Saarland University
Faculty of Computer Science

Master's Thesis

FeatherHair: Design and Implementation of a Gesture-Controlled Hair Interface

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Abstract

Hair interfaces tap into a high potential for the design of natural touch interactions on the body. By integrating naturally-occurring human behavior such as twirling or sliding into the design space of hair-based gestures, users can draw on familiar movement patterns and experience the natural haptic sensation of hair. Simultaneously, designers can rely on existing form factors to unobtrusively integrate the necessary technology into familiar shapes. But the design of a hair interface is also a sensitive matter, emerging from the prevailing social significance of hair. So, people use, e. g., their hair cut as a means to express a political orientation, their hair style to express a cultural affiliation, or interactions with other people's hair to conceive emotions. Against this background, it is surprising that the focus of prior research on hair interfaces is on a general technical feasibility whilst the practical implementation and social aspects of this technology have hardly been addressed. These aspects include, e. g., the implementation of natural gestures and their appropriateness in a social situated context. We address this gap of knowledge with a two-step approach:

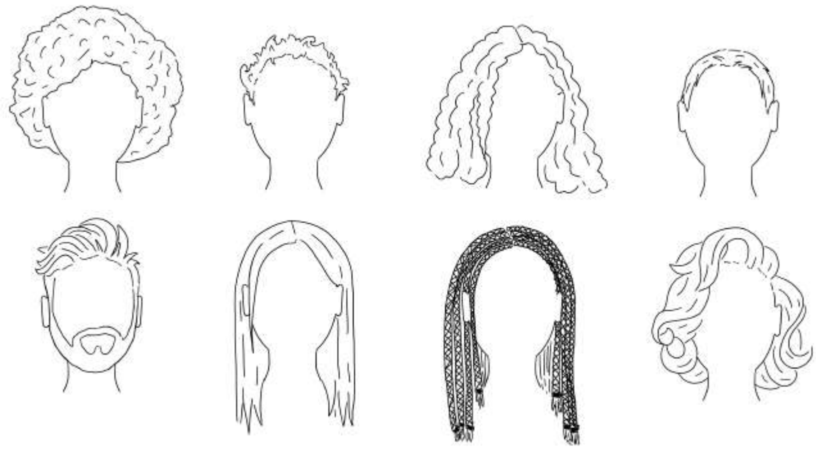
1) Our first contribution is the implementation of a real-time gesture-controlled hair interface. We present a proof-of-concept prototype which consists of feather hair extensions augmented with resistive and capacitive touch sensing capabilities. As part of a data collection with ten participants, we use the prototype to collect 2500 samples for a set of five gestures. With this dataset, we implement a gesture recognizing system, evaluating the efficiency of various classifiers linked to a comparison of the suitability of both time series- and statistics-based features.

2) Our second contribution is a discussion of the social implications of hair interfaces. We approach this objective inspired by research through design: Using our gesture-controlled hair interface, we conduct a field study in which we provide the participants with realistic hands-on experience in public. The results of the study give us insights into the potential of hair interfaces for natural and hidden interactions and the dependency of the perceived appropriateness of both appearance and gestures on the targeted user groups and the social context.

We synthesize the findings into four major design incentives, covering wearability of hair interfaces, hair-based gestures, and considerations of both users' diversity and the primary social context in which the interface shall be deployed. These incentives serve as an initial guideline for designing hair interfaces that are perceived both usable and socially acceptable by its users.

Contents

1 Introduction



Hair is hair is hair? Not exactly. It is also a powerful symbol of the self. (Anthony Synnott, 1987 [87])

Hair has been a culturally loaded subject for thousands of years. Alongside with its protective and ornamental functions, it has also had great social significance in many cultures all over the world [82]. So might the hair style reveal information about social class or clan affiliation, age, marital status, the place of birth, or religious and political orientations. But to what extent is hair appropriate for the design of interfaces against this background? In this chapter, we elaborate on this question by discussing chances and challenges of hair for interface design. We then shed light on the current status and gaps of literature on hair interfaces, followed by an outline of the aim of this thesis. We conclude this chapter with the presentation of related research questions and an overview of the thesis structure.

1.1 Motivation

Many devices that we use in our daily life are screen-based. But screen-based technologies which involve, e. g., touching glass surfaces to provide input do not correspond to the way we typically interact with our physical environment. Furthermore, providing us with visual feedback, the technology requires our entire focus of attention for interaction. This causes the technology to often be perceived as disruptive and unsuitable in social situational contexts. Thus, research interest on on-body user interfaces that seamlessly merge with the human body and our physical world has grown substantially over the last decades to counteract this trend. These on-body technologies include, but are not limited to, skin-based [35, 99, 101], nail-based [41, 51, 96], and hair-based interfaces [24, 91, 94]. In the subsequent subsection, we detail on the particular potential of hair for the design of on-body technologies before touching on the current status of literature on hair interfaces and how it interrelates to the goals of this thesis.

1.1.1 Hair for Interface Design

The potential of hair has been known for thousands of years, especially as a means of communication and base for ornamental and symbolic adornments [82, 87]. So, e. g., early cave paintings already depict people wearing feathers, bones, or shells in their hair [82]. In addition, hair has been used in many cultures to provide information about social class or clan affiliation, age, marital status, and many other personal aspects of life [82], conceived through its length, color, style, or attached accessories [87]. This malleability of hair, which has been accepted in our society for centuries [82], enables the designer of a hair interface to draw on a broad variety of existing form factors for a seamless integration of the required technology into familiar shapes. On the other hand, as people use their hair as public display for communicating their inner state of mind to others, hair is both a public and a private affair, turning the design of a hair interface into a sensitive matter which needs to account for both of these opposing characteristics.

Furthermore, hair interfaces tap into a potential for the design of touch interactions which are based on common human behavior, encompassing both naturally-occurring conscious and unconscious interactions with our hair [84, pp.36–38]. E. g., there are people who deliberately twirl their hair when flirting or unconsciously when being nervous. Others touch their friends' hair to show affection and enhance their interpersonal touch. The richness of interaction that is hidden here in plain sight enables a natural way to input a hair interface in a manner that exceeds the prevailing status quo of (screen-inspired) touch interactions which oftentimes ignores surrounding human movements, activity, and behavior and is, thus, trapped in a "flatland of touch" [39]. Consequently, hair provides researchers with an interesting form factor for the design of natural touch interactions through which users can draw on familiar movement patterns to input the interface. But this potential also poses a challenge for the design of gestures since the movements that suggest a natural way to input a hair interface might simultaneously suffer from misunderstandings and suggestiveness for spectators, depending on their meaning with which they are typically associated in a socially situated context. So could, e. g., a twirling gesture be misinterpreted as flirting in Western cultures. We can subsume those chances and challenges of hair for interface design mentioned up to this point under the term *social complexity* since they exclusively emerge

from the socially situated context in which the hair interface is used.
But alongside with this social complexity, the design of hair interfaces also poses technical challenges. Whilst, e. g., skin-based interfaces are argued to be attractive due to their large and always available input surface [35, 99], these properties do not necessarily transfer to hair interfaces as there are people that have bald or short hair. In addition, different hair structures and lengths might require different interface and interaction designs, limiting the target group for which the specific technology is applicable. Both these social and technical challenges turn the use of hair as base for an interface and the design of accompanying hair-based interactions into a highly sensitive matter that requires in-depth knowledge.

1.1.2 Hair Interfaces in Literature

Literature demonstrates a general technical feasibility of hair interfaces with a particular emphasis on functionality and aesthetics [24, 94, 90, 7, 52, 91]. They show that hair interfaces can be equipped with various input and output modalities, ranging, e. g., from gesture-controlled input [48, 24, 94] to visual output through color [52, 24, 90] and shape change [24] and name a broad field of applications. Yet, existing literature oftentimes ignores the accompanying need to discuss aspects that shape the social complexity of the designed hair interface and hair-based interactions. Since the participants of the evaluation studies were hardly provided with realistic hands-on experience with the designed hair interfaces neither in lab nor in field, many findings that concern the usability and appropriateness of hair interfaces and hair-based interactions in practice are based on the participants' imagination, limiting the ecological validity of the outcomes. Consequently, the actual complexity of hair interfaces as on-body technology has remained underexplored to date.

1.1.3 Aim of the Thesis

The aim of this work is to address the gap of knowledge on the (social) complexity of hair interfaces. In particular, we focus on the usability of gestures for hair-based interactions in practice and the extent to which the social context and the personal social significance of hair influence the perceived appropriateness and comfort of this technology. With that, we strive to derive design recommendations for usable and socially acceptable hair interfaces.

1.2 Research Questions

Inspired by research through design [108], we approach this aim from a human computer interaction perspective. For that, we first implement a proof-of-concept prototype which is able to classify a multitude of gestures in the first part of the thesis. The prototype can then be deployed in lab, field, or showroom [108]. This objective is addressed in RQ1:

> **RQ1:** How might we realize a gesture-controlled hair interface?

To answer RQ1, we investigate the following questions: 1) How might we reliably detect and distinguish gestures and false activations? 2) How feasible is a user-independent gesture classification? And 3) how can we generalize the results to new users? For that purpose, we implement a real-time gesture-controlled hair interface for which polymerized feather hair extension make up the base. We leverage this proof-of-concept prototype to investigate its social complexity in the second part of the thesis. We address this goal with RQ2:

> **RQ2:** What are the social implications of a gesture-controlled hair interface?

Answering RQ2 includes examining the following two aspects: 1) What factors influence the social acceptability of a hair interface? And 2) How can we leverage this knowledge to derive design incentives for hair interfaces? Whilst meanwhile, many research has been carried out on social acceptability of wearables in general, Koelle et al. point out that there have been only few papers evaluating technology's social acceptability in the wild [45]. As this observation also holds for hair interfaces, we answer the question with a field study, using our gesture-controlled prototype built in the first part of the thesis. Identifying a set of factors influencing the prototype's usability and acceptability, we put them in the context of prototype design and implementation and synthesize these findings into design incentives. These serve as a set of guidelines for designing hair interfaces with a primarily focus on usability and social experiences.

1.3 Outline

This document covers all aspects of the work done within the scope of this thesis. The subsequent chapter provides background on existing work related to hair interfaces, social acceptability, and gesture recognition. We present the hardware implementation of a gesture-controlled hair interface in Chapter 3, followed by the construction of a dataset in Chapter 4. Given this dataset, we then detail on the implementation of a gesture recognizing system and compare the suitability of two different approaches as part of Chapter 5. In Chapter 6, we detail on the user study and analyze the results. Based on these results, we derive design incentives in Chapter 7 and provide an overview of limitations and future directions for research on hair interfaces. Finally, we conclude with a summary in Chapter 8.

2 Related Work

The design of hair interfaces is challenging in both technical and social terms. Therefore, this chapter provides a multi-faceted overview of approaches and methods related to our work on a gesture-controlled hair interface. In addition to discussing previous work on hair interfaces, we detail on social acceptability, social context, and methods for studying the social dimensions of an interface. We briefly review the history of feathers in history, art, and HCI as feather hair extensions constitute the basis of our hair interfaces and finally discuss gesture-related terminology, including an overview of gestures that have application in the context of hair interfaces.

2.1 Hair Interfaces

Hair interfaces belong to a class of on-body technologies that are worn in close proximity to the body, revealing new interaction forms that go beyond the classic screen- and keyboard-driven approaches. There is a vast amount of literature conceiving these novel technologies which also include, e. g., eTextiles [66, 70], digital jewelry [57, 72], interactive cosmetics [42, 95], skin-based interfaces [35, 99, 101], and nail-based interfaces [41, 51, 96]. Considering hair and nails as regrowing appendage of skin [97], we can subsume skin-, hair-, and nail-based interfaces under the term of on-skin technologies. To further frame hair interfaces in this context, we can specify a working definition as follows:

> A hair interface is a wearable body modification that replaces, encapsulates, or attaches to body hair in order to augment it with functionality for its wearer or their spectators. It merges with the body in a manner that retains or extends the wearer's naturally-occurring interaction with hair.

Here, body hair refers to all type hair, also comprising, e. g., head, beard, and arm hair. Through this definition, we exclude headpieces such as hats [22] and caps [23] since they do not modify, replace, or merge with the wearer's hair but include body modifications that range from functional hair dye and cosmetics [90, 7, 6], to extensions [94], artificial braids [48, 24, 52], and wigs [91]. In the following subsections, we detail on contributions of related literature that conforms with this definition. These contributions comprise the technical feasibility, input- and output modalities, and applications of hair interfaces. Figure 2.1 provides an overview of some hair interfaces presented in literature.

2.1.1 Technical Feasibility

Literature demonstrates a general technical feasibility of hair interfaces in versatile ways. There is, e. g., SmartWig that consists of a wig that hides sensors and vibration motors inside [91]. Artificial hair is also used by Vega et al. who built HairWare, a hair interface consisting of chemically metalized hair extensions that are connected to a microcontroller [94]. The Unseen, a London-based group of chemists, engineers, textile designers and commercial strategists, invented Fire, the world's first color-change hair dye using thermochromic pigments with which they can turn real human hair into a sensor [90]. MAGHair augments skin hair through the application of passive magnetic cosmetics that reacts to changes in a magnetic field which is controlled through a wearable device [7]. Its predecessor, called M-Hair, follows the same principle but used a non-wearable device to control the external magnetic field [6]. Another approach is taken by Dierk et al. who invented HäirIÖ, leveraging artificial braids that can be attached to the hair [24]. Similarly to these braids, Li et al. designed a hair decoration consisting of a set of body- and end-glowing optical fibres called LightingHair Slice [52]. As part of a more technical work, Ku et al. developed ThreadSense, a new sensing technique for touch input on thin thread [48]. As an application case of their work, they propose to integrate this technique in a braided headband which allows gestural input to be carried out on hair. As part of our thesis, we contribute a further method to realize a hair interface which is made of feather hair extensions that are augmented with electrical functionality through polymerization.

2.1.2 Input Modalities

There are various input options for hair interfaces that include, but are not limited to, the use of biosensors such as a heart rate or photosensors [52], GPS and buttons [91], external devices such as smartphones [52], and touch sensing [24, 48, 94]. Whilst a majority of the interfaces uses touch sensing, we found that their underlying implementation varies considerably. I. e., both Hairware and HäirIÖ implement capacitive touch sensing where Hairware uses chemically metalized hair extensions and HäirIÖ a Swept Frequency Capacitive Sensing approach on a wire braided into the plait. ThreadSense implements a sensing technique relying on impedance sensing for one-dimensional touch input on a thin thread. Whilst the latter is able to locate up to two touches concurrently, other interactive hair allows for the detection of single touch only. Moreover, considering the evaluation of the proposed input modalities, we found that most studies focused on the overall functionality whilst the appropriateness of the proposed input modalities and their influence on the users' and spectators' acceptance of the associated hair interface remains underexplored. We compensate for this gap with the implementation of a gesture-controlled hair interface for which we evaluate the appropriateness of the designed gestures in the field.

Figure 2.1: From left to right: Smartwig consisting of a wig with integrated sensors [91]. User touching the chemically metalized hair extensions of HairWare [94]. HäirIÖ braid with shape changing properties [24]. HäirIÖ braid with color changing properties [24]. User wearing several units of LightingHair Slice [52]. ThreadSense integrated in a braided headband [48].

2.1.3 Output Modalities

Complementary to the versatile input options, hair interfaces offer a considerable variety of output modalities. These range from color change realized with thermochromic pigments [24, 90] and lighting through optical fibres [52] to shape change through Shape Memory Alloy [24] and tactile feedback [91, 7, 6]. But the proper use of output modalities for hair interfaces was found to be challenging: E. g., Tobita et al. demonstrate that the implementation of vibrotactile feedback directly at the head is troublesome for the wearer due to the head area's high sensitivity [91] whilst the tactile sensation caused at other body hair locations such as the arm was perceived as rather pleasant and positive [7, 6]. Moreover, when providing a hair interface with visual output which the wearer possibly cannot observe themselves, the use of the interface becomes a public affair as particularly spectators notice the visual feedback. However, research has not yet investigated the extent to which such output modalities influence users' and spectators' acceptance of this technology in practice.

2.1.4 Applications

Literature identifies a wide range of practical applications for hair interfaces. These range, e. g., from the use as a security device [94], to haptic and visual notification systems [24], and for navigation assistance [91]. Furthermore, some also touch on the social chances of hair interfaces, suggesting to use them as a means to conceive affective touch [7, 6], engage interpersonal touch [24], or enhance social interactions at concerts or on stage, turning the interface in a public display [52, 24]. But these social aspects have been hardly discussed in-depth, so far. Here, our work complements the existing literature with in-depth insights into the use of hair interfaces in a socially situated context.

2.2 Social Context, Perceptions, and Acceptability

Coming with technical progress that allows to conceive novel interaction forms and interfaces, we arrived at the Third Wave in human computer interaction shifting technology's focus towards social awareness, aesthetics, and emotion [5, 92]. That said, factors that go beyond the pure functionality play an increasingly important role in the user's acceptance of a device. In addition to aesthetics, these factors include, but are not limited to, the consideration of the social context in which the user interacts with the device and the way the user as well as potential spectators perceive this interaction. This is relevant as such factors might shape the acceptability of a novel technology. When we speak of social acceptability, we refer to the definition proposed by Koelle et al. and call a hair interface social acceptable "*if its presence or the user's interactions with it are consistent with the user's self-image and external image, or alter them in a positive way*" [45]. That said, the interface should meet or enhance, e. g., the cultural, social, and fashion demands of the user. Hence, when investigating social acceptability, researchers are required to address questions like the following: How does the user feel when using this device? How does a spectator feel, observing the user interacting with the device? Which factors influence their attitudes? Based on these questions, we first discuss the choice of a suitable research method in the subsequent subsection, followed by an investigation of factors that might shape the social complexity of a device.

2.2.1 Research Methods

The choice of a suitable research method is of crucial importance when investigating the social acceptability of a prototype as it might provide the researcher with deep insights or even uncover unanticipated social acceptability issues [45]. But since different study methods also bring their own advantages and disadvantages, the choice of an appropriate method is not always apparent. That is, laboratory experiments allow for a good replicability due to their high level of control but usually prevent the participant from being put in a natural setting. Field trials with a lower level of control on the other hand provide a higher ecological validity which helps to identify unexpected social acceptability issues but suffer from a lower replicability [45]. To date, several researchers substantiate the influence of the research method on the findings related to social acceptability and emphasize that more natural settings and hands-on experiences allow participants to develop more realistic and profound opinions regarding the introduced interfaces and devices [1, 76]. These opinions would differ from the impressions developed by participants through video demonstrations and imaginary use cases. Consequently, this allows for a more realistic analysis of factors that influence social acceptability. There is, e. g., Ahlström et al. who showed that hands-on experience has indeed an influence on the evaluation of the social acceptability of gestures [1]. They explored the experiences of users and bystanders when performing around-device gestures in public and found that the reactions of others influenced the participants behavior in a way that they got selective about where and in front of whom they chose to perform the gestures. The authors outline that in their study, the evaluation of gestures by people who had not had hands-on experience so far was much better. Similarly, Rico et al. investigated and compared the evaluation of the influence of location and audience on the social acceptability for a predefined set of gestures when the participants were provided with a video demonstration only to the evaluation when participants were provided with hands-on experience in a realistic setting [76]. For that, the participants were asked to select from a predefined list all locations and audiences where they would want to perform the gestures. It turned out that the participants that were provided with a realistic setting could indeed develop and report more in-depth opinions. A specific example of a design for a field research on social acceptability with a high ecological validity can be found, e. g., in work by Lucero and Vetek who aimed to evaluate interactive glasses in public [53]. The researchers prompted the participants to interact with these interactive glasses during a pedestrian navigation task where a fixed route in the city center was followed. The route was designed to include public locations with different characteristics such as bus stops, a playground, or a shopping street. With that, the authors could get deep insights into the appropriateness of proposed interaction techniques and the influence of the social context on the interaction with interactive glasses. Although these examples emphasize the importance of providing the participants with hands-on experience, Koelle et al. uncover a discrepancy between used research methods investigating the social acceptability of interfaces [45]. As most of the research methods found in literature present a high to moderate level of control whereas few studies are conducted with a low level of control only, the authors call for using mixed methods with varying levels of control as they may well complement each other. As this discrepancy also holds for studies conducted in the context of hair interfaces, this work follows this call to action by complementing the existing studies on hair interfaces with a field experiment similar to the one designed by Lucero and Vetek.

2.2.2 Factors Shaping the Social Complexity

When investigating the social complexity of an interface, there are many influential factors to be considered. E. g., Rico et al. suggest to examine the influence of location and audience which makes up two intertwined dimensions of social complexity [76]. However, Udhe et al. point out that current approaches to describing contextual influence, such as the location-and-audience axes, tend to be inflexible and therefore fail to capture the complexity of social contexts [93]. For this reason, instead of relying on discrete categories, they propose to interpret social context as a temporary set of interactions between co-located social practices that can support or hinder each other. Due to the co-location of social practices, we can categorize their interactions as compatible or incompatible instead of relying on discrete categories to capture the nuances of social context. E. g., we could say that a person who phones loudly in a library would hinder the co-located people reading books. Thus, these practices would be considered incompatible. The identification of the (in)compatibilities makes it possible to place the (un)acceptability of interactions in a social context. On the other hand, several researchers point to a versatile set of factors influencing the social acceptability which are possibly not fully captured by the social practice theory. There are amongst others the role of aesthetics [67], specific gesture properties such as their duration and size [1], as well as the type of interaction including hidden or revealed interactions [73].

However, to the best of our knowledge, there is no work that provides us with an exhaustive, standardized list of factors that shape the social complexity of a technology. Furthermore, the social complexity of hair-based interfaces is to date a completely underexplored research area. We contribute to this gap of knowledge by identifying a set of factors which influence the perception of hair interfaces and hair-based interactions.

2.3 Feathers in History, Art, and HCI

Feathers have a long tradition almost everywhere in the world [14]. Besides their rich historic and symbolic meaning [12], they have been used for centuries, e. g., to adorn hats, masks, dresses, and hair [33], for carnival costumes [4], or as hair extensions [74]. But feathers also play a role in the intersection of art and HCI due to their appealing look and haptics. There exist, e. g., several kinetic featherworks in which feathers are moved by motors in response to biometric data of the wearer [65] or to surrounding electromagnetic signals [62, 63, 64]. Apart from kinetic work, recent advances in polymerization make it possible to transform a broad range of materials, including feathers, into touch sensors by augmenting them with electrical functionality [40]. In 2021, Briot et al. used this method to turn feathers into soft capacitive touch sensors, generating sound waves when a finger approaches [13]. Inspired by this approach, in this work, we augment feather hair extensions, which constitutes the core of our gesture-controlled hair interface, with touch sensing capabilities through polymerization.

2.4 Gestures

Coming with technological progress, also the demand for novel interaction forms as input to new technologies increases. To date, there exists already a considerable range of interactions such as free-hand gestures [3, 37], microgestures [81, 83], or skin-based touch input [35, 99] – just to name a few. However, there are different prominent perspectives on the definition of gestures in literature [61]. For this reason, we first introduce two of the most common definitions of gestures and discuss the extent to which they are suited for hair-based interaction. We then briefly review further gesture-related terminology that we use in the context of this work. Finally, we detail on gestures that could have potential application for the design of our gesture-controlled hair interface.

2.4.1 Gesture Definitions

According to Kendon, a gesture is a deliberate expressive body movement governed by communicative intent where observers are able to identify these movements as fully intentional and intentionally communicative [43]. He points out that nervous or incidental movements, movements used to change the position or orientation, as well as movements that aim at the manipulation of objects do not fulfill these requirements. Similarly, Kurtenbach and Hulteen state that a gesture in the context of human-computer interaction refers to a body movement that carries informational content for an observer where the observer might be a person or a device [49]. Although both definitions point to the informational content of the movement that is at the core of a gesture, they differ in terms of the presence of the user's intention in performing the movement. This difference is relevant when designing natural gestures that rely on body movements which might occur both incidental and fully intentional. One such exemplar body movement in the context of hair-based interactions is twirling. A person might, e. g., twirl their hair intentionally when flirting or incidental when being nervous. Whilst only the first variant would be considered a gesture according to Kendon, the concept of Kurtenbach and Hulteen allows to refer to both movements as gestures since also the second one carries potential information for a hair interface, albeit being incidental. So might, e. g., a hair-based anxiety tracker rely on these types of naturally-occurring movements (or *gestures*) as indication for anxiety. For this reason, we refer to Kendon and Hulteen's concept of a gesture for the remainder of this thesis.

2.4.2 Further Terminology

For a more fine-grained classification of hair-based gestures, we stick to the taxonomy provided by Wobbrock et al. who introduces four dimensions of a gesture of which two are relevant in this thesis [102]. First, there is the form dimension which allows us to categorize gestures either as static or dynamic. Here, a static gesture requires a posture to be held for a specific duration and a dynamic gesture is made of a specific movement pattern [105]. Second, the flow dimension comprises discrete and continuous gestures where a discrete flow implies that a gesture is recognized only after its execution whereas a continuous flow is recognized during the execution.

2.4.3 Hair-Based Gestures

Albeit interactions with hair are oftentimes limited alongside one axis, literature provides us with various discrete gestures that have potential application in the design space of hair-based interactions. To this end, we draw on gestures proposed in the context of both hair-based and cord-based interfaces [60, 59] since we found that cord-based interactions compare to hair-based interactions due to their similar form factors, requiring a similar way of interaction as well. Among the inspected papers, the most classic gesture is arguably the single-touch event, which is used in different variations for interaction. So is, e. g., a simple touch/no touch detection implemented as part of HäirIÖ [24], the area of the touch (top, middle, top) is additionally localized as part of HairWare [94], and ThreadSense even enables the localization of touch on a continuous scale [48]. Other commonly mentioned gestures include movement patterns that we can group under the terms of sliding (fingers move along the interface) [24, 94, 48, 60], twirling (fingers twirl the interface several times) [24, 94], and flicking (directional movements along or orthogonal to the interface) [60]. Olwal et al. propose to introduce further variation to these movement patterns by changing the style in which the cord is touched, ranging from applied pressure, to contact time, and contact area [59]. So can a single touch event, e. g., be performed through grabbing in a fist, tapping with the flat of the hand, or pinching between any two fingers [59, 60]. By combining these gesture types and styles, we can already draw on an established set of gestures applicable for the interaction with our hair interface.

2.5 Summary

In this chapter, we reviewed literature related to the design of hair interfaces and found that particularly the functionality, ranging from application scenarios to input and output modalities, has been broadly investigated to date. We discovered gaps in knowledge related to the social complexity of this technology, including its appropriateness in specific social contexts and gesture design. To account for these gaps, we discussed the choice of a suitable research method and factors that shape the social complexity. We then reviewed the role of feathers in the HCI, art, and history community. Finally, we introduced gesture terminology that we use throughout this work and concluded with a collection of common gestures for hair-based interfaces.

3 Touch Sensing (Feather) Hair

Touch sensing constitutes the basis for the gesture-controlled interaction with our hair interface. In the first part of this chapter, we present common techniques used to implement touch sensing. Afterward, we describe the construction of a touch sensing hair interface consisting of feather hair extensions in hardware and software. The resulting prototypes were used for the studies described in Chapters 4 and 6.

3.1 Background

To realize objects that detect the occurrence of physical touch, there are many different approaches comprising but not being limited to acoustic-, optical-, resistance-, or capacitance-based touch sensing [31]. As part of this thesis, we especially focus on variations of the latter two options since prior work on hair interfaces demonstrated their suitability for hair-based touch sensing technologies. In the following, we sketch the underlying working principles. This serves as a theoretical background for the construction of our touch sensing hair interface.

3.1.1 Resistive Sensing

Variable resistors (similar to a potentiometer) are resistors that have an adjustable electric resistive value and are commonly used, e. g., as volume controls and for resistive touch sensing [80, p. 320] where the latter is used to detect and locate the occurrence of touch. Common resistive touch screens are realized through two layers coated with conductive sheets that are physically separated by some non-conductive microdots [80, p. 536]. When a voltage gradient is applied across one of the conductive layers and a layer surface is touched, the conductive sheets make contact and close an electrical circuit. By measuring the incoming voltage on the other layer, we can infer the position of touch.

3.1.2 Piezo-Resistive Sensing

Piezo-resistive sensing can be understood as force-sensitive resistive sensing [80, p. 544]. Emanating from a two-layer layout as for the resistive touch sensor, the main difference is that the harder one of the layers is touched and the closer the two conductive sheets move, the more the resistance between these two layers decreases. This can be, e. g., realized through a polymer located in between, containing conductive and non-conductive particles that move closer when being pressed. By measuring the resistance, we can detect the occurrence of touch as well as infer the pressure applied to the sensor. Refer to Figure 3.1 for an illustration.

3.1.3 Capacitive Sensing

Capacitive touch sensing makes it possible to detect both physical touch and proximity [80, p. 539]. This technique is, e. g., used by HairWare [94]. A capacitive touch sensor relies on the working principle of a capacitor and consists of a conductive sensor plate connected to a microcontroller and a sensor plate that is represented by any approaching conductive surface such as a finger. The approaching finger results in a change of capacitance where the capacitance corresponds to the energy stored in the electrical field between these two plates and varies according to their distance. Refer to Figure 3.5 for an illustration. Applying voltage to the circuit, we can measure the present capacitance based on the time required to (dis)charge the capacitor where the charging time follows an exponential pattern and increases with increasing capacitance.

3.1.4 Swept Frequency Capacitive Sensing

A variation of the described capacitive touch sensing is Swept Frequency Capacitive Sensing (SFCS) which is, e. g., used by HäirIÖ [24]. Hereby, instead of exciting the conductor with a DC power source of fixed frequency, SFCS applies frequency multiplexing [79]. The resulting measured reactions of the excited object might be frequency-dependent and object-specific This, in turn, enables us to detect both touch occurrences and complex configurations of, e. g., approaching hands or body postures.

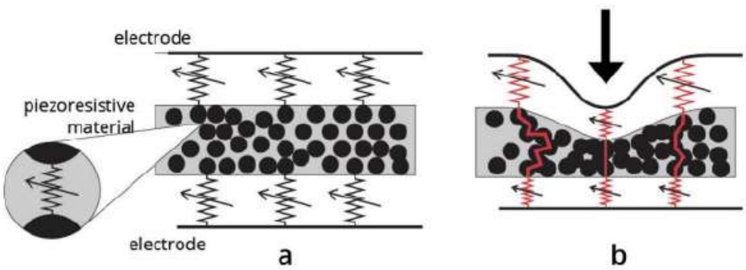


Figure 3.1: Left: The conductive (black) molecules of the piezo-resistive material do hardly touch each other when the sensor is at rest. Consequently, the resistance is large. Right: The sensor is pressed, resulting in the conductive molecules moving closer together. The measured resistance decreases accordingly (indicated through the red colour). Source: PolySense [40].

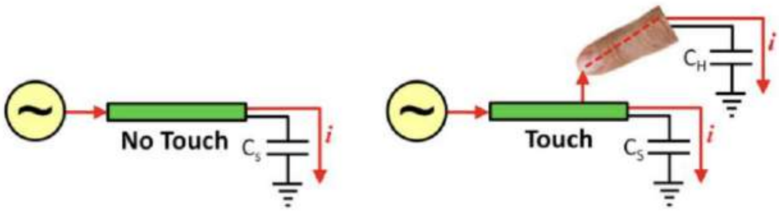


Figure 3.2: Left: The capacitive sensor is at a steady state with capacitance C_S. Right: The capacitance increases at the sensor plate when the finger approaches. Source: Walker [98].

3.1.5 Impedance Sensing

Impedance touch sensing is the underlying technology of ThreadSense [48]. ThreadSense uses the measurable impact of touch on the electrical impedance to infer the touch location relying on a small alternating current. Electrical impedance is a measure that extends the principle of resistance to AC power sources[1]. This is necessary since applying a DC power source to a circuit results in magnitude changes whereas the use of an AC power source results in both changes in magnitude and phase which the impedance measure can account for. Consequently, to measure touch (or gestures) using impedance sensing, an AC power source is applied to the circuit where the occurrence of touch results in measurable magnitude and phase shifts.

3.1.6 Hybrid Sensing

Researchers demonstrate that the combination of several touch sensing methods is a powerful tool to obtain even more robust measurements of touch [28]. E. g., Strohmeier et al. combine resistive and capacitive touch sensing to a hybrid sensing approach [86]. They state that the combination of the capacitive and resistive measurements improved the identification of gestures, and, in turn, helped to reduce false activations as part of their gesture classification. As we aim for a gesture recognition approach on a level similar to the one proposed by Strohmeier et al., we find that a hybrid sensing method is promising for our hair interface as well. Since the position of a hair interface is susceptible to disturbances such as jerky movements, wind, or proximity to the body, the quality of resistive or capacitive sensing technologies might suffer when being considered as stand-alone technologies. Being the first to try hybrid sensing on hair, we elaborate on this combination of resistive and capacitive sensing in the subsequent sections of this chapter.

[1] Based on article by Electrical4U: https://bit.ly/3cj2rsX (Retrieved November 17, 2021)

Figure 3.3: Left: Demonstrator used in the data collection study (c.f., Chapter 4). Right: Wearable prototype used in the field study (c.f., Chapter 6).

3.2 Hardware Setup

Our prototypes relies on a hybrid sensing approach, combining piezo-resistive and capacitive touch sensing. In this section, we first introduce the main components that the hardware is made of. We then discuss the implementation of piezo-resistive and capacitive touch sensing and conclude with an explanation how these two parts can be combined and integrated into a prototype. Two of these prototypes are depicted in Figure 3.3.

3.2.1 Components

Our physical hair interface prototype consists of two main components. The first component is the microcontroller that controls the piezo-resistive and capacitive measurements in software. We decided to use an ItsyBitsy M0 Express[2] as it is a tiny and lightweight commodity microcontroller. Since it has capacitive touch sensing support integrated in hardware, we do not need any further hardware components to implement capacitive touch sensing. The second component are feather hair extensions from FeatherLocks[3]. The feather extensions are grouped in bundles of three, 20-25 centimeters long, and partially colored. These feathers are a widely used accessory and constitute a potentially familiar form factor for users. Furthermore, their haptic properties are similar to that of human hair, providing them with a natural experience.

[2] Introduction of the ItsyBitsy M0 Express: https://learn.adafruit.com/introducing-itsy-bitsy-m0/overview (Retrieved November 17, 2021)

[3] FeatherLocks homepage: https://conditionculture.com/collections/featherlocks (Retrieved November 17, 2021)

3.2.2 Piezo-Resistive Touch Sensing

For the first part of the hybrid sensing approach, we turned the feather hair extensions into a piezo-resistive sensor. In the following, we first sketch the working principle of this sensor, before detailing on the three main construction steps.

3.2.3 Working Principle

The working principle of our piezo-resistive sensor is inspired by Perner-Wilson's piezo-resistive fabric sensor introduced on Kobakant [69]. It consists of two parts, each made up of several conductive, piezo-resistive feathers. We decided to use three feather bundles in total for this sensor as it needs to be large enough to be easy to grasp ans squeeze, but as small as possible to not look clumsy. This amount of bundles appears to be a good compromise between functionality and style. One part of the feather sensor is connected to an analog output pin of the microcontroller to which we apply a fixed output voltage. The second part of the sensor is connected to an analog input pin. When both parts are pressed together, the piezo-resistive feather layers make contact and we can measure the incoming voltage on the input pin. When the feathers are not pressed together, we measure values close to zero Volt. Changes in the amount of incoming voltage enable to detect the occurrence of touch.

3.2.4 Construction

To implement the sketched working principle, we first augmented the feathers with electrical functionality. Second, we added connectors to the feather bundles, and, third, used these connectors to solder the feathers to the microcontroller. We detail on these steps in the following paragraphs.

Augmentation With Electrical Functionality Inspired by Briot et al. [13], we augmented the feather bundles with electrical functionality through polymerization as described in PolySense [40]. Here, polymerization is a chemical process through which conductive polymers form in and around the feathers' fibres, turning them into piezo-resistive sensors. Refer to Appendix A for details about the used polymerization procedure and comments on the reliability of this process for nature products. Refraining from the samples for which polymerization was not successful (e. g., those without pre-treatment), the remaining feathers exhibited a measurable resistance with a mean of 0.5 MΩ (SD 0.3 MΩ) which is sufficiently conductive to guarantee a proper functionality of the sensor. The resistance was measured for each feather once with a multimeter on a length of 10 cm.

Preparation of the Connectors Since it is infeasible to directly mount the soft feathers' ends to the microcontroller pins in a manner that the connection is sufficiently tight and stable, we added solderable connectors to the feathers' ends. The procedure for the construction of the connector follows the *Wire Circuit* tutorial of Hartman [36, pp. 14–17] and is illustrated as part of Figure 3.4. As

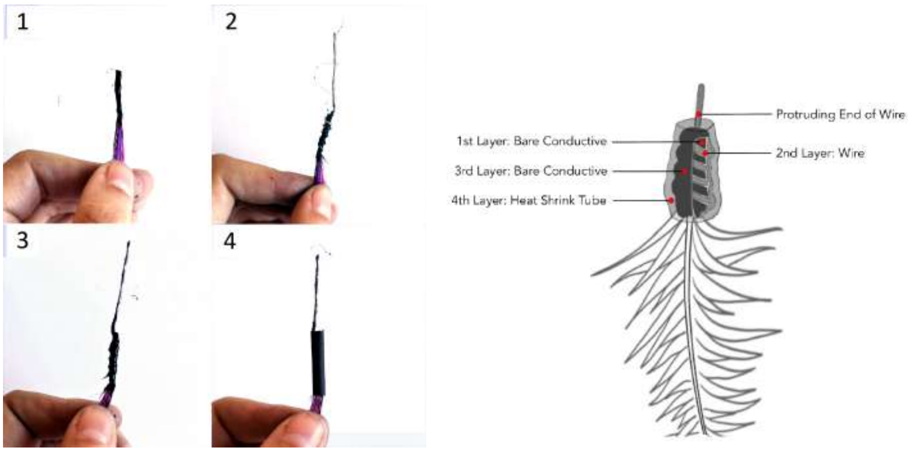


Figure 3.4: Left: Images of the connector construction: 1) applied bare conductive, 2) wrapped conductive thread, 3) another layer of bare conductive, 4) heat shrinked tubing. Right: A semi-transparent cross-section of the connector layers.

demonstrated in this figure, the connector is made of several layers where the innermost layer consists of bare conductive that keeps the feather bundle together, acting as a conductive adhesive. For the second layer, a wire is wrapped tightly around the area that is covered with the conductive adhesive. The protruding end of the wire serves as a solderable connection point. The third layer consists again of a conductive adhesive to ensure that the conductive parts are tightly connected whilst a shrinking tube at the outmost layer insulates the inner conductive parts. We followed this construction to prepare the ends of both parts of the piezo-resistive sensor.

Connection to the Microcontroller The two sensor parts are soldered to the microcontroller, using the connectors' protruding ends of the wire. Here, we use pins `A0` and `A1`, which act as analog output and input pins of the ItsyBitsy M0 Express, respectively.

3.2.5 Capacitive Touch Sensing

For the second part of the hybrid sensor, we added capacitive touch sensing capabilities to the feather hair extensions. Similarly to the piezo-resistive implementation, we detail on the main construction steps in the following subsections.

Augmentation with Electrical Functionality A thread of *Bart & Francis Inox (steel) 0.035 mm* yarn is wrapped tightly around a feather and carefully fixed with transparent glue at the top, middle, and bottom to prevent it from slipping from its place (c.f., Figure 3.5). The glued points should be as small as possible as the glue is insulating and hardens when being dried. A large area of glue, in turn, distorts both the haptic sensation and the measurements. Afterward, we prepared the connector for the feather as described in Subsection 3.2.2.

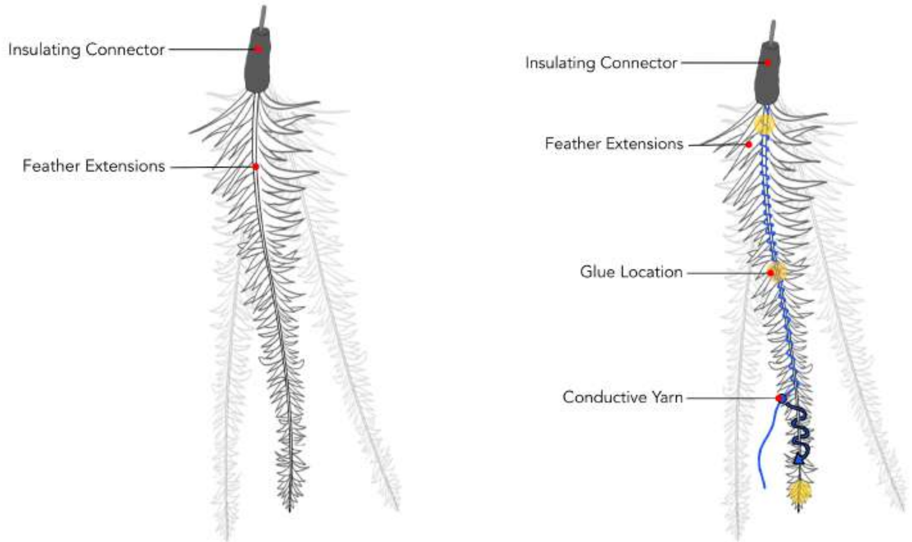


Figure 3.5: Left: Resistive sensor consisting of polymerized feather extensions and an insulating connector. Right: Capacitive sensor consisting of the insulating connector and a conductive yarn that is wrapped around a non-polymerized feather extension. The yellow areas represent the areas in which the yarn is glued to the feather quill.

Connection to the Microcontroller As specific commodity microcontrollers including the ItsyBitsy M0 Express comprise pins that realize capacitive sensing in hardware, there is no further hardware included in the circuit. Consequently, the protruding end of the wire is directly soldered at a pin supporting capacitive sensing. As the capacitive sensor should be located close to the piezo-resistive one, we decided for pin `A2`.

3.2.6 Putting It Together

Figure 3.6 shows the complete circuit with both sensing approaches being put together. We embedded this circuit into three types of prototypes which we describe in the following.

1. The microcontroller is integrated within a styrofoam head and fixed with insulating foam clay such that the feathers protrude from the head. A USB cable is installed within the head and connects the microcontroller to the PC unobtrusively. By pulling the feathers through a hole in the wig that sits on top of the styrofoam head, the technical components of the prototype remain hidden. Figure 3.7 (left) shows some construction steps, Figure 3.3 (left) the final prototype.

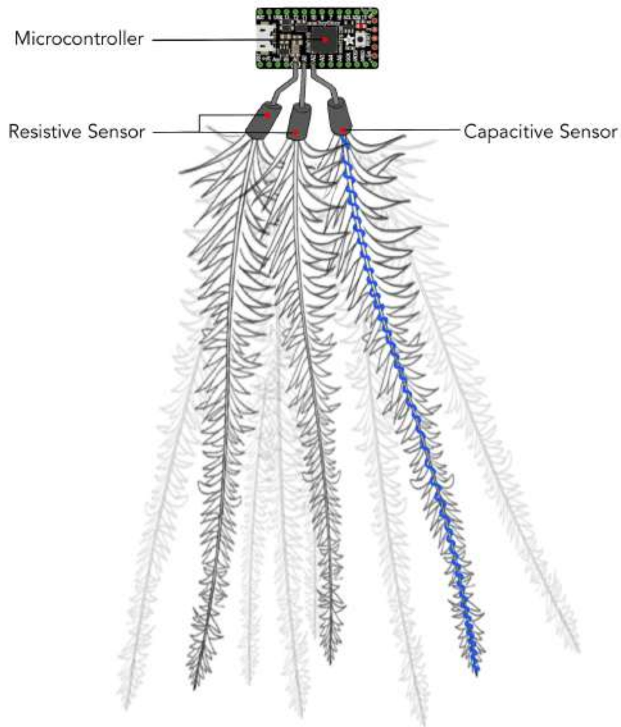


Figure 3.6: The final circuit consists of a microcontroller, the two resistive sensor plates, and the capacitive sensor. The sensors are soldered to the microcontroller pins through the protruding connector wires.

2. The microcontroller is embedded within a 3D printed PLA case that has a hair clip integrated[4]. With that, the prototype can be easily attached to the user's hair. Figure 3.7 (right) shows some of the construction steps and the final prototype.

3. We embedded the microcontroller within a tiny 3D printed PLA case[5] that is attached to an elastic hair band. Velcro tapes make the hair band adjustable in size. We decided to attach tiny beads to the two non-functional feathers of the capacitive feather bundle to add perceivable haptic landmarks to the prototype (c.f., Figure 3.8 (left)). Figure 3.8 (right) and Figure 3.3 show a closeup of the prototype and the prototype worn in the hair, respectively.

3.3 Software Setup

To make the prototype functional, we need a software implementation that manages the capacitive and resistive measurements. In this section, we first describe the

[4] Blender file of the clip: https://github.com/zitos97/FeatherHair/tree/main/Blender
[5] Blender file of the case: https://github.com/zitos97/FeatherHair/blob/main/Blender/studycase_repaired.3mf

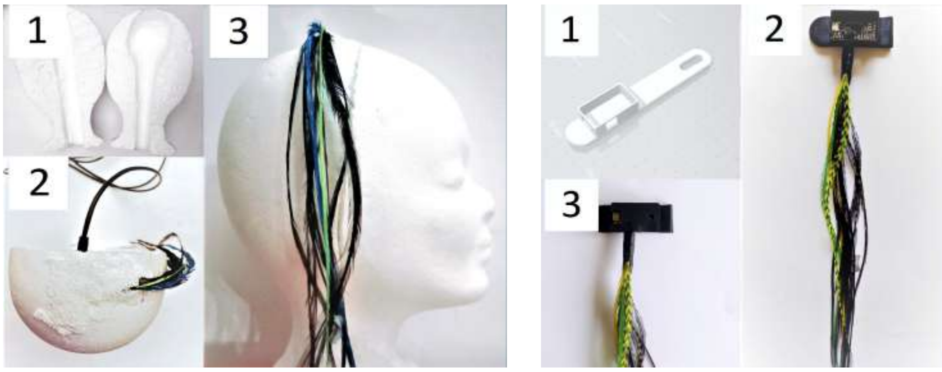


Figure 3.7: Left: Construction steps of the demonstrator: 1) Hollowing the styrofoam head, 2) integrating the microcontroller and cable into the head and insulating it with styrofoam clay, 3) the glued head. Right: Construction steps of the wearable: 1) 3D model of the case, 2) the wearable prototype with lid open, 3) the wearable prototype with lid closed.

Figure 3.8: Left: One of the beads attached to the feathers in order to provide haptic feedback. Right: The final prototype with integrated beads, attached to an adjustable elastic band.

software apparatus and then specify the algorithms underlying piezo-resistive and capacitive touch sensing.

3.3.1 Apparatus

The software implementation was done with CircuitPython 7.0.0[6]. CircuitPython is a programming language that is based on Python and enriches it with hardware support[7]. The CircuitPython script implementing both resistive and capacitive sensing can be accessed in the thesis' GitHub repository[8]. If the code is executed

[6] Get CircuitPython 7.0.0 for ItsyBitsy M0 Express: https://circuitpython.org/board/itsybitsy_m0_express/ (Retrieved November 17, 2021)

[7] CircuitPython homepage: https://circuitpython.org/ (Retrieved November 17, 2021)

[8] Get the code from the GitHub repository: https://github.com/zitos97/FeatherHair/blob/main/itsybitsy%20files/HybridSensingExample.py

Figure 3.9: Voltage (green) and capacitance (blue) peaks appear when the prototype is touched.

and the hardware works properly, peaks are visible for both the capacitive and resistive measurements when the feathers are touched (c.f., Figure 3.9).

3.3.2 Piezo-Resistive Sensing

We used CircuitPython's `analogio` library to assign an analog output to pin `A0` and an analog input to `A1`. With that, we can control when to give out a voltage of 3.3 V on pin `A0` and when to measure the incoming voltage on pin `A1`. To smooth the data, the resistive measurements are averaged across a specified number of samples. This is a common practice that was, e. g., used for the implementation of zPatches [86]. Choosing a larger number of averaging samples results in smoother data that make the prototype less prone to noise, but also slows the touch detection down. Algorithm 1 formulates the measurements across two pins in one way.

Algorithm 1 Resistive Touch Sensing

function ANALOGREAD(samples)
  resistance, resistanceIn $\leftarrow$ 0 # Initialize the variables
  analog_in $\leftarrow$ ANALOGIN(A1) # Use pin A1 for analog input
  analog_out $\leftarrow$ ANALOGOUT(A0) # Use pin A0 for analog output
  analog_out.value $\leftarrow$ 3.3 Volt # Send 3.3 V out
  for $i \in \{1, 2, \ldots, samples\}$ **do**
    resistanceIn $\leftarrow$ analog_in.value # Read analog in value
    resistance $\leftarrow$ resistance + resistanceIn # Sum it up
  end for
  return resistance / samples # Compute the mean
end function

3.3.3 Capacitive Sensing

We used CircuitPython's `touchio` library to assign touch capabilities to pin `A2` which enables to use it directly for capacitive measurements. Analogously to resistive sensing, the capacitive values are smoothed by averaging the measurements across a specified number of samples. Algorithm 2 formulates the capacitance measurements.

Algorithm 2 Capacitive Touch Sensing

```
function CAPACITIVEREAD(samples)
    capacitance, capacitanceIn ← 0                    # Initialize the variables
    touch_in ← TOUCHIN(A2)                            # Use pin A2 as capacitive touch pin
    for i ∈ {1, 2, . . . , samples} do
        capacitanceIn ← touch.raw_value               # Read capacitive value
        capacitance ← capacitance + capacitanceIn     # Sum it up
    end for
    return capacitance / samples                      # Compute the mean
end function
```

3.4 Summary

In this chapter, we detailed on several capacitance- and resistance-based touch sensing technologies. We then discussed the realization of our own touch sensing hair interface combining capacitive and piezo-resistive sensing. We specified the underlying hardware and software implementation and used the resulting raw circuit for the construction of three hair interface prototypes – two wearables and one that serves as a visionary demonstrator which hides the technology inside a styrofoam head.

4 Dataset

A carefully collected dataset is crucial for any system making use of machine learning. In this chapter, we discuss the collection of a six-gesture strong dataset based on a user study with ten participants. The design of the data collection study is built on results of a preliminary user study with three participants. Therefore, before detailing on the design of the data collection study, we first present the preliminary user study in the next section. We conclude with a presentation of the resulting dataset containing the gestures samples which are used for the implementation of gesture recognition in Chapter 5.

4.1 Preliminary Data Collection Study

In order to use machine learning for gesture recognition, the collected training data needs gesture-specific characteristics with which the gestures can be distinguished. With a preliminary user study, we aimed to investigate the extent to which this is the case for a tentative set of gestures performed on our prototype. Subsequently, we first detail on the creation of this tentative gesture set, followed by a description of the used prototype and the study procedure. We conclude with an overview of the resulting dataset and a discussion of the collected data.

4.1.1 Participants

We recruited three participants including the researcher (2 f, 1 m, mean age = 50.7). The participants are all right-handed and draw on varying motoric skills (playing instruments, gardening, painting, . . .). The participation was voluntary.

4.1.2 Gestures

We created a tentative set of six gestures that is inspired by gesture types and styles presented in Subsection 2.4.3. The gesture types comprise *Tap*, *Hold*, *Slide*, and *Twirl*. They are illustrated as part of Figure 4.3. *Tap* is a gesture which requires the user to quickly touch the hair. It is the basis of touch/no-touch recognition. The detection of this gesture is the minimal requirement for a working touch sensing system. *Hold* is an extended version of *Tap*, requiring to hold the feathers for several seconds in a static pose. *Slide* is a gesture type for which the fingers must move slowly from top to bottom along the feather hair. *Twirl* requires the participants to twist the hair between their fingers for about several seconds. Whilst the latter two naturally-occurring types of touch weave natural human behavior patterns with direct interface interaction, they provide us also with an interesting starting point for a discussion of their social implications as they might be prone to misinterpretations and suggestiveness for spectators. For all four gesture types (i. e., *Tap*, *Hold*, *Slide*, *Twirl*), the participants were free to decide whether to pinch the feathers between two fingers (*Pinch*) or touch it with the flat of their hand (*Stroke*). We decided to inspect the impact of these two gesture styles on the measurements separately for a single *Tap* event, yielding two further gesture classes, i. e. pinching and stroking *Tap*.

4.1.3 Apparatus

The study apparatus is split into hardware and software components on which we detail in the following.

Hardware We used a preliminary version of the demonstrator presented in Section 3.2 (c.f., Figure 4.1). It differs from the other prototypes by the fact that the feather used for the capacitive sensing was augmented with functionality through polymerization whilst subsequent versions of the prototype opt for the use of conductive yarn. There are two further minor differences concerning the material used for mounting the hardware and the used microcontroller which is an Adafruit QT Py[1] with an ATSAMD21E18 32-bit Cortex M0+ processor running at 48 MHz. The PC used for the study has an Intel® Core i7-10510U™ processor running at 2.30 GHz.

Software The microcontroller implementation was realized with `Circuit-Python 6.3.0` and relies on the capacitive and resistive measurement methods introduced in Section 3.3. The recording of the measurements starts automatically based on an experimentally determined capacitive threshold and stops after two seconds. Data is measured every 0.1 seconds, yielding in total 20 resistive and capacitive data points per gesture sample. During the study, the measurements were manually recorded, labeled, and stored on the PC.

4.1.4 Procedure

The study was conducted in a quiet environment and consisted of two parts. In the first part, we introduced the four gesture types (i. e., *Tap*, *Hold*, *Slide*, *Twirl*) and two gesture styles (i. e., *Pinch*, *Stroke*) to the participants, demonstrating them for clarity on the demonstrator. They were further instructed that the intensity and exact position at which the gesture is performed at the interface is left up

[1] Introduction of the Adafruit QT Py: https://learn.adafruit.com/adafruit-qt-py?view=all (Retrieved December 18, 2021)

Figure 4.1: The preliminary hair interface attached to a wig on a styrofoam head.

to them since this provides us with more varying and realistic data. Afterwards, the participants could train until they felt confident with the gestures and the prototype. This first phase took up to 15 minutes. In the second part of the study, the participants performed each of the trained gestures 15 times in a row, prompted by textual outputs of the PC and announcements of the researcher. This part took approximately 20 minutes.

4.1.5 Dataset

We collected a total of 270 (3 participants $\times$ 6 gestures $\times$ 15 repetitions) gesture samples. The line graph depicted in Figure 4.2 exemplifies representative resistive data samples for participant P2, covering all six gestures.

4.1.6 Results and Discussion

The analysis of all participants' data reveals that the resistive data of *Tap*, *Hold*, *Slide*, and *Twirl* exhibit user-independent and gesture-specific properties. We further find that there is no clear distinction of *Pinch* and *Stroke*. Although we identify a trend of *Pinch* having slightly larger resistive magnitudes, these differences are not substantial and might even be user-dependent. Contrary to the resistive data, the capacitive data yielded completely unusable measurements, hardly showing any measurable changes during the occurrence of touch. We assume that this traces back to the electrical functionality of the polymerized feather which was too weak to implement stable capacitive sensing. Therefore, we decided to opt for conductive yarn for the subsequent prototypes. Finally, as the resolution of our sensors appears to be unsuited for a fine-grained distinction of varying gesture styles, we decided to keep the focus of the gesture design space on gesture types.

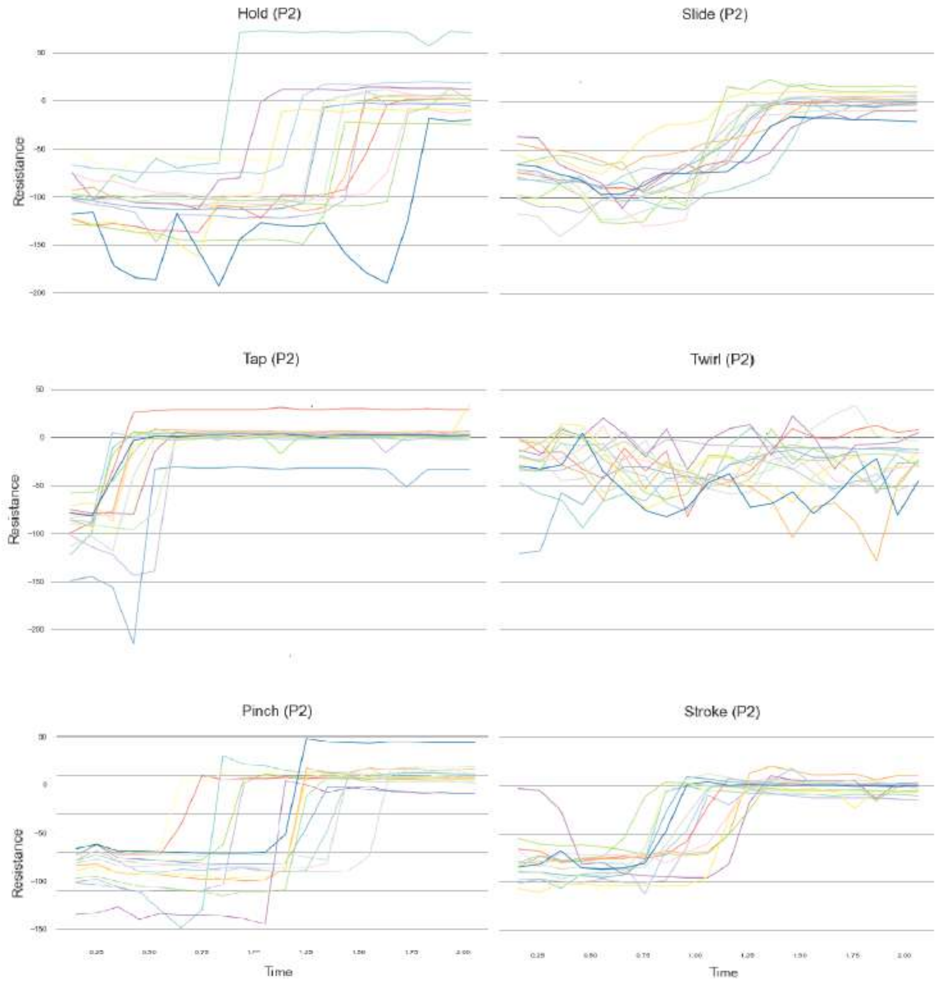


Figure 4.2: The measured raw resistive data (P2) already shows distinct characteristics for each gesture (from left to right, top to bottom): *Hold*, *Slide*, *Tap*, *Twirl*, *Pinch*, *Stroke*. Each graph shows 15 measures per gesture type. The resistive values were normalized so that zero corresponds to the resting baseline state of the feather sensor.

4.2 Study Design

The observations of the preliminary user study revealed that a careful selection of gestures and a proper study design is crucial in order to collect usable data. As part of this section, we detail on the final study design, providing information about recruited participants, the gesture set, used prototypes, and the procedure.

4.2.1 Participants

We recruited 10 participants (5 f, 5 m), aged from 11 to 76 (mean = 33.9, median = 23). Participation was voluntary and the participants received a chocolate bar for compensation. The recruited participants are all right-handed, have different hair structures and lengths, ranging from short and straight to long and curly, and draw on varying motoric skills (gaming, gardening, crafting, . . .). We manually measured the hand dimensions of participants following the BigHand2.2M approach [106] and found mean distances from the wrist to the tips of thumb - 61.5mm (SD=6.6mm), index - 90.2mm (7.8mm), middle - 98.9mm (12.8mm), ring - 93.2mm (11.9mm), pinky - 73.4mm (9.5mm). See Appendix C for further participant-specific details.

4.2.2 Gestures

Based on the findings of the preliminary study described in Subsection 4.1.6, we refrained from using varying gesture styles and extended the set of gesture types to *Tap*, *Doubletap*, *Hold*, *Slide*, and *Twirl* (c.f., Figure 4.3) which all have to be executed through a pinching style. We added *Doubletap* to the set since we believe that particularly *Doubletap*, *Slide*, and *Twirl* are interesting to initiate a discussion about the perceived appropriateness of gesture for hair interfaces with our participants in the subsequent user study (c.f., Chapter 6).

4.2.3 Apparatus

The study apparatus is split into hardware and software components on which we detail in the following.

Hardware Both prototypes that we used in the study were introduced in Section 3.2. The first one is a wearable hair interface that is attached to the participant's hair through a 3D printed hair clip in which the microcontroller is embedded. The other prototype consists of a hair interface integrated in a styrofoam head. The use of the latter one is three-fold: First, it helps us to demonstrate the gestures to the study participants – that is why we call the prototype *demonstrator*. Second, it allows for a higher level of control whilst measuring capacitive and resistive data. Since we could not predict the impact of the wearable's proximity to the skin on the quality of the capacitive measurements properly, we intended to minimize the risk of collecting unusable data by using both the wearable as well as the demonstrator. Third, it provides the participants with a visionary look where the

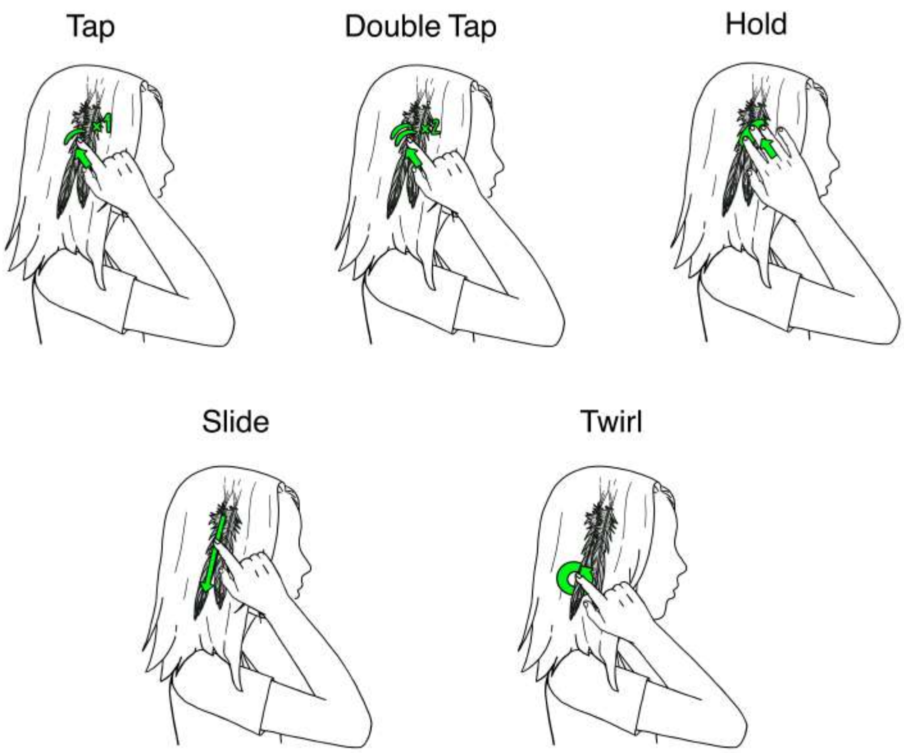


Figure 4.3: Illustration of the gestures that the participants had to perform during the data collection study.

technology is miniaturized to an extent where it gets completely invisible. Both prototypes use an ItsyBitsy M0 express having an ATSAMD21G18 32-bit Cortex M0+ processor running at 48 MHz. The microcontroller communicates with a Python script on a PC through bidirectional serial communication. The PC that we used for the study uses an Intel® Core i7-10510U™ processor running at 2.30 GHz.

Software The software implementation is programmed in `CircuitPython 7.0.0` on the microcontroller and in `Python 3.8.3` on the PC. The main purpose of the microcontroller is measuring and sending the resistive and capacitive data relying on the methods that were introduced in Section 3.3. Measurements are taken every 0.1 seconds, yielding in total 100 resistive and capacitive data points per gesture sample. The Python scripts manages the synchronization between the PC and the microcontroller and stores the incoming data. Furthermore, the Python script includes a graphical interface through which communication with the study participant takes place. The graphical user interface is implemented with the `tkinter 8.6` library and runs on a 1920 x 1080 pixel display. The GUI displays the gestures that the participant is asked to perform next. The whole software communication pipeline is illustrated in Figure 4.4. The implementations for both the wearable and demonstrator as well as the Python script can be retrieved

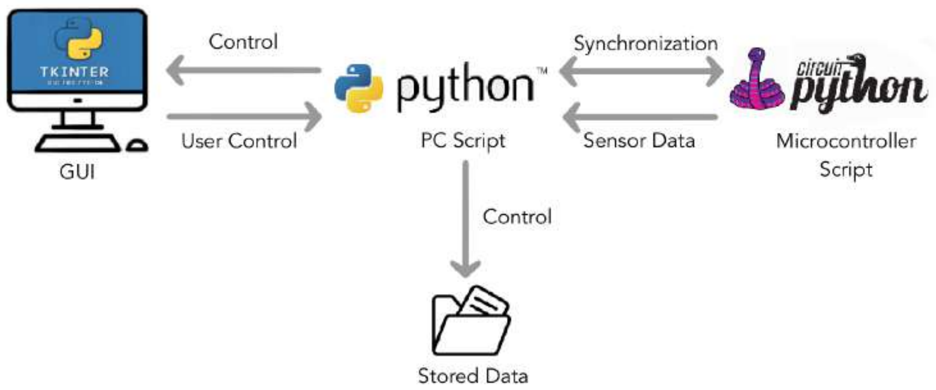


Figure 4.4: Schematic overview of the software communication pipeline implemented for the data collection.

in the GitHub repository[2][3].

4.2.4 Procedure

The study was conducted in a quiet environment. External factors including temperature and humidity were kept constant as best as possible. Prior to the data collection, the participants were given an informed consent and asked to fill out a questionnaire. Both can be found in Appendix B.1. At the beginning of the study, the experimenter demonstrated five gestures (i. e., *Tap*, *Doubletap*, *Hold*, *Slide*, *Twirl*) to the participants for clarity with the help of the demonstrator. In addition, we introduced nine different calibration gestures (i. e., gentle, comfortable, and strong *Tap* at the top, middle, and tip of the feathers, respectively). Afterwards, the participants could familiarize themselves with both the calibration gestures and the main gestures using the demonstrator until they felt confident. The introduction and training phase took 5–10 minutes. The subsequent main phase of the study was organized into six phases and took in total up to 60 minutes, including breaks. 1) In the first phase, participants had to perform each of the nine calibration gestures once on the demonstrator. On-screen prompts presented the gestures accordingly (c.f., Figure 4.5). As soon as the gestures appeared on the display, the participants had ten seconds to perform it. In the allotted time period for the participant to perform a gesture, the resistive and capacitive data were recorded. 2) Next, the participants were asked to perform 25 trials of each gesture on an arbitrary position on the demonstrator. We randomized the order of the gestures and prompted the gestures accordingly. The further procedure was analogous to the first phase. 3) We attached the wearable prototype into the participant's hair. Inspired by zPatch [86], we meanwhile recorded the resulting noisy data for a period of 50 seconds, ten samples per second. We use this data later to train the system to identify false

[2] Access the CircuitPython scripts: https://github.com/zitos97/FeatherHair/tree/main/itsybitsy%20files
[3] Access the Python scripts: https://github.com/zitos97/FeatherHair/tree/main/Python%20GUI

Figure 4.5: User interacting with the demonstrator in accordance to on-screen prompts in the final data collection study.

activations. 4) Similar to phase one, participants were prompted to perform nine calibration gestures on the wearable prototype. The procedure is analogous to the procedure on the demonstrator. 5) In the fifth phase, participants were asked to perform 25 trials of each gesture in a randomized order on an arbitrary position on the wearable. 6) Finally, we removed the prototype from participants' hair and again recorded noisy data for 50 seconds. Note that as part of phases three through six, we provided the participants with a mirror so that they could locate the feathers in their hair more easily . Furthermore, the participants were given the opportunity to take a break at the end of each phase and halfway through phases two and five.

4.3 Dataset

Before using the collected data for machine learning, it is crucial to clean the collected data and conduct a preliminary exploration in order to get to know the data we are working with. In the following, we first describe the collected dataset, and then detail on preliminary preprocessing steps and findings of the data exploration. We conclude with the final dataset which is then used as-is in Chapter 5.

4.3.1 Collected Data

We collected a total of 2500 (2 conditions $\times$ 25 repetitions $\times$ 5 gestures $\times$ 10 participants) main gestures and 180 (2 conditions $\times$ 1 repetition $\times$ 9 gestures $\times$ 10 participants) calibration gesture samples with a sample length each of ten seconds. Furthermore, we gathered 20 (1 condition $\times$ 2 repetition $\times$ 10 participants) noise samples each of length 50 seconds.

4.3.2 Data Preprocessing

We processed the collected data in four steps, comprising outlier detection, noise filtering, cutting the data frames, and synthesizing further noise samples. We briefly summarize the approach and findings below.

Visualization and Outlier Detection We first visualized the data and discarded outliers. These include samples in which participants did not perform the prompted gesture or where general problems with the measurements occurred, e. g., when the feathers got tangled with the hair. In addition, we removed several invalid samples of P7 since the capacitive sensing feather of the wearable broke during their study.

Noise Filtering We carried out a frequency analysis to identify if there was some periodic noise pattern that requires filtering. Since we could not detect any such interfering frequency, there was no need to prefilter the data at this point.

Cutting the Data Given the cleaned samples, we cut the data to variable lengths based on the individual duration of the performed gestures. Here, we used a simple estimation based on the ratio between the current capacitive value and the baseline measured at the beginning of the recording to identify start and end of a gesture. Some gestures for which this heuristics did not work properly were cut by hand afterward.

Synthesizing Noise Samples We synthesized more noise samples out of the 20 recorded samples. Hereby, we used a sliding window approach with a window size of eight seconds and a step size of one second which moves along the 50 seconds noise frame. We decided on a length of eight seconds since this corresponds approximately to the maximum duration of a variable-length gesture.

4.3.3 Preliminary Data Exploration

Prior to using a dataset for machine learning, a preliminary data exploration is recommended in order to get to know the data and reason about further required data preparation steps. In the following, we provide a short overview of the investigated aspects.

Calibration Gestures Given the preprocessed samples, we explored the data starting with the calibration gestures. For that purpose, we compared the user-specific calibration samples and tried to find location- and force-dependent patterns in the resistive and capacitive data, respectively, which could be used to calibrate the prototype. As Figure 4.6 exemplifies for participant P7, no such patterns are discernible for any of the participants. Since there is no further justification for using the collected calibration data, we retrospectively decided to remove these samples from the final dataset.

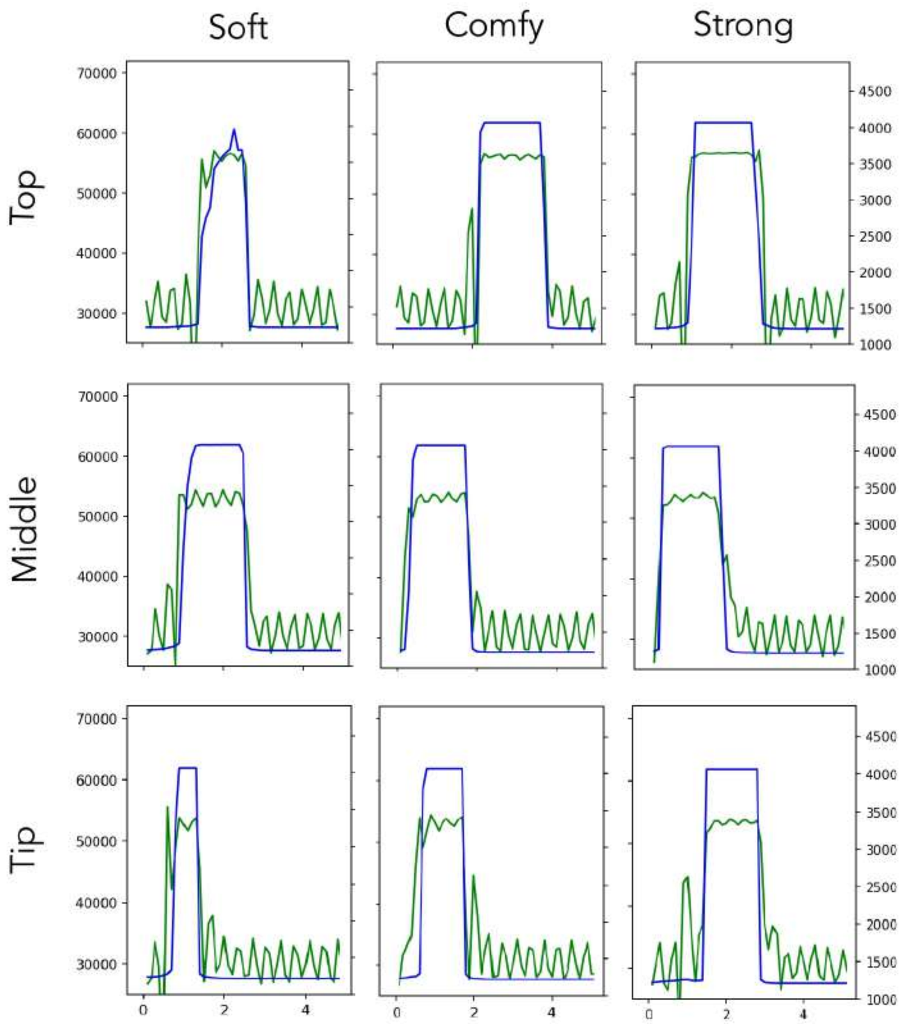


Figure 4.6: Calibration data of participant P7 performed on the demonstrator. The calibration samples comprise tapping at the top, middle, and tip of the interface in a soft, comfy, and strong manner, respectively. The blue lines represent the capacitive values, the green ones the ratio of incoming voltage which is antiproportional to the resistance.

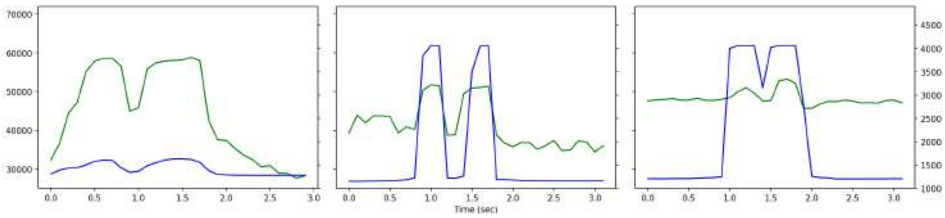


Figure 4.7: Left: *Doubletap* performed on the wearable by participant P2. Middle: *Doubletap* performed on the wearable by participant P10. Right: Another repetition of *Doubletap* performed on the wearable by participant P10. The green lines illustrate the ratio of incoming voltage, the blue lines the capacitance.

Gesture Characteristics Particularly *Twirl* and *Slide* appear almost unpredictable and indistinguishable as their individual measurements vary considerably. Consequently, further preprocessing steps such as smoothing should be applied to the raw data before usage. However, the specific method and degree of smoothing depends on the classifier that is used for the implementation and is subject to further investigation in Chapter 5.

Demonstrator- vs. Wearable-Specific Characteristics Next, we compared the measurements originating from the demonstrator and the wearable as this affects the way we use the dataset. More specifically, a difference would imply the need to particularly weight the data originating from the wearable if we were to train a wearable gesture recognition system. However, since we could not find any substantial differences, we treat both data origins equally for the implementation in Chapter 5.

Person-(In)Dependent Characteristics Finally, we investigated person-(in)-dependent gesture characteristics and found that they vary not only across participants but also for a given participant themself. This includes both the resistive and capacitive baselines as well as the duration of individual gestures. For an example, refer to Figure 4.7 which illustrates *Doubletap* samples of participants P2 and P10.

4.3.4 Final Dataset

After discarding both the individual outliers and the calibration gestures, the final dataset consists of 3074 samples in total (c.f., Table 4.1). The table shows the sample distribution among the individual participants and gestures. The complete dataset can be retrieved from the thesis' GitHub repository[4]. The files are named such that the data can be traced back to either their demonstrator- or their wearable-based origin. We provide an overview of naming conventions in Appendix D.

[4] Get the dataset: https://github.com/zitos97/FeatherHair/tree/main/Dataset

Participant	Gestures						Total
	Tap	Doubletap	Hold	Slide	Twirl	Noise	
P1	49	50	50	43	50	81	323
P2	45	48	49	43	45	82	312
P3	47	49	47	45	50	74	312
P4	50	50	48	49	49	74	320
P5	40	49	45	47	49	55	285
P6	50	47	49	49	48	50	293
P7	43	41	46	30	32	86	278
P8	44	42	47	48	45	77	303
P9	47	47	48	47	49	86	324
P10	49	40	50	50	50	85	324
Total	464	463	479	451	467	750	3074

Table 4.1: An overview of the number of collected samples for each of the five gestures and *Noise*, distributed among the participants.

4.4 Summary

In this chapter, we detailed on the design of a preliminary user study and the final data collection study. We preprocessed and analyzed the collected data and concluded with an overview of the resulting dataset. This data makes up the core of the implementation discussed in Chapter 5.

5 Machine Learning

Inspired by research through design, we investigate the social complexity of hair interfaces as part of a two-step approach. Hereby, the first objective is the realization of a gesture-controlled hair interface (RQ1) which can then be deployed in lab, field, or showroom. In this chapter, we contribute to this objective by investigating the feasibility of user-(in)dependent gesture classification. For that purpose, we first detail on the required background on machine learning. Next, we use the dataset constructed as part of Chapter 4 to implement gesture recognition. We approach the implementation from two different perspectives, namely a time series- and a statistics-based approach, and compare their suitability for the deployment in our proof-of-concept prototype. We conclude this chapter with the presentation of a software pipeline for real-time gesture detection and recognition.

5.1 Background

Machine learning is a powerful tool for classification as it allows to learn from a set of sample data without being explicitly programmed on that particular task [25]. Here, a classification task is a process in which each sample s of a problem domain S can be categorized through a class label l where the label l is taken from a defined set of classes $C := \{c_1, \dots, c_M\}, M \in \mathbb{N}$. In supervised learning, a classifier $H : S \to C$ is trained with a known set of sample-class assignments $\{(s_i, l_i) \in S \times C \mid 1 \leq i \leq N\}, N \in \mathbb{N}$. After training, the classifier H is expected to predict for each unknown sample $s_i \in S$ a class label $H(s_i) = p_i \in C$ such that $p_i = l_i$ where $l_i \in C$ is the true class label. If $|C| = 2$, we speak of *binary* classification. For $|C| > 2$, the task is called *multiclass* classification. In the context of this thesis, we aim for such a multiclass classification since our gesture-controlled hair interface should be able to classify six different gesture classes in total. In the following, we present theoretical background on machine learning relevant for the implementation of this interface, detailing on feature engineering and various types of machine learning classifiers.

5.1.1 Feature Engineering

A *feature* is a measurable input variable used for a machine learning task – here classification. Features can be, e. g., numerical values of raw or processed sensoric data, time series, or categorical values. *Feature engineering* is a process with which one tries to find the best representation of the input data done preliminary to model training, resulting in more flexibility for model selection, simpler models, and better results [15]. A challenge in this thesis with regard to feature engineering involves the transformation of the colleced raw time series data, i. e., a sequence of data which is ordered in time and exhibits strong temporal dependencies, into a useful set of features which allows to solve the classification task accurately. We present three common methods of feature engineering in the following paragraph. Afterward, we sketch possible directions of feature engineering for this thesis.

Feature Engineering Methods The first method is *feature selection* in which a subset of useful features is automatically selected from the raw dataset, reducing the dimensionality of the problem by discarding irrelevant features [34, p. 28]. *Feature construction* is the process in which the researcher manually constructs new features such as statistical descriptors from the raw dataset [15]. Lastly, *feature extraction* is the automation of feature construction from raw data, taking the manual load from the researcher [34, p. 28]. These approaches are not mutually exclusive and can complement each other. So might, e. g., an initial manual feature construction be combined with some automated feature selection, possibly making a big difference in the final model performance [15].

Features in This Thesis To do feature engineering for our collected variable-length time series, we propose two commonly used approaches [18, 107]. First, we can use the (raw or filtered) time series directly as features, resulting in a high-dimensional feature space. Second, we can use descriptive statistical features that are constructed from the original time series, reducing data dependencies and dimensionality. Whilst the direct use of time series as features restricts the choice of model selection as only few models are suited for (variable-length) time series, the latter option enables a larger choice between conventional models on the cost of time-consuming feature engineering [18]. However, a larger set of possible models can be beneficial for finding a model that best suits the problem. Here, suitability particularly refers to accuracy and speed of classification since our prototype should be able to classify gestures in real-time with a high recognition score. We explore a range of suitable models for both the time series-based and statistics-based approach in the subsequent section.

5.1.2 Machine Learning Models

As discussed in the previous section, we require models which are suitable for either time series-based or statistics-based features in terms of accuracy and speed. We provide an overview of models that might be a fit for at least one of these approaches, sketching their underlying working principles in the following. This serves as a theoretical background and decision guidance for the selection of the most promising model for the implementation of our gesture-controlled hair interface.

Decision Tree A decision tree has a hierarchical tree structure, consisting of decision rules that are formed by its branches, inner nodes, and leaf nodes. A classic method to train decision trees is the Classification and Regression Tree algorithm (CART) as introduced by Breiman et al. [11]. It splits the training set into two halves based on the feature that achieved the highest information gain in the context of classification. This process is repeated for the resulting subsets of data until no further information gain is achieved. Consequently, each inner node represents a splitting condition for a feature in the sample, its outgoing branches represent a decision each, leading to a subsequent child node. The child node is either again an inner node or a leaf node. A leaf node carries the final prediction. A new sample is classified following the path provided by the decision tree. Due to the algorithmic simplicity and speed, decision trees appear suited for our statistics-based approach. Its usefulness has already been demonstrated for similar applications such as for the implementation of HairWare [94]. However, decisions might particularly suffer from noisy data and overfitting[1]. Furthermore, as decision trees are not able to resolve temporal dependencies of time series, they have no application for time series.

Bagging Bagging is an ensemble learning method in which multiple estimators are combined to form the final prediction through majority vote [9]. Each estimator is trained with a subset of the training data where each sample of the subset is randomly drawn from the original dataset with replacement. As for other ensemble learning methods, the goal of this strategy is to increase the robustness of the underlying single classifier. Similarly to decision trees, we suggest that bagging is suited for the statistics-based approach, additionally profiting from the introduced robustness of the underlying individual decision trees with which it reduces proneness to overfitting[2].

Random Forest A Random Forest is another ensemble learning method composed of decision trees, sometimes considered an improvement to the bagging estimator [10]. The prediction is achieved through a majority vote of individual tree predictions where each tree is trained on a random subset of the training data drawn with replacement. Contrary to the bagging estimator, a further dimension of randomness is introduced by limiting the feature space to a random subset for the splitting decision at each node. This reduces the correlation between the trained trees, resulting in more robustness towards outliers of noisy data. Consequently,

[1] Decision trees: https://scikit-learn.org/stable/modules/tree.html (Retrieved December 21, 2021)

[2] Bagging meta-estimators: https://scikit-learn.org/stable/modules/ensemble.html (Retrieved December 21, 2021)

the Random Forest also appears suited to the statistics-based approach. Furthermore, its effectiveness has been demonstrated for similar applications such as for zPatches where features extracted from multivariate time series were used to implement gesture recognition [86].

AdaBoost AdaBoost is an adaptive boosting algorithm introduced by Freund and Schapire [29]. Contrary to the two previously discussed ensemble methods, boosting estimators are constructed of several sequentially built estimators. AdaBoost makes predictions through a majority vote of the individual estimators where the prediction of each estimator is weighted. Assigning each training sample the same weight at a first iteration of training, both the subsequent data and prediction weights are adapted for the next iteration in accordance to the errors of the current individual estimator. In turn, the adapted weights cause subsequent learners to focus on those training samples that were misclassified by their predecessors. Similar to the other ensemble methods, AdaBoost is able to deal with the statistics-based features and is relatively robust to overfitting. However, it is not optimized for speed since the individual trees are built sequentially, potentially making it slower than the other methods [58].

Gradient Boosting Gradient boosting is a more generic boosting algorithm that builds subsequent decision trees with the goal to minimize some arbitrary differentiable loss function of the previous predictor, transforming classification into a numerical optimization problem [30]. The algorithm fits the new predictor such that it minimizes the overall error function of the ensemble classification. In contrast to AdaBoost, it does not adjust sample and estimator weights, but freezes preceding predictors. Similarly to AdaBoost, it is able to deal with the statistics-based features but lacks speed. Furthermore, it might overfit to really noisy data [19] which might make it unsuited for hair-based gesture classification in the wild if we do not process the features adequately.

k-Nearest Neighbors k-Nearest Neighbors classifier (kNN) extends nearest neighbor classification to a set of k nearest neighbors that are considered for classification where neighbors are computed with the help of some distance metric [27]. A majority vote of the sample's k neighbors decides to which class the new sample belongs. Whilst being suitable for the statistics-based approach, the implementation can also be extended to variable-length time series when Dynamic Time Warping (DTW) similarity is used as distance metric [89]. DTW captures (dis)similarities of temporal patterns even if they vary in speed and length [78]. It implements some non-linear matching of individual data points of a time series to their counterpart(s) in the other time series with the goal to minimize their distance. Albeit having application for both the time series-based and the statistics-based approach, kNN might particularly suffer from low speed for time series-based features since the use of DTW exhibits a high computational complexity [107].

Support Vector Machine Given a set of data points in some vector space, a Support Vector Machine (SVM) determines a hyperplane which linearly separates two classes such that its distance to the nearest data points of both classes is maximized [20]. If the data points are not linearly separable as it is the case for our collected data, a kernel function is applied that transforms the problem into a vector space of a higher dimension in which the data can be separated through a hyperplane. Similar to kNN, the SVM implementation can be extended to time series using Global Alignment Kernels (GAK) where GAK is a differentiable extension of DTW [21]. Hence, dependent on the choice of the kernel, SVM is suitable for both time series- and statistics-based features. Its effectiveness for time series classification has been already demonstrated by Olwal et al. implementing gestures for cord-based interactions [60] which exhibit gesture characteristics similar to our hair-based gestures. However, as our data requires the application of a complex kernel function, the computational costs might make the training process particularly slow.

Convolutional Neural Network A Convolutional Neural Network (CNN) is a class of powerful feed-forward neural networks able to capture complex data which is, e. g., required for natural language processing, image segmentation, object detection, or audio analysis [15, p. 449]. A CNN processes the given input tensor through a sequence of convolutional, pooling, and fully connected layers, and activation functions. The more layers have already processed the data, the more complex the network becomes. At the same time, this allows increasing parts of the tensor to be interpreted. There are various architectures presented in literature that vary in the number and order of individual layers used. Amongst the most prominent ones can be found, e. g., LeNet-5 [50], AlexNet [47], and GoogleNet [88]. Due to their ability to capture complex data, CNNs are suitable for the interpretation of time series. However, requiring a large amount of training data [18], it might not be of use for this thesis since our six-gesture dataset is comparatively small. Thus, we propose to refrain from its usage for the remainder of this work.

Recurrent Neural Network A Recurrent Neural Network (RNN) is a neural network that receives a series of data that exhibit, e. g., temporal dependencies, as input [15, pp. 501–509]. Hereby, it leverages information from preceding input data as additional information when processing the next data point of the sequence. The Long Short-Term Memory (LSTM) architecture adds memory cells to the RNN [15, pp. 519–524]. These memory cells decide which of the previous information to store, maintain, or remove. For regulation, each cell uses input, output, and forget gates. With that, the LSTM can detect even long-term dependencies of sequential data. However, its use for time series-based classification is controversial since its inferiority to less complex models was often demonstrated and is still an active area under investigation [17]. Since we introduced other models as part of this section that might provide us with more reliable performances and lower complexity, we propose to refrain from the usage

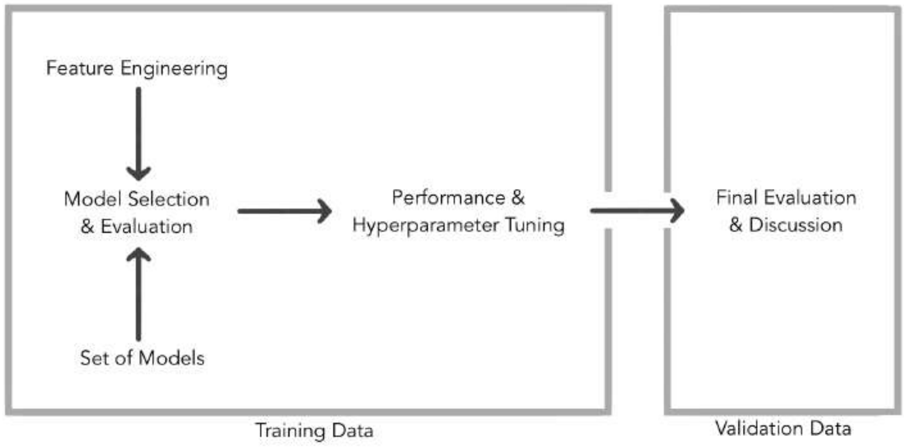


Figure 5.1: Schematic overview of the procedure used to implement multi-class gesture classification.

of both RNNs and CNNs in the scope of this thesis.

5.1.3 Roadmap

With this background in mind, we approach the implementation and evaluation of gesture recognition as illustrated in the schematic overview of Figure 5.1. First, we do feature engineering for both the time series- and statistics-based approaches as described in Subsection 5.1.1. Next, we validate and compare the performances of selected models (c.f., Figure 5.2) for both approaches. As discussed in the previous section, we decided to leave out neural networks, preferring dedicated time series classification algorithms that rely on less complex models, i. e., kNN and SVM. After comparing the model performances, we select the most efficient models for both the time series- and statistics-based approaches and fine-tune their performances. Finally, we evaluate the tuned models on the validation set.

5.2 Time Series-Based Approaches

Time series exhibit a temporal dependency between the individual points of the data sequence. In this section, we evaluate the extent to which we can use such time series as features for our gesture-recognizing system. For that purpose, we first detail on the apparatus of our experiments and discuss options for feature engineering. We then touch on the procedure of the experiments, followed by an evaluation of the results. Finally, we select the most efficient model and discuss ways to improve performance. We conclude with an evaluation and discussion of the suitability of the trained model in the context of this thesis.

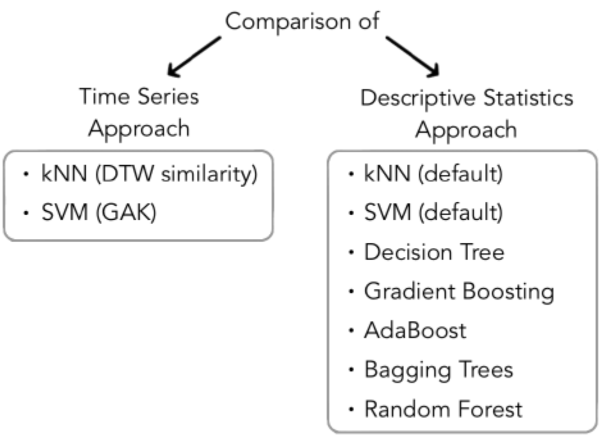


Figure 5.2: Listing of models that we compare against each other.

5.2.1 Apparatus

The technical setup consisted of a 64-bit PC with a 2.30 GHz Intel® Core i7-10510U™ processor running Windows 10 Home. The implementation was done with `Jupyter Notebook 6.4.5`. For the time series-based machine learning tasks, we used `Python 3.8.3` and the `tslearn 0.5.2` library [89]. The latter provides us with two estimators for variable-length time series which include

- `TimeSeriesSVC(random_state = rng)`
- `KNeighborsTimeSeriesClassifier()`

where we eliminated the randomness through a fixed random generator `rng` to enable recreation of results. Since there is no randomness in kNN, there is no random state to be fixed. All other model settings were left at their default values. Further details about used libraries can be found in Appendix E and in the corresponding notebook file. The latter can be accessed via the GitHub repository[3]. To outsource some auxiliary functions for readibility, we used a second Jupyter Notebook called `data_preparation.ipyn` which is also provided as part of the thesis' GitHub repository[4].

5.2.2 Feature Engineering

There are three options for the feature space. These comprise either the use of resistive data only, capacitive data only, or their hybrid combination. Since we could not know in advance which of these three variants is most effective for the implementation of an accurate gesture recognition, we compared their accuracy

[3] Access the script from the GitHub repository: https://github.com/zitos97/FeatherHair/blob/main/gestureRecognition/Thesis%20Part%20I%20%20-%20Ts-Based%20Gesture%20Recognition.ipynb

[4] Access the auxiliary functions from the GitHub repository: https://github.com/zitos97/FeatherHair/blob/main/gestureRecognition/data_preparation.ipynb

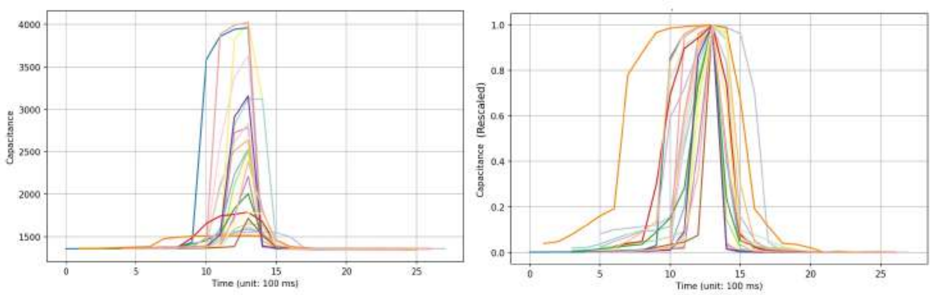


Figure 5.3: Left: Raw capacitive *Tap* samples performed at the demonstrator by participant P4. Right: Normalized samples.

scores during subsequent evaluations (“*There is no free lunch in Machine Learning*” [104]). Before doing so, however, we prepared the data through smoothing and normalization as described below.

Smoothing As the resistive data is particularly noisy, we prepared the time series of the raw resistive data through smoothing with a moving window average of window size 5. The following equations formalize the procedure for some time series $TS := \{t_1, t_2, \ldots, t_N\}$ where t_i is a sample at time $i \in \{1, \ldots, N\}, N \in \mathbb{N}$:

$$t_i = t_i \qquad \textit{if}\ 1 \leq i \leq 4$$
$$t_i = \frac{\sum_{k=i-4}^{i} t_k}{5} \qquad \textit{else}$$

Normalizing As the baselines and magnitudes of the time series are not comparable, we sample-wise normalized the smoothed data to an interval $[0, 1]$. We used the following method to transform a time series TS to its normalized counterpart $TS_{norm} := \{t_{1_{norm}}, t_{2_{norm}}, \ldots, t_{N_{norm}}\}$:

$$t_{i_{norm}} = \frac{t_i - \min TS}{\max TS - min TS} \qquad \forall t_i \in TS$$

The effect of scaling is exemplified in Figure 5.3.

5.2.3 Procedure

Before evaluating the models, we split our dataset into two disjoint sets, called *training* and *validation* set. The latter consisted of the data of participants P9 and P10 which were selected randomly. The evaluation involved three steps: 1) The evaluation of models for person-dependent gesture classification on the training set. 2) The evaluation of models for person-independent gesture classification on the training set and 3) the evaluation of the final model performance on the validation set. We detail on the former two steps in the subsequent paragraphs, followed by a discussion of the evaluation metrics.

Person-Dependent Performance Dealing with a small dataset, the quality of the evaluation might severely depend on the way the data is split. To compensate for this problem, we validated the estimator performance per participant using stratified 10-fold cross-validation as sample classes are not perfectly balanced (see Table 4.1). k-fold cross-validation is a validation method for which the training set is further split into k disjoint sets (called *folds*). Whilst the model is trained on $k - 1$ folds, it is validated on the held-back k^{th} fold. This is repeated for all combinations of the folds. Averaging the individual validation scores yields the final cross-validation score.

Person-Independent Performance To evaluate if the results generalize to new participants, we implemented 8-fold leave-one-person-out cross-validation. It assigns the samples to the participant from which it originated. Next, it splits the data into folds where one fold represent one specific participant. The final averaged cross-validation score gives insights into the feasibility of person-independent gesture classification.

Evaluation Metrics Alongside with the accuracy scores, we determined the times required for training and for a single prediction for both the person-dependent and -independent evaluation. These measurements serve as a guideline to compare the ratio between the individual model speeds but should not be understood as an absolute measure for the time needed for real-time recognition. The reason for this is that the experiments were performed under optimal, constant conditions using the PC's full capacity whereas the speed might vary with the underlying hardware in real-time applications. Note that we recorded the times required by kNN and the SVM for training and prediction only once as we observed in previous experiments that the measurements remained comparable for a specific estimator class across varying feature spaces. Hence, we sped up the experiment by increasing the number of jobs that run in parallel for those combinations for which we did not measure time.

5.2.4 Model Selection & Evaluation

In this section, we discuss the performances of the models by first presenting the person-dependent and then the person-independent results. We conclude with a discussion and the selection of the most efficient combination of feature space and model.

Person-Dependent Results Table 5.1 shows the performance of the gesture classification in a person-dependent setting. Final accuracy scores, prediction and training times were averaged across the individual outcomes of each person. The best average accuracy was achieved by the SVM with 86.7% using both hybrid features, followed by the SVM using capacitive features with 85.0% and 80.5% using resistive features. kNN in combination with the resistive features performed by far the worst with 52.3%. Whilst the SVM was superior to kNN regarding the

Estimator	Feature	Accuracy	Average Performance Training Time (sec)	Single Pred. Time (sec)
KNeighbors	Res.	0.523	-	-
	Cap.	0.734	-	-
	Hybrid	0.707	**0.10015**	**0.08186**
SVM	Res.	0.805	-	-
	Cap.	0.850	-	-
	Hybrid	**0.867**	15.46751	0.11161
Mean		0.748	-	-
SD		0.123	-	-

Table 5.1: Performance of the person-dependent stratified 10-fold cross-validation. The final results were averaged across the individual results for all of the eight participants. Bold prints mark the best performance of each of the three categories.

accuracy scores, it was inferior to kNN w.r.t. training times. Contrary, there was no substantial difference in the context of the average prediction time for a single sample as both models needed less than a second.

Person-Independent Results Comparing these observations to the results of the person-independent training (c.f., Table 5.2), we find that the overall average accuracy score dropped from 74.8% to 72.0%. The SVM using hybrid features still yielded the best accuracy with 85.3%. The order of estimator performance remained unchanged to the person-dependent setup. We observe that both training and particularly the prediction times increased substantially in comparison to person-dependent training which traces back to the larger set of training samples. Nevertheless, the prediction times were still within an acceptable range of approximately one second.

Discussion Apart from the time measurements, we find no substantial differences between person-dependent and -independent performances. This matches our observations in Subsection 4.3.3 where we discovered both person-specific and person-unspecific patterns involved in most gestures. The advantage of a person-independent approach is that it helps overcoming the burden of initial training and calibration sessions for a new user. The latter would require a system able to adapt in real-time to new data. We find that the SVM appears particularly unsuited for real-time adaptation in a sense that it is too slow – contrary to kNN which exhibits fast training and prediction times. In terms of accuracy scores, however, this situation turns, as the SVM combined with hybrid features appears superior to kNN. This is beneficial as the interplay of capacitive and resistive values might make the system more robust in the field, creating a better user experience in turn. Combining these considerations, we decided to opt for a person-independent

Estimator	Feature	Average Performance		
		Accuracy	Training Time (sec)	Single Pred. Time (sec)
`KNeighbors`	Res.	0.464	-	-
	Cap.	0.724	-	-
	Hybrid	0.661	**0.88904**	**0.85484**
`SVM`	Res.	0.775	-	-
	Cap.	0.843	-	-
	Hybrid	**0.853**	2539.95570	1.03291
Mean		0.720	-	-
SD		0.145	-	-

Table 5.2: Performance of the 8-fold leave-one-person-out cross-validation. Bold prints mark the best performance of each of the three categories.

gesture recognition, fine-tuning the SVM with hybrid features in the subsequent subsection.

5.2.5 Performance & Hyperparameter Tuning

To boost the model performance, we first analyzed the cumulative confusion matrix of the 8-fold leave-one-person-out cross-validation. Afterward, we tuned the hyperparameters of the model.

Confusion Matrices A cumulative confusion matrix accumulates the confusion matrices of each individual cross-validation iteration, giving us an overview of gestures that might be particularly prone to confusion. As we can see in the left matrix depicted in Figure 5.4, *Noise* achieved highest accuracy with 99.3% across all gestures, yielding only 4 false activations out of 579 noise samples. *Tap* followed with 91.9% accuracy. The lowest accuracy was 68.8% for *Twirl* and 71.8% for *Slide*. It is particularly striking that *Slide* was misclassified with *Twirl* for 19.5% of its samples and vice versa for 15.0% of samples. Furthermore, *Twirl* is misclassified with *Noise* for 15.2% of its samples. Consequently, we observe that both *Twirl* and *Slide* were involved in above-average confusion rates, dropping the overall model accuracy. For that reason, we evaluated the performance of the SVM when leaving out one of these gestures each to investigate how the overall model performance would change. The resulting cumulative confusion matrices are shown in Figure 5.4 (right). First of all, we notice that the overall accuracy scores increased substantially from 85.3% for all gestures to 90.6% and 91.0% without *Slide* and *Twirl*, respectively. Note that there were no false activations triggered when removing *Twirl*. Similarly, only 0.52% false activations were triggered when removing *Slide* where the false activations stem from the confusion with *Twirl*. Vice versa, we observe that there were still high misclassifications rates for *Twirl* being misclassified as *Noise* for 17.1% of its samples. In contrast to this, the confusion rates were lower and split more evenly without *Twirl* where the highest confusion rate was given for *Hold* being misinterpreted as *Noise* for 9.5% of its samples. Against these observations, we are facing a trade-off between providing the participant with a system able to recognize the full set of gestures or a system with a high recognition accuracy on the cost of removing one gesture. As we aim to provide the users with a satisfying experience when interacting with the system, reducing bias towards concerns regarding system reliability, we decided for the latter option. Although the performance difference between the removal of *Slide* and *Twirl* was not substantial, we removed *Twirl* from our set of gestures since overall gesture confusion rates were minimized here.

Hyperparameter Tuning As a next step, we fine-tuned the parameters of the SVM through a cross-validated grid search. The parameters of the grid comprise the regularisation parameter C and γ which is related to the bandwidth of the internal Gaussian kernel used for GAK. The resulting tuned estimator configuration consists of $C = 100.0, \gamma = 100.0$, yielding an improvement of 0.9% to a mean leave-one-person-out cross-validated accuracy score of 91.9%.

5.2.6 Final Evaluation & Discussion

Finally, we validated the tuned estimator on the held back set that consisted of the data of participants P9 and P10. In the following, we first present the results, followed by a discussion of their meaning.

Results The trained estimator achieved accuracy scores of 92.0% and 90.5% for the validation sets of participant P9 and P10, respectively. Table 5.3 shows precision, recall, and F1 scores for the five gestures averaged across the two validation sets. Highest precision scores were achieved by *Noise* and *Tap* with 100% and 92%, respectively. *Noise* also achieved best recall results with 98%, followed by *Hold* with 94% recall. This also means that no false activations were triggered on the test set as well as only 2% of all data was misclassified as *Noise*. Lowest results were achieved for *Doubletap* and *Slide*, both with 80% precision and 80% and 89% recall, respectively.

Discussion As both the performance on the training data and the generalization to new data yielded high accuracy scores, we suggest that the tuned model is neither under- nor overfitted [16]. Furthermore, it appears able to generalize well to new users as its accuracy stayed within the range of the accuracy of the tuned estimator on the training set. On the other hand, we also need to account for the fact that only the removal of *Twirl* enabled this performance boost of breaking the 90% accuracy mark. But having an accuracy of $> 90\%$ might minimize a feedback bias towards concerns regarding the general system reliability and helps to maintain the focus of the final user study in Chapter 6 on social and practical aspects of the interaction.

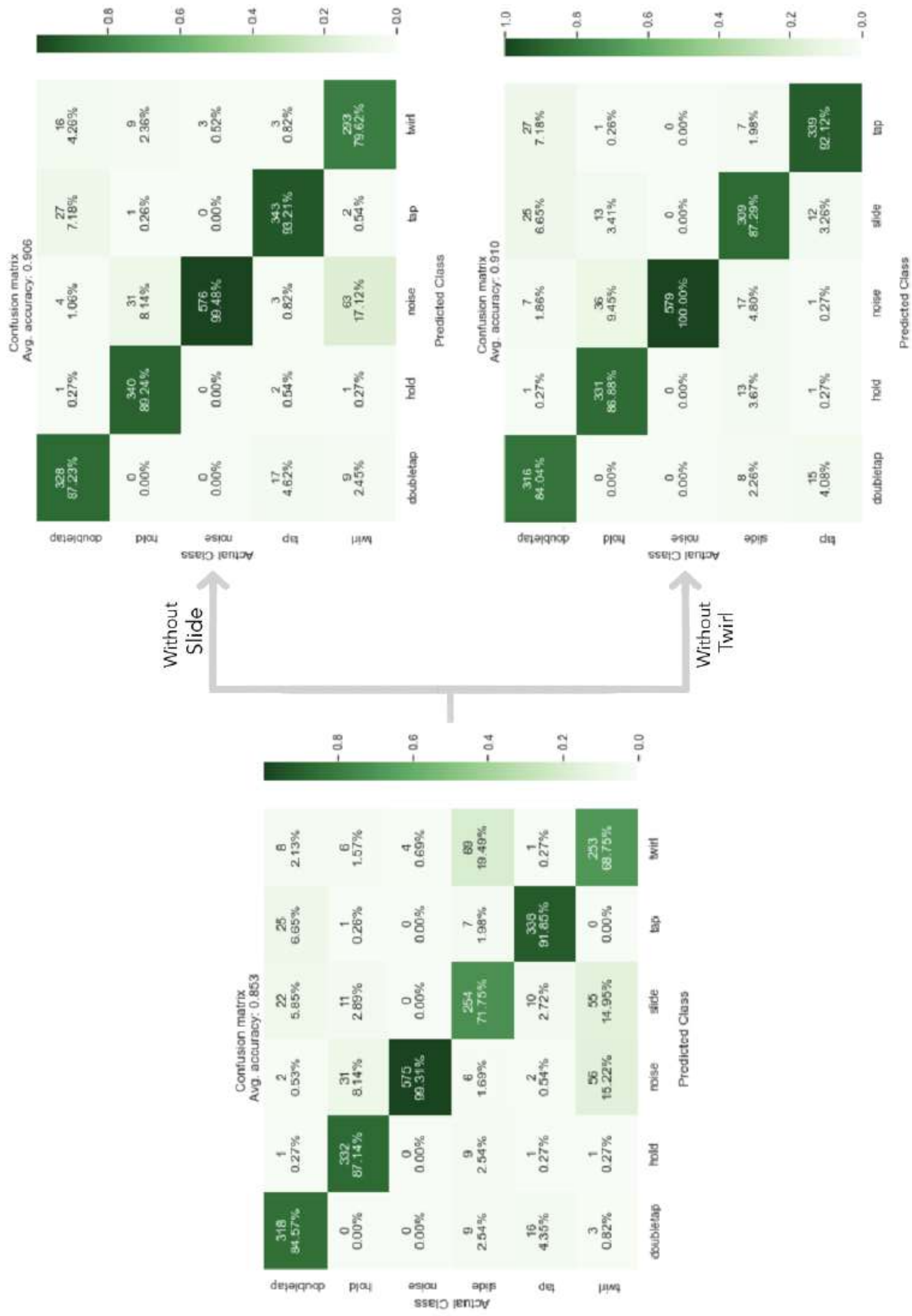


Figure 5.4: Cumulative confusion matrices of the gesture classification using `TimeSeriesSCV` for all gestures and after leaving out gestures with an initial high confusion rate.

Gesture	Average Performance		
	Precision	Recall	F1-Score
`Doubletap`	0.80	0.80	0.80
`Hold`	0.99	0.94	0.96
`Noise`	1.0	0.98	0.99
`Slide`	0.80	0.89	0.84
`Tap`	0.92	0.89	0.90

Table 5.3: Classification performance of the tuned estimator on the test set. The results were averaged across the individual outcomes of the two participants' data.

5.3 Statistics-Based Approaches

As time series-based features are highly complex due to their temporal dependencies, we present an alternative, statistics-based approach that limits the exhibited complexity of features and underlying models. Analogously to Section 5.2, we first detail on the used apparatus and the process of feature engineering. We then introduce the procedure of the experiments, followed by a first evaluation of the results. Finally, we discuss ways to improve the overall performance of the selected model, and conclude with an evaluation and discussion of our findings.

5.3.1 Apparatus

As in Subsection 5.2.1, we used a 64-bit PC with a 2.30 GHz Intel® Core i7-10510U™ processor running Windows 10 Home. For the machine learning related tasks, we used the `scikit 1.0` library [68]. This library provides us with implementations of the (meta-) estimators that we aim to evaluate. These include

- `AdaBoostClassifier(random_state = rng)`
- `BaggingClassifier(DecisionTreeClassifier (random_state = rng), random_state = rng)`
- `DecisionTreeClassifier(random_state = rng)`
- `GradientBoostingClassifier(random_state = rng)`
- `KNeighborsClassifier()` (Note: There is no randomness to control.)
- `RandomForestClassifier(random_state = rng)`
- `SVC(random_state = rng)`

where `rng` is some fixed random generator which enables result recreation. All other settings were left at their default values. Further details about the other libraries used can be found in Appendix E and in the corresponding notebook file.

The latter can be accessed via the GitHub repository[5]. As for the time series-based approach, the auxiliary functions are provided as part of the Jupyter Notebook `data_preparation.ipyn`[6].

5.3.2 Feature Engineering

To resolve the temporal dependencies of time series, we use descriptive statistics which are based on those time series to provide simpler features for machine learning. In the subsequent paragraphs, we describe the procedure for building a suitable feature space.

Smoothing and Normalizing Analogously to Subsection 5.1.1, we first smoothed the resistive data and then normalized capacitance and resistance to the interval $[0, 1]$.

Feature Construction To select meaningful statistical descriptors with discriminatory power from the time series, we constructed an initial set of more than 40 classic statistical descriptors, ranging, e. g., from mean, standard deviation, kurtosis in the temporal domain to descriptors in a wavelet-transformed domain, computed by the Discrete Wavelet Transform (DWT). Hereby, we relied on time-independent statistic descriptors only. I. e., we discarded features such as the gesture duration or the sum of data points as they might be prone to the gestures' high variability in length. Through an educated guess [34][pp. 63–64], we refined the constructed feature space to twelve features.

Feature Selection Univariate feature selection using ANOVA F-value for each sample implemented in the `sklearn` library reduced this tentative set to six features.

Final Feature Set Given the normalized capacitive and filtered resistive time series $TS_{cap} := \{t_{1_{cap}}, t_{2_{cap}}, \ldots, t_{N_{cap}}\}$ and $TS_{res} := \{t_{1_{res}}, t_{2_{res}}, \ldots, t_{N_{res}}\}$, respectively, we can formulate the six selected features as follows:

- $correlation(TS_{cap}, TS_{res})$
- $mean(TS_{cap}) + mean(TS_{res})$
- $SD(TS_{cap}) + SD(TS_{res})$
- $meancrossing(TS_{cap}) + meancrossing(TS_{res})$
- $zerocrossing(dwt_{l_1}(TS_{cap})) + zerocrossing(dwt_{l_1}(TS_{res}))$

[5] Access the script from the GitHub repository: https://github.com/zitos97/FeatherHair/blob/main/gestureRecognition/Thesis%20Part%20I%20%20-%20Stat-Based%20Gesture%20Recognition.ipynb

[6] Access the auxiliary functions from the GitHub repository: https://github.com/zitos97/FeatherHair/blob/main/gestureRecognition/data_preparation.ipynb

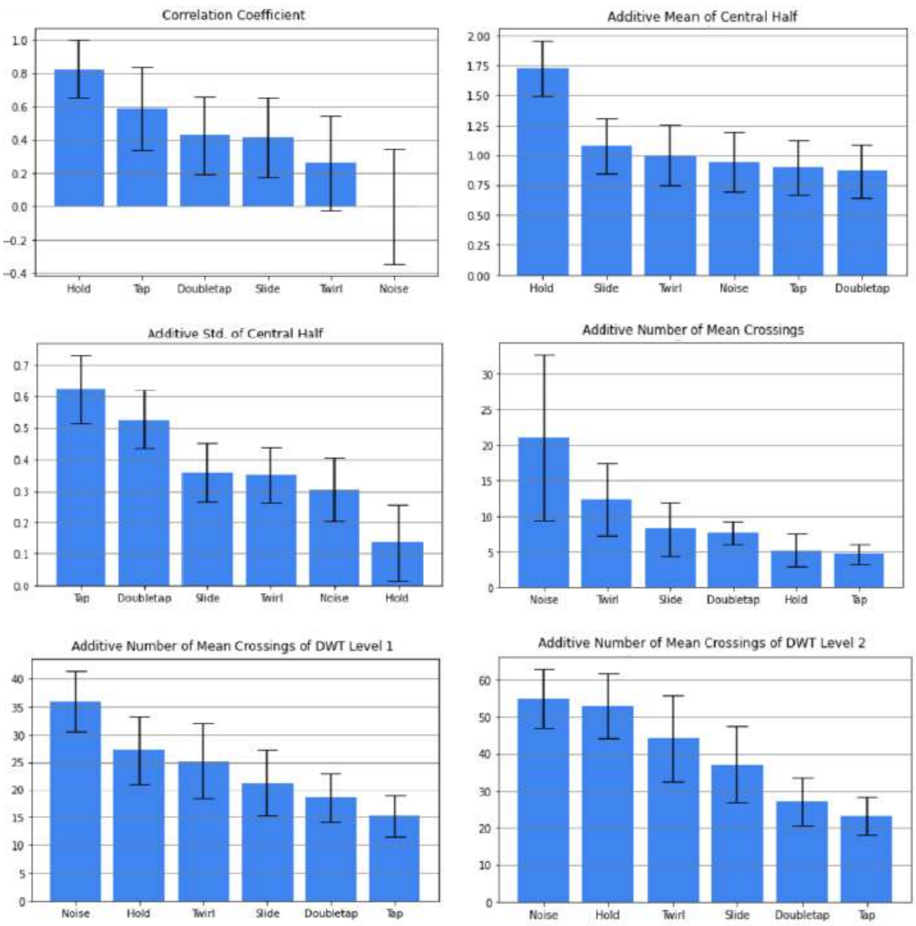


Figure 5.5: The descending ordered average scores of the gestures in the train set for all six features. The half error bars depict the standard deviation.

- $zerocrossing(dwt_{l_2}(TS_{cap})) + zerocrossing(dwt_{l_2}(TS_{res}))$

where $meancrossing(\cdot)$ returns the number of mean crossings, $zerocrossing(\cdot)$ the number of zero crossings, and $dwt_{l_1}(\cdot)$ and $dwt_{l_2}(\cdot)$ the detail coefficients at level one and two of the DWT, respectively. We illustrate the discriminating power of these features in Figure 5.5.

5.3.3 Procedure

As for the time series approach, we split our data in train and test sets where the latter one consisted of data of participants P9 and P10. To validate our model, we proceeded analogously to the time series-based approach by first validating the estimator performance per participant using stratified 10-fold cross-validation. We then evaluated the models' generalizability to new participants through 8-fold leave-one-person-out cross-validation.

Estimator	Average Performance		
	Accuracy	Training Time (sec)	Single Prediction Time (sec)
`AdaBoost`	0.494	0.04933	0.00017
`Bagging`	0.770	0.01601	0.00004
`Decision Tree`	0.727	0.00085	**0.00001**
`GradientBoost`	0.768	0.37123	0.00002
`KNeighbors`	0.685	**0.00052**	0.00004
`Random Forest`	**0.803**	0.09452	0.00024
`SVM`	0.673	0.00232	0.00003
Mean	0.703	0.07640	0.00008
SD	0.103	0.12454	0.00008

Table 5.4: Performance of the person-dependent stratified 10-fold cross-validation. The final results were averaged across the individual results for all of the eight participants. Bold prints mark the best performance of each of the three categories.

5.3.4 Model Selection & Evaluation

In this section, we present the results of the person-dependent and -independent training and conclude with a discussion of the most suitable model for the statistics-based approach.

Person-Dependent Results Table 5.4 shows the performance of the gesture classification in a person-dependent setting. The best average accuracy was achieved by the Random Forest with 80.3%, followed by the Bagging Classifier with 77% and Gradient Boosting with 76.8%. This is striking since all these estimators are ensemble methods made of Decision Trees. Also the accuracy of the single Decision Tree was above the overall achieved mean of 70.3% . AdaBoost performed by far the worst with 49.4%. Regarding the training and single prediction times, there is no substantial difference as all estimators needed a split second.

Person-Independent Results Comparing these observations to the results of the person-independent classification performance shown in Table 5.5, we find that the overall average accuracy score dropped from 70.3% to 68.6%. The Random Forest still yielded the best accuracy with 75.6% but was almost on par with Gradient Boosting with 75.4%. Whilst the two classifiers that achieved the lowest accuracy scores in the user-dependent setting also performed worst in the user-independent setting, they were also the only two whose accuracy slightly increased for the user-independent setting, probably profiting from the increased training set. Analogously to the person-dependent setting, all classifiers exhibited short training and prediction times.

Estimator	Average Performance		
	Accuracy	Training Time (sec)	Single Prediction Time (sec)
`AdaBoost`	0.522	0.11789	0.00002
`Bagging`	0.736	0.05490	**0.00000**
`Decision Tree`	0.676	0.00818	**0.00000**
`GradientBoost`	0.754	1.48812	0.00001
`KNeighbors`	0.677	**0.00358**	0.00002
`Random Forest`	**0.756**	0.25330	0.00004
`SVM`	0.682	0.07039	0.00013
Mean	0.686	0.28519	0.00003
SD	0.075	0.49732	0.00004

Table 5.5: Performance of the 8-fold leave-one-person-out cross-validation. The green marking is used if the accuracy performance improved in contrast to the person-dependent performance illustrated in Table 5.4. Bold prints mark the best performance of each of the three categories.

Discussion Similarly to the time series-based approach, it is neither surprising that the individual training times increased for the person-independent setting nor that there were no substantial performance differences between the person-dependent and -independent training settings. For the final estimator, we had to choose between the Random Forest and the Bagging classifier as they exhibited the highest accuracy scores and performed particularly similar in the person-independent setting. Against the background that the Random Forest is considered an improvement of a Bagging Classifier that reduces the sensitivity to noise (c.f., Subsection 5.1.2), we decided to opt for the Random Forest.

5.3.5 Performance & Hyperparameter Tuning

We proceeded analogously to the time series-based approach by first investigating the cumulative confusion matrix before turning to hyperparameter tuning.

Confusion Matrices To boost the model performance, we first analyzed the cumulative confusion matrix of the 8-fold leave-one-person-out cross-validation. As we can see in the left matrix depicted in Figure 5.6, *Hold* achieved highest accuracy with 90.0% across all gestures, followed by *Noise* recognition with 87.6%. The lowest accuracy was 50.3% for *Twirl* and 52.5% for *Slide*. It is particularly striking that *Slide* was misclassified with *Twirl* for 21.8% of its samples and vice versa for 25.3% of samples. Furthermore, *Twirl* was misclassified with *Noise* in 17.8% and both *Slide* and *Tap* were confised with *Doubletap* in at least 13.3% of all cases. Consequently, we found that *Twirl*, *Slide*, and *Doubletap* are involved in above-average confusion rates. For that reason, we evaluated the performance of the Random Forest when leaving out one of these gestures for comparison. The resulting cumulative confusion matrices are shown in Figure 5.6 (right). First of all, we notice that the overall accuracy scores increased substantially from 75.6% for all gestures to 84.5% and 85.8% after removing *Slide* and *Twirl*, respectively. Contrary, the accuracy hardly increased without *Doubletap*. For the latter option, we notice that the high confusion rates of *Slide* and *Twirl* pushed the overall performance down. Note that false activations were triggered only in 4.66% with a total of 27 out of 579 trials without *Twirl*. In contrast to this, 12.61% false activations were triggered without *Slide* and 13.47% without *Doubletap*, emerging from the overall confusion between *Noise* and *Twirl*. Similar to the argumentation of the time-series based approach, we decided to remove a gesture from the set in order to increase the overall system reliability. Since the minimization of false activations in combination with high overall accuracy scores is a desirable property for a robust interface, we chose to remove *Twirl*.

Hyperparameter Tuning Next, we fine-tuned the parameters of the Random Forest through a cross-validated grid search implemented as part of the *sklearn* library. The parameters of the grid comprised the number of estimators, the maximum depth of the tree, maximum number of features to consider, minimum number of samples required to be at a leaf node, number of samples to draw from the training set to train each base estimator, and the method to associate weights with classes. The resulting tuned estimator configuration consisted of balanced subsample class weights, a maximum tree depth of seven, and used 10% of samples from the original training set to train each base estimator. All other settings remained at their default. The tuned estimator achieved a mean leave-one-person-out cross-validated accuracy score of 86.4%, yielding a slight improvement of 0.6%.

5.3.6 Final Evaluation & Discussion

Finally, we validated the tuned estimator on the held back validation set. Subsequently, we first present the results and conclude with a discussion of their meaning.

Results The trained estimator achieved accuracy scores of 89.5% and 87.6% for the validation sets of participant P9 and P10, respectively. Table 5.6 shows precision, recall, and F1 scores for the five gestures averaged across the two test datasets. Highest precision scores were achieved by *Hold* and *Noise* with 99% and 93%, respectively. They also achieved best recall results with 93% and 100%. This also means that no false activations were triggered on the test set as well as only 7% of all data was misclassified as noise. Lowest results were achieved for *Doubletap* with 77% precision and 74% recall.

Discussion Since the results suggest that the model is able to generalize well to new users even exceeding the accuracy of the tuned estimator on the training set, we suggest that the tuned model is neither under- nor overfitted [16]. This improvement may also occur because the trained model used more data as, compared to

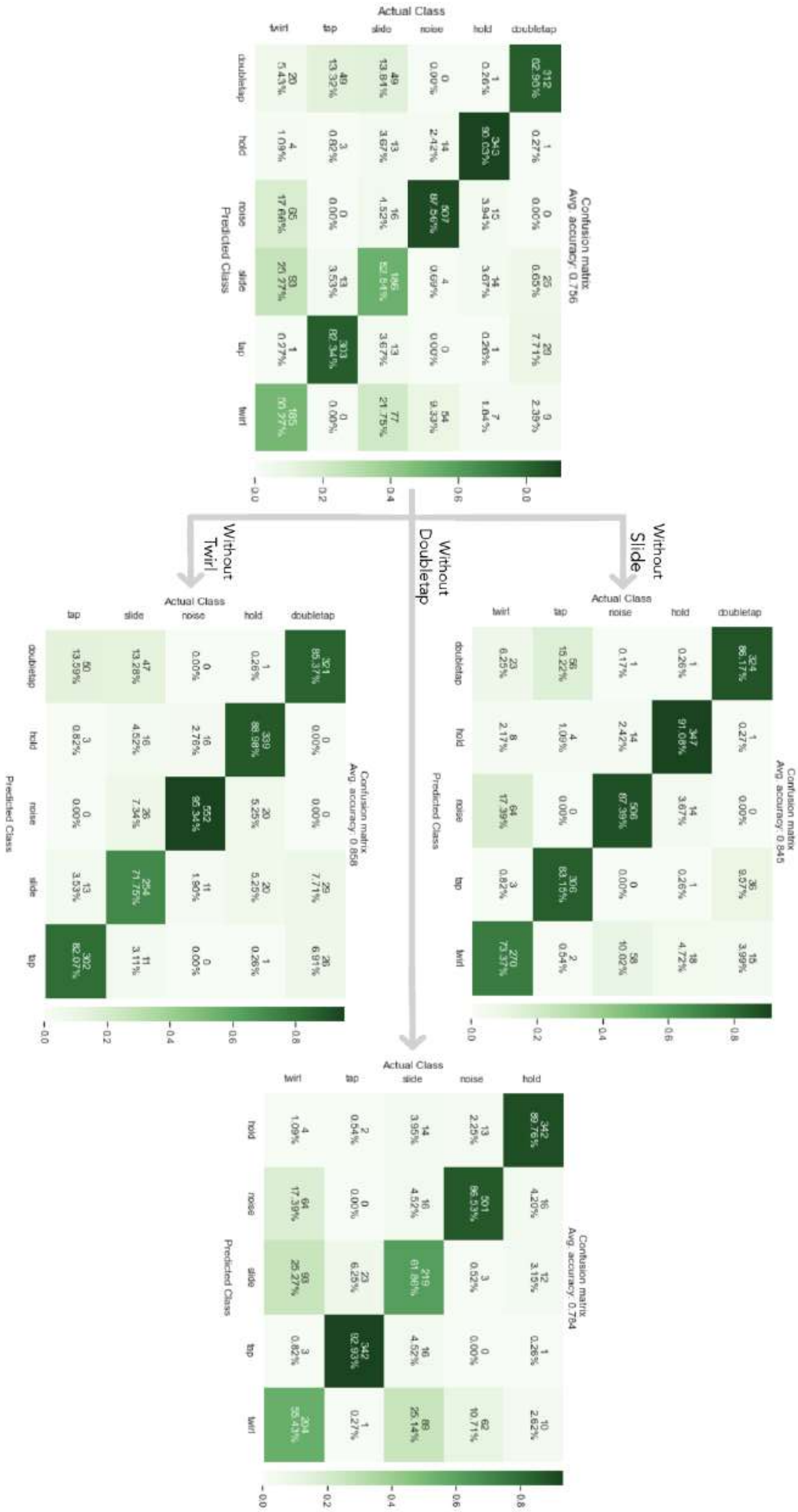


Figure 5.6: Cumulative confusion matrices of the gesture classification using Random Forest for all gestures and after leaving out gestures with an initial high confusion rate.

Gesture	Average Performance		
	Precision	Recall	F1-Score
`Doubletap`	0.77	0.74	0.75
`Hold`	0.99	0.93	0.96
`Noise`	0.93	1.00	0.96
`Slide`	0.88	0.83	0.84
`Tap`	0.85	0.84	0.84

Table 5.6: Classification performance of the tuned estimator on the test set. The results were averaged across the individual outcomes of the two new participants.

the cross-validated approach, no data was held back. In turn, this suggestion might imply that further training data could boost the performance of person-independent gesture recognition, possibly breaking the 90% mark.

5.4 Approach Comparison

The models that we developed in the previous sections exhibit several benefits and drawbacks which we analyze and compare as part of this section. We contrast the most important results of the two models again in Table 5.7.

5.4.1 Accuracy

The overall average accuracy on both person-independent train and validation sets was superior for the time series-based SVM. Also, we could see in the initial six-gesture person-dependent setting that the SVM outperformed the Random Forest by 6.5%. Analyzing classification performances on the final validation set, we could furthermore observe that the former triggered less false activations. Having a stronger robustness against noise and a better generalizability in both user-dependent and -independent settings, the time series-based SVM appears to be the method of choice in the context of accuracy. This is crucial when designing prototypes for a user study since low accuracy scores could introduce feedback bias by the participant being concerned about the overall system reliability [26].

5.4.2 Speed

Whilst the Random Forest was inferior with regard to accuracy, it outperformed the SVM in speed by a factor 10000 for training, and more than a factor 25000 for a single prediction. Albeit this difference, the single prediction times of both approaches were in an acceptable range with approximately one second. However, it depends on the integration of the model into a specific gesture detection and recognition pipeline if such a small-scale speed difference kicks in as slow response times might trigger delays in system response, leading to a frustrating

Estimator	Average Performance			
	Accuracy Train Set	Accuracy Validation Set	Training Time (sec)	Single Prediction Time (sec)
`Random Forest`	0.864	0.886	**0.25330**	**0.00004**
`TimeSeriesSVC`	**0.919**	**0.913**	2539.95570	1.03291

Table 5.7: Performance comparison of Random Forest and TimeSeriesSVC based on the achieved accuracy scores of the tuned models on the leave-one-person-out cross-validated train set and the validation set, and the average training and single prediction times as specified in Table 5.2 and 5.5, respectively. Bold prints mark the best performance of each of the four categories.

user experience. Consequently, when time is a critical aspect in the system implementation, Random Forests should be preferred.

5.4.3 Real-Time Adaptation

Another aspect which is in the nature of the underlying Random Forest and SVM implementation is their ability to be fine-tuned during use. Whilst the used implementation of the Random Forest offers a function that allows the trained model to adapt to incoming data or could be even completely retrained during execution, none of this is possible for the time series-specific SVM. First, its training speed does not allow for any real-time adaptation. Secondly, the underlying implementation does not provide a function with which incoming data could be added to the system. If we require a system capable of real-time adaptation, the Random Forest is the method of choice.

5.5 Final Pipeline in Prototype

To run the gesture-controlled prototype, we implemented a software pipeline that detects and recognizes gestures in real-time. In this section, we first describe the apparatus of the implementation, then the idea of the underlying algorithm. As the practical implementation might put limitations on the choice of the underlying classifier, we conclude this section with a short discussion on the suitability of the trained classifiers.

5.5.1 Apparatus

For the implementation, we used a Python script that observes the incoming resistive and capacitive measurements of the wearable prototype and manages gesture detection and recognition through one-directional serial communication. The software implementation was realized with `CircuitPython 7.0.0` on the microcontroller and `Python 3.9` for the script running on a (micro)computer (c.f., Subsection 6.1.1). The implementation for both the wearable prototype and the Python script can be retrieved in the GitHub repository[7][8].

5.5.2 Implementation

The overall procedure was inspired by Wolf et al. who implemented gesture detection based on sensorical data for a mobile device in real-time on an Android smartphone [103]. We can divide the algorithm into four main steps. We sketch their working principles in the following. For more details, please refer to the implementation in the GitHub repository.

Detecting the Start of a Gesture The wearable prototype send resistive and capacitive measurements continuously every 0.1 seconds through a serial communication port. To segment a gesture without knowing its start or end time, the algorithm relies on the ratios of both the current capacitive sample to the capacitive baseline and the current resistive sample to the resistive baseline, where the baselines are computed through moving window average. If these ratios exceed some experimentally determined thresholds, it assumes the initialisation of a gesture. As long the end of the gesture is not detected, it stores the incoming resistive and capacitive data and freezes the computation of baselines.

Detecting the End of a Gesture The end of a gesture is reached either when the current capacitive and resistive ratios fall below a threshold and remain there for one second or once the duration of the gesture exceeds ten seconds. Note that the latter variant was our maximum value in the data collection study and serves as an emergency stop in case the new capacitive and resistive baselines after the execution of the gesture do not match the old baseline values. Having detected the end of a gesture with this heuristics, the algorithm stop recording incoming data and resumes updating the capacitive and resistive baselines.

Framing Similar to Wolf et al. and the way we cut the time series to variable length in Subsection 4.3.2, the algorithm frames the recorded gesture sample with one second of data received right before and after the execution.

Classifying the Gesture Lastly, it transforms the recorded variable-length time series into the required feature space and predicts the gesture using the trained model.

[7] Access the CircuitPython script: https://github.com/zitos97/FeatherHair/blob/main/itsybitsy%20files/real_time_gesture_detection_itsybitsy.py

[8] Access the Python script: https://github.com/zitos97/FeatherHair/blob/main/Raspberry/real_time_gesture_recognition.py

5.5.3 Discussion

The sketched algorithm only calls the classifier when a gesture is detected. Since this makes the system robust against accumulating classification delays in case of a slow predictor, both the SVM and the Random Forest have application for the implementation. However, the final decision depends on the used hardware which can put further restrictions on the model's allowed computational complexity (c.f., Subsection 6.1.1).

5.6 Summary

In this chapter, we detailed on background on machine learning and leveraged this knowledge as a basis for decision taking for the implementation of gesture recognition. We compared the effectiveness of time series-based features to statistics-based features. We found that the time series approach is superior with regard to accuracy whilst the selected statistics-based approach provides us with higher speed. Furthermore, we proposed a software pipeline implementing real-time gesture detection and recognition. We use the implementation for the prototype in Chapter 6.

6 Hair Interfaces in Practice

Prior work on hair interfaces lacks in-depth knowledge on the appropriateness of hair interfaces and hair-based interactions in practice. For this purpose, the second objective of this thesis involves the investigation of the social complexity of a gesture-controlled hair interface (RQ2). We approach this objective through qualitative data gathering in the field, providing participants with hands-on experience with our prototype. In this chapter, we detail on the method used to gathering qualitative user data, followed by an analysis of results related to design, gesture interactions, and social tensions of hair interfaces and hair-based interactions.

6.1 Method

A carefully designed study is crucial in order to gather insightful data. As part of this section, we first detail on the used apparatus for the study, recruited participants, and the procedure. Since the collected data requires an appropriate analysis to extract as much information as possible, we conclude with a description of the used data analysis method and a positionality stance.

6.1.1 Apparatus

The apparatus is split into hardware and software components on which we detail in the following.

Hardware We used the wearable prototype introduced in Section 3.2 which is integrated in an elastic hair band. The prototype uses an ItsyBitsy M0 and communicates with a Python script running on a microcomputer through one-directional serial communication. The script runs on boot when the microcomputer is powered. The microcomputer is a Raspberry Pi Zero WH[1] and uses single-core CPU running at 1 GHz. It is connected to an Adafruit PiOLED display with a resolution of 128x32. Figure 6.1 shows an image of the worn prototype.

[1] Raspberry Pi Zero WH: https://www.raspberrypi.com/products/raspberry-pi-zero-w/ (Retrieved December 18, 2021)

Figure 6.1: Interaction with FeatherHair in a public setting. The display in the hand depicts the recognized gesture.

Software The software was realized with `CircuitPython 7.0.0` on the microcontroller and `Python 3.9` on the microcomputer. The main purpose of the microcontroller is measuring and sending the resistive and capacitive data relying on the methods that were introduced in Section 3.3. The Python scripts manages the gesture detection and recognition as described in Section 5.5. For compatibility issues between 64- and 32-bit hardware architectures, we had to retrain the model on the Raspberry. We used the Random Forest since the training and execution of the time series-based SVM appeared infeasible on the microcontroller's single CPU due to the high computational costs. Furthermore, we provided visual output through the connected display depicting the detected gesture. Similarly to Williamson and Brewster who evaluated social acceptability of gestures [76], we decided against the implementation of a specific functionality to not draw attention from performed gestures. Other alternatives would have been the implementation of very generic tasks such as declining calls or muting the phone (c.f., Ronkainen et al. [77]). The used scripts can be retrieved from the GitHub repository[2][3].

6.1.2 Participants

We recruited seven participants (4 f, 3 m), aged from 22 to 28 (mean = 24.9, median = 25). Six participants are right-handed, one left-handed. All are German. They have different hair structures and lengths ranging from short and curly to

[2] Access the CircuitPython script: https://github.com/zitos97/FeatherHair/blob/main/itsybitsy%20files/real_time_gesture_detection_itsybitsy.py

[3] Access the Python script: https://github.com/zitos97/FeatherHair/blob/main/Raspberry/real_time_gesture_recognition.py

Participant	Characteristics
P1	25; m; PhD (CS); long and straight hair worn in a ponytail; right-handed; limited expertise on hair styling; hair must conform his practical needs
P2	28; m; student (emSys), IT support; short and curly hair; right handed; no expertise on hair styling
P3	26; m; student (CS); shoulder long and rather straight hair; right-handed; limited expertise on hair styling
P4	22; f; student (CS); long and straight hair; right-handed; expertise on hair coloring and styling; styles her hair for special events
P5	26; f; PhD (chemistry); long and straight hair; right-handed; some expertise on hair styling; hair should be particularly functional and conform to practical needs; styles her hair for special events
P6	22; f; student (CS); shoulder long and straight hair; left-handed; some expertise on hair styling
P7	25; f; student (tax economics); long and rather straight hair; right-handed; strong expertise on hair coloring and styling; describes herself as very eager to try out new things with her hair

Table 6.1: Overview of participants' demographics and hair-related characteristics.

long and straight, and draw on varying expertise on hair modifications (colouring, braiding, cutting, ...). See Table 6.1 for further details about the participants. Participants received a chocolate bar for compensation for their participation.

6.1.3 Study Design

Our study design is inspired by the study conducted to evaluate NotifEye by Lucero and Vetek [53]. Our goal was to provide the participants with realistic hands-on experience with the prototype during a guided walk in the wild. This is crucial since the experience of interaction in a natural setting allows participants to develop and report in-depth opinions about the technology [1, 76]. In the subsequent paragraphs, we first detail on the general procedure before presenting the specific walking route.

Procedure The overall study procedure consisted of six steps. 1) Before starting the study, the experimenter introduced the participant to the study goals through an informed consent and a presentation of the prototype. The consent can be found in Appendix B.2. 2) The experimenter demonstrated the gestures and provided the participants with the option to train the gestures until they felt confident. This phase lasted approximately 2 minutes. None of the participants requested further time for training. 3) The walking route was designed to let the participant experience hair-based interactions in varying social contexts. The first phase of the walking route consisted of walking across the university campus together with the experimenter (9–12 minutes). At specific locations, the participants were asked to perform a gesture. The order of prompted gestures was fixed and assigned to specific locations. Here, the participants could slowly get used to walking while dealing with hair interactions and collect first experiences of the usage of a hair interface in public. Throughout the walk, the experimenter interviewed the participants about their experiences in a conversation-like manner. 4) The participants had to walk the second part of the route alone to reduce bias of the researcher being present. They were provided with a sheet containing information about which gesture they should perform at specific locations. The experimenter and the participants met again at the end of the second part of route, discussing the experiences in a follow-up semi-structured interview (4–9 minutes). 5) For the third part of the guided route, the participants could freely explore the prototype for 5–10 minutes with the researcher being present. Here, the participants should imagine that they were the designer of a hair interface and were prompted to brainstorm and try out, e. g., different interaction styles, discuss other ways to realize a hair interface, etc. Ideas were discussed in a conversation-like manner. 6) After arriving at the end of the route, we conducted follow-up semi-structured interviews, covering questions that were not yet answered during the walking conversation (5–15 minutes). All conversations were audio recorded. The questions of the interviews can be found in Appendix B.2.

Route We picked a route on campus of Saarland University as this is a place which has both busy and quiet places. The full route is depicted in Figure 6.2 and involves, e. g., bus stops, crossings, indoor and outdoor locations, marked accordingly in the figure. Most participants (6/7) were familiar with the passed university areas.

6.1.4 Data Analysis

To analyze the data, recordings were partially transcribed for each of the seven participants, covering essential utterances. We then analyzed the qualitative data through several interpretation rounds, using a combination of qualitative content analysis (QCA) [54] and semantic thematic analysis (TA) [8], where both methods follow an inductive approach, i. e., codes can be built and modified throughout the coding process. Doing a QCA in the first part, we analyzed the transcripts objectively with a focus on usability of the hair interface and hair-based interactions. In the second part, inspired by TA, we looked over the text with a focus on participants' perceived social and emotional aspects of hair interfaces and interactions. Both parts consisted of several iterations each in which we reviewed, merged, and discarded categories and themes to construct a final cohesive analysis of participants' reactions. Finally, we returned to the original transcripts to confirm that the categories and themes were cohesive with participants' reported experiences.

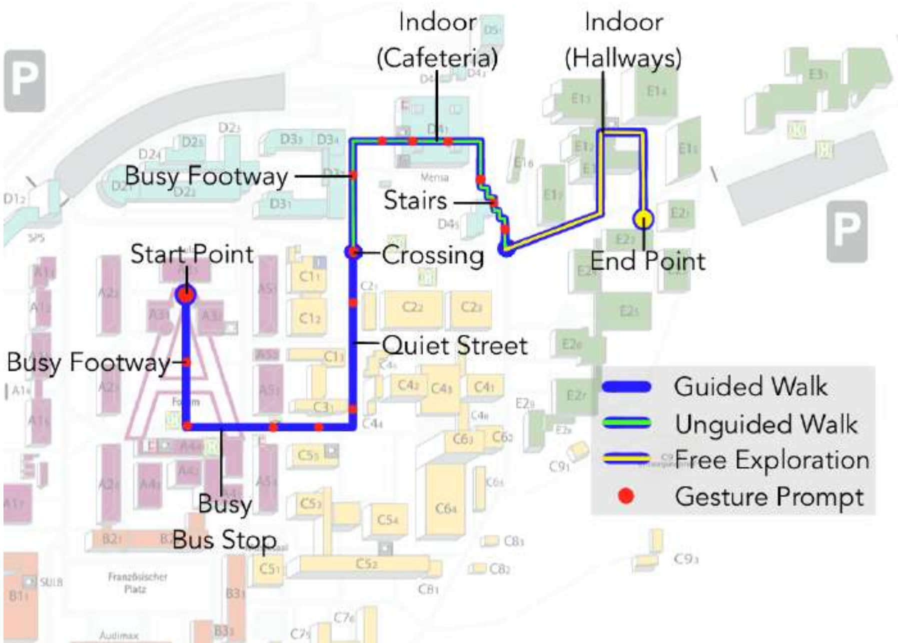


Figure 6.2: The route walked as part of the user study. It is split into three parts: 1) Guided walking route, 2) unguided walking route, and 3) free exploration.

6.1.5 Positionality Stance

The reflection of the process and choices made for designing and evaluating technology is important as underlying normative assumptions might influence the results. In the following, we first review the need of a positionality in literature with a particular focus on hair interfaces. Afterward, we take a firm stand on underlying assumptions in the scope of this work.

The Need for a Positionality in Literature All prior work on hair interfaces (c.f., Section 2.1) is affected by a general problem in TEI that Spiel outlines in their survey on norms and assumptions in the design of embodied interaction [85]. They point out that many of the depicted bodies in literature are youthful and light-skinned. They mention that these normative tendencies become especially striking in the context of HäirIÖ. Whilst the authors introduce HäirIÖ as an interface suitable for straight and long hair, they refer to this type of hair as "*human hair*". This is problematic since these characteristics tend to conform to non-Black hair only. Consequently, Spiel remarks that the authors of HäirIÖ implicitly label Black hair as less-than-human. Similarly to HäirIÖ, many of the other proposed hair interface designs [24, 91, 94] tend to be unsuited for non-Western hair types and styles as well. Spiel mentions that even though it might be impossible for a scientific work to account for all types of oppression, researchers must be willing to admit imperfections, failures, and limitations. For that, a first step might be to clearly mention the normative tendencies underlying their work. To date, hardly any of the papers mentioned here have done so. Since the acceptance of body diversity and a realistic shape embodiment are ubiquitous topics of increasing importance, these considerations also affect this work.

The Author's Positionality The author of this work has continually lived, learned, and researched in Central Europe. She is white, binary, and does not identify as disabled. Thus, for the following presentation of results, we cannot exclude normative Western world assumptions underlying the argumentation although trying to stay neutral. Furthermore, we acknowledge that the positioning as researchers at a Western academic institution influences our perception towards designing socially acceptable technology. We do not claim generalizability of the design and our findings since the prototype and the study were designed with a focus on Western styles and traditionally straight white hair in mind. We are aware that it is also possible to design hair interfaces for other hair styles and types, possibly linked to different experiences and opinions in the context of perceived social appropriateness of hair interfaces and hair-based interactions.

6.2 Design of Hair Interfaces

Analyzing the gathered user data, we found various aspects that are involved in the design of a hair interface. These comprise its wearing comfort, the localization of the interface in the hair, the haptic sensation, and ways to attach it to hair. Finally, we report the extent to which malleability and robustness for a hair interface are desirable properties.

6.2.1 Wearability

Participants liked that the interface merges with the hair: "*What I like about it that it is integrated in full hair and does not hang loosely, but I can take it together with my hair [everywhere].*" (P3) Furthermore, P5 stated that the hair band causes the weight of the interface to evenly distribute over the head, making it comfortable to wear. Similarly, two other participants emphasized that the prototype is lightweight and comfortable. However, "*the case [in which the microcontroller is embedded] is a bit distracting.*" (P2) As the head is not flexible, P3 added that the interface should be integrated such that one might lay down on the interface without hurting the head because of a bulky case. Alongside with a flat layout, "*you have to pay attention that it is relatively smooth and can be easily pulled out of the hair… it is maybe a material thing. Rubberized things may not be so good with the hair because they will get tangled.*" (P3) Consequently, we find that the perceived wearability of hair interfaces is multi-faceted and can be shaped, e. g., by the choice of material and form factor.

6.2.2 localization in the Hair

P1 for who we integrated the prototype into a ponytail found that the interface needs to be attached further at the top of the head, making the interaction with the device easier. Furthermore, P1, P2, and P7 mentioned that the more the interface is located towards the front of the head, the easier is the interaction as the arm needs to be moved around less. "*I would use the front strand of hair. This is natural, but if I have to do it further backward, it gets unnatural.*" (P7) Thus, the interface should be placed at a reachable position of the head such as the upper part of the foremost strand in order to increase overall comfort during interaction.

6.2.3 Haptics

All participants agreed that the feather extensions feel like hair: "*You don't feel that there is technology in your hair.*" (P5) Five out of seven participants further expressed the desire and expectation that a hair interface should have haptic properties similar to real hair. On the other hand, as the feather extensions exhibit hair-like haptics, all participants reported that it was hard to find the feathers in the hair. We acknowledge that this problem could only be uncovered since we provided our participants with practical hands-on experience with the prototype. To increase the detectability of the interface, two participants suggested to use at least one landmark located on the top of the interface or more landmarks for long hair, acting as an initial orientation mark: "*You have only one indicator at the top [of the interface], which you can feel relatively easily, and then take the hair and pull it down.*" (P2) The interactional significance of landmarks has been highlighted in the context of on-skin technologies because they ease on-body interactions by supporting the localization of the interface, providing guidance during gestural input, and reminding the user about the presence of an input technology [99]. On the other hand, this poses a trade-off between desired naturalness and required detectability of the interface in the hair.

6.2.4 Attachment to Hair

The participants proposed several alternatives to the hair band in order to attach a hair interface to the head. These expand the set of proposed attaching form factors in literature [24, 94], e. g., by bobbles to make it suited for pigtails, hats and caps, bandanas, Alice bands, and extension glue. Whilst the latter option would make the attachment of the interface permanent, P1 and P6 stated that this is not a desirable property since the hair interface would slowly grow out of the hair and needs to withstand all daily activities such as showering and hair straightening.

6.2.5 Malleability

Four participants reported that they change their hair style throughout the day, requiring the form factor of the interface to be flexible. Furthermore, two participants wished for the ability to change the appearance of the interface whenever desired: "*I think it should be somewhat variable, so that you can choose the colors, for example. [...] [One should be able to choose:] Do I want to wear it as fashion accessory? Do I want to wear it as hair strand replacement or extensions? Or do I want it to be unobtrusive?.*" (P5) Consequently, the malleability of a hair interface appears crucial both in a practical and in a fashionable sense in order to adapt to the user's varying needs and increase the overall usability.

6.2.6 Robustness

Several participants worried about the robustness of the prototype. So, two participants mentioned, e. g., the fear of pulling the prototype out of the hair or breaking it. Furthermore, three added that it has to withstand daily interactions with our hair, including combing or hair style changes. "*I think that it breaks very easily. [. . .] In the winter. . . you'd have to be careful with hats, [. . .] with scarves, sweaters, jackets, whatever you take off over your head, you'd always have to take [the interface] off first, because I don't think it would withstand that very well.*" (P7) As robustness influences the perceived wearing comfort of hair interfaces, this aspect should be considered early on in the design process, i. e., for the choice of both material and the attaching form factor.

6.3 Gestural Interactions with Hair Interfaces

Analyzing the gathered user data, we found various aspects that are involved in the design and perception of hair-based interactions. One of these aspects is the perceived naturalness, ease, and unobtrusiveness of gestures. Next, we contrast static and dynamic gestures as well as discrete and continuous ones. Furthermore, we discuss the participants' perception of false activation proneness and conclude with a collection of further possibilities for hair-based interactions.

6.3.1 Perceived Naturalness, Ease, and Unobtrusiveness

None of the participants required any further training of the gestures after being presented to them, indicating that the gestures were very easy to learn. P6, the left-handed participant, stated: "*I think it's okay for left-handers with the right hand, too, at least for me, because it's not complicated movements.*" The majority of participants (5/7) immediately reported that *Slide* was the most natural gesture. Two argued that it resembles pulling the hair behind the ear: "*It's like a classic 'My hair is hanging in my eyes!', and, bang, you pull it back [behind the ear].*" (P3) Furthermore, most participants mentioned that they like the natural gestures as they are least obtrusive and observable. Contrary, two participants disagreed with this perception: "*Slide is the most conspicuous and unnatural gesture.*" (P5) P5 added that she is used to all gestures but *Slide* because of her wireless earphones that require artificial interactions similar to *Tap*, *Doubletap*, and *Hold*. Another participant mentioned, albeit natural, *Slide* " *is not that easy, especially if [the interface] is tangled with hair.*" (P3) Furthermore, three participants stated that *Tap* and *Doubletap* are less unobtrusive and comfortable than *Slide*, albeit being quicker. P4 reflected: "*It is nothing what everyone is doing. [. . .] This is nothing you do with your hair naturally.*" Similarly, P7 said: "*Tap is, of course, also an unusual movement [. . .]. It's new, it's unusual, but it's not a movement that you think you could ever feel normal in your life.*" *Hold* was oftentimes considered the least natural and most obtrusive gesture: "*Something like this Hold is not done naturally.*" (P4) "*Hold feels like raising your arm and waving.*" (P1) Another participant compared it to having "*a telephone receiver in [his] hands*"

(P2). Summing up, whilst the perception of naturalness is person-dependent, we observe that the naturalness and familiarity of gestures can boost the perceived unobtrusiveness and ease of use which are desirable properties for our users. This conforms to other findings of earlier work which investigated user preferences for interaction with technology for which easy and subtle interactions were usually preferred as well [2, 56, 76].

6.3.2 Perceived Cognitive Load

All participants managed to perform the gestures whilst walking. However, one participant needed some time until he could easily walk whilst performing a gesture: "*[Hold] feels like I would want to stop walking when performing the movement.*" (P1) Four participants mentioned that particularly *Hold* is challenging whilst doing other tasks. "*Hold is too exhausting.*" (P2) Furthermore, two participants stated that they would not perform *Slide* when crossing the street whilst four participants emphasized that the movement does not require attention as they are used to it. Similarly, two participants said that *Tap* has a low cognitive load. People particularly disagreed on the attention required to perform *Doubletap* when walking. Whilst three stated that the gesture requires some attention also because "*the retention time is long*" (P7), two other participants summarized the cognitive load as low: "*You do not have to pay much attention to [the interactions]. It is definitely better than something screen-based such as a smartphone, [...] or a smartwatch.*" (P4) But P6 contrasted: If "*I always have to search for the interface, which requires some concentration, I don't feel 100% comfortable with it. So, I couldn't look if there was a car coming. [. . .] I would rate [the gestures] as somewhat critical because you have to get used to it*" (P6), but if the interface would be easier to find "*then it would probably be better. Because just grabbing your hair and pinching it is completely fine, I don't have to concentrate for that.*" (P6) Consequently, hair-based gestures that are perceived natural might lower the cognitive load if the reachability and detectability of the interface is given [2]. This is desirable since it allows people to interact with the device without drawing too much attention from their primary activity.

6.3.3 Static and Dynamic Gestures

Two participants mentioned that they prefer dynamic gestures over static ones. "*It should be rather one flowing movement and not, e. g., like Hold, where I have to make a static touch. That feels more natural and less awkward in public. [. . .] And it is less obtrusive.*" (P1) Most participants (5/7) proposed that the duration of *Hold* should be not more than three seconds. "*It feels a bit awkward to hold the arm up there that long. [. . .] Hold feels twice as long as it should be.*" (P3) This is complemented by another participant that liked particularly *Tap* at it is quick and not as static as *Hold*. P2 added that the "*gestures should not waste too much of [his] time.*" This conforms to findings by Ahlström et al. stating that users are likely to start feeling uncomfortable after a few seconds where the overall acceptance of the technology drops rapidly after six seconds [1]. Thus, for the design of hair-based gestures, we should refrain from long static gestures such as *Hold* since they increase physical fatigue [2] and strongly affect users' comfort.

6.3.4 Discrete and Continuous Gestures

Some (natural) gestures allow for a continuous recognition as they require some dynamic body movement or static gesture to last several seconds. These gestures include, e. g., *Hold*, *Slide*, and *Twirl*. There were some participants holding the feathers in their hands while waiting until the system recognizes the gesture: "*Does it directly tell you when it recognized Hold? Or do I have to let it go first?*" (P1) Whilst we are aware that these observations only implicitly imply the desire for continuous gestures, P2 explicitly wished for such a continuous gesture-recognizing system. Similarly, Williamson found as part of a study on user experience of performing gesture-based interactions in public that continuous gestures might appear less abrupt and, thus, exhibit better acceptability than their discrete counterparts [100]. This implies that if specific hair-based interactions allow for both continuous and discrete recognition, the former might be preferable in order to increase the comfort of the user.

6.3.5 Proneness to False Activations

A small majority of participants (4/7) were thinking about false activations. Two participants identified *Slide* as the the most prone to false activations due to its naturalness. P7 proposed to prevent false activations of *Slide* by implementing a minimal required sliding distance before detecting the gesture. Furthermore, she identified *Hold* as least prone to false activations: "*Hold is the most concise gesture if you want to ensure that the gesture is working.*" She proposed that this could be particularly important for critical actions such as calling the police. Two participants suggested to use some force-sensitive sensor that requires a specific amount of force in order to activate the gesture recognition. "*I think it's quite good if these things are not super sensitive, but if you have to apply a little pressure... that you actually make a conscious gesture.*" (P3) Consequently, we acknowledge the ineligibility of specific touch sensing technologies such as capacitive sensing as stand-alone since it is not able to resolve the ambiguity between conscious and unconscious interactions with hair unless the gestures are designed such that they are completely disjunctive from naturally-occurring hair-based interactions.

6.3.6 Other Ways to Interact with a Hair Interface

All participants could think of further hair-based interactions that might be suited for hair interfaces. These comprise, e. g., multitouch, variations of the distance between the fingers for multitouch, the area of touch, or its location. Two participants mentioned to (gently) pull or rub the hair between the fingers. Two participants proposed to scratch the head or tear hair. P2 suggested to use knots and braids to act as permanent switches in the hair, e. g., used to mute the smartphone: "*Braiding* *is like some kind of button. If I knot my hair... like I mute my phone. [...] That would be cool because it is like a switch which you are taking with you.*" P6 mentioned to use upward sliding, albeit raising concerns that it the execution was tricky. P5 reflected that it would be "*risky*" to base interactions on bare movements of hair rather than touch-based interactions due to possible interference with the natural movement of hair caused by wind or other body movements.

6.4 Social Tensions of Hair Interfaces

As discussed in previous chapters, the design of a hair interface and hair-based gestures also involves a discussion of their social complexity since social factors shape the perception of technology [76, 55]. In this section, we present the results of our semantic analysis. First, we provide a high-level summary and then delve into individual themes. When it came to discussing the perception of the hair interface, participants demonstrated that they care about its appearance and factors that shape it. Furthermore, participants reported that the usage of hair interfaces and hair-based interactions can challenge interpersonal interactions. Simultaneously, they also noticed how interpersonal interactions can be enhanced using this technology. We conclude the investigation of the social complexity by summarizing participants' thoughts about the extent to which the use of a hair interface would change their usual behavior and to which extent the experience of hair interfaces and hair-based interactions generalizes to other types of users.

6.4.1 The Appearance Matters

All participants reflected on how the appearance of FeatherHair matches their personal preferences and perceived requirements. Some mentioned design aspects of hair interfaces that are related to their gender-specific perception. We also explored the extent to which a hair interface is perceived as fashionable item and how this influences the obtrusiveness of the interface.

Personal Preferences and Perceptions People had varying perceptions of the interface that stem from their personal preferences. E. g., P4, a 22 years old female, stated that "*[the] feathers are sweet and beautiful*" but they do not match her personal taste. Contrary, P7, a 25 years old female, also thought that the feathers were sweet and even conform to her style: "*I could imagine walking around [with the interface] outside of this study setting.*" Furthermore, for people that care about the opinions of others, the requirements for the appearance are influenced by the extent to which the technology is established in society. So, many participants desired an unobtrusive interface in the beginning, remaining invisible for bystanders. P6 explained: "*I can imagine that when everyone would use such an interface one day [...], then I might also want to wear a more noticeable one. Otherwise, I am someone who doesn't like to be stared at. [...] Currently, I would prefer something unobtrusive.*" (P6) Lastly, the appearance of the interface can also shape the perception and concerns of others. Many participants reported that the less obtrusive and bulky the appearance was, the less it might distract others. Here, two participants were even comparing hair interfaces to Google Glasses. P4 reflected: "*If [the interface consists of] feathers, people probably have less concerns [that there is, e. g., a microphone integrated] than for glasses which have a large interface.*" Summing up, we find that the appearance requirements are influenced by personal taste of the user, the level of prevalence of the technology, and the perception of the bystanders. Simultaneously, the appearance might be used to shape the latter, thus, exhibiting a reciprocal relation.

The Role of Gender During the study, we found that gender appears to play a role in some considerations related to appearance requirements of a hair interface. E. g., we found that there might be men who would refrain from wearing a hair interface if it is linked to being attached to hair through a (visible) accessory as "*[most attaching form factors] are not gender-neutral*" (P3) and "*hair clips are rather a thing for women*" (P4). P2, a 28 years old male, mentioned: "*As a man, I would not want to wear any hair accessories.*" Similarly, P3, a 26 years old male, mentioned that he would not want to walk around with feathers visible in his hair. Making the interface more unobtrusive, however, might change this perception: "*It really depends on how visible it is. If it would be completely [invisible], then I could again imagine [wearing] it.*" (P2) "*For boys, a hair clip really stands out. Here, it would be okay if it is clearly a gadget [in the hair]. But currently, I think that a simple gadget design would be more suitable.*" (P3) Contrary, a gadget design might not suit everyone, as P7 raised the concern that "*for [her], [. . .] a female non-technophile person, unobtrusiveness is important*", outlining a relation between the interface appearance and both her non-technological background and gender.

Unobtrusiveness Through Fashionability Participants, independent of their gender, perceived FeatherHair as a fashionable item. P3, a 26 years old male, stated: "*One can use [the appearance] of such interfaces as design factor that is kind of cool.*". Generally, the fashionable nature of the interface seems to be prevailing in any context: "*I think in general it is more difficult to make [FeatherHair] obviously an interface than a fashion accessory.*" (P3) Several participants reported a relation between the fashionable nature of the interface and its unobtrusiveness for bystanders: E. g., "*If one integrates the technology nicely such that it looks like an accessory, then [the bystanders] would not care about it [being an interface].*" (P2) "*The interface is rather unobtrusive. I would rather see it as fashionable accessory than something distracting or noticeable.*" (P5) Thus, the fashionability of a hair interface is directly related to its perceived unobtrusiveness and the concomitant social acceptance.

6.4.2 Hair Interfaces Challenge Interpersonal Interactions

The challenging nature of hair interfaces appears to be prevailing particularly in public and for interpersonal interactions. Participants reported how bystanders might shape their perception of the usage of a hair interface. They acknowledged that the social context also is of crucial importance and reflected on the proneness to emerging misinterpretations and suggestiveness of hair-based interactions.

The Role of Bystanders' Opinions During the experiments, passers-by's most common reactions were to ignore the participant. Only three participants reported a few passengers that appeared curiously or confused. They suggested that these reactions were not triggered by the hair interface itself: "*They looked at me, but I think rather because I was holding a piece of paper and a device in my hands. If it had been a smartphone, it wouldn't have been noticed*" (P5). Our participants had different opinions about the extent to which such reactions matter and shape their perception of the interactions. So, some stated that they do not care about it at all, whilst others admitted that those reactions influence their feelings. "*It feels a little strange. The arm is hanging in the air. [The others might ask] 'What is he doing?'.*" (P3) P6 reported that she does not like others staring at her and consequently described her experience as unpleasant: "*Before entering the cafeteria, I expected that there would be many people. [This expectation] felt unpleasant.*" We conclude that for some users, the design of the interface and interactions is directly related to the perception of bystanders which influences the perceived comfort in wearing the hair interface. Similar observations were, e. g., made by Williamson et al. who found that even the expectation of drawing unwanted attention from bystanders is sufficient to prevent interaction in public places [100].

The Context-Dependent Nature of Perceived Appropriateness All participants appeared open to use a hair interface in a social situated context as long as it does not distract or involuntarily involves others. E. g., P5 mentioned that the use of the interface is uncritical if it is not linked to applications that involve others in case of false activations such as accidentally triggering phone calls. Whilst this could distort others that are not necessarily physically present, P1, a person who likes visiting concerts, was thinking about the risk to intrude others' physical space: "*I can imagine that it gets more uncomfortable the denser the crowd, because one has to move the arms around a lot. [. . .] One would distract others with that.*" Apart from that, participants agreed that the sensitivity to distraction depends heavily on the specific interpersonal situation. Particularly in situations where people are watching the user, participants stated that the interaction with a hair interface might feel very inappropriate. Here, inappropriate situations might comprise presentation-like situations but also very personal interactions. P4 reflected: "*In situations where one sits together at a table, talking, eating, it can be distracting watching the counterpart [interacting with an interface]. [. . .] If people don't pay attention to you, [if you are] sitting in the office or somewhere else, then no one is paying attention to the [interactions] or is triggered by you.*" Also the prevailing attitude of the audience to technology plays a role. P5 elaborated on that: "*I think among young people at university, [the technology] would not be a problem. [. . .] When being with the family, where everyone is paying attention how you behave, I could imagine [that the interaction with the hair interface is inappropriate].*" Two participants even stated that they would not want to wear the interface in front of (elderly) technophobe people as it would feel uncomfortable when being asked actively why they are interacting with their hair. That people perceive gestures as inappropriate in specific situations where it might interfere with communication or (physically) distracts others is a common problem in literature, e. g., also faced by Williamson and Brewster investigating usable gestures for the interaction with mobile interfaces [76]. Thus, this context-sensitivity should be respected during the design of technology.

Evoking Misinterpretations and Suggestiveness Some participants were concerned about hair-based interactions evoking misinterpretations of spectators. The majority of participants raised concerns to signal their counterparts in a personal conversation to be mentally absent when touching the hair: "*I want to give others my attention. And when my hand is [at my head], [...] I would feel like my counterpart is mentally absent.*" (P2) Other participants associated only particular gestures a social meaning: "*Twirl... the standard flirting gesture.*" (P2) "*If I start twirling my hair, it depends on the context, but I might not always want to demonstrate insecurity or playfulness.*" (P7) Another participant mentioned that *Doubletap* might hint towards a quirk if performed too often. Similarly, P7 explained: "*If there are people, you would feel more uncomfortable when having the hands in the hair for a long time. [...] I would perceive it as a hint towards scruffiness.*" On the other hand, there are disagreements in the individual perceptions of the participants. P3 stated: "*[These gestures] happen often enough in a usual context such that there are no suggested effects that emerge from the gestures*" (P3). Others thought that the misunderstandings only emerge from specific circumstances in which the gesture is executed, particularly being related to the degree of personal interaction between the user and the spectator. So, P5 and P6 stated that they would not care for suggestive effects when there are passers-by. Further: "*No matter if it is interpreted as flirting gesture or as being distracted, the probability for misinterpretations would be higher [in direct conversations, no matter who it is]. Not for larger groups.*" (P5). And P6 added: "*It depends on how you execute the gesture. When I am looking at you in a strange way, then it might appear [suggestive].*" Consequently, we observe that the extent to which a hair-based gesture might evoke misunderstandings depends primarily on the context in which it is performed whilst associated prevailing meanings of specific movements appear to play a secondary role only.

6.4.3 Hair Interfaces Enhance Interpersonal Interactions

Participants reported that hair interfaces do not only challenge but also enhance interpersonal interactions. These perceptions trace back to situations where it is desirable to hide interactions with technology or to support interpersonal touch.

Hiding Interactions From Others Participants found that the interactions appear unobtrusive and less distracting than screen-based ones. "*I think it is really appropriate. You do not perceive [the interactions]. For [...] parties, where there* *are bystanders, it is good that it is unobtrusive.*" (P2) Moreover, hair interfaces offer the possibility to unobtrusively call for help or decline calls in situations where people around you should not see that an interaction is happening. "*So, I am sitting in a meeting and signalling my colleague 'Get me out of here!' and then my smartphone sends the message.*" (P2) This generalizes to social situations where it would feel inappropriate or dangerous to take the smartphone out of the pocket: "*If it is integrated in your hair and you are on your way home alone, then you can send an emergency call through your hair. It is less obtrusive.*" (P7) Hence, a hair interface appears particularly suited for hidden interactions. A similar finding was also made during the evaluation of HäirIÖ, discovering that more than half of the study participants preferred the more subtle interactions, profiting from the embedded, ubiquitous nature of hair [24].

Enhancing Interpersonal Touch Due to the exposed position of the hair, other people can easily interact with the interface or get curious about it. So, P4 saw a chance in that: "*If [. . .] you have your hands busy [. . .], you can tell your counterpart 'Can you decline the call?' and [let them] press the interface.*" But she also raised concerns about the intimate meaning of hair: "*Of course, you wouldn't let do this everyone, but only close friends and family. [. . .] I wouldn't let any stranger touch my hair.*" On the other hand, P3 suggested to use it as communicating display with bystanders if visual output was integrated: "*[The interface] is exposed and one can see it far away. One can use it for external monitoring when you know what's up and also want to show it to others [. . .].*" Because or albeit hair is personal, hair interfaces tap into a potential to enhance interpersonal communication and collaboration. This was also discovered by Dierk et al. [24] and Li et al. [52] who proposed, e. g., to contrast a social network at parties through visual output or enhance interpersonal touch between friends.

6.4.4 Hair Interfaces Influence the User's Behavior

Participants disagreed on whether a Hair Interface affects usual hair interactions. Particularly participants who stated that they do not touch their hair frequently assumed that this would definitely not change their usual behavior. "*I do not use my hair for communication, so others would not start wondering what I am doing just because I am wearing the interface*" (P4). However, two other participants acknowledged that the hair interface would increase their awareness of hair and hair-based interactions. "*I would be more conscious of what I do with my hair and also how I style them, so whether it conforms to the action I plan to do with it.*" (P7) Similarly, P5 reflected: "*I would touch my hair more often than usual. [. . .] I would touch my hair more consciously.*" Thus, the influence of the hair interface appears to depend on the extent to which the hair is usually used during daily life.

6.4.5 Generalizability Challenges Hair Interfaces

Participants acknowledged that hair interfaces might lack generalizability. Their concerns arise from both the overall interface design and the design of gestures.

Limited Generalizability of the Design A majority of the participants mentioned that the design lacks generalizability to other hair cuts and structures, although not being affected themselves. They stated that the interface might be unsuited for extremely wavy or short hair: "*It's difficult to attach [the interface] unobtrusively to curly hair. It's also difficult for people with shorter hair to use it without being extremely noticeable. I think especially for men and women with very short hair it might not be possible at all, because they have nothing to which you can attach [the interface]. One could feel discriminated. It is just really only for the group of people having long hair.*" (P7) Consequently, hair cuts, styles, and structures should be considered during the design process of the physical prototype.

Limited Generalizability of Gestures Besides the perceived limits of the interface design, participants also acknowledged that the design of gestures is challenged for other hair types and styles: "*One cannot transfer all gestures 100% to other types of hair interfaces.*" (P4) There are gestures that do not have application for short hair as they are unnatural or infeasible to perform. On the other hand, also long hair challenges specific gestures: "*Twirling only works with medium or shorter hair. If the hair has the length of the back, then it no longer works. I can not twirl my hair so far down.*" (P1). Moreover, gestures might not generalize to beards: "*Beards are different from hair. They are not that flexible [. . .] and follow a specific form.*" (P3) Summing up, hair cuts, styles, and structures should not only be considered for the design of the physical prototype but also for the design of the gesture space.

6.5 Summary

In this chapter, we detailed on the design of a field study in which the participants gathered hands-on experience with FeatherHair in a social situated context. We analyzed the data and grouped them into usability (design and gestures) and social aspects. We found that hair interfaces appears particularly suited for hidden interactions, profiting from the integration of naturally-occurring hair-based interactions. These interactions (e. g., *Slide*, *Twirl*) were often preferred over artificially created ones (e. g., *Hold*, *Doubletap*) as the latter lack naturalness and unobtrusiveness. Moreover, we found that the perceived appropriateness of hair-based interactions in a social situated context is highly personal and context-sensitive. Whilst the interactions with a hair interface were often considered less distracting than screen-based ones, they might be prone to misinterpretations in personal conversations. In summary, we acknowledge that the appropriateness of a hair interface and hair-based interactions is dependent on the particular situation in which it is used and offers both chances and challenges in a social situated context.

7 Discussion

Identifying factors that shape the usability and perception of new technology is crucial as it helps to ensure a continued engagement of users in interacting with the prototype. In this chapter, we discuss incentives for the design of usable and socially acceptable hair interfaces, leveraging the findings of the user study of Chapter 6. We conclude with comments on the limitations of the thesis and how they might serve as starting points for future directions of research on hair interfaces and hair-based interactions.

7.1 Design Incentives

Design incentives serve as an initial starting point for the design of technology. We synthesize design incentives for hair interfaces and hair-based interactions based on the results of the previous chapter, covering thoughts on how to shape the wearing comfort and the perceived appropriateness of the interface. This is possible since the results of the study are based on realistic and profound opinions of our participants which could be developed as they were provided with hands-on experience with a functional prototype in a natural setting [1, 76]. We formulate design incentives in terms of four major design goals: Designing for wearability, designing gestures for hairwear, designing for diverse users, and designing for social context. Whilst the two former discuss design- and implementation-related aspects for the realization of a gesture-controlled hair interface (RQ1), the latter two are synthesized from the social tensions of hair interfaces (RQ2). We acknowledge that there is no 'ultimate' design for hair interfaces and that the aspects discussed in the following exhibit a complex interplay. By addressing these aspects, we suggest that a hair interface which shall be considered both usable and socially acceptable by its users can be neither a one-fits-all nor a general-purpose device.

7.1.1 Designing for Wearability

Wearability of on-body technology is important for the perceived comfort of the user and is influenced by various factors [32, 44]. In the scope of this thesis, we built a physical prototype that consists of soft feather hair extensions which are

attached to the hair through an elastic hair band and investigated its wearability. We identified several major aspects which increase the wearing comfort of a hair interface. These involve low weight, a flexible form factor, easy attachment, robustness, accessibility, and malleability. Whilst the feather extensions exhibit an appropriate lightweight and flexible form factor which merges with the hair and the elastic hairband is easily attachable to the hair, we discovered that particularly robustness, accessibility, and malleability were not perfectly realized in the design of our prototype. Thus, we suggest that a more robust but flexible material and an attaching form factor that sticks to the head more tightly are required to withstand daily strains such as combing or pulling clothing over the head sufficiently well. Accessibility can be improved by placing the hair interface at the upper foremost strain of hair such that the arm movement is kept minimal during interaction. Lastly, malleability of the hair interface is important since it is attached to an exposed body part which everyone can see. Consequently, its form factor should be flexible to adapt to several hair styles whilst its design should be modular such that the appearance can be dynamically changed according to the users' fashion requirements which might vary throughout the day. HäirIÖ is an example of such a malleable/customizable prototype as the individual braids can be swapped and customized w.r.t. color and shape [24].
Furthermore, we found that the desired natural haptic sensation of hair interfaces is in conflict with the required detectability of the interface in the hair. In consequence, as the naturalness of the interface makes it difficult to interact with the interface, the cognitive load and discomfort of interactions increases whilst the overall wearing comfort is reduced. The resulting trade-off between haptic unobtrusiveness and detectability in the hair is still an unsolved issue. But landmarks, such as the tiny beads integrated in FeatherHair, which are added to the interface at carefully selected locations, seem to be an initial starting point to overcome this burden because they can support the localization of the interface and provide guidance during gestural input [99].
Summing up, various (interrelated) aspects must considered to increase the wearing comfort of the hair interface whilst the natural haptics of the interface and detectability needs to be balanced simultaneously in order to find the optimum point between comfort, usability, and naturalness.

7.1.2 Designing Gestures for Hairwear

We implemented a gesture-controlled hair interface able to recognize five gestures (i. e., *Tap*, *Doubletap*, *Hold*, *Slide*, *Noise*). We found that for this particular application, person-independent gesture recognition is as feasible as a person-dependent one since the gesture characteristics exhibit variances both across and for individual users. Achieving accuracy rates between 86% and 92% on both validation and training sets with an SVM and a Random Forest, we suggest that conventional models are sufficient for our application, thus, not requiring more complex models like neural networks. Similarly to other work on hair interfaces [24, 94, 48], however, we find that an initial calibration step might be helpful to further boost the recognition performance as this improves the overall user experience of the

hair interface [75]. But since our collected calibration data was not useful, it is yet unclear to which extent and how calibration indeed affects the performance.
Furthermore, we found that hair-based gestures (e. g., *Slide*, *Twirl*) tap into a potential of natural body-based interactions and experiences. The naturalness that can be integrated in the design space of hair-based interactions reduces the obtrusiveness as well as the overall cognitive load for the user, making the interactions easier to learn [2]. However, the implementation of natural interactions simultaneously increases the system's proneness to false activations whilst also both natural and unnatural interactions risk to evoke misunderstanding for bystanders. Similar findings were, e. g., made for the design of gestures for the interaction with body-worn cameras [46] and as part of a generic study of user perceptions of novel multimodal interactions using gesture, speech, and non-speech sounds [75]. Based on suggestions of our participants, we propose to minimize false activations for natural hair-based interactions through force-sensitive sensing that requires users to apply more force to the prototype for conscious than for unconscious interactions. Whilst we consequently acknowledged the ineligibility of using capacitive touch sensing only due to its proneness to false activations in the previous chapter, we suggest that a hybrid combination similar to ours might help to overcome the shortcomings of individual sensing technologies. On the other hand, minimizing misunderstandings evoked by hair-based movements is yet an open issue to address. Here, the consideration of visual output, lighting up during interactions with the hair interface, might serve as an initial starting point for further investigations and elaboration. This suggestion traces, e. g., back to work by Williamson and Brewster who state that the ability to demonstrate that an action is part of technology positively alters the gesture acceptability [76].
Summing up, naturalness appears to be a desirable property for hair interfaces due to their unobtrusiveness at a very exposed position of the body but involves also many open challenges to be solved. Thus, during the design of gestures, it needs to be considered how close they can get to the optimum of naturalness whilst keeping the risk of misinterpretations and discomfort for both users and spectators minimal.

Designing for Diverse Users Users' individual hair styles, types, and cuts challenge a holistic one-fits-all design approach. We found that both the interface design and the implemented gestures do not generalize well to all types of users. E. g., curly hair might require another interface form factor than straight hair, long hair requires a different form factor than short hair, a twirling gesture might be neither suited for short nor for very long hair... Neglecting this lack of generalizability impacts the social acceptance of hair interfaces as it might alter the perception of the user in a negative way, particularly since the hair interface is attached to an exposed body location which everyone can see. For this reason, we propose to refrain from a generalizable design and opt for individual designs that account for the specific hair types and cuts, but also try to respect personal preferences. Similar argumentations against an one-suits-all design approach can be found in literature. So, e. g., Knibbe et al. discussed the problem of this approach for the

development of eTextiles [44] whilst Spiel explicitly calls for refraining from normative tendencies in the design of embodied interactions [85]. This also conforms, e. g., to findings by Himmelsbach et al. who analyzed diversity dimensions in research and stated that more awareness should be raised to diversity of users and their situatedness in a social context [38].
Furthermore, we learned from the experiments, that the personal preferences of the user for the design of hair interfaces and hair-based interactions are altered by the desired level of gesture and interface unobtrusiveness in order to avoid negative attention. This aspect is tightly interrelated to the fashionability of the hair interface since fashionability can boost the perceived unobtrusiveness of the interface if and only if the designed interface matches the user's preferences in fashion. Specifically, it appears infeasible to decouple the subjective fashion component from the design of the interface since the interface is visible to other people, thus, requiring it to match the user's external image. This conforms, e. g., to findings of Pateman et al. who argued that aesthetics is of importance in use and continued engagement of users [67] and Profita et al. discussing the chances of fashion-oriented wearables to decrease stigmatization [71].
Thus, during the design and development process, it needs to be considered which gestures and form factors are applicable for the targeted user group and how their fashion requirements match their desired level of unobtrusiveness.

Designing for Social Context Interwoven with the user's personal preferences for the design of hair interfaces and hair-based interactions is the importance of the social context in which the user interacts with the interface because it can influence the perceived appropriateness of technology. This suits, e. g., observations of Williamson and Brewster who demonstrated the influence of location and audience [76] and Uhde et al. discussing the influence of surrounding social practices on social acceptability [93]. For hair interfaces, we found that particularly the type of interpersonal interaction influences the perceived appropriateness of the interactions. Since playing with hair might signal insecurities or being absorbed in thoughts, users might completely refrain from using hair-based interactions in personal conversations. Except from these highly personal situations, hair interfaces appear particular suited for hidden interactions due to their natural unobtrusiveness. However, there are also situations in which obtrusiveness is desirable. E. g., if a hair interface aims for collaborative use and enhancement of interpersonal touch, visibility might be a first step to encourage others for interactions. The use of visual feedback for hair-based interactions in a social context was, e. g., proposed by Dierk et al. [24] and Ku et al. [52]. Similarly, Williamson et al. found that the ability to switch dynamically between the use of hidden or performative interactions is an important property for socially accepted interfaces that are supposed to support a variety of performances [100].
Alongside with the type of interpersonal interactions, the audience's general attitude to technology influences the perceived appropriateness of the hair interface [76]. During our experiments, we found that particularly a revealed interaction might feel inappropriate in situations where the audience is not yet familiar with

hair interfaces or exhibits a general skepticism against technology. On the other hand, previous literature hints towards the fact that both hidden and revealed interactions with an interface can increase the acceptability of bystanders [55], creating a trade-off between the desirability of unobtrusiveness and the requirement of visible interactions. In the context of hair interfaces, this is still an open issue which requires further investigations.
Summing up, during the design and development process, one should identify the primary social context (interpersonal interactions, audience) in which the interface is deployed and the concomitant required level of unobtrusiveness for both the appearance and hair-based interactions.

7.2 Limitations and Future Directions

In this work, we exemplified how to realize a real-time gesture-controlled hair interface and explored how users perceive its appropriateness in a social context. In the following, we outline limitations of this approach and motivate directions for future work.

7.2.1 Technological Limitations and Directions

Our prototype used hybrid sensing to detect touch-based interactions and implemented a generic application able of displaying recognized gestures. Furthermore, the gesture set was limited to a set of five gestures, leaving room for the implementation and evaluation of further touch sensing technologies, interaction types, and functionalities. Future work could go a further step forward, investigating the implementation and evaluation of hair interfaces that detect, e. g., deformations of hair or head movements.
Furthermore, as this work implemented input modalities only, there remains uncertainty about the integration and appropriateness of output modalities for hair interfaces which is also a crucial aspect due to the exposed position of the head. Consequently, future work could complement the findings of this work by investigating the appropriateness of output for hair interfaces. These output modalities could comprise visual, vibrotactile, and self-deforming hair form factors that communicate with the environment.

7.2.2 Design Limitations and Directions

The design of the hair interface was tailored towards long, straight head hair worn down. This design is not necessarily generalizable to other hair styles, cuts, and types. Thus, future work could consider the design of hair interfaces and hair-based interactions for a diversity of hair types, investigating how these differences influence the interaction and design incentives proposed in the scope of this thesis.

7.2.3 Socio-Cultural Limitations and Directions

We acknowledge that the results of the user study might be influenced by the presence of the experimenter and the technology that the participants were holding in their hands. Albeit hardly observing any bystanders' reactions, these factors could have changed their behavior, simultaneously influencing the perception of the participants.
Furthermore, the interface was designed with Western traditional hair styles in mind and evaluated with participants who grew up in Central Europe. This limits the generalizability of our findings and incentives to Western standards. However, it is yet unknown to what extent the perceived appropriateness of hair interfaces transfers to other cultures. This includes both appearance-related aspects as well as the design of gestures. Future work could take this up and investigate the role of culture in the perception of hair interfaces and hair-based interactions. This might include, e. g., cross-cultural field studies, focus groups, and expert interviews. The gathered insights, in turn, could be leveraged to design both socially and culturally accepted hair interfaces.

7.3 Summary

In this chapter, we synthesized the findings of the field study (c.f., Chapter 6) into design incentives that serve as an initial starting point for the design and implementation of hair interfaces and hair-based interactions that are considered usable and socially acceptable. The core aspects of the design process involve wearability, the implementation of natural interactions and both the derivation of design requirements for diverse users and specific social situated contexts. Finally, we reflected on limitations of this work and derived future directions for research on hair interfaces and hair-based interactions.

8 Conclusion

The goal of this thesis was to derive design incentives for gesture-controlled hair interfaces that are both usable and socially accepted to their users. With that, we aimed to address the gap of knowledge on the implementation and appropriateness of hair interfaces and hair-based interactions in a social situated context. We approached this objective in two steps.

First, we realized a proof-of-concept prototype capable of user-independent gesture recognition of five gestures. Evaluating several machine learning classifiers that were trained with the dataset created as part of a data collection study, we demonstrated that conventional models (i. e., SVM and Random Forest) are sufficient to reach accuracy scores above 85% for this particular application using both time series-based and statistics-based features.

Second, we leveraged FeatherHair to conduct a user study in the wild, providing participants with realistic hands-on experience in a social situated context. Since this enabled users to develop and report profound opinions about the interaction with a hair interface, we could identify both aspects relevant to the design of the physical prototype and hair-based gestures and aspects that contributed to a better understanding of prevailing social tensions of hair interfaces. These revealed, inter alia, the particular potential of hair interfaces for natural and hidden interactions and the dependency of the perceived appropriateness of both appearance and interactions on the targeted user groups, bystanders' reactions, and the social context in which the interface is used.

We synthesized our findings into four major design incentives which serve as initial starting point for the design of usable and acceptable hair interfaces and hair-based interactions. Alongside with multi-faceted design- and implementation-related aspects of wearability and gestural interactions which influence the usability of the interface, we drew attention to the social complexity of hair interfaces, emphasizing the need to design for diverse users and social context. As our physical and gestural designs were found to exhibit limited generalizability to hair types other than that of traditional Western hair, this indicates that hair interfaces are neither one-fits-all nor general-purpose devices.

In summary, this thesis provides in-depth insights into the design and implementation of gesture-controlled hair interfaces that are usable and socially acceptable. The work is embedded into a body of literature which contributes to the overall objective of making wearables less disruptive and more accounting for (body) diversity, interpersonal interactions, and cultural and social influences. Future research on hair interfaces will have to further address the socio-cultural dimension in order to design usable hair interfaces that are both socially and culturally acceptable.

A Polymerization

This appendix is referenced in Subsection 3.2.2.
To augment the feather extensions with electrical functionality, we used polymerization, a chemical process that lets conductive polymers form in and around the material's fibres. In the following, we first describe the polymerization process and then detail on two modifications of this process that we also tried in the scope of this thesis. We conclude with final remarks about the reliability of the polymerization process for natural materials.

A.1 Polymerization Process for Feathers

This section describes the polymerization process. It is closely linked to the procedure presented by Honnet et al. [40].

1. **Pre-treatment with 30% hydrogen-peroxide (H_2O_2)** *15 minutes*
   Cover the feathers with H_2O_2 to roughen the feather fibres. Stir them from time to time to ensure that all feathers get in contact with H_2O_2. After 15 minutes of soaking, pour the H_2O_2 away.

2. **Soaking in a pyrrole dilution** *25 minutes*
   Mix 6.25 ml pyrrole and 250 ml water. Let the mixture soak into the feathers for 25 minutes. Stir from time to time to ensure that all feathers soak it up.

3. **Polymerization** *30 minutes*
   Add 2.5 g iron (III) chloride powder to the pyrrole dilution. If the iron is clumpy, pulverize it before adding it to the mixture. Stir the oxidizing mixture regularly such that the polymers can form around all feathers evenly. The feathers should turn black during the process. After 30 minutes, pour away the mixture and rinse the feathers with cold water.

4. **Iterations** *3×45 minutes*
   Repeat step 2 (for 15 min) and step 3 (for 30 min) three times, such that the feathers run through four polymerization iterations in total.

5. **Rinsing and drying**
   Rinse the feathers with cold water and let them try.

Following this procedure, we reached a resistance within the $k\Omega$ range, with a mean of 0.5 $M\Omega$, and SD of 0.3 $M\Omega$ (including only feathers for which the polymerization was successful). We measured the resistance once for each feather with a multimeter on a distance of 10 cm.

A.2 Modifications

Due to limited resources, we made some experimental modifications of the given recipe. These are mentioned below and were documented for the transparency of this thesis.

A.2.1 Pre-Treatment with 3% H2O2

Some feathers were pre-treated with 3% H_2O_2 instead of 30% H_2O_2. Here, we doubled the soaking time to 30 minutes. The resulting resistance of the polymerized feathers did not differ from the ones pre-treated with 30% H_2O_2. However, it is subject to further investigation how this modification influences the extent to which the polymerized material stains.

A.2.2 Re-Polymerization

After the data collection study, we found that the conductivity of most feathers decreased substantially which made them unusable for further studies. Thus, we re-polymerized the feathers. In doing two further polymerization iterations as described in Section A.1, we could boost the conductivity of the feathers by pushing the resistance back into the $k\Omega$ range, with a mean of 0.6 $M\Omega$, and SD of 0.3 $M\Omega$. This indicates that re-polymerization of already polymerized objects is feasible, albeit we cannot exclude that this finding might be material-dependent.

A.3 Note on the Reliability of This Procedure

The success of this procedure might vary with the quality of the individual feathers, e. g., their surface texture, the way they were colored, ... There is no guarantee, that polymerization is equally successful for all feathers even if they were polymerized as part of the same batch. We have to keep in mind that these feathers are nature products, making no pair of feathers completely identical. For that reason, it might be advisable to first test the overall suitability of the feathers for polymerization with a first iteration before continuing with the remaining three iterations. Also the extent to which the polymerized feathers stain off and, in turn, the extent to which they lose conductivity over time might vary. Consequently, it might be necessary to adjust the procedure for different types of feathers, e. g., increasing the number of iterations until the sweet spot for the conductivity of the polymerized feathers is reached.

B Informed Consents & Co.

In this chapter, we provide an overview of the informed consents, questionnaires, and questions which we used for the data collection and the field study.

B.1 Data Collection Study

This appendix is referenced in Subsection 4.2.1.
In the subsequent two pages, we show the informed consent and questionnaire used for the data collection study ("*Study for Detecting Gestures with Polymerized Feather Hair Extensions*").

B.2 Field Study

This appendix is referenced in Subsection 6.1.2.
After the informed consent of the data collection study, we show the informed consent and questionnaire used for the field study ("*Walking Conversations on Hair Interfaces*"). Finally, we list the interview questions that were asked during the walking conversation.

STUDY FOR DETECTING GESTURES WITH POLYMERIZED FEATHER HAIR EXTENSIONS

Welcome
Thank you for participating in our study.
I am Marie Mühlhaus (Master's student at Human-Computer Interaction Group, Saarland University, Germany), together with Marion Koelle, we are conducting a study with the goal to collect enough sensoric data required to recognize hand movements, otherwise known as gestures, while interacting with hair adorned with feather hair extensions.

Procedure
We will present you with a demonstrator wearing the feather hair extensions and a wearable prototype which you are asked to clip into your hair. We would request you to perform gestures on these two protoypes, such as sliding and tapping. The hand movements are captured through the prototypes via the measurement of changes in its capacitive and resistive properties. The study will approximately take around 60 minutes, and you may request breaks during the session.

Data Management
The resistive and capacitive data will be continuously recorded.
We additionally measure hand dimensions and ask you for specific information related to your hair and your hand and its motor skills. We pseudonymize the study data by giving a unique ID to each participant for storing the sensor data. We intend to report and publish the collected data for academic research purposes. We will report them in an anonymized fashion such that it does not contain any information about the participant's identity

Compensation
You will receive a chocolate bar as compensation for your participation in the study.

Safety Instructions

- As a safety measure due to current COVID-19 situation, we sanitize the objects and our hardware setup after every participant's trial. Additionally, we request you to wear the face mask throughout the study.
- If you want to take a break at some point, feel free to ask.
- If anything is unclear to you, please ask us at any point in the study.

By signing this document, I agree to participate in the described procedure, and I confirm that I received all
necessary information and the compensation (one chocolate bar).

Name:____________________________________

Contact:__________________________________

Signature:_________________________________

Place & Date-time:____________________________

Participant ID (to be filled out by the researcher):________

Basic Information

- Age: ____
- Gender:______________________________________
- Profession:__________________________________
- Things I regularly do with my hands (e.g., gardening, playing an instrument, painting, crafting):
  ____
  ____
  ____
- I use the following hand care products:
  ____
  ____
  ____
- Today (before the study), I used the following hand care products:
  ____
  ____
  ____
- The length of my hair is
  O shorter than shoulder long
  O at least shoulder long
- The structure of my hair is
  O straight
  O curly
- I am
  O left-handed
  O right-handed
- Today (before the study), I used the following hair care products (e.g., hair spray, conditioning oil):
  ____
  ____
  ____
- Distance (mm) from the wrist to the tips of:
  - thumb:_______________
  - index:_______________
  - middle:______________
  - ring:________________
  - pinky:_______________

WALKING CONVERSATIONS ON HAIR INTERFACES

Welcome
Thank you for participating in our study.
I am Marie Mühlhaus (Master's student at Human-Computer Interaction Group, Saarland University, Germany), together with Marion Koelle, we are conducting a study with the goal to examine practical aspects of hair interfaces, with a particular focus on the appropriateness of gesture-based hair interactions in a socially situated context.

Procedure
Together we will walk a designated route around campus. During this guided walk, we will ask you to wear our prototype in your hair. In the first half of the walk, we would request you to perform prompted gestures on this prototype at specific locations of the route. After each execution of the gesture, we will discuss in a conversation-like manner your perception of the interaction with the prototype, e.g., the perceived appropriateness of the interaction in the prevailing social context, factors that influenced this perception, etc. In the second part of the walk, you can freely explore the interaction with the prototype. After the walk, we will ask some final questions regarding your thoughts about hair interfaces in practice. The study will approximately take around 60 minutes in total, and you may request breaks at any time.

Data Management
- We ask you to provide demographic information in the subsequent questionnaire. We pseudonymize the provided data by giving a unique ID to each participant such that it does not contain any information about your identity.
- Conversations will be audio recorded for transcription. After transcription, but no later than on 31/12/2022 all audio files will be deleted. You may request the deletion of your audio recording at any time.
- We intend to report and publish the collected data for academic research purposes. We will report them in a pseudonymized fashion such that it does not contain any information about your identity.

Compensation
You will receive a chocolate bar as compensation for your participation in the study.

Safety Instructions
- As a safety measure due to the current COVID-19 situation, we request you to follow the 2G+ rules. Also, it is necessary to wear a mask whenever we enter a building or if we cannot maintain a distance of 1.5m to each other or to other people around us (also outside).
- If you want to take a break at some point, feel free to ask.
- If anything is unclear to you, please ask us at any point in the study.

By signing this document, I agree to participate in the described procedure, and I confirm that I received all necessary information and the compensation (one chocolate bar).

Name: ____

Contact: ____

Signature: ____

Place & Date-time: __________________________________

Participant ID (to be filled out by the researcher): ________

Basic Information

- Age: ________________________________
- Gender: ______________________________
- Nationality: __________________________
- Profession: ___________________________
- I am
  O left-handed
  O right-handed

B.2.1 Interview Questions

We list the questions asked during the field study with the hair interface below. During the study, these questions were not asked in this specific order but integrated in the conversation as suited.

Introductory Questions These questions were asked to uncover person-specific attitudes towards hair:

- Would you say that you are eager to try out things with your hair? If yes, what did you do? What is your expertise on hair dye, styling, extensions?
- Which aspects of your hair do you care about when being in public?

Interface-Related Questions Each of the below listed questions is associated with at least one of the three parts of the walking route (c.f., Figure 6.2). Several questions (4, 5, 6) were asked repeatedly after each execution of a gesture.

1. What do you think about the interface appearance, e. g., about its size, style? How does it fit your requirements? (Part 1)
2. How does the interface merge with and feel in the hair? How does it fit your requirements? (Part 1)
3. How easy was it to learn the gestures? How intuitive are they? Do the gestures feel (un)natural (in comparison to how you usually interact with your hair)? (Part 1)
4. How challenging is it to perform them whilst walking, whilst walking down the stairs, whilst crossing the street? How much attention does the interaction require? (Part 1, 2)
5. Which problems occur while executing the gestures? What causes these problems? (Part 1, 2)
6. How (confident) do you feel performing these gestures? Which factors influence this feeling (i. e., in which situations does it feel (in)appropriate, are there specific gesture styles that feel better than others) and why? (Part 1, 2)
7. Are there any specific situations in which it feels particularly (in)appropriate using the interface? (Part 2)
8. What would you do differently if you were the one that designs the hair interface? Are there gestures that you would not want to include? Are there gestures that should be included? Or is there another preferred way of interaction with hair in public? (Part 3)
9. How might the use of a hair interface change your usual behavior with your hair? (Final questions)
10. In comparison to interactions with screen-based devices such as smartwatches or smartphones, which benefits and drawbacks do you see in using a hair-based interface? Do you see any risks in using a hair interface? (Final questions)

C Participants

This appendix is referenced in Subsection 4.2.1.
Below, we report background on the participants of the data collection study in a pseudonymized fashion. Table C.1 lists the participants' hand dimensions. Table C.2 provides an overview of basic demographics and hair-specific characteristics and Table C.3 lists information which might give insights into the motor skills of their hands.

	Finger Length (mm)				
Participant	Thumb	Index	Middle	Ring	Pinky
P1	60	86	93	84	67
P2	65	94	107	102	72
P3	60	87	97	90	69
P4	62	94	102	96	76
P5	71	98	117	105	87
P6	71	101	115	113	90
P7	64	94	101	96	78
P8	51	77	77	73	60
P9	57	92	98	92	70
P10	54	79	82	81	65
Mean	61.5	90.2	98.9	93.2	73.4
SD	6.6	7.8	12.8	11.9	9.5

Table C.1: Finger measures of users who participated in the data collection study. We manually measured the hand dimensions of participants following the BigHand2.2M approach [106].

Participant	Characteristics					
	Age	Gender	Profession	Hair at least shoulder long	Curly hair	Hand Care Products Used
P1	60	f	caregiver	no	yes	no
P2	70	m	retired (former pharmacist)	no	no	no
P3	11	m	pupil	yes	slightly	no
P4	24	f	student (law)	yes	slightly	no
P5	76	m	retired (former teacher)	no	no	yes
P6	23	m	student (CS)	no	slightly	no
P7	23	m	student (mediainformatics)	no	no	no
P8	12	f	pupil	yes	no	no
P9	17	f	pupil	yes	no	no
P10	23	f	PhD candidate (CS)	yes	yes	yes

Table C.2: Basic demographics and hair-based characteristics of the participants.

Participant	Hobbies related to hand motorics
P1	Frequently: painting and gardening, infrequently: playing piano and harp
P2	None
P3	Gaming, writing, playing flute
P4	Writing, lettering
P5	Gardening
P6	Writing on the computer
P7	Gaming
P8	Frequently: writing, infrequently: crafting
P9	Writing, painting
P10	Frequently: tinkering and crafting, infrequently: playing piano and crocheting

Table C.3: Further hand-related characteristics of the participants which give insights into their hands' motor skills.

D Naming Convention

This appendix is referenced in Subsection 4.3.4.
We stored the dataset in the GitHub repository[1]. Each sample of the dataset is stored in an individual .csv file and conforms with the following naming convention:

<participant>_<gesture>_<condition>_<repetition>_cut.csv

E. g., the file named P1_tap_demonstrator_1_cut.csv contains the data of the first *Tap* sample of participant P1 performed on the demonstrator. The data is stored in the following format:

```
1:      Time (sec), Resistance, Capacitance,
        Baseline (Resistance), Baseline (Capacitance)
2:      0.0, <res.#1>, <cap.#1>, <res.  baseline>,
        <cap.  baseline>
3 - X:  ...
X + 1:  <end time>, <res.#X>, <cap.#X>, <res.  baseline>,
        <cap.  baseline>
```

[1] Access the dataset from the GitHub repository: https://github.com/zitos97/FeatherHair/tree/main/Dataset

E Libraries

This appendix is referenced in Subsection 5.2.1 and 5.3.1.
Below listed are the versions of the libraries used for the implementation of the Jupyter notebook codes. We cannot guarantee a proper working code execution if other versions are used.

- `Python 3.8.3`
- `Numpy 1.19.5`
- `Pandas 1.3.0`
- `Seaborn 0.11.2`
- `PyWavelets 1.1.1`
- `scikit 1.0`
- `tslearn 0.5.2`

Jupyter Core Packages

- `IPython 7.28.0`
- `ipykernel 6.4.1`
- `ipywidgets 7.6.5`
- `jupyter_client 7.0.3`
- `jupyter_core 4.8.1`
- `qtconsole 5.1.1`

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