodate different fits and patterns, indicating also different use cases. This applies to different garment types, as well, since constructing a lower body garment is different from constructing an upper body garment. Leg movement is distinct from torso movement and therefore has different requirements on robustness of sensors, and therefore also to material properties. It encounters higher pressure, strain or abrasion in certain areas, through, for example, sitting down or walking. The development of smart garments for lower body data collection must account for these aspects.

In the trousers, the tube like panels on the inner leg conceal the wiring - something that would not have been possible if not taken into account from an early manufacturing stage. This contrasts also work of textile sensing in which circuitry and sensors are deployed on a finished garment that is purchased and hand-manipulated in a post-production stage to house all electronics, see e.g. Ribas Manero et al. (2016); Liu et al. (2019), or Cha et al. (2018). The integration of the sensor matrix followed the seam lines and pattern pieces of the trousers, so that precise locating of sensors can be achieved. Another advantage of tailor made wearable sensors is the saving of materials. Knowing where and how conductive materials are required on the body and considering that when manufacturing the garment works towards zero (or as little as possible) waste of material, see Figure 7.7b.

In conclusion, acknowledging and integrating pattern cutting into the design of e-textiles can lead to new applications, processes and optimised designs that are more cost efficient and more pleasant to wear. This is important for a more comprehensively interdisciplinary approach, combining the 'art' of bespoke tailoring, couture, and textile craftsmanship (Kettley et al., 2010). In some areas of the fashion industry, we find 'fully fashioned' knits and weaves (pattern blocks knitted in shape) for the purpose of zero-waste material, as well as custom fit sized pieces. Bringing these disciplines and technological developments, that are traditionally related, together could transform the practices of smart clothing research. Finally, the historical and cultural resemblance between the appearance of textiles and pattern cutting, with the process of pattern making emerging much later than its textile relative is worth discussing and investigating further, both in its traditional use and for human centred computing. With the idea that the material itself affects the manufacturing process, and also determines its applications (Schmelzer-Ziringer, 2015), future tasks will include bringing these aspects together for a cohesive, and optimised, functioning product.

7.4.2 Dressing Up for Conversation: Clothing in Interaction

Physical Allowances of Clothing

The fit and form of garments also influences the social interactions we have, not least through the practices of pattern cutting. While clothing itself is commonly described as an extension of our cultural and bodily self, and serves as a tool of expression, it also determines our interactions on a more fundamental level. The clothes we wear, their materials, textile structures, shapes and construction techniques allow or restrict certain body movement, make the performance of postures easier or harder. Clothing in this sense not only limits and enables movement, but also directs it (Ekman and Friesen, 1969a; Harrigan and Rosenthal, 1983; Koch-Mertens, 2000a,b; Candy, 2005, 2007).

Throughout history, the fashions of dressing have contributed to these regulations and were sometimes intentionally imposed to their wearers. Fashion has always been carefully designed for specific actions or inactions, e.g. 'unpractical', decorative domestic dresses of 19th Century compared to the first corset free dresses in the early 20$^{\text{th}}$ Century (Koch-Mertens, 2000b). Worn in different scenarios, these two examples very clearly and obviously predetermined the types of movement a wearer's body can carry out in them. It goes as far as not being able to sit down or lift a leg when wearing specific pieces of garments. In some cases, this not only affects the wearer, but also interaction partners, for example being restricted in how close they are able to stand next to each other by the sheer circumference of a 18$^{\text{th}}$ Century French court dress, or also by spikey leather jackets and razor blades in lapels established in the 1980s Punk subculture (Schmelzer-Ziringer, 2015). In general, the use of different materials and clothing styles is acknowledged to "demand a different gait, posture and demeanour" (Sweetman, 2001; Candy, 2005), and followingly can affect our nonverbal behaviour (Candy, 2007).

Clothing Eliciting Social Cues

We can therefore ask, how much our style of dressing affects the bodily social signals we transmit. How much does our clothing physically interact with our body? What consequences does 21st Century (western) clothing has on our 'freedom of movement' and ability to interact with others? For example, do skinny jeans enable different social cues than loosely cut suit trousers? Are the legging-like smart trousers of this research indirectly determining the participants' postural behaviours in a different manner than jogging pants or non-elastic wool or denim trousers would? These questions are less about the communicative component of clothing as a tool for personal and cultural expression, and more about the physical formations and coordination our wardrobe allows our body to perform, in regards to materials as well as pattern construction. Questions that emerge from the conducted research and that this chapter only addresses briefly and in part speculatively. Nevertheless, questions in relation to what these explorations imply for future design pathways.

Arguably, the rigid components used in the prototypes of the sensing trousers can cause irritation and hesitation in how movements are performed. Although trying to minimise such disruption by placing the circuit board and the battery in the hem of the trousers, participants' consciousness of their presence might have influenced their postural behaviour. For the second prototype, no rigid components were attached when tested, so conclusions can only be drawn from the participants' reactions in the study reported in Chapter 5. Assuming that it is possible to overcome issues of bulky, rigid electronic components by new technologies and smaller devices like batteries or microcontrollers, there are still elements of the trousers that can be influential in determining wearers' movements. The fit close to the body is not comfortable for all people, and making body parts visible to interaction partners can cause discomfort, as also indicated by Harrigan and Rosenthal (1983). This issue can be addressed by suggesting second layer trousers, or exploring looser fits for trousers incorporating the sensor layer of fabrics as it done for upper body garments (Bello et al., 2021; Hardy et al., 2019; Harms et al., 2008).

Fashion and Conversation Analysis

Despite the ability of clothing to partake in communication in this sense, forming another layer of nonverbal signals, it is only marginally mentioned in social and behavioural studies, or in conversation analysis. Ekman and Friesen (1969a), for example, acknowledge the restriction of movement induced by clothing, and repeatedly talk of the mini skirt as an item that prevents marked movements, but also mention socks and how they omit the view on toes and therefore the restriction on executing bodily social cues with toes. Also Harrigan and Rosenthal (1983) describe what observees of dyadic interactions are wearing for the purpose of discussing visibility of certain body parts. They add, however, the function of clothing not only to communicate and express, but also to conceal information, e.g. on gender. This argument of the visibility of body parts and the following instrumentalisation of them is linked to the mini skirt as well. While it restricts marked leg postures, such as spreading legs, it makes the legs visible differently from trousers (Ekman and Friesen, 1969a). The skirt being a posture imposing piece of clothing is also acknowledged by Noroozi et al. (2021), who discuss these observations in relation to gender specific postures and movements.

Interestingly, Ekman and Friesen (1969a) wrote about the mini skirt when it was at its peak of fashion popularity in Europe (Koch-Mertens, 2000b), which raises yet another question as to how the cycles and seasons of fashion, as well as the manifestation of certain fashion appearances like the mini skirt influence social interaction through the lens of postural movement and nonverbal behaviour.

The prevalence and familiarity of the clothes we wear should provide us with the same possibilities in regards to interaction. For example, does fashion styles affect overall variation of physical behaviour and hence non-verbal cues when silhouettes, materials and fits determine, afford or restrict the range of possibilities for such? These perspectives are rarely taken in literature on fashion theory, e.g. Barthes (1983, 2006) or Simmel (2003), even though a lot of attention is given to the social role clothing, and fashion, plays and what power it has in our cultural and societal environment. They discuss, amongst other aspects, what role fashion has in our society and how it sits between us as an interface for communication. Therefore, understanding human interaction better would be beneficial for the design of clothing, and enabling clothing to measure interactional behaviour would also extend the interactional functions of clothing and enable the development of new products

Open Questions

The relation of fashion, clothing and performed social behaviour sparks questions for the design processes of smart garments that go beyond the scope of this thesis. For example, how do fashion designers need to engineer and construct clothing, so that their wearers are all given equal opportunities to perform and transmit bodily cues? What items designed for which scenarios (e.g. casual wear versus formal wear) allow for and enable certain movements? In regards to the trousers designed and tested here, these concerns were taken into account to the degree that there were no differences in the design and fit of the different models each participant was wearing. All pairs of trousers showed the same properties, not distinguishing between gender related pattern constructions or size related restrictions.

7.5 Summary

This chapter serves as an exploratory approach to aspects of design engineering that have emerged through the developments and tests in previous chapters. Learning from challenges faced and errors made, the original design was reviewed and improvements are suggested and a new prototype is tested. These led to further design territories for sensing trousers that can be addressed in the future and that are touched upon here in a mostly idea-based and speculative discussion. Followingly, areas crucial to the developments of garments like pattern construction are acknowledged and concluded in an appeal for a more prominent role of such areas in the field of wearable technology.

Contributions

The contributions that derive from the design developments, and the pilot study documented in this chapter can be summarised as follows:

- A suggestion for an improved design of smart trousers was presented and tested. This proposed prototype refines the design pathways for sensing lower body garments.
- The consideration of integrating electronic components in an early design stage, a pre-production level, is different to many works in posture recognition and affective computing. Accounting for techniques of embedding circuitry leads to improved design and fit of the wearable system.
- Highlighting and acknowledging the role of pattern cutting and tailoring in smart garment design.

The discourse on design aspects started here leaves many open questions this work does not answer in the scope of this thesis, too. There are limitations to the above claims: Further tests are needed to verify the findings of this small pilot study on a larger scale. This includes tests with more participants, as well as in more natural settings than the one presented here, responding to suggested application areas and putting the trousers “into the wild”.

Chapter 8

Discussion

Chapter Overview

In this chapter, the results of the previous studies are summarised and discussed, highlighting contributions and limitations of this work. The discussed findings are divided into contributions to behavioural studies, contributions to the social sensing domain, as well as contributions to the design of smart clothing and textiles. These core themes determine the structure of the following chapter when discussing and concluding the work of this thesis.

Here, I revisit the key themes deriving from the presented work in Chapters 3 to 6, its outcomes, processes and implications, and compare similarities, overlaps, as well as differences of the findings throughout. I expand on ideas touched upon, identified limitations, and elaborate on remaining challenges, open questions and potential future implications of this interdisciplinary research.

8.1 Summary of Contributions

The key findings deriving from the developments and evaluations of the chair covers and trousers divide into contributions to behavioural studies, as well as to the field of textile sensing. In that order, these findings are summarised as follows:

- "We gather from the buttocks": Throughout the studies, the lower body, including legs and buttocks, emerged as a potentially interesting and significant body part to examine as a transmitter of social signals. The buttocks showed crucial when distinguishing speakers from listeners, as well as when picking up laughter and postural shifts. The attention this large muscle receives in this work extends the knowledge about lower body movement and social signals, that is, in comparison to our knowledge about upper body signals, yet limited.

- The above indicates as well, that sensors on the lower body are able to pick up upper body movement, and have also shown that local peaks in pressure distribution can correlate with fine grained postural shifts. The sensors in the trousers allowed an in-depth exploration of a variety of nonverbal cues, examining listener movements and postural shifts in relation to different conversational states. Part of these explorations exposed the individual differences of postural patterns.

- In addition to the many use cases textile sensors have been demonstrated as successful, this work adds the detection of speakers and listeners through textile pressure sensing. This is explored further in the thesis and more fine grained social behaviours and body movements are measured, contributing to the initially set goal to establish textiles as a suitable modality for behavioural studies and proposing textiles as a tool to analyse conversation, and more generally, to measure human interaction. In particular the use of trousers as a wearable sensing system to assess social behaviour in unstaged face to face conversation has been explored in this research for the first time.

- I presented a new design of sensing 'smart' trousers, developing existing textile pressure sensing matrices further by adapting them to trouser patterns and mapping them onto legs following patterns of touch interactions and pressure applications in sitting postures. The design engineering of the trousers promotes the role of tailoring techniques when developing smart garments and shows how existing techniques can be combined for fabrication improvements and the integration of a wearable circuitry. The consideration of textile and garment manufacturing techniques for the deployment of body worn sensors is different to many existing studies on posture recognition and in nonverbal behavioural studies.
- With the explorations into simple machine learning techniques, I furthermore contribute to the discussion of suitable data analysis methods for smart clothing and body-worn, textile sensing systems. With the classification models used here, it was possible to determine smart textiles as reliable sensors to capture body postures. Further analysis and feature engineering showed that wearable sensing in trousers achieve comparable results to static sensing systems.
- Lastly, the presented data set further adds to a sparse corpus of non-acted data sets for nonverbal behavioural studies involving full body movement, and its results show that such natural settings can yield comparable accuracies with acted data sets. The design and experimental evaluation of the chair cover contributes to a large corpus of pressure sensors in chairs to detect sitting postures by adding the discrimination of speakers and listeners, while the validation of the trouser design through the sitting posture study shows that a wearable pressure sensing network can detect a large variety of sitting postures with as good results as chairs.

The studies conducted in this research have opened new avenues for smart clothing and textiles to explore, extending the yet dominant use of smart textiles in settings where interpersonal, social relationships do not play a lead role. Vice versa, the textile sensors present an unexplored modality in behavioural studies and affective computing, able to capture details of postural movement that have been left unattended by other modalities. Altogether, this work promotes textiles as a suitable measurement for automatic detection of nonverbal signals, providing unobtrusiveness through their material and structural properties.

8.2 Embodying Interaction

8.2.1 Additional Conversational Cues

The questions around detecting nonverbal cues the lower body provides, focused on three active listener signals: backchannels, nods, and laughter. However, the variety of movements so far categorised as 'incidental listening in Chapter 5 can be split into further sub-classes like fidgeting or shoulder shrugging, which might improve classification accuracy, in particular in regards to the 3 and 5 class discrimination I reported on. Such additional movements include overt, large scale shifts as well as micro-movements that are difficult to capture with the naked eye. This suggestion is supported by the findings in Chapter 6's peak detection, showing that local peaks of pressure change does not always correlate with the most dominant conversational roles, and can, for example, be elicited by addressees rather than speakers. Classifications could also be modelled with some of the behavioural features identified in Chapter 6, analysing body movement in regards to type, direction and body part. However, these followingly smaller datasets could also create less accurate and therefore less reliable results, e.g. distorted through outliers and large individual variation.

In settings like the ones used for the studies - seated conversations with the presence of a table occluding the sight on legs and feet movement, events like leg bouncing or tip-toeing often go unnoticed, but can be tracked. It was also seen that the chairs and trousers are able to pick up movements that are mainly induced by the upper body. These appear to translate to the seating surface so that pressure sensors on the lower body can detect them, too, as the results of the classifications for laughter and nodding suggest - even if that holds true mainly for individual data sets. Also the observational peak detection findings in Chapter 6 indicate that the lower body, in particular the area around the buttocks, picks up upper body postures and behavioural cues. This suggests a pressure sensing system can be used to explore even more fine grained movements and conversational states than the ones addressed in this work. Brought to an extreme, it could provoke questions like: Can trousers detect the raising of an eyebrow? Can our clothes identify a tongue-in-cheek moment? Based on the findings in Chapter 5 and 6, additional postural dynamics and behavioural correlations could be explored. Here, the basic conversational roles and cross-participant relations were investigated: speakers and listeners, and primary addressees and listeners who are not addressed and consequently more passive. Although the nonparametric analysis in Chapter 6 yields not many significant correlations between specific behaviours and body movements, and Additionally, it seems some of the annotated movements are not intentional, audience designed signals that occur in response to the situation, some tending to occur out of sight - arguably because people are sensitive to the way they might distract speakers.

8.2.2 Talking Through Your Arse

Whether looking at interpersonal or individual cues, my finding across Chapters 3, 5, 6 evaluating the textile sensor performance in spontaneous conversation, was that the buttocks are potentially useful areas to measure social interaction from. The sensor importance analysis in Chapter 5, as well as the factor analysis in Chapter 6 draws attention to the buttocks as a sensing area for social signals that has so far been left unattended, and confirms also the findings from Chapter 3, where listeners and speakers could be distinguished from the pressure applied on the buttocks.

The buttocks contain one of the largest muscles in the body (the gluteus maximus) making pressure changes easy to detect. They provide the principle support surface for the body when seated. This makes them especially useful for pressure sensing of movements by seated participants. Moreover, buttocks as the centre of the body, the link between torso and legs, pose new research questions for the studies of nonverbal behaviours. Could it be, that this apparently very active part of and centre of our body can capture both, upper and lower body movement, presenting the surface on a seat where the social cues of the different body parts meet?

Revisiting the results of the chairs and trousers, we can see that distinctions between listeners and speakers, as well as between different active listener behaviours can be made with sensors on the buttocks as dominant sensing areas. This appears to work equally well with coarse grained sensor patches on the seat's surface and the fine grained resolution of data points of a sensor matrix in trousers. This work is the first to mention this body part as interactionally and socially relevant.[1] Drawing attention to this, from significant embodied behaviour previously excluded body part contributes to all studies examining full body posture and movement and challenges the assumption that the upper body is the most informative part for social signals.

This finding emerged as a theme across all studies and sensing design. On the chair, the right buttock appeared particularly important for the detection of speakers and backchannels, while laughter seems to be transmitted more from the centre of the body (Chapter 3). Also the analysis in Chapter 5 extracted the sensing areas on the upper buttocks as important when distinguishing between different behaviours. There, the buttocks appeared relevant for all identified behaviours and both, in the community model and for individual participants. These results are backed up with the factor analysis done in Chapter 6, that suggests the buttocks as a sensing area accounting for most of the variance when identifying posture shifts in relation to conversational states.

If simple pressure sensors on the seat surface can detect conversational states, how much else can we extract from them? What other interactionally relevant information may buttocks alone hold? For example, it remains possible that there are distinct movements of the buttock muscles that provide unique signals - e.g. clenching when anxious, however the data collected here doesn't provide any direct support for this. The work here focuses on few basic conversational states, while postural cues indicating affective states have not been studied. So, while trousers work well for detecting some behaviours, they may not work for others. For example, they may not be capable of replacing face recognition technology extracting fine grained features in the face.

8.2.3 Postural Asymmetry

Another interesting finding is the seemingly asymmetric postural behaviour in social signals. Across all studies, I have observed that sensors and sensor clusters that are of particular importance when distinguishing between conversational behaviours are not distributed equally and symmetrically around both legs and buttocks. And although buttocks on both sides of the body have been discussed as important areas to capture movement from, I found differences as to which 'bum cheek' appeared more relevant than the other for certain behaviours. For the chair covers, talking and laughing could be detected best with the sensors on the right half of the buttocks (together with the sensors underneath the thighs), while backchanneling is associated with the left body half in general. Asymmetric appearance emerged again in Chapter 6 in the factor analysis. Indications of this asymmetry could also be seen when examining the sensor importance in Chapter 5, where the sensors most relevant for discriminating the 2 - 5 class scenario were distributed unequally across the two legs. This was shown for community models, for which it could be argued that it results from a small data set of very diverse individuals. Examining individuals' feature importance for all classes[2], however, implies a slightly asymmetric behaviour for each participant, too.

What does this asymmetry mean? What can this finding tell us about embodied social behaviour? One suggestion that was briefly mentioned in Chapter 6 was the potential correlation with right- or lefthandedness. In that sense, we could further ask, whether it is possible to determine something like a 'footedness' or 'legness' that could be described as a more active behaviour, or more movement with one half of the body compared to the other. here is evidence for differences in leg dominance

[1] Only in British comedy, the importance of "gathering from the buttocks" has been expressed in relation to acting classes. See reference in Chapter 3, Fry & Laurie.

[2] See additional visualisations of those in Appendix C.

similar to hand asymmerties. Both are linked to lateralisation (Sadeghi et al., 2000). So in addition to having a dominant hand with which we gesture and act more than with the other, do we also have a dominant leg or lower body half with which we execute nonverbal cues more than with the other? It is unlikely this asymmetry is due to the seating position of participants, since they were arranged in a circle. Another, perhaps more plausible explanation for this asymmetry could be the body movement of participants primarily into a certain direction, for example leaning towards a recipient or the speaker, or performing postural mimicry with certain conversation partners. This again could be determined by the spatial arrangement people find themselves in. With further analysis, it may be possible to determine the social structure from looking at the pressure distribution of the two body halfs. For example, information about where the speaker was sitting may be extracted by looking at the pressure changes on thighs and buttocks of a listener? By knowing towards which direction an observee leans towards, what can we tell about other conversation partners? Exploring these questions would build on, and possibly expand on the work of Kendon (1970), Schegloff (1998) defining and understanding the interactional space we build between each other during social encounters. There is, however, also the possibility that this seemingly asymmetric behaviour is due to the dynamics of posture shifts as such, indicating body movement, or the individual variation that the results need to account for. The peak detection in Chapter 6 takes movement into account, while in Chapter 5 and 3, instantaneous data was examined. The asymmetric results may also be an indication of posture shifts and other postural movement that was not taken into account here.

8.3 Notes on Classification Features

8.3.1 Individual Variation

A finding that seemed to play an important part in the achieved results was the differences between individuals. This was shown in particular through the poor classification results in the "leave-one-out" scenario, excluding the data of one participant in the training set and testing it on them. However, when all participants were included in both, training and test sets, the percentage of correct classifications is reasonably high (much better than chance) for the identified behaviours. This indicates that while there seem to be large overlaps in general in the ways we embody certain conversational states, the models do not hold well when evaluating an individual against the remaining community. The details of how we perform nonverbal behaviours and movement is subject to large individual variation. The implications of individual variation have already been acknowledged in the first study, and confirms notes in related literature (Scheflen, 1973b; Ekman, 1999). Individuals develop their own behavioural patterns and establish mutual conventions with their interaction partner over the course of an encounter. This also depends on the general relationship participants maintain with each other, which can determine the movements, the space between them, and also the markedness of signals (Vinciarelli et al., 2008). This could mean that the results are limited to the specific conditions under which the conversations took place. Additional stages of data processing and analysis could look into these correlations and test, how the postural shifts we perform vary in different groupings, e.g. with more participants, or with certain relations to other participants.

In the case of the data processed here, it can be argued that one obvious parameter that might help to improve these performances is a larger data set. The sensor data evaluated here stems from 27 participants on chairs, and 20 trouser wearing people. For the explorations in Chapter 6, an even smaller subset of participants was examined. A larger group of participants to test on would impact the F-Measure results, as well as the patterns of sensor importance for both group and individual models. Similarly, more data from the same participant would provide more clarification on the here indicated unique but systematic motion signatures we exhibit in interaction.

The Implications of Feature Importance

The visualisation of the feature importance yields groups of sensors that are more significant than others to discriminate target classes, and that spark discussions as to how many sensors are needed to detect behavioural cues. Future iterations of trousers can be designed to address this aspect of further feature reduction. With a large variety of more and less important features across individuals, this may result in different densities of sensors needed to detect behaviours, depending on that individual's training data set. In the context of bespoke tailored smart clothing, this could further mean that sensor placement in addition to sensor amount can be individually determined to track body movement accurately for one person only, allowing for 'bespoke identification' applications. Trousers as well as chairs may be able to recognise their wearer or occupier by their individual movement patterns.

Aiming at a community level classification, design engineering parameters like the resolution of the recording frequency, the robustness of hard-soft connections, and additional classifiers like time sensitive approaches could minimise the large individual variations, too. Nevertheless, the data set of a wider community, or the test of an individual against a community model may not be desired. But where could these results be useful? Could a weak performance on a withheld community level and a good performance on an individual level unveil an advantage for a potential application of smart trousers? I have briefly touched on the idea of trousers identifying their wearers in Chapter 5, for which a data set of a community is not needed. If the trousers perform reliably in detecting their wearer (or a chair its occupant), they could be just as reliable in detecting a stranger.

8.3.2 Limitations on Classification Methods

The success of identifying embodied social behaviours very much depends on the parameters of the data collection. In Chapters 3 - 5, a limited amount of conversational states and behavioural cues was set out to be distinguished between. The data analysis approach used here required predetermined categories, or classes. It was only in Chapter 6 that I expanded on it and created a more fine grained annotation scheme, which derived from a data driven exploration to identify moments of big changes in pressure and examined their correlation with conversational behaviours and events.

Pathways to Unsupervised Methods

The factor analysis, as well as the sensor importance drawn from the Random Forest classifier revealed patterns of movement characteristic for different conversational behaviours, and serves a starting point for further explorations towards data driven feature engineering. The peak detection analysis highlights the potential significance of peaks in posture movements that have received relatively little attention in the literature. The peak detection showed that these movements can be overt postural changes, as well as small and sudden shifts of nonverbal behaviour. While in this thesis, the majority of data analysis relies on a supervised take on the data set, the explorations in Chapter 6 revealed it would be interesting to explore unsupervised methods further, too. Especially when having sensors so close to the body, able to pick up micromovements and brief touch points between different body parts, new patterns of postural shifts and nonverbal signals could be detected that are not previously identified or annotated for. This could be achieved with approaches of clustering, as well as a Principal Component Analysis (PCA) or Linear Discriminative Analysis(LDA), which are briefly mentioned in Chapter 5. These methods are not only useful to detect patterns beyond the predetermined classes, but also to reduce the amount of features used to detect these classes. Similar to the factor analysis, these approaches can help to understand the classification process better and also visualise potential sensor correlations.

Dynamic Features

This thesis mostly focuses on classifications based on instantaneous samples of data, and does not included time sensitive approaches. However, when examining moments of bodily movement and dynamic posture shifts, further experimentation with time series analyses may improve the performance of the models. For the peak detection, a rolling window was used to segment the sensor data and identify local major changes of pressure. There are other techniques that could be used when preparing the data for classification models, for example applying Fourier Transformations on the sensor data. This step happens in the pre-processing stage of the data analysis, providing different variations to generate a continuous view on the sensor data and accounting for changes over time, but also when classifying the processed data, different methods may offer different results. Other potential methods that account for the parameter of time more are Conditional Random Fields (CRF) or sequence analysis (LSTM).

Imbalanced Data Sets

In addition to these suggestions that may improve the results of the classifiers, the size of the data set overall, as well as the variations in size of the different subsets of data could affect the performance of the models. I have accounted for imbalanced data sets in Chapter 5 and 6 by modifying the weighting of the classifier and by using analysis approaches that account for individual variation in small data sets better. Nevertheless, larger data sets would help to clarify the findings. This could be achieved by collecting more data of more people, which may yield better results in community models as well as feature reductions for sensor groups. It could, however, be achieved by collecting more data of the same participants as well. Accounting for the individual variation discussed above, a larger data set of the same participant would provide even higher accuracies in identifying individuals and detecting more subtle changes of movements. All approaches to balance data sets, however, may also distort the proportions of natural occurrences of the annotated behaviours. In unstaged, spontaneous interaction, different behaviours create different data sizes because they occur less often. For applications investigating natural face-to-face conversation in everyday environments, the data sets created to train classification algorithms would be naturally imbalanced. For example, speaking forms a much larger data set than backchanneling simply because of the duration of the two events.

8.4 Tailoring Smart Textiles

8.4.1 Implications for Technical Refinements

Reviewing the sensor importance and factor analysis in Chapters 5 and 6, it is obvious that the high number of sensors integrated in the trousers' matrix may not be necessary for further iterations. This concerns the overall resolution of sensors, but also the placement of sensors across the thighs and buttocks. The findings show that the inner thigh, and the upper buttocks are more relevant in detecting nonverbal cues than the side of the legs. This derived from the series of observations and from inspecting the feature importance for the classified behaviours in Chapter 5: speaking, laughing, backchanneling, and nodding. It holds true for most participants and only varies in the exact sensor which yielded more or less significant in individuals. It is possible to design trousers that would embed a high resolution sensor matrix, but could activate specific sensors or sensor groups for detecting specific movements, or to track movements tailored to their wearer. For example, if we encountered a task in which we are interested to detect the posture of tucking hands between the thighs, or detecting hands resting on the lap, as done in Chapter 4, only specific sensor groups on the inner thighs or upper thighs are needed. The intended oversampling helped to identify a wide range of such postures and their relevant sensing areas that can be refined for future prototype designs. This approach of determining important sensor placements on the human body by first oversampling data for test scenarios before extracting relevant features can be adapted to other smart clothing designs, for example for the upper body, too.

The role and importance of pattern cutting was discussed as part of the process of developing wearable textile sensing systems in Chapter 7, too. Paired with the findings on sensor importance, the construction of a smart garment can take these parameters into account by moving seams to most convenient places, by utilising seam allowances and inner lining to conceal wiring, and to avoid broken connections in a fabric circuit. Moreover, pattern cutting techniques can accommodate both, seamlessly integrated sensors as well as modular forms that allow for easy detachment of components, as is often desired especially for washing purposes and the removing of rigid electronic components, or replacing batteries.

8.4.2 Open Questions for Future Smart Textiles

Considering the outstanding technical improvements and only marginally mentioned challenges for higher tier prototypes for smart garments, further questions addressed to the designers and makers of such soft systems arise. Such questions concern textile sensing on the body and in form of smart clothing, as well as questions of scalability of the individual resources and processes.

The lab environment the prototypes have been used in did not require to solve some of the common issues smart garments encounter as a product for a wider market, or in 'real world' situations. For example, I have not investigated how durable the here presented design solutions are in regards to washing the trousers and chair covers, what other powering possibilities there are to reduce the amount and size of rigid components (for example solar cells integrated in the textile surface, as in Smelik et al. (2016)), and how the connection to the microcontroller can be designed in a way that it does not pose a problem when debugging the sensing system but also when washing the fabrics.

Garments can detect acceleration, tilt, pressure, temperature and probably many other measurable elements that a human body provides when in social interaction with others. But could jumpers ever capture gaze or voice as well, or detect laughter? Where are the limits of sensing garments? And towards which areas of sensing human behaviour could garments enrich our world? These questions are not least directed at garment designers, being confronted with potential changes to their work processes when integrating sensor systems on an industrial levels. How much can aesthetics of garments vary, how flexible and unrestricted is a clothing designer if, for example, a sensor matrix was to be integrated in suit trousers? How much do the choices of textile sensor design affect the rest of the design decisions? What design elements are interchangeable and what are fixed parameters when embedding sensors? With wearable technology on the rise to be introduced in everyday products, currently often through devices deployed in sportswear for personal use, the skill set of designers is shifting, too. A new generation of fashion designers therefore may have to adapt basic skills of electronic engineering, and an engineer developing a wearable sensing system has to be aware of the possibilities textile materials offer.

8.4.3 Towards Socially Aware Smart Textiles

The general idea that interfaces like computers can be socially aware was coined by Pentland (2005), calling upon a better consideration of social context in human-device interaction, and arguing for better, ubiquitous integration of technology in dialogue with societal needs. It appears that with textiles, which are part of our social structure in a natural way, the premises for this appeal are fulfilled. In order for pieces of technology to become socially aware, however, we must accept them into our everyday environment, consent to the data acquisition that is taking place. The success or failure of a product of technology can be measured by how well it is accepted into our everyday life and actions, or how willingly we adapt to it (Candy, 2007). The unintrusive integration of digital technologies and sensing networks for a better social acceptance is desired in many research projects (Kettley, 2008). The social perception of visible or invisible technology is an important aspect to consider when testing the performance of an introduced device itself, as mentioned in Rekimoto (2001); Profita et al. (2013) and Riener and Ferscha (2008).

In regards to an appeal of unintrusively embedding technology in our environment and products of everyday life, the base fabrics used for the trousers and chairs, cotton and viscose with a small percentage of elastane, are commonly used as surface materials for these products and are a material we have already accepted into our social environment. The context in which the textile sensors are placed shows that they alter human behaviour only minimally, if at all. The participants' reactions reported in Chapter 7 for the second trouser prototype confirm that, emphasising the comfort and unintrusiveness of the design. Chapter 7 furthermore discussed aesthetics as a method to overcome issues with social acceptance. Fashion design offers solutions and could be a gateway to establish textile sensing on a broader level.

8.4.4 Speculative Clothing to Enhance Communication

Having looked at some conversational states in detail, for example distinguishing listeners from speakers, can we design trousers that encourage speaking? Or trousers that support laughter? Remembering the basic differences of these conversational states from the chair cover study in Chapter 3, which suggested listeners having a minimally more slouched posture than speakers with more pressure on buttocks and less on thighs (a posture indicating lifting of the legs and shifting the weight towards the tailbone), trousers could either exaggerate this posture or compensate it. Pattern cutting techniques can be used to construct garments so they afford certain sets of postures better than others - postures we linked with certain social behaviours. With the claim that not only behaviour elicits embodiment, but also embodiment elicits behaviour (Barsalou et al., 2003), we could explore whether our clothing can elicit postures and followingly embodied behaviours, too. For example, an upright posture has been associated with better attention levels (Bull, 2016; D'Mello et al., 2007a) compared to a slumped posture, as have been tucked in legs compared to stretched out legs (signalling boredom or disinterest (Bull, 2016)). Therefore, a question we could explore in the future, is, that if trousers allow their wearers to sit more comfortably in them having their legs tucked in, will that make them more attentive?

While the pattern construction of this work's trousers does not take these possibilities into consideration, they could serve as a prototype in the development of such garments, and further determine the correlations of postures and behavioural cues. Where so far, fabrics and their colours have been able to reveal status of wealth and religious affiliation (Koch-Mertens, 2000a), they may be able to take a role in understanding and encouraging social interaction in the future. Nonverbal cues allow for an immediate decoding of a social encounter. A brief glance is enough to identify speakers and addressees. Clothing can enhance these roles, supporting the correlating postural movements through such proposed construction procedure. The idea to communicate conversational states through clothing adds a layer to the complexity and fine granularity that clothing entails as a cultural and social instrument.

8.5 Future Directions

Speculative suggestions like the one above, as well as some discussion sections in previous chapters, form a base of potential future pathways this research can take. During the explorations on textiles as a sensing system to detect nonverbal social signals, there were many avenues to pursue along the way, created by the findings of the studies, whether that concerned the selection of behaviours and postures, the experimental interactional settings, including the type of participant group, or the design parameters of the chairs and trousers. To close with a brief outlook, some of the emerged and discussed themes are summarised below.

8.5.1 Multimodal Sensing Systems

The sensing trousers explore the possibilities of textile pressure sensing to detect touch and postural states. Using the same materials and data processing techniques, however, other sensing modalities can be captured. Stretch sensors can be used for measuring the bending of a limb, for example. Considering to take multidimensional measurements to capture additional aspects of bodily action, a combination of capacitive and piezo-resistive sensing has been explored, being able to measure approaching touch, touch as an event itself, and the pressure applied, as presented in the works of Strohmeier et al. (2018), Nachtigall (2016), and Schoonen (2013). A design combining these sensing techniques presents an example in which the same piece of fabric is able to distinguish between these events of touch - one sensor for three different measurements.

The use of appropriate sensor types also depends on the textile surface these sensors are deployed on. The use of pressure sensors has proven suitable both for interior objects as well as wearable solutions like clothing. If the data that is aimed to be collected is, for example EMG data, the base fabric surface needs to be in close contact to the skin. Measuring muscle activity, or heart rate narrows the possibilities as to where a sensor can be placed as well as in which product they can be deployed in. In projects where EMG data is used, the sensors are attached to a finished garment (Ribas Manero et al., 2016; Olugbade et al., 2019), or even on the skin directly (Liu et al., 2019) and the garment only serves to hide the sensors and wiring. In these and other examples, the garment serves as a base fabric or shell where all components of a sensing system and electrical circuit are attached at a "post-production" stage. The prototypes offer a sensing system that is fully embedded in the manufacturing stage of the garment construction, which allows for a better customisation of the sensor design and a softer overall circuitry with fewer hard-soft connections.

8.5.2 Beyond Seated Conversation

Many of the social signals that were captured with the trousers and chairs still derive from the upper body. While it can be argued that for leg postures, the study settings of seated conversations were suitable, most of the torso and head movements that were picked up with our trousers can be performed in free standing conversations as well. This sparks the question as to what textile sensing systems may be suitable when it comes to picking up cues that occur in a larger range of spatial arrangements. Integrated sensors on upper body garments could be designed and used to explore subtle signals of head and gesture movements more accurately than the trousers have, and could also expand the use cases for detecting such cues.

The trousers focused on postural movement and touch interactions induced by their wearer alone. Although in reaction and in coordination with others, the changes in pressure measured stem from one person only. There are scenarios, however, in which external touch becomes relevant, for example in greetings or accidental touch in crowds. Sensors in garments could be used to explore, if the relation of such touch interactions is amicable or hostile. Some nonverbal encounters differ from other "rules" and conventions of interpersonal signals and behaviours apply, as acknowledged by Kendon (1990a); Harrigan and Rosenthal (1983), and exploring them may require different sensor placements on the body, as well as considering other types of sensing garment as the trousers in this research.

Investigations towards touch detection can be a gateway for a wider research area on affective computing, and have been of interest to detect in relation to emotions (Ekman and Friesen, 1969a), too. In Chapter 4, postures involving hand touch - such as tucking hands between thighs or resting them on the lap were explored. The accuracy of detecting these touch interactions and distinguishing them from other postures has been high and also the small amount of misclassifications with other (sitting) postures was promising. A suggestion in regards to hand touch is, for example, that discomfort is displayed through rapid hand movement on the thigh or tucking hands between the thighs. These types of self touch are *self-adaptors* (Ekman and Friesen, 1969b), commonly understood as behaviours not directed at interaction partners, but have also been discussed as more active parts of conversation, displaying engagement (Streeck, 2020). Detecting self touch with textiles fosters the idea of unintrusive human-centred sensing to further investigate social interaction between humans, but can also contribute to interaction with virtual agents, where self touch is reported as important interactional parameters, too (Koda and Mori, 2014). it would be interesting to connect to the large corpus of work on self touch, exploring it from a textile perspective.

8.6 Not On The Last Leg: Closing Remarks

Smart textiles have been well explored in different areas in Human-Computer-Interaction as ubiquitous sensing technologies and soft, tangible interfaces. Something that has been largely missing, however, is an approach of exploiting textiles as a sensing material to capture human behaviour. First, expanding the understanding of nonverbal behaviour in regards to the lower body. Postural changes and sitting postures in unscripted multiparty conversation were examined through ethnographic observations and quantitative methods, exploring what information we can infer from the lower body and from measuring postural movement around the legs and buttocks. The findings provide insights into the potential richness of conversational cues the lower body contains. Second, the potential of textile sensors to capture social signals is explored. I have introduced two sensing systems to capture embodied social behaviour without augmenting familiar surroundings: smart chairs and trousers with embedded textile pressure sensors. In a series of four user studies, these designs were tested for their performance of identifying body movement and conversational states, as well as for their aesthetic and social acceptance as a ubiquitous sensing object in an interactional context. I show that it is possible to identify basic social behaviours, as well as a large variety of body movements through selfmade textile sensors embedded in our everyday clothing.

Overall, these explorations add to our understanding of human behaviour in social interaction. Such understanding is key to many applications in health care, soft robotics, and in the lifestyle segment. The shifts in pressure distribution on the lower body that were examined here would have remained unnoticed if I had not analysed the peaks of the pressure sensor data captured by the trousers. These findings expand on previously used modalities and can have implications for future studies of (seated) interaction. If chairs are able to distinguish speakers from listeners and trousers pick up laughter and detailed information on small scale movement, what other fabric surfaces could be instrumentalised to detect social signals? Soft furnishings may be able to assess the social performance of a building or room the same way our clothes may be able to monitor our performance in social encounters. Sensing pressure in seating areas, for example, could explore how lively a conversation is, who is most and least active, or detect loudmouths. For trousers, we can carry forward *Wallace & Gromit*'s robotic "Wrong Trousers"[3] and reimagine "Right Trousers" that assist in daily activities, identify their wearer, monitor one's wellbeing and react to it, too. Moreover, studying nonverbal social behaviour can be used for designing the clothes we interact in, making fashion a potential tool to enhance, direct, balance and encourage conversation.

[3]referring to the 1993 animated short film "The Wrong Trousers" by Nick Park. See https://wallaceandgromit.com/films/the-wrong-trousers

Appendix A

Chapter 3 Additional Material

A.1 Ethics Approval

A.1.1 Ethics Committee Approval Letter

Queen Mary
University of London

Queen Mary, University of London
Room W117
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Mile End Road
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Queen Mary Ethics of Research Committee
Hazel Covill
Research Ethics Administrator
Tel: +44 (0) 20 7882 7915
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c/o Professor Pat Healey
CS 410
Department of Computer Science
Queen Mary University of London
Mile End Road
London

6th July 2016

To Whom It May Concern:

Re: QMREC1778a – A Sensing Chair – Exploring the Social Performance of Interior Furnishing.

I can confirm that Ms Sophie Skach has completed a Research Ethics Questionnaire with regard to the above research.

The result of which was the conclusion that her proposed work does not present any ethical concerns; is extremely low risk; and thus does not require the scrutiny of the full Research Ethics Committee.

Yours faithfully

Ms Hazel Covill – QMERC Administrator

Patron: Her Majesty the Queen
Incorporated by Royal Charter as Queen Mary and Westfield College, University of London

A.1.2 Consent Form

<u>Consent form</u>

Please complete this form after you have read the Information Sheet and/or listened to an explanation about the research.

Title of Study: A Sensing Chair - Exploring the Social Performance of Interior Furnishing
Queen Mary Ethics of Research Committee Ref: _____QMREC1778a______

%L. • Thank you for considering taking part in this research. The person organizing the research must explain the project to you before you agree to take part.

%L. • If you have any questions arising from the Information Sheet or explanation already given to you, please ask the researcher before you decide whether to join in. You will be given a copy of this Consent Form to keep and refer to at any time.

%L. • *I understand that if I decide at any other time during the research that I no longer wish to participate in this project, I can notify the researchers involved and be withdrawn from it immediately.*

%L. • *I consent to the processing of my personal information for the purposes of this research study. I understand that such information will be treated as strictly confidential and handled in accordance with the provisions of the Data Protection Act 1998.*

Participant's Statement:

I ____ agree that the research project named above has been explained to me to my satisfaction and I agree to take part in the study. I have read both the notes written above and the Information Sheet about the project, and understand what the research study involves.

Signed: Date:

Investigator's Statement:

I ____ confirm that I have carefully explained the nature, demands and any foreseeable risks (where applicable) of the proposed research to the volunteer

A.1.3 Participant Information Sheet

Queen Mary
University of London

Information sheet

Research study
"A Sensing Chair - Exploring the Social Performance of Interior Furnishing"
information for participants

We would like to invite you to be part of this research project, if you would like to. You should only agree to take part if you want to, it is entirely up to you. If you choose not to take part there won't be any disadvantages for you and you will hear no more about it.

Please read the following information carefully before you decide to take part; this will tell you why the research is being done and what you will be asked to do if you take part. Please ask if there is anything that is not clear or if you would like more information.

If you decide to take part you will be asked to sign the attached form to say that you agree.

You are still free to withdraw at any time and without giving a reason.

The study you take part looks into social behaviour through exploring the relationship of postural states and social behaviour in group discussions.

For this, we will ask you to discuss a moral dilemma. The task is to collaborate with your partners to resolve this "Balloon"- dilemma. Please see the instruction for the task on the separate sheet provided.

All texts are anonymised and will contain no distressing content.

The duration of the experiment is approximately 30 minutes and takes place in the Performing Lab, in the Engineering Building of Queen Mary University of London. Depending on the conclusion and agreement of the moral dilemma discussed, the experiment may be slightly shorter or longer than the set time. You are allowed to take a break in between whenever you want and return to complete the experiment at any time. You will also receive a participant number and your data will be stored according to QMUL guidelines.
It is up to you to decide whether or not to take part. If you do decide to take part you will be given this information sheet to keep and be asked to sign a consent form.

If you have any questions or concerns about the manner in which the study was conducted please, in the first instance, contact the researcher responsible for the study. If this is unsuccessful, or not appropriate, please contact the Secretary at the Queen Mary Ethics of Research Committee, Room W117, Queen's Building, Mile End Campus, Mile End Road, London or research-ethics@qmul.ac.uk.

A.1.4 Participant Task Sheet

Participant Instruction Sheet: Balloon Task

The task is to collaborate with your partners to resolve a dilemma.

The situation

Three people are in a hot air balloon. The balloon is losing height and about to crash into the mountains. Having thrown everything imaginable out of the balloon, including food, sandbags and parachutes, their only hope is for one of them to jump to their certain death to give the balloon the extra height to clear the mountains and save the other two. But who is it to be?

The three people are:

Dr. Nick Riviera – a cancer research scientist who believes he is on the brink of discovering a cure for most common types of cancer. He is a good friend of Tom and Susie Derkins.

Mrs. Susie Derkins – a primary school teacher. She is over the moon because she is 7 months pregnant with her second child.

Mr. Tom Derkins – the balloon pilot. He is the husband of Susie, who he loves very much. He is also the only one with any balloon flying experience.

Your Task

Between the three of you, you should come to an agreement about who should be thrown off the balloon...

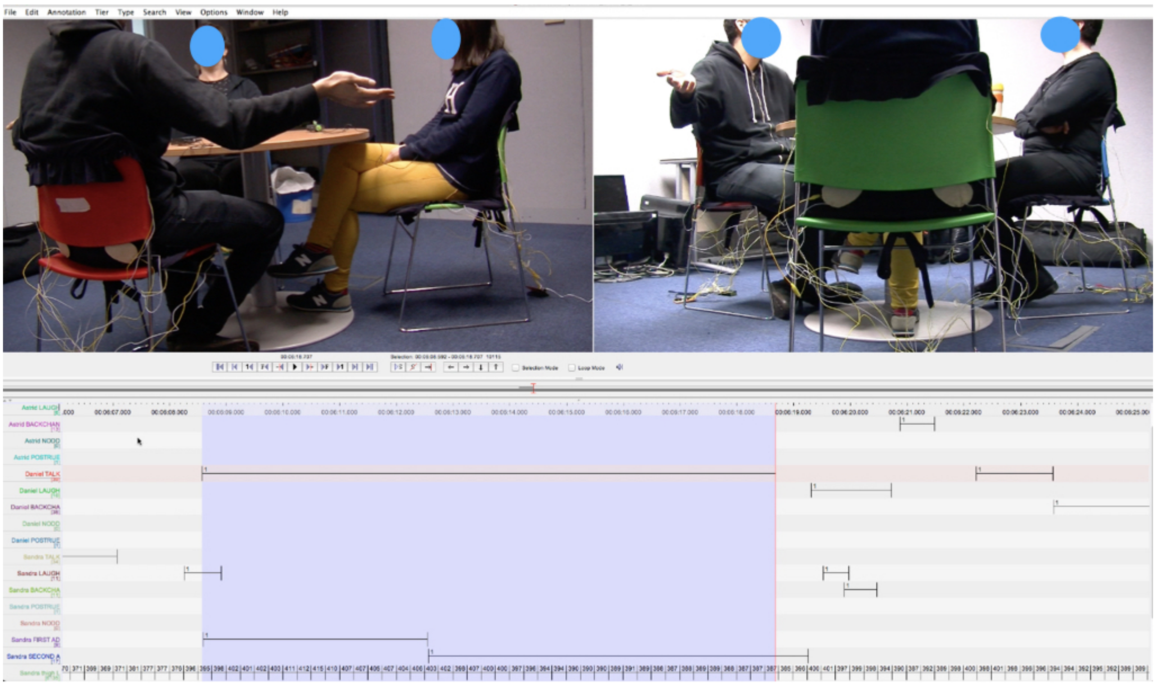
A.2 Sample Clip Stills

A.2.1 Stills from Study Sessions

Here are screenshots from stills of the recorded video from two different sessions. In both sequences, a small postural change is noteable that affected the sensor readings. The stills also show the two different camera angles from which the conversation was filmed.

A.2.2 Annotation Interface Example

Screenshot of how the recorded conversations were annotated and synchronised using the software package Elan (Brugman and Russel, 2004).



A.3 Statistical Analysis

A.3.1 Multivariate Tests

This section lists the detailed results from the Multivariate tests conducted, including Pillai's Trace, Wilk's Lambda, Hotelling's Trace and Roy's Largest Root. The results highlighted in yellow are pointed out in chapter 3.6.

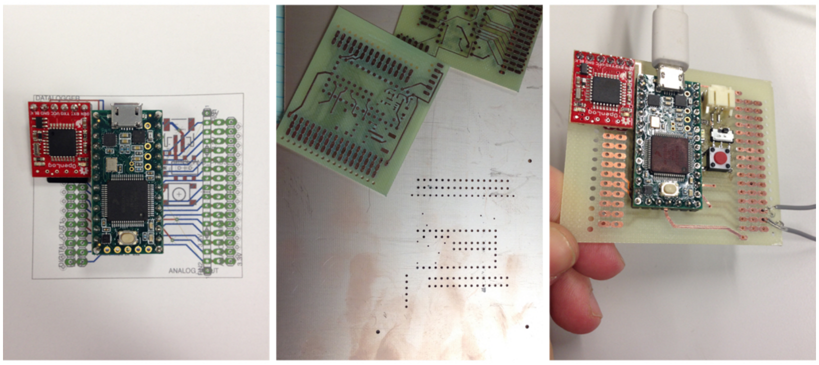
Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power[d]
Intercept	Pillai's Trace	.180	2273.092[b]	8.000	82933.000	.000	.180	18184.732	1.000
	Wilks' Lambda	.820	2273.092[b]	8.000	82933.000	.000	.180	18184.732	1.000
	Hotelling's Trace	.219	2273.092[b]	8.000	82933.000	.000	.180	18184.732	1.000
	Roy's Largest Root	.219	2273.092[b]	8.000	82933.000	.000	.180	18184.732	1.000
TALK	Pillai's Trace	.001	9.679[b]	8.000	82933.000	.000	.001	77.430	1.000
	Wilks' Lambda	.999	9.679[b]	8.000	82933.000	.000	.001	77.430	1.000
	Hotelling's Trace	.001	9.679[b]	8.000	82933.000	.000	.001	77.430	1.000
	Roy's Largest Root	.001	9.679[b]	8.000	82933.000	.000	.001	77.430	1.000
BACKCHANNEL	Pillai's Trace	.001	10.210[b]	8.000	82933.000	.000	.001	81.684	1.000
	Wilks' Lambda	.999	10.210[b]	8.000	82933.000	.000	.001	81.684	1.000
	Hotelling's Trace	.001	10.210[b]	8.000	82933.000	.000	.001	81.684	1.000
	Roy's Largest Root	.001	10.210[b]	8.000	82933.000	.000	.001	81.684	1.000
LAUGH	Pillai's Trace	.001	6.946[b]	8.000	82933.000	.000	.001	55.570	1.000
	Wilks' Lambda	.999	6.946[b]	8.000	82933.000	.000	.001	55.570	1.000
	Hotelling's Trace	.001	6.946[b]	8.000	82933.000	.000	.001	55.570	1.000
	Roy's Largest Root	.001	6.946[b]	8.000	82933.000	.000	.001	55.570	1.000
Person	Pillai's Trace	5.647	12441.759	128.000	663520.000	.000	.706	1592545.20	1.000
	Wilks' Lambda	.000	18595.949	128.000	598051.084	.000	.765	1944193.49	1.000
	Hotelling's Trace	35.833	23216.529	128.000	663450.000	.000	.817	2971715.77	1.000
	Roy's Largest Root	14.051	72835.744[c]	16.000	82940.000	.000	.934	1165371.91	1.000
TALK * BACKCHANNEL	Pillai's Trace	.002	22.626[b]	8.000	82933.000	.000	.002	181.009	1.000
	Wilks' Lambda	.998	22.626[b]	8.000	82933.000	.000	.002	181.009	1.000
	Hotelling's Trace	.002	22.626[b]	8.000	82933.000	.000	.002	181.009	1.000
	Roy's Largest Root	.002	22.626[b]	8.000	82933.000	.000	.002	181.009	1.000
BACKCHANNEL * LAUGH	Pillai's Trace	.001	7.000[b]	8.000	82933.000	.000	.001	56.004	1.000
	Wilks' Lambda	.999	7.000[b]	8.000	82933.000	.000	.001	56.004	1.000
	Hotelling's Trace	.001	7.000[b]	8.000	82933.000	.000	.001	56.004	1.000
	Roy's Largest Root	.001	7.000[b]	8.000	82933.000	.000	.001	56.004	1.000
TALK * LAUGH	Pillai's Trace	.000	1.718[b]	8.000	82933.000	.089	.000	13.741	.756
	Wilks' Lambda	1.000	1.718[b]	8.000	82933.000	.089	.000	13.741	.756
	Hotelling's Trace	.000	1.718[b]	8.000	82933.000	.089	.000	13.741	.756
	Roy's Largest Root	.000	1.718[b]	8.000	82933.000	.089	.000	13.741	.756
TALK * BACKCHANNEL * LAUGH	Pillai's Trace	.000	.[b]	.000	.000	.	.	.	.
	Wilks' Lambda	1.000	.[b]	.000	82936.500	.	.	.	.
	Hotelling's Trace	.000	.[b]	.000	2.000	.	.	.	.
	Roy's Largest Root	.000	.000[b]	8.000	82932.000	1.000	.000	.000	.050

Appendix B

Chapter 4 Additional Material

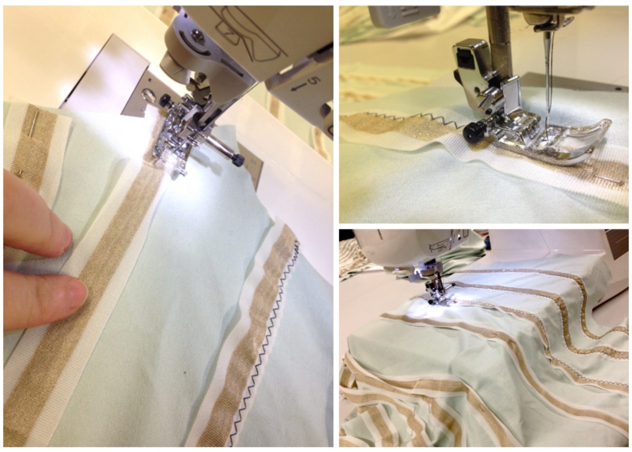
B.1 Trousers Making Of

B.1.1 Circuit Board Development



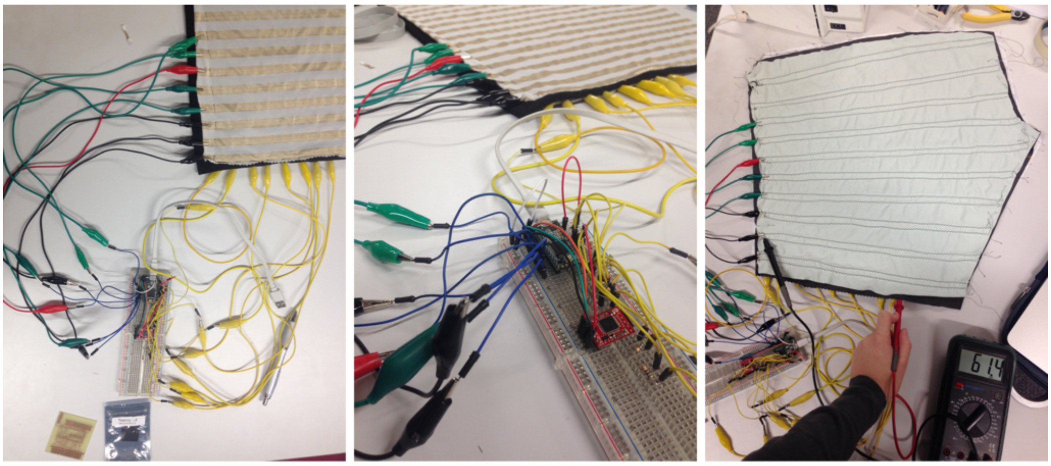
Documentation of circuit board development

B.1.2 Sewing Process



Sewing of rows and columns of the sensor matrix

B.1.3 Sensor Matrix Early Development



Prototyping and testing of a first iteration of the sensor matrix

B.2 Task List

19 different postures were performed, each participant performed each posture 3 times (in 3 cycles). For 10 participants, this results in 570 data samples in total, and ca 30 samples per posture. This task sheet was printed, read out by an instructor and shown to participants.

TASK ORDER, INSTRUCTIONS FOR PARTICIPANTS:

1. STANDING UP STRAIGHT 5sec
2. SITTING UP RIGHT, NO KNEES TOUCHING, NO HANDS == **"HOME POSITION" 5sec**
3. SITTING WITH KNEES TOUCHING, NO HANDS 5sec
4. HOME POSITION 3sec
5. LEANING BACK 5sec
6. HOME POSITION 3sec
7. LEANING FORWARD 5sec
8. HOME POSITION 3sec
9. SLOUCHING 5sec
10. HOME POSITION 3sec
11. LEG CROSSING: LEFT TO RIGHT 5sec
12. HOME POSITION 3sec
13. LEG CROSSING: RIGHT TO LEFT 5sec
14. HOME POSITION 3sec
15. LEG CROSSING: LEFT TO RIGHT WITH ANKLE ON KNEE 5sec
16. HOME POSITION 3sec
17. LEG CROSSING: RIGHT TO LEFT WITH ANKLE ON KNEE 5sec
18. HOME POSITION 3sec
19. HANDS ON KNEE LEANING BACK 5sec
20. HOME POSITION 3sec
21. HANDS ON KNEE LEANING FORWARD 5sec
22. HOME POSITION 3sec
23. HANDS IN CROTCH 5sec
24. HOME POSITION 3sec
25. HANDS BETWEEN LEGS, KNEES TOUCHING 5sec
26. HOME POSITION 3sec
27. HANDS ON MID THIGHS 5sec
28. HOME POSITION 3sec
29. ELBOW ON THIGHS, LEANING FORWARD 5sec
30. HOME POSITION 3sec
31. LOWER FEET: STRETCHED OUT 5sec
32. HOME POSITION 3sec
33. LOWER FEET: BENT IN, NOT CROSSED 5sec
34. HOME POSITION 3sec
35. LOWER FEET CROSSED 5sec
36. HOME POSITION 3sec
37. STANDING UP, END 5sec

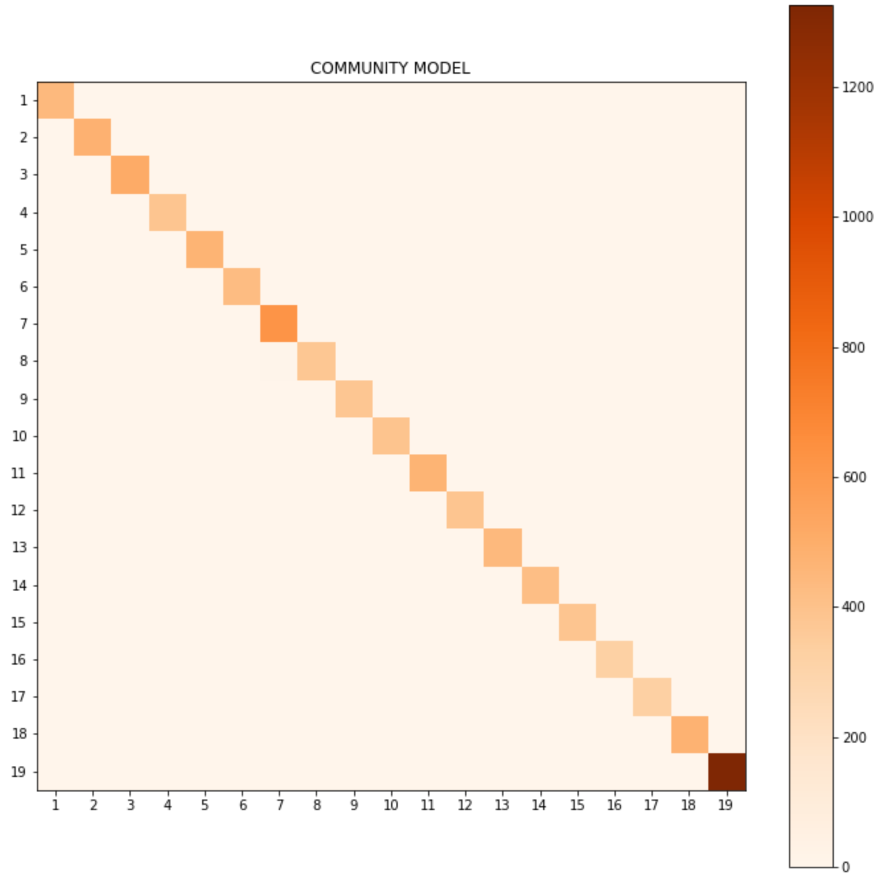
This sequence of tasks was used to instruct participants. A timer was used to change between postures. In total, this resulted in the following amount of time recorded per participant:
20x5sec positions + 17x3sec home position + ca 37x2sec for interchange = 225sec = 3.75min x 3 = 11.25min

Trouser sizes used: S (smallest size): 3x ; M (medium size) 3x ; L (large) 4x

B.3 Results

B.3.1 Community Model Confusion Matrix

Confusion matrix of correct and incorrect classifications for the community model of 6 participants running a Random Forest classification, with 10-fold cross validation.



=== Confusion Matrix ===

a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	s	<-- classified as
445	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	1	0	a = ELBOWS_ON_THIGHS_FORWARD
0	477	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	b = HANDS_BETWEEN_LEGS
0	2	513	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	c = HANDS_IN_CROTCH
0	0	0	386	0	1	1	0	0	0	0	0	0	0	0	0	0	1	0	d = HANDS_ON_KNEE
0	0	1	5	471	1	0	0	0	1	0	0	0	0	0	0	0	0	0	e = HANDS_ON_KNEE_FORWARD
1	4	1	0	0	426	0	0	0	0	0	0	0	0	0	0	0	0	0	f = HANDS_ON_THIGHS
0	0	0	0	0	0	626	3	0	0	0	0	0	0	0	0	0	0	0	g = HOME_POSITION
0	0	0	0	0	0	6	377	0	0	0	0	0	0	0	0	0	0	1	h = KNEES_TOUCHING
0	0	0	0	0	0	1	1	380	0	0	0	0	0	0	0	0	1	0	i = LEAN_BACK
0	0	0	0	0	0	1	0	1	389	0	0	0	0	0	0	0	0	0	j = LEAN_FORWARD
0	0	0	0	0	0	0	0	0	0	471	0	0	1	0	0	0	1	0	k = LEG_CROSS_2_L_TO_R
0	0	0	2	0	0	0	0	0	0	1	386	0	0	0	1	0	0	0	l = LEG_CROSS_2_R_TO_L
0	0	0	0	1	0	0	0	0	0	0	0	445	0	0	0	0	0	0	m = LEG_CROSS_L_TO_R
0	3	0	0	0	0	0	1	0	0	2	2	2	417	0	1	0	0	0	n = LEG_CROSS_R_TO_L
0	1	0	0	0	0	0	0	0	0	0	0	0	0	387	0	2	1	0	o = LOWER_FEET_BENT
0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	325	0	0	0	p = LOWER_FEET_CROSSED
0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	329	0	0	q = LOWER_FEET_STRETCHED
0	0	0	0	0	0	4	0	0	0	0	0	1	0	0	0	0	476	0	r = SLOUCHING
0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	1327	s = STANDING

B.3.2 Misclassifications: Confusion Matrices

Participant A

This participant performed best with an overall accuracy of 99.75% and very high F-Measures between 0.989 and 1.000 for all 19 postures. Below is the confusion matrix of the individual model of participant A, as well as the model where A's data is not contained in the training set, but used to test the classification.

```
=== Confusion Matrix ===

   a   b   c   d   e   f   g   h   i   j   k   l   m   n   o   p   q   r   s   <-- classified as
 100   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 |   a = ELBOWS_ON_THIGHS_FORWARD
   0  97   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 |   b = HANDS_BETWEEN_LEGS
   0   0  87   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 |   c = HANDS_IN_CROTCH
   0   0   0  80   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 |   d = HANDS_ON_KNEE
   0   0   0   1  90   0   0   0   0   0   0   0   0   0   0   0   0   0   0 |   e = HANDS_ON_KNEE_FORWARD
   0   0   0   0   0  63   0   0   0   0   0   0   0   0   0   0   0   0   0 |   f = HANDS_ON_THIGHS
   0   0   0   0   0   0 152   0   0   0   0   0   0   0   0   0   0   0   0 |   g = HOME_POSITION
   0   0   0   0   0   0   0  68   0   0   0   0   0   0   0   0   0   0   0 |   h = KNEES_TOUCHING
   0   0   0   0   0   0   0   0  70   0   0   0   0   0   0   0   0   0   0 |   i = LEAN_BACK
   0   0   0   0   0   0   0   0   0  62   0   0   0   0   0   0   0   0   0 |   j = LEAN_FORWARD
   0   0   0   0   0   0   0   0   0   0  80   0   0   0   0   0   0   0   0 |   k = LEG_CROSS_2_L_TO_R
   0   0   0   0   0   1   0   0   0   0   0  80   0   0   0   0   0   0   0 |   l = LEG_CROSS_2_R_TO_L
   0   0   0   0   1   0   0   0   0   0   0   0  79   0   0   0   0   0   0 |   m = LEG_CROSS_L_TO_R
   0   0   0   0   0   0   0   0   0   0   0   0   1  69   0   0   0   0   0 |   n = LEG_CROSS_R_TO_L
   0   0   0   0   0   0   0   0   0   0   0   0   0   0  50   0   0   0   0 |   o = LOWER_FEET_BENT
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0  38   0   0   0 |   p = LOWER_FEET_CROSSED
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0  47   0   0 |   q = LOWER_FEET_STRETCHED
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0  74   0 |   r = SLOUCHING
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 202 |   s = STANDING
=== Confusion Matrix ===

   a   b   c   d   e   f   g   h   i   j   k   l   m   n   o   p   q   r   s   <-- classified as
  73   0   0   0  27   0   0   0   0   0   0   0   0   0   0   0   0   0   0 |   a = ELBOWS_ON_THIGHS_FORWARD
   0  46   0  45   0   0   0   0   0   0   0   0   6   0   0   0   0   0   0 |   b = HANDS_BETWEEN_LEGS
   0   3   9  59   0   0   0   0   0   0   0   0   0  13   0   0   0   3   0 |   c = HANDS_IN_CROTCH
   0   0   0  62  18   0   0   0   0   0   0   0   0   0   0   0   0   0   0 |   d = HANDS_ON_KNEE
   0   0   0   1  87   0   0   0   0   0   0   0   0   0   0   0   0   0   3 |   e = HANDS_ON_KNEE_FORWARD
   0   7   0  43   0   1   0   0  12   0   0   0   0   0   0   0   0   0   0 |   f = HANDS_ON_THIGHS
   0   4   0  23   0   0  67  34   1  18   0   0   0   0   0   5   0   0   0 |   g = HOME_POSITION
   0   0   6   8   0   0   0  39   0  15   0   0   0   0   0   0   0   0   0 |   h = KNEES_TOUCHING
   0   0   0   0   0   0  37   0  11   0   0   0   0   0   0   0   9  13   0 |   i = LEAN_BACK
  16   0   0   0  18   0   1  19   0   8   0   0   0   0   0   0   0   0   0 |   j = LEAN_FORWARD
   0   0   0   0   0   0   0   0   0   0  80   0   0   0   0   0   0   0   0 |   k = LEG_CROSS_2_L_TO_R
   4   0   0   0  14   0   0   0   0   0   0  63   0   0   0   0   0   0   0 |   l = LEG_CROSS_2_R_TO_L
   0   0   0   0   3   0   0   0   0   0   0   0  77   0   0   0   0   0   0 |   m = LEG_CROSS_L_TO_R
   0   0   0   0   0   0   0   0   0   0   0   0   0  70   0   0   0   0   0 |   n = LEG_CROSS_R_TO_L
   0   0   0   0   0   0   0   0   0   0   0   0   0   0  50   0   0   0   0 |   o = LOWER_FEET_BENT
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0  38   0   0 |   p = LOWER_FEET_CROSSED
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0  47   0   0 |   q = LOWER_FEET_STRETCHED
   0   0   0   0   0   0   0  17   9   3   0   0   0   0  11   3   0  31   0 |   r = SLOUCHING
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 202 |   s = STANDING
```

B.3.3 Participant C and D

Here are the confusion matrices of the participants who misclassified standing postures. All other participants had no misclassifications between sitting and standing postures.

```
=== Confusion Matrix ===

   a   b   c   d   e   f   g   h   i   j   k   l   m   n   o   p   q   r   s   <-- classified as
  42   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 |   a = ELBOWS_ON_THIGHS_FORWARD
   0  59   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 |   b = HANDS_BETWEEN_LEGS
   0   0  70   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 |   c = HANDS_IN_CROTCH
   0   0   0  54   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 |   d = HANDS_ON_KNEE
   0   0   0   0  49   0   0   0   0   0   0   0   0   0   0   0   0   0   0 |   e = HANDS_ON_KNEE_FORWARD
   0   0   0   0   0  53   0   0   0   0   0   0   0   0   0   0   0   0   0 |   f = HANDS_ON_THIGHS
   0   0   0   0   0   0 129   2   0   0   0   0   0   0   0   0   0   0   0 |   g = HOME_POSITION
   0   0   0   0   0   0   0  54   0   0   0   0   0   0   0   0   0   0   0 |   h = KNEES_TOUCHING
   0   0   0   0   0   0   0   0  58   0   0   0   0   0   0   0   0   0   0 |   i = LEAN_BACK
   0   0   0   0   0   0   0   0   0  61   0   0   0   0   0   0   0   0   0 |   j = LEAN_FORWARD
   0   0   0   0   0   0   0   0   0   0  56   0   0   0   0   0   0   0   0 |   k = LEG_CROSS_2_L_TO_R
   0   0   0   0   0   0   0   0   0   0   0  50   0   0   0   0   0   0   0 |   l = LEG_CROSS_2_R_TO_L
   0   0   0   0   0   0   0   0   0   0   0   0  74   0   0   0   0   0   0 |   m = LEG_CROSS_L_TO_R
   0   0   0   0   0   0   0   0   0   0   0   0   0  77   0   0   0   0   0 |   n = LEG_CROSS_R_TO_L
   0   0   0   0   0   0   0   0   0   0   0   0   0   0  51   0   0   0   0 |   o = LOWER_FEET_BENT
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0  63   0   0   0 |   p = LOWER_FEET_CROSSED
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   1   0  41   0   0 |   q = LOWER_FEET_STRETCHED
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0  57   0 |   r = SLOUCHING
   0   0   0   0   0   0   1   0   0   0   0   0   0   0   0   0   0   0 162 |   s = STANDING
```

```
=== Confusion Matrix ===

   a   b   c   d   e   f   g   h   i   j   k   l   m   n   o   p   q   r   s   <-- classified as
 100   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 |   a = ELBOWS_ON_THIGHS_FORWARD
   0  86   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 |   b = HANDS_BETWEEN_LEGS
   0   1 100   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 |   c = HANDS_IN_CROTCH
   0   0   0  75   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 |   d = HANDS_ON_KNEE
   0   0   0   2 100   0   0   0   0   0   0   0   0   0   0   0   0   0   0 |   e = HANDS_ON_KNEE_FORWARD
   1   1   0   0   0  77   0   0   0   0   0   0   0   0   0   0   0   0   0 |   f = HANDS_ON_THIGHS
   0   0   0   0   0   0  80   1   0   0   0   0   0   0   0   0   0   0   0 |   g = HOME_POSITION
   0   0   0   0   0   0   1  57   0   0   0   0   0   0   0   0   0   0   0 |   h = KNEES_TOUCHING
   0   0   0   0   0   0   0   0  61   0   0   0   0   0   0   0   0   0   1 |   i = LEAN_BACK
   0   0   0   0   0   0   0   0   0  62   0   0   0   0   0   0   0   0   0 |   j = LEAN_FORWARD
   0   0   0   0   0   0   0   0   0   0  97   0   0   0   0   0   0   0   0 |   k = LEG_CROSS_2_L_TO_R
   0   0   0   0   0   0   0   0   0   0   0  73   0   0   0   0   0   0   0 |   l = LEG_CROSS_2_R_TO_L
   0   0   0   0   0   0   0   0   0   0   0   0  65   0   0   0   0   0   0 |   m = LEG_CROSS_L_TO_R
   0   0   0   0   0   0   1   0   0   0   0   0   0  70   0   0   0   0   0 |   n = LEG_CROSS_R_TO_L
   0   1   0   0   0   0   0   0   0   0   0   0   0   0  81   0   0   0   1 |   o = LOWER_FEET_BENT
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   2  52   0   0   0 |   p = LOWER_FEET_CROSSED
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0  68   0   0 |   q = LOWER_FEET_STRETCHED
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0  70   0 |   r = SLOUCHING
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 262 |   s = STANDING
```

Leave-One-Out Confusion Matrices

The confusion matrices here are from the model where the participant is not included in the training set of the classifier. The Random Forest is trained on the remaining 5 participants. The confusion matrices from this Leave-One-Out model are from participants B - F.

```
=== Confusion Matrix ===

   a   b   c   d   e   f   g   h   i   j   k   l   m   n   o   p   q   r   s   <-- classified as
  23   0   0   0  31   0   0   0   0   0   0   3   0   2   0   0   0   0   0 |   a = ELBOWS_ON_THIGHS_FORWARD
   0   0   0   0   0   0   0   0   0   0  28   0  18   8   0   0   0   0   0 |   b = HANDS_BETWEEN_LEGS
   0   0   0   0   0   0   0   0   0   0   0  43   0  26   0   0   0   0   0 |   c = HANDS_IN_CROTCH
   0   0   0   0   0   0   0   0   0   0   0  43  11   0   0   0   0   0   0 |   d = HANDS_ON_KNEE
   0   0   0   0   0   0   0   0   0   0  37  15   0   1   0   0   0   0   0 |   e = HANDS_ON_KNEE_FORWARD
   0   0   0   0   0   0   0   0   0   0  18  44   0   0   4   0   0   0   0 |   f = HANDS_ON_THIGHS
   0   0   0   0   0   0   7   0  36   0   0  11   0   0  33   0   0   0   0 |   g = HOME_POSITION
   0   0   0   0   0   0   0   0  25   0   0   9   0   0  29   0   0   0   0 |   h = KNEES_TOUCHING
   0   0   0   0   0   0   8   0   3   1   0  13   0   0  47   0   0   0   0 |   i = LEAN_BACK
   0   0   0   0   0   0   0   0   1   0   0   1   0  18  55   0   0   0   0 |   j = LEAN_FORWARD
   0   0   0   0   0   0   0   0   0   0  77  20   0   0   0   0   0   0   0 |   k = LEG_CROSS_2_L_TO_R
   0   0   0   0   0   0   0   0   0   0   9  61   0   0   0   0   0   0   0 |   l = LEG_CROSS_2_R_TO_L
   0   0   0   0   0   0   0   0   0   0   4   1   6   0  79   0   0   0   0 |   m = LEG_CROSS_L_TO_R
   0   0   0   0   0   0   0   0   0   0  21   0   0  55   0   0   0   0   0 |   n = LEG_CROSS_R_TO_L
   0   0   0   0   0   0   0   0   0   0   0   0   0   0  56   0   0   0   0 |   o = LOWER_FEET_BENT
   0   0   0   0   0   0   0   0   0   0   0   5   0   0  56   0   0   0   0 |   p = LOWER_FEET_CROSSED
   0   0   0   0   0   0   0   0   2   0   0   0   0   0   4  19  28   0   0 |   q = LOWER_FEET_STRETCHED
   0   0   0   0   0   0   5   1  31   1   0  41   0   0  33   0   0   0   0 |   r = SLOUCHING
   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 393 |   s = STANDING
=== Confusion Matrix ===

   a   b   c   d   e   f   g   h   i   j   k   l   m   n   o   p   q   r   s   <-- classified as
   0   0   0   0  10   0   6   0   1   8  13   0   0   0   0   0   0   4   0 |   a = ELBOWS_ON_THIGHS_FORWARD
   0   0   1   0   0   4  30   0   0  21   0   0   0   2   0   0   0   1   0 |   b = HANDS_BETWEEN_LEGS
   0   0  27   0   0  13   2   0   0  14   0  11   0   1   0   0   0   2   0 |   c = HANDS_IN_CROTCH
   0   0  21   0   0   9  15   0   3   0   0   0   0   3   0   0   0   3   0 |   d = HANDS_ON_KNEE
   0   2   0   0   8   0  17   1   0  14   0   0   0   2   0   0   0   5   0 |   e = HANDS_ON_KNEE_FORWARD
   0   0  11   0   0  10  27   0   0   4   0   0   0   1   0   0   0   0   0 |   f = HANDS_ON_THIGHS
   1   0   0   0   2   0  14   0   1  22   0  87   0   0   0   3   0   0   1 |   g = HOME_POSITION
   0   0   0   0   1   0  12   0   0  12   0  14   0   2   0   2   0   6   5 |   h = KNEES_TOUCHING
   0   0   0   0   2   0   0   0   0   5   0  51   0   0   0   0   0   0   0 |   i = LEAN_BACK
   0   0   0   0   0   0   0   0   0  10   0  51   0   0   0   0   0   0   0 |   j = LEAN_FORWARD
   0   0   0   2   0   0   1   0   0   0  47   2   0   1   0   0   0   3   0 |   k = LEG_CROSS_2_L_TO_R
   0   0   0   1   1   2   3   0   2  33   1   1   0   1   0   0   0   5   0 |   l = LEG_CROSS_2_R_TO_L
   0   0   0  26   0   0  15   0   2   0   0  13   0   4   0   2   0  11   1 |   m = LEG_CROSS_L_TO_R
   0   0   0   4  15   1   3   0   2   0   3  10   3  36   0   0   0   0   0 |   n = LEG_CROSS_R_TO_L
   0   0   0   0   0   0   7   1   0   0   1   2   0   2  38   0   0   0   0 |   o = LOWER_FEET_BENT
   0   0   0   0   0   1  32   0   8   0   0   0   0   1   0   0   2  18   1 |   p = LOWER_FEET_CROSSED
   0   0   0   0   0   0   9   0  13   1   1   0   0   1   1   0   0   1  15 |   q = LOWER_FEET_STRETCHED
   0   0   0   0   0   0   0   0   0   7   0  50   0   0   0   0   0   0   0 |   r = SLOUCHING
   0   0   0   0   0   0   1   0   0   0   0   0   0   0   0   0   0   0 162 |   s = STANDING
```

```
=== Confusion Matrix ===

  a   b   c   d   e   f   g   h   i   j   k   l   m   n   o   p   q   r   s   <-- classified as
 32   0   0   0  22   0   0   0   0   0   5   0   0   0   0   0   0   0  41 |   a = ELBOWS_ON_THIGHS_FORWARD
 11   0   0   0  41   0   0   0   0   0   3  23   0   0   0   0   0   0   8 |   b = HANDS_BETWEEN_LEGS
  3   0   0   0  76   0   0   0   0   0   0   0   0   0   0   0   0   0  22 |   c = HANDS_IN_CROTCH
  2   0   0   0  43   0   0   0   0   0  11   0   0   0   0   0   0   0  19 |   d = HANDS_ON_KNEE
  4   0   0   0  57   0   0   0   0   0   8   0   0   8   0   0   0   0  25 |   e = HANDS_ON_KNEE_FORWARD
 18   0   0   0  26   0   0   0   0   0   0   2   0   0   0   0   0   0  33 |   f = HANDS_ON_THIGHS
 17   0   0   0  39   0   0   0   0   0   1   0   0   0   0   0   0   0  24 |   g = HOME_POSITION
 21   0   0   0   5   0   0   0   0   0  14   0   0  18   0   0   0   0   0 |   h = KNEES_TOUCHING
  0   0   0   0   3   0   0   0   0   0   0   0   0   0   0   0   0   0  59 |   i = LEAN_BACK
 19   0   0   0  16   0   0   0   0   0   9   0   6   4   0   0   0   0   8 |   j = LEAN_FORWARD
  2   0   0   0  35   0   0   0   0   0  12   0   0   0   0   0   0   0  48 |   k = LEG_CROSS_2_L_TO_R
 12   0   0   0  20   0   0   0   0   0  23   2   0   0   0   0   0   0  16 |   l = LEG_CROSS_2_R_TO_L
  1   0   0   0  19   0   0   0   0   0   4   0   0   0   0   0   0   0  41 |   m = LEG_CROSS_L_TO_R
  5   0   0   0  26   0   3   0   0   0   8   0   1   0   1   0   0   0  27 |   n = LEG_CROSS_R_TO_L
  0   0   0   0  10   0   0   0   0   0   0   0   0   0   0   0   0   0  73 |   o = LOWER_FEET_BENT
  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0  54 |   p = LOWER_FEET_CROSSED
 15   0   0   0  39   0   0   0   0   0   1   0   0   1   0   0   0   0  12 |   q = LOWER_FEET_STRETCHED
  9   0   0   0  10   0   4   0   1   0   2   0   0   0   0   0   1   0  43 |   r = SLOUCHING
 48   0   0   0 124   0   2   0   0   0   8   2   0   0   0   0   0   0  78 |   s = STANDING
```

```
=== Confusion Matrix ===

  a   b   c   d   e   f   g   h   i   j   k   l   m   n   o   p   q   r   s   <-- classified as
 23   0   0   1   0   0   0   0   0   0   0   8  14  33   0   0   0   0   0 |   a = ELBOWS_ON_THIGHS_FORWARD
  0  45   0   5   0   0   0   0   0   0   0   0   0  20   0   0   0   0   0 |   b = HANDS_BETWEEN_LEGS
  0  18   0  22   0   0   0   0   0   0   0  18  18   0   0   0   0   0   0 |   c = HANDS_IN_CROTCH
  0   6   0   5   0   0   0   0   0   0   0   4  37  21   0   0   0   0   0 |   d = HANDS_ON_KNEE
 38   1   0   1  44   0   0   0   0   0   0  20   2   0   0   0   0   0   0 |   e = HANDS_ON_KNEE_FORWARD
  0  15   0   4   1   0   0   0   0   0   0  21  18  23   0   0   0   0   0 |   f = HANDS_ON_THIGHS
  0  98   1   2   0   0   0   0   0   0   0   1   2   0   1   0   0   0   0 |   g = HOME_POSITION
  0  66   0   3   0   0   0   0   0   0   0   0   0   0   0   0   0   3   0 |   h = KNEES_TOUCHING
  0   2   2  35  22   0   0   0   0   0   0   0   3   0   0   0   0   1   0 |   i = LEAN_BACK
 38   1   0   3   9   0   0   0   0   3   0   3   1   9   0   0   0   0   0 |   j = LEAN_FORWARD
  0   0   0   0   0   0   0   0   0   0  86   0   0   0   0   0   0   0   0 |   k = LEG_CROSS_2_L_TO_R
  0   0   0   0   0   0   0   0   0   0   1  44   3  19   0   0   0   0   0 |   l = LEG_CROSS_2_R_TO_L
  0  10   0   5   0   0   0   0   0   0  10  25  31   0   0   0   0   0   0 |   m = LEG_CROSS_L_TO_R
  0   1   1   1  17   0   0   0   0   0  10   7   4  29   0   0   0   0   0 |   n = LEG_CROSS_R_TO_L
  0   0   0   0   0   0   0   0   0   0   8   0  21   0  39   0   0   0   0 |   o = LOWER_FEET_BENT
  0   8   0   0   0   0   0   0   0   0   2   5  36   0   0   0   0   0   0 |   p = LOWER_FEET_CROSSED
  0  20   0   0   0   0   0   0   0   0   0   0  36   0   0   3   0   0   0 |   q = LOWER_FEET_STRETCHED
 19  17   0  11   7   4   0   0   0   0   5   7  12   3   0   0   0   0   0 |   r = SLOUCHING
  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 132 |   s = STANDING
```

```
=== Confusion Matrix ===

  a   b   c   d   e   f   g   h   i   j   k   l   m   n   o   p   q   r   s   <-- classified as
 65   0   0   0   0   0   0   0   0   2   0   0   0   1   0   0   0   0   0 |   a = ELBOWS_ON_THIGHS_FORWARD
  0   0   0  57   0  26  20   0   0   0   0   0   0   0   0   0   0  11   0 |   b = HANDS_BETWEEN_LEGS
  0  10   0  42   0   2  23   0   0   6   0   0   0   0   0   0   0  31   0 |   c = HANDS_IN_CROTCH
  0   0   0  36   9   0   3   0   0   3   0   0   0   0   0   0   0   2   0 |   d = HANDS_ON_KNEE
 69   0   0   1   6   0   1   0   0   0   0   0   0   1   0   0   0   0   0 |   e = HANDS_ON_KNEE_FORWARD
  0   0   0  48   0  20  15   0   1   1   0   3   0   0   0   0   0   1   0 |   f = HANDS_ON_THIGHS
  0   0   0   0   0   0  73   0   0   0   0   0   0   0   0   0   0   0   0 |   g = HOME_POSITION
  0   0   0   0   0   0  28  22   4   0   0   0   0   0   0   0   0  15   0 |   h = KNEES_TOUCHING
  0   0   0   0   0   0  37   0  14   0   0   0   0   0   0   0   4   1   0 |   i = LEAN_BACK
 15   0   0   0   0   0  18   0   2  29   0   0   0   0   0   0   0   0   0 |   j = LEAN_FORWARD
  0   0   0   0   0   0   0   0   0   0  56   0   0   1   0   0   0   0   0 |   k = LEG_CROSS_2_L_TO_R
  0   0   0   1   0   0   1   0   0   0   0  45   0   0   0   0   0   2   0 |   l = LEG_CROSS_2_R_TO_L
  0  12   0   0   0   0   0   0   0   0   0   0  37   7   0   0   0   0   0 |   m = LEG_CROSS_L_TO_R
  0   3   0   0   0   0   0   0   0   0   0   0   0  61   0   0   0   0   0 |   n = LEG_CROSS_R_TO_L
  0   0   0   0   0   0  21   0   1   0  10   0   0   0  34   0   0  17   0 |   o = LOWER_FEET_BENT
  0   0   0   0   0   0  55   0   2   0   0   0   0   0   0   2   1   1   0 |   p = LOWER_FEET_CROSSED
  0   0   0   0   0   0   3   0   0   0   0   0   0   0   0   0  57   1   0 |   q = LOWER_FEET_STRETCHED
  0   0   0   0   0   0  15   0  66   0   0   0   0   0   0   0   0   2   0 |   r = SLOUCHING
  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 177 |   s = STANDING
```

Appendix C

Chapter 5 Additional Material

C.1 Ethics Approval

C.1.1 Ethics Committee Approval Letter

Queen Mary
University of London

Queen Mary, University of London
Room W117
Queen's Building
Queen Mary University of London
Mile End Road
London E1 4NS

Queen Mary Ethics of Research Committee
Hazel Covill
Research Ethics Administrator
Tel: +44 (0) 20 7882 7915
Email: h.covill@qmul.ac.uk

c/o Professor Pat Healey
CS 410
School of Electronic Engineering
and Computer Science
Queen Mary University of London
Mile End
London

15th March 2018

To Whom It May Concern:

Re: QMREC2133a - Sensing Trousers - Exploring Social Behaviour through Smart Clothing.

I can confirm that Sophie Skach has completed a Research Ethics Questionnaire with regard to the above research.

The result of which was the conclusion that her proposed work does not present any ethical concerns; is extremely low risk; and thus does not require the scrutiny of the full Research Ethics Committee.

Yours faithfully

Mr Jack Biddle – Research Approvals Advisor

Patron: Her Majesty the Queen
Incorporated by Royal Charter as Queen Mary and Westfield College, University of London

C.1.2 Consent Form for Participants to Sign

Queen Mary
University of London

Consent Form

Please complete this form after you have read the Information Sheet and/or listened to an explanation about the research.

Title of Study: A Sensing Chair - Exploring the Social Performance of Interior Furnishing
Queen Mary Ethics of Research Committee Ref: **___QMREC2133a____________**

%L. • Thank you for considering taking part in this research. The person organizing the research must explain the project to you before you agree to take part.

%L. • If you have any questions arising from the Information Sheet or explanation already given to you, please ask the researcher before you decide whether to join in. You will be given a copy of this Consent Form to keep and refer to at any time.

%L. • *I understand that if I decide at any other time during the research that I no longer wish to participate in this project, I can notify the researchers involved and be withdrawn from it immediately.*

%L. • *I consent to the processing of my personal information for the purposes of this research study. I understand that such information will be treated as strictly confidential and handled in accordance with the provisions of the Data Protection Act 1998.*

Participant's Statement:

I ____ agree that the research project named above has been explained to me to my satisfaction and I agree to take part in the study. I have read both the notes written above and the Information Sheet about the project, and understand what the research study involves.

Signed: Date:

Investigator's Statement:

I ____ confirm that I have carefully explained the nature, demands and any foreseeable risks (where applicable) of the proposed research to the volunteer

C.1.3 Information Sheet for Participants

Queen Mary
University of London

Information sheet

Research study

“Sensing Trousers - Exploring Social Behaviour through Smart Clothing”

information for participants

We would like to invite you to be part of this research project, if you would like to. You should only agree to take part if you want to, it is entirely up to you. If you choose not to take part there won’t be any disadvantages for you and you will hear no more about it.

Please read the following information carefully before you decide to take part; this will tell you why the research is being done and what you will be asked to do if you take part. Please ask if there is anything that is not clear or if you would like more information.

If you decide to take part you will be asked to sign the attached form to say that you agree.

You are still free to withdraw at any time and without giving a reason.

The study you take part looks into social behaviour through exploring the relationship of postural states and social behaviour in group discussions.

For this, we will ask you to discuss a moral dilemma. The task is to collaborate with your partners to resolve this “Balloon”- dilemma. Please see the instruction for the task on the separate sheet provided. All texts are anonymised and will contain no distressing content.

Additionally, we will ask you to wear a pair of trousers that we use for additional data collection. The trousers can be worn on top of your clothes, or can be worn underneath. Changing rooms are provided. You are also free to not wear the trousers or take them off at any time, if you feel uncomfortable wearing them.

The duration of the experiment is approximately 20 minutes and takes place in the Human Interaction Lab, in the Computer Science Building of Queen Mary University of London. Depending on the conclusion and agreement of the moral dilemma discussed, the experiment may be slightly shorter or longer than the set time. You are allowed to take a break in between whenever you want and return to complete the experiment at any time.

It is up to you to decide whether or not to take part. If you do decide to take part you will be given this information sheet to keep and be asked to sign a consent form.

If you have any questions or concerns about the manner in which the study was conducted please, in the first instance, contact the researcher responsible for the study. If this is unsuccessful, or not appropriate, please contact the Secretary at the Queen Mary Ethics of Research Committee, Room W117, Queen’s Building, Mile End Campus, Mile End Road, London or research-ethics@qmul.ac.uk.

C.2 Annotations

C.2.1 Average Duration of Each Coded Behaviour

AVERAGE DURATION, defined as the total duration of the annotations with the same value divided by the number of occurrences

Participant	TALK	BACKCHANNEL	LAUGHTER	NODDING	ACTIVE LISTENER	INCIDENTAL MOVEMENT
P 1	3.81	0.69	1.90	1.36	1.41	4.33
P 2	2.68	0.45	2.68	2.42	2.45	3.05
P 3	3.34	0.65	2.21	1.80	1.64	3.54
P 4	4.44	0.91	1.90	1.95	1.44	4.31
P 5	2.93	0.53	2.20	1.70	1.20	7.11
P 6	3.70	0.86	1.31	1.26	1.12	8.42
P 7	2.76	0.36	3.16	1.14	1.53	3.08
P 8	2.53	0.81	2.42	1.15	1.25	8.50
P 9	4.27	0.49	1.80	0.89	0.82	3.06
P 10	3.67	0.70	1.50	1.34	1.20	7.04
P 11	3.88	0.68	1.43	1.00	0.97	7.86
P 12	1.75	0.71	1.60	1.28	1.21	4.53
P 13	3.72	0.61	1.88	1.28	1.28	6.52
P 14	2.51	0.74	1.57	1.08	1.25	4.73
P 15	2.63	0.72	1.50	1.47	1.32	3.39
P 16	3.81	0.63	1.28	1.00	0.97	7.41
P 17	4.11	0.74	1.64	2.12	1.93	4.81
P 18	2.41	0.87	1.97	0.85	1.37	4.16
P 19	2.24	0.68	2.10	1.13	1.18	5.72
P 20	2.98	0.83	1.90	2.80	1.96	11.15
Average	3.2085	0.683	1.8975	1.451	1.375	5.636
Minimum	1.75	0.36	1.28	0.85	0.82	3.05
Maximum	4.44	0.91	3.16	2.80	2.45	11.15

1

C.2.2 Overall Occurrence of Each Coded Behaviour

OCCURENCE / number of annotations

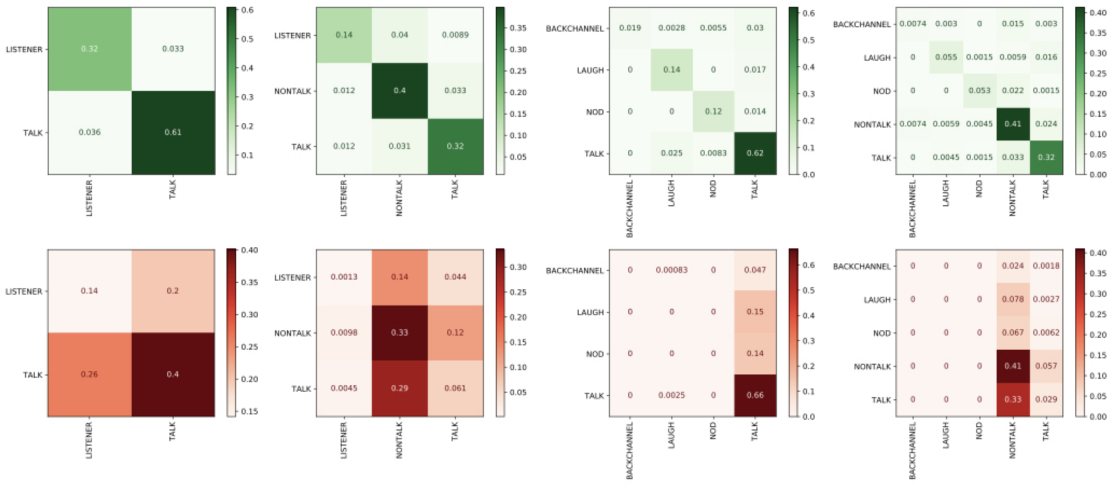
Participant	TALK	BACKCHANNEL	LAUGHTER	NODDING	ACTIVE LISTENER	INCIDENTAL MOVEMENT
P 1	126	31	30	62	113	163
P 2	132	38	68	121	196	272
P 3	143	47	42	56	132	177
P 4	106	51	17	19	80	165
P 5	66	65	18	42	121	155
P 6	91	85	28	26	129	50
P 7	133	73	62	135	241	313
P 8	127	47	14	38	92	88
P 9	139	109	23	42	160	231
P 10	92	40	6	69	106	33
P 11	60	37	17	21	72	91
P 12	120	45	29	28	94	185
P 13	34	28	11	51	80	40
P 14	54	86	57	69	174	199
P 15	204	89	76	88	230	162
P 16	48	37	15	3	47	17
P 17	126	27	40	73	122	111
P 18	219	54	57	36	137	135
P 19	162	98	32	57	168	58
P 20	62	32	31	32	89	79
Average	112.2	55.95	33.65	53.4	129.15	136.2
Minimum	34	27	6	3	47	17
Maximum	219	109	76	135	241	313

1

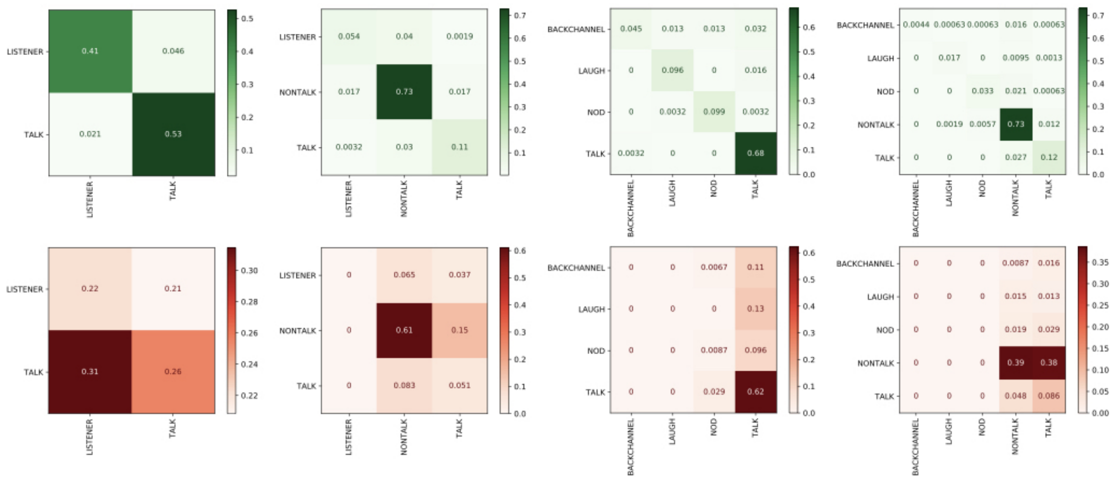
C.3 Results

In Chapter 5, the results shown are summarised for individual participants. For visualisations, one participant was selected to be shown alongside the community models of the Random Forest classifications. Here, the confusion matrices and feature importance of six more randomly selected participants are shown.

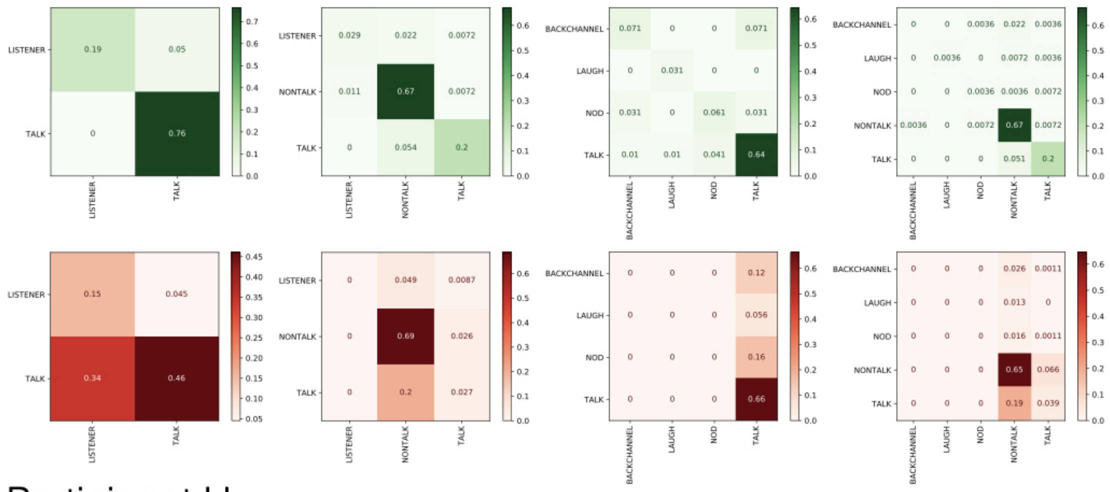
C.3.1 Confusion Matrices



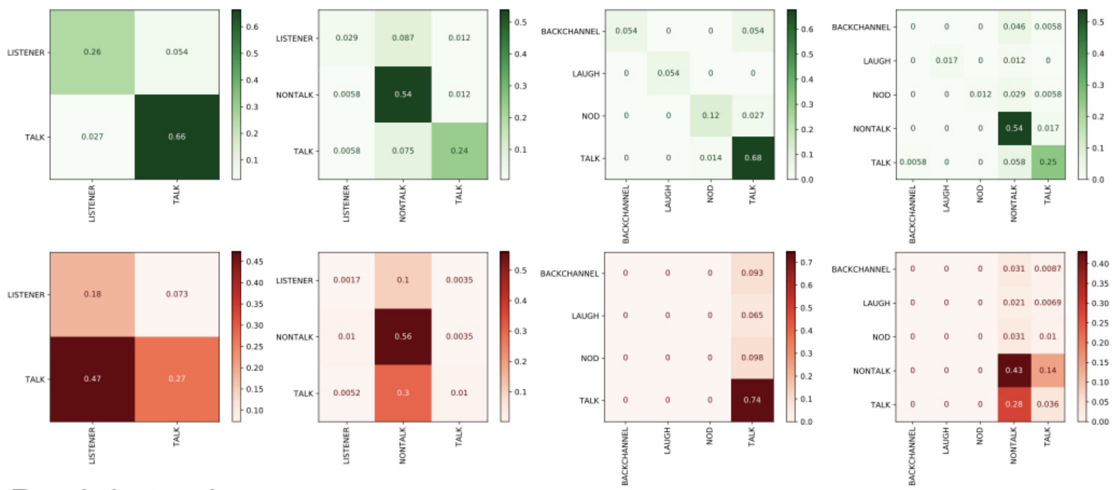
Participant C



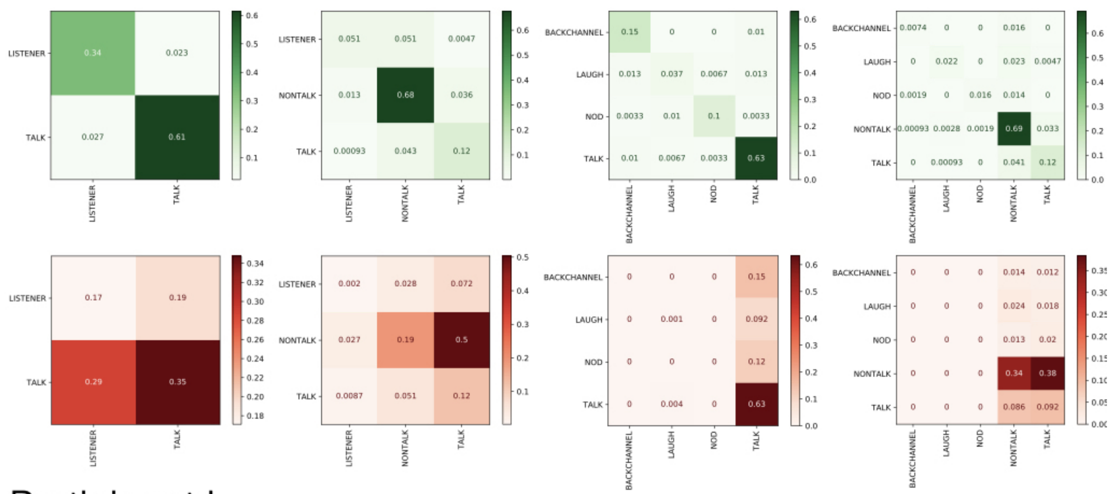
Participant E



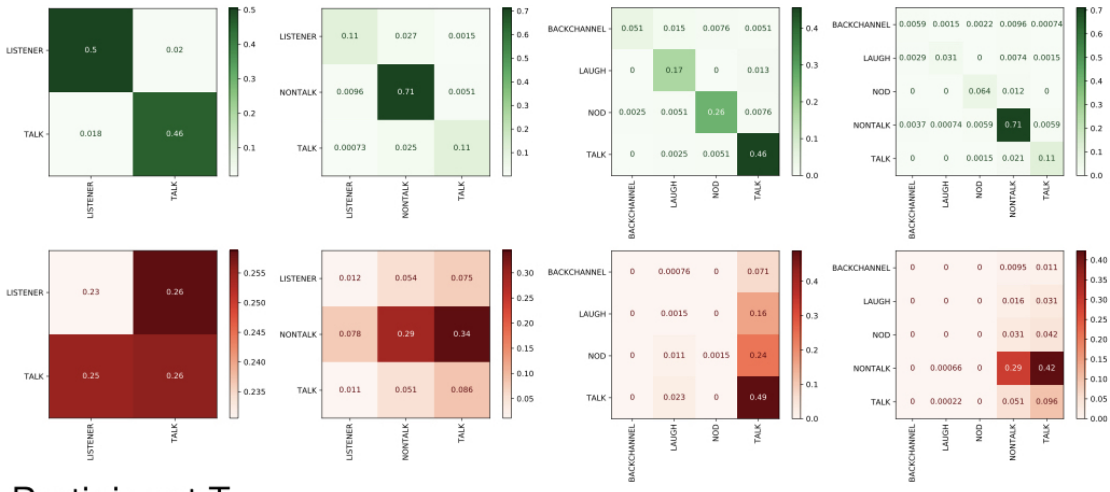
Participant H



Participant I

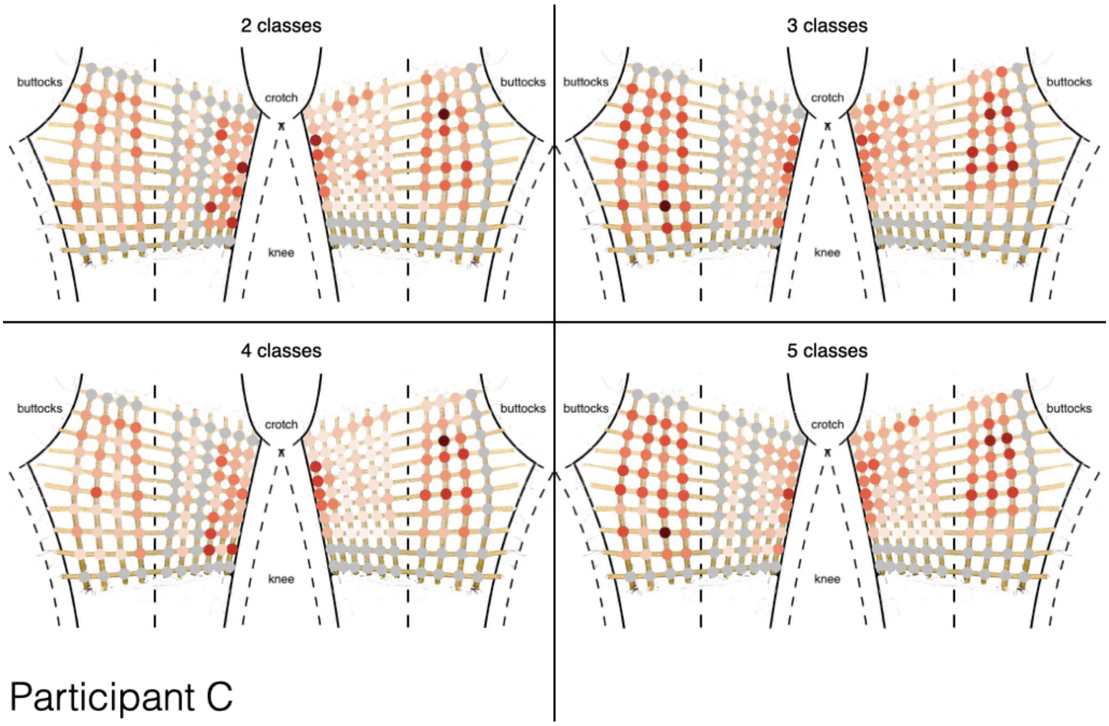


Participant L

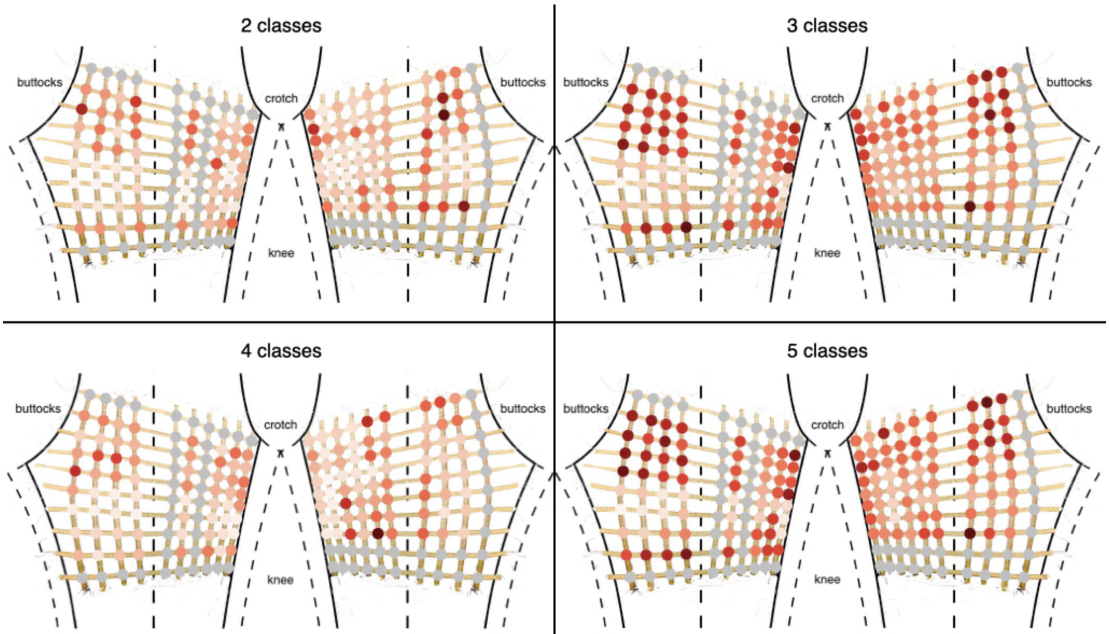


Participant T

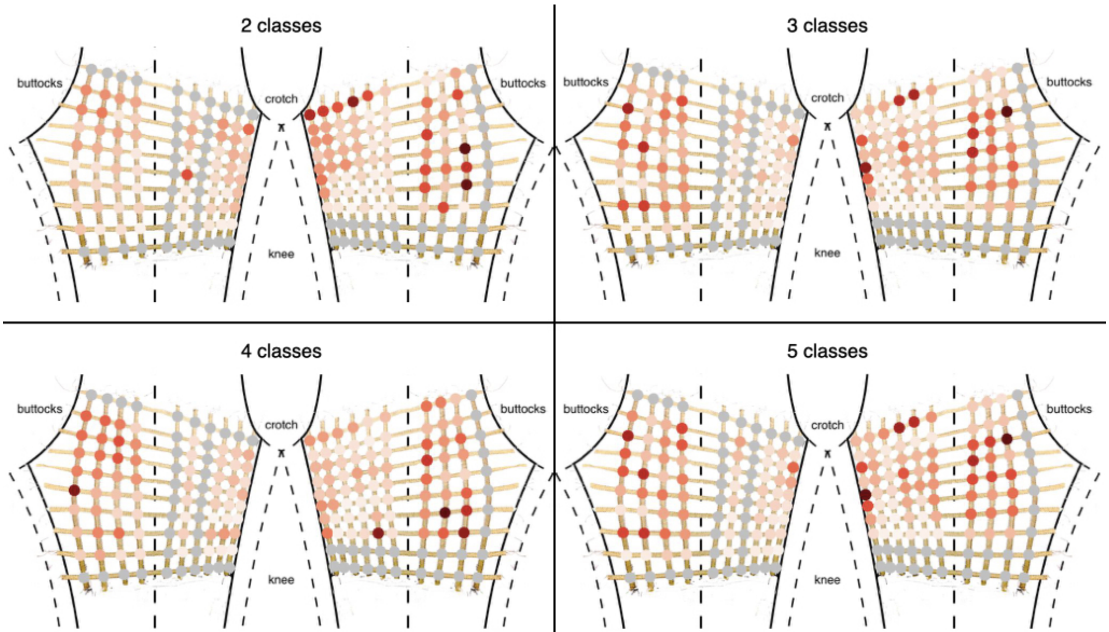
C.3.2 Feature Importance



Participant C



Participant E



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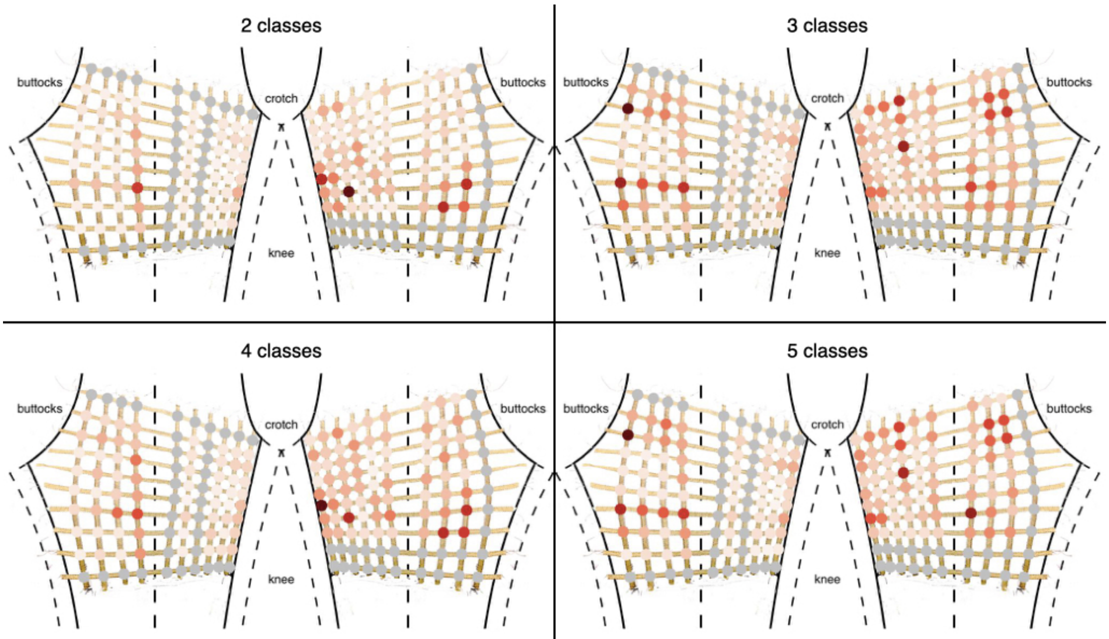
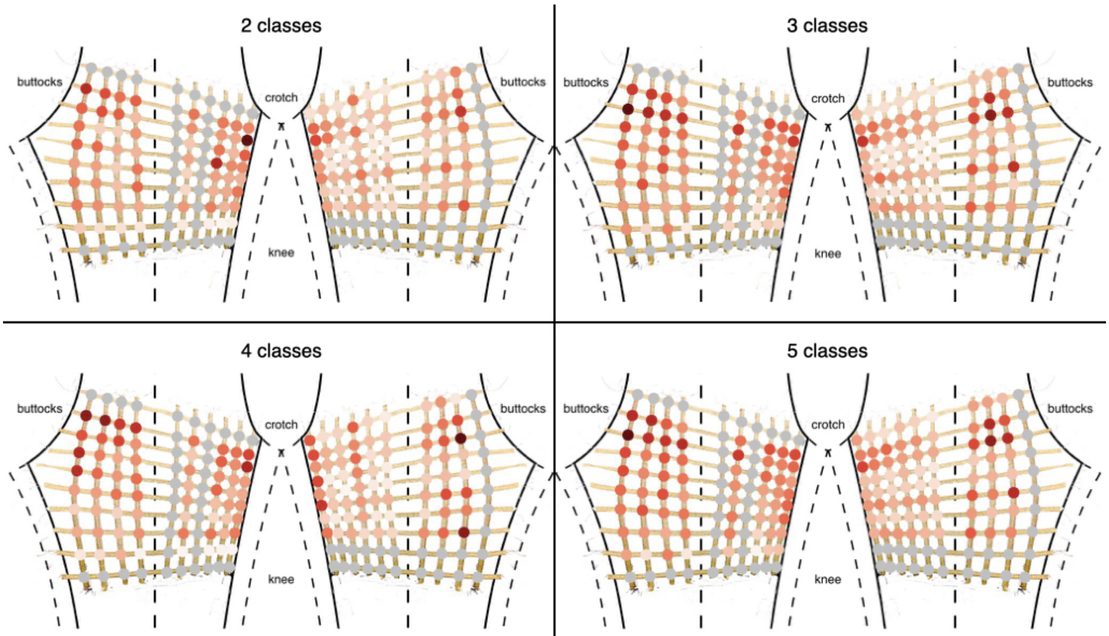
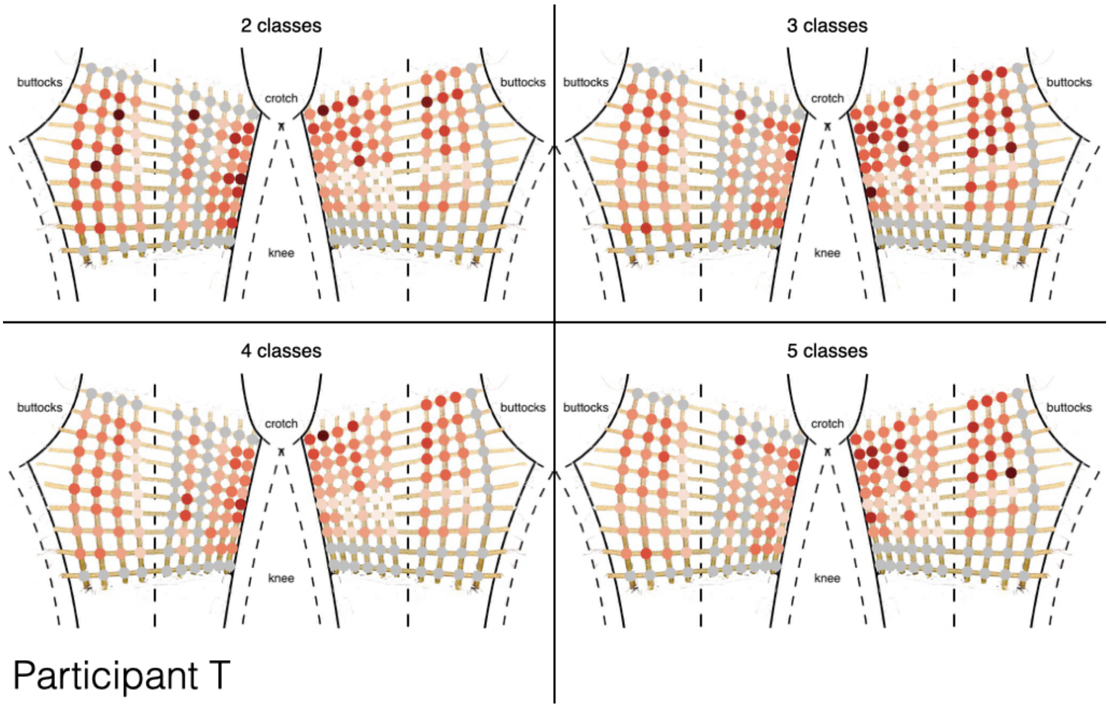


Participant I



Participant L



Participant T

Appendix D

Chapter 6 Additional Material

D.1 Factor Analysis

D.1.1 Total Variance Explained

Total Variance Explained						
	Initial Eigenvalues	Extraction Sums of Squared Loadings				
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	55.151	34.255	34.255	55.151	34.255	34.255
2	36.034	22.381	56.637	36.034	22.381	56.637
3	23.190	14.404	71.041	23.190	14.404	71.041
4	11.958	7.427	78.468	11.958	7.427	78.468
5	8.823	5.480	83.947	8.823	5.480	83.947
6	6.055	3.761	87.709	6.055	3.761	87.709
7	3.444	2.139	89.848	3.444	2.139	89.848
8	2.613	1.623	91.470	2.613	1.623	91.470
9	2.408	1.495	92.966	2.408	1.495	92.966
10	1.352	0.840	93.806	1.352	0.840	93.806
11	0.967	0.601	94.406			
12	0.784	0.487	94.893			
13	0.746	0.463	95.357			
14	0.717	0.445	95.802			
15	0.658	0.409	96.210			
16	0.530	0.329	96.540			
17	0.460	0.286	96.825			
18	0.423	0.263	97.088			
19	0.363	0.226	97.313			
20	0.334	0.208	97.521			
21	0.307	0.191	97.712			
22	0.279	0.173	97.885			
23	0.270	0.167	98.053			
24	0.226	0.141	98.193			
25	0.199	0.123	98.317			
26	0.179	0.111	98.428			
27	0.163	0.101	98.529			
28	0.158	0.098	98.628			
29	0.143	0.089	98.717			
30	0.130	0.081	98.798			
31	0.126	0.078	98.876			

The spreadsheet above shows 31 components yielded from the Factor Analysis, with the first 9 accounting for 94.218% of the total variance, and the remaining covering a total of 98.876% together, with components 11 - 31 only accounting for less than 1% of the variance each.

D.1.2 Component Matrix

Below are further results of the Factor Analysis conducted in Chapter 6. The analysis yielded 9 components accounting for 94.218% of variance - listed as columns in the matrix. The rows present the individual sensors of the textile sensor matrix - 165 in total (after removing faulty and broken sensors).

L stands for left, R for right leg. The numbers correspond to the position of the sensor on the leg: numbers 20-30 correspond to the second row above the knee, 90-100 to the top row around the buttocks and crotch area, running from bottom to buttocks. 21 would be positioned on the top inner leg, 30 on the back inner leg, running across the outer side from front to back.

Component Matrix									
Sensor Number	Component								
	1	2	3	4	5	6	7	8	9
L21	0.836	-0.207	0.289	0.022	0.073	-0.179	-0.225	-0.012	-0.055
L22	-0.514	-0.427	0.088	0.503	0.364	0.194	-0.115	0.040	-0.095
L23	0.134	-0.811	0.142	0.474	-0.084	-0.038	-0.006	0.010	-0.040
L24	0.224	-0.836	0.008	0.459	-0.018	0.024	0.030	-0.019	-0.100
L25	-0.214	-0.667	-0.087	0.517	0.092	0.335	-0.217	-0.039	0.053
L27	0.868	-0.311	-0.009	0.186	0.154	0.056	-0.149	0.077	-0.011
L28	0.532	0.403	0.656	-0.061	0.137	-0.020	-0.246	0.010	0.034
L29	0.476	0.407	0.665	-0.097	0.010	0.018	-0.307	0.006	0.054
L30	0.231	0.214	0.817	0.112	-0.090	0.228	-0.283	0.028	0.050
L31	-0.020	-0.114	0.653	0.303	0.577	-0.125	-0.128	0.136	-0.102
L32	-0.777	-0.062	-0.105	0.295	0.425	0.187	-0.093	0.060	0.034
L33	0.124	-0.634	-0.443	0.327	0.394	0.021	-0.007	0.004	0.101
L34	0.364	-0.769	-0.298	0.354	0.121	-0.038	-0.063	0.021	0.032
L35	0.329	-0.386	-0.697	0.054	0.355	0.046	-0.146	-0.002	0.048
L37	0.760	-0.197	-0.279	0.120	0.418	0.092	-0.228	0.126	0.024
L38	0.404	0.373	0.635	0.010	0.489	-0.024	-0.081	0.062	-0.017
L39	0.324	0.168	0.879	0.144	0.179	-0.042	-0.136	0.047	-0.030
L40	0.554	-0.183	0.705	0.249	0.201	0.017	-0.101	0.041	-0.083
L41	0.431	-0.138	0.817	0.209	0.118	-0.104	0.008	-0.009	-0.164
L42	0.242	0.420	0.569	0.174	0.508	-0.117	-0.074	0.060	0.162
L43	0.852	-0.264	-0.124	0.076	0.279	-0.081	0.037	-0.034	0.149
L44	0.739	-0.399	0.342	0.314	0.075	-0.080	-0.022	-0.011	0.070
L45	0.637	-0.611	-0.268	0.192	-0.117	0.189	-0.084	-0.049	0.037
L47	0.624	0.002	-0.312	0.087	0.488	0.259	-0.310	0.170	0.059
L48	0.445	0.143	0.829	0.136	0.016	0.184	-0.035	-0.053	-0.109
L49	0.470	0.261	0.687	0.015	0.164	0.284	-0.116	-0.076	-0.154
L50	0.490	-0.150	0.655	0.197	0.080	0.325	-0.057	-0.082	-0.209
L51	0.135	0.341	0.413	-0.149	0.732	-0.058	0.189	0.075	-0.210
L52	0.660	-0.041	-0.223	0.078	0.621	-0.011	0.087	0.004	0.053
L53	0.878	0.023	-0.283	-0.185	0.175	-0.065	0.058	-0.055	0.176
L54	0.884	-0.053	0.257	0.128	0.191	0.072	0.031	-0.117	0.102
L55	0.082	-0.473	-0.667	0.163	0.218	0.435	-0.020	-0.080	-0.007
L57	0.833	-0.252	-0.274	0.080	0.280	0.099	-0.116	0.094	0.009
L58	0.560	0.489	0.159	-0.281	0.397	0.292	0.171	-0.072	-0.175
L59	0.538	0.545	0.269	-0.350	0.198	0.328	0.069	-0.115	-0.161
L60	0.669	0.163	0.076	-0.229	0.168	0.521	0.122	-0.167	-0.232
L61	0.604	0.348	0.013	-0.369	0.533	-0.091	0.152	0.019	-0.103
L62	0.778	-0.451	0.243	0.279	0.084	-0.088	0.078	-0.012	0.002
L63	0.885	0.003	-0.200	-0.141	0.169	-0.054	0.116	-0.088	0.249
L64	0.914	-0.182	0.014	0.088	0.153	-0.011	0.085	-0.126	0.166
L65	0.245	-0.446	-0.735	0.065	0.009	0.397	-0.036	-0.093	0.068
L67	0.891	-0.295	-0.210	0.067	0.079	0.076	-0.080	0.047	0.015
L68	0.647	0.457	0.139	-0.338	0.237	0.245	0.240	-0.089	-0.069
L69	0.029	0.717	0.004	-0.440	0.290	0.354	0.167	-0.028	0.024
L70	-0.032	0.401	-0.167	-0.319	0.095	0.740	0.191	-0.081	-0.038
L71	0.630	0.257	0.445	-0.252	0.158	-0.136	0.353	-0.001	0.021
L72	0.592	-0.616	0.089	0.374	0.061	-0.092	0.195	-0.020	0.091
L73	0.446	-0.323	0.446	0.369	0.187	-0.003	0.357	-0.088	0.349
L74	0.824	-0.379	0.018	0.170	0.087	-0.102	0.176	-0.088	0.172
L75	0.251	-0.620	-0.517	0.202	-0.131	0.376	0.044	-0.107	0.130
L77	0.752	-0.229	-0.478	-0.006	0.303	0.017	-0.010	0.089	0.039
L78	0.755	0.104	0.519	-0.100	-0.091	0.064	0.261	-0.071	0.002
L79	0.530	0.295	0.506	-0.250	-0.220	0.015	0.302	-0.083	0.127
L80	0.561	0.087	0.583	-0.069	-0.301	0.175	0.313	-0.004	0.069
L81	-0.317	0.371	0.817	0.096	0.150	-0.036	0.076	0.098	0.020
L82	-0.351	-0.153	0.717	0.523	0.090	0.043	0.045	0.054	0.106
L83	-0.091	-0.087	0.804	0.439	-0.014	0.106	0.103	-0.019	0.279
L84	0.351	0.207	0.797	0.250	0.020	0.049	0.007	-0.059	0.214
L85	0.127	-0.586	-0.177	0.339	-0.274	0.505	-0.029	-0.064	0.204
L87	0.782	-0.164	-0.394	0.006	0.215	0.086	-0.070	0.185	0.076
L88	0.069	0.203	0.909	0.105	-0.201	0.087	0.119	0.034	-0.014
L89	-0.284	0.129	0.848	0.253	-0.224	0.067	0.055	0.122	0.011
L90	-0.257	0.147	0.871	0.241	-0.180	0.101	0.035	0.106	-0.005
R21	-0.178	0.716	-0.623	-0.021	0.146	0.074	0.039	0.142	0.047
R22	0.156	0.876	-0.331	0.132	0.139	-0.136	-0.053	-0.098	0.011
R23	-0.013	0.828	-0.364	0.298	0.150	-0.184	-0.002	-0.115	-0.051

1

R24	-0.206	0.741	-0.589	0.133	0.022	0.129	0.026	0.128	0.016
R25	-0.026	0.847	-0.436	0.228	-0.099	0.103	-0.027	0.018	0.020
R27	0.191	0.826	0.381	-0.127	0.079	-0.055	-0.062	0.143	0.090
R28	0.057	0.955	0.031	0.014	-0.032	0.100	-0.043	0.164	0.077
R29	0.050	0.902	-0.348	-0.023	0.034	0.077	0.005	0.178	0.053
R30	0.681	-0.244	-0.510	0.267	-0.074	-0.126	0.082	0.181	-0.108
R31	0.453	0.585	0.543	-0.305	-0.095	0.031	-0.160	-0.020	0.112
R32	0.572	0.748	0.105	0.185	0.048	-0.213	-0.032	-0.015	-0.012
R33	0.198	0.921	0.010	0.263	0.048	-0.161	0.000	0.011	-0.007
R34	0.262	0.832	-0.131	0.309	-0.261	0.138	-0.016	0.148	0.022
R35	0.202	0.861	0.008	0.258	-0.305	0.160	-0.060	0.070	0.055
R37	0.599	0.621	0.444	-0.144	-0.026	-0.093	-0.089	0.056	0.046
R38	0.714	0.587	0.293	-0.016	-0.177	0.013	-0.083	0.062	0.034
R39	0.753	0.606	0.147	-0.063	-0.088	-0.069	-0.050	0.080	0.029
R40	0.589	-0.348	0.342	0.525	-0.172	0.021	0.061	0.138	-0.166
R41	0.679	0.479	-0.391	0.083	0.105	-0.167	0.111	0.217	-0.032
R42	0.562	0.410	-0.474	0.445	-0.014	-0.190	0.009	-0.131	-0.105
R43	0.002	0.757	-0.448	0.346	0.108	-0.171	-0.020	-0.191	-0.047
R44	0.119	0.740	-0.586	0.236	-0.045	0.060	0.057	0.131	-0.006
R45	-0.061	0.813	-0.522	0.201	0.010	0.038	-0.003	-0.009	0.018
R47	0.736	0.272	-0.488	0.092	-0.053	-0.056	0.067	0.192	-0.098
R48	0.744	0.175	-0.598	0.105	-0.081	-0.035	0.069	0.107	-0.073
R49	0.530	0.292	-0.770	-0.024	-0.078	0.082	0.031	0.087	-0.012
R50	0.609	-0.158	-0.702	0.165	-0.023	0.056	0.124	0.074	-0.137
R51	0.838	-0.041	-0.254	0.258	-0.326	0.047	0.049	0.074	-0.067
R52	0.651	0.149	-0.587	0.344	-0.098	-0.131	-0.014	-0.167	-0.082
R53	-0.056	0.733	-0.531	0.243	0.186	-0.163	-0.011	-0.190	-0.030
R54	0.276	0.682	-0.285	0.486	-0.259	0.117	0.060	0.170	-0.013
R55	-0.011	0.856	-0.405	0.188	-0.140	0.161	-0.038	0.002	0.063
R57	0.817	-0.236	-0.118	0.136	-0.377	0.142	-0.018	0.005	-0.107
R58	0.844	-0.228	0.044	0.213	-0.347	0.046	0.025	-0.042	-0.131
R59	0.887	-0.207	-0.109	0.118	-0.318	-0.002	0.006	-0.021	-0.075
R60	0.563	-0.580	-0.026	0.425	-0.279	0.090	0.111	-0.001	-0.180
R61	0.909	-0.052	-0.106	0.030	-0.332	0.011	-0.027	0.037	-0.020
R62	0.748	0.139	-0.465	0.272	-0.028	-0.255	-0.013	-0.173	-0.073
R63	-0.306	0.736	-0.072	0.449	0.147	-0.040	0.052	-0.234	-0.089
R64	0.250	0.799	-0.065	0.399	-0.261	0.106	-0.001	0.156	0.004
R65	0.074	0.941	-0.188	0.140	-0.133	0.110	-0.063	0.010	0.059
R67	0.851	0.012	0.288	-0.221	-0.234	0.009	-0.105	-0.018	-0.046
R68	0.724	0.084	0.617	-0.043	-0.245	-0.064	-0.088	-0.037	-0.023
R69	0.850	0.044	0.408	-0.121	-0.261	-0.070	-0.099	-0.043	-0.002
R70	0.569	-0.107	0.703	0.130	-0.275	0.050	-0.047	0.005	-0.057
R71	0.611	-0.481	-0.284	0.001	-0.280	-0.054	0.160	0.269	0.018
R72	0.820	-0.054	-0.310	0.242	-0.048	-0.322	0.015	-0.147	-0.074
R73	-0.368	0.601	0.203	0.530	0.119	-0.030	0.101	-0.201	-0.105
R74	0.034	0.851	-0.301	0.203	-0.184	0.185	0.024	0.170	0.059
R75	-0.018	0.927	-0.297	0.012	-0.028	0.090	-0.067	-0.020	0.076
R77	0.707	0.160	-0.187	-0.477	-0.091	-0.008	-0.078	0.113	-0.024
R78	0.557	0.053	0.713	-0.084	-0.277	-0.034	-0.023	0.108	-0.009
R79	0.875	0.037	-0.072	-0.348	-0.075	-0.156	0.031	0.103	0.043
R80	0.507	-0.393	-0.268	-0.248	0.205	-0.157	0.240	0.232	-0.008
R81	-0.677	0.089	0.344	0.524	0.050	0.106	0.146	0.123	0.033
R82	0.129	0.634	-0.080	0.579	-0.005	-0.130	-0.040	-0.303	0.028
R83	-0.199	0.693	0.099	0.581	0.040	-0.058	0.058	-0.256	-0.054
R84	-0.215	0.812	-0.091	0.487	0.005	0.020	0.058	0.014	0.037
R85	0.046	0.920	-0.143	0.230	0.002	0.000	-0.009	-0.068	0.094
R87	-0.763	-0.013	0.095	0.288	0.105	0.147	0.156	0.202	-0.050
R88	-0.697	-0.012	0.478	0.470	0.056	0.049	0.127	0.120	-0.046
R89	-0.755	0.047	0.383	0.395	0.182	0.001	0.154	0.156	-0.030
R90	-0.521	-0.441	-0.057	0.465	0.250	-0.112	0.270	0.262	-0.088
average	0.346507936	0.1504	0.04374	0.1354	0.0425	0.0415	0.0140	0.0148	0.0024
minimum	-0.777	-0.836	-0.770	-0.477	-0.377	-0.322	-0.310	-0.303	-0.232
maximum	0.914	0.955	0.909	0.581	0.732	0.740	0.357	0.269	0.349

2

D.2 Additional Notes of Posture Shifts Observations

PARTICIPANT 1 (Female) (session 3)
- just before speech, but only completed during speech (04.15; 05.26; 06.37; 12.38)
- or start posture change in last 2sec of speech, then finish posture change after finishing speech (finish speech during posture change), e.g. at 05.47 ; 06.51 ; 07.26
- elongated posture shift, completed 4sec before talk (05.00 - 05.15 / 16.24-16.28)
- overlap with 2sec before speech: 07.06 ;
- overlap with 2sec after speech: 07.20 ; 14.43
- posture shift 4sec before speech: 07.23
- 08.55-08.57: start in scope of 2sec before speech, but then speech utterance only very brief, and posture change completes after stopped talking (so posture change before, during and after speech at the same time)
- juliana often bounces legs in uncomfortable situations, often slightly versetzt mit speech (in both directions)
- 09.13: during backchannel, 3sec after speech
- 09.19 without any talk relation, 10.02 , 11.04, 11.51, 12.55 (but still in response to someone else, sometimes in relation with laughter, backchannels, nodding, etc)
- 09.32 with laughter aligned
- during talk, start of posture shift at very beginning of talk: 13.14
- during middle of talk: 15.37 ; 16.38
- start posture change 3sec before speech: 13.58 ;
- other observations: fewer gross body postures after a few mins into the conversation: then moving from gross to subtle posture shifts (confirming knapp&wiemann?)
- she sometimes seem to perform postural changes in response to disagreement to speaker

PARTICIPANT 2 (Male) (session 7)
- more fidgeting than gross movement, and more bobbing up and down
- right after talk (within 2sec): 08.27, 09.37 ; 11.15 ; 13.09 ; 13.31 ; 15.27 ; 17.44; 17.57; 22.05
- after talk with slight delay: 12.09 ; 12.33 ; 15.14 ; 15.59; 18.55 ; 20.04
- right before talk (into 2sec frame): 13.20 ; 20.40
- before talk and into talk: 20.50
- without talk relation: 08.39; 10.58 ; 12.21 + 12.54 (with laughter) ; 14.43 ; 19.21 ; 19.27 ; 19.31; 20.28; 22.16
- 5sec before talk: 09.13 ; 13.48 ; 15.00 ; 19.56
- during talk: 09.34 ; 15.54 ; 17.24
- at beginning of talk, then into talk: 11.38
- 3sec after talk: 11.56 ; 20.16
- 3sec before talk: 18.41
- in between two talk utterances: 17.51

PARTICIPANT 3 (Female) (session 7)
- 3sec after talk: 07.38 ; 21.27
- 3sec before talk: 13.54; 16.09
- during talk: 07.34; 20.33
- in between talk: 8.13 ; 12.26
- during backchannel: 08.20 (small shift) ; 09.01;
- just before talk (within 2sec window): 09.36; 14.50; 19.12
- just before talk and during beginning of talk: 18.04; 18.07
- immediately after talk (with 2sec window): 12.58; 18.27 ; 19.20
- during talk until end of utterance: 09.38
- end of talk until right after talk: 09.55 ;
- beginning with talk: 10.01; 12.16 ; 18.56 ; 21.16
- after 2sec of talk: 10.12;
- without talk: 10.29 ; 11.46; 15.54 ; 20.04; 21.10
- right before, during and until after talk: 11.11; 12.51
- some posture shifts seem related to extensive gesturing (e.g.12.20)
- sometimes during listening without any movement, and then in preparation of talk posture shift
- in response to speaker's posture shift (15.54), but doesn't perform any other response behaviour
- shifts posture in preparation of talk, especially when talk utterance becomes very engaged (with lots of gesturing and longer utterance — delivering a statement rather than an answer or so) —> posture shifts occur not only in response to what a speaker may have said, but also in response to speakers' movement.

PARTICIPANT 4 (Male) (session 6)
- without talk (when other speaker starts utterance): 04.03 ; 07.28 ; 08.41 ; 13.20
- between talk: 06.23; 10.36 ; 12.25
- just after talk: 07.01 ; 10.20 ;
- 3sec before talk: 08.26; 09.38 ; 10.09
- delayed after talk: 17.49
- during talk 11.14; 14.35 ; 14.37 ; 15.30 (until end of talk) ; 18.36 ; 18.38
- just before talk, into talk: 11.54
- end of talk, goes into pause between talks 12.48; 13.38 ; 14.24 ; 16.26
- end of talk: 17.02 ; 18.33

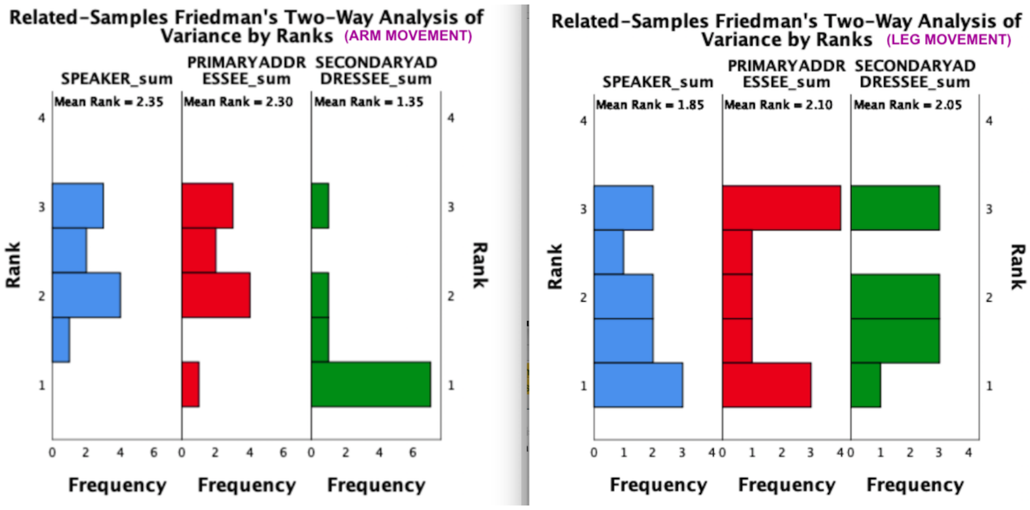
PARTICIPANT 5 (Female) (session 1)
- ca 3sec before talk (no overlap wth 2sec window): 04.49; 13.22 (with overlap of 2sec window); 18.36 (with overlap of 2sec window);
- before talk within 2sec window: 04.52
- just before talk, into talk: 07.22
- during talk: 07.22 ;07.35 ; 12.57
- before, during and after talk: 16.14
- in between and during talk: 04.55
- in synchrony with laughter often posture shifts performed 05.32; 06.01; 08.35; 10.07; 10.51 only feet shift posture ; 11.38 ; 13.16
- active listener / without talk: 06.37 ; 08.23; 14.03; 14.36; 15.06; 15.27; 17.27
- at end within talk: 07.01
- after talk within 2sec window: 09.30 ; 09.43; 11.21; 16.04 ; 18.44
- after talk at end + outside 2sec window: 10.47
- posture shifts seem to occur simultaneously or with a slight timely shift with other active listener behaviours, such as backchannels, laughter or nodding, or represent an active non-verbal listener behaviour themselves.
- she has more short postural shifts, that are mostly performed by trunk movement, but are still marked “small but obiovus”
- 08.02-08.07: starts during talk, lasts until end, in between and into new talk utterance a bit (bridging gaps of talks)
- some postural shifts between talks appear to bridge speaker pauses: starting towards the end of an utterance, being performed fully when speaker stopped, but only finish when speaker has taken up talking again (if no-one else in the meantime takes the turn)
- with beginning of talk, continuing after talk: 13.11
- before starting new conversation topic: very obvious posture change: both torso and lower body change of position
- sometimes also when switching from inattentive to attentive listener (just before or at start of e.g.nodding, see 19.01)

PARTICIPANT 6 (Female) (session 6)
- during talk / end of talk 05.31; 05.44;
- during talk 05.51; 07.01
- between talks: 07.11 -07.15
- end of talk - after talk: 09.16 ; 17.11; 18.44
- just after talk (within 2ec window): 13.33 ; 14.10; 14.43 ; 15.22; 16.58
- 3sec after talk: 09.43 12.44; 13.36; 17.46; 21.15
- 3sec before talk: 14.02; 17.28
- just before talk: 17.03; 17.07
- sometimes posture shift and fidgeting during talk, and then stops when talk stops, too (in very overt fidgeting movements, that has been marked as postural shifts, too)
- movement itself sometimes appears as a bit bouncy: back-forth-back-forth - each time less overt / less energetic.
- during talk, posture shifts sometimes attempt to punctuate speech (e.g. 09.32 “oh, i’m just on the brink”)
- no talk / active listener (response?) 11.13; 12.11; 13.39;15.37; 16.25; 16.29 ; 17.25; 19.42
- around 10.02 nodding become more embodied when closer to next turn

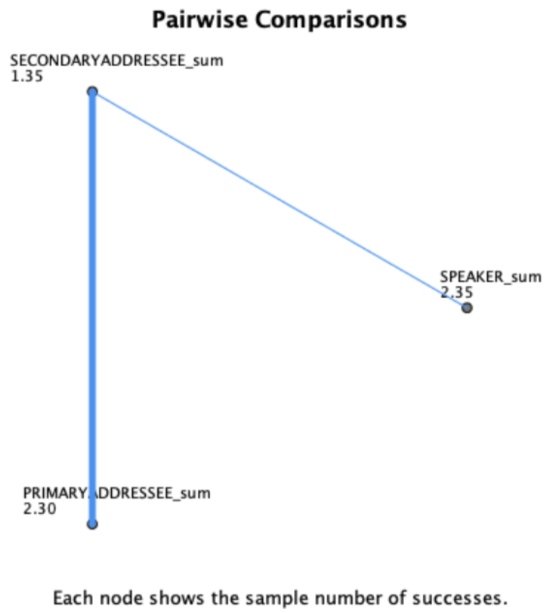
D.3 Plots of Non-Parametric Tests for Peak Detection

D.3.1 Participant Role: Friedmans Related Samples Two-Way Analysis

A comparison of Arm and Leg Movement results of the Two-Way Analysis of Variance by Ranks):

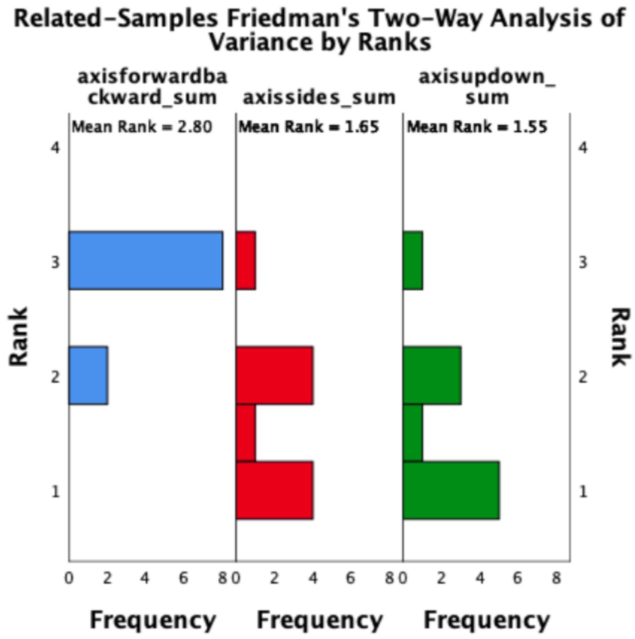


D.3.2 Participant Role: Pairwise Comparison

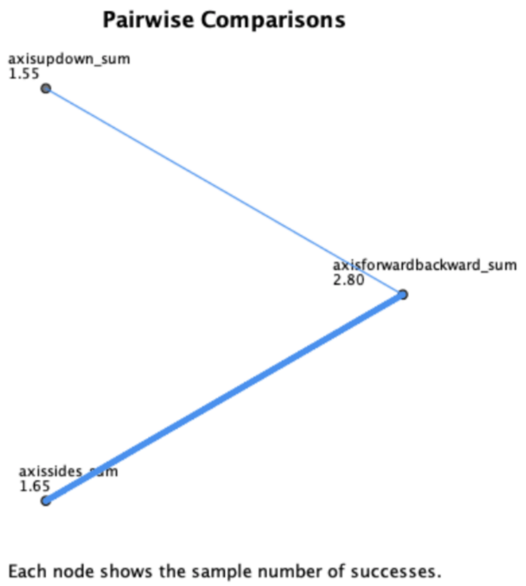


D.3.3 Axis Movement: Friedmans Related Samples Two-Way Analysis

Results of the Two-Way Analysis of Variance by Ranks:

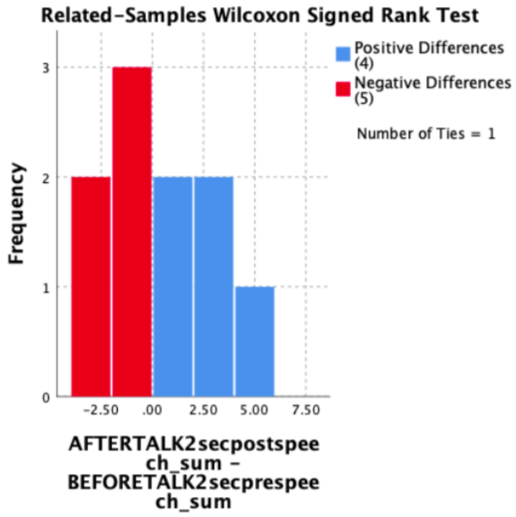


D.3.4 Axis Movement: Pairwise Comparison



D.3.5 Preparatory Movement

Results of the Related Samples Wilcoxon Signed Rank Test. Comparison of counts of peak movements 2 seconds before and 2 seconds after speaking for each participant.


Related-Samples Wilcoxon Signed Rank Test
Positive Differences (4)
Negative Differences (5)
Number of Ties = 1
Frequency
0
1
2
3
-2.50
.00
2.50
5.00
7.50
AFTERTALK2secpostspeech_sum - BEFORETALK2secprespeech_sum

Appendix E

Chapter 7 Additional Material

E.1 Questions to Participants on Prototype 1

The following questions were asked to all 42 participants that took part in the study reported in Chapter 5. This short survey was carried out informally and as part of the study sessions, after the data recording had stopped and the trousers were taken off, during debriefing with participants. The questions were asked by the author and only handwritten notes were taken as a recording of the given answers. The questions were:

- *Did you feel any restriction in movement, discomfort or similar when wearing the trousers?*
- *Did you feel that the trousers modified your movement in any way? Did you adjust any movement or positions consciously because of the trousers?*
- *Was there anything you were concerned about when wearing, taking off or putting on the trousers?*

E.2 Notes of Participant Comments on Prototype 2

The following informal notes of feedback were taken by the author and by hand (written into a paper notebook) during the interactions with the 10 participants who tried the second prototypes of the sensing trousers:

Participant 1:

- felt 'good' and 'casually dressed'
- said would wear this design also outside of lab context
- suggested trousers as an item of home-wear
- liked design and touch of fabric
- appeared to be straight forward / not hesitant when taking and putting on the trousers (no obvious careful handling – when asked afterwards, replied that it was because "they didn't look different or as if I need to be careful somehow")

- had no style-related preference between the new and old prototype
- commented on the 'shiny' surface of the conductive fabric, and that it was "very light and summery, comfortable on the skin"
- felt no restriction when performing postures

Participant 2:

- said it was easy to put on and take off trousers
- no observed hesitation when putting trousers on and taking them off, either
- no reported feeling of wearing something 'electronic' or 'smart'
- thought paracords were meant to be on outside and added as decorative material ("would be cool when having them as fringes, could be nice when moving around or dancing")
- continued to perform standing postures and danced and did stretch exercises while still wearing the trousers (after the sitting posture task)
- said they felt better than first prototype
- said trousers feel comfortable and practical, would continue to wear them

Participant 3:

- feels light to wear, light-weight smooth fabric
- said it feels 'nice' and comfortable
- no concerns over movement
- noted they did not think about being able to rip something when handling the trousers
- said it could be fund to have the cords like fringes as part of design element
- liked it slightly more than the old trousers, commented on improved design

Participant 4:

- feels unfamiliar to wear (not their usual style of dressing)
- inspected trousers' inside before putting them on, but did not ask for assistance and was then "not really more careful" when putting trousers on and wearing them
- found touch of fabric nice
- said they may prefer this design over prototype 1, but could not remember the details of how they felt in previous study
- wouldn't know that sensors are integrated if not told (said it was the same with old prototype)

- trousers were tight when worn - this participant would have benefitted from a slightly larger size
- was surprised the resistive fabric can act as sensor layer ("looks like 'normal' leggings fabric")

Participant 5:

- was careful and hesitant when putting trousers on, but more confident when taking them off (after wearing them for the posture tasks)
- commented on touch of soft fabric, said it felt smooth and 'nice'
- wondered whether it would be better to have the fabric wires on the outside of the trousers
- trousers were a bit tight for this participant

Participant 6:

- feels comfortable and in style suitable for sports applications
- said it was nice to not feel electronics
- examined inside of trousers carefully before putting them on, but didn't seem concerned about wearing them
- felt not affected or restricted in movement, no conscious hesitation or caution when performing posture tasks
- had no preference between old and new trousers, said it would depend on occasion or weather as the only notable difference remembered was the thickness of the fabric

Participant 7:

- would wear trousers for themselves
- was fast in putting them on (no obvious difference in handling the trousers)
- "was all good" ; "would wear them out for a gig, to go dancing"
- said it was easy to wear, take off and put on the trousers
- also commented on soft touch of fabric choice, also conductive and resistive fabric layer
- said they felt 'free' (not restricted) in moving around

Participant 8:

- liked the design of the trousers ("feels good, easy to wear")
- no concerns about performing postures, did not appear restricted or affected in their natural postural movement

- said it felt very comfortable to wear both in style and feel of fabric
- preferred it over the old trousers (prototype 1), but noted that in old trousers, they were not aware of the wiring while here they could see the wires (cords)

Participant 9:

- was first hesitant about how to put trousers on, asked where wires should go
- was then also slow when putting them on, but faster, less hesitant and less careful when taking them off
- noted that after being reassured trousers were robust and should be treated as 'normal' trousers, the handling was easier and they felt more confident
- commented on high wearing comfort ("feels cozy and soft")

Participant 10:

- this participant would probably have needed a smaller size
- also noted that if trousers were tighter, they might have been bothered by wires pressing against skin or affecting the silhouette of the legs
- not sure if would wear this outside lab situation because of the above wire related concern
- also suggested that "maybe it would be better if the wires were outside?"
- asked about the effect of conductive fabric in touch with skin
- said "overall, they [the trousers] are comfortable and feel soft and nice"

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