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Use of a 3DOF accelerometer for foot tracking and gesture recognition in mobile HCI

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Abstract

Touch screens as a mean for interacting with mobile applications are limited. Since the hands are already busy handling the phone or tablet, this paper proposes an innovative solution in handling digital entities with the feet. A three-axis accelerometer is arranged on a shoe in order to recognize its movement and to determine its position. Extraction of both information improves mobile interaction in different situations, especially in gaming and working in limited space. The contribution of this paper is an algorithm designed in order to extract both feet tracking (pose) and movement recognition such as kicking, sliding and rotating.

Keywords: Feet tracking; feet motion recognition; mobile application

1. Introduction

Tracking systems are now a necessity in our professional or personal daily life. This technology is a key feature of many domains ranging from navigation to Human Computer Interaction (HCI). In HCI, various tracking systems had to be developed to fulfil the requirements of applications in the field. For example, one counts mechanical tracking systems that exploit a physical link to track an object of interest (a user, a human body part or a specific object) while offering the opportunity to move along a some specific Degree of Freedom (DoF). Mechatronic devices like the PHANTOM Omni developed by SensAble Tech [1], limit the movement of the observed object as well as the workspace due to the physical link. Although being inexpensive, the use of this type of system is restricted to specific applications like virtual object manipulation [2]. Increasing the workspace introduces other issues like those found in cable-driven mechanism where interferences between mechanical link and the user should be managed [3]. These mechanical constraints can be alleviated with electromagnetic, acoustic or optical tracking systems. Electromagnetic tracking systems count a transmitter, a receiver and an electronic unit. The transmitter and receiver are composed of three coils. The transmitter propagates an electromagnetic field in a surrounding sphere of few meters, whereas the receiver collects the magnetic flux according to the position thereof with respect to the transmitter [4]. A major issue with this type of tracking is that it does not work in presence of metal parts since they interfere with the electromagnetic field and generate a second magnetic field which disturbs the additional measures. Acoustic tracking systems exploit the propagation time of ultrasonic waves in air to determine the distance between two points. Since the speed of sounds depends on the temperature, ultrasonic trackers are hugely influenced by the temperature of the air. Moreover, these sensors are easily noisy by all devices that emit an ultrasound or by reflected sounds. Optical tracking systems combine light sources and light-sensitive sensors. The light sources are usually made from Light Emitting Diodes (LED). These systems are widely used nowadays in Virtual Reality (VR) applications since they are very accurate. However, beyond being quite expensive they require a special setup. Because of this, they cannot be used in mobile applications.

When dealing with mobile applications (applications running on Smartphone, or tablets), a major constraint regarding tracking comes from the fact that such applications can be used in multiples uncontrolled environments (indoor –at home, at work-, outdoor –in the street, in public transport-). Because of that, systems presented above do not allow to track the user, neither his body part nor an object of interest.

On the other hand, we observe that considerable amount of works have been done in order to exploit an accelerometer for tracking of objects. For example, several applications use the accelerometer inside the WiiMote™ for interactions with board games [5] or with robot [6]. Because of that, it seems that an accelerometer or a gyroscope can be exploited to allow users to interact with mobile applications. Moreover, considering that current interactions with mobile devices are restricted to the hand, here foot-based interactions are investigated. For this, there was a need to develop a system that tracks foot gestures. For example, when playing a game on a tablet, real gestures of the foot (sliding, kicking or phase of the gait), could be directly mapped to the virtual avatar of the user. This paper then proposes an insole interface that allows tracking positions of a user in the real scene and recognizes some foot gestures such as kicking or sliding using a 3DOF accelerometer. Both gesture recognitions and tracking will help to develop intuitive interaction. Indeed, gesture recognitions, mainly those of the foot, will improve tracking motion in mobile virtual reality and then improve interaction. This inexpensive and non-intrusive sensor thus seems to be a promising solution for the field of mobile HCI.

2. Related work

Foot gestures have been studied in several mobile applications including remote control actions for a SmartPhone, interaction between users, dancing and virtual environment as noted in [7] and [8]. In these studies, several gestures have been evaluated such as tap, double-tap, shake, trace symbol (circle or S-shape) and different kind of kicks (right, left, forward and backward such as those presented in [9]). Moreover, as noted by Yamamoto et al. [10], these gestures must be socially acceptable when the device is used in public place. Some design use camera already available in the phone for gesture recognition. In [7], the authors designed a mapping between gestures from video streaming and a command to execute on the SmartPhone. Our design offers a wearable shoe sensor which is inexpensive, transparent and non-vision-based system. The contribution of this paper concerns the design and integration of a foot gesture differentiation oriented to reproduce with high fidelity some human interactions with virtual object in a mobile virtual reality application.

3. Model for foot tracking and gesture recognition

In order to control digital entities through foot gestures, a housing containing an accelerometer was attached with a clip to the outer side surface of a shoe. As shown in Fig. 1a, the acceleration signal provided by an ADXL335 is acquired with a PIC24 microcontroller and is sent to a SmartPhone via

Bluetooth. The received signal is then subjected to a signal processing algorithm allowing the extraction of information on the foot gesture and position.

Gestures may be kicking, foot rotating, lateral movement and four gait phases including *heel strike* (S1), *midstance including double stance support* (S2), *toe off* (S3) and *swing* (S4). One can note that other gait phases could be detected using a second accelerometer located on the other foot. These four phases are interesting for simulating an avatar movement while the user is playing seated on a chair. These phase differentiations inside the gait are also primordial for computing the tracking of the user in real scene using an integration algorithm.

A better understanding of the acceleration waveforms needs an insight of the human gait. Human gait is usually composed of two periods in one cycle of walking: *stance phase* and *swing phase*. During the stance phase, the muscles are solicited for maintaining balance while during the *swing phase*, the leg accelerates forward in front of the walker like a double pendulum. The *double stance support* occurs between the transition from the *stance phase* to the *swing phase*; it represents about 10% of the walking cycle. This name comes from the fact that both feet support the whole body. A walking cycle begins with a *double stance support* and contains another one after 50% of the cycle. *Stance phase* has duration of approximately 60% of the walking cycle. It may be divided into three parts: the first *heel strike* on the ground (the *contact* in the initial *double stance* support), the *midstance* and the *propulsion* where the toes apply a force to the ground. As the system uses only one accelerometer attached to one foot, the *double stance support* is not detected and hence it is included in the *midstance phase*.

For computing foot movements and allowing tracking inside a virtual scene, our algorithm use a double integration which could diverge over the time. In fact, for avoiding any error accumulation over the time, the integration of the accelerometer signal should be computed only during the *swing* (S4) phase which corresponds to 40% of the gait cycle. Otherwise, the double integration initial condition is resettled for each walking step. The error (coming from MEMS noise and drift) accumulated could be evaluated online during the stance phase and also offline. It is indeed proportional to the square root of the time of the integration [11]. Since the drift is not constant, without any correction, the position computed could be similar to a quadratic function. Finally, the position computed needs to be calibrated in order to reproduce a proportional movement in the virtual scene. This calibration is done in a training phase where the user gives its own gesture to an optimization algorithm.

By doing a successive tap with the foot (reproducing the human gait) on the ground, the avatar gait will be simulated with a high level of accuracy in the virtual scene. Also, interaction with a ball or others virtual object can be performed using the foot gesture recognition module. Therefore this paper offers three major contributions in the Mobile HCI domain. The first contribution concerns the tracking of the user position thanks to an shoe-mounted accelerometer whereas the second involve the simulation of an avatar that mimics a human gait according to the player’s one. The third contribution targets the manipulation of a virtual object via foot gestures.

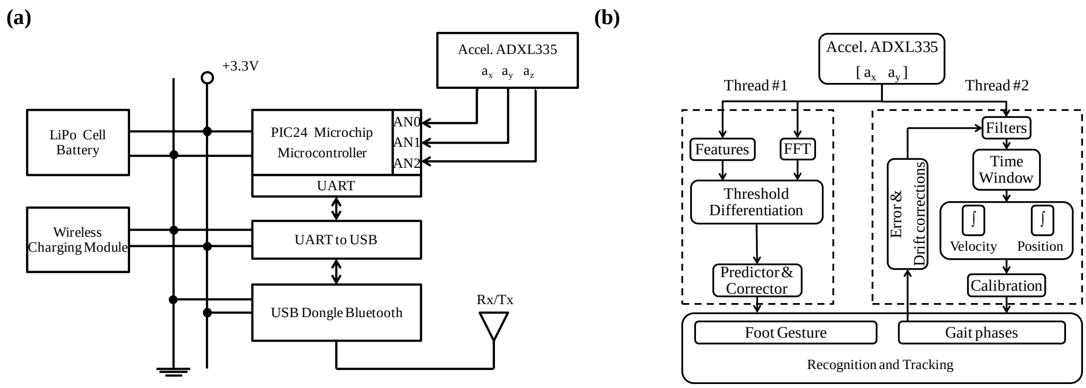

Fig. 1. (a) Circuit diagram of the embedded device (b); Signal processing algorithm

4. Experiments of the shoe-mounted accelerometer

This experiment aims at the evaluation of the proposed system for tracking a user in a real scene, identify the four phases of the gait and identify some specific gestures that can be used in a soccer game. Five healthy subjects did experiment the system. They are graduated students; none of them had no gait abnormalities and no environmental disturbance, and the case fixed on their shoe did not hinder their movements. Table 1 presents some characteristics of these subjects.

Equipped with the proposed system, subjects were invited to realize three different tasks. In the first one subject had to work with normal gait inside of the experimental room for a period of 20 seconds. In the second one the subjects were tasked with the same experience but with quicker and shorter step length. This aims at evaluating whether the proposed algorithm is able to see the difference between the pitches' length of the stride movement or not. In the last one, the subjects were asked to execute three different movements with the foot (kicking, foot rotation and lateral movement).

Subject	Age [y]	Weight [Kg]	Height [cm]	Shoe Size [US size]
1	24	82	182	10.5
2	35	66	172	8.5
3	31	89	186	11
4	24	70	176	9.5
5	25	65	180	11

Table 1 Subject Characteristics

4.1. Evaluation of the tracking system

At the beginning, the acceleration is acquired from the three axis accelerometer, described in the previous section, which are transmitted via a Bluetooth connection to transfer the data to an Android OS. It was noted that the X and Y axis signals present repetitive peaks throughout the gait. These peaks occur at different times for both signals. In fact, they represent two phases of the human gait which are the *heel strike* (S1) and the *toe off* (S3). Knowing that these two phases provides enough information for the evaluation and prediction of the four gait phases, the Z axis acceleration is not used in the proposed algorithm. Because of that, for estimating the position of a shoe, until now, only the X and Y axes of the accelerometer which give respectively the a_x and a_y measures are used by the algorithm as shown in Fig. 2a.

(a) **(b)**

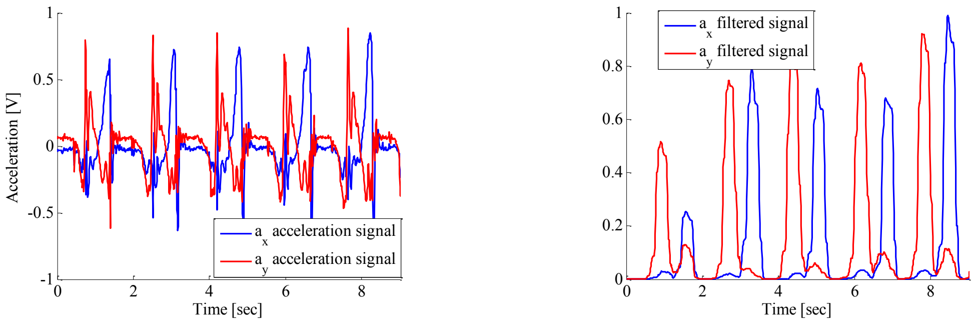

Fig. 2. (a) Raw a_x and a_y acceleration signals; (b) Filtered signal for analysing the heel strike

In a first thread, in order to detect the a_x and a_y acceleration signals' peaks, many successive filters are applied on each acceleration signal. This operation is required to reduce the noise in the raw signal, and delimits the different gait phases: *heel strike* (S1), *midstance* (S2), *toe off* (S3) and *swing* (S4). Those filters are taken from a peak detection algorithm used in the electrocardiogram signal processing (for QRS-detection) as shown in [12]. From Fig. 2b, a sliding window of 0.25 second is used to find the maximum value which the time position is stored in memory. These peak positions are shown in Fig. 3b.

In a second thread, during the peaks detection, the Fast Fourier Transformation (FFT) is computed in order to improve the gait analysis and the avatar tracking. A higher energy was noted in the *heel strike* (S1) and the *toe off* (S3) phases, much more important than the other phases. This energy will enable the detection of different phases using a statistic model. The FFT shown in Fig. 3a informs about the frequency of the steps so offers the possibility to predict the stride length and the position of the foot. The first harmonic frequency given by the FFT is involved in the gait duty cycle. Using this assumption, when the first harmonic decreases, it is likely that the user reduces its speed. Otherwise, when the first harmonic increases, its speed increases proportionally. This prediction combined with the values obtained from the peaks detection time provide effective translation to faithfully reproduce the movement of the avatar in the virtual scene.

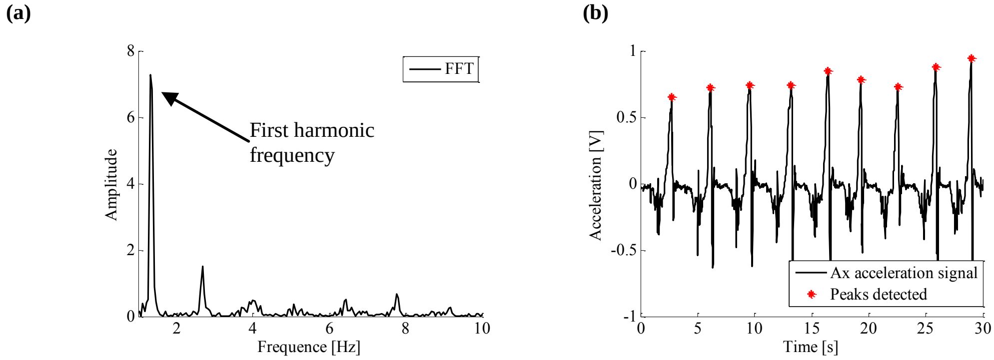

Fig. 3. (a) FFT of the a_x acceleration with a fundamental frequency at 1.3 Hz; (b) Peaks detection for a_x acceleration (subject 1)

The time associated with each peak of the acceleration signal defines the beginning and ending of two phases of the gait. In particular, the measurement of the peak time in the X axis determines the toe off event. The other signal is used to find the heel strike event as shown in Fig. 2b. To improve the robustness of the algorithm, two additional conditions were added: (1) no peak in a_y signal will be detected until the detection of a peak in the a_x signal and (2) the number of a_x and a_y peaks has to be the same. Knowing the percentage of gait cycle associated with each phase, it is possible to estimate, inside a time window, the time interval of each phase. Subsequently, the integration is applied between the time interval defined by the peaks detected on the X and Y axis which corresponds to the swing phase.

The integration function uses a trapezoidal method as described in [13], with modifications to impose initial and final conditions such as: (1) null pose and velocity at the *toe off phase* and (2) null velocity at the *heel strike*. Using these conditions, we consider a static position of the foot during the *stance phase*. In other word, these conditions are valid when the foot is stick on the soil surface (without sliding). The position of the foot is estimated during the swing phase then computed and corrected at the *heel strike*. Such an algorithm was recently presented in [14] and [15]. In order to increase the accuracy of the integration, the errors coming from noise and drift can be minimized by periodic recalibration using the *stance phase* (static position of the foot) to estimate the noise effect and to compute the drift level. The noise effect is reduced using an adaptive Gaussian filter. The drift level is a constant value subtracted from the raw acceleration. Finally, a calibration is applied to get the position in meter unit.

The first integration gives us the velocity and the four gait phases as shown in Fig. 5b. Such detection of gait phases was presented in some researches but using force sensing resistors located under the foot [16]. The second integration, gives the position of the foot inside the virtual environment shown in Fig. 4.

(a) **(b)**

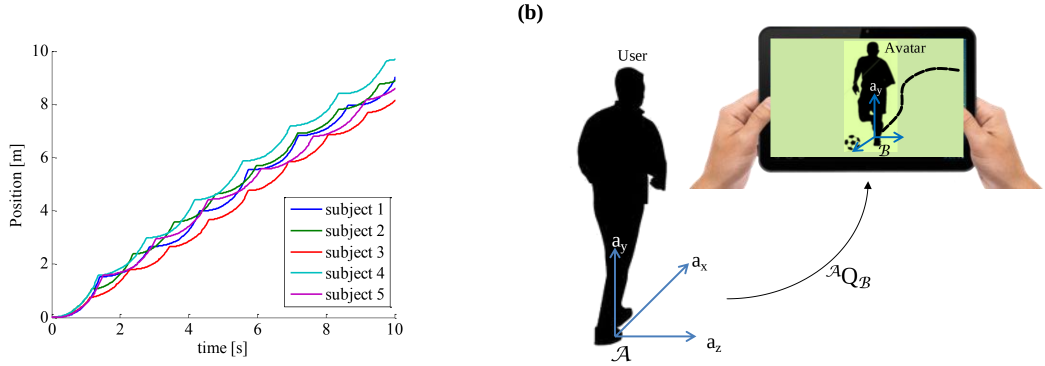

Fig. 4 (a) Calibrated foot position for the five subjects inside the virtual environment; (b) Application to a soccer game

4.2. Evaluation of the gait analysis

The analysis of the gait could be computed using a statistical model. Used model is composed of six features computed from the acceleration signal: *standard deviation*, *mean*, *kurtosis*, *skewness*, *energy* and *variance*. These features, selected in the proposed algorithm, depends upon the events to differentiate as suggested by [17] and [18]. The algorithm uses a windows length 0.25 times the first harmonic period given by the FFT from the Fig. 3a. A 10 % overlap of the previous analysis is used in order to find each phase. The statistical model, described in (1), gives a level L computed from the sum of n features F_i weighted by a factor W_i in order to detect the actual gait phase:

$$L = \sum W_i \times F_i \qquad (1)$$

The factor W_i is optimized for each user in a learning phase before using the game. As shown in the Fig. 5a, four gait phases for every step can be differentiated using this statistical model. The real-time differentiation of the gait phases could then be executed using three thresholds computed using the half of the minimal distance between each curves. This algorithm applied in real-time gives the gait phase intervals shown in Fig. 5b.

(a) **(b)**

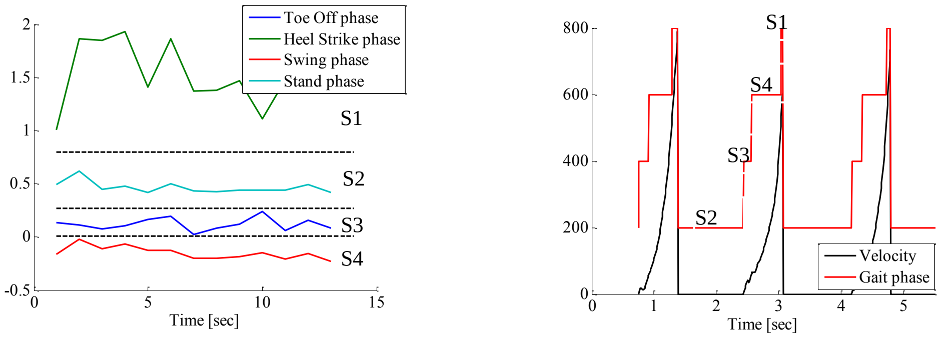

Fig. 5. (a) Features for different phases of the gait (subject 1); (b) Velocity and gait phases (subject 1).

4.3. Evaluation of the foot gesture recognition

Three foot gestures were recorded with the accelerometer from the five subjects. The gesture recognition uses a statistical model similar to the gait analysis algorithm which gives value located between two thresholds. As for the phase differentiation, these thresholds are found with an optimization algorithm during the training phase. Fig. 6a gives one sample of the raw acceleration signal for each gesture. On this figure, an offset is given for each gesture for viewing purposes. After the training phase, for each gesture and for each participant, we compute (1) for the three acceleration axis. The level coming from the statistical model is given in Fig. 6b for the three acceleration axis and the three gestures. From this figure, it appears that each participant needs a customization for the foot gesture differentiation.

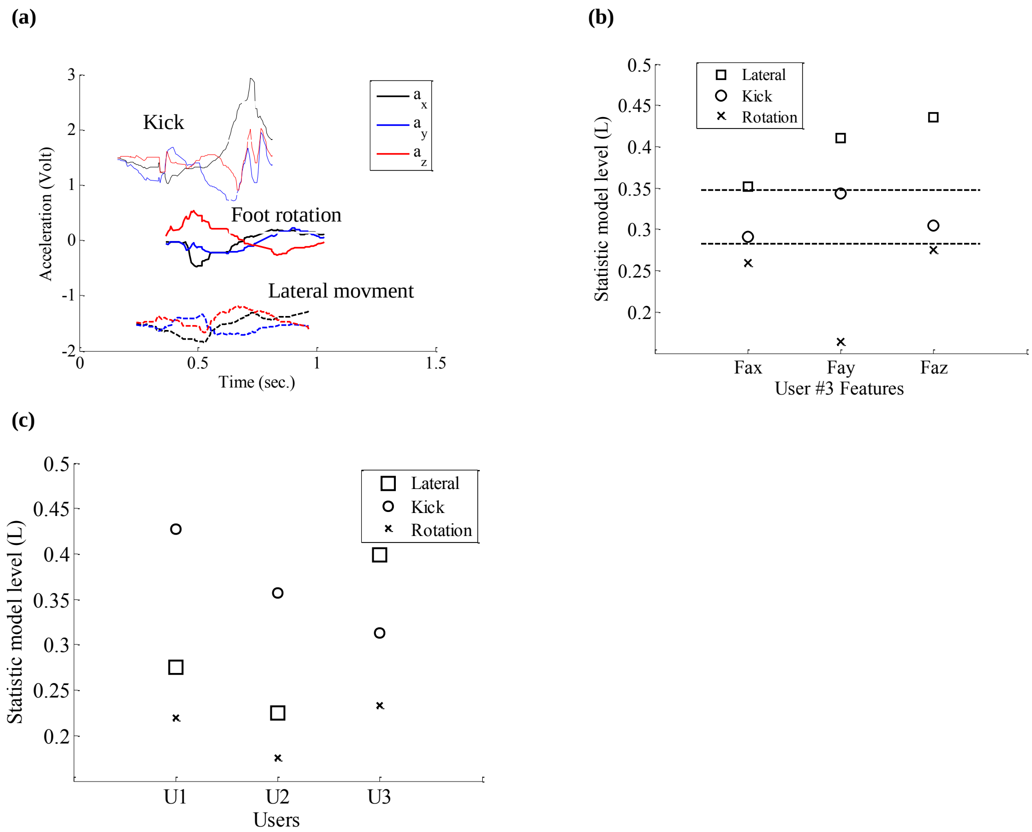

Fig. 6. (a) Accelerations acquisitions for different movements; (b) Differentiation with the statistic model for one user on each axis; (c) Mean (three axis) of the statistic model for three users

5. Conclusion and future works

This paper addresses the use of a shoe-mounted accelerometer for tracking a user in a real environment and mapping gestures in virtual environment. In order to offer a realistic interaction between the user and the mobile virtual scene, several aspects of tracking algorithm are investigated. The first one concerned the tracking of the user position. Thanks to the proposed system, during the position tracking the principal phases of the human gait are extracted and can thus be mapped on a virtual avatar that can thus faithfully simulate the player’s gait. Moreover, this paper have studied the use of such a system for foot gesture recognition in order to provide more natural interaction with virtual object such a soccer ball. Although proposed algorithm can be improved in terms of accuracy and utilities, the designed system can be used for different fields and applications like gait analysis systems, Smartphone games and tracking applications. Future work will involve the design of serious games with the aim of improving balance capacity of people with reduced mobility. In particular, those games will focus on the analysis of the gait on different types of soil. These analyses will be very useful as a diagnostic aid during a long term evaluation of performance progression.

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