Multi-Factor Authentication based on Movement and Gesture

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Zusammenfassung

Sicherheit und Usability sind zwei Seiten derselben Medaille. Je sicherer und aufwendiger eine Sicherheitsmethode (z. B. Authentifizierungsmethode) implementiert wird, desto benutzerunfreundlicher wird sie, wie bei der Nutzung von Chipkarten anstatt einfacher Passwörter zu beobachten ist. Ferner meiden Nutzer die Anwendung von komplexen Sicherheitsmethoden. Dieses paradoxe Verhalten führt letztlich zu weniger Sicherheit.

Das Hauptziel dieser Arbeit ist, neuartige Verfahren für Authentifizierungsprozesse zur Verfügung zu stellen, um die Sicherheit und die Handhabbarkeit dieser Prozesse zu verbessern. In dieser Arbeit werden dafür drei Verfahren vorgestellt, die basierend auf Signalerfassung von verschiedenen Sensoren in mobilen Geräten oder zusätzlichem Zubehör eine geeignete Nutzersignatur zwecks Authentifizierungsprozess extrahieren.

Das erste Verfahren „*Authentication Based on Movement and Audio Analysis*" nutzt den eingebauten Bewegungssensor und das Mikrofon (Erfassung von Umgebungsgeräuschen, die bei Nutzerbewegungen entstehen) eines mobilen Gerätes zum Extrahieren eines eindeutigen Musters, das dem Bewegungsverhalten eines Nutzers entsprechend (z. B. beim Laufen) erzeugt wird. Diese Signatur wird dann zur kontinuierlichen und impliziten Autorisierung verwendet.

Das zweite Verfahren „*MagiTact*" nutzt den eingebauten Magnetometersensor (Kompass). In diesem Verfahren kann der Nutzer mithilfe eines externen (permanenten oder elektrischen) Magneten das natürliche elektromagnetische Feld um das Gerät verändern. Diese Veränderungen werden durch Verfahren der künstlichen Intelligenz so interpretiert, dass der Nutzer durch eine dreidimensionale Geste in die Luft eine eindeutige Signatur zwecks Autorisierung erzeugen kann.

Das dritte Verfahren „*Pingu*" verwendet eine neue Hardware in Form eines Fingerringes, die auch alle typische Sensoren von mobilen Geräten (Bewegungssensor, Gyroskop, Magnetometer) in sich integriert und mit Berührungssensor und Bluetooth-sensor zur Verbesserung der Bedienbarkeit und Verbindung mit anderen Geräten wie dem PC erweitert wird. Die neue Hard-

ware erlaubt die Implementierung und Verbesserung der Methoden gestenbasierter Authentifizierung aus den zuvor vorgestellten Verfahren.

Ferner werden in dieser Arbeit als Basis für die oben genannten Verfahren die allgemeinen Gestenerkennungsmethoden und der Einfluss auf Gestendesign bzw. Applikationsdesign sowie auf die Nutzerinteraktion diskutiert.

Abstract

Security and usability are in constant touch with each other. It is in the nature of security methods that, the more secure they are, the more they complicate interactions. Yet users dislike using complex interactions, particularly frequent ones such as unlocking a mobile phone for calling.

The primary goal of this work is to provide novel engineering methods for the authentication process in order to improve the relationship between security and usability. Therefore, this work introduces three methods: "Authentication Based on Movement and Audio Analysis, "MagiTact" and "Pingu." The first two approaches focus primarily on mobile devices since they use sensors embedded in them such as accelerometers, gyroscopes, and magnetometers for recognizing movement and gestures. The third method introduces a self-designed finger ring with the same sensors, which enables users benefit from gesture-based methods on non-mobile devices. Furthermore, the ring includes a touch sensor for improving interactions, an LED and force sensor for feedback and a Bluetooth sensor for connectivity to other devices like a PC. This work additionally explores the impact of interaction design on implementing gesture-based methods.

The first method, Authentication Based on Movement and Audio Analysis, is intended to aid in extending security functionalities on mobile handsets and presents our research results concerning both the analysis of movements in addition to the ambient audio signals captured by mobile devices. This method presents how the identity of a user can be verified by his or her mobile device based on the pattern of his or her regular physical activities such as walking. This allows for implicit and continuous re-identification of the user. The implicit process does not

require the active participation of the user and allows authentication during regular daily activities [1].

Magitact proposes a new approach for the "around device interaction" based on magnetic field interaction. The new approach takes advantage of the digital compass embedded in the new generation of mobile devices. The user movements of a suitably shaped magnet around the device deform the original magnetic field. The magnet is taken or worn around the finger. The changes made in the magnetic field pattern around the device constitute a new way of interacting with the device. The mobile device samples the temporary status of the field. The field changes, caused by hand gestures, are used as a basis for sending interaction commands to the device. We have tested the proposed methodology for a variety of applications such as interactions with the user interface of a mobile device, character (digit) entry, user authentication, gaming and touchless mobile music synthesis [2].

Pingu presents a self-designed finger ring with a multi-sensor for providing a highly secure access system. It allows users to make a 3D signature and record the temporal pattern of the signature via an advanced set of sensors. As a result, the user creates a 3D signature in the air using his or her finger. This approach has two main contributions: (1) compared to other wearable devices, a finger ring is more socially acceptable, and (2) signatures created via a finger in the air or on a surface leave no visible track and, thus, are extremely difficult to forge. In other words, a 3D signature allows much higher flexibility in choosing a safe signature. The experiments with this ring illustrate that the proposed hardware and methodology could result in a high level of user authentication/identification performance [2, 3].

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Glossary

ADI	Around Device Interaction
ANOVA	Analysis of Variance
ASCI	Advanced School for Computing and Imaging
ASG	Acceleration Sensing Glove
ATM	Automated Teller Machine
ATT	Attractiveness
AUC	Area Under the Curve
BDT	Binary Decision Trees
BTAS	Biometrics Theory, Application and Systems
CAPTCA	Completely Automated Public Turing test to tell Computers and Humans Apart
CISIS	Complex, Intelligent, and Software Intensive Systems
DC	Direct Current
DOF	Degree of Free
DSP	Digital Signal Processor
DTW	Dynamic Time Warping
FFT	Fast Fourier Transform

FP	False Positive
GPS	Global Positioning System
HAVE	Haptic Audio-Visual Environments and Games
HCI	Human Computer Interaction
HQ	Hedonic Quality
ICB	Conference on Biometrics
IJCB	International Joint Conference on Biometrics
IR	Infrared
ISWC	International Symposium on Wearable Computers
MBR	Measurement-Based Recognition
MLP	Multi-Layer Perceptron
NB	Naïve Bayes
NN	Neural Networks
PDA	Personal Digital Assistants
PIN	Personal Identification Numbers
PQ	Pragmatic Quality
ROC	Receiver Operating Characteristic
SOUPS	Symposium on Usable Privacy and Security
SVM	Support Vector Machines
T-Labs	Deutsche Telekom Innovation Laboratories

TP	True Positive
WLAN	Wireless Local Area Network

Chapter 1
Introduction

Since the invention of information technology, we have been facing authentications issues. Depending on the required level of security, each authentication method has its strengths and weaknesses. In general, these methods require parameters such as user ID, password, tokens or biometrics, which are termed "authenticators" in this work. Authenticators can be categorized into three groups: “what you have” (e.g., tokens and chip cards), “what you know” (e.g., passwords and pins) and “what you are” (e.g., fingerprint, voice, and iris) [4].

In general, the complexity of an authentication method increases with security requirements. At the same time, usability and acceptance decrease in relation to complexity. Obviously, it is not only the required level of safety that determines the implementation of the authentication method but also user acceptance and usability. For instance, protecting mobile devices such as mobile phones or Personal Digital Assistants (PDAs), which we use frequently for short tasks like checking messages and appointments, with a password is annoying. This fact is the main reason why Personal Identification Numbers (PIN) are barely used on mobile devices.

“Convenience often trumps security, especially if nothing enforces certain policies” [5]. The same argument can also be applied to other means of authentication such as fingerprints [6], face profiles [7], and voice-based verification [8]. All these approaches are sporadic and therefore vulnerable to attacks, e.g., an unauthorized user can access the device either by stealing a password or exploiting an open account of an authorized user [9].

The purpose of this work is to present new authentication methods, identifying a person particularly in the category of “what you are” without using insecure biometric authenticators. This work additionally investigates usability engineering aspects. This means that we introduce new authentication methods which can be used for better usability. As we want to investigate usability issues, we also explore many other use cases based on gestures in order to additionally consider the usability of gesture-based interaction in general. We

believe that the usability of gesture and movement-based authentications will increase provided that the user accepts such methods for other applications (e.g., gaming, navigation and book reading) as well. This is the reason for exploring the general gesture-based interaction framework in this work.

The current work primarily introduces three methods for user authentication:

1. Gestures, movement, and audio based authentication (Chapter 2)
2. MagiTact-based authentication (Chapter 3),
3. Pingu-based authentication (Chapter 4).

1.1. Authentication Based on Movement and Audio Analysis

The first method introduces an authentication method based on movement and audio analysis. The primary motivation of this research is to find a convenient authentication method for frequently used mobile devices such as cell phones. We were initially motivated based on our experience in the Deutsche Telekom Laboratories (T-Labs) project: "Activity Based Verification" [10], in which users' typing behavior patterns were used for continuous verification of the user on PC [11]. Therefore, we were interested in a similarly applicable method for such ongoing verification on mobile devices. With this in mind, the idea of our colleague, Mr. Ulrich Heister, of "using walking patterns for user verification" and the, at that time, recent research results of Dr. Hamed Ketabdar concerning monitoring activity with mobile phones [12–14] directed us to the idea of recognizing walking patterns. Walking patterns were detected based on the phone accelerometer sensor to achieve continuous verification. Later, during the experiment, we improved the method by using additional data from ambient audio.

The next chapter "Authentication Based on Movement and Audio Analysis" also introduces the fundamental research's results of analyzing movements and ambient audio captured by the mobile handset for extension the security functionalities of the device. In the same chapter, several scenarios are presented to depict security threats related to data or services on mobile devices (e.g., a phone being lost or stolen). The experiments demonstrate how unexpected movements or ambient audio captured by the device can deliver information which can be substantial for considering security issues. In addition, we present how the identity of a user can be verified (or identified)

by his or her mobile device based on the patterns of his or her regular physical activities such as walking. This allows implicit and continuous re-identification of the user. The implicit process does not require the active participation of the user and allows continuous verification during normal daily activities. The suggested method can also be used to enhance conventional authentication techniques to protect, for example, an open account on a mobile phone. It can also help to reduce the number of re-authentications required by verifying that the same user continuously operates the mobile device since the last regular authentication. Our final goal is to devise a correlation model describing the relationship between the ambient audio of a mobile device as well as movements, and security related issues[1][16].

1.2. MagiTact

The next method investigated, referred to as MagiTact (magnetic interaction), is a novel technology based on the embedded compass sensor in mobile devices. As early as during our research work on movement and audio analysis methods, where the sensor data of cell phones were processed, we had the idea to experiment with the embedded compass data as an additional feature. We realized that it is more efficient to affect the compass data via an external permanent or non-permanent (electrical) magnet to create a magnetic pattern. In consequence, the idea of MagiTact was born.

At that time (2009) the theory of "around device interaction" (ADI) had already gained a lot of attention in the field of human-computer interaction (HCI). As an alternative to the classic data entry methods, such as a keypad and touch screen interaction, ADI proposes a touchless user interface that extends beyond the peripheral area of a device. For this reason, the MagiTact technique was proposed as a new approach for around mobile device interaction. MagiTact takes advantage of magnetic field changes in the vicinity of the device. The magnet is taken or worn around the finger. The changes made

[1] *This idea has been patented by Deutsche Telekom AG* [1]. *Furthermore this method has been presented in ACHI 2011* [15] *and won the best paper prize.*

in the magnetic field pattern around the device constitute a new way of interacting with the device. Thus, the magnetic field encompassing the device plays the role of a communication channel and encodes the hand/finger movement patterns into temporal changes sensed by the compass sensor. The mobile device continuously samples the temporary status of the magnetic field. The field changes, caused by hand (finger) gestures, are used as a basic pattern for sending interaction commands to the device. The pattern of change is matched against pre-recorded templates or trained models to recognize a gesture [2, 17].

This thesis introduces how the proposed methodology has been successfully tested for a variety of applications such as interaction with the user interface of a mobile device, character (digit) entry, user authentication, gaming, and touchless mobile music synthesis. The experimental results reveal high accuracy in the recognition of simple or complex gestures in a wide range of applications. Requiring only an internally embedded sensor and a magnet, the proposed method provides a practical and straightforward framework for touchless interaction with mobile devices [2].

The basic idea and technology is introduced at the beginning of the chapter, followed by an exploration of corresponding recognition methods. Before starting with the experiments on authentication methods, we ran several initial interaction tests in gesture recognition and alternative methods for digit/letter entry. With these experiments, the power, user acceptance and gesture recognition accuracy of MagiTact were demonstrated [18–20].

After these tests, we ran authentication-specific trials, where the user signature an arbitrary hand movement in the air such as the writing of a name is recorded as a 3D magnetic pattern. We also introduced algorithms in order to provide reliable user identification/verification. We found that we can reach a high accuracy by a true positive rate of 95% and false positive rate of 0.3% [2, 21, 22].

Finally, we indicate that the application design has a high impact on the accuracy, user acceptance and usability of the MagiTact technology.

In order to prove the usability of MagiTact, three use cases in music and gaming are introduced based on simple gestures. In these experiments, we

limit the gesture recognition only to the detection of a simple triggering movement with a permanent magnet. For these experiments, the help of graphical user interface experts was used for running supervised user tests, in order to measure user satisfaction with these applications. We also prove that well-designed applications, even with simple triggering interactions, increase usability. This proof was examined in long-term user experiments based on the gaming and music applications mentioned above [2, 15].

Furthermore, we demonstrate how we can simulate 3D mouse interaction without extra hardware, by using only the impact of visual feedback on users. We illustrate that, with this simple design element, users can adapt the device's behavior to simulate mouse functionality.

1.3. Pingu

Though we extended the MagiTact concept to non-mobile devices such as car navigation, door access devices or signature recognition for payment, we realized that the limitation of the interaction distance of this method also restricts the use cases of MagiTact. MagiTact's interaction radius is limited to 30 centimeters using a magnet with an acceptable size and interaction accuracy. As a consequence, we considered an alternative technology to overcome this drawback. We planned to develop a new technology combining most of the significant advantages of the previous approaches. We quickly realized that none of the hardware used can support the combination of methods based on accelerometers, magnetometers and proximity sensors. In order to fulfill all requirements, we decided to design new hardware for this sensor combination, which is wearable and also enables reliable touchless interaction. Thereby, the idea of Pingu was born.

Pingu is the third method introduced in this thesis regarding touchless interaction and authentication. Pingu is a new ADI input device in the form factor of a finger ring that allows users to interact with any nearby computing device with wireless connectivity in a ubiquitous environment. The ring form factor was chosen for our prototype design because it is socially acceptable and is commonly worn in everyday social contexts. Based on previous research, the information entropy of interaction by fingers is greater than the

entropy for any other parts of the human body. The current Pingu prototype consists of a composure set of sensors with visual and vibrotactile feedback mechanisms enabled with wireless connectivity which makes it a unique input device for human-computer or human-human interaction in the form of gestures, tactile and touch. Its usage can range from advanced, tiny and novel gestural interactions with a variety of devices, to mobile and networked sensing, and social computing [23].

In the first step, we introduce the necessary hardware technology and a few potential use cases of Pingu such as social interaction, context recognition, in-car interaction, and physical activity analysis[23]. In the next step, we focus on general gesture feasibility, and present the results based on experiments exploring Pingu's use as a general gestural interaction device. Our analysis, based on simple machine-learning algorithms, reveals that simple and sharp gestures performed by a finger can be detected with high accuracy, thereby establishing Pingu as a wearable ring to control a smart environment effectively [24].

Finally, this work proves the usability of our multi-sensor based standalone finger ring, which represents a highly secure access system. This authentication method allows users to make a 3D signature and record the temporal pattern of the signature via an advanced set of sensors. As a result, users can create a 3D signature in the air using their fingers. This approach offers two principal contributions: first, compared to other wearable devices, a finger ring is more socially acceptable; second, signatures created via a finger in the air or on a surface leave no visible track and are thus extremely problematical to counterfeit. In other words, a 3D signature allows much higher flexibility in choosing a safe signature. The experiments introduced in this thesis confirm that the proposed hardware and methodology could result in a considerable level of user authentication/identification performance [3, 24].

1.4. Thesis Structure

This thesis is organized as follows: The subsequent chapters introduce the technologies mentioned above and their specific experiments to explore the technical issues and usability aspects. Firstly, the underlying technology is introduced followed by experiments regarding the essential features analysis and their feasibility in their particular environment. Lastly, we present the

final experiments for the authentication use case with each specific method. The related works for each technology are embedded in their own chapters.

Chapter 2
Authentication Based on Movement and Audio Analysis

The primary results of this work have been presented in [1, 16, 25].

Mobile devices are one of the essentials in our daily life, used for communication, storage, and service access. As mobile devices' technology develops, they are increasingly employed in storing data, text, audio, photos, etc. Some of this data can obviously have private or confidential content. Also, mobile devices are also becoming a gateway to connect with many different services such as email, e-banking, etc. Most of these services can also be related to business or other private and confidential aspects of a user's life. Unfortunately, there is always a risk that these sensitive data or services are exposed to unauthorized people, for instance when a mobile phone is lost or stolen [1].

If a person left his or her PDA or smartphone in a cab, a power-on password would prevent anyone who found it from casually browsing content, making calls, and using email accounts. However, passwords can be shared, guessed, or stolen. Enforcing minimum password length and complexity rules can make password authentication more efficient, but they do not improve usability. In contrast to laptops, PDAs and smartphones are used far more frequently and for much shorter tasks, demanding near-instantaneous availability. Authentication methods that obstruct using these frequently used shorter tasks are disabled. This is the principal reason why PINs are unused on mobile devices. Convenience often trumps security, especially if nothing enforces policy [5]. We can also apply the same argument to other means of authentication such as fingerprints [6], face profiles [7], and voice-based verification [8]. All these approaches are intermittent and therefore susceptible to attack, e.g., an unauthorized user can access a portable computer either by stealing a password or exploiting the open account of a user [1, 9].

In this chapter, we propose a new paradigm for increasing the security of data and service access on mobile devices based on an analysis of the physical activity and audio signals captured by the mobile device. The new paradigm enables the online, implicit, and continuous protection of data without involving the active user's attention. We demonstrate that the analysis of physical activity (movement) and audio signals captured by a mobile device can indicate an anomalous situation which can lead to having the device being lost or stolen. We also illustrate how an analysis of audio and movement signals during a user's regular physical activities (e.g., walking) can allow user authentication based on movement patterns. The suggested method is an implicit authentication process, i.e., it does not need the active user's attention, and is performed continuously while the user is regularly using or carrying the device [16, 25]. The accelerometer sensors and microphones embedded in modern mobile devices can capture the physical movements and audio data. Such a paradigm can be used to increase the security of data and service access on mobile devices as either a standalone technique or complementary to conventional authentication methods. It can, for instance, protect an open account from an unauthorized user. Furthermore, as a complement of conventional authentication techniques (e.g., PINs, signatures, fingerprints), the number of regular re-authentications can be reduced if our method detects that the same user has been continuously using the device. Moreover, the implicit security protection process can be used to implement a "Graded Security" scheme for data and service access. In this system, a safety-level score is calculated based on the outcome of audio and movement analysis so we can stabilize different access policies according to the level of security calculated. This scheme allows protecting data and services according to their importance and the security threat level of the mobile device.

In this chapter, we demonstrate two cases related to audio and movement analysis for enhancing the security functionalities in mobile devices. The first use case is detecting unexpected events which can lead to having the mobile device being lost or stolen. This might be, for instance, a situation in which a phone falls accidentally out of a user's pocket/bag and remains unattended. The second case is using audio and movement analysis for user identification/authentication. In this case, we use movement and audio data captured during the physical activities of the user as a basis for his or her

identification. We discuss the first use case in Section 2.2, and the second use case in Section 2.3.

2.1. Analysis of Movement and Audio Data

Information about the movement of the mobile device is obtained by an analysis of data provided by integrated acceleration sensors originally used for automatic screen rotation and navigation [26–28].

Acceleration sensors integrated into a mobile device provide linear acceleration information along the x, y, and z directions. The acceleration sensed by the mobile device can be due to different sources. In this work, we are principally interested in components of acceleration caused by the physical activities of the user, or unexpected events such as free falls and impacts. According to our experiments, these elements usually appear in the high-frequency content of acceleration signals. Lower frequency components can be due mainly to gravitational force, as well as the movements of a user in a vehicle. In most of the cases, we pre-process the acceleration signals with a time derivative operation which acts as a high pass filter. Audio data is also captured using the microphone embedded in the mobile device.

In order to analyze data captured by the accelerometer or microphone, we usually extract several features from the data in certain time intervals (windows). These features are based on the average, variance, and rate of change of the recorded signals in the interval. For instance, the average of the norm of the acceleration signals (along the x, y, and z directions) in a time interval can indicate the level of the device's physical movement during the interval.

2.2. Detection of Anomalous Events

Abnormal events experienced by a mobile device can imply security threats. In this section, we review a few unexpected scenarios (Figure 1) which can lead to security risks related to mobile devices. We further discuss how these situations can be detected based on the analysis of captured motion and audio information using the sensors and the microphone embedded in a cell phone.

We start with a simple but practical case: a cell phone accelerometer has not detected motion for a relatively long period, which might be an indication of a lost or forgotten device. This situation may result in a security risk for data or services accessed by the phone. We can identify such a situation by analyzing motion data captured from the device's acceleration sensors. Since the rate of motion data, in this case, is quite low over a long period, the device can be locked and request a user re-authentication.

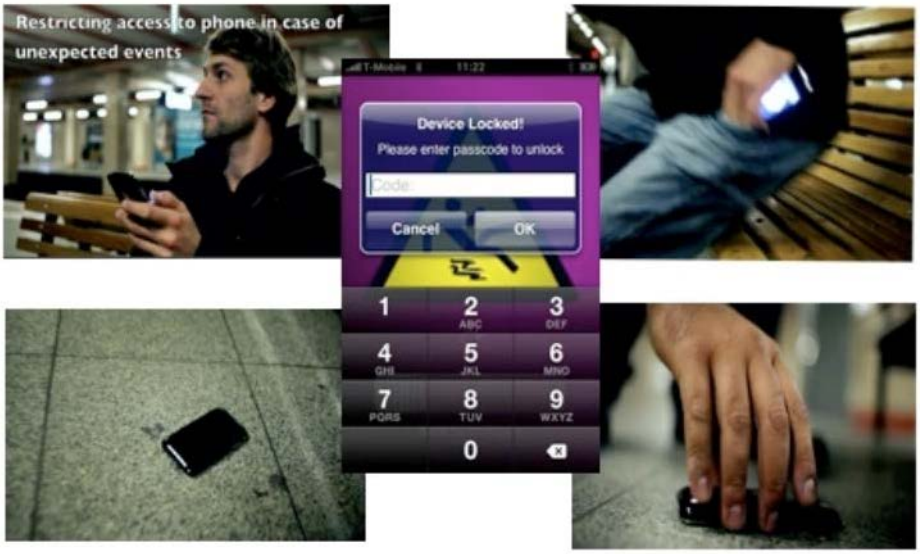


Figure 1 *Risk situations on mobile phone: Lost or stolen[16].*

Running and sports activities are other risky situations in which users might pay less attention to their devices, increasing the potential of losing them. We can enhance the security level of the device by recognizing this situation based on signals from the integrated accelerometer sensor. For this case, our experiments demonstrate significantly higher averages of values and variances in acceleration signals compared to normal situations (we assumed that the device is carried somewhere on the user's body.).

A typical situation in which a user might lose his or her device without noticing is when the mobile phone falls out of the user's pocket or bag. The user might leave it unattended for a while and leave the place in which it was lost or stolen. We have focused our study on such as case in order to detect

this scenario based on analyzing audio and acceleration signals. We have modeled this unexpected event based on three situations: freefall, shock (impact with the floor), and no activity (movement) after the shock. The device experiences a free fall situation by falling and a shock situation by hitting the floor. The "no activity (movement)" situation identifies the risky event when the user does not pick up the phone imminently.

We have arranged user studies to evaluate our algorithm for detecting the last-mentioned scenario. The experimental setup is similar to [29]. We have used an iPhone 3G for the experiments. Acceleration and audio data are recorded by a data collection application developed for iPhone in order to record the signals from embedded microphone and sensors. For the experiments, we have recorded a database of normal and anomalous (in accordance with those previously defined) situations. In this database, there are 98 samples of normal circumstances, and 36 samples of physical shock. In order to record physical shock situations, we allowed the iPhone to fall on a carpet or wooden floor from a distance of approximately 75 cm. To record normal condition samples, we let five users carry the iPhone normally in their pocket, hand or bag for 10 seconds. These users execute different day-to-day activities such as walking, jogging, taking the elevator and walking on stairs. We tried to model a wide variety of situations, particularly those potentially related to a shock (due to high physical activity) such as walking on stairs and taking the lift. This allowed us to ensure that our algorithm can distinguish between such cases and an actual risky shock [29].

Algorithm	Accuracy	True Alarm	False Alarm
3 step definition	94.4	34	4
Only impact	86.1	31	9

Table 1 Results for the detection of an anomalous situation which can lead to having a mobile device being lost or stolen[16, 25].

As mentioned earlier, we have defined the "no activity" period after a free fall as a risky situation. We monitor the norm of acceleration signals (along x, y, and z directions) and identify the fall situation when this signal falls

below a predefined threshold. We identify the no-activity period when the average of the norm of acceleration signals in an interval of eight seconds falls below a threshold.

We identify the shock situation by comparing features extracted from acceleration and audio signals with a statistical model created for shock situations. Our model in this experiment is a Multi-Layer Perceptron (MLP) trained using samples of impacts (shock) and normal situations, collected as mentioned before. Ín this work, we used the average and variance of acceleration and audio signals to enable the MLP to classify new samples of features such as impacts. The "anomalous situation" is sensed upon the detection of a free fall, a shock, and a period of "no-activity" in the correct order. Table 1 presents the primary results. Our studies demonstrate that defining the three steps for recognizing risky events can significantly reduce the number of false alarms (Table 1). The first row in the table present the results when the three-step definition is used, and the second row illustrates the outcomes when only the impact is considered as a risky event.

2.3. Implicit Identity Verification/Identification Based on Audio and Movement Analysis

Another possibility for using audio and movement analysis to enhance security functionalities in mobile devices is for user authentication/identification based on a regular user's physical activities such as walking and running. While the user is carrying his or her mobile device (e.g. in the pocket), we are able to capture samples of audio and motion signals and check for biometric patterns in them. This process allows the identification of the user continuously and implicitly. While the user performs his or her regular physical activities, the authentication/verification method looks for a biometric sign in his or her pattern of activities. As previously discussed, this implicit authentication method can be used alone or complementary to conventional authentication methods. The device can automatically recognize that it is not being carried or used by the same user anymore and requests re-authentication. As a supplementary advantage, this technique can reduce the required number of normal authentications. If the mobile device implicitly detects that the same person has continuously used it since the last authentication, the device will not ask for a re-authentication process for the same service. In this way, we can reduce the number of

annoying re-authentications. Furthermore, such an implicit authentication process can be used to set up different security levels for the mobile device, allowing the implementation of a graded security scheme.

In the following section, we present our initial experiments concerning user identification/authentication based on audio and motion signals captured by a mobile phone during normal physical activities. We demonstrate that we can classify users with high accuracy based on physical activity patterns captured from the device in their pant pocket.

2.4. Experiments and Results

We conducted initial experiments to investigate the possibility of implicit user authentication/identification based on the user's regular physical activities (walking, in our case).

For experiments, we recorded device motion information (using embedded acceleration sensors) as well as ambient audio (using an integrated microphone). The recording is done during regular physical activities such as walking. The device is carried in the user's pant pocket. We have used an iPhone as a mobile device and we recorded the signals using a data collection application we developed for the iPhone.

We have invited nine users for this experiment. We captured acceleration data at 50 Hz and audio signals at 8 kHz using integrated sensors in the device (iPhone 3G). We allowed the device to be normally placed in the pant pocket, without fixing its orientation or position. The test participants were asked to walk in their normal way for approximately two minutes in outdoor and indoor locations. We repeated the recording for each user over three different days and different sets of shoes and pants in order to consider the effect of variability in clothing on the authentication process.

The first processing step is feature extraction. We extract two series of features, one from the audio data and one from acceleration data. We extracted features over a window of two seconds of acceleration and audio

data. For acceleration signals, the extracted features are based on variance, average, and magnitude of acceleration signals. Here is a list of features:

- The average of the Euclidian norm of field strength along x, y, z.
- The average field strength along x, y, and z directions.
- The variance field strength along x, y, and z directions.
- The variance of the Euclidian norm of field strength along x, y, and z.
- The piecewise correlation between field strength along "x and y", "x and z", and, "y and z".

Regarding the audio signal, extracted features are based on the average, variance, and energy of the audio signal in each window. The variance of the audio signal's Fourier transform is also used as a feature.

Extracted features are fed as inputs to perception for the purpose of user classification/identification. Table 2 presents classification results for different feature sets. We report the results for using audio-based features, movement-based features, and a combination thereof. As the result, Table 2 illustrates that the combination of movement and audio features provide the best user accuracy (90.1%). Table 3 displays the identity verification (authentication) measures for some of the users.

Feature source	Accuracy
Movement	88.3
Audio	47.8
Movement + Audio	90.1

Table 2 User authentication results using different feature sets (movement, audio, movement+audio)[1, 16].

User ID	Precision	Recall	F-Measure	ROC Area
1	0.89	0.95	0.92	0.98
2	0.92	0.87	0.90	0.96
3	0.92	0.91	0.92	0.98
4	0.92	0.92	0.92	0.97
Weighted	0.91	0.91	0.91	0.97

Table 3 User identification measures for some users [1, 16].

As we can see in Table 3, the Receiver Operating Characteristic (ROC) measurements demonstrate a compromise between true and false alarms representing significant user authentication results.

In this experiment, we have presented initial results for user identification over a window period of two seconds. This means that we can re-authenticate the user every two seconds. However, such a short-interval continuous re-authentication may not be necessary for normal applications. Also, an authentication measure every minute might be sufficient for normal daily use. In such a case, short-interval authentication results can be utilized in a voting structure. The result in Table 3 demonstrate that the accuracy of user identification rises to 97.5% using a combination of acceleration and audio based features.

2.5. Demonstrator

We have developed a demonstrator based on the proposed methodology for the Apple iPhone mobile device. The demonstrator can detect an unexpected situation involving a free fall, an impact and a period of no activity. Upon detection of such a risky unexpected situation, the demonstrator can automatically block access to the phone and ask for a password. It can also

optionally send a message, including the location of the mobile phone, to a designated number.

Chapter 3
MagiTact

The primary results of this work have been presented in [2, 15, 17–22, 24, 30, 31].

Conventionally, a compass has been extensively used for navigation purposes. A regular compass is principally a magnetized needle which tends to position itself parallel to the south-north axis of the Earth's magnetic field. Recent developments in electronics have introduced compact, cheaper and higher performing electronic devices such as magnetometers, gyroscopes, and accelerometers.

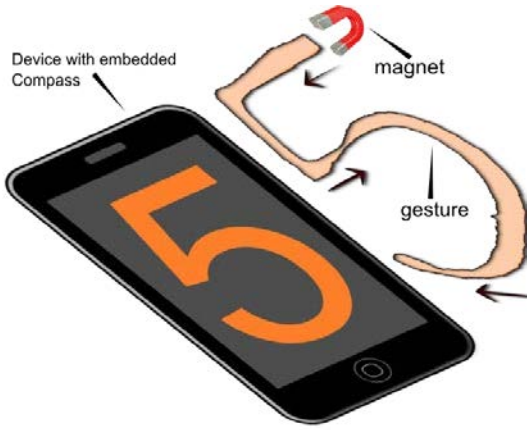


Figure 2 *Gesture based interaction with a cell phone by a magnet taken (or worn) around a finger, based on using embedded compass sensor [30].*

In recent years, digital compasses, along with other kinds of sensors such as GPS, accelerometers and dual cameras have been embedded within cell phones to enhance the functionalities of the phone. Digital compasses have

been used in concernt with GPS to provide navigation to the user. However, we demonstrate that the usability of the digital compass can be extended beyond navigational applications, providing a new user interaction approach to mobile devices [19].

The magnetic sensor in a mobile device acts like a regular compass. Any slight displacement of the device in relation to the Earth's magnetic field is sensed and registered by the device. A similar type of influence can be imposed upon the magnetic field of the device magnetometer if we move a permanent magnet around the device. Particularly, a small magnet that slide around the device influences the magnetic field around the magnetomeer, and therefore generates a temporal pattern which changes along the x, y and z axes depending on the magnets' movement. This sample can be used to create a touchless interaction framework as a means of interaction between the user and the device (Figure 2). Namely, the user creates a specific gesture while moving the magnet, which generates a temporal pattern of change in the magnetic field sensed by the magnetometer. This pattern can then be compared to the pre-recorded templates or pre-trained models in order to identify the gesture and translate it as a command.

This touchless input method addresses some of the limitations commonly associated with traditional input methods such as keypad or touch screen interaction. One of the fundamental restrictions in designing small electronic devices is that the size of the user input interface needs to be large enough to comply with human physical characteristics. A small suitably shaped magnet, e.g., in the shape of a rod, ring or pen, can move freely in the 3D space around the device, which is substantially larger than the surface of a handheld device's screen. By a suitably shaped magnet, we mean a magnetic material that can be taken or worn on a finger comfortably and naturally, thus rendering the design of small handheld devices with an appropriate user interface mechanism feasible. Moreover, the 3D characteristic of the suggested method offers considerable potential for augmented and virtual reality applications on mobile phones. Furthermore, since the magnetic field can penetrate through occluding bodies, it enables interactions even though the device is covered by other items or while the device is inside the user's pocket or handbag. For instance, the user may be able to dial a number, enter a pin code, or select a music album without taking the mobile device out of his pocket/bag. For the

same reason, space at the back of the device can also be freely used for interaction (Figure 3). This is in contrast with touch screens where interactions are only possible when the device is in direct contact with the user.

The compass (magnetic sensor) is a small, cheap sensor which can be internally embedded in the hardware. Acquiring such utility does not impose any change in the physical specifications of a device, which is a significant advantage for small mobile devices. Replacing keypads or touch screens with such a data entry technique in small devices allows savings in cost and reduces complexity in design. Compared to the touch screen, the magnetic sensor can be much simpler, smaller and cheaper, and can be internally embedded inside the device.

The proposed methodology [19] can be applied using multiple magnets, allowing for concurrent multi-gesture or multi-user interactions with a mobile device. If the magnets used come with different shapes or polarities, their influence in the magnetic field could be potentially separated.

Figure 3 *Back of device interaction based on MagiTact framework [19, 30].*

The proposed method opens up a variety of possibilities for touchless interaction with mobile devices in different contexts and applications. In this chapter, we examine a few of these applications developed within the

framework of our research. As is indicated in the following sections, the proposed approach can be used as a means for gesture-based interactions with the user interface of a mobile device (Figure 4). This can be, for instance, turning pages in an e-book or a photo gallery, zooming, and answering or rejecting a call. All this is accomplished by simple gestures in the space around the device. We also demonstrate that the method is precise enough to be used for touchless text entry by drawing a character-shaped gesture with a digit in front of the device. Moreover, we also introduce a new concept in mobile security called "Magnetic Signatures". The user simply signs using a magnet in the 3D space around the device to be both identified or authenticated. Finally, we also talk about using the method for mobile entertainment, including gaming and music synthesis on mobile devices. We demonstrate that the method can provide a new way of playing different music instruments in a touchless manner. For instance, we explain the implementation of an AirGuitar which is a guitar that can be triggered in air.

The proposed touchless interaction method can also be useful in assistive technologies. The fact that such a data entry approach does not entail a user's eyes makes it a pragmatic communication solution. This can be of substantial benefit to visually impaired people, interaction in a vehicle, and interaction in darkness. Regular gesture-based recognition techniques based on computer vision methods cannot be performed in darkness. The proposed method can also be suitable in scenarios where direct touch is not favorable, such as entrance doors in public places and medical or scientific experiments.

In the next sections, we first provide further details on theoretical aspects of magnetic field and compass sensor interactions. We also compare the proposed method with state-of-the-art ADI methods. Various modeling and recognition approaches used for identifying gestures are presented. We continue with a review of our studies and implementations of the gesture interaction method in different contexts and applications and demonstrate that the proposed interaction framework can be efficiently employed in various applications.

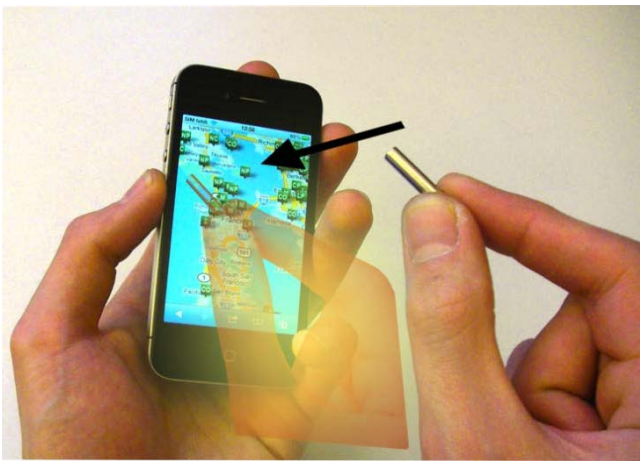


Figure 4 *Interaction with the user interface of a mobile phone using the space around the phone based on changes in a magnetic field [19].*

3.1. Related Works for MagiTact

Around Device Interaction (ADI) has been recently investigated as an efficient interaction method for mobile and tangible devices. ADI techniques are based on using different sensory inputs such as cameras [32], infrared distance sensors [33], touch screens at the backs of devices [34], proximity sensors [32], magnetic fields [35], and electric field sensing [36].

There are also different gesture recognition approaches which have been developed in recent years and which can be categorized into two groups: non-optical and optical gestural recognition methods.

In optical-based gestural recognition methods, optical sensors like cameras (e.g., SixthSense [37] and Gesture Pendant [38]) or infrared (IR) sensors (e.g., SideSight [39]) are the essential components in recognizing the movements of fingertips and hands and interpreting them as different commands. Although these approaches perform gesture recognition in some applications accurately, they do not support applications that are required to work with no direct line of sight (occlusion problem). Furthermore, optical data is sensitive to illumination conditions and, therefore, can only be used in

certain circumstances. Finally, the user should wear an additional cap or pendant which may be obtrusive and socially unacceptable.

To mitigate the problems of optical-based methods, non-optical gestural recognition methods use sensors such as magnetometers [3, 23, 40], and accelerometer [40–43], and proximity sensors [44].

Although a proximity sensor solves the illumination problems, it still has the occlusion problem, as the gestures must be captured in the sensors' line of sight. Other methods based on an accelerometer [41–43] do not have the occlusion and illumination problems, but since the acceleration data is sensitive to noise, complementary sensors should be used. Techniques based on a magnetometer send interaction commands when the magnetic field around the computing device is deformed. The benefit of this method is that there are no occlusion or illumination problems as in previous methods.

The gesture recognition techniques can also be categorized into types of wearable devices in which they are embedded. In some techniques, the user should wear extra gloves such as an Acceleration Sensing Glove [43] to interact with the computing device. The disadvantage of working with gloves is that they can be socially unacceptable or obtrusive. Other techniques like SixthSense [37] or Gesture Pendant [38] which require users to wear an extra hat and pendant suffer from the same problems.

One possible solution is to develop the gestural recognizer as a ring or wristwatch, which may be socially more acceptable. Pinchwatch [45] is a system which uses a wristwatch for finger gesture recognition with the help of a camera. Users invoke functions by pinching and enter parameters by performing sliding and dialing motions. However, again, this suffers from the line-of-sight problem. More recently [40], a magnetically tracked finger ring was developed which includes a permanent magnet in the form of a finger ring and worn-watch wireless tracking bracelet. While the magnetometer is used to track the ring's position, a Bluetooth radio allows the bracelet to send ring inputs to the user's devices. Nenya [40] supports only 1D input in comparison to Pingu (chapter 3.5) [23], which supports 3D inputs. Furthermore, it consists of two accessories in contrast to Pingu, which includes sensors and radio in only one ring. Magic Ring [46] is another finger-worn device which is developed for using static finger gestures, and it uses accelerometer data to

detect different gestures. Magic Ring is tested with six different finger gestures undertaking several predefined tasks. In our approach, we classify nine finger gestures with four machine learning algorithms to derive the accuracy of gesture recognition.

3.2. Magnetic Interaction Methodology

This section primarily focuses on ADI with a mobile phone. For cell phones, optical techniques such as cameras or infrared sensors are proposed. Compared with camera-based methods, extracting useful information from the compass is algorithmically simpler than implementing computer vision methods. Our method does not impose a major change in the hardware specifications of mobile devices or installing many optical sensors (e.g., in the front, back or edges of the device). It is only based on the internally embedded compass in the new generation of mobile devices. In contrast to the compass, which is internally embedded, installing optical sensors occupies considerable physical space, which may be a critical issue in small devices.

Our approach is not influenced by illumination variation and occlusion problems. The employment of optical techniques can be limited when the camera or sensor is occluded by an object, including the body of the user. Occlusion is not a critical problem in our approach, as a magnetic field can pass through many different materials. Since the back of a mobile device is usually covered by hand, optical ADI techniques (e.g., camera and infrared based) can face difficulties in capturing interactions at the back of the device. The space at the back of the device can be efficiently used in our method, as a magnetic field can pass through the covering hand (Figure 5). Also, interaction is yet possible even if the device is not in the line of sight, or when it is covered (e.g., in a pocket or bag). User can, for instance, accept or reject a call, or change a music track, without taking the phone out of their pockets/bags.

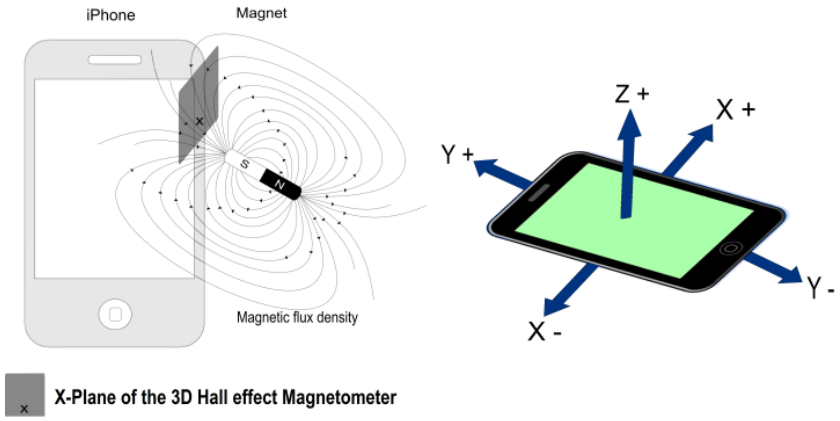


Figure 5 *A magnet affecting embedded sensor readings of a mobile device along different axes.*

In this chapter, we suggest influencing the embedded compass sensor in mobile devices using the motion of an external magnet for ADI purposes. We call our proposed approach "MagiTact". A digital compass (magnetic) sensor embedded in mobile devices contains a 3-axis Hall Effect sensor which registers the strength of a magnetic field along the *x*-, *y*-, and *z*-axes. The Hall Effect sensor produces a voltage (Hall potential V_H) proportional to the magnetic flux density (B in Tesla) due to the Hall Effect. The output of the sensor is provided in the *x*, *y* and *z* coordinates of the device (Figure 5). For the iPhone 3GS platform, the range of values for these axes varies between ±128 μT.

Sliding a permanent magnet across the peripheral area of a device deforms the default magnetic field patterns surrounding the device. Hence, by recording the momentary values of the magnetic flux density along the *x*, *y* and *z* coordinates; it is possible to obtain a sequence of 3D vectors that reflects the temporal pattern of field deformation due to the movement of the magnet by the user. As mentioned before, the magnet can be held in fingers or worn as a ring (Figure 6).

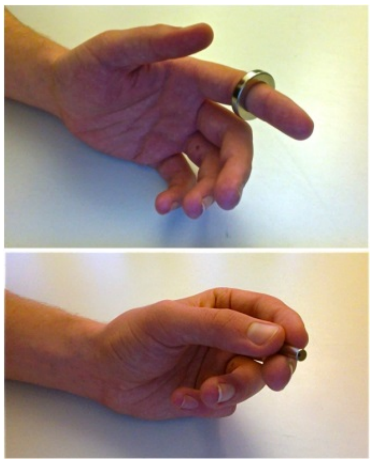


Figure 6 *The external magnet can be taken by hand or worn on a finger.*

In the method presented here, we use this interaction between the magnet and the embedded compass to send gestural commands to the mobile device. When the magnet is moved in the shape of a certain gesture, it causes a certain change in the pattern of the magnetic field sensed by the compass sensor. Analyzing the pattern of change can lead to recognizing the gesture which can be then interpreted as a command for the device.

The overall effect of the magnet trajectory on the device is recorded in the form of a sequence of vectors in which each element contains an instantaneous sample of the sensor values along each coordinate. The resulting vector sequence can be used by the device to infer the user's command or data. In this section, we demonstrate some methods for analyzing and interpreting the output of the magnetic sensor.

The compass sensor is constantly under the influence of Earth's magnetic field. This is an undesired effect which plays no role in interpreting gestures created by an external magnet. In most cases, it would simplify the rest of the processing steps if the effect of Earth's magnetic field is removed. The effect of Earth's magnetic field can be considered an almost constant (DC) component in the output signals. Therefore, one can consider using a high pass filter for removing it. The high pass filter highlights high-frequency

elements of the signals caused by the motion of the external magnet and eliminates the effect of Earth's magnetic field. In order to achieve the high pass filtering effect, we normally apply a time derivative function on the output signals.

Besides earth's magnetic field, there can be other sources of magnetic noise in the environment. However, in practice, we such sources have a negligible influence on the performance of the proposed technology. The main reason is the fact that magnetic field strength decays rapidly with distance from the source of the field. Therefore, unless a powerful external magnet comes as close as, e.g., 5 cm to the mobile device, the influence of noise associated with it is negligible.

If the output of magnetic sensor along the *x*, *y*, and *z*-axis is represented by *x(t)*, *y(t)* and *z(t)* respectively, the output vector can be written as

$$p(t) = [x(t)\ y(t)\ z(t)]$$

Moreover, the time derivative operation is obtained as:

$$v(t) = \frac{\partial p}{\partial t} = \left[\frac{\partial x}{\partial t}\ \frac{\partial y}{\partial t}\ \frac{\partial z}{\partial t}\right] = [v_x(t)\ v_y(t)\ v_z(t)]$$

In practice, we have observed that interpreting *v(t)* can be simpler than *p(t)*. In the rest of the chapter, whenever we refer to magnetic signals, we mean *v(t)* components, i.e., the time derivative of sensor readings, unless explicitly clarified.

3.3. Applications and Implementations

We have studied the proposed interaction framework within different gesture recognition contexts and applications. These vary from basic gesture recognition for controlling the user interface of a mobile device to character recognition, signature verification, and entertainment. As presented in this section, the proposed methodology can be used for tasks such as controlling a music player in a mobile device (loudness, music track change), or turning pages. This involves recognizing basic gestures indicating certain commands for the user interface. Also, we have investigated more complicated and de-

tailed gesture patterns such as digits. In this case, the user is requested to write a textual command or a number in the air. The device can then recognize the command or the digit. Moreover, we have proposed what we term “3D Magnetic Signatures”. In this case, a user is authenticated based on a signature that he or she makes in the air. We have also investigated the proposed methodology for entertainment purposes, including music synthesis and gaming. In the rest of the section, we summarize our studies and results for the previously mentioned application scenarios.

3.3.1. General Gesture Recognition

We have investigated the application of our proposed magnetic-based interaction to infer simple user gestures by monitoring the movements of the magnet held in the user’s hand [19]. The main motivation behind this experiment is to serve as a proof-of-concept of our magnetic interaction proposal. The gestures studied can be used for interaction with the user interface of a mobile device and comprise basic hand or finger motions (Figure 7). These gestures could be utilized for communicating basic commands to the device such as turning pages in a reading application, changing a music track, or controlling music volume.

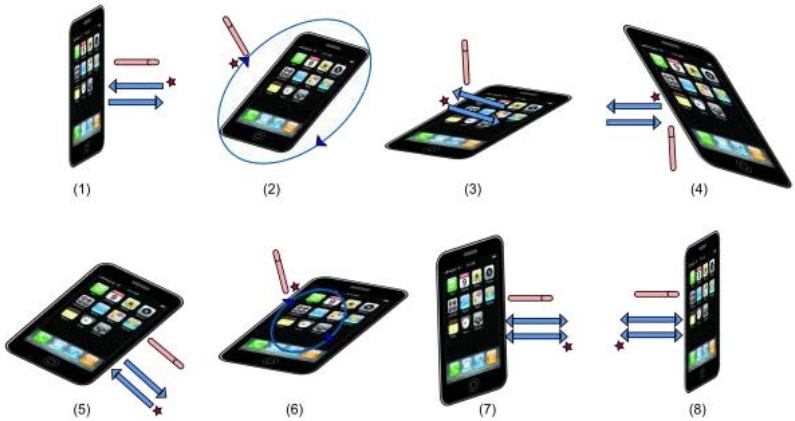


Figure 7 *Different gestures used in general gesture recognition studies. Gestures 7 and 8 can be interpreted as quick repetitions (twice) of gestures 1 and 3 (as in double click vs. click) [19].*

In order to investigate the accuracy of the gesture recognition system, we have set up some experiments using gestures presented in Figure 7. In these experiments, we invited six subjects to make eight simple hand gestures while holding a rod-shaped permanent magnet. The gestures are simple movements such as vertically moving a magnet in front of the phone, moving the magnet from the backside of the phone and so on, as illustrated in Figure 7. Every subject is asked to repeat each gesture 15 times. We have used MLP for gesture modeling and recognition. We have also used a ten-fold cross-validation scheme to avoid over-fitting.

Users	Gestures	Number of repetitions by each digit	X-fold cross validation
6	8	15	10

Table 4 User statistic og the generel gesture recognition experiment..

The result of this experiment yields an accuracy of 91.4% on average for recognizing different gestures. We can see in the confusion matrix in Table 5, that in each row the highest recognition rate occurs in the column corresponding to the right gesture (where the column number equals the row number). The value in the other columns represent the probability (normalized frequency) of misclassifying a gesture as an occurrence of the gesture corresponding to that column. As we can see in the matrix, the

highest level of confusion is between gestures 3 and 6, as well as 1 and 7, because of similarities between these gestures. Gesture 3 can be regarded as being similar to gesture 6 (circle) if the right-left trajectory in this gesture is different from the left-right trajectory. Also gesture 7 can be interpreted as a quick repetition (two times) of gesture 1 (double click vs. click).

Gesture Index	1	2	3	4	5	6	7	8
1	0.89	0.02	0.01	0	0	0	0.08	0
2	0.01	0.93	0.03	0.01	0.01	0.01	0	0
3	0.01	0.01	0.86	0.01	0.02	0.08	0.01	0
4	0	0	0	0.90	0.06	0.04	0	0
5	0	0.02	0.01	0.03	0.92	0.02	0	0
6	0	0.03	0.01	0.04	0	0.91	0	0.01
7	0.02	0	0.03	0	0	0	0.95	0
8	0	0	0.01	0.01	0	0.02	0	0.96

Table 5 Confusion matrix for gesture recognition using the MLP classifier. It shows the actual gesture entries (rows) and the classification results (columns). The numbers in each row are normalized so that the sum of values in each row becomes one [19].

One critical factor in obtaining the results presented here is how to detect the beginning and the end of the gesture trajectories. This can be highly influential on the accuracy of the results. For the current setup, the start and the end of the gestures are detected by comparing the magnitude of the magnetic field with a threshold. In other words, the beginning of the gesture is when the magnet is brought close enough to the device, and the end is when the magnet is away from the device.

The acceptable results obtained from typical gesture recognition experiments encouraged us to attempt the more complex gesture patterns presented in the next subsections.

We have also developed several demonstrators based on simple gestures for Apple's iPhone 3GS [19]. They primarily demonstrate interaction with a mobile device's user interface such as turning pages in a photo view application, zooming/un-zooming, and controlling an audio player (volume and track change). As the gestures are simple and few in terms of classes, we have used a measurement-based approach for interpreting the gestures. For instance, in order to detect a left-to-right gesture, we evaluate the amplitude of the magnetic field along the x axis. A negative value can indicate a right-to-left motion, and a positive value indicates the reverse.

3.3.2. User Authentication Based on 3D Magnetic Signatures

Mobile computing devices are frequently used to store and access sensitive information during daily life. Hence, user authentication/identification seems to be an essential part of these devices for granting access to certain information or services. While conventional password-based authentication methods can be easily copied and distributed, there is a rapidly growing demand for new security systems for mobile computing devices that should be fast, easy and reliable.

In [20], we have introduced *MagiSign*, a new touchless, gesture-based authentication solution based on 3D magnetic signatures created in the space around a mobile device.

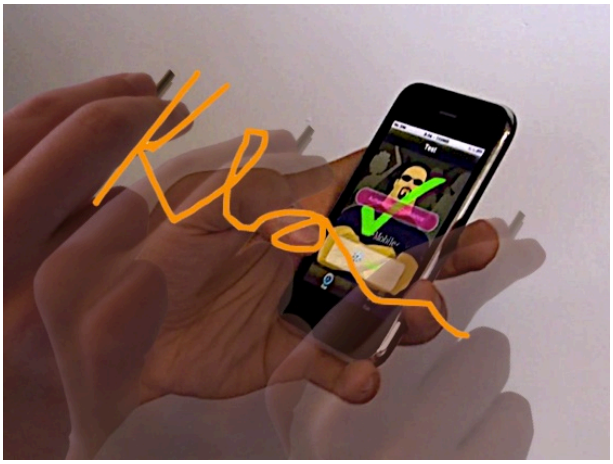


Figure 8 *Using a magnet as a user entry medium for authentication [20].*

The user moves a permanent magnet (e.g., a pen or a ring) by hand along an arbitrary 3D trajectory around the cell phone to create a unique 3D signature (Figure 8). The embedded magnetometer in the device captures the changes in the temporal patterns of the magnetic field around the device as the 3D magnetic signature. Subsequently, for user authentication, the temporal pattern of a new magnetic signature is compared against the models or templates of the registered signature.

Users	Number of repeats by each signature	X-fold cross validation
15	15	10

Table 6 User statistics of Magisign experiment.

We conducted an experiment to evaluate the accuracy of the proposed technology for user authentication/identification. We invited 15 subjects for the experiments and asked each of them to make an arbitrary 3D magnetic signature 15 times (Table 6). We utilized MLP as a classifier, and we used a ten-fold cross-validation for training and testing the data. The results reveal an overall accuracy of 95.2% for user identification. Furthermore, for user authentication, we measured the Area Under the Curve (AUC) in the ROC, the False Positive (FP) rate and the True Positive (TP) rate averaged over all

users. The authentication results show a positive balance between true and false alarms, as can be seen in Table 7.

Measure	AUC	TP rate	FP rate
Value	0.991	0.952	0.003

Table 7 User authentication averaged over all users [20].

Magnetic authentication has several potential advantages over classical authentication methods such as a higher level of security and more flexibility. Unlike regular signatures, it is difficult to replicate such a signature because it is created in the air, with no trace remaining. As a magnetic signature can be drawn variably in 3D space, it provides a wider choice for user authentication. Moreover, the proposed authentication method does not impose changes in the hardware or physical specifications of mobile devices and can be particularly useful for authentication in small models. Unlike face-recognition-based authentication, our method does not suffer from illumination and occlusion problems.

The proposed method can be further enhanced by providing a second layer of security and personalization. To create the signatures, a user can employ a magnet with a personalized shape and polarity. In this way, the data registered by the magnetic sensor will be a function of both the form of the magnet, as well as the way it is moved in the air. This can be considered as using a physical key in addition to the movement-based signature of the authentication process.

Finally, we implemented a demonstration application for an Apple iPhone 3G based on the proposed touchless, gesture-based authentication framework. The demonstrator allows a user to register a few templates of his or her 3D magnetic signature using a magnet in his or her fingers, and then try the authentication process with a new sample of his or her 3D signature. Although here the authentication method is designed for mobile devices, the application can be extended for user authentication at ATM machines.

3.3.3. Touchless Character (Number) Entry

An important part of interaction with mobile and tangible devices involves entering textual data, e.g., for sending a text message or dialing a number.

Text entry requires direct physical interaction with mobile and tangible devices via keypads or touch screens. As the size of these devices is becoming smaller, it may no longer be comfortable to operate small buttons or touch screens for text entry.

Recently in [2] and [30], we have presented a new technique (MagiWrite) based on the proposed touchless interaction framework for text entry that can overcome the limitations of existing keypads and touch screen input interfaces. Our method expands the text entry space beyond the physical boundaries of keypads and touch screens and uses the whole area around the device for writing text. The user simply writes characters, or textual commands in the air and the device recognizes them.

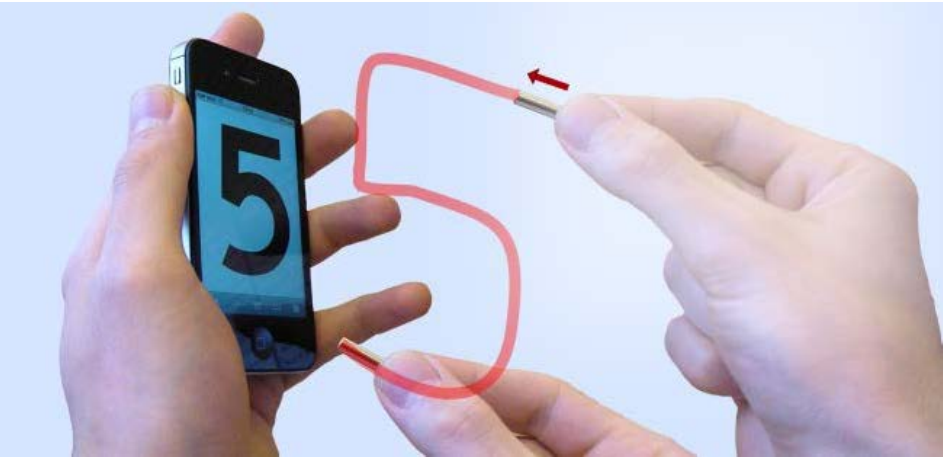


Figure 9 *MagiWrite: Entering text (digits) using magnetic interaction [2, 30].*

In MagiWrite [2, 30], we focused on entering digit data for simplicity. However, the same methodology can be applied for entering other characters, symbols, or textual commands. This is completed by drawing gestures shaped like digits in the 3D space around the device (Figure 9) using an appropriately shaped magnet. The user can register one or more templates for each digit in the training phase. The template for each digit is stored as a time sequence of magnetic signals sampled along x, y, and z directions.

During a digit entry (testing the system), a new digit gesture drawn in the space around the device is compared to registered templates available for different digits using DTW. The digit class exhibiting a higher score (i.e., better match) is selected as the recognized digit.

Users	Digits	Number of repeats by each digit	X-fold cross validation
8	10	15	8

Table 8 Digit entry experiment statistic [18, 47].

In order to evaluate the accuracy of the proposed digit-entry approach, we invited eight subjects to participate in our experiments. We asked each subject to draw 10 digits (from 0 to 9) in the space around the mobile device by holding a magnet in their hands (Table 8). For each digit, we collected 15 different templates per subject. We then ran an eight-fold cross validation on each subject's sampled data and on each fold we increased the number of templates by 1. Figure 10 represents the experimental results of using DTW for digit recognition. Each curve in the graph corresponds to the data obtained from one user. We can see that DTW recognition results converge rapidly after only 3 or 4 templates for each digit indicating that we can obtain high accuracy with the proposed method even if the number of templates is limited. This characteristic is particularly important in everyday mobile applications where the user may not want to enter many templates for each digit. According to our experiments, the average accuracy and standard deviation of the proposed digit entry approach is 0.8535 ($\pm$ 0.075) using only three templates for each digit [18, 47] .

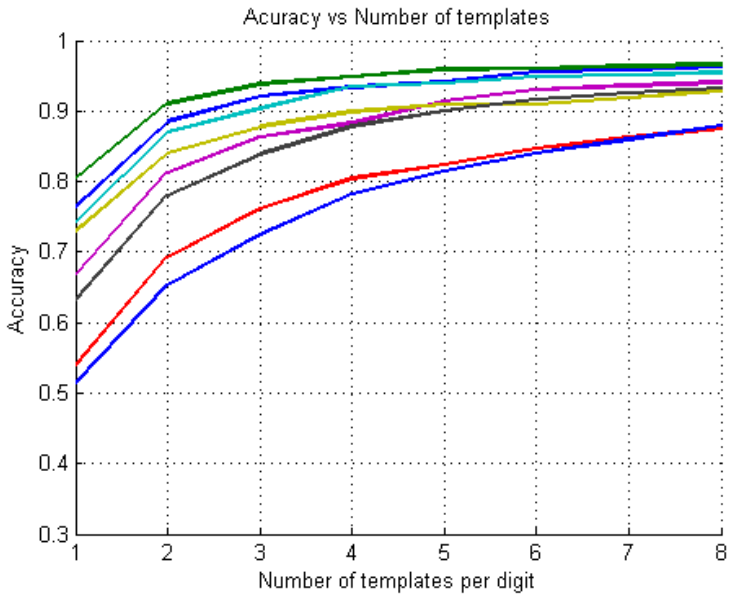


Figure 10 *Number of templates versus accuracy. Each curve presents the data collected from one user [2, 30, 47].*

Since the interaction in this technique is based on a magnetic field which can pass through different materials, the device does not necessarily need to be in either line of sight or in hand for the user to enter textual data. Data entry can be potentially possible even if the device is in a handbag or pocket. For example, the user can enter a textual command, a pin code, or dial a number or textual command without taking the mobile device out of his or her pocket/bag. A demonstration application on Apple's iPhone 3GS has been developed to demonstrate the effectiveness of a digit-entry application [18].

Despite the fact that the text (digit) entry experiments indicate the accuracy of the approach in recognizing more complicated gestures, a usability study of the concept should be performed as well. According to our interviews with users, they all find the idea of writing in air to send commands to the device attractive. However, they also mentioned that they might use it only in certain circumstances where a casual text entry is required such as dialing a default number or rejecting a call with a predefined rejection message.

3.3.4. Magnetic Interaction for Entertainment Purposes

We have also investigated the application of the proposed technology in the context of mobile device entertainment, primarily for digital music synthesis and gaming.

Mobile devices have become popular digital instruments for musical performances [15, 48–50]. Numerous applications in music have been developed, using the touch screen and accelerometer for interaction, in order to simulate traditional instruments on mobile devices. However, playing musical instruments on the surface of mobile devices is limited and usually requires both of the user's hands on a small screen. Moreover, the applications that use accelerometers require the user to repeatedly turn and tilt the device to generate a certain sound which makes the user lose direct sight of the screen.

In order to address these limitations, in [15] we presented a novel approach for music performance applications based on the proposed touchless interaction methodology. The proposed magnetic-based interaction framework provides a higher degree of flexibility for music performance because the interaction space is extended to the 3D space around the device. This allows users to play music on mobile devices using highly intuitive hand gestures such as those used when playing real instruments.

Playing musical instruments usually requires the harmonic movements of hands with the instruments. In the proposed musical performance method, we establish a mapping between the motions of a hand (or fingers) and the movement of a magnet (taken in hand) in the space around the device. The position, movement, shape, and orientation of the magnet can be utilized as an input for altering or adjusting the parameters and characteristics of the music. In the rest of this section, we elaborate on some music synthesis applications implemented for mobile devices based on the proposed technology.

3.3.5. Applications Design for Triggering Interactions

Apart from the gesture recognition methods presented earlier, there are easier forms of magnetic based interaction which can be used for designing novel applications. The gesture recognition described can have practical issues in daily life. For example, when the device is covered (e.g., the device is a

pocket) and the user does not know the position and direction of the device. In this case, the magnetic gestures have to be designed in a way that enables the calculation of the direction. This might require designing more complex gestures. In order to avoid this issue, we designed novel applications which require only a magnetic-triggering interaction.

3.3.5.1. Airguitar

Two distinct actions play traditional guitars. A user presses pitches on different strings along the neck of the guitar with one hand, while the other periodically strums the guitar strings. The combination of these two actions produces different tones. In current mobile phone touch screen based guitar applications, both of these activities (i.e., holding notes and strumming strings) are performed on the small screen of the device. Such a user interface setup can be limited, as it requires using both hands on a small screen.

In our proposed guitar application (*AirGuitar)* [15], the holding action remains on the touch screen, but the strumming action is replaced with a 3D gesture in the space around the device. The user can periodically move his or her hand (holding a magnet) in the space around the device (equipped with an embedded compass) imitating the natural strumming actions in a real guitar. The rapid movements of a hand in the air (carrying a magnet) in a fashion similar to strumming creates rapid temporal changes in the magnetic field around the device.

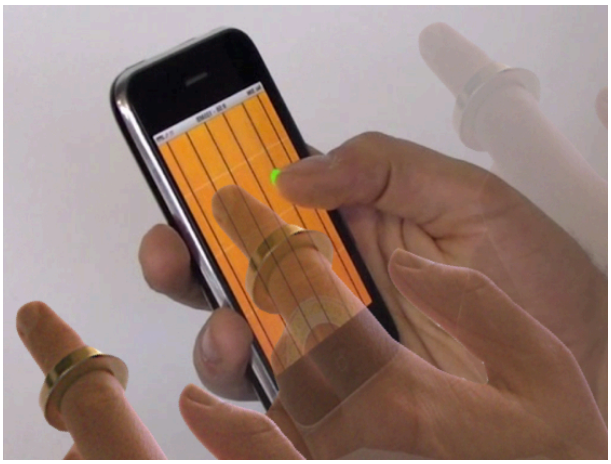


Figure 11 *Gestural interaction with AirGuitar application using magnetic interaction around a mobile device[30].*

We can discover this by comparing the variance of the magnetic field (expected over an interval/window) with regard to a predefined level. One or many tones are played if their corresponding pitches are held on the screen with the other hand of the user.

An Apple iPhone demonstration has been developed for our proposed music performance application, as shown in Figure 11. When the *AirGuitar* application is launched, the user can see guitar strings on the screen. The user holds the strings on display with one hand and strums in the 3D space around the device, using the other hand, with a magnet. If a string is touched, the corresponding sound of the string is played.

3.3.5.2. Drum-Kit

We have also developed an *AirDrum* based on the proposed magnetic interaction framework. Two factors are important in playing a drum: the strength of the hit and the radius of the hitting point to the midpoint of the drum surface. Several drum applications have been introduced for mobile devices, however, in these apps only the location of the hit can affect the generated sound. The touch screen cannot detect the strength of the hit. The power of the hit can be captured as a part of the hitting gesture [15].

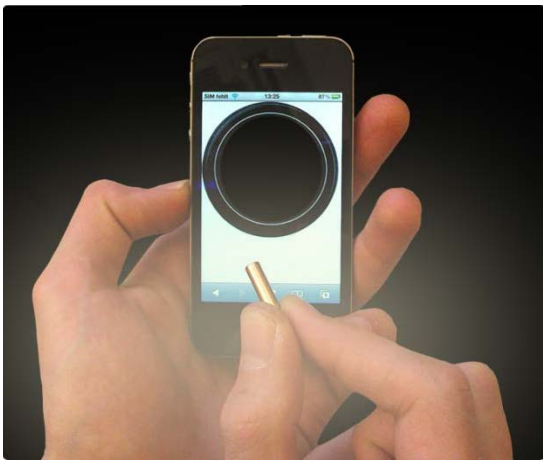


Figure 12 *User is playing the Drum-Kit application on Apple iPhone by moving a magnet[30].*

The drum application that we have developed (Figure 12) interprets the second time derivative of the Z component signal of the magnetic sensor as the strength of the hit. The higher the force (energy) is, the louder the sound generated will be. On the other hand, the *X* factor of magnetic field signal corresponds to the radial distance to the center of the drum surface.

Moreover, in order to demonstrate the wide range of potential applications that can be developed based on the proposed magnetic interaction framework we have developed several other musical instrument applications such as Harmonics, and Theremin; several sound composition applications like sound modulation and effecting; and DJ interface applications [15].

Besides the music performance applications, the proposed touchless interaction framework can be employed for mobile entertainment applications such as gaming [30, 51]. The major challenge facing mobile gaming applications design is that interaction with the small touch screen and buttons on mobile devices is neither user-friendly nor convenient. Besides, the current user interfaces limit the interaction speed of players. In [30, 51] we have presented a new technique based on the proposed touchless interaction framework for mobile gaming applications. The framework extends the interaction space to the 3D space around the device, thus leading to faster and more flexible

interactions. The user can employ hand/finger gestures to control the actions of a character in a mobile game application. Moreover, the user can use multiple magnets with different shapes and polarities to perform multiple commands simultaneously. Thus, the proposed framework can potentially enhance the usability and playability of mobile games by employing more natural, intuitive and faster methods of interaction.

3.4. Concepts for the Realization of a 3D Mouse Using MagiTact Technology

We have introduced a MagiTact framework based on the existing embedded magnetic sensors in smartphones. This approach has the following drawbacks:

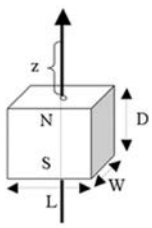
- It is not possible to determine the exact location of the magnetic element based on the measurements of a single built-in magnetic sensor. This fact limits the sophistication of Magitact technology's interactive control.
- Implementation of the technology is restricted to a specific type of electronic device. In other words, the technology is only applicable to an electronic device which has a built-in magnetic sensor.

There are several methods by which these deficiencies might be overcome. The first obvious solution is to provide the device with accessories which provide another magnetometer in addition to the device's embedded sensor or, second, an accessory which comprises at least two magnetometers. In both cases, we will be able to calculate the position of the external magnet in a 3D space. Furthermore, the second case allows the Magitact technique to also be used by devices that lack an embedded magnetometer. However, both solutions require additional hardware [17]. Figure 13 presents such an accessory.

Figure 13 *Accessory cover with additional embedded magnetometer.*

A further solution is an algorithm which is based on experimental measurement of magnetic flux considering the specific behavior of the magnetometer sensor and used magnet. The calculation of the magnetic flux has many dependencies such as device type, magnetometer sensor and the shape and power of the permanent magnet used [52]. Therefore, the calculation of the real 3D coordinates for realizing a 3D mouse would be a complex and non-linear function.

$$B = \frac{B_r}{\pi}\left[\arctan\left(\frac{\mathrm{LW}}{2Z\sqrt{4Z^2 + L^2 + W^2}}\right) - \arctan\left(\frac{\mathrm{LW}}{2(D+Z)\sqrt{4(D+Z)^2 + L^2 + W^2}}\right)\right]$$



B_r: Remanence field, independent of the magnet's geometry
z: Distance from a pole face on the symmetry axis
L: Length of the block
W: Width of the block
D: Thickness (or height) of the block

The unit of length can be selected arbitrarily, as long as it is the same for all lengths.

Figure 14 *Formula for the B field on the symmetry axis of an axially magnetized block magnet [53]*

Figure 14 illustrates the calculation of magnet field B field on the symmetry axis of an axially magnetized block magnet [53].

An alternative to this approach can be implemented by devices' specific calibration program that stores the specific sensor values for all display positions for a specific permanent magnet. Though this method is feasible, it does not fulfill high usability requirements. Therefore, we were looking for a better and easier method for realization of mouse functionality with MagiTact.

We came to the solution as we were rethinking the basic technology of MagiTact. The most important technology for MagiTact is the pattern recognition accomplished by machine learning methods. We have been so focused on increasing the usability of this technology that we forgot about human ability and flexibility in adapting an interaction's behavior such as we often do by learning a music instrument. Our theory was: as humans can play piano or guitar without looking at the keys or strings; they are also able to adapt a semi-mouse interaction using MagiTact. The only precondition is implementing a feedback mechanism for the user, which allows him or her to realize the impact of his or her interaction.

Figure 15 *MagiBird app on A ndroid, We have reimplemented the Angry Bird application for our tests. We did not publish this application.*

To prove our theory, we reimplemented the famous angry bird application (Figure 15) by using the MagiTact framework. Since, in this application, the user receives continuous visual feedback of the bird's position, he or she can adapt the correct distance and angle of the permanent magnet to the device for correct interaction, no matter which kind of magnet or device is used.

Though the user can adapt the interaction depending on using a magnet or a device, we increase the usability of the application with a simple calibration to adjust the specific magnetometer behavior and display size. With this method, we provided an easy semi-mouse behavior with the MagiTact framework. This application enables users to trigger and manipulate the angle and amplitude of the game's key component (a bird in a catapult) by moving a magnet next to the device. Since the user is continuously receiving visual feedback of the bird's position in the catapult, he or she is able to adapt the correct distance and angle of the permanent magnet to the device for correct interaction no matter which kind of magnet or device is being used. Being motivated to succeed in the game, we assumed a steep learning curve for adapting the new interaction method.

We support the following thesis:

- Users are able and willing to understand and adapt to our interaction system and metrics just by using the system and receiving visual feedback on their actions.

As already mentioned the idea behind our thesis is that users can adapt to many kinds of interaction metrics through the same principle as learning to play a musical instrument. The only precondition would be implementing a feedback mechanism such as visual feedback which allows the user to recognize the impact of his or her interaction.

3.4.1. The Role of Visual Feedback

In [54, 55] Saunders et al. applied classical perturbation techniques to study the control strategy used by the hand-eye coordination system of humans. They experimented with hand movements, providing the user visual feedback with perturbations in early and later movement phases. Their results provide direct evidence for a continuous visual control signal from the moving hand. By measuring nearly equivalent latencies for reactions to early and late perturbations, they found strong evidence that visual feedback from the moving hand is incorporated into continuous online control through reaching movements. Further studies such as [56, 57] followed the insights of Saun-

ders et al. by implementing further experiments supporting and refining their understanding of continuous online control.

Whiteley et al. revealed in [58] that humans possess an internal model of visual processing uncertainty which they would use to guide their decisions, e.g., on how to react to perturbations. They compared the model of visual processing uncertainty to an optimization function based on Bayesian probabilities and suggest that humans would steadily train this model when observing experiences.

3.4.2. Proofing of the Visual Feedback Concept for a 3D Mouse by User Experience

To find proof of our concept and assumptions we executed a user study and evaluated the user experience for interactions with three different types of magnets.

Figure 16 *Visualization of the three magnet types A, B, and C.*

The three types of magnets utilized for the interactions are presented in Figure 16. Magnet A had the shape of a stick with magnetic poles on both ends. Magnet B had the form of a ring which could be worn on the finger. The magnetic axis of this magnet runs through the ring like a diameter. Magnet C was also a ring which could be attached to a fingertip, the magnetic poles being situated on the front and back side. When doing the survey, we were indicating where the relevant magnetic poles are.

3.4.2.1. Measuring User Experience

In 2003 Hassenzahl et al. introduced AttrakDiff [59] a survey model to analyze user experiences of products. In a time of steady software, web and interface innovations AttrakDiff became a de facto standard tool for implementing user studies.

AttrakDiff consists of a list of pairwise contradicting attributes, each with a seven-point Likert scale in between. Users can express their opinion regarding the user experience presented by choosing one of the radio buttons. The radio button in the middle stands for a neutral position, and the others range to a weighted agreement with the left/right attribute the nearer they are to the corresponding attribute label.

The list of pairwise contradicting attributes is divided into four aspects of user experience. Each pair of attributes belongs to one of the categories. Those are:

- **Pragmatic Quality** stands for the percepted ability of a product to achieve certain goals by providing useful and usable functionalities.
- **Hedonic Quality – Stimulation** means the ability of a product to satisfy the user's needs for improving his or her knowledge and skills.
- **Hedonic Quality – Identity** stands for the usefulness of a product to communicate self-worth messages to relevant others.
- **Attractiveness** stands for global judgments in a range from positive to negative regarding the overall product.

3.4.2.2. Survey

We started with an AttrakDiff mini survey [59], which is a minimum version of the AttrakDiff method commonly applied to the field of measuring user experience. We soon discovered that users had more trouble understanding the survey than understanding the interaction with the game. We saw that results were highly dependent on how well the study was moderated. To meet this problem and guarantee a high standard of moderation though having different moderators and personal backgrounds, we ex-tended the questionnaire. This should lead the user to a better understanding of the context of the AttrakDiff mini survey and provide more insights beyond it. The introductory questionnaire asked for the perceived relative number of attempts needed to feel comfortable with using each magnet (A, B, and C). Survey participants could rate on a seven-point Likert scale ranging from "almost no attempts" to "too many attempts". The same question was asked concerning the perceived

handling of the three types of magnets. Then participants were asked to rate how large the perceived differences in handling were after getting used to the system through training. Furthermore, they were invited to rate the originality of the interaction and at which rate they could imagine using the interaction in other applications. Participants were also asked for their age category (15-25, 25-40 or more than 40 years), gender and the time they normally spent on their smartphones per day. The amount of time spent on their smartphones was split into a Likert scale of 7 categories ranging from "not any" to "almost all free time in the day".

Before answering the AttrakDiff mini questionnaire, participants tried all three types of magnets and had to complete our introductory questionnaire. They were then introduced to the AttrakDiff mini questionnaire by the following text:

"*In this question, we do not want you to interpret the app or the game, but we ask you to demonstrate your idea about the interaction between the app and the magnets. Therefore, we ask you to choose an option without thinking a long time about its correctness. There isn't any true or false answer; this is only about your feeling and personal opinion for the experiment you have just done. Please note that there might be some answers/word pairs which do not fit to the experiment you have done, it is not that important, cross an answer nevertheless.*"

Now participants had to answer ten Likert scales with seven categories each. The ends of the Likert scales were labeled by the contradicting attributes of the AttrakDiff mini.

Age group	male	Female	Total
15-25	26	15	41
25-40	7	3	10
Older than 40	8	5	13
Total	41	23	64

Table 9 Participant statistics for 3D mouse simulation experiment.

We found 64 participants (Table 9) who answered our extended version of the AttrakDiff mini questionnaire. The outcomes are described in the next section.

3.4.2.3. Results and Discussion

In the following subsections, we present and discuss the results of the AttrakDiff mini questionnaire and examine significant correlations between the results and personal attributes such as age, gender or the participants' time spent on smartphones per day. Furthermore, we evaluated the differences between the magnet types and further insights obtained from the introductory questionnaire. We also investigated significant correlations found between questions from different parts of the questionnaire.

3.4.2.4. AttrakDiff Mini Questionnaire

From our AttrakDiff mini questionnaire, we accumulated each participant's ratings for the various groups of attributes to derive an overall score on the pragmatic quality, the hedonic quality and the attractiveness of the interaction method.

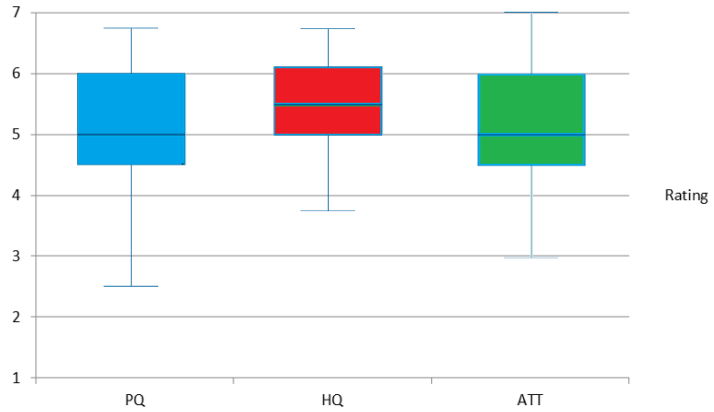


Figure 17 *Boxplots for the evaluated pragmatic quality (PQ), hedonic quality (HQ) and attractiveness (ATT).*

Figure 17 presents boxplot graphs on how the product, representing the device interaction with magnets, performed in the AttrakDiff survey regarding

pragmatic quality, hedonic quality, and attractiveness. Hedonic quality groups all items from the two subcategories of identity and stimulation together.

The boxplot graphs demonstrate that the medians, as well as the first and the third quartiles of all three categories, lay in the upper part of the chart. As a higher number stands for better results and 4 stands for neutral, this implies a high acceptance of our 64 survey participants regarding all categories. The perception of hedonic quality performed best. Figure 18 shows where the pragmatic and hedonic qualities are compared and used to draw further insights.

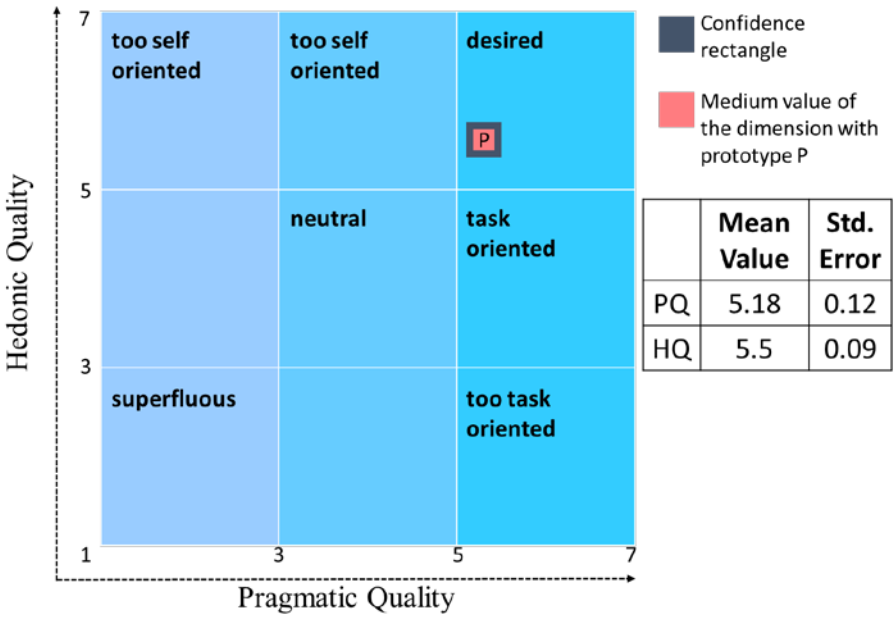


Figure 18 *AttrakDiff profile on he donic and pragmatic quality, positioning the average performance of our prototype P, an interaction method in the context of AttrakDiff's performance categories.*

Figure 18 demonstrates that the product falls into the category "desired", meaning that both, the hedonic and pragmatic quality were rated well. For the hedonic quality, there is little space for optimization whereas the pragmatic quality was not perceived to be similarly outstanding. The confidence rectangle ranges slightly into the "self-oriented" category. This might indicate that

for some users the pragmatic quality still has room for improvement. Taking into account that the attractiveness score was also positive, we can conclude that users accepted our interaction method. The AttrakDiff mini survey asked for the user experience independent of the different magnet types used. In the following section, perceived differences are analyzed by evaluating questions from the introductory questionnaire, particularly the question of the users' ability to adapt to different system metrics.

3.4.2.5. Different Shapes and Types of Magnets

To compare the interactions with various kinds of magnets, we asked participants for the number of attempts needed to use each magnet correctly, and how they perceived the handling. To ensure an unbiased overall rating the order in which participants could try out the different magnets was shuffled.

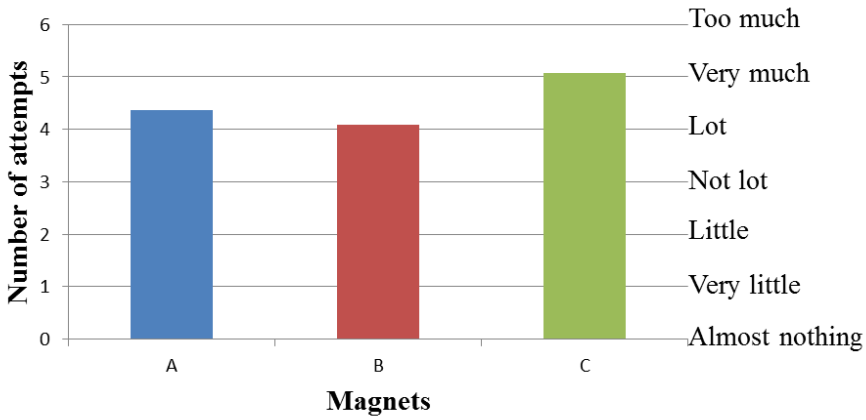


Figure 19 *The mean ratings of attempts needed to adapt to magnet types A, B, and C. A rating of 4 means that the user needed quite a few attempts while a rating of 5 means that the user needed many attempts.*

When comparing magnets A, B and C Figure 19), there was a significant difference between the number of attempts required to use magnet C and the attempts needed to use magnet A or B correctly. A repetitive measures

ANOVA[2] with a Greenhouse-Geisser correction determined that the mean rating of attempts needed to learn the interaction with magnets differed statistically significantly between the magnet types A, B, and C ($F(1.803, 113.600) = 18.876$, $P < 0.001$). Participants had to fill a seven-point Likert scale ranging from "almost no attempts" to "too many attempts". Post hoc tests using the Bonferroni correction revealed that the mean of the attempts required to learn the interaction with magnet A was slightly larger than the average of attempts needed to learn an interaction with magnet B (4.36 ± 1.484 vs. 4.09 ± 1.244, respectively). This was not statistically significant ($p = 0.165$). However, the mean of attempts needed to learn the interaction with magnet C was larger, with a mean rating of 5.08 ± 1.429, which was statistically significantly, in contrast to magnet A ($p = 0.001$) and magnet B ($p < 0.001$). Therefore, we can conclude that participants, in general, needed "only some" to "many" attempts to learn the correct interaction and they needed significantly more effort to learn the interaction with magnet C than with magnets A or B.

A similar correlation between magnet C and the other two was obtained for the question how effective the handling of each magnet was. The repeated measures ANOVA with a Greenhouse-Geisser correction determined that the mean rating of handling for the three types of magnets differed statistically significantly between the magnet types A, B, and C ($F(1.949, 122.793) = 19.131$, $P < 0.001$). Participants had to complete a 7-point Likert scale ranging from an "extremely difficult" to an "extremely easy" handling. Post hoc tests using the Bonferroni [3]correction revealed that the mean handling with magnet A was a little lower, and hence, worse than the mean handling of magnet B (4,72 ± 1.201 vs. 5.00 ± 1.141, respectively), which was not statistically significant ($p = .146$). However, the mean handling with magnet C

[2] "Analysis of Variance: a statistical procedure that uses the F-ratio to test the overall fit of a linear model. In experimental research, this linear model tends to be defined in terms of group means and resulting ANOVA is therefore an overall test of whether group means differ." [60].

[3] Bonferroni correction: a correction applied to the α-level to control the overall Type I error rate when multiple significance tests are carried out. Each test conducted should use a criterion of significance of the α-level (normally 0.05) divided by the number of tests conducted. This is a simple but effective correction, but tends to be too strict when lots of tests are performed [60].

was even smaller hence worse with a mean rating of 4.08 ± 1.225, which was statistically significantly, in contrast to magnets A ($p < 0.001$) and B ($p < 0.001$). Therefore, we can conclude that the handling of the overall interaction was rated as easy and the usage of magnet C was perceived to be significantly more challenging than the usage of magnets A and B (Figure 20).

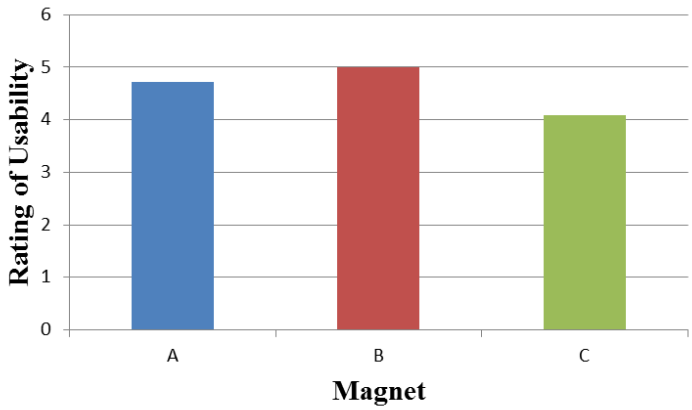


Figure 20 *The mean of the ratings for the handling of magnet types A, B, and C. A rating of 4 means that the user has a neutral position concerning the perceived handling while a rating of 5 means that the handling was easy.*

3.4.2.6. Perceived Differences Between Magnets After Training

In the previous subsection, we established that users perceived a significant difference in handling and numbers of attempts between magnet C and the other two. The third question in our introductory questionnaire asked how significant the perceived difference between the types of magnets was after a phase of training with each of them. Participants should complete a seven-point Likert scale ranging from “no difference at all” to “huge difference”. The mean rating for the perceived difference was 3.39 with a standard deviation of 1.352 which lies in the area between a rating of 3 which means “minor difference” and 4 which means “a little difference”. Considering the perceived differences described in the previous subsection, this confirms our assumption that users can adapt to different interaction metrics and types. Even though there was a significantly higher number of attempts required to

learn the interaction with magnet C and the handling of magnet C was rated to be more challenging, participants agreed that the difference after training with all magnets was only minor or small (Figure 21). As the magnets used were of different shapes and had different magnetic characteristics, we interpreted this result as a positive indicator of the user's ability to adapt to new and different kinds of interaction metrics. The device was not adapting to the various characteristics of magnets A, B, and C. Hence, users had to adapt their behavior to succeed in interacting with the game MagiBird. In the next section, we also investigate the correlations between age and the ability to adapt to different interaction methods and metrics.

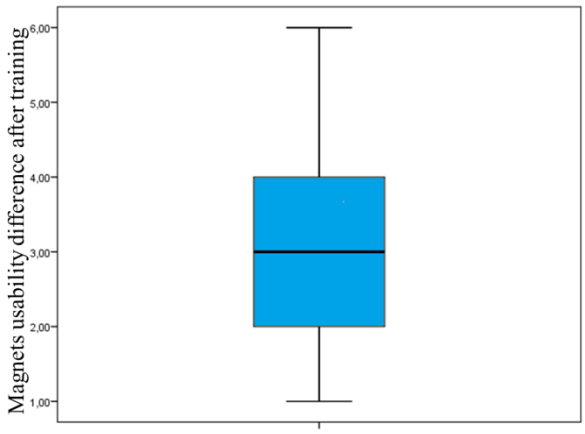


Figure 21 *The differences users perceived between magnets A, B and C after training.*

3.4.2.7. Originality and Portability

In the fourth and fifth question of the introductory questionnaire, users were asked to rate the originality and portability of the interaction. Originality means that they were giving a seven-point Likert scale rating on how innovative they think the interaction is. Portability asks whether they could imagine using this interaction method in other 3D games. Answers were given on a seven-point Likert scale ranging from "not at all" to "very practical". Figure 22 presents the boxplot graphs considering the participants' ratings. One can see that the originality was rated positively in general. The median rating was saying that the interaction method is very innovative. The portability was rated to be in a range between "possible" and "practical". We interpreted

these results as an indicator that people, in general, accepted the interaction method and are curious to see further applications in the future.

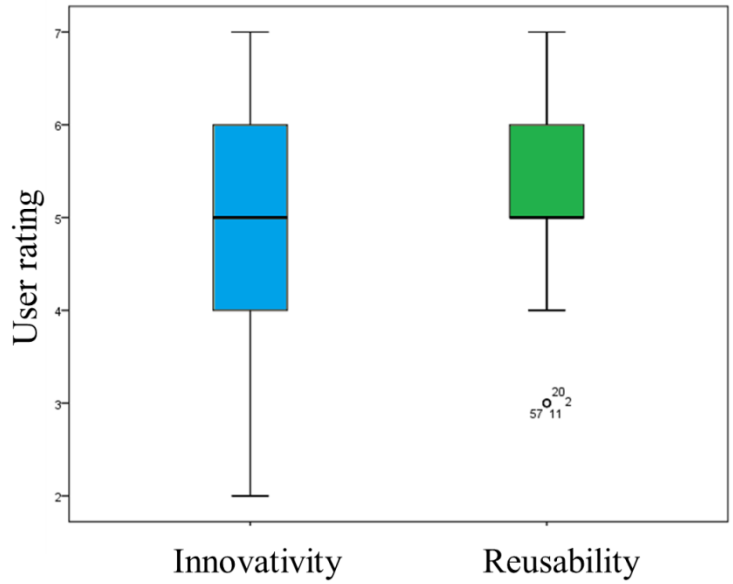


Figure 22 *User rating for innovativity and reusing the interaction concept in other contexts.*

3.4.2.8. Correlations

To gain an understanding of the diverse backgrounds of our participants, we also asked them for their age, gender and the time they usually spend at their smartphones per day. Some of these factors had significant correlations to the ratings in the AttrakDiff mini survey.

The participants' age had a significant negative correlation to the rating of attractiveness ($r = -0.455$; $p < 0.001$), hedonic quality ($r = -0.434$; $p < 0.001$) and pragmatic quality ($r = -0.373$; $p = 0.002$). This implies that younger users tend to rate the interaction better than older ones.

Figure 23 illustrates the mean ratings and corresponding confidence intervals for the pragmatic quality, hedonic quality and attractiveness for the different age groups. We can see the described correlation in the chart when observing

the distribution of mean values. Age group “15-25” and age group “40>” significantly differ in all categories. Their confidence intervals never overlap. Regarding the attractiveness rating, there was also a significant difference between age group “15-25”, age group “25-40” and age group “40>”. Age group “15-25” gave significantly better ratings than age group “25-40” and ”40>”. When looking at the hedonic quality, one can see that age group “40 gave significantly worse ratings than age group 0 and 1. All in all, each age group gave positive ratings, but the older participants tended to rate closer to a neutral position, and the younger ones rated more positively.

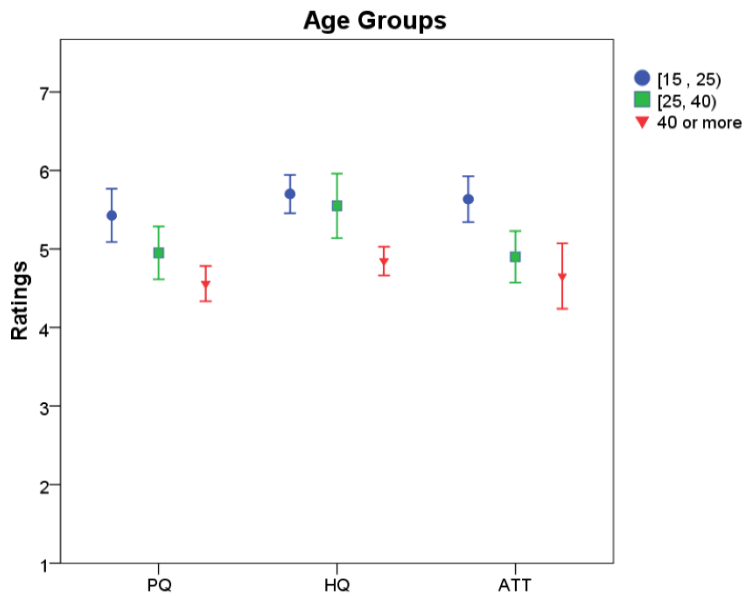


Figure 23 *Correlation between age groups and the AttrakDiff categories ATT, HQ, and PQ.*

Moreover there was a significantly positive association between the time participants spend at their smartphones and the ratings of the pragmatic quality ($r = 0.567$; $p < 0.001$), hedonic quality ($r = 0.584$; $p < 0.001$) and attractiveness ($r = 0.599$; $p < 0.001$). As expected by the authors, there is also a significant negative correlation between the time participants spend at their smartphones and their age ($r = -0.509$; $p < 0.001$). In Figure 24, we can see how the average rating for the time spent at the smartphone decreases in relation to increasing age. The absolute values of Pearson correlations between the time (Figure 25) spent at smartphones, and the AttrakDiff mini

ratings were all higher than the absolute values of Pearson correlations between the participant's age and the AttrakDiff mini ratings. Considering this and the fact that there is a significant correlation between age and time spent at smartphones, we believe that the time users spent at their smartphones per day is one of the key factors why younger people were giving more positive ratings on average. Hence, the time spent at smartphones plays a more important role than age. A possible interpretation is that users who use their smartphones more often have more positive associations with the new interaction type because they might feel more comfortable with new technology. The participants' openness to new technology—which may have a negative correlation with age—and more intense use of smartphones perhaps helps them understand our new interaction method more intuitively.

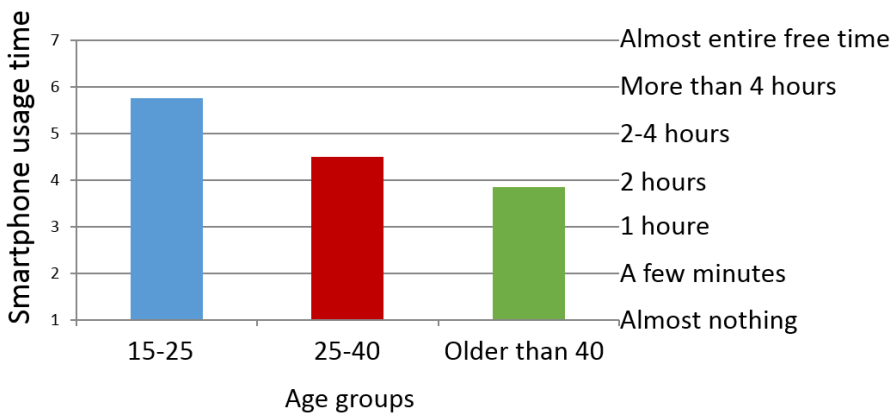


Figure 24 *Correlation between age and the average estimated time spent at the smartphone per day.*

There were similar interrelationships when examining the perceived difference between magnets after training. There was a significantly positive association between the participants' age and the perceived difference ($r = 0.345$; $p = 0.05$) which means that older people perceived a higher difference between the magnet types after training with them than younger ones.

Furthermore, there was a significantly negative correlation between the time spent on smartphones per day and the perceived difference after training ($r = -0.448$; $p < 0.001$). This means that participants who spend more time on their smartphones per day perceived fewer differences in handling between the different magnet types after training. This correlation is also shown in Figure 25. Our interpretation of those correlations is that younger people and people who are using new technology like smartphones more frequently are also more flexible in adapting to new interaction methods.

Note: Originally we had seven categories of "Usage Time". Since there were no users in upper and lower categories, we have placed all categories into three groups.

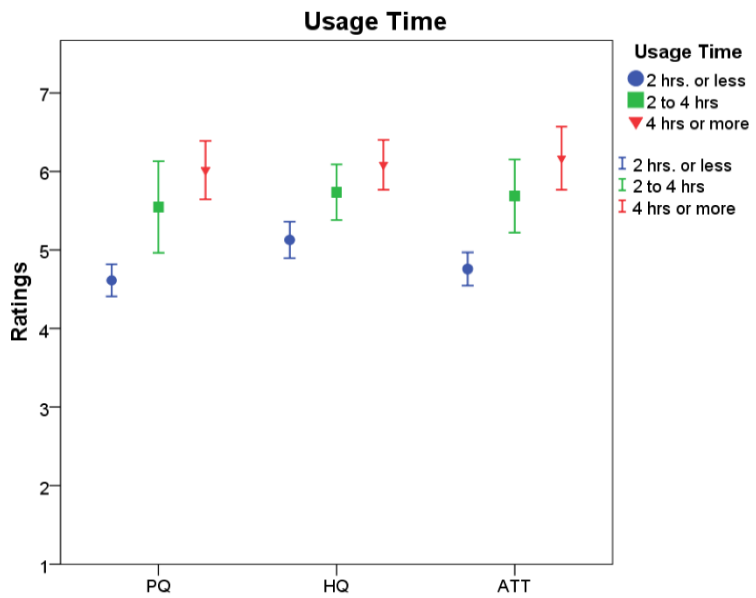


Figure 25 *Correlation between the estimated times spent at smartphones and the average rating for perceived differences after training.*

When looking at gender, there were no significant correlations to the AttrakDiff ratings. Figure 26 presents the mean values and confidence intervals for female and male participants. One can see that the confidence intervals do not differ significantly, but the ones of female participants were

slightly larger which might be interpreted as a sign that they gave more extreme or diverse ratings.

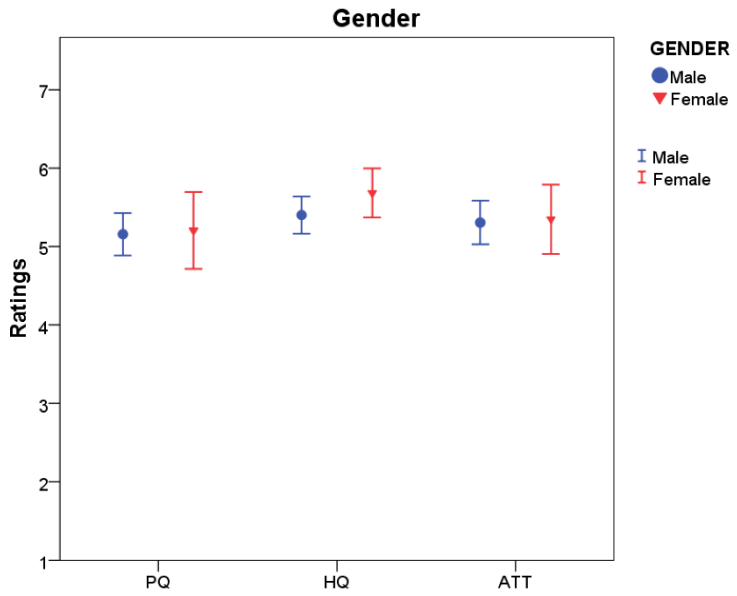


Figure 26 *Correlation between gender and the AttrakDiff categories ATT, HQ, and PQ.*

3.4.3. Interpretation of Results

As already mentioned in our first approaches, we did not consider the user's capabilities to adapt to the applictaion's interaction. In this method, we have analyzed the user's competence in order to improve the design of our applications. By aiming for intuitiveness and simplicity when designing interactive systems, developers sometimes forget about the flexibility and cognitive capabilities of human beings. What seems to be unintuitive can become intuitive after gaining experience. The results presented reveal that participants, in general, were experiencing fewer differences between the different types of magnets after training. For younger participants and participants who use their smartphones more frequently, the perceived difference after training was even smaller. In general, they tended to give more positive

ratings in most categories. In general, we found a high degree of proof for our thesis:

- *Users are able and willing to understand and adapt to our interaction system and metrics just by using the system and receiving visual feedback on their actions.*

By executing our extended version of the AttrakDiff mini survey with 64 participants, we found proof for our thesis. In sum, the results showed that the study's participants favored two of the three permanent magnet types and they met our expectations concerning adaptability to interaction metrics. The evaluation of the AttrakDiff categories demonstrated that the interaction method was desired and rated to be attractive in general.

The authors demonstrated how visual feedback and human cognitive capabilities could be used to solve usability issues in around-device interaction systems. Even though it seems obvious that human behavior plays an important role when designing user interfaces, this provided an excellent example of how human device interaction can sometimes benefit from including capabilities derived from the user's perspective instead of trying to overfit a system to each user.

3.5. Long-Term Test

Apart from the first demonstrator's applications, which we developed to prove the feasibility of the methods introduced, we also developed some real applications which we could launch in a wider test environment for long-term tests.

The idea of the long-term experiment is asking subjects to run the applications not only in well-defined labor environments but either in different real-life environments such as the way to work or school, at home and so forth. The next sections explore the applications and the experiment's results.

3.5.1. MagiBoxing

"MagiBoxing" is an interactive multiplayer boxing game for iPhone. This application simulates real touchless physical boxing like Nintendo Wii Boxing (Figure 27).

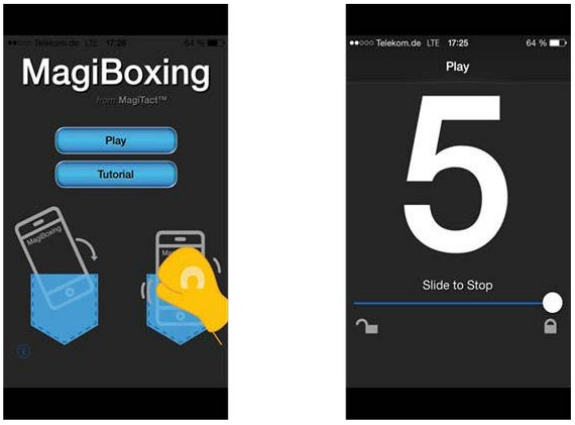


Figure 27 *Screenshots of MagiBoxing: Start Panel and Play Pane (left to right).*

3.5.2. Magiguitar

"MagiGuitar" is a musical game for iPhone in the style of "Guitar Hero". The user must move a magnet in the vicinity of the mobile device to trigger the notes of a predefined melody which is accompanied by music playback (Figure 28)

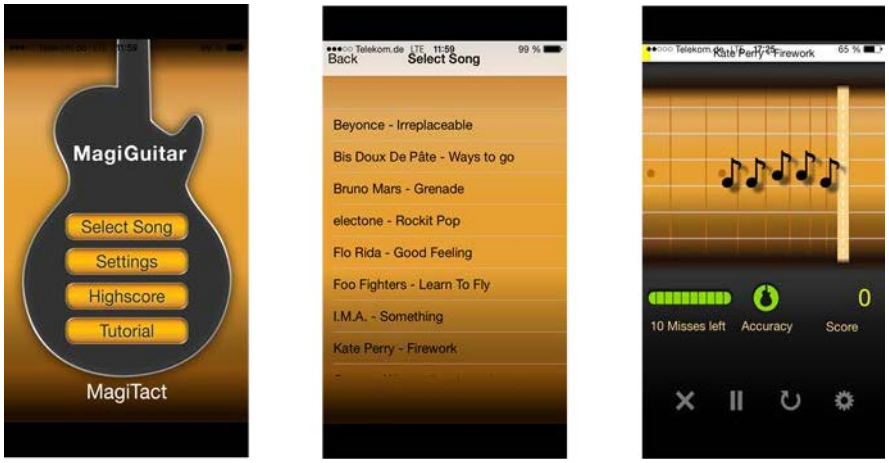


Figure 28 *Screenshots of MagiGuitar: Start Panel, Song Selection Panel, and Notes Triggering Pane (from left to right).*

3.5.3. Magitact Music

"MagiTact Music" is a music application allowing the user to play music in a new way. Having a magnet in hand, the user can perform high-quality drum samples, generate sounds or apply to his or her favorite music through hand motions (Figure 29).

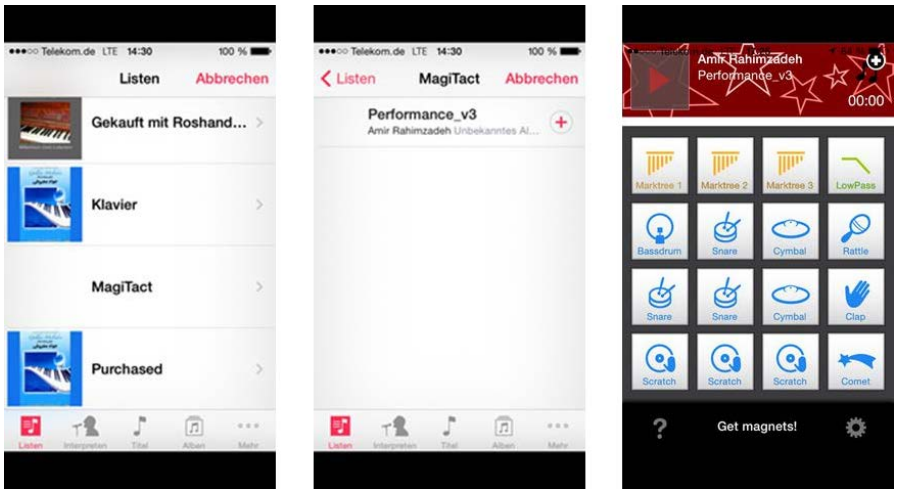


Figure 29 Screenshots of MagiTact Music: List Selection Panel, Song Selection Panel, and Play Panel (from left to right).

3.5.4. Results of the Long-Term Experiment

In this experiment, we had, similar to our 3D Mouse experiment, three age clusters of users (ca. 40% male and 60% female): 10-15, 15-30, and older than 30 (Table 10) for one month. Subjects were asked to use the applications every day for at least few minutes and in different environments.

Age group	male	Female	Total
10-15	5	5	10
15-30	2	6	8
Older than 30	4	7	11
Total	11	18	29

Table 10 Participant statistics for long-term experiment.

For this experiment, we also started with an AttrakDiff mini survey [59]. This version is a minimum version of the AttrakDiff method which is commonly

applied to the field of measuring user experience, and here we also extended the AttrakDiff survey with several introductory questions to ensure results with the same quality (see Chapter 3.4.2.2).

In the first question, subjects were asked to rate the difficulty of the applications. The difficulty rate was split into a Likert scale of 7 categories from extremely easy to extremely difficult. Figure 30 presents the users' rating for this question. In order to analyze the user rating, it is necessary to restate the complexity of the interaction logic of each application. The BoxingApp has the easiest interaction logic since there is only a simple triggering required. The MusicApp required two hand interactions, where the user has to choose the music effect with one hand and trigger it with the other hand. Therefore, it has slightly more complexity than the BoxingApp. The GuitarApp required triggering a certain music rhythm; therefore, it has the most complex interaction logic. Even though the users rated all applications as almost easy, we see a trend to more difficulty by increasing the complexity of the interaction logic.

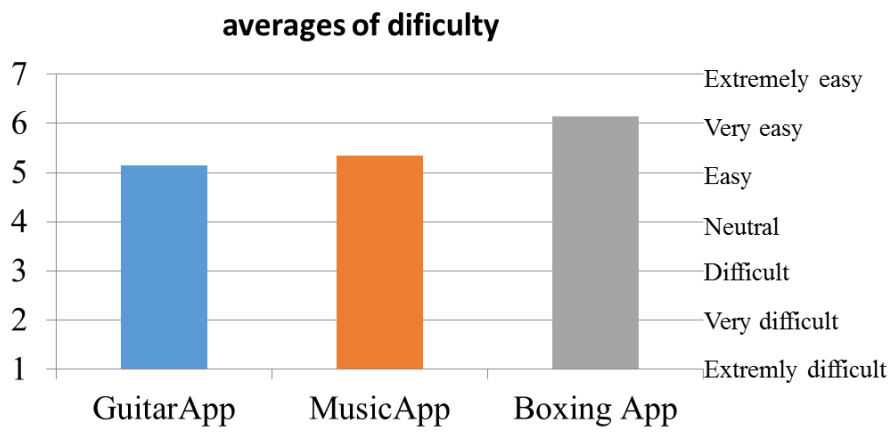


Figure 30 *User rating for interaction difficulty (1 means extremely difficult, and 7 means extremely easy.).*

The questions below offer additional proof of the user's statements concerning the ease of the interaction method.

- *"How innovative is such an interaction in your view?"*

- *"Could you suppose using this technology in other applications too?"*

An average user rating of 5.8 and 5.6 for these questions verify the rating in Figure 30.

After these introductory questions, subjects were asked to go through the AttrakDiff mini survey. In this section, we present the results of the AttrakDiff mini questionnaire and examine significant correlations between the results and personal attributes like age, gender or the participants' time spent on smartphones per day.

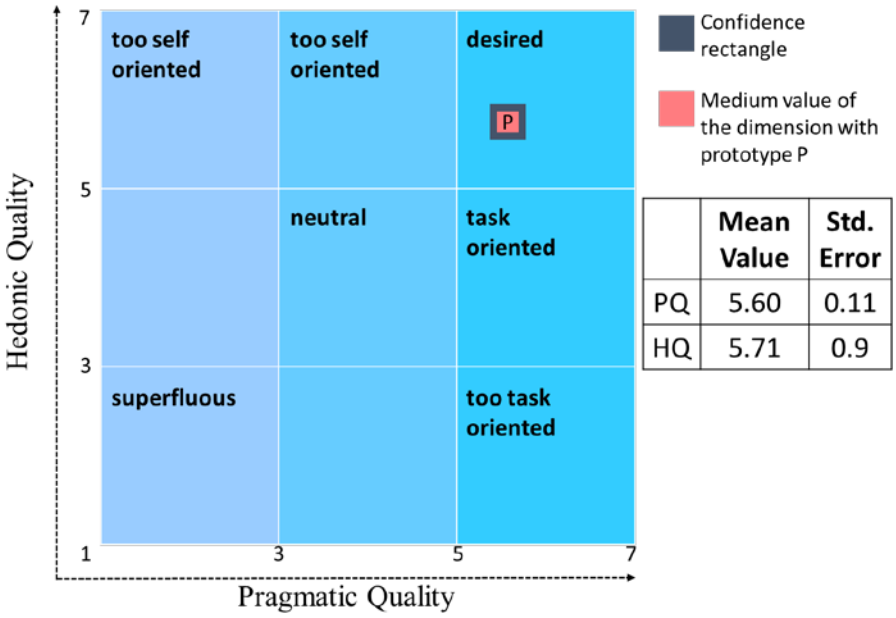


Figure 31 *AttrakDiff profile on he donic and pragmatic quality, positioning the medium performance of our prototype P, an interaction method in the context of AttrakDiff's performance categories for the long-term experiment.*

The boxplot graphs (Figure 31) indicate that the medians, as well as the first and the third quartiles of all three categories, lay in the upper part of the chart. As a higher number stands for better results and 4 stands for neutral, this implies high acceptance of our 29 survey participants regarding all categories.

Comparing this graph shows that the user acceptance is even higher than that of the general experiments with different magnets (section 3.4). This fact might imply user wishes to simplify the interactions. Also, the results of user acceptance for the individual applications (Figure 30) prove this statement. The perception of hedonic quality performed best. This can also be seen in Figure 31where the pragmatic and hedonic quality are compared and used to draw further insights. Figure 31 demonstrates that the product falls into the category "desired" meaning that both the hedonic and pragmatic quality were rated well (PQ mean value = 5.5, HQ mean value = 5.9). For the hedonic quality, there is little space for optimization whereas the pragmatic quality was not perceived as similarly outstanding. The confidence rectangle is ranges slightly into the category of "self-oriented". This might indicate that for some users the pragmatic quality still has room for improvement. Taking into account that the attractiveness score was also positive, we can conclude that users accepted the simple design of our applications.

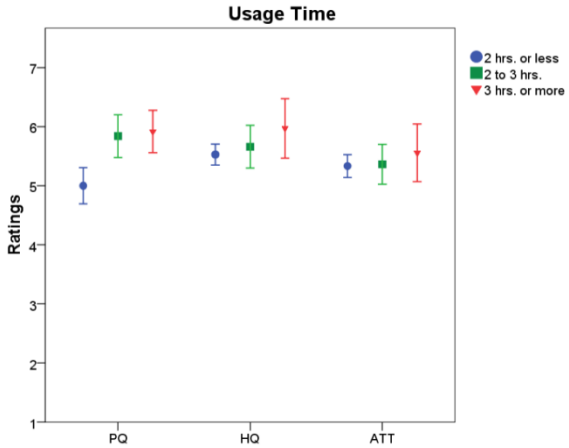


Figure 32 *Correlations: Usage time and user rating.*[4]

[4] Note: originally we had seven categories of "Usage Time". Since there were no users in upper and lower categories, we have placed all categories into three categories

3.5.4.1. Correlations of Age, Gender and Uses Time

In order to verify the user's rating, we have also classified the users according to their ages, genders and mobile phone use. Some of these factors had significant correlations to the ratings in the AttrakDiff mini survey.

This experiment also reveals (Figure 33, 32, 33) that gender has no significant impact on the user rating. In contrast to our last experiment, we see here that user age has no major impact on user rating as well. The only factor with higher significance in this experiment is the usage time with the rating of attractiveness ($r = 0.153$; $p < 0.427$), hedonic quality ($r = 0.6$; $p < 0.001$), and pragmatic quality ($r = 0.31$; $p < 0.102$). This result implies that experienced users (users with higher usage times) tend to rate the interaction better than inexperienced ones.

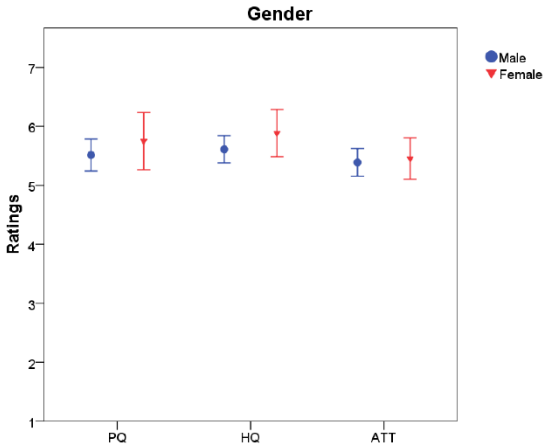


Figure 33 *Correlations: Gender and user's rating.*

Our previous experiments with complex gestures have established that there are considerable differences in the user behavior between these three age categories. However, this long-term experiment with triggering interactions only has revealed that user behaviors for such simple interactions are similar across all three age groups. It means that applications designed for simple interactions provide higher usability for all ages and demonstrates better acceptance

The long-term test with these applications has indicated that even the simplest methods of gesture interaction like triggering can provide high usability for the users. The design of the application has an even higher impact on the usability of the kind of interactions. Since we have designed these applications with the focus of triggering interaction, we could reach a high level of user satisfaction

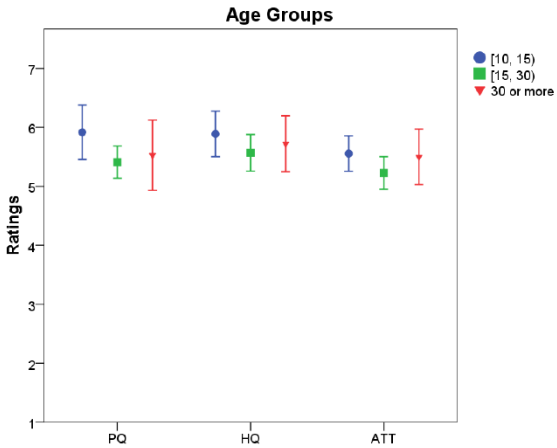


Figure 34 *Correlations: Age, gender and usage time.*

		Age	Gender	Usage Time
ATT	Pearson Correlation	-0.046	-0.067	0.153
	Sig. (2tailed)	0.812	0.729	0.427
PQ	Pearson Correlation	-0.252	-0.189	0.600
	Sig. (2tailed)	0.187	0.327	0.001
HQ	Pearson Correlation	-0.127	-0.259	0.310
	Sig. (2tailed)	0.511	0.175	0.102

Table 11 Correlations: Age, gender and usage time.

Chapter 4
Pingu

The primary results of this work have been presented in [3, 23, 24].

As previously mentioned in Chapter 1, touch sensing surfaces have evolved the way that humans interact with computing devices for years. Touch screens allow humans to interact with computers directly with their fingers in a more natural way instead of using the traditional user I/O devices like mouse and keyboard. Despite tremendous progress in developing touch-based technologies, this form of HCI depends primarily on human factors such as the size of users' fingertips. While many computing devices are continuously decreasing in size, their touch screen interface cannot be scaled smaller due to the surface area required for user interactions [35]. On the other hand, touch-based interactions occlude parts of the display screen that reduce the usability of the computing devices. We have already addressed these issues in Chapter 3 and proposed MagiTact as a new method of ADI techniques in order to overcome such challenges. Though MagiTact solved many disadvantages of touch-based interactions, we realized that MagiTact is not always the best ADI method. MagiTact interaction is based on influencing the magnetic field with a permanent or electrical magnet. Since magnetic field strength decays rapidly with distance to the source of the field, the interaction distance around the device in limited to 10-20 cm at best by using a magnet with an acceptable size and power. Therefore, the MagiTact technique is unsuitable for interaction with devices which are at a greater distance such as TVs or video projectors. We also found that MagiTact is not the best or easiest solution for realizing a precise 3D mouse. In consequence, we were thinking about a solution in which we can compensate for the disadvantages of MagiTact by maintaining the usability and 3D feasibility. This thought led us to the Pingu approach. In this method, we constructed new hardware in the form of a ring. In this chapter, we describe this hardware. Furthermore, we

repeat all the MagiTact use cases in order to show the feasibility of Pingu, and we introduce new use cases for this method.

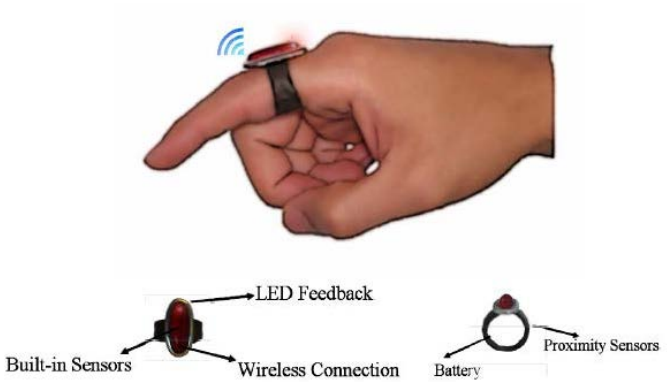


Figure 35 *The Pingu design concept and sensors [23].*

Pingu is a new miniature wearable and tangible device in the form of a finger ring (Figure 35) which allows interaction with any electronic device in ubiquitous computing environments in more intuitive and natural ways. Pingu is equipped with an advanced set of sensors and wireless connectivity. Given rings are commonly used due to different beauty, fashion, cultural or family reasons, we believe these features allow Pingu to become a valuable device in the field of human-computer or human-human interaction.

4.1. Related Work

In recent years, different gestural recognition approaches were developed which are either used to generate 3D signatures such as MagiTact (chapter Chapter 3) or can potentially be used to generate a 3D signature [2, 37, 38, 40, 45].

In our previous work, MagiSign [20], a 3D signature is created via influencing the magnetic field of a magnetic (compass) sensor embedded in mobile devices. However, the space of interaction is limited to the proximal 3D space around the device. Moreover, while Pingu can work with any computing device, MagiSign works only with smartphones (e.g., an iPhone). Finally, using multiple sensors in Pingu leads to more accurate gesture recognition in comparison to only one magnetic sensor in MagiSign.

In other approaches, which can potentially be utilized for 3D signatures such as an Acceleration Sensing Glove [43], a user has to wear extra gloves to interact with the computing device. The disadvantage of this approach is that gloves can be socially unacceptable or obtrusive. Other frameworks, such as Gesture Pendant [38] and SixthSense [37], require users to wear a pendant and an extra hat, which suffer from the same problems. Moreover, in approaches like SixthSense and Gesture Pendant, there is a need for an optical sensor (e.g., a camera) which causes problems when gestures performed are not in the direct line of sight of the sensor.

Finger rings or wristwatches can be used to solve the problem of social awkwardness. Pinchwatch [45] uses a wristwatch for finger gesture recognition with the help of a camera. Functions are invoked by performing sliding and dialing motions. However, it still has the occlusion problem. More recently, Nenya [40], a magnetically tracked finger ring, has been developed which includes a permanent magnet in the form of a finger ring and a wristwatch wireless tracking bracelet. The magnetometer is used to track the ring's position, and a Bluetooth radio allows the bracelet to send ring inputs to the user's device. However, Nenya only supports 1D input in comparison to the 3D inputs supported by Pingu. Furthermore, the IR ring provides an innovative method which can be used for authenticating users' touches on a multi-touch display [61].

4.2. The Pingu Prototype Design

The major challenge facing current wearable input devices is to ensure that they are socially acceptable and as unobtrusive as possible [12–14]. One possible way to design such a device is to embed it in traditional wearable accessories such as pendants [38], rings [42] or wristwatches [26]. Among common accessories, rings are commonly worn in everyday social. Hence, they are suitable accessories to embed sensory devices in for natural and unobtrusive HCI.

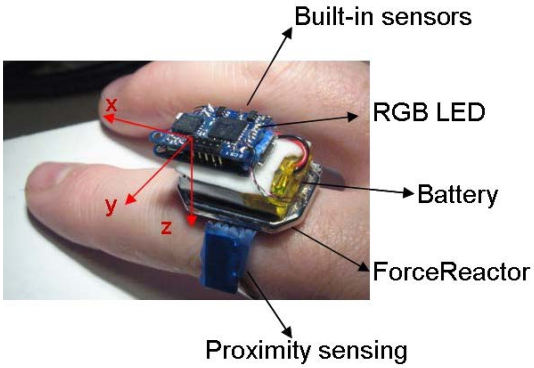


Figure 36 *Pingu, our multi-sensor framework, for interaction with a smart environment [23].*

According to the experiments conducted by Card et al. [62], the information entropy of interaction by the finger is much larger than any other body part that is currently used for interaction. It is shown that the arm is rated at 11.5 bits/s, the wrist at 25 bits/s while the entropy of interaction by the finger is at 40 bits/s. Hence, user interface devices operated by a finger have a greater potential for faster interaction.

In this section, we introduce a new prototype in a form factor of a finger ring called *Pingu* that allows interaction in a ubiquitous computing environment. As the device is mounted on a finger, it allows for simple, sharp, and tiny gestures using finger movements. *Pingu* comprises six degrees of freedom (DOF) inertial sensing systems, a 3-DOF magnetometer and two channels of proximity sensing. Also, *Pingu* is equipped with wireless connectivity and visual and vibrotactile feedback mechanisms (Figure 36), which can make it a unique device for human-computer or human-human interaction in the form of gestures, tactile and touch. *Pingu* can sense absolute orientation and direction, linear and rotational movements and the proximity of other fingers with its proximity sensing plates. The current prototype dimensions, excluding battery and battery charging connector, are 10mm* 22mm* 4.2mm, with a total mass of 50 g. In our first prototype, the battery is located under the sensor platform (Figure 36) although in the final version it will be augmented at the ring band (Figure 35). *Pingu* contains a rechargeable Lithium-Polymer battery, which can be connected to the power supply with an internal micro-USB connector. The typical operating time per battery charge is about 2 hours with up to 6 hours in standby mode.

Pingu can detect motion using accelerometer and gyroscope sensors, which allows the device to be used for gestural interaction. The accelerometer senses linear acceleration along three axes as indicated in Figure 36. When the device is stationary, it can be used to extract static orientation relative to gravity. The gyroscope (i.e., angular rate sensor) measures the angular rate movement of the ring. There are three channels of sense data, one each for pitch (rotation about the y-axis), roll (rotation about the x-axis) and yaw (rotation about the z-axis). The gyroscope sensor complements the accelerometers to provide a full six degrees of freedom inertial sensing capability that can be utilized for detecting the dynamic 3D trajectories of the ring.

In addition, the device is equipped with a magnetometer, allowing for orientation detection, as well as intra-finger interaction. The magnetometer senses the magnetic field in 3D space around the ring along its x, y, and z-axes. It is the only sensory information that can provide the orientation with respect to the Earth's fixed magnetic field. In addition, the magnetic field around *Pingu* can be deformed by a permanent magnet worn on any other finger of the user [19]. This ability allows the possibility of more complex intra-finger interaction.

Pingu also has several channels of capacitive proximity sensing, allowing for touch-based interaction. The installation of the proximity sensors also allows for intra-finger interaction. The combination of proximity and motion sensing on *Pingu* can provide many options for flexible and usable interactions.

We explain some of the possible applications of *Pingu* proximity sensors in the subsequent section. Finally, *Pingu* has an RGB LED and tactile feedback mechanisms. *Pingu* contains an inbuilt Alps ForceReactor vibration transducer that allows haptic sensations to respond to movements or gestures. The RGB LED can also be used to visualize the path of a gesture in the air.

Pingu has an integrated Bluetooth module, which enables interaction in a ubiquitous and networked fashion. *Pingu* can connect, transfer data and interact with any computing devices that provide Bluetooth wireless connectivity in real time. The output data rate for all sensor channels is set to 200 Hz. The

current *Pingu* setup has one onboard DSP (Digital Signal Processor) micro-controller to handle real-time data filtering and communication protocols. The list of sensors embodied in the current *Pingu* prototype and their specifications are summarized in Table 12.

Type of Sensor	Description
3-axis Accelerometer	+/- 8g
3 axis Magnetometer	+/- 2 gauss
3-axis Gyro	+/- 2000 deg/s
LED	configurable RGB LED for visual feed-back
ALPS ForceReactor	vibration transducer
proximity sensing	2 channels
Bluetooth	range 2 meters or greater
Temperature	-20/ 85 degrees C

Table 12 List of the built-in sensors at current Pingu prototype [23].

4.3. Applications

Pingu is a general e-companion wearable device that is designed in the form of a socially acceptable finger ring. In this section, we present and discuss a number of potential *Pingu* applications, the primary results from mobile device interaction, social computing and human-to-human interaction.

4.3.1. General Gesture Interaction

The main application of *Pingu* is for gestural interaction with computing devices. Based on previous research on gestural interaction [19], the user can interact with mobile and tangible devices that have an embedded magnetometer by moving a permanent magnet around the device in the form of different hand gestures. This approach requires the user to perform gestures by hand only near a device with an embedded magnetometer. However, *Pingu* can be utilized not only for ADI with mobile and tangible devices but also for gesture-based interaction with smart environments, where a user may want to interact with devices even though they are not in the vicinity of the user. In addition, the *Pingu* form factor requires a user to perform simple, sharp, and tiny gestures using finger movements.

The three-dimensional accelerometers and the gyroscope embedded in *Pingu* can be exploited to provide relative finger/hand movement in the 3D space. This capability can be applied for controlling household appliances in a smart home. In order to evaluate *Pingu* for general gesture usages in smart environments, we have defined a set of nine simple hand and finger movements shown in Figure 37.

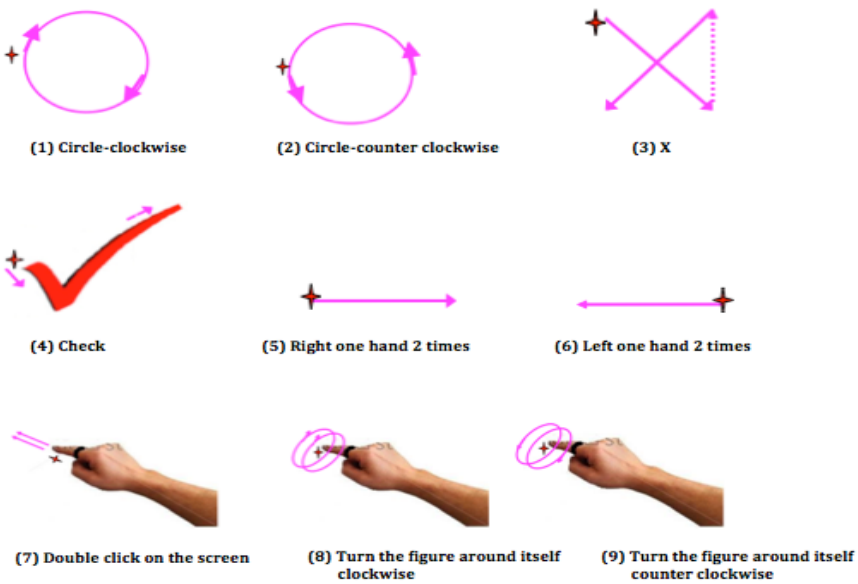


Figure 37 *A set of nine general gestures used in this work [23].*

We recruited 24 participants for the experiments and asked each of them to repeat each gesture 15 times. A set of features such as average, variance, magnitude and frequency contents are extracted from each sensory data. The extracted features are grouped together in a feature vector and passed to the Multi-Layer Perceptron (MLP) classifier using a 10-fold cross-validation scheme to avoid over-fitting. The results demonstrate an overall accuracy of 97% in recognizing different gestures.

Figure 38 *Interaction with Smart TV using Pingu prototype.*

Figure 38 depicts an example application of *Pingu* to interact with a smart TV. The user moves his or her hand in different directions while wearing *Pingu* to select TV menu sections. In the current design, the user is required to touch the proximity sensing plate in order to indicate the start of a gesture command. This mechanism helps the system to differentiate the user's gesture command from the user's everyday hand movements.

This gesture-based interaction does not suffer from occlusion problems which occur in vision-based systems (e.g., Kinect), hence it can be used in noisy environments, where part or the whole of a user's body is occluded.

4.3.2. Social Interaction

Humans use hand gestures in daily human communications and it would be helpful if a system could track such movements in different social contexts. *Pingu* provides a powerful framework for context-based human-to-human interaction modalities. Therefore, we introduce a new concept for studying and analyzing human-human interaction using *Pingu*. For instance, detecting and analyzing human relations (e.g., handshakes, social proximity in conferences or meetings) can provide a rich source of information about the social network of *Pingu* users. Based on this information, the system can suggest people as *Pingu* users to connect through online social networks (e.g., Facebook, LinkedIn). This functionality is different from the current "People You

May Know" suggestions in online social networks that are only based on user's current networks (i.e., circle of friends) and friend lists (Figure 39)

Figure 39 *A handshaking activity between two Pingu users.*

4.3.3. Physical Activity Analysis and Recognition

Fingers are commonly used in many activities and tasks during daily human life explicitly as well as implicitly. Pointing to things, drawing on a table, and gesturing are natural movements that humans do—often inattentively (e.g., to support the spoken word). It appears that the movements of the fingers reflect many activities—ranging from micro-activities such as walking and running to fine motor movements called macro-activities such as writing, typing, driving, and eating.

Therefore, analyzing the motions and behaviors of human fingers provides a rich source of information about the physical activities of the users. Such activity monitoring can be applied to a wide range of applications such as healthcare monitoring for elderly people or emergency help services.

Pingu can store or send information about the physical activities of users. It can send data using Bluetooth, or over a network via the data services of a mobile phone. In this case, *Pingu* is connected to the mobile device via Bluetooth and uses data service facilities in the cell phone to send data over the network. Data can be stored or monitored in a remote server. In this manner, the user can constantly receive reports of his or her physical activities

and extract health-related factors using the data stored in *Pingu* or a remote server. A medical assistant can also analyze data in more detail or provide warnings in case of irregular or unregulated physical activities. As *Pingu* can send data to the network in a continuous and online manner using, e.g., data services in a mobile phone, it can be used for online monitoring of elderly people or people after surgery. Not only can the activity of one user be monitored by wearing *Pingu*, but also the activities of a group of users living or working in the vicinity can be tracked and recognized in a network-sensing fashion. Group activity recognition among networks of *Pingu* users opens a new perspective on human social behavior analysis.

Figure 40 *Typing on the Mac keyboard.*

4.3.4. Context Recognition and User Interface

As mentioned in the previous section, finger motion can provide considerable information on human activity and status. By the same token, contextual data may also be extracted from finger motions which can be captured by *Pingu*. Most of these contextual data are related to the context of a user's physical activity or a group of *Pingu* users. For instance, *Pingu* can detect if a user is walking, running, eating, sleeping or typing.

We propose such context/activity detection for adapting smart devices. These smart devices can be smart facilities in an intelligent home environment such as illumination facilities, TV and music sets, a mobile device, or a lap-top/workstation. We assume that *Pingu* is connected to these devices using a

Bluetooth link. Depending on the level or status of a user's physical activity reported by *Pingu*, the illumination or background music in a smart environ-

Figure 41 *Rest or relax for 1-2 minutes.*

ment can be adjusted. If the user is sleeping, lights and a TV set can be turned off. The user interface of a mobile device or a workstation can also be adapted based on the actual status of the user reported by *Pingu*.

Figure 42 *Typing on the iPad screen.*

Figure 43 illustrates accelerometer readings along the x-axis captured for one user for six activities: *Typing on the Mac keyboard (Figure 40), Typing on*

the iPad screen (Figure 42), Rest or relax for 1-2 minutes (Figure 41), Hand Shaking (Figure 39), Running on the spot, and Walking. As is demonstrated, the spatial and frequency characteristics of activities are clearly differentiable.

While these activities are highly general in nature, each of these activities can be easily extended to monitor the physical activities of a user. For example, if the data collected from sensors indicate that the user is taking a break after running, the computing device can switch to a music track with a symphony that helps the user relax.

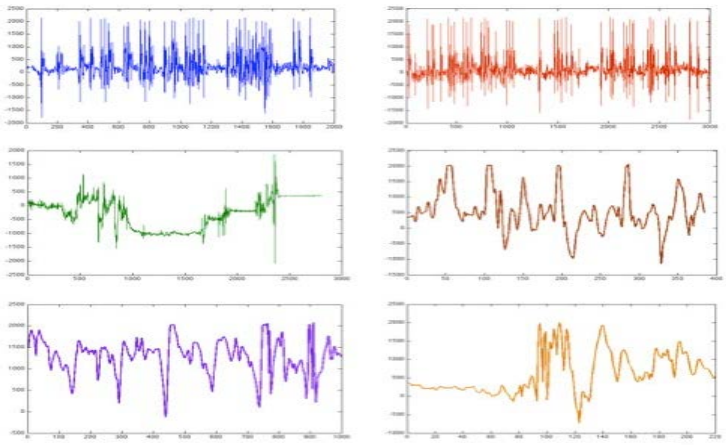


Figure 43 *Accelerometer readings (along X-axis) for each of the six activities.*

Context detection by *Pingu* can have marketing potential too. For instance, it can be used for semantic advertisements based on the context of users' physical activities during daily life, or their interaction with other users. As *Pingu* is equipped with force/vibration feedback facilities, it can be used for receiving alerts from smart devices and environments. As *Pingu* can be continuously and remotely available using, e.g., communication facilities in a mobile phone, it can receive remote alerts. For instance, a user can be informed by tactile feedback if something is going wrong in the kitchen, or somebody is entering the apartment or if lights are left on. Obviously, the user can send interaction commands back in order to deal with the situation using gestural or touch facilities embedded in *Pingu*.

4.3.5. In-Car Interaction

Cars are currently equipped with a variety of built-in devices and systems that require drivers' attention. Interacting with these devices such as navigation, information, and entertainment systems may influence driving performance and increase the risk of driving [63]. A *Pingu* user can perform tiny gestures with his or her fingers while driving to control music in the car, interact with a navigator, check emails, and make calls. On the other hand, combining gestural modality with a speech interface may improve the current in-car user interfaces. Figure 44 depicts a *Pingu* user controlling the navigation system by moving both fingers similar to the zoom gesture in touch screen devices.

Figure 44 *In-car interaction using Pingu.*

4.4. Gestures Recognition with Pingu

In this section, we describe our experimental results regarding gesture recognition with the above-introduced framework of *Pingu* [23]. While gestures made by any part of the body can be used for interacting with a computing device, previous research based on experiments conducted by Card et al. [62] establishes that the information entropy of a finger-based interaction is much larger than the interaction based on any other human body part. For instance, the interaction with the arm and wrist has the information rates of 11.5 and

25 bits/s respectively, while the data rate of the finger is 40 bits/s. This capability was the main reason why we configured Pingu as a finger ring.

Pingu is also capable of accepting 3D inputs from different gestures which are performed either in the air or on surfaces such as a user's palm or the top of a table. These gestures can be used in developing several interesting applications, including remote controlling or signature recognition. In this section, we analyze Pingu's recognition of a range of simple gestures. The main contribution of this section is to present results based on a multi-sensor interaction framework and efficient classification algorithms. Our analysis reveals that these generic gestures can be recognized with high accuracy.

4.4.1. Experiment

This section evaluates Pingu for general gestural interaction. For this purpose, we used the set of nine general gestures defined in Figure 37. As previously established, the gestures are highly general in nature and can be used to control smart environments. For example, gesture 1 and 2 can substitute for the volume control buttons on a remote control and gesture 5 and 6 can change music tracks forward and backward. To evaluate Pingu for general gestural interaction in smart environments, we perform all the nine gestures in three ways, as follows:

1. *General gestures in the air,* in which a gesture is performed in the air.
2. *General gestures on the table,* in which a gesture is performed on the top of the table.
3. *General gestures on the palm,* in which a gesture is performed on a user's palm.

The three mediums of air, palm, and desk provide a variety of surfaces for gesturing. In this way, the methodology can be tested under more variable yet practical scenarios. Both palms and desks are surfaces commonly available for users during the gesturing process. The air medium also provides the fantasy of writing in air for the user, when the two other mediums are not available. Our results are based on a dataset collected from 24 users.

Total Users	Male	Female	Right Handed	Left Handed
24	10	14	20	4

Table 13 User statistics table [23].

4.4.1.1. Feature Extraction

Each of the nine gestures in Figure 37 is performed 15 times per user. The sensor readings specific to each of the nine gestures are then captured via a Java desktop application developed for Mac OS. To evaluate the interaction made by Pingu, we classify gestures based on the sensor readings collected for each gesture. In particular, we adopt the following approach:

We mix the data collected from all the 24 users and cross-validate it. For this purpose, we form a feature vector containing data specific to each sensor. For example, a feature vector obtained from the accelerometer used in Pingu contains the following:

1. Mean of the linear acceleration along x, y, and z-axis (3 features),
2. Variance of the linear acceleration along x, y, and z-axis (3 features),
3. Mean of the Euclidian norm of the linear acceleration along x, y, and z-axis (1 feature),
4. Variance of the Euclidian norm of the linear acceleration along x, y, and z-axis (1 feature),
5. Standard deviation of the linear acceleration along x, y, and z-axis (3 features),
6. Piecewise correlation between linear acceleration along x, y, and z-axis (3 features), and
7. Frequency features along x, y, and z-axis (3 features).

As illustrated in Figure 37, the mean and variance of the sensor readings obtained for gestures 1 and 2 may not be able to differentiate between these two gestures. Therefore, we included the piecewise correlation, and the frequency features specific to each sensor. The feature vector for the angular movement rate of the ring (i.e., from the gyroscope) is obtained in a similar manner. Each feature vector for each sensor, therefore, contains 17 elements. Since multiple windows provide more detailed information in gesture classification, our results are based on four windows. Feature vectors obtained from each window are concatenated to form a new feature vector of 68 (=17×4) features. To further validate that Pingu is effective in gestural interaction in a smart environment, we do not use the magnetometer readings in this analysis.

4.4.2. Gesture Classification

The feature vectors obtained for each of the three experiments are then used as an input to a classification algorithm for gesture classification. Specifically, we have classified the gestures with four classifiers:

1. Decision Tree (DT), a decision tool that uses graphs and a model of decisions to derive the outcomes and consequences,
2. Multi-Layer Perceptron (MLP), a feed-forward artificial neural network that models the relationship between inputs and outputs to find the patterns,
3. Naïve Bayes (NB), a probabilistic classifier that uses Bayes' theorem with strong independence assumptions, and
4. Support Vector Machines (SVM), a set of hyperplanes in high dimensional space for using classification and regression.

Our analyses are based on the implementation of these classifiers in the Weka machine learning toolkit [64, 65]. Table 14, Table 15and Table 16 list the classification results obtained for all the three experiments. As shown in Table 14 and Table 15, MLP classifier outperforms all the other three classifiers for gestures performed in air and on the table, with more than 97% and 93% accuracy respectively. Table 16 demonstrates that SVM has better results with more than 77% accuracy.

Algorithm	**Accuracy**
MLP	**97.8%**
DT	87.0%
NB	57.4%
SVM	96.4%

Table 14 Gesture classification results for general gestures in the air [24].

Algorithm	Accuracy
MLP	**93.7%**
DT	73.1%
NB	49.2%
SVM	83.9%

Table 15 Gesture classification results for general gestures on the table [24].

Algorithm	Accuracy
MLP	71.1%
DT	71.1%
NB	33.4%
SVM	77.5%

Table 16 Gesture classification results for general gestures on the palm [24].

To illustrate further how different precise gestures can be distinguished, confusion matrices obtained from the MLP classifier for general gestures performed in the air are presented in Table 17. As demonstrated, all nine gestures are usually distinguishable, but more specifically the confusion matrices indicate that gesture 1 and gesture 2 are somewhat harder to classify. Similarly, we note that gesture 8 and gesture 9 are classified with lower accuracy due to the inherent similarity in performing these gestures. On the other hand, gesture 4 is the easiest to be classified, as it is easily distinguishable from other gestures. These results confirm that gesture recognition by Pingu is generally trustworthy.

Gesture	1	2	3	4	5	6	7	8	9
1	333	3	0	0	0	1	0	3	0
2	3	334	2	0	0	0	0	0	1
3	2	1	336	0	1	0	0	0	0
4	1	1	0	343	0	0	1	1	0
5	0	0	0	1	338	2	0	0	0
6	1	0	0	0	3	324	0	0	0
7	0	1	0	0	0	0	340	2	0
8	7	0	1	0	0	0	0	320	12
9	0	0	0	0	0	0	0	14	332

Table 17 Confusion matrix obtained from MLP for the results shown in Table 15 [24].

4.5. Authentication Based on 3D Signatures Using Pingu

Traditional methods of authenticating a user, including a password, a PIN, or a more secure PIN entry method (A PIN entry method resilient against shoulder surfing [66]), can be stolen or accessed easily and, therefore, render authentication insecure. In this section, we present the usability of Pingu by providing a highly secure access system. Specifically, Pingu allows users to create a 3D signature and record the temporal pattern of the signature via an advanced set of sensors. As a result, the user creates a 3D signature in the air using a finger. Our approach has two main contributions: (1) compared to other wearable devices, a finger ring is more socially acceptable, and (2) signatures created via a finger in the air or on a surface leave no visible track and, thus, are extremely hard to counterfeit. In other words, a 3D signature allows much higher flexibility in choosing a safe signature. Our experiment shows that the proposed hardware and methodology could result in a high level of user authentication/identification performance.

The following experiment explores the usability of Pingu in providing a secure authentication method for users to access their computing devices. To illustrate further, we conducted a user study with 24 participants, where each user performs his or her signature in the form of a gesture, and we record the corresponding sensor data. We demonstrate that the recorded sensor data

provide rich information for each gesture made by a user. These gestures can be classified by utilizing simple classification algorithms. In consequence, we can authenticate users based on their signatures with high accuracy.

4.5.1. Experiment

To evaluate the usability of Pingu in secure authentication, we perform gestures defined as a signature. Since Pingu is worn on a finger, even sharp and tiny gestures can be used for the purpose of authentication. When the user performs a gesture, the associated sensor data are collected. The sensor readings define the temporal pattern of the signature and, thus, can be used in matching the signature for authentication. Our experiments were divided into two categories:

1. Signature in the air

2. Signature on the table

Setting the two mediums as air and desk provides a variety of surfaces for gesturing. In this way, the methodology can be tested under more variable yet practical scenarios. The desk-surface is a surface which is commonly available for users during the gesturing process. The air medium also provides the fantasy of writing in air for the user, when the two other mediums are not available.

Signatures for each user are recorded on two different mediums to evaluate Pingu for its dynamic usability. In other words, these two experiments ensure that the usability of Pingu in secure authentication is irrespective of the surface (or medium) of interaction. Each signature is first performed in the air and then on the table. Multiple templates per signature are collected. Specifically, when a signature is performed, the 3D trajectory of the ring is recorded in the form of sensor readings. For example, as the ring moves, the accelerometer, embedded in Pingu, measures the linear acceleration along the three axes: x, y, and z.

Since Pingu enables the user to generate sharp and tiny gestures, any general gesture can be used as a signature pattern. When a user performs a gesture,

the sensor data of the particular gesture are compared to the previously recorded signature pattern (template) for the user. The two patterns can be compared via a Dynamic Time Warping (DTW) technique, and if the difference between the two patterns is less than a predefined threshold, the signature is accepted. Next, we provide details on the datasets and the classifiers used to analyze signatures made by the users.

Figure 45 *An example of a 3D signature made in the air[3].*

4.5.2. Data Collection

Our dataset consists of six signatures, obtained from 24 users. Every user performs each of these six signatures 15 times. The sensor data of each signature are captured via a Java desktop application. To classify the signatures based on the sensor readings captured, we extract an extended set of features, for sensor data captured for each signature performed by a user. To extract a feature vector from these sensor data, we use the following approach for feature extraction:

We mixed the data collected from all the 24 users and cross-validated it. For this purpose, we formed a feature vector containing the data of each sensor. For example, the feature vector specific to accelerometer contains the following:

- Mean and variance of the linear acceleration along x, y, and z-axes (6 features),

- Mean and variance of the Euclidian norm of the linear acceleration along x, y, and z-axes (2 features),

The feature vector from the gyroscope is obtained in a similar manner. Each feature vector for each sensor, therefore, contains eight elements. Since multiple windows provide more detailed information in gesture classification, our results are based on four windows. Feature vectors obtained from each window are concatenated to form a new feature vector of 32 (=8x4) features.

4.5.3. Signature Classification

The feature vectors obtained from each sensor are then concatenated to form a large feature set that represents the features defining each signature. To classify users based on their signatures, we use a set of four classifiers:

(a) Decision Tree (DT), a decision tool that uses graphs and a model of decisions to derive the outcomes and consequences,

(b) Multi-Layer Perceptron (MLP), a feed-forward artificial neural network that models the relationships between outputs and inputs to find the patterns,

(c) Naïve Bayes (NB), a probabilistic classifier that uses Bayes' theorem with strong independence expectations, and

(d) Support Vector Machines (SVM), which set hyperplanes in high dimensional space for using classification and regression.

The current implementations available for these classifiers in the Weka machine learning toolkit version 3.7.0 [64, 65] on Mac OS X are used. Table 18 and Table 19 list the classification accuracy obtained for both sets of experiments. As demonstrated, MLP and SVM outperform the other two classifiers (i.e., DT and NB). We additionally note that using simple features (i.e., the mean and variance of sensor readings) can enable us to classify users (based on their signature patterns) with an accuracy of approximately 99% in both experiment categories.

Classifier	Accuracy
MLP	98.9%
DT	82.2%
NB	97.5%
SVM	99.2%

Table 18 Signature classification for 24 users regarding signatures in the air [3].

Classifier	Accuracy
MLP	99.2%
DT	87.0%
NB	97.5%
SVM	99.4%

Table 19 Signature classification for 24 users regarding signatures on the table [3].

4.5.4. Correlation and Energy Features

To illustrate the effect of a feature set on the accuracy of classification techniques, we extract piecewise correlation and frequency features of sensor readings. Frequency features measure the intensity in the movement of the ring and are calculated as the sum of squared discrete FFT (Fast Fourier Transform) magnitudes. The correlation features, on the other hand, help differentiate between sharp and tiny gestures made by users. Together, these features help capture the periodicity in sensor readings. Thus, we performed another study of classifying signatures with a feature set that contains frequency and correlation features in addition to the mean and variance extracted from each of the three sensors. Specifically, the piecewise correlation between linear acceleration along x, y, and z-axes (3 features), and frequency domain features along x, y, and z-axes (3 features).

Each feature vector for each sensor, therefore, contains 14 elements. With a window size of 4, the size of the feature set is 56 (=14x4). To classify, we again use the four classifiers listed earlier. Tables 4-5 present our results obtained for the experiments performed in air and on the table. The results indicate that with correlation and frequency features, the accuracy can be 100%.

Classifier	Accuracy
MLP	100%
DT	86.7%
NB	98.3%
SVM	100%

Table 20 Signature classification for 24 users regarding signatures in the air (with correlation and frequency features) [3].

Classifier	Accuracy
MLP	100%
DT	86.7%
NB	99.2%
SVM	99.7%

Table 21 Signature classification for 24 users regarding signatures on the table (with correlation and frequency features) [3].

4.6. Text Recognition Using Pingu

In order to have a positive comparison with MagiTact, which is discussed in Chapter 5, we have also run the experiments for text and digit recognition with the Pingu framework. Therefore, we applied the same methodology as already introduced in section 4.4.1. We collected gesture data of the digit "0-9" from the categories (1) in the air and (2) on the table. Furthermore, we

provided the format for the digit entry (Figure 46) in order to increase the accuracy of the digit recognition which has been done even by different users.

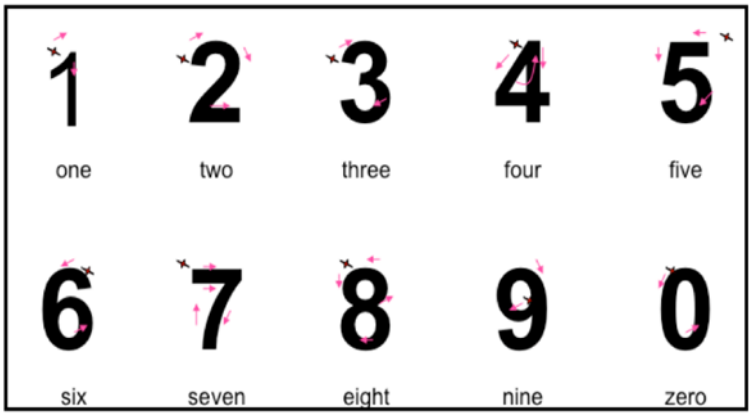


Figure 46 *Digit formats used for entry.*

Here are our results based on a dataset collected from 24 users (Table 13). We mix the data gathered from all users with cross-validation. For this purpose, we formed a feature vector containing data of each sensor for each of the three experiments. For example, the feature vector specific to the accelerometer contains:

- Mean and variance of the linear acceleration along x, y, and z-axis (6 features),
- Mean and variance of the Euclidian norm of the linear acceleration along x, y, and z-axis (2 features).

Figure 47*A gesture for Digit entry in Air.*

We collected the feature vectors from the gyroscope and magnetometer in a similar way, so that we had 8 elements for the feature vector of each sensor. Here we also used four windows for gesture classification. Therefore, we obtained a new feature vector of 32 (=8x4) elements for each sensor

4.6.1. Text/Digit-Gesture Classification

The feature vectors obtained for each of the three experiments are used as an input to a classification algorithm for gesture classification. We classified the gestures with four classifiers: MLP, DT, NB and SVM, a set of hyperplanes in high dimensional space for using classification and regression. Our analysis is based on the implementation of these classifiers in the Weka machine learning toolkit [64, 65].

Classifier	Accuracy
MLP	96.1%
DT	82.7%
NB	49.3%
SVM	90.4%

Table 22 Digits Entry in Air.

Classifier	Accuracy
MLP	89.5%
DT	68.9%
NB	36.8%
SVM	75.3%

Table 23 Digits Entry on Table.

Table 22, Table 14 and Table 23 list the classification results obtained from all the experiments in the air and on the tablet. As shown in these tables, the MLP classifier outperforms all the other three classifiers for gestures per-

formed in the air and on the table, with more than 96% and 89% accuracy respectively.

We did not use the magnetometer sensors for the first two experiments (i.e., Digits in Air and Digits on Table, Table 22, Table 14, and Table 23). We have repeated the experiment on the table in order to discover if the reading of the magnetometer sensor will improve our results. Table 24 demonstrates that the impact of the magnet sensor is almost negligible except by NB classifier.

Classifier	Accuracy
MLP	89.7%
DT	67.1%
NB	42.2%
SVM	76.0%

Table 24 Digits entry with magnet on the table.

We repeated the experiments for the digit recognition also with the two additional feature vectors: (1) piecewise correlation between linear acceleration along x, y, and z-axis (3 features), and (2) frequency domain features along x, y, and z-axis (3 features).

Classifier	Accuracy
MLP	97.4%
DT	81.8%
NB	56.0%
SVM	94.5%

Table 25 Digits entry in air with frequency and correlated features.

Table 25 and Table 26 present the results of these experiments without the magnetometer and with a magnetometer. These tables indicate that the additional features have a unique impact on the results.

Classifier	Accuracy
MLP	92.5%
DT	70.4%
NB	47.0%
SVM	88.0%

Table 26 Digits entry on table with frequency and correlated features.

Table 27 shows that the on-table experiment with a feature from the magnetometer even here could not improve the results.

Classifier	Accuracy
MLP	91.5%
DT	68.2%
NB	50.7%
SVM	85.0%

Table 27 Digits entry using magnet with frequency and correlated features on table.

Finally, Table 28 shows the confusion matrix obtained for MLP from the results presented in Table 22. This table indicates that the pattern of all digits can be clearly differentiated.

Digit	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**0**
1	320	0	0	3	1	0	0	0	1	0
2	0	318	4	0	0	0	2	0	0	3
3	0	2	317	0	0	1	0	3	1	0
4	1	1	1	314	1	0	1	1	1	1
5	0	0	0	2	321	2	0	1	1	1
6	0	2	0	2	1	315	0	2	1	2
7	1	3	0	0	1	2	322	1	0	3
8	0	2	0	1	0	0	0	328	0	0
9	1	1	2	0	1	2	2	0	321	2
0	4	0	0	1	0	1	1	1	7	317

Table 28 Confusion matrix obtained for MLP in the results shown in Table 22.

Chapter 5
Conclusion and Future Work

Security and usability have a paradoxical relationship to each other. The higher the security levels, the more complex are the methods. Particularly concerning the authentication process, we are facing increasing challenges in protecting access to our applications such as online banking and private data on daily used devices such as mobile phones and computers. The challenge in this thesis was to unravel this paradox of usability and security in the authentication process. In general, the authentication methods require parameters such as user ID, passwords, tokens or biometrics, which have been termed as "authenticators" in this work. We categorized the authenticators into three groups: “what you have” (e.g., tokens and chip cards), “what you know” (e.g., passwords and pins) and “what you are” (e.g., fingerprint, voice, and iris) [4].

We demonstrated that the third category: “what you are” is one of the key factors of improving the security and usability of authentication methods since users do not need to carry additional artifacts for this kind of authenticator. It is clearly annoying to have to memorize several pins and passwords for different applications and devices. Furthermore, such authenticators are insecure. Therefore, we have focused on user behavior patterns and established that they are also unique and can be used as highly secure identification.

This thesis demonstrated three novel methods based on user behavior patterns to help advance more secure and usable authentication processes for mobile and stationary devices.

5.1. Authentication Based on Movement and Audio Analysis

The first method introduced, “Authentication Based on Movement and Audio Analysis” (Chapter 2) presented our initial investigations on the correlation

between motion and audio information captured using embedded sensors in a mobile device for enhancing security functionalities related to the mobile device. We primarily investigated two cases:

In the first case, we detect unexpected events, based on analyzing audio and movement dates. We confirmed that an unexpected event such as a phone fallen and left unattended could be identified with a high accuracy of up to 94.4% by applying a "three steps" situation (freefall, shock, and "no-activity") recognition.

For the second case, we proposed the implicit identification of the user based on audio and movement analysis during regular physical activities (e.g., walking). We demonstrated that a user could be verified with high accuracy on this basis. The results of such analysis can be used to arrange a graded security scheme for mobile and handheld devices based on their actual status. The framework suggested can be used as a standalone implicit security enhancement technique or as a complement to conventional user authentication methods. These results can initiate a new security concept for enhancing security functionalities in mobile devices based on analyzing movement and audio signals. By this experiment, we have realized a significant difference between pattern analyzing based on accelerometer signals, audio signals and a combination of both signals. While we could reach an accuracy up to 88.3% with the accelerometer signal and only 47.8% based on the audio signal, we could reach an acceptable rate higher than 90% with a combination of both [1].

5.1.1. Future Work

This work can be further developed by extending investigations into finding a general model describing the correlation between the movements of a mobile device as well as ambient audio, and security risks. There are many other factors such as where the device is carried (e.g., bag and pocket) which can also be highly correlated with the security of data and services on the device. Our proposed method can also be used for mechanical profile management when a mobile device is used by several users [1].

Secondly, recognition of security situations can be extended by other parameters such as GPS enriched with the location information (restaurant or home) or WLAN (Wireless Local Area Network) for better recognition in

indoor areas. This capability would enable a context-aware security which would allow configuring more precise and situational levels of safety.

Furthermore, it is noticeable that our experiment illustrates only the feasibility and accuracy of the method introduced. It is necessary to explore also the usability and acceptance of this approach with a higher number of users with several different applications and situations.

Lastly, we suggest extending this idea for realizing CAPTCHA (Completely Automated Public Turing test to tell Computers and Humans Apart) functionality for mobile devices. A history of movement behavior can easily prove if a real human user is using the device.

5.2. Magitact

With this method, we detailed a novel magnet-based interaction framework. Our work has been motivated by the space constraints on the small handheld device, and the limits which result from the use of touch screen, accelerometer, IR-sensor and joystick modalities. The Magitact framework extends the input space beyond the physical dimensions of a device. Therefore, Magitact offers not just a pragmatic solution to the space constraint, but also a more natural and flexible means of interacting with mobile devices. The proposed method relies only on a magnet and the compass sensors which are embedded in the new generation of mobile devices. Therefore, it does not require expensive hardware setup or modifications to the physical specifications of the device. It can be considered an easy and cheap-to-integrate interaction possibility, particularly for small mobile devices.

We presented several use cases for the proposed method on mobile devices. This approach includes gestural interaction with the user interface of a mobile device, character (digit) entry, “Air Instruments” and, lastly, the primary focus of this thesis’s behavior-based user identification (MagiSign).

With Magisign we have studied a new simple yet effective technique for identification/authentication based on what we call “3D Magnetic Signature” or “MagiSign”. The user can use the 3D space around the device to flexibly

create 3D signatures using an appropriately shaped magnet. The 3D magnetic signature provides a wider choice for authentication as it can be flexibly drawn in the 3D space around the device. Unlike regular signatures, no hard copy of the magnetic signature can be easily produced, resulting in higher security. "MagiSign" is a touchless mode of authentication. Therefore, it can also be used in a hygienic environment such as hospitals and laboratories [20].

We have also conducted an additional experiment wherein we enabled users to employ Magitact techniques by providing visual feedback. We proved our assumption:

Users are able and willing to understand and adapt to our interaction system and metrics just by using the system and receiving visual feedback on their actions.

Therefore, we have provided a new application "Magibird" with a visual feedback mechanism which enables the users to adapt the impact of Magitact-based interaction by seeing the mouse pointer movement on display and asked them to operate the application with three different magnet types. After the training phase, we verified the user's impression by an AttrakDiff-based questionnaire. The applied method in this experiment took advantage of users' capabilities to adapt the machine's behavior similar to users' exposure to musical instruments. The experiments results confirmed that participants, in general, got used to the handling of all magnet types after the training phase. For younger participants, and participants who use their smartphones more frequently, the perceived difference after training was even smaller. In general, they were tending to give more positive ratings in most categories. The key result of this experiment was: how visual feedback and human cognitive capabilities can be used to solve usability issues in around-device interaction systems. Even though it seems obvious that human behavior plays an important role when designing user interfaces, this offered an excellent example of how human device interaction can sometimes benefit from including capabilities derived from the user's perspective instead of trying to overfit a system to each user.

Furthermore, we realized that Magitact's usability could be increased by an interaction design which adapts application contexts and simplifies gestures. We implemented three additional applications: MagiGuitar, MagiMusic, and

MagiBoxing with only triggering gestures and ran a long-term experiment involving 12 users over one month.

Our previous experiments with complex gestures revealed that there are considerable differences in user behavior between different age categories. The long-term experiment with only triggering interactions demonstrated that user behaviors for such simple interactions are similar across all age groups. In contrast to our 3D mouse experiment, we could observe that even elderly subjects rate such interactions as very usable. The only significant factor of this experiment was the user's usage time (the time that the user uses his or her mobile device). Users with higher usage times tend to offer better ratings to our applications. It means that applications designed for simple interactions provide higher usability for all ages and show better acceptance.

5.2.1. Future Work

There are plenty of possibilities for further improving the Magitact framework. First of all, this work illustrated the feasibility of Magitact and provided the engineering method for many scenarios. Therefore, these works should be extended by more comprehensive user tests with a focus on usability and user acceptance. Secondly, even though we have explored several methods where we established the impact of application design, there are a lot of other scenarios such as using Magitact in car, industry or medical environments, where a scenario-specific investigation in design could provide valuable insights.

Since the core physically necessary components in Magitact are the magnet and the sensor, it is recommended to investigate how improved or new designs of these elements can increase the application domain of Magitact. For instance, it is already possible to differentiate a user's interaction by varying the magnetic pole for each user. This behavior can be improved by using different magnet shapes which have their own specific patterns. Such shape-specific patterns can be used as unique keys to differentiate multi-user interactions or improve the Magisign (see chapter 3.3.2). Furthermore, enhancing the sensitivity of the magnetometer sensor will have a significant impact on

the precise pattern recognition and, in consequence, better gesture recognition.

The experiments in this work are limited to a few simple gestures. Therefore, there are many possibilities to improve the Magitact technique by designing context-specific gestures.

Lastly, we could consider designing plugin accessories which extend the single magnetometer sensor to a multiple-sensor environment. Using more than one magnetometer would enable the developer to extend the Magitact framework for realizing precise 3D mouse functionality. Furthermore, such an accessory would allow us to use the Magitact technique beyond mobile device platforms. In such cases, a magnetic sensor or sensor package should be integrated or provisioned in the devices to be controlled [67]. This capability enhances the application of a magnetic-based gesture recognition framework in different cases, such as entrance gates and automotive environments.

5.3. Pingu

The two previously introduced methods indicated the benefits of movement, gesture-based interactions and usable authentication processes based on them. However, they also have their limitations such as applicability only to mobile devices, limitations of distance for gesture interaction and incapability with precise 3D mouse functionality. With Pingu, we have presented a new miniature wearable device in the form of a finger ring in order to eliminate the limitations mentioned above. Pingu integrates a collection of different sensors, a wireless connectivity module, touch, and feedback facilities on a regular ring. The integrated sensors and communication facilities enable Pingu to be used in various ubiquitous computing contexts.

In the three papers we have published, we have introduced Pingu in three steps: an introduction of the ring and its sensors, experiments with general gesture recognition and, lastly, concepts and experiments for gesture-based authentication.

In general, the advantages of Pingu are based on its design as a wearable finger ring and a combination of several sensors. The ring provides to the user precise gestures with high information entropy of 40bit/s compared with the

arm (11.5 bit/s) and wrist (25 bit/s). The combination of accelerometer, gyroscope, and magnetometer provide a six degree of freedom (DOF) inertial sensing system and 3-DOF magnetometer. Additionally, Pingu provides two channels of proximity sensing, equipped with wireless connectivity, and visual and vibrotactile feedback mechanisms, which can make it a unique device for human-computer or human-human interaction in the form of gestures, tactile and touches. Therefore, *Pingu* can sense absolute orientation and direction, linear and rotational movements and the proximity of other fingers with its proximity sensing plates.

With Pingu, we have presented different applications ranging from gestural interaction to context and activity recognition, and social interaction. The installation of various sensory and feedback facilities can turn Pingu into a general-purpose e-companion.

In the second step, we presented our results for gestural recognition with Pingu based on a set of nine predefined general gestures that can be used to interact in a smart environment. The experiments we conducted were based on an extensive dataset of 24 users and nine gestures. These experiments have demonstrated that with simple classification algorithms, different gestures can be distinguished from each other with accuracy of up to 97.8% (see chapter 4.4.2). The experimental results allow us to rank Pingu as a reliable device for many interesting applications such as remote control, physical activity analysis and sign-language recognition. In order to improve the accuracy of the gesture recognition, we conducted the experiments in three versions: Gestures in the air, gestures on the table and gestures on the palm. We have shown that the accuracy of the gestures in the air with 97.8% is much higher than the gestures on the table (93.7%) and gestures on the Palm (77.5%). Furthermore, we have shown with a confusion matrix of all nine gestures that generally, Pingu's gesture recognition is trustworthy.

Lastly, in the third step, we have proposed Pingu for implementing a gesture-based authentication method such as Magisign (see chapter 3.3.2). We presented the results of experiments with a database of 24 user's signatures. We established that, with simple classification algorithms, the signature per-

formed by a user can be recognized with very high accuracy. Also in the signature recognition experiments, we drew the signatures in the air and on the palm in order to compare the accuracy of the recognition in different situations. In accordance with our expectations, we demonstrated that the accuracy of signature recognition (up to 99.2% by signature in the air) is higher than the general gesture recognition (up to 97.8). The primary reason for this phenomenon is that signatures are in fact complex gestures with well-distinguished patterns. Therefore, it is much easier to classify the patterns. This fact is also the key factor in the recognition accuracy of signature in the air (up to 99.2%) and on the table (up to 99.4%) being very similar. We further established that Pingu provides a significantly reliable authentication solution for many applications.

5.4. Future Work

In this method, we have focused on engineering aspects and improved the accuracy of gesture recognition. Similar to other methods it is recommended to extend the experiments with dedicated usability tests with more users and different applications and setting such as automotive, medical and laboratory environments.

This work has presented gesture recognition methods for limited numbers of simple gestures. Therefore, we suggest extending the experiments with more complex and context-specific gestures. We expect higher accuracy and usability results.

In the case of signature recognition, we have only demonstrated that signatures of different users can be classified as dependable. Based on our experience with other pattern-based authentication methods like “Activity Based Verification” [10] recognition, we expected attacking these methods to present difficulties. In the case of MagiSign and Pingu we conducted only a few experiments in order to prove the security of these methods. Therefore, we recommend wider user-attacking experiments with attacking scenarios.

Also, gesture-based interaction can be extended by wearing a permanent magnet ring on fingers. Placing this magnet ring near Pingu can be detected by the embedded magnetometer in Pingu. This capability can be used for designing more complex and usable gestures based on both hands.

Furthermore, the hardware we have used in our experiments was only prototypical with a focus on functionality and sensors. There are still many improvements possible regarding the design and performance of the hardware, such as improving the battery life, improving the charging interface to a wireless inductive charging mechanism and further miniaturizing the ring hardware.

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