Online motions recognition method using mobile phone accelerometer

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Abstract

Accelerometers can obtain data about the movements of some person. The continued study of this information can help to a doctor to establish a correct diagnosis or a rehabilitation plan for a person with mobility problems. This paper focuses on a new method to implement a motion recognition process with accelerometer sensor data contained in a mobile device. All the steps are described, from the data collection to motion recognition through statistical study data and machine learning algorithms.

Nowadays, mobile phones have big processing capacity to execute complex programs. In the last step of this process, a classification function is implemented in a mobile phone for online motion recognition. The practical experience showed an overall accuracy of 91% when recognizing four activities.

1 Introduction

Currently a lot of mobile devices incorporate sensors like accelerometers and gyroscopes that enable us to measure acceleration and respectively orientation. Accelerometers provide quantitative measures of a person movements. They are capable of identifying specific changes in older adults and they can be used to objectively quantify ambulatory activity levels. Furthermore, accelerometers have many potential uses in monitoring of patients in rehabilitation. They provide an added objective and quantitative dimension to motion analysis when combined with clinical assessment and they have the potential to facilitating early initiation of appropriate therapeutic intervention, thus reducing rehabilitation time. Nowadays, the clinicians and biomedical engineers are joining forces to make this technology part of everyday clinical practice.

Many works had been used the retrieval data of accelerometers sensors to study chronic diseases, strokes or rehabilitation processes. These data can be used to obtain objective information about patients with limitation of their motion capacity.

Motions recognition is a discipline that has been around for last years in the human-computer interaction research community. The motions recognition is a similarly hard problem as speech or gesture recognitions. It is a field with a wide variety of applications. Many devices can be used like cameras, gyroscopes, accelerometers, etc. to identify the motion done. This article focuses on the motion recognition applied to medicine using accelerometers.

Accelerometers measures acceleration and they can help to discover what motions or activities a person has done. But that recognition contains a common problem: human movements can be very complex, with many actions taking place both sequentially and simultaneously. Because there are so many different combinations of sequential and simultaneous human movement actions, it is impossible to model them all explicitly. For example, it is not the same if a motion like stand up is done by a young boy or by a grandfather. A similar case could be two persons with the same age, but one of them has injury in one of this legs. Firstly, the time to do the movement between these persons would not be the same. Secondly, if these persons carry out a device with accelerometers the captured data would be different and the recognition will be more difficult. Another problem is the positioning of the device. The accelerometer data can be different if the same person carries out that device in a different pocket of his trousers or even in the same pocket.

This article describes a complete method to recognize human motions via a mobile phone with accelerometer. This process covers from the data collection to the results of the recognition. Section 2 describes the related work and it emphasizes the online characteristic of this method. In Section 3, the process description starts with the data capture. Firstly, in 3.1, the mobile phone used for data collection (Openmoko Free Runner) is described. Secondly, the section 3.2 deals the studied movements or activities. Section 4 presents the proposed feature selection strategy based on discriminate power for generated features. Section 5 describes the machine learning used for the classification. In Section 6, the results from the experimentation are related. It is divided in offline and online results. Finally, conclusions and future work are described in Section 7.

2 Related work

Many previous works have focused on motions recognition using accelerometers data. This kind of articles differ in the devices used, the movements studied, the method to obtain the data, the study of the patient previous activity, the machine learning used and the way to do the testing.

In the last years, researchers from the Technical Research Centre for Dependency Care and Autonomous Living of Polytechnic University of Catalonia (Spain) have published several studies[1] about motions recognition. They have created a hardware module for capturing movements called IMOA.

Accelerometers have been proposed by previous studies as a tool to monitor and assess physical activities of subjects in a free living environment without many constraints on patients. The acceleration signals recorded through accelerometer have been used to classify daily living activities (such as sitting, standing and even walking) [1-3]. Most notable accelerometry studies which discriminate walking from other activities. For example, fall detection using a cell phone [4]. Some methods use other technologies like RFID [5] or video [6]. Likewise, a wide variety of classification methods are used: KFD algorithms[4], bayesian and neural networks[7], support vector machines[1] or decision trees[8]. But all of these works describes an offline recognition. First the data is collected and then the movements are recognized. That is the principal problem we have tried to solve with this paper. In this article, an online method is related to permit the time-real movement recognition with a minimum delay.

3 Information collection

In this section the device used and the way to obtain data from the accelerometer is related. Next the activities to be classified are described.

3.1 Openmoko NeoFreeRunner

To implement and test our system, we use the Openmoko mobile phone Neo FreeRunner. Openmoko is a project to create mobile phones with an open software stack, that is, Openmoko is a Linux distribution designed for open mobile computing platforms, such as, but not limited to, cellphones. It is not tied to any particular mobile phone and Gives developers capability to easily create and deploy applications. Nowadays, Openmoko is currently selling the Neo FreeRunner model. Inside this mobile phone, there are two three-axis accelerometers sensors and the information from both of them is exported through two different input event based file mappings. In our work, we started to design a simple program to take the retrieval signals from one of the accelerometers (the orientation is showed in Figure 1) to study the behavior patient. An accelerometer simply measures acceleration, either due to motion or due to gravity. Acceleration is measured in m/s2. The acceleration at near the surface of the earth is around 9.8m/s2, which can be an unwieldy number, so 9.8m/s2 is often labeled 1G.This means that if you drop an object from some height (assuming a vacuum), after 1 second it will be falling at 9.8m/s, a speed of 19.6m/s after 2 seconds, and so on.

Figure 1: Axis orientation in Openmoko Neo Freerunner accelerometer

The retrieval data of the accelerometer, which it obtains in 3-column values (X, Y and Z) in G measure, provide us the base to study the patient behavior in his rehabilitation exercises. The data processing permits to find out the movements and this information will give to the doctor the necessary information to decide if the patient does his exercises correctly or, on the contrary, it can be a signal to correct the way to do the rehabilitation plan.

It's worth pointing out that the duration of the movement depends on the person who carries out the movement. For example, for a young man the stand up movement can last less than 1 second and for old men the time can be equal to or greater than 1.5-2 seconds. In this second case, the occurrences of the transition state of the movement will be larger than the first case. In our experiment, the Openmoko device located on the user's chest sampled at 100 Hz (100 XYZ samples per second).

3.2 Activities

The next classification describes the four activities that we have studied:

- Sit down: a person who sitting down. This movement ranges last 1-25 seconds.
- Stand up: a person who standing up. This action also ranges 1-2.5 seconds. It is similar as an inverse of sitting down.
- Walk: this activity including various steps.
- Stop: We consider the stop motion the steady stand and the sit action. In both of these movements the mobile phone stays in the same position (on the chest of the person). Accordingly, the data obtained are very similar and the movements will be considered the same.

Any of these movements implies a lateral movement (X-axis in the device), hence the data of the Y and Z axes will be more important for the motion-based recognition. In Figure 2 shows the Z axis for each motion for 500 XYZ-values. The data is recorded in specific files inside the device. Now, the next step will be the study of these data through statistical features.

4 Features extraction

We start the processing data using a large number of statistical classification techniques (like angle calculations, the acceleration module, increments or averages) to obtain the best classifiers and determinate the patient movement. With the experience of previous studies [1], we have obtained the best results with the following nine statistical formulas:

• The standard deviation and the range of the orientation θ angle. This angle is based on the earth gravity allows to calculate the orientation of the sensor device.

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

• The standard deviation and the minimum value of the forward acceleration (*AF*). This acceleration uses the θ angle to calculate the accelerations in the earth fixed reference frame by applying the rotation matrix of the X axis.

$$std(AF), min(AF) \mid AF = cos(\theta) * X + sin(\theta) * Z$$

• The standard deviation of the vertical acceleration (*AV*). The vertical acceleration is similar to the forward acceleration and it uses the θ and φ orientation angles.

$$std(AV) \mid AV = cos(\varphi) * X + sin(\theta) * X + sin(\varphi) * Y + cos(\varphi) * Z$$

$$\varphi = arctan(Y, Z)$$

• The standard deviation and the minimum values of the Y values of the window.

$$std(Y), min(Y)$$

• The standard deviation and the minimum values of the Y values of the window.

$$std(Z), min(Z)$$

The features selected depend on the activities which will be studied. In this case, none of these activities implies a lateral movement. In the accelerometer, lateral movements are represented by the X axis, hence the features which include Y or Z axis will be better classifiers.

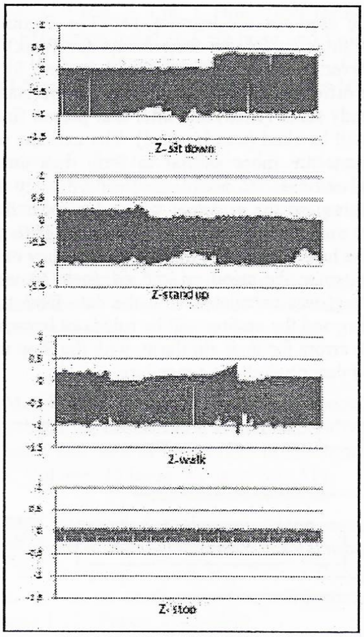

Figure 2: Acceleration (G) in Z-axis-values during the stand up, sit down, walk and stop motions

As we described in the last section, the device records the values from accelerometer into a file (in xyz 3-column format). Once the movement is finished, we divide the file data in different windows of 100 XYZ samples. For each window, the nine statistical features are calculated by a program executed inside the phone. They form a new register which is recorded in another file. Once all registers are calculated we decide which ones will serve to the learning for the classification machine.

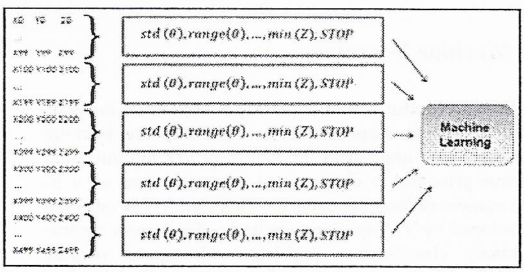

Figure 3: Features calculation sample for Stop (Walk) motion

For the Stop and Walk motions, we consider that all registers are useful for machine learning training. Hence all of them can be used for the learning set. The Figure 3 describes that situation for the Stop (same for Walk) movement. However, the cases of the Stand up and Sit down motions are different. Before a person sits down (stands up) he stays steady stand (sited) and after that person finish the motion he will be sited (steady stand). The extreme parts of the movements are more similar to Stop than the Stand up/Sit down motions Consequently, we will only include for the learning set the registers which are located in the center of the movement. That means that the registers in the centre will be labeled with the movement and they only will serve to recognize the stand up and sit down movements. The others registers calculated with the data from the motion beginning and the ending will be ruled out because they can generate errors for their similarity with the Stop motion. The Figure 4 describes all the procedure.

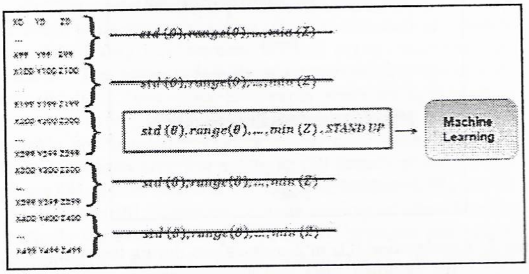

Figure 4: Features calculation sample for Stand up (Sit down) motion

Once we have the data necessary to train the machine learning, the basic goal will be to determinate the activity associated with a register with nine values of the statistical features. When the label of activity from all registers are predicted, we can obtain an estimate of the patient behavior, that is, the movements set that the patient have done during the program has been run.

5 Machine Learning

A Support Vector Machine (SVM) is used to do the classification process. Support Vector Machines are learning machines which implement the structural risk minimization inductive principle to obtain good generalizations on a limited number of learning patterns. This theory was originally developed by V. Vapnik on the basis of a linearly separable binary classification problem with signed outputs {-1,+1}[9]. Many papers generalizing the original bi-class approach to multi-classification problems through different algorithms exist, such as 1-v-r SVM or 1-v-1 SVM. The SVM Classification algorithm used in this paper is based on 1-v-1 SVM with different normalization outputs [10] and it was developmented in Matlab. In this implementation, the user introduces a set of examples and one part is for the training and another is for testing. These parts change in the course of the execution to obtain the best classification function. The user can configure other parameters like the size of the training/testing sets and the times to execute the machine learning. For each execution three SVMs are obtained and the best one is chosen.

In this paper, SVM learns the behavior of a patient derived from the data of the Openmoko NeoFreeRunner accelerometer through hundreds of labeled instances which is formed by nine variables and a label. In a first step, the SVM is trained by multiple labeled registers (supervised learning). After the execution, the result obtained from the training of a SVM is a trained classification function to classify new examples without label. Automatically, the program calculates the classification function with the training set and tests it with the testing set. After the execution the program shows the accuracy and the necessary parameters to implement directly the classification function in the mobile phone.

6 Experimentation

We have worked with a database of approximately 1300 entries by observing the various movements in the same person. The phone was placed on the chest of the person by a special belt to hold the device to the person. Every activity (stand up, sit down and walk) was performed 100 times. With that information and the machine learning it is possible to predict the movements made by the patient.

The experimentation has been divided between the offline and the online recognition tests. The difference is the decision to implement the classification function into the mobile device. In the offline experimentation we only need the phone to obtain the training and testing sets.

6.1 Offline recognition

For the offline experimentation we do not need to implement the classification function into the Openmoko phone. Firstly, the training and testing set are obtained. To increase the system robustness, it is necessary do the same movements with a lot of people with different age and health state. In our practical experience, with one patient, we collect 100 samples for each motion (sit down, stand up, walk and stop). Secondly, the SVM is trained with the training set to obtain a function to recognize new registers (each one with nine values of the statistical features). To design the best classification function we have to test the SVM with different parameters. The next step is the optimization of the function classification with the best parameters values to obtain the maximum accuracy. It is necessary to run the SVM procedure many times with different parameters values to find out the best configuration. Our SVM tests had been executed in a share memory server installed at the Andalusian Scientific Computer Center (CICA) in Seville

(Spain). This server has 16 processing cores and 256 Gigaytes of RAM. With that big processing capacity, this machine can executes all together different threads of any scientific program and it can obtain the results in an acceptable time. Finally, in the last step, the testing set is used to recognize movements. The testing set contains registers without labels. When the function adds the label to each register, we can discover the motions done by a patient. And finally, that motions report can be used by a doctor to make a diagnosis or a rehabilitation plan. We have obtained an average accuracy of 91% with this method (when we have considered the four activities).

6.2 Online recognition

We are now working in this point. We have to implement the SVM classification function into the mobile phone to obtain the online recognition results.

7 Conclusions and future work

As a future work we have to implement the SVM into the mobile phone. Furthermore, to continue this work it is necessary to test the method with volunteers with different sex, age and health conditions. We also propose to test the method with other features and activities.

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