Mnemonical Body Shortcuts for Interacting with Mobile Devices

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Abstract. Mobile devices' user interfaces have some similarities with the traditional interfaces offered by desktop computers, which are highly problematic when used in mobile contexts. Gesture recognition in mobile interaction appears as an important area to provide suitable on-the-move usability. We present a body space based approach to improve mobile device interaction and on the move performance. The human body is presented as a rich repository of meaningful relations which are always available to interact with. Body-based gestures allow the user to naturally interact with mobile devices with no movement limitations. Preliminary studies using RFID technology were performed, validating the mnemonical body shortcuts concept as a new mobile interaction mechanism. Finally, inertial sensing prototypes were developed and evaluated, proving to be suitable for mobile interaction and efficient, accomplishing a good recognition rate.

Keywords: Gestures, Mnemonics, Shortcuts, RFID, Accelerometer, Mobile

1 Introduction

Mobile computers are currently omnipresent, and became a part of the user's daily life. Their capabilities are diverse: communications, GPS, video and music players, digital cameras, game consoles and many other applications. The characteristics of these multiple-task devices surpass the desktop user interfaces and give more importance to new possibilities in human-computer interaction (HCI).

Mobile devices' interaction differs from the usual interaction with desktop computers due to their different physical characteristics, input/output capabilities and interaction demands. They have to be small and lightweight to be carriable therefore limiting battery resources and processor capabilities. Input and output capabilities are reduced. The interaction while mobile is also different because users' visual attention is not always focused on the device, making eyes-free and low-workload important characteristics to create a suitable mobile interface. Also, there is a core of applications that are used recurrently, and their menu access is often too slow due to the limited input capabilities. This implies the growing importance of shortcuts: users need fast application access. To achieve this goal, mobile phones provide voice and key shortcuts. Voice shortcuts are not suited to noisy environments, are too intrusive, have a low recognition rate and low levels of social acceptance. Key shortcuts don't provide any auxiliary memorization about which shortcut is in which key.

To overcome mobile shortcuts issues and ease on-the-move mobile device interaction, a gestural input technique is proposed. Gestures are a natural and expressive method of human communication and are often combined with body hints to empathize an idea (i.e. reaching the heart to show an emotion). It is possible to apply different technologies to enhance mobile devices with gesture recognition, making those gestures a meaningful triggering method to the main functions of the device. We give special attention to the body space and related mnemonics to increase shortcut usage and therefore improve user mobile performance.

2 Related Work

There are many options to detect body or device movement and allow a response to the movement. This response may be a shortcut to an application or any other effect in internal or external applications. The most common techniques and works in gestural recognition for mobile devices were studied, namely Radio Frequency Identification (RFID), Accelerometers, Cameras, Touch Screens, Electromyography, Capacitive Sensing and Infrared Laser beams.

RFID Technology is now starting to be incorporated in mobile devices, making it possible to read a tag (a small sized chip with an antenna emitting radio frequency waves and usually storing a unique identifier) with an approximation gesture with the device. Those gestures can only be based on single/multiple point recognition as the gesture information is not recorded. A mobile gestural interaction with RFID demands a permanent presence of tags, which is possible with their embodiment (attaching it to clothes, wallets, etc.) Following this idea, Headon and Coulouris [1] created a wristband to control mobile applications with gestures, based on reading a grid of RFID tags attached to the user's shirt. The inconvenience of this solution is the need to stick tags in clothes or personal objects.

An accelerometer is a small electromechanical inertial sensor device that measures its own acceleration, and its currently being used in commercial mobile phones. With an accelerometer on a mobile device is possible to recognize gestures such as hand gestures based on vibrational [2], tap [3] and tilt [4] input or innumerous arm movements. For example, Choi et al [5] used a mobile phone with inertial sensing to recognize numbers drawn in the air to trigger phone calls or delete messages with a double lifting, while Ängeslevä et al [6] presented preliminary studies on the possibility to associate gestures with parts of the body and trigger applications using those body space mnemonics.

Pressure sensitive surfaces are commonly integrated with screens in some devices like PDAs. They are able to detect 2D gestures, such as taps, directional strokes or characters, allowing eyes-free interaction with the device. Pirhonen et al [7] prototyped a mobile music player placed on the belt, controllable with metaphorical finger gestures, like a sweep right-left to the next track or a tap to play and pause. There are other approaches: Friedlander et al [8] suggested a gestural menu selection based on directional strokes to select an entry on a concentric ring of options.

However, applications in touch screens may only be used in over-sized devices and are limited to 2D gestures.

Other approaches also relevant but not so common include mobile cameras reading visual tags or processing their optical flow to recognize movement, rotation and tilting of the phone, electromyography where the user can subtly react to events by contracting a monitored muscle, capacitance sensing where the user can scroll a presentation, control a DVD or MP3 player by approaching his finger to the sensor, and laser beams also used to detect finger movements near an handheld device being even able to recognize characters.

The fact that those techniques can be implemented in mobile devices doesn't make them suitable to be used on-the-move. Current applications lack the possibility of using gestural shortcuts in mobile scenarios. Furthermore, the gesture selection does not provide enough mnemonical cues for them to be easily remembered.

3 Task Analysis

In order to capture the actual panorama considering shortcuts in mobile devices, 20 individuals were interviewed and observed. The task analysis consisted on a first part with questions about current habits on mobile phone interaction and in a second part where users were asked to reach the most used applications and contacts. It was found that 75% of the interviewed used key shortcuts, while none used voice shortcuts due to its social constraints and low recognition rates. An average of 5 key shortcuts is used, where 93% of the users execute them on a daily basis. Users with more programmed shortcuts reported difficulties in their memorization. In user observation, results show that people needed an average of 4 keystrokes to access the 3 most used applications and 5 keystrokes to call the 3 most used contacts. Key shortcuts seem to be used but observation results reflect a large number of keystrokes. Users often make mistakes or simply forget to use them and apply menu selection. Mobile device interaction still needs to find new suitable input forms to increase interaction efficiency.

4 Proposed Approach

We propose the creation of mnemonics based on the association between applications and the body space. Mobile gestural interaction has to be strongly based on a high recall of commands and the human body with its meaningful associative space offers the needed, and always available, mnemonical cues. The user should be able to create shortcuts to applications with a simple approximation to the body part associated with that specific application. For example, the user should be able to trigger a clock with a gesture towards the wrist or open the music player with an approximation to the ears (Fig. 1). These associations are intended to act as a mnemonic when recalling each application gestural command. As the body limits the number of possible associations, applications can be related with the same body parts (with a gesture or button to recall for the other applications associated with the performed gesture). The body functions as an application organizer where the user is able to keep his most used ones to easily recall them.

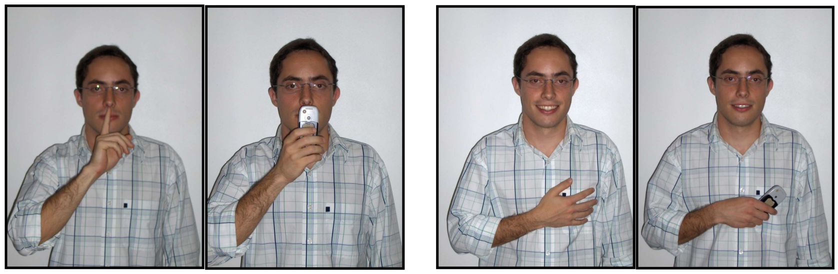

Fig. 1. Mnemonical Body Shortcuts – The expressivity of gestures

4.2 Preliminary Evaluation

To validate our approach we developed a RFID-based prototype able to associate body parts (through sticker tags) with any given mobile device shortcut (i.e. an application or a call to a certain contact). We selected RFID technology to apply our approach because it provides direct mapping, easing the creation of body shortcuts. Other solutions were clearly limited as they restrict the scope of interaction (touch screens, cameras, laser beams and EMG).

The prototype was evaluated with 20 users in a controlled environment using a Pocket LOOX 720 with a compact flash ACG RF PC Handheld Reader. In the first stage of the evaluation the users were asked to select the five most frequently tasks effectuated with their mobile phones and associate them both with a body part and a mobile device key (in their own mobile device). Considering body shortcuts, it is interesting to notice that 89%, out of 18 users, related message writing with the hand, 88%, out of 17 users, related making a call to their ear or mouth and 91%, out of 11 users, related their contacts to their chest, among other meaningful relations (Table 1). An hour later, the users were asked to access the previously selected applications, following both approaches (body and key shortcuts). For each of the approaches the users were prompted randomly 20 times (5 for each application). Although several users selected already used key/application relations, 50% (10 users) made at least one error, with an average of 9% errors/user. Considering body shortcuts, only 15% (3 users) made a mistake with an average of 0.8% errors/user.

The results were still very favorable for Mnemonical Body Shortcuts one week later, with an error rate of 22% for key shortcuts and 6% for the gestural interaction. The results showed that, even against some established key shortcuts, gestural mnemonics had better results and may surpass the problem of low memorization of key shortcuts, providing also a wide range of possible associations, when compared with the physical limit of keys present on a mobile device.

Table 1. Most common associations gesture-application

	Mouth	Hand	Chest	Head	Wrist	Eye	Finger	Ear
SMS		10	1				6	
Call	3			1				12
Contacts		3	5	2				1
Clock					10	1		
Photos				2		8		
Calculator		3						
Mp3								2
Agenda		1	3	1				
Alarm-clock				2	2	2		3

5 Accelerometer Prototypes

Task analysis suggests that a new interaction paradigm is important to increase mobile devices' usability and evaluation of the RFID prototype demonstrated that mnemonical gestures are a good candidate solution, since it surpasses the memorization issue existent on key shortcuts. However, a RFID-based system is inconvenient regarding the need of using RFID tags on clothes or personal objects to allow an always available interaction. Following the line of the major part of the related work on this area, we decided to use accelerometers for a new prototype, mainly because of its precise measure of acceleration and self-contained hardware, already present in some mobile devices. We used a Bioplux4 wireless system and an ADXL330 MEMS tri-axial accelerometer. The three channels of the accelerometer were connected to three of the analog channels of the device that delivers the RAW data of the accelerometer through Bluetooth connection, with a sample rate of 1024 samples per second.

Focusing on mnemonical body shortcuts recognition, we followed two approaches using the accelerometer data. In both approaches the gesture starts in the chest, with the screen facing the user, and the user has to press an action button during the whole gesture. The first approach is based on the final position and rotation of each gesture, while the second one is a feature based algorithm, using a set of 12 features and classified using both Naive Bayes and K-Nearest Neighbours learners. Our goals constructing these algorithms were a high recognition rate and the importance of being lightweight to be executed on mobile devices with low processing capabilities

5.1 Position-Based Prototype

In this prototype data was captured and processed on a Pocket LOOX 720 using .Net programming (C#). We decided to map the dislocation of the mobile device on a 2D plan, calculating the distance between an initial and fixed point (the chest) and a final point (relative position). The distance calculation was based on a double integration of the signal (Fig. 2). However, since this integration delivers some error and the mobile device may suffer some unexpected rotation, we also applied a moving average filter and a threshold to isolate the part of the signal where the real movement was present. With this processing, it was possible to detect the movement on both x and y axis. This approach is suitable for movements fixed in the x,y axis, but the users are likely to perform gestures that are characterized by their rotation. Those gestures are recognized taking in account the final rotation of the device (divided in six different classes) and reusing the position calculation, since it varies even when gestures have the same final rotation. Using this method, it is possible to join the recognition of gestures with or without rotation. The recognized gesture has to belong to the same final rotation class of the performed gesture and is the one with the minor Euclidean distance when compared with the position changes of the performed gesture.

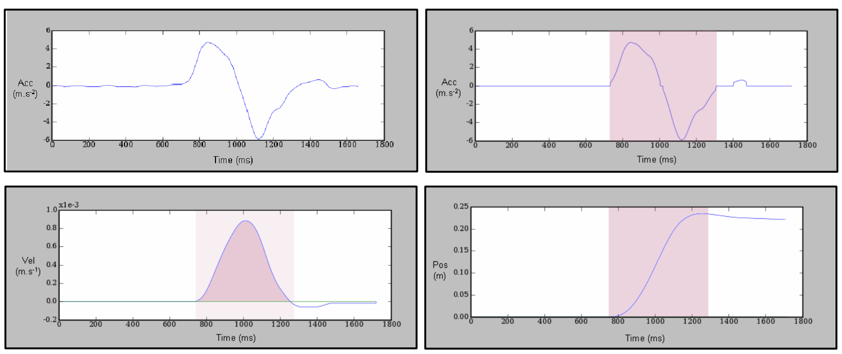

Fig. 2. Signal Processing Evolution a) Raw Signal b) Filtered c) Velocity d) Position

There are two different modes to interact with the system:

- *Train the system and relate the given values with body parts:* The train set will be used to calculate the mean of each position results and the majority of final rotation classes. To recognize which gesture was made, the algorithm finds the nearest position of a training gesture within the same rotational class.
- *Pre-process data based on samples of correct gestures:* This mode permits default gestures based on the height of the person, thus removing the need of further training. We defined 10 default gestures, based on the body points users most referenced during the validation of the concept: Mouth, Chest, Navel, Shoulder, Neck, Ear, Head, Leg, Wrist and Eye.

5.2 Feature-Based Prototype

The first step to create a feature-based model is to choose features that characterize each gesture with accuracy. Since this was the second prototype, we already have some prior knowledge about which characteristics better define the body based gestures. We decided to choose 12 different features, considering gesture starting in the chest and finishing in a body point. Firstly, we use the maximum and the minimum values from the X, Y and Z axis. These 6 features are essential to determine the direction and position variation of the gesture. Similarly to what was done in the position-based prototype, we added 3 features with the final value of each gesture, corresponding to the final rotation. Finally, the signal's amplitude was also considered, since some gestures have different amplitude variation. The maximum and minimum values were added, as well as the amplitude mean value during the whole gesture (Fig. 3). The captured signal is usually noisy and not suitable for a correct feature extraction. We used a smooth algorithm based on the Hanning window, which has a better performance compared with a Moving Average approach, because each sampled signal within the window is multiplied by the Hanning function, giving more importance to the middle than those in the extremities of the window [9].

Focusing on the classification problem we had in hands, we decided to use both K-nearest-neighbors with Euclidean distance and Naïve Bayes algorithm to test the effectiveness of the selected features and to decide which was the best classifier to use.

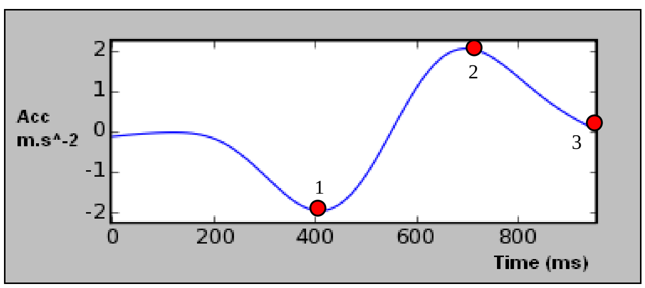

Fig. 3. Features from y axis 1) Minimum value 2) Maximum value 3) Final rotation

6 Evaluation

We user evaluated the developed prototypes to distinguish which approach suits better the mnemonical body gestures scenario. These tests intend to select the solution with highest recognition rate.

6.1 Position-Based Prototype Evaluation

Both approaches present on this prototype were separately tested. User tests were made with 10 users averaging 24 years. First, default gestures were tested. After a brief demonstration of each gesture, users were prompted to perform 5 random different gestures out of the available 10 gestures, 4 times each, totaling 20 gestures. The general recognition rate was set on 82%.

Training gestures was also tested. Users were free to choose 5 free gestures and then repeat those gestures 5 times each, serving as a training set. After, they were prompted to perform 4 times each gesture, as it was done with default gestures. Results showed a recognition rate of 71%.

6.2 Feature-Based Prototype Evaluation

This prototype evaluation was based on signal acquisition of 12 default gestures. Those gestures were similar to those tested with the position-based prototype, adding a gesture towards the hip and the back, and they were performed while standing. A total of 20 users were asked to perform the 12 gestures, 5 times each. Then, an offline evaluation was performed, using different training and testing sets and both Naïve Bayes and KNN classifiers.

Table 2. Feature-Based Test results

	Knn	Bayes
User Training		
12 Gestures		
1 Training	79,5%	88,5%
2 Trainings	86,8%	92,4%
3 Trainings	91,9%	92,8%
5 gestures		
1 Training	88,2%	90,8%
2 Trainings	96,1%	98,2%
3 Trainings	96,3%	97,9%
Total Training Set		
12 Gestures	93,6%	92,8%
5 Gestures	97,3%	96,2%
Total Training Set + User Training		
12 gestures		
1 Training	93,8%	93,2%
2 Trainings	94,3%	92,4%
3 Trainings	95,8%	95,0%
5 gestures		
1 Training	97,1%	9,7%
2 Trainings	96,1%	95,8%
3 Trainings	96,8%	97,9%

The test was divided in two phases:

User Training

In this first phase, we tested the recognition rate using as training set only the gestures performed by the user. The training set varied between 1, 2 or 3 gestures.

This approach was tested using the whole set of 12 gestures but also using 5 random gestures, which was the mean number of key shortcuts a user commonly have available.

Total Training Set

The second phase was based on using the whole set of training from all the users, excluding one that was discarded due to its difficulties of performing some gestures. This set of 1080 gestures worked as a training set, and each user's gestures were classified using that training set, adding none, one, two or three user trainings, also using the 12and 5 gestures set. The final results of these tests are available in Table 2 and the Confusion Matrix of 12 and 5 gesture test using only the training set (without user training) and KNN classifier are available in table 3 and 4 respectively.

Table 3. Confusion Matrix for Total Training Set with 12 gestures
1140 gestures, Recognition Rate of 92.8%

Gestures	Mouth	Shoulder	Chest	Navel	Ear	Back	Head	Wrist	Neck	Leg	Eye	Hip
Mouth	**87,5%**	6,2%	0,0%	0,0%	5,1%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%
Shoulder	4,2%	**90,7%**	2,0%	1,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%
Chest	0,0%	1,0%	**94,9%**	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%
Navel	0,0%	0,0%	3,0%	**95,8%**	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%
Ear	4,2%	0,0%	0,0%	0,0%	**92,9%**	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%
Back	3,1%	0,0%	0,0%	1,0%	1,0%	**97,8%**	0,0%	0,0%	0,0%	0,0%	0,0%	2,9%
Head	1,0%	2,1%	0,0%	0,0%	0,0%	0,0%	**97,8%**	0,0%	0,0%	0,0%	2,0%	0,0%
Wrist	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	2,2%	**94,6%**	0,0%	0,0%	1,0%	4,8%
Neck	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	3,3%	**100,0%**	0,0%	2,0%	0,0%
Leg	0,0%	0,0%	0,0%	0,0%	0,0%	1,1%	0,0%	0,0%	0,0%	**95,5%**	0,0%	9,5%
Eye	0,0%	0,0%	0,0%	0,0%	1,0%	0,0%	0,0%	1,1%	0,0%	0,0%	**94,9%**	0,0%
Hip	0,0%	0,0%	0,0%	2,1%	0,0%	1,1%	0,0%	1,1%	0,0%	4,5%	0,0%	**82,9%**

Table 4. Confusion Matrix for Total Training Set with 5 gestures
475 gestures, Recognition Rate of 96,2%

Gestures	Mouth	Shoulder	Chest	Navel	Ear	Back	Head	Wrist	Neck	Leg	Eye	Hip
Mouth	**89,5%**	7,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%
Shoulder	0,0%	**93,0%**	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%
Chest	0,0%	0,0%	**100%**	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%
Navel	0,0%	0,0%	0,0%	**100%**	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%
Ear	0,0%	0,0%	0,0%	0,0%	**100%**	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%
Back	5,3%	0,0%	0,0%	0,0%	0,0%	**100%**	0,0%	0,0%	0,0%	0,0%	0,0%	5,7%
Head	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	**100%**	0,0%	0,0%	0,0%	0,0%	0,0%
Wrist	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	**93,8%**	0,0%	0,0%	0,0%	0,0%
Neck	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	4,2%	**100%**	0,0%	0,0%	0,0%
Leg	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	**100%**	0,0%	3,8%
Eye	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	**100%**	0,0%
Hip	5,3%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	2,1%	0,0%	0,0%	0,0%	**90,6%**

6 Discussion

After evaluation, it is clear that feature-based algorithm is a better solution, but there are some considerations to make about each prototype.

6.1 Position-Based Prototype

The evaluation on the first prototype revealed some limitations. The recognition rate of 5 different gestures was 82%, which is very considering the reduced number of gestures to be recognized. A system with such a recognition rate would probably make users unconfident and consequently drop out its use. Besides, this recognition rate is based on default gestures, which does not provide users the possibility to choose personal gestures. This option was tested in the second test phase, but the gesture recognition dropped to 71%. This lower recognition rate occurred because users sometimes chose gestures with similar final rotation and position, which were not correctly recognized. Besides, there was no outlier detection, so one training error or bad gesture spoiled some recognitions. One main conclusion is that position is not so effective to disambiguate gestures outside x,y plan, and to enhance this algorithm three things should be modified: the position calculation should work correctly even with rotations, a KNN algorithm has to be implemented and outliers should be discarded.

6.2 Feature-Based Prototype

A feature based approach achieved a high recognition rate in the majority of the tests, both using user training and the general training set of 1080 gestures. Naïve Bayes and KNN algorithms were tested, and Naïve Bayes performed better when only user training was present (low number of sample gestures), while KNN achieved better results with a large set of training.

Considering the results of isolated user training of the 12 gestures set, the best recognition was achieved with 3 trainings with 92,76%. This recognition rate, although acceptable, is still vulnerable to some possible misjudge gestures. However, we do not believe users would want to use simultaneously all the 12 gestures. The test using a reduced set of 5 gestures achieved, using Naïve Bayes, a recognition rate of 98,24% with only 2 gestures, with no positive impact of a third training. For those default gestures, user training seems to be a good approach, but it is not guaranteed the same recognition rate using free gestures. It is also problematic if users perform training gestures inconsistently, because it would reflect a lower recognition rate.

Results were also positive considering the usage of the training set of 1080 gestures (1140 gestures minus the 60 gestures performed by each user). Using all the 12 gestures, we achieved a recognition rate of 93,6%. Although not very high, this recognition rate is achieved without any user training, which is a crucial point for a good user acceptance. This value reaches 97,3% when considering 5 gestures. When we increasingly introduce the training set of the user, the recognition rate didn't increase significantly using KNN algorithm, but it influenced positively Naïve Bayes by 2 percentual points. Yet, KNN algorithm still has the best performance using the total training set. User training could be added not by explicitly asking the user to train the system, but instead using an adaptative approach: when a user correctly performs a gesture, it should be possible to enrich the training set and successively increase the recognition rate.

The study on this prototype proved the feature-based approach as the most successful and appropriate, but possible free gestures were not tested. However, we tend to believe that recognition rates would decrease but maintain an acceptable margin, capable to perform as a suitable gestural interaction algorithm.

7 Conclusions and Future Work

During previous chapters, a novel interface for mobile devices was discussed. Mobile devices interfaces are still chained to the desktop user interfaces, but there are some potentialities of mobile interaction that can be explored. Our approach, based on the creation of shortcuts using gestures and the associtative potential existent in different body parts, proved to be a suitable method of interaction using a RFID based prototype. Users were more likely to remember which gesture indexes a certain application using our Mnemonical Body Shortcuts than using the common key shortcuts.

In order to accomplish a self-contained interface, we decided to create accelerometer-based prototypes. Accelerometers already exist in some mobile devices, and might be increasingly used in the future. With accelerometers, we followed two different approaches. One prototype was based on position variation and the final rotation of the device to recognize different gestures. The second approach is a feature-based prototype, using 12 different features from the inertial data, and classified using two different learners, Naïve Bayes and Knn. The first approach only achieved a recognition rate of 82% for a set of 5 pre-defined gestures and 71%, while the second had a better performance. Using only user training and Naïve Bayes algorithm, with 3 training repetitions is possible to achieve almost 93% for 12 gestures or 98% for a set of 5 recognizable gestures. We also experimented using as training the whole set of performed gestures, achieving 93,6% and 97,3% recognition rate with no user training, for 12 and 5 gestures set respectively. This results show that choosing an accelerometer to recognize mnemonical body shortcuts is a valid approach.

In the future, we will evaluate the usability of a full-developed solution (featuring audio and vibrational feedback) under real-life scenarios, namely while users are moving.

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References

[1] Headon, R., Coulouris, G. Supporting Gestural Input for Users on the Move. Proc IEE Eurowearable '03, pp 107—112 2003.

[2] S. Strachan, R. Murray-Smith. *Muscle Tremor as an Input Mechanism*. In Annual ACM Symposium on User Interface Software and Technology 2004.

[3] Jang, I.J. Park, W.B. Signal processing of the accelerometer for gesture awareness on handheld devices. In The 12th IEEE Int. Workshop on Robot and Human Interactive Communication, 2003.

[4] J. Rekimoto, Tilting operations for small screen interfaces, Proceedings of the 9th annual ACM symposium on User interface software and technology, pp.167-168, 1996.

[5] E. Choi, W. Bang , S. Cho, J. Yang, D. Kim, S. Kim. Beatbox music phone: gesture-based interactive mobile phone using a tri-axis accelerometer, ICIT 2005**.**

[6] Ängeslevä, J., Oakley, I., Hughes, S. and O'Modhrain, S. (2003), 'Body Mnemonics: Portable Device. Interaction Design Concept', *UIST 2003*.

[7] N. Fiedlander, K. Schlueter, and M. Mantei, "Bullseye! When Fitt's Law Doesn't Fit," ACM CHI'98, pp. 257 - 264, 1998.

[8] P. Pirhonen, S. A. Brewster, and C. Holguin, "Gestural and Audio Metaphors as a Means of Control in Mobile Devices," ACM-CHI'2002, pp. 291 - 298, 2002.

[9] F. J.Harris, "On the use of windows for harmonic analysis with the discrete Fourier-transform" Proc. IEEE, vol. 66, pp. 51-83, 1978.