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Online motion recognition using an accelerometer in a mobile device

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ABSTRACT

This paper introduces a new method to implement a motion recognition process using a mobile phone fitted with an accelerometer. The data collected from the accelerometer are interpreted by means of a statistical study and machine learning algorithms in order to obtain a classification function. Then, that function is implemented in a mobile phone and online experiments are carried out. Experimental results show that this approach can be used to effectively recognize different human activities with a high-level accuracy.

1. Introduction

Motion recognition is a discipline that has been around lately in the human–computer interaction research community (Nayak, Sarkar, & Loeding, 2009; Parera, Angulo, & Rodriguez-Molinero, 2009). Motion detection is a similarly hard problem as speech or gesture recognition since these are complex acts in human beings. Nevertheless, this field has a wide variety of applications. For example, a continued study of this information can help a doctor to establish a correct diagnosis or a rehabilitation plan for persons with mobility problems.

Many mobile phones can be found nowadays fitted with devices such as accelerometers, gyroscopes, cameras, etc., enabling us to obtain data from their users such as their movements. Furthermore, these mobile phones have a really high processing capacity to execute complex programs. This feature allows us the implementation of reliable methods to recognize movements using the data from the accelerometer. However, that recognition process implies a common problem: human movements are very complex because many actions can take place both sequentially and simultaneously. Due to that, there are many different combinations of sequential and simultaneous human movements so it is almost impossible to model them all explicitly. Using an accelerometer with a person, the data collected can be different depending for example on the age of the person who stands up, i.e., a young boy or an elder person.

Another similar situation could be considered when two persons with the same age do a lateral movement and one of them has one of his/her legs injured. To begin with, the time in which these persons would do the movement would not be the same. Secondly, if these persons have a device fitted with accelerometers the data captured would be different. Hence, a recognition method has to be designed in order to recognize movements in persons of different sex, age or physical condition. Another problem is where to place the recognition device, since the data retrieved from the accelerometer can be different if the same person has the device in a different pocket of his trousers or even in the same pocket.

From the medical point of view, many works have been developed using the data retrieved from the accelerometers' sensors to study chronic diseases, strokes or rehabilitation processes. Accelerometers have a high potential use in monitoring patients undergoing rehabilitation processes because the information provided together with a clinical assessment can help shortening the duration of the rehabilitation plan by applying the appropriate therapeutic intervention earlier. Clinicians and biomedical engineers are joining forces to make this technology part of the routine in clinical practice (Bobick & Davis, 2001; Sminchisescu, Kanaujia, Li, & Metaxas, 2006). Hence, the processing of data from the accelerometer allows determining the rehabilitation activities a patient would require. This information, for example, could on the one hand help a doctor to determine if a patient is doing his/her exercises correctly or, on the other hand, it could be taken as a sign that helped to correct the rehabilitation plan.

The acceleration signals recorded via the accelerometers have been used in many works to classify daily life activities (such as sitting, standing and even walking) (Li & Ge, 2009; Parera et al., 2009). Most notable accelerometry studies discriminate one movement from other activities, e.g., fall detection (Zhang, Wang, Liu, & Hou, 2006). Some methods use other technologies rather than accelerometry such as RFID (Alvarez, Perez, Angulo, & Ortega, 2007; Hein & Kirste, 2007) or video recording (Matta & Dugelay, 2009). Likewise, a wide variety of classification methods are used: KFD algorithms (Zhang et al., 2006), Bayesian and neural networks

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(Bu, Okamoto, & Tsuji, 2009), support vector machines (Cao, Masoud, Boley, & Papanikolopoulos, 2009; Parera et al., 2009) or decision trees (Rogez, Rihan, & Ramalingam, 2008). All these works describe online recognition, consisting of collecting data and then recognizing the movements. However, in this paper, we describe a new solution and implement an online method to recognize human movements in real time using a phone with an accelerometer.

The rest of this paper is structured as follows: Section 2 describes the data captured and the activities studied. The feature selection strategy based on discriminate power for generated features is presented in Section 3. Data interpretation and processing is described in Section 4. Experimentation is carried out in Section 5 and the last section contains the conclusions drawn.

2. Information collection

In this section, the relation between the device used and the way to obtain data from the accelerometer are explained. The activities to be classified are described next.

2.1. Data collection

An accelerometer measures acceleration (measured in m/s^2) caused either by a motion or by the gravity. Acceleration near the surface of the earth is around 9.8 m/s^2, which is used as unit of measure and is denoted as G, that is, 1 G = 9.8 m/s^2. The data retrieved from an accelerometer can provide the necessary data to study the behaviour of a person, e.g., the patient movements in his rehabilitation exercises. In this paper, the input signals are obtained from a triaxial accelerometer of the sensor device located on the user's chest sampled at 100 Hz. This position has been chosen because, despite the asymmetry of the human body, usually in both men and women the centre of mass (a pivot point around which the system can revolve (Wikia Education, 2010)) is around the chest. The data from the triaxial accelerometer is represented in 3-column values ($X;Y;Z$) measured in G. The orientation of the three axes is variable and depends on the device; hence it is an important step before doing any test to establish a common axis orientation in order to be able to compare it later with other motion recognition methods or with the same method implemented in different devices. Data from the accelerometer is stored into text files for the next step and then it is normalized (that is, the mean value is zero and the standard deviation value is one) in order to avoid problems with outliers.

2.2. Activities

The final objective of this work is to identify a set of four daily activities performed by the user while he/she is wearing the sensor device. The activities to be classified are (the orientation of *XYZ* axes are shown in):

- Sitting down: this movement ranges from 1 to 2.5 s.
- Standing up: this action also ranges from 1 to 2.5 s. It is similar to an inverse action of sitting down.
- Walking: this activity includes taking various steps.
- Stop: the stop motion is considered as the steady standing and sitting action. In both cases the mobile phone stays in the same position, and hence the data obtained is very similar and the movements are considered to be the same.

Fig. 1 shows an example of the *Z*-axis readings of an accelerometer for each activity. It is worth noting that the duration of the movement depends on the person who carries out the movement.

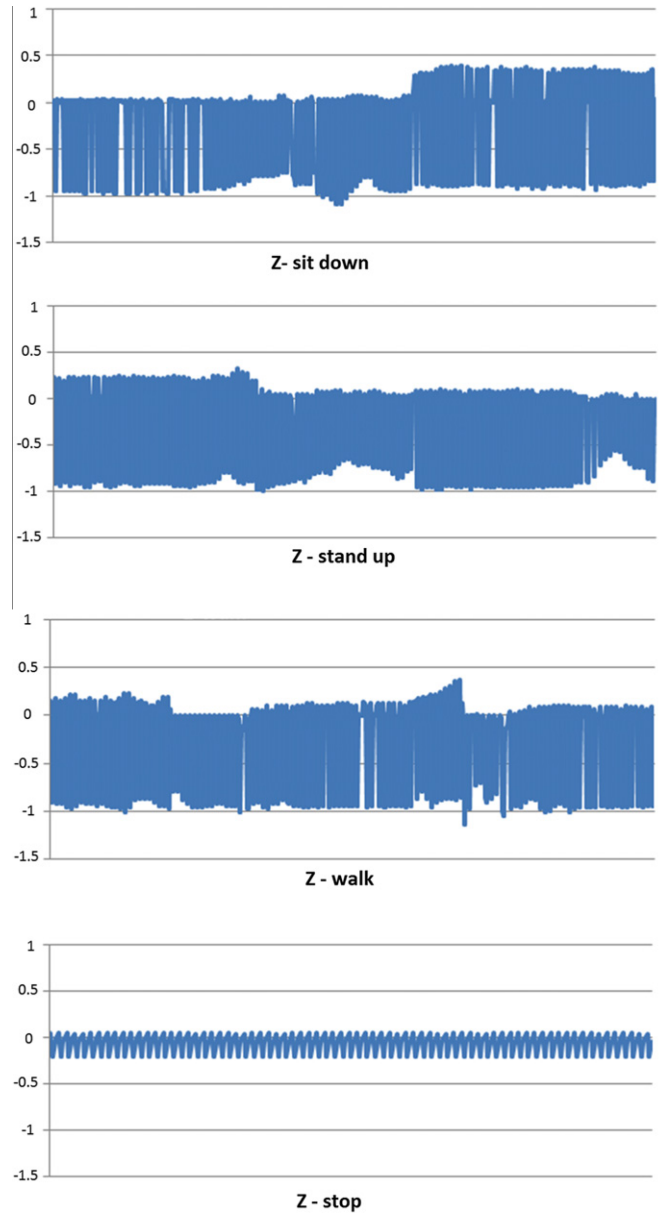

Fig. 1. *Z*-axis readings for different movements.

For example, a young man can take less than 1 s to stand up while in an elder person the time can be equal to or longer than 1.5–2 s.

3. Features extraction

Once the data is collected, more than 100 related features were considered such as angle calculations, the acceleration module, increments and averages. A deep statistical analysis was carried out in Parera et al. (2009) and previous data analysis tools were used (e.g., boxplot, the Fourier transform, etc.) to choose the next nine features.

- The standard deviation and the range of the orientation θ angle. This angle based on the earth gravity allows computing the sensor device orientation.

$$std(\theta),\ range(\theta)|\theta = \arctan\left(X, \sqrt{Y^2 + Z^2}\right). \tag{1}$$