Enriching Mobile Interaction with Garment-Based Wearable Computing Devices

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ABSTRACT

Wearable computing is on the brink of moving from research to mainstream. The first simple products, such as fitness wristbands and smart watches, hit the mass market and achieved considerable market penetration. However, the number and versatility of research prototypes in the field of wearable computing is far beyond the available devices on the market. Particularly, smart garments as a specific type of wearable computer, have high potential to change the way we interact with computing systems. Due to the proximity to the user‘s body, smart garments allow to unobtrusively sense implicit and explicit user input. Smart garments are capable of sensing physiological information, detecting touch input, and recognizing the movement of the user.

In this thesis, we explore how smart garments can enrich mobile interaction. Employing a user-centered design process, we demonstrate how different input and output modalities can enrich interaction capabilities of mobile devices such as mobile phones or smart watches. To understand the context of use, we chart the design space for mobile interaction through wearable devices. We focus on the device placement on the body as well as interaction modality.

We use a probe-based research approach to systematically investigate the possible inputs and outputs for garment based wearable computing devices. We develop six different research probes showing how mobile interaction benefits from wearable computing devices and what requirements these devices pose for mobile operating systems. On the input side, we look at explicit input using touch and mid-air gestures as well as implicit input using physiological signals. Although touch input is well known from mobile devices, the limited screen real estate as well as the occlusion of the display by the input finger are challenges that can be overcome with touch-enabled garments. Additionally, mid-air gestures provide a more sophisticated and abstract form of input. We present a gesture elicitation study to address the special requirements of mobile interaction and present the resulting gesture set. As garments are worn, they allow different physiological signals to be sensed. We explore how we can leverage these physiological signals for implicit input. We conduct a study assessing physiological information by focusing on the workload of drivers in an automotive setting. We show that we can infer the driver´s workload using these physiological signals.

Beside the input capabilities of garments, we explore how garments can be used as output. We present research probes covering the most important output modalities, namely visual, auditory, and haptic. We explore how low resolution displays can serve as a context display and how and where content should be placed on such a display. For auditory output, we investigate a novel authentication mechanism utilizing the closeness of wearable devices to the body. We show that by probing audio cues through the head of the user and re-recording them, user authentication is feasible. Last, we investigate Electrical Muscle Stimulation (EMS) as a haptic feedback method. We show that by actuating the user‘s body, an embodied form of haptic feedback can be achieved.

From the aforementioned research probes, we distilled a set of design recommendations. These recommendations are grouped into interaction-based and technology-based recommendations and serve as a basis for designing novel ways of mobile interaction. We implement a system based on these recommendations. The system supports developers in integrating wearable sensors and actuators by providing an easy to use Application Programming Interface (API) for accessing these devices.

In conclusion, this thesis broadens the understanding of how garment-based wearable computing devices can enrich mobile interaction. It outlines challenges and opportunities on an interaction and technological level. The unique characteristics of smart garments make them a promising technology for making the next step in mobile interaction.

ZUSAMMENFASSUNG

Tragbare Computer stehen kurz davor, sich im Massenmarkt durchzusetzen. Die ersten auf dem Markt eingeführten Fitnessarmbänder und Smartwatches erreichten beachtliche Verkaufszahlen. Vergleicht man aber den Entwicklungsstand und die Vielfalt von Forschungsprototypen und die verfügbaren Geräte am Markt, zeigt sich, dass es nur ein Bruchteil der Prototypen zum marktreifen Produkt geschafft hat. Insbesondere intelligente Kleidung zeigte in Forschungsprotypen großes Potenzial, das dominierende Interaktionsgerät der Zukunft zu werden. Die Nähe zum Benutzer bringt einige Vorteile im Vergleich zu handelsüblichen, nicht stoffbasierten tragbaren Geräten, wie der Möglichkeit der impliziten als auch expliziten Eingabeerfassung. Sie kann physiologische Benutzer-Daten messen und Druckeingaben und Bewegungen des Benutzers erkennen.

In dieser Arbeit wird untersucht, wie intelligente Kleidung die mobile Interaktion bereichern kann. Mithilfe eines benutzerzentrierten Gestaltungsprozesses wird gezeigt, wie verschiedene Eingabe- und Ausgabemodalitäten die Möglichkeiten mobiler Geräte wie Smartphones oder Smartwatches erweitern können. Zur Erforschung des Benutzungskontextes wird der Gestaltungsraum der mobilen Interaktion mit tragbaren Computern untersucht. Hier wird insbesondere auf die Positionierung der Geräte sowie verschiedener Eingabe- und Ausgabemodalitäten Wert gelegt. Es wird ein auf Forschungsproben basierender Ansatz genutzt, um systematisch die Eingabe- und Ausgabemöglichkeiten für intelligente Kleidung zu untersuchen. Es werden sechs verschiedene Forschungsproben vorgestellt, die aufzeigen, wie die mobile Interaktion von tragbaren Computern profitieren kann und welche Anforderungen tragbare Computer an mobile Betriebssysteme stellen.

Bezüglich der Eingabemöglichkeiten wird explizite Eingabe durch Berührung und Gesten untersucht. Herausforderungen, wie der begrenzte Eingaberaum und die Verdeckung bei der Eingabe durch den Eingabefinger, können durch druckempfindliche Kleidung gelöst werden. Zusätzlich ermöglichen Gesten in der Luft eine elegante und wirkungsvolle Form der Eingabe. Es wurde ein benutzerdefiniertes Gestenset entwickelt, welches den besonderen Herausforderungen der mobilen Interaktion gerecht wird. Durch das Tragen von intelligenter Kleidung können verschiedene physiologische Signale des Nutzers erfasst werden, welche als implizite Eingabe genutzt werden können. Hierfür wird eine Benutzerstudie im automobilen Kontext durchgeführt, die durch gemessene physiologische Signale Rückschlüsse auf die Arbeitslast des Nutzers zulässt.

Neben den Eingabemöglichkeiten bietet intelligente Kleidung auch Ausgabemöglichkeiten. Hierbei werden die wichtigsten Ausgabemodalitäten betrachtet. Es wird untersucht, wie niedrigauflösende Bildschirme als Kontextbildschirme genutzt werden können, wo diese platziert werden und wie Inhalte auf diesem Bildschirmtyp gestaltet werden können. Bezüglich der auditiven Ausgabe wird ein neues Authentifizierungsverfahren vorgestellt, welches die Nähe von tragbaren Computern zum Körper des Anwenders nutzt. Durch das Senden von Audiosignalen durch einen Knochenleitkopfhörer wird ein biometrisches Authentifizierungsverfahren geschaffen. Zuletzt wird eine haptische Ausgabe durch elektrische Muskelstimulation durchgeführt. Durch das Stimulieren bestimmter Muskeln des Nutzers wird eine körpernahe Ausgabe realisiert.

Durch diese Forschungsprojekte wurden Gestaltungsrichtlinien abgeleitet, welche sich auf die Interaktion sowie die Technologie beziehen und als Grundlage zur Gestaltung neuartiger mobiler Interaktion dienen. In der Umsetzung eines Systems zur Entwicklung mobiler Interaktion fanden diese Gestaltungsrichtlinien Anwendung. Dieses System unterstützt Entwickler bei der Einbettung tragbarer Sensoren und Aktuatoren durch eine einfach zu nutzende Entwicklerschnittstelle.

Zusammengefasst vergrößert diese Arbeit das Verständnis über die Erweiterung mobiler Interaktion durch kleidungsbasierte tragbare Computer. Es werden Herausforderungen und Möglichkeiten sowohl im technologischen Bereich als auch in der Interaktion aufgezeigt. Die einzigartigen Eigenschaften von intelligenter Kleidung machen diese zu einer vielversprechenden Möglichkeit, den nächsten Schritt in Richtung mobiler Interaktion zu gehen.

PREFACE

This thesis contains work created over the last couple of years at the University of Stuttgart. Since the developed wearable computing devices require different types of expertise, this thesis has been done in close collaboration with experts from the University of Stuttgart, partners within the SimpleSkin project, and external experts bringing in knowledge from their respective fields. These collaborations resulted in publications which are a core part of this thesis. The contributing authors (i.e., co-authors of papers) are clearly stated at the beginning of each chapter together with the reference to the publication when applicable. To emphasize these collaborations, I use the scientific plural ("we") throughout this thesis.

ACKNOWLEDGMENTS

First and foremost, my special thanks goes to **Albrecht** for supervising this thesis and explaining how all the different aspects of research work. In addition to providing feedback when needed, he somehow managed to allow me to follow my own ideas and make my own mistakes which was extremely educational. Also, I would like to thank my committee members **Paul**, **Björn**, and **Stefan** for their valuable feedback and discussions.

I had the great honor to meet several amazing people during my Ph.D. studies. I really appreciated discussing ideas, sharing knowledge, traveling to conferences, or simply spending time together. I need to particularly mention **Flo** who not only offered me his flat for the first couple of months after arriving in Stuttgart but basically taught me how to publish ideas and supervise students (and still does). I further have to thank my colleagues who already were in Stuttgart when I arrived: **Anja** (for supporting procrastination and keeping all the computer science people connected to the real world), **Basti** (for sharing the office for my first 3 years), **Ali** (for countless trips to the grocery store and lots of discussions), and **Elba** (for simply smiling all day and being one of the most positive person I have ever met). Actually the journey of pursuing my Ph.D. started back in Essen. I am very grateful to **Dagmar** who initially forced me to get in touch with research in the automotive domain and convinced me to start as her student assistant. I am also grateful to **Tanja**, **Paul**, and **Nicole** who initially showed how much passion is involved in research.

Since I started my Ph.D., Albrecht decided to increase the size of the group quite a bit. I particularly like to thank: **Niels** (for all the discussions and changes in perspective that opened up several new views on research), **Tilman** (for being an awesome party-chair), **Markus** (for countless conference trips), **Pascal**, **Romina** (for all the discussions on research and your knowledge on football), **Mariam** (for a great collaboration within the SimpleSkin project), **Dominik** (for providing new notification locations), **Yomna** (for all the amazing Egyptian food and great thermal imaging projects), **Thomas**, **Tonja**, **Lars**, **Sven** (for organizing all the BBQ events), **Katrin**, **Miriam**, **Thomas**, **Jakob**, **Passant**, **Alex** (for a great diploma thesis), **Murielle** (for understanding that timesheets are not my top-priority), and all the colleagues I might have forgotten.

I also had the great opportunity to work with many different students supporting me in realizing ideas. Particularly, I would like to thank the student assistants I was allowed to work with over the last years: **Dominique**, **Johannes**, **Benjamin**, **Frank**, **Michael**, **Sophie**, **Saied**, **Tobias**, and **Francisco**.

In addition to the great people I was able to meet in Stuttgart, I am extremely thankful for meeting so many researchers and being able to collaborate with them. In particular, I would like to thank **Max** and **Michael** (for all the work on EMS), **Andreas** (for all the usable security projects we did), **Oliver** (for co-editing the handbook), **Joey** and **Jingyuan** (for collaborations within the SimpleSkin project and providing great hardware), and **Nora** (for all the great 3D projects, planning countless user studies and how to evaluate them, and, most importantly, becoming a very good friend).

Commuting between Stuttgart and Mülheim provided many challenges that I would never could have tackled on my own. That is why I am grateful to all the amazing friends and neighbors I had: **Britta**, **Sandra**, **Thorben**, **Mark**, and **Fabi** who always made me feel home and took care of the everyday tasks I could not do while traveling. Last but definitely not least, I would like to thank my parents **Petra** and **Gerd** as well as my sister **Christina** for all their support and patience.

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List of Acronyms

ASL	American Sign Language
API	Application Programming Interface
ANOVA	Analysis of Variance
ATM	Automated Teller Machine
AIDL	Android Interface Definition Language
BCI	Brain Computer Interface
BLE	Bluetooth LE
BTemp	Body Temperature
DCT	Discrete Cosine Transform
ECG	Electrocardiography
EEG	Electroencephalography
EMS	Electrical Muscle Stimulation
EMG	Electromyography
EER	Equal Error Rate
ER	Error Rate
FAR	False Acceptance Rate
FRR	False Rejection Rate
FES	Functional Electrical Stimulation
FPGA	Field Programmable Gate Array
GPS	Global Positioning System
HCI	Human-Computer Interaction
HR	Heart Rate
HRV	Heart Rate Variability
LCD	Liquid Crystal Display

LSD	Least Significant Difference
LED	Light Emitting Diode
MFCC	Mel Frequency Cepstral Coefficients
NFC	Near Field Communication
NN	Nearest Neighbor
OLED	Organic Light Emitting Diode
OS	Operating System
PSD	Power Spectral Density
PIN	Personal Identification Number
POI	Point of Interest
ROC	Receiver Operating Characteristic
SCA	Skin Conductance Activity
SDK	Software Developer Kit
SPI	Serial Peripheral Interface
SUS	System Usability Scale
TAN	Transaction Authentication Number
TAR	True Acceptance Rate
TCT	Task Completion Time
TENS	Transcutaneous Electrical Nerve Stimulation
UI	User Interface
UX	User Experience
UART	Universal Asynchronous Receiver Transmitter
VR	Video Rating

I

Introduction and Background

Chapter 1

Introduction

In the last years, mobile devices became the leading everyday computing platform. More and more smart phones, smart watches, and eyewear computers are becoming mainstream. With constantly increasing processing capabilities, mobile devices replaced the personal computer and laptop for the majority of everyday tasks. At the same time, the number of application scenarios for these devices increased from simply placing phone calls and receiving notifications to complex information retrieval, social networking, and entertainment. The input and output possibilities of these devices increased dramatically as well to allow the user to perform all the novel tasks. While early mobile phones used only hardware buttons, the mobile phone evolved into a sensor-rich device that enables a wide variety of interaction techniques using a touch screen, microphone, and sensors such as accelerometer or magnetometer to control myriads of applications. Particularly, the availability of these contextual sensors allowed creating novel interaction techniques such as performing gestural input by moving the phone through mid air. Despite all the sensors, the form factor of the smart phone is still one of the limiting factors restricting interaction. The touch-enabled display has a limited size and provides only limited input (i.e., direct touch input). This can lead to cumbersome ways of interacting with a steadily increasing number of applications. Additionally, information about the user are not taken into account such as the user‘s posture, movement of other parts of the user‘s body, or biosignals generated by the user. All these information could help increasing the interaction capabilities but are currently not often taken into account for mobile devices.

One way to further extend the sensing and actuating capabilities of mobile devices is using wearable computers as additional interaction means. They offer a rich set of sensors and actuators at various locations on the user‘s body allowing novel interaction techniques. These interaction techniques could be of explicit as well as implicit nature. Thus, wearable computing has huge potential to shape the way we interact with mobile devices in the future. Currently, mainly wearable gadgets are used for this purpose. For example, fitness bracelets are used to extend the functionality of mobile phones by the possibility of measuring the arm movement and heart rate of the user. These information are used to infer on the steps by the user which is exploited for sports tracking as well as quantified self applications.

In contrast to wearable gadgets, smart garments allow even more sensing and actuating possibilities due to closeness to the user‘s body. Humans naturally use garments for several reasons such as protection or aesthetics. Many parts of the human body are naturally covered by garments which can be enriched with technology. Smart garments can thereby either implicitly sense information about the user or be used for direct input and output. This can be done similar to wearable gadgets without the necessity of attaching additional sensing but only wearing enriched clothing. In addition, the area of the user‘s body which can be used for interaction is increased since clothing can comfortably cover more locations compared to wearable gadgets.

We expect that with further advancement in smart garments, regular garments eventually get substituted by smart garments. As soon as smart garments are producible for similar costs and offer similar properties with regards to their wearability and durability compared to regular cloth, smart clothing will become pervasive. Every piece of garment will incorporate technology that can be used for designing novel ways of interacting. These novel interaction techniques imply a fundamental change in human-computer interaction, particularly with mobile devices. However, several challenges still need to be tackled. This thesis investigates how smart garments can be used for interaction and be integrated as building block into the interaction with mobile devices. Through research probes of potential applications, we show the versatility of smart garments and demonstrate ways of how basic fabrics can be used for different interaction techniques and application scenarios. One of the core challenges involves the integration of sensors and actuators into the mobile device eco-system of offering interfaces so that application programmers and end-users can use them.

Research Question	RQ	Part
Interaction centered		
How to structure a design space for wearable interaction?	RQ1	I
How to realize input methods using garment based sensors?	RQ2	II
How to realize output methods using smart garments?	RQ3	III
Technology centered		
How to integrate sensors and actuators in mobile platforms?	RQ4	IV
How to represent sensor data for developers and end-users?	RQ5	IV

Table 1.1: Summary of research questions addressed in this thesis.

1.1 Research Questions

When technology is integrated into everyday garments and the resulting smart garments become mainstream, fundamental challenges have to be addressed. Two main groups of challenges tackled in this thesis are *interaction centered* and *technology centered* challenges, posing important research challenges. The corresponding research questions are presented in Table 1.1.

Smart garments can cover almost the whole body of the user and can be built using a huge variety of different sensors and actuators. Understanding the design space is necessary to understand the full capabilities of smart garments. Therefore, the first research question focuses on how a design space needs to look like and how such a design space can be structured (RQ1). Similar to applications on nowadays smart phones, the number of applications which can be realized using smart garments is manifold. Thus, the same sensor can be used for several different applications (RQ2). While garment based sensing technologies are well explored, the output side remains mainly unexplored. However, textiles offer huge potential for output. The question is how each type of output can be realized (RQ3).

After understanding the interaction based challenges, technology based challenges need to be tackled. Garment-based sensors and actuators are just one of the building blocks necessary to developed a functional system. Interfaces between the physical sensor and the virtual application need to be defined. Thus, the integration of sensors into the mobile software and hardware infrastructure needs to be explored (RQ4). Further, the extracted data needs to be provided to the application developer. Thereby, the application developers need to be supported and the end-users need to understand the implications sharing their data with an application could have (RQ5).

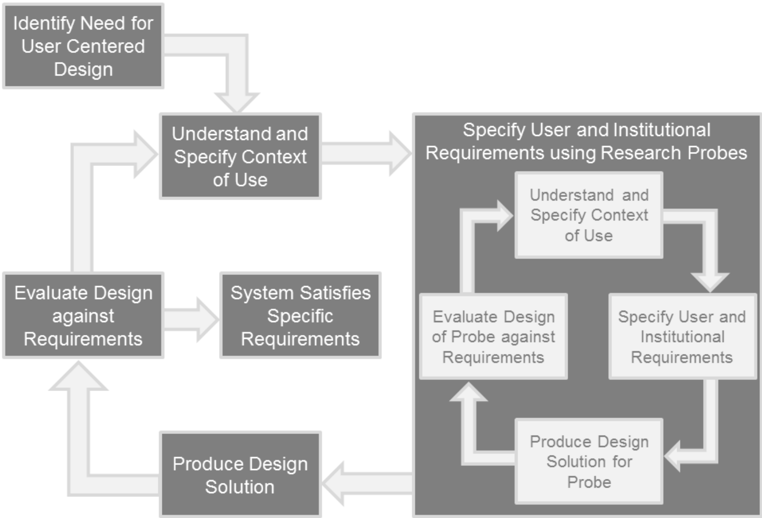


Figure 1.1: The User-Centered Design methodology extended with a probe based approach. Within the requirements elicitation step, research probes are used to explore these requirements. The probe based approach itself uses a nested user-centered design methodology.

1.2 Methodology

Wearable computing is a field driven by advances in technology. Starting with the first electrical wearable computer in the 1960s [257], most evaluation methodologies focus on showing the feasibility of novel technology. Examples include demonstrating that a sensor is capable of detecting a specific phenomenon (e.g., performed gesture) or the possibility to develop an actuator capable of communicating certain information. In most cases, the user is not taken into account for the development process and the evaluation of novel technology. Reasons include complex setups or low robustness. With the recent move of some of the prototypical sensors and actuators to the mass market as consumer devices, the possibilities changed. Prototypes gained robustness and were easier and faster to develop. Developed prototypes made out of sensor, actuators, and processing boards are usable in evaluations beyond feasibility level allowing user centered evaluations. However, focusing on the user is still not considered a core activity when evaluating wearable devices.

We apply the user-centered design process [120] as main methodology in this thesis to investigate how a system should be designed to help integrating garment-based wearable computing into mobile interaction (cf., Figure 1.1). User-centered design is an iterative process with dedicated steps that needs to be performed. This iterative design is also reflected in other processes or methodologies such as Design Thinking [70]. In addition to that, the involvement of potential users is the core aspect behind each of the steps [93]. In a fist step, we develop a design space to understand the context of use of such a system. Taking the diversity of garment-based wearable computing devices into account, we use a probe based research methodology for assessing the requirements. Within this step, we again apply the user-centered design process for each research probe. Thus, we create a number of prototypes, evaluate them, and extract requirements from each of these probes focusing on interaction and technology centered requirements. The probes were chosen to cover input and output techniques which are mainly realized with wearable computers. These requirements feed back into the user-centered design process of the overall system. Finally, we derive design principles for a system that integrates garment-based sensors and actuators into the mobile interaction. Additionally, we present a reference implementation of such a system. This system supports the integration of garment-based sensors in the mobile eco-system, the development of applications using garments as sensors and actuators, and supports the user in understanding privacy implications of such a system.

1.2.1 Understand and Specify the Context of Use

To understand and specify the context of use, we developed a design space. The design space covers all possible garment-based wearable computing devices. It further groups them based on the interaction and location, helping to systematically address all important groups of devices. Each research probe developed in the course of this thesis covers a dedicated part of the design space.

1.2.2 Specify User and Institutional Requirements

To specify requirements, we applied a research probe approach. We focus on developing as diverse as possible research probes and covering as much of the design space as possible. Every research probe covers a different application scenario and poses its own requirements. Within each probe, we again used a nested user-centered design approach as methodology (cf., Figure 1.1 – right).

This includes understanding and specifying an application scenario, specifying the requirements of a prototype, producing a prototype (cf., Table 1.2), and evaluating the prototype. The developed prototypes solve a challenge within a certain application scenario. They have been developed and evaluated in close collaboration with colleagues, students, and external researchers. Expertise in different fields such as machine learning, interaction with displays, or haptic feedback helped shaping the probes in a way that they represent the current state of research. For evaluating the prototypes, we chose different research questions commonly investigated in the field of Human-Computer Interaction (HCI) for devices used in public space (we provide an overview of currently used research questions for interacting in public space [10]). These research questions include investigating user experience, user acceptance, and user performance. Even though not all requirements can be covered using a probe based approach, we gain insights into the most important requirements from a technical as well as interaction centered perspective.

1.2.3 Produce Design Solution

Taking the requirements extracted from the different research probes, we developed design principles and a prototypical system for allowing utilizing garment-based wearable sensors and actuators for enriching mobile interaction. The system provides interfaces for sensor developers as well as application developers. Sensors and applications are used as building blocks for an overall system. Thus, users can exchange them based on their needs.

1.2.4 Evaluate Designs

To evaluate the developed system, we conducted several evaluations. First, we evaluated the research probes with regards to their performance. Next, we evaluated the feasibility of the general approach on a technical level by showing the interchangeability with different physical sensors and actuators.

1.2.5 Ethics

The research presented in this thesis has been conducted within the scope of the SimpleSkin project. Within the project we used an ethic process derived from the pd-net project [144]. Each of the studies was conducted in line with this ethics process as well as the declaration of Helsinki[1].

1.3 Summary of Research Contributions

This thesis makes three main contributions to the field of smart garments. First, we present a design space for using smart garments in the field of mobile human-computer interaction. Second, we explore possible applications of future smart garment systems and derive requirements. Third, we provide a mobile system that leverages the communication between hardware sensors and actuators and applications using the derived requirements.

1.3.1 Research Context

The research leading to this thesis was mainly carried out during the last three years at the University of Stuttgart in the Human-Computer Interaction Group. During this time, different collaborations with project partners as well as other researchers influence this thesis and the presented results.

SimpleSkin

The main part of this thesis was conducted within the *SimpleSkin* project[2] within the European Union FP7 Programme. By bringing together experts for each step that is necessary to create garment-based wearable computing devices, this project investigated novel ways of bridging the gaps between each of them. This helped to increase the understanding for the challenges of each field and their respective possibilities which created valuable input for this thesis.

Furthermore, the *Smart Textiles – Fundamentals, Design, and Interaction* book was edited together with Oliver Amft. It will be published in the Springer HCI Series. The book reflects on the ideas of the project and helps identifying the different challenges that need to be tackled to create smart textiles and garment.

[1] `http://www.wma.net/en/30publications/10policies/b3/index.html`

[2] `www.simpleskin.org`

Max-Planck Institute

Together with Andreas Bulling, an expert for perceptual user interfaces and usable security, we realized a novel auditory authentication mechanism for wearable computers. Besides this work, we also worked towards understanding the authentication with mobile devices in general leading towards publication at Ubicomp 2014 [239] and MobileHCI 2015 [9].

University of Munich

Several cooperations with Florian Alt shaped the understanding of how user interact with pervasive displays. In the context of this thesis, particularly the work towards wearable displays helped understanding how on-body displays can be used and what requirements they pose. In addition, the cooperations resulted into publications beyond the scope of this thesis at various venues [5, 6, 7, 8, 10, 32, 33, 34, 35, 36, 37, 96, 183, 221, 222, 223, 224].

Leibniz University Hanover

Together with Max Pfeiffer and Michael Rohs we explored using EMS as a technology for providing haptic feedback. We conducted several studies that helped understanding the potential of EMS especially in the context of garment-based wearable computing. This collaboration led to an award winning publication at CHI 2015 [191] and several other publications [193, 194, 195].

University of Stuttgart

Beside the work presented in this thesis, we realized various projects at the University of Stuttgart over the last years. These projects increased the understanding of how different input and output technologies can in the future be used [16, 17, 84, 101, 129, 131, 167, 196, 198, 214, 236, 238, 265, 275].

1.3.2 Research Prototypes

This thesis contains different prototypes that helped exploring the requirements for each interaction technique. The hardware for each prototype is mainly realized using off-the-shelf hardware, electronic platforms [140], or prototypes developed within the SimpleSkin project. An overview of the developed prototypes is presented in Table 1.2.

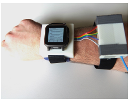
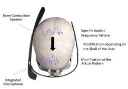
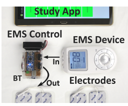
Prototype	Description	Chapter
	The *GestureSleeve* prototypes uses touch-sensitive fabric to detect simple 2-dimensional gestures such as strokes or basic shapes (e.g., circle). It is connected to a smart watch that shows the graphical user interface of a simple running application. With each gesture, a certain command can be executed such as pausing the application or starting the next round.	Chapter 3
	The GestureWatch is a combination of a smart watch and a capacitive wristband. This research probe was mainly used to record different hand gestures and use this data to post-hoc analyze it.	Chapter 4
	We developed a low-resolution *WearableDisplay* by using two 8x8 led matrices connected to an Arduino. Each of the pixels can individually controlled using an Android application. The communication between Android device and *WearableDisplay* is realized using Bluetooth. In addition, the display is capable of displaying points of interest that are outside the viewport of a mobile device.	Chapter 6
	The *GlassAuthenticator* consists of an Android application that runs on Google Glass. It is capable of sending and recording arbitrary audio files. The recorded files can be analyzed using Mel Frequency Cepstral Coefficients (MFCCs) and compared to a group of pre-saved pattern. Thereby, a lightweight k-Nearest Neighbors approach is used.	Chapter 7
	The *EMSActuator* consists of an Android application controlling an off-the-shelf EMS devices. The mobile phone connects via Bluetooth to an Arduino which is capable of changing the intensity of the EMS device.	Chapter 8

Table 1.2: Prototypes developed within the scope of this thesis. Each prototype is used in a single research probe which is presented in a dedicated chapter within this thesis.

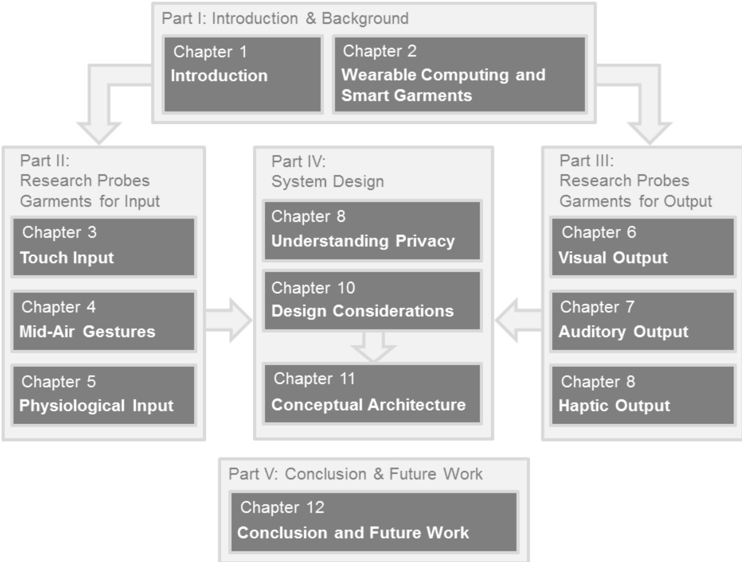


Figure 1.2: Outline of this thesis with the connection between the different chapters and parts.

1.3.3 Thesis Outline

This thesis consists of eleven chapters grouped into five parts. The overview is depicted in Figure 1.2. The first part introduces the topic of this thesis. The *Background* part provides an in-depth introduction to wearable computing and smart textiles and a design space for interacting with smart garments. It is followed by the two main parts of the thesis. The *Research Probes: Garments for Input* and the *Research Probes: Garments for Output* parts present different application scenarios, including authentication, controlling smart gadgets, and garment-based output. These scenarios are relevant to extract requirements for a operating system managing integration and usage of smart garments. The *System Design* part presents an analysis of the end-user´s privacy concerns, derived design recommendations, and a prototypical system managing garment-based sensors and actuators. In the last part, the *Conclusion and Future Work* are presented.

Part I: Introduction & Background

Chapter 1 - Introduction. The first chapter motivates the topic of this thesis. Furthermore, it contains a description of the used research methodology and research context. Last, the contribution of the thesis and a brief outline are presented.

Chapter 2 - Foundations and Design Space. In this chapter, smart garments are introduced in-depth. The most important terms used throughout this thesis are defined and differentiated from each other. An overview of research in the field of wearable computing is presented. Additionally, a design space is presented that helps gaining an overview of used approaches and build prototypes. The different systems are grouped based on three dimensions, namely, input, output, and body location.

Part II: Research Probes: Garments for Input

Chapter 3 - Touch Input. One of the most common input techniques known from nowadays smart watches is touch input. Beside the simple tap, gestures are becoming more and more common such as the pinch gesture for zooming. In this probe, we explore different stroke-based gestures performed on touch-enabled textiles on the forearm. As an application scenario, we evaluate the usage of gestures to control a fitness application running on a smart watch. We show that these gestures can outperform state of the art input techniques and provide a benefit for the user.

Chapter 4 - Mid-Air Gestures. Mid-air gestures are well known from devices such as Microsoft Kinect[3] or Leap Motion[4]. These devices, however, are build for a static setup. To achieve similar input in a mobile setup, smart garments can be used to sense the movement (i.e., movements as gestures) of the user. In particular, we use a smart watch scenario in this research probe. One of the drawback of smart watches is that the user needs both hands for operating them. We utilize a textile-based capacitive watch strap for controlling content on the watch with gestures performed by the hand wearing the watch. Thus, the other arm of the user is not occupied for the interaction.

Chapter 5 - Physiological Signals. The closeness of smart garments to the user‘s body allows measuring physiological signals of the user. This input can be used – in contrast to the touch and mid-air gestures presented before – as

[3] `https://dev.windows.com/en-us/kinect`

[4] `https://www.leapmotion.com/product/desktop`

implicit input. In this research probe, we report on a user study in the automotive domain measuring different physiological signals and inferring on the context of the driver. We explore the requirements measuring physiological signals pose from a technical perspective. We further present application scenarios in which physiological signals can be used as everyday implicit input.

Part III: Research Probes: Garments for Output

Chapter 6 - Visual Output. Visual output is the main source of output for computing devices. Due to the large body area covered with smart textiles, visual output can be presented on many different locations. This makes visual output interesting for smart garments. However, garment based displays are fundamentally different to conventional displays with respect to display resolution and presented content. As an example application scenario, a focus and context display is presented in this chapter. The design space of such a display is explored and the performance evaluated using an off-screen location visualization example.

Chapter 7 - Auditory Authentication. Auditory output is well explored for providing feedback and entertaining the user. In contrast to the classical usage of auditory output, we explore an authentication application scenario. We developed an auditory biometric authentication system using the bone-conduction speaker and a microphone of an off-the-shelf eye-wear computer. A sound cue is played back with the speaker and again recorded with the microphone creating a closed loop. Since the difference between the recorded and played-back signal is based on the anatomy of the user, this approach can be exploited for identifying and authenticating the user. We show the general feasibility in a user-study (N=10).

Chapter 8 - Tactile Output. While current mobile devices mainly use vibro-tactile feedback as tactile feedback, smart garments allow due to the closeness to the body the usage of EMS as tactile feedback. In this probe, we conduct studies showing that EMS works as simple feedback but also provides the possibility to actuate the user. This allows generating an embodied feedback extending the possibility of vibro-tactile feedback. To highlight the novelty, we provide application scenarios in which EMS can be further applied.

Part IV: System Design

Chapter 9 - Understanding Users´ Perceived Privacy. This chapter explores the user´s understanding of sensor data from wearable sensors. We explore the difference between data (e.g., pressure value) and information level (e.g., step count) using a web survey. We show that users understand both levels differently.

Chapter 10 - Design Recommendations. Different aspects need to be considered when enriching mobile interaction with smart garments. By analyzing each of the developed research probes in Part II and Part III, Design Recommendations are distilled. These Design Recommendations help to develop a usable way of interacting with garments and to create a system capable of being used for multiple applications.

Chapter 11 - Conceptual Architecture. Knowledge in different fields is necessary when developing smart garments. This ranges from hardware aspects such as fabric production, sensor and actuator development, and textile connecting to software aspects such as communication with sensors and actuators, data storage, and the development of algorithms. Using the design consideration stated in Chapter 10, we present an operating system for smart garments in this chapter tackling the software aspects of smart garments.

Part V: Conclusion and Future Work

Chapter 12 - Conclusion and Future Work. This chapter summarizes the contribution of this thesis and reflects back to the research questions stated in the beginning of the thesis. Furthermore, it outlines open questions that still need to be tackled in future developments.

Chapter 2

Wearable Computing and Smart Garments

Smart garments have huge potential to shape the way we interact with computing systems in the future. Current interaction techniques on mobile devices mainly realize dedicated input actions from the user with touch and speech to execute certain commands. In contrast, smart garments move the interaction from the tip of the finger more closely to the body. The ubiquity of clothing in our everyday life allows a continuous surveillance of the whole body. This again allows implicit measurements of the user‘s physiological conditions and posture as well as the detection of explicit user input through full-body and hand gestures. Another important aspect that makes smart garments increasingly promising is their unobtrusiveness. While many current wearable devices are add-ons to the user, the clothing of the user can be enriched with smart textiles so that - on a first glance - the clothing did not change. By doing so, explicit and implicit interaction techniques allow users to control computing systems while input and output devices stay unobtrusive and weave themselves into the clothing of the user. In this chapter, we introduce the most important terms in the field of smart garments. We provide an overview of the history of wearable computing and smart garments in particular, explain the current development and evaluation process, and present challenges that need to be tackled to allow smart garments to become mainstream. Last, we present a design space with an in-depth discussion of the different dimensions.

This chapter is based on the following publications:

- S. Schneegass and O. Amft. Introduction to Smart Garments. In S. Schneegass and O. Amft, editors, *Smart Textiles – Fundamentals, Design, and Interaction*. Springer HCI Series, 2016
- S. Schneegass, T. Olsson, S. Mayer, and K. van Laerhoven. Mobile Interactions Augmented by Wearable Computing:. *International Journal of Mobile Human Computer Interaction*, 8(4):104–114, Oct. 2016

2.1 Wearable Computing, Smart Garments, and Smart Textiles

A *Wearable Computer* is a computing device that is body worn and, thus, closely connected to the user. It has the potential of interweaving itself with its users and their everyday life achieving true pervasiveness. In contrast to mobile devices such as smartphones, wearable computers are always on, always ready, and always accessible [162]. They do not need to be explicitly switched on but automatically react to the wearer's explicit (e.g., a voice command) or implicit (e.g., change in heart rate) input. There are many different definitions of wearable computing. For example, Steve Mann defines a wearable computer as follows:

> **Wearable Computer** is a data processing system attached to the body, with one or more output devices, where the output is perceptible constantly despite the particular task or body position, and input means where the input means allows the functionality of the data processing system to be modified.
>
> *Steve Mann [159]*

There are two strands of wearable computing devices that need to be distinguished. First, *Wearable Gadgets*, for example fitness bracelets or eyewear computers, are miniaturized computers that can be attached to certain body parts such as the wrist or head. They provide input and output capabilities as well as connectivity to either a central device or directly to the world wide web. Nevertheless, the user needs to attach these devices explicitly, may forget or chose not to use the device, and the device is always an addition to the user. In contrast, *Smart Garments* (also referred to as smart clothing) are clothes which are enriched by certain functionality.

These particular garments are mainly built using *Smart Textiles* for sensing or actuating the wearer. Although some Smart Textiles are not used as garments, we focus in this thesis mainly on Smart Textiles used for Smart Garments. These textiles offer the same functionality as regular textiles and are on first glance indistinguishable from them. In addition to that, these textiles have certain functionality so that they are able to track the users postures, gestures, or physiological properties or provide feedback to the user. Van Langenhove and Hertleer define Smart Textiles as follows:

> **Smart Textiles** are textiles that are able to sense stimuli from the environment, to react to them and adapt to them by integration of functionalities in the textile structure. The stimulus and response can have an electrical, thermal, chemical, magnetic or other origin.
>
> *Lieva Van Langenhove and Carla Hertleer [142]*

Cherenack et al. defined three different categories of Smart Textiles [49]. The first category of smart textiles uses the textiles as carrier to integrate off-the-shelf electronic components. Conductive yarns and fibers replace cables to connect different sensors, actuators, or processing boards. In the second category, more and more of the electronics is substituted by textiles. Textiles serve as sensors or actuators and only some parts of the system use traditional electronics. In contrast to the first two categories, the approach in the third category significantly differs. The idea for these textiles is rather smarting up textiles and not including electronics in textiles. Logic boards and electronic components such as transistors are made out of textiles in this category [97].

2.2 History of Wearable Computing

In a broad sense wearable computing refers to devices that support wearers with data input/output and functionality based on context awareness. The history of wearable computing dates back long before the actual development of computers as known today. Glasses and watches provide a benefit to the users and enhanced their senses. Providing explicit input, abacus calculators that could be worn as rings were developed by Chinese pioneers back in the Qing Dynasty era (1644-1911)[5]. While this device is neither electrical nor adopting, it incorporates basic input and output features.

2.2.1 The first (electrical) Wearable Computer

Edward O. Thorp conceived the first electronic wearable computer in 1955 [257]. The goal of this machine was to calculate roulette probabilities. Thorp realized his idea together with Claude Shannon and others in 1961 by using switches in the shoe for input, acoustic output came through a tiny ear-plug, and a small hand-made computing unit was worn at a belt [20]. They achieved a 44% performance increase when playing roulette. The first wearable computer that was systematically researched was published in 1968. Back then, Ivan Sutherland presented a head mounted display using small CRT displays placed in front of the the user's eyes [249]. Using half-silvered mirrors the user was able to see the virtual as well as the physical environment. After this seminal work, the main focus in the field of wearable computing was on eyewear computing. One of the pioneer in this field, Steve Mann, developed several prototypes that use a near-eye display, on-body computer, and one-handed input device [161].

As of today, the number of wearable gadgets increases significantly. In addition to eyewear computing, different sensors and actuators placed at different locations on the user's body were used to get knowledge about many different aspects of the user such as the current health status or performed activity.

2.2.2 Smart Garments and Smart Textiles

In the early 90's, the benefits of smart textiles became apparent. The unobtrusiveness of augmented clothing [158] and the possibility to interact with this type of wearable computer even at night [160] motivated a new strand in wearable computing research. One of the first textile-based wearable computers was the Sensor Jacket [76] which allowed measuring the posture of the wearer‘s upper body utilizing eleven knitted stretch sensors placed over the joints. Detecting the posture was researched in various projects. For example, Shyr et al. use a

[5] http://www.chinaculture.org/classics/2010-04/20/content_383263_4.htm

textile strain sensor to infer on the flexion angle showing that the resistance of the sensor linearly correlates to the flexion angle of the leg or arm of the user [242]. Cho et al. compared different conductive textiles and their performance for measuring joint angles [50]. By integrating these sensors into a knee sleeve, Munro et al. showed that they were able to prevent injuries for athletes [177]. They used conducting polymer technology and audible feedback as soon as they reach 25 and 45 degree knee flexion to keep the leg in an optimal range. In another example, Helmer et al. show that by using strain sensors they were able to analyze Australian football kicking actions without interfering the normal movement of the athlete [105].

In addition to physical measures, physiological status of the wearer is a investigation focus across many research projects. One of the first approaches was the Georgia Tech Wearable Motherboard [206, 92] that allowed developers to plug in different sensors into a single garment. Paradiso et al. presented a smart garment that can be used as wearable healthcare system [184]. In the multinational European MyHeart project, a underwear was developed and evaluated in cardiovascular diseases, providing electrocardiogram (ECG), respiration, and several other measurements [11]. The SimpleSkin shirt combines physiological and physical sensing [229].

In particular the integration of electrodes and measurement of cardiorespiratory activity has received broad attention. Cho et al. developed an ECG shirt [50] and compared three different types of ECG electrodes (i.e., embroidered, knitted, and a combination of both). They showed that the combined fabric achieves the best performance. Choi and Jiang presented a system intended for cardiorespiratory measurement to monitor sleep condition [51]. They used belt worn sensors for measuring respiratory cycle and RR-wave interval using polyvinylidene fluoride film and two sensors made of conductive fabric.

The overall construction principles of smart textiles and garments are continuously extended. Dunne et al. provided an overview on textile integration strategies and component attachments [71]. Key challenges regarding the interpretation of garment-sensors is their varying attachment depending on movement and body shape. Harms et al. provides an overview on a prediction framework dealing with errors due to loose fitting in orientation, skin contact, and strain sensing [98].

2.3 Production of Smart Garments

Several steps need to be taken to create smart garments. While some of the steps overlap with the steps needed to create classical wearable computing devices, smart garments have additional challenges in the production process that need to be tackled.

2.3.1 Fabric Production

In contrast to gadget based wearable computing, the usage of fabrics yield several challenges. The production of these fabrics is the first challenge especially when taking mass-production into account (cf., Poupyrev et al. work on Project Jacquard [202]). Classic production techniques include Fleece, Warp Knit, Weft Knit, Weave, Braid, and non-comp fabrics (cf., Goenner for an overview of textile production techniques [91]). Each used technique combined with the used type of yarn impact the wearability of the garment and allows generating different properties such as stretchability.

2.3.2 Sensors and Actuators

Several research prototypes of textile based sensors and actuators have been developed. Most of these sensors and actuators consist of a textile electrode and electronics interpreting the measured signal or applying a signal to it. The majority of research focuses on the sensing part. Using touch resistive textiles as pressure sensors (e.g., Zhou and Lukowicz [283]) or textiles capable of measuring the bend angle of joints (Lorussi et al. [151]) highlight only two types of textile sensors. On the output side, visual output has gained center stage (e.g., the work of Peiris [188] or Devendorf et al. [63]). Furthermore, haptic feedback using EMS received considerable attention due to the possible integration of the electrodes into textiles [125]. The one common aspect between all these approaches is that they use the textile in combination with an electronic board. This necessity of an electronic board can be overcome by integrating more complex structures into the textile (cf., Varga and Troester for a summary of textile electronics [261]).

2.3.3 Contacting and Integration

Different methods exist to connect textiles with electronics. The methods can be grouped into non-reversible (i.e., the electronics cannot be easily removed from the textile) and reversible methods (i.e., the electronics can be removed for charging or washing of the textile). The non-reversible methods include form-locked connections (e.g., sewing) and cohesive joining (e.g., soldering, epoxy based methods, etc.). Besides the simple reversible methods such as using push buttons, magnets, or hooks, more sophisticated methods such as ball-grid connectors [169] proved to be a more usable approach. Mehmann et al. provide an overview of different types of connectors [170].

2.3.4 Communication and Operating Systems

In order to use the sensor values or provide feedback through actuators, information needs to be transferred from the electronic board (e.g., Arduino, Field Programmable Gate Array (FPGA)) to a more powerful entity that realizes the intended application. While textile solutions exists (e.g., textile antennas [168]), the most common way is connecting the electronics to a mobile phone or computer. Interfaces used for such a connection are Serial Peripheral Interface (SPI) (synchronous 1:N communication) or Universal Asynchronous Receiver Transmitter (UART) (asynchronous 1:1 communication) which can be used to connect devices offering the same interface. By connecting Bluetooth modules to these interfaces, consumer devices such as mobile phones can communicate to sensors and actuators.

2.4 Evaluation of Smart Textiles and their Applications

We identified three different groups of methods used to evaluate smart garments and their potential applications. While different contributions require different evaluation methods, it is important to chose the evaluation method fitting to the investigated issue. In general, different evaluation methods are valued differently in each field of research related to smart textiles.

2.4.1 Asking and Observing Users

One very basic approach that is mainly used in HCI is asking and observing the user. The observation of the user (also known as *Ethnographic Research*) generates new opportunities or challenges for applying smart textiles. Researchers observe users without interfering with their tasks and habits. They derive new possible application areas or products from their observations. In contrast, asking the user directly involves them. Several methods are available such as surveys, interviews, or elicitation studies. The main objective is to understand the likes and dislikes of users. This is mostly done by presenting a prototype or a final system and asking the user certain questions about the (proposed) system and can be combined with *Laboratory Studies*.

2.4.2 Laboratory Study

In laboratory studies, a certain system is evaluated with regards to a certain aspect in a controlled environment. These aspects could be focusing on feasibility (e.g., showing that a proposed system works), technical aspects (e.g., system performance or reliability), or the user (e.g., usability, user performance). Since smart textile research is still at the beginning, the main goal of evaluation is oftentimes limited to demonstrating the feasibility of a specific approach. This includes testing of materials, for example, how well does a certain material work as a textile sensor. One large strand of work shows that approaches that are currently realized with non-textile based systems can be realized with textile based sensors. In this case, the textile under investigation is compared to a non-textile baseline which has been previously shown to realize the task.

2.4.3 Field Studies and Research through Deployed Systems

In contrast to laboratory studies, field studies aim at evaluating smart textiles in realistic settings. This evaluation method poses additional challenges to the smart textile under evaluation with regards to robustness and functionality. Parameters such as the placement of the textiles cannot be controlled as in a laboratory study. Data collection and power consumption are further challenges that make these types of evaluation cumbersome. All this leads in the end to a reduced internal validity. However, facing these challenges, the evaluation benefits from high ecologic validity. It is a further step towards a usable system since aspects such as privacy implications and social effects can hardly be assessed in the lab.

Taking the evaluation a step further, research trough deployed systems allows gaining insights into the user‘s behavior with almost no interfering of an artificial study setup. This method is currently mainly used for evaluating mobile phones [108] due to their ubiquitous availability. In the future, smart textiles definitely need to go along this line to fully understand the symbiosis between users and textiles.

2.5 Design Space for Effectively Utilizing the Human Body

Since the interaction possibilities of mobile devices are limited, wearable computing and in particular smart garments create a much broader design space for input and output technology. To create a operating system supporting the majority of sensors and actuators, the whole design space needs to be understood. In the following, we present a design space similar to the work of Card et al. [43] for wearable devices that can be used to augment mobile interaction. We thereby present examples for each dimension which are not restricted to garment-based wearable computing but might be in the future realizable with garments. This design space is based on an extensive review of products and literature. We present a matrix representation of the design space (Figure 2.1) and discuss each of the dimensions.

2.5.1 Body Location

An important design consideration for wearable computing devices is the body part on which the sensors, actuators, and processing unit are placed. We differentiate between six different parts of the body and external systems. The body parts are segmented into upper body (hands, arms, torso, and head) and lower body (legs and feet). Specific sensors need to be placed at specific positions on the user’s body. Physiological input, for example, needs to be measured at specific parts to sense the desired physiological properties. Accelerometers for detecting the activity of the user needs to be placed at dedicated locations distributed on the user´s body [19] and a wristband for detecting the hand movement of the right hand needs to be placed exactly at this location [47]. On the other hand, to actuate specific parts of the body, the actuators need to be placed at the respective location or at the muscle responsible for the desired actuation. Vibrational feedback, for instance, at the arm requires the placement of a vibrational engine exactly at the dedicated location, that is, the arm. However, when actuating the user's hands using electrical muscle stimulation, the electrodes need to be placed at the arm [150] and turning the legs for changing the walking direction requires a placement of the electrode on the inner side of the legs [191]. Thus, the body part that is used needs to fit the use-case of the devices but the destination of sensing and actuation is not always the same location the sensor or actuator is placed. This can be further explored during the development process, for example, through user-centered design [2].

2.5.2 Input and Output

Most wearable computing devices focus either on input or on output, and the ones focusing on input are in the majority. Devices focusing on input strive to detect the user‘s activity, posture, or explicit input. This can be sensed through three different classes of sensing mechanism. First, physical movement generates pressure or movement that can be sensed through, for example, pressure sensors [282] or strain sensors [152]. This can be used to detect, for instance, the posture [152], performed gesture [47], or activity [19] of the user. By moving his or her body, the user physically generates pressure that is sensed by pressure sensors or changes the posture that forces stretch sensors to expand. Second, changes in the physiological properties of the human body can be detected. This includes Electrocardiography (ECG) or the body temperature of the user. Garment based systems are especially used to measure physiological properties due to the close and fixed connection between body and sensor. Several systems show that measuring ECG [78] or respiratory frequency [65] is possible and beneficial for mobile health-care applications. Carpi and De Rossi presented an overview and background knowledge on smart textiles and smart garments as well as their opportunities [44]. In addition to health-care applications, such sensors enable systems to detect changes in the physiological state of the user to adapt services to the current needs (e.g., simplify a User Interface while the user is strained [235]). Last, a system can sense contextual data from the environment the user currently is in. Examples range from environmental audio from integrated microphones [154] to QR codes scanned through head-mounted camera which can all be used to enhance the mobile interaction.

On the output side, the wearable computing device gives feedback to the user mainly using visual or auditory cues. Visual output can be either designed for the users themselves [75] or as an output medium for others as a public [217]. The visual output ranges from color changing fabric [141], small LEDs embedded into bracelets [79] or clothing [73] to rich displays that can be placed somewhere on the body [74, 180]. While auditory feedback can be used for notification or entertainment similar to visual feedback, it can also be exploited for purposes such as user identification and authentication [233]. Additionally, the usage of physical actuators such as vibrational feedback [109] or feedback through Electric Muscle Stimulation (EMS) provides feedback to users [195]. It provides feedback to the user directly at the intended position, for example, to enhance the posture of the user [268] or to give directional cues [164]. In addition to that, some types of output are used to create physiological output. These systems directly manipulate the human body. Examples include EMS to directly manipulate the user‘s muscles [150, 191] or changing the body temperature [121]. Last, the contextual output is used for systems that are not limited to wearable output themselves but used the mobile device or other systems (e.g., a public display [220]) as an output medium. An important aspect is the combination of several output devices such as several displays [94] creating novel experiences for the user.

2.5.3 Design Space Visualization

Due to the rapidly increasing capabilities of both mobile and wearable devices there are numerous possible use cases in which (garment-based) wearable sensors and actuators could augment the input or output in mobile interaction. This thesis presents five prototypes (cf., Table 1.2) which we classify in the visual representation of the design space (cf., Figure 2.1).

The *GestureSleeve* uses physical input through a touch-enabled fabric on the arm of the user. This input is transferred to a smart watch which processes the information and presents visual (i.e., physical) output at the same arm. In contrast uses the *GestureWatch* prototype physical input of the user´s hand. Physical output as well as processing is done using a smart watch on the arm of the user. The *WearableDisplay* presents output on the arms and torso of a user. Again, processing is done on the user´s smart watch. The *GlassAuthenticator* uses the physical form of the user´s head to generate a specific auditory frequency response. This response is captured through a microphone build into a Google Glass which also serves as processing unit. Last, the *EMSActuator* solely focus

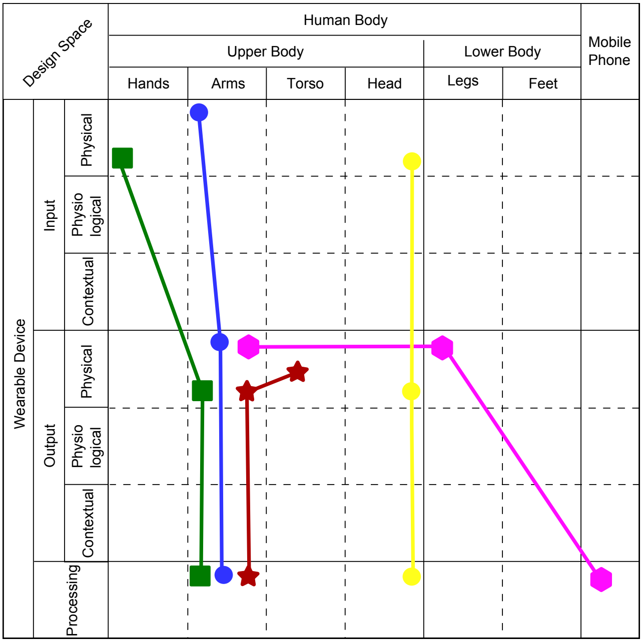


Figure 2.1: Visual representation of the Design Space including the five prototypes presented in this thesis: GestureSleeve (blue circle), GestureWatch (green square), WearableDisplay (red star), GlassAuthenticator (yellow circle), and EMSActuator (pink hexagon).

on providing physical output (i.e., movement) of the user´s limbs. The high-level processing is done on a mobile phone.

2.6 Current Challenges for Smart Garment

2.6.1 Integration

Users nowadays have their own microcosm of computing devices. In addition to a mobile phone, these devices include watches, TVs, cars, and many more. By integrating the smart textiles in this microcosm, the textile can act as a further interaction medium. The user can explicitly enter commands (e.g., controlling the watch using touch gestures on smart textiles) or the textile can be used to implicitly track the user‘s status (e.g., turning of the TV when textile based sensor detect that the user is sleeping). Due to this integration, the smart textile becomes an integral part of the user. However, interfaces between garment and environment need to be created.

2.6.2 Privacy and Control

Privacy has been an important topic since the advent of pervasive computing. The more devices move to the background, the less the devices remind the user of potential privacy violations. Since smart textiles have the potential to become indistinguishable from regular clothing the privacy of the user is an important criterion which needs to be considered during the whole design process (cf., Lengheinrich‘s work on privacy by design [143]). Textiles are closely connected to the user‘s body and allow sensing various information types hardly possible with current regular computing devices. The degree to which the user‘s privacy is protected will determine how accepted smart textiles will be in the future. Thus, smart textiles need to allow the user to stay in control of the data. The user should decide which information is shared with whom and this process needs to be as transparent as possible.

2.6.3 User-Centered Evaluations

While most smart textiles are nowadays evaluated with regards to their technical soundness, taking the user into account during the evaluation process has become best practice in other areas of research. For current smart textile research, however, the user mainly plays a minor role during evaluations. The approach of starting by exploring the technical feasibility allows rapid development of novel textile sensors and actuators and is a valid first step. Since the development of smart textiles has matured, the next step in evaluating smart textiles needs to be taken. Applying, for instance, the user-centered design process [93] to the development of smart garments allows the refinement of requirements for these and present – in return – novel challenges for the design of textile based sensors and actuators.

II

Research Probes: Garments for Input

OUTLINE

In the following part of the thesis we investigate three different approaches to use smart garments as explicit input devices. We realize gesture-based input which is known from mobile devices such as mobile phones or smart watches. Thereby, we present work using smart garments for detecting 2D gestures on a surface (cf., Chapter 3) and free-hand mid-air gestures (cf., Chapter 4). Both approaches can be realized using the same textile. However, the 2D gesture input uses a resistive sensing board and the mid-air gesture input uses a capacitive sensing board. This highlights one of the core challenges for garment-based computing. To make garment-based computing successful in the mass market the production of the garments needs to kept simple. By using only one type of textile with different sensing hardware and applications, this goal is fulfilled. In addition to explicit input, we present work on how smart garments can be used for implicit input. Since smart garments are closely connected to users' bodies, different implicit input techniques can be realized. The current posture [152] or movement [284] of the user can be detected as implicit input. Further, assessing the users' biosignals can be realized with smart garments [78, 184]. These signals yield promising insights on the user which can be used as implicit input (cf., Chapter 5).

This part includes the following three chapters:

- **Chapter 3 – Touch Gesture.** Touch input is the most common input technique for mobile devices such as smart phones and tablet computer. Touch sensitive fabrics allow making each piece of clothing to be fully touch enabled similar to the displays of these devices. Thus, the input that is currently performed on the mobile device can also be performed on clothing. In this chapter, we present a system that detects simple tabs and 2D gestures. We use this system to control a sports application on a smart watch. In an evaluation, we show that this system outperforms direct touch input on a smart watch.

- **Chapter 4 – Mid-Air Gestures.** Mid-air gestures are a well known input technique mainly used in the entertainment sector (e.g., Microsoft XBox[6]). The input is detected using devices such as the Microsoft Kinect[7] or Leap Motion[8]. While these devices are hardly usable in a mobile setting, smart garments yield the potential to detect similar gestures. In this chapter, we present a system which is able to detects mid-air gestures using a capacitive wristband. Since there is no unified gesture set yet, we conduct a gesture elicitation study and derive a gesture set. We show how these gestures can be used to control different application on a smart watches.

- **Chapter 5 – Physiological Signals.** Different physiological signals can be measured using smart garments. In this chapter, we explore these signals in the context of an automotive use case. We measure physiological signals of ten participants while they are driving. We show that we can use these values to infer on the workload of the driver and compare the results with a subjective measure of workload. Further, we highlight application scenarios of implicit input using physiological signals.

[6] `http://www.xbox.com/`

[7] `https://developer.microsoft.com/de-de/windows/kinect`

[8] `https://www.leapmotion.com/`

Chapter 3

Touch Input

Touch enabled textiles are gaining importance (e.g., Project Jacquard [202]). These textiles detect touch input similar to touch screens. Thus, they are capable of detecting taps as well as 2D gestures. In contrast to touch screens, touch enabled textiles have similar properties as regular textiles. They are similarly comfortable to wear and flexible – they can achieve a similar wearability [88]. By including patches made from such textiles in everyday life clothing or producing clothing made fully out of touch sensitive textiles, novel input possibilities can be created.

Mobile devices such as smart watches or smart phones can be controlled using touch sensitive textiles as input. Particularly smart watches can benefit from this technology. For example, during sports activities, smart watches provide benefit compared to smart phones due to their fixed location at the user‘s wrist and their reduced weight. Users can still perceive content without the necessity of getting their phones out of their pockets. This allows reading incoming messages and performance measures from fitness applications. Even though they offer quick information access and can be controlled while on the move, they suffer from the drawback of the limited input space. Current smart watches have touch-enabled displays similar to smart phones. Due to the reduced size of the displays, touch-based interaction becomes even more cumbersome compared to smart phones (cf., Leiva et al. [147]). Combining the high resolution display of a smart watch with touch enabled clothing, the draw backs of both devices can be overcome.

Figure 3.1: A user wearing the GestureSleeve at the forearm made out of touch-enabled textile. The GestureSleeve is capable of detecting gestures extending the input space of mobile devices.

In this chapter, we introduce *GestureSleeve*, a novel input system for mobile devices such as smart watches using a touch sensitive textile at the forearm (cf., Figure 3.1). The textile is compensating the drawback of the smart watches‘ limited input space. At the same time, the smart watch provides output as well as processing power that is not integrated in the textile itself. Showing the feasibility of GestureSleeve, we implemented a fitness tracking application on the user‘s smart watch. The application can be controlled with touch gestures performed on the touch-enabled textile on the forearm and with touch input on the smart watch. In a user study, we compare both approaches and show that touch enabled textiles are a feasible solution for controlling applications on smart watches.

This chapter is based on the following publication:

- S. Schneegass and A. Voit. GestureSleeve: Using Touch Sensitive Fabrics for Gestural Input on the Forearm for Controlling Smart Watches. In *International Symposium on Wearable Computers (ISWC)*. ACM New York, NY, USA, 2016

3.1 Related Work

The basic interaction techniques of nowadays smart watches have been adopted from mobile phones. The screen is touch-enabled and allows direct touch as well as small gestures. However, due to the reduced device size, the display size is reduced as well. One way to deal with the small display size is adopting the interface. This has mainly be done for text entry. Zoomboard, for example, uses multiple taps for entering characters [181]. With the first tap, the a broad region on a qwerty keyboard is s selected and, with the second tap, the actual character is selected out of a zoomed-in part of the keyboard. In addition, Funk et al. developed a touch-sensitive wristband for text entry on a smart watch [83]. Moving the interaction beyond the touch screen, Partridge et al. proposes adding tilt movements to ease up the text input [185]. Text is entered by tilting in a certain direction and pressing a button. Moving this concept even further, Xiao et al. use tilting in addition to panning, twisting, and clicking to control watches [277]. They show different example applications that can be controlled using these operations without occluding the screen.

Different approaches for gesture based input that utilize the space around the smart watch are explored. This is realized using simple depth sensors [271], cameras [247], or magnetic field sensors [14]. Due to the placement at the wrist, smart watches are capable to detect wrist and hand gestures of the hand the watch is placed by augmenting the watchstrap with sensors. Examples include the capacitive wristband by Rekimoto [207] which is capable of sensing the movement of the wrist and fingers. Similarly, Zhang and Harrison use electrical impedance tomography detecting similar movements [281].

In contrast to mid-air gestures, 2D gestures on the user‘s body can also be used to control smart watches. These gestures are more socially acceptable in comparison to mid-air gestures because they are less expressive [208]. While using 2D gestures for controlling smart watches is sparsely used, different approaches for on-body gestures have been explored. Skinput, for example, is capable of detecting taps on the arm measuring acoustic signals inside the body [100]. However, the authors are mainly focusing of detecting taps rather than more sophisticated gestures. Garment-based sensors, in contrast, allow a variety of different touch gestures integrated into the clothing of the user. Using simple stitched buttons, Komor et al. explored textile based input on the strap of a messenger bag [135]. They present different layouts and analyze their performance while swiping over or pressing the buttons. Focusing on interaction with smart glasses, Dobbelstein et al. propose performing swipe gestures on the belt [68]. However, the approach could also be extended to smart watches. In addition to using button based approaches, fabrics with similar functionality as touch screens have been proposed with various spatial resolutions and refresh rates (cf., Zhou et al. for an overview [282]). An early example using these fabrics is GesturePad [207], a textile touchpad that can be integrated in clothes of the user. Similarly, Heller et al. used a touch sensitive fabric at the tights showing the influence of different activities such as walking, sitting, and standing on input performance [104]. In contrast, we use a fabric at the forearm of the user which offers an easy to reach input space while looking at the smart watch‘s display.

3.2 Hardware Prototype: The GestureSleeve

Performing gesture input on the forearm provides a large input area. Different touch enabled fabrics have been proposed such as the work of Zhou et al. [282] or Project Jacquard [202]. These fabrics are similar to regular, non-interactive fabrics and allow manufacturing clothes with similar comfort and wearability (cf., Gemperle et al. [88]). We present GestureSleeve which augments the forearm with touch functionality. Using this functionality, we can detect various kind of input such as taps or stroke gestures. We envision using this input as a means to control smart watches. Thereby, GestureSleeve fills the blanks between touch input on devices with small form factor and complex and not always socially accepted, mid-air gestures.

We use a touch enabled fabric with the size of 16×16 cm (cf., Figure 3.2). The fabric consists of three layers. On top and bottom, groups of 32 parallel stripe electrodes of 3 mm width and 2 mm spacing between two electrodes are attached to the top and bottom fabric. Both fabrics with electrodes are placed perpendicular to each other. A force sensitive fabric is placed between both layers changing the resistance based on the applied vertical pressure. The final fabric is fixed with Velcro tape around the arm of the user. The fabric is connected via cables to a processing board[9] (cf., Figure 3.2 – top right) measuring the resistance for each of the 32×32 (i.e., overall 1024 pressure sensors) points where two stripe sensors overlap. The sampling rate is 50 Hz. The measured values are transfered via Bluetooth to the smart watch. As a smart swatch, we use the Simvalley AW 414.GO running Android 4.0.

[9] The board was developed by Zhou - cf., Zhou et al. for more details [282].

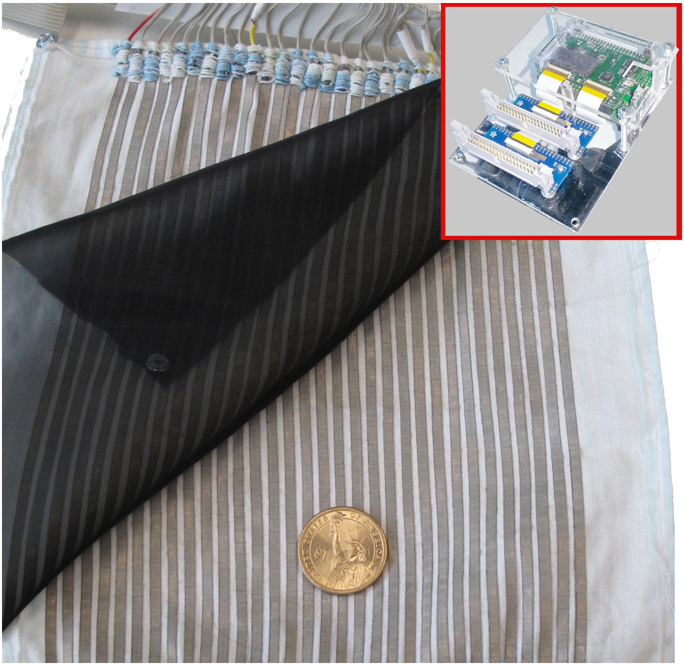


Figure 3.2: The touch enabled textile used for the Gesture Sleeve. Two layers of stripe electrodes placed perpendicular to each other with a force sensitive fabric in between. The processing electronics is shown on the top right.

3.2.1 Sensor Placement

Even though related work suggests placing the touch enabled textiles at the thighs might perform slightly more intuitive compared to the user‘s lower arm [111, 256], we decided using the lower arm since our system is designed to be used while on the move. The thigh might not be easily reachable due to the movement, especially during sport activities such as running. In contrast, the lower arm is reachable most of the time. The proximity to the smart watch further increases the placement at the forearm. Users can observe the feedback on the watch while entering commands on the sleeve. In addition, Profita et al. investigated in a study the social acceptance of inputs on smart clothes [203] and found out that interactions on the forearm and the wrist are mostly social accepted. While we used a patch of touch enabled fabric for our prototype, we envision the full sleeve being touch-enabled so that the user does not need to find the touch sensitive area.

3.2.2 Gesture Detection

Due to the placement of the GestureSleeve on the forearm and its continuous movement, the sensor data is noisy. When the user shakes his or her arm, the GestureSleeve reacts on this movement in terms of changing the values of some of the 1024 pressure sensors. Tackling this, we included an empirical determined threshold defining a minimum pressure value counting as an intended input. To prevent folds in the fabric from generating unintended input, we dismiss all sensor values exceeding the threshold which do not have at least 6 neighbors that also exceed the threshold. Even though the user just taps the fabric, the resistance of the adjacent sensors also exceed the threshold. As soon as an intended input is detected, we instantly start a new gesture. Since most of the time the pressure value changes for more than a single sensor, we always use the sensor with the highest pressure as intended input. The position of this sensor in the 32×32 matrix (i.e., the "pixel" position as known from touch screens) is added to a list that stores the currently performed gesture. We add the sensor position with the current highest value to the list until no further input is detected for at least 10 frames (i.e., 200 ms). Afterwards, the gesture detection is started with the recorded data.

In the initial version of GestureSleeve, we focus on detecting taps as well as stroke gestures. For detecting the stroke gestures, we used the $P algorithm [263] with $N = 64$ points. A gesture is recognized if the sum of all Euclidean distances between the points of the performed and a respective template gesture is smaller than 7 px. For detecting taps, we extended the gesture recognizer. It detects a tap when the length of a gesture is between 10 and 50 points and the Euclidean Distance between all points smaller than 7 px.

3.3 Evaluation: Sports Tracking Application

We conducted a user study to evaluate our GestureSleeve using a sports tracking application as use case. Interacting during running activities gains more and more importance. In addition to controlling sport tracking applications, other use-cases for interacting while running are proposed. Wozniak et al. present an approach for remote cheering to the runner [276]. They use a watch like device providing visual and haptic feedback and a single button to ask for and acknowledge remote cheering. In contrast, Smus and Kostakos used foot gestures for controlling music

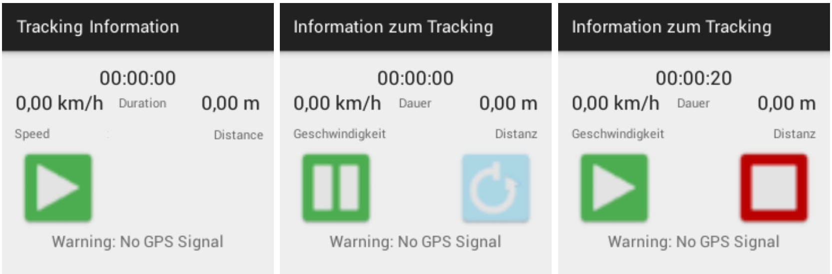


Figure 3.3: The running application used in the user studies. The user interface at the beginning (left), after the participant started the recording (middle), and after pressing pause (right).

player while running [246]. Nevertheless, we focus on basic features of running applications.

3.3.1 Sports Tracking Application

We developed a prototype of a sport tracking application that is capable of tracking jogging activities (cf., Figure 3.3). The application can be controlled either via touch buttons on the smart watch or via gestures on the GestureSleeve. In a first step, we investigated how current sports application are designed. We analyzed the user interface of the top three Android applications (Endomondo[10], Runtastic[11], and SportsTracker[12]) offering the functionality we wanted to use in the study (i.e., start the tracking, pause the tracking, stop the tracking, and initiate a new training lap). Then, we derived our user interface from these applications. The *start button* is placed left and turns into *pause button* as soon as the user starts the training. The button for starting the *next lap* is placed on the right and appears as soon as the training is started. When the runner pauses the training, the *next lap* button turns into the *stop button*. The design is deliberately chosen to be minimalistic to that the interface does not distract the runner.

For the gesture based input, we chose four different gestures – one for each command. These gestures are derived from the icons that are shown in the user

[10] `https://play.google.com/store/apps/details?id=com.endomondo.android`

[11] `https://play.google.com/store/apps/details?id=com.runtastic.android`

[12] `https://play.google.com/store/apps/details?id=com.stt.android`

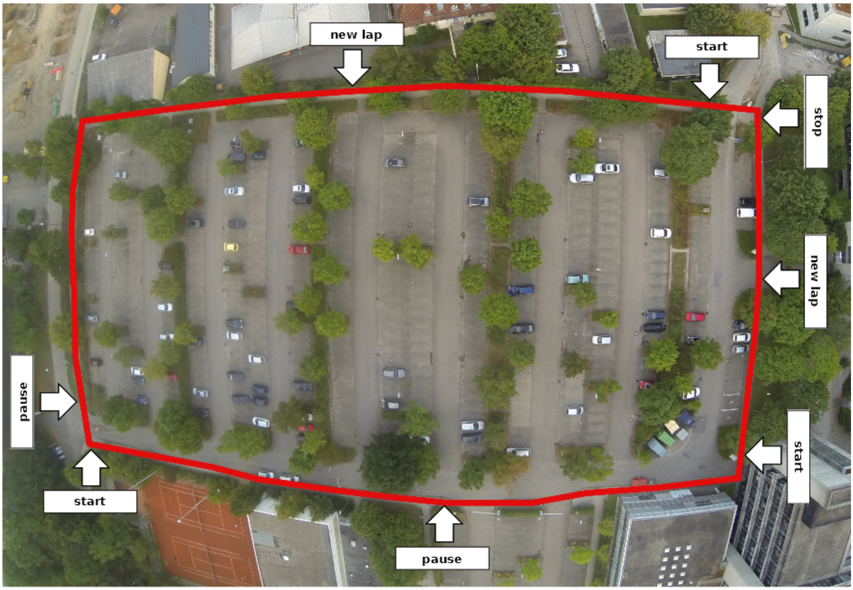


Figure 3.4: The trail used for the user study of approximately 400 m. The positions of the signs are indicated where the participants performed a task.

interface of the different sports applications (cf., Figure 3.6). The training is started with an arrow gestures (derived from the triangle symbol of the running app‘s play button), paused by a stroke (derived from the pause symbol with but with a single line), and stopped by a simple tap (similar to a square of the stop button). A new lap is started by drawing a circle indicating the lap in a stadium. We defined templates for the gesture detection and asked 14 persons to perform each of the gestures 15 times to train our system. None of them took part in the user study afterwards.

3.3.2 Participants and Procedure

We invited 16 participants (6 female, 10 male) aged between 21 and 38 years ($M = 27.3$, SD $= 4.6$) through university mailing lists. Each of the participants received 10 € as remuneration. After participants arrived in our lab they filled in a consent form and we equipped them with a smart watch and the GestureSleeve. The processing board was placed in a back pack with an external battery pack.

Next, we explained the GestureSleeve and the four gestures as well as the smart watch application and the touch interface. We allowed the participants to get familiar with both interfaces. Before each condition we repeated this instruction so that participants knew which gesture to perform, how the gesture looks like, and how the application was controlled using the touch screen.

We designed our study as a within subject study and, thus, each participant took part in both conditions, namely controlling the smart watch application with gestures and with touch input. The order of the conditions was alternated. We prepared a jogging trail of about 400 meters (cf., Figure 3.4). Along the trail, we distributed paper signs with commands (e.g., "pause"). We instructed the participants to jog along the trail and perform the commands seen on the signs as soon as they reach the line in front of the signs. We also told them not to pause for executing the commands. In total, each participant should perform "start" three times, "new lap" and "pause" twice, and "stop" once per condition. We deliberately chose the "pause" commands in areas were the participants needed to cross the street and we instructed them to carefully cross the street.

We logged the user interaction with the smart watch and the GestureSleeve (i.e., the raw pressure sensor values and the detected gestures). Further, we videotaped the whole study for post-hoc video annotation of interaction times and to understand issues during the interaction. We used high quality video setting with a frame rate of 60 FPS for the videotaping. We selected the video frame in which the user‘s hand starts moving into the direction of the GestureSleeve or the touch screen of the smartwatch and the one the participant lifted the finger again from the input device (cf., Figure 3.5). We deliberately chose this method since we wanted to investigate the whole interaction time including the time the user needs to select the input areas on the smart fabric or the buttons on the touch screen of the smart watch. Therefore, we did not only measure the time needed to perform the gesture and the time the button was pressed.

3.3.3 Results

We analyzed objective measurements (Task Completion Time (TCT), Error Rate (ER)) and the conducted semi-structured interviews with all participants after they performed both conditions.

Figure 3.5: Video recordings of a user performing three different inputs. The user performs input on the smart watch using touch (top) and two different gestures on the GestureSleeve (middle and bottom).

Performance Measures

In general, the GestureSleeve performed well and every participant was able to use the system to control the smart watch. Examples of the detected gestures are depicted in Figure 3.6. We excluded two participants for technical reasons. One participant interacted while pressing the arm against his body so that we could not identify the starting point of interaction using the video recording. The other participant took a shortcut of the trail and, thus, did not perform all commands. We first compared the TCT. We extracted the TCT by manually encoding the start and end time of each interaction from the video data (cf., Figure 3.5). As soon as a participant moved his or her arm towards either the GestureSleeve or the touch screen of the smart watch, we started measuring the interaction time. The end point was defined as the video frame in which the participant first lifts the finger.

We conducted a dependent t test comparing both interaction techniques with regards to the TCT and ER. For the TCT, the results show that participants controlled the smart watch application significantly faster using the GestureSleeve ($M = 1.50s$, SD $= 0.09$) compared to touch input ($M = 1.85s$, SD $= 0.12$), $t(13) = -3.583$, $p = .003$, $r = .78$. The ER for using the GestureSleeve ($M = 0.28$, SD $= 0.37$) was higher compared to touch input ($M = 0.17$, SD $= 0.27$). The t test, however, could not show any statistically significant differences, $t(13) = 1.649$, $p = .123$, $r = .33$.

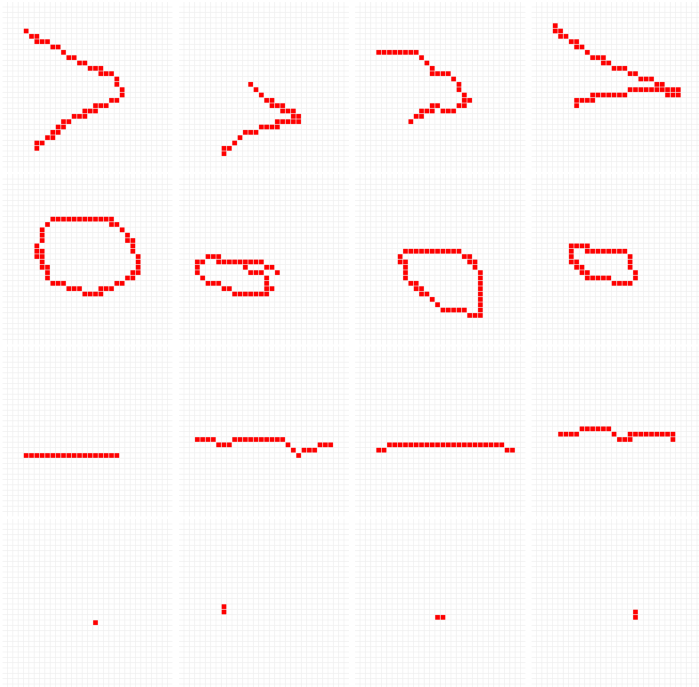


Figure 3.6: Examples of the performed “start”, “new round”, “pause”, and “stop” gestures of four different participants recorded during the user study.

Qualitative Feedback

In the semi-structured interviews, we ask the participants questions about the GestureSleeve and the perceived performance. The participants stated using gestures is *fun, novel* [P2], and *easy* [P5]. However, they also noted that they would have needed more time to perfectly master the gesture input [P6]. One participant acknowledged that he needed to look at the sleeve for performing the gestures but is confident that this would not be necessary with more practice [P14]. Additionally, participants agreed on the fact that the ease of input is mainly influenced by the used gestures. Tap and stroke gestures were easier to perform compared to circles. Especially when the fabric was not tightly fitted to the arm, the circle gesture was not easy to perform. Furthermore, participants noted that performing gestures without looking at the GestureSleeve was possible which was not the case for touch input on the smart watch [P2, P9].

3.4 Discussion

The evaluation of the GestureSleeve yields promising results. We showed users are capable of faster entering commands compared to touch input on the smart watch‘s display. The error rate is slightly higher which could be caused by the fact that gestures have the inherent drawback that they need to be learned and remembered. There is no cue reminding user‘s which gesture needs to be performed to fulfill the desired task. This is also supported by statements of the participants during the interviews. Even though we derived the gestures from the well known icon set of known running applications, participants needed to think about which gesture is mapped to which command (as stated by, for example, [P6, P14]). By giving participants more time to practice the gestures, we believe that the error rate will be further reduced and eventually match or even surpass the error of the smart watch interface. Further, the used smart watch is an off-the-shelf product which we compared to our prototype of a GestureSleeve. A more mature version of the GestureSleeve would most likely perform even better.

We decided to focus on interacting on the arm due to the closeness between input and output medium. In the summer, however, wearing short-armed shirts is common in many regions. While a similar gesture-based interaction could be applied using the skin as input surface (cf., Skinput [100] or iSkin [269]), using other parts of the body can also enhance the interaction with smart watches. As related work suggests [111, 256] the thighs are another promising area for entering commands. Situations in which thighs are especially useful include, for example, sitting on a chair in a meeting or watching movies on a sofa. The user is then able to easily enter commands on the thighs. Thus, the GestureSleeve concept could be applied to the thighs as well.

In this work, we used a prototypical version of the GestureSleeve which we designed as an add-on patch to the normal clothing of the user. We believe that in the future, clothing will be produced using touch enabled fabric [48]. Thus, the user can perform gestures on the whole sleeve and is not restricted to a certain patch. However, since we used a patch of 16×16 cm, we believe that the size did not influence the results of our study. The forearm of the participants was always completely covered by the GestureSleeve.

We focus on gestures performed on the sleeve since gestures are not influenced by a decoupled input and output space. However, additional types of input are also possible with our system. One example could be mapping different parts of the GestureSleeve to parts of the smart watch (e.g., the four quarters of the display space). Thus, a touch event on the upper left quarter of the GestureSleeve is mapped to an input on the upper left quarter of the smart watch. More fine grained direct touch input (e.g., mapping a QWERTY keyboard to the touch-sensitive textile) would probably require a visual feedback using textile display elements [189].

In addition to controlling the smart watch while running, GestureSleeve has the potential to be used for various applications beyond the fitness domain. One example could be, for instance, using the gestural input to start applications as proposed by Poppinga et al. for smart phones [201]. By performing stroke gestures linked to certain applications, the user has quick access to these applications. Furthermore, pre-defined answers to received text messages could be defined. When the user receives a message, he or she could, for instance, perform a gesture similar to a tick mark to send a quick reply. Even though we deliberately chose enriching the input of smart watches, GestureSleeve can also be used in combination with other smart devices such as eyewear computer.

The performed study used a jogging trail of 400 meters and presenting dedicated commands to the participants. Allowing the participants using a jogging distance they normally use and to perform the commands they actually would perform for measuring their performance could have increased the ecologic validity of the study. However, we believe that for an initial evaluation of our GestureSleeve concept, the usage of a more controlled setup is appropriate. Additional aspects we did not investigated are the environmental conditions. We conducted the study in the summer during days of sunshine. We did not evaluate how the GestureSleeve performs during rain or snow and how gloves impact the interaction.

In this chapter, we used a prototypical version of the GestureSleeve. We believe that in the future, clothing will be produced using touch enabled fabric [48]. Thus, the user can perform gestures on the whole sleeve and is not restricted to a certain patch.

3.5 Lessons Learned

This research probe shows how touch-enabled textiles can be used as input means for mobile devices such as smart watches or smart phones. We can derive the following two insights from the research probe:

- **Enable touch-gesture input on the smart textile.** As the research probe shows, gesture input is an easy to use way of entering commands to mobile devices. Detecting these gestures is similar for several different application and can, thus, be done on an OS level. This will also help using a unified gesture set for all applications.

- **Provide API calls on different abstraction layers.** From an application developer perspective, the raw sensor data is important in order to have all opportunities for the application development. We explored different modifications to the algorithm to be able to detect different gestures which would not have been possible without the raw sensor output. However, this research probe also shows that detecting gestures can be challenging. Thus, allowing application developer to automatically include gesture input without the necessity of implementing the detection algorithm eases up application development in some cases. This could, for example, be done using callbacks that are triggered as soon as a specific gesture is detected.

3.6 Conclusion

In this chapter, we explore touch gestures on smart garments as an additional input means for mobile devices. We present the GestureSleeve prototype. By providing a large input area, GestureSleeve helps overcoming the drawback of the limited input space which is a common issue for mobile devices – especially smart watches. To evaluate our approach we developed a fitness application and conducted a user study in which we compared gestural input on the GestureSleeve and touch input on the smart watch. Our results show that the GestureSleeve outperforms touch input with regards to the task completion time. While our prototypical version is build as an add on to the normal clothes of the user, we believe that in the future sleeves of regular clothes can incorporate similar interaction possibilities.

Chapter 4

Mid-Air Gestures

While touch gestures on smart textiles (cf., Chapter 3) provide an easy way of entering commands, performing mid-air gestures yield several advantages. The expressiveness of the gestures is increased due to the additional degree of freedom and only the hand performing the gesture is needed for input. A number of technologies have been proposed that would allow single-handed mid-air gesture input ranging from camera based solutions [18] to wrist worn devices [128]. Especially wrist worn devices seem to be promising. One of the first solutions is presented by Rekimoto who proposed to use capacitive sensors integrated into a wristband to sense gestures performed with the same hand [207]. In addition to requiring only one hand for input, the approach has the potential advantage that the wrist does not move extensively, which is especially important when entering commands to smart watches placed at the same hand.

Smart watches have been proposed as devices that provide users with almost instant and ubiquitous access to digital information. Miniaturization only recently enabled devices that combine displays, allow outdoor usage, allow pervasive internet access, and have long battery time. Therefore, smart watches gained major commercial attention in the last years. From a technical perspective, current smart watches provide almost the same input functionality as current smart phones. However, combining smart watches with the possibility of one-handed input yield promising results since smart watches are already attached to the hand (i.e., input and output mechanisms are placed at the same position). This allows the hand currently unused for input to be involved in other tasks (cf., Figure 4.1). Previous work on smart watches proposed touch-based input

Figure 4.1: Interacting with a smart watch can be troublesome when the second hand is needed, for example, to hold an umbrella or to carry a briefcase. Moreover, sometimes users cannot use the touchscreen (e.g., when wearing gloves or having wet fingers).

techniques (e.g., [155]), additional artifacts, such as magnets that are moved around the device [99] or using proximity sensors to track the movement of the opposite hand [41, 137]. While these input techniques have certain advantages, they require the hand not wearing the watch for input. Thus, both hands are not free for other tasks while using these input techniques.

In this chapter, we provide a holistic assessment of hand gestures for wrist-worn devices. In an initial guessability study we explore potential gestures for smart watches without considering technical constraints. In a controlled user study, we compare the collected gestures and assess their suitability from three user perspectives. We determine participants' preference, social acceptance, and the ability to perceive content on the screen while interacting. From the results we derive a gesture set for typical applications such as map navigation or phone call control. We show that with basic algorithms, these hand gestures can be detected and used as input providing a promising performance while not requiring two hands. As a research prototype, we use a smart textiles placed at the wrist of the user capable of detecting gesture-based input. Such a textile can in the future be integrated into the cuff of a shirt or in textile-based watch straps.

This chapter is planned to be published as follows:

- S. Schneegass, M. Hassib, A. Reiss, K. Wolf, N. Henze, J. Cheng, P. Lukowicz, and A. Schmidt. Exploring Gestures for One-handed Smart Watch Interaction

4.1 Related Work

In this section, we draw upon different areas of related work. First, we show ways to enable smart watch input for both, two-handed and one-handed interaction. Then, we present work on gathering gesture design suggestions from users.

Two-handed Smart Watch Interaction

Various approaches have been proposed using two hands for interacting with devices, for example, in touch-based interaction. Even for interacting with very small devices such as smart watches, two-handed interaction has been investigated in a large body of work. Since most smart watches are equipped with a touch enabled display, investigating touch input is the first step in making the interaction easier for the user. For instance, Lyons et al. presented Facet, a wrist worn device with a multitouch display [155]. It supports multi-segment touch, resulting in a rich set of touch input techniques. However, since smart watches are smaller than other mobile devices such as smart phones or tablets, researchers explored ways to extend this interaction space. Ashbrook et al. studied the errors when interacting with buttons placed around the rim of the watch [15]. Blasko and Feiner used tactile landmarks on a watch's bezel [28]. Even the watchstrap has been explored for interaction by making it touch sensitive, as shown by Funk et al. [83]. They used capacitive sensors on the watchstrap to enable touch input for text entry.

Baudisch and Chu proposed to use the rear of very small devices, such as necklaces and watches, for interaction [21]. However, the back of the watch cannot directly be accessed for direct touch interaction, thus, a strand of work investigated interaction around the watch using different sensors and interaction techniques. Thus, gesture input in the space above the watch is explored. Harrison and Hudson presented Abracadabra, a watch with an embedded magnetometer [99]. The user is able to interact with the watch by moving a magnet around the device. Similarly, Ashbrook et al. used a magnetic finger ring [14]. The rotation of the ring serves as input tool for a watch worn on the same hand and that has a built-in magnetometer. Thereby, they allow one-handed and two-handed input. All these approaches, however, require an additional dedicated input device. In contrast, an array of proximity sensors is used to detect movement around devices in several research prototypes (e.g., [41, 137]). The GestureWatch [133], for instance, allows simple direction-based gestures to be executed by the other hand with the use of proximity sensors, but it requires both hands for interaction.

One-handed Smart Watch Interaction

Smart watches are used in everyday life including situations in which one hand is unavailable for entering commands. Thus, we explore one-handed input that allows interacting with smart watches even when one hand is currently occupied.

Since touch-based interaction and most other interaction techniques require a second hand for input, Morganti et al. explored one-handed mid-air gestures for smart watches [173]. They use an accelerometer, a gyroscope, and a magnetometer to track the gestures. These gestures, however, have the drawback that the watch needs to be moved while performing the gestures resulting in potential issues in reading the content shown on the watch. In contrast, armband or wristband-style gesture sensors have been proposed in the past using a variety of techniques, including acoustic [64], pressure sensors [62], orientation sensing [40] or photo reflector and distance sensing [81]. Moreover, Rekimoto presents a capacitive sensing technique exploited for gesture input with the wrist [207]. GestureWrist allows for detecting simple hand gestures (stretched index finger, stretched index and middle finger or with clenched fist) through measuring the hand capacitance with sensors that are integrated in a wristband. Although not all of these works are proposed for smart watch control, they would be directly applicable to a modern smart watch through allowing for forearm or hand pose detection.

Moreover, one-handed gestures sensed through a range of wearable sensing technologies have been used for hand modeling and gesture detection, and most of them could also serve for one-handed smart watch interaction. For instance, Digits is an inner wrist mounted camera combined with a laser light projector that points to the fingertips when the fingers are bent [132]. Measuring the laser light‘s reflection time enables the prediction of the finger bending angle and the hand configuration. However, like all computer-vision based approaches, the Digits interface suffers from strong limitations due to occlusion. Fukumoto and Tonomura augmented each finger and the wrist of one hand [82]. They have shown with a body-coupled FingerRing that accelerometers can be used for detecting finger tapping. Another non-optical approach was proposed by Hrabia et al. using inertial sensors embedded in finger rings [115]. They model the whole hand using eight finger-worn sensors. Others (e.g., [47, 134]) use muscle signals to detect gestures, and, for instance, Saponas et al. shows that muscle sensing can be used to track gestures even when the hands are busy with carrying bags [216].

Eliciting Input from Users

Eliciting input from users to, for example, define gestures for controlling various interactive systems puts the user first ensuring a model of participatory design that is essential in the field of human-computer interaction. User-defined gesture approaches aim to provide easy-to-master interaction with various modalities [174]. Wobbrock et al. [273] investigated creating a set of user-defined gestures for tabletop interaction. They conducted a think-aloud guessability study for defining one- and two-handed gestures for surface interaction. Using agreement scores, they reached a coherent final set. Qualitative measures like ease and goodness of the gestures were also measured, and a taxonomy classification of surface gestures was proposed.

Afterwards, researchers followed this approach to collect user-defined gestures for a variety of context. Ruiz et al. investigated user-defined motion gestures for smart phone interaction. They classified the gestures according to physical characteristics and real life metaphors [211]. Mauney et al. conducted a study across nine countries to discover the cultural differences and similarities in eliciting user input to define gesture sets on small touch hand-held devices [165]. Kray et al. collected user-defined gestures across different device configurations, namely phone-to-tabletop, phone-to-public display and phone-to-phone. Physical properties of the gestures, such as the distance between the devices, rotation, touch between the devices, and the location of the phone in 3D space were analyzed [138]. Henze et al. generated a user-defined gesture set for a music playback application. Two classes of gestures, static and dynamic, were identified and a qualitative and quantitative assessment of the gesture set was conducted [107]. Wolf et al. gathered user-defined gestures for a WIMP-based auditory interface that can be tracked with touch and inertia sensors of hand-held devices [274]. Gestural interaction with smart TVs was researched by Vatuva [262] where a guessability study was conducted using a Microsoft Kinect to determine gestures for 12 TV commands. Pfleging et al. proposed a gesture and voice based system for performing simple commands in the car [197].

Summary

Overall, previous work shows different ways to interact with smart watches using either one-handed or two-handed input. However, gestural input has been explored with a second hand performing the gestures using either an additional item (e.g., magnetic ring) or sensors to directly track the second hand. In contrast, we propose using only one hand (i.e., the hand with the watch) to perform the gestures. Thus, we keep the second hand free. Furthermore, previous work shows that conducting formative studies is a well recognized approach to gather gesture in various contexts. In contrast, however, we focus not only on the opinion of the participant but also on three additional factors that take the specific context of a smart watch into account.

4.2 Hardware Prototype: The GestureWatch

Currently, most smart watches utilize touch screens as their main input means. This incorporates two main challenges which we tackle in our approach. First, current smart watches use small touch-enabled displays (e.g., 1.5 inch (SimValley AW-420[13])). These displays use similar input methods as mobile phones or tablets but on a much smaller scale and hence face similar challenges that research in the area of mobile devices is also currently facing. The fat finger problem [243] becomes even a more crucial challenge to solve for smart watches with the reduced screen size. Secondly, smart watches are designed to be worn all day long and in many different situations. One of their main benefits should be that the time needed to check notifications and messages should be shorter compared to mobile phones. However, in many situations, the second hand needed to interact with the watch is occupied and it takes, again, time to start the interaction.

In this probe, we tackle both issues by using one-handed gesture input through a garment-based wearable computing device for smart watches. While we are using the hand on which the watch is placed, we allow the other hand to be occupied (cf., Figure 4.1) giving the user the ability to interact with the watch with a single hand. For this approach, several different sensing modalities can be used. Since smart watches are currently equipped with sensors similar to smart phones (e.g., accelerometer), it seems obvious that these sensors can be used for gesture input as well. However, these sensors either need an additional device (e.g., magnetic item for the magnetometer [99]) or more excessive movement of

[13] `http://www.simvalley-mobile.de/Android-Watch-IP67-PX-1795-919.shtml`

the arm (e.g., raising the whole arm). Thus, interaction is sometimes unsuitable and socially unacceptable in public spaces or the content shown on the watch barely readable. To address these challenges we strive to design the interaction in a way that it does not need excessive movement. Starting with the pioneering work of Rekimoto et al. [207], many different approaches are presented that allow measuring the movement of the user‘s hand by using pressure sensors [62] or capacitive sensors [47]. In contrast to resistive sensors, capacitive sensors focus rather on the movement within the arm and are, thus, more suited to measure small movements that do not generate much movement at the user‘s wrist (e.g., tiny movements of the user‘s fingers).

As a first prototype, we developed a wristband with four capacitive sensors[14]. Four pairs of conductive textile strips form four capacitive sensors (cf., Figure 4.2). The same analog design is used as in previous work [47], but the prototype is advanced in two aspects. First, the sensor strips are made of conductive threads and woven into the strip, thus fully flexible. Second, the data is broadcasted no longer through Zigbee but BLE, allowing connections with computers and mobile devices. Because in the paper we focus on exploring gestures, we broadcast the raw data to a PC and perform analyze there.

On top of the watchstrap, we placed a Simvalley AW420 smart watch running Android 4.2. It includes different sensors such as an accelerometer and magnetometer and offers wireless connectivity via WiFi and BLE. To minimize the influence of the watch on the sensor, we 3D printed a case to prevent direct physical contact. The setup is depicted in Figure 4.2.

4.2.1 Capacitive Sensing

Capacitive sensing is a well-known sensing modality that senses the mechanical or material change between two conductive pads through the change of capacitance between them. When applied to human body, these changes are then the mechanical change of the pads and the material near the pads (including clothes and human tissues like skin and muscle). Using pads made of conductive textiles, capacitive sensors can be fully integrated into normal clothes and have several attractive properties.

[14] The board was developed by Cheng - cf., Cheng et al. for more details [47].

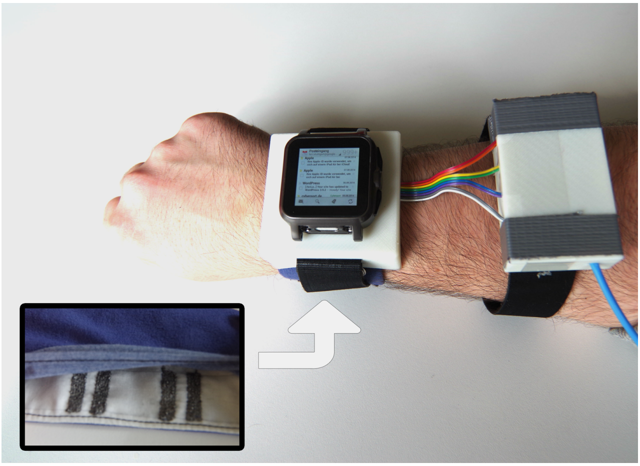


Figure 4.2: Prototype of the smart watch with capacitive watch strap. The textile sensors are placed below the watch that sticks on a protective case preventing direct contact. The device at the arm of the user is for processing and communication and can in the future be integrated in the watch.

Freedom for both Hands and "local" sensing

The selected sensing modality allows not only interaction with just one hand, but also gives certain freedom to the hand which wears the watch, because all the fingers and palm can be still free. Finger gestures can be still detected (although with less accuracy as discussed later) through the movement of skin and muscle on the wrist, while these are hard to detect using the state of art IMU embedded in smart watches. For example, tapping one finger can be used as control gesture when riding a bicycle, where the user needs to hold both handles with hands. While in such scenario the accelerometer/gyroscope outputs are dominated by the riding accelerations and turns, capacitive sensing focuses on the "local" changes of skin and muscle which is not much influenced by the riding itself.

“Look-inside” capability

Capacitive sensors also react to changes taking place deeper underneath the electrodes, effectively providing the capability to “look inside the body”. With careful analog design, Cheng et al. managed to get a user’s pulse from the wrist using textile capacitive sensing [46]. This additional information provides further benefits compared to pressure sensor based approaches (e.g., [62]).

4.2.2 Wearability

The garment-based electrode consists of conductive textile pads can be soft and flexible. A watch‘s strap consisting of this material achieves a high wearability. The sensing electronics can be integrated into watches themselves. Because the capacitance change is sensed through electromagnetic field which propagates through almost all material, there is no need for the electrodes to touch the user’s skin directly. Thus, there are no special requirements for the material between the electrodes and the skin except that it should be nonconducting. In particular, this is an advantage compared to EMG, the typical muscle activity sensing modality, which requires conductive electrodes directly on the skin and thus limits the design space and might cause allergies.

Furthermore, the used technology is also combinable with the textile used for the *GestureSleeve* in Chapter 3. The stripes which are woven into a fabric for our prototype can be substituted with a patch of the same mass-producible fabric as used for the resistive sensing. Thus, a shirt can be created with only a single garment and could be sensing enabled for different sensing technologies and applications.

4.3 Eliciting Gestures

Since free-hand gestures using the lower part of the arm (i.e., wrist and fingers) are not commonly used, we conducted a formative study to explore and generate initial gestures for tasks used for interacting with a smart watch.

4.3.1 Task Definition

We first started with defining commonly used tasks which are currently performed with smart watches. To do so, we explored current smart watches as well as different applications that are used on them. The resulting list of 17 abstract tasks is presented in Table 4.1. Since we strive to generate gestures that are applicable to other instances as well, we used an abstract task definition. Similar to the work of Ruiz and Lank [211], we grouped the abstract tasks that can be done on a smart watch into three main groups depending on the functionality: Navigation (e.g., item selection, scrolling), Media (e.g., audio, video, and camera controls), and Communication (e.g., accepting or declining a phone call).

#	Group	Task	Description
1	Navigation	Select	Select item from a list or start an app
2		Back	Go back to the previous screen
3		Home	Switch directly to the home screen
4		Move Up	Select/scroll to the previous item in a list
5		Move Down	Select/scroll to the next item in a list
6		Move Left	Pan content left/show next screen
7		Move Right	Pan content right/show previous screen
8		Zoom In	Zoom into screen content
9		Zoom Out	Zoom out of screen content
10	Media	Volume Up	Increase the volume of audio
11		Volume Down	Decrease the volume of audio
12		Mute Audio	Mute the audio
13		Take Picture	Take a picture instantly
14		Record Video	Start a video recording instantly
15		Stop Video	Stop a video recording
16	Communication	Accept Call	Accept an incoming call
17		Decline Call	Decline an incoming call

Table 4.1: The 17 abstract tasks and their description used in the formative user study. We grouped these tasks based on the categories navigation, media, and communication.

4.3.2 Participants and Procedure

In total, we invited 15 participants (3 female) aged between 20 and 42 years ($M = 24.67$, SD = 5.43) to participate in our formative user study. After the participants arrived in our lab, we asked them to fill in a consent form and to wear a smart watch so that performing the tasks becomes more realistic. We then asked the participants to perform all 17 gestures in a randomized order by providing them a screenshot of the current application state, the desired application state, and a brief abstract textual description. An example is depicted in Figure 4.3. We explained that we focus on one-handed input and that we focus on gestures of their forearm, wrist, and fingers. During this process, participants were encouraged to think aloud and to explain the rationale behind choosing a gesture. One researcher noted the gestures participants performed for each task as well as the user‘s comments. Furthermore, the sessions were video recorded for a post-hoc video analysis of the performed gestures.

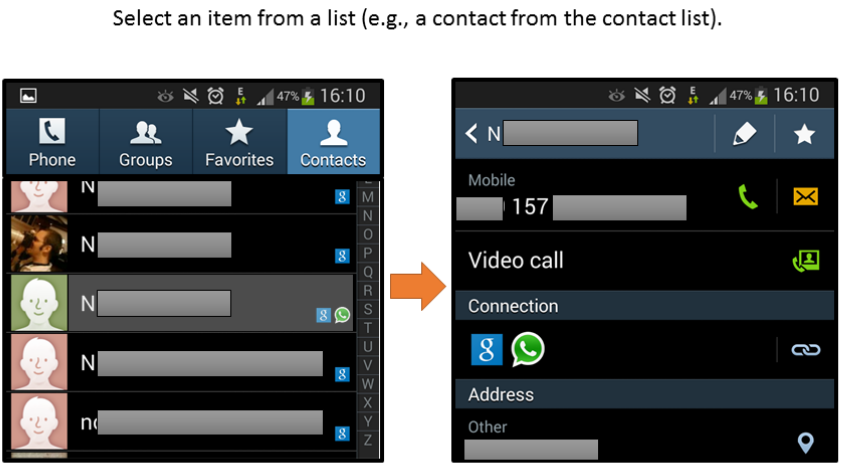


Figure 4.3: The *select* task example (select a contact) used in the formative user study. A textual description of the abstract task and two images representing the initial and final state. Screenshots from SimValley smart watch.

4.3.3 Results

We depict the results of the formative user study in two sections. Analyzing the think-aloud protocols recorded on video, we first provide a thorough qualitative analysis. This analysis explores the different mental models and concepts of the users that rationalizes and groups their gesture choices. Secondly, we quantitatively analyze the elicited user gestures to determine the most frequently suggested gestures.

Qualitative Analysis

We used a bottom-up and open coding approach to categorize the user-defined gesture ideas in five main categories: real-world metaphors, mental models, touch-screen gestures, shortcuts, and gesture combinations. Results of user-designed ideas often base on prior knowledge and expertise of the participants, which are triggered through the experiment questions. For instance, metaphors are used for gesture design through previous experiences with real-world objects [119], and mental models describe experience-based procedural and abstract knowledge, such as spatial image schemata, which provide a common understanding that

#	Task	Gesture 1	Gesture 2	Gesture 3	Score
1	Select	Index finger click	Tap thumb & middle fingers	Move wrist down	0.09
2	Back	Wrist to the left	Arm to the left	Tap thumb & ring finger	0.11
3	Home	Shake wrist	Arm down		0.10
4	Move Up	Index finger up	Wrist away from body	Wrist up	0.24
5	Move Down	Index finger down	Wrist Down		0.26
6	Move Left	Index finger right	Wrist to the left	Arm to the left	0.14
7	Move Right	Index finger left	Wrist to the right	Arm to the right	0.19
8	Zoom In	Pinch with index & thumb	Pinch with all fingers	Wrist up	0.19
9	Zoom Out	Pinch with all fingers	Pinch with index & thumb	Wrist down	0.24
10	Volume Up	Index finger up	Wrist up	Tap index & thumb & move up	0.11
11	Volume Down	Index finger down	Wrist down		0.10
12	Mute Audio	Make a claw/half fist	Make a fist &turn wrist		0.08
13	Take Picture	Turn wrist & make a fist	Arm to front & wrist down	Index finger click	0.14
14	Record Video	Make a fist & thumbs up	Index finger click		0.08
15	Stop Video	Make a fist	Turn wrist	Make a fist & turn wrist	0.09
16	Accept Call	Raise hand to ear	Wrist to the right	Arm from left to right	0.16
17	Decline Call	Shake wrist	Wrist to the left	Form a fist	0.14

Table 4.2: Top 3 gestures and agreement scores for each of the 17 abstract tasks.

an *UP* gesture rather relates to commands like *increase volume*, while a *DOWN* gesture would most likely be used to *decrease volume* [118]. Previous knowledge was also used for generating new gestures as some generated ideas were influenced by established touch-gesture commands like pinching for zooming. Other gestures are unrelated to a specific context but rather defined for certain tasks. These are mainly abstract and clear. We combined them in the shortcut category. Finally, combinations of the described ideas build the fifth category. In the following paragraphs we explain exemplary gesture ideas arranged by the five categories described before.

Real-world Metaphors In accordance with [211] many participants suggested real-life metaphors for certain gestures. For example, a number of participants suggested raising their hands to their ears for accepting a call as they would do with both a smart phone and a land line phone. For going back to the main home menu, a number of participant shook their hand stating that this made sense to them like they were 'erasing' all their progress. Other participants suggested a closing and opening of the fist resembling *camera aperture motion* to instantly take a photo, and moving their wrists in a circular motion to start a video like the way a video recorder would move while recording.

Mental Models Furthermore, the participants applied different mental models for navigating through a list or in a map. On one hand, participants wanted to move the digital map with their finger as commonly done for navigating with digital maps on smart phones (i.e., moving the map). On the other hand, participants moved their wrist or arm to the side they want to navigate to (i.e., moving the viewport). Moving the wrist up/down was used to scroll up/down through a list, and moving the wrist to the right would navigate to the next screen, while a move to the left would get the previous one.

Touchscreen Gestures Throughout the study, participants performed a variety of gestures that are known from smart phones. For instance, they applied pinch gestures for zooming-in and zooming-out. For panning and moving through a map left and right, many participants used finger movements in the 2D space to depict such gestures, which they also said was similar to what they would do on their smart phones. For answering and rejecting an incoming call, participants who were familiar with the Android OS performed the same swipe right/left for such tasks.

Shortcuts Within the idea collection, we also found shortcuts that were mainly used to perform rather abstract tasks that are not part of certain interaction flow. We have particularly noticed that in tasks that are special like snapping a photo, starting a video, or going back to the home screen. Participants suggested to use *finger-tap gestures* (i.e., moving the thumb to one of the other fingers like the index, middle, or ring finger) to trigger these shortcuts. Accordingly, participants proposed to use these gestures for user-defined functions: "*One could use each of the four fingers as a shortcut to one application*" (P2). Other participants suggested tapping their palm to the face or to the upper leg as gesture to go to the home screen. They suggested that such gestures would be easily memorized and hence be often used. Other shortcut gesture ideas, like making a fist or making a thumbs up, were suggested for various tasks including starting or stopping a video as well as to go to the home screen.

Gesture Combinations Participants proposed also to use combinations out of two simple gestures to release commands. These gestures are performed one after another. For example, they proposed to first make a fist and then turn their wrist or raising their arm then pointing up with their wrist for a variety of commands. For the recognition part of the evaluation, we treat such gestures as two gestures that need to be detected one after another.

Quantitative Analysis

After the qualitative analysis, we also conducted a quantitative one. We went through the notes as well as the video recordings for each of the 255 performed gestures and grouped the most similar gestures together considering using the same body parts as well as the same body motions as similarity. We then computed the agreement scores, defined by Wobbrock et al. [273], to calculate the agreement of user-defined gestures per task as shown in Equation 1:

$$A_t = \sum_{P_i} \left(\left| \frac{P_i}{P_t} \right| \right)^2 \tag{4.1}$$

In this equation the agreement score of one task from the task set T is given as A_t and is in the range of $[0,1]$. P_t is the set of all user-defined gestures for this particular task and P_i is the repeated gestures which are a subset of P_t.

By applying this equation to our set of 17 defined tasks we get the agreement scores for each of the tasks. We also defined the top three most performed gestures for each task, which, together with the agreement scores, are depicted in Table 4.2.

Since the participants were encouraged to freely choose any gesture with the finger, hand, or wrist with no restrictions, the choice of gestures varied a lot. For this reason, we received many different gestures for each task. Aiming to identify gestures with high agreement scores, we excluded gestures which were only mentioned once in the remainder of the analysis. Thus, some of the tasks only have two gestures defined. This also explains why the agreement score is lower compared to previous work (e.g., [273])

By taking a closer look at the top gestures for each task we can draw some conclusions based on the previous qualitative and quantitative analysis. Navigation gestures almost always fall in one of two categories: the spatial image schema mental model or the touchscreen gesture model which we discussed earlier. For example, up is often depicted as moving the wrist up, suggesting an increase (e.g., in volume or a vertical scroll) whereas down is depicted as moving the wrist down suggesting a decrease. Gestures which are by their semantic nature defined to be the opposite image schema to each other (e.g., up/down, left/right, and zoom in/zoom out) have similar agreement scores.

We also noted that the agreement scores for special abstract tasks such as taking a photo (0.14), starting a video (0.08), or stopping a video (0.09) are comparatively low. This coincides with our previous qualitative analysis where we noted that such tasks are not following a specific interaction flow. In such cases participants created self-defined abstract gestures that were not based on any models or the variety of possible models was huge and depicted them as 'shortcuts' to a certain functionality or application. Due to the freedom given to participants in choosing the gestures as well as due to the lack of existing metaphors or mental models, we have found little agreement regarding shortcut gesture designs.

4.4 Evaluation of the Elicited Gestures

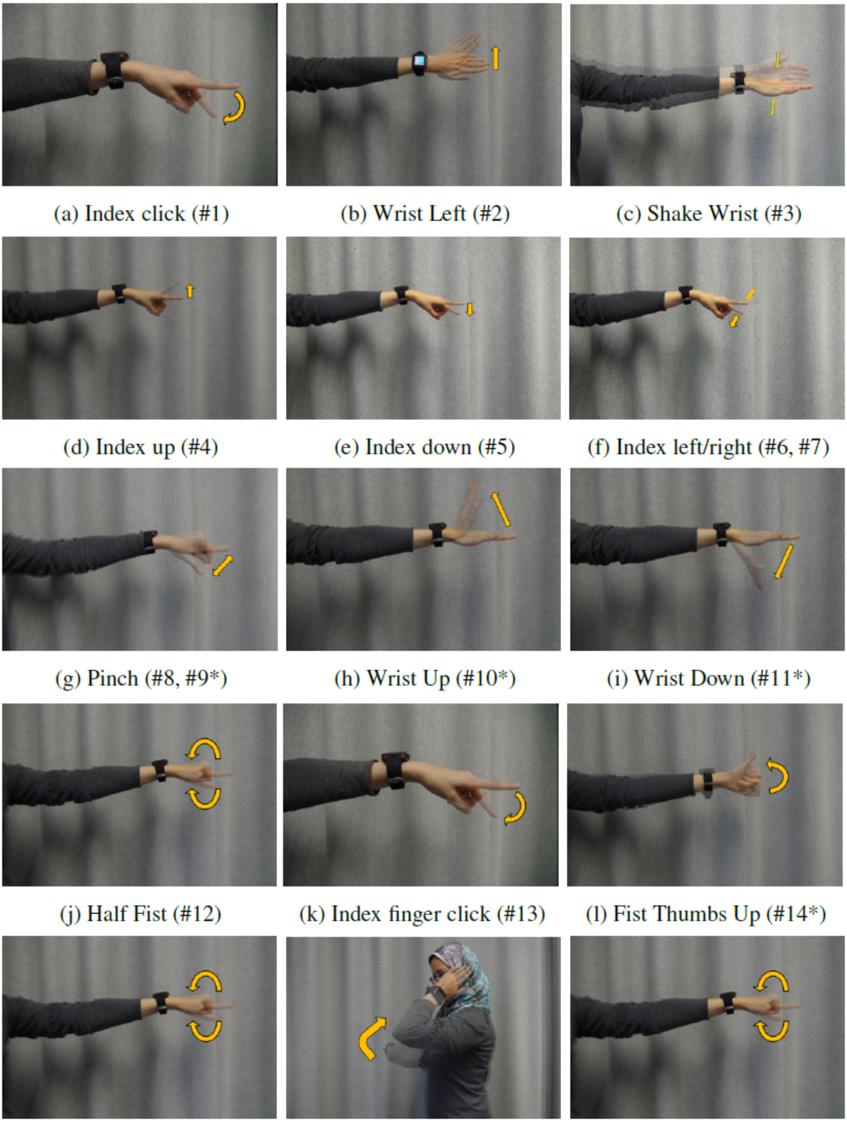
To further evaluate which gestures are most suitable to comprise our final gestures, we use three different measures: user rating, watch content visibility, and social acceptability. In contrast to other formative studies that simply generated a gesture set out of the most frequent gestures that are not duplicated, we focus on these three measures. We did that since we believe that the applicability of the gestures performed on smart watches not only depends on the users' preferences but on each of the three aspects. In the following subsections we describe a second user study to subjectively gather information about the three qualitative measures via a questionnaire.

4.4.1 Participants and Procedure

To collect information about the three subjective measures, we invited 10 users aged between 20 and 31 years ($M = 25.4$, $SD = 2.9$) to take part in our user study. None of these participants took part in the formative study. After participants arrived in the lab, we briefly introduced them to the purpose of the study and explained how we gathered the gestures beforehand. Afterwards, we went through the 17 tasks and explained them the top mentioned gestures. Then, we presented each task to the participant and asked them to rate the three top chosen gestures on a seven point Likert item (1 = totally agree, 7 = totally disagree). Thereby, we presented a statement for each measure to the participant regarding to (1) how they liked the gesture, (2) if they would perform this gestures in public, and (3) how much can they see the content of the watch during the gesture. In contrast to Rico et al. [208], we chose to particularly investigate the social acceptability of performing gestures in public settings. We did that since the public setting is described as the most challenging setting for people performing gestures.

#	Task	Gesture 1			Gesture 2			Gesture 3		
		Rating	Visibility	Social	Rating	Visibility	Social	Rating	Visibility	Social
1	Select	6.0 (1.7)	5.5 (1.8)	7.0 (0.4)	5.0 (1.1)	6.5 (1.8)	7.0 (1.3)	4.0 (1.8)	4.5 (2.0)	5.0 (1.8)
2	Back	6.0 (1.1)	6.5 (1.0)	5.0 (2.1)	4.0 (1.6)	6.5 (2.0)	6.0 (2.6)	4.0 (2.0)	6.0 (0.9)	7.0 (0.7)
3	Home	6.5 (1.7)	5.5 (1.5)	4.5 (2.5)	5.0 (1.6)	5.5 (1.6)	2.5 (2.8)			
4	Move Up	6.0 (1.2)	6.0 (1.3)	7.0 (0.8)	4.5 (2.1)	6.5 (2.3)	5.0 (2.1)	5.5 (1.6)	4.0 (1.7)	5.5 (1.3)
5	Move Down	6.0 (1.8)	6.0 (0.9)	7.0 (0.8)	5.0 (1.9)	5.5 (1.6)	6.5 (2.1)			
6	Move Left	4.5 (2.1)	7.0 (1.1)	7.0 (0.8)	5.0 (2.1)	6.0 (1.7)	7.0 (1.6)	6.0 (2.1)	6.0 (2.5)	5.0 (2.5)
7	Move Right	4.5 (2.2)	7.0 (1.1)	7.0 (0.8)	6.0 (1.8)	6.0 (1.7)	7.0 (1.6)	6.0 (2.1)	3.5 (2.6)	4.0 (2.3)
8	Zoom In	7.0 (0.7)	6.5 (0.8)	7.0 (0.7)	6.0 (0.9)	5.0 (1.3)	7.0 (0.8)	2.5 (1.4)	4.0 (2.2)	5.5 (1.9)
9	Zoom Out	7.0 (1.0)	6.5 (1.2)	7.0 (1.1)	6.0 (0.9)	6.0 (1.1)	7.0 (0.7)	3.0 (1.6)	4.0 (2.3)	5.5 (1.9)
10	Volume Up	5.5 (1.1)	6.5 (1.5)	7.0 (1.0)	6.5 (1.4)	6.5 (1.2)	5.5 (1.3)	6.5 (1.9)	3.0 (2.0)	2.0 (2.6)
11	Volume Down	5.5 (1.1)	6.5 (1.5)	7.0 (0.9)	6.5 (1.4)	6.0 (1.1)	6.0 (1.4)			
12	Mute Audio	3.5 (2.2)	4.0 (2.4)	6.5 (1.9)	4.0 (1.6)	5.5 (1.4)	4.0 (2.1)			
13	Take Picture	3.5 (1.8)	5.0 (1.9)	2.5 (2.4)	4.0 (1.9)	5.5 (2.0)	5.5 (2.1)	6.0 (2.0)	6.5 (1.7)	7.0 (0.7)
14	Record Video	3.5 (1.8)	2.0 (2.4)	2.0 (1.9)	5.0 (1.2)	6.0 (1.3)	7.0 (1.0)			
15	Stop Video	6.0 (0.7)	7.0 (1.1)	7.0 (1.0)	4.0 (1.7)	5.5 (1.5)	3.0 (2.2)	4.0 (1.4)	5.0 (2.1)	3.5 (2.2)
16	Accept Call	7.0 (1.0)	6.0 (2.4)	4.5 (2.6)	3.5 (1.9)	6.0 (1.4)	6.5 (1.4)	4.0 (1.8)	5.0 (2.1)	6.5 (1.8)
17	Decline Call	6.0 (2.0)	6.0 (2.1)	4.5 (1.9)	4.0 (1.6)	5.5 (1.3)	5.5 (2.0)	5.0 (2.2)	6.0 (1.4)	6.5 (0.9)

Table 4.3: Median ratings of the participants for each gesture with regards to how they rated the suitability of the gesture (*Rating*), the visibility of the content is during interaction (*Visibility*), and the social acceptability (*Social*). The standard deviation is shown in brackets.



(a) Index click (#1)
(b) Wrist Left (#2)
(c) Shake Wrist (#3)
(d) Index up (#4)
(e) Index down (#5)
(f) Index left/right (#6, #7)
(g) Pinch (#8, #9*)
(h) Wrist Up (#10*)
(i) Wrist Down (#11*)
(j) Half Fist (#12)
(k) Index finger click (#13)
(l) Fist Thumbs Up (#14*)
(m) Fist (#15)
(n) Hand to Ear (#16)
(o) Form Fist (#17)

Figure 4.4: Final gestures for each of the tasks.

4.4.2 Resulting Gestures

The result of user study is shown in Table 4.3. We chose a single gesture for each of the 17 tasks. These gestures are determined on the basis of Table 4.2, while taking several constraints and the three different measures into account. The first constraint is that, following Wobbrock [273], a gesture should be used for a single task only. Another constraint is defined by opposites: Either both gestures of an opposite pair are included or both are excluded. The final gestures for each task are shown in Figure 4.4.

4.5 Evaluation: Controlling Smart Watch Applications

In the previous section, we derived a consistent set of 17 gestures for abstract tasks. We used abstract tasks to make the gestures applicable for a wide range of potential applications. In this section we investigate the suitability of gesture input for three specific smart watch applications from a technical perspective (i.e., menu navigation, phone call control, and camera application).

4.5.1 Participants and Procedure

We conducted a user study with ten participants aged 25 to 31 years ($M = 26.2$, $SD = 1.8$) to record signal data for each of the gestures determined for the 17 abstract tasks. Again, none of these participants took part in the previous studies. After the participants arrived in the lab, we explained them the purpose of the study and equipped them with the prototype. During the study, we recorded the signals from the capacitive sensors of the watchstrap as well as from the accelerometer and magnetometer built in the smart watch itself to analyze whether these sensors might be sufficient for gesture detection. These signals were sent to a PC for later offline analysis and labeling.

The study consisted of two blocks to reduce sequence effects. In each block participants performed each gesture five times resulting in a total of ten recordings for each gesture. Thereby, we reduced the probability that participants perform a gesture exactly the same and to avoid the effects of potential sensor drifts.

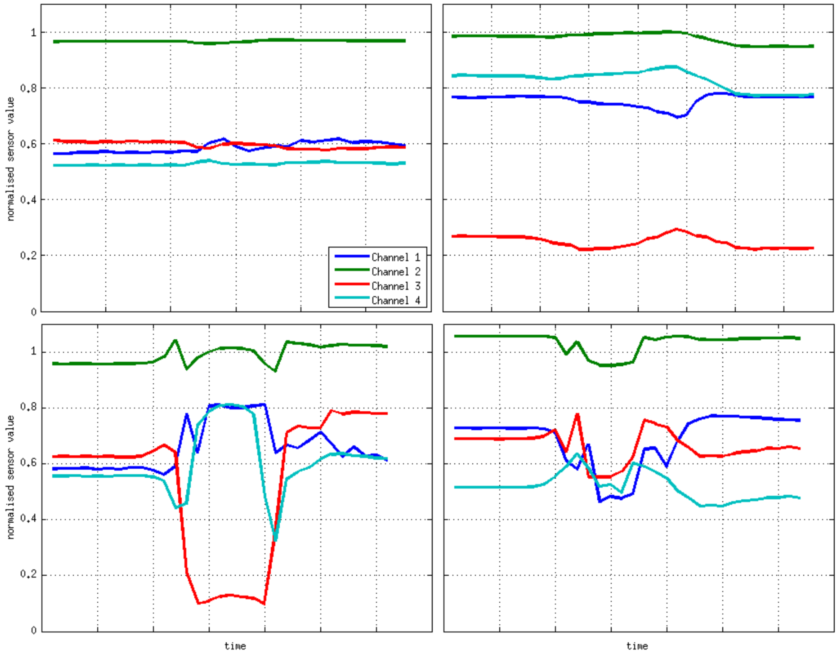


Figure 4.5: Four-channel signals from the capacitive watchstrap performed by P1. Top row: Index finger Down/Up, Bottom row: Wrist Down/Up.

Additionally, we randomized the order of the gesture to further reduce sequence effects and account for learnability.

4.5.2 Data Analysis

For the analysis, we consider the recognition of the gestures as a time-series classification problem, where the goal is to distinguish the different gestures from each other. From each of these gestures, ten samples are available for each of the ten participants. These samples can be regarded as separately labeled segments, a signal from each of the four capacitive sensor channels. Example segments of a four gestures are shown in Figure 4.5. The shown signal patterns correspond to the skin and muscle alignment changes underneath the respective capacitive sensors, while a gesture is performed. From visual inspection of the signals, it is clear that different gestures produce different signal patterns, thus distinguishing them is generally possible. Nevertheless, detecting gestures is a challenge due to (1) signal changes of not all sensor channels are significant and (2) signal changes from the finger gestures are relatively small.

We use the nearest neighbor (NN) algorithm to classify the time-series data [66, 116]. Therefore, we use the 1-NN classifier for the defined gesture classification problem. As distance measure, we use derivative dynamic time warping (DDTW), which generally performs well on small training sets [66, 127]. Since the recorded gesture set is highly subject dependent, we performed 5-fold cross-validation for each of the participants separately and then combined the results. Training was controlled to avoid class skew. Furthermore, we performed the same evaluation procedure, but using the internal sensors of the smart watch (i.e., accelerometer and magnetometer) instead of the capacitive watchstrap. In this case, each gesture segment consists of a six-dimensional signal.

4.5.3 Applications

Input commands can be globally the same for controlling a device, but often commands are defined particularly for certain applications. We have selected three common smart watch applications to exemplary calculate the differentiation accuracy of the corresponding gestures for each of the three applications. To evaluate the elicited gestures and to transfer them into useful contexts, we describe three different use cases that are typically known from using smart watches: *Menu Navigation* and *Phone Call Control* and a *Camera Application*. We calculate for each application the accuracy of the according user-defined gestures using the method described before. An overview of the results of the capacitive sensors and the internal sensors of the smart watch as well as the combination of both are presented in Table 4.4.

Menu Navigation

Smart watch menus are commonly list-based structured. They allow the user to navigate to the *next item* in the list (Table 4.2, #4), to *select* (#1) an item, and to go *back* (#2) to a higher menu level. Thus, three gestures cover the most common commands needed for menu navigation. The accuracy for differentiating these gestures using our approach is 88%.

Application	Capacitive Sensors	Internal Sensors	Combination
Menu Navigation	88%	63%	85%
Phone Call Control	96%	96%	98%
Camera Application	88%	66%	80%

Table 4.4: The three applications and the detectability values using the capacitive sensors, internal smart watch sensors, or a combination of both.

Phone Call Control

Managing incoming phone calls, two different gestures are necessary, namely *accepting calls* (#16) and *declining calls* (#17). The accuracy for differentiating these gestures is 96%.

Camera Application

To control the camera within the smart watch, four gestures are needed. First, the user can *take a picture* (#13). Second, it is necessary to *start* (#14) and to *stop* (#15) video recordings. Additionally, a command to return *back* (#2) within the menu is needed. These gestures can be differentiated with 88% accuracy.

4.6 Discussion

In the course of our investigation it became apparent that one-handed interaction with wrist worn devices is desirable and increases the utility of such devices. In many situations, ranging from carrying bags to cycling, access to information and issuing commands on a smart watch should be possible without requiring the second hand for input. Not using the touch screen requires people to rethink how to input. Similarly to first touch screen the interaction language is new but as the study shows easy to understand. For instance, some of the gestures (e.g., swipe) that were very popular in the study are already known from smartphone interaction. Theses gestures are very successful in touch-based interaction but they do not work well for free-hand interaction in 3D space. Although the gesture itself is detectable, the specific zoom factor would be hardly detectable with the proposed system. When designing a gesture set for a specific application, this needs to be taken into account.

For the machine learning approach, we used basic algorithms. Although these algorithms provided good results, by using more sophisticated algorithms, the detection of the gestures can be increased. In the current prototype, the classification processing was done offline and a data acquisition box was added. In a future version we imagine that the processing is done in real time and that the data acquisition and processing hardware is fully integrated with the watch. The implementation and study show that using capacitive sensing integrated into the strap of a watch is feasible and different gestures can be recognized. The hardware required to implement this sensing modality is minimal and completely unobtrusive. Embedding capacitive pads within the strap will be possible with a broad range of materials such as the one used for the touch-enabled fabric in Chapter 3.

4.7 Lessons Learned

This research probe explored mid-air gestures using garment-based capacitive sensors to detect finger, hand, and arm movement. We gained two major insights from this research probe:

- **Knowledge of placement of the sensors.** Different sensor positions allow sensing different input. While most sensors have their dedicated location, garment-based sensors can be applied at different body positions such as the arm or at the neck. Thus, taking the location of a sensor into account is mandatory to understand what information are measured.
- **Take the context of use into account.** In contrast to the context of other elicitation studies, the presented gesture-based input approach is used in various public settings. When creating a gesture set for garment-based wearable computing devices, different aspects such as social acceptability need to be taken into account.

4.8 Conclusion

In this chapter, we show how garment-based wearable computing devices in form of a textile strap can be used to detect gestures. Since this type of interaction is novel, we explored how we can design gestures so that are usable, socially acceptable, and still allow perceiving content of a smart watch placed at the same arm. Thereby, we developed a consistent set of gestures for 17 tasks commonly performed on smart watches. We first conducted a user-defined gesture study to elicit potential gestures from users. In a next step, we analyzed these gestures with regards to three different factors (i.e., user rating, watch visibility, and social acceptability) in a further user study. We then extracted the preferred gesture for each task based on these measures. We finally show for typical use cases that theses gestures are well differentiable using capacitive sensing and basic algorithms. Overall, capacitive sensing using a fabric based electrode is a promising gesture sensing modality and superior compared to the sensors embedded into current smart watches.

Chapter 5

Physiological Signals

In addition to explicit input using touch and mid-air gestures, smart garments allow realizing different types of implicit input. Due to the closeness of clothing to the user‘s body, sensors integrated into clothing are capable of assessing different physiological signals. Early examples include the Georgia Tech Wearable Motherboard [92] or the MagIC System [65] measuring the user‘s physiological signals such as Electrocardiography (ECG). The ECG can in return be used to assess the user‘s workload [210] or quality of sleep [51]. It has also been demonstrated that other physiological signals can be assessed with smart garments. Examples include SCA [103], respiration rate [184], or a combination integrated in a multipurpose garment [182]. Focusing on the user‘s head, Brain Computer Interfaces (BCIs) are becoming popular in the mass market as well as in HCI. They are using Electroencephalography (EEG) to measure the activity in the user‘s brain. This information is then used, for example, to detect highlights in video clips [215] or to recognize different cognitive activities such as reading and listening to music [241]. While most devices are wearable gadgets, the integration into garment-based headgear will help to increase the usability as well as social acceptability of these devices.

In addition to physiological signals, garments can be used to detect the flexion of the user‘s limbs. Examples include clothing that detect the flexion angle of the arm [242] or leg [177]. This information can then be used in different application scenarios such as measuring the exercises a user performs in a gym [284] or provide feedback on the way users perform football kicks [105]. Summing up the flexion angles of different limbs, insights on the posture of the user can be derived as well. This allows full body tracking of the user.

In this chapter, we focus on sensing physiological signals. We use off-the-shelf sensing gadgets because of the robustness and ease of use in a user study setting compared to textile-based sensors. The presented study takes place in an automotive setting in which the physiological signals could provide insight into the current status of the driver. These measurements could be used to identify high workload situations as well as situations in which the driver is tired and not focused on the driving task. With highly automated driving, the measurement can be used to gain insights into the time the driver will need to take over the vehicle. These application scenarios make the automotive setting perfect for exploring physiological signals.

This chapter is based on the following publications:

- S. Schneegass, B. Pfleging, N. Broy, F. Heinrich, and A. Schmidt. A data set of real world driving to assess driver workload. In *Proceedings of the 5th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, pages 150–157. ACM, 2013[a]

Parts of this chapter are also planned to be published as follows:

- M. Hassib, S. Schneegass, N. Henze, F. Alt, and A. Schmidt. EngageMeter: A System for Implicit Audience Engagement Sensing Using Electroencephalography

[a] Parts of this paper are also included in the PhD thesis of Bastian Pfleging.

5.1 Related Work

Different physiological signals exist that reflect different phenomena in the human body. Due to the closeness to the human body, smart garments have a unique opportunity to assess physiological signals in a natural and implicit way. In HCI, the following physiological signals are mainly used as implicit input for interactive systems.

5.1.1 Electrocardiography

ECG is the process of measuring the electrical signal generated by the heart. The signal frequency lies between 0.05 to 100 Hz with a dynamic range of 1-10 mV [53]. Different values can be derived from this EEG signal. Most prominently, the Heart Rate (HR) and Heart Rate Variability (HRV) can be derived. Research showed strong correlations between these values and user‘s physiological states. For example, HR is a valid method to assess the workload of users [210] whereas HRV is especially important for long-term health monitoring [157].

5.1.2 Skin Conductance Activity

A SCA sensor (also referred to as galvanic skin response (GSR), electrodermal activity (EDA), or skin conductance response (SCR)) measures the sweat gland activity. It is mostly applied to the user‘s hand. Physiological states such as stress and arousal can be measured with such a sensor. Especially gaining insights in the workload of users has been in the focus of HCI research. For example, Michaels [171] showed that the SCA is related to the amount of traffic the driver is facing at the moment. The direct relation to the workload is shown by Collet et al. in an experiment with air traffic controllers [54].

5.1.3 Electroencephalography

EEG signals from the brain can be used for explicit and implicit interaction. While the possibility to code information for explicit interaction is rather low (i.e., only some bytes), research showed that many different information about the user can be assessed using EEG. Scenarios for implicit interaction include neurofeedback applications for giving feedback to the user about their mental state. Other examples for using EEG include, for example, for retaining focus during reading tasks [250] or personalizing computer games by adapting the content and difficulty depending on the player‘s state of mind [279].

Current commercial EEG headsets are low-cost, portable, and wireless. One example of the commercially available EEG headsets is the Neurosky’s Mindwave headset[15]. It provides access to the raw EEG data at 512 Hz which can be used to extract different EEG frequency bands. There are five frequency bands comprising

[15] `http://neurosky.com/biosensors/eeg-sensor/biosensors/`

Band	Frequency (Hz)	Description
Delta (δ)	1-3	Deep sleep, dreamless state
Theta (θ)	4-7	Light sleep, meditation
Alpha (α)	8-13	Deep relaxation, closed eyes, imagination
Beta (β)	14-30	Waking state of consciousness, alertness
Gamma (γ)	30-50	High brain activity, information processing

Table 5.1: Description of the different EEG frequency bands

EEG signals that provide insights into the user's cognitive and mental state (cf., Table 5.1 for a description). Literature has extensively studied EEG frequencies and their relation to cognitive states [26, 89, 146].

5.2 Assessing Users Physiological Signals

In this probe, we focus on an automotive setting to explore assessing physiological signals of a user. While controlling a car, different events influence drivers which is reflected in changes of their physiological signals. We expect these changes to be greater and occur more often compared to interacting with mobile devices while strolling up and down the street.

5.2.1 User Study

The driver's physiological signals are an important indicator to estimate the driver's ability to maneuver a car. Despite the primary task of driving a car, nowadays drivers are engaged in various other tasks. These tasks are not only related to the actual driving task but also comprise secondary and tertiary tasks [87, 130]. While secondary tasks are related to increase the safety of the car, the driver and the environment, tertiary tasks (e.g., using mobile phones) are related to infotainment and communication and are factors that influence the driver's ability to maneuver a car. By using physiological measurements, we are able to understand the current situation of the driver (i.e., the physiological state of the driver). In this study, we are particularly interested in the workload of the driver. Different methods to assess the driver's workload have been explored in the automotive domain. The methods are either subjective (e.g., asking the user) or objective (e.g., measuring the users physiological properties or performance).

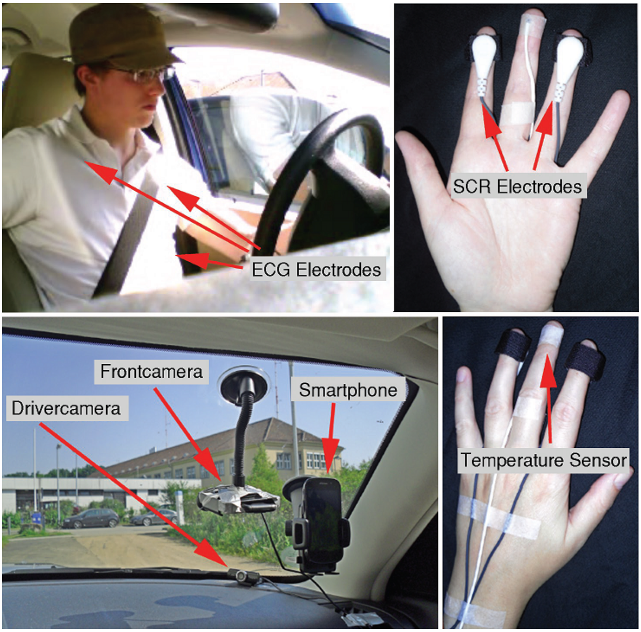


Figure 5.1: Study setup: Two cameras and a smart phone are placed within the car (bottom left). The driver is connected to electrodes measuring the HR (top left). SCA (top right) and BTemp (bottom right) are measured at the drivers left hand.

We record a mixture of subjective (VR – created post-hoc by the participants using video recordings from two perspectives) and objective (SCA, BTemp, and HR – measured during the driving study) measures.

Apparatus

To assess the physiological properties of the user, we used an off-the-shelf Nexus 4 Biofeedback system[16]. We used SCA sensor, BTemp sensor, and an ECG Sensor. The SCA and BTemp sensors were attached to the participant‘s left hand whereas the ECG was attached to the participant‘s chest. The ECG (in μV) is recorded at 1024 Hz and is used to calculate the HR (beats per minute) and HRV at 128 Hz. The SCA (in μS) and BTemp (in degree Celsius) are recorded at 128 Hz, respectively. The Global Positioning System (GPS) position was

[16] www.mindmedia.nl

collected through an Android Smartphone (Google Nexus S) to gain knowledge about the road type. Two webcams (Logitech QuickCam Pro 9000 and Creative VF0610 Live! Cam Socialize HD) were used to record the driving scenario (passenger view onto the road) and a view of the driver as shown in Figure 5.2. As all data sets were recorded with different sampling frequencies, timestamps were used to synchronize all data post-hoc.

Participants and Procedure

In total, ten participants (3 female, 7 male) aged between 23 and 57 years ($M = 35.60$, $SD = 9.06$) took part in this study. We recruited the participants within the employees of our institute to be covered by insurance. All of them owned a valid driver's license and brought their own car which was used during the study. The participant and the participant's car were first equipped with the different sensors by a researcher. Then, the participant was instructed to drive a specific route (cf., Figure 5.3) with the researcher guiding them by simple voice commands (e.g., "on the next intersection: please turn left") from the backseat. After returning from the drive, the participant was guided to our lab and directly performed a *video rating*, evaluating the perceived workload from high to low using a slider. The video shown was a side by side composition of the video recorded while driving (cf., Figure 5.2).

Route

The selected route for our study has a total length of 23.6 km and consists of various road types (cf., Figure 5.3). For the evaluation of our study, we classified five different road types: 30 km/h zone, 50 km/h zone, highway, freeway, and tunnel. The *tunnel* in general is an ordinary road. However, we chose to add it as a special road type, because of the special conditions that may influence the driver (e.g., lighting). Furthermore, we defined different points of interest: 2x on-ramp, 2x freeway exits, 2x roundabouts, 20x traffic lights, and 2x curvy roads. Due to the fact that we conducted a real world driving study, we cannot control the environment (e.g., traffic, weather). However, we strove for a consistent setting among all participants: none of the participant drove during rush hours and the study was only conducted during daylight.

Data Preparation

Before evaluating the recorded data, it needs to be prepared to remove noise effects as well as to normalize the physiological properties of each participant.

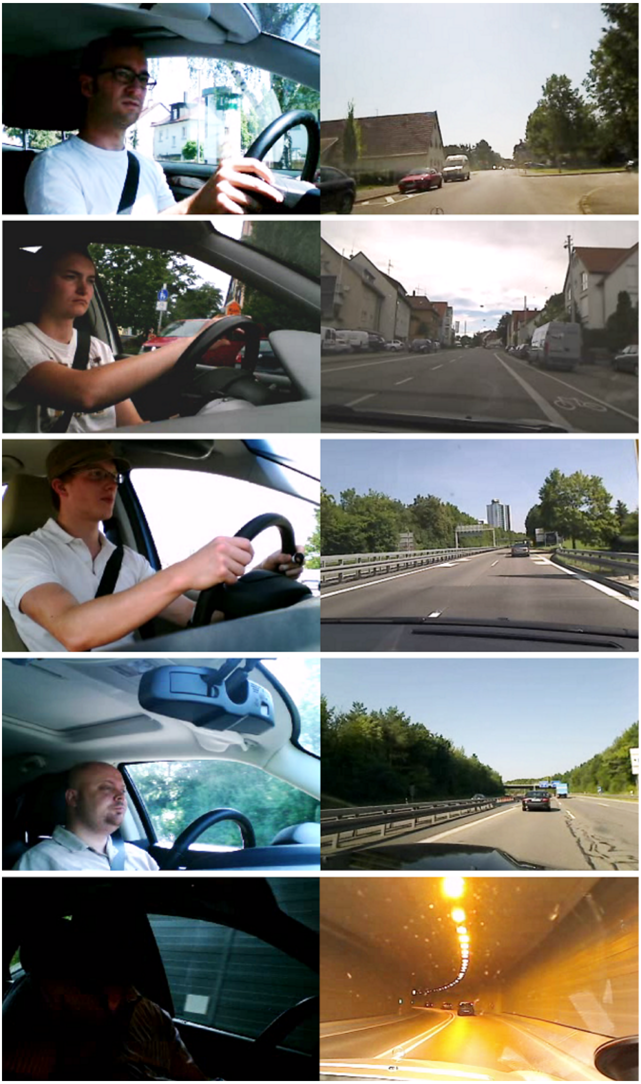


Figure 5.2: The five different road types: 30 km/h zone, 50 km/h zone, highway, freeway, and tunnel. The view of the driver camera is shown on the left side and the front view on the right side. This side by side composition video was shown to the participant during the video rating session.

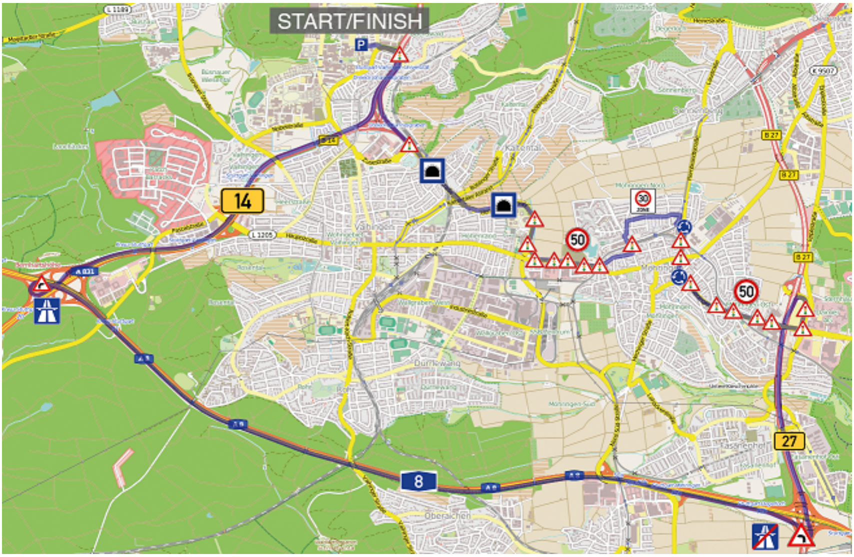


Figure 5.3: Map of the route each participant drove during the study. Each type of road is marked accordingly (A8: freeway, B14/B27: highway, ordinary streets (50 km/h), 30 km/h zone. All points of interest (freeway on-ramp/exit, roundabout, traffic lights, roundabouts, tunnel entry/exit) are shown with the respective symbols. Map ©OpenStreetMap contributors, tiles CC-BY-SA 2.0.

We sampled the data up to one sample per second. We normalized the biosignals as well as the VR results to achieve comparable values between all participants in the range of 0 to 1.

5.2.2 Results

In the following we present the results of the study. We focus on two biosignals (SCA and BTemp as suggested by related work (cf., [171, 172])) and the results of the VR. In particular, we investigate how the physiological signals and subjective VR correlate. Additionally, we explore how the type of road or POI influences the physiological signals and subjective feedback of the user.

Figure 5.4: A participant is performing the video rating task.

Comparing Subjective and Objective Workload Data

We compared the measured physiological properties (SCA and BTemp) with the video rating (VR). First, we compared the subjective measurement (VR - cf. Figure 5.4) with the objective measurements (SCA and BTemp). For this, we conducted correlational research using Pearson‘s correlation coefficient. The SCA and VR, $r(17725) = .202$, $p < .001$, as well as the BTemp and VR, $r(17725) = .128$, $p < .001$, are positively correlated. The correlations are both statistically significant; however, the effect size is small.

Evaluating all participants individually, we see a high variability in the correlational patterns across participants. For instance, the data of participant # 10 shows high correlation for VR with SCA, $r(1903) = .689$, $p < .001$, and VR with BTemp, $r(1903) = .449$, $p < .001$ (cf., Figure 5.5). In contrast, the data of participant # 6 shows a significant correlation for VR with BTemp, $r(1710) = .072$, $p < .01$, but we could not show statistical significant relationship between VR and SCA, $r(1710) = .043$, $p = .078$. This variability needs to be taken into account when using physiological signals of users in an automotive but also in a mobile setting.

Impact of Road Types

Next, we evaluated the differences between the five road types. Since the measurements highly depend on each other and the different road types are not equally

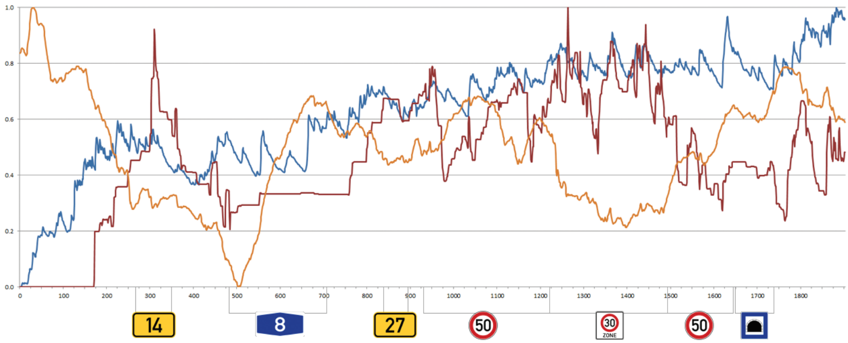


Figure 5.5: The Graph shows the normalized SCA (blue), normalized BTemp (orange), and the normalized result from the VR (red) of a single user (User #10).

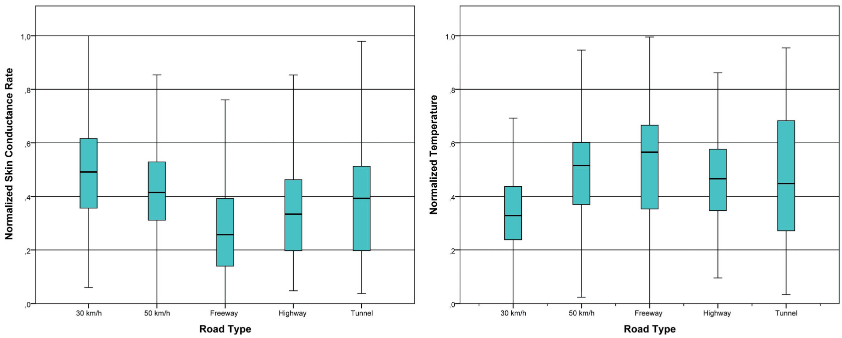


Figure 5.6: Boxplots for SCA and BTemp for each of the five road types.

distributed within our sample (cf., Figure 5.5), we chose to use the mean values of each participant on each type of road. In doing so, we eliminated most of the dependencies in the data and create an equal distribution.

The results show that the physiological data (SCA and BTemp) is influenced by the road type. The variability in the data is high (cf., Figure 5.6), which indicates that all types of roads have situations in which the workload is high. We used a repeated measures Analysis of Variance (ANOVA) to investigate statistically significant differences. A Shapiro-Wilk test shows for all cases that the assumption of normal distribution is not violated.

Road Type	M_{SCR}	SD_{SCR}	M_{BTemp}	SD_{BTemp}
30 km/h zone	.482	.178	.357	.152
50 km/h zone	.423	.152	.484	.137
Highway	.343	.110	.487	.156
Freeway	.271	.121	.522	.155
Tunnel	.394	.223	.468	.266

Table 5.2: Overview of the mean and standard deviation of the normalized skin SCA and BTemp on the different road types.

Skin Conductance Activity The SCA is lowest for the freeway and highest for the 30 km/h zone (cf., Table 5.2). Mauchly‘s test indicates that the assumption of sphericity had been violated, $\chi^2(9) = 17.890$, $p = .041$. Therefore, degrees of freedom were corrected using Greenhouse-Geisser estimation of sphericity, $\varepsilon = .529$. The ANOVA reveals statistically significant differences between the five road types, $F(2.116, 19.042) = 6.756$, $p < .05$, $\eta^2 = .429$. A Least Significant Difference (LSD) post-hoc test reveals a statistically difference for all pair-wise comparisons, $p < .05$, except for the comparisons of Tunnel with 50 km/h zone, $p < .438$, and highway, $p < .439$. This can be explained by the fact that the Tunnel in our route is at a highway with a speed limit (50 km/h).

Body Temperature The BTemp is lowest for the 30 km/h and highest for the freeway (cf., Table 5.2) indicating that the workload is highest for the 30 km/h zone and lowest for the freeway. Again, Mauchly‘s test indicated that the assumption of sphericity had been violated, $\chi^2(9) = 27.069$, $p = .002$. Therefore, degrees of freedom were corrected using Greenhouse-Geisser estimation of sphericity, $\varepsilon = .357$. After the correction, the ANOVA does not reveal statistically significant differences within the road types $F(1.427, 12.842) = 1.305$, $p = .292$, $\eta^2 = .127$.

Video Rating In the VR session, the participant rated the highway lowest and the 30 km/h zone highest (cf., Table 5.2). The assumption of sphericity had been violated, shown by Mauchly‘s test of sphericity, $\chi^2(9) = 20.589$, $p = .017$. Thus, degrees of freedom were corrected using Greenhouse-Geisser estimation of sphericity, $\varepsilon = .601$. Between the road types, the ANOVA does not reveal any statistically significant difference, $F(2.405, 21.647) = 1.249$, $p = .312$, $\eta^2 = .122$. Again, the largest difference is between the 30 km/h zone and the other road types.

Points of Interest

We identified five different categories of POI: on-ramps, exits, roundabouts, traffic lights, and very curvy road segments. In this evaluation we focus on the freeway on-ramp and exit. Hence, we compare the SCA, BTemp, and VR at these POI with the average of the freeway by using a series of t tests.

The SCA increases at two POI (on-ramp: $M = .409$, $SD = .095$; exit: $M = .328$, $SD = .152$) compared to the average of the freeway ($M = .271$, $SD = .122$). A repeated-measures t test shows that the difference between on-ramp and freeway average is statistically significant, $t(9) = -3.546$, $p < .05$. However, we could not show a statistically significant difference between exit and freeway, $t(9) = -1.624$, $p > .05$.

Investigating the BTemp, we see a reduced BTemp on the on-ramp ($M = .437$, $SD = .210$) compared to the average of the freeway ($M = .522$, $SD = .155$) but an increased BTemp on the freeway‘s exit ($M = .561$, $SD = .145$). A dependent t test could not show statistically significant differences comparing the average freeway‘s BTemp with on-ramp, $t(9) = 1.668$, $p > .05$, and exits, $t(9) = -1.176$, $p > .05$.

5.2.3 Discussion

Interpreting the physiological signals, the road type has an influence on the driver‘s workload. The workload seems to be high especially in the 30 km/h zone (low BTemp and high SCA and VR) that contains spots in which the driver has to decide who has the right of way. This may, in turn, increase the workload. Furthermore, there are many parked cars that are potentially sources for unexpected events such as pedestrians crossing the street, playing children, or car doors that are carelessly opened. In contrast, the freeway (high BTemp and low SCA) is very predictable and does not need that much attention due to larger distances between the cars. These results are similar to the results from Micheals et al. [171] as well as from Mittelmann and Wolff [172].

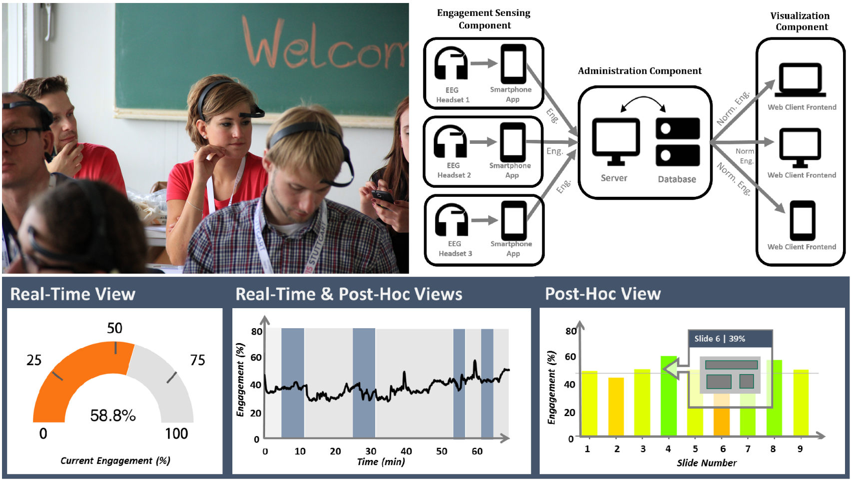


Figure 5.7: Implicit audience sensing: Participants during an initial user study wearing an off-the-shelf BCI connected to their mobile phone (top left) and the overall system architecture with sensing, administration, and visualization component (top right). Three different visualizations for analyzing the audience engagement in real time and post-hoc (bottom). The post-hoc view enables fine-grained analysis of each presented slide.

5.3 Application Scenarios

Physiological signals as a source of implicit input enable various applications. In this section, we briefly introduce two different application scenarios in which physiological signals support users in interacting with mobile systems.

5.3.1 Implicit Audience Sensing

Obtaining information on an audience's physiological and cognitive state is valuable for many applications, including but not limited to recommendation systems [258], teaching and education [67], marketing and businesses [86], and media and performance arts [205]. Active and explicit audience feedback techniques have long existed. Voting systems, for example, are used during live performances, movie screenings, product advertisements, or lectures to gather feedback [13, 38, 45, 186, 255]. While these methods have their virtues and are straight forward to interpret, they create challenges. Clickers and other types of real-time feedback usually add effort and workload to the person providing feedback [124, 259]. Other forms of subjective and explicit feedback are usually collected at the end of the performance, advertisement or lecture, depending on the context. While this provides a holistic overview, these methods miss out on important fine-grained feedback [145].

As physiological signals can be assessed with smart garments, there is an opportunity of employing such sensors to implicitly sense physiological and cognitive properties of the audience. Prominent research in the past few years already started exploring implicit sensing for audience response systems in performance arts [145, 244] and in one-on-one context in learning [250, 251]. The mobile device of the user can connect to a central server and can implicitly provide insights on the physiological and cognitive state by measuring physiological signals. Since this can be realized in real time, it is possible to react to the audience and adapt the performance or lecture. We started exploring this concept in a real world user study using BCIs (cf., Figure 5.7). We equipped participants with off-the-shelf BCIs which send their measured engagement score via the participants‘ mobile phone to a central entity. The presenter can access this information during the presentation and afterwards. Thus, he or she is capable of reacting to changes in the engagement of the participants in-situ and analyze the presentation afterwards.

5.3.2 Adaptive In-Car User Interfaces

Mobile devices play a central role in nowadays cars. The mobile device is used for placing phone calls, stream the user‘s favorite music, or access the calender. However, while driving the car, interacting with the interface – even though using hardware controls provided by the car – is challenging and potentially dangerous. This is especially the case when the driver‘s workload is high due to bad weather and lighting condition or high traffic. Using smart garments to asses physiological signals of the user can help identify these situations and adapt the interface in a way that the driver can safely operate the mobile device. Hence, an interface with a reduced complexity would be easier and more safe to operate. For instance, a workload adaptive navigation system could be easier to operate in high-workload conditions. A system that uses different settings for the driver assistance systems can react to the different workload and increase its involvement in the driving task (e.g., pre-load the brake pressure). Another benefit of sensing physiological signals with smart garments is to make the driver aware of his or her workload. This could be done using on-body displays [231] or haptic feedback [195].

5.4 Lessons Learned

Using physiological signals poses a number of different challenges. In particular, we gained two insights from this research probe.

- **Allow individual calibration of physiological signals.** During the evaluation of the user study it became apparent that the physiological response differed considerably between users'. A system managing these signals needs to allow the user calibrating the values or – if possible – automatically calibrate.
- **Provide derivations of the physiological properties.** Access to the raw physiological signals (i.e., ECG, EEG) is useful for experts in the field of physiological signals. However, most application developers of mobile applications do not have the expertise to derive meaningful information from these values (e.g., workload or stress). Using abstract levels for physiological signals (i.e., high HR, low SCA) helps application developers to interpret the user‘s physiological signals.

5.5 Conclusion

In this chapter, we present our work on exploring physiological signals. Physiological signals are one of the core features of many research prototypes in the field of smart garments. However, interpreting and using this data beyond applications for reflection (e.g., quantified self) remains still challenging. Especially using these signals as implicit input for interactive systems is not fully understood yet. We conducted a user study with off-the-shelf sensors and explore requirements this particular type of data poses. In addition, we describe two application scenarios in which physiological signals can enrich the interaction with mobile devices.

III

Research Probes: Garments for Output

OUTLINE

In contrast to using garments for input, this part of the thesis investigates garments as output modalities. For exploring the output possibilities, we use the three most common output techniques for wearable computers, namely, visual, tactile, and auditory output. Each output is, again, explored by creating a prototype, an application, and an evaluation. However, since textile based actuators still have technical drawbacks, we substitute them with their non-textile counterparts to achieve a stable and robust prototype. We nevertheless take constraints of garments into account when developing the non-textile output devices. By doing so, we are able to evaluate the prototypes in user studies gaining more insights into what requirements these output modalities have.

This part includes the following three chapters:

- **Chapter 6 – Visual Output.** Visual output is the most common output modality. In contrast to mobile devices such as smartphones and smartwatches, garments have a way bigger surface. Even though the resolution of current garment-based displays is low, garment based displays can be used to extend displays and present additional information such as off-screen content or notification. In this chapter, we explore different locations for garment based displays and present a user study in which we use a display to extend a display of a smartwatch. As an application example, we use off-screen locations of a navigational system and compare our approach with on-display off-screen visualizations.
- **Chapter 7 – Auditory Authentication.** Auditory output is normally used to provide feedback to the user which is well explored and understood. By integrating speakers into hats or caps, smart garments can gain the opportunity to present auditory output. In addition to presenting feedback, we use auditory output to authenticate and identify users by using bone-conduction audio. While playing an audio signal, we record the same signal

that is influenced by the user´s head. In a user study, we show the general feasibility of this approach.

- **Chapter 8 – Haptic Output.** Since smart garments are closely connected to the user's body, tactile output can be generated on almost arbitrary locations on the body. EMS is a promising way of realizing tactile output for smart garments. In addition to creating feedback, EMS allows actuating muscles as well. In this chapter, we present a user study that actuates users in a way that they automatically perform gestures. We investigate how these gestures can be used to represent emotions. Furthermore, we present application scenarios that underline the variability of EMS as haptic feedback.

Chapter 6

Visual Output

Visual output is the most common output form for current mobile devices. Mostly rectangular pixel based displays are used to provide output such as in mobile phones or smart watches. These devices, however, have a limited screen size and may not always be visible to the user. In this research probe, we develop a prototype incorporating visual output for a potential garment-based on-body display. Even though early research prototypes of garment based displays exist, we used a wearable display made out of light emitting diodes (LEDs). We chose LEDs since they have similar properties as current textile based displays with regards to display resolution and size [12]. In particular, we focus on the interplay of high resolution wearable displays (i.e., smart watches) and low resolution textile displays. We see an opportunity here for fusing both types of displays to create what has been previously coined *focus and context screens* [22]. In 2001, Baudisch et al. presented an approach that allowed the display space of a high-resolution Liquid Crystal Display (LCD) screen to be extended with a low-resolution projection while at the same time maintaining the context. Similarly, low-resolution on-body displays can extend the visual output capabilities of a high-resolution smart watch or smart phone. In this way it does not only become possible to show additional, contextual information – for example, the location of a hotel a user is currently navigating to but whose position is currently off the smart watch screen – but also to first draw the attention towards the on-body display and then allow more fine-grained information to be accessed through the smart watch – for example, showing a heart rate curve on the on-body display and providing detailed physiological data as the user is out running.

Figure 6.1: The wearable on-body display used in a t-shirt. The heart rate visualized on the chest (left) and a progress bar, weather information, and e-mail notification on the forearm (right).

In the remainder of this chapter, we first present the wearable display research probe. For this probe we used an off-the-shelf LED matrix display. In the future, these displays can be exchanged with textile based displays offering similar properties (cf., [12, 189]) We report on the design space and implementation of this probe. Thereby, we use a navigational application scenario in which off-screen content is displayed at the wearable display. In a lab study, we show that the display is able to increase users' performance as they interact with the display compared to current off-screen visualization techniques.

This chapter is based on the following publication:

- S. Schneegass, S. Ogando, and F. Alt. Using On-Body Displays for Extending the Output of Wearable Devices. *Proceedings of The International Symposium on Pervasive Displays - PerDis '16*, 2016

6.1 Related Work

Our work draws from several strands of prior research, most notably, on-body display technologies, focus and context screens, and wearable display applications.

6.1.1 On-body Display Technologies

On-body displays can be realized using various technologies. To allow displays to be worn on the body, there is an inherent need to design them flexibly so as to fit the user's physiology.

Single (small-sized) displays can be easily attached to different parts of the human body. Examples for such displays are smartwatches or displays in the form of a brooch [30, 74]. Furthermore, larger displays that would have otherwise been difficult to attach to the body directly have been integrated with backpacks [4] and handbags [55].

Building larger on-body displays is challenging, since their form needs to fit the user's body shape. On one hand, displays can be explicitly manufactured so as to *fit a particular body part*. For example, von Zadow built a prototype of a display in the form of a sleeve [266]. On the other hand, a more flexible approach is to create displays consisting of a *matrix of smaller displays*. The small displays in such a matrix can consists of small but high-resolution displays themselves [180]. Or, to add further flexibility, they can consist of small pixels (e.g., single LEDs).

Furthermore, on-body displays can be directly *integrated with fabric*. Solutions include optical fibres to create *light-emitting fabric*[17]. Combining this technology with a controlling unit, Koncar used such fibers to create a display jacket [136]. Another approach is using electroluminescence which can be printed in a matrix design to realize a multifunction display or in custom shaped segments [179, 189]. Besides the application on paper and other stiff material, it can also be printed onto fabrics [12] or woven into fabrics [90].

Finally, on-body displays can be realized using *projection*. Harrison et al. suggest using projections to augment the human skin with visual output [100]. Similarly, Freeman et al. projected cues on the user's hand to support learning gestures [80]. Following this idea, Olberding et al. presented applications and interaction possibilities for augmented skin, focusing on the forearm [180].

[17] http://www.lumigram.com/

In our work we focus on fabric-based displays which can be in the future integrated into everyday clothing. However, due to technical limitations of current displays (e.g., resolution, color), we use low-resolution LED displays as a prototype, simulating fabric-based displays that could be integrated into clothing in the near future.

6.1.2 Wearable Display Applications

Wearable and on-body displays have been used for a variety of applications. Meme Tags were among the first digital wearable public displays. Worn around the neck, they allowed 64 character messages (memes) to be shown to the public [30]. Since the meme tags did not have any input capabilities, messages were authored by means of a kiosk system that then pushed the messages to the tags. One year later, BubbleBadge was a wearable display in the form of a brooch [74]. Based on a GameBoy, it allowed notifications and quotes to be presented to the public. Ten years later, Alt et al. presented the concept of a contextual, mobile display integrated with the user's clothes which was capable of displaying information based on the users' context, such as location [4]. In this way it was possible to, for example, provide information about a nearby sight. SleeD was a wearable display designed as an interaction device for large interactive screens [266]. In particular, it allowed interaction to be personalized as multiple people interact. Finally, Colley et al. presented a wearable display in the form of a handbag allowing users to observe the content of the bag [55].

While in previous work most applications were developed with a particular task in mind, the aim of our work is to provide a wearable display that is capable of supporting various tasks. Furthermore, we use it to enlarge the display real-estate of small high-resolution displays, such as smart watches.

6.1.3 Focus and Context Screens

Dealing with limited screen real-estate when it comes to displaying information has been at the focus of InfoVis research since its inception. We believe this so-called presentation problem to be an immanent challenge for the design of wearable displays. Prior approaches employed in desktop and mobile applications include zoomable user interfaces [24, 190] as well as overview and detail interfaces [114]. However, it is often important to maintain the context of a visualization. A popular solution to this is the use of Fisheye views [85]. However,

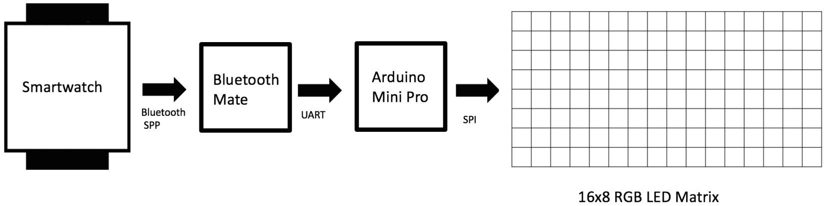


Figure 6.2: The components used for the Wearable Display research probe.

this form of a visualization that maintains the context infers distortion which we believe to be a major challenge for small (wearable) displays, in particular if presenting text.

Hence, we employ the concept of focus and context screens introduced in 2001 [22]. At that time, the concept aimed to address a similar challenge as today's wearable displays: on one hand, small high-resolution displays were available (LCD screens) which could be complemented with large, but lower-resolution projections. Applying this concept to wearable displays seems reasonable, since as of today, both small high-resolution displays are available in the form of smart watches whereas display technology integrated with fabric is still low-resolution but can considerably extend the available display space and be used for contextual information.

6.2 Hardware Prototype: WearableDisplay

We created an on-body display prototype, called *WearableDisplay*, using two 8×8 multicolor LED matrices (cf., Figure 6.2). We deliberately chose a display with a low resolution since we strive to explore garment-based displays which will at the beginning have a lower resolution. Both LED displays are attached to an Arduino[18] that is connected via Bluetooth to a smart watch. The smart watch used for the implementation is a Simvalley Mobile AW-414 smart watch with a 240×240 px, 1.5 in touch screen running Android. The content of the display is controlled via an Android application that defines the color of each LED and sends the values to the Arduino.

[18] `https://www.arduino.cc/`

6.3 Design Space for On-Body Displays

In the following we present a design space for on-body displays. The design space is centered around four dimensions – user, context & application, interaction, and technology. This design space is useful for designers of applications for on-body displays.

6.3.1 User

On-body displays allow the content to be targeted towards the wearer or towards third persons. While we envision – similar to the smart phone – most applications to be targeted towards use by the wearer (e.g., notifications or a navigation app), interesting use cases may be created by presenting information to others. As an example, at work, colleagues may be informed that the wearer is currently deeply engaged in a task, leading to that an inquiry is postponed. There may also be cases where content is targeted towards both the wearer and bystanders (i.e., joint use), for example a multi-player game where the on-body display serves as a shared game board. As a result, designers need to consider the following dimensions:

Observer People observing the display may be the wearer himself or third persons, such as passersby, or both. As a result, designers need to think where to place a display and whether there needs to be a mirror feature (i.e., wearers might want to see what is being displayed on their back).

Content Origin The displayed content can either be generated by the wearer or the observer. For many use cases, the wearer and the observer are the same person. However, for some use cases, the wearer could create content for the observer. One example would be visualizing physiological parameters of the wearer so that the observer could take them into account (e.g., stress level).

6.3.2 Context & Application

Wearable displays enable a myriad of applications that can be used in a variety of contexts, such as at home, at work, during commuting, or while being in a public space. Of particular interest for the designers of applications is whether or not on-body displays extend existing applications or are self-contained. In addition, privacy considerations may need to be taken into account, i.e., whether content should be only perceivable by the wearer or also by bystanders.

Application Purpose Apps for wearable displays may be manifold. Examples include, but are not limited to *navigation*, *quantified self*, *notifications*, and *entertainment*.

Extension of Application In cases where on-body displays are being used together with smart watches or phones, designers need to think about how existing applications can be extended, using the on-body display. *Direct* extension, for example, includes showing content that does not fit on the smart device screen, such as off-screen locations in a navigational task or additional information on a played music track. In contrast, *indirect* extension includes presenting notification (e.g., for messages or calendar) or physiological data (e.g., pulse).

Privacy Applications may be private, personal, or public. *Private* applications may provide access to sensitive data (e.g., the user's current account balance or a Transaction Authentication Number (TAN) the user is supposed to enter at an Automated Teller Machine (ATM)). Such information should be shown in a way such that passersby cannot easily shoulder-surf it. In *personal* applications, for example, information that is relevant for people who know each other may be shown. For instance, two people may want to exchange an address. In this case, a display application should account for that information is visible to a close bystander while not being visible from afar. Finally, *public* applications show primarily content that is meant for a wider audience or for which it is uncritical if perceived by bystanders. Such information can include advertisements, current time, or news headlines.

6.3.3 Interaction

The third dimension concerns interaction with the wearable display: input modality, output, and flow of interaction.

Input Modality Different input modalities can be supported by an on-body display [176]. This may include *touch input* (e.g., directly on the display or on a connected mobile phone or smart watch), *gesture-based input* (e.g., gestures performed in front of the body, recognized through a camera integrated with the users' glasses), *gaze input* (e.g., using a camera / eye tracker integrated with glasses), or *speech* (e.g., using a microphone integrated into clothing).

Feedback Today, displays mainly provide visual feedback to users. Yet, there is also research on displays using other modalities such as *haptic*, *auditory*, or even *olfactory*.

Flow of Interaction Wearable focus and context displays enable two different ways of how interaction can flow. On one hand there may be a flow of the interaction *from the focus display to the context display*. This is the case if interaction starts at the smart device (e.g., entering a location a user wants to navigate to) and then extends to the context display (for example, showing information on the distance and direction of the nearest subway station). In other cases, interaction may flow *from the context display to the focus display*. The user might receive abstract information on heart rate on the context display while running but then at some point decide to look up additional, more specific information on time and distance covered.

6.3.4 Technology

Finally, the available / employed technology needs to be considered when creating on-body display applications.

Size We expect future on-body display to come in arbitrary sizes. While primarily being limited by the available garment surface, future research on-body displays may seek to extend the available space through projection (e.g., on the part of the floor the user is standing on).

Shape On-body displays can be manufactured in many different shapes, matching the intended body location and/or screen real-estate required by the application.

Orientation Based on whom the content is being targeted to, the orientation of the display needs to be taken into account. Whereas for the wearer the display should be oriented in a way such that content can be optimally perceived, the direction from which third persons are approaching is often not clear and hence orientation would need to be flexible. In this case, application designers may also need to take into account that the user is moving and hence update the orientation dynamically.

Position on Body In case only parts of the body serve as a display, designers need to consider different aspects: who are the users, how many users need to be supported, how do they interact, and from where do they see the display.

Display Technology Current on-body displays need to make a trade-off between wearability [88] and spatial, temporal, and color resolution. While displays completely fabricated using garments have a low resolution, flexible Organic Light Emitting Diodes (OLEDs) achieve similar performance as smart phone screens but with reduced flexibility and, thus, reduced wearability. Again the application for which such a display is used is important. Simple notification for a single purpose are easily realizable with garment based displays but more complex User Interfaces (UIs) would currently require flexible OLEDs.

Display Factors Finally, display properties may be chosen based on the intended use case. Properties may include *color depth*, *brightness*, and *resolution*.

6.4 Exploring Location and Visualizations

In the first study, we explored at which location potential users prefer on-body displays for either personal or public usage. In addition, we explored different visualizations for each of the application scenarios.

6.4.1 Participants and Procedure

We invited 16 participants (3 female, 13 male) between 20–31 years ($M = 23.6$, $SD = 2.9$) via university mailing lists. After participants arrived at the lab, we first introduced them to the purpose of the study. We showed them our physical prototype of an on-body display. To make the idea of an on-body display more tangible to participants, we presented 6 different application scenarios. These scenarios were developed through a review of available products in the filed of wearable computing and current smart watch applications. Each of them can utilize the on-body display as an additional context display.

Heart Rate Physiological measures are becoming more and more important and the number of wearable devices capable of measuring them is increasing.

While the sensing part can be easily integrated into clothing, the communication of the measured information is mainly done via smart phones. Using an on-body display, this information is instantly accessible for the user.

Step counter Fitness bracelets allow the steps made by the user to be measured. However, most of the time, output is limited due to the small device size. Exploiting a larger on-body display, users can easily keep track of their steps.

Message notifications The number of notifications being generated on mobile phones is steadily increasing. Utilizing on-body displays helps to quickly and unobtrusively notifying users of incoming messages.

Navigation Providing navigational cues to the user becomes more an more common due to navigational systems being available on smart phones. However, carrying the phone in the hand while walking can be cumbersome and, thus, an on-body display can help presenting necessary navigational information.

Calendar On-body displays allow proving instant access to the calendar by showing the next appointment, the time till it starts, or the location.

Weather As an example of simple, static information, we chose weather information.

The application scenarios were presented in counter-balanced order (Latin square). For each of the scenarios, participants were given two tasks. First, we wanted them to think about the perfect location of the display on the body given a particular task. Therefore, participants were asked to mark the position on a print-out of a human body (cf., Figure 6.3). In addition, we asked them to sketch a visualization for the output on the wearable display (cf., Appendix VII – Questionnaire).

6.4.2 Results

Location Preferences

We identified 6 different options to place the display: forearm, upper arm, torso, head, legs, feet. Overall participants preferred placing the display on the forearm when used by themselves (68.8%) and torso when used by others (67.8%). The main reason for this might be the display size which can be perceived from a

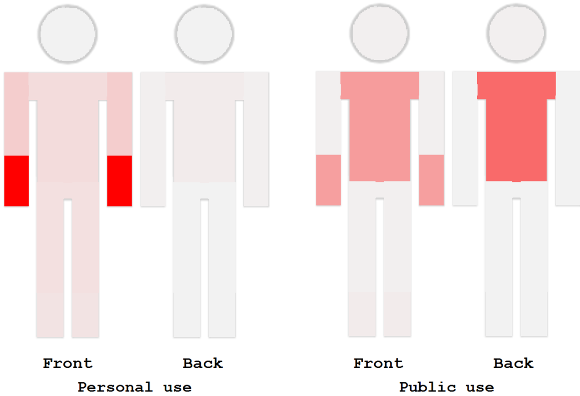


Figure 6.3: Heatmaps of the location preferences of the participants in the first study when the display is showing content for the wearer (left) and public (right).

greater distance on the torso compared to small displays on the forearm. While most participants naturally located the display on the front of the user for personal use, the front (57.0%) and back (43.0%) was evenly chosen for public usage. An overview of the chosen locations is depicted in Figure 6.3.

Participants also expressed the need for a mapping between content and location. For instance, two participant would display the heart rate next to the actual position of the heart at the torso. Similarly, placing measurements from fitness applications such as the number of steps made today directly at the feet or legs supports an easy and intuitive understanding of the information.

Visualizations

Participants envisioned various visualizations for the proposed use cases. Most visualizations are adopted from current visualizations known from smart phone applications to the requirements of the on-body display. For example, many participants depicted arrows for the navigational scenario or a mail icon for incoming email notifications. Examples of the drawn visualizations are shown in Figure 6.4.

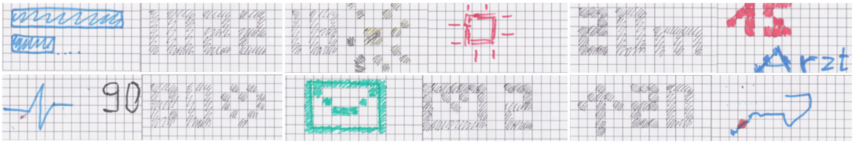


Figure 6.4: Two of the visualizations for each application scenario drawn by the participants in the first study. Top row: step count, weather, and calendar – bottom row: heart rate, notification, and navigation.

6.5 Use Case: Navigation

As a next step, we decided to implement a particular application – a navigation application – and explore how it could be adapted to our wearable focus and context display. Both the focus display (smart watch) as well as the context display were placed next to each other. The map is shown on the smart watch. Presenting off-screen objects such as POIs is a common challenge when designing navigational systems. Research explored different ways of visualizing this. Most prominently, Baudisch and Rosenholtz present *Halo* [23]. Halo surrounds off-screen objects with large enough rings to reach the border of the display view port. Thus, the user can infer the location of the off-screen object by estimating the center of the ring. Burigat et al. compared Halos to Arrows [39]. They show that arrows perform similar compared to Halos. Furthermore, their results suggest that Halos perform better the less off-screen objects are presented. We believe that on-body displays have the potential to present off-screen elements in a more natural way and communicate the distance and direction to an object simply by showing it accordingly on the display. In a user study, we compared all three visualizations with respect to the task completion time, errors, usability, and user preferences.

6.5.1 Prototype

We used our display prototype and created an Android navigational application based on Google Maps. The application is capable of displaying a map on the smart watch and the off-screen points of interest on the on-body display. We included in total 4 different maps with 10 different locations each. None of the location was known to the persons beforehand. As a baseline in our user study, we re-implemented two techniques: halos (following the explanation of Baudisch and Rosenholtz [23] – Figure 6.5, left) and arrows (as used by Burigat et al. [39] –

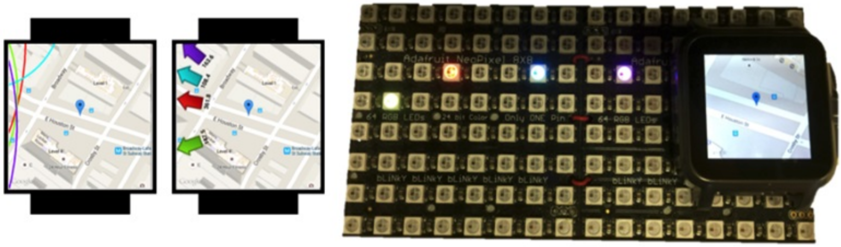


Figure 6.5: The three off-screen visualizations used in the user study: halos (left), arrows (center), and low resolution on-body display (right).

Figure 6.5, center). In addition to that we used our on-body display and presented colored dots at the location the points of interest are (cf., Figure 6.5, right). Thus, the spatial ratio between points in the real world and in the visualization stays the same, similar to the size of the halos.

6.5.2 Participants and Procedure

We invited 16 participants (5 female, 11 male), aged 18–26 years ($M = 21.94$, $SD = 2.05$) to take part in the user study through University mailing lists. After participants arrived at the lab we explained them the purpose of the study. The main study consists of two tasks, namely, locate the closest POI and locate a specific POI. The zoom function was disabled for both tasks. For each task, we equipped the participant with a smart watch and the on-body display on the forearm. Then, they performed each task. After the participants performed both tasks they filled in a final questionnaire.

Locate the Closest POI

First, the participant should identify the closest point of interest on a map. As an example, we provided them the scenario of finding the closest restaurant. We presented the three off-screen visualization technique (i.e., halos, arrows, and on-body display) in Latin-squared order. Participants received one task as an example so that they could make themselves familiar with the technique. After understanding the visualization, participants should locate three times the closest POI for each technique. We measured task completion time and errors. After performing the task with each technique, participants filled in a System Usability Scale (SUS) questionnaire. We also asked how easy participants could estimate

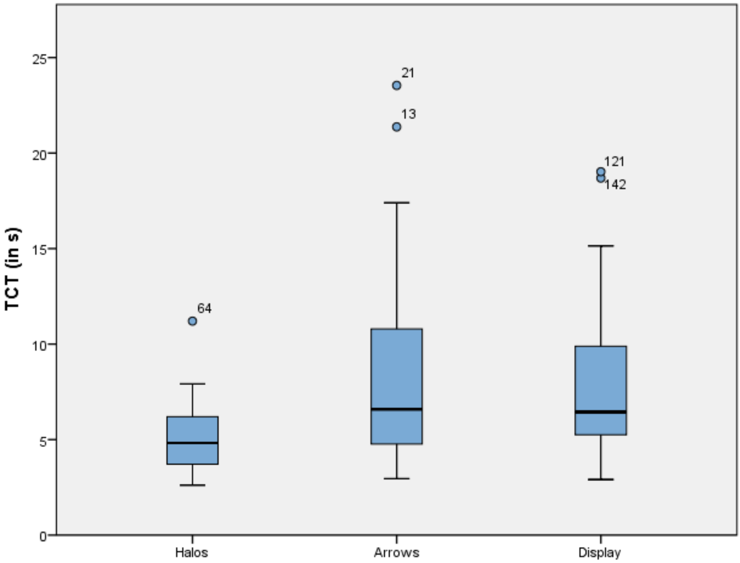


Figure 6.6: The task completion time of the three different visualization techniques for the locate the closest POI task.

the distance and direction to a target on two 5-Point Likert items (1=simple; 5=complicated).

Locate a Specific POI

Second, participants should identify a certain item out of a group of items. This was introduced as a certain restaurant a table was booked at. In this task, we furthermore explored the influence of the display size of the on-body display on the task completion time and error rate. Thus, we used four different sizes: 1×4, 4×4, 6×6, and 8×8 pixel for visualizing the off-screen content. Again, each technique was used three times and each display size was used three times as well. We measured the task completion time and errors.

6.5.3 Results

Overall, we recorded 144 performed search tasks. We removed all data points in which participants did not select the correct POI (Halos 5, Arrow 8, Display 12).

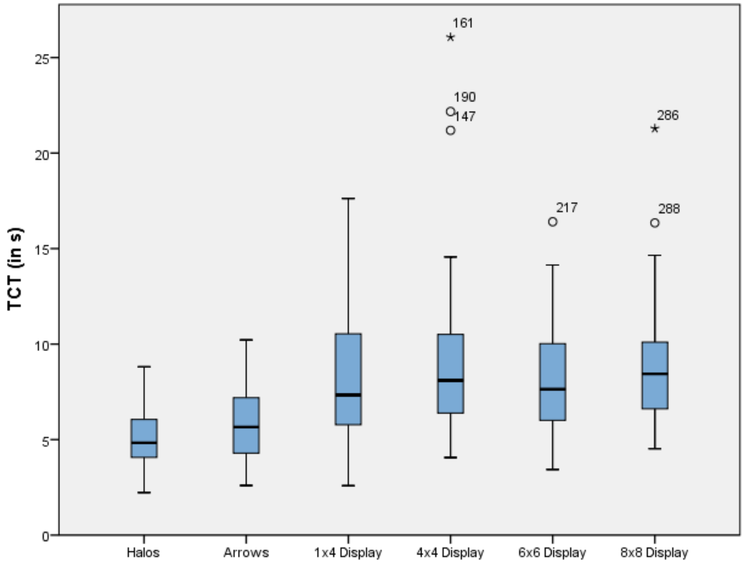


Figure 6.7: The task completion time of the three different visualization techniques and different display sizes for the locate a specific POI task.

Overall, participants rated the usability of the on-body display ($M = 79$, $SD = 13$) and halos ($M = 79$, $SD = 14$) higher compared to arrows ($M = 78$, $SD = 16$) using the SUS questionnaire. For the locate the closest POI task, participants using the halos ($M = 5.1s$, $SD = 1.8$) method located the POI faster compared to arrows ($M = 8.3s$, $SD = 4.8$) and on-body display ($M = 8.3s$, $SD = 4.1$). The result of a repeated measures analysis of variance shows a statistically significant difference between the task completion times, $F(2,28) = 8.096$, $p = .002$. Bonferroni corrected post-hoc t tests show participants performed statistically significant faster using halos compared to arrows ($p = .018$) and on-body display ($p < .001$). The post-hoc tests did not show any statistically significant differences for arrows and on-body display ($p = 1.000$) In contrast, the on-body display ($M = 1.69$) outperformed halos ($M = 2.50$) and arrows ($M = 2.75$) with regard to ease of distance judging as stated by the participants in the Likert items question.

For identifying a specific POI, participants performed best for the halos ($M = 5.2s$, $SD = 1.3$) condition, followed by using arrows ($M = 6.0s$, $SD = 2.0$) and on-body display ($M = 8.8s$, $SD = 4.2$). When comparing the different display sizes, the results show that participants perform best using 6×6 px displays ($M = 8.3s$, SD $= 3.1$) followed by 1×4 px displays ($M = 8.8s$, SD $= 5.6$) which both outperform 4×4 px ($M = 9.3s$, SD $= 4.6$) and 8×8 px ($M = 8.9s$, SD $= 3.3$) displays. A repeated measures analysis of variance shows that these differences are statistically significant as well, $F(5,60) = 8.602, p < .001$. The Bonferroni corrected post-hoc t tests reveal that halos perform statistically significant faster compared to the on-body display versions. All other comparisons did not show any statistically differences. In contrast, using the Likert items question, participants rated the arrows ($M = 1.19$) best, followed by on-body display ($M = 1.50$) and halos ($M = 2.31$).

6.6 Discussion

The presented results show that on-body displays are a valuable alternative to current off-screen visualization techniques. We used a display with a low number of pixels that could in the future be integrated into clothing. In particular in the user ratings, the display outperforms the halos and arrow methods.

Another benefit of the on-body display is that the off-screen visualization does not mask parts of the map. While this was not an issue in the study since the participants did not need to take care of streets or possible modes of transportation, this could further increase the usability in a real world application.

6.7 Lessons Learned

Through the development of this research probe probe we learned the following lessons.

- **Support different display types and purposes.** Different types of displays should be supported such as low resolution context and high resolution focus displays. Each display type need different ways of being addressed. While high resolution displays are capable of displaying regular content as known from mobile phones (e.g., array of pixel), low resolution displays need specially designed content. This content could be presented on an information level (e.g., low heart-rate, POI at 95 °) rather than array of pixels and interpreted by the display based on its capabilities.

- **Specify display location.** The location of the displays on the human body needs to be influenceable by the developer so that different displays can be combined. Application could need special grouping of on-body locations to achieve the desired effect. For instance, the off-screen locations need to physically match the high resolution map.

6.8 Conclusion

We explore in this research probe pixel-based on-body displays. These displays offer the possibility to present various types of information similar to displays known from mobile devices. We conducted a user study showing that different use cases can be covered with a limited display size. Due to the placement possibilities on the whole body, these displays can provide useful information to the wearer as well as to people in the vicinity. Thus, they are able to serve as public and private display. While we used a smart watch placed at the wrist of the user, in the future, a (non-textile based) focus display could also be placed on the lower arm. This would enable a low-resolution context display expanding all directions.

Additionally, the analysis of related work reveals that non-pixel based displays provide also a benefit to the user (cf., [179, 189]). Especially the ease of integration into smart garments provides a huge benefit. These displays can then serve as an additional notification channel or to communicate the physiological state of the user. For instance, a heart shaped display created out of 10 tiles could fill up based on the heart rate of the user.

Chapter 7

Auditory Authentication

In addition to entertainment purposes such as playing music or videos, auditory output is used as one of the main notification and feedback mechanisms for mobile devices. Short auditory cues are played to get the attention of the user for incoming calls oder messages. Currently, several projects utilize such cues for garment based wearable computer projects to provide feedback about their sensing results. Helmer et al. used, for example, auditory feedback to communicate the flexion of the knee while performing sports activity [105]. However, these cues can be disturbing in quiet environments (e.g., in a library or restaurant). Thus, bone conduction audio embedded into caps, hats, or scarfs could be a more subtle solution for providing auditory feedback.

Audio as feedback and for entertainment purpose is well understood through research and products in the mobile computing domain and also used in wearable computing projects. Thus, we investigate how audio can be used in other application scenarios. We exploited audio cues in combination with a microphone to create an authentication system in this research probe. By integrating a bone-conduction speaker and a microphone in, for example, a hat or cap, this garment can be used to identify the person wearing it. A feedback loop emerges through the closeness of the system to the human body. This loop can also be realized with other input and output modalities.

Exploring this feedback loop using audio for authentication, we present in this probe *SkullConduct*, a biometric system that uses bone conduction of sound through the user's skull for secure user identification and authentication. Bone conduction has been used before as a transmission concept in different consumer devices, such as hands-free headsets and headphones, bone anchored hearing aids, as well as special-purpose communication systems, such as for diving or high-noise environments. Bone conduction has also recently become available on eyewear computers, such as Google Glass, as a privacy-preserving means of relaying information to the user. Therefore, we use a Google Glass as research tool to explore our concept. SkullConduct uses the microphone readily available in this device to analyze the frequency response of the sound after it traveled through the user's skull (cf., Figure 7.1).

This chapter is based on the following publication:

- S. Schneegass, Y. Oualil, and A. Bulling. SkullConduct: Biometric User Identification on Eyewear Computers Using Bone Conduction Through the Skull. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, New York, NY, USA, 2016. ACM[a]

[a] A video of the SkullConduct system is available at YouTube: `https://www.youtube.com/watch?v=BX1-RE9krSM`.

7.1 Related Work

Secure user authentication is important for mobile phones given that these devices store an increasing amount of personal information. Current authentication schemes such as Personal Identification Number (PIN), password, or graphical password [239] have the inherent drawbacks that the user needs to remember the secret to authenticate and the secret can be stolen by user centered attacks (e.g., shoulder surfing) while authenticating in public. To address limitations of established knowledge-based authentication schemes, such as passwords and PINs, recent works exploit the sensors readily integrated into mobile devices. For example, previous works proposed the analysis of keystroke dynamics [122, 156], gait patterns [163], ambient sound [123], micro-movements while interacting [29], the shape of the user's ear [112], bioimpedance [58], or the way a user places or answers a phone call [56]. In contrast, secure user authentication using audio cues remains largely unexplored.

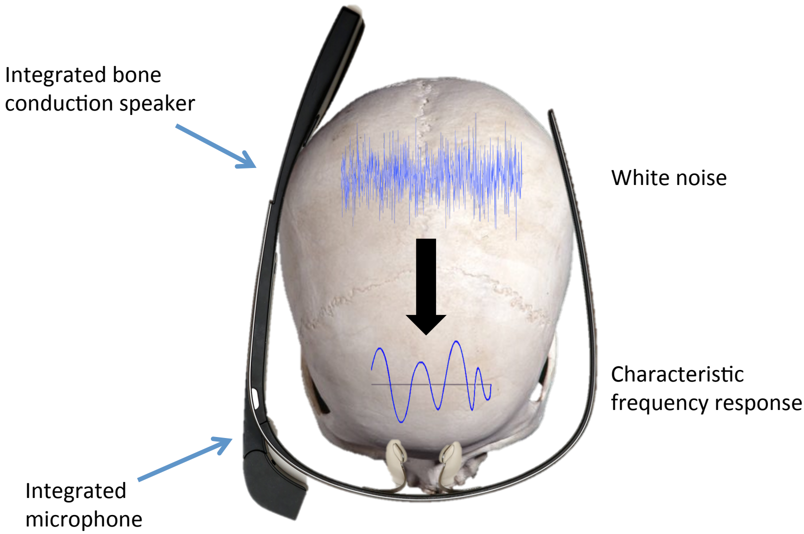


Figure 7.1: SkullConduct uses the bone conduction speaker and microphone readily integrated into the eyewear computer and analyses the characteristic frequency response of an audio signal sent through the user's skull.

7.2 Hardware Prototype: The SkullConduct System

There are, in general, two different pathways audio can take to get from a source to the user. The most widely used pathway, as for example in the case of headphones or speakers, is via air conduction in which the audio travels through the air and the auditory channel to the user's inner ear. The second pathway is via bone conduction, that is directly through the skull to the inner ear. Especially for eyewear computers or garments that already are located close or even at the head of the user, using bone conduction yields the advantage that the audio is not well audible to bystanders and thus more private.

So far, systems typically used speech to identify different users (see [204] for an example). In contrast, SkullConduct exploits the characteristic changes in an audio signal while it travels through a user's skull (see Figure 7.1). When audio is played back with a bone conduction speaker (i.e., the audio travels through the head) it is modified by the user's head. If recorded with a microphone, the changes in the audio signal reflect the specific characteristics of the user's head. Since the structure of the human head includes different parts such as the skull, tissues, cartilage, and fluids and the composition of these parts and their location differ between users, the modification of the sound wave differs between users as well. First, the speed of sound transmission differs for each of the parts of the human head [178] and, second, the different signal frequencies are damped differently [248]. In this work we opted for Gaussian white noise as the input signal since it covers the whole frequency range and therefore all frequency bands that might get affected by individual skull characteristics.

We implemented SkullConduct on Google Glass as one of the most common used smart eyewear devices having similar speaker and microphone placement as could be realized for hats or caps. We developed an application that plays back an audio file using the integrated bone conduction speaker and records concurrently with the integrated microphone. The recording is saved on the Glass as a byte file with 44100 samples per second, a single channel (i.e., mono), and a precision of two bytes per sample. To authenticate users, the system is capable of extracting features from the recording and comparing it to a training set using a 1-Nearest Neighbor (NN) classifier.

7.2.1 Recognition Pipeline

Our recognition pipeline to identify and authenticate users combines Mel Frequency Cepstral Coefficients (MFCC) [60] as acoustic features with a computationally light-weight 1-NN classifier (cf., Figure 7.2). MFCC are commonly used in speech classification and speaker identification but were shown to also perform well for non-speech event classification (cf., [200] for an example). In a first step, the signal as a whole is transformed using a Fourier transform. Afterwards, the power spectrum is mapped to the Mel scale using a Mel Filter Bank. Then, the Discrete Cosine Transform (DCT) is calculated after taking the logarithm. Finally, the MFCC are given by the 2-13 DCT coefficients. In this work, we extend the 12 MFCC features with their first derivatives (deltas) resulting in 24 features. All features are then used as input to a 1-NN classifier to identify or authenticate users. As a distance measure we used the sum of the Euclidean distances of each feature of a sample.

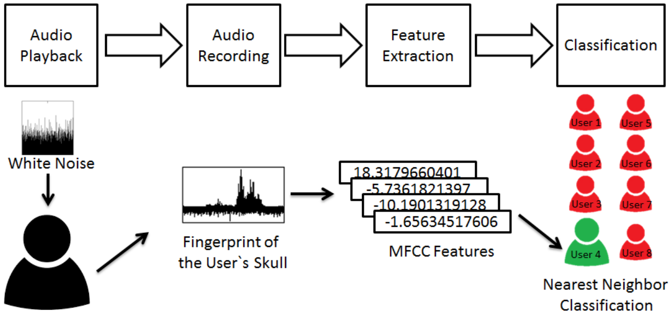


Figure 7.2: The recognition pipeline we used to authenticate users: (1) white noise is played back using the bone conduction speaker, (2) the user's skull influences the signal in a characteristic way, (3) MFCC features are extracted, and (4) a 1-NN algorithm is used for classification.

7.2.2 Application Scenarios

We envision two main application scenarios in which our system will be useful.

Personalization

Mobile devices such as eyewear computers are used in an increasing number of applications, such as for training in laboratories [117], medical documentation [1], educational purposes [153], or even during surgeries [175]. In all of these domains, multiple users may use a single device on a regular basis. As soon as a user puts on the device, SkullConduct can immediately identify the user and configure user-specific settings, such as preferred applications or system preferences.

Protecting Private Content

Mobile phones are personal devices that contain sensible information about the owner, such as social media logins or bank account details. Current protection mechanisms, such as PINs and passwords, are vulnerable against different attacks such as shoulder surfing or smudge attacks [239]. User authentication could automatically be triggered after SkullConduct has been put on by a user. In addition, as soon as specific applications are started, such as the banking application, SkullConduct could re-authenticate the user to ensure he is allowed to access the application data.

7.3 Evaluation: User Recognition

We evaluated SkullConduct with respect to the two main operating modes of biometric systems, namely user identification and authentication [199]. We designed a user study to record characteristic frequency responses for multiple people wearing Google Glass in a controlled laboratory setting.

7.3.1 Data Collection

We recorded data of 10 participants (9 male, 1 female) aged between 21 and 36 years ($M = 28$, SD $= 4.35$). The recording took place in a quiet room without any other source of noise and the participants sat down on a chair in the middle of the room. In this initial evaluation of the approach, we opted to have no confounding audio sources that may influence our results, such as sounds of other electronic devices or people. We used a randomly generated Gaussian white noise audio signal with a length of 23 seconds. We recorded each participant 10 times with the same audio signal. After five recording trials, we asked participants to take off the device and put it back on to include different placements of the device on the participant's head.

7.3.2 Analysis

After recording the samples of all users, we analyzed the recorded data using 10-fold cross validation. In each fold, similar to Holz et al. [112], we excluded all recordings of one participant (i.e., the attacker). Within each fold, we did an additional two-fold cross validation. To this end, we grouped the recordings of the nine remaining participants into two folds. The first five recordings went into the first fold and the second five recordings, recorded after taking off Google Glass and putting it back on, went into the second fold. In total, we trained our system with 45 recordings (i.e., fold 1) of the nine known participants and used 55 recordings (i.e., fold 2, 45 recordings from known and 10 from unknown participants) for testing. We deliberately chose to split the data of each user since the placement of the bone-conducting speaker might influence the results [106, 248].

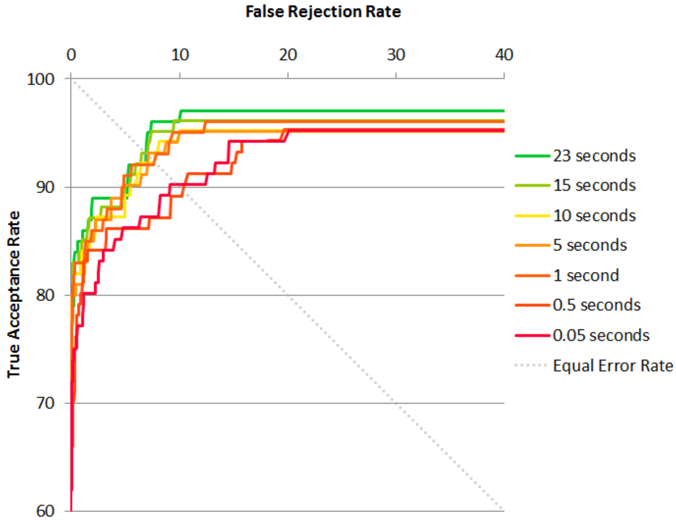


Figure 7.3: ROC curves summarizing the performance in terms of true acceptance rate vs. false acceptance rate for different recording lengths.

User Identification

The first evaluation task for our SkullConduct system is to identify a known user. In our case, the system achieves a 97.0% accuracy (cf., Figure 7.3 – True Acceptance Rate (TAR)). Thus, the lowest Euclidean distance between the new sample is with a recorded sample of the same user. In only 3% of the cases, a user is mistaken with another one.

User Authentication

The second evaluation task for our system is to authenticate a known user while rejecting unknown ones. The main measure of goodness for authentication system is the Equal Error Rate (EER) which is the point for which the False Acceptance Rate (FAR) and the False Rejection Rate (FRR) are equal [199]. We calculate both rates for our system for specific thresholds that decide whether a user will be authenticated or rejected (i.e., the euclidean distance between a training data and the authentication data needs to be lower than the threshold). Next, we calculated the EER out of the FAR and FRR (cf., [199]). The FAR is the percentage of samples that are mistakenly granted access even though they are from an unknown user. In contrast, the FRR is the percentage of samples that

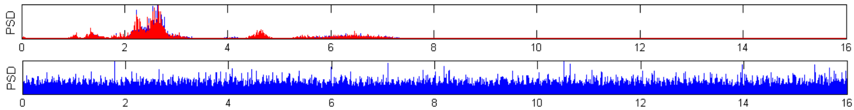


Figure 7.4: The user-specific modification (top) of the white noise input signal (bottom) takes place in the range of 1 kHz to 8 kHz with most modifications occurring between 2 kHz and 4 kHz.

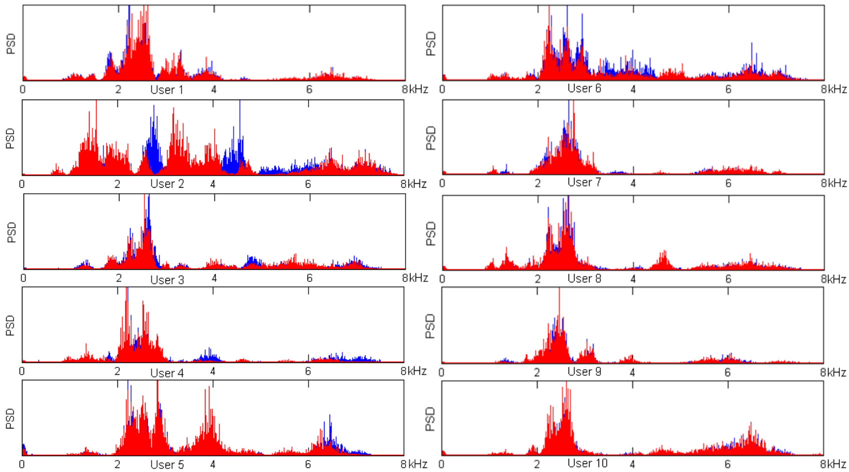


Figure 7.5: The power spectral density visualized for two recordings of each of the ten participants before and after removing and putting the device back on (trial 1 shown in red and trial 2 in blue) in the range of 0 kHz to 8 kHz. The changes in the power spectral density are almost similar for the different placements but differ between participants.

are mistakenly refused to access even though they are from known users. In our case, both rates were the same at 6.9%. The ROC curve in Figure 7.3 shows the SkullConduct precision for different thresholds. For a high true authentication precision (97.0%), the FAR was 10.2%.

7.3.3 Influence of Different Frequency Bands

As related work suggested [248], different frequencies are influenced in characteristic ways by the head and skull. To investigate this phenomena, we calculated the Power Spectral Density (PSD), which describes how the power of the signal traversing the skull is distributed over the frequency range (see Figure 7.4). As can be seen from the figure, the head and skull for each participant influenced the PSD of the original signal in a specific way (cf., Figure 7.5). This influence varies among participants but is constant for the same user even over several trails (i.e., only slightly affected by misplacement of the eyewear computer). Furthermore, the user-specific differences are skewed towards the lower frequency ranges and the main influence of the user's skull is for frequencies between 2 kHz and 4 kHz.

7.3.4 Influence of Audio Length

Current authentication systems on mobile devices require about 1.5 seconds to authenticate a user [239]. We used audio recordings of 23 seconds length which would take significantly longer for a user to authenticate. Therefore, we evaluated the performance of our system using audio with shorter lengths. Specifically, we cut each recording after 15, 10, 5, 1, 0.5, or 0.05 seconds and calculated a ROC curve for each length of audio samples using the same procedure as described before. As shown in Figure 7.3, the EER significantly drops when using audio samples shorter than 1 second.

7.4 Discussion

The evaluation of our system yielded promising results. We showed that bone-conduction audio is well suited as a biometric security system. However, we tested our approach only in a controlled setting without any background noise. Thus, we used a best-case scenario for our user study to explore the general feasibility of our approach. It will be interesting to see if and how much additional noise, such as other people talking in the room or appliances, reduces performance. One potential solution to this problem are algorithms that preserve the specific characteristics of each skull but remove the environmental influences [42]. Furthermore, there might be additional influences such as hair growth or gained weight that might impact the accuracy of our approach and need to be evaluated in the future. Although we show that a white noise signal of 1 second is sufficient to achieve high authentication accuracy, white noise signals may be unpleasant for the user. In the future, we envision that white noise could be replaced by more pleasant audio sounds such as common start-up jingles or even short music clips. Any alternative sound, however, needs to cover a sufficient number of frequency bands to discriminate well between different users.

We used a Google Glass as a research prototype. Even though the same speaker and microphone could also be integrated into garment based wearable computing devices, minor differences could influence the accuracy of our system (e.g., movement of the garment during playback). In the future, a garment based version of the prototype needs to be developed to gain insights if such an effect exists and how large the influence is.

7.5 Lessons Learned

We derive the following insights from the research probe.

- **Interaction in the Loop** One of the main ideas of this research probe is to create a loop involving sensing and actuating. In this loop the user can be continuously authenticated. This loop might also be created with other input and output modalities such as a combination of Electromyography (EMG) and EMS. However, a loop always requires the combination of sensing and actuating devices. Wearables therefore might depend on each other and should not only be considered isolated.

- **Wearables for Authentication** Wearable devices yield high potential to be used as a tool for user authentication and identification. Especially the pervasiveness of clothing allows an implicit and continuous way of authentication. In contrast to using similar approaches on the mobile phone (e.g., [61]), wearables are not limited to the actual interaction but might be used between the actual interactions as well. This enables systems to gain increased security but also challenges current metrics used to rate authentication systems. For example, a single unsuccessful login of an implicit authentication system might not necessarily indicate an intrusion or violation of systems integrity.

7.6 Conclusion

In this research probe, we present SkullConduct, a biometric system that exploits the characteristic frequency response of the human skull for user identification and authentication on devices equipped with bone conduction technology. While other biometric systems require the user to enter information explicitly (e.g., place the finger on a fingerprint reader), our system does not require any explicit user input. We demonstrated that our approach works well and can differentiate 10 users in a lab-based user study users with 97.0% accuracy as well as an EER of 6.9%. We implemented our system on Google Glass but we believe that in the future, bone conduction speaker can also be integrated into garments such as hats, caps, or scarfs. The presented approach of creating a feedback loop is especially interesting for smart garments. The closeness of to the user´s body allows probing into the body to perceive information normally not accessible for mobile interaction.

Chapter 8

Haptic Output

Humans perceive feedback generated by computing systems mainly through their visual and auditory senses. These senses are also highly occupied while walking in the city center, sitting in a restaurant, or watching TV. When providing feedback to the user, using a different modality that does not occupy a sense that is currently in extensive use helps acquiring the attention of the user. Haptic has shown to be useful in these situations. Hence, it is widely embedded into mobile phones and wearable devices such as fitness bracelets.

Van Erp et al. distinguish two types of haptic feedback, namely, cutaneous and kinesthetic feedback [260]. Cutaneous feedback includes mechanical, thermal, chemical, and electrical stimulation to the skin. Examples include the work of Werner et al. who utilize vibro-tactile feedback communicating the heartbeat of a beloved person using a ring [270] and Heuten et al. communication navigational cues through a vibro-tactile belt [109]. Kinesthetic feedback, in contrast, includes body force, body position, limb direction, and joint angle. This sensation is generated in muscles, tendons, and joints. Exoskeletons or force feedback devices, for example, allow providing such kind of feedback. EMS is capable of generating both types of feedback. Using a weak signal on the skin provides a cutaneous feedback similar to vibro-tactile feedback. However, EMS devices also offer the possibility to provide an embedded type of kinesthetic feedback. By applying a certain amount of current to the muscles of the user, the specific muscle is actuated and starts contracting.

In this chapter, we use EMS for actuating the user, thus, we are generating *force feedback*. This actuation is designed in a way that the user is performing a certain gesture. We defined six gestures representing three different emotions (i.e., amusement, anger, and sadness). Three of them are based on a literature review of natural human movement and three are based on the American Sign Language (ASL). In a user study, we explore how well users can link the different gestures to the emotions. The main idea is to use these gestures to communicate the feelings of a remote partner to the user. Due to the EMS, these feelings are more embodied and create a closer connection between them.

This chapter is based on the following publications:

- M. Pfeiffer, T. Dünte, S. Schneegass, F. Alt, and M. Rohs. Cruise Control for Pedestrians: Controlling Walking Direction using Electrical Muscle Stimulation. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, New York, NY, USA, 2015. ACM[a]
- S. Schneegass, M. Pfeiffer, M. Hassib, F. Alt, and M. Rohs. Emotion Actuator: Embodied Emotional Feedback through Electroencephalography and Electrical Muscle Stimulation. In *Paper under Submission*
- M. Pfeiffer, S. Schneegass, F. Alt, and M. Rohs. A Design Space for Electrical Muscle Stimulation Feedback for Free-Hand Interaction. In *Proceedings of the CHI Workshop on Assistive Augmentation.*, 2014
- M. Pfeiffer, S. Schneegass, F. Alt, and M. Rohs. Let Me Grab This: A Comparison of EMS and Vibration for Haptic Feedback in Free-Hand Interaction. In *Proceedings of the 5th Augmented Human International Conference*, 2014

[a] A video of the CruiseControl system is available at YouTube: `https://www.youtube.com/watch?v=GxhapXZJ2Sc`.

8.1 Related Work

Electrical Muscle Stimulation sends an electrical signal to the human body using electrodes. Different types of electrodes exists such as textile based electrodes, non-invasive surface electrodes placed on the skin, or implantable electrodes which are mainly used in a medical setting. Depending on the placement of the electrodes and the used current, different sensations can be achieved. Weak currents, for example, can be used to provide realistic haptic feedback which is similar to vibro-tactile feedback [195]. In addition to that, when placing the electrodes on top of muscle fibers, EMS elicits action potentials on motor nerves resulting in a contraction of the muscle.

EMS has a long tradition in rehabilitation engineering under the term Functional Electrical Stimulation (FES). FES is used to restore motor functions of paralyzed patients. Application in the rehabilitation domain include knee joints movement, cycling, standing up, keeping body balance, and walking (see [280] for a review). Inducing EMS to muscles for helping users to walk, for example, is a complex task because many independent muscles have to be controlled in a coordinated way [25]. Further, each involved joint has multiple degrees of freedom. Other aspects which need to be considered are time delays between signal and response and muscle fatigue.

The haptic sensing capabilities of humans are based on the different nerves in the skin, tissue, and muscle. For electrical impulses of a duration longer than 10 ms a current of 10-20 mA stimulates only the sensory nerve fibers, of 20-40 mA in addition stimulates the motoric nerve fibers, and of more than 40 mA also stimulates the pain nerve fibers [77]. Depending on the body position, the density of the different types of nerves varies which needs to be taken into account when calibrating EMS devices. Beside the electrode (e.g., size and material), the following characteristics have an influence on the haptic perception when it comes to applying the current: the strength of the applied current, the applied duration, the impulse form, the impulse frequency, and the impulse duration. The form of the impulse is mostly following the characteristics of a sine wave, a square wave, or a sawtooth wave. Frequencies between 1 Hz and 1 kHz are typically used with short impulses of 100 μs. This is done because the skin resistance decreases with short impulses. In contrast, long pulse durations increase the skin resistance. For contacting a muscle, typically impulse durations of up to 400 μs are used.

In the field of HCI, the usage of EMS starts with the work of Tamaki et al. who controlled the user‘s hand [252]. After this seminal work, many different application scenarios using EMS have been envisioned in HCI. Connecting EMS feedback with physical objects, Lopes et al. show that the intended way of using objects can be communicated [150]. They apply EMS to the hand and arm so that simple movements such as turning or grabbing can be communicated and understood by the user. Kruijff et al. use EMS feedback in 3D games [139], whereas Lopez and Baudisch extend mobile devices with EMS to provide haptic

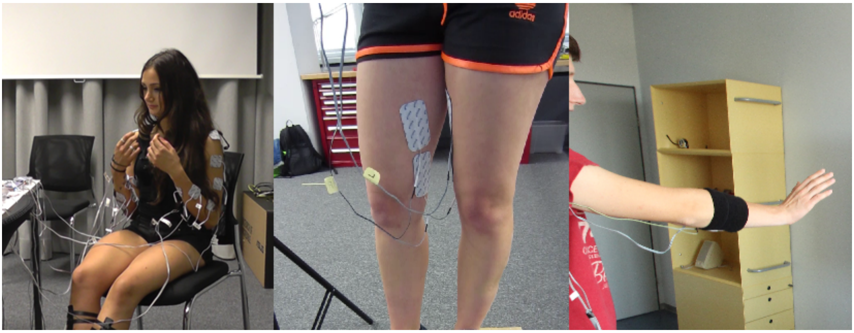


Figure 8.1: Different placements of EMS electrodes for different application scenarios. Performing gestures with the arms (left), turning the leg (center), and providing feedback on the forearm (right).

feedback [148]. Research also show that EMS can be used as a feedback method for virtual reality applications [149] or as novel notification method [237].

The main challenge in using EMS for HCI applications is that it needs to be attached to specific body locations to achieve the intended effect (cf., Figure 8.1). Textile electrodes can help tackle this challenge. Integrating the electrodes into smart garment allows reducing the overhead of attaching self-adhesive electrodes.

8.2 Hardware Prototype: EMS Actuator

We used an off-the-shelf EMS/Transcutaneous Electrical Nerve Stimulation (TENS) devices[19] connected to an Arduino nano (cf., Figure 8.2). The Arduino controls the EMS device and is capable of modifying the intensity of the signal generated by the EMS device (cf., Pfeiffer et al. for an in-depth description of the EMS system and a toolkit supporting easy prototyping of haptic feedback [192]). It contains two galvanically isolated circuits so that the actual EMS signal is only generated by the EMS device itself and the handling of the communication is done by the other. We used an Android application connected to the Arduino via Bluetooth LE (BLE) which sends control commands such as switching the EMS on or off or adjusting the intensity. Using the application, a muscle can be actuated by pressing a button whereas the intensity is controlled using a slider.

[19] Breuer Sanitas SEM 43

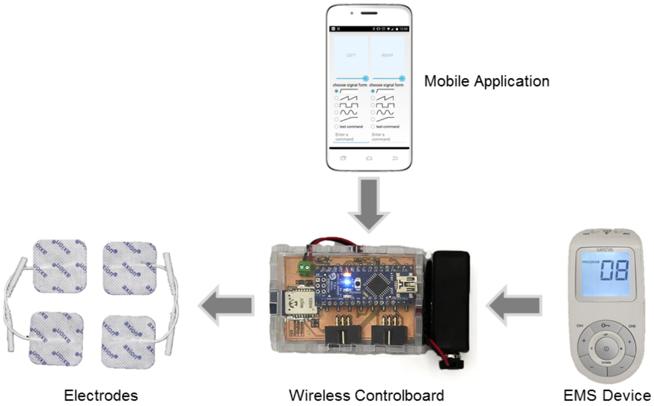


Figure 8.2: The electrodes, Arduino-based controlboard, EMS device, and the user interface of the Android application.

8.3 User Study: Communicating Emotions

We conducted a user study in which we explored actuating users‘ muscles to perform certain movements. These movements are designed in a way that they represent gestures. Thus, we let users perform gestures. As a use case, we explored the feasibility of communicating emotions through gestures. The main idea is to let the user perform a gesture that he or she links to a certain emotion and, thus, perceives the emotion in an embodied way. We thereby explored how well different gestures are suited for communicating the emotion.

The human body reveals emotional states through measurable signals, such as movements and EEG signals (cf., Chapter 5 for an introduction to physiological signals). However, such manifestations of emotional states are difficult to communicate to others over distance. While more and more people are living in long-distance relationships, communicating the emotions and maintaining a social connectedness becomes a challenging task. Today, people are relying on text, voice, and video communication to exchange and express their emotions to their partners. In this research probe, we proposed communicating emotions via EMS gestures. By actuating certain muscles, the user performs gestures linked to specific emotions such as sadness, anger, or happiness. The feedback is provided by the own body allowing the user to feel more connected to the remote person.

8.3.1 Linking Emotions and Movement

Human emotions are linked to the user‘s movement and body language [69, 72, 209]. In a first step, we conducted a literature review to explore which movement is *naturally* linked to which emotion. We focused on *anger*, *sadness*, and *amusement* as three core emotions and well-distributed in Russel’s model of affect [212]. From this review of literature, we elicited gestures (i.e., movements inducible via EMS) that represent each emotion (*natural gesture* from here on). We did not take actuating the face into account for emotion output. Even though facial expressions are a strong indicator for emotions [72], attaching EMS pads to the face would be socially not acceptable. Furthermore, we used gestures known from the ASL[20]. Although ASL is an artificial language, the gestures are designed in a way that they have some sort of connection to the word they are used for.

Amusement The gesture related to amusement is mostly linked to lifting up both arms [69] and keeping the hands high [95]. It is described as an open gesture extending the body of the user [267]. Thus, we designed the natural gesture as lifting both hands and keeps them up in the air (cf., Table 8.1, top). The ASL gesture for amusement consists of making a fist with the right hand and then open and close the index and middle finger while lifting the lower arm up to the face (cf., Table 8.1, bottom).

Anger Anger is an emotion that is linked to an aggressive forward positioning of the body [59]. The core part of the gesture linked to anger is clenching one’s fists [69], sometimes in combination with shaking the fists [267]. We designed the gesture as making a fist with both hands that is slightly lifted (cf., Table 8.1, top). The related ASL gesture is to form a claw with the right hand in front of the face (cf., Table 8.1, bottom).

Sadness Sadness is generally characterized as either putting both hands into the pocket [59] or folding them in the lap [69]. The movements are performed rather slowly and gently [267]. Thus, we designed the gesture in a way that the user folds both hands on the lap (cf., Table 8.1, top). In the ASL, the gesture consists of moving the right hand up in front of the upper body and slowly sliding them down the chest (cf., Table 8.1, bottom).

[20] https://www.signingsavvy.com/sign/

8.3.2 Study Design

In the user study, we compared both groups of gestures (i.e., ASL and natural gesture) against each other for each emotion. We used a repeated-measures study design, thus, each participant performed each gesture. To prevent sequence effects, we used a Latin squared order of gestures.

8.3.3 Participants and Procedure

In total, we invited 8 participants (4 female) aged 20-28 years ($M = 22.4$, SD = 2.7) via institutional mailing lists. Each participant received a 15 € compensation for about 60-90 minutes of study. After arriving at our lab, we first explained the purpose of the study. Then the participant filled out a consent form (an example can be found in Appendix VII – Consent Form) and a demographic questionnaire. We introduced the EMS system by introducing the participants slowly to the desired effect. Thereby, we applied the EMS signal to the extensor digitorum muscle in the lower arm of the participant. As soon as the participant experienced the movement sensation, we started calibrating the participant for the main task. First, we equipped the participant with the electrodes required to actuate the muscles for the intended movements (cf., Table 8.1). Next, we calibrated each muscle individually so that the desired effect is achieved. We did not actuate complete gestures to not bias the participants. They experienced the gestures linked to each emotion for the first time in the study. We also did not show a depiction of the gestures to the participants.

After the calibration, the participants were actuated to perform each gesture in Latin-squared order. Each gesture was performed multiple times. We did that to allow the participants to get used to the actuation of this particular muscles. After being actuated with a gesture, we presented the statement "this gesture fits to the emotion" to the participants. We asked them to rate on a 7-point Likert items (1 = strongly disagree, 7 = strongly agree) how well each gesture represented the three emotions (i.e., amusement, anger, and sadness). Additionally, we asked the participants in a semi-structured interview to describe the gesture we let them perform.

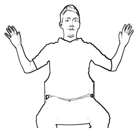
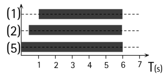
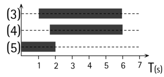
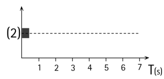
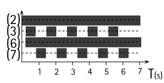
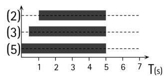
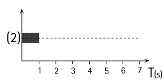
		Gesture	Movement	Timing	Muscle
Natural	**Amusement**		Hand up (5), lower arm up (2), upper arm up (1) (left and right)		Extensor digitorum muscle (5), biceps brachii muscle (2), and deltoid muscle (1)
	Anger		Hand up (5) claw hand (3), hand down (4) (left and right)		Extensor digitorum muscle (5), flexor digitorum superficialis muscle (3), flexor digitorum profundus muscle (4)
	Sadness		Lower arm up (2) (left and right)		Biceps brachii muscle (2)
American Sign Language	**Amusement**		Lower arm up (2), claw hand (3), tow finger down (6), two finger up (7)		Biceps brachii muscle (2), flexor digitorum superficialis muscle (3), flexor digitorum profundus muscle inside (6), extensor digitorum muscle inside (7)
	Anger		Hand up (5), claw hand (3), lower arm up (2)		biceps brachii muscle (2), flexor digitorum superficialis muscle (3), extensor digitorum muscle (5)
	Sadness		Lower arm up (2)		Biceps brachii muscle (2)

Table 8.1: Linking emotions to gestures and elementary movements. Different muscles are used to evoke certain movements with a specific timing so that the combination of the different muscle movements results in a gesture.

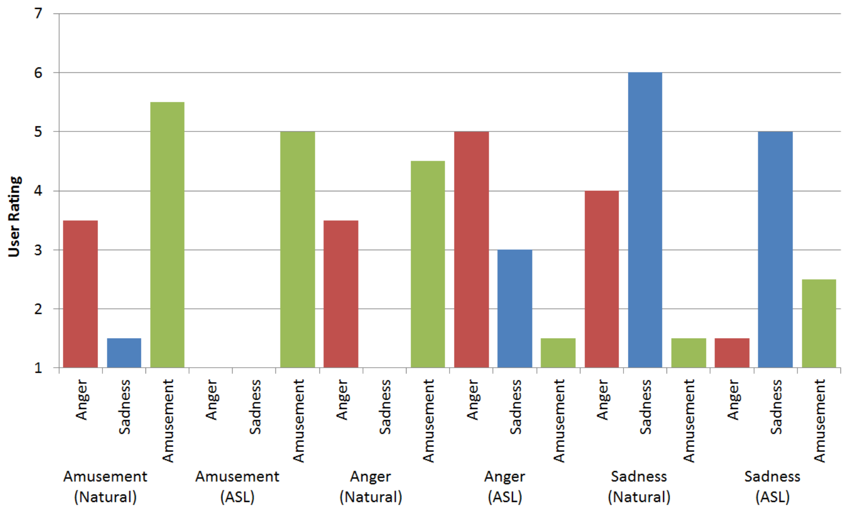


Figure 8.3: Median rating of how well the gesture fits the emotion for amusement, anger, and sadness on 7-point Likert items.

8.3.4 Results

Overall, the study shows that users are capable of linking gestures to emotions. As shown in Figure 8.3, the emotion linked to the gesture received the best rating in all cases except for the natural anger gesture.

Overall, participant described the emotion they linked with the gesture in the intended way. The amusement gestures derived from the natural movement was mainly described as "funny" due to raising the hands [P1]. Similarly, the amusement gestures was described as "exciting" [P6]. Looking at the feedback we received for the anger gestures, participant overall described feelings closely linked to anger. One participant stated that the natural gesture felt like he wants to box someone [P5]. However, we also found that the natural anger gesture was misinterpreted as representing amusement by two of the participants [P7, P8]. The ASL gesture for anger was described as aggressive and defensive [P7]. Participants described the natural gesture for sadness as defensive [P6] and that it made them look puzzled [P8]. The ASL gesture was rather described in a way that it made them feel thoughtful [P7].

Overall, the ASL gestures performed slightly better compared to the naturally derived gestures. The ASL gestures not only managed to convey each emotion correctly, but were more distinctive and slightly favored by our participants.

8.3.5 Discussion

The results show that gestures can be induced using EMS. Even rather complex gestures with more then a single muscle involved are feasible. When communicating emotions through these gestures, the performed user study reveals that most gestures can be linked to the dedicated emotions. Even though the communicated information is not entirely distinctive, the feeling participants had when perceiving the gesture is similar to the feeling describing the original gesture.

8.4 Application Scenarios

EMS can be used in many different application scenarios. In this section, we outline two examples we are currently investigating: First, we explore how walking can be enriched using EMS. Second, we show work that builds upon the actuation used in the user study described in this chapter. We show further examples in which letting the user perform gestures is beneficial.

8.4.1 Controlling Walking

In recent work, we showed that changing the walking direction is feasible with EMS [191]. We actuated the musculus sartorius in the upper leg of the user which is in charge of turning the leg outwards (cf., Figure 8.4 – left). As soon as this actuation happens while the user is walking, he or she implicitly changes direction. This change depends on the intensity of the signal applied to the muscle. To evaluate this approach we conducted a lab study and a field study (cf., Figure 8.4 – right). The lab study showed the general feasibility of our approach. By actuating the musculus sartorius using EMS the walking direction can be manipulated. In the field study, we explored a realistic application. Simulating a navigational system, a Wizard of Oz walking behind the participant used a mobile application which could actuate the participant‘s muscles in both legs. The participants were

Figure 8.4: Exploring EMS for navigation. The general principle of turning the leg outwards (left) and the conducted user studies in the lab (right – top) and field (right – bottom).

steered through a park and could avoid obstacles such as other pedestrians or trees.

In a next step, we strive to extend the amount of control from simple control over the walking direction to control over the balance of the user. Therefore, we propose actuating a set of muscles to prevent users from losing balance and falling. Falling while walking is especially dangerous for elderly but might also help in everyday situation in which users oversee obstacles. When applying EMS to certain muscles, the user can be automated in a way that in case of losing balance the EMS system helps the body to automatically regain balance. The same approach could also be applied during sports (e.g., skiing). As soon as the athlete looses balance or does not move in an optimal way, muscles are actuated so that he or she stays in balance.

8.4.2 Performing Gestures

When interacting with gesture based systems, communicating the available gestures is one of the main challenges [176]. The user needs to understand which gestures are understood by the system and which command is linked to which gesture. When using EMS, for example integrated into everyday clothes, the user can be actuated in a way that he or she performs certain gestures. As soon as the user approaches a system controllable by gestures, the system automatically lets the user perform available gestures. This helps to overcome certain challenges such as understanding interactivity, communicating the way of interaction, and explaining how the (gesture based) input could look like. Another aspect is that due to the embodiment of the gestures the user might learn the gestures faster and more precise compared to currently used picture based introductions.

Using EMS to enable users can also be used in application scenarios beyond gesture input. The possibility to let the user perform gestures can also be exploited as a way to communicate using sign language. This overcomes the challenge of communicating with deaf people. When the user speaks, the EMS is used to let the user form sign language gestures. Even though the amount of gestures and precision is still challenging with surface electrodes, a simple set of words could also enable basic communications.

8.4.3 Ethical Implications

EMS allows computing systems to take control over specific parts of the user´s body. Thereby, the user is not entirely in control of the movement even though capable of consciously overriding the applied signal. This is particularly important to consider since even small actuation might result into dangerous situations such as when the user is steering a vehicle. Due to security leaks in computing systems, intruders might be able to take control of certain muscles of users. By controlling the access and minimizing the possible signal strength, harm for the user can be reduced. In contrast, many different applications can be create that support users and their health. In addition to preventing users from falling as introduced in the *controlled walking* application scenario, several other potential harms can be prevented using EMS. Examples include preventing users from touching hot stove plates or stepping on icy parts of the sidewalk in winter.

8.5 Lessons Learned

We derive the following insights from the performed user study and postulated application scenarios.

- **Provide a fine grained way of feedback.** Let the application developer define location of feedback, intensity, and pattern. For creating meaningful and implicit feedback with EMS, the developer needs to decide on these factors. Thus, the developer needs more control compared to other types of haptic feedback due to the increased number of design decisions.
- **Embodied Feedback.** The study shows that embodying feedback provides further benefits compared to regular haptic feedback. While actuation can be used to implicitly control the user, it also is more substantially perceived by them.

8.6 Conclusion

In this chapter, we presented how EMS can be used to actuate users. We show the potential of actuating users in a way that they implicitly perform gestures. By postulating further application scenarios, we show the diversity of the capabilities of EMS. However, there are also drawbacks that became apparent during the user study. Main drawbacks are that electrodes need to be placed at certain body locations and the system needs to be individually calibrated to generate the desired effect. Another drawback is the usage of self-adhesive electrodes which need to be sticked to the muscles for each interaction. When using smart garments, the closeness to the user‘s body helps to overcome this drawback. Smart garments cover the majority of muscles and can have integrated textile electrodes. Thus, EMS is especially well suited as a haptic feedback method for smart garments.

IV

System Design

OUTLINE

One of the core challenges when designing mobile interaction with smart garments is the technical integration. Developers of mobile applications need to be able to access sensors and actuators and utilize them for their ideas. Several different aspects need to be considered for making the access as easy and transparent as possible. In this part, we present a system that allows integrating wearable computing devices into the cosmos of the already existing mobile devices. We report on privacy implications of such a system and the design recommendations derived from Part II and Part III.

This part includes the following three chapters:

- **Chapter 9 – Understanding Users' Perceived Privacy.** Due to the closeness to users' body, smart garments are a potential threat to users' privacy. Users are wearing garments every day. As soon as the smart counterparts are not easy to differentiate from the non-smart counterparts, the user might not be aware of the information extracted. To understand users‘ privacy concerns, we conducted a web survey showing that users do not understand the connection between (physical) sensors and extracted information. This chapter reports on the results of this survey.
- **Chapter 10 – Design Recommendations.** This chapter summarizes the design recommendations distilled from the presented research probes as well as the survey tackling the user's understanding of privacy. We derive 12 recommendations focusing on the core interaction and technology aspects.
- **Chapter 11 – Conceptual Architecture.** In this chapter, we apply the design recommendation distilled in Chapter 10 to design and implement a system managing garment-based sensors and actuators for mobile interaction. We present details on the implementation and on developed physical sensors and actuators which can be connected to the system.

Chapter 9

Understanding Users‘ Perceived Privacy

Since the presented research probes are investigated in a lab-based setting, we did not look into how the devices used in these probes affect the user‘s privacy. However, keeping the user‘s data private and gaining informed consent is crucial.

The diversity of wearable devices hitting the mass-market is constantly increasing. These devices contain myriads of integrated sensors that are specialized for extracting different types of information concerning the user, which can consequently be relied on by a variety of applications [27]. While most of these devices are wrist-worn and the information extracted from the wrist is limited, smart textiles are gaining importance and prominence (e.g., Project Jacquard [202]). Given their close proximity to the user’s body, smart textiles allow for a more pervasive (and robust) assessment of physiological responses, such as breathing rate or pulse [184]. In other words, recent developments allow for more personal data to be extracted, which has an increasing potential to violate user-desired levels of personal privacy.

Wearable technology poses an implicit contradiction that users and designers have to resolve. On the one hand, users are led to believe that it is desirable to track and share their activities, for example through motivational applications that are based on fitness trackers. On the other hand, privacy and data security are prevalent concerns in everyday life, especially with regards to money transactions via online banking or when using GPS services on the mobile phone. Most recently, this was demonstrated by the controversial use of Google Glasses in public spaces. This initiated a debate over the permissible extent of data collected via wearables and resulted in a blanket ban of Google Glass from a number of public locations [187]. While this particular discussion was centered around the issue of non-consensual photography, user-based information that can be extracted from other wearable sensors (e.g., physiological sensors) constitute a new dimension of privacy threats. In these cases, users are mainly unaware of their private information being collected and tracked by others [113]. Allowing the users to make informed consents on what and with whom their data is shared with is a central challenge that remains unexplored.

Thus far, related work has mainly focused on a generic and easy to understand situation, in which users' privacy is threatened, namely the extraction of location information from GPS sensors [253, 254]. In contrast, wearable sensors pose novel and multi-faceted challenges. Here, the recognition of possible threats to the user's privacy requires the user to understand the potential privacy violations that could result from the information extracted from the sensor data. Almuhimedi et al. [3] show that raising the awareness of data access of mobile applications could lead participants to reconsider their previous willingness to share information with applications. Even putting potential privacy threats more into the focus when installing mobile applications affects the user‘s decision on installing applications which potentially share private information [126]. However, it remains unclear how well users understand potential privacy risks by allowing access to specific sensors.

In this chapter, we explore users' understanding regarding which information can be derived from wearable sensor data. For this purpose, we conducted an online survey that assessed users' willingness to share their data when the data was requested either at the sensor level (e.g., accelerometer) or at the level of information that can be derived from the sensor data (e.g., step count). Henceforth, we will refer to these two different levels as the *representation levels* of users' private data. We show that the willingness to share physiological information varies as a function of the representation level – sensor data vs. derived information. This is especially interesting because the latter can be readily inferred from the former but not vice versa. In addition, we find that the type of the derived information influences users' willingness to share. In particular, users prefer to share information regarding Sport & Fitness over Health & Wellbeing information.

This chapter is planned to be published as follows:

- S. Schneegass, R. Kettner, and T. Machulla. Understanding the Impact of Information Representation on Users‘ Willingness to Share Private Information

9.1 Representation Levels

To begin, we performed a literature review on wearable sensors and the information that can be derived from them. For further exploration, we selected five sensors targeting physical movement and physiological measurements: accelerometer, heart rate sensor, skin conductance activity (SCA) sensor (also referred to as GSR), temperature sensor, and light sensor. In addition, we identified ten types of user-centered information that could be derived from these sensors.

The accelerometer is one of the most common sensor found in wearable devices. The amount of information that can be derived from it is huge and includes information that could potentially violate user privacy. Most commonly, data from wrist-worn accelerometer is used to derive information on *step count* [213] and the amount of *active minutes* [57]. Besides this, *sleep quality* [52], coarse *location* [278], and the type of *activity* [31] can also be inferred from accelerometer data. The heart rate sensor plays an important role with respect to the user's *health status* [245] and *life expectancy* [285]. The level of skin conductance, as measured by the SCA sensor, is determined by the activity of the humans sweat glands. Therefore, this sensor provides information about the user's *stress level* [264]. For monitoring *training intensity*, measurements from the skin temperature sensor can be used [218]. The light sensor provides information about ambient brightness and can, therefore, indicate the amount of *sunlight* that the user is exposed to [166]. The information derived from the above sensors can be grouped into three broad categories, namely, Health & Wellbeing information (sleep quality, stress, and health status), Sport & Fitness information (step count, active minutes, training intensity, and life expectation), and Context & Activity information (sunlight exposure, location, and activity).

9.1.1 Target Audience

We identified four different target audiences for information sharing ranging from *everybody* to *no one*. To obtain more fine-grained results, we also included a *certain person* (e.g., a close friend) and a *theme-based community* (e.g., a sports group).

9.2 Survey on Sharing Behavior

To assess users’ willingness to share information from wearables, we conducted an online survey. We were particularly interested in the effect that the representation levels as well as the different target audiences might have on participants’ willingness to share sensor information. To this end, we presented participants with 15 different statements, each addressing the participants’ willingness to share a certain type of information (i.e., five types of sensors and ten types of derived information). The presentation order of these statements was randomized between participants. Each statement was further subdivided into four simultaneously presented variations – one for each target group (e.g., “I would share the accelerometer data with a theme-based community.”). Participants rated their agreement with each of the four variations on a 7-point Likert item (1 = totally disagree; 7 = totally agree). In addition, we collected information about participants’ demographic background.

9.2.1 Value Proposition

To motivate users to share private data, we provided a scenario that involved them in acquiring a new wearable device. Setting up this device required them to install an application on their mobile phone. Subsequently, users were asked to grant the application access to their personal data for the purpose of sharing. We presented the scenario at the beginning of the questionnaire and, thus, it applied to each of the 15 statements.

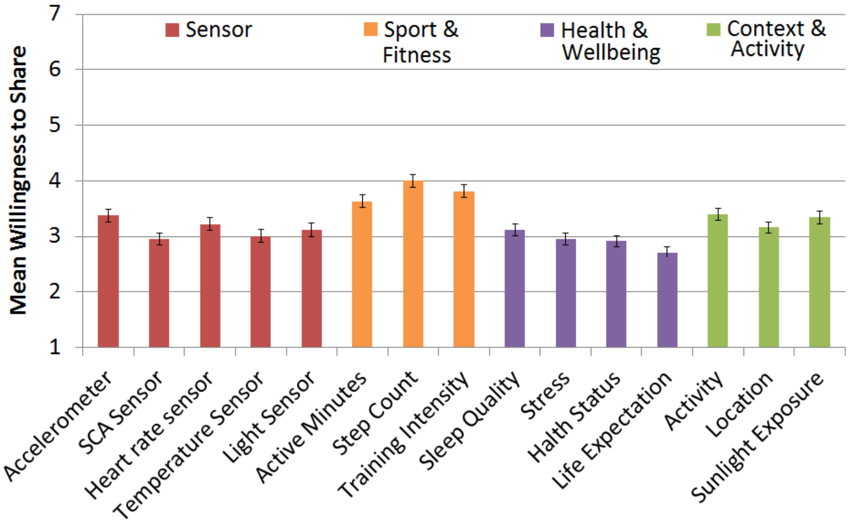


Figure 9.1: The mean values for each data presentation averaged across the four target audiences. The error bars show the standard error.

9.3 Results

Our online survey was completed by 249 participants (127 male, 115 female, 7 did not specify). Their mean age was 34.3 years (SD = 12.2). Our participants had diverse backgrounds that included: computer science (20%), natural science (12%), commercial occupations (31%), social science (7%), craft industry (7%) and not specified (23%). Before analyzing the data, we excluded any participants whose survey completion time was more than one standard deviation below the group mean ($M = 10.2$ minutes, SD = 6.4 minutes). This criterion applied to four datasets. One more dataset was excluded since completion took longer than one hour.

For all subsequent analyses, the polarity of the Likert item for the target audience *no one* was inverted to correspond to the polarities of the Likert items for the other three target audiences (i.e., stronger agreement equals higher willingness to share). As a first step, we analyzed the overall sharing preferences as a function of *representation level* (i.e., sensor data vs. derived information) and the *target audience* (i.e., no one, person, community, public) using a two-way repeated measures ANOVA. For this, we first calculated the mean over all sensor statements and over all derived information statements for each target group.

Overall, participants are more willing to share derived information ($M = 3.3$, SD = 1.6) than to share sensor data ($M = 3.1$, SD = 1.5), $F(1,248) = 22.051$, $p < .001$, $\omega = .28$). With regard to the *target audience*, the participants preferred sharing their data with a *certain person* ($M = 4.4$, SD = 2.0) followed by sharing the data with *no one* ($M = 3.7$, SD = 2.2), sharing with a *theme-based community* ($M = 2.9$, SD = 1.8), and sharing with *everybody* ($M = 1.9$, SD = 1.5), $F(3,744) = 156.740$, $p < .001$, $\omega = .62$). Post-hoc Holm-Bonferroni corrected t tests reveal statistically significant differences between all four groups, all $p < .001$. Further, the effect of *representation level* is modulated by the size of the *target audience*, $F(3,246) = 124.889$, $p < .001$, $\omega = .62$. This interaction can be mainly attributed to the fact that participants were more likely to share derived information than sensor data as the target audience decreased.

To explore our findings regarding representation level in more detail, we conducted ten pairwise comparisons, one for each type of sensor and each type of information derived from that sensor (e.g., motion sensor vs. sleep quality; two-tailed paired-samples t tests with Holm-Bonferroni correction for the overall number of t tests performed on each data set). For this, we averaged the Likert scores across the four different target audiences for each participant and each statement. Table 9.1 presents detailed statistics for each comparison.

The results reveal a more complex answer pattern as initially suggested by the ANOVA. Of the ten comparisons, eight are statistically significant, indicating that participants exhibit differential preferences regarding the sharing of sensor data vs. derived information. Interestingly, participants indicated a higher willingness to share sensor data in four of these cases. In contrast, they indicated a higher willingness to share derived information in four other cases. These findings will be discussed in the following section.

9.4 Discussion

In this section, we discuss the presented results and present limitations to our research.

Sensor	**Information**	**t**	**p**
Sport & Fitness			
Accelerometer	Active Minutes	−3.236	.001∗
Accelerometer	Step Count	−6.900	<.001∗
Body Temperature	Training Intensity	−8.010	<.001∗
Health & Wellbeing			
Accelerometer	Sleep Quality	3.020	.003∗
SCA Sensor	Stress	0.037	.970
Heart Rate Sensor	Health Status	4.450	<.001∗
Heart Rate Sensor	Life Expectation	6.424	<.001∗
Context & Activity			
Accelerometer	Activity	−0.174	.862
Accelerometer	Location	2.255	.025∗
Light Sensor	Sunlight Exposure	−2.502	.013∗

Table 9.1: The ten Holm-Bonferroni corrected *t* tests conducted between sensor data and information data derived from the sensors. Statistically significant comparisons are marked with *.

9.4.1 Sensor Data vs. Derived Information

The results of our online survey demonstrate that users' understanding of the relationship between sensor data and the information derived from these data is still limited. Primarily, users were not consistent in their willingness to share their sensor data and information derived from this data in a way that could be explained by privacy concerns.

If users were purely concerned with data privacy, they should have demonstrated greater willingness to share derived information rather than sensor data. Each type of derived information makes use of only a subset of the available sensor data. In other words, several different types of information can be derived from a single sensor (e.g., active minutes and step count from the accelerometer). Thus, the overall amount of disclosed data is less with derived information. Our results indicate that users exhibit this trend only for Sports & Fitness information. In contrast, they were more likely to share sensor data compared to the derived information when it comes to information related to Health & Wellbeing. This behavior is paradoxical since the derived information on Health & Wellbeing can be easily extracted from the sensor data. This finding suggests that users are currently not fully aware of what information can be extracted from sensor data.

9.4.2 Willingness to Share

Our survey revealed that there is an overall tendency of users to be more liberal when it comes to sharing derived information as compared to sensor data. Upon closer inspection of the data, we found that this preference is not uniform across different types of information. On the one hand, participants' willingness to share information regarding Sports & Fitness as well as Sunlight Exposure was higher than their willingness to share the associated sensor data. On the other hand, their willingness to share Health & Wellbeing information as well as their location information was lower than their willingness to share the associated sensor data. One possible reason for the increased willingness to share derived information related to Sport & Fitness is that it has mainly positive connotations, such as being athletic, competitive, or disciplined. Even when actual physical performance is not extraordinary, the sharing of such information can communicate a willingness for self-improvement (e.g., increased fitness, weight loss, etc.) and will generally be met with support and approval by the target audience. In short, there are usually no negative repercussions to sharing this information. In contrast, derived information related to Health & Wellbeing or to a person's location can have negative consequences, such as disclosing poor health to an employer or one's whereabouts to an unknowing spouse. In sum, there is an influence of the type of derived information on the willingness to share.

9.4.3 Target Groups

The participants of the online survey showed the highest preference for sharing their data with single persons and lowest preference for sharing with the general public. Thus, we believe that in general, users are comfortable with sharing their sensor and information data as long as they retain some control over whom they are sharing this information with.

9.4.4 Limitations

The current work is limited in the following ways. First, the present study addresses only a subset of the sensors that are currently available and a subset of information that can be derived from these sensors. Second, we chose the types of derived information based on previous research findings. While for some of these types of information the extraction from sensor data is reliable or has even been implemented in commercially available wearables, for others only the general feasibility of extraction has been shown. Last, the selected target audiences are just a subset of possible audiences. In particular, users' ratings might differ depending on the community to share with (e.g., colleagues vs. soccer club).

9.5 Conclusion

In this chapter, we investigated users' willingness to share wearable sensor data and the personal information derived from these data. We report two major findings. First, users show differential preferences concerning the sharing of raw sensor data and the information that is derived from these data. We believe that this reflects a lack of understanding regarding the relationship between these two representation levels. In particular, users do not seem to be fully aware of the type of information that can be derived from different sensors. Second, the willingness to share varies according to the type of derived information. Health & Wellbeing related information is less readily shared than Sport & Fitness related information, possibly due to potential negative consequences that sharing may have for the individual.

Chapter 10

Design Recommendations

This thesis contains six in-depth application driven research probes informing the design of mobile interaction using garment-based wearable computing devices. In this chapter, we present design recommendations distilled from the previous chapters. These design recommendations are tackling mobile interaction from an interaction and technological perspective.

10.1 Interaction-Centered Design Recommendations

In this section, we postulate design recommendations regarding the interaction with garment-based wearable computing devices. Smart garments have the potential to provide novel ways of interacting with mobile devices implicitly as well as explicitly.

Design Recommendation 1. *Take social acceptability into account when creating input and output methods.*

Smart garments are already used pervasively in myriads of situations. These situations include public situations such as in restaurants, bar, and malls. When conducting the evaluation steps of our different research probes it became apparent that social acceptability is one of the main criteria for smart garments. Particularly for mid-air gestures (cf., Chapter 4), social acceptability was a main aspect when identifying suitable gestures. This was also reflected in the extension of the *user-defined gestures* method by using three criteria (i.e., social acceptability, content visibility, and suitability) instead of one criterion (i.e., suitability – cf., Wobbrock et al. [272]) for rating the gestures.

Design Recommendation 2. *Allow input on arbitrary locations.*

While related work preferred the thighs as input location for touch-based input, we show that performing input on the forearm is also beneficial. Particularly while doing sports, using the forearm yields advantages compared to the thighs. The preferred input area highly depends on the situation. This became apparent during the exploration of touch-input on the sleeve (cf., Chapter 3). For example, during meetings in which interacting with the mobile phone is not appropriate, unobtrusive gesture commands on the thighs could be performed. As soon as regular garments get substituted by their smart counterparts, the user is capable of interacting on arbitrary locations. This needs to be taken into account when creating touch input.

Design Recommendation 3. *Create unified input mechanisms.*

Both research probes which explore explicit input (cf., Chapters 3 and 4) show that gesture-based input is a valuable approach of entering commands with smart garments. However, the necessity to learn gestures is a major drawback that also became apparent in this work. Learning gestures is the main challenge. Using a unified set of gestures elicited through a user-defined gesture study reduces this drawback. When the user is capable of using known gestures even for an unknown application, the hurdle of learning new gestures to enter commands is removed.

Design Recommendation 4. *Design for enriched tactile feedback.*

Current mobile devices such as smart watches and smart phones only use simple vibro-tactile feedback. This limits application developers to only choose the duration of feedback. The research probe focusing on garment-based haptic output (cf., Chapter 8) showed that EMS is a novel and promising way of creating haptic feedback. EMS is capable of actuating muscles and, thus, uses the user's body as output medium. When designing an interface to allow application developer to create haptic feedback using EMS, additional aspects need to be considered. First, the location at which the electrodes are placed needs to be taken into account. The feedback can achieve an entirely different implication on the user depending on the location. Second, the intensity and duration of the feedback need to be controlled in a way that the resulting feedback achieves its purpose. This includes a calibration of the EMS device so that the signal is in a comfortable range but achieves its purpose (i.e., it is capable of actuating a muscle).

Design Recommendation 5. *Combine sensing and actuation hardware.*

Currently, most research prototypes of smart garments either focus on sensing or on actuation. Nevertheless, an OS needs to combine the sensing and actuation to allow applications to use both generating a more holistic user experience. Especially for feedback methods such as EMS (cf., Chapter 8) and sensing of the user‘s physiological signals (cf., Chapter 5) this poses additional challenges. Textile electrodes could be reused for different sensing and actuating methods. Since specific sensors and actuators needs to be placed exactly at the same place, the system needs to communicate with sensors to switch modes and enable or disable specific parts, for instance, to reduce energy consumption.

Design Recommendation 6. *Utilize pre-defined visual output possibilities.*

Garment-based visual output differs from visual output as it is known from mobile phones. Even though the used display in the research probe is pixel-based (cf., Chapter 6), related work shows that most of the currently developed displays do not work on a strict pixel-based level. Thus, interfaces need to be designed in a way to allow the presentation of information instead of pixels. A garment-based display, for example, could be specialized on physiological signals. Thus, the display could visualize different heart rates and stress levels. Instead of developing a visualization on a mobile phone and sending the pixels to the display, the information could be sent and the display handles the output based on its capabilities. For example, the display could be shaped like a heart which is filled based on the heart rate.

10.2 Technology-Centered Design Recommendations

In addition to interaction-centered design recommendations, the presented research probes allowed deriving design recommendation towards mobile platforms.

These recommendations help to integrate garment-based sensors and actuators and help application developers as well as end-users.

Design Recommendation 7. *Allow fine-grained selection of permissions.*

While current wearable systems (e.g., Android Wear) mainly request access at the sensor level, the user may not be aware of the full extent of the information that can be derived from these wearable sensors. Our results suggest that users make fine grained distinctions on the information they want to share (cf., Chapter 9). Especially when several types of information can be extracted from the same sensor, users are not willing to share them equally. Thus, users want to choose based on the information level which enables them to protecting their privacy. Regarding potential permission systems for wearable sensors, this implies that users should be presented with a larger number of derived information requests, which users can individually allow or deny. Particularly, when moving from wearable gadgets – which need to be additionally attached to the body – to smart garments, the implicit possibility of measuring information (cf., Chapter 5) may not be easy to understand for the user.

Design Recommendation 8. *Create secure and privacy-aware access to mobile devices.*

Using (garment-based) wearables devices to identify the user yields promising results. We used auditory output in combination with auditory input to create an authentication loop (cf., Chapter 7). The signal traveling through the head of the user changes in a way which allows identifying the user based on the composition of the head. Thus, the head can be used as a biometric. Besides this probe, smart garments allow for different types of biometrics such as exploiting the user‘s physiological signals or gait. In order to allow garments to manage the access to private data on mobile devices, the communication and connection needs to be secured.

Design Recommendation 9. *Support developers with algorithms.*

During the development process of the research probes different algorithms needed to be implemented. We used the $P algorithm [263] for detecting gestures (cf., Chapter 3) and used MFCC [60] and k-NN for identifying users (cf., Chapter 7). Even though these algorithms are state of the art and detailed instructions exist on how to implement them, implementing them on one‘s own is timely and error-prone. Thus, these algorithms should also be implemented so that developers simply can apply them to sensor data.

Design Recommendation 10. *Provide developers access on information and raw data level.*

For the most common aspects (e.g., gesture input), algorithms should be applied automatically to specific input (cf., Chapters 3 and 4). This is the case for implicit as well as for explicit input. Implicitly sensed physiological signals usually require normalization based on the actual user in order to be interpretable. For example, the information on the user‘s current condition is more valuable than the raw ECG data for most application developers. They are most likely more interested in the current workload or engagement level. However, for creating some applications (e.g., medical life logging), the ECG data may also be useful in some cases. Thus, the system should provide data access on raw data (e.g., ECG, EEG) as well as useful derivations (e.g., stress, workload, or engagement). This is also the case for explicit input. For example, as soon as the user uses a resistive sensing fabric placed in a location in which gesture input is feasible (e.g., sleeve, thighs), the system should listen for specific gestures. The developer may then be able to receive call-backs (e.g., circle gesture detected) instead of polling the data. This allows even novice developers to use gesture based input without the necessity to learn how to detect gestures. Furthermore, many applications can listen for these call-backs and do not have to run their own algorithms which is computation intense. In order to achieve that, the system needs to predefine interfaces which are used by sensor developers as well as application developers.

Design Recommendation 11. *Dependency of resources, abstraction, and application.*

Different resources need to be managed. These resources include the sensors integrated in the garments, actuators serving as feedback channel to the user, communication channels, processing of the measured data, applications, and the generated data itself. These resources rely on each other (e.g., an application needs a specific sensor). Furthermore, the user needs to be in charge of controlling it. For privacy reasons the user might not want to grant access to specific resources for every application. Additionally, abstraction layers need to be integrated so that the applications can be deployed on different garments since different garments can provide the same sensing or actuation functionality (e.g., a step counter can be achieved with smart socks as well as with smart trousers). An application should run if any garment is available that provides the necessary functionality and should not depend on an actual type of garment.

Design Recommendation 12. *Create an API supporting the variety of wearable sensors, wearable actuators, and application scenarios.*

Providing an easy to use API is one of the key aspects to gain a huge number of applications for a system. The API should provide possibilities for beginners to rapidly develop small application with low complexity but should allow a low level access to the sensing and actuating possibilities of the garments for expert developers. In addition to the knowledge usually required for application development (e.g., on mobile phones), developing effective applications for smart garments requires more knowledge. Knowing the most efficient algorithms for activity recognition and gesture spotting as well as interpreting physiological reactions are only two areas in which the application developer needs knowledge and experience. Since not all application developers are experts in this areas, the API should take this tasks off the developer. To allow novice developer to use this functionality, the API needs to provide off-the-shelf integration of algorithms that solve these issues and provide simple events, application developer can easily use (e.g., waving-gesture detected).

Chapter 11

Conceptual Architecture

In this chapter, we apply the proposed design recommendations (cf., Chapter 10) to a mobile system – called Garment OS. The system is capable of managing wearable sensors and actuators focusing on supporting application developers as well as end-users using the developed applications. First, we present the concept and implementation as an Android service and application. The system serves as an add-on to Android using the already existing interfaces to wireless communication technologies and mobile applications. We discuss each developed entity as well as the interfaces in detail. Second, we introduce physical sensors and actuators developed in the course of this thesis. Besides single purpose sensors and actuators, a physical prototype of a sensor-equipped smart shirt is introduced.

This chapter is based on the following publication:

- S. Schneegass, M. Hassib, B. Zhou, J. Cheng, F. Seoane, O. Amft, P. Lukowicz, and A. Schmidt. SimpleSkin: Towards Multipurpose Smart Garments. In *Adjunct Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2015 ACM International Symposium on Wearable Computers*, UbiComp/ISWC'15 Adjunct, pages 241–244, New York, NY, USA, 2015. ACM
- S. Schneegass, M. Hassib, T. Birmili, and N. Henze. Towards a Garment OS: Supporting Application Development for Smart Garments. In *Proceedings of the 2014 ACM International Symposium on Wearable Computers: Adjunct Program*, ISWC '14 Adjunct, pages 261–266, New York, NY, USA, 2014. ACM

11.1 Designing a Garment OS

11.1.1 Integration into the End-Users‘ Device Infrastructure

The integration into the microcosm of the end-users´ devices is a crucial success criterion. Mobile devices serve as central communication tool, maintain all of the users‘ data, and are one of the main sources of entertainment. While the benefit for the mobile device has been discussed in the research probes, the linkage is beneficial for the smart garment as well. They can exploit the processing, memory, and connection capabilities the mobile phone offers. Thus, the garments do not need an additional high-level processing platform which dramatically reduces the complexity of the electronics on the garment itself.

11.1.2 Separation of Concerns

Developing mobile interactions with smart garments is a challenging task that need different types of expertise. The process can be grouped into four distinct

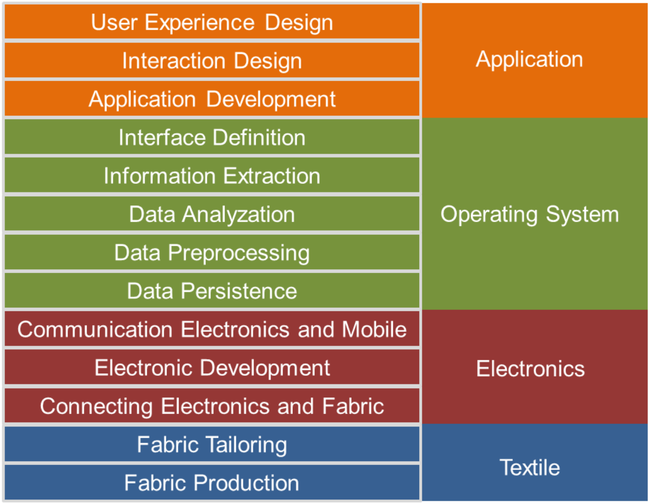


Figure 11.1: The main expertises necessary to develop a mobile system utilizing garment based sensor or actuator as input or output.

groups of expertises (cf., Figure 11.1). First, the textile itself needs to be developed. This includes expertise in producing fabrics and tailoring fabrics into a piece of garment. In a second step, the preprocessing electronics needs to be developed which includes developing the custom electronics, connecting the textile electrode with preprocessing electronic, and communication protocol. Next, the retrieved data needs to be processed, analyzed, interpreted, and persisted. For this step, knowledge in computer science and algorithm development is needed. Last, the gained knowledge on the user needs to be used to create a benefit for the user. This could be a certain application that is generating a positive impact on the user´s health or wellbeing, allow easier control of the user´s device, or adopt system based on the user‘s current activity. All this requires expertise in interaction design, HCI, and User Experience (UX) design. The OS we propose in this chapter mainly tackles the third step (cf., Figure 11.1 – green).

11.1.3 Diversity of Sensors and Actuators

The diversity of consumer devices is huge. Myriads of devices exist fulfilling the same sensing or actuating task. For example, heart rate sensors exist in

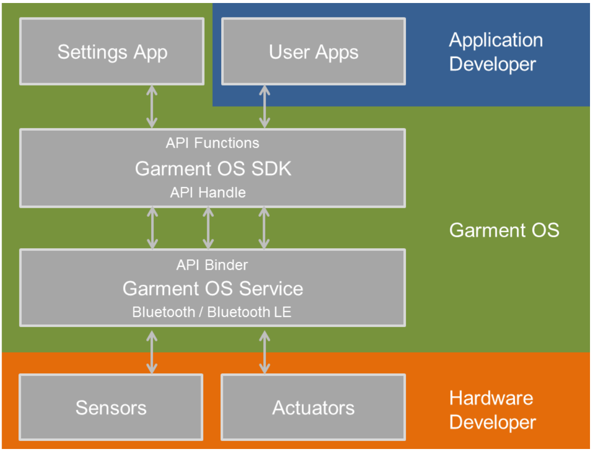


Figure 11.2: Conceptual Architecture of the Garment OS. The actual Garment OS (green) and its connections to third party applications (blue) and to sensors and actuators (orange).

form factors of chest straps, wrist worn devices, or integrated into garments. All of these devices are capable of providing the heart rate among others. An OS needs to abstract on the actual hardware and provide interfaces for application developers working independently of the devices.

11.2 Garment OS

The developed Garment OS is mainly divided into three parts (cf., Figure 11.2): (1) the Garment OS Service, (2) the Settings Application, and (3) the Garment OS SDK. The main part of the system is the *Garment OS service*. It handles the connection of the sensors and actuators via Bluetooth and BLE, persists the incoming sensor data, and allows sensing data to actuators. The main user interaction takes place in the *Settings Application* in which the user can connect sensors and actuators. The *Settings Application* connects to the *Garment OS SDK* similar to applications developed by application developers via an API.

11.2.1 Garment OS Service

The main part of the Garment OS Service runs as a service in the background and handles the sensors, persistence, communication and visualization.

Connectivity

One of the most important parts is the communication between the Garment OS and the external sensors and actuators. Current mobile phones offer a variety of different communication methods, most prominently Near Field Communication (NFC), Wi-Fi, and Bluetooth. Each of these methods has its own advantages and disadvantages. While Wi-Fi offers the highest data rate, the power consumption is high as well. Additionally, most mobile phones are already connected to a Wi-Fi which would force wearable devices to connect to the same network or require an additional server in between. In contrast, NFC allows only a small distance and low data rate. Bluetooth as well as BLE have the advantage ob being at the same time energy-efficient and allowing a high data rate. Thus, we mainly focus on Bluetooth (using the Serial Port Profile) and BLE connections as the default way of communication.

Persistence

The amount of data created using garment-based wearable sensors is huge. Thus, persisting the data for long-term use as well as for analysis using larger time windows is mandatory. We store all data generated by sensors first on the user's mobile phone via text files. These files can be easily accessed and exported to cloud services as a backup, for example for long term measurements. Further, these files can be used for analysis by more powerful computing devices later on. We implemented three cloud services, namely Dropbox[21], OneDrive[22], and Google Drive[23]. Before uploading the files to the cloud service, they are packed and encrypted to ensure that the data is secure and the privacy of the user is preserved.

Driver

Different garment-based sensors have different data formats. Thus, we developed a driver for each sensor that interprets the received data stream and extracts the

[21] `http://www.dropbox.com`

[22] `https://onedrive.live.com/about/`

[23] `https://drive.google.com`

```java
private boolean initializeDriver() {
    try {
        mDriver = Class.forName("de.ustutt.vis.wearable.os.sensorDriver."
                                        + mSensor.getDriverName());
        mReceiver = mDriver.newInstance();
        Method sendInitData = mDriver.getMethod("sendInitData",
                                                OutputStream.class);
        sendInitData.invoke(mReceiver, mOutputStream);
        mEncodeData = mDriver.getMethod("encodeData", String.class);
    } catch (Exception e) {
        Log.e(TAG, "Failed to initialize driver: " + e.getLocalizedMessage());
        return false;
    }
    Log.i(TAG, "Driver " + mSensor.getDriverName() + " for sensor "
                         + mSensor.getSensorName() + " initialized");
    return true;
}
```

Listing 11.1: Drivers are dynamically loaded at runtime.

values. Further, each driver implements a number of specific interfaces. These interfaces define which information can be extracted from a sensor. The heart-rate interface indicates that a sensor is capable of providing the heart rate. It is, for example, implemented by the *ECGZ* driver and by the *Polar HR* driver. A list of interfaces can be found in Listing 11.2. In general, drivers are dynamically loaded at runtime (cf., Listing 11.1). When the driver is successfully loaded, the `sendInitData` method is immediately invoked to potentially set up sensor properties. Then, the `encode` method is loaded and passed to the thread that executes the method as soon as new data is received. The `encode` method encodes the received data and extracts information.

The drivers used for the actuators are sending strings to the actuators. These strings can be simple strings (e.g., “heart rate 90”) or serialized matrices of vectors (e.g., for LED matrix). The simple strings are pre-defined within the Garment OS.

11.2.2 Settings Application

In order to control the Garment OS we developed an Android application that keeps the user in control (cf., Figure 11.3). In this application the user can manage preferences such as privacy, persistence, or the used sensors and actuators. The *Settings Application* uses a specific API that has additional functionality compared to the regular application API such as management functions for the sensors and actuators.

Manage Sensors and Actuators

Managing the sensors and actuators is one of the main tasks of the Settings Application. The view presents a list of available devices (i.e., sensors and actuators). In this view, the user can add new devices (connected via Bluetooth or BLE), enable existing devices (i.e., start a connection to a Bluetooth device), remove existing devices, or view device details. The device detail view presents information about the device (i.e., name, available driver) and a visualization of the current sensor values. Within the visualization, a graph-based and text-based visualization is available that can be used to see the raw data of a sensor. Furthermore, there are text-based visualizations (e.g., the values of each pressure sensors of a pressure sensor matrix).

Manage Privacy

In the privacy view, the user can select which application is allowed to access certain devices. The user choses the device based on the information level (cf., Design Recommendation 7) requested by an application. For example, the application requests the user‘s heart rate. In the view, the user is able to select all available sensors that provide heart rate information such as an ECG device or a dedicated heart rate chest strap. This also makes sure that the user has all necessary sensors and actuators for an application (cf., Design Recommendation 11).

Manage Storage

The user can upload the measured sensor data to cloud services or to the local file system. Further the user can enable and disable the encryption of the data which is in line with Design Recommendation 8.

11.2.3 Garment OS SDK

The SDK provides an API to connect applications to events (i.e., using callbacks), to get the current value of sensors (i.e., polling), or to send data to actuators. Further, it includes a developer module to support novice developers.

Application Programming Interface

We developed an API that can be used by the application developer to create applications for the garment OS which is in line with Design Recommendation 12.

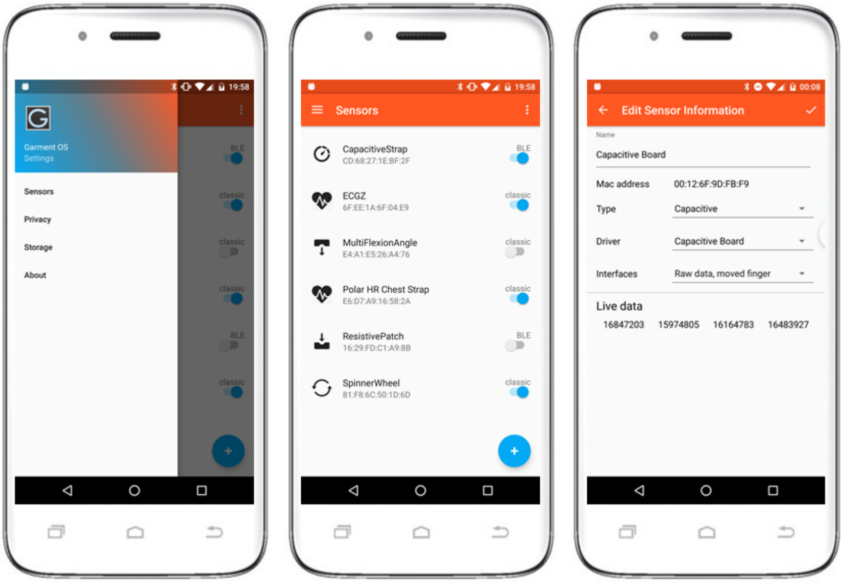


Figure 11.3: Three views of the settings application of the Garment OS. The main menu (left), sensors view (center) and the sensor information view (right).

An excerpt of the AIDL file of the API calls can be found in Listing 11.2. While these functions cover a large set of typical sensors and actuators, specific sensors might need different functions and, thus, the API could need to be extended in future. In general, the API is divided into two parts. The first part consists of calls that return the sensor and actuator objects themselves, so that developers can use the sensor objects to access their values and the actuator objects to send information to them. The second part has predefined functions returning popular information such as heart rate and step count (cf., Design Recommendation 9 and 10).

If an application developer wants to create a basic fitness application, he or she can do the following using the API. After registering the application to the Garment OS (`registerApp(String app);`), the developer would use the heart rate and visualize it as a graph. This can easily be done by calling the API function `API_getHeartRate(String app, int numValues);`. When requiring a more sophisticated algorithm, the application developer could also use the raw

ECG values (`API_getECG(String app, int numValues);`) and extract the heart rate manually. In a second step, the developer could get the object of a *resistive sensing matrix* sensor (`API_getPressureSensor(String app);`). The end-user needs to place this sensor into the shoe sole. Then, the developer calls the `API_getPressure(String app, int numValues)` function that reports the values of the sensor. With this, the developer can calculate how the user treads. This data could be used to apply custom algorithms to count steps or analyze the pressure distribution of the feet. The above presented simple steps are sufficient to create a basic application.

11.3 Physical Prototypes

We developed basic sensors and actuators to show the capabilities of the developed system. These sensor and actuators were also used to explore different interaction concepts and help realizing novel ideas in workshops conducted within the scope of this thesis [219, 226].

11.3.1 Visual Output

We developed two different visual outputs. First, the LED matrix displays described in Chapter 6. This display allows visualizing 8×16 pixels and is connected via Bluetooth. It displays arbitrary content that is sent as an array of RGB values. Additionally, we used a small 32×32 pixel display that is capable of displaying the heart rate. Depending on the the value sent to the display, the frequency in which the heart blinks changes.

11.3.2 Heart Rate Sensors

We implemented two types of heart rate sensors. First, we connected an off-the-shelf Polar chest strap via breakout board to an Arduino. The Arduino connects via Bluetooth to the Garment OS and sends the heart rate every second. Furthermore, the *ECGZ* device is able to provide the heart rate which is extracted out of the ECG data. The *ECGZ* is also connected via Bluetooth.

```
interface IGarmentAPI {
   void        registerApp(String app);
   void        registerCallback(String app, IGarmentCallback cb, int ID);
   void        unregisterCallback(String app, IGarmentCallback cb, int ID);
   PSensor[]      API_getAllSensors(String app);
   PSensor[]      API_getAllSensorsByType(String app, int sensorType);
   PSensor    API_getSensorById(String app, int id);

   // Functions for the App to get the default Sensor
   PSensor API_getECGSensor(String app);
   PSensor API_getHeartRateSensor(String app);
   PSensor API_getTemperatureSensor(String app);
   PSensor API_getBioImpedanceSensor(String app);
   PSensor API_getBioPotentialSensor(String app);
   PSensor API_getPressureSensor(String app);
   PSensor API_getPressureMatrixSensor(String app);
   PSensor API_getCapacitiveSensor(String app);
   PSensor API_getTwoDSensor(String app);
   PSensor API_getAccelerometerSensor(String app);
   PSensor API_getGPSSensor(String app);
   PSensor API_getDefaultSensorByType(String app, int sensortype);

   // Functions for the apps to get the sensor values from their default
     sensors
   PSensorData API_getECG(String app, int numValues);
   PSensorData API_getHeartRate(String app, int numValues);
   PSensorData API_getTemperature(String app, int numValues);
   PSensorData API_getBioImpedance(String app, int numValues);
   PSensorData API_getBioPotential(String app, int numValues);
   PSensorData API_getMaxPressurePoint(String app, int numValues);
   PSensorData API_getCapacitiveValues(String app, int numValues);
   PSensorData API_get2DPoint(String app, int numValues);
   PSensorData API_getLastGesture(String app, int numValues);
   PSensorData API_getSkeleton(String app, int numValues);
   PSensorData API_getAccelerometer(String app, int numValues);
   PSensorData API_getPressure(String app, int numValues);
   PSensorData API_getGPS(String app, int numValues
   PSensorData API_getDefaultValues(String app, int numValues, int
     sensortype);

   // Function calls forward to Sensor object
   boolean    SENSORS_SENSOR_isEnabled(String app, int sid);
   boolean    SENSORS_SENSOR_isConnected(String app, int sid);
   boolean    SENSORS_SENSOR_connectSensor(String btMac, String driverName,
     boolean on);
   String        SENSORS_SENSOR_getDisplayedSensorName(String app, int sid);
   String        SENSORS_SENSOR_getDriverName(String app, int sid);
   int       SENSORS_SENSOR_getSampleRate(String app, int sid);
   int       SENSORS_SENSOR_getSensorType(String app, int sid);
   PSensorData SENSORS_SENSOR_getRawData(String app, int sid);
}
```

Listing 11.2: Excerpt of the API from the Android AIDL.

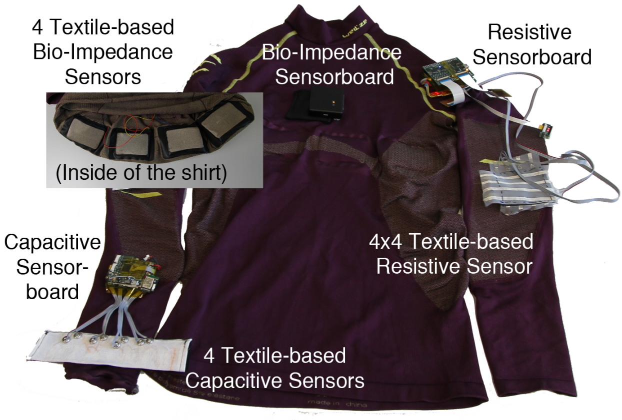


Figure 11.4: First prototype of the SimpleSkin Shirt. The sensors are put out of their pockets for visibility.

11.3.3 Posture Detection

We further included two types of sensors that are capable of estimating flexion angles of joints. First, the resistive pressure matrix (cf., Chapter 3) is connected via BLE. It uses a resolution of 4×4 pressure values which are sent in four packages. As a low resolution alternative, we built a bend sensor out of two stripes made of conductive fabric with force-resistant fabric in between. The sensor is connected to an Arduino sending the measured values at 100 Hz using Bluetooth.

11.3.4 Multipurpose Garment

We combined three sensing modalities within a single shirt, namely capacitive sensing, resistive sensing, and bio-impedance sensing. We used each of the three sensing modalities on dedicated locations within the shirt. Since bio-impedance sensors detect vital parameters of the user (e.g., heart rate), we placed them on the chest area of the shirt. We placed the capacitive sensor on the wrist area of the shirt. With this placement, we are able to detect movement of the wrist and fingers as well as the head (cf., [46, 110]). Lastly, we used resistive sensor arrays (cf., [282]) at the user‘s elbow. It is intended for detecting the angle of the elbow and, thus, give insights about the current posture of the user. We integrated all three sensing modalities in an off-the-shelf long-sleeved shirt (cf., Figure 11.4). The sensor is fixed by sticking it into the sleeve of the shirt, whereas the sensor board is using an enclosure attached at the forearm. For the resistive sensor array, we used a small patch of textile with a 4×4 pressure sensors similar to Zhou et al. [282]. We placed it at the right elbow to explore the feasibility of posture detection with this sensing modality. Both fit into a pocket at the elbow. Additionally, for bio-impedance sensing, we glued four fabric cushions inside the shirt. These cushions are connected to the sensor sitting on the outside of the shirt. All three control boards are connected via Bluetooth and BLE and continuously send their data to the developed system architecture.

11.4 Discussion

In this chapter, we discuss a potential architecture for integrating garment-based wearable computing devices into a mobile device infrastructure. The focus hereby lies on the specific context of garment-based wearable computing. In particular, different parts of wearable computing devices and applications are identified. Interfaces between these parts help separating the concerns for different types of developer.

The proposed layered architecture is one way to deal with the challenges arising. Other approaches such as, for example, a service oriented architecture, might also achieve similar results. Nevertheless, the design recommendations (cf., Chapter 10) as well as the design considerations for creating a garment OS (cf., Section 11.1) should be taken into account for all different architectures. By following these recommendations, the architecture will be capable of realizing the most common applications using the main interaction methods.

V

Conclusion and Future Work

Chapter 12

Conclusion

This thesis explores the usage of garment-based wearable computing devices in the context of mobile interaction. We follow the user-centered design process extended through a probe-based approach for understanding the requirements. In the following, we summarize the research contribution, answer the research question, and point towards future work.

12.1 Summary of Research Contribution

Overall, we provide four main contributions in this thesis. First, we apply and extend the user-centered design process to design mobile interaction enriched by garment-based wearable computing. Second, we present research probes increasing the understanding of how different input and output modalities should be designed. Third, we provide a set of design recommendations helping to integrate smart garments into the mobile interaction. Fourth, we present a reference architecture implementing the design recommendations.

12.1.1 User-centered Design

We applied the user-centered design process to the field of wearable computing. We analyzed how a mobile platform should look like that is capable of enriching mobile interaction. In a first step, we charted a design space to understand the specific context of use and its characteristics. To specify the requirements from a technical and interaction point of view, we extended the user-centered design process with a probe-based research approach. By designing, implementing, and evaluating research probes tackling different input and output possibilities, we learned fundamental aspects that resulted in design recommendations. In the last step, we developed and evaluated a mobile platform. This platform is capable of managing wearable sensors and actuators, supports the developer of mobile applications, and allows users to manage their privacy preferences.

12.1.2 Garment-based Interaction

The developed research probes provide insights into how the interaction can be enriched with smart garments. Nowadays mobile devices mainly rely on touch input on displays and speech input. In contrast, we outline interaction techniques currently not used for mobile devices. While still technical challenges with regards to miniaturization and robustness need to be tackled, we show the general feasibility of the interaction techniques.

Input using Garments

We explored touch-based input on smart garments to control mobile applications. We thereby showed the benefit of smart garments in comparison to interacting on the mobile device itself. Due to an increased input surface and non-obtrusion of the display, user´s are capable to interact faster. In a next step, we used capacitive sensing to detect mid-air gestures. Integrating the electrodes into the cuff of a shirt or the wrist strap of a watch, the input can be performed with the same hand leaving the other hand available for other tasks. While using mid-air gestures has been explored before, we used the developed prototype to conduct a gesture elicitation study. We defined three criteria to rank the gestures taking socially acceptability, visibility, and the user´s ranking into account. The study revealed insights into how the user wants to perform gestures in contrast to taking the gestures that are easy to differentiate. One of the key advantages of smart garments is the closeness to the user‘s body. We show in an automotive use-case that we can use biosignals to infer on the current level of workload of the driver. This information can in the future be used to create automotive user interfaces that react on the condition of the driver and provides a safer driving experience.

Output using Garments

On the output side, we looked into on-body displays. We fostered the understanding of how content can be displayed. We also explored where on the body these display should be placed at. The results showed that the arms and chest are preferred for most of the presented application scenarios. Further, we explored a navigational use-case in more detail by showing the advantages of on-body displays for showing points of interests located outside the viewport of a mobile device. The results suggest that such a display can be used as context display helping to extend the focus display of a smart watch. Using auditory feedback, we created a novel type of biometric. We used the characteristic frequency response the user´s head to identify and authenticate the user. This approach can be implicitly used to continuously and implicitly authenticate users. Last, we outline the benefit of EMS as haptic feedback. We show that this technology allows actuating users in a way that they perform gestures or change their walking direction. Due to the embodiment, this type of haptic feedback has a more natural and intense feeling compared to feedback nowadays known from mobile devices. Another aspect we outline is that using EMS gestures, emotions from a remote partner can be communicated.

12.1.3 Design Recommendations

We present 12 design recommendations supporting the integration of smart garments into mobile interaction. These recommendations are grouped into interaction and technology centered. They were distilled from the lessons learned of the research probes. The interaction centered recommendations support interaction designers to cope with the special combination of garment based sensors and actuators and mobile interaction. In contrast, the technology centered recommendations help to design an OS for that copes with the challenges of integrating garment based sensors and actuators.

12.1.4 Reference Architecture

We provide a technical contribution by showing how an OS should be designed. We developed a prototypical system called Garment OS. It consists of an Android service and an Android application. The service handles the connection to the sensors and actuators, persists and interprets the data, and provides interfaces for application developers. The application is used to control the service, add and remove sensors and actuators, and manage the user‘s privacy preferences. Mobile application developers can access the information extracted from the sensors and send information back to the user using actuators.

12.1.5 Limitations

We use research probes throughout this thesis to explore different input and output possibilities. By using this methodology, we achieved (1) an in-depth view into all parts of the development process of garment-based wearable computer and (2) a variety of different input and output possibilities by selecting specific probes. However, we focused on the interaction and, thus, did use prototypes to as tools. These prototypes have fundamental differences compared to the envision products in the future. For example, the *GestureSleeve* presented in Chapter 3 used additional Velcro layers to be adjustable and, thus, usable for different users in the user study. For other prototypes, we used non-garment-based hardware. The EMS electrodes used in Chapter 8 are off-the-shelf products that need to be attached to the user´s body. All these differences might impact the user studies and, thus, the results. Nevertheless, the gained insights of each research probe should be valid even when changing the used technologies.

12.2 Research Questions

In the beginning of this thesis, we stated five research questions. During the course of the thesis, we gained knowledge to answer the questions as follows.

RQ1: How to structure a design space for (enriching) mobile interaction?

Through an in-depth analysis of related literature, we charted a design space. The design space allows structuring wearable computing applications particularly with taking mobile interaction into account. We identified the most important dimensions of the design space, namely, the location on the body and the type of interaction. All research prototypes developed in the course of this thesis are classified using the design space as examples (cf., Chapter 2).

RQ2: How to realize different input methods using garment based sensors?

To analyze the different input methods we developed three research probes. We covered with these research probes explicit touch and gesture-based input as well as implicit input through biosignals. Touch-enabled fabric offers similar possibilities as touch screens. We showed that touch on the sleeve of a shirt provides benefit compared to direct input on mobile devices by overcoming issues such as occlusion and the limited input space (cf., Chapter 3). Additionally, we presented a gesture set for mid-air gestures (cf., Chapter 4). These gestures can be used to control a mobile device. Both input modalities can be combined using the same fabric. This eases up the production process and enables mass-producibility.

RQ3: How to realize output on smart garments?

Tackling the output side of smart garments, we present research probes addressing the most common output modalities. For visual output, we gained knowledge on the placing behavior which depends on the purpose of the display. Particularly, extending the output space of smart watches showed promising results. The research probe focusing on auditory output shows that by creating a loop with input and output, novel application scenarios can be realized. We further investigates EMS as novel way of providing haptic feedback. Due to the closeness to the body, smart garments compensate some of the drawbacks of EMS. In addition, we show that the feedback is more versatile and rich compared to regular haptic feedback in the mobile domain.

RQ4: How to integrate sensors and actuators in mobile platforms?

We used different types of hardware to develop the research probes (i.e., different Arduinos, FPGAs). Each of them having its own type of transmitted data, sampling frequencies, and methods of connection. Looking at current mobile devices, Bluetooth emerges as one of the key technologies for wirelessly attaching devices. We identified Bluetooth as common interface for attaching sensors and actuators to mobile devices. We developed an Garment OS that manages the communication with the devices and provides access through an API. The API allows easy access to the sensors and actuators on a software level.

RQ5: How to represent sensor data for Application Developers and End-users?

Representing data is a core challenge in using garment-based wearable sensors. The raw data extracted from a sensor is mainly designed to achieve a high data throughput. Thus, extracting information out of this data stream can be a challenging task. Application developers as well as end-users need to understand what information is available for the application. We identified two core levels at which the data can be accessed. After the the raw data is preprocessed by removing communication overhead, transforming binary data, and chunking the received data to actual values, the raw data is transformed to a *data level*. This is particularly important for application developers which want to run own algorithms or extract exotic information. However, we showed that end-users do not understand what information is actually extracted from the sensor (cf., Chapter 9). Thus, we proposed using a second layer, namely, *information layer*. In this layer the actual information is provided. Besides allowing the end-user to understand the privacy implications of allowing application accessing the data, this also supports the application developer. As we showed in the API, providing access on the information level helps application developers to use the most common information without the necessity of implementing algorithms on their own. Detecting gestures from touch input, calculating steps from different pressure sensors, and extracting the heart-rate from an ECG signal are just three examples in which such an *information level* supports the application developer.

12.3 Future Work

This thesis provides a common ground for future research in the area of enriching mobile interaction and interaction with smart garments. However, during the course of this thesis, several additional research challenges have arisen which are beyond the scope of this thesis. This section explains these research challenges in detail.

12.3.1 Smart Garment as Enabler for Interaction in Public Space

As discussed in this thesis, the input possibilities of smart garments is manifold. Explicit gesture and touch input as well as implicit input offer a rich set of input techniques. However, the visual output possibilities are rather limited. Textile displays are offering low resolution output which is capable of covering many application scenarios. Combining the input possibilities of smart garments with the recent advent of public displays, this drawback can be overcome. Displays in public space can be exploited as an additional output mean. The user can walk up the display and interact with it using input via smart garments [220]. For example, gesture based input has been widely used in public display research [10]. The challenge when deploying displays in the wild is the usage of camera systems such as the Kinect which is used for the research prototypes. Smart garments, for example, allow detecting gestures with strain sensor in long-sleeved shirts. Future research needs to explore how an infrastructure needs to be designed to enable such an interaction. How can user‘s be identified and their performed input be understood as input for the public display.

12.3.2 Evaluation of Wearable Computing Devices in the Wild

Current evaluation methods for wearable devices such as smart garments are mainly limited to feasibility studies in the lab. While these evaluations include a high internal validity and show the general feasibility of the envisioned devices, moving from the lab to field is the necessary next step. In this thesis, a first step towards this goal is made. We investigate smart garments in studies at the boarder between lab and field. However, there is still room for further increasing the ecologic validity. A first step would be to deploy several wearable computing devices in a long-term deployment. The way user‘s interact with these systems will show how usable and utilitarian wearable devices actually are. In a next step, the evaluation needs to be pushed from a field evaluation into the wild. With the recent advent of evaluations through deployed systems [108], novel methods for conducting evaluations received considerable attention. Transferring this methodology to wearable computing devices will allow gaining more in depth knowledge of how actual user‘s interact with wearable devices in realistic scenarios.

12.3.3 User Identification through Wearable Computer

In the auditory feedback research probe (cf., Chapter 7), we showed how user's can be identified and authenticated by *looking into* their body [233]. In this case, we used the changes in an audio signals send through the user's head to differentiate users. We conducted a very controlled study. Aspects such as the influence of background noise, different audio cues (e.g., music files), or microphones and speakers capable of recording and producing audio signals in higher quality need to be investigated in more depth.

The presented approach can also be adopted to several other signals and locations. Identifying further body parts such as the wrist or chest may provide similar unique responses as we showed using the user's head. Additionally, other signals such as generated through EMS devices can be used to develop similar systems. As discussed in the Chapter 8, the response of the user's muscles highly differs between users. Exploring whether this difference can be served as a biometric will open up myriads of novel research challenges.

12.4 Concluding Remarks

This thesis investigates how garment based wearable computing devices can be used to enrich the interaction with mobile devices. It addresses fundamental challenges designers and developers of such system will face in the future. When we reach the point where smart garments that offer similar wearability, durability, and quality for about the same price as their non-smart counterparts, smart garments will replace their non-smart counterparts. We see the first steps made when Google started exploring Project Jacquard[24] and Ralph Lauren announced their tech shirt[25]. However, development has not progressed far enough to substitute every garment but, eventually, research will be able to meet market requirements with regard to price and quality. From then on, understanding how this development influences the interaction and system design of mobile devices becomes crucial.

[24] `https://www.google.com/atap/project-jacquard/`

[25] `http://www.ralphlauren.com/product/index.jsp?productId=69917696`

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BIBLIOGRAPHY

Bibliography

[1] U.-V. Albrecht, U. von Jan, J. Kuebler, C. Zoeller, M. Lacher, O. J. Muensterer, M. Ettinger, M. Klintschar, and L. Hagemeier. Google glass for documentation of medical findings: evaluation in forensic medicine. *Journal of medical Internet research*, 16(2), 2014.

[2] M. Alhonsuo, J. Hapuli, L. Virtanen, A. Colley, and J. Häkkilä. Concepting Wearables for Ice-Hockey Youth. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services Adjunct*, MobileHCI '15, pages 944–946, New York, NY, USA, 2015. ACM.

[3] H. Almuhimedi, F. Schaub, N. Sadeh, I. Adjerid, A. Acquisti, J. Gluck, L. F. Cranor, and Y. Agarwal. Your location has been shared 5,398 times!: A field study on mobile app privacy nudging. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, CHI '15, pages 787–796, New York, NY, USA, 2015. ACM.

[4] F. Alt, A. Schmidt, and C. Evers. Mobile Contextual Displays. In *Proceedings of the First International Workshop on Pervasive Advertising*, PerAd'09, Nara, Japan, jun 2009.

[5] F. Alt and S. Schneegass. A Conceptual Architecture for Pervasive Advertising in Public Display Networks. In *Proceedings of the 3rd Workshop on Infrastructure and Design Challenges of Coupled Display Visual Interfaces*, 2012.

[6] F. Alt and S. Schneegass. Towards Understanding the Cognitive Effects of Interactivity. In *Experiencing Interactivity in Public Spaces (Workshop at CHI 2013)*, 2013.

[7] F. Alt, S. Schneegass, J. Auda, R. Rzayev, and N. Broy. Using eye-tracking to support interaction with layered 3D interfaces on stereoscopic displays. *Proceedings of the 19th international conference on Intelligent User Interfaces - IUI '14*, pages 267–272, 2014.

[8] F. Alt, S. Schneegass, M. Girgis, and A. Schmidt. Cognitive effects of interactive public display applications. In *Proceedings of the 2nd ACM International Symposium on Pervasive Displays*, pages 13–18. ACM, 2013.

[9] F. Alt, S. Schneegass, A. Sahami, M. Hassib, and A. Bulling. Graphical Passwords in the Wild - Understanding How Users Choose Pictures and Passwords in Image-based Authentication Schemes. *MobileHCI '15 Proceedings of the 17th international conference on Human-computer interaction with mobile devices and services*, 2015.

[10] F. Alt, S. Schneegass, A. Schmidt, J. Müller, and N. Memarovic. How to evaluate public displays. In *Proceedings of the 1st International Symposium on Pervasive Displays*, page 17. ACM, 2012.

[11] O. Amft and J. Habetha. Smart medical textiles for monitoring patients with heart conditions. In L. v. Langenhove, editor, *Book chapter in: Smart textiles for medicine and healthcare*, pages 275–297. Woodhead Publishing Ltd, Cambridge, England, Feb. 2007. ISBN 1 84569 027 3.

[12] O. Amiraslanov, J. Cheng, P. Chabrecek, and P. Lukowicz. Electroluminescent based Flexible Screen for Interaction with Smart Objects and Environment. *3rd IUI workshop on Interacting with Smart Objects. International Conference on Intelligent User Interfaces (IUI-14)*, pages 43–46, 2014.

[13] R. Anderson, R. Anderson, K. M. Davis, N. Linnell, C. Prince, and V. Razmov. Supporting active learning and example based instruction with classroom technology. *SIGCSE Bull.*, 39(1):69–73, Mar. 2007.

[14] D. Ashbrook, P. Baudisch, and S. White. Nenya: Subtle and Eyes-free Mobile Input with a Magnetically-tracked Finger Ring. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '11, pages 2043–2046, New York, NY, USA, 2011. ACM.

[15] D. Ashbrook, K. Lyons, and T. Starner. An investigation into round touchscreen wristwatch interaction. In *Proceedings of the 10th International Conference on Human Computer Interaction with Mobile Devices and Services*, MobileHCI '08, pages 311–314, New York, NY, USA, 2008. ACM.

[16] P. Bader, S. Schneegass, N. Henze, V. Schwind, and K. Wolf. A Mobile See-through 3D Display with Front- and Back-touch. In *Proceedings of the 8th Nordic Conference on Human-Computer Interaction: Fun, Fast, Foundational*, NordiCHI '14, pages 1063–1066, New York, NY, USA, 2014. ACM.

[17] P. Bader, V. Schwind, N. Henze, S. Schneegass, N. Broy, and A. Schmidt. Design and Evaluation of a Layered Handheld 3D Display with Touch-sensitive Front and Back. In *Proceedings of the 8th Nordic Conference on Human-Computer Interaction: Fun, Fast, Foundational*, NordiCHI '14, pages 315–318, New York, NY, USA, 2014. ACM.

[18] G. Bailly, J. Müller, M. Rohs, D. Wigdor, and S. Kratz. Shoesense: A new perspective on gestural interaction and wearable applications. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '12, pages 1239–1248, New York, NY, USA, 2012. ACM.

[19] L. Bao and S. S. Intille. Activity Recognition from User-Annotated Acceleration Data. In A. Ferscha and F. Mattern, editors, *Pervasive Computing*, volume 3001 of *Lecture Notes in Computer Science*, pages 1–17. Springer Berlin Heidelberg, 2004.

[20] T. A. Bass. *The eudaemonic pie*. Houghton Mifflin Harcourt, 1985.

[21] P. Baudisch and G. Chu. Back-of-device interaction allows creating very small touch devices. *Proceedings of the SIGCHI conference on Human ...*, pages 1923–1932, 2009.

[22] P. Baudisch, N. Good, and P. Stewart. Focus Plus Context Screens: Combining Display Technology with Visualization Techniques. In *Proceedings of the 14th Annual ACM Symposium on User Interface Software and Technology*, UIST '01, pages 31–40, New York, NY, USA, 2001. ACM.

[23] P. Baudisch and R. Rosenholtz. Halo: A Technique for Visualizing Off-screen Objects. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '03, pages 481–488, New York, NY, USA, 2003. ACM.

[24] B. B. Bederson, J. D. Hollan, K. Perlin, J. Meyer, D. Bacon, and G. Furnas. Pad++: A zoomable graphical sketchpad for exploring alternate interface physics. *Journal of Visual Languages & Computing*, 7(1):3–32, 1996.

[25] J.-M. Belda-Lois, S. Mena-del Horno, I. Bermejo-Bosch, J. C. Moreno, J. L. Pons, D. Farina, M. Iosa, M. Molinari, F. Tamburella, A. Ramos, A. Caria, T. Solis-Escalante, C. Brunner, and M. Rea. Rehabilitation of gait after stroke: a review towards a top-down approach. *Journal of NeuroEngineering and Rehabilitation*, 8(1):1–20, 2011.

[26] C. Berka, D. J. Levendowski, M. N. Lumicao, A. Yau, G. Davis, V. T. Zivkovic, R. E. Olmstead, P. D. Tremoulet, and P. L. Craven. Eeg correlates of task engagement and mental workload in vigilance, learning, and memory tasks. *Aviation, Space, and Environmental Medicine*, 78(Supplement 1):B231–B244, 2007.

[27] G. Bieber, M. Haescher, and M. Vahl. Sensor requirements for activity recognition on smart watches. In *Proceedings of the 6th International Conference on PErvasive Technologies Related to Assistive Environments*, PETRA '13, pages 67:1–67:6, New York, NY, USA, 2013. ACM.

[28] G. Blasko and S. Feiner. An interaction system for watch computers using tactile guidance and bidirectional segmented strokes. *Eighth International Symposium on Wearable Computers*, 1:0–3, 2004.

[29] C. Bo, L. Zhang, X.-Y. Li, Q. Huang, and Y. Wang. SilentSense: Silent User Identification Via Touch and Movement Behavioral Biometrics. *Proceedings of the 19th annual international conference on Mobile computing & networking - MobiCom '13*, page 187, 2013.

[30] R. Borovoy, F. Martin, S. Vemuri, M. Resnick, B. Silverman, and C. Hancock. Meme Tags and Community Mirrors: Moving from Conferences to Collaboration. In *Proceedings of the 1998 ACM Conference on Computer Supported Cooperative Work*, CSCW '98, pages 159–168, New York, NY, USA, 1998. ACM.

[31] T. Brezmes, J.-L. Gorricho, and J. Cotrina. Activity recognition from accelerometer data on a mobile phone. In S. Omatu, M. P. Rocha, J. Bravo, F. Fernández, E. Corchado, A. Bustillo, and J. M. Corchado, editors, *Distributed Computing, Artificial Intelligence, Bioinformatics, Soft Computing, and Ambient Assisted Living: 10th International Work-Conference on Artificial Neural Networks, IWANN 2009 Workshops, Salamanca, Spain, June 10-12, 2009. Proceedings, Part II*, pages 796–799, Berlin, Heidelberg, 2009. Springer Berlin Heidelberg.

[32] N. Broy, F. Alt, S. Schneegass, N. Henze, and A. Schmidt. Perceiving layered information on 3D displays using binocular disparity. In *Proceedings*

of the 2nd ACM International Symposium on Pervasive Displays, pages 61–66. ACM, 2013.

[33] N. Broy, F. Alt, S. Schneegass, and B. Pfleging. 3D Displays in Cars: Exploring the User Performance for a Stereoscopic Instrument Cluster. In *Proceedings of the 6th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, AutomotiveUI '14, pages 2:1—-2:9, New York, NY, USA, 2014. ACM.

[34] N. Broy, M. Guo, S. Schneegass, B. Pfleging, and F. Alt. Introducing Novel Technologies in the Car: Conducting a Real-world Study to Test 3D Dashboards. In *Proceedings of the 7th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, AutomotiveUI '15, pages 179–186, New York, NY, USA, 2015. ACM.

[35] N. Broy, S. Schneegass, F. Alt, and A. Schmidt. FrameBox and MirrorBox: Tools and Guidelines to Support Designers in Prototyping Interfaces for 3D Displays. In ACM, editor, *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, New York, NY, USA, 2014. ACM.

[36] N. Broy, S. Schneegass, M. Guo, F. Alt, and A. Schmidt. Evaluating Stereoscopic 3D for Automotive User Interfaces in a Real-World Driving Study. In ACM, editor, *Adjunct Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, New York, NY, USA, 2015. ACM.

[37] N. Broy, B. J. Zierer, S. Schneegass, and F. Alt. Exploring virtual depth for automotive instrument cluster concepts. In *Proceedings of the extended abstracts of the 32nd annual ACM conference on Human factors in computing systems - CHI EA '14*, pages 1783–1788, New York, NY, USA, 2014. ACM.

[38] F. Bry, V. Gehlen-Baum, and A. Pohl. Promoting awareness and participation in large class lectures: The digital backchannel backstage. In *Proceedings of the IADIS Int. Conf. e-society*, pages 27–34, Spain, Avila, Mar. 2011.

[39] S. Burigat, L. Chittaro, and S. Gabrielli. Visualizing Locations of Off-screen Objects on Mobile Devices: A Comparative Evaluation of Three Approaches. In *Proceedings of the 8th Conference on Human-computer Interaction with Mobile Devices and Services*, MobileHCI '06, pages 239–246, New York, NY, USA, 2006. ACM.

[40] J. Burstyn, P. Strohmeier, and R. Vertegaal. DisplaySkin: Exploring Pose-Aware Displays in a Flexible Electrophoretic Wristband. *Proceedings of the Ninth International Conference on Tangible, Embedded, and Embodied Interaction - TEI '14*, (Figure 1):165–172, 2015.

[41] A. Butler, S. Izadi, and S. Hodges. Sidesight: Multi-"touch" interaction around small devices. In *Proceedings of the 21st Annual ACM Symposium on User Interface Software and Technology*, UIST '08, pages 201–204, New York, NY, USA, 2008. ACM.

[42] P. Cano, E. Batlle, E. Batle, T. Kalker, and J. Haitsma. A review of algorithms for audio fingerprinting. In *Multimedia Signal Processing, 2002 IEEE Workshop on*, pages 169–173, 2002.

[43] S. K. Card, J. D. Mackinlay, and G. G. Robertson. The design space of input devices. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '90, pages 117–124, New York, NY, USA, 1990. ACM.

[44] F. Carpi and D. De Rossi. Electroactive polymer-based devices for e-textiles in biomedicine. *IEEE Transactions on Information Technology in Biomedicine*, 9(3):295–318, 2005.

[45] A. T. Chamillard. Using a student response system in cs1 and cs2. In *Proceedings of the 42Nd ACM Technical Symposium on Computer Science Education*, SIGCSE '11, pages 299–304, New York, NY, USA, 2011. ACM.

[46] J. Cheng, O. Amft, G. Bahle, and P. Lukowicz. Designing sensitive wearable capacitive sensors for activity recognition. *Sensors Journal, IEEE*, 13(10):3935–3947, 2013.

[47] J. Cheng, G. Bahle, and P. Lukowicz. A simple wristband based on capacitive sensors for recognition of complex hand motions. In *2012 IEEE Sensors*, pages 1–4. IEEE, Oct. 2012.

[48] J. Cheng, P. Lukowicz, N. Henze, A. Schmidt, O. Amft, G. A. Salvatore, and G. Troster. Smart Textiles: From Niche to Mainstream. *Pervasive Computing, IEEE*, 12(3):81–84, 2013.

[49] K. Cherenack, L. V. Pieterson, C. In, M. Of, and S. Materials. Smart textiles: Challenges and opportunities. 091301(2012), 2012.

[50] G. Cho, K. Jeong, M. J. Paik, Y. Kwun, and M. Sung. Performance Evaluation of Textile-Based Electrodes and Motion Sensors for Smart Clothing. *Sensors Journal, IEEE*, 11(12):3183–3193, 2011.

[51] S. Choi and Z. Jiang. A wearable cardiorespiratory sensor system for analyzing the sleep condition. *Expert Systems with Applications*, 35(1–2):317–329, 2008.

[52] J. Chuan, Z. Sheng, and L. Xiaokang. An effective way to improve actigraphic algorithm by using tri-axial accelerometer in sleep detection. In *17th International Conference on Computational Science and Engineering (CSE)*, pages 808–811. IEEE, Dec 2014.

[53] A. Cohen. Biomedical Signals: Origin and Dynamic Characteristics; Frequency-Domain Analysis. In J. D. Bronzino, editor, *The Biomedical Engineering Handbook*, chapter 52. CRC Press LLC,, 2 edition, 2000.

[54] C. Collet, G. Delhomme, and A. Dittmar. Subjective aspects of mental workload in air-traffic control, 2003.

[55] A. Colley, M. Pakanen, S. Koskinen, K. Mikkonen, and J. Häkkilä. Smart handbag as a wearable public display - exploring concepts and user perceptions. In *Proceedings of the 7th Augmented Human International Conference 2016*, AH '16, pages 7:1–7:8, New York, NY, USA, 2016. ACM.

[56] M. Conti, I. Zachia-Zlatea, and B. Crispo. Mind how you answer me!: transparently authenticating the user of a smartphone when answering or placing a call. *Proceedings of the 6th ACM Symposium on Information, Computer and Communications Security*, pages 249–259, 2011.

[57] A. Cooper, A. Page, K. Fox, J. Misson, et al. Physical activity patterns in normal, overweight and obese individuals using minute-by-minute accelerometry. *European Journal of Clinical Nutrition*, 54(12):887–894, 2000.

[58] C. Cornelius, R. Peterson, J. Skinner, R. Halter, and D. Kotz. A Wearable System That Knows Who Wears It. In *Proceedings of the 12th Annual International Conference on Mobile Systems, Applications, and Services*, MobiSys '14, pages 55–67, New York, NY, USA, 2014. ACM.

[59] N. Dael, M. Mortillaro, and K. R. Scherer. Emotion expression in body action and posture. 12(5):1085–1101, 2012.

[60] S. Davis and P. Mermelstein. Comparison of parametric representations for monosyllabic word recognition in continuously spoken sentences. *IEEE Transactions on Acoustics, Speech, and Signal Processing*, 28(4), 1980.

[61] A. De Luca, A. Hang, F. Brudy, C. Lindner, and H. Hussmann. Touch me once and I know it‘s you! Implicit authentication based on touch screen patterns. *Chi 2012*, pages 987–996, 2012.

[62] A. Dementyev and J. A. Paradiso. WristFlex: Low-power Gesture Input with Wrist-worn Pressure Sensors. In *Proceedings of the 27th Annual ACM Symposium on User Interface Software and Technology*, UIST '14, pages 161–166, New York, NY, USA, 2014. ACM.

[63] L. Devendorf, J. Lo, N. Howell, J. L. Lee, N.-W. Gong, M. E. Karagozler, S. Fukuhara, I. Poupyrev, E. Paulos, and K. Ryokai. "i don't want to wear a screen": Probing perceptions of and possibilities for dynamic displays on clothing. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, CHI '16, pages 6028–6039, New York, NY, USA, 2016. ACM.

[64] T. Deyle, S. Palinko, E. S. Poole, and T. Starner. Hambone: A bio-acoustic gesture interface. In *2007 11th IEEE International Symposium on Wearable Computers*, pages 3–10, Oct 2007.

[65] M. Di Rienzo, F. Rizzo, G. Parati, G. Brambilla, M. Ferratini, and P. Castiglioni. MagIC System: a New Textile-Based Wearable Device for Biological Signal Monitoring. Applicability in Daily Life and Clinical Setting. In *Engineering in Medicine and Biology Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference of the*, pages 7167–7169, 2005.

[66] H. Ding, G. Trajcevski, P. Scheuermann, X. Wang, and E. Keogh. Querying and mining of time series data: Experimental comparison of representations and distance measures. In *Proc. PVLDB*, pages 1542–1552, 2008.

[67] S. D'Mello, R. W. Picard, and A. Graesser. Toward an affect-sensitive autotutor. *IEEE Intelligent Systems*, 22(4):53–61, July 2007.

[68] D. Dobbelstein, P. Hock, and E. Rukzio. Belt: An Unobtrusive Touch Input Device for Head-worn Displays. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, CHI '15, pages 2135–2138, New York, NY, USA, 2015. ACM.

[69] S. E. Duclos, J. D. Laird, E. Schneider, M. Sexter, L. Stern, and O. Van Lighten. Emotion-specific effects of facial expressions and postures on emotional experience. *Journal of Personality and Social Psychology*, 57(1):100–108, 1989.

[70] D. Dunne and R. Martin. Design thinking and how it will change management education: An interview and discussion. *Academy of Management Learning & Education*, 5(4):512–523, 2006.

[71] L. E. Dunne, C. Simon, and G. Gioberto. E-Textiles in the Apparel Factory: Leveraging Cut-and-Sew Technology toward the Next Generation of Smart Garments. In *Fundamentals of Wearable Computers and Augmented Reality, Second Edition*, pages 619–638. CRC Press, July 2015.

[72] P. Ekman and W. V. Friesen. Head and body cues in the judgment of emotion: A reformulation. *Perceptual and motor skills*, 24(3):711–724, 1967.

[73] Y. Åženol, T. Akkan, E. Y. Bulgun, O. Kayacan, E. Yazgan Bulgun, and O. Kayacan. Active T-shirt. *International Journal of Clothing Science and Technology*, 23(4):249–257, 2011.

[74] J. Falk and S. Björk. The BubbleBadge: A Wearable Public Display. In *CHI '99 Extended Abstracts on Human Factors in Computing Systems*, CHI EA '99, pages 318–319, New York, NY, USA, 1999. ACM.

[75] C. Farion and M. Purver. Message Bag: Can Assistive Technology Combat Forgetfulness? In *Proceedings of the 4th Augmented Human International Conference*, AH '13, pages 134–137, New York, NY, USA, 2013. ACM.

[76] J. Farringdon, A. J. Moore, N. Tilbury, J. Church, and P. D. Biemond. Wearable sensor badge and sensor jacket for context awareness. In *Wearable Computers, 1999. Digest of Papers. The Third International Symposium on*, pages 107–113, 1999.

[77] V. Fialka-Moser, G. Ebenbichler, and O. Gillert. *Elektrotherapie*. Pflaum Physiotherapie. Richard Pflaum Vlg GmbH, 2005.

[78] B. Firoozbakhsh, N. Jayant, S. Park, and S. Jayaraman. Wireless communication of vital signs using the Georgia Tech Wearable Motherboard. In *Multimedia and Expo, 2000. ICME 2000. 2000 IEEE International Conference on*, volume 3, pages 1253—-1256 vol.3, 2000.

[79] J. Fortmann, V. Cobus, W. Heuten, and S. Boll. WaterJewel: Design and Evaluation of a Bracelet to Promote a Better Drinking Behaviour. In *Proceedings of the 13th International Conference on Mobile and Ubiquitous Multimedia*, MUM '14, pages 58–67, New York, NY, USA, 2014. ACM.

[80] D. Freeman, H. Benko, M. R. Morris, and D. Wigdor. ShadowGuides: Visualizations for In-situ Learning of Multi-touch and Whole-hand Gestures. In *Proceedings of the ACM International Conference on Interactive Tabletops and Surfaces*, ITS '09, pages 165–172, New York, NY, USA, 2009. ACM.

[81] R. Fukui, M. Watanabe, T. Gyota, M. Shimosaka, and T. Sato. Hand shape classification with a wrist contour sensor: Development of a prototype device. In *Proc. UbiComp*, pages 311–314, 2011.

[82] M. Fukumoto and Y. Tonomura. Body coupled fingerring: wireless wearable keyboard. In *Proceedings of the ACM SIGCHI Conference on Human factors in computing systems*, pages 147–154. ACM, 1997.

[83] M. Funk, A. Sahami, N. Henze, and A. Schmidt. Using a touch-sensitive wristband for text entry on smart watches. In *CHI '14 Extended Abstracts on Human Factors in Computing Systems*, CHI EA '14, pages 2305–2310, New York, NY, USA, 2014. ACM.

[84] M. Funk, S. Schneegass, M. Behringer, N. Henze, and A. Schmidt. An Interactive Curtain for Media Usage in the Shower. *Proceedings of the 4th International Symposium on Pervasive Displays (PerDis'15)*, pages 225–231, 2015.

[85] G. W. Furnas. Generalized Fisheye Views. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '86, pages 16–23, New York, NY, USA, 1986. ACM.

[86] M. P. Gardner. Mood states and consumer behavior: A critical review. *Journal of Consumer Research*, 12(3):pp. 281–300, 1985.

[87] G. Geiser. Man Machine Interaction in Vehicles. *ATZ*, 87:74–77, 1985.

[88] F. Gemperle, C. Kasabach, J. Stivoric, M. Bauer, and R. Martin. Design for wearability. *Digest of Papers. Second International Symposium on Wearable Computers (Cat. No.98EX215)*, 1998.

[89] L. George and A. Lécuyer. An overview of research on ”passive” brain-computer interfaces for implicit human-computer interaction. In *International Conference on Applied Bionics and Biomechanics ICABB 2010 - Workshop W1 ”Brain-Computer Interfacing and Virtual Reality”*, Venice, Italy, Oct. 2010.

[90] S. Gimpel, U. Mohring, H. Muller, A. Neudeck, and W. Scheibner. Textile-Based Electronic Substrate Technology. *Journal of Industrial Textiles*, 33(3):179–189, 2004.

[91] K. Goenner, H. Horter, P. Chabrecek, and W. Gaschler. Precision Fabric Production in Industry. In S. Schneegass and O. Amft, editors, *Smart Textiles – Fundamentals, Design, and Interaction*. Springer HCI Series, 2016.

[92] C. Gopalsamy, S. Park, R. Rajamanickam, and S. Jayaraman. The Wearable Motherboard: The first generation of adaptive and responsive textile structures (ARTS) for medical applications. *Virtual Reality*, 4(3):152–168, 1999.

[93] J. D. Gould. How to design usable systems. *Handbook of Human-Computer Interaction*, pages 757–789, 1988.

[94] J. Grubert, M. Kranz, and A. Quigley. Design and Technology Challenges for Body Proximate Display Ecosystems. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services Adjunct*, MobileHCI ’15, pages 951–954, New York, NY, USA, 2015. ACM.

[95] H. Gunes and M. Piccardi. Bi-modal emotion recognition from expressive face and body gestures. *Journal of Network and Computer Applications*, 30(4):1334 – 1345, 2007. Special issue on Information technology.

[96] J. R. Häkkilä, M. Posti, S. Schneegass, F. Alt, K. Gultekin, and A. Schmidt. Let me catch this! Experiencing Interactive 3D Cinema through Collecting Content with a Mobile Phone. *Proceedings of the 32nd annual ACM conference on Human factors in computing systems - CHI ’14*, pages 1011–1020, 2014.

[97] M. Hamedi, R. Forchheimer, and O. Inganas. Towards woven logic from organic electronic fibres. *Nat Mater*, 6(5):357–362, May 2007.

[98] H. Harms, O. Amft, and G. Tröster. Does loose fitting matter? Predicting sensor performance in smart garments. In *Bodynets 2012: Proceedings of the International Conference on Body Area Networks*, pages 1–4. ACM, 2012. ISBN: 978-1-936968-60-2.

[99] C. Harrison and S. E. Hudson. Abracadabra: Wireless, High-precision, and Unpowered Finger Input for Very Small Mobile Devices. In *Proceedings of the 22Nd Annual ACM Symposium on User Interface Software and Technology*, UIST '09, pages 121–124, New York, NY, USA, 2009. ACM.

[100] C. Harrison, D. Tan, and D. Morris. Skinput: Appropriating the Body As an Input Surface. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '10, pages 453–462, New York, NY, USA, 2010. ACM.

[101] M. Hassib, M. Khamis, S. Schneegass, A. S. Shirazi, and F. Alt. Investigating user needs for bio-sensing and affective wearables. In *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems*, CHI EA '16, pages 1415–1422, New York, NY, USA, 2016. ACM.

[102] M. Hassib, S. Schneegass, N. Henze, F. Alt, and A. Schmidt. EngageMeter: A System for Implicit Audience Engagement Sensing Using Electroencephalography.

[103] J. Healey. GSR Sock: A New e-Textile Sensor Prototype. In *15th Annual International Symposium on Wearable Computers*, pages 113–114, 2011.

[104] F. Heller, S. Ivanov, C. Wacharamanotham, and J. Borchers. FabriTouch: Exploring Flexible Touch Input on Textiles. In *Proceedings of the 2014 ACM International Symposium on Wearable Computers*, ISWC '14, pages 59–62, New York, NY, USA, 2014. ACM.

[105] R. J. N. Helmer, D. Farrow, K. Ball, E. Phillips, A. Farouil, and I. Blanchonette. A pilot evaluation of an electronic textile for lower limb monitoring and interactive biofeedback. *Procedia Engineering*, 13:513–518, 2011.

[106] P. Henry and T. R. Letowski. Bone Conduction : Anatomy , Physiology , and Communication. (May), 2007.

[107] N. Henze, A. Löcken, S. Boll, T. Hesselmann, and M. Pielot. Free-hand gestures for music playback: Deriving gestures with a user-centred

process. In *Proceedings of the 9th International Conference on Mobile and Ubiquitous Multimedia*, MUM '10, pages 16:1–16:10, New York, NY, USA, 2010. ACM.

[108] N. Henze, A. S. Shrazi, A. Schmidt, M. Pielot, and F. Michahelles. Empirical Research through Ubiquitous Data Collection. *Computer*, 46(6):74–76, 2013.

[109] W. Heuten, N. Henze, S. Boll, and M. Pielot. Tactile Wayfinder: A Non-visual Support System for Wayfinding. In *Proceedings of the 5th Nordic Conference on Human-computer Interaction: Building Bridges*, NordiCHI '08, pages 172–181, New York, NY, USA, 2008. ACM.

[110] M. Hirsch, J. Cheng, A. Reiss, M. Sundholm, P. Lukowicz, and O. Amft. Hands-free gesture control with a capacitive textile neckband. In *Proc. ISWC*, pages 55–58. ACM, 2014.

[111] P. Holleis, A. Schmidt, S. Paasovaara, A. Puikkonen, and J. Häkkilä. Evaluating capacitive touch input on clothes. pages 81–90, 2008.

[112] C. Holz, S. Buthpitiya, and M. Knaust. Bodyprint: Biometric User Identification on Mobile Devices Using the Capacitive Touchscreen to Scan Body Parts. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, CHI '15, pages 3011–3014, New York, NY, USA, 2015. ACM.

[113] Y. Hong, T. B. Patrick, and R. Gillis. Protection of patient's privacy and data security in e-health services. In *BioMedical Engineering and Informatics, 2008. BMEI 2008. International Conference on*, volume 1, pages 643–647. IEEE, 2008.

[114] K. Hornbæ k, B. B. Bederson, and C. Plaisant. Navigation Patterns and Usability of Zoomable User Interfaces with and Without an Overview. *ACM Trans. Comput.-Hum. Interact.*, 9(4):362–389, 2002.

[115] C.-E. Hrabia, K. Wolf, and M. Wilhelm. Whole hand modeling using 8 wearable sensors: biomechanics for hand pose prediction. In *Proc. AH*, pages 21–28. ACM, 2013.

[116] B. Hu, Y. Chen, J. Zakaria, L. Ulanova, and E. Keogh. Classification of multi-dimensional streaming time series by weighting each classifier's track record. *Proceedings - IEEE International Conference on Data Mining, ICDM*, pages 281–290, 2013.

[117] G. Hu, L. Chen, J. Okerlund, and O. Shaer. Exploring the use of google glass in wet laboratories. In *Proceedings of the 33rd Annual ACM Conference Extended Abstracts on Human Factors in Computing Systems*, pages 2103–2108. ACM, 2015.

[118] J. Hurtienne and L. Blessing. Design for intuitive use-testing image schema theory for user interface design. *Guidelines for a Decision Support Method Adapted to NPD Processes*, 2007.

[119] J. Hurtienne, C. Stöß el, C. Sturm, A. Maus, M. Rötting, P. Langdon, and J. Clarkson. Physical gestures for abstract concepts: Inclusive design with primary metaphors. *Interacting with Computers*, 22(6):475–484, 2010.

[120] ISO-9241-210. ISO 9241-210:2010(en) – Ergonomics of human-system interaction – Part 210: Human-centred design for interactive systems, 2010.

[121] R. Jagodzinski, G. Wintergerst, and P. Giles. Thermal Display, based on the separated presentation of hot and cold. In H. Reiterer and O. Deussen, editors, *Mensch & Computer 2012 - Workshopband: interaktiv informiert - allgegenwärtig und allumfassend!?*, pages 155–162, München, 2012. Oldenbourg Verlag.

[122] R. Joyce and G. Gupta. Identity authentication based on keystroke latencies. *Communications of the ACM*, 33(2):168–176, Feb. 1990.

[123] N. Karapanos, C. Marforio, C. Soriente, and S. Čapkun. Sound-Proof: Usable Two-Factor Authentication Based on Ambient Sound. *arXiv:1503.03790 [cs]*, 2015.

[124] R. H. Kay and A. LeSage. Examining the benefits and challenges of using audience response systems: A review of the literature. *Computers & Education*, 53(3):819–827, Nov. 2009.

[125] T. Keller and A. Kuhn. Electrodes for transcutaneous (surface) electrical stimulation. *Journal of Automatic Control*, 18(2):35–45, 2008.

[126] P. G. Kelley, L. F. Cranor, and N. Sadeh. Privacy as part of the app decision-making process. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '13, pages 3393–3402, New York, NY, USA, 2013. ACM.

[127] E. Keogh and M. Pazzani. Derivative dynamic time warping. In *Proc. SDM*, 2001.

[128] F. Kerber, P. Lessel, and A. Krüger. Same-side Hand Interactions with Arm-placed Devices Using EMG. In *Proceedings of the 33rd Annual ACM Conference Extended Abstracts on Human Factors in Computing Systems*, CHI EA ’15, pages 1367–1372, New York, NY, USA, 2015. ACM.

[129] D. Kern, M. Müller, S. Schneegass, L. Wolejko-Wolejszo, and A. Schmidt. CARS-Configurable Automotive Research Simulator. In *Mensch & Computer Workshopband*, pages 256–260, 2008.

[130] D. Kern and A. Schmidt. Design space for driver-based automotive user interfaces. In *Proceedings of the 1st International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, AutomotiveUI ’09, pages 3–10, New York, NY, USA, 2009. ACM.

[131] D. Kern and S. Schneegass. CARS–Configurable Automotive Research Simulator CARS–Konfigurierbarer Fahrsimulator zur Bewertung der Fahrerablenkung. *i-com*, 8(2):30–33, 2009.

[132] D. Kim, O. Hilliges, S. Izadi, A. D. Butler, J. Chen, I. Oikonomidis, and P. Olivier. Digits: Freehand 3d interactions anywhere using a wrist-worn gloveless sensor. pages 167–176, 2012.

[133] J. Kim, J. He, K. Lyons, and T. Starner. The gesture watch: A wireless contact-free gesture based wrist interface. In *11th IEEE International Symposium on Wearable Computers*, pages 15–22, Oct 2007.

[134] J. Kim, S. Mastnik, and E. André. EMG-based hand gesture recognition for realtime biosignal interfacing. *Proceedings of the 13th international conference on Intelligent user interfaces IUI 08*, 39:30, 2008.

[135] N. Komor, S. Gilliland, J. Clawson, M. Bhardwaj, M. Garg, C. Zeagler, and T. Starner. Is It Gropable? Assessing the Impact of Mobility on Textile Interfaces. In *Wearable Computers, 2009. ISWC ’09. International Symposium on*, pages 71–74, Sept. 2009.

[136] V. Koncar. Optical Fiber Fabric Displays. *Optics and Photonics News*, 16(4):40–44, 2005.

[137] S. Kratz and M. Rohs. HoverFlow: Expanding the Design Space of Around-device Interaction. In *Proceedings of the 11th International Conference on Human-Computer Interaction with Mobile Devices and Services*, MobileHCI ’09, pages 4:1—-4:8, New York, NY, USA, 2009. ACM.

[138] C. Kray, D. Nesbitt, J. Dawson, and M. Rohs. User-defined gestures for connecting mobile phones, public displays, and tabletops. In *Proceedings of the 12th International Conference on Human Computer Interaction with Mobile Devices and Services*, MobileHCI '10, pages 239–248, New York, NY, USA, 2010. ACM.

[139] E. Kruijff, D. Schmalstieg, and S. Beckhaus. Using neuromuscular electrical stimulation for pseudo-haptic feedback. In *Proceedings of the ACM Symposium on Virtual Reality Software and Technology*, VRST '06, pages 316–319, New York, NY, USA, 2006. ACM.

[140] T. Kubitza, N. Pohl, T. Dingler, S. Schneegass, C. Weichel, and A. Schmidt. Ingredients for a new wave of ubicomp products. *IEEE Pervasive Computing*, 12(3):5–8, July 2013.

[141] K. Kuusk, M. Kooroshnia, and J. Mikkonen. Crafting Butterfly Lace: Conductive Multi-color Sensor-actuator Structure. In *Adjunct Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2015 ACM International Symposium on Wearable Computers*, UbiComp/ISWC'15 Adjunct, pages 595–600, New York, NY, USA, 2015. ACM.

[142] L. V. Langenhove and C. Hertleer. Smart clothing: a new life. *International Journal of Clothing Science and Technology*, 16(1/2):63–72, 2004.

[143] M. Langheinrich. *Privacy by Design — Principles of Privacy-Aware Ubiquitous Systems*, pages 273–291. Springer Berlin Heidelberg, Berlin, Heidelberg, 2001.

[144] M. Langheinrich, A. Schmidt, N. Davies, and R. José. A Practical Framework for Ethics: The PD-net Approach to Supporting Ethics Compliance in Public Display Studies. In *Proceedings of the 2Nd ACM International Symposium on Pervasive Displays*, PerDis '13, pages 139–143, New York, NY, USA, 2013. ACM.

[145] C. Latulipe, E. A. Carroll, and D. Lottridge. Love, hate, arousal and engagement: Exploring audience responses to performing arts. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '11, pages 1845–1854, New York, NY, USA, 2011. ACM.

[146] J. C. Lee and D. S. Tan. Using a low-cost electroencephalograph for task classification in hci research. In *Proceedings of the 19th Annual ACM Symposium on User Interface Software and Technology*, UIST '06, pages 81–90, New York, NY, USA, 2006. ACM.

[147] L. A. Leiva, A. Sahami, A. Catala, N. Henze, and A. Schmidt. Text Entry on Tiny QWERTY Soft Keyboards. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, CHI '15, pages 669–678, New York, NY, USA, 2015. ACM.

[148] P. Lopes and P. Baudisch. Muscle-propelled force feedback: Bringing force feedback to mobile devices. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '13, pages 2577–2580, New York, NY, USA, 2013. ACM.

[149] P. Lopes, A. Ion, and R. Kovacs. Using Your Own Muscles: Realistic Physical Experiences in VR. *XRDS*, 22(1):30–35, Nov. 2015.

[150] P. Lopes, P. Jonell, and P. Baudisch. Affordance++: Allowing Objects to Communicate Dynamic Use. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, CHI '15, pages 2515–2524, New York, NY, USA, 2015. ACM.

[151] F. Lorussi, N. Carbonaro, D. De Rossi, and A. Tognetti. Strain and angular sensing fabrics for human motion analysis in daily life. In S. Schneegass and O. Amft, editors, *Smart Textiles – Fundamentals, Design, and Interaction*. Springer HCI Series, 2016.

[152] F. Lorussi, W. Rocchia, E. Scilingo, a. Tognetti, and D. De Rossi. Wearable, Redundant Fabric-Based Sensor Arrays for Reconstruction of Body Segment Posture. *IEEE Sensors Journal*, 4(6):807–818, 2004.

[153] P. Lukowicz, A. Poxrucker, J. Weppner, B. Bischke, J. Kuhn, and M. Hirth. Glass-physics: Using google glass to support high school physics experiments. In *Proceedings of the 2015 ACM International Symposium on Wearable Computers*, pages 151–154, 2015.

[154] P. Lukowicz, J. Ward, H. Junker, M. Stäger, G. Tröster, A. Atrash, and T. Starner. Recognizing Workshop Activity Using Body Worn Microphones and Accelerometers. In A. Ferscha and F. Mattern, editors, *Pervasive Computing*, volume 3001 of *Lecture Notes in Computer Science*, pages 18–32. Springer Berlin Heidelberg, 2004.

[155] K. Lyons, D. Nguyen, D. Ashbrook, and S. White. Facet: A Multi-Segment Wrist Worn System. *Proceedings of the 25th annual ACM symposium on User interface software and technology - UIST '12*, pages 123–130, 2012.

[156] E. Maiorana, P. Campisi, N. González-Carballo, and A. Neri. Keystroke dynamics authentication for mobile phones. *Proceedings of the 2011 ACM Symposium on Applied Computing SAC 11*, pages 21–26, 2011.

[157] M. Malik and A. J. Camm. Heart rate variability. *Clinical Cardiology*, 13(8):570–576, 1990.

[158] S. Mann. Eudaemonic computing ('underwearables'). In *Wearable Computers, 1997. Digest of Papers., First International Symposium on*, pages 177–178, 1997.

[159] S. Mann. Introduction: On the bandwagon or beyond wearable computing? *Personal Technologies*, 1(4):203–207, 1997.

[160] S. Mann. Smart clothing: The wearable computer and wearcam. *Personal Technologies*, 1(1):21–27, 1997.

[161] S. Mann. Wearable computing: a first step toward personal imaging. *Computer*, 30(2):25–32, Feb. 1997.

[162] S. Mann. Wearable Computing as means for Personal Empowerment. In *Proceedings of the First International Conference on Wearable Computing*, 1998.

[163] J. Mantyjarvi, M. Lindholm, E. Vildjiounaite, S.-M. Makela, and H. A. Ailisto. Identifying users of portable devices from gait pattern with accelerometers. In *Acoustics, Speech, and Signal Processing, 2005. Proceedings. (ICASSP '05). IEEE International Conference on*, volume 2, pages ii/973–ii/976 Vol. 2, 2005.

[164] V. Mateevitsi, B. Haggadone, J. Leigh, B. Kunzer, and R. V. Kenyon. Sensing the Environment Through SpiderSense. In *Proceedings of the 4th Augmented Human International Conference*, AH '13, pages 51–57, New York, NY, USA, 2013. ACM.

[165] D. Mauney, J. Howarth, A. Wirtanen, and M. Capra. Cultural similarities and differences in user-defined gestures for touchscreen user interfaces. In *CHI '10 Extended Abstracts on Human Factors in Computing Systems*, CHI EA '10, pages 4015–4020, New York, NY, USA, 2010. ACM.

[166] U. Maurer, A. Rowe, A. Smailagic, and D. P. Siewiorek. eWatch: a wearable sensor and notification platform. In *International Workshop on Wearable and Implantable Body Sensor Networks (BSN'06)*, pages 4 pp.–145, April 2006.

[167] S. Mayer, K. Wolf, S. Schneegass, and N. Henze. Modeling Distant Pointing for Compensating Systematic Displacements. In ACM, editor, *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, New York, NY, USA, 2015. ACM.

[168] A. Mehmann and G. Tröster. Textile Antennas. In S. Schneegass and O. Amft, editors, *Smart Textiles – Fundamentals, Design, and Interaction*. Springer HCI Series, 2016.

[169] A. Mehmann, M. Varga, K. Gönner, and G. Tröster. A Ball-grid-array-like Electronics-to-textile Pocket Connector for Wearable Electronics. In *Proceedings of the 2015 ACM International Symposium on Wearable Computers*, ISWC '15, pages 57–60, New York, NY, USA, 2015. ACM.

[170] A. Mehmann, M. Varga, and G. Tröster. Reversible contacting for smart textiles. In S. Schneegass and O. Amft, editors, *Smart Textiles – Fundamentals, Design, and Interaction*. Springer HCI Series, 2016.

[171] R. M. Michaels. Effect of expressway design on driver tension responses. *Highway Research Board Bulletin*, 1962.

[172] B. Mittelmann and H. G. Wolff. Affective states and skin temperature: Experimental study of subjects with "cold hands" and raynaud's syndrome. *Psychosomatic Medicine*, 1(2):271–292, 1939.

[173] E. Morganti, L. Angelini, A. Adami, D. Lalanne, L. Lorenzelli, and E. Mugellini. A smart watch with embedded sensors to recognize objects, grasps and forearm gestures. *Procedia Engineering*, 41(0):1169 – 1175, 2012. Proc. IRIS.

[174] M. R. Morris, J. O. Wobbrock, and A. D. Wilson. Understanding users' preferences for surface gestures. In *Proceedings of Graphics Interface 2010*, GI '10, pages 261–268, Toronto, Ont., Canada, Canada, 2010. Canadian Information Processing Society.

[175] O. J. Muensterer, M. Lacher, C. Zoeller, M. Bronstein, and J. Kübler. Google glass in pediatric surgery: An exploratory study. *International Journal of Surgery*, 12(4):281–289, 2014.

[176] J. Müller, F. Alt, D. Michelis, and A. Schmidt. Requirements and design space for interactive public displays. In *Proceedings of the 18th ACM International Conference on Multimedia*, MM '10, pages 1285–1294, New York, NY, USA, 2010. ACM.

[177] B. J. Munro, T. E. Campbell, G. G. Wallace, and J. R. Steele. The intelligent knee sleeve: A wearable biofeedback device. *Sensors and Actuators B: Chemical*, 131(2):541–547, 2008.

[178] W. D. J. O'Brien and Y. Liu. Evaluation of acoustic propagation paths into the human head. Technical Report 2005, 2005.

[179] S. Olberding, M. Wessely, and J. Steimle. PrintScreen: Fabricating Highly Customizable Thin-film Touch-Displays. *Proceedings of the 27th annual ACM symposium on User interface software and technology*, pages 281–290, 2014.

[180] S. Olberding, K. P. Yeo, S. Nanayakkara, J. Steimle, O. B. Processor, and V. a. L. L. Recent. AugmentedForearm: Exploring the Design Space of a Display-enhanced Forearm. In *Proceedings of the 4th Augmented Human International Conference*, AH '13, pages 9–12, New York, NY, USA, 2013. ACM.

[181] S. Oney, C. Harrison, A. Ogan, and J. Wiese. ZoomBoard: A Diminutive Qwerty Soft Keyboard Using Iterative Zooming for Ultra-small Devices. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '13, pages 2799–2802, New York, NY, USA, 2013. ACM.

[182] P. S. Pandian, K. Mohanavelu, K. P. Safeer, T. M. Kotresh, D. T. Shakunthala, P. Gopal, and V. C. Padaki. Smart Vest: Wearable multi-parameter remote physiological monitoring system. *Medical engineering & physics*, 30(4):466–477, 2008.

[183] P. Panhey, T. Doering, S. Schneegass, D. Wenig, and F. Alt. What People Really Remember: Understanding Cognitive Effects When Interacting with Large Displays. In *Proceedings of the 2015 International Conference on Interactive Tabletops & Surfaces*, pages 103–106, Madeira, Portugal, 2015. ACM New York, NY, USA.

[184] R. Paradiso, G. Loriga, and N. Taccini. A wearable health care system based on knitted integrated sensors. *Information Technology in Biomedicine, IEEE Transactions on*, 9(3):337–344, Sept. 2005.

[185] K. Partridge, S. Chatterjee, V. Sazawal, G. Borriello, and R. Want. TiltType: Accelerometer-supported Text Entry for Very Small Devices. In *Proceedings of the 15th Annual ACM Symposium on User Interface Software and Technology*, UIST '02, pages 201–204, New York, NY, USA, 2002. ACM.

[186] M. Patry. Clickers in large classes: From student perceptions towards an understanding of best practices. *International Journal for the Scholarship of Teaching and Learning*, 3(2):17, 2009.

[187] I. Pedersen. Are wearables really ready to wear? *Technology and Society Magazine, IEEE*, 33(2):16–18, 2014.

[188] R. L. Peiris. Integrated Non-Light-Emissive Animateable Textile Displays. In S. Schneegass and O. Amft, editors, *Smart Textiles – Fundamentals, Design, and Interaction*. Springer HCI Series, 2016.

[189] R. L. Peiris, A. D. Cheok, J. K. S. Teh, O. N. N. Fernando, W. Yingqian, A. Lim, P. Yi, D. Polydorou, K. P. Ong, and M. Tharakan. AmbiKraf: An Embedded Non-emissive and Fast Changing Wearable Display. In *ACM SIGGRAPH 2009 Emerging Technologies*, SIGGRAPH '09, pages 1:1—-1:1, New York, NY, USA, 2009. ACM.

[190] K. Perlin and D. Fox. Pad: An Alternative Approach to the Computer Interface. In *Proceedings of the 20th Annual Conference on Computer Graphics and Interactive Techniques*, SIGGRAPH '93, pages 57–64, New York, NY, USA, 1993. ACM.

[191] M. Pfeiffer, T. Dünte, S. Schneegass, F. Alt, and M. Rohs. Cruise Control for Pedestrians: Controlling Walking Direction using Electrical Muscle Stimulation. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, New York, NY, USA, 2015. ACM.

[192] M. Pfeiffer and M. Rohs. Let Your Body Move: A Prototyping Toolkit for Wearable Force Feedback with Electrical Muscle Stimulation. In *MobileHCI '16 Proceedings of the 18th international conference on Human-computer interaction with mobile devices and services*, 2016.

[193] M. Pfeiffer, S. Schneegass, and F. Alt. Supporting interaction in public space with electrical muscle stimulation. *Proceedings of the 2013 ACM conference on Pervasive and ubiquitous computing adjunct publication - UbiComp '13 Adjunct*, pages 5–8, 2013.

[194] M. Pfeiffer, S. Schneegass, F. Alt, and M. Rohs. A Design Space for Electrical Muscle Stimulation Feedback for Free-Hand Interaction. In *Proceedings of the CHI Workshop on Assistive Augmentation.*, 2014.

[195] M. Pfeiffer, S. Schneegass, F. Alt, and M. Rohs. Let Me Grab This: A Comparison of EMS and Vibration for Haptic Feedback in Free-Hand

Interaction. In *Proceedings of the 5th Augmented Human International Conference*, 2014.

[196] B. Pfleging, S. Schneegass, D. Kern, and A. Schmidt. Vom Transportmittel zum rollenden Computer–Interaktion im Auto. *Informatik-Spektrum*, 37(5):418–422, 2014.

[197] B. Pfleging, S. Schneegass, and A. Schmidt. Multimodal interaction in the car: combining speech and gestures on the steering wheel. In *Proceedings of the 4th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, pages 155–162. ACM, 2012.

[198] B. Pfleging, S. Schneegass, and A. Schmidt. Exploring user expectations for context and road video sharing while calling and driving. In *Proceedings of the 5th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, pages 132–139. ACM, 2013.

[199] P. J. Phillips, A. Martin, C. L. Wilson, and M. Przybocki. Introduction to evaluating biometric systems. *Computer*, 33(2):56–63, 2000.

[200] A. Plinge, R. Grzeszick, and G. A. Fink. A Bag-of-Features approach to acoustic event detection. In *2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 3704–3708, 2014.

[201] B. Poppinga, A. Sahami Shirazi, N. Henze, W. Heuten, and S. Boll. Understanding Shortcut Gestures on Mobile Touch Devices. In *Proceedings of the 16th International Conference on Human-computer Interaction with Mobile Devices & Services*, MobileHCI '14, pages 173–182, New York, NY, USA, 2014. ACM.

[202] I. Poupyrev, N.-W. Gong, S. Fukuhara, M. E. Karagozler, C. Schwesig, and K. E. Robinson. Project jacquard: Interactive digital textiles at scale. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, CHI '16, pages 4216–4227, New York, NY, USA, 2016. ACM.

[203] H. P. Profita, J. Clawson, S. Gilliland, C. Zeagler, T. Starner, J. Budd, and E. Y.-L. Do. Don't mind me touching my wrist: A case study of interacting with on-body technology in public. In *Proceedings of the 2013 International Symposium on Wearable Computers*, ISWC '13, pages 89–96, New York, NY, USA, 2013. ACM.

[204] S. Pruzansky. Pattern Matching Procedure for Automatic Talker Recognition. *The Journal of the Acoustical Society of America*, 35(3):214–215, 1963.

[205] J. Radbourne, K. Johanson, H. Glow, and T. White. The audience experience: Measuring quality in the performing arts. *International Journal of Arts Management*, 11(3):pp. 16–29, 2009.

[206] R. Rajamanickam, S. Park, and S. Jayaraman. A Structured Methodology for the Design and Development of Textile Structures in a Concurrent Engineering Framework. *The Journal of The Textile Institute*, 89(3):44–62, 1998.

[207] J. Rekimoto. GestureWrist and GesturePad: unobtrusive wearable interaction devices. In *Wearable Computers, 2001. Proceedings. Fifth International Symposium on*, pages 21–27. IEEE, 2001.

[208] J. Rico and S. Brewster. Usable Gestures for Mobile Interfaces: Evaluating Social Acceptability. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '10, pages 887–896, New York, NY, USA, 2010. ACM.

[209] J. Riskind and C. Gotay. Physical posture: Could it have regulatory or feedback effects on motivation and emotion? *Motiv. and Emot.*, 6(3), 1982.

[210] A. H. Roscoe. Heart rate as a psychophysiological measure for in-flight workload assessment. *Ergonomics*, 36(9):1055–1062, 1993. PMID: 8404834.

[211] J. Ruiz, Y. Li, and E. Lank. User-defined motion gestures for mobile interaction. *Proceedings of the 2011 annual conference on Human factors in computing systems - CHI '11*, page 197, 2011.

[212] J. A. Russell. A circumplex model of affect. 39(6):1161–1178, 1980.

[213] C. G. Ryan, P. M. Grant, W. W. Tigbe, and M. H. Granat. The validity and reliability of a novel activity monitor as a measure of walking. *British journal of sports medicine*, 40(9):779–784, 2006.

[214] A. Sahami Shirazi, Y. Abdelrahman, N. Henze, S. Schneegass, M. Khalilbeigi, and A. Schmidt. Exploiting thermal reflection for interactive systems. *Proceedings of the 32nd annual ACM conference on Human factors in computing systems - CHI '14*, pages 3483–3492, 2014.

[215] A. Sahami Shirazi, M. Funk, F. Pfleiderer, H. Glück, and A. Schmidt. *MediaBrain: Annotating Videos based on Brain-Computer Interaction*, pages 263–272. Oldenbourg Wissenschaftsverlag, 2012.

[216] T. S. Saponas, D. S. Tan, D. Morris, R. Balakrishnan, J. Turner, and J. A. Landay. Enabling always-available input with muscle-computer interfaces. In *Proceedings of the 22Nd Annual ACM Symposium on User Interface Software and Technology*, UIST '09, pages 167–176, New York, NY, USA, 2009. ACM.

[217] H. Sasaki, T. Terada, and M. Tsukamoto. A System for Visualizing Human Behavior Based on Car Metaphors. In *Proceedings of the 4th Augmented Human International Conference*, AH '13, pages 221–228, New York, NY, USA, 2013. ACM.

[218] Z. J. Schlader, S. E. Simmons, S. R. Stannard, and T. Mündel. Skin temperature as a thermal controller of exercise intensity. *European journal of applied physiology*, 111(8):1631–1639, 2011.

[219] S. Schneegas, S. Mayer, T. Olsson, and K. V. Laerhoven. From Mobile to Wearable - Using Wearable Devices to Enrich Mobile Interaction. In *Adjunct Proceedings of MobileHCI*, 2015.

[220] S. Schneegass. There is More to Interaction with Public Displays Than Kinect: Using Wearables to Interact with Public Displays. In *Proceedings of the 4th International Symposium on Pervasive Displays*, PerDis '15, pages 243–244, New York, NY, USA, 2015. ACM.

[221] S. Schneegass and F. Alt. SenScreen - A Toolkit for Supporting Sensor-enabled Multi-Display Networks. In *Proceedings of the 3rd ACM International Symposium on Pervasive Displays*, PerDis '14, pages 92–97, New York, NY, USA, 2014. ACM.

[222] S. Schneegass, F. Alt, J. Scheible, and A. Schmidt. Midair Displays: Concept and First Experiences with Free-Floating Pervasive Displays. *Proceedings of The International Symposium on Pervasive Displays (PerDis'14)*, pages 27–31, 2014.

[223] S. Schneegass, F. Alt, J. Scheible, A. Schmidt, and H. Su. Midair Displays: Exploring the Concept of Free-Floating Public Displays. In *CHI '14 Extended Abstracts on Human Factors in Computing Systems*, New York, NY, USA, 2014. ACM.

[224] S. Schneegaß, F. Alt, and A. Schmidt. Demo: mobile interaction with ads on public display networks. In *Proceedings of the 10th international conference on Mobile systems, applications, and services - MobiSys '12*, page 479. ACM Press, 2012.

[225] S. Schneegass and O. Amft. Introduction to Smart Garments. In S. Schneegass and O. Amft, editors, *Smart Textiles – Fundamentals, Design, and Interaction*. Springer HCI Series, 2016.

[226] S. Schneegass, J. Cheng, K. Van Laerhoven, and O. Amft. Workshop on Smart Garments: Sensing, Actuation, Interaction, and Applications in Garments. In *Proceedings of the 2014 ACM International Symposium on Wearable Computers: Adjunct Program*, ISWC '14 Adjunct, pages 225–229, New York, NY, USA, 2014. ACM.

[227] S. Schneegass, M. Hassib, T. Birmili, and N. Henze. Towards a Garment OS: Supporting Application Development for Smart Garments. In *Proceedings of the 2014 ACM International Symposium on Wearable Computers: Adjunct Program*, ISWC '14 Adjunct, pages 261–266, New York, NY, USA, 2014. ACM.

[228] S. Schneegass, M. Hassib, A. Reiss, K. Wolf, N. Henze, J. Cheng, P. Lukowicz, and A. Schmidt. Exploring Gestures for One-handed Smart Watch Interaction.

[229] S. Schneegass, M. Hassib, B. Zhou, J. Cheng, F. Seoane, O. Amft, P. Lukowicz, and A. Schmidt. SimpleSkin: Towards Multipurpose Smart Garments. In *Adjunct Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2015 ACM International Symposium on Wearable Computers*, UbiComp/ISWC'15 Adjunct, pages 241–244, New York, NY, USA, 2015. ACM.

[230] S. Schneegass, R. Kettner, and T. Machulla. Understanding the Impact of Information Representation on Users‘ Willingness to Share Private Information.

[231] S. Schneegass, S. Ogando, and F. Alt. Using On-Body Displays for Extending the Output of Wearable Devices. *Proceedings of The International Symposium on Pervasive Displays - PerDis '16*, 2016.

[232] S. Schneegass, T. Olsson, S. Mayer, and K. van Laerhoven. Mobile Interactions Augmented by Wearable Computing:. *International Journal of Mobile Human Computer Interaction*, 8(4):104–114, Oct. 2016.

[233] S. Schneegass, Y. Oualil, and A. Bulling. SkullConduct: Biometric User Identification on Eyewear Computers Using Bone Conduction Through the Skull. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, New York, NY, USA, 2016. ACM.

[234] S. Schneegass, M. Pfeiffer, M. Hassib, F. Alt, and M. Rohs. Emotion Actuator: Embodied Emotional Feedback through Electroencephalography and Electrical Muscle Stimulation. In *Paper under Submission*.

[235] S. Schneegass, B. Pfleging, N. Broy, F. Heinrich, and A. Schmidt. A data set of real world driving to assess driver workload. In *Proceedings of the 5th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, pages 150–157. ACM, 2013.

[236] S. Schneegaß, B. Pfleging, D. Kern, and A. Schmidt. Support for modeling interaction with automotive user interfaces. *Proceedings of the 3rd International Conference on Automotive User Interfaces and Interactive Vehicular Applications - AutomotiveUI '11*, page 71, 2011.

[237] S. Schneegass and R. Rzayev. Embodied notifications: Implicit notifications through electrical muscle stimulation. In *Extended Abstracts of the 18th International Conference on Human-computer Interaction with Mobile Devices and Services*, MobileHCI EA'16, New York, NY, USA, 2016. ACM.

[238] S. Schneegass, A. Sahami, T. Döring, D. Schmid, and A. Schmidt. NatCut: An Interactive Tangible Editor for Physical Object Fabrication. In *CHI '14 Extended Abstracts on Human Factors in Computing Systems*, New York, NY, USA, 2014. ACM.

[239] S. Schneegass, F. Steimle, A. Bulling, F. Alt, and A. Schmidt. SmudgeSafe: Geometric Image Transformations for Smudge-resistant User Authentication. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, UbiComp '14, pages 775–786, New York, NY, USA, 2014. ACM.

[240] S. Schneegass and A. Voit. GestureSleeve: Using Touch Sensitive Fabrics for Gestural Input on the Forearm for Controlling Smart Watches. In *International Symposium on Wearable Computers (ISWC)*. ACM New York, NY, USA, 2016.

[241] A. S. Shirazi, M. Hassib, N. Henze, A. Schmidt, and K. Kunze. What's on your mind?: Mental task awareness using single electrode brain computer

interfaces. In *Proceedings of the 5th Augmented Human International Conference*, AH '14, pages 45:1–45:4, New York, NY, USA, 2014. ACM.

[242] T.-W. Shyr, J.-W. Shie, C.-H. Jiang, and J.-J. Li. A textile-based wearable sensing device designed for monitoring the flexion angle of elbow and knee movements. *Sensors*, 14(3):4050–4059, 2014.

[243] K. Siek, Y. Rogers, and K. Connelly. Fat finger worries: How older and younger users physically interact with pdas. In *INTERACT '05*, pages 267–280. 2005.

[244] F. Silveira, B. Eriksson, A. Sheth, and A. Sheppard. Predicting audience responses to movie content from electro-dermal activity signals. In *Proceedings of the 2013 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, UbiComp '13, pages 707–716, New York, NY, USA, 2013. ACM.

[245] N. Sims, N. Colquitt, M. Wollowitz, M. Hickcox, and M. Dempsey. Life sign detection and health state assessment system, Nov. 3 2004. US Patent App. 10/595,672.

[246] B. Smus and V. Kostakos. Running Gestures: Hands-free Interaction During Physical Activity. In *Proceedings of the 12th ACM International Conference Adjunct Papers on Ubiquitous Computing - Adjunct*, UbiComp '10 Adjunct, pages 433–434, New York, NY, USA, 2010. ACM.

[247] J. Song, G. Sörös, F. Pece, S. R. Fanello, S. Izadi, C. Keskin, and O. Hilliges. In-air Gestures Around Unmodified Mobile Devices. In *Proceedings of the 27th Annual ACM Symposium on User Interface Software and Technology*, UIST '14, pages 319–329, New York, NY, USA, 2014. ACM.

[248] S. Stenfelt and R. L. Goode. Transmission properties of bone conducted sound: measurements in cadaver heads. *The Journal of the Acoustical Society of America*, 118(4):2373–2391, 2005.

[249] I. E. Sutherland. A Head-mounted Three Dimensional Display. In *Proceedings of the December 9-11, 1968, Fall Joint Computer Conference, Part I*, AFIPS '68 (Fall, part I), pages 757–764, New York, NY, USA, 1968. ACM.

[250] D. Szafir and B. Mutlu. Pay attention!: Designing adaptive agents that monitor and improve user engagement. In *Proceedings of the SIGCHI*

Conference on Human Factors in Computing Systems, CHI ’12, pages 11–20, New York, NY, USA, 2012. ACM.

[251] D. Szafir and B. Mutlu. Artful: Adaptive review technology for flipped learning. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI ’13, pages 1001–1010, New York, NY, USA, 2013. ACM.

[252] E. Tamaki, T. Miyaki, and J. Rekimoto. Possessedhand: A hand gesture manipulation system using electrical stimuli. In *Proceedings of the 1st Augmented Human International Conference*, AH ’10, pages 2:1–2:5, New York, NY, USA, 2010. ACM.

[253] K. P. Tang, J. I. Hong, and D. P. Siewiorek. Understanding how visual representations of location feeds affect end-user privacy concerns. In *Proceedings of the 13th International Conference on Ubiquitous Computing*, UbiComp ’11, pages 207–216, New York, NY, USA, 2011. ACM.

[254] K. P. Tang, J. Lin, J. I. Hong, D. P. Siewiorek, and N. Sadeh. Rethinking location sharing: Exploring the implications of social-driven vs. purpose-driven location sharing. In *Proceedings of the 12th ACM International Conference on Ubiquitous Computing*, UbiComp ’10, pages 85–94, New York, NY, USA, 2010. ACM.

[255] J. Teevan, D. Liebling, A. Paradiso, C. Garcia Jurado Suarez, C. von Veh, and D. Gehring. Displaying mobile feedback during a presentation. In *Proceedings of the 14th International Conference on Human-computer Interaction with Mobile Devices and Services*, MobileHCI ’12, pages 379–382, New York, NY, USA, 2012. ACM.

[256] B. Thomas, K. Grimmer, J. Zucco, and S. Milanese. Where does the mouse go? An investigation into the placement of a body-attached touchpad mouse for wearable computers. *Personal and Ubiquitous computing*, 6(2):97–112, 2002.

[257] E. O. Thorp. The invention of the first wearable computer. *Second International Symposium on Wearable Computers*, pages 4–8, 1998.

[258] M. Tkalcic, A. Kosir, and J. Tasic. Affective recommender systems: the role of emotions in recommender systems. In *Proceedings of the RecSys 2011 Workshop on Human Decision Making in Recommender Systems*, pages 9–13. Citeseer, 2011.

[259] A. R. Trees and M. H. Jackson. The learning environment in clicker classrooms: student processes of learning and involvement in large university-level courses using student response systems. *Learning, Media and Technology*, 32(1):21–40, 2007.

[260] J. B. F. van Erp, K.-U. Kyung, S. Kassner, J. Carter, S. Brewster, G. Weber, and I. Andrew. *Haptics: Generating and Perceiving Tangible Sensations: International Conference, EuroHaptics 2010, Amsterdam, July 8-10, 2010. Proceedings*, chapter Setting the Standards for Haptic and Tactile Interactions: ISO's Work, pages 353–358. Springer Berlin Heidelberg, Berlin, Heidelberg, 2010.

[261] M. Varga and G. Tröster. Electronics Integration. In S. Schneegass and O. Amft, editors, *Smart Textiles – Fundamentals, Design, and Interaction*. Springer HCI Series, 2016.

[262] R.-D. Vatavu. User-defined gestures for free-hand tv control. In *Proceedings of the 10th European Conference on Interactive Tv and Video*, EuroiTV '12, pages 45–48, New York, NY, USA, 2012. ACM.

[263] R.-D. Vatavu, L. Anthony, and J. O. Wobbrock. Gestures as point clouds: A $p recognizer for user interface prototypes. In *Proceedings of the 14th ACM International Conference on Multimodal Interaction*, ICMI '12, pages 273–280, New York, NY, USA, 2012. ACM.

[264] M. V. Villarejo, B. G. Zapirain, and A. M. Zorrilla. A stress sensor based on galvanic skin response (gsr) controlled by zigbee. *Sensors*, 12(5):6075–6101, 2012.

[265] A. Voit, T. Machulla, D. Weber, V. Schwind, S. Schneegass, and N. Henze. Exploring notifications in smart home environments. In *Proceedings of the 18th International Conference on Human-Computer Interaction with Mobile Devices and Services Adjunct*, MobileHCI '16, pages 942–947, New York, NY, USA, 2016. ACM.

[266] U. von Zadow, W. Büschel, R. Langner, and R. Dachselt. SleeD: Using a Sleeve Display to Interact with Touch-sensitive Display Walls. In *Proceedings of the Ninth ACM International Conference on Interactive Tabletops and Surfaces*, ITS '14, pages 129–138, New York, NY, USA, 2014. ACM.

[267] H. G. Wallbott. Bodily expression of emotion. *European Journal of Soc. Psych.*, 28(6):879–896, 1998.

[268] Q. Wang, W. Chen, A. A. A. Timmermans, C. Karachristos, J. B. Martens, and P. Markopoulos. Smart Rehabilitation Garment for posture monitoring. In *Engineering in Medicine and Biology Society (EMBC), 2015 37th Annual International Conference of the IEEE*, pages 5736–5739, Aug. 2015.

[269] M. Weigel, T. Lu, G. Bailly, A. Oulasvirta, C. Majidi, and J. Steimle. iskin: Flexible, stretchable and visually customizable on-body touch sensors for mobile computing. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, CHI '15, pages 2991–3000, New York, NY, USA, 2015. ACM.

[270] J. Werner, R. Wettach, and E. Hornecker. United-pulse: Feeling Your Partner's Pulse. In *Proceedings of the 10th International Conference on Human Computer Interaction with Mobile Devices and Services*, MobileHCI '08, pages 535–538, New York, NY, USA, 2008. ACM.

[271] A. Withana, R. Peiris, N. Samarasekara, and S. Nanayakkara. zSense: Enabling Shallow Depth Gesture Recognition for Greater Input Expressivity on Smart Wearables. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, CHI '15, pages 3661–3670, New York, NY, USA, 2015. ACM.

[272] J. O. Wobbrock, M. R. Morris, and A. D. Wilson. User-defined gestures for surface computing. *Proceedings of the 27th international conference on Human factors in computing systems - CHI 09*, page 1083, 2009.

[273] J. O. J. Wobbrock, H. H. H. Aung, B. Rothrock, and B. A. Myers. Maximizing the Guessability of Symbolic Input. In *CHI '05 Extended Abstracts on Human Factors in Computing Systems*, CHI EA '05, pages 1869–1872, New York, NY, USA, 2005. ACM.

[274] K. Wolf, C. Dicke, and R. Grasset. Touching the void: Gestures for Auditory Interfaces. *Proceedings of the fifth international conference on Tangible, embedded, and embodied interaction - TEI '11*, page 305, 2011.

[275] K. Wolf, S. Schneegass, N. Henze, D. Weber, V. Schwind, P. Knierim, S. Mayer, T. Dingler, Y. Abdelrahman, T. Kubitza, M. Funk, A. Mebus, and A. Schmidt. TUIs in the Large: Using Paper Tangibles with Mobile Devices. In ACM, editor, *Extended Abstracts of the ACM CHI'15 Conference on Human Factors in Computing Systems*, volume 2, pages 1579–1584, New York, NY, USA, 2015. ACM.

[276] P. Woźniak, K. Knaving, S. Björk, and M. Fjeld. RUFUS: Remote Supporter Feedback for Long-Distance Runners. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services*, MobileHCI '15, pages 115–124, New York, NY, USA, 2015. ACM.

[277] R. Xiao, G. Laput, and C. Harrison. Expanding the Input Expressivity of Smartwatches with Mechanical Pan, Twist, Tilt and Click. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '14, pages 193–196, New York, NY, USA, 2014. ACM.

[278] S.-Y. Yeh, K.-H. Chang, C.-I. Wu, H.-H. Chu, and J. Y.-j. Hsu. Geta sandals: a footstep location tracking system. *Personal and Ubiquitous Computing*, 11(6):451–463, 2007.

[279] M.-S. Yoh, J. Kwon, and S. Kim. Neurowander: A bci game in the form of interactive fairy tale. In *Proceedings of the 12th ACM International Conference Adjunct Papers on Ubiquitous Computing - Adjunct*, UbiComp '10 Adjunct, pages 389–390, New York, NY, USA, 2010. ACM.

[280] D. Zhang, T. H. Guan, F. Widjaja, and W. T. Ang. In *Proceedings of the 1st International Convention on Rehabilitation Engineering & Assistive Technology: In Conjunction with 1st Tan Tock Seng Hospital Neurorehabilitation Meeting*, pages 221–226, New York, NY, USA, 2007. ACM.

[281] Y. Zhang and C. Harrison. Tomo: Wearable, Low-Cost Electrical Impedance Tomography for Hand Gesture Recognition. In *Proceedings of the 28th Annual ACM Symposium on User Interface Software & Technology*, UIST '15, pages 167–173, New York, NY, USA, 2015. ACM.

[282] B. Zhou, J. Cheng, M. Sundholm, and P. Lukowicz. From Smart Clothing to Smart Table Cloth: Design and Implementation of a Large Scale, Textile Pressure Matrix Sensor. In E. Maehle, K. Roemer, W. Karl, and E. Tovar, editors, *Architecture of Computing Systems - ARCS 2014*, volume 8350 of *Lecture Notes in Computer Science*, pages 159–170. Springer International Publishing, 2014.

[283] B. Zhou and P. Lukowicz. Textile Pressure Force Mapping. In S. Schneegass and O. Amft, editors, *Smart Textiles – Fundamentals, Design, and Interaction*. Springer HCI Series, 2016.

[284] B. Zhou, M. Sundholm, J. Cheng, H. Cruz, and P. Lukowicz. Never skip leg day: A novel wearable approach to monitoring gym leg exercises. In *International Conference on Pervasive Computing and Communications (PerCom)*, pages 1–9. IEEE, 2016.

[285] U. Zulfiqar, D. A. Jurivich, W. Gao, and D. H. Singer. Relation of high heart rate variability to healthy longevity. *The American journal of cardiology*, 105(8):1181–1185, 2010.

VII

Appendix

Additional User Study Documents

- Consent form used for all user study involving EMS technology.
- Questionnaire to investigate placement and visualization possibilities for on-body displays.

University of Stuttgart
Germany

Human Computer Interaction Group (MCI), VIS

Prof. Dr. Albrecht Schmidt

Consent Form

DESCRIPTION: You are invited to participate in **a research study** on finding out if certain **muscles** can be used to **influence the human balance** if actuated by **EMS** (Electronic Muscle Stimulation).

IMPORTANT! You can **not** participate in the study under the following circumstances:

- High fever
- Cardiac Arrhythmia or other heart conditions
- Seizure disorder (e.g., epilepsy)
- Pregnancy
- Cancer
- After operations where intensified muscle contractions can disturb the healing process
- Skin diseases
- After alcohol consumption

TIME INVOLVEMENT: Your participation will take approximately **60 minutes.**

DATA COLLECTION: For this study we will actuate certain muscle groups using ems and record the center of gravity as well as the weight distribution. Also we will measure the circumference of the thighs, lower legs and arms. We may take some pictures of the study setup. Also, you will need to fill in questionnaires.

RISKS AND BENEFITS: No risk associated with this study. The collected data is securely stored. We do guarantee no data misuse and privacy is completely preserved. Your decision whether or not to participate in this study will not affect your grade in school. You can decide whether the recorded pictures can be published or not.

PARTICIPANT'S RIGHTS: If you have read this form and have decided to participate in this project, please understand your **participation is voluntary** and you have the **right to withdraw your consent or discontinue participation at any time without penalty or loss of benefits to which you are otherwise entitled**. **The alternative is not to participate.** You have the right to refuse to answer particular questions. The results of this research study may be presented at scientific or professional meetings or published in scientific journals. Your identity is not disclosed unless we directly inform and ask for your permission.

CONTACT INFORMATION: If you have any questions, concerns or complaints about this research, its procedures, risks and benefits, contact following persons:
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Human Computer Interaction Group (MCI), VIS

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PICTURE DATA: (select one)

- ☐ Please **do not publish** the pictures recorded during my participation of study.
- ☐ I allow you to **publish** the pictures recorded during my participation of study.
- ☐ I allow you to **publish** the **anonymous** pictures recorded during my participation of study.

By signing this document I confirm that I agree to the terms and conditions.

Name: _________________________ *Signature, Date:* _________________________

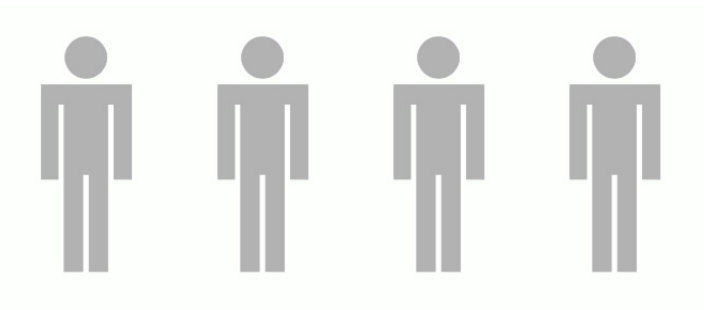
Questionnaire B.1 PID___

Use-Case 1: Heartrate Visualization

The heartrate is visualized for example in context of fitness trackers.

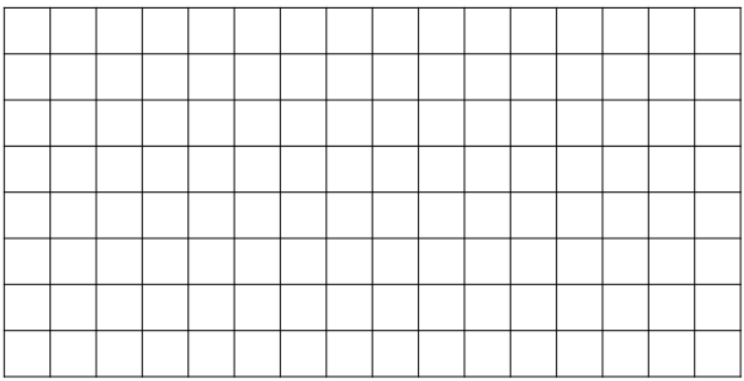
Where on the body should the display be placed to display this information? (Please mark below)

For yourself **For others**



Front **Back** **Front** **Back**

How should this information be displayed (16x8 display)?



Additional Comments:

Stefan Schneegass

Enriching Mobile Interaction with Garment-Based Wearable Computing Devices

Wearable computing is on the brink of moving from research to mainstream. The first simple products, such as fitness wristbands and smart watches, hit the mass market and achieved a considerable market penetration. However, the number and versatility of research prototypes in the field of wearable computing is far beyond the available devices on the market. Particularly, smart garments as a specific type of wearable computer have high potential to change the way we interact with computing systems. Due to the proximity to the user`s body, smart garments allow to unobtrusively sense implicit and explicit user input. Garments are capable of sensing physiological information, detecting touch input, and recognizing the movement of the user.

The core question of this thesis is how garment-based wearable computing devices can enrich mobile Interaction. Interaction centered and technology centered challenges are tackled by exploring six different research probes. These probes cover different input and output methodologies and lay the foundation for a set of twelve design recommendations. Based on these design recommendations, a reference architecture is presented easing up the integration of applications and hardware through an operating system layer.

This thesis broadens the understanding of how garment-based wearable computing devices can enrich mobile interaction. It outlines challenges and opportunities on an interaction and technological level. The unique characteristics of smart garments make them a promising technology for making the next step in mobile interaction.