Mnemonical Body Shortcuts: Improving Mobile Interaction

Tiago Guerreiro
IST/INESC-ID
Avenida Professor Cavaco Silva
IST Tagus Park, 2780-990
Porto Salvo, Portugal
tjvg@immi.inesc-id.pt

Ricardo Gamboa
IST
Avenida Professor Cavaco Silva
IST Tagus Park, 2780-990
Porto Salvo, Portugal
ricardo.gamboa@tagus.ist.utl.pt

Joaquim Jorge
IST/INESC-ID
Rua Alves Redol
1000-029
Lisboa, Portugal
jaj@inesc-id.pt

ABSTRACT

Motivation – To study and validate a body space based approach to improve mobile device interaction and on the move interaction performance.

Research approach – We developed and user evaluated (20 + 10 users) an adaptive inertial sensing based system featuring default and personalized body space gesture recognition with suitable feedback.

Findings/Design – Results present gestures as suitable shortcut for on the move action triggering, improving mobile interaction performance.

Research limitations/Implications – The evaluations were performed in a controlled scenario. Further studies should be performed in more demanding situations (public transportations, stairs).

Originality/Value – The research makes a contribution on the validation of body-space gestures to improve on the move interaction performance.

Take away message – Mnemonical Body Shortcuts improves shortcut triggering both in still and on the move scenarios.

Keywords

Gesture, Recognition, Mnemonics, Shortcuts, RFID, Accelerometer, Mobile, Feedback.

INTRODUCTION

Over the last few decades, we have witnessed an extraordinary development on mobile technology. Not so long ago, computers were meant to be used only in static environments. However, communication development, component miniaturization and a general education on the use of computers dictated the emergence and success of portable computational devices. In their genesis, those mobile devices generally had an awkward design, large size and only a couple of simple functionalities besides standard communication. These multi-task devices are still under a significant development and constant mutation in available functionalities, communication facilities and design. Considering interaction, mobile devices have adopted a button-based approach featuring visual display and extensive menus, in some aspects copying and adapting user interfaces developed for desktop computers. It is important to study the main limitations that characterize mobile interaction. A typical user wants to interact with the mobile device in variable conditions: noisy environments, light variations, while moving or even in emergency situations. A successful user interface for mobile devices has to be usable in all those conditions and also surpass the input/output and processing limitations inherent to a mobile device. In truth, recent mobile interfaces do not take in account some interaction issues. While visual attention on desktop computers can always be given, that does not happen while interacting with mobile devices in various conditions, when the user has to choose between the mobile device and other main task. Mobile devices are not suited with a direct selection interfacing scheme, which leads to the creation of multiple menus and difficulties when a specific task is required. Touch screens support direct selection but represent a visually demanding interaction. When using desktop computers, there is an eminent need to control multiple tasks at the same time, but mobile devices are used to make one task simultaneously with other activities in the physical world. This characteristic implies the growing importance of how fast one can reach the applications and move to second plan the ability to manage and access different ones.

Given the existence of a core of applications that are constantly used, one solution is the creation of appropriate shortcuts to ease access to the most used functionalities. Some solutions were developed and applied in commercial devices, namely key shortcuts and voice recognition. Key shortcuts are the most used ones, yet they fail on long-term usage because they do not provide any auxiliary memorization about which application is related to each key. This fact leads people to forget the mapping between functions and keys and return to the slow and visually demanding menu selection. Regarding voice shortcuts, there are some unresolved issues that compromise their performance: low recognition rates, especially in noisy environments;

Figure 1 - Meaningful Gestures

low acceptance on a public usage; voice commands do not provide much privacy because they are too revealing on the task to perform. To provide mobile devices with a more appropriate interface, our approach focuses on the creation of gesture-based shortcuts. Gestures are one of the most important means of communication between humans, and one could say more: they were certainly one of the first. It is remarkable that they surpass speech since they are rather international. When people do not share the same language, gestures are usually a very effective resource. Our approach is based not only in the interaction capabilities of gestures but also in the extended meaning that gestures have when combined with body parts (Ängeslevä, 2003). In regular communication between humans, gestures are often combined with body hints to empathize an idea (i.e. sincerely apologising with a hand over the heart, asking for the time with a touch on the wrist or asking someone to be quiet with a finger on the mouth - Fig. 1).

Using the undeniable capacities of gestures and the possibility of joining them with the rich significance of the different body parts is possible to create strong associations between them and provide a new interaction modality for mobile devices. There are multiple potential Mnemonical Body Shortcuts, depending on the different mnemonics that each user may want to choose (an approximation to the ears opens the music player; a gesture to the heart calls a beloved person; a gesture towards the wrist triggers the clock or time information; a movement to the head shows the contact list). This approach cannot be only based on gesture recognition and shortcut triggering, but it also takes in account the importance of an appropriate feedback such as audio, vibrational or visual feedback to fully complete the interaction. We present a description on performed user studies to assess the actual panorama on mobile device usage. The problems and limitations assessed gave us the opportunity to define several design guidelines that were taken into account while developing a gesture based approach to improve mobile device usage performance. The developed prototype was evaluated with real users both standing and while moving, validating the concept as a suitable method for mobile interaction.

RELATED WORK

There are several available technologies to detect body or device movement. The most common techniques in gestural recognition for mobile devices are 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 and not in the whole gesture. 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 (Headon, 2003) 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. Moreover, the RFID displacement on a grid lacks meaning when interacting with the applications.

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 it is possible to recognize explicit gestures such as hand gestures based on vibrational (Strachan, 2004a), tap (Jang, 2003) and tilt (Rekimoto, 1996) input or several arm movements. For example, Choi et al (Choi, 2005) 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 (Ängeslevä, 2003) 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 (Pirhonen, 2002) 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. Friedlander et al (Fiedlander, 1998) 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 (Madhavapeddy, 2004) (Rohs, 2004); Electromyography where the user can subtly react to events by contracting a monitored muscle (Constanza, 2005); Capacitance Sensing used to scroll a presentation, control a DVD or MP3 player by approaching a finger to the sensor (Rekimoto, 2001); Laser beams, used to detect finger movements near an handheld device (Metzger, 2004) (Perrin, 2004).

The fact that the above techniques can be implemented in mobile devices does not 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.

MNEMONICAL BODY SHORTCUTS

We define Mnemonical Body Shortcuts as gestures made using a mobile device towards different body areas, resulting on the triggering of applications within the device that are culturally or personally associated with that specific body part. Such an interface will ease shortcut remembrance while maintaining the natural aspects of a gestural-based interaction and the advantages of using gestures while on-the-move.

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 phase with questions about current habits on mobile phone interaction, to know the type of mobile device users have, which are the most used applications, frequency of use and finally if and how users interact with both key and voice shortcuts. In a second phase, users were asked to reach the most common applications and contacts. They performed those actions while observed in a controlled environment, and the numbers of buttons pressed for each action was registered.

First part results present some already expected conclusions: the majority of users have classic mobile devices instead of PDAs and use them more than 10 times per day, usually to make calls, send SMS, consult the contact list, agenda, clock, set the alarm clock and take and visualize photos. The average number of the most used contacts was set on 6 (most used contacts are contacts that users call at least one time per week). Results on shortcut usage reported that 75% of the interviewed uses key shortcuts, while none used voice shortcuts. When asked about why they do not use voice shortcuts, three main reasons were presented: they are not available in their mobile device; they used it but the recognition rate was low in many situations; finally, there are usage limitations under diverse social environments. It was clear that the remaining analysis had to be focused on the current habits on key shortcut interaction. We concluded that an average of 5 programmed key shortcuts is used, and 93% of the users execute them on a daily basis. When asked about memorization issues on their key shortcuts, we observed that users with more programmed shortcuts reported more difficulties, and they stated that because of that difficulty they generally only use a couple of shortcuts.

Considering observation, results showed that users need an average of 4 keystrokes to access the 3 most personally common applications and 5 keystrokes to call the 3 most used contacts. In fact, users were more likely to choose menu selection when prompted on the applications and contacts they defined as the most used rather than using key shortcuts available in the majority of the cases. The usage of menu selection was reflected in a larger number of keystrokes and task errors, resulting on a slow selection of the wanted task.

Problems and Limitations

With the user observation we performed, some issues on current mobile interaction were found. Firstly, it is clear that voice recognition is still not used by a general audience. The most important reasons are not only the inexistence of this modality on many mobile devices but also the difficulties that this method presents when used on noisy or socially busy environments. Voice recognition on mobile devices still has a long way to be able to perform well on complex environments, but there are some social issues inherent to this kind of interaction that cannot be surpassed. In the context of key shortcuts, the most important problem seemed to be their memorization and efficiency. User observation showed that, even when asked to perform actions that should be rapidly repeated using available key shortcuts, users spent a large number of key presses and often returned to the classical menu operations to reach the intended application. A conclusion to be made based on these results is that mobile interaction even most of the times based on repeated actions, is still slow, key-stroke consuming and does not give full appropriate support to rapidly reach those actions.

Design Guidelines

After user observation, we concluded that mobile interaction still has diverse issues that need to be addressed in order to provide a more usable mobile interaction. Using that knowledge together with the main issues that are also present or referenced in the literature on this area, we can list a set of design guidelines for a mobile gestural interface that we intent to accomplish:

Support Shortcut Memorization. The expressivity of a gesture is a powerful tool to create metaphors and mnemonics when interacting with computers. This tool is often given a small use because the same gestures are used in most of the works. Generally, simple directional strokes, tilt or characters are performed with gestures to interact with the device. Those gestures, although useful, are not practical to a wider range of applications and do not always provide a correct creation of memory aids to associate gestures with actions. There are two options to make them more natural to the user. The first one is trying to create mnemonics to static operations on a device, such as twisting the hand simulating key unlock which could unlock the cell phone, point it to the sky to retrieve meteorological information or associate gestures with body positions as it was done in [1]. One other approach is the personalization of gestures. If users could make their personal gestures, they would apply their memories, personal information and subjective thoughts making gestures meaningful to them. A good approach should be using some default gestures with well defined mnemonics, suggest some others but let the user to choose its own gestures to interact with the mobile device.

Give appropriate Feedback. The majority of current gestural input applications have researched in the implementation problem, technical solution, algorithmic difficulties or possible gestures to be used. However, there is a main problem that is forgotten in a general way – users need suitable feedback. Gestural input is normally intended to achieve non-visual interaction, making visual feedback useless. However, when screens are used, it should be possible to retrieve visual feedback as an auxiliary method. Prototypes that implemented some feedback generally use it in audio format to advise the users about the state of the gesture detection. The origin of the audio is not usually studied. It can be performed by the device, but it is not appropriate for specific social environments. Earpieces are a good solution, especially when users are already listening to music, but they would hardly be used only as a feedback channel. The type of sounds can be single beeps, multiple beeps or continuous increasing/decreasing sound. When gestures are performed with the mobile device in the hand, vibrational feedback also has a great potential to inform user with subtleness and give the gestural action more haptic sense. Projects in gesture input interaction should analyze which is the most appropriate feedback to the diverse range of applications, and test those different approaches with users, focusing on audio and haptic feedback.

High Recognition Rate. A good gestural interface has to be supported on an excellent recognition rate. As we have noticed in user observation, the lack of a good recognition rate of voice shortcuts is sufficient for users to drop its usage and go back to a button-based interaction that they are accustomed and intend as reliable. Users have to be confident on the system and know that it will respond as it is supposed to.

Grant social and user acceptance. There have been some commercial applications using gestural input, but the fact is that they are not common and seem to have some problems when entering the market. There is a full hand of mobile devices with gesture recognition but they are not a success (many were discontinued). The main problem seems to be the user acceptance on this novel method and also the social implications that actions based on gestures can have. User acceptance seems to be the minor problem, because it should only take some more practice to make users more interested in this natural technique. Social acceptance is an issue that has to be carefully analyzed. Some people might be constringed to make gestures in a public area because it is usually not accepted if it does not come along with a clear action or speech. These social constraints may limit the use of gestures when interacting with mobile and wearable devices. The chance of having personalized gestures opens the door to an interface with better user and social acceptance. Another issue is the subtleness of interaction: if the system recognizes and distinguishes subtle gestures the user will be more prone to be social and user accepted as interaction is intimate.

Allow Mobile Interaction. When developing an interface for mobile devices, we should not forget that they are intended to be used while standing or sitting, but also while moving. When mobile, visual attention has to be focused on other main task, especially for safety reasons. For example, it is not unusual to see regular users of mobile devices sending text messages without looking to the mobile device, freeing their eyes to perform other actions at the same time. A desirable gestural interaction platform has to provide sufficient tools to be used in different mobility settings so its potential of providing a rapid and natural access to the main functions of the device can be fully explored. One of the most important features to achieve a suitable mobile interaction is the existence of a suitable and personalized feedback, compatible with the variant environments where the system can be used.

Body Space Interaction

This new method is based both in the powerful characteristics of gestures when used in HCI but also in the body as a rich repository of different meanings and personal associations.

Gestures in Human Computer Interaction

Gestures are a communication method commonly used by humans. The first picture that may appear in our minds when referencing gestural communication is the sign language, mainly used by deaf individuals, but gestures are constantly used by non-disabled people. We use gestures by maintaining different body postures, facial expressions or making gestures with our hands and arms. Furthermore, when people with different languages meet, their communication has to be based on gestures. This fact shows one of the most important characteristics of gestures: they are a universal form of communication, and people have intrinsically recorded the meaning of many gestures that are valid all over the world.

Human Body: A Rich Meaningful Space

The human body is a set of diverse part where each one plays a different role in what we call “life”. The hands are our work tool, our brain the space where all the decisions are made, the mouth and tongue essential not only to feed us but also in the way that we communicate with each other. Our body is a space densely rich on functions, and because of that fact it is possible to think those diverse parts as a symbol for emotions and actions. For example, the heart, one of the most important organs in our bodies, is often related with emotional feelings; our hands are related with physical work and our shoulder with our intention to comfort someone in hard times. The human body is full of this type of associations, which are typically transversal to many societies, but can also be very personal and intimate.

Mobile Body-related Mnemonical Gestures

One basic idea emerge from the last sections: we have, at the reach of our hands, meaningful tools that are often used to communicate. Those tools are the gestures we can perform but also our body as a strong meaningful space. In fact, gestures are often combined with body hints to emphasize an idea. There are many examples of the relation between gestures and body parts: someone reaches his heart to apologize, touches his mouth to ask for silence or puts a hand in the head when he forgot something. When we combine gestures with body parts, a whole new set of possible relations and meanings appear, and they can be universal like those described, but they can also be very personal. A gestural interaction with mobile devices might be created using a free set of gestures, with any direct relation with the task that is intended to perform, but such approach would fall in the same memorization issues that exist while using key shortcuts. We are convict that cooperation between the possibility of making gestures with a mobile device and the ability to direct it to a body part may create diverse strong mnemonical cues that could be easily remembered and performed by users, in distinct mobility conditions. It is easier to remember how we perform a gesture towards a body part than gestures that are performed with any type of mnemonical aid. We will, from now on, reference these gestures as Mnemonical Body Shortcuts. It is important to validate the concept of Mnemonical Body Shortcuts with users, test if this method really enhances memorization, when compared with the most used type of shortcut interaction. It is worth mentioning that although body space gestures are not a new concept (Ängeslevä, 2003) (Strachan, 2004b), it lacks user validation as well as a scalable implementation and user evaluation with a meaningful and user-dependent gesture set.

RFID Concept Validation

Before we have started a full implementation of the Mnemonical Body Shortcuts, we decided to perform an evaluation of the concept and test if it would perform as expected. The best technologies to provide a fast implementation of gestural interaction for mobile devices are RFID, EMG and Touch Screens. Touch screens are clearly not able to reproduce body-space gestures, while EMG can recognize contractions on different body parts but our intention is to perform gestures with a handheld device and not all body areas have voluntarily contractible muscles. RFID appears as an excellent choice because it is possible to stick RFID tags on clothes and read them using a RFID reader in the mobile device, simulating gestures towards different body parts. This methodology gave us the possibility to make a preliminary test the Mnemonical Body Shortcuts concept. This prototype was developed using a Pocket Loox 720 with a compact flash ACG RF PC Handheld RFID reader. In terms of software, the system was able to discard multiple tag reading and keep the log about all the tag readings during evaluation.

With the RFID-based prototype we were able to simulate the association of body parts (through sticker tags) with any given mobile device shortcut (i.e. an application or a call to a certain contact). The prototype was evaluated with 20 users in a controlled environment. In the first stage of the evaluation 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, users were asked to access the previously selected applications, following both approaches (body and key shortcuts). For each of the approaches they 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. Results were still very favourable for Mnemonical Body Shortcuts one week later, with an error rate of 22% for key shortcuts and 6% for the gestural interaction.

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 mobile devices keys. These results were a main motivator to follow this approach and find a solution that does not have the inconveniences of using RFID tags on clothes to perform gestures with a mobile device.

THE PROTOTYPE

The use of an RFID prototype, even with a high recognition rate and being extremely appropriate for a demonstration on Mnemonical Body Shortcuts, is not

	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

Table 1 – Associations Gesture/Application

suitable for a full-scale deployment, mainly considering aesthetics and acceptance issues. On the other hand, accelerometers are cheap, small, available and promising regarding the information on performed gestures. An accelerometer is classified as an Inertial Sensor because it is able to measure acceleration, possibly in multiple axes. It measures not only the dynamic acceleration (the acceleration provoked by a movement of the object attached to the accelerometer) but it also measures static acceleration (gravity force present in each axes).

The first step to create a feature-based model is to choose features that characterize each gesture with accuracy. In the Feature Extraction module 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. We added 3 features corresponding to the final rotation (X, Y and Z). 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. The captured signal is usually noisy and not suitable for a correct feature extraction. We used a smooth algorithm based on the Hanning window, applying it in the Feature Extraction module even before the feature extraction process takes place. After feature extraction, we were able generate training sets, fill the feature space and use classifiers to detect the class of each new gesture. The classifiers used were k-Nearest Neighbours (k=50) when a large test set is available and Naïve Bayes for reduced test sets.

User Interface

By default, we consider gestures starting in the chest and finishing in a body point making it possible for any individual to use the system with a default training set (12 body points trained with 20 users). Nevertheless, the user can train different gestures as long as they remain consistent. This is possible as the selected features are independent from the physical location selected; they are only related with the path of the gesture. To launch an application the user performs a gesture and marks the start and end of the gesture by pressing an action key.

Feedback

The system offers 3 types of feedback: visual (the name of the application to be launched and a progress bar), audio (the application to be launched) and vibrational (according to the recognition certainty, i.e., when some doubt lingers the vibration is longer). The vibrational feedback is truly important has it can be used even in a public space and besides warning the user when the system is uncertain it also eases real non-visual confirmation.

User Control Features

After a gesture and appropriate feedback, the user has the opportunity to cancel or alter his selection. The user can abort a shortcut, within a preset time frame, represented by a progress bar. This mechanism is useful when the user makes a mistake or gives up launching an application. On the other hand, even when the user draws a desirable gesture, the system can trigger the wrong application. This happens when two or more gestures are associated with the same body point or when a gesture is misrecognized (close body points). Thus, the user can navigate through a list of shortcuts, ordered by recognition certainty (*Multi-Choice*). This mechanism offers the possibility to map several gestures with the same areas but also to relax gesture performance as even with an imperfect interaction the application will probably be one-click away. Both mechanisms allow users to effectively control shortcut triggering and therefore be confident on its use.

RESULTS AND DISCUSSION

We evaluated the prototype both considering recognition ratios and system usability

Offline recognition studies

We tested the feature-based algorithm with an offline analysis on its recognition. For this test, we collected 60 gestures from 20 users, and cross-tested all those gestures in various conditions. The users were asked to perform a set of 12 gestures, five times each. In a 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 gesture executions. This approach was tested using the whole set of 12 gestures but also using 5 random gestures (mean number of shortcuts a user has available; retrieved from task analysis). The second phase was based on using the whole set of training from all users. This set of 1140 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 with the 12 and 5 gestures set. We achieved interesting results using kNN and Bayes classifiers, such as a 97,9% recognition rate with only three trainings (for 5 random gestures) and 97,3% recognition rate without considering any training from the user (only the data from other participants), also for 5 random gestures. The confusion matrix of the evaluation with 5 and 12 gestures using only the training set (without user training) and kNN classifier are available in Table 2 and 3 respectively.

Usability Evaluation

Usability tests were performed and focused on finding the recognition results for both personalized and default gestures (including while on-the move - Fig. 2), but also to test the user interface and gather user feedback on the prototype. In this evaluation, we intended to study not only the recognition rate but all the interaction process, from the gesture execution, feedback, user response and overall tasks success. The trials were performed with 10 users. We began the evaluation first phase by asking users to make their own associations between body parts and applications, in a total of 5 Mnemonical Body Shortcuts. This is important because they did not have contact with the default gestures, so these associations were really personal and authentic. After this step, users trained the system with one gesture for each

Mnemonical Body Shortcut, and then they were randomly prompted to perform those gestures 20 times while standing and other 20 times while moving. The process was repeated for 2 and 3 trainings for each gesture. This phase allow us to know what would be the recognition rate of the system for personalized gestures in a realistic scenario.

Figure 2 – Gestures to the ear and to the mouth

We also made available 12 default Mnemonical Body Shortcuts, which can be used without any training. In this phase, we demonstrated each one of the default gestures to the users and then they had to perform 24 gestures considering all the 12 default gestures, one set of 24 while standing and other while mobile. The process was repeated but we randomly selected 5 gestures from the total set, and users had to perform 20 gestures using the new set, also in the two mobility situations. Using these results, we will know how the default gestures perform, with special interest on the recognition rate using a set of 5 gestures, because it is closer to the number of gestures users would want to use in a daily basis.

Effectiveness. The effectiveness of the prototype is mainly related with recognition accuracy. Considering a self-training set, we had a performance of 80.5% recognition while moving and 89.5% while standing. Considering default gestures, the values reach 90% while moving and 92.5% standing. We believe that these results show that our system has a good effectiveness, suitable to the demanded task. It is also important to justify why recognition results dropped from the recognition studies to the final evaluation. Both prototypes used the same classification algorithm, and the differences are essentially on the test scenario. While users were on a standing position and repeated the each type of gestures 5 times consecutively in the recognition studies, in the final usability tests they were also moving and were prompted to perform gestures randomly. Besides, in the first studies we did not perform a study with truly personalized gestures (training results were constructed with gestures we asked users to perform). In fact, usability tests on the final prototype were far more demanding, which reflected results more close to the results it would achieve in real-life utilization.

Usefulness. We measured the usefulness of the prototype by the number of errors produced during tests (entering an unwanted application). It happened in 3.3% of the cases as in only in 1.3% users had to stop their movement to interact with the mobile device. Furthermore, users only needed an average of 2.5 clicks and 3.8 seconds to trigger a shortcut. It is important to notice that as the evaluation sessions evolved the users became confident on vibrational feedback and *Multi-Choice* feature, and although relaxing their gestures, the overall success was achieved. Although we achieved good recognition rates, it is important that the control mechanisms offer the user the possibility to fail and recover easily from that failure. Moreover, there are several situations where the gesture is erroneous or the situation itself is error prone (i.e., in a bus or train). The MultiChoice mechanism with proper feedback showed to circumvent this problem demanding a low cognitive process to access the desired applications.

Learnability. To analyze the system learnability we observed the recognition improvement across training phases. For example, for a standing position, the recognition evolved from 70% with one train, to 81% with two trains and 89.5% with three trains. We believe that the system has a great potential to learn with users and achieve even better recognition rates. As a user confirms an action the system can improve its training set and therefore improve certainty.

Likability. We used a final questionnaire to assess users' opinion, rating some characteristics from 1 to 5. Within the most relevant results, we found that users preferred audio feedback (4.9), classified the alteration feature as very important (4.8), classified it as a good mechanism to use while mobile (4), to rapidly access applications (4.2) and generally appreciated it (4.8).

CONCLUSIONS AND FUTURE WORK

We presented a gesture approach to improve mobile device interaction. An inertial sensing prototype was evaluated achieving high recognition rates even while moving and gathered consensual satisfaction. This interface is usable in diverse mobile and social environments and provides fast and accurate gesture recognition. The recognition algorithm proved to be suitable to the task of recognizing body-based gestures, not only while standing but in demanding mobility settings. It is possible to use the system without any training, also with appropriate recognition accuracy. The feedback and control mechanisms added provided the user with the necessary flexibility to use the system while on the move and in public, noisy and crowded environments. The system achieved overall user satisfaction. In the future, we will evaluate our approach with blind users that can highly benefit from a fast-launching interface. Moreover, we will evaluate the system in adverse situations (i.e., in a bus/train, while climbing stairs).

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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 2 - Confusion Matrix with 12 default gestures (*Columns – Expected Result; Lines – Classification Result)*

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%

Table 3 - Confusion Matrix with 5 default gestures (*Columns – Expected Result; Lines – Classification Result)*