Use of ecological gestures in soccer games running on mobile devices

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Abstract

The strong integration of "intelligent mobile devices" into modern societies offers a great potential for a wide spread distribution of mobile serious games. As in the case of Virtual Reality based systems, in order to be useful and efficient, these serious games need to be validated ecologically. In this context, this paper addresses the use of ecological interactions for a mobile serious game. We exploit a wearable insole in order to let users interact with a virtual soccer game via real-world soccer movements. We analyzed the concept of ecological interactions. The system used for recognition of ecological gestures is also detailed. A primary study showed that proposed system can be exploited for real time gesture recognition on a mobile device.

Keywords: *ecological interactions, gesture recognition, mobile serious games*

1. Introduction

With the latest technological developments, we now have at our disposal mobile devices that beyond communication means (3G, 4G, Wi-Fi, Bluetooth, infrared etc.) show amazing capabilities regarding several aspects such as computational power and display capabilities. In addition, these handheld computers are riddled with several sensors such as GPS, accelerometer, camera, etc. In recent years, there is no doubt that users have very much preferred these advanced devices. The 2012 survey realized by the Information Solution Groups (ISG) pointed that only 40 percent of mobile device owners in the US and UK were using a standard mobile phone. Almost forty-six percent have a Smartphone and eighteen percent have a tablet. Moreover, many own more than one mobile device, including 15% who own both a phone and a tablet [1]. In addition to the amazing capabilities of these devices, at first glance, one can refer to the multitude and the huge diversity of applications that exists over the centralized market (Google play, Apple store, BB market, etc.) in order to analyze such a success. In a recent study regarding tablet usage, Müller et al. noticed that people exploit their tablets for various activities like: email checking, games playing, social networking, looking up information, listening to music, watching TV/videos, shopping, browsing, reading a book, lightweight creation, checking the weather, etc [2]. Another surprising finding regards the fact that tablets are used more during weekdays; that a portion of tablet activities includes a transition from/to other devices or actions in the real world. Indeed, the researchers also found that tablets are often used while doing other activities (e.g., watching TV, eating, cooking, and waiting). Considering that tablets and more generally mobile devices are designed to support mobility, we argue that they could be used in other places if adequate possibilities are offered. Mainly, it seems that the game playing activity which is generally done while waiting can be performed in public transportation or in a park. As in many situations, we do think that video games represent a fertile ground for the expansion of these intelligent mobile devices.

The exploitation of Virtual Reality (VR) technologies in the fields of education, rehabilitation and neuroscience is increasingly recognized. In particular, it has been shown that for a majority of cases, the use of VR technologies tends to be more efficient, useful and suitable than traditional approaches because of their *ecological validity* [3]. However, the high cost associated to development and maintenance of such systems tends to limit the exploitation of this technology. Serious games running on workstations seem to be an alternative that may require a lower cost compared to a VR system [4]. However, the acquisition cost of such systems is still high for an average person. To this end, and given the strong integration of mobile devices in the consumer, some works have been directed towards the use of serious games running on mobile devices. Several studies have shown that this new approach seems to be effective for different types of games. However, some studies have clearly demonstrated the limitations imposed by constraints of mobile devices (small screens, conditions, etc.). This work addresses this point. Mainly it targets the exploitation of a wearable insole interface that allows ecological interactions with a mobile soccer game. For this, the described work details the exploitation of signals coming from an accelerometer attached to a shoe in order to recognized real world soccer movements in real time.

In this paper, we briefly present motivation for using ecological gestures in a serious game (section 2). We review work related to the use of the foot for interacting with numerical environments and the literature on gesture recognition (section 3). Proposed system is described in section 4. Realized experiment is discussed in section 5, before the conclusion in section 6.

2. Motivation for using ecological interactions in a serious game

2.1. Preliminaries on ecological interactions

Here, the term ecological refers to its etymological root. It thus suggests the relationship of organisms with the surrounding environment. Psychologist James Gibson is the one who proposed the exploitation of an ecological approach for the study human perceptions [5]. This approach allows differentiating sensations from the human perception. From information that comes to the sensory modalities (visual, auditory, olfactory and haptic) and based on the environmental context, past experiences, the perception emerges. This suggests that sensory information is complemented to form what is named *affordance*, before being interpreted. This point explains why one is not emotionally affected by Halloween costumes. In fact, the *affordance* of these costumes conveys enjoyable information that is opposed to their associated primary sensations.

As a result, when designing interfaces it appears that a huge attention should be paid regarding the affordance of such an interaction. This is why we want to exploit what we call an ecological interaction in order to promote the intuitiveness of such an interaction. Doing so, we want to arrive with an interaction having an affordance that completely matches its usage.

2.2. Benefits expected in using ecological gestures in a serious game

In the video game industry, introduction of the *Nintendo Wii* has marked a radical change toward the use of ecological interactions. While interactions with traditional games were essentially based on keyboard and mouse, when using the *Nintendo Wii* it is rather the natural that prevails; there is no need for buttons or arrows in order to move. The user just has to gesture as one used to perform in the real world [4]. Thus, several researches have exploited gesture recognition in order to have ecological interactions in various types of serious games running on non-mobile systems [6]. Here, we briefly summarize some of the benefits:

1. *Better usability:* Katzourin et al. [7] have used ecological gestures in order to let a user interact in a virtual game. Based on a panel of 50 participants, their study reported that even users who had no prior experience with video games were able to get used to the game about five minutes.
2. *Motivate and engage player:* To address the fact that patients used to complain about the boring and repetitive aspects of stroke rehabilitation exercises, Burke et al. have exploited three games working with a webcam that has arm gestures recognition capabilities [8]. The initial experiment realized with three stroke survivors suffering varying degrees of impairment, showed that the game helped to motivate and engage the players.
3. *Improve performances:* Boyle et al. [9] have analyzed the impact of using a *Wiimote* for gesture recognition on motor skills while performing surgical tasks. Realized experiment showed that novice users, who received a week of structured practiced sessions playing a game on the *Nintendo Wii*, performed better than a control group.

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3. Related work

The proposed work concerned the exploitation of ecological interactions in a soccer game on mobile devices. A soccer game was chosen because it represents a fertile ground for exploitation of ecological interactions although such an approach remains limited in current soccer games. To achieve this goal we designed a system that allows the recognition of gestures that players would perform in real world soccer games. In this section we briefly review used of ecological gestures in virtual soccer, foot-based interactions with mobile devices and techniques exploited for gesture recognition.

3.1. Used of ecological gestures in virtual soccer games running on non-mobile devices

Technological advancements of the last two decades have promoted the developments of various simulators in the sport industry [10, 11]. For soccer games, Fernandez et al. have worked toward the development a virtual environment in order to help goalkeepers at improving their performances [12]. In this game a player equipped with tracking sensors mimics the launch of a free kick. In front the goalkeeper has to block the ball. Although this game takes advantages of using ecological gestures, two drawbacks can be seen: It is limited to the free kick aspect and more importantly the virtual environment setup prevents from using it on mobile devices. In the same way, other soccer games exploited interfaces like the *Kinect* or the *Wiimote* in order to promote ecological gestures of the player. As a result these games are highly engaging however as previously mentioned they are not usable on mobile devices. The proposed work targets this aspect; it aims at designing a virtual soccer game that let a user exploits ecological gestures while playing on a mobile device.

3.2. Used of foot in interactions with mobile devices

Last years have been marked by a huge integration of mobility into modern societies. These devices are carried and used everywhere. As an alternative to hand usage, several research teams have investigated the possibility of using foot gestures to operate a cell phone when the hand is too dirty or busy [13]. Alexander et al. have investigated foot gestures that can be in replacement of hand gestures for interactions such as: answering/ignoring incoming calls, lock/unlock a phone, play/pause music [14]. In the same way, Han et al. [15] have studied how kick gestures (as kicking a ball) could be exploited in interactions with a mobile device. In order to detect the kick, an *Xbox Kinect* camera was used. Recently, Bailly et al. have attached an Xbox *Kinect* camera to a shoe in order to detect hand gestures performed by a user. Detected gestures are then interpreted to interact with the phone [16]. Similar studies are performed by Scott et al. [17] through the use of foot gesture as mean of communication to provide hand and eyes-free access to a device’s features.

3.3. Techniques used for gesture recognition

The techniques used for gesture recognition in the literature can be mainly divided in two categories. The computer vision based and the accelerometers based techniques. Here we briefly discuss these two aspects.

In order to recognize gestures, different methods exist. Some of them use computer vision to achieve this goal. In the method proposed in [15] the main problem was the *Kinect sensor* which is by definition a non-mobile sensor in terms of computation weight and energy consumption. Paelke et al. [18] and later Lu et al. [19] have used computer vision like in [15] but change the sensor for the mobile's back cameras in order to recognize the foot and track its movements. There is still a series of problems with this method directly related to the use of vision. These problems are mainly cause by the camera itself. Akl et al. point four of them in [20]. First the recognition rate will change with the number of camera. Second, the big amount of data from a camera will cause latency by the usage of heavy algorithms. Then, the environment, such as ambient lighting, can have a strong impact on the recognition. Another problem is the clothes color which can be the same as the environment (e.g. a black shoe on a black floor) and consequently drastically reduce the algorithm performance. All these drawbacks make difficult the usage of computer vision for real-time gesture recognition on mobile.

During the last decade, many studies have focused on motion recognition using accelerometers. Some of them simply compare unknown signals to a template library by using a distance function as is the case described in [21]. Others relay on a more complex approach by using Hidden Markov Models (HMM) to recognize patterns in the accelerometer's data like in [22]. In this case, algorithms extract features from the raw data (e.g. transformation to frequency domain or decorrelation) and present them to a HMM which will end the recognition process. Other methods, as proposed by Bailador et al. [23], relay on a recurrent neural network to classify gestures. To accomplish this, a predicator is trained for each movement to recognize. When the raw data comes, the predicator will anticipate the future value of the signal. When the next value arrives, an error is computed between the real value and the predicted one. This error will determine the gesture recognition since the lowest error will signify the best prediction and as the predicators are trained for one movement the best predicator is the one defined for the movement. More recently, Akl et al. in [20] presented a novel accelerometer based gesture recognition system. They use Affinity Propagation and Dynamic Time Warping (DTW) to compute clusters on a learning set, each cluster defines by an exemplar. Next, they used DTW distance computation between the unknown signal and all the exemplar values to choose best fit signals before project them using Random Projection in order to reduce the recognition problem as a l1 minimization problem. This technique achieves pretty good results with a recognition rate near 100%. Although being well known in the gesture recognition community, various constraints limit their straightforward applications to mobile devices. The proposed work, among others points, addresses also that particular issue.

4. Proposed system

Within the context ecological interactions with a mobile device this work aims at the exploitation of a wearable insole interface in a mobile soccer game. Here we present the interface and sample interactions that are targeted.

Also known as Football, Soccer is the most played sport in the world. Because of its international characteristic, it appears as a common heritage that can bring people together: in many western countries it has served for the integration of migrants into the host society [24]. Since it necessitates a minor investment in terms of equipment, soccer has the potential for promoting social diversity. Moreover, being a sport team, it allows on one side to develop team spirit while the other one it helps to expand the social network while practicing an enjoyable physical activity. Andersen et al. stated that football is a popular team sport that contains positive motivational and social factors that may facilitate compliance and persistence with the sport and contribute to maintenance of a physically active lifestyle [25]. Although some forms of social interaction may be supported through actual soccer video games, it is clear that an important aspect concerning physical activities is neglected. Indeed core movements of the game (running, jumping as well as kicking or passing the ball) are supported through metaphors that do not necessitate any real word physical movements. The proposed interface targets this point by exploiting ecological interactions for main movements of a soccer game.

4.1. Exploited interface

This interface is based on the fact that the foot can be exploited to interact with a virtual 3D world. With this interface, by using several sensors (such as force sensors, flexion sensor, accelerometer, gyroscope and magnetometer), gestures performed with the foot are interpreted in order to let the user interact in the virtual world. All the sensors are connected to an IOIO board (a special board that helps to communicate with Android) and a Bluetooth communication between the interface and a tablet is responsible to transmit data from sensors to Android that deals with data. Here we do exploit only data that comes from the accelerometer (an ADXL 335) in order to let the user interact via real world soccer movements he performs. Moreover, thanks to several actuators distributed in the sole, a bidirectional communication can be performed between the user and the virtual world. This aspect is not exploited in the current study. Being located inside a shoe, this interface is fully compatible to constraints related to mobiles devices. Indeed, being a wearable and transparent device it can be carried everywhere and therefore can be exploited everywhere. In addition, this interface can allow discreet interactions with mobile devices while the hand of the user can be still free for other tasks. In a more general way, this interface is a novel, lightweight and transparent wearable interface enabling direct, foot-based and “environment-independent” interactions with mobile devices (mainly tablets). Moreover, being equipped with haptic actuator, it may provide bidirectional communications in order to provide a better user experience [26, 27, 28]. Fig. 1 shows a user having a tablet in hands while being equipped with proposed interface. More details concerning this interface can be found in [29, 30].

4.2. Ecological gestures that can be supported thanks to the proposed interface

Interactions with traditional virtual soccer games are performed via hands movements. With PC and console games: keyboard, mouse and/or joystick are the most common input devices, whereas the tactile screen dominates when it comes to tablets and Smartphones. Although being highly attractive, it is clear that such interactions are far from what is done when playing a physical game. Moreover they do not support any true real physical activity. With the described insole wearable device, it is rather the natural that prevails. No more need for buttons or arrows in order to control, pass or kick the ball, thanks to implemented gesture recognition approaches, the user may perform actions as in the real world. With such ecological interactions, because of their natural aspect, the player is more likely to give credits in his task and hence to be engaged in it. With more engagement, one can expect more fun. This aspect is particularly important since it has been noted that people do use tablets primarily for fun and enjoyment [2].

Fig 1. The proposed interface and the soccer application usage

Thanks to the accelerometer integrated into this interface, several foot gestures can be recognized. In the case of the virtual soccer game we can interpret more than 17 gestures. Some are dedicated to the manipulation of the ball while others are typical gestures that soccer players used to realize while playing. In the first group one counts: kicking, passing to left, passing to right, passing backward, passing forward, rotate foot in X, Y or Z axis direction. For each of these gestures, because of the raw data coming from the accelerometer, in addition to the identification, this signal allows to determine the strength of the gesture. For example, for a kick, as opposed to a kick performed via a *button press* the user has a total control over the kick both in terms of direction and amplitude. Doing so, by practicing, one can expect an improvement of the user's ability in kicking.

5. Method used in order to recognize gestures performed by the user

Before describing the proposed algorithm, we would like to define two expressions that will be used later. First, a movement represents a random change of position detected by an accelerometer. Whenever a movement can be associated to a predefined one, we named it a gesture. A gesture recognition algorithm is used to provide a real-time identification of realized movements. This section describes the proposed algorithm and details an evaluation of performances observed on a mobile device.

5.1. Proposed algorithm

To be able to recognize a gesture, whenever a movement is realized, we have to select resembling signals contained in a predefined set of signals (a database). Finally, we have to identify the most appropriated signal from those previously selected. As a result, the proposed algorithm counts three main steps. The first step: *movement detection* serves to detect whether a movement is realized or not. The second step: *selection of exemplars* helps to select potential gestures. The last one is the *selection of best suited signal*. This one confirm the previous choice by determine which signal in the training data set is the best suited.

5.1.1. Movement detection

Real-time movement detection is crucial in order to be able to exploit ecological gestures for the interaction. One may note that most of the time, data coming from the sensors is due to electric noises or an irrelevant movement. For this reason, we have to detect the start and the end of any movement, which may be a relevant gesture. For this, we choose the thresolding method. In this method, whenever the strength of one signal axis reaches a certain value (named the threshold) the movement starts. It ends when the strength of all signal axis become lower than the threshold. Rather than the strength, we decide to use the Simple Moving Average (SMA) of the signal [13]. The SMA consists in calculating the average of n last values of the signal. This technique helps to smooth out short-term fluctuations (e.g. noise) and highlights trends (e.g. a movement). A movement spotting using a simple moving average is represented in Fig. 2. In addition to this detection, minimum and maximum movement duration can also be used to avoid random peak or involuntary movements.

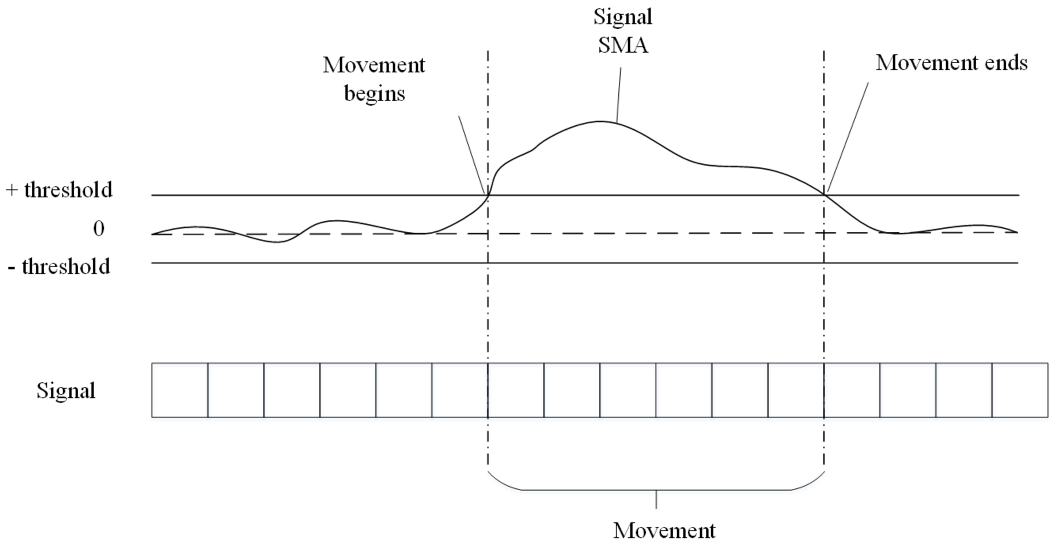

Fig. 2: Simple Moving Average movement detection

5.1.2. Gesture recognition

Once a portion of the signal is selected as being a movement, this step helps at identifying the gesture that this signal represents. This identification step is based on the work presented in [20] with a different method for selection of signals to process. Since we wanted to perform this task in real-time on a mobile device, a particular attention was put on the performances that such an algorithm may exhibit. Because of that, as said in [31], an algorithm like the Dynamic Time Warping (DTW) has been avoided. A feature extraction-based algorithm has been used instead since it may offer a low computational cost making the identification faster and lightweight. In this case, seven values which are: mean, median, standard deviation, variance, extrema (minimum and maximum values), RMS value and finally the Signal Vector Magnitude (SVM)[31] were chosen. This identification has two steps: *selection of exemplars* and *selection of the best suited signal*.

5.1.2.1. *Selection of exemplars*

This step aims at selecting signals of the database that may correspond to the detected movement. From the seven signal features, we compute a "*similarity probability*" that determine how much similar two signals are. In proposed algorithm, these two signals are the incoming movement and an exemplar from the learning set. The exemplars are defined using *Affinity Propagation* on all the training set and represent a cluster of signals. To determine the "*similarity probability*", we create for each feature a *Gaussian* normalize to 1, centered in the value of the exemplar feature as shown in Eq. (1) (with x the incoming gesture feature value, σ the *Gaussian* standard deviation and μ the exemplar feature value). Doing so, we can easily compute the probability and configure the algorithm tolerance by modifying the *Gaussian* standard deviation (named σ) Fig. 3-4 (this standard deviation is a configuration value and is not modify during the algorithm execution). Once these probabilities are found, we average them. This defines the "*similarity probability*". We perform this calculation on each axis of the signal to have a similarity value for each of them. If all these values are greater than a defined threshold, the exemplar and its signals are selected for the next step. If no exemplars are chosen, the movement is not identified. Obviously, if only one exemplar is selected, the process is completed.

$$e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{1}$$

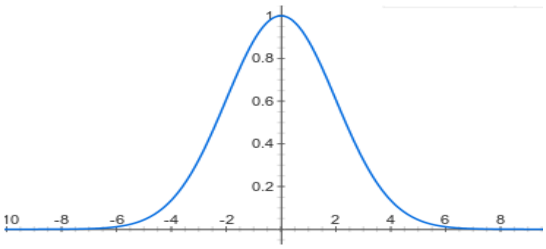

Fig 3. Gaussian with sigma = 2

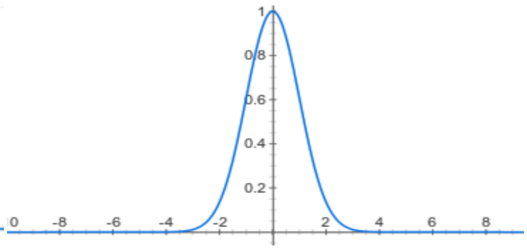

Fig 4. Gaussian with sigma = 1

5.1.2.2. *Selection of the best suited signal*

Once the exemplars and their signals are selected we have to finalize the choice by selecting the *best suited signal* from the previously selected ones. Indeed, it is possible that different gesture exemplars were selected in the previous step. This problem is due to signal fluctuations between learning dataset and signals captured by the accelerometer. As a result, it is possible that the good exemplar is not the one with the best "*similarity probability*". In order to achieve this task, we compare each selected signal to the unknown one as defined in [20].

We first create three matrices, one for each accelerometer signal axis. These matrices are R_x , R_y and R_z respectively. They contain each selected signal consequently; they are $l_{max} * n$ matrices with n the number of chosen signals and l_{max} the maximum signal length. For signals having a length smaller than $l_{max,}$ null values are added. These matrices are created by the application of Eq. (2). In the same way and with Eq. (3), we create three vectors Y_x, Y_y and Y_z which contains the unknown signal.

$$R_{i,j} = \begin{cases} S[j]_i & if\ i \leq size\ S[j] \\ 0 & if\ i > size\ S[j] \end{cases} \quad with\ S\ a\ table\ containing\ each\ selected\ signals \tag{2}$$

$$Y_j = \begin{cases} y_j & if\ j \leq size\ y \\ 0 & if\ j > size\ y \end{cases} \quad with\ y\ the\ gesture\ to\ identify \tag{3}$$

Thereafter, to speed up the final treatment, we make a Random Projection to project all the matrices and vectors on a lower sub-space. This allows having a reduction of data dimension and, as the further steps depend on this dimension (operations on matrices), this can speed up all the next selection process as said in [20]. This last treatment begins by the creation of a $l_k * l_{max}$ matrix (labeled A) defined by Eq. (4). With such a projection, we have finally a $l_k * n$ matrix for R matrices and a $l_k * 1$ vector for Y vectors.

$$a_{i,j} = \sqrt{3} * \begin{cases} +1 \ with \ probability \ \frac{1}{6} \\ 0 \ with \ probability \ \frac{2}{3} \\ -1 \ with \ probablity \ \frac{1}{6} \end{cases} \tag{4}$$

Of course, in order to project on a lower space, l_k has to be lower than l_{max}. In fact, l_k is the maximum sparsity level of all the chosen gestures. When this matrix is defined, we can safely project Y and R by using Eq. (5) and (6) in order to obtain a lower-space form of these matrices called $\overline{R_x}$, $\overline{R_y}$ and $\overline{R_z}$ for the R matrices and $\overline{Y_x}$, $\overline{Y_y}$ and $\overline{Y_z}$ for the Y vectors.

$$\bar{R} = A * R \tag{5}$$

$$\bar{Y} = A * Y \tag{6}$$

Finally, the relation between $\bar{R}$ and $\bar{Y}$ can be formulated as:

$$\bar{Y} = \bar{R}\theta \tag{7}$$

In Eq. (7), every element of θ is theoretically 0 except one, which will be 1: *the best suited signal*. In fact, due to time variations between signals, we cannot have this perfect solution. We thus decide to keep the maximum value in the θ vector to define the identified signal and consequently the recognized gesture.

5.2. Experiment

This experiment aimed at evaluating the performances of the proposed algorithm for real-time recognition of ecological gestures that can be used in serious soccer-game running on a mobile device. For this, we want to compare this algorithm to the well known DTW [20] and the FastDTW (a well known DTW optimization [32]) algorithms.

As explained previously, the whole recognition process counts mainly three steps: the *windowing*, the *selection of exemplars*, and the *selection of the best suited signal*. One may note that the *selection of exemplars* is the step that differentiates the three experimented algorithms. For this selection indeed the algorithm that we described is based on signal features whereas the two others, as their names suggest, use respectively DTW and FastDTW. Moreover, this step allows determining if a movement is a listed one or not. For this, the comparison of the three algorithms will be centred on this step. Five parameters will serve for this comparison. They are: the selection time, the number of chosen exemplars, the recognition time and recognition rate for listed and unlisted gestures.
The selection time is the computational time required for the *selection of exemplars* (the second step). This is the main comparison point since it is the only change between the three recognition processes. The numbers of exemplars selected by each algorithm is the second parameter used for the assessment since the execution time of the next step (*selection of the best suited signal*) will directly depends on this number. The third parameter is the recognition time. It defines the amount of time required for the whole recognition process. Since we want to use this method in a real time application, the whole recognition process must be as fast as possible in term of computation time. Finally, the recognition rate will provide a great indicator on two important facts: how well the algorithms can recognize gestures and how well they can avoid a false recognition of an unknown gesture.

5.2.1. Experimental process

A *Samsung Galaxy Tab 3 10.1* is used for the test. Eight different ecological gestures that correspond to real world soccer movements are used for the test. They are represented in Fig. 7. For this test, we first create a database that contains ten signals for each gesture. For this, each gesture is repeated ten times by a user. A total of 80 signals are saved in the database, created by a single user who repeats ten times each gesture with the presented insole.

On this database, we execute the learning phase in order to obtain a training dataset. And finally, based on this last one, we create an application that will test the algorithm performances. The application takes all the signals in the training database and modifies them in order to present the modified one to the recognition algorithm. Two modifications are performed: addition of random noise and reduction or increase of length. To avoid cross modifications, the application runs in two passes. It first adds noise and then changes the size of the signals. During the test, the application will create 200 modifications patterns. Half of them will add to each signal a progressively increasing random noise between 0 and 10% of the signal mean. The other half will progressively change each signal size with a factor between 0.5 and 2. Each algorithm analyses the modified signals in order to determine whether it recognizes the associated ecological gestures or not. Results of this experiment are presented in the following section.

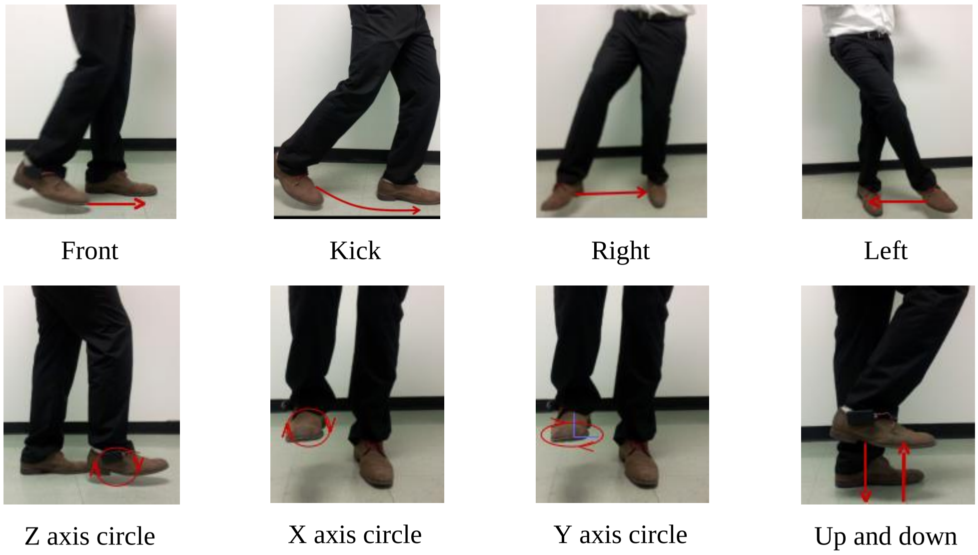

Fig. 7: The 8 soccer gestures selected for the test.

5.2.1. Results and discussion

Measurements made on the five parameters are reported in Tab. 1. With the proposed algorithm, we observe an average of 0.53 ms for the selection time, 0.66 ms for the recognition one and an average of 0.58 exemplar chosen. Concerning the DTW algorithm, we observed an average of 25.6 ms and 51.94 ms for selection and recognition time respectively and 1.72 exemplars chosen. Regarding the FastDTW algorithm, we find the same range of results as DTW with 27.24 ms to select an average of 1.72 exemplars and 57.93 ms for the recognition time. Regarding recognition rates of listed gestures, we observed that DTW and FastDTW perform better recognition than the proposed algorithm. Indeed, it obtains only 57% whereas DTW and FastDTW achieve 89.8% of good recognition. On the other hand, when dealing with gestures that are not listed in the database, the proposed algorithm always (100%) comes to notice that such a signal is not identifiable whereas DTW and FastDTW never succeed (0%).

Realized test clearly shows that the proposed algorithm, based on a light feature comparison is better suited to mobile devices in term of computation weight than DTW and FastDTW. This aspect is explained by the fact it takes less time to select less exemplars. This point represents an aspect of outmost importance since we want to arrive with a system that will be able to recognize performed gestures in real-time (50Hz in this case). Proposed algorithm has a loop frequency about 1.5kHz respects this point, whereas algorithms based on DTW and FastDTW turn around 19Hz and 17Hz respectively. On the other hand, it is also clear that the recognition rate of the proposed algorithm needs to be improved. However, it should be noted that the modification on the signal length does not affect the recognition capabilities of DTW and FastDTW algorithms. For this modification, recorded values show indeed 100% recognition rate for DTW and fast DTW, while the proposed algorithm exhibits 60%. These aspects will be addressed in a future work where we plan to use a genetic algorithm that may help at determining features that should be exploited for the selection of exemplars. We also plan to increase the learning dataset since the recognition rate depends on the size of that database.

	Features based	DTW based	FastDTW based
Selection time (ms)	0.53	25.6	27.24
Number of chosen exemplars	0.58	1.72	1.72
Recognition time (ms)	0.66	51.94	57.93
Recognition rate for listed gestures (%)	57.6	89.8	89.8
Recognition rate for unlisted gestures (%)	100	0	0

Table 1. Test results for each selection method. Reported parameters are: selection time, number of chosen exemplars, and recognition time and recognition rate for listed and unlisted gestures.

6. Conclusion and future work

Knowing that mobile devices are becoming a mass product in this paper, we have studied the possibility of exploiting ecological gestures to interact with a soccer game running on a mobile device. We analyzed the importance of ecological interfaces in the video games industry and have shown that interactions with foot gestures are now possible. To be able to take advantage of ecological gestures when playing soccer on mobile devices, thanks to an accelerometer attached to the foot of the user, we have described an algorithm that can be used for real time recognition of realised gestures. Realised experiment showed that the proposed algorithm is well adapted for the deployment on mobile devices. When compared to well known DTW and FastDTW algorithms, better computation speed are observed. The experiment also showed that the proposed algorithm can detect unlisted movements contrary to the two other algorithms tested in this paper. However, we also observed that the recognition rate of proposed algorithm needs to be improved.

This paper represents a major step in the creation of a soccer based serious game on a mobile device. In a near future, we will evaluate the added value of ecological interactions on a serious soccer game running on mobile devices. More exactly, it will be necessary to prove the impact of such interactions on player motivation, engagement and performances. Finally, it will be useful to show the impact of this type of interactions on the soccer skills of the player, and within the framework of the serious games.

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