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# Design of Cognitive Interfaces for Personal Informatics Feedback

Camilla Birgitte Falk Jensen

DTU

# Summary

The emergence of embedded low-cost sensors in mobile devices allows us to capture unprecedented data about human behavior. Hence personal informatics systems are becoming an integrated part of our everyday life: Capturing various aspects from our health, work-life, to economic balance, and utility consumption. All of which are aimed to provide knowledge of oneself, on which we can reflect. Many personal informatics systems are characterized by mainly focusing on collecting and analyzing data, rather than translating the data into meaningful feedback. This dissertation presents challenges related to personal informatics systems, and propose an approach to design cognitive interfaces, which considers both users' motivations, needs, and goals.

In this thesis I propose a new personal informatics framework, *the feedback loop*, which incorporates lean agile design principles. Including hierarchical modeling of goals, activities, and tasks to create minimal viable products. While considering how *micro-interactions* based on an understanding of data, couples with user needs and the context they appear in, can contribute to creating cognitive interfaces. Designing cognitive interfaces requires a focus on translating data into meaningful feedback, which the users can reflect on in order to gain insights. Thus I present tools such as personalized baselines and thresholds to enable reflection, while creating personalized goals, scenarios, trade-offs in order to provide actionable feedback, which can help users to adjust their behavior. Although feedback can be provided in many different ways, it basically consists of audio, visual, and haptic components, which combined may reinforce each other to support the underlying interaction.

The papers included in this thesis cover selected parts of *the feedback loop*. For instance, examining emotional responses to pleasant and unpleasant media content from brain activity, reveals the large amount of data and extensive analysis required to apply this to future personal informatics systems. In addition we analyse challenges related to temporal aspects of *the feedback loop*, when users attempt to self-regulate their brain activity based on a real-time feedback. This leads to identification of underlying audio, visual and haptic feedback components, which combined may support the underlying interaction within personal informatics. And with the emerging availability of sensor packed wearable devices, haptic feedback may become an inherent part of personal informatics systems, which could enhance the interaction based visual feedback.

# Resume

Udviklingen af billige mobile sensor teknologier giver os mulighed for at indsamle hidtil usete mængder data om menneskelig adfærd. Derved er *personal informatics* systemer ved at blive en integreret del af vores hverdag, med opsamling af data om forskellige aspekter fra sundhed, arbejdsliv til økonomisk balance, og ressource forbrug. Dette har til formål at opbygge viden om en selv, hvorpå vi kan reflektere. Mange *personal informatics* systemer er karakteriseret ved primært at fokusere på at indsamle og analysere data, snarere end at oversætte data til meningsfuld feedback. Denne afhandling præsenterer udfordringer i forbindelse med *personal informatics* systemer, og foreslår en tilgang til design af kognitive grænseflader, som omfatter brugernes motivationer, behov og mål.

I denne afhandling opstiller jeg en ny ramme for *personal informatics* systemer, *the feedback loop*, som inkorporerer lean agile design principper. Heriblandt hierarkisk modellering af bruger behov relateret til mål, aktiviteter og opgaver som basis for design af *minimal viable products*. Hvis *mikro-interaktioner* baseres på en forståelse af data, brugernes behov og den sammenhæng de optræder i, kan de bidrage til at skabe kognitive grænseflader. Design af kognitive grænseflader kræver fokus på at oversætte data til meningsfyldt feedback, som brugerne kan reflektere over, og få indsigt i. Således præsenterer jeg værktøjer såsom personlige referencepunkter og grænseværdier, der muliggøre refleksion og opfyldelse af personlige mål. Scenarier, afvejninger, og hensyn til konteksten medfører at feedbacken bliver handlingsorienteret og dermed kan hjælpe brugerne til at justere deres adfærd. På trods af at feedback kan blive præsenteret på mange forskellige måder, består de grundlæggende af auditive-, visuelle- og haptiske komponenter, der kan kombineres og derved forstærke hinanden og understøtte den underlig-

gende interaktion.

Artiklerne der er inkluderet i denne afhandling illustrerer aspekter af *the feedback loop*. Heriblandt undersøges følelsesmæssige reaktioner på behagelige og ubehagelige billeder ud fra hjerneaktivitet, hvilket illustrerer den omfattende data indsamling og analyse som kræves for at dette kan anvendes i fremtidige *personal informatics* systemer. Derudover analysere vi udfordringerne forbundet med tidsmæssige aspekter af *the feedback loop*, når brugere forsøger at selvregulere deres hjerneaktivitet baseret på et *real-time feedback*. Dette fører til identifikation af underlæggende auditive, visuelle og haptiske feedback-komponenter, der på tværs af modaliteter kan understøtte den underliggende samspil med personal informatics systemer. Med udviklingen af mobile sensor teknologier, *wearables*, vil haptisk feedback kunne blive en integreret del af *personal informatics* systemer, hvilket kan supplere interaktion med den visuelle feedback.

# Preface

This thesis was prepared at the Department of Applied Mathematics and Computer Science in the Cognitive Systems Section at the Technical University of Denmark in fulfillment of the requirements for acquiring a Ph.D. degree in engineering.

The thesis consists of an extensive summary report and a collection of five research papers written during the period from August 2012 to August 2015.

Lyngby, 15-August-2015

Camilla Birgitte Falk Jensen

# List of Publications

## Papers included in this thesis

A  Arkadiusz Stopczynski, Carsten Stahlhut, Michael Kai Petersen, Jakob Eg Larsen, **Camilla Birgitte Falk Jensen**, Marieta Georgieva Ivanova, Tobias S Andersen, and Lars Kai Hansen. Smartphones as pocketable labs: Visions for mobile brain imaging and neurofeedback. *International journal of psychophysiology*, 91(1):54–66, 2014.

B  **Camilla Birgitte Falk Jensen**, Michael Kai Petersen, and Jakob Eg Larsen. Emotional responses as independent components in EEG. In *Cognitive Information Processing (CIP), 2014 4th International Workshop on*, pages 1–6. IEEE, 2014.change

C  **Camilla Birgitte Falk Jensen**, Michael Kai Petersen, Jakob Eg Larsen, Arkadiusz Stopczynski, Carsten Stahlhut, Marieta Georgieva Ivanova, Tobias Andersen, and Lars Kai Hansen. Spatio temporal media components for neurofeedback. In *Multimedia and Expo Workshops (ICMEW), 2013 IEEE International Conference on*, pages 1–6. IEEE, 2013.

D  Mohamad Eid, Georgios Korres, and **Camilla Birgitte Falk Jensen**. Soa thresholds for the perception of discrete/continuous tactile stimulation. In *Quality of Multimedia Experience (QoMEX), 2015 Seventh International Workshop on*. IEEE, 2015.

E  **Camilla Birgitte Falk Jensen**, Georgios Korres, Carsten Bartsch, and Mohamad Eid. Vibrotactile alarm system for reducing sleep inertia. *Affective Computing, IEEE Transactions on*, 2015. Submitted for publication.

# Additional publications not included in this thesis

F **Camilla Birgitte Falk Jensen**, Marieta G Ivanova, Arkadiusz Stopczynski, Michael Kai Petersen, Tobias Andersen, and Carsten Stahlhut. Training your brain on a tablet. In *34th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2012.

G **Camilla Birgitte Falk Jensen**, Michael Kai Petersen, and Jakob Eg Larsen. Differentiating emotional responses to images and words. In *34th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2014

H David Kristian Laundav, **Camilla Birgitte Falk Jensen**, Per Bækgaard, Michael Kai Petersen, and Jakob Eg Larsen. Your heart might give away your emotions. In *Multimedia and Expo Workshops (ICMEW), 2014 IEEE International Conference on*, pages 1–6. IEEE, 2014.

# Acknowledgements

# Contents

CHAPTER 1

# Introduction

Today, there is a personal informatics system for almost any aspect of a person's life, such as moods felt, health symptoms experienced, exercises performed, computer applications used, steps taken, electricity consumed, and hours slept. - Human behavior and our cognitive and emotional states have been studied in many domains, including psychology, sociology and neuroscience. With the technological development of sensors, mathematical models and increasing computational power, many aspects of our lives have become digital, making it easy to monitor everything from global systems such as transportation, utility usage, transactions to individual monitoring of everything from steps, heart rate, coffee consumption etc. Thus, data on human behavior, cognition and emotions are no longer reserved for the scientific community, but are steadily being applied in governmental planning and legislation; in business strategies for consumer products; and in the everyday life of individuals, who seek knowledge and insight into their behavior, physical and psychological being. This is a new era of personal informatics and cognitive systems, which poses challenges related to the design of interfaces enabling people to interact with their own data and gain insights.

## 1.1 Cognitive Interfaces for Personal Informatics

Personal informatics is a quantitative approach to obtaining knowledge of oneself on which we can reflect [Li et al., 2010]. The field of personal informatics stretches from information on physical and psychological conditions (heart rate, insulin levels, mood etc.) to behavioral information (gps location, shopping expenses, shopping preferences, music taste) or social connections (Facebook, conversation patterns and dominance, physical closeness to bluetooth visibility). In this thesis I will map out challenges related to personal informatics applications, and propose an approach to design interfaces and systems that not only fulfill users needs, but can be thought of as cognitive interfaces.

Cognition may be defined as the ability to infer meaning from perceptual sensory data by applying aspects of attention, memory, knowledge, and reasoning [Reisberg, 1997]. Thus we consider cognitive interfaces as systems that can translate data into meaningful *feedback*, systems that can potentially learn from user behavior and interaction, thereby becoming adaptable.

As in programming, where *'Hello World'* is the simplest version of an interface, one of the simplest cognitive interfaces of personal informatics is FitBit[1]. The step counter, FitBit, translates accelerometer data into steps, calories, stairs climbed and relates them to personal goals. Thereby the otherwise meaningless data becomes accessible and meaningful to the user. More advanced systems such as GN ReSound's hearing aids[2] use data streams from phones to adapt to the surrounding environment. These kinds of context-aware systems are sprouting up everywhere, as well as systems such as Google Now[3], which based on sensor data learns from our past patterns, habits, routines, and interactions. Google Now provides contextual updates, which it believes the user will be interested in, such as sports scores from his favorite team, and traffic information about his usual commute at the appropriate time. Thereby Google Now tries to accommodate user needs and desires.

Some of the most complex cognitive systems we have to date are able to comprehend semantic relations, such as IBM with Watson's[4] natural language processing. Watson is able to translate speech to text, interpret information (or questions), connect it to underlying concepts, make decisions (or provide answers) based on trade-off analysis or confidence levels. Although Watson is not

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[1]fitbit.com
[2]gnresound.dk
[3]google.com/landing/now/
[4]ibm.com/smarterplanet/us/en/ibmwatson/

a dedicated personal informatics system, it can quickly become one, by feeding it personal data, like health data.

I will focus on how we can incorporate ways of inferring meaning from data to make cognitive interfaces that can help people gain insights and make behavioral changes in their lives. In this process I will also touch upon emotional aspects, such as motivation, preferences and emotional responses. Emotions have traditionally been presented as the 'black sheep' of cognitive science, due to their ability to distort memories and because they can be the reason for irrational or illogical decisions [Reisberg, 1997]. However, recently, emotions have started to be viewed as inherently integrated with cognition, in the sense that emotions help adjust cognitive processes such as perception, attention, memory, experience, self-belief [Damasio, 2008]. Thus I will consider emotional aspects in relation to personal informatics and creating personalized interfaces.

## 1.2 Outline & Contributions

In addition to the current chapter, the thesis consists of six chapters, four published papers, and one submitted paper. The chapters ties together the contributions from the papers and relate them to the context of cognitive interfaces for personal informatics. In summary, the remainder of the thesis is structured as follows:

**Chapter 2** provides a foundation for the rest of the thesis, by defining personal informatics and describing the motivation of Quantified Self'ers, and the challenge between early adopters and users expecting a functional product. In addition the widespread personal informatics framework, Stage-based Model [Li et al., 2010] is described and its limitations are discussed. This provides motivation to establish a new personal informatics framework that accommodates lean agile design principles.

**Chapter 3** presents the framework, *the feedback loop*, build on an iterative loop, consisting of personal informatics stages including *scope*, *data collection*, *analysis & visualization*, *infer meaning*, *adjust behavior* and *outcome*. The framework incorporates lean agile design principles, such as a hierarchical modeling of high-level outcomes scoped in relation to activities and tasks, resulting in a minimal viable product. In addition it describes *micro-interactions* which contributes to the users experience: With triggers accommodating context and the users routines; rules consisting of algorithms

analyzing the data; and feedback, translating the data into meaningful information. If done right, these *micro-interactions* can make systems seem intelligent, and can be referred to as cognitive systems.

**Chapter 4** illustrate how personality traits can provide insights to users' motivations and preferences, which can help to scope a personal informatics system to a specific type of users. Personality traits reveal only overall attributes of large groups of people, while more individual preferences are needed for a truly personalized system. Additionally methods for extracting individual emotional responses to pleasant and unpleasant pictures from brain activity are examined. This stresses the amount of data analysis and extensive machine learning techniques required.

**Chapter 5** presents examples of visualizations of time-series data and how patterns, trends, and outliers of time-series data can be enhanced through visualizations. Furthermore we focus on how to infer meaning from data by use of baselines and thresholds, which can enable reflection. While making the feedback more actionable from personalized goals, presenting different scenarios and trade-offs and providing feedback at the appropriate time and in the right context in order to facilitate behavior change.

**Chapter 6** describes previous neurofeedback interfaces and demonstrates how the design of these interfaces can have an effect on the training outcome. This also illustrates the importance of considering the temporal aspects of feedback, especially when the feedback is provided in real-time and and changes are measured on a temporal level of milliseconds. The feedback interfaces are examined as a combination visual, audio or haptic components, which combined may reinforce each other can support the training activity.

**Chapter 7** centres on haptic feedback, since the development of sensor packed wearable devices, makes haptic feedback an obvious candidate for personal informatics systems. It examines how a few haptic components can be combined to create a perceived continuous motion. While a second experiment reveals how fast different haptic patterns are perceived and whether they are considered to be more pleasant or unpleasant than others. However if these haptic patterns should not only serve as a means for providing information, but also enhance the user experience and create associations of real touch interaction, they can benefit from other interface components, like the combination of visual and haptic feedback in the beating heart from Apple Watch.

**Chapter 8** discusses aspects touched upon in the thesis, their implications for further research. This includes considerations of temporal aspects of feedback, and the tight coupling between stages in the feedback loop. Also con-

siderations on how to access users high-level motivations, needs and goals, which are essential for scoping the personal informatics systems. Last a discussion on moving from classical scientific experimental setup into the everyday context of personal informatics systems.

**Chapter 9** summarizes the main contributions presented in this dissertation.

**Paper A Smartphones as pocketable labs: Visions for mobile brain imaging and neurofeedback**, presents the Smartphone Brain Scanner which is build from a consumer EEG headset connected to a mobile device. In addition the technical limitation of noise in a mobile environment are discussed, while prospects of using 3D source reconstruction techniques can aid these limitations. The paper presents a platform for developing EEG applications with real-time 3D source reconstruction. Examples of experiments carried out with the Smartphone Brain Scanner, including imagined finger-tapping, emotional responses from written words, and neurofeedback training.

**Paper B Emotional responses as independent components in EEG**, discusses the possibilities for discriminating emotional responses, with the perspective of applying these to create more personalized interfaces that adapt to our preferences in real-time. While hypothesizing that retrieval of emotional response in mobile usage scenarios could be enhanced through spatial filtering, we compared a standard electrode-based analysis against an approach based on independent component analysis.

**Paper C Spatio temporal media components for neurofeedback**, outline previous neurofeedback interfaces used to train the ability to self-regulate brain activity, which can be viewed as an example of a personal informatics system. The paper presents an experiment involving two different designs of neurofeedback training and demonstrates how these interfaces are constructed from audio, visual components and temporal settings, which appear to have a strong influence on the ability to control brain activity.

**Paper D SOA thresholds for the perception of discrete/continuous tactile stimulation**, sets out to identify the lower and upper threshold of the Stimulus Onset Asynchrony (SOA) for perceived continuous motions. The range between lower and upper thresholds can be utilized to create continuous stimulation of the skin, which can be perceived at moving at various speeds.

**Paper E Vibrotactile alarm system for reducing sleep inertia**, utilizes the haptic feedback in an alarm clock, eliminating the noise disturbance, when sharing the same sleeping space with roomates, spouses or family

members. The paper investigates the emotional ratings and attention level of attention towards different haptic patterns, in order to choose a haptic pattern that complements a pleasant awakening.

FORM OF THE PAGES.

TEMPERANCE.

Eat not to dulness: drink not to elevation.

|      | Sun. | M. | T. | W. | Th. | F. | S. |
|------|------|----|----|----|-----|----|----|
| Tem. |      |    |    |    |     |    |    |
| Sil. | *    | *  |    | *  |     | *  |    |
| Ord. | *    | *  | *  |    | *   | *  | *  |
| Res. |      | *  |    |    |     | *  |    |
| Fru. |      | *  |    |    |     | *  |    |
| Ind. |      |    | *  |    |     |    |    |
| Sinc.|      |    |    |    |     |    |    |
| Jus. |      |    |    |    |     |    |    |
| Mod. |      |    |    |    |     |    |    |
| Clea.|      |    |    |    |     |    |    |
| Tran.|      |    |    |    |     |    |    |
| Chas.|      |    |    |    |     |    |    |
| Hum. |      |    |    |    |     |    |    |

**Figure 2.1:** Benjamin Franklin's chart, showing his 13 virtues (Temperance, Silence, Order, Resolution, Frugality, Industry, Sincerity, Justice, Moderation, Cleanliness, Tranquility, Chastity, Humility) and the weekdays

deceit; think innocently and justly, and, if you speak, speak accordingly). While some of these would be easy to map down in a binary system, others would require evaluation of what is 'just' or how others would perceive a certain behavior, is it 'hurtful'? Even by evaluating his life in this orderly fashion, Benjamin admitted that he was never able to live the virtues perfectly, but felt he had become a better and happier man for having made the attempt[1]. Today we would refer to Benjamin Franklin as a *first mover* or *early adopter* within personal informatics.

EARLY ADOPTERS Terms like *early adopters*, *first movers* or *lead users* describe a group of people, who are the first to develop and use new technologies and applications. These innovators and visionaries are of special interest when developing new products, because they can help articulate behaviors, desires, and needs that might be dwelling in the rest of the population, but which are less visible and distinguishable. This user-driven development is commonly found in extreme sports, but within personal informatics, the *early adopters* are known as Quantified Self'ers. Thus we will take a closer look at this group of people - their motivation and needs, and the barriers they experience. We will examine how to create personal informatics systems that not only motivate but may adapt and become action-

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[1] artofmanliness.com/2008/06/01/the-virtuous-life-wrap-up/
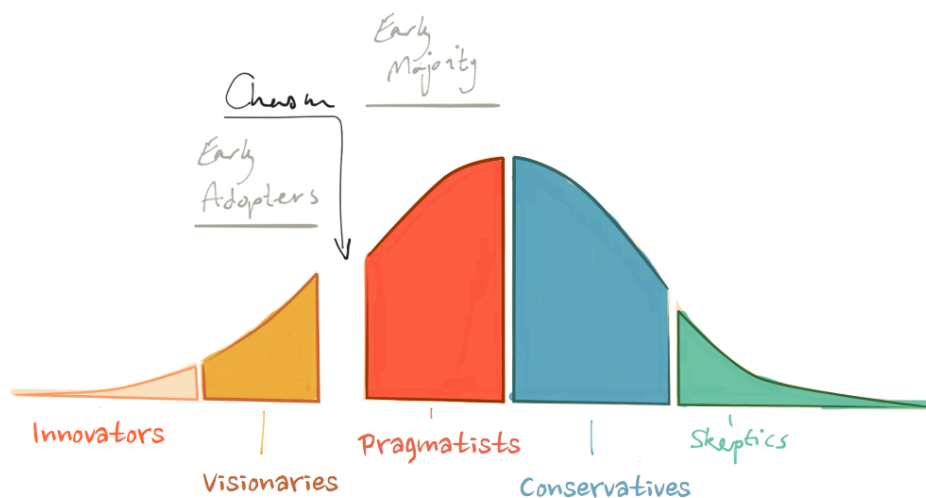
**Figure 2.2:** Moore argues that a chasm exists between the engaged and forgiving early adopters and the majority expecting a fully functional product [Moore, 2002].

able. This must be done while keeping in mind that a product will only become a success if it bridges the chasm between *early adopters* of a technology and *early majority* expecting a fully functional consumer product[Moore, 2002], see Figure 2.2.

## 2.1 Quantified Self

The Quantified Self-movement became a reality when Gary Wolf and Kevin Kelly introduced the concept in the tech-magazine Wired, and created the forum, quantifiedself.com. Today Quantified Self'ers is a diverse group of life hackers, data analysts, computer scientists, health enthusiasts, productivity gurus and patients [Choe et al., 2014]. While some use existing personal informatics tools, others access api's, create plug-ins, or build their own. The needs and motivations of these users are likewise diverse: Some suffer from chronic or life-threatening diseases that require immediate attention. Others strive to live healthier lives through exercise, diets or life-work balance. And for some it is curiosity about their habits and behavior that motivate them, such as how their music consumption patterns

QUANTIFIED
SELF

evolve [2]. From a study in 2014 examining Quantified Self'ers' tools, motivations and insights, Choe et al. stated the most popular tracking categories are: Physical activity (40%), food (31%), weight (29%), sleep (25%), and mood (13%). However many also report tracking other things including cognitive performance, blood glucose, location, heart rate, symptoms, knowledge, stress, body fat, productivity, snoring, movies, posture, medicine, skin condition, home energy usage, clothes, and public transit usage[Choe et al., 2014].

Although this group of people is still relatively small, we see examples of how their needs are affecting broad populations through federal regulations, such as in the case of the Nightscouts. The Nightscouts is a group of parents with children suffering from diabetes who have a strong need for accessible applications monitoring their children's glucose levels in real-time. However, they grew tired of waiting for the slow development of applications due to legislation. So under the slogan #WeAreNotWaiting[3] they created an open source solution by hacking an existing product from DexCom. They wanted to get access to their own data accepting the responsibility that follows. Thereby they gained access to glucose data from a DexCom monitor strapped around the abdomen. The hardware sensor in itself needed a high level of regulatory approval (class III product) from the FDA (Food and Drug Administration). However the application, which only displays data, is now being classified as Class II, which means that it does not need an approval but only to be registered by the agency and follow certain controls. This can be seen as an example of how the government has been forced to allow easy development of personal informatics apps that integrate with sensors. This is evidence of how much power a small group of people have, and how personal informatics systems are crossing the chasm.

These are examples of highly motivated people, creating systems that accommodate their own personal needs. However if we want to create successful personal informatics systems that can cross the chasm, we need a framework enabling us to navigate through the design process of personal informatics systems.

## 2.2 Personal Informatics Frameworks

STAGE-BASED MODEL

An attempt has been made by Li et al., to provide a theoretical foundation for personal informatics [Li et al., 2010]. By doing so they have created a framework, the Stage-Based Model, dividing the process into sequential stages, see Figure 2.3:

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[2]quantifiedself.com/2014/10/tim-ngwena-music-listening-habits/

[3]twitter.com/hashtag/wearenotwaiting
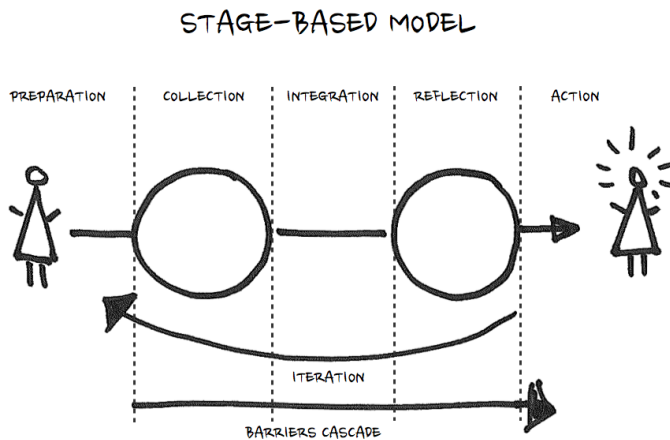
**Figure 2.3:** Illustration of the Stage-Based Model inspired from Li et al.'s illustration[Li et al., 2011].

**Preparation** is where the user decides what to track and which tools to use.

**Collection** during which data is collected.

**Integration** is where the data is prepared, combine and transformed.

**Reflection** here the user can reflect upon the data.

**Action** where users can take action on their newly gained knowledge, change behavior or set new goals.

They suggest that design of personal informatics systems should be holistic: Considering all stages and the barriers that could occur and even cascade through the stages. Li et al. also describe these stages as being iterative. However this is primarily in respect to users' changing information needs, focus or tools. Hence after tracking the amount of calories consumed, the user might find it more interesting to track nutritional value of the food, and therefore changes tool.

In the final stage, the *action* stage, Li et al. describe how users can choose to change behavior based on their new-found knowledge, and how they might tailor their behavior to match their goals, indicating that many users of personal informatics systems are goal oriented.
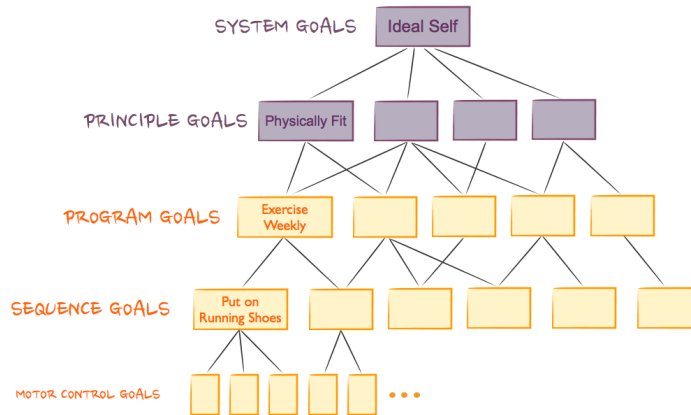
**Figure 2.4:** Goals can be viewed as a hierarchy from high-level, *system* goals, to *sequences* of actions or tasks which constitute the higher-level goals.

## 2.2.1  Hierarchical Goals

In addition to the Stage-Based Model, Li et al. examine the goals of different personal informatics users[Li et al., 2011]. Relying on Powers' theory of perceptual control that describes goals as a hierarchy, from idealistic *system* goals, to very specific *sequence* goals, see Figure 2.4[Powers, 1973]:

**System Goals** is the thought of an ideal self: an ideal relationship, society.

**Principle Goals** are the goals required to achieve the ideal self. This could be becoming physically fit, looking attractive, or becoming more effective.

**Program Goals** are more specific and often measurable. This could be exercising 3 times a week, loosing 10 pounds, or only checking emails once a day to avoid distractions while working.

**Sequence Goals** are the sequence of actions or activities, what makes *program goals* possible. This could be putting on running shoes, going outside, avoiding sugar, or turning off email notification etc.

According to Li et al. the *program goals* are essential to achieve behavioral changes. However they do not describe how the *program goals* should be defined

on the basis of the *principle goals*. Should a person, whose *principle goal* is to become physically fit, run three times a week, once every day, or instead swim twice a week? This might depend on the user's personal preferences or past experiences. In addition Li et al. ignore the effect of the *sequence goals*. Consequently, they ignore the fact that these *sequence goals* can easily become barriers that hinder the user in achieving his goals, for example, sitting down on the couch when getting home from work instead of putting on running shoes. The importance of these *sequences of actions* are supported by the work of Kim et al. [Kim and Paulos, 2010]. Kim et al. claim that users who succeed in sustaining the use of personal informatics applications are those who adopts the tool into their daily routines. In order to adopt the usage into the user's routines it is the *sequence of actions* leading to a specific behavior which is important.

### 2.2.2 Properties of the Stages

The stages in the Stage-Based Model are described as being either user-driven or system-driven, where either the user or system is in charge of the tasks within that stage. In a user-driven system, the user might be collecting data manually and/or afterwards analyzing it himself. This can become very time and attention consuming, which can easily lead to fatigue and lack of motivation. In contrast, a system-driven setup typically has automatic data collection, driven by the advances in sensor technology. This makes it possible to collect data continuously, such as heart rate or respiration, thereby providing a more detailed picture of how they fluctuate. Another advantage is that sensors can collect data on behavior that we are unconscious about, for example by tracking sleep phases. The downsides of a system-driven approach can be less accurate data, e.g. by mistaking lying passively on the couch with sleeping. A system-driven approach can also be limited in the visualization and analysis it provides, thereby not illustrating the data of interest to the user.

USER- OR SYSTEM-DRIVEN

Li et al. recommend an *"appropriate balance between user- and system-driven"* systems [Li et al., 2010]. However if we want the personal informatics systems to cross the chasm, the tedious and difficult tasks such as collecting data and analyzing data need to be minimized, e.g. by automation. Instead the focus should be on creating better rules, for translating data and inferring meaning enabling the user to reflect on it, and gain insights. Thus the systems should be designed to accommodate potential incorrect data, by allowing users to edit and correct data, and learn from these mistakes. Analysis should be based on personal baselines, thresholds, and goals.

MULTI- OR UNI-FACETED

Li et al. also describe systems as either uni-faceted or multifaceted. Uni-faceted means that they are only concerned with one aspect about the behavior. e.g. physical activity (including heart rate, calorie spend, distance covered, pace etc.). Whereas multi-faceted considers multiple aspects in combination, such as physical activity and sleep patterns. Recently more systems have started monitoring multiple aspects, but only few are combining the data streams, looking at how these aspects affect each other. An example of a multi-faceted system is Spire[4], which combines the physical activities (sitting, standing, and moving) with breathing patterns (like deep breaths or quick gasps). By analyzing these, Spire claims to *"infer state of mind (tense, calm, focus)"* [4]. However it does not provide tools for analyzing how physical activity and mental states affect each other on a long-term scale. Will regular exercise stabilize mood swings? Thus many of these multi-faceted applications lack the ability to infer meaning from the data. This results in applications that mainly display huge amounts of data with no clear user need or goal in mind.

Li et al. advocate for multi-faceted systems, however these will only work if they have a clear understanding of which behavioral patterns and physiological measures effect each other, and how to infer meaning from them. Instead systems should rather be excellent at solving one specific need rather than trying to grasp everything - they should start of as a minimal viable product.

### 2.2.3 Barriers

CHANGING TRACKING TOOLS

Li et al. describe several barriers within each stage, which might affect later stages. Among the barriers are, exporting and importing data: If the user decides to change between tools that do not support importing and exporting data, old data might be lost. This will lead to fragmented or scattered data in the *reflection stage*.

Another example of barriers is during the *collection stage*, where the data might depend on subjective measures, such as an estimate of calories in a meal, or if there is no standard for entering data such as judgment of relationship or mood. This will affect the quality of the measures and the ability to compare it and reflect upon it.

WHICH DATA TO COLLECT

In the recent study from Choe et al., the motivation, tools and insights from enthusiastic Quantified Self'ers have been examined [Choe et al., 2014]. The study

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[4]spire.io

revealed more barriers, including tracking the right things. E.g. instead of tracking when and where a panic attack happens, it would be interesting to track the triggers and context. As Choe et al. point out, a common mistake in personal informatics is failing to capture the triggers and context, instead only focusing on tracking e.g. symptoms or outcome measures [Choe et al., 2014]. This problem of not tracking the triggers, is actually a result of not understanding the users' needs or the relations between behavioral aspects.

Another problem  is tracking too many thing, which occurs in the *collection stage* and is often associated with the multi-faceted systems. Tracking too many things can quickly become overwhelming and exhausting, which might lead to inconsistent tracking or even to lack of motivation and tracking fatigue: *"I can honestly say that I've made the classic newbie self-tracking mistake which is that I track everything"* [Choe et al., 2014]. The problem is also relevant later in the *integration stage*, where the data format or simply the extensive amount of data makes it difficult to analyze, to find correlations between data streams and therefor to interpret the data: *"It's not that we lack the information, we're virtually drowning in it. The obstacle is that we don't have the proper tools to interpret the significance of our data"* [Choe et al., 2014].

TRACKING TOO
MUCH

Both of these problems are actually related to a lack of scoping in the design process: What are the questions you seek answers to? What are the needs and motivation? It also shows a lack of understanding of the behavioral measures. The fact is that we are now able to monitor and cross examine a lot more biometrics and behavioral measures without being certain of which are affecting each other. Thus there is a risk of mistaking correlations with causality; what is the relationship between behavioral aspects? E.g. are we drinking coffee because we are tired, or are we lacking sleep because of the caffeine in the coffee we are drinking (Figure 2.5)?

## 2.3   Limitations of Current Frameworks

In summary Li et al.'s stage-based personal informatics framework can be understood as a socio-technical model in the sense that it tries to merge engineering aspects such as data *collection* and *integration* with user-centered aspects such as *reflection* and behavioral aspects of the *action* stage. Although there are a lot of good considerations, it is not clear how to apply the Stage-Based Model in an iterative design process. The Stage-Based Model lacks detailed considerations of needs, motivations and goals: Li et al. focus on action as an outcome and limit

**Figure 2.5:** Causality of data: Does your coffee consumption reflect your lack of sleep? Or do you lack sleep due to your coffee consumption?

reflection to a single stage. They only consider iterations in terms of changing needs, rather than it being an integrated part of the design process.

SCOPE & OUTCOME
The framework does not address the links between needs, motivations or how these are connected to high level values and goals. Likewise there is no consideration of how to transform these high level goals to more tangible goals. Furthermore the *sequences of actions* required to reach the desired goals are ignored. Instead the main focus is limited to the barriers and how these might cause the user to fail in reaching the final stage, *action*, which seems to be the ultimate goal. Thus the goal seems to be changing behavior and improving oneself, rather than gaining insight, which is only briefly mentioned as a side product of *Reflection*. This is not an uncommon approach in personal informatics, as has also been pointed out by Baumer, who criticizes personal informatics studies for focusing more on outcomes related to *Reflection* rather than reflection itself [Baumer et al., 2014].

INFER MEANING
Perhaps this is due to the misleading definition of reflection as a stage between *integration* and *action*. Some would argue that reflection can happen at different times and on different cognitive levels. Already when the user decides to start tracking, reflection is happening to some degree. The user might want to investigate how he is using his time, thereby indirectly he has reflected on his current usage or at least on his assumed usage. Reflection could also happen during the *collection* or *action* stage: When the user finds himself checking facebook updates while being aware that his computer usage is now being monitored with RescueTime[5]. Thus the mere awareness of tracking behavior can lead to reflection. Others like Baumer have also noted that many personal informatics studies

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[5]rescuetime.com

use reflection as a keyword without defining it[Baumer et al., 2014]. And many of those who do, refer to Schön's concept of *reflection-in-action* [Schön, 1983]. *Reflection-in-action* describe the ability to improvise or make decisions during an activity. This would be described as learning by doing or by experience. However Schön also describes a concept of *reflection-on-action*, which is more similar to Li et al.'s reflection on data, where the process of reasoning on past behavior leads to insights. Instead of *reflection* we will refer to this as *inferring meaning* from data, which might lead to reflection or even insights.

Finally, Li et al. suggest that systems should be iterative between stages. However the model only describes iterations from *action* to *preparation*, mainly in respect to prospects of incorporating new data, tool and processes. Thereby the framework becomes somewhat flexible to the users' changing information need - to a redirection of the user's goal or questions. However, the stage-based model does not consider iterations in a shorter loop, through only some of the stages. By doing this, we can consider the user's transitions between stages, from knowledge, reflecting on it leading to action: How the data should be visualized to infer meaning from data, upon which the user can reflect and hopefully gaining insights. Or in the case where behavior change is the goal, considerations on how systems can accommodate action leading to successful behavior change.

ITERATIONS &
LOOPS

Thus we propose an alternative model with needs and motivations as the starting point, while incorporating both high-level and low-level goals. The model will include iterations between stages, a feedback loop. We will suggest elements within the stages that can help infer meaning from data, aiming at providing insights.

# 2.4   Summary

Personal informatics systems are becoming more common in our everyday life and span from systems monitoring our health, work-life, to economic balance, and utility consumption. So far these systems have been highly influenced by the Quantified Self'ers, who have tested, evaluated, discussed, and modified systems to accommodate their own needs. This group of people are highly motivated and more tolerant towards bulky, unstable or demanding systems. In contrast, the majority of the market would not be able to modify the system nor be as forgiving. For personal informatics systems to cross the chasm, we need a design framework relying on lean agile development processes.

In contrast the established personal informatics frameworks are limited by:

- Not focusing on the *scope & outcome* - including understanding users needs, motivation and goals which might be changing behavior, or exploring patterns and gaining new insights.

- Not focusing on how to *infer meaning* from data, enabling reflection and insights - including an understanding of relations between behavioral patterns and physiological measures; and personalizing the data analysis and visualization.

- Not considering the iterative feedback loop taking place when using a personal informatics system - including when and how feedback is provided to the user and how feedback is provided to the system through interaction and behavioral patterns.

CHAPTER 3

# The Feedback Loop

We will start by establishing a model that is centered around an iterative feedback loop. Focusing on the *scope* and its relation to high level *outcome*, which remains essential in lean design process, will help to define the minimal viable product.

**Scope** is where the user decides what to track and how. This is based on the underlying user needs and motivation, which is connected to the user's values and goals.

I will examine the connectivity between motivations, needs, and goals, while linking them to an iterative design process. The coupling between personality traits and motivations will be described and emotional responses to pleasant and unpleasant stimuli will be investigated.

**Data Collection** is where data related to physical sensors or behavioral patterns are gathered.

The difficulties and complexity of data collection and analysis are illustrated in relation to capturing individual emotional responses.

**Analysis & Visualization** is where the data is integrated, transformed, analyzed and presented.
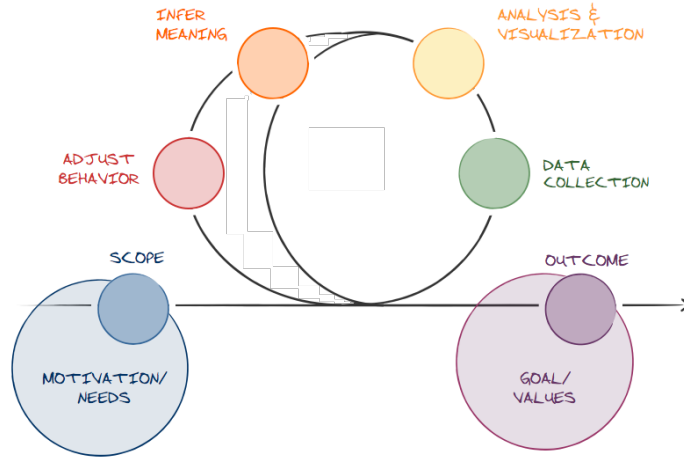
**Figure 3.1:** The feedback loop, consists of the following stages: *scope*, *data col-
lection*, *analysis & visualization*, *inferring meaning*, *adjust behavior*
and *outcome*, while focusing on the underlying motivation, needs
and goals.

The tight coupling between analysis and visualization will be illustrated
with neurofeedback interfaces.

**Infer Meaning** is where the user can infer meaning from data by means of
visualization, and by interacting with it - zooming, selecting, and filtering.
Furthermore, this might lead to reflection.

I explore how visual elements can help inferring meaning and enable re-
flection and association. While applying some of these in a neurofeedback
inferface to study the effect it has on training.

**Adjust Behavior** is where the user can adjust behavior, based on the inferred
meaning.

Neurofeedback training demonstrates users ability to adjust behavior based
on the visualization. In addition I illustrate how haptic feedback can initiate
behavioral change.

**Outcome** is where the user sees the effect of tracking, either by having achieved
or failed his high level goal, or by simply gaining insight, which can lead to
a changing focus, goal or question, and perhaps setting a new scope.

The effect of the outcome and the temporal aspects of the feedback loop is
discussed when designing neurofeedback interfaces.
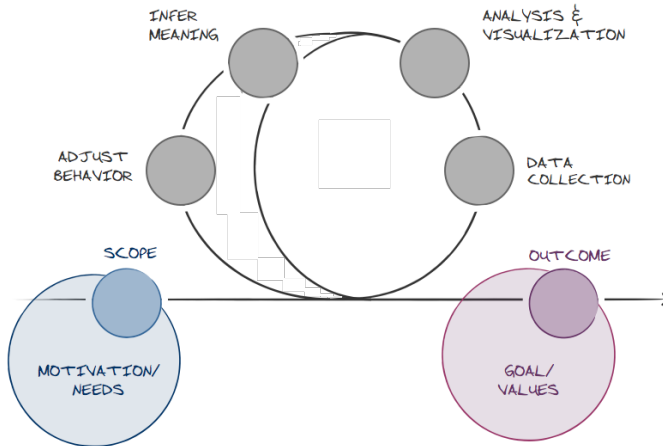
**Figure 3.2:** Being able to *scope* the system based on users' motivation, needs, and goals; the desired *outcome*, is essential for creating a successful personal informatics system.

The loop through *data collection*, *analysis & visualization*, *infer meaning* and/or *adjust behavior* is continuous, as long as the user has the same need and goal in mind. The loop can be applied on many levels to describe small *micro-interactions* or at a larger scale, to achiever goals on different levels. By looping through these stages several times, the user can gain insight on long-term trends and patterns, or might see the effect of behavior changes. Moreover, the system might also learn from the user's interaction and behavioral patterns, and become adaptable, and can be described as a cognitive system.

We will examine how we can incorporate aspects of lean agile design processes into the feedback loop, as a guideline for developing personal informatics systems.

## 3.1   Lean Agile Design Process

In any design process it is important to set the right scope for the system. This is easier said than done as it requires understanding the users, their needs and what motivates them, and narrowing these down to create a minimal viable product. The minimal viable product is the minimal version of product, which solves a problem for the user, while allowing developers to gain insights through

testing. It is a strategy for fast development with minimum effort and resources [Ries, 2011].Thus we will start by zooming in on the *scope* and *outcome* of the feedback loop, see Figure 3.2.

<div style="float: left; text-align: right; width: 150px;">MOTIVATIONS & NEEDS</div>

Motivation represents both desires and needs and is one of the reasons for self-imposed, planned behavior and reflects personal preferences and values. Needs are basic elements that can be objective such as food and shelter, or subjective such as self-esteem or feeling secure. However in this thesis we will view needs a little more broadly. They are not just what provides a foundation to live 'healthy' lives, they are rather what is necessary to live 'our' lives, both in a practical and ideal sense. Thus, needs explain *what* and motivation can explain *why*. In this sense, motivation and needs can be seen as the starting point to achieving goals, which is therefor tightly connected to the desired *outcome*.

<div style="float: left; text-align: right; width: 150px;">GOALS & SEQUENCES</div>

In the previous chapter we saw how motivation, needs, and goals, are often taken for granted when describing personal informatics systems. They assume that motivation naturally leads to behavior change: If you want to become physically fit, you will naturally succeed at this, if you have a *program* goal, like running three times a week. There is no consideration of how these goals are defined, or which fits the individual user. They also neglect the *sequences of actions* required to achieve the desired goal.

Thus, we will investigate how to incorporate both high-level goals and *sequences* of actions in the design process. Going from abstract measures of motivations, needs and goals to tangible tasks which can be transformed into programmable flow-charts.

### 3.1.1 User Story Mapping

<div style="float: left; text-align: right; width: 150px;">USER STORY MAPPING</div>

One way of connecting high level goals with activities and *sequences* is by the use of *User Story Mapping* [Patton and Economy, 2014]. *User Story Mapping* is a tool for agile software development and is used for scoping user needs into activities and a hierarchy of prioritized tasks: A story line is created from the different users and their needs or goals. To achieve these goals one requires a set of activities, which in turn translate to a sequence of actions. Each of these activities consists of a set of tasks. These are the detailed steps supporting the activity. By defining these tasks to avoid dependencies between them, and by prioritizing them in a hierarchy, the developer can scope the system into a minimal viable product, see Figure 3.3. From here the developer can improve the system with more nice-to-have features in the later iterations. Through this

MAXIMUM VIABLE PRODUCT

1st ITERATION    2nd ITERATION    3rd ITERATION    4th ITERATION

MINIMUM VIABLE PRODUCT

1st ITERATION    2nd ITERATION    3rd ITERATION    4th ITERATION
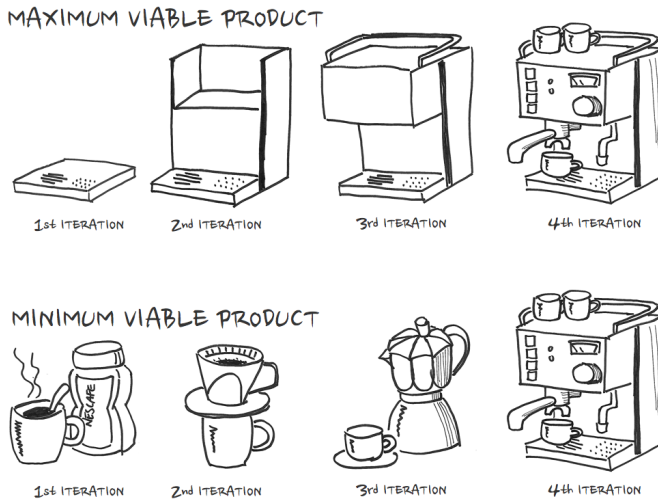
**Figure 3.3:** By decoupling tasks and prioritizing them, the first iteration of product development can be usable as a minimal viable product.

process it becomes clear which tasks are necessary, and which do not contribute to the activities and goals.

By focusing on one user, and his main goal or need, the activities and tasks required to solve this, we have started defining a minimal viable product. Based on this, a prototype is created and tested, enabling the developers to get insight and evaluate the goals, activities and tasks, which can lead to altering the original scope, see Figure 3.4.

By applying the *user story mapping* to our feedback loop we can both transform the high level goals into sequences of actions, and describe these actions or activities as a set of tasks, which can easily turn into programming flow-charts, see Figure 3.5.

### 3.1.2 Micro-Interactions

These tasks can be described in details as *micro-interactions*. *Micro-interactions* provide a detailed flow-chart view of the underlying rules and triggers that define a system and can enhance the user experience [Saffer, 2013]. *Micro-interactions*

MICRO-INTERACTIONS
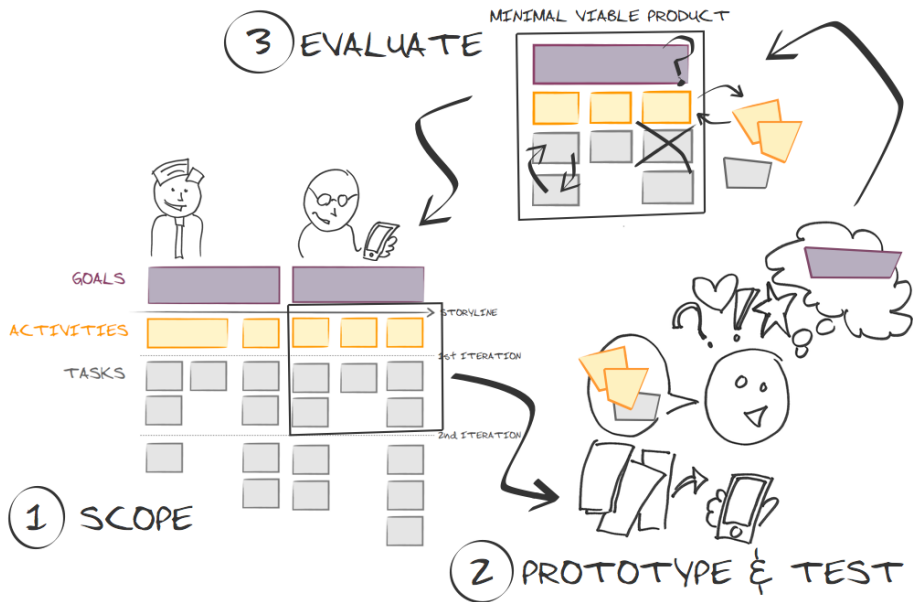
**Figure 3.4:** User Story Mapping as part of an iterative process, helping to scope the product by testing prototypes, thereby evaluating and redefining the scope of the product.
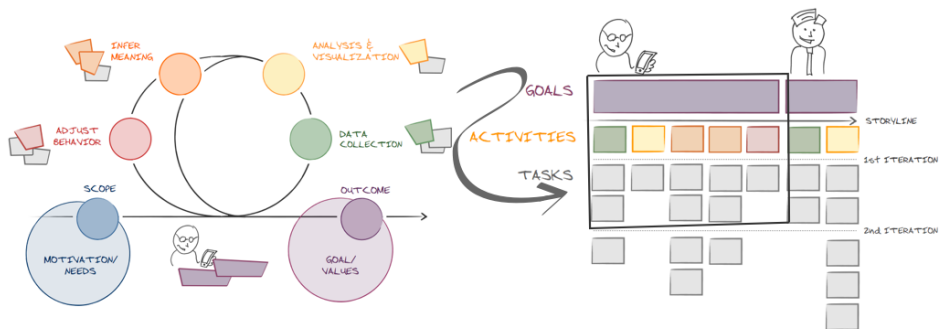


**Figure 3.5:** By considering the activities of each stage in the feedback loop, we can transform this into the lean design framework, *User Story Mapping.*
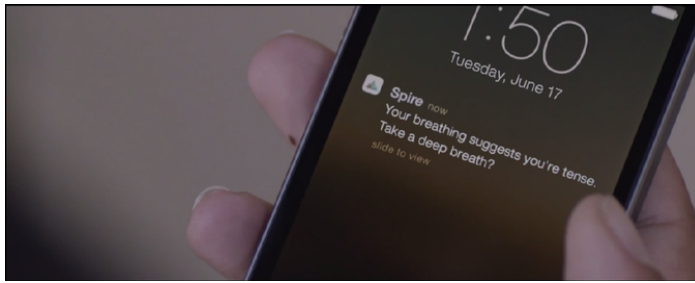
**Figure 3.6:** Spire consists of micro-interactions - interpreting whether the user is tense or relaxed based on breathing patterns and activity level.

consist of a chain of events which can be described as five different types of actions:

**Triggers** initiate a change of state or mode

**Rules** determine what change entails

**Feedback** signals that a rule has been activated and preferably what it entails

**Modes** are meta rules, that overwrite the current rule

**Loop** determines when to exit a mode, based on time past, new triggers or previous history

The triggers can be either user or system initiated. A user initiated trigger could be when the user switches his phone to silent mode, or when he taps a button to set an alarm, whereas a system initiated trigger could be when a system switches to a silent night-mode after 10pm. The rule is then to replace previous audio notifications or incoming calls with a vibration or simply a visual display. The phone would stay in this mode until the user switches it back to audio. The feedback is the small vibration indicating that the silence button is switched on and an audio icon indicating audio on and off. The modes are meta rules, thus when the user has set an alarm, this will go off even though the phone is on silent mode. The alarm mode will then overrule the previous silence rule. The loops determines when to return to the previous mode. Thus when the phone is on night-mode, this will continue looping over this mode until morning.

These *micro-interactions* are often small fundamental elements that contribute to the user experience, and the rules are what makes these systems seem intelligent.

PERSONAL
INFORMATICS
SYSTEM

In personal informatics we see them in systems like Spire[1]. For Spire the *scope* is to *"reduce tension and guide the user towards a calm and focused mind"*[1]. Spire relies on the natural human feedback mechanism breathing rate, which is one of the few ways of consciously influencing the nervous system. Changing the state of mind simply by changing your breathing pattern. Taking a deep breath when angry or tense might result in becoming more relaxed. This is done by transforming accelerometer data into breathing rate as well as activity modes (sitting, standing, and moving). If the user's breathing rate has increased without the user moving much, the system will interpret this as the user being tense. The system notifies the user while suggesting to take a deep breath, see Figure 3.6. Here the trigger is a combination of data thresholds - a fast breathing pattern and low physical activity. While the rule is the interpretation; being tense, calm or focused. The feedback is the notification. However if the user does not agree with the systems interpretation, and does not feel tense - the system can easily seem unintelligent. Thus getting these micro-interactions right is important in striving to create cognitive interfaces.

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[1]spire.io

## 3.2   Summary

By establishing a model around an iterative feedback loop, we have created a starting point for a personal informatics system around the basic component of providing feedback to the user and receiving feedback on which the system can learn from the user's interaction and behavioral patterns, and thereby become cognitive. The feedback loop consists of the following stages:

- scope

- data collection

- analysis & visualization

- infer meaning

- adjust behavior (optional)

- outcome

The feedback loop focuses on the *scope & outcome* of the system, which are essential for creating a minimal viable product. We incorporate *User Story Mapping* in order to get from high-level needs and goals to sequential activities which can be fitted into the user's routines, and tasks on programming level. With *User Story Mapping* the goals, activities and tasks can be decoupled and prioritized helping to scope a minimal viable product, which can be prototyped, tested, evaluated and modified until ready to be programmed into a commercial product.

The detailed interaction with the systems are referred to as *micro-interactions*. These small fundamental elements are what contributes to the user experience and makes the system seem intelligent, but only if done right. The micro-interactions consist of triggers, rules, feedback, modes, and loops. In personal informatics systems the triggers, rules, and feedback are what makes the system cognitive. This includes understanding the users and their routines, understanding the data in relation to correlation and causality, and how to translate and *infer meaning* from data.

CHAPTER 4

# Personalization

As we saw in the previous chapter, understanding users, their motivations, and preferences is essential for *scoping* the product. This chapter focuses on how we can gain insights to users' motivations and preferences based on personality traits, in order to personalize the content, and provide feedback in an appealing way. In addition, I examine the prospects of accessing users' emotional responses from cortical brain activity. This will illustrate the importance of the *scope* and how extensive *data collection* and *analysis* can be, see Figure 4.1.

Since personality and personality traits often reflect behavior, preferences, motivations and values in life, there has been extensive work on understanding and analyzing these in a systematic way. One of the most well-known and thoroughly researched frameworks is the *big five* developed by McCrae et al. [McCrae and Costa, 2003]. The *big five* is a categorization of five primary personality traits:

PERSONALITY TRAITS

**Agreeableness** a person scoring high in agreeableness, will often show compassion towards others, be helpful, cooperative while being modest and have a high morale. A person with a low score would be self-centered, proud, have a hard time trusting others, and think that people should rely on themselves instead of others.
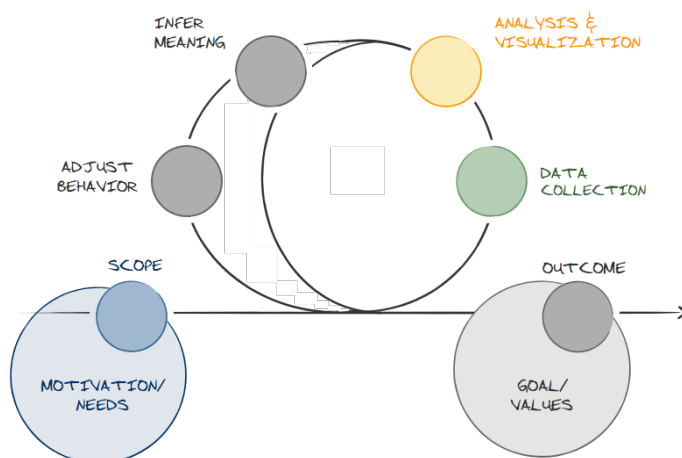
**Figure 4.1:** We explore how we can get insights into users' motivations, pref-
erences and emotional responses, while illustrating the complexity
of collecting and analyzing brain data of individual emotional re-
sponses.

**Conscientiousness** a person scoring high in conscientiousness will be described
as driven, organized, responsible, and persistent. While a person scoring
low will be carefree, unstructured, self-doubting, and feel content with no
need for ambitious goals.

**Extraversion** a person scoring high in extraversion would be very energetic,
optimistic, seeking the company of others, and is comfortable taking charge
and leading groups. A person scoring low would be calm, laid back, private,
serious and need time for himself.

**Neuroticism** a person scoring high will be anxious, insecure, fiery and sensitive
to others' opinions, while a person with low scores would be confident,
self-controlled, content, and calm under pressure.

**Openness** a person scoring high in openness is appreciative of art, imaginative,
has a philosophical approach, challenges authorities and is eager towards
new experiences and various activities. A person scoring low will rely on
familiarity and traditions, is pragmatic, prefers facts and is respectful of
authorities.

Each of the five primary traits has six facets, which further characterize the

individual. A person might have a combination of these traits, however some are more strongly represented than others.

By understanding what motivates the users with different personalities, we can get an indication of their preferences and values. This is why IBM's Watson[1] has been trained to infer personality types from social media profiles such as Facebook and Twitter [Golbeck et al., 2011]. The outcome is measures of which characteristics are most prominent in a user, compared to the average of the population of Facebook or Twitter users. In this way, Watson offers companies insights on their customers' personalities through social media logins, thereby helping companies target products and marketing more effectively. We can therefore easily imagine that information about users' personality traits will become accessible to developers of personal informatics systems. Thus we can start to include aspects such as motivation when designing systems, which can effect the way of presenting data, content, purpose, and whether the system should be actionable or explorative, allowing for detailed interaction with the data.

IBM WATSON

## 4.1 Designing for Personalities

Even though users with different personalities have similar needs, different ways of solving these needs might have an appeal to different personality types. This has been demonstrated in people's preferences towards book-reviews [Nass and Lee, 2000], where people preferred reviews presented by a reviewer with a personality trait similar to their own (introvert vs. extrovert), and were even more likely to buy the book. Thus applications can be adjusted to personality traits, by customizing the content, how it is presented and what needs it should fulfill. To demonstrate this, we look at three applications which help the user keep track of consumed calories.

Carrot Hunger[2], has a very simple interface. The main screen provides feedback on the amount of remaining calories, in three ways - from the size of the avatar (skeleton, normal and overweight), the number on the pedestal, and the level of green slug. The simple, yet artistic interface could easily appeal to people with high *Openness*. The application has a sarcastic commentator, that will ruthlessly shame the user whenever he consumes more calories than the daily threshold, and will electrocute his avatar, unless he pays a small fee or he will be publicly shamed on his twitter account. Thus people who choose to use Carrot Hunger will likely

PERSONAL INFORMATICS SYSTEMS

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[1] watson-pi-demo.mybluemix.net
[2] www.meetcarrot.com/hunger
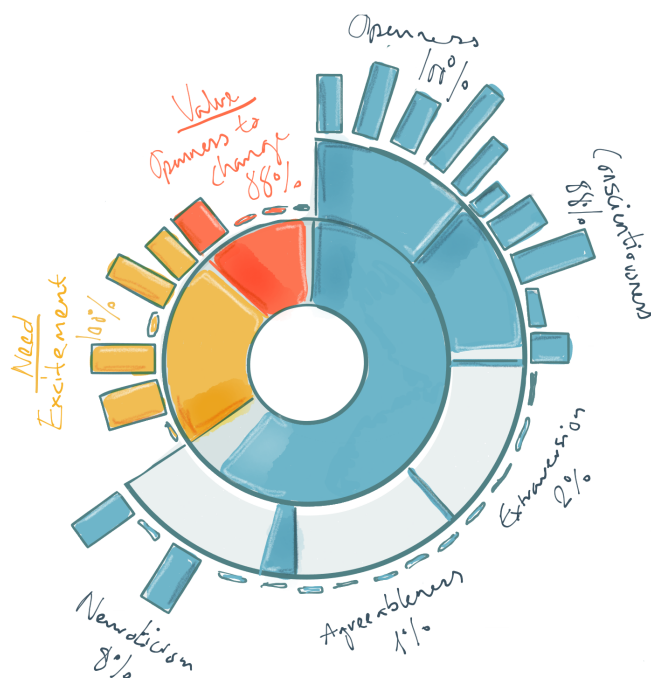
**Figure 4.2:** Illustration of how Watson would present personality traits of a person with high *Openness* and *Conscientiousness*.

**(a)** Carrot Hunger    **(b)** MyFitnessPal    **(c)** MealLogger
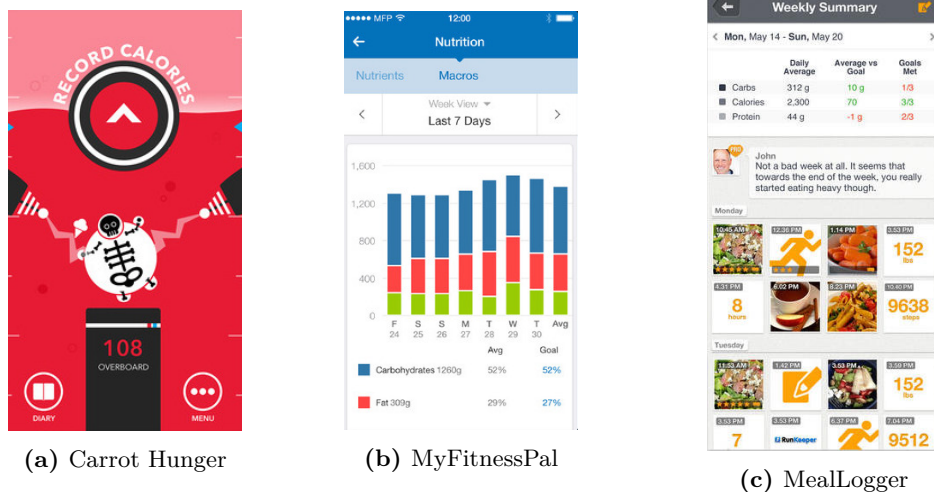
**Figure 4.3:** Three different approaches to personal informatics systems for tracking calories. (a) Carrot Hunger display a clear warning, when the consumed calories have exceeded the daily threshold, with the red colors and electrocution of the avatar. (b) MyFitnessPal shows a classic bar plot with three colors indicating the amounts of carbs, fat, and protein consumed during the past week. (c) MealLogger displays a score board in the top of the screen and depicts meals and activities as items in a grid.

be cheerful and perhaps competitive, both of which are facets of *Extraversion*. The application is also very action oriented, with one big button in the center of the screen for recording calories. And it only provides a limited history of behavior - the number of days the user has been able to stay within the calorie threshold. Thus the user does not need to spend much time engaged in the app, which is also perfect for people who score high on *Extraversion* - they tend to live busy, fast-paced lives. Carrot Hunger excels by having a clear-cut *scope* and users of Carrot Hunger are likely to be motivated by its simple, yet candid interface, which is only meant for a bare minimum of interaction.

In contrast MyFitnessPal[3] provides a more extensive interface with a detailed history. The history includes a diary of all consumed food, which the user can investigate for nutritional information, and which allows the user to correct inaccurate food entries. The average nutritional information of fat, protein, carbs,

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[3]myfitnesspal.com

sugar, fiber, cholesterol etc. from past days, weeks, and months are displayed in traditional bar and pie charts. This interface appeals to users who are interested in the details of their behavior. Thus people who choose MyFitnessPal would be likely to score high in *Conscientiousness* and low in *Openness*, since these will prefer traditional approaches. They have a need for structure and are motivated by feeling in control.

Another diet application is MealLogger[4], where people share pictures of their meals in communities. People in the communities can comment on each other's pictures, get recipes and motivate each other. This concept is appealing to people with high *Agreeablesness*, who care care for the opinions of others. The history is presented as a grid of photos and icons, which leads to more information when tapped. The interface is intended for the user who spends time on exploring nice photos, recipes and engaging in the community. Thus this application might be interesting for people with *Extraversion*, who find the company of others rewarding and motivating.

These three examples illustrate how interfaces can appeal to people with different personality traits. This applies both in terms of how actionable or exploratory an interface should be, the content, the level of detail, and how it is delivered (e.g. sarcastic as in Carrot Hunger).

QUANTIFIED
SELF'ERS
If we look at the personality types of *early adopters* including many of the Quantified Self'ers[5], these would be likely to score high in *Openness*, being open towards new technologies, driven by a curiosity that questions the common ways of doing things. They could also score high in *Conscientiousness*, being determined to get the answers they are looking for and dedicated to use the technologies in order to achieve their goals. This is how Watson would portray these personality characteristics, their facets, see Figure 4.2. These personality characteristics can be used to explain what needs and values a person has, which can explain how a person would behave and what motivates him.

Though there has been a lot of research focusing of the effect of personality traits and consumer behavior, there are only a few examples within personal informatics. Most of these focus on implications on scenarios with gamification or educational purposes. One study examines correlations between personality traits, preference towards different game affordances (challenges, rewards, progress, etc.), and what behaviors they tracked [Karanam et al., 2014]. They found that people with high *conscientiousness* and *openness* preferred rewards,

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[4]meallogger.com
[5]quantifiedself.com/personality/
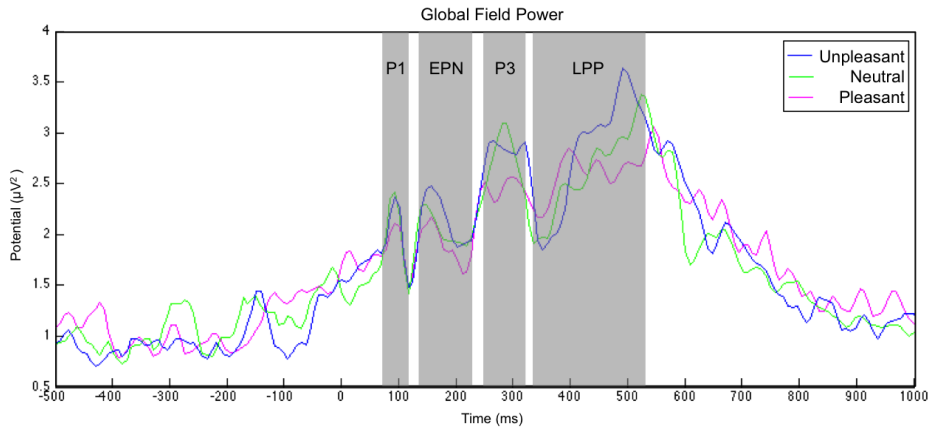
**Figure 4.4:** The averaged global field power plotted for the three conditions, neutral (green), pleasant (red), unpleasant (blue), used to define relevant windows for further analysis.

whereas people with high *extraversion* and *openness* were motivated by challenges. This illustrates some broad tendencies coupling motivational factors with personality traits, which are relevant in the context of personal informatics and the design of feedback interfaces. However if we can access emotional responses to content in real-time, we will be able to create more effective systems that can adapt to users' preferences, without extensive training or prior usage.

Yet this standard way of categorizing users by personality traits will only reveal overall attributes. To make a system truly personal, it requires access to individual differences, which amongst other things are affected by past experiences, memories and emotions.

## 4.2 Emotional Responses in EEG

Being able to tap into users' personal experience and emotional responses would be of great value and enable the possibility of personalized content. With the development of new types of mobile neuro-imaging headsets, this can become a reality in the future. In an outline we demonstrate the tentative beginning with a series of activities and experiments, Appendix A[Stopczynski et al., 2014]. However as we will see in the following, working with brain data is not trivial.

In prospect of extracting emotional responses from brain activity, we conducted an experiment displaying affective pictures, Appendix B [Jensen et al., 2014]. The pictures were a subset of pictures from the International Affective Picture System (IAPS) [Lang et al., 1997] which consist of almost 1000 photos ranging from everyday objects to mutilated bodies and erotic nude scenes. These photos were originally rated by 100 college students on a valence and an arousal scale and have been scientifically accepted as a normative rating.

EVENT RELATED POTENTIALS

By recording electroencephalography (EEG) while participants view the photos, we capture the electric potential from the scalp representing the neural activity in the cortex. Traditionally, emotional responses have been analyzed by averaging the waveform appearing immediately after the stimulus is presented, known as the event related potential (ERP). The emotional responses appear as slight $\mu$V changes, which is highly susceptible, if captured in a noisy mobile environment. Thus we compare a classic electrode-based analysis, the Global Field Power, to an independent component analysis (ICA), in hope of getting a more robust neural signature which could potentially be applied in a mobile context recording emotional responses.

We presented a series of affective pictures to four male participants while recording their neural activity on a standard BioSemi ActiveTwo system using 64 electrodes. The pictures were a subset of the IAPS from two studies on emotional responses, one with 96 pictures [Lang and Bradley, 2007], the other with 66 pictures [Larsen et al., 2003]. The total of 162 pictures were divided into three conditions (pleasant, unpleasant and neutral), based on their valence and arousal ratings.

ELECTRODE-BASED ANALYSIS

In the classic electrode based analysis we used the Global Field Power to identify relevant time windows (P1 (75-125ms), EPN (130-225ms), P3 (250-315ms), and LPP(325-525), see Figure 4.4), and a scalp map of those time windows to identify relevant electrodes, see Figure 4.5. Based on these we plotted the average ERPs across all participants, and found only a significant effect in the early posterior negativity (EPN) window 4.6. This early negativity corresponds well to earlier findings [De Cesarei and Codispoti, 2006] and has been related to an increased attention demand, and primarily captures difference in valence, whether a picture is pleasant or unpleasant. These early responses might even be visible before the stimulus is fully processed, suggesting that perhaps the dominating color of skin in nude scenes and colors of skin and blood in mutilated bodies are decisive. These early responses to pleasant and unpleasant images can relate to the basic approach or avoidance instinct [Lang and Bradley, 2010]. Whereas early ERP components are believed to relate to bottom-up processing of stimuli, the later components have been suggested to indicate higher-order processes such as
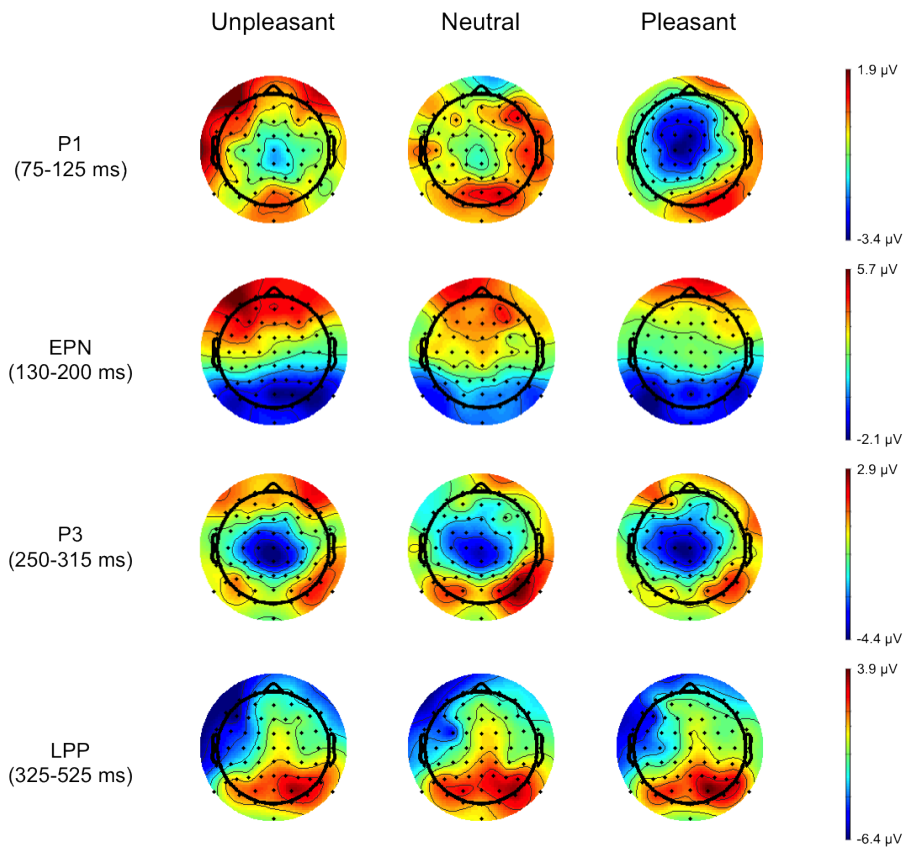
**Figure 4.5:** Scalp maps for the time periods P1, EPN, P3 and LPP for each of the conditions (unpleasant, neutral and pleasant).
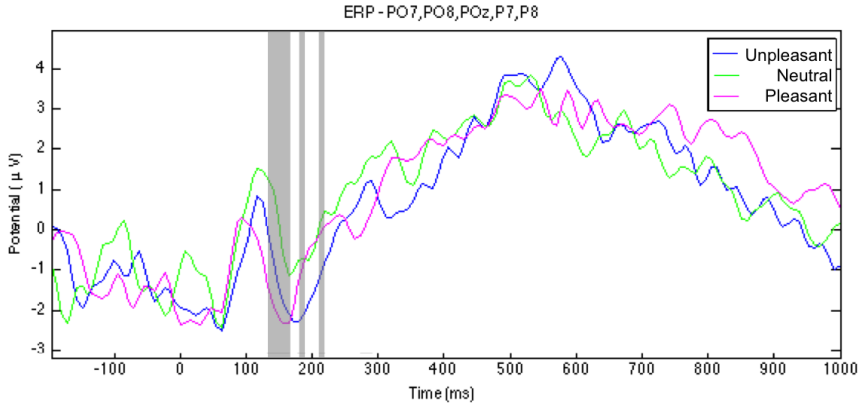
**Figure 4.6:** An average ERP of channels covering the temporal occipital lobe (P7, P8, POz, PO7, and PO8) shows the three conditions pleasant (red), unpleasant (blue) and neutral (green). A statistical one-way anova on each channel marks the significant areas ($\alpha$=0.01) of the ERPs in grey.

memory retrieval, and semantic evaluations [Foti et al., 2009]. Thus the lack of later ERP components could indicate that these are more sensitive to individual processing.

COMPONENT-
BASED
ANALYSIS

By using ICA we decomposed the EEG data into scalp maps which where then grouped and reduced by PCA. After this, we clusted similar ICA components by a K-means algorithm, thereby following the standard EEGlab procedure [Delorme et al., 2011]. From this, three out of 20 clusters revealed several significant time windows showing difference between one or more conditions. All three clusters were shared among all participants and consisted of a large amount of independent components. The most profound cluster, cluster 6, showed both early and late emotional responses to pleasant pictures. These results are somewhat similar to those found by applying principal component analysis (PCA) on emotional responses [Foti et al., 2009], with early responses distinguishing pleasant from unpleasant images, whereas later responses were affected by high arousal scores. This indicates that these later responses are characterized by the intensity of emotional involvement [Gianotti et al., 2008], which could be associated with memory coding and semantic processing.
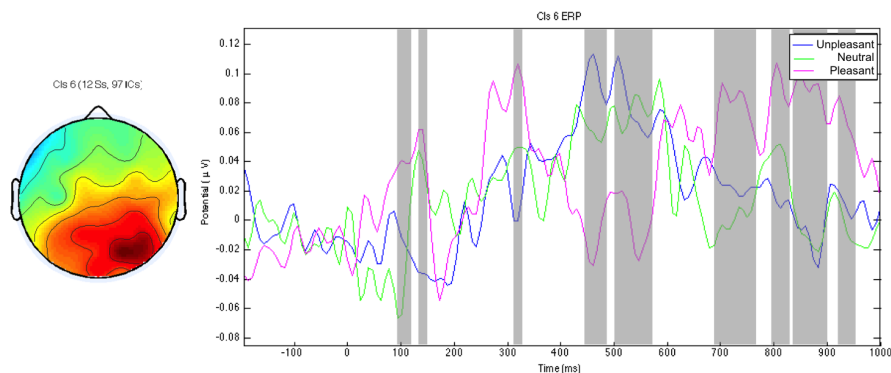
**Figure 4.7:** Cluster 6, based on PCA dimensionality reduction and K-means clustering (K=10,$\sigma$=3) of 97 ICA scalp maps found within all conditions, with corresponding ERPs for pleasant (red), unpleasant (blue) and neutral (green) images. Significant intervals for differentiating between the emotions are indicated in grey.

Where many personal informatics systems suffer from poor scoping, we need an extremely well defined scope when dealing with brain data. As illustrated with the electrode-based analysis, we need a well defined scope, in terms of clear definitions of relevant time windows, and of relevant electrode and a clear distinction between emotions as illustrated in the strong contrast of IAPS, from mutilated bodies to erotic nude scenes. And even with all this, it still requires many samples across multiple participants to distinguish between brain responses to pleasant and unpleasant stimuli.

The prospects of not only identifying basic emotional responses of attraction or avoidance, but also accessing more individual responses, such as the later responses related to associations, memories and past behavior, requires more advance machine learning methods. As we saw with the component-based analysis, transforming raw EEG data into usable components required both ICA, PCA and K-means clustering, which are far beyond the classic excel analysis used in many existing personal informatics systems.

For these new types of mobile brainscanners to become usable in personal informatics, making them adaptable by generating personalized content, they not only have to do these types of extensive analysis, they will also have to do them on a single trial level, preferably without any extensive training period.

As just illustrated, gaining insights to users' individual emotional responses is not trivial. However, gaining insight into the users' general personality traits, and thereby what motivates the users, can be used to scope the systems. Personality traits also reveal preferences on how feedback is presented, both in terms of how actionable or exploratory it should be, and in terms of the content - the level of detail, and how it is delivered. Thus we will take a close look at feedback, in terms of visualization of data, and how we can infer meaning from it.

## 4.3   Summary

Systems like IBM's Watson has demonstrated how it is possible to extract personality traits from people's Facebook and Twitter accounts. Personality traits can provide insight into users' motivations and preferences, which can help in scoping a personal informatics systems to a specific type of people, both in terms of how actionable or exploratory it should be, the content, the level of detail, and how it is delivered.

These personality traits reveal only overall attributes of large groups of people. However, if we want to access more personal differences, we need to gain knowledge of past experiences, memories and emotions. With the development of new types of mobile brainscanners, it could become possible to create individual personalized context and make systems that could adapt to the individual emotional responses.

As we illustrate in an experiment on emotional responses from pleasant and unpleasant pictures, it requires a large amount of data and extensive machine learning to extract meaningful results. At the moment, this is far beyond the classical *data collection* and *analysis* of any existing personal informatics system.

# Cognitive Interfaces

As touched upon in the introduction, cognitive systems include systems that are able to learn from the user's past behavior, or are based on contextual information. However, interfaces can also be cognitive in their ability to translate data into meaningful feedback. And by making the feedback not only meaningful but also actionable, the user is more likely to adjust behavior if this adjustment is necessary to achieve his goals. This corresponds to the *analysis & visualization*, *infer meaning*, and *adjust behavior* stage of the feedback loop, see Figure 5.1.

In order to benefit from the collected data, they need to be accessible and translated into something understandable in order to get insights. To do this, the data are often visualized. This thesis will not cover all types of visualization, but will focus on visualizations of time-series data and how we can apply analytic tools, such as filtering, baselines, thresholds, etc. to infer meaning from the data.
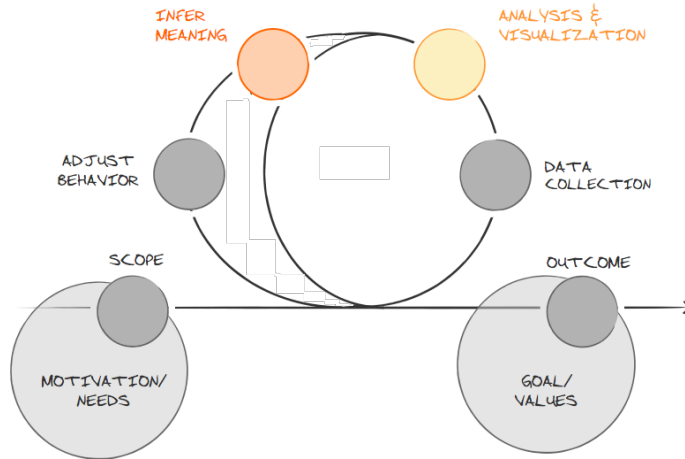
**Figure 5.1:** By translating data with the use of analytic elements, such as base-line and thresholds, we can infer meaning enabling reflection and insight, thereby creating cognitive interfaces.

## 5.1   Visualization

How to visualize the data depends on the insights we want to provide. If the user wants to change behavior, the visualization should be actionable. However, if the goal is to explore unknown territory or is to answer a specific question, the visualization should incorporate interaction, allowing the user to dig down in the details. Thus before visualizing any data, decisions have to be made on what message the data should convey and therefor also decisions need to be made on the underlying analysis of the data, and the level of interaction. Thus a personal informatics system assumes to know what the user wants and which questions they want answers for.

The visualization also depends on the type and amount of data we have - are they discrete, continuous or in a network? Are they events, pictures, or annotations, etc.? When visualizing data, we try to exploit the abilities of the human eye to detect structures, patterns, correlations, trends or outliers. Thus we should present the data in a way that makes these patterns, correlations, trends or outliers clear.

TIME-SERIE DATA     Common for a lot of personal informatics data is that they are a time-series, since

**Figure 5.2:** Moves app, shows a summary of physical activities using circle sizes and stacked bars as a detailed timeline with colors characterizing types of physical activities and icons illustrating events in-between the physical activities.

we often compare present and past behavior. Thus we might want to examine the temporal location of the data; when does the data element exist in time? Is there a temporal texture of the data; how often does the data occur? What is the changing rate of the data? Are they repeating in a pattern? Do data elements occur in a specific order, a sequence? Do data elements co-occur (synchronization or correlation between data)?

Most personal informatics applications providing temporal data choose to display them as a linear time axis, with either line graphs, like classical financial trading developments, or bar plots for comparing entities. However most of our patterns are typically circular, such as seasonal changes or daily routines, which tend to repeat on a temporal level. Other data can be structured as a sequence where one data element follows another in order, or data can be a hierarchical structure where one data element can be followed by a number of possible data elements. E.g. you might not wake up at the same time every day, however even if you wake up later one day, the next thing you do is take a shower and get dressed. And then you might eat breakfast followed by brushing your teeth, or you might skip breakfast.

Some of the most classic visualizations within personal informatics are bar plots, line graphs, pie charts and other visualizations which are also common in ex-

MODIFIED BAR PLOT
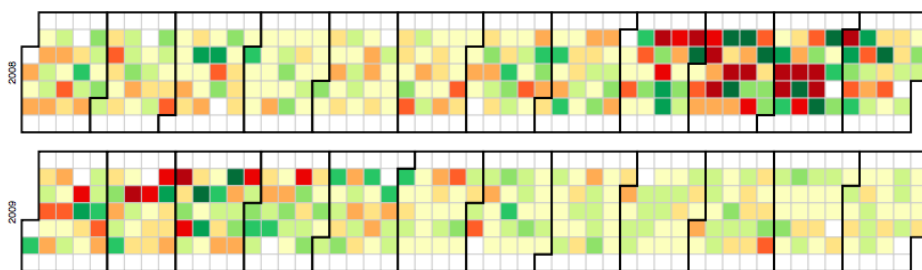
**Figure 5.3:** Calendar heat map showing Dow Jones index value of each day as colored cells, arranged into rows of weeks and blocks of months [2].

cel. These can easily be modified like Moves[1], that tracks the whereabouts and amount of walking, running, and biking. Moves consists of colored circles representing different physical activities (walking, running, biking), see Figure 5.2. The size of the circles increases with increasing activity, and works as a summary of the current day's activity. Below them is a more detailed view of the history, a stream (of stacked bars) with colors corresponding to the activities and the length indicates the duration. The bars are divided by small maps, indicating time spent in one place, and the description of the place (from Google Maps api). This app is fairly simple and can provide the user with a one-glance overview of the day's activity. However, it is not very helpful as a guide or tool to change behavior, since it has no threshold indicating the effect of the physical activity and even though they collect data from millions of users, there is no crowd-sourcing allowing the user to compare himself with others.

HEAT MAPS & SPIRALS
If we expect there to be a sequential pattern in the data, this could become more clear with a heat map, aligning the data by hour, day or week to spot patterns. In Figure 5.3 Dow Jones data is displayed as a heat map[2]: the values are visualized by the colored cells. Each cell represents a day, which is arranged into columns, by week, month and year. The data is constructed into a calendar heat map. Here we see high fluctuations in the data in October and November of 2008, likewise in February and March of 2009, whereas the index is more moderate the rest of the time. This view is especially helpful when the focus is on both extreme high and low values. Recently, the heat map has been modified into a spiral pattern, creating a more seamless and continuous flow [Larsen et al., 2013], with no break between the last and first hours of the days or between Saturday and Sunday.

DATA AS NETWORK
In a few cases we see examples of time series visualized as a network. Baur

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[1]moves.com
[2]bl.ocks.org/mbostock/4063318

**Figure 5.4:** Visualization of Last.fm history as a network and with integration of calendar events and photo stream.

created an exploratory visualization of the streaming history from Last.fm [Baur et al., 2010]. The data are a sequence of music tracks, where some tracks are in the history and are transformed into a network. This is a simple centralized network, where each node represents the same music track. This is a fairly simple network, and does not provide us with much more information other than how many times a track was played over a period of time. However this could easily be transformed into more complex networks by connecting tracks by the same artist, genre etc.

The classic approach for exploratory interfaces is the ability to select, filter, re-configure, elaborate and connect data. In this example, some of this is done by applying different colors according to the genres, and changing the size of the nodes to illustrate which are being played the most and by applying different temporal filters, such as dates, and time of day. What is more interesting though, is how calendar events and photo streams (discrete events) are used to get another level of personal data (Figure 5.4). By adding these, the tool is transformed from an exploratory tool, which might get tedious with time, to a more emotional system for reliving old events, through music and pictures. The user can then choose to see photos from a period as a slide show while the most popular music tracks of that period are being played.

ZOOMING, SELECTING & FILTERING

These three systems illustrate how data in time series can be visualized in different

ways. They also illustrate different levels of detail and interaction, from the spare time line of Moves - providing an overview and a simple history, to the Last.fm visualization - allowing the user to explore past behavior by applying filters and selecting tracks, artists, genres etc. This lets the user specify the content according to his needs.

## 5.2 Infer Meaning

BASELINE & METHAPHORS

In order to gain insight based on the data visualization, one of the key elements is a reference point or a baseline. As Huang et al. mention in their review of visualization studies *"Making comparisons is a fundamental way to gain insights from data"*[Huang et al., 2015]. In other words, a single number does not give much meaning in itself. E.g. knowing that you have burned 1900 calories in a day, does not give you much insight. However, *metaphors* can help translate the numbers into commodities such as seven burgers or walking a distance of 20km, hence it becomes easier to understand. The number can also be compared to prior data - a personal baseline; an average across days, weeks, months, years; or to the average of others. However knowing which baselines to choose will depend on the goals, context of use, and on personal preferences. E.g. should a household's energy consumption be compared to other families of the same size, or households of the same demographic context? Thus designing visualizations with the flexibility to change baseline depending on goal and preferences can accommodate useful insights.

THRESHOLD

Just as baselines are important, thresholds are equally important. Are seven burgers a lot or not? Some thresholds are universal (such as a bank balance below 0 being unwanted), but most are individual. The threshold might depend on height, weight, gender, age, or amount of activity. Thresholds can thereby help the user to analyze and understand the data. Common is their ability to convey a message easily and quickly. This is important, if the user needs to act upon it. Thresholds are not static, they can just as easily vary with the behavioral patterns. Thus the amount of sleep needed might depend on the lack of sleep previously or on the amount of physical activity. Thresholds are easy to act upon, because they transform data into binary results or decisions.

## 5.3 Actionable Feedback

When it comes to behavior change initiated by the personal informatics system, this is often referred to as persuasive design, which nudges people towards a certain behavior (whether they are consciously aware of it or not). Recently, there has been a lot of discussion about whether personal informatics systems should be persuasive or not, and if so, to what degree [3]. The critique of personal informatics is often that it is one-size fits all solutions: Often with fixed thresholds, such as a good night's sleep is 7-9 hours; or standard suggestions such as do not drink coffee after 7pm; or standard goals, such as TripIt's[4] leader board, showing who is traveling the most in the user's network. However, this is misleading if the user is trying to reduce his traveling due to environmental impact or spending more time with his family [Munson, 2012].

This can of course be solved, by making it possible to establishing personal goals. Thus systems should accommodate personal goals, which could be distinctly opposite. But it is not only important that the user can set his own goals. The system should also suggest goals which are realistic and which can be adjusted if they are too ambitious. Systems like Micoach[5] have different training programs according to the user's goals (run 5km, 10km etc), and to the user's physical fitness, however if the user fails to follow the program, there is no possibility for adjusting it, only to start a new one. Thus being able to set appropriate goals is essential for the user to succeed, and will increase their motivation and control. Likewise thresholds and suggestions should be personalized, through learning algorithms or crowd sourced data such as Last.fm's[6] music suggestions. Having data on users' preferences might lead to better suggestions.

PERSONALIZED GOALS

By modifying and personalizing the system, we make systems less persuasive and instead make them provide actionable feedback. This can be done by creating scenarios. Scenarios are especially useful if the effect of an action is not visible right away, but has more long-term effects, or when data points show discouraging results, despite the user's effort to change behavior. This is typical for behavioral changes which require persistence and a long time before results are visible. This often leads to lack of motivation. In some cases this could be helped by not focusing on single data points but on more global trends or by presenting different scenarios and their trade-offs, showing the user different ways of obtaining the

SCENARIOS & TRADE-OFFS

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[3] quantifiedself.com/2012/03/personal-informatics-in-practice-reflection-and-persuasion-in-personal-informatics/

[4] tripit.com

[5] http://micoach.adidas.com/

[6] last.fm
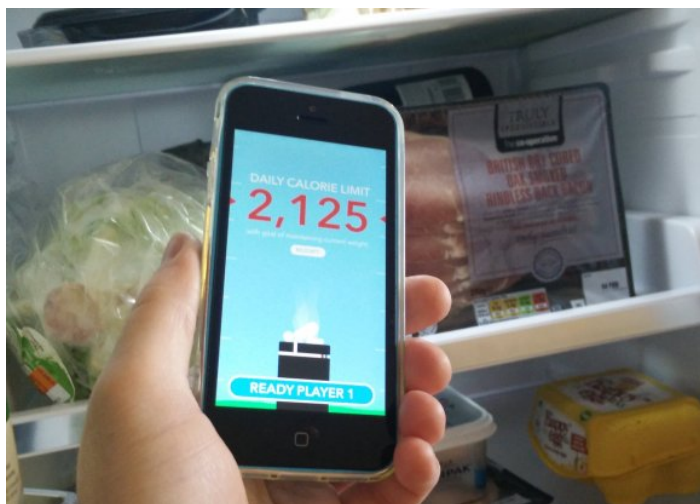
**Figure 5.5:** A beacon placed in the fridge, sensing when a smartphone is near, makes Carrot Hunger context aware, prompting the user to enter the food he is about to consume.

goals. For example, if the user wants to lower his energy consumption, the system could show what the effect of changing half of the bulbs to energy saving ones would be, and compare that to the effect of changing them all. Or it could show what the effect of lowering the temperature on the thermostats would be. Having multiple scenarios can help the user evaluate the trade-off from different behavior, and make decisions based on that.

SEQUENCES & ROUTINES

To provide actionable feedback, and encourage action or even change behavior,- certain elements should be considered. The system should first of all provide feedback in the right situation - when the choice/action is being made, and should fit into the physical environment and context of use. We see running applications that are excellent at giving feedback on one's pace while running, however they are less successful at getting the user out running. This requires the system to obtain information which contributes to understanding the contextual and sequential circumstances: This could be calendar events, GPS locations, or weather information, e.g. if the user only runs in the morning and only on days when it is not raining. The system could use weather data and calendar events to figure out which mornings would be most suited for running. And with knowledge of the *sequence* of actions required to perform an activity or task, the system could suggest setting an earlier alarm, giving extra time for running in the morning,

and suggest having the running gear ready next to the bed. By accommodating and adjusting to the user's routines, the likelihood of success is increased.

An example of a context-aware system is the Carrot hunger[7]. Like many other systems that track calories, it lets the user enter what food is consumed. However, it can also be hooked up to a beacon that senses the proximity of a connected smart-phone. By placing the beacon inside the fridge, it will recognize the smart-phone once the fridge opens, see Figure 5.5. This triggers a notification, telling the user to input the food he is about to consume. A clever detail when the phone is within range of the beacon is that a little Carrot Hunger icon appears in the bottom left corner of the lock screen, which enables fast entry to the system, similar to the camera icon function on many phones. Both the notification and the icon on the lock screen are examples of *micro-interactions*. It also has a bar-code scanner that the user can use instead of typing in the food, which will make the interaction quicker, which is essential if the user needs to input this multiple times a day. Thus if the visualization is to lead to action, it should provide in-the-moment data for real-time awareness with respect to the context (place, behavior, routine etc).

CONTEXT AWARE SYSTEMS

In the next chapter we apply individual baselines and thresholds to neurofeedback interfaces, and examine the tight coupling between these interface elements and the temporal aspects of the feedback loop.

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[7]meetcarrot.com/hunger/

## 5.4   Summary

Providing feedback is the basic component of any personal informatics system. The feedback is typically based on data that have been analyzed and presented, often by a visualization. Since most personal informatics are a type of time-series data, we saw how different types of visualization could be created from simple Excel charts to illustrate relative amounts of activity by circles or a history of events by stacked bars. We saw also how visualizations could underline sequential patterns of acute high or low values from heat maps.

If the data are not only visualized but also translated into something meaningful, it becomes easier to reflect upon them and gain insights. This could be done by the use of personalized baselines and thresholds. Furthermore, the feedback can be actionable by allowing personalized goals, or by presenting scenarios and trade-offs of alternative ways of achieving goals. It could consider the user's individual routines and *sequences of actions* that the system should be part of. And it should be context aware - knowing where and when in a user's *sequence of actions* to provide feedback.

CHAPTER 6

# Neurofeedback Training

Feedback can be provided at many different levels and in different ways. Feedback is often a confirmation or declaration of an action. We often see them in relation to micro-interactions as a confirmation or indication of a rule being triggered - when switching off the sound on a phone, a bell icon with a cross will appear and the phone might vibrate as feedback to the user. In personal informatics, feedback is often presented in relation to a baseline or a threshold, basically a change in condition. Feedback can be provided on different temporal levels, from real-time feedback, provided from milliseconds, seconds or minutes of data, to feedback illustrating tendencies from minutes or hours, such as heartbeat when exercising, or from days, weeks and months, such as sleep patterns. Feedback can be described as *active* when given in real-time, for example a coach monitoring a person's running pace and telling him to speed up or slow down. It can also be *passive* information available on demand, such as the summary of a run, showing the distance covered. In other words, the feedback is a clarification of the behavioral output, which is fed back as input to the user on which the user can reflect and choose to act.

FEEDBACK

We will explore how feedback can be used to *infer meaning* and can affect how we *adjust behavior* by considering the temporal aspects of data. Likewise we will examine the effect of the *outcome* due to feedback, see Figure 6.1.
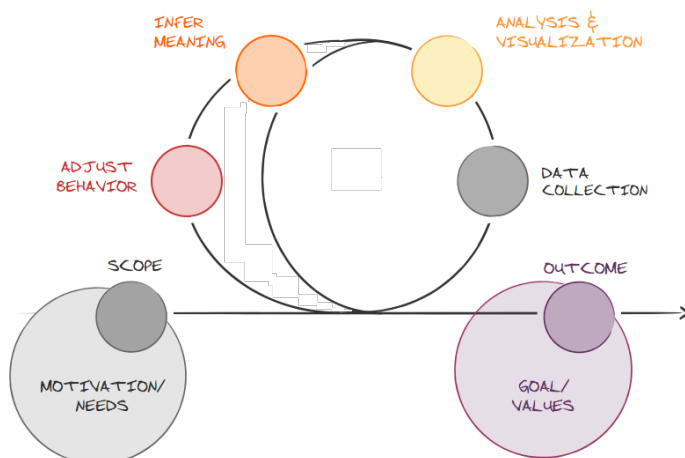
**Figure 6.1:** We view the feedback loop in relation to neurofeedback training, while focusing on the effect of the interface, and on providing feedback at multiple temporal levels.

## 6.1 Neurofeedback

We look at the feedback in the context of neurofeedback training. Neurofeedback training is a method for self-regulating neural activity based on real-time feedback of the brain activity. Neurofeedback training is primarily used as part of treatment for various psychological disorders, but is also used in attempts to enhance cognitive ability such as concentration or focus and has slowly become part of the personal informatics segment.

NEUROFEED-
BACK & THE
FEEDBACK
LOOP

In traditional neurofeedback systems, the *scope* would involve decisions on which brain waves should be trained and from which cortical areas. This is of course closely coupled with the disorder that is being treated or the cognitive ability one wishes to train. Then comes the *data collection*, where the cortical activity is monitored, followed by the *analysis & visualization* where the data are baseline corrected. This is of great importance when dealing with EEG because the amount and oscillation of brain activity is highly individual. Thus it is always the relative cortical activity changes which are visualized. Next is the *inferring meaning*, this however has often been neglected in traditional neurofeedback interfaces. It has been assumed that users can regulate their brain activity regardless of how it is presented. Based on the feedback from the interface, the user can respond by changing mental strategy or trying to achieve a certain state of mind in the
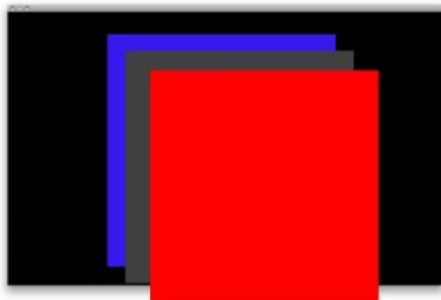
**Figure 6.2:** A traditional neurofeedback interface, with a single square providing real-time feedback of the neural activity by changing colors from blue to grey and red when activity is below, equal and above baseline, respectively

next *adjust behavior* step. Depending on the user's ability to regulate his brain activity and the amount of training, the subsequent *outcome* can be seen in the brain activity and in addition is often measured by a cognitive test or behavioral evaluation based on a *response*. The loop between *data collection*, *analysis & visualization* and *adjust behavior* is completed in milliseconds, creating the real-time feedback loop between brain activity and visualization.

With the temporal resolution of the EEG brain scanning neurofeedback training can provide instant feedback. However, by repeating this loop multiple times, the reflection might span across seconds, minutes or hours during which the user can explore different mental strategies to optimize his training, by receiving real-time feedback on the cortical activity. Due to the brevity of the loop before the change in brain activity is fed back as input, the way of providing the feedback becomes extremely important.

### 6.1.1   Previous Neurofeedback Interfaces

Many traditional training interfaces provide feedback, indicating whether the activity has increased, decreased or is similar to baseline. The typical feedback is visual, audio or both. Previous experimental setups have typically used bar diagrams or colored squares indicating high or low brain activity. These interfaces provide feedback based on a personal baseline, but provide no other affordances to guide the user.

Rather than providing a visual stimulus, other neurofeedback systems such as that of Egner et al. have used audio feedback to increase the alpha/theta ratio [Egner et al., 2004]. A background sound resembling either a 'babbling brook' or 'ocean waves' was used to indicate a relative increase of alpha and theta activity respectively. These sounds would create associations which some might find supportive to the mental training. Additionally, a high-pitched or low-pitched gong sound would be executed when the activity exceeded a pre-set threshold of alpha and theta, respectively. The subjects aimed to increase the amount of theta sound representation, whereas the gong sound would indicate reaching a 'significant' activity level, representing succeeding or failing.

Recently a commercial neurofeedback system, Muse[1], was developed - a personal informatics system to *"enhance your meditation"*. Muse consists of only four electrodes used to measure brain activity with the goal of helping the user maintain his focus for a longer period of time. Muse provides real-time feedback by two audio-streams. The task is for the user to close his eyes and count his breaths. When the user is focused on counting, the volume of the waves will increase. However if the user's mind starts wandering, the sound of the wind in the audio track will increase. If the user manages to keep focused for 20 consecutive seconds, the sound of birds will appear, which serves both as a threshold and a motivational feedback. This way of providing feedback is similar to that of Egner et al., with audio tracks providing real-time feedback on increased or decreased brain activity and a threshold sound: The 'babbling brook' and the threshold gong have been replaced with the sound of blowing wind and birds. The chosen audio streams of waves and wind are not coincidental, since these have often been associated with meditation. While Muse provides real-time feedback by audio streams, it is only after the training session that the history of past activity is visualized as a graph chart. Though the sounds of waves and blowing wind may help the user get into a relaxed state, it is only the audio thresholds that serve as affordances in both Muse and Egner's neurofeedback interface.

## 6.1.2 Feedback on Multiple Temporal Levels

We wanted to design an interface that not only defined thresholds but presented them within a spatiotemporal context that could contribute to the user's reflection on his mental state. Thus we created a real-time history. Our interface consisted of multiple squares. Each square would represent a real-time feedback of the brain activity, with the square changing colors from black (merging into

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[1]choosemuse.com

Brain activity          Brain activity              Brain activity exceeding          Increasing activity
below baseline          equal to baseline           3 times the baseline              above baseline
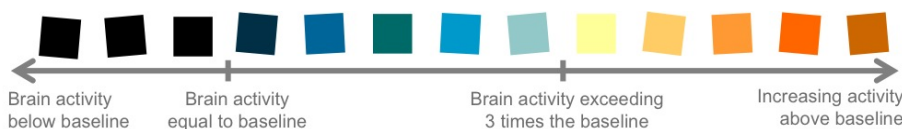
**Figure 6.3:** The intensity of the brain activity alters the color of the squares from black, then blue-scaled to orange-scaled when the brain activity is below, above and more than three times the baseline, respectively

the black background), to blue and orange. Activity below baseline would be represented with a black square, which would not be visible on the black background. If activity increased above baseline, the square would be dark blue, and become lighter with greater increase. If the increase had a magnitude of three times the baseline (which was determined in a pilot study), the square would become yellow towards orange with a even greater increase, see Figure 6.3. The color of the squares changed continuously according to the attained brain activity calculated from a running mean of 2 seconds within a sliding window. In this way, we stabilized the fluctuating pattern of brain activity. After one second, the square would freeze in the current color and a new square would appear and change color depending on the brain activity. Thus the square would create a history of past activity on which the user could reflect. Thus the feedback would now consist of data from multiple seconds. The squares were also binned into 15-second bins, starting from the left towards right. Thus the number of visible squares within each bin would represent the number of times the brain activity was above baseline and their color would represent the intensity. Our hypothesis was that the history would make it easier for the users to try out different mental strategies and compare them across seconds and minutes. The result of the interfaces is a more continuous and smooth representation of the data with the intention of accommodating the mental state of the users.

### 6.1.3   Neurofeedback Experiment

To see whether this threshold and history had a measurable effect on the neurofeedback training, we tested it against the traditional interface, Appendix C [Jensen et al., 2013]. The traditional interface was similar to that of Zoefel et al. with a colored square, representing the brain activity [Zoefel et al., 2011]. If activity was below baseline the square would turn blue. If it was equal to baseline it would be grey and if it was above baseline it would turn red, see see Figure 6.2.
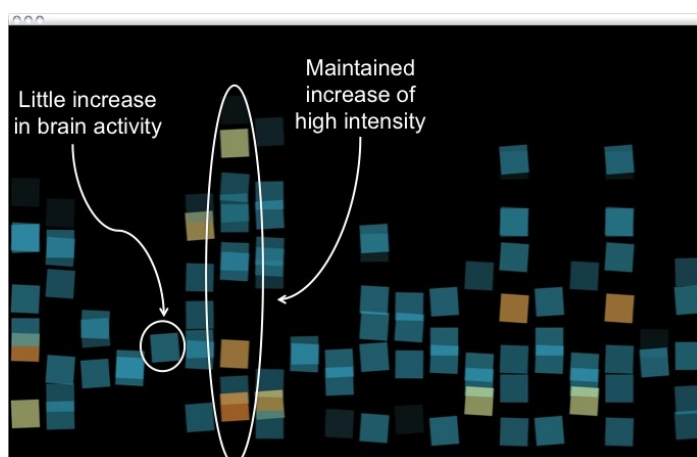
**Figure 6.4:** The neurofeedback interface provides feedback on real-time brain activity. With an increase in activity translated into small colored squares arranged in columns representing 15 seconds of the training. By displaying the columns side by side, the activity of the 5-minute training is represented as a horizontal time line.

The color changed with the sampling rate of 128Hz providing a feedback every 125 ms. This meant that the square would flicker if the brain activity fluctuated.

The two interfaces were tested on two different groups, aiming to increase their upper alpha activity (approximately from 10-12Hz). A group of 11 participants, including 5 females, trained using the traditional interface. The other group of 13, including 6 females, trained using our interface. Non of the participants had any experience with neurofeedback training. The experiment was conducted with a 16-channel mobile neuro-headset, Emotiv. The live feedback was provided from the two occipital channels, O1 and O2, which cover the visual center, where high levels of alpha power can be monitored. Each interface was tested on five consecutive days from Monday to Friday and each day started with a baseline recording, which would be used as the baseline for the following five training sessions of each five minutes. At the end of the day a second baseline recording was made, to see if the training had any effect on the baseline.

RESULTS    The results showed a significant increase of upper alpha amplitudes for participants training on our interface, though this effect was not transferred to a change in baseline, see Figure 6.5. This indicates that the interfaces had a helping effect during the training, but not on the overall baseline, suggesting that it was easier
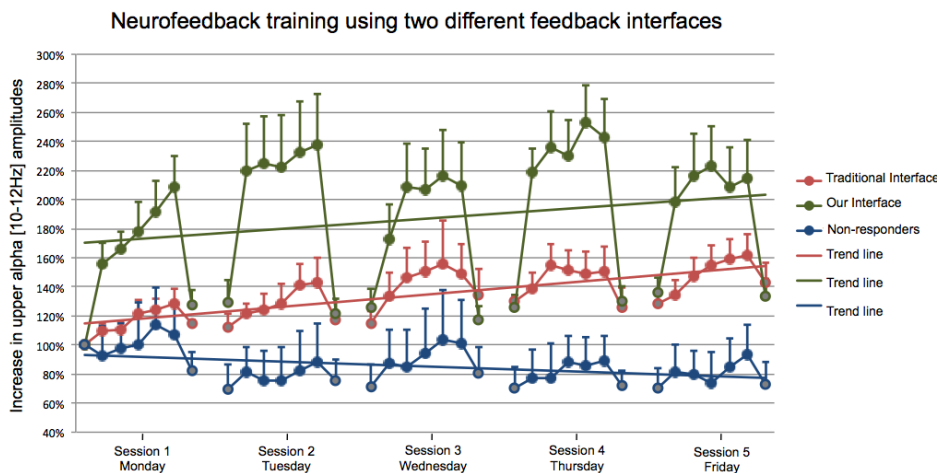
**Figure 6.5:** The difference in the participants' ability to increase upper alpha brain activity when using the classic red/blue interfaces (plotted in red) or using our multi-square interface(plotted in green). The participants using our interfaces increased their brain activity significantly compared to those using the classic interface. Those who were not able to increase their brain activity are referred to as non-responders[2] (plotted in blue). The bars indicate the standard error of the mean.

for the participants to reflect on their brain activity and reach the required mental state using our interface. But it had no effect on their general brain activity in the longer term. In cases where neurofeedback is used as treatment for children with Attention Deficit Hyperactivity Disorder (ADHD), this would mean that the subjects might have an easier time entering a focused state of mind, when asked to. However, they would not naturally become more focused when not intended.

Whether the effect is due to the properties of the visual components or the temporal aspects of the representation is unknown. Statements from the participants revealed that those using our interface would compare different mental strategies, which was enabled by the temporal feedback history. It might be that the sliding time window of our feedback interfaces was crucial, in its ability to create a stabilized visualization of the brain activity. This was supported by other statements revealing that the gradient color change in the feedback could be perceived as more smooth and continuous, compared to the disruptive flickering of the traditional interface. This suggests that the feedback should, if possible, support the mental state which is required for the training, whether it is a relaxed peaceful mind or a focused and sharp mind, or something completely different. Also, feedback provided in more continuous flow might help sustain the mental state, and help the user feel more in control of his brain activity.

These results indicate that not only does the interface influence our response, but the time window of the feedback is crucial in our ability to act upon our insights. Thus with neurofeedback, the feedback loop is very short, providing real-time information which requires instant reflection. If the user is unable to reflect, the feedback can be provided from a longer time period, a history. However with if the feedback only resembles past behavior, it becomes less actionable. This is just like the fact that increasing one's pace while running is easier with real-time feedback, compared to viewing past data on one's pace and increasing it next time one goes running.

In traditional neurofeedback interfaces, there has been limited or no focus on how the feedback was provided. This indicates that there has been little thought on how to *infer meaning* from the data, which could guide the user to the acquired state of mind. It also illustrates that the temporal level of feedback can contribute to the user's feeling of control.

(a) New York City Skyline [3]



(b) Our neurofeedback interface
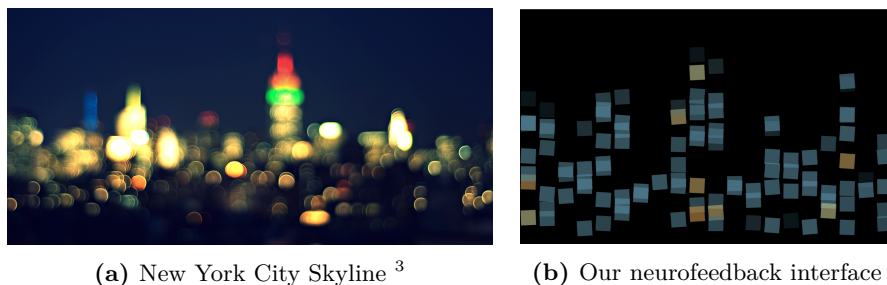
**Figure 6.6:** Our interface could create associations to the blinking lights of a skyline. While the blurring filter applied to the picture, may create a dreaming effect, allowing the user to project himself into the atmosphere.

## 6.2 Interface Components

Whether the neurofeedback is provided by sounds or colors, we suggest that these audio and visual components in combination can create associations and atmospheres which can help to pull the user into the wanted state of mind.

### 6.2.1 Visual Feedback Components

A simplified characterization of the visual feedback can be reduced to the following components:

- geometric primitives (connected segments)
- color (discrete, gradients)
- size (proximity, scale-ability)
- movement (horizontal, vertical)
- composition (spatial distribution)

In our interface we experience a combination of these components, where small squares, geometric primitives, are composed around vertical stacks and a horizontal line, while changing colors from dark blue to more yellow and orange tomes.

This could be associated with a skyline of rising towers with blinking lights in the horizon as shown in Figure 6.6[3].

## 6.2.2   Audio Feedback Components

Similarly the auditory feedback can be constructed from the following components:

- pitch (low, high)
- volume (soft, loud)
- timbre (dark, light)
- duration (short, long)
- rhythm (temporal distribution)

In Muse, the audio interface consists of audio streams of blowing wind and ocean waves which is a combination of continuous and rhythmic changes in the frequency spectrum. The feedback is provided by a volume change in the audio streams, and by having short high-pitched bird tweets sounding. In this case, ocean waves, blowing wind, and bird sounds will naturally lead the user to an imaginary beach. The rolling sound of the waves can be associated with the inhaling and exhaling of the user, thereby accommodating the task of focusing on breathing.

## 6.2.3   Haptic Feedback Components

In line with the audio and visual components, we can further expand with haptic components:

- frequency
- amplitude (intensity)
- duration (short, long)

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[3]ispynyc.wordpress.com/2011/11/21/the-skyline-lights
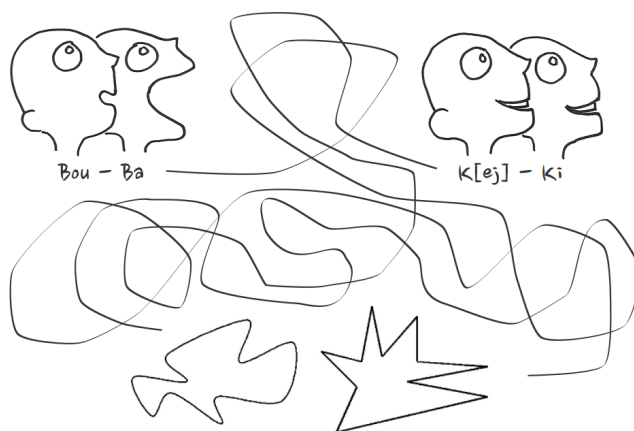
**Figure 6.7:** The *Bouba-Kiki* effect illustrates the associative coupling between the visual shapes and the shape of the mouth when pronounced: Which of these shapes resembles *Bouba* and which resembles *Kiki*?

- rhythm (temporal distribution; overlapping, inter-burst duration)
- composition (spatial distribution)

Consequently, when designing new neurofeedback interfaces, our focus should not only be on how to visualize an increase or decrease of brain activity, but should consider how combinations of components might affect the user's imagination, associations, or trigger related memories, supporting entering the wanted state of mind.

### 6.2.4 Multi-Modal Compositions

Above we see all the components separated. However, by combining these it is possible to create feedback which not only provides the necessary actionable information, but which can also support the interaction at other levels. Some of these components are inherently connected. We see this tight coupling between visual, audio, and haptic components in the *Bouba–Kiki effect.*

The *Bouba–Kiki effect* was first discovered in 1947 by Köhler, who found that people associated certain visual stimuli with the nonsense words, *Maluma* and *Takete.* An even more pronounced effect was found in 2001 with the words *Bouba*

BOUBA-KIKI
EFFECT

and *Kiki*, showing that 95% of the participants connected the round shape with *Bouba* and the pointy shape with *Kiki* [Ramachandran and Hubbard, 2001], see Figure 6.7. This effect has been seen across cultural boundaries, in pre-lexical toddlers [Maurer et al., 2006] and for populations with no written language [Bremner et al., 2013]. It has been suggested that the coupling is due to associations between the visual shape and articulatory characteristics of the vowels when pronounced [Ramachandran and Hubbard, 2001]. In the study by Fryer, the visual stimuli were transformed with 2D and 3D representations and a similar effect was found between the haptic stimuli and the auditive [Fryer et al., 2014]. However, for participants with visual impairment, the effect was significantly lower, suggesting that the effect is tightly coupled with visual imagery, and that visual imagery plays an active role in cross-modal integration. This tight coupling between haptics and visual imagery might be because both sensory modalities provide geometric information.

We will investigate the effect of different haptic components in creation of perceived continuous motion and how haptic patterns of different modulations are perceived as pleasant, unpleasant, calm and energetic.

## 6.3 Summary

With neurofeedback training we see the tight coupling between temporal aspects of the *analysis* and we see how the *visualization* can provide feedback ot different temporal levels, from milliseconds to minutes. By the use of a sliding window in the analysis, it is possible to stabilize the visualization of brain activity, which might provide the user with a feeling of control. The history of past activity enables the user reflect on and compare past mental strategies. The neurofeedback training also illustrated how the *visualization* and being able to *infer meaning* from it influences the *outcome*, the ability to access a successful state of mind.

This kind of monitoring and training of mind is now moving from the scientific and clinical settings to the consumer arena. Disregarding the effect of the feedback and inferring meaning from the data can no longer be tolerated. Thus focus should not only be on how to visualize an increase or decrease of brain activity, but should consider how combinations of visual, audio, or haptic components might create associations and support the user in entering the desired state of mind.

CHAPTER 7

# Haptic Interfaces

The previous chapter demonstrated the effect of combining different audio and visual components into helpful feedback. In this chapter, I focus on how haptic feedback can be used to *infer meaning* by providing distinguishable patterns, which is commonly used as a notification for the user to *adjust behavior*, see Figure 7.1. Haptic feedback is of special interest because of its direct skin contact, which makes it personal and intimate. This makes it an obvious candidate for several personal informatics systems providing real-time feedback. Within personal informatics systems, it has only been applied to a few systems, for example Spire[1], which provides a haptic notification if the user has been sedentary for too long, indicating that the user should stand up or change position. With actuators becoming an integrated part of smart-watch interaction, we will probably see even more efforts towards design of haptic feedback, which not only sends a message, but which also is connected to tactile associations of touch.

Physical contact with objects and people is a natural part of how we interact and communicate with our environment. In contrast to our other sensory modalities (vision, taste etc.), haptic interaction is responsive: when touching something you will be touched in return. This is referred to as active (touching) and passive

ACTIVE & PASSIVE TOUCH

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[1]spire.io
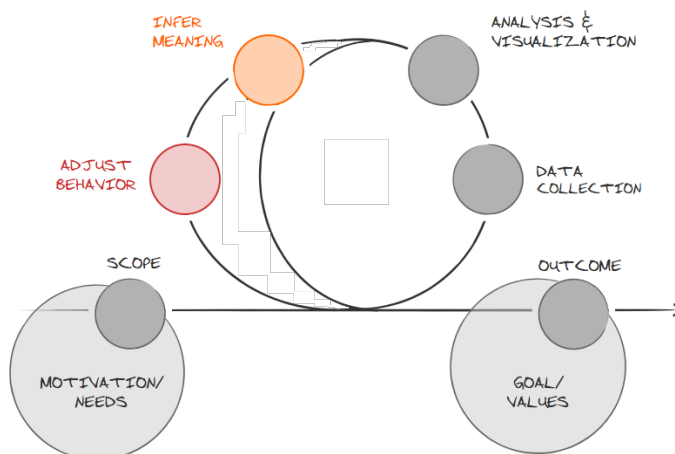
**Figure 7.1:** Taking a closer look at the stages *inferring meaning* and *adjusting behavior*, in relation to haptic feedback - including how haptic feedback can be used as notifications for adjusting behavior, or how it can create associations that support other types of feedback, such as visualizations.

(being touched) touch. The responsive interaction enables us to refine and adjust our motor activation - enabling us to lift heavy items, gently interact with fragile items, or caress the skin of a loved one. It might also be the reason why touching something often results in a strong personal experience. Thus when we experience haptic feedback from phones or smart-watches this can easily feel invasive, if not done in the right way.

The strong effect of haptic interaction can be illustrated by looking at our brains - the primary somatosensory cortex and the primary motor cortex (see Figure 7.2) [Reisberg, 1997]. Here we see how somatosensory and motor cortices are mapped to different body regions, illustrating the areas devoted to processing and integrating information. Large parts of these areas are mapped to the hands and mouth input and output, which makes sense from a primitive survival perspective, in which our hands play a significant role in both defending us from danger and hunting or gathering food. The pictogram in Figure 7.2. also illustrates a hierarchical range, from a precision grip demanding high coordination of finger movements, to grasping a heavy object using the whole hand.

The haptic sensory information comes from receptors located in our skin (mechanore-
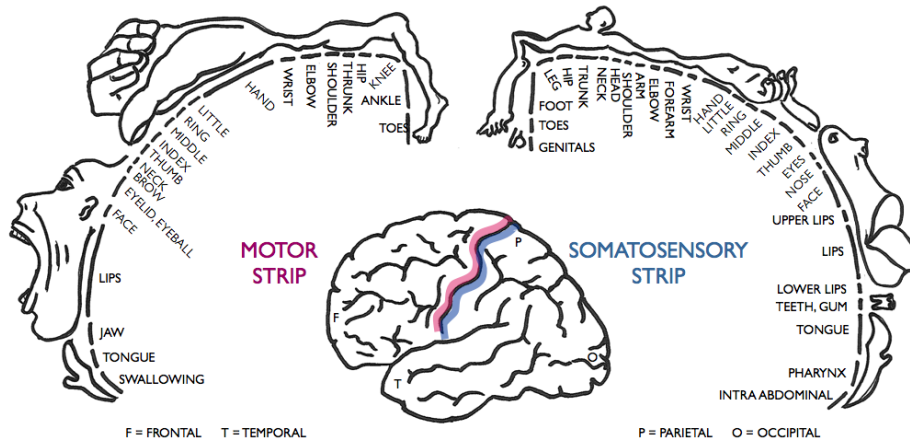
**Figure 7.2:** A pictogram mapping areas of the somatosensory and motor cortex devoted to processing information and executing movements of the different body regions. Inspired by Reisbergs illustration in [Reisberg, 1997]

ceptors and thermoreceptors) as well as receptors in muscles, spindles and tendons (proprioceptors)[Carbon and Jakesch, 2013], thus research on haptic interaction has been divided into two areas:

**Tactile feedback** is the stimulation of nerves in the skin, including feeling heat and texture

**Force feedback** describes interactions that lead to activation of muscles and tendons, which would be the feeling of a force (such as weight) or reaction force (such as hardness)

From these receptors we are able to get information about geometric (size, shape, etc.) and material properties (texture, hardness, temperature). The geometric properties are also provided by our visual system and can therefore confirm our haptic perception. However the material properties, such as quality assessments, can provide additional information. Thus, if we can not rely on our visual system to distinguish whether a doorknob is made of metal, plastic or wood, we can get information about the material properties from touching the handle. Thus haptic feedback can both strengthen the visual information in regards to geometric information, and provide additional information on material properties.

In the following sections I will provide state-of-the-art examples of haptic feedback, which is divided into two types of haptic feedback:

**Direct haptic feedback** describes a haptic stimulation which is invented and often serves to provide information, such as navigation or notifications.

**Indirect haptic feedback** mimics a real haptic sensation which comes from interacting with the physical world, this could be plucking a guitar string, a tap on the shoulder etc. and is often accommodated by either audio or visual feedback.

## 7.1   Direct Haptic Feedback

DICRECT
HAPTIC
FEEDBACK

Despite the strong and personal effect haptic feedback can have, it has only been applied in a few applications. The early research on haptic feedback focused on applications aiding blind or visually impaired people such as needles on fingers providing direction indications for navigation [Ertan et al., 1998]. The braille tactile writing system for visually impaired is a good example of how fine tuned our tactile perception is at our finger tips and of the resolution in which vwe can distinguish tactile patterns. However most of the *direct haptic feedback* we see today is not attached to our finger tips but comes from phones in our pockets or clips attached to our waistline. The feedback we receive is primarily notifications of incoming calls, text, calendar event, etc. With the recent Apple Watch, haptic feedback is now constantly available on the user's wrist. Because of its invasive effect, the watch needs to be configured as a filter, allowing only urgent information to pass through. The advantage of haptic feedback is that it is invisible to the environment. Thus in situations where it would be inappropriate to interact with a smartphone, either because it would be impolite or disturbing, the user can rely on interaction with a smart-watch. Besides from the normal notification function, the haptic feedback is also used to confirm *micro-interactions* when navigating with the watch. Since most haptic feedback is used to provide information, the primary focus has been on creating distinguishable haptic patterns.

There are different methods for creating haptic patterns, including vibrotactile actuators, electrodes, shape memory alloys, electro-mechanical actuators etc. I will focus on vibrotactile stimulation, since this has been available in mobile phones for decades and is the most prominent type of haptic feedback in other personal informatics devices.
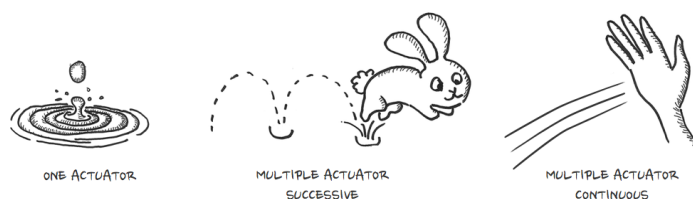
**Figure 7.3:** Tactile associations to haptic modulations.

The Apple watch consists of only one actuator, thus the patterns can only be designed from modification of the following components:

- frequency
- amplitude (intensity)
- burst duration (short, long)

By modifying these, the vibrations can feel like a subtle tap or a hard poke, or perhaps even the ripple effect of water rings.

However, with more actuators, the patterns could also be modified by:

- rhythm (temporal distribution: overlapping, inter-burst duration, direction)
- composition (spatial distribution: close together, far apart)
- spatial direction

By modifying these a *continuous* motion from an overlap of vibration from actuators could be created. This feeling could be translated into the stroke of a hand. The pattern could also be based on *successive* bursts by having an inter-burst interval, making actuators vibrate separately, one after another. The could be perceived as a step-wise motion, like a hopping rabbit, see Figure 7.3.

We describe patterns as being based on the following three modulations:

**Simultaneous** where all actuators are vibrating simultaneously.
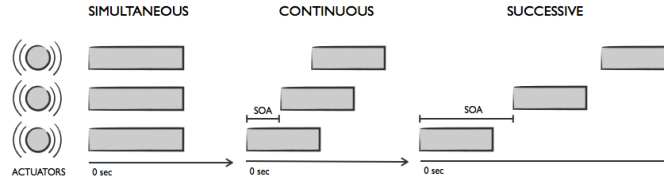
**Figure 7.4:** The rhythm and perceived stimulation of three haptic modulations - simultaneous, continuous, and successive - is illustrated.

**Continuous** where there is an overlap of vibration, before the first actuator stops vibrating the next will start.

**Successive** where there is a time period in between two actuators' vibrations, an inter-burst duration.

### 7.1.1  Perceiving Continuous Motion

Though these patterns seem straightforward, the understanding of how each parameter contributes to the perceived sensation and our translation to known tactile interactions is limited. Thus attempts to understand continuous motion, includes motion created from three different patterns: continuous (also referred to as saltation), amplitude modulation and a hybrid pattern [Yatani and Truong, 2009]. Also studies on the effect of frequency, burst duration [Israr and Poupyrev, 2011b], intensity and body site [Israr and Poupyrev, 2011a, Cholewiak and Collins, 2000] have been examined.

It may be possible to create haptic feedback which could assist in enhancing an emotional experience in scenarios such as long-distance relationships. Therefor, in the hope of overcoming the lack of physical contact when communicating through standard interpersonal communication systems such as Skype[2], or in a virtual environment such as SecondLife[3], we investigated the control space of creating perceived continuous motions which could be associated with a caressing stroke, Appendix D [Eid et al., 2015]. We investigated the upper and lower thresholds of perceived continuous motion on the forearm, by altering the stimulus onset asynchrony (SOA). The SOA is defined as the time between onset of vibrations coming from two actuators. If SOA is shorter than the vibration (burst duration),

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[2]skype.com
[3]secondlife.com
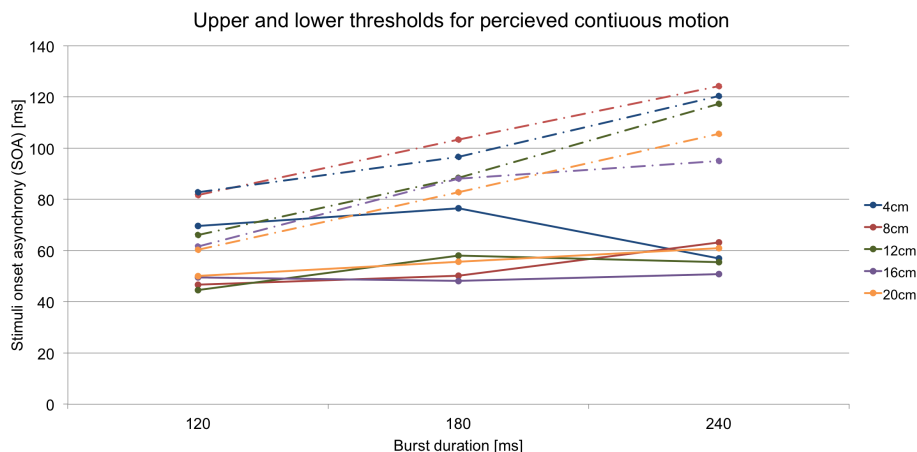
**Figure 7.5:** The upper (dashed lines) and lower thresholds (solid lines) for creating perceived continuous patterns, with actuators at different distances and with different burst durations.

there will be an overlap of vibration from the actuators, see Figure 7.4. Is SOA is greater than the burst duration, there will be a period of time between the two vibrations. The lower threshold is where the vibrations are perceived as coming from both actuators simultaneously rather than a continuous motion. The upper threshold is where the vibration is perceived as coming from two successive actuators, one at a time.

We found the thresholds for five different spatial distributions by placing actuators at 4, 8, 12, 16, and 20cm apart. At each spatial distribution the thresholds were found for three different burst durations, 120, 180, and 240ms. The results in Figure 7.5 show the lower and upper thresholds of the SOA, indicating that the area in between is perceived as a continuous motion. Thus we found that the relationship between inter-bust duration and the burst duration was linear at all distances except for the lower thresholds at the shortest distance (4 cm). This could be because the actuators at 4 cm are placed too closely together for the subject to distinguish between simultaneous and continuous motion. Thus, this might be an indication of the resolution at which we can distinguish patterns on our forearm.

RESULTS

| Pattern | Modulation | Feature |
|:---:|---|---|
| 1 | Simultaneous | Intensity |
| 2 | Simultaneous | Intensity + Speed |
| 3 | Continuous | Intensity |
| 4 | Continuous | Intensity + Speed |
| 5 | Continuous | Intensity + Direction |
| 6 | Successive | Intensity |
| 7 | Successive | Intensity + Speed |
| 8 | Successive | Intensity + Direction |

**Table 7.1:** Eight different haptic patterns based on the three modulations: simultaneous, continuous, successive.

## 7.1.2   Designing Haptic Patterns

Although most studies examining preferences towards vibro-tactile feedback report preferences towards more continuous stimulation, this might not be the most suitable haptic feedback in all cases. When implementing haptic stimulation in a wrist-worn alarm clock, the stimulation should not only be pleasant, but also attract attention. In this case, a soothing continuous motion might not draw enough attention upon itself to cause the user to wake up. Instead it might become integrated into the user's sleep. However, using an arousing and aggressive stimulation could result in an unpleasant awakening that might lead to a dislike of the system. Thus we examined both the subjective emotional ratings of different haptic patterns as well as the response time, how fast 12 participants' attention shifted towards the different haptic patterns, Appendix E [Jensen et al., 2015].

The emotional ratings are based on the classic 9-point valence and arousal scales. The valence level indicates how pleasant or unpleasant the haptic pattern is, whereas the arousal level indicates how calm or exiting the stimulus is. The patterns' ability to attract attention was measured with a dual attention task. The dual attention task consisted of two tasks performed at once. The first task was a visual identification task, where the participant had to identify the correct target among different distractor stimuli. While the user did this test, a haptic pattern would start. Once the participant perceived the haptic stimulation, he was to abandon the visual task and respond to the haptic stimuli by pressing a button. This response time would indicate how quickly the participant's attention shifted to the haptic pattern.

HAPTIC PATTERNS We created eight different patterns based on the three modulations (*simultaneous*,
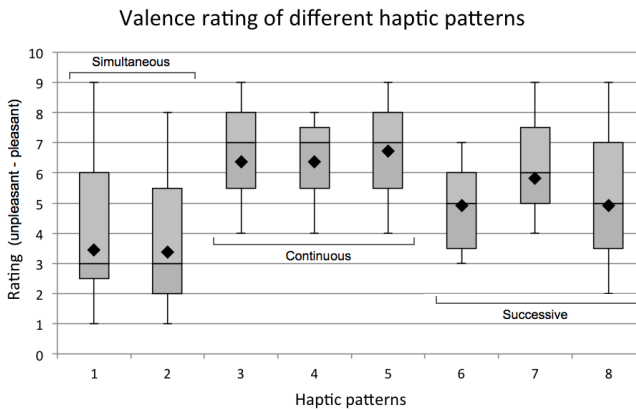
**Figure 7.6:** The subjective valence ratings (pleasant-unpleasant) of eight differ-
ent haptic patterns, show a preference towards patterns based on
the *continuous* modulation. Results are shown as box plots with
median, upper and lower quartiles, min and max values, while dia-
monds represent the means.

*continuous*, and *successive*). The first two (pattern 1 and 2) were based on the
*simultaneous* modulations. The next three (pattern 3, 4, and 5) were based on
the *continuous* modulation. The last three (pattern 6, 7, and 8) were based
on the *successive* modulation. All of the eight patterns increased in amplitude
(intensity), starting from not being perceivable and slowly increasing until the
user perceived it and responded to it. Pattern 1, 3, and 6 were only modulated
by this intensity increase. Pattern 2, 4, and 7 were in addition changed in speed,
from slow to fast vibrations. This was done by decreasing the SOA interval,
decreasing the inter-burst interval in pattern 2 and 7, and by increasing the
overlap in pattern 4. The last two patterns, 5 and 8 changed in direction (from
left to right and right to left) in addition to the increase in intensity.

Starting with the valence rating, the three patterns based on *continuous* modula-    RESULTS
tion were rated as the most pleasant, and the two based on *simultaneous* modula-
tion as the least pleasant, see Figure 7.6. However, we also obtained greater error
bars for the *simultaneous* patterns, indicating that some participants found these
pleasant whereas others did not. The arousal rating in Figures 7.7 shows a less
clear picture, with no distinguishable difference between the patterns. However,
the error bars reveal that some, but not all participants, found the *continuous*
patterns more calm compared to the others. The response time shows a much
faster response to the *continuous* modulations compared to any of the others, see

Arousal rating of different haptic patterns
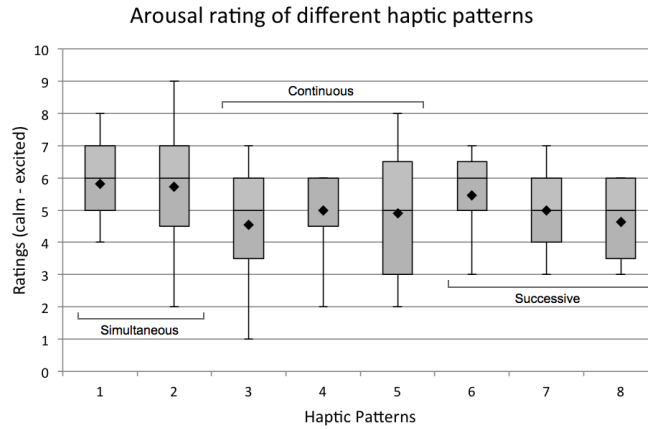


**Figure 7.7:** The subjective arousal ratings (calm-exciting) show great variabil-
ity for some patterns. Results are shown as box plots with median,
upper and lower quartiles, min and max values, while diamonds
represent the means.

Response time to different haptic stimulations
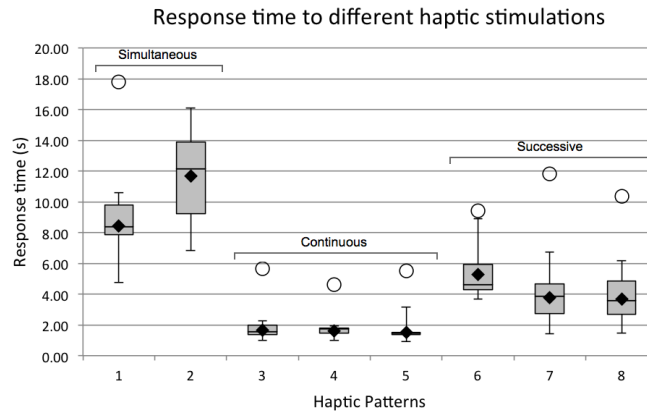


**Figure 7.8:** The response times of the eight different patterns show significantly
faster responses to patterns based on *continuous* modulations and
*successive* modulations compared to those based on *simultaneous*
modulations. Results are shown as box plots with median, upper
and lower quartiles, min and max values, diamonds representing
the mean, and circles representing an outlier.

Figure 7.8, indicating that the *continuous* modulation of these patterns might be the easiest to perceive or that these patterns confirmed the participants' suspicion, once even a slight vibration was perceived. Thus, it would seem natural to choose a pattern based on a *continuous* modulation for the haptic feedback of a wrist-worn alarm clock.

## 7.2   Indirect Haptic Feedback

From a focus on providing information, haptic feedback has been applied to enhance user experience and simulate real haptic interactions. In 1997, Nintendo introduced a game controller providing feedback, the Rumble Pack for Nintendo 64. Depending on the game, the controller would vibrate when shooting with a machine gun or when a race car was pushed into the verge on the side of the road. This type of feedback is more *indirect* and has typically served as an extension of the gaming experience. This has also been implemented for other entertainment scenarios, such as seats in movie theaters etc. Attempts have been made to create haptic feedback as an extension to emotional and interpersonal communication, in the hope of providing a physical connection for long distance relationships. Examples of these are everything from small gesture-based sensors to large devices and jackets simulating hugs [Arafsha et al., 2012, Tsetserukou et al., 2009]. However, these products for haptic interpersonal communications have not become successful as a common commercial product, perhaps because mimicking real social interaction is much more difficult compared to the crude shaking of a machine gun. The most convincing attempt is perhaps Babybe, which is a device used in health care that simulates physical contact between mothers and their premature babies[4]. Babybe consists of a sensor recording the mother's chest movements and heartbeat, which are transmitted to a cushion on which the infant lies, raising and lowering the cushion.

The Apple Watch also provides *indirect* feedback, however currently only in one application. This is the case, with transmitting the user's heartbeat, recorded from a sensor in the watch, to another user, while enhancing the tactile feedback with the visual outline of a heart pumping. This visual feedback is crucial in order for the receiver to associate the sudden haptic stimulation with the sender's heartbeat, instead of just a rhythm of taps. This is a good example of how hard it is to provide an affective haptic feedback and why it is often accompanied with either visual or audio feedback. Concurrently with Apple Watch's growing

INDIRECT HAPTIC FEEDBACK

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[4]babybemedical.com

market, we are likely to see many more of these haptic micro-interactions being used to boost and expand traditional interaction and feedback patterns.

# 7.3 Summary

The recently developed sensor-packed wearable devices are obvious candidates for future personal informatics systems. This implies there will be an increasing focus on how to create haptic feedback, which can be used not only to *infer meaning* by providing distinguishable patterns, but also to create patterns associated with real tactile touch, which produce personal emotional experiences.

In this chapter we examined the how the human sensory abilities define an upper and lower threshold for creating a perceived continuous motion. We also illustrated how having multiple actuators enables further design components, which widens the possibilities for creating more advanced haptic patterns. We also showed how an experiment revealed that haptic patterns based on continuous modulations were considered more pleasant than simple simultaneous bursts. This suggests that these could be associated with affective natural interaction patterns such as stroking and caressing.

CHAPTER 8

# Perspectives

This thesis has covered several aspects of cognitive interfaces for personal informatics feedback. First we looked at high-level aspects of design processes such as *scope* and *outcome*. We also looked at stages of activities, from *data collection* to *infer meaning* and *adjust behavior*, which are a fundamental part of personal informatics systems aiming to obtain self-knowledge. Furthermore, peeling off a layer, we examined ways of inferring meaning from data, suggesting use of baselines, thresholds, context awareness, scenarios, etc. to enable the user to reflect and make feedback actionable. Finally, we looked at separating interfaces into a low-level view of visual, audio and haptic feedback components, and how these can be combined to create supportive feedback. Thus we can see this as a hierarchy going from high-level aspects of *scope* and *outcome* to low-level feedback components. This last chapter will summarize the significant contributions of this thesis and discuss its implications and how we move on from here.
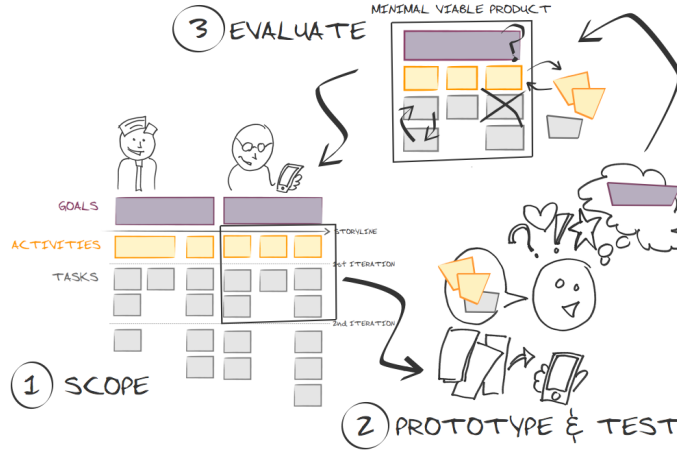
**Figure 8.1:** User Story Mapping as part of an iterative design process, helping
to scope the product by testing prototypes, thereby evaluating and
redefining the scope of the product.

## 8.1   Integration of Design Principles

With many personal informatics systems being driven by the ability to collect
large amounts of data, and with no scoping of the systems, they are likely to
provide meaningless data, which are hard to reflect on and gain insight from. Or
as a Quantified Self'er describes:  *"It's not that we lack the information, we are
virtually drowning in it. The obstacle is that we don't have the proper tools to in-
terpret the significance of our data"* [Choe et al., 2014] Although this Quantified
Self'er might be looking for the ultimate analytical tool, the quote does capture
a common problem within personal informatics systems: Focusing on collecting
and analyzing data, rather than supporting the users' motivations, needs, and
goals [Ohlin et al., 2015].

Thus we present a framework, *The feedback loop*, which incorporates these high-
level aspects *scope* and *outcome* that are essential in lean design processes to help
define the minimal viable product. Scoping a system requires translation of the
of the users' motivations, needs, and goals into *sequence of activities* and tasks
within each of the stages, which are decoupled and prioritized as in Figure 8.1.

One way of scoping a personal informatics systems is by the use of personality
traits. Personality traits can provide insight into users' motivations and prefer-

ences, both in terms of how actionable or exploratory the system should be, and in terms of the content's level of detail and how it is delivered. Thus, personality traits can be used to scope the high-level motivation, needs and goals as well as the tangible activities and tasks. Thus the design process can be seen as a way of transitioning between high-level *scope* and *outcome*, and the middle layer of *sequences of activities* and tasks.

An example of the importance of scoping personal informatics systems in relation to intended high-level *outcome* can be seen with neurofeedback interfaces.

## 8.2   Creating Supportive Interfaces

Previous neurofeedback studies have merely viewed the actual feedback as a way of informing the user of his current brain activity level - above, below or equal to baseline [Vernon et al., 2003, Zoefel et al., 2011]. To the best of my knowledge, no previous studies on neurofeedback have suggested that the way of providing feedback could influence the results of the training, until now.

The traditional interfaces have typically consisted of simple geometric primitives such as a square or bar, indicating high or low brain activity by altering components such as color, size or movement. All of which could be viewed as a binary information feedback: red vs. blue, big vs. small, high vs. low. In contrast, our interface would provide a smoothly changing color gradient, which based on the underlying moving window for sampling the data would stabilize the visualization of brain activity. The statements from participants also suggested that this smooth gradient provided the user with an enhanced feeling of control. In addition, the spatio-temporal layout of gradient squares generates a history of past activity, enabling the user to reflect and reuse previous successful attempts to enhance the alpha activity.

By comparing our interface with a traditional interface, we found an effect during training, but not on the overall baseline. This suggests that it was easier to increase and maintain an increased alpha activity. However, we could not replicate earlier results indicating that the neurofeedback training would alter the individual alpha baselines [Zoefel et al., 2011]. Whether the training effect was due to color-indicated threshold, the temporal aspects, or other properties of the visual components is unknown. But one thing is clear: We need to consider feedback which is supportive of the activities that underpin the desired outcome. In this case it should support and guide the user to attain the desired state of mind -

whether it is a relaxed, peaceful state of mind; a focused, sharp state of mind; or something completely different.

Thus neurofeedback interfaces are a great example of how we need to consider high-level needs, motivations and goals when we design personal informatics systems. It illustrates the tight the coupling between all the stages of the loop: *data collection*, *analysis & visualization*, *infer meaning*, and *adjust behavior*.

### 8.2.1   Towards Multi-Modal Interface Components

The interfaces described in this thesis all consist of a combination of components: visual, audio and haptic such as geometric primitives, colors, pitch, volume, and many more. The components could be smooth, gradual color change, as in our neurofeedback interface; the smooth fading volume changes between ocean waves and blowing wind in Muse; or continuous or rhythmic haptic patterns from vibrating actuators.

Perhaps by providing feedback in a continuous manner rather than the binary high-low indication of brain activity, we can accommodate the sequence of increasing and decreasing brain activity and thereby the progress of training. An analysis of the effect of individual components was undertaken in the case of the haptic interface experiments. While we may be able to isolate each individual component, as in the experiment identifying how the haptic parameters of intensity and rhythm are perceived in isolation, we in reality often combine modalities as exemplified by the cross modal *Bouba-Kiki effect*: coupling sound with visual shapes.

## 8.3   Moving Science into the Wild

In the experiment examining the upper and lower thresholds of perceived continuous motion, we isolated the haptic feedback to consist of only three haptic components: rhythm by changing the SOA; burst duration for 120ms, 180ms to 240 ms; and composition by changing the distance between the actuators. Though we did find the upper and lower thresholds, this is unlikely to provide associations towards affective human interaction such as a caressing hand. This illustrates how isolation of components might lead to specifications of designing haptic feedback, but it does not contribute much to the full user experience. For

that we need to consider multi-modal feedback, such as the combination of visual and haptic feedback of heart beats from Apple Watch.

The same constraints are valid when it comes to investigating emotional responses using brain signals: First, by removing eye movements and blinks, whose power are magnitudes stronger than the brain activity. Secondly, by separating emotional responses in EEG into relevant time windows. Still, in order to get a measurable difference of how we perceive pleasant or unpleasant images, we not only have to move beyond electrode-based analysis by employing a range of machine learning approaches, we also have to use extreme visual stimuli consisting of mutilated bodies or erotic scenes. But these extreme images are rarely encountered in an everyday context, and therefor unlikely to be used for personal informatics systems.

Thus we remain far from being able to monitor these underlying emotional parameters outside controlled lab conditions and we are still unable to continuously collect and analyze such signals 'in the wild' in relation to personal informatics systems. We may therefore need to examine alternative ways of extracting individual responses: from other physiological measures, such as eye-tracking, skin conductance or heart rate monitoring; or from behavioral patterns. Or maybe we can use the general insights of users' motivations and preferences from personality traits and build on these with the individual physiological and behavioral measurements, which could easily be retrieved from smart-phones and smart-watches.

CHAPTER 9

# Conclusion

This thesis should be viewed as a response to the challenges of designing personal informatics systems, where people seek to gain knowledge of them-selves by tracking various aspects of their lives, ranging from physiological measurements to behavioral patterns. In particular, this thesis aims to provide a new personal informatics framework that incorporates lean agile design principles, thereby focusing on scoping high-level goals, activities and tasks to create minimal viable products. The created framework stretches from high-level aspects of users' motivation, needs, and goals to guidelines for creating cognitive interfaces, seeking to infer meaning from data, and even provide actionable feedback.

With neurofeedback interfaces, I showed design of these interfaces can have an effect on the training outcome. This suggests that the temporal aspects of the feedback appear to have an effect. However, further research on this area is needed. I described how interfaces can be constructed from different visual, audio and haptic components and argue that by combining these we can hope to create interfaces which not only provide meaningful feedback, but also enhance the user experience and support the underlying interaction.

Finally, I hope that this thesis will mark a break with the existing focus on data collection or data analysis, which has characterized many personal informatics

systems [Ohlin et al., 2015], and rather focus on supporting the users' motivations, needs, and goals.

# Smartphones as pocketable labs: Visions for mobile brain imaging and neurofeedback

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# Smartphones as pocketable labs: Visions for mobile brain imaging and neurofeedback

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## ARTICLE INFO

## ABSTRACT

Mobile brain imaging solutions, such as the *Smartphone Brain Scanner*, which combines low cost wireless EEG sensors with open source software for real-time neuroimaging, may transform neuroscience experimental paradigms. Normally subject to the physical constraints in labs, neuroscience experimental paradigms can be transformed into dynamic environments allowing for the capturing of brain signals in everyday contexts. Using smartphones or tablets to access text or images may enable experimental design capable of tracing emotional responses when shopping or consuming media, incorporating sensorimotor responses reflecting our actions into brain machine interfaces, and facilitating neurofeedback training over extended periods. Even though the quality of consumer neuroheadsets is still lower than laboratory equipment and susceptible to environmental noise, we show that mobile neuroimaging solutions, like the *Smartphone Brain Scanner*, complemented by 3D reconstruction or source separation techniques may support a range of neuroimaging applications and thus become a valuable addition to high-end neuroimaging solutions.

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## 1. Introduction

Only recently have wireless neuroheadsets, capable of capturing changing electrical potentials from brain activity through electrodes placed on the scalp using Electroencephalography (EEG), made mobile brain imaging a reality. The emergence of low-cost EEG sensors and the increasing computational power of smartphones may transform neuroimaging from constrained laboratory settings to experimental paradigms, allowing us to model mental state in an everyday context. This presents a paradigm shift, making it possible to design new types of experiments that characterize brain states during natural interaction over extended periods of time. Until recently most neuroimaging experiments have been performed with subjects who are at rest, under the assumption that the brain responses being measured will not be influenced by subjects sitting or laying down. However, this may be inaccurate, as animal studies using mice indicate that neurons in the visual cortex double their visually evoked firing rates if they run on a treadmill rather than stand still (Niel and Stryker, 2010). Since the discovery of parietal–frontal circuits of mirror neurones, which fire both when we grasp an object and when we observe others doing the same (Pellegrino et al., 1992; Gallese et al., 1996), the sensorimotor system can no longer be considered as only involved with motion.

Consequently, these mechanisms should rather be understood as forming an integral part of cognition, allowing us to generalize the goals of actions based on motor representations in the brain (Rizzolati and Sinigaglia, 2010).

While there is already significant literature concerned with dynamic brain states during natural complex stimuli in conventional laboratory experiments (see e.g., Hasson et al., 2004; Bartels and Zeki, 2004; Dmochowski et al., 2012), there has been a growing call to design studies that relax the constraints of the lab and widen the focus to map out how we perceive our surroundings under naturalistic conditions (Makeig et al., 2009). For example, natural motion has been incorporated into laboratory experiments using tools such as the MoBi Lab Matlab plugin (2009) in order to correlate motion capture data of moving limbs with the brain responses being triggered (Gramann et al., 2011). Even adding a few degrees of freedom may provide an understanding of how cortical responses differ by simply changing posture (Slobounov et al., 2008), either by measuring how theta brainwave activity is attenuated in sleepy subjects once they stand up (Caldwell et al., 2003), or by analyzing the modulation in spectral power within alpha and beta brainwaves appearing when one foot hits the ground and the other foot is lifted, as subjects are no longer transfixed on a chair in front of a computer screen (Gwin et al., 2011). This provides a foundation for extending standard EEG paradigms, such as the P300 event-related potential, to measure how we consciously perceive visual objects when participants are no longer required to sit motionless but are able to walk on a belt during the experiment (Gramann et al., 2010). It also makes it

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possible to eventually move a P300 experiment outside the lab, as has recently been demonstrated by Debener and colleagues (2012) by combining the wireless hardware from a consumer neuroheadset[1] with standard EEG cap electrodes[2] and using a laptop to record the cortical responses, thus providing a portable lab which can be stored in a backpack and easily carried by the subjects participating in the experiment.

Taking the idea of bringing EEG into the wild one step further, the *Smartphone Brain Scanner* (SBS2) open-source software project (http://github.com/SmartphoneBrainScanner) introduced in Stopczynski et al. (2011, 2013), makes it possible to build brain imaging applications for real-time 3D source reconstruction or neurofeedback training. By combining a wireless EEG cap with an Android smartphone or tablet, the SBS2 allows for presenting time-locked audiovisual stimuli such as text, images, or video, and it allows for capturing elicited neuroimaging responses on the mobile device, thereby transforming low-cost consumer hardware into a pocketable brain imaging lab. As the *Smartphone Brain Scanner* project potentially allows for designing novel types of brain imaging paradigms, we have initially validated the SBS2 framework in three experiments related to BCI motor control, embodied semantics, and neurofeedback interfaces in order to illustrate the feasibility of capturing mental state in a mobile context. In the following sections we briefly review existing mobile EEG sensors, outline the architectural design of the *Smartphone Brain Scanner* system for real-time 3D reconstruction, describe aspects of source separation and spatial filtering in relation to mobile brain imaging, and give examples of applications built on top of the open-source software framework for mobile Android devices related to imagined finger tapping, emotional responses to text, and design of neurofeedback interfaces (Fig. 1).

## 2. Mobile EEG acquisition

A wide range of prototype electrode designs, suitable for mobile neuroimaging, are currently under development, based on MEMS microelectromechanical systems utilizing spring-loaded dry contact pins or hard carbon nanotubes that press against the scalp (Ruffini et al., 2008). For long-term EEG measurement without gel, another option is electrodes made from soft foam covered with conductive fabric (Lin et al., 2011), or new types of non-contact high input impedance sensors capable of capturing EEG signals on the basis of capacitive coupling (Chi et al., 2012), even when resting on top of several layers of hair. In contrast to gel-based EEG electrodes, dry contacts need no skin preparation, and can therefore more easily be utilized for neuroimaging as participants are able to put on a neuroheadset without any assistance. However, even though pin or nanotube contacts easily penetrate the hair and therefore offer more possibilities for placement than conductive foam-based sensors attached to the skin of the forehead, a spring-like setup may still be susceptible to noise when users move. Capacitive sensors provide an alternative for unobtrusive physiological monitoring, but require an integrated ultra-high impedance front-end for non-contact biopotential sensing (Chi et al., 2011). So-called Ear-EEG is a promising technology for long-term EEG data collection, offering improved comfort and esthetics (Looney et al., 2012). Benchmarks of prototype capacitive non-contact and mechanical sensors in an experiment related to decoding a steady state visual evoked potential in the 8–13 Hz frequency band showed only little signal degradation when compared to standard gel-based Ag/AgCl electrodes (Chi et al., 2012), showing that these novel sensors may, in longer term, provide the increased usability that may assure the transformation of neuroimaging from fixed laboratory setups to an everyday mobile context.



**Fig. 1.** SBS2 mobile EEG recording with real-time 3D source reconstruction, on an Android smartphone connected wirelessly to an Easycap 16 electrode setup based on Emotiv hardware.

Among existing commercial solutions, the ThinkGear module manufactured by NeuroSky[3] provides the foundation for several EEG consumer products which integrate a single dry electrode along with a reference and a ground attached to a headband. It provides A/D conversion and amplification of one EEG channel, is capable of capturing brain wave patterns in the 3–100 Hz frequency range, and records at 512 Hz sampling rate. Even a single-channel EEG setup, using a passive dry electrode, such as the NeuroSky, positioned at the forehead and a reference (typically an earlobe), may allow for measuring mental concentration and drowsiness by assessing the relative distribution of brainwave frequencies (Yasui, 2009). More comfortable neuroheadsets using conductive Ni/Cu covered polymer foam, such as Mindo[4], measure brain activity from the forehead on three EEG electrodes plus a reference channel attached to the earlobe. Integrating analog to digital conversion at 256 Hz sampling rate for acquisition of bandpass filtered signals in the 0.5–50 Hz range, the neuroheadset offers 23 h of battery life and wireless Bluetooth communication, and has been demonstrated in BCI brain machine interfaces used in games based on controlling the power of alpha brainwave activity (Liao et al., 2012). Other consumer neuroheadsets such as the Emotiv EEG, provide both wireless communication via a USB dongle and analog to digital conversion of 16 EEG channels (including reference and ground) at 128 Hz sampling rate while using moist felt-tipped sensors which press against the scalp with a simple spring-like design. Originally designed as a mental game controller capable of tracing emotional responses and facial expressions, the majority of electrodes are placed over the frontal cortex and have no midline positions (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 with P3/P4 used as reference and ground). However, as mentioned earlier, Debener and colleagues (2012) recently demonstrated that it is possible to merge the wireless hardware from the Emotiv neuroheadset with high quality, conductive, gel-based electrodes in a standard EEG cap. Repackaging the electronics and battery into a small box (49 mm × 44 mm × 25 mm) which can be attached to the EEG cap and rewired through a connector plug to 16 sintered Ag/AgCl ring electrodes can occur, thus providing a fully customizable montage which allows the electrodes to be freely placed in the EEG cap according to the 10–20 international system (in the present

experiment Fpz, F3, Fz, F4, C3, Cz, C4, TP9, TP10, P3, Pz, P4, O1, O2 with AFz/FCz used as reference and ground).

We have tested both the original Emotiv neuroheadset as well as the modified EEG cap setup in connection with the *Smartphone Brain Scanner* open-source software project in the experimental designs outlined below.

## 3. Software framework: *Smartphone Brain Scanner*

The *Smartphone Brain Scanner* (SBS2) is a software platform for building research and end-user oriented multi-platform EEG applications. The focus of the framework is on mobile devices (smartphones, tablets) and on consumer-grade (low-density and low-cost) mobile neurosystems. SBS2 is freely available under an MIT License at https://github.com/SmartphoneBrainScanner. Additional technical details about the framework can be found in Stopczynski et al. (2013).

The framework is divided into three layers: low-level data acquisition, data processing, and applications. The first two layers constitute the core of the system and include common elements used by various applications. The architecture is outlined in Fig. 2.

### 3.1. Key features

With focus on the mobile devices, SBS2 is a multi-platform framework. The underlying technology – Qt – is an extension of C++ programming language and is currently supported on the main desktop operating systems (Linux, OSX, Windows) as well as mobile devices (Android, BB10, partially iOS) (see http://qt.digia.com/Product/Supported-Platforms/).

The additional acquisition and processing modules can be created as C++ classes and integrated directly with the core of the framework. The framework supports building real-time applications; data can be recorded for subsequent offline analysis, most of the implemented data processing blocks aim to provide real-time functionality for working with the EEG signal. The applications developed with SBS2 are applications in the full sense, as they can be installed on desktop and mobile devices, can be started by the user in the usual way, and can be distributed via regular channels, such as repositories and application stores.

The most demanding data processing block is the real-time source reconstruction aimed at producing 3D images as demonstrated in Fig. 4. Source reconstruction is carried out using Bayesian formulation of either the widely used Minimum-norm method (MN) (Hämäläinen and Ilmoniemi, 1994) or the low resolution electromagnetic tomography (LORETA) (Pascual-Marqui et al., 1994). Further description about the

inverse methods implemented in the *Smartphone Brain Scanner* will be given later.

## 4. Methods

### 4.1. Brain computer interface based on imagined finger tapping

One of the arguably most widely used paradigms of the brain computer interface literature is a task in which a subject is instructed to select between two or more different imagined movements (Müller-Gerking et al., 1999; Babiloni et al., 2000; Dornhege et al., 2004; Blankertz et al., 2006). Mental imagery is the basis of many BCI systems, originally conceived to assist patients with severe disabilities to communicate by 'thought'. The rationale is that the patient, while having problems carrying out the actual movements, may still be able to plan the movement and thereby produce a stable motor-related brain activity, which can be used as an input to the computer/machine. In this contribution we replicate a classical experiment with imagined finger tapping (left vs. right) inspired by Blankertz et al. (2006). The setup consisted of a set of three different images with instructions, *Relax*, *Left*, and *Right*. In order to minimize the effect of eye movements, the subject was instructed to focus on the center of the screen, where the instructions also appeared (3.5″ display size, 800 × 480 pixel resolution, at a distance of 0.5 m) (Fig. 3).

The instructions *Left* and *Right* appeared in random order with an equal probability. A total of 200 trials were conducted for a single subject. We selected 3.5 s duration for the 'active' instruction (*Left* or *Right*) and 1.75–2.25 s randomly selected for the *Relax* task, similar to Blankertz et al. (2006). The main motivation for random duration of the *Relax* task was to minimize the effect of the subject anticipating and starting the task prior to the instruction. The experiment was conducted with an Emotiv EEG neuroheadset transmitting wirelessly to a Nokia N900 smartphone. To illustrate the potential for performing such a study in a completely mobile context, all stimulus delivery and data recording were carried out using the SBS2. Analysis and post-processing and decoding were conducted off-line using standard analysis tools. In particular, we applied a common spatial pattern (CSP) approach (Müller-Gerking et al., 1999) to extract spatial filters which would maximize the variance for one class, while minimizing the variance of the other class and vice versa. A quadratic Bayesian classifier for decoding was applied on features transformed as in Müller-Gerking et al. (1999).



**Fig. 3.** SBS2 mobile neuroimaging apps for neurofeedback training, presentation of experimental stimuli, and real-time 3D source reconstruction, running on Android mobile devices via a wireless connection to an Emotiv or Easycap EEG setup.
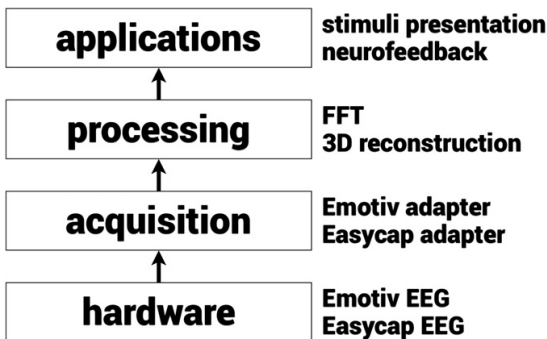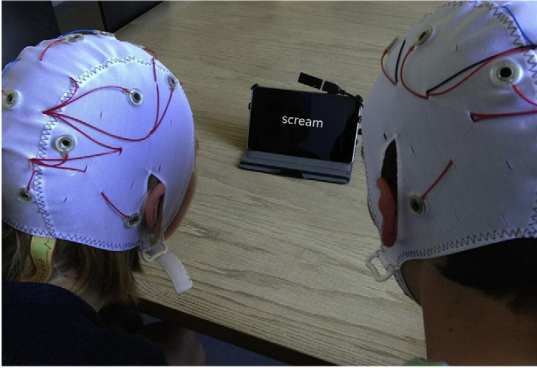


**Fig. 2.** Layered architecture of the SBS2 framework. Data from connected EEG hardware is extracted by specific adapters, processed, and used by the applications.

Fig. 4. SBS2 app for presentation of visual stimuli and mobile EEG recording, using an Android tablet connected wirelessly to an Easycap 16 electrode setup based on Emotiv hardware.

## 4.2. Source reconstruction and source separation

Compared to standard EEG laboratory setups, mobile neuroimaging is extremely susceptible to noise, as the ability to move around simultaneously introduces artifacts into the neuroimaging data induced by the EEG sensors, as well as originating from motion-related muscle activity. Likewise, mobile neuroimaging is much more exposed to environmental noise than experiments taking place under controlled conditions in a shielded laboratory. Combining sensor and source features, however, has been shown to improve classification in brain-computer interfaces (Ahn et al., 2012), even though these paradigms often involve activation of sensorimotor circuits where the location of sources is already quite well known. There might be an even larger potential by integrating source information for decoding complex brain states involving a range of different cognitive tasks. In particular, spectral analysis of changes in power may offer additional information on activity within specific brain-wave bands, which, based on the frequency, determines whether it reflects local or more distributed cortical field potentials. We therefore suggest that incorporating prior knowledge on what constitutes brain-generated signals may overall enhance the feasibility of performing experiments using mobile neuroimaging solutions (see also Besserve et al., 2011).

One approach to localize the actual brain activity in EEG is to tackle the inverse problem of retrieving the distribution of underlying sources from a scalp map by using a forward head model to estimate the projection weights which are captured by the electrodes. The problem is, however, severely ill-posed, as typically tens of EEG electrodes will capture volume conducted brain activities which may have been generated by tens of thousands of equivalent dipoles representing post-synaptic activity within macrocolumns of the cortex (Hämäläinen and Ilmoniemi, 1994; Pascual-Marqui et al., 1994; Baillet et al., 2001). A regularization that reduces the number of solutions is therefore applied, using methods such as low resolution electromagnetic tomography (LORETA), which assumes both the activity of neighboring neurons is synchronized and their orientation and strength can be modeled as point sources in a 3D grid reflecting 'blurred-localized' images of maximal activity (Pascual-Marqui et al., 1994). With $\mathbf{F} \in \Re^{N_c \bar{n} N_v}$ representing the forward model relating the $N_v$ cortical current sources, $\mathbf{V} \in \Re^{N_v \bar{n} N_t}$, to the $N_c$ measured scalp electrodes, $\mathbf{X} \in \Re^{N_c \bar{n} N_t}$, the forward problem for a set of time points ($N_t$) is given by, $\mathbf{X} = \mathbf{FV} + \mathbf{E}$, when the noise contribution $\mathbf{E}$ is assumed additive. The Minimum-norm method (MN) (Hämäläinen and Ilmoniemi, 1994) and LORETA methods can be represented as a single method, with MN as a special case of LORETA, namely, when no spatial coherence of neighboring sources is assumed as prior. From a Bayesian perspective the LORETA method is formulated as

$$p\left(\mathbf{X}|\mathbf{V}\right) = \prod_{t=1}^{N_t} \mathcal{N}\left(\mathbf{x}_t \middle| \mathbf{Fv}_t, \beta^{-1}\mathbf{I}_{N_c}\right) \tag{1}$$

$$p(\mathbf{V}) = \prod_{t=1}^{N_t} \mathcal{N}\left(\mathbf{v}_t \middle| 0, \alpha^{-1}\mathbf{L}^T\mathbf{L}\right) \tag{2}$$

in which $\beta$ denotes the precision of the noise (inverse variance), $\alpha$ the precision parameter of the sources, and $\mathbf{L}$ the spatial coherence between the sources $\mathbf{V}$. As the MN method assumes no spatial coherence between neighboring sources, the spatial coherence matrix becomes an identity matrix, $\mathbf{L} = \mathbf{I}$. In contrast, for LORETA this spatial coherence matrix typically takes the form of a graph Laplacian, implementing geometrical neighborhood driven smoothness. Given the likelihood, $p(\mathbf{X}|\mathbf{V})$, and prior distribution, $p(\mathbf{V})$, of the current sources, the most likely source distribution can be obtained by maximizing the posterior distribution over the sources as

$$p\left(\mathbf{V}|\mathbf{X}\right) = \prod_{t=1}^{N_t} \mathcal{N}\left(\mathbf{v}_t \middle| \boldsymbol{\mu}_t, \boldsymbol{\Sigma}_v\right)$$

$$\boldsymbol{\Sigma}_v = \alpha^{-1}\mathbf{I}_{N_v} - \alpha^{-1}\mathbf{F}^T\boldsymbol{\Sigma}_x\mathbf{F}\alpha^{-1}$$

$$\boldsymbol{\Sigma}_x^{-1} = \alpha^{-1}\mathbf{F}\mathbf{L}^T\mathbf{L}\mathbf{F}^T + \beta^{-1}\mathbf{I}_{N_c} \tag{3}$$

$$\bar{\mathbf{v}}_t = \alpha^{-1}\mathbf{F}^T\boldsymbol{\Sigma}_x\mathbf{x}_t. \tag{4}$$

The hyper-parameters $\alpha$ and $\beta$ are optimized on-line using a standard Expectation–Maximization (EM) approach (Bishop, 2006).

Rather than aiming to solve the inverse problem of determining the 'what' from 'where' of brain activity, an alternative approach is to apply methods based on higher-order statistics such as independent component analysis (ICA) (Comon, 1994). This allows to separate individual processes ('what') when they stand out as temporally independent in the native, spatially overlapping scalp representation (Makeig et al., 1996).

The ability of ICA to identify temporally independent events also allows for enhanced detection and automatic removal of artifacts (Delorme et al.). Eye blinks manifest themselves as low 1–3 Hz as well as higher frequency activity, which translates into stereotypical ICA scalp maps consisting of a single frontal dipole (Delorme et al., 2007). When comparing this method against a regression approach using an electrooculogram (EOG) eye movement correction procedure (EMCP) to remove eye blink artifacts, ICA turns out to yield almost perfect correction (Hoffmann and Falkenstein, 2008). Also, other kinds of muscle activity stand out distinctly in the corresponding scalp maps. Overall, applying ICA as a preprocessing step improves artifact detection compared to analysis based on the raw EEG data (Delorme et al., 2007). With particular relevance to mobile neuroimaging, it has been demonstrated that independent component-based gait-artifact removal makes it possible to capture neural correlates in standard EEG experiments, even when walking or running (Gwin et al., 2010).

EEG experiments have traditionally focused on analysis of event-related time-domain waveform deflections and frequency-domain perturbations in power, but neither of these approaches fully captures the underlying brain dynamics when averaging data over multiple trials, or ignoring phase resetting that contributes to the ERP (Makeig et al., 2004). When first applying ICA to the EEG data, the event-related time series waveforms come to represent independent components generated by temporally independent, physiologically decoupled local field potentials, and their corresponding scalp maps that resemble dipolar projections of the underlying sources (Delorme et al., 2012). This indicates that ICA may be used for more than denoising, e.g., it can

be used to find the modes of event-related changes in power, as the independent components framed by the dimensions of frequency, power, and phase consistency across trials. Even when electrodes are accurately placed, the recorded potentials may still vary due to individual differences in cortical surface and volume conduction. ICA may also here provide a common framework for comparison of the underlying brain activity in EEG data, regardless of the actual electrode positions. We thus compared ICA of the EEG data retrieved from both the Emotiv neuroheadset containing no central electrodes and the Easycap EEG montage including midline electrodes. In particular, we used the retrieved scalp maps and activation time series, as well as event-related changes in power spectra, to perform a statistical group comparison across experimental conditions and trials. As a preprocessing step, we reduced dimensionality based on principal component analysis (PCA) and subsequently applied K-means clustering to the independent components, in order to identify common patterns of brain activity across the two different mobile EEG setups (Delorme et al., 2011).

### 4.3. Visual stimulus to investigate emotional responses

Over the past decades, neuroimaging studies have established that language is grounded in sensorimotor areas of the brain; highly related neuronal circuits seem involved whether we literally pick up a ball or in a phrase refer to grasping an idea (Pulvermüller and Fadiga, 2010). Exploring whether such brain activation can be detected using a mobile EEG setup, the SBS2 framework was used to display the stimulus consisting of a subset of action verbs related to emotional expressions, face, and hand motion as used in a recent fMRI experiment (Moseley et al., 2011). The framework was also used to record the EEG signal for subsequent offline data analysis.

Two mobile 16 channel EEG setups were compared; the low cost Emotiv neuroheadset using saline sensors positioned laterally at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4 (P3/P4 used as Common Mode Sense (CMS) reference/Driven Right Leg (DRL) feedback) — versus a standard electrolyte gel-based EEG cap (Easycap, Germany) similar to what has previously been used for mobile P300 experiments (Debener et al., 2012) enabling an EEG setup including central and midline Ag/AcCl ring electrodes positioned at Fpz, F3, Fz, F4, C3, Cz, C4, TP9, TP10, P3, Pz, P4, O1 and O2 (AFz/FCz used as CMS reference/DRL feedback) according to the international 10–20 system.

A single subject pilot study was performed to compare the Emotiv and Easycap EEG setups based on $2 \times 10$ trials, each consisting of $3 \times 20$ action verbs presented in a randomized sequence on the smartphone display (Nokia N900). Each verb was exposed for 1000 ms in a large white font on black background (3.5″ display size, $800 \times 480$ pixel resolution) at a distance of 0.5 m, preceded by a fixation cross 500 ms pre-stimuli, and followed by 1000 ms post-stimuli black screen. Using the EEGLAB plug-in for MATLAB (MathWorks, USA), epoched EEG data was extracted offline (−500 ms to 1000 ms) and baseline corrected (−500 ms to 0 ms). As some of the recorded potentials are induced by muscle activity, we rejected abnormal data epochs by specifying that the spectrum should not deviate from baseline by $\pm 50$ dB at 0–2 Hz and manually removed eye blinks (Delorme et al., 2011). To facilitate a comparison between the different electrode placements used in the two experiments, we applied the extended Infomax algorithm to linearly project the EEG data recorded from individual electrodes onto a space of basis vectors, which were temporally independent from each other, using independent component analysis ICA to estimate the scalp maps and time courses of individual neural sources (Delorme et al., 2007).

To assess the degree to which the Emotiv neuroheadset and the Easycap EEG setups capture common patterns in brain activity despite their differences in electrode montage, rather than simply measuring event-related responses from the 14 electrodes, we applied ICA in a single-subject study to retrieve 14 independent components from each of the $2 \times 10$ trials, related to the Emotiv and Easycap experiments, respectively: we analyzed $2 \times 10 \times 14$ independent components

generated from the time-locked responses to reading $3 \times 20$ emotion, face, and hand-related action verbs in each trial. Retrieving the ICA components enabled us to initially compare the event related responses across the 3 action verb conditions, which in turn enabled us to identify similar independent sources within trials using the EEGLAB studyset functionality. Secondly, to identify common patterns of brain activity both within and across the Emotiv and Easycap experiments, the EEGLAB studyset functionality and MATLAB Statistical Toolbox were used to cluster the $2 \times 10 \times 14$, in total 280 ICs based on scalp maps, power spectra, and amplitude time series. After initially applying ICA for artifact rejection in each trial, the 280 ICA weights were recomputed as a basis for a statistical analysis using the EEGLAB studyset functionality (Delorme et al., 2011), where the dimensionality of the feature space was reduced to $N = 10$ by applying PCA principal component analysis (Jolliffe, 2002). The pre-clustering function PCA compresses the multivariate EEG features into a smaller number of mutually uncorrelated scalp projections, and computes a vector for each component to define normalized distances in a subspace representing the largest covariances in the ICA-weighted data. This means that the vectors contain the 10 highest PCA components for the ICA-weighted time series responses, scalp maps, and power, related to the three conditions. Next, the $K$-means algorithm ($K = 10$) was applied to cluster common ICA components within the 10 trials ($\sigma = 3$), related to the Emotiv neuroheadset (Fig. 13) and the Easycap EEG setup (Fig. 14), respectively. Comparing functionally equivalent groups of ICs makes it possible to assess whether they resemble recurring neural sources retrieved from multiple sessions, and to determine if the clustered ICs remain shared across the two different experimental EEG setups (Fig. 5).

### 4.4. Mobile interfaces for neurofeedback

In contrast to personal informatics apps, neurofeedback interfaces require the user to interact in real time with audiovisual representations of EEG data in an attempt to control the ongoing brain activity. Neurofeedback experiments aiming to increase power in the upper alpha range have been shown to improve cognitive performance in several studies (Hanslmayr et al., 2005; Zoefel et al., 2011). While there is often a peak in individual alpha brainwave power around 10 Hz, neurofeedback training makes it possible to control and shift the activity towards the upper alpha range of 12 Hz. In relation to neurofeedback, an ability to consciously control alpha brainwave oscillations, which as a gating mechanism appears to be involved in selective attention (Foxe and Snyder, 2011), might thus potentially help explain the previously reported training effects on cognitive performance. Likewise, an association between higher alpha frequency and good memory performance has previously been shown (Klimesch, 1999) (Fig. 6).

However, designs for neurofeedback interfaces are often conceptualized with little attention to how the actual feedback of audiovisual elements might affect the user's ability to control brain activity. Normally, User Experience (UX) design of graphical interfaces involves initial modeling of user needs and selection of design patterns for organizing content and navigational layout reflecting gestalt principles. This may
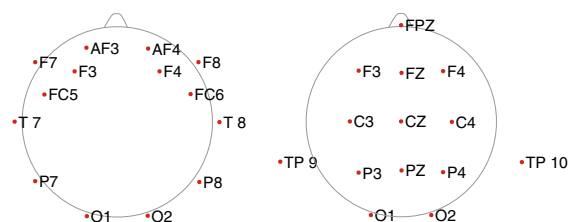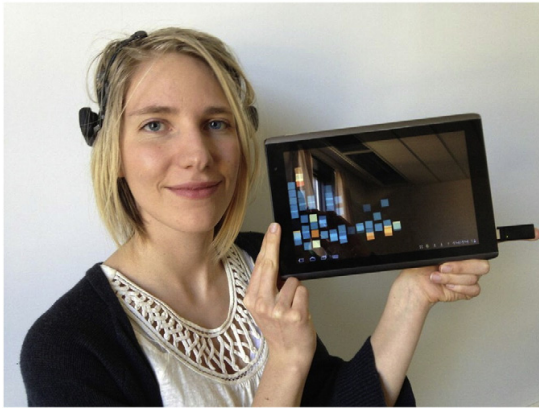
**Fig. 5.** Electrode locations for two mobile 16 channel EEG setups; the Emotiv neuroheadset using saline sensors positioned laterally (left), versus a standard gel-based Easycap EEG montage including central and midline positions (right).

**Fig. 6.** SBS2 neurofeedback training app running on an Android tablet, where a blue to orange shift in color horizontally over time represents an increase in upper alpha power.

subsequently be translated into frameworks for interaction ranging from scrollable timeline lists to multilayered contextual map metaphors (Tidwell, 2011). Neurofeedback applications on the other hand have typically concentrated on mapping EGG amplitude values directly onto audiovisual components. For example, sounds of ocean waves or high- or low-pitched gongs (Egner et al., 2004; Hinterberger et al., 2004) would map to visual designs based on vertical scales and squares of changing colors (Zoefel et al., 2011; Neumann et al., 2003; Vernon et al., 2003). When targeted towards children, these elements have been incorporated into more complex scenarios built around airplanes, a 3D car racing environment, or a pole-vaulting cartoon mouse (Gevensleben et al., 2009; Heinrich et al., 2007). In summary, these designs may be understood as based on contrasting combinations of the following audiovisual components (Jensen et al., 2013):

- pitch (low, high)
- volume (soft, loud)
- timbre (dark, light)
- duration (short, long)
- rhythm (temporal distribution)

- geometric primitives (connected segments)
- color (discrete, gradients)
- size (proximity, scalability)
- movement (horizontal, vertical)
- composition (spatial distribution).

To explore the influence that such components might have on the efficacy of neurofeedback training, we tested two different interfaces developed for the SBS2. We conducted an experiment with 25 subjects aiming at increasing their upper alpha frequency band (Jensen et al., 2012). The neurofeedback experiment consisted of two iterations, testing the two different interfaces. In the first iteration, 12 healthy subjects (7 males and 5 females) with an average age of $23.6 \pm 1.9$ did neurofeedback training on a replication of an existing interface (Zoefel et al., 2011). This interface indicated brain activity based on only two components (color gradients framed by a square primitive). In the second iteration another 13 healthy subjects (7 male and 6 female) with an average age of $26.6 \pm 5.5$ performed neurofeedback training using an interface developed on basis of the common features extracted from the first group of subjects. The second interface combined four components (scaled down
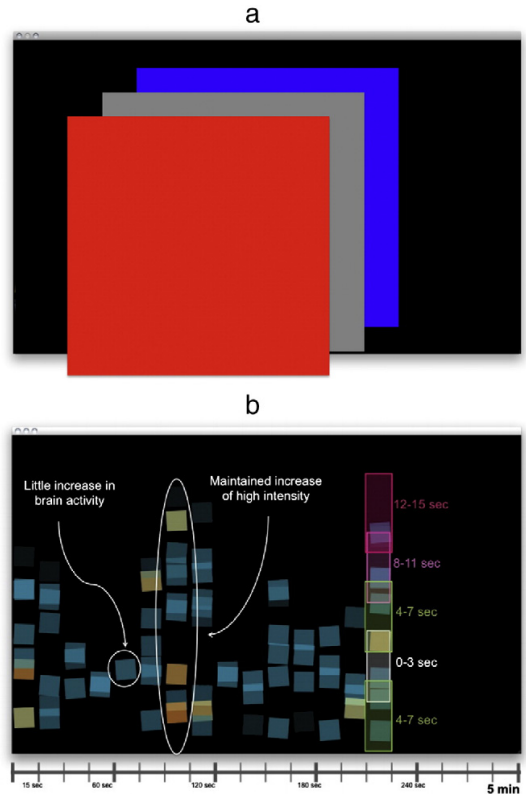


**Fig. 7.** (a) In the interface from the first version of the neurofeedback application, the current brain activity is visualized by the square changing colors; blue indicating activity below, gray — equal to, and red — above baseline. (b) The interface of the neurofeedback application from the second iteration is shown with additional illustrations describing how it is constructed: The 5-minute timeline shown in the bottom illustrates how the training session is divided into columns of 15 s. Within a column squares would appear first (0–3 s) in a window in the lower part of the screen, then (4–7 s) in windows above and below the first window and lastly (8–11 s and 12–15 s) in windows above the first two windows. The windows are shown in the rightmost column which was not shown during the experiments. The encircled column illustrates how the user can easily compare the ability to increase brain activity in different time intervals.

color gradients framed by square primitives spatially distributed horizontally and vertically).

The EEG signal from all of Emotiv's 16 electrodes was recorded and the real-time feedback was constructed from O1 and O2. Additionally, an offline re-referencing of P3 and P4 with the frontal electrodes AF3, AF4, F3 and F4 allowed for P3 and P4 to be included in the later data processing, thus covering a larger area of the relevant cortical area. The power of the brain activity was calculated using Fast Fourier Transformation.

Both iterations consisted of five sessions during one week from Monday to Friday. Each session started and ended with a 5-minute baseline recording measuring the average brain activity during a simple task. In between the baseline recordings five 5-minute training sessions were conducted. After each session, we gathered qualitative data on the thought patterns of the subjects leading to an increase of alpha brain activity based on informal interviews. Each subject received a total of 25 training recordings and 10 baseline recordings.
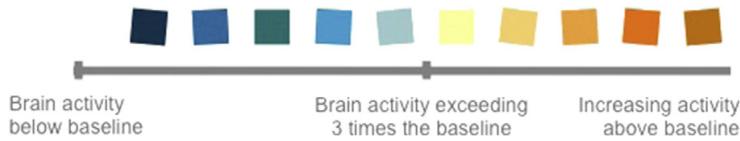
**Fig. 8.** The colors of the squares indicate the intensity of the brain activity.

The interface used in the first iteration was similar to the one used in a study by Zoefel et al. (2011), where the feedback consisted of a square of changing colors gradually from blue, gray to red. Respectively each color represented real-time amplitudes below, equal to baseline, or above baseline, respectively, see Fig. 7a. The subjects were instructed to make the square turn red. For the baseline recording a similar interface setup was used but with random color changes, making the visual stimuli similar to those of the training recordings and therefore more compatible. The subjects were asked to count the number of times the square turned red. This would ensure a similar cognitive task across the subjects while recording the baseline, thereby making these recordings comparable.

The feedback interface used in the second iteration consisted of small squares being generated once a second, if the alpha amplitudes exceeded the baseline. Over a 15 second interval the squares (maximum 15 squares) were assembled into a column, after which a new column of squares was incrementally generated along a horizontal axis. At the end of the 5 minute training recording, the interface would consist of 20 columns of squares, see Fig. 7b. Thus the interface not only showed the current amplitudes, but also the previous, allowing the user to easily compare methods for increasing the amplitudes. The squares not only indicated when the amplitudes exceed baseline, but also the degree of increase by a change in color, ranging from dark blue to orange (see Fig. 8). The degree of increase was calculated from a running mean creating a smooth color flow. The subjects were instructed to create as many squares as possible and preferably with yellow and orange colors. For the baseline recording a similar interface was used, although with squares appearing randomly in the columns and with random color. The subjects were asked to count the yellow and orange squares.

All subjects of both iterations were asked to keep their eyes open for as long as possible, and avoid muscle movements, jaw movements, and swallowing during all recordings to limit artifacts.
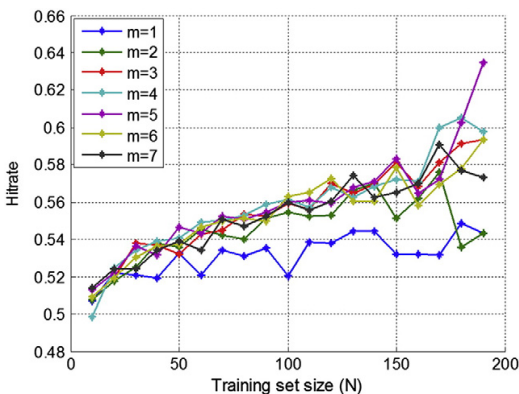
# 5. Results and discussion

In this section we present the results of the experiments, validating the performance of the software, platforms used, and EEG hardware.

## 5.1. Brain computer interface based on imagined finger tapping

In order to validate the applicability of the platform in decoding imagined left and right finger tapping, the EEG data was bandpass filtered (8–32 Hz) and we used the data in the interval 0.75–2.00 s after stimuli onset as input to the common spatial pattern (CSP) algorithm (Müller-Gerking et al., 1999). One important parameter in the CSP algorithm to be controlled is the number of spatial filters. To determine the number of spatial filters we applied cross-validation and examined the performance (accuracy of classifier) as a function of the training size (number of trials used for training), see Fig. 9. The classifier was trained on a balanced set of trials (i.e. equal number of left and right trials), which was carried out 200 times for each training set size.

Fig. 9 indicates that we need more than a single spatial filter ($m > 1$). When $m = 2$, for example, two spatial filters are used to maximize the variance for class 1 while minimizing the variance for class 2 and an additional two spatial filters are used to minimize the variance for class 1 while maximizing the variance for class 2. It is interesting that only a few spatial filters are required to obtain an accuracy close to 60%. We also note that performance is increasing as a function of samples, hence, even better performance can be expected if more samples are collected.

### 5.1.1. Source reconstruction and source separation

For further validation we applied standard statistical evaluation for significance and correction for multiple comparisons. Thus, we performed a Monte Carlo permutation test (Maris and Oostenveld, 2007) to check for significant electrode differences between left and right finger tapping. Fig. 10 demonstrates a scalp map of the effect of the averaged response based on left finger tapping minus averaged response based on right finger tapping. The significant channels at given time intervals are highlighted in accordance with the Monte Carlo permutation test conducted using Fieldtrip (Oostenveld et al., 2011). Both positive and negative effects are detected as significant with Monte Carlo p-values of 0.012 and 0.001, respectively. A set of 1000 random permutations were performed. Inspecting Fig. 10 reveals significant differences over the left and the right hemisphere and more importantly the electrodes contributing to the significant difference between left and right imagined finger tapping are electrodes located close to the premotor area. Thus, it seems that these electrodes are taking over the often reported electrodes C3 and C4 as the main drivers, as C3 and C4 are not present in the Emotiv EEG sensor configuration.

To examine the ability to perform reliable 3D EEG imaging based on the data acquired using an Emotiv neuroheadset, source reconstruction was carried out on the bandpass-filtered imagined finger tapping data (8–32 Hz) also used for the classification task and in the non-parametric statistical test. Fig. 11 illustrates the mean power of the difference between left and right imagined finger tapping in the interval 0.75–2.00 s post-stimuli. Premotor areas are typically involved in executing the task and in differentiating a left from right imagined movement. This is also the case here to some extent with minor



**Fig. 9.** Mean accuracy of left and right imagined finger tapping classification for a single subject. Mean accuracy is based on 200 splits in training and test data. Classification is based on CSP and a quadratic Bayes classifier focusing on bandpass filtered data 8–32 Hz in interval 0.75–2.00 s after onset.
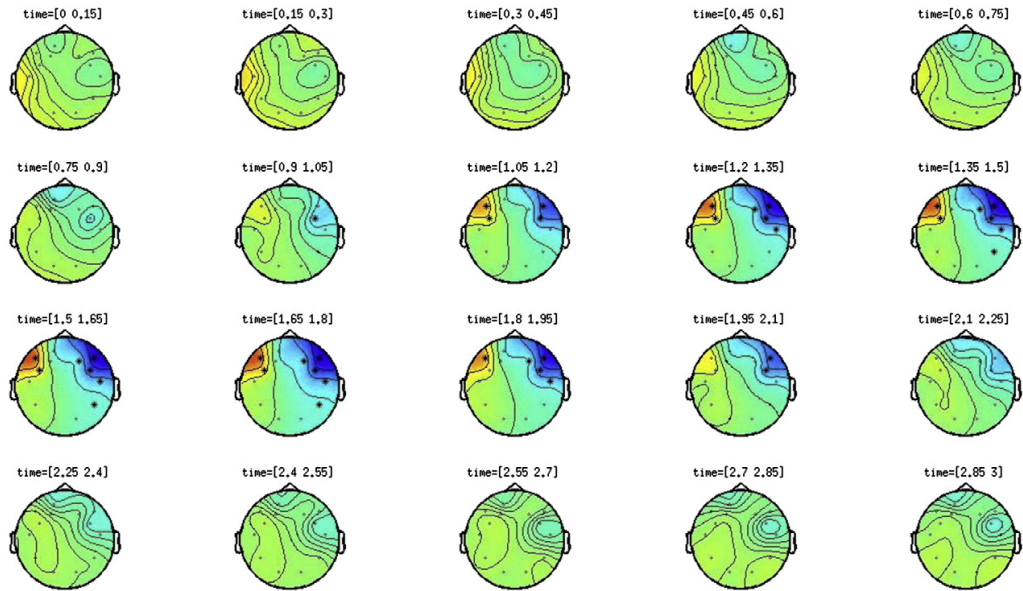
**Fig. 10.** Monte Carlo permutation test for significant difference between averaged left imagined finger tapping response and averaged right imagined tapping. Electrodes located close to the premotor region are detected as significant in the time interval 0.9–2.1 s after stimuli.

discrimination in the premotor areas and more pronounced discrimination in the more frontally located areas. Note the polarity of the power difference map, with the left hemisphere indicating a positive difference and the right hemisphere indicating a negative contribution. During the imagined finger tapping part, the contralateral premotor/motor regions desynchronize (resulting in a decrease in power within the specific frequency range) while the ipsilateral premotor/motor regions first desynchronize shortly and right after synchronize (meaning increased power within the frequency range). The main explanation for the displacement more frontally found in Fig. 11,

is the uneven distribution of sensors for the Emotiv EPOC system, with most of the sensors positioned frontally.

However, large proportions of the occipital and temporal areas are also found to be active by the reconstruction. These apparent visual and temporal source activation differences may, however, be explained by the fact that re-referencing to an average channel is performed prior to source estimation. Since the distribution of the sensor locations is highly unevenly distributed, with the majority placed frontally, re-referencing data with a strong frontal activation (e.g. eye blink/movement) to an average reference channel will map part of the
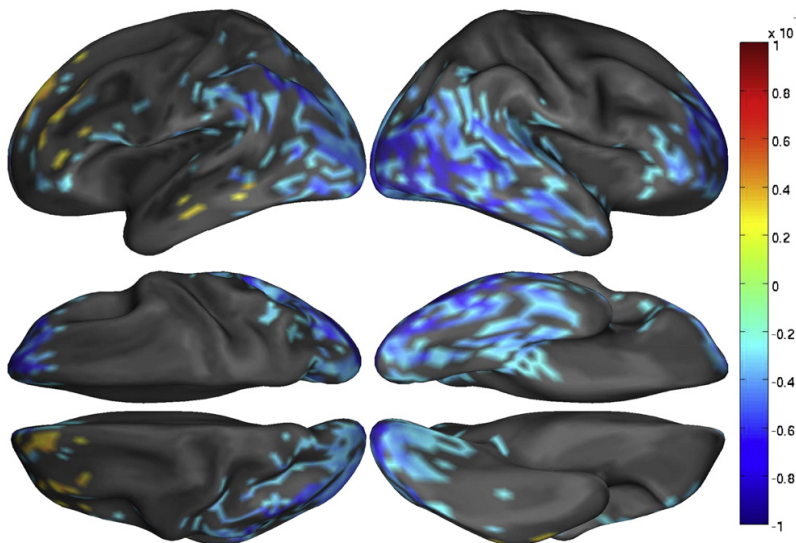


**Fig. 11.** Source reconstruction of mean difference power map between left and right imagined finger tapping.
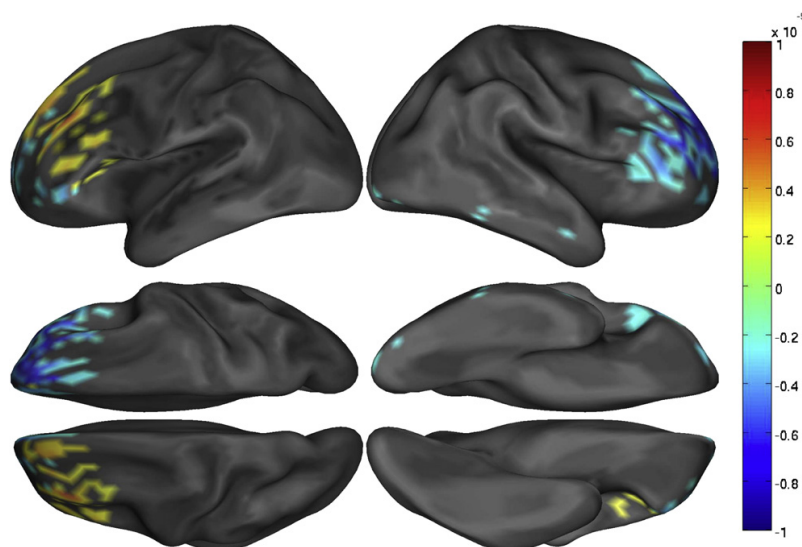
**Fig. 12.** Source reconstruction of mean difference power map between left and right imagined finger tapping. Emotiv EEG data corrected by removal of ICA component associated with eye movement.

frontal activity to the temporal and occipital electrodes. To further test this hypothesis, we investigated the influence of artifacts caused by eye motion on the source reconstruction estimates by removing an eye-related ICA component. Indeed, the removal of the eye movement component seems to improve the source estimates significantly, as demonstrated in Fig. 13. The operating regions (frontal areas and slightly pre-motor regions) are more highly visible in this power difference map between the averaged left minus right imagined finger tapping conditions. Similarly, as in Fig. 11, the sources are displaced more frontally than typically, and this can be explained by the sensor positioning offered by the Emotiv EPOC system. The source reconstruction was performed offline to ensure a fair comparison with and without removal of the ICA component related to eye movement. The ICA decomposition was performed using the extended Infomax algorithm supported by EEGLAB (Fig. 12).

### 5.2. Visual stimulus to investigate emotional responses

Within the Emotiv data, $2 \times 18$ ICs have been clustered in 10 out of 10 trials, indicating that these independent components are consistently activated across all trials (Fig. 13). Similarly, in the Easycap data, 23 ICs have been clustered within 3 standard deviations of the K-means centroids in 10 out of 10 trials, while 9 ICs have been grouped in 7 out of 10 trials, confirming that temporally independent activations are also grouped across trials in this study (Fig. 14). Taking the relative

polarity of ICs into account when comparing the two studies, the clustered scalp maps in both experiments suggest left lateralized prefrontal as well as parietal activations in language areas, which integrate motor and semantic aspects connected through the dorsal and ventral streams in the brain (Rolheiser et al., 2011; Axer et al., 2012).

This is in line with results obtained in a recent MRI experiment (Moseley et al., 2011) using the same verbs as in the present EEG study, indicating that premotor neural circuits are activated when passively reading verbs related to face and hand motion and when seeing emotional expressions. Mobile neuroimaging could potentially extend our ability to explore such action-based links between actual motion and emotion in an everyday context, which might in turn reflect imitation of gestures or facial expressions involving mirror neuron circuits in the brain, possibly providing a foundation for higher level feelings of empathy and theory of mind.

### 5.3. Mobile interfaces for neurofeedback

All signal processing of the data for the *Neurofeedback* experiment was done off-line using the EEGLAB (Delorme and Makeig, 2004) plug-in for MATLAB.

Since the alpha frequency band has shown to vary depending on age, possible neurological diseases, and memory performance (Klimesch, 1999), the upper alpha frequency band had to be determined for each individual. By identifying the peak in the power spectrum, the



**Fig. 13.** Single-subject EEG neuroimaging study with Emotiv 16 channel neuroheadset: PCA dimensionality reduction and K-means clustering ($K = 10$, $\sigma = 3$) of 140 IC scalp maps, activation time series and event-related changes in power spectra based on 10 trials, each consisting of reading $3 \times 20$ emotion (blue), face (green) and hand (pink) related action verbs.

**Fig. 14.** Single-subject EEG neuroimaging study with Easycap 16 channel EEG setup: PCA dimensionality reduction and K-means clustering ($K = 10, \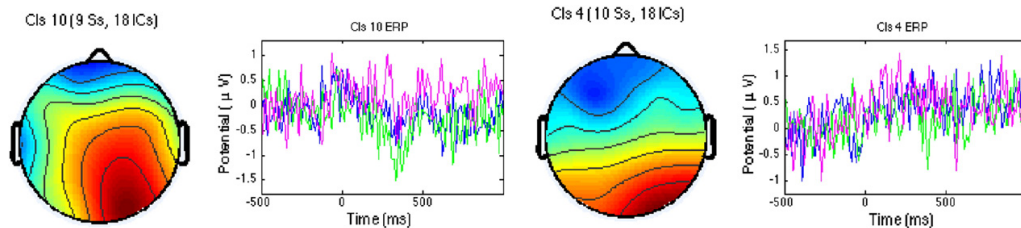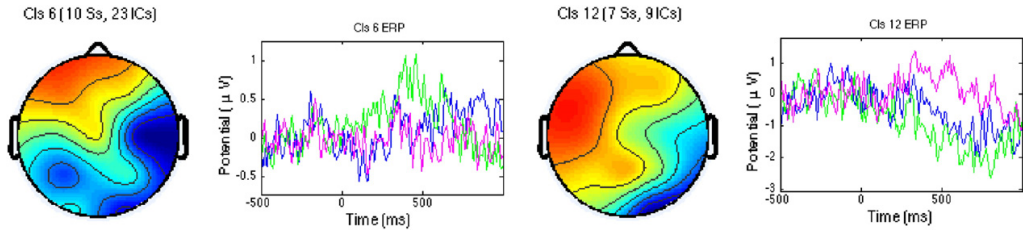sigma = 3$) of 140 IC scalp maps, activation time series and event-related changes in power spectra based on 10 trials, each consisting of reading $3 \times 20$ emotion (blue), face (green) and hand (pink) related action verbs.

individual alpha peak (IAF), the upper alpha frequency band was set as a band of 2 Hz above IAF (from IAF to IAF + 2Hz). Thus the individuals' upper alpha frequency band were determined from the first baseline recording of every session, and the mean amplitude was calculated for all baseline and training recordings. Two subjects (1 male and 1 female) from the first iteration of the experiment did not complete all training sessions, and were therefore excluded from further analysis.

In addition, it has repeatedly been reported that some subjects, usually called non-responders, are unable to change amplitudes of the brain frequencies significantly (Zoefel et al., 2011; Gevensleben et al., 2009; Fuchs et al., 2003; Lubar et al., 1995). Subjects who did not show a significant increase in the upper alpha frequencies when comparing the very first baseline (baseline 1 in session 1) with the training recordings from Friday (session 5) were considered non-responders. As a result, 3 subjects (2 female, 1 male) from the first iteration and another 3 subjects (2 male, 1 female) from the second iteration were considered non-responders. These left 7 subjects in the first iteration (5 male, 2 female) and 10 subjects in the second iteration (5 male, 5 female) remain for statistical analysis.

The individuals' EEG results from the baseline- and training recordings were normalized in respect to the first baseline Monday (session 1), thereby showing the ability to increase upper alpha (UA) amplitudes in relation to the first baseline in percentage. The results obtained over the week (Monday to Friday) have been plotted in Fig. 15. Each

line represents a subject's ability to increase UA amplitudes: The red lines represent subjects from the first iteration, the black lines represent subjects from the second iteration and the bold lines represent the non-responders. From the graph it is clear that some subjects are more capable of increasing their UA amplitudes and increase above 400%, whereas others experience a decrease (usually the non-responders). In addition, the subjects who get the highest increase are mainly those who use the second iteration interface. However, the variance in the subject ability to increase their UA is also greater.

These results suggest that the ability to control neural activity is very individual and that the interface should be supportive of the individual's strategies.

Following the approach of Zoefel et al. (2011), we fitted regression lines to the individual UA amplitudes as a function of session number (1–35) and used a one-sample, one-sided $t$-test to test whether they were significantly greater than zero, which they were in both iterations ($p < 0.05$ and $p < 0.03$ for the first and second iterations respectively). We also compared the regression lines between the iterations using a two-sample, two-sided $t$-test and found no significant difference ($p > 0.70$). This result, in itself, could indicate that the two types of feedback are equally effective.

This approach does not, however, separate the effect of training (a lasting increase in UA amplitude) from the feedback effect (an immediate increase in UA amplitude during feedback). To isolate the training
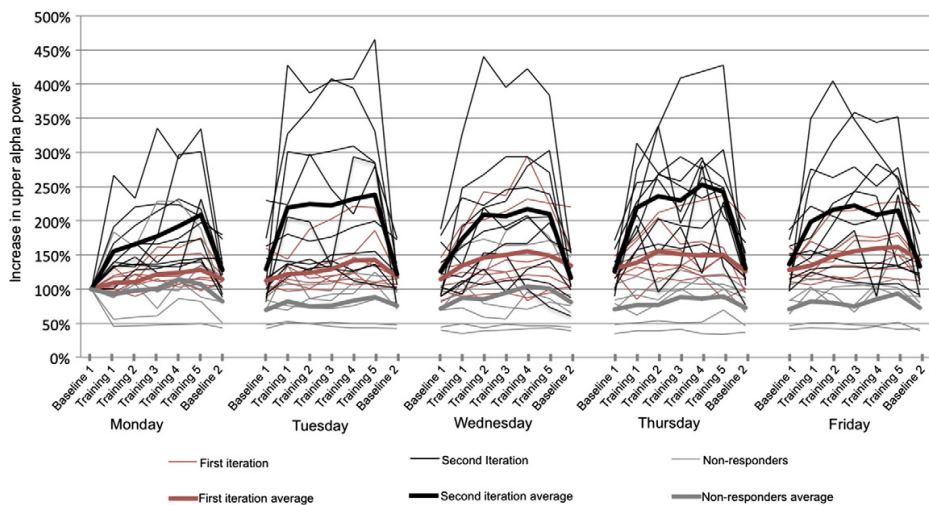


**Fig. 15.** The individuals' upper alpha (UA) amplitude in percentage of the UA amplitude from the fist baseline recording on the first day (Monday). Subjects from first and second iterations as well as the non-responders from both iterations are plotted in red, black and gray, respectively. The average of these groups is marked by bold lines in corresponding colors. All baseline-and training recordings have been plotted in sequence across the week, e.g. Monday will show results from the first baseline, then the 5 training recording, ending with the second baseline, giving a total of 7 points of each day. The results illustrate a large variance in the individual subjects ability to increase UA amplitudes, where subjects from the second iteration were capable of reaching a greater increase, although some subjects were unable to achieve any increase at all (referred to as non-responders).

effect, we again follow the approach of Zoefel et al. who quantified the training effect as the difference between UA amplitude during the first baseline recording in the first session and the first baseline recording in the last session and tested for an increase with a one-sample one-sided $t$-test. Using this approach we found a significant effect in the first iteration ($p < 0.002$) but not in the second iteration ($p > 0.14$). This result indicates that the interface used in the first iteration was more effective for neurofeedback training.

In addition to this, we are also interested in isolating the feedback effect, which we quantify as the difference between the mean UA amplitude across feedback recordings and the mean UA amplitude across the first and last baseline recording for each session. We compare the feedback effect from the two iterations using a repeated-measures ANOVA with session number as within subject factor and iteration as between groups factor. We found a significant effect of iteration ($F(1,15) = 11.85, p < 0.005$) but no significant effect of session number or the interaction between session and iteration. Based on the lack of effect of the session number, we averaged the feedback effect across session number and subjects within an iteration and found that the mean feedback effect was 0.17 for the first iteration and 0.67 for the second iteration. This result indicates that the interface used in the second iteration was more effective for inducing an immediate increase in UA amplitude.

That the feedback effect was higher in the second group without a corresponding increase in the training effect suggests that the magnitude of UA amplitude during feedback does not completely determine the training effect. This could be due to a ceiling effect, so that UA amplitude during training has no effect above a certain level. Alternatively, it could also mean that the two groups used different strategies for increasing UA amplitude during training and that although the second group's strategy was more efficient for increasing UA amplitude during feedback, it did not increase the training effect. Such strategic differences could be facilitated by the difference in the visual feedback stimulus. In the first group participants needed to constantly look at the feedback stimulus to get feedback, whereas the second group could look elsewhere intermittently and return their gaze to the feedback stimulus only when they wished to learn about their performance. This could change the UA amplitude during feedback without increasing the training effect as could the mere physical differences in the feedback signals.

In summary, our neurofeedback study confirms the findings of Zoefel et al. (2011), provides new insights into the effects of the type of feedback provided, and confirms that neurofeedback training is possible with a mobile setup based on the *Smartphone Brain Scanner*.

# 6. Further perspectives

## 6.1. Hardware

Current consumer-grade and research-oriented mobile EEG systems are only the first iteration of the hardware. We predict two major directions of the development.

On one hand, the high-density systems will become mobile, pushing for the best possible quality of the acquired signal in naturalistic conditions. The development of these systems will not be primarily focused on making them unobtrusive, fashionable, or consumer-operated. From the spectrum of the features offered by the new EEG hardware, these systems will focus on mobility, portability, and low-cost. They will be used in the more or less classical experiments, controlled and initiated by the researchers.

On the other hand, more consumer-oriented devices will emerge. They will be fitted for particular use-cases, which will allow to make them smaller, concealed, and user-friendly. Such *sensors* will not necessarily be seen as EEG devices, but rather as cognitive state monitoring devices, and in addition to the EEG signal, they may include other electro-physiological signals, such as EMG, ECG, and skin conductance.

Still, the data available from a large number of such systems bought and worn by the consumers for their particular function, may offer an unparalleled opportunity for understanding human brain and cognitive states. Gaining privacy-preserving access to, and analyzing noisy, not-at-all or poorly annotated data originating from brain state, from hundreds or thousands of subjects and collected over days, weeks, or months can become one of the grand challenges for cognitive neuroscience in the next few years.

The development of neuroheadsets and sensors accompanies the development of mobile devices, smartphones and tablets, allowing for personal hubs for interconnected, wearable devices. The increasing processing power and low-energy protocols (e.g., Bluetooth 4.0, NFC) turn our personal space into a busy network of devices (phones, Bluetooth headsets, smart watches, glasses, hearing aids etc.). EEG sensors, even if equipped with a single electrode, can fit naturally in such systems, as long as they can provide certain well-defined value for the user.

## 6.2. Software

The evolution of the software will be closely coupled with the use-cases of the hardware solutions. For the research-focused high-density mobile hardware, the minimal requirement of data collection and possibly transmission on mobile devices can be easily satisfied with simple software. In such cases, the already existing frameworks, such as EEGLAB, can utilize significant processing power of desktop or even server systems, and can even be used for data processing and transmitting the extracted features back to the user.

For more consumer-oriented sensors, real-time applications, possibly operating directly on mobile devices without server connection, need to be developed. The *Smartphone Brain Scanner* is the first framework that enables such development; pushing the limits of what can be done in terms of creating user value by enabling novel EEG applications. As the mobile devices performing the processing grow more powerful, more complex algorithms can be enabled to compensate for noise and low density of the systems.

## 6.3. Experiments

The vast majority of studies of neural and cognitive functions have so far been set in the laboratory, where the subject is severely restrained in movement, isolated from the surrounding world, and is required to carry out the same limited task repeatedly. This is an impoverished environment that we normally live in and are optimized to function in; it totally ignores human agency.

Taking EEG out of the laboratory and into the natural world will allow us to move beyond these constraints. Measuring the EEG of a freely moving subject will allow us to characterize the neural activity of many important functions. With wearable EEG we can study natural motion such as walking and complex composite motion. We can also study the many cognitive tasks that we constantly perform in their full complexity. Examples include preference-based choice as we select given consumer goods over others, the constant updating of working memory throughout our daily work, and the use of speech in natural social interactions. Measuring the EEG of subjects in rich natural environments will allow us to characterize the neural function of the perceptual systems when they are met with rich multimodal stimuli in which attention is constantly needed to select the relevant stimuli and filter out irrelevant stimuli.

The complexity and variability of data collected in the natural environment will be tremendous compared to the data collected in the laboratory. In order to derive anything meaningful from it, the amount of necessary data will be equally tremendous. Wearable EEG offers an immediate solution as hours, days, even weeks of data can be collected outside of the laboratory; something which is completely unrealistic in lab-based experimentation.

# 7. Conclusions

Mobile brain imaging, here realized as an EEG system, offers huge promise for many research areas. Here we show our initial work with the *Smartphone Brain Scanner* framework, which can record, analyze, and 3D real-time visualize EEG signals directly on a mobile device, using low-cost, consumer-grade neuroheadsets. The signal obtained in the studies, although of low dimensionality (14 channels) and noisy, can still be successfully used for multiple classical neuroscience applications, including brain-computer interfaces (BCIs), analysis of high-level brain activity, and neurofeedback. The features of the presented system make it possible to use in domains such as cognitive psychology, medical applications, social science research, as well as for "self monitoring" as promoted by the Quantified Self community[5].

As the presented framework runs on mobile devices, including tablets and smartphones, it can be coupled with other embedded sensors in a natural way. In this sense, EEG serves as an extension of the sensing capabilities of the already existing devices, and can be used in an integrated way with the other collected data (e.g. location, social interactions, activity level).

We argue that the presented framework enables a wide variety of experiments, and the initial set of these presented in this paper serves as a validation and showcase of the versatility of the framework and general approach. It is now clear that we are at the stage where hardware is powerful and inexpensive enough to be used for mobile brain imaging, while at the same time available algorithms can handle noisy data, allowing us to recover significant information.

The approach to user-oriented and mobile EEG does not end with the notion of researchers using the mobile devices and consumer-grade neuroheadsets to collect the data from the subjects. We can easily imagine that the systems will eventually be able to deliver interesting data to the public, giving them incentive to invest in their own hardware. In this shift, the data would be collected and uploaded by the participants themselves, distributing the cost and difficulty of running experiments. This presents yet more challenges, such as data quality control and privacy. On the other hand, it does give a promise of extremely large datasets created for large populations and over long periods of time, for only little costs.

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# Emotional responses as independent components in EEG stimulation

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# EMOTIONAL RESPONSES AS INDEPENDENT COMPONENTS IN EEG

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## ABSTRACT

With neuroimaging studies showing promising results for discrimination of affective responses, the perspectives of applying these to create more personalised interfaces that adapt to our preferences in real-time seems within reach. Additionally the emergence of wireless electroencephalograph (EEG) neuroheadsets and smartphone brainscanners widens the possibilities for this to be used in mobile settings on a consumer level. However the neural signatures of emotional responses are characterized by small voltage changes that would be highly susceptible to noise if captured in a mobile context. Hypothesizing that retrieval of emotional responses in mobile usage scenarios could be enhanced through spatial filtering, we compare a standard EEG electrode-based analysis against an approach based on independent component analysis (ICA). By clustering scalp maps and time series responses we identify neural signatures that are differentially modulated when passively viewing neutral, pleasant and unpleasant images. While early responses can be detected from the raw EEG signal, we identify multiple early and late ICA components that are modulated by emotional content. We propose that similar approaches to spatial filtering might allow us to retrieve more robust signals in real-life mobile usage scenarios, and potentially facilitate design of cognitive interfaces that adapt the selection of media to our emotional responses.

***Index Terms***— EEG, ICA, Affective Computing, Affective Response

## 1. INTRODUCTION

Many of the neuroimaging experiments that use electroencephalograph (EEG) when measuring affective responses from pleasant or unpleasant images have identified two main components; early posterior negativity (EPN) emerging before 300ms and triggering a relative negative peak in the EEG amplitude [1], and a late positive potential (LPP) emerging after 300ms [2]. Recent studies indicate that several event-related potential (ERP) components may be influenced as early as 50-80ms by emotional words and faces [3]. After

that an N1 component at 130ms, characterized by a parietal negativity, is modulated by emotional versus neutral content, followed by the EPN occipital negativity described above. The early negativities are thought to reflect an increased allocation of attentional resources elicited in response to what is initially perceived as salient in contrast to neutral. Subsequently, after 300ms, an initial P3 parietal component, followed by an occipital positive deflection corresponding to the LPP described above, and a later central positivity (LCP) appear likewise to be modulated by emotional content. These three positive components (P3, LPP and LCP) characterized by shifting scalp topologies might be related to memory encoding and further semantic processing of the emotional content [4].

The promising results for distinguishing emotional responses lead to the perspective of applying these to create more personalised content in real-time [5, 6, 7]. Additionally the emergence of wireless electroencephalograph (EEG) neuroheadsets and smartphone brainscanners [8] widens the possibilities for this to be used on consumer level. However, even when recording EEG under ideal conditions in a lab, emotional ERP responses are defined by only slight $\mu$V changes within single electrodes that would remain highly susceptible to noise in a mobile context. An example of this can be seen in a recent EEG experiment using an auditory oddball paradigm indicating that the P300 amplitudes might be reduced by 35% when walking compared to sitting on a chair [9]. In contrast, a similar mobile EEG experiment recording P300 responses while standing, walking and running showed no difference in amplitudes [10] when applying spatial filtering based on independent component analysis ICA [11]. Although the rows in the matrix of EEG data are initially defined by voltage differences measured over time between each electrode and the reference channel, they are based on ICA transformed into temporally independent events that are spatially filtered from the channel data. While aspects of volume conduction within the brain are not taken into consideration, the ICA decomposition frequently results in components that resemble neuroanatomical projections of dipoles, which in turn reflect synchronous activity of local

field potentials projected throughout the scalp [12].

Hypothesizing that retrieval of affective responses (ERPs) might be enhanced through spatial filtering, we compare a standard EEG electrode-based analysis against an approach based on independent component analysis (ICA). In the subsequent sections we outline the experimental methods, derived results and discuss our findings.

## 2. METHODS

In this study we used pictures from two studies, both showing successful discrimination of affective stimuli. One, based on 96 stimuli from the International Affective Picture System (IAPS) [13] consisting of 32 pleasant (mean valence/arousal 7.0/5.5), 32 neutral (mean valence/arousal 4.9/3.4), and 32 unpleasant (mean valence/ arousal 2.4/5.9) pictures[1]. The other study [14] was also based on stimuli from IAPS, consisting of 22 pleasant (mean valence/arousal 5.3/5.2), 22 neutral (mean valence/arousal 5.2/ 5.2) and 22 unpleasant (mean valence/arousal 5.0/ 5.3)[2].

The stimuli were presented in a random order for 6 seconds in blocks of 5 pictures. Between blocks, the participant was presented with a pause screen and was instructed to press enter when he was ready to continue the experiment. A scrambled image was generated by randomising the stimuli to achieve a mean luminosity equivalent to that found across all pictures. The scrambled picture was displayed 3 seconds before stimuli presentation, while the baseline was recorded. After the stimuli presentation, a grey screen was presented for 3 seconds.

The subjects (four right-handed males) were seated in a darkened, sound isolated room, at 50 cm distance from the screen. All stimuli were presented in colour on a 19 inch ViewSony GF90 screen. Prior to the experiment, the subjects were instructed to avoid excessive blinking during the baseline and picture presentation, and to avoid muscle and jaw tension and head movements.

EEG data was collected from 64 active AgCl electrodes (placed according to the international 10-20 system) recorded on a BioSemi ActiveTwo system at 512 Hz sampling frequency, while the impedance of each electrode was kept

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[1]IAPS stimuli numbers; pleasant: 2208, 2250, 2260, 2501, 2560, 2650, 4611, 4617, 4640, 4653, 4659, 4666, 4687, 4694, 5621, 8041, 8080, 8090, 8116, 8120, 8161, 8180, 8200, 8280, 8300, 8320, 8330, 8370, 8380, 8400, 8420, 8465; neutral: 2020, 2190, 2200, 2210, 2214, 2215, 2220, 2221, 2235, 2240, 2270, 2272, 2278, 2383, 2393, 2410, 2441, 2491, 2493, 2514, 2579, 2745.1, 2749, 2752, 2810, 2850, 2870, 2890, 3210, 5455, 7550, 9210; unpleasant: 2120, 2205, 2520, 2590, 2691, 2730, 2750, 2800, 3015, 3030, 3053, 3100, 3170, 3180, 3181, 3400, 3500, 3530, 3550, 6210, 6211, 6212, 6821, 6834, 6838, 9041, 9250, 9254, 9341, 9405, 9800, 9921
[2]IAPS stimuli numbers; pleasant: 1660, 4656, 4534, 7460, 4680, 5300, 4520, 8460, 4641, 7430, 2208, 8210, 8501, 8080, 8185, 8370, 5910, 2340, 2057, 1710, 1750, 2050; neutral: 5972, 4230, 4004, 4000, 6930, 2661, 8060, 5920, 7010, 6150, 7217, 7002, 7050, 7006, 4800, 8260, 5731, 1121, 8311, 7600, 4598, 4571; unpleasant: 3130, 3100, 2800, 9570, 3261, 9810, 3400, 9500, 9560, 6260, 3160, 6610, 6561, 9520, 1274, 5971, 1052, 9102, 4302, 4770, 1930, 3250

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below 50 kΩ. The data was referenced to two mastoid electrodes. After recording, the data was processed using the EEGLAB plug-in for MATLAB (MathWorks, USA). The data was filtered offline from 1 to 30 Hz and down sampled to 128 Hz. Epochs of 3000ms (1000ms pre- and 2000ms post onset) were obtained for each stimulus from the continuously recorded EEG. The mean voltage of a 1000ms segment preceding picture onset was subtracted as the baseline. Then, extreme noise from movement (muscle activity) or sensor artefacts was controlled by rejecting epochs with large amplitudes and thresholding the data on all electrodes (except the frontal electrodes) to +/- 150 $\mu$ V. This resulted in rejection of 30.3% of the epoch for one subject in contrast to rejection of 4.1% for the other subjects. Thus one subject was excluded from further analysis. In the next step, statistically deviating sensors were replaced with spherical interpolation based on the remaining sensors. Independent component analysis (ICA) was used to find distinct source activity across electrodes, such as non-brain components from eye and muscle activity. Vertical and horizontal eye movements were automatically removed using EyeCatch based on a library of over half a million independent component scalp maps [15].

Traditionally emotional responses have been analysed from ERPs by assessing the time windows of the relevant components (P1, N1, P2, ENP, P300, LLP, slow wave, etc.) from a Global Field Power plot. This was either followed by inspection of individual sensor's ERPs in order to access which sensors should be included in the statistical analysis, or by relying on sensor locations from previous studies for the statistical analysis.

Thus we assessed the relevant time windows from a Global Field Power plot, and used sensor locations identified from scalp maps of relevant time windows for the statistical analysis. The statistical analysis consisted of one-way repeated anova tests which compared how a within-subjects experimental group performed in the three experimental conditions (neutral, pleasant and unpleasant). Thereby we compared whether the individual average of selected electrodes for each condition differed significantly from the aggregate mean across the experimental conditions.

Furthermore, some studies use methods for topographic analysis such as Global Map Dissimilarity [16], principal component analysis [4, 17] or minimum norm analysis [2]. Similarly we used machine learning methods to identify common patterns of brain activity across the subjects, by combining PCA, ICA and K-mean clustering, following the standard EEGlab procedure [19].

We decomposed the EEG data into ICA scalp maps and time series components, which were grouped by initially reducing the dimensionality of the feature space to N=10 based on principal component analysis PCA [18], which as a pre-clustering function computes a vector for each component to define normalized distances in a subspace representing the largest covariances within scalp maps and time

series changes in power. Subsequently we applied a K-means algorithm (K=10) to cluster similar ICA components and separate outliers that remain more than three standard deviations removed from any cluster centroid, thereby following the standard EEGlab procedure [19].

## 3. RESULTS

The Global Field Power (plotted in Fig. 1) is the squared electrical activity over all sensors, trials, and subjects according to the procedure of [2]. The following relevant time windows are drawn based on the Global Field Power: P1 (75-125ms), EPN (130-225ms), P3 (250-315ms) and LPP (325-525ms).
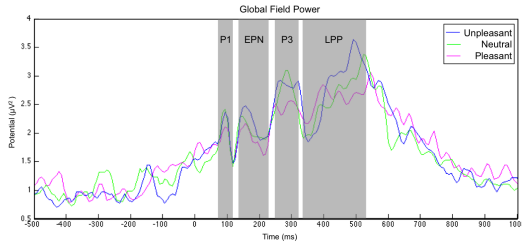


**Fig. 1**. The averaged global field power plotted for the three conditions, neutral (green), pleasant (red), unpleasant (blue)

By plotting the activity of sensors in the corresponding time windows, we used the following scalp plots to identify the sensors of interest.
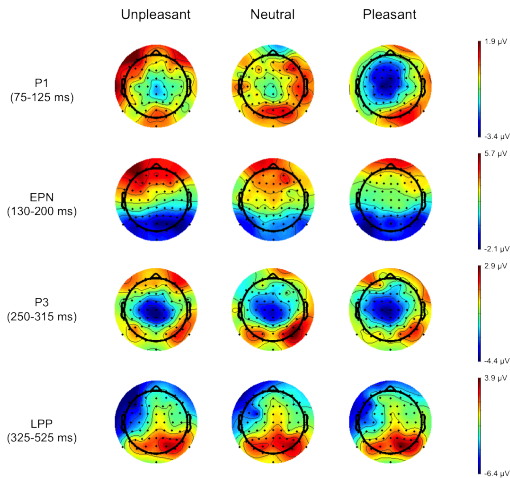


**Fig. 2**. Scalp maps for the time periods P1, EPN, P3 and LPP for each of the conditions (unpleasant, neutral and pleasant).

The scalp maps in Fig. 2 reveal sensors contributing to the deviating activity shown in Global Field Power. In the time window of P1, the activity is centered around the centro parietal area (Cz, CPz, CFz) and part of the occipital right hemisphere (POz, PO4, Oz, O2 and PO8). Although there is little consistency in which electrodes are examined across studies, both [20, 21] examine sensors covering the occipital lobe of an early effect. Thus sensors covering the centro parietal area and the right occipital hemisphere were examined for an effect in P1 by an average EPR and this was followed by a statistical anova analysis. Sensors in the temporal occipital area (P7, P8, POz, PO7, and PO8), corresponding to the sensors used in [22, 21] were analysed for an effect within the EPN time window. Likewise the sensors covering the centro parietal (Cz, CPz, CFz) and the temporal parietal area (PO3, PO4 PO7, PO8, P7 and P8) corresponding to the sensors used in [22, 21] and the sensors Pz, P1, P2, P5, P6, PO3, PO4, PO7, and PO8 corresponding to the sensors used in [20] were analysed in regard to P3 and LPP respectively.

From the paired one-way anova test of each average ERP, the only significant effect was found in the EPN time window, see Fig. 3.
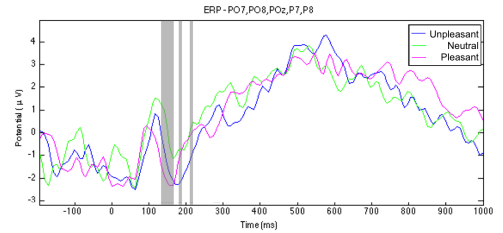


**Fig. 3**. An average ERP of channels covering the temporal occipital lobe (P7, P8, POz, PO7, and PO8) shows the three conditions pleasant (red), unpleasant (blue) and neutral (green). A statistical one-way anova on each channel marks the significant areas ($\alpha$=0.01) of the ERPs in grey.

This showed a number of short significant time windows at 133-164ms, 180-188ms and 211-219ms. The first significant time window distinguishes the neutral condition from those elicited by pleasant pictures, whereas the amplitudes of negative pictures are significantly lower in the second and third windows. These findings are consistent with results from [21], showing a significant effect for pleasant stimuli versus neutral and unpleasant in the early time window (150-300ms).

From the 20 clustered ICA components, three clusters are described in this paper (cluster 6, 10, and 12). These three were shared among all subjects (indicating that these components could include more general processing). They were also based on a relatively large amount of ICs and all of them

showed a significant difference between one or more conditions. Among these, only one cluster (cluster 6) showed a significant difference of conditions across both early (<300ms) and late (>300ms) time windows from a unpaired balanced one-way anova test. This suggests that cluster 6 represents neural activity contributing to both early and late emotional responses. The time course activations corresponding to the averaged ICA scalp maps in clusters 10 and 12 represent only short intervals, with a significant effect of condition limited to late responses.

In Fig. 4, 5, and 6, the averaged ICA scalp maps and corresponding ERP of clusters 6, 10 and 12 are shown.
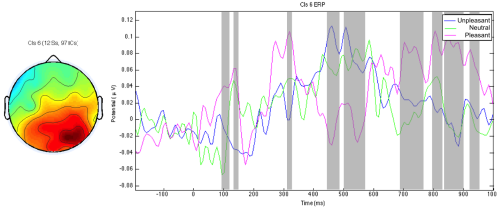


**Fig. 4**. Cluster 6, based on PCA dimensionality reduction and K-means clustering (K=10,$\sigma$=3) of 97 ICA scalp maps found within all of the 12 sessions, with corresponding ERPs for pleasant (red), unpleasant (blue) and neutral (green) images. Significant intervals for differentiating between the emotions are indicated in grey.



**Fig. 5**. Cluster 10, based on PCA dimensionality reduction and K-means clustering (K=10,$\sigma$=3) of 69 ICA scalp maps found within all of the 12 sessions, with corresponding ERPs for pleasant (red), unpleasant (blue) and neutral (green) images. Significant intervals for differentiating between the emotions are indicated in grey.

From the ERPs we see a significant effect ($\alpha$=0.01) of conditions in short windows of both early (94-177ms and 133-148ms), medial (312-328ms) and late (445-484ms, 500-570ms, 688-766ms, 797-828ms, 836-898ms and 922-953ms) temporal responses. Within these time windows the significant effect is mainly between pleasant and neutral/unpleasant, while we only see a significant effect of unpleasant pictures



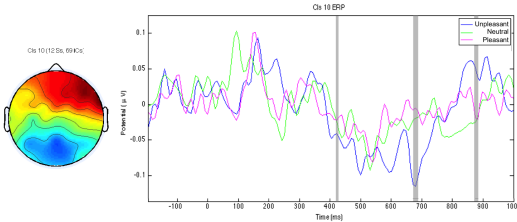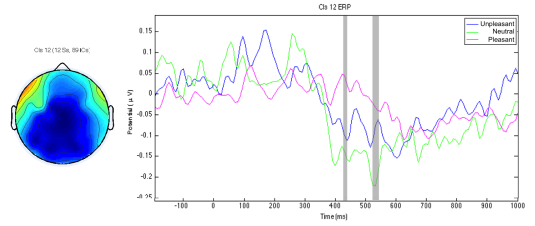**Fig. 6**. Cluster 12, based on PCA dimensionality reduction and K-means clustering (K=10,$\sigma$=3) of 89 ICA scalp maps found within all of the 12 sessions, with corresponding ERPs for pleasant (red), unpleasant (blue) and neutral (green) images. Significant intervals for differentiating between the emotions are indicated in grey.

in the early time window (133-148ms).

## 4. DISCUSSION

Our retrieval of affective ERP components based on a standard EEG analysis shows that we can differentiate pleasant from unpleasant and neutral images within three intervals 133-164ms, 180-188ms and 211-219ms. Even though this corresponds well to earlier reports on N1 and EPN [4, 21], we see no significant effect in the more pronounced P300 or LPP from the basic ERP analysis. Although this could be due to the low number of subjects (making it harder to reach a significant level), it might also indicate that the later components are more sensitive to individual processing. Thus, using P300 or LPP as a marker for real time classification of emotions might require extensive training of the classifier to accommodate the individual differences in late EPR oscillations. In contrast, using an earlier low-level marker such as EPN has proved to be sensitive to physical stimulus factors and indexes early sensory processing within the visual cortex.

However, a spatial filtering based on clustering ICA scalp maps and time series indicates that we can identify multiple early and late responses that are modulated by emotional content. Here, cluster 6 based on 97 ICA scalp maps shows an early difference at 130ms between pleasant compared to unpleasant as well as neutral content. In later time windows it additionally shows a difference between pleasant versus unpleasant/neutral content at 300ms, 450-600ms and 700-950ms. The cluster is characterized by a topology indicating a right lateralized activation in the extrastriate visual cortex and a polarity shift in the time series changes in power around 300ms. We found similar polarity shifts after 300ms in clusters 10 and 12 in our experiment, but here the significant differences between emotional and neutral content were limited to short intervals between 450 and 900ms after picture onset. However in clusters 10 and 12, based on 69 and 89

ICA scalp maps respectively, the corresponding time course polarity shifts around 300ms resemble the early negativities and late positivities reported earlier. In our experiments the averaged ICA scalp topologies of local field potentials also resembled these posterior early negativity and late positivity scalp distributions identified previously in affective ERP responses [23].

Our results are in line with the findings in a recent temporal-spatial PCA analysis of emotional ERP responses [4]. Here, the analysis establishes that the overlapping latencies within early negativities and late positivities represent distinct ERP components that reflect consecutive stages of neural processing [4]. Within that study, virtual epochs were extracted as described by the time course factor loadings for pleasant, unpleasant and neutral images, indicating that a reduced set of principal components is modulated by emotional content corresponding to the N1, EPN, P3 and LPP time windows. In our study, we also applied PCA as a preprocessing step before clustering ICA scalp maps and their corresponding ERPs, and similarly found that the significant intervals for differentiating between the pleasant and unpleasant images are within an early (<300ms) time window. In contrast, components emerging later (>300ms) rather indicated the difference between pleasant versus unpleasant and neutral, as has previously been reported [17]. This confirms that the early emotional ERP responses primarily capture the polarity of valence, that is, whether the images represent something pleasant or unpleasant. However, the later ERP responses incorporate complementary aspects of arousal that characterize the intensity of the emotional involvement relative to a neutral state [16].

In order to capture these components in even more noisy environments, like when accessing audiovisual media in real-life usage scenarios, other types of spatial filtering might be required to retrieve robust signals from EEG data, as exemplified by the real-time 3D source reconstruction used in the Smartphone Brain Scanner open-source software project [24], [8]. This would enable us to gain a more thorough understanding of the consecutive steps in affective responses, ranging from allocation of attentional resources and memory encoding to aspects of semantic processing. This in turn could potentially lead to incorporating these components into next generation cognitive interfaces capable of adapting the selection of content to our emotional responses.

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# Spatio temporal media components for neurofeedback

**Camilla Birgitte Falk Jensen**, Michael Kai Petersen, Jakob Eg Larsen, Arkadiusz Stopczynski, Carsten Stahlhut, Marieta Georgieva Ivanova, Tobias Andersen, and Lars Kai Hansen. Spatio temporal media components for neurofeedback. In *Multimedia and Expo Workshops (ICMEW), 2013 IEEE International Conference on*, pages 1–6. IEEE, 2013.

# SPATIO TEMPORAL MEDIA COMPONENTS FOR NEUROFEEDBACK

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## ABSTRACT

A class of Brain Computer Interfaces (BCI) involves interfaces for neurofeedback training, where a user can learn to self-regulate brain activity based on real-time feedback. These particular interfaces are constructed from audio-visual components and temporal settings, which appear to have a strong influence on the ability to control brain activity. Therefore, identifying the different interface components and exploring their individual effects might be key for constructing new interfaces that support more efficient neurofeedback training. We discuss experiments involving two different designs of neurofeedback interfaces and suggest further research to clarify the influence of different audiovisual components and temporal settings on neurofeedback effect.

***Index Terms***— Interfaces design, BCI, Neurofeedback Training, Audiovisual Components, User Experience

## 1. INTRODUCTION

Over the last couple of years the number of personal informatics apps has skyrocketed, allowing smartphone users to; track their sleeping patterns by combining remembrance of espressos past with built-in motion sensors [1]; upload photos of their lunch for peer approval of the number of calories consumed [2]; or share their exercise progress when running [3] accompanied by minutely detailed monitoring of heartbeat and respiration rates [4]. When it comes to personal informatics apps for monitoring mental state, mobile interfaces have largely been limited to subjective measurements of mood with e.g. MoodPanda [5] or measuring brain agility with standard cognitive tasks using e.g. Quantified Mind[6]. However the recently launched smartphone brainscanner open-source project

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[1]sleepcycle.com.
[2]https://itunes.apple.com/en/app/meal-snap-calorie-counting/id425203142?mt=8
[3]endomondo.com.
[4]http://www.zephyr-technology.com/products/bioharness-3/
[5]moodpanda.com.
[6]qualified-mind.com

[7] [1], enables continuous monitoring of cortical activity in an everyday context. The smartphone brainscanner combines a wireless EEG neuroheadset with a smartphone which allows for real-time 3D brain imaging [2] as well as altering brain activity on the basis of neurofeedback. With neurofeedback training, the individual can learn to increase or decrease the activity of particular brainwave frequencies on the basis of real-time feedback.

These types of brain machine apps will require novel approaches to the design of multimedia interfaces, as the user is no longer simply passively accessing a history of self-tracking events. Instead the user is actively carrying out a training session by generating data in real time by interacting with audio-visual representations of brainwave activity using a mobile device.

In the following sections we outline existing neurofeedback training paradigms, and extract the underlying audiovisual components from the interfaces. We propose a framework to describe these interface components as part of a feedback loop, serving as a basis for designing neurofeedback interfaces. This work serves as a first step towards understanding the effect of interface components on neurofeedback training. Likewise we conduct an experiment with two different interfaces, illustrating an effect on upper alpha activity depending on the feedback interface.

## 2. TRAINING FREQUENCY BANDS

Training neural activity by neurofeedback training has been applied on various frequency bands. E.g. decreasing theta (4-7Hz) and increasing beta (15-18 Hz) and cortical sensory-motor rhythms (12-15 Hz) amplitudes have been applied as treatment for children with Attention Deficit Hyperactivity Disorder (ADHD) [3]. Increasing the theta-to-alpha ratio has shown an increase in artistic performance among musicians [4]. When it comes to alpha band activity, this has recently been associated with a more basic cognitive process [5].

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[7]https://github.com/SmartphoneBrainScanner

An increase of alpha brainwave (8-12Hz) activity is typically associated with inhibition of neural activity, and is referred to as event-related synchronisation. Event-related alpha synchronization may block information processing in task-irrelevant areas of the brain like the occipital cortex when closing our eyes [5]. By inhibiting task-irrelevant activity, the decrease in alpha activity improves the signal-to-noise ratio. In this sense inhibition is an active process for information processing [5]. Regarding the upper alpha band (10-12 Hz), it has been shown that amplitude/power increases as a function of memory load during the retention period in a memory test. This probably reflects the effort of keeping a growing number of items in short-term memory [6]. In contrast, a decrease in alpha activity (referred to as event-related desynchronisation) in the upper alpha band (10-12Hz) is typically observed during actual retrieval of semantic information. The magnitude reflects cortical activation [7], meaning that excitation of neurons increases the more well integrated the information is [8]. Considering the distribution of brainwave frequencies, an alpha mean frequency of 10 Hz can be interpreted as the center around which the neighboring brainwave bands of delta, theta, beta and gamma constitute the harmonics at 2.5, 5, 20 and 40 Hz, respectively. Such a phase-coupling of, e.g. alpha and beta brainwave activity, is often observed, but if the power is shifted towards the upper 12.4 Hz or lower 8.4 Hz range, the alpha activity becomes maximally decoupled as the frequency ratios between brainwave bands approach an irrational number and oscillations no longer synchronize [9] [5].

Thus neurofeedback experiments aiming to increase power in the upper alpha range represent a decoupling of alpha activity from the surrounding frequency bands. Therefore any improvement in cognitive performance could reflect an association between higher alpha frequency and good memory performance which has previously been shown [8]. However, when it comes to the design of neurofeedback interfaces, they are often conceptualised with little attention to how the actual feedback of audiovisual elements might affect the user's ability to control brain activity.

### 3. AUDIOVISUAL COMPONENTS

Irrespective of whether the training aims at increasing or decreasing one or multiple types of brain waves, it has commonly been represented by a simple scaling of visual components; like the height of a bar and a color change, or audio components; like high and low pitch tones and a volume change. The most common auditive component used for auditive or audiovisual feedback is the pitch of a sound [10, 11, 4]. A short high-pitched or low-pitched sound indicates that the increase or decrease in brain activity has reached a threshold. Thus the pitch often represents a successful or failed trial. Although pitch is the most common auditive component used in neurofeedback training, other more continuous sounds could be used with components such as rhythm and volume as indi-
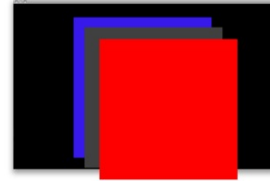


**Fig. 1**: In this interface gray indicates brain activity equal to an average activity (baseline), and gradually turns blue when activity decreases and red when activity increases.

cators.

In visual interfaces there is more variety in the use of components. Some studies use simple interfaces where e.g. a square changes color gradually from blue to gray and red indicating activity below, equal to and above an average baseline activity [12] (see Figure 1). This gradual color change from blue to red can be associated with cold and warm temperatures. Other interfaces indicate increases in activity by altering the size of a graphical element, such as the height of a bar [13], which resembles a vertical scale like a tuning bar. Another method is moving an object on a vertical or horizontal axis [14], resembling a high or low activity. These interfaces all consist of geometric primitives (e.g. a square), altered by another component such as color, size or the spacial distribution within the screen.

Besides representing brain activity, components might be added to create an atmosphere or simply to make the training more interesting. An example of this is the neurofeedback study of Egner et al. [4] using an auditive feedback to increase the alpha/theta ratio. A background sound resembling either a 'babbling brook' or 'ocean waves' was used to indicate a relative increase of alpha and theta activity respectively. Additionally, a high-pitched or low-pitched gong sound would be executed when the activity exceeded a pre-set threshold of alpha and theta, respectively. The subjects aimed to increase the amount of theta sound representation. Thus the background sound would not only indicate the relative activity but also contribute to achieving a mental state, whereas the gong sound would primarily indicate reaching a 'significant' activity level; a 'success'/'fail' scenario. Another example is the visual interface used for neurofeedback training of children with ADHD in Heinrich et al. [15]. Here, the aim is to make a famous German cartoon mouse do a pole-vault. This is achieved when a threshold is met; indicated by a pole changing color from white to blue or red to show a relative decrease or increase, respectively. In this interface, the color change of the pole is the main indicator of the brain activity, much like the interface with a blue/gray/red square mentioned above. However, the cartoon mouse creates a 'story' supporting the training, and might encourage imagination or trigger-related memories.

Thus these game-like interfaces are basically constructed from a combination of the same simple components and substitute generic primitives with more game-like features such as airplanes [15] or pacmans [3]. 3D games have also been developed, where high or low activity is represented by e.g. the speed of a racing car or a dancing robot [16]. These 3D interfaces can be described as a combination of multiple visual components. A car speeding up is created by changing the size and spatial distribution of the surrounding elements at a faster frequency. These game-like interfaces are commonly used in clinics for treatment of e.g. ADHD. Whereas the more primitive interfaces typically occur in scientific settings.

Summing up, we have identified the following audiovisual components, which in combination can describe any interface. All of these change with the EEG sampling frequency and the screen update frequency.

Auditive components include:

- pitch (low, high)
- volume (soft, loud)
- timbre (dark, light)
- duration (short, long)
- rhythm (temporal distribution)

Visual components include:

- geometric primitives (connected segments)
- color (discrete, gradients)
- size (proximity, scalability)
- movement (horizontal, vertical)
- composition (spatial distribution)

Consequently, when designing new neurofeedback interfaces, focus should not only be on how to visualize an increase or decrease of brain activity, but should consider how components (and combinations of these) might affect the user's imagination, or trigger-related memories, etc. Furthermore, no studies have examined which components are in reality causing the greatest effect.

## 4. TEMPORAL ASPECTS OF NEUROFEEDBACK

The importance of these interface components is due to the real-time feedback, which creates a tight coupling between the visual interface and the brain activity. To understand this relationship and aspects of real-time feedback, we illustrate how a neurofeedback application is constructed, see Figure 2.

Neurofeedback applications consist of four stages, which constitute the feedback loop:

**Preparation** deciding which brainwaves to train and from which area

**EEG data acquisition** collecting data on cortical activity
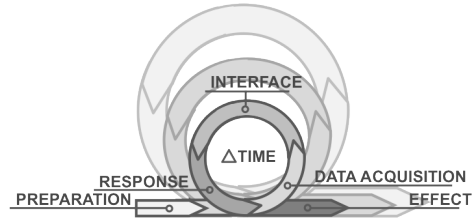


**Fig. 2**: An illustration of the stages represented in neurofeedback applications, with a loop connecting the data acquisition, interface and response stage. Varying the time span may cause a measurable effect, from changes in plasticity of neural networks [17], to behavioral and neuro-psychological [18].

**Interface** visualizing the relative cortical activity (increase or decrease) enabling reflection

**Response** changing behavior or mental strategy

**Effect** all of which might lead to a long-term effect on cognitive, physiological or behavioral measures.

The loop between data collection, visualization and response is completed in milliseconds, creating the real-time feedback loop between brain activity and visualization. Since changes in brain activity are monitored at the level of milliseconds, it allows the user to instantly change mental states on the basis of real-time feedback. Thus this time span should be considered when developing neurofeedback applications. Repeating this loop several times creates a continuous representation of brain activity during the time span of seconds, minutes or hours. Within this time span the user can explore the effect of different strategies of thoughts by receiving and reflecting on the information provided by the instant real-time feedback.

## 5. TESTING TWO NEUROFEEDBACK INTERFACES

To explore the influence components might have on the efficacy of neurofeedback training, we test two different interfaces; one indicating brain activity based on only a color component (a blue/gray/red square) and the second interface using multiple components as indicators.

### 5.1. Experimental Design

We conducted an experiment with 25 subjects aiming at increasing their upper alpha frequency band (10-12Hz) using one of the two different neurofeedback interfaces. The first group of 12 healthy subjects (7 males and 5 females) with an age average of 23.6 ±1.9 did neurofeedback training on a replication of an existing interface [12]. The interface is similar to that mentioned earlier, consisting of a single square, with the color being the only component changing. The color
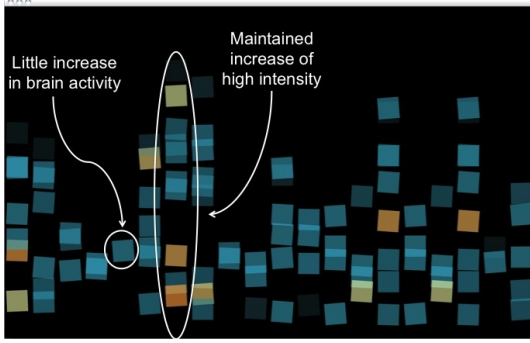
**Fig. 3**: The second neurofeedback interface where small squares colored from blue to red that build up columns along a horizontal temporal plane represent the user's ability to increase upper alpha brainwave activity.
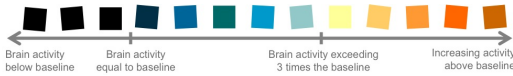


**Fig. 4**: The color of the squares indicates the intensity of the brain activity

changed gradually from blue to gray and red when the brain activity was below, equal to and above baseline (an average relaxed brain activity), respectively (see Figure 1). The subjects were instructed to make the square turn red. During the baseline recording, the subjects were presented with an interface similar to the training interface, however the input values were randomly generated. The subjects were instructed to only focus on counting the number of times the square turned red. This simple cognitive task would help prevent their mind to wander off, and would make the recording more compatible across subjects. In addition they were told to avoid any muscle tension and jaw clinching as well as to reduce eye blinks to a minimum during all recordings.

The second group of 13 healthy subjects (7 male and 6 female) with an age average of $26.6 \pm 5.5$ did neurofeedback training using an interface consisting of multiple parameters. A pattern of small squares was generated once a second, if the alpha activity exceeded the baseline activity. These squares created a column of squares, incrementally generated along a horizontal axis. This formed a virtual timeline of columns illustrating the brain activity over a 5-minute training session, where the color of the squares changed continuously according to the attained power measure calculated from a running mean of 2 seconds (see Figure 3). A small increase above baseline resulted in a dark blue square, which turned lighter and gradually changed from yellow to orange, reflecting the magnitude of the attained power measured using EEG (see Figure 4). Thus this interface consisted of the

following components: a composition of geometrical primitives (formed as squares), changing colors gradually within a color range (see Figure 4) and the spatial distribution along a horizontal and vertical axis. The subjects were instructed to generate as many squares as possible within the columns and preferably make them turn yellow or orange. During the baseline recording the subjects were presented with an interface similar to the training interface, however the input values were randomly generated. The subjects were instructed to only focus on counting the number of times the squares turned orange. This simple cognitive task would help prevent their mind from wandering off, and would make the recording more compatible across subjects. In addition they were told to avoid any muscle tension and jaw clinching, as well as to reduce eye blinks to a minimum during all recordings.

The training of both groups consisted of five sessions during one week from Monday to Friday. Each session started and ended with a 5-minute baseline recording, and in between five, 5-minute training sessions were conducted. Each subject received a total of 25 training recordings and 10 baseline recordings.

To record the brain activity the Smartphone brainscanner was used, transmitting EEG signals to a USB-dongle connected to a tablet. The setup had a sampling frequency of 128 Hz with feedback every 125 ms, giving the user an impression of live feedback. The Emotiv neuroheadset used in the experiment consisted of 16 electrodes, including 2 reference electrodes (P3/P4). The remaining electrodes were positioned at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 according to the international 10-20 system. The live feedback was constructed from O1 and O2.

### 5.2. Data Analysis

For the analysis we were interested in cortical information from the occipital lobe covered by O3, O4, P3 and P4. Since P3 and P4 were reference electrodes, the signal could be reconstructed by re-referencing. Thus the signal from the frontal electrodes AF3, AF4, F3 and F4 (furthest away from the area of interest) was averaged and referenced to P3 and P4, allowing P3 and P4 to be included in the data processing. This and all the following data processing was done offline using EEGLAB [19]. The raw signal from the electrodes was transformed into a power spectrum using Fast Fourier Transformation.

With the alpha frequency band varying with age, possible neurological diseases and memory performance [8], the upper alpha frequency band had to be determined for each individual. By identifying the peak in the power spectrum (the individual alpha peak (IAF)), the upper alpha frequency band was set as a band of 2 Hz above IAF (from IAF to IAF+2Hz). The upper alpha frequency band was determined for each subject by the first baseline recording of each session. The mean amplitude of the upper alpha band was calculated for all baseline
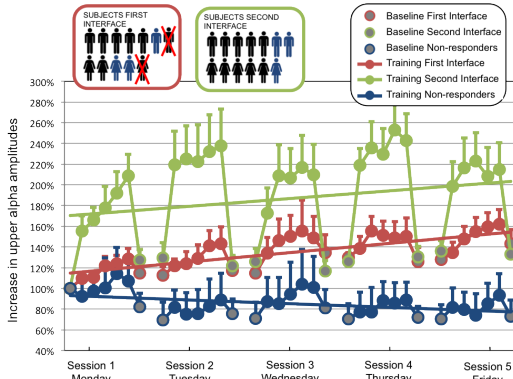
**Fig. 5**: A comparison of the first interface (plotted in red) and second interface (plotted in green) shows a significant difference in the users' ability to increase upper alpha brain activity when using the second interface for training. In contrast non-responders experience a slight decrease. The bars indicate the standard error of the mean.

and training recordings using a fast Fourier transformation. However two subjects (1 male and 1 female) from the first iteration of the experiment did not complete all the training sessions, and were therefore excluded from further analysis. In addition it has repeatedly been reported that some subjects, referred to as non-responders, are unable to change amplitudes of the brain frequencies significantly [3, 14, 20, 12]. The reasons for this have not been determined, but might be due to pure physiological reasons [14] such as the thickness of the skull. Thus subjects who did not show a significant increase between the very first baseline (baseline 1 in session 1) and the training recordings from the last session (Friday) were considered non-responders. As a result, 3 subjects (2 female, 1 male) from the first iteration and another 3 subjects (2 male, 1 female) from the second iteration were considered non-responders and where excluded from the statistical analysis.

Each subject's EEG results from all recordings was normalized in respect to the first baseline Monday (session 1), thereby showing the ability to increase UA amplitudes in relation to the first baseline in percentage. The average results of the two groups have been plotted in Figure 5. The results show a steady increase in the baselines (gray dots) for both groups, which is similar to the results from Zoefel et al. [12]. In contrast the non-responders (blue) experience a slight decrease in baseline activity. Furthermore the plot shows a clear increase in brain activity during the training recordings of subjects of the second iteration (green) compared to the subjects of the first iteration (red).

From the results above a paired, one-tailed t-test was con-

ducted for both the first and the second group, testing the effect of training (difference between the very first baseline and the very last baseline) on the responders. Both interfaces showed a significant increase from the first baseline of the first session (Monday) to the first baseline of the last session (Friday), with $t(6)=4.46$, $p=0.002$ and $t(9)=3.47$, $p=0.003$ for the first and the second group, respectively. To compare the results of the two groups using different interfaces, we conducted 2, two-sample t-tests (assuming unequal variance); one testing the difference in training effect; the other testing the difference in feedback effect. The tests showed no significant difference between the two interfaces in training effect ($t(14)=0.66$, $p=0.522$. In contrast the tests did show a significantly greater effect of feedback (the difference between the average baseline and average training recording across all sessions) for the second group ($t(14)=2.70$, $p=0.020$).

This suggests that neurofeedback interfaces should not only relay the attained power in specific brain wave frequency bands, but also take into consideration how different interface components affect the user interaction. Thus we suggest investigating the efficiency of the individual visual components in order to combine them into supportive interfaces.

## 6. CONCLUSION

In contrast to many traditional media interfaces, the audio-visual components and the temporal aspects of neurofeedback interfaces have a direct influence on training abilities. Thus, considering how the user responds to the audiovisual representation (the user experience) should be included when designing neurofeedback interfaces. This calls for more research on the influence of specific audiovisual components and the temporal aspect. This could be done by either constructing a thorough bottom-up analysis of the individual components; or by a top-down meta-analysis of previous studies, exploring best-practice combinations of components, which have led to successful neurofeedback training.

## 7. ACKNOWLEDGMENTS

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# SOA thresholds for the perception of discrete/continuous tactile stimulation

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# SOA Thresholds for the Perception of Discrete/Continuous Tactile Stimulation

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*Abstract*— **In this paper we present an experiment to measure the upper and lower thresholds of the Stimulus Onset Asynchrony (SOA) for continuous/discrete apparent haptic motion. We focus on three stimulation parameters: the burst duration, the SOA time, and the distance between successive actuation points. The experimental setup is based on a set of six (6) vibrotactile actuators to investigate effects of the distance between successive actuation points (over the range 4 cm to 20 cm) on the respective SOA thresholds. We found that as the burst duration increases, subjects detected the simultaneous-discrete boundary at decreasing SOA. Furthermore, we found that the larger the inter-actuator distance, the more linear the relationship between the burst duration and SOA. Finally, the large range between lower and upper thresholds for SOA can be utilized to create continuous movement stimulation on the skin at "varying speeds". The results are discussed in reference to designing a tactile interface for providing continuous haptic motion with a desired speed of continuous tactile stimulation.**

*Keywords— Funneling Illusion; Vibrotactile Feedback; Tactile Interface Design, Haptics Technologies.*

## I. INTRODUCTION

An increased demand for computer-mediated interpersonal interaction has spurred research to improve the sense of touch using haptic devices (both kinesthetic and tactile) [1]. Tactile sensation provides a very powerful means of communication in our daily interactions, in particular to learn about the physical characteristics of the ambient world. For instance, it enables us to explore surfaces and textures, and in several cases develop personal and emotional connections with objects and individuals we touch. Furthermore, tactile stimulation can be used as a substitute modality for interaction with people with visual impairment or blindness [33].

The spectrum for vibrotactile stimulation applications is wide, and ranges from training and education [17] to health care [18-19], social interaction [20], and gaming and entertainment [21-22]. For instance, the authors in [23] provide the musicians with vibrotactile feedback about their bowing and posture using vibration motors that are positioned on their arms and torso. A ubiquitous wearable vibrotactile belt is proposed to support a novel application of teaching participants choreographed dance [17]. In the medical field, a vibrating tactile probe is presented [18] that can be used to distinguish among different materials. The sensing capabilities

could be exploited in various biomedical applications, such as catheterism and surgical resection of tumors.

Tactile devices are primarily composed of an array of actuators where multiple actuation technologies can be utilized, such as vibrotactile motors, electrodes, piezoelectric ceramics, pneumatic tubes, shape memory alloys, electromechanical actuators (voice coils). In general, tactile arrays are of low resolution due to the size of the actuators and the coarse sensitivity of two-point limen on the skin [8]. Therefore, in order to provide a more apparent and subtle information with low spatial resolution devices, such as continuous sensation, researchers investigated the display of detailed shapes using human sensory illusions [9-10].

Various sensations can be induced via tactile stimulation, such as hardness and softness, roughness of a surface, vibration, and warmth and cold [2]. Furthermore, there is no doubt that complex emotional sensations such as the pleasantness are associated with tactile sensations [3]. These complex sensations would be derived from the dynamic spatial-temporal patterns of tactile stimulations.

Funneling [4] and saltation [5] are well-known illusory feedback techniques associated with tactile stimulation. Funneling refers to stimulating the skin at two distinct points with different amplitudes and eliciting tactile sensation in the somewhere in between [4]. On the other hand, saltation involves stimulating the skin at two locations with proper actuation overlap time to give a perceived stimulation in between. Varying the amplitude (funneling) and/or time interval (saltation) between two adjoining actuators to give continuous tactile stimulation has been a subject for research for a few years [6, 7].

The authors in [35] demonstrated that the variables producing robust apparent tactile motion are the stimuli duration and the stimulus onset asynchrony (SOA). The SOA is defined as the time between onsets of subsequent actuations [35]. In this paper, we develop a wearable tactile display using low-resolution vibrotactile actuators to study the upper and lower thresholds of the SOA based on a known human sensory phenomenon called the "funneling illusion" [11]. The paper presents an experimental study to determine the upper and lower thresholds of the SOA to achieve continuous/discrete tactile movement using discrete actuators. We investigate the effects of spatial and temporal attributes to obtain a smooth,

continuous movement sensation. Moving tactile sensation is a common and effective way to communicate, express, alert and direct user's attention [12].

The remainder of the paper is organized as follows: In section II we present an overview of the related studies on human tactile stimulation. Section III introduces the psychophysical experiment setup, apparatus, procedure, and implementation details for the tactile armband device. In section IV, we present our results and a discussion about the interesting findings. Finally, in section V we summarize the paper findings and provide perspectives for future work.

## II. RELATED WORK

The concept of tactile stimulation has been around for decades, since Geldard [13] in the 1950s studied the ability of the skin to make temporal and spatial discriminations close to those achieved by eyes and ears, and highlighted the underutilization of tactile channel for presenting information. More recently, there has been an increasing interest in developing tactile displays in multimodal interfaces (such as [14-16]).

Research in developing high-resolution tactile displays has an immense historic background. Early studies reported that the intensity of tactile stimulation can be varied linearly and logarithmically to provide continuous vibrotactile motion [24]. Tan et al. developed a 3x3 vibrotactile array to study the impact of a sensory illusion called "sensory saltation" to be used as a haptic navigation system to convey directional information on the back of a human body [25]. Tactile display devices may also be used to represent text or images on the skin with high granularity [26]. However these devices are still in their infancy due to the poor and limited resolution of tactile stimulation, as well as their high cost, maintenance, bulkiness and power requirements.

Researchers are conducting psychophysical experiments in order to investigate the spatial/temporal resolution of vibrotactile stimuli at various parts of the human body (such as the forearm [27], the back [28], and the neck [29]). For instance, the authors in [27] evaluated 13 test items of display methods, namely stationary and moving vibrotactile stimuli. Both display methods show best localization accuracy in the vicinity of the joints (elbow and wrist), followed by the locations of the actuators themselves.

Researchers have also focused on the perceptual illusions of vibrotactile movement such as the research presented in [15-16, 30]. For instance, Bonanni et al. [31] used a static vibration method to provide affectionate touch via illusory vibrotactile movement. Patterns of movement that resemble the act of smoothing on the skin were created and tested.

Vibrotactile movement was explored by comparing three different presentation methods, namely saltation, amplitude modulation, and a hybrid condition [32]. Results demonstrated that modulation method was rated significantly more continuous and pleasant, and less arousing compared to both the saltation and the hybrid methods. Another effort to measure the control parameter space of apparent haptic motion using a variety of stimulation attributes and body sites is presented in

[14]. In one experiment, they measured the range of SOA for straight-line apparent motion on the skin in relation to variation in frequency, duration and direction of stimulation [25]. Based on the measurements, a model that related the perceived illusory motions to the stimulation parameters was developed. The work was extended in [28] to vary frequency, intensity, duration, and body site.

Designing tactile displays based on apparent tactile motion is challenged by the fact that there is insufficient understanding of the parameter space where the motion exists. Previous studies have focused on identifying variables that control the illusion by demonstrating various control values [34], and the design of control algorithms that are based on psychological modeling of apparent tactile motion [28]. In this paper, our goal is to extend the knowledge about such parameters by measuring the lower and upper thresholds of SOA timing for continuous/discrete apparent tactile motion.

## III. METHOD

### A. Participants

Ten voluntary participants, 5 female and 5 male, took part in the experiment (mean age 27.4 years, SD = 6.97). All the participants had a normal sense of touch by their own report and were naïve with respect to tactile stimulation display devices.

### B. Hardware Platform and Software Interface

A hardware platform was developed to stimulate a series of six vibrating points on the skin of the forearm using vibrotactile actuators. The Vibrotactile Actuators are controlled by a microprocessor that receives actuation patterns from the computer and generates actuation signals that control a driving circuit, which eventually feeds the vibrotactile motors with appropriate current/voltage. The actuators can be driven separately, simultaneously or in sequence. A snapshot of the experimental setup is shown in Fig. 1.
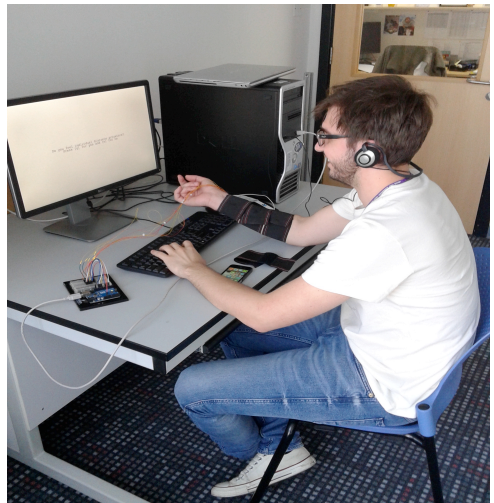


Fig. 1 Experimental setup.

The armband providing the vibrotactile stimulus was constructed with six actuators (Pico Vibe 310-177, Precision Microdrives) vibrating with a frequency of 700 rpm at the minimum intensity 0.25g, and 1400 rpm at the maximum intensity of 1.75g. They were placed at a distance of 4 cm from center to center of the actuators. A snapshot of the actuators configuration in the armband device is shown in Fig. 2.
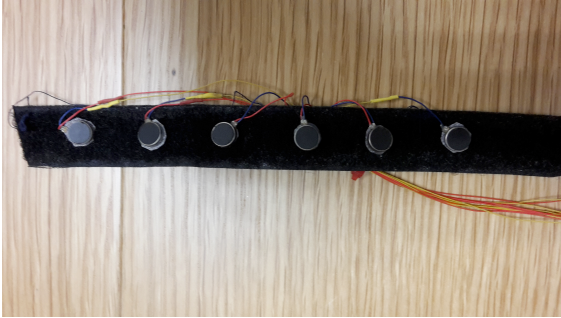


Fig 2: Armband device configuration.

## C. Stimuli

The stimuli were designed to be generally favorable for the vibrotactile movement on the forearm region. To keep the length of the experiment at a reasonable level, five different burst sequence patterns were used: 11, 101, 1001, 10001, and 100001 (shown in Fig. 3), which are equivalent to physical distances of 4 cm, 8 cm, 12 cm, 16 cm, and 20 cm respectively between successive actuation points. Furthermore, three burst actuation durations, 120ms, 180ms, and 240ms, were used to design the stimuli. All fifteen possible combinations of these two parameters were used to stimulate the participants' forearm. The movement of the stimuli traveled between the elbow and the wrist.



Fig 3: Visual representation of the Stimulation patterns used in the study (distance center-to-center is 4 cm).

## D. Procedure

The tactile armband device was attached to the dorsal side of the forearm with the elastic straps, so that the center of the first actuator was 4 cm from the wrist. The actuators were placed on the non-dominant hand, thus if the subject was right handed, the actuators were place around the left wrist. While the experiments took place the subjects were listening to pink noise in order to mask any noise from actuators.

The experiment condition was tested in two threshold cases: (1) Lower threshold of SOA: the onset threshold between the total simultaneity and apparent movement of stimulation points, and (2) Upper threshold of SOA: the onset threshold between the total discreteness of stimulation points and apparent movement of stimulation points.

We utilized a one-interval, two-alternatives forced-choice (1I-2AFC) paradigm combined with one-up one-down adaptive procedure to determine the upper and lower thresholds of SOA, as used in [28, 14].

For the runs determining the upper threshold of SOA, the start value of SOA was selected large enough so that the participant clearly feel independent stimulation points. In every trial participant was asked if s/he could feel individual "discrete" actuators. They responded by pressing a button marked "yes" or "no" using the keyboard. A new trial started immediately after the response. For every "yes" response the SOA value decreased and for every "no" response the SOA value increased for the subsequent trial. Similarly, for the runs determining the lower threshold of SOA, the start value of SOA was selected small enough such that the participant feels simultaneous stimulations (no sense of directionality of stimulation). In every trial they were asked if they felt actuators "simultaneous". For every "yes" response the SOA increased and for every "no" the SOA decreased for the subsequent trial.

The SOA value was changed initially by 16 ms and then by 4 ms after the first two reversals. A reversal occurred when the participant's response changed from "yes" to "no", or vice versa. The experimental run terminated after six reversals at the 4 ms step-size. Each run typically took 10 trials, which lasted about 10-15 minutes. Participants sat comfortably on the chair facing towards the computer screen displaying experimental protocol.

## E. Data Analysis

The average SOA threshold was computed by taking the mean value of the last five reversals of each run. Repeated measures Analysis of Variance (ANOVA) tests were utilized to determine significant effects ($\alpha = 0.05$) of test conditions.

## IV. RESULTS

Three parameters are considered in this study: the burst duration, the burst overlap time, and the actuators distance (distance between actuation points). We aim at exploring the relationship between these three parameters for the sake of generating continuous tactile stimulation, and find the upper and lower thresholds for the SOA values.

## A. Upper Threshold for SOA

The grand average of the upper threshold for the SOA time against the burst duration, for various actuators distances, is shown in Fig. 4. From the plot in Fig. 4 we clearly see a linear correlation between the SOA timings and the burst overlap time, with an exception at 4 cm actuators distance, which might

indicated that these actuators are place too closely together for the subject to discriminate the continuous tactile stimulation.
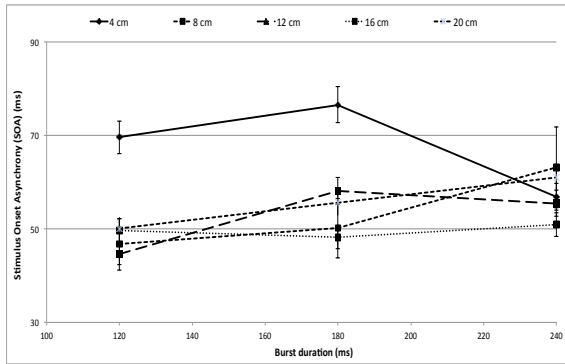


Fig. 4: Upper threshold for the SOA against burst time.

Fig. 5 depicts the SOA time in milliseconds against inter-actuator distance for the upper threshold for three different burst duration values (120 ms, 180 ms, and 240 ms). The error bars of Fig. 5 represent the standard variation thresholds whereas the trends line shows the linear interpolation trends against the distance between successive actuation points. Fig. 5 shows clearly that the further the distance between successive stimulation points (4 to 20 cm), the more linear is the relationship between the burst duration and the SOA. Note that the interpolation line shown in Fig. 5 represents the upper thresholds of the linearized distance/SOA relationships for the three types of burst duration. The interpolation demonstrates that a linear relationship between the SOA and the inter-actuator distance produces a perceivable tactile apparent motion. Therefore, we suggest that these equations sufficiently describe the upper threshold for the inter-actuator distance/SOA relationship for continuous tactile stimulation.
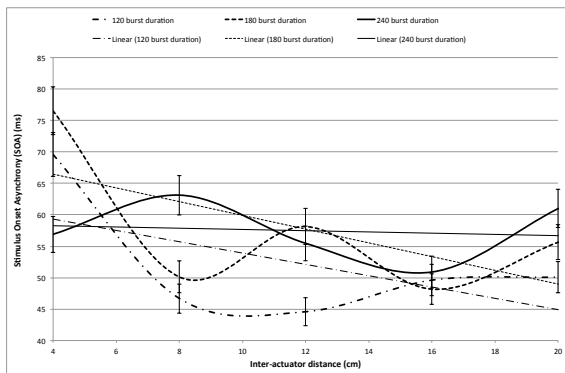


Fig. 5: Upper threshold for the SOA against inter-actuator distance.

## B. Lower Threshold for SOA

The grand average of the lower threshold for the SOA time against the burst duration is shown in Fig. 6. Fig. 6 clearly shows a linear correlation between the burst duration and the burst overlap time, except around the 4 cm distance between successive actuation points. Again, the reason might be because these actuators are place too closely together for the subject to discriminate the continuous tactile stimulation.
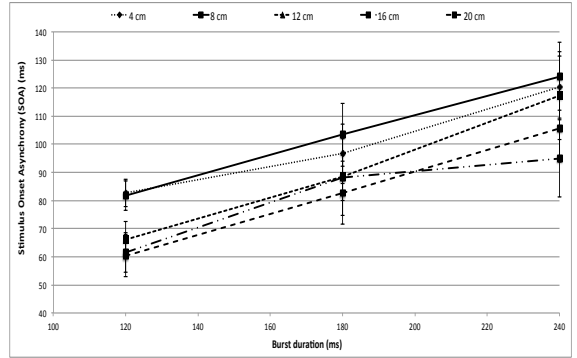


Fig. 6: Lower threshold for the SOA against burst time.

Fig. 7 presents the SOA time against the inter-actuator distance, for the lower threshold at 120 ms, 180 ms, and 240 ms burst duration values. Fig. 7 also shows the standard deviations and trends for the SOA time. Fig. 7 shows clearly that the further the distance between successive stimulation points (4 to 20 cm), the more linear is the relationship between the burst duration and the overlap time. Note that the interpolation line shown in Fig. 7 represents the lower threshold of the linearized inter-actuator distance/SOA relationships for the three values of burst duration.
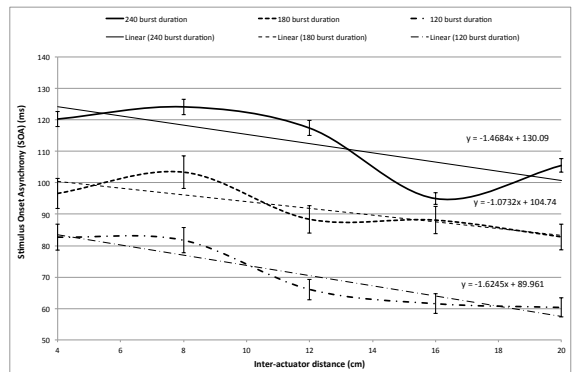


Fig. 7: Lower threshold for the SOA against inter-actuation distance.

The interpolation line in Fig. 7 demonstrates that a linear relationship between the SOA and the inter-actuator distance produces a perceivable tactile apparent motion. Therefore, we

suggest that these equations sufficiently describe the lower threshold for the distance-overlap relationship for continuous tactile stimulation.

### C. Discussion

A thorough one-way ANOVA analysis suggested that the burst duration was a significant factor for both the upper and lower thresholds of SOA [F(2,12) = 196, p<0.01 for upper threshold and F(2,12) = 69, p<0.01 for lower threshold]. As the burst duration increased, both the upper- and lower-thresholds also increased. However, the SOA range between upper- and lower-thresholds was greater for larger burst durations, indicating broader margins for creating continuous apparent tactile motion on the skin.

In the present experiment one-way ANOVA analysis has also shown that the upper and lower thresholds for the SOA were not significantly affected by the distance between successive actuation points [F(4,10)=0.044, p=0.995]. This suggests that by placing the actuators anywhere between 4 cm and 20 cm apart, continuous movement stimulation can still be generated on the skin – with the exception of measurements taken at 4 cm distance.

The one-way ANOVA analysis for comparison between the upper and lower thresholds of the SOA suggested significant differences between upper and lower SOA thresholds [F(1,26)=6.11, p<0.05].

All configurations of stimulation patterns are shown to generate continuous stimulation with corresponding upper/lower thresholds. Furthermore, within upper/lower overlap time interval, continuous stimulation can be produced at various speed of stimulation. This implies that the designer for the tactile display device may simulate various 'speeds' of tactile stimulation according to the application requirements. For instance, a bullet tactile effect would be rendered as a fast continuous stimulation whereas an insect walking across the human skin would be simulated using slow continuous stimulation.

Fig. 2 indicates that the upper threshold (with exception of the 4 cm pattern) is almost independent of the placement of the actuators. However this is not the case for the lower threshold, where we see a lower threshold for the 4 cm and 8 cm patterns compared to the other patterns. This implies that the lower threshold for a continuous motion can be lower as actuators are placed closer together. Consequently, bringing the actuators closer to each other has resulted in a wider SOA space between the lower- and upper-thresholds, while maintaining a non-linear relationship between the burst overlap and the burst duration.

The final threshold (average of upper and lower) for the SOA marks the value below which the stimuli are perceived to be simultaneous, and above which the stimuli are perceived to be discrete. Values of SOA at the average threshold and upwards can be used to control the speed of movement of the stimulus.

It is also worth highlighting that the 4 cm configuration (for both upper and lower thresholds) is characterized by a non-linear behavior, probably because the actuators are placed too close to each other for the user to discriminate spatial differences.

A similar experiment by Israr et al. [28] compares the upper and lower thresholds of patterns created from three actuators with distance of 2.35 inches (app. 6 cm) and 4.7 inches between actuators with the burst durations 240 ms. Israr et al. found a significant difference of spacing with larger variance of the upper threshold. If we look at the threshold values, the upper and lower threshold is quite similar when the burst duration is 120 ms for both experiments. However this is not the case when we look at the results for burst durations of 240 ms: here our results show significantly higher values for both lower and upper threshold. The reason for this is unknown, but it could indicate that stimulation of the actuators from our experiments and that of Israr et al., feels different when the burst duration is increased. We therefore suggest a further investigation of the perception of continuous motion using different actuators.

## V. CONCLUSION AND FUTURE WORK

The motivation of this work has been to derive specifications for the design and development of tactile stimulation interfaces based on psychophysical experiments. The long-term goal is to study tactile stimulation for affective communication. The key contribution of this paper was to measure the SOA space for continuous tactile stimulation (upper- and lower-threshold SOA values). We also investigated and reported the effects of burst duration, burst overlap time, and the distance between successive actuation points on generating continuous tactile stimulation.

Our immediate future work is to expand our work to various parts of the human body such as shoulder, back, or neck (the current study is focused on the forearm). We also would like to study further for correlations between continuous tactile stimulation and emotional developments. This would enable several applications in social media and gaming by enabling users to communicate emotions over the Web. Finally, we plan to develop an authoring tool through which users may create their own tactile stimuli and use the tactile device to display the corresponding stimulus.

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# Vibrotactile Alarm System For Reducing Sleep Inertia

Camilla Birgitte Falk Jensen, Georgios Korres, Carsten Bartsch, Mohamad Eid

**Abstract**— There has been a vast development of personal informatics devices combining sleep monitoring with alarm systems, in order to schedule the alarm to reduce sleep inertia. Many of these systems implement algorithms based on psychophysiological measurements such as heart rate, body movement or brain signal. In contrast to these devices, we present a wireless armband alarm system, named Aegis that uses vibrotactile stimulation as a silent alarm to wake up the user and thereby minimizing sleep inertia. Furthermore, the utilization of haptic modality as an alarm eliminates noise disturbance of roommates, spouses or family members sharing the same sleeping space. The paper investigates the emotional ratings and level of attention towards different haptic patterns, in order to choose a haptic pattern that complements a pleasant awakening. Performance evaluation of the proposed solution has successfully demonstrated the ability of Aegis to identify various sleep stages (awake, REM and non-REM). The results from the attention task and the subjective valence rating suggest that the vibrotactile stimulation should be based on the continuous modulation, since this not only is very perceivable but also highly rated with positive attention.

**Index Terms**—H.5.1.d Evaluation/methodology, H.5.2.g Haptic I/O, J.8.h Health care, J.9.d Pervasive computing, J.4.b Psychology, H.5.2.q User-centered design.

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## 1 INTRODUCTION

ACCORDING to the National Sleep Foundation (NSF), sleep is a physical and mental resting state that is essential for a person's health and wellbeing [1]. Irritability, moodiness, daily sleepiness, and disinhibition are some of the first signs a person experiences from lack of sleep [2]. Furthermore, the degradation in sleep quality is associated with long-term health consequences such as chronic medical conditions such as diabetes, high blood pressure, and heart disease, among others [3].

### 1.1 Sleep Phases

Researchers have identified four different stages of sleep, known as N1, N2, N3 and N4; cycling over and over throughout the night [4]. For simplicity, we classify sleep into awake, REM (Rapid Eye Movement) and non-REM phases. Non-REM phases include N1 (conscious awareness of the surroundings slowly disappears within 20 minutes after sleep onset) and N2 (increased appearance of sleep spindles and complete withdrawal from external awareness). Adults spend at least 50% of total sleep time in light sleep (non-REM).

REM phases include N3 and N4, commonly summa-

rized as slow wave sleep (SWS) or deep sleep [5]. Together, N1 and N2 are known as light sleep, characterized by the lowest arousal threshold (level of stimulation needed to wake up an individual while in a particular stage) of all sleep stages.

The REM phase is identified by rapid eye movement and intense atony of skeletal muscles. Abruptly waking someone during the REM phase can cause sleep paralysis, which is defined as the sudden experience of an inability to move combined with terrifying visions to which one is unable to react due to this paralysis. This phenomenon occurs due to the particular biological attributes seen in REM sleep: complete muscle paralysis, dreaming, and irregular breathing and heart rate [2]. A sudden snap back to consciousness often results in the brain's recognition of these sensations as panic, suffocation, and visual hallucinations.

Immediately after REM, however, a period of light sleep returns, and the body has completed one entire sleep cycle. Therefore, waking during light sleep limits sleep inertia effectively. An individual moves through several sleep cycles of approximately 90 minutes in which non-REM and REM alternate [6].

### 1.2 Methods For Sleep Monitoring

Nowadays there exist several methods to measure the quality of sleep and identify sleep phases, such as the polysomnography (PSG) procedure [7], self-rated questionnaires instruments such as Pittsburgh Sleep Quality Index (PSQI) [8], and lately using biosensors [9]. Although PSG provides accurate monitoring and assessment of sleep quality, it is highly expensive, intrusive, and requires specialized centers [7]. PSQI is commonly used,

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however, its subjective nature makes it less reliable [8].

Sleep has also been monitored using sophisticated bio-sensor equipment, including the electroencephalograph (EEG) to capture brain signal, electrooculogram (EOG) to read eye movements, electrocardiograph (ECG) for capturing heart signal, and electromyogram (EMG) to measure muscles activities [10]. More technologies have been developed such as measuring respiration and wrist/body movement using ECG sensor, accelerometer or event audio and video. With the improvement in mobile sensor and sensing technologies, it is now possible to monitor sleep ubiquitously.

Sensory technologies are used nowadays to continuously and automatically detect sleep cycles and provide a quantitative means to measure the quality of sleep [11, 12]. A common and simple technique uses actimeter/actigraph [13, 14]; a watch shaped accelerometer worn on the wrist to measure the user activity during sleep. Other researchers have used HRV and respiratory signals (captured using an ECG sensor) to detect sleep fragmentations (number of sleep micro-arousals) and detect sleep cycles [15, 16].

Several sleep-tracking applications (mostly mobile phone applications) and related devices already exist in the market, such as Sleep Cycle alarm clock [17], SOMNOwatch™ plus EEG 6 device [47] and SleepMiner [18]. For instance, SleepMiner is an Android-based smart phone application that predicts the quality of sleep based on daily contexts [18]. Several features such as daily activity, living environment and social activity are extracted from mobile phone data, and then a machine-learning algorithm is proposed to measure the sleep quality. In the performance evaluation, we use the SOMNOwatch™ plus EEG 6 device as a reference device due to its high repulation as a robust and reliable commercial system for detecting sleep stages.

**1.3 Adaptive Alarm Systems**

In contrast to regular alarm clocks, an adaptive alarm clock chooses an optimal time to wake up the user using contextual knowledge (such as calendar information, sleep quality, and psychophysiology). Most alarm systems use auditory modality to display the alarm signal. Sony has recently patented an alarm pillow with electrodes on the surface to come in contact with the head to read brain wave signals [7]. The system analyzes the collected signals to determine when the user goes into the REM or non-REM stages and turns on a buzzer attached to the pillow as soon as the person gets out of the deep sleep. The alarm pillow may not provide continuous sleep monitoring since contact between the sleeper and the pillow is not guaranteed.

An adaptive alarm clock was developed in [19] where the clock predetermines in what state the observed user will be at the time of supposed alarm-firing, and adjusts that instant to a more favourable one such as when the user is in light sleep. A webcam is used to measure movements and estimate the quality of sleep. However a webcam may compromise the sleeper confidentiality.

Several projects are available to download and run on various mobile device platforms such as Nokia, Apple iPhone, Windows Mobile, etc. HappyWakeUp application [20] is available to Nokia and iPhone mobile platforms that wake the sleeper during shallow sleep (non-REM stage). The application detects user movements in a bed using the microphone of the mobile phone. Macjek Drejak Labs developed a sleep cycle mobile application that uses embedded accelerometers that are equipped with modern smart phones [21]. The user makes different movements in bed during different sleep phases, which is used to detect sleep cycles. Similar prototypes are also available such as the Zeo Personal Sleep Coach [22], EASYWAKE-me [23], and wakeNsmile [24].

Aegis system, introduced in our previous work [25], utilizes acceleration data to measure a movement index and define the firing time for the alarm, and uses haptic modality (vibrotactile feedback) for displaying the alarm signal where four (4) vibrotactile motors vibrate simultaneously, with constatnt vibration intensity, to stimulate tactile sensation. In this paper, we study various tactile stimulation patterns (such as simultaneous, successive and continuous) that result in minimized sleep inertia.

The remainder of the paper is organized as follows: In section 2 we present the software architecture and hardware implementation of the Aegis system and details of the sleep stage extraction algorithm. Section 3 introduces the vibrotactile stimulation literature and defines stimulation patterns to be examined in this study. In section 4, we present the experimental setup, performance analysis and discuss our findings. Finally, in section 5 we summarize the paper and provide perspectives for future work.

## 2 AEGIS DESIGN AND IMPLEMENTATION

Aegis utilizes the accelerometer embedded in a armband to determine the optimal times to wake up the sleeper. When the user is ready to go to sleep, he/she puts on the armband device and sets an interval for the alarm time. During sleep, the Aegis system records the nighttime movements of the user and analyzes them using the body movement index algorithm presented in [46] to detect sleep stage. The system searches for a point – within the time interval provided by the user – where the user is in non-REM sleep and provides vibrotactile stimulation to wake him/her up so as to minimize sleep inertia.

Fig. 1 shows an overview of the proposed Aegis system. The user's movements are captured by the armband device and sent to the sleep management center that is hosted on a mobile device (or a nearby computing device) via Zigbee technology. The sleep management center processes the collected data and identifies sleep phases (awake, REM and non-REM), and sets a vibrotactile alarm. Furthermore, the collected data are stored and may be streamed to a third party (such as a family member or a therapist) using the Data Center module. In the following a brief introduction to Aegis components is given.
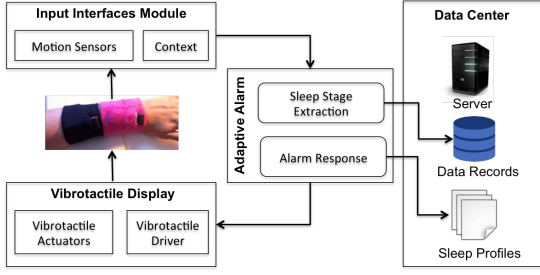
Fig. 1. Software architecture for the Aegis system.

## 2.1 Input Interfaces Modules

The Input Interfaces Module reads psychophysiological data about the user, along with the context, and passes the collected data to the Sleep Management Center. The components of the Input Interfaces Module are described briefly here:

- Motion Sensors: Hand movement is tracked using an accelerometer to identify deep and shallow sleep so that the alarm can be set accordingly. Other motion sensors may be added to the Input Interfaces Module to achieve a higher accuracy of detecting sleeping phases.

- Context: The context component collects information related to the place, time, and circumstances around the sleeping user. Examples of contextual information include, but not limited to, location, ambient noise and light conditions.

## 2.2 Adaptive Alarm

The Adaptive Alarm module is the heart of the Aegis system. It includes the Sleep Stage Extraction component and the Alarm Response component that defines the vibrotactile stimulation pattern that should be used to wakeup the sleeper.

### 2.2.1 Sleep Stage Extraction

The Sleep Stage Extraction component analyzes body movement from the accelerometer to classify sleep stages into awake, REM and non-REM. Signal artifacts, caused mostly by sleeper movements that may severely deteriorate the accelerometer readings and thus the motion estimation, are removed via a preprocessing phase. The sleep stage extraction flowchart is shown in Fig. 2.
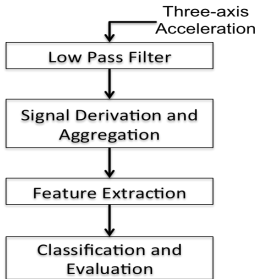


Fig. 2. Sleep stage extraction flowchart.

The preprocessing phase is adopted from the work presented in [48]. The raw three-axis acceleration data are converted first into the SI units ($m/s^2$) by a calibration procedure. The three signals ($a_x, a_y, a_y$) are then passed through the following phases:

*(i) Low Pass Filter:* A second order low-pass filter with a cutoff frequency of 18 Hz is applied to cancel out high frequency noise. The transfer function of this filter is:

$$H(z) = \frac{0.0625 + 0.125z^{-1} + 0.0625z^{-2}}{1 + 1.3z^{-1} - 0.!\,z^{-2}}, \tag{1}$$

*(ii) Signal Derivation and Aggregation:* A second order derivative operation is applied to remove baseline wander and gravity components. The transfer function for the derivative operation is shown in equation (2). Next, the three axis-acceleration signals were combined into a single (axis-independent) signal by calculating the absolute sum.

$$H(z) = \frac{1}{T^2}\left[1 - z^{-1}\right]^2 \tag{2}$$

*(iii) Feature Extraction:* Before extracting features, two separate integration operations are applied over two seconds ($I_2$) and four seconds ($I_4$) window. The two signals have different response characteristics to different periods of movement activity. Feature extraction was based on the calculation of the body movement index [46]. For each 30-second epoch ($e$) a movement index $M(e)$ was calculated using equation (3). The average over a window of 18 subsequent epochs of the body movement index is used for each epoch.

$$M(e) = \sum_e (I_!/I_4)^2 \tag{3}$$

*(iv) Classification and Evaluation:* Naïve Bayes classifiers [49] are used to distinguish awake, REM and non-REM sleep using the body movement index feature. Evaluation was performed by recording data with the SOMNOwatch™ plus EEG 6 device [REFx]. Two healthy subjects (one male and one female) were recorded during seven consecutive nights. Aegis system was placed at the subject's arm, while reference hypnograms were collected using the SOMNOwatch™ plus EEG 6 device.

The reference data is also divided into 30-second epochs from the accelerometer signals, and was preprocessed with the DOMINOlight software (SOMNOmedics GmbH). The body movement index feature was used together with the ground truth information recorded from the SOMNOwatch™ plus EEG 6 device to train the Naïve Bayes classifiers extract sleep stage (awake, REM and non-REM). A snapshot comparing results we got using Aegis system and the SOMNOwatch™ plus EEG 6 device for detecting awake, REM and non-REM over 8 hours of sleep is shown in Fig. 3.

A total of 12550 epochs were collected from the two subjects and used for training and evaluation, 18.2% of those epochs were REM-epochs. Results for classification of REM, non-REM and Awake phases are given in Table I
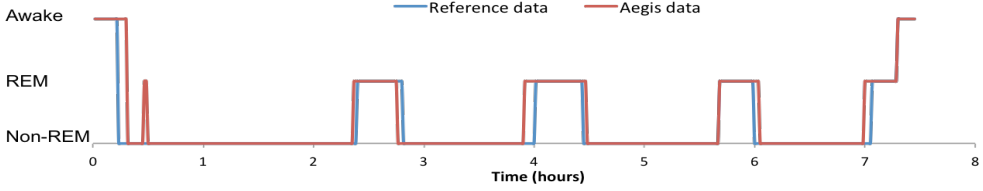
Fig. 3. Example hypnogram with the different sleep stages (Awake, REM and non-REM) over around 8 hours of sleep.

for each subject and over a course of seven days. The classifier has an average accuracy of 94.24% compared to the reference SOMNOwatch™ plus EEG 6 measurements.

TABLE 1
CLASSIFICATION ACCURACY (AWAKE, REM AND NON-REM)

| Days | Subject 1 (male) | | Subject 2 (female) | |
|---|---|---|---|---|
| | Error | SleepTime | Error | SleepTime |
| 1 | 6.06 % | 7.45 hrs | 6.48 % | 7.90 hrs |
| 2 | 5.69% | 8.03 hrs | 6.21% | 7.69 hrs |
| 3 | 5.22% | 7.82 hrs | 5.62% | 7.21 hrs |
| 4 | 5.81% | 7.45 hrs | 5.12% | 7.68 hrs |
| 5 | 6.12% | 6.81 hrs | 5.90% | 7.10 hrs |
| 6 | 5.10% | 6.65 hrs | 6.01% | 7.32 hrs |
| 7 | 5.26% | 7.88 hrs | 5.80% | 7.22 hrs |
| Average | 5.67% | 7.37 hrs | 5.84% | 7.40 hrs |
| Stddev | 0.42% | 0.53 hrs | 0.37% | 0.25 hrs |

## 2.2.2 Alarm Response

The Alarm Response component is responsible for determining, based on the corresponding sleep stage, the vibrotactile stimulation pattern that must be applied to wakeup the sleeper. There are three types of vibrotactile stimulation patterns that we are exploring: simultaneous stimulation where all actuators vibrate at the same time, successive stimulation where actuators vibrating separately one after the other, and continuous stimulation created from an overlap of vibration from different actuators. Fig. 4 explains graphically the differences between the three types of stimulation patterns.
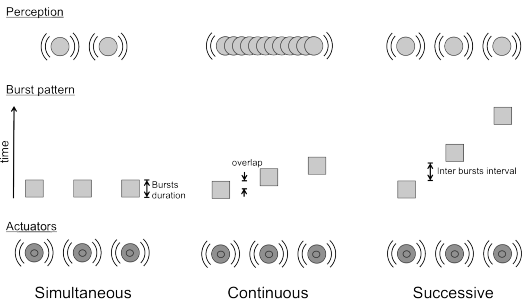


Fig. 4. The burst pattern and how this is perceived for three different modulations; simultaneous, continuous and successive.

## 2.3 Data Center

The Data Center is a repository to store data related to the Aegis system and a streaming server to share the collected data with a third party. The streaming server delivers real-time data as well as previously captured data (historical data), as needed.

- Server: The server is a facility that is capable of streaming data stored in the Data Center to a third party via a Web Service Architecture or a cloud computing architecture (this component is not implemented in the current prototype).
- Data Records: The Data Records component is a database that saves data about the sleeping behavior of the user as well as the history of sleep patterns. For instance, the Data Records component includes the time-stamped movement information and a snapshot of the context at every phase of the sleeping cycle. The database tables the following information:
  - The time at which the user set his/her alarm
  - The time Aegis chose to wake him/her up
  - Duration of sleep
  - Location of sleep
  - Ages of cohabitants
  - Age of user
  - Chronotype architecture for the Aegis system
- Sleep Profile: The Sleep Profile stores the user's personal information including age and gender, preferences as for sleeping context (ambient noise, light condition, room temperature, etc.).

## 2.4 Aegis System Implementation

The prototype implementation, as shown in Fig. 2, is composed of an accelerometer to measure user's hand movements, a microprocessor to read acceleration data, implement the sleeping management logic, activate the vibrotactile motors, and communicate sleep-related data to a remote server, and a battery.

The wristband device is composed of the following components:
- ADXL-335 accelerometer
- Arduino Mini Pro
- XBee transceiver module
- Six vibrotactile actuators
- DeadOn DS3235 RTC (Real Time Clock)
- Power cell and 3.7 V Lithium battery and voltage regulator

## 3 VIBROTACTILE STIMULATION

The concept of tactile stimulation has been around for decades, since Geldard [27] in the 1950s studied the temporal and spatial aspects of tactile discrimination on skin and wrote: "for some kinds of messages the skin offers a valuable supplement to ears and eyes". Early research on haptic stimulation has focused on applications aiding blind or visually impaired people [28], but later develop-

ments included entertainment and gaming [29], mobile and touchscreen interaction [30], emotional and interpersonal communication [31, 32, 33], and health care (such as physical rehabilitation) [34].

In relation to these novel application areas, there has been a growing interest in the subjective responses to different haptic patterns. The haptic pattern can be described from the following modulations; simultaneous, continuous and successive stimulation (as shown in Fig. 4). Simultaneous stimulation comprises all actuators vibrating at the same time. This is known to cause an illusion of sensation displacement, know as the Funnel illusion [35]. Continuous motion can be created from an overlap of vibration from different actuators. Actuators vibrating separately create the successive stimulation.

These modulations can be modified by changing the frequency, amplitude (intensity), Burst Duration (BD), Inter-Burst Interval (IBI), spatial distribution and direction, which result in different haptic patterns.

Many studies have compared the subjective ratings of different haptic patterns using the classic 9-point valence and arousal scale (commonly used to measure emotions [36]). The valence level indicates how positive or negative a stimulus is, whereas the arousal level indicates how calm or exiting the stimulus is. An example of how emotions can be distributed into these two scales is shown in Russell's model [37] shown in Fig.5. In addition some studies compares different patterns on additional scales such as cognitive scales of continuity [38], smoothness [39], strength and rhythm [40], or speed [39].

Due to the multiple possibilities for modulating haptic patterns, many studies choose to keep some parameters fixed, while concentrating on the effects of others, which often results in different varying results. However many studies on affective haptic report continuous motion being perceived as pleasant, whereas simultaneous stimuli were rated more unpleasant [41, 39]. Other studies focus more on how the different parameters contribute or affect the continuous feeling [29, 38, 42].

Raisamo et al. [41] found a correlation between continuous motion being perceived as pleasant, whereas simultaneous stimuli were rated more unpleasant. While others examined the effect of frequency, amplitude, duration,

direction and body site on continuity and subjective preferences [29, 38], Rahal et al. showed an effect of gender, limb size and intensity [42].

Although most studies on affective haptic report preferences towards more continuous stimulation, this might not be the most suitable haptic stimulation when used as an alarm clock. In this case a soothing continuous motion might not draw enough attention upon itself to cause the user to wake up. Instead it might become integrated into the user's sleep or even dream. However using a very arousing and aggressive stimulation could result in an unpleasant awakening that might lead to a dislike of the product. Thus we are interested in examining not only the subjective emotional ratings of haptic patterns but also how fast the subject's attention is shifted to the different haptic patterns.

The majority of attention research has focused on single sensory modalities, such as vision, audition, touch and even olfaction and gustation. However in everyday life we commonly operate across different sensory modalities to facilitate the selection of relevant information. The classic "cocktail party problem", where we direct our auditory attention to one particular voice in order to have a conversation in a noisy environment is actually misleading: we often rely on many other sensory modalities as visual information from lip-movements, facial expressions, and gestures. In addition we often ignore irrelevant sensory inputs, such as the feel of one's clothes (tactile), the smell of someone's perfume (olfactory), and perhaps even the taste of one's drink (gustatory).

Attention can be divided into endogenous and exogenous attention: The endogenous attention describes the voluntarily direction of attention to a particular point, such as attending to one person at a cocktail party. In contrast, exogenous or involuntary attention is the reflexive shifts of attention to unexpected or uninformative event, such as someone calling your name at a cocktail party, or if a fly suddenly lands on your arm [43].

However it is difficult to say what our attention is directed towards when we sleep, since this might depend on the sleep phase and the individual. Hypothesizing that our attention is not necessarily directed towards tactile inputs, we are interested in measuring the exogenous attention towards different haptic stimuli in a multimodal scenario.

## 4 PERFORMANCE EVALUATION

This section introduces the design, setup, and evaluation of an experiment investigating 1) the effectiveness of vibrotactile stimulation to draw the user's attention and 2) the emotional responses to different stimulation patterns. Thus we created a dual-task paradigm, where the subject is performing two tasks at once, thereby forced to divide her attention between the two tasks [44, 45]. The paradigm consists of a haptic detection task (where the user has to respond when detecting a haptic stimulus) and a visual identification task (where the subject has to identify the correct target among different distractor stimuli).
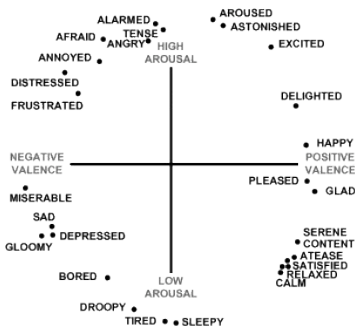


Fig. 5. Russell's model [37] illustrates how the valence and arousal scale can be used to describe different emotions.

## 4.1 Vibrotactile Armband Device

The tactile armband device is composed of 6 vibrotactile actuators that are aligned 4 cm apart along the arm. The armband device is capable of producing three types of tactile stimulation: simultaneous stimulation, successive stimulation and continuous stimulation. The three modes are explained in equation (4). A demonstration of the continuous stimulation algorithm is shown in Fig.6.

$$\tau = \alpha * T, \qquad (4)$$

$$where \begin{cases} \alpha = 0 & \quad simultanoeus\ stimulation \\ \alpha < 1 & \quad continuous\ stimulation \\ \alpha > 1 & \quad successive\ stimulation \end{cases}$$

Where T is the burst duration, $\tau$ is the inter-burst interval and $\alpha$ is the mode factor. Simultaneous stimulation involves stimulating the motors at the same time ($\alpha=0$ or $\tau=0$) to produce the highest sense of vibration possible where intensity of vibration can also be controlled. Successive stimulation has one motor stimulated at a time ($\alpha>1$ or $\tau>T$); there is no inter-burst stimulation. Continuous stimulation is based on the funneling illusion concept [35] and produces apparent tactile motion along the armband surface.
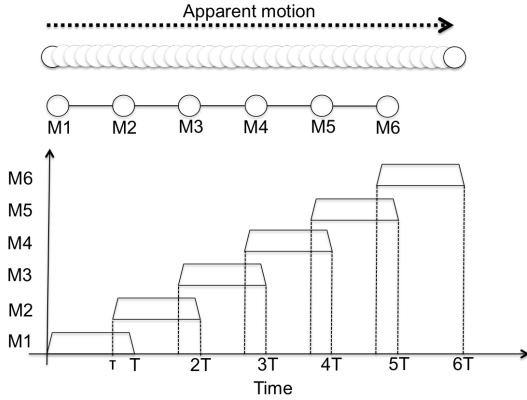


Fig. 6. Tactile stimulation algorithm.

The stimulation intensity is controlled by adjusting the duty cyle of the Pulse Width Modulation (PWM) signal that feeds the vibrotactile actuators. Increasing the duty cycle of the PWM signal would increase the effective voltage applied to the actuator and thus the vibration intensity. The change in the intensity of vibration is linear over time, and is described by equation (5).

$$I = I_{min} \mp (I_{max} - I_{min}) * \frac{StepSize}{100}, \qquad (5)$$

where Imin = 0.25g, Imax = 1.25g, and StepSize = +10 when intensity increase and StepSize = -10 when intensity decreases.

## 4.2 Experimental Setup

The wristband providing the vibrotactile stimulus was constructed with six actuators (Pico Vibe 310-177, Precision Microdrives) vibrating with a frequency of 700 rpm at the minimum intensity 0.25g, and 1400 rpm at the maximum intensity 1.75g. They were placed at a distance of 4 cm from center to center of the actuators. We created 8 patterns based on the three modulations described earlier: simultaneous, continuous and successive. A summary of the stimulation patterns is shown in Table 2.

Similar to other alarm clocks with increasing volume, our patterns increase in amplitude (intensity) as time passes. This was chosen partially to examine how easily the different patterns were perceived and in attempt to make a smooth waking. Thus all of the patterns started from an intensity of 0.25g, which is almost not perceivable and ended after 35 to 40 seconds with an intensity of 1.75g, which is easily perceived. The intensity increased linearly with time.

Three of the patterns, one from each modulation type, were altered by this intensity increase: the simultaneous stimulation has burst duration of 100 ms and an inter-burst interval of 300 ms. The relatively short burst duration was chosen due to the effect of multiple actuators vibrating simultaneously, which intensifies the stimulation. The continuous stimulation was characterized by a burst duration of 300 ms and an overlap of 120 ms (corresponding to 40% of the burst duration). The successive stimulation comprised of a 150 ms burst duration and an inter-burst interval of 150 ms.

In an attempt to avoid the bias that the stimulus would become integrated in the user's sleep, the next patterns were created with either increasing speed or changing direction to increase variations.

Three patterns (one for each modulation) were, in addition to the intensity increase, altered by an increase in velocity. This implied a change in the inter-burst interval from 500 ms to 100 ms for the simultaneous modulation. As for the continuous stimulation, this resulted in a change in burst duration from 500 ms to 100 ms, while the overlap changed from 200 ms to 40 ms. Furthermore, the successive stimulation increased in velocity by a change in burst duration from 250 ms to 50 ms and in inter-burst interval from 250 ms to 50 ms.

The last two patterns are based on continuous and successive modulation and vary in intensity and change in direction, starting with vibration of the first to the sixth actuator, and then in reversed order.

The experiment was conducted on 12 participants, all of them were students or employees of NYU Abu Dhabi, 5 were female and 7 males. Two of the male participants were left-handed all others were right-handed. The average age of the participants was 29.2 years ranging from 19 to 41 years. A snapshot of this experimental setup is shown in Fig 7.

The actuators were placed on the non-dominant hand, thus if the subject was right handed, the actuators were place around the left wrist. While the experiments took place the subjects were listening to pink noise in order to mask any noise from actuators.

TABLE 2
OVERVIEW OF THE DIFFERENT PATTERNS

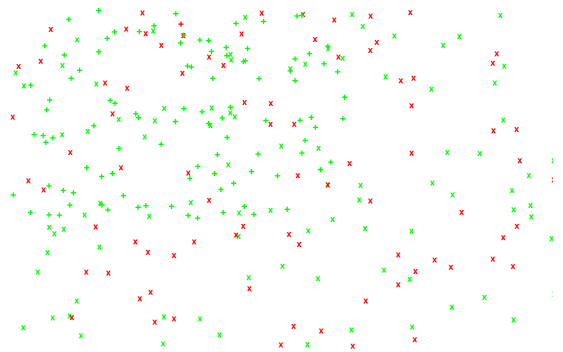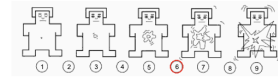| Pattern | Modulation | Feature | Attributes |
|---|---|---|---|
| 1 | Simultaneous | Intensity increase | Imax=1.25g, Imin=0.25g, StepSize=0.1g, Duration=2 sec, α=0 |
| 2 | Simultaneous | Intensity + velocity increase | Imax=1.25g, Imin=0.25g, StepSize=0.1g, Duration=2 sec, α=0, timeStepSize=0.1sec |
| 3 | Continuous | Intensity increase | Imax=1.25g, Imin=0.25g, StepSize=0.1g, Duration=2 sec, α=0.5 |
| 4 | Continuous | Intensity + velocity increase | Imax=1.25g, Imin=0.25g, StepSize=0.1g, Duration=2 sec, α=0.5, timeStepSize=0.1sec |
| 5 | Continuous | Intensity increase + direction change | Imax=1.25g, Imin=0.25g, StepSize=0.1g, Duration=2 sec, α=0.5, timeStepSize=0.1sec |
| 6 | Successive | Intensity increase | Imax=1.25g, Imin=0.25g, StepSize=0.1g, Duration=2 sec, α=3 |
| 7 | Successive | Intensity + velocity increase | Imax=1.25g, Imin=0.25g, StepSize=0.1g, Duration=2 sec, α=3, timeStepSize=0.1sec |
| 8 | Successive | Intensity increase + direction change | Imax=1.25g, Imin=0.25g, StepSize=0.1g, Duration=2 sec, α=3, timeStepSize=0.1sec |



Fig. 7. The experimental setup.



Fig. 8. The visual search task, where the subject is seeking to identify a red cross (+).

Arousal (calm - exciting)



Press [F1] to [F9] follow by [space] to confirm

Fig. 9. The 9-point arousal scale used to rate how arousing the haptic simulation was.

The experiment consisted of two parts; 1) the dual-task paradigm followed by 2) subjective emotional ratings of the haptic patterns. The dual-task paradigm combined a visual (conjunction) search task [39] with a simple haptic detection task. In the visual search task, the subject searched for a target, a red plus sign "+", among distractors that share two visual properties, color and orientation, green and red letters "x" and green plus signs "+". An example with the target present is shown in Fig. 8. If the target was identified, the user responded by pressing "c" for cross, but if there is no target, the user should press "n" for no cross. In 40 % of the trials the user would also be presented with a haptic stimulus, and should respond to this by pressing space. To minimize anticipation effects of simultaneous changes of visual stimuli and appearance of haptic stimuli, the haptic stimulus would start randomly within the first 3 seconds from the beginning of the trial. Each haptic pattern started with an intensity of 0.2g, which is almost not perceivable. The intensity then increased over time until it reached 1.6g. Meanwhile the step size for increase in the intensity was the same across patterns. All 8 patterns were presented 3 times in random order. The experiment stopped as soon as the user detected all 8 haptic patterns, three times.

Before the experiment, the user was instructed to first of all respond to the haptic stimuli as fast as possible. After which he should respond correctly to the visual search task, and lastly doing this as fast as possible. The user would be notified whether his/her response was correct or incorrect after each trial, so that he/she could adjust his/her strategy. In addition the subject was told to place his/her right and left index fingers on the "n" and "c" keys respectively. With these keys place at equal distances to the space key and by instructing the subject to use index finger of the dominant hand to press the space, we hoped to minimize effects on the response time.

In the second part of the experiment the user was presented a haptic pattern and was asked to rate this on a 9-point valence and arousal scale (see Fig. 9). The user

could repeat the stimulus by pressing "r". Before the experiment, the valence and arousal scale was explained to the user and three practice trials were performed, so the subject was familiarized with the scale. The stimulus presented in the practice trials was not used in the actual experiment. One subject did not complete the second part of the experiment and was therefore excluded from the analysis of the emotional ratings.

### 4.3 Analysis and Results

The average response time of the three trials for each haptic pattern and for every subject was calculated. The data is plotted in a standard box plot (see Fig. 10); showing the mean as black diamonds and the median, upper and lower quartile in boxes while the whiskers represent the maximum and minimum values. The numbers on the x-axes correspond to the pattern numbers in Table 2. The outliers are marked as circles, all of which came from the same subject. Indicating that this subject had a different threshold for tactile stimulation. A larger response time for the patterns based on the simultaneous modulation is clearly observed from Fig. 10, which is supported by the following statistical tests.

Conducting one-way ANOVA analysis, both with and without outliers, showed no influence of outliers on the results. Thus we included the outliers in our analysis, and the results showed a significant effect of the patterns $F(7,88)=25.61$, $p<0.001$.

To test for interaction effects two two-way ANOVA tests were conducted. One was testing two modulations (continuous and successive) with three features (intensity, intensity+velocity, intensity+direction). The other was testing three modulations (simultaneous, continuous, and successive) with two features (intensity and intensity+velocity). The first ANOVA test showed only a significant effect of modulation $F(1,71)=42.249$, $p<0.001$, suggesting that perception of patterns based on the continuous pattern are significantly different from patterns based on the successive pattern. The second ANOVA showed likewise a significant effect of modulation $F(2,71)=80.33$, $p<0.001$, however it also revealed an interaction effect between modulations and features $F(2,71)=3.79$, $p=0.028$. To examine the interaction effect, a permutation test with
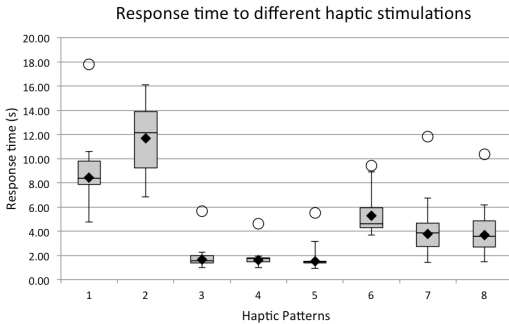


Fig. 10. The response time of 8 different haptic patterns, with diamond representing the mean and circles the outliers (consisting data from only one subject).
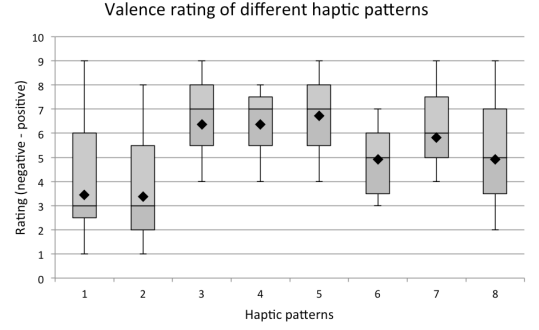


Fig. 11. The subjective valence (negative-positive) ratings of 8 different haptic stimulations, with diamond representing the mean.
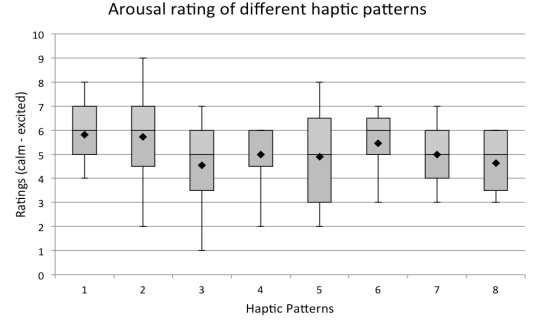


Fig. 12. The subjective arousal (calm-energetic) ratings of 8 different haptic stimuli, with diamond representing the mean.

paired t-test (and 10000 reputations) and a Bonferroni correction of the significance level ($\alpha=0.05/15$) is conducted. The results revealed significant difference with $p=<0.007$ on all levels except from the tests where modulation was similar and features were different. This indicates that the features have different effects depending on the modulation, however not as significant as with the effect of feature.

The results of the emotional ratings on valence and arousal are shown in the boxplots below, Fig. 11 and Fig. 12. The boxes represent the median, upper and lower quartile; the black diamonds represents the mean; and the whiskers represent the maximum and minimum values. The valence data shows a large individual difference amongst subjects, which in most cases are larger compared to the arousal ratings.

By conducting a repeated one-way ANOVA test we found a significant difference between the valence ratings of the patterns with $F(7,81)=7.39$, $p<0.001$, however we found no significant difference for the arousal ratings. To examine the valence data further, two two-way ANOVA tests were conducted: one testing two modulations (continuous and successive) for three features (intensity, intensity+velocity, intensity+direction), the other testing the three modulations (simultaneous, continuous, and successive) with two features (intensity and intensity+velocity). The first ANOVA showed no significant effect of modulation and feature. There was no significant

difference between any of the patterns based on the continuous or successive patterns. The second ANOVA showed only a significant effect of modulations F(2,65)=20.29, $p<0.001$. Post hoc t-test with Bonferroni correction ($\alpha=0.05/3$) revealed patterns based on the simultaneous modulations were significantly different from those based on both continuous ($t=6.16$, $p<0.001$) and successive ($t=3.96$, $p<0.001$).

To sum up, the results on response time showed a clear effect of modulations. With the subjects responding quickest to the continuous patterns and slowest to the simultaneous. However the slow reaction times for the simultaneous patterns (especially pattern 2) might be explained by the long inter-burst interval (of 500ms). However it is also surprising to see how fast and similar the response times of the continuous patterns (pattern 3, 4, and 5) across subjects are.

The results from the emotional ratings show greater differences amongst subjects, compared to the response times, suggesting that there might be personal preferences towards different haptic patterns. Similar to earlier reports on valence ratings, we also see higher ratings towards patterns with more continuous motions, suggesting that these are preferred over discrete motions. However we do not see any significant effect of the arousal data and no correlations between arousal and valence data.

Therefore, in order to create an effective haptic alarm, that is not only effective but also smooth and pleasant for waking up a person, our results suggest to preferably utilizing the continuous modulation.

## 5 CONCLUSION AND DISCUSSION

This paper presents a novel clock alarm system named Aegis – a smart wireless wristband arm system for sleep management and reducing sleep inertia. An experimental study was conducted to investigate vibrotactile patterns as silent clock alarm response to wake a user in a smooth and pleasant manner. The results from the attention task and the subjective valence rating suggest that the haptic alarm for the Aegis system should be based on the continuous modulation, since this not only is very perceivable but also rated as more positive.

However, as the prototype evolves, further improvements can be made to the system. The hardware could be optimized in terms of size (for example, the circuit should move to a smaller microprocessor board for even more compact assembly), and sensory data may be saved in internal non-volatile memory. A mobile device application may also be developed to provide a convenient interface to configure the system. In addition more usability studies could be performed over longer time intervals to further analyze the system and derive a more robust and personalized performance. One can imagine that the haptic patterns could provide the user with more information than the alarm onset. E.g. different patterns could indicate how close the systems alarm onset is to the users preset alarm time, thereby indicating how fast one needs to get ready. This is similar to Lylykanga's examination of patterns representing information on motion (e.g. decelerate, accelerate or keep speed constant) [39].

For future research it would be interesting to test the effectiveness of the different patterns in real waking-up scenarios and whether the haptic patterns could also be used to influence a users sleep phase, e.g. moving them from a deep sleep to light sleep before waking the user. In this case it might be useful to create patterns based on the simultaneous modulation, which are not that easily perceived.

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