Smartphone-Centric Human posture Monitoring System

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Abstract— **The popularity of smartphones around the world has the potential to dramatically improve healthcare, due to the high portability, computing capability, and ease of usage. Today's smartphones are easily programmable and come with a growing set of powerful embedded sensors such as accelerometers, gyroscopes, microphones, and cameras. Indeed, the smartphones equipped with such miniaturized sensors will potentially reshape the future of healthcare by facilitating proactive personal wellbeing management and ubiquitous health monitoring including physiological signs and human posture observation. In this paper, we present the design and implementation of a smartphone-centric software for monitoring the human posture by using the acceleration sensors which are embedded in smartphones. Additionally, an emphasis is given to interpreting the obtained data from the acceleration sensors to achieve context-awareness suitable for healthcare applications. Such the smartphone-centric monitoring softwares are also more cost-effective and less complex compared to its conventional counterparts where multiple wearable sensors are incorporated.**

Keywords—Smartphone; posture monitoring; activity recognition; acceleration sensor; health monitoring

I. Introduction

Smartphone not only serves as the key communication device of choice, but it also comes with a rich set of embedded sensors, such as a 3-axes accelerometer, digital compass, GPS, microphone, as well as built-in camera. Collectively, these sensors are enabling new smartphone applications across a wide variety of realms, such as healthcare [1], environmental monitoring [2], and transportation [3] that give rise to new area of research, which is recently referred to as the smartphone-centric sensing. With advances in technology, such systems can become increasingly compact with versatile applications that posture monitoring and activity recognition are amongst. Accelerometers can be used as activity detectors [4] as well as for body-motion and gesture sensing [5]. Active research is being carried out in exploiting this feature for determining user context and activity [6]. Users' context can be utilized in healthcare applications [7] and it is useful to reducing human intervention in ubiquitous monitoring systems.

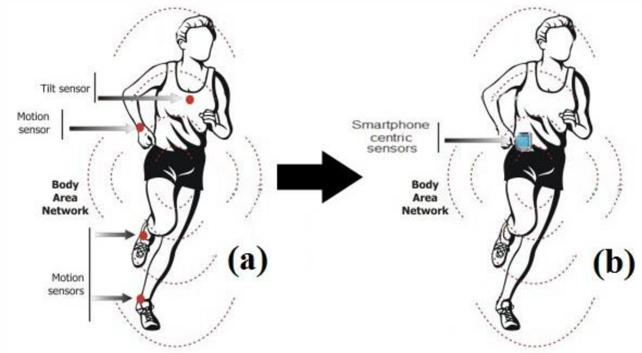

Fig. 1. All wearable sensors integrate to Smartphones-centric sensors [10].

Pervasive healthcare, the use of pervasive computing technologies to integrate posture and activity monitoring seamlessly into people's lives, is a rapidly extending area of research that has attracted many researchers in recent years. Research on sensor based body activity recognition was started by Ailisto et al. that resulted in the first publication on this topic in 2005 [8]. Until recently mobile sensing research such as activity recognition, where people's activity is classified and monitored [9], required specialized wearable sensors to be fabricated as shown in Fig. 1a.

Posture and activity monitoring can be very effective in medical advice, context-awareness, calorie-burning guides, and etc. Previous works in this area were based on wearable sensors which are placed on different parts of the human body (Fig. 1a). One of the main disadvantages of utilizing wearable sensors is low availability of these devices on the market as opposed to the high availability of smartphones. Additionally, they are commonly dependent on a second coupled device for collecting and calculating data besides their limited programmability and cost.

In this paper, the design and implementation of a new method for performing posture monitoring based on several machine learning techniques is presented. In contrary to the posture monitoring systems, which are currently available, the proposed monitoring system utilizes the sensors (i.e., acceleration sensors) embedded in a smartphone as schematically shown in Fig. 1b. It is also noteworthy to mention that the key difficulty in realizing useful and robust context-aware smartphone applications is noise cancellation and data filtering, which are dealt with in this where needed.

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II. DATA COLLECTION

Acceleration sensors are commonly integrated into many smartphones and can be effectively used to record the data related to the human postures and activities. These results show that accelerometer-based activity recognition is a reasonable supplement to existing authentication methods on smartphones. For instance, while the user is doing an activity, an authentication process (smartphone-based) can be started without acquiring the user to input extra information.

In this work, we use the information provided by the acceleration sensors that includes the time and a tri-axial data set which consists of the acceleration values measured along the *x, y* and *z* axes. By performing two stages of post-processing on the obtained acceleration data, from which the velocity and displacement can also be estimated. We used the embedded tri-axial accelerometer with part number BM150, which is capable of sensing accelerations up to ±8g with tolerance within 2%. The sampling rates for accelerometer can be set from 25 Hz up to 100 Hz. The latter value is high enough to capture all the details with respect to the user's movements.

A. Location of smartphone

Location and state of smartphone directly affect on quality of data as well as its richness in terms of providing necessary information to enable the software to estimate a given posture. Therefore finding the best place and state for placement on the human body is essential. To this end and in order to find the best location, several experiments were conducted when the cellphone (i.e., Sony Ericsson Xperia arc s) was placed at different location on the human body for a few basic movements. The outcome results revealed that placing the cellphone around the waist, outmost to the right or left of the body, will enrich the data obtained from the acceleration sensors with respect to a posture. In contrary to waist placement, holding a cellphone by a user in hand while motion data is collected, can simply cause masking the data related to a posture due to excessive and habitual hands' movement.

B. Gravity of earth

The earth gravity, is shown by *g*, refers to the acceleration that the earth affects to objects on or near its surface. This acceleration is measured in meters per second squared. It is approximately 9.81 (m/s2). The three axes of acceleration sensor are affected by the gravity [11] depends on the orientation of the smartphone as it is shown in Fig. 2. As a consequence the location and orientation of smartphones can alter the measurement results. Therefore, the obtained acceleration values should be carefully handled and processed.

C. Data sets of accelerometer

We collected data for a set of these activities: walking, jogging, running, and falling, and collect data for these postures: sitting, standing, and sleeping. We chose these activities because they correspond to the most basic and common activities in people's daily lives and are useful for

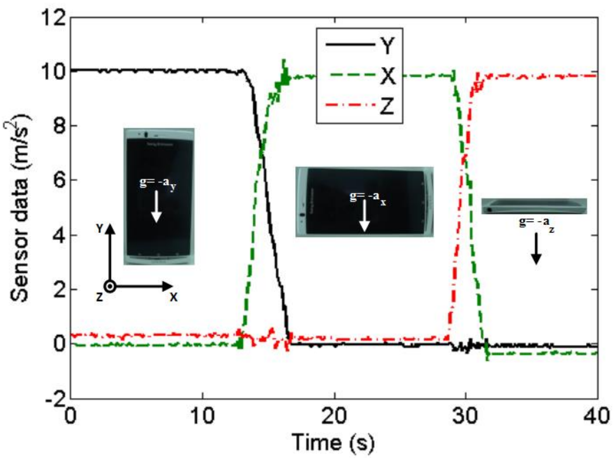

Fig. 2. The measurement results showing effect of earth's gravity on the acceleration sensors.

applications such as human activity monitoring and assisted living for elderly people and babies. The target of our data collection was to estimate the possibility and accuracy of posture and activity based on realistic data. The data sets consist of the results obtained from 20 individuals at different postures and while performing various activities. The measured were repeated for 10 times in order to increase the accuracy of the data sets. By observing the recorded data, a periodic repetition can be seen particularly after a few steps in the course of an activity which is a cycle usually used for estimating the posture and activity of the human body.

III. CLASSIFICATION AND RESULTS

A. Feature selection

In order to recognize and consequently to monitor postures and activities of the human body, we initially need to classify the obtained data sets. Thereafter the incoming data (real-time data) will be compared to the learning data sets without compromising accuracy and speed while issues such as memory usage and cost are taken into account. By doing so, one will be able to extract features from the measurement results.

Features were computed out of 200 data sets collected for specific for each activities and postures. The extracted features were mean, energy, entropy, and correlation. The mean of data sets is a meaningful metric for almost every kind of sensor. This metric can be calculated with small computational cost [6] and minimal memory. The energy of the signal can be computed as the squared sum of its spectral coefficients normalized by the length of the data sets. The entropy metric can be computed using the normalized information entropy of the discrete Fast Fourier Transforms (FFT) coefficient magnitudes excluding the DC component. Entropy helps to differentiate between signals with similar energy but correspond to different activity and posture patterns. Signal correlation is used to measure the strength and direction of a linear relationship between two signals. These features have been used in several activity recognition approaches. For example, Bao et al. [12] have used frequency-domain entropy to identify between activities with similar energy levels.

B. Classification

The activity recognition algorithm should be able to recognize the acceleration data sets corresponding to every activity and posture. Posture and activity recognition of the mentioned the postures and activities mentioned in Section II-C, was performed by using Naïve Bayes, Support vector machines (SVM), instance-based learning (K-nearest neighbors), C4.5 decision tree. These classifiers can be found in the Weka Machine Learning Algorithms Toolkit [7]. Under the classification, classifiers were trained on each posture and activity and the learning data sets were obtained and evaluated. In Naïve Bayes classifiers, it is assumed that all attributes of the data sets are independent for a given context in the class. Data sets classification based on selected features, are the most probable class for features [13]. Support vector machines (SVM) builds a model that assigns new examples into one class, making it a non-probabilistic binary linear classifier. An SVM model is a representation of the examples as points in data sets, mapped so that the examples of the separate categories are distinct [13]. K-Nearest Neighbors algorithm (KNN) classified the object by a majority vote of its neighbors for selected features, with the object being assigned to the class most common among its K nearest neighbors [12]. Decision Tree is a schematic tree-shaped diagram used to determine a course of action or show a statistical probability. The tree structure shows how one choice leads to the previous or next steps with a certain probability [13].

The collected data sets are categorized in two sections, first classification is for the activities and second section is for classification for the postures. Table 1 shows the recognition result of data sets as well as the accuracy obtained in recognizing a posture. As it is indicated in Table I, different classifiers have been used for recognition of an activity or a posture with different accuracy.

Table 1. Accuracy of classifiers

Classifier	Classification accuracy for activities	Classification accuracy for postures
Naïve Bayes	97.5 %	89.23 %
SVM	98.5 %	90.53 %
KNN	99.5 %	92.1 %
Decision Tree	96 %	85.79 %

C. Quality of posture and activity

As initially mentioned, one way to reach the personal wellbeing management and healthcare monitoring is posture and activity monitoring. Posture monitoring can help us to

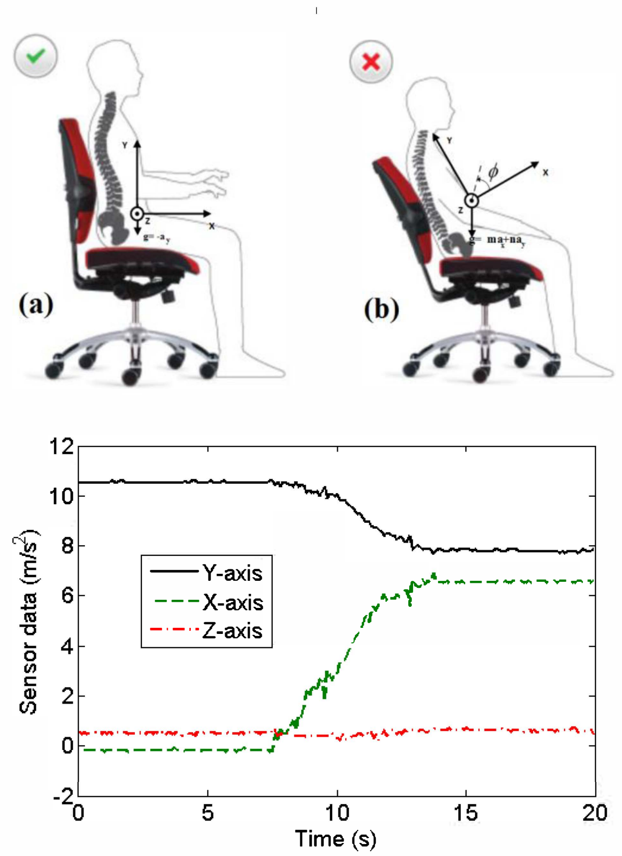

Fig. 3. The acceleration results related to a sitting posture.

alert the person about quality of the posture and activity. For calculating the quality of posture and activity we need a way to differentiate correct and incorrect posture and activity. The quality of the posture can be calculated based on the efficacy of gravity to acceleration sensor data. Fig. 3 shows the correct and incorrect sitting posture. The quality of sitting is based on the location of the smartphone used and how the person sits on a chair. In Fig. 3a, the gravity of earth parallel with y-axis of accelerometer therefore only it affects on one axis. Whereas in Fig. 3b due to posture of the person the gravity does not only affects one acceleration sensor axis. This scenario will be later discussed in Section IV where complex postures and activities are monitored.

IV. Mobile Application Description

The developed mobile application consists of two distinct parts. The first part collects data sets for generating learn data and classifications, whereas the second part was implemented in order to recognize new sets belong to real-time posture and activity. Data sets were directly stored in the cellphone's memory for further calculating and finally estimating a posture or an activity.

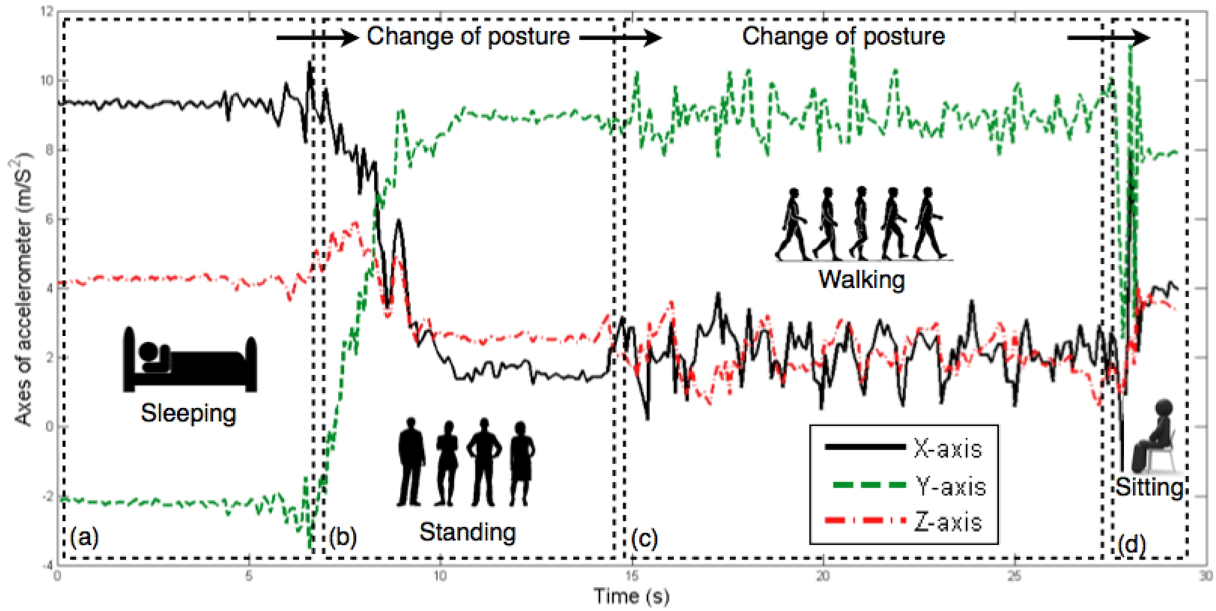

Fig. 4. The scenario considered for evaluating the performance of the developed mobile application.

To illustrate the functionality and performance of the developed mobile application, we considered a scenario as shown in Fig. 4. In this scenario, a person is in sleeping position stands up and decides to walk for about 5 meters. Finally the scenario ends when the person sits as demonstrated in Fig. 4d. The acceleration values measured by the cellphone are also shown in Fig. 4. At each new posture or activity the developed software recognizes the situation based on its artificial intelligence and shows a schematic corresponding to the person's posture or real-time activities. It is also worth mentioning that the software is able to detect quick and harsh activities, which may be harmful for the person and announces it. Such the harsh posture change, i.e., from walking to sitting position, can be observed in Fig. 4b where the acceleration values change rapidly.

V. CONCLUSION

The design and implementation of a smartphone-centric software based on its embedded acceleration sensors for activity and posture monitoring were successfully addressed and the obtained results were demonstrated. It was presented that instead of using distributed wearable sensors over the human body, a smartphone incorporating its embedded sensors (i.e., acceleration sensors) can be utilized for performing posture and activity monitoring. The developed application classified the data sets and recognizes the real-time postures and activities out of the acceleration results which are excessively noise prone. We used four classifiers for categorizing activities and postures that the best choice was KNN, with an accuracy close to 99.5% for activities and 92.1% for postures classification.

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