Potential Usage of Smartphone Inertial Sensors in Healthcare Applications

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Abstract. The increasing availability of the smartphones on one hand and the necessity to improve healthcare on the other hand, are encouraging the development of smartphone healthcare applications. In this paper an idea of transforming the smartphone into a healthcare device capable of recognizing everyday activities and detection of fall events is presented. This approach firstly use inertial sensors data as an input, then the data is preprocessed and segmented, and finally artificial intelligence methods are applied which recognize the user's activity and detect a fall event. The thorough evaluation of the methods showed that it is possible to achieve satisfactory performance for both tasks using only one inertial sensor embedded in a smartphone.

Keywords: Smartphone, inertial sensors, artificial intelligence, machine learning, activity recognition, fall detection.

1 Introduction

Production of mobile phones is in constant increase. Currently, more than 85% of the world population owns a mobile phone [1]. This shows that in a very short time, mobile devices will become easily accessible to virtually everybody. In recent years, the number of smartphones, which are a new generation of mobile phones, is in constant increase. In 2012, 1 billion smartphones were in use and this number is expected to be doubled in the next 3 years [2]. Smartphones, in contrast to the basic telephones, are offering many features such as multitasking and the deployment of a variety of sensors: inertial, compass, GPS, light, pressure etc.

The intelligent use of these sensors is the basis to many applications. In recent years, studies in the Ambient Intelligence (AmI) field have shown that body-worn sensors, especially the inertial ones, give rich information about the user. This information can be used in many healthcare applications: automatic recognition of daily activities, detection of alarming situations (fall), step counters, energy expenditure estimation, etc. The early studies in this area were conducted by using intrusive body-worn sensors and were not applicable for everyday use. Later, with the increasing accessibility and miniaturization of sensors and microprocessors, the intrusiveness reduced significantly. Finally, when these sensors were introduced in the smartphones, a whole new era for practical usage has started. By applying intelligent techniques, such as the ones described in this study, any smartphone user can benefit from the rich information that his/hers smartphone sensors can provide.

In this paper, our idea of transforming the smartphone into a healthcare device capable of recognizing activities and detection of fall situations is presented. First, we present the general concept of a smartphone implementation. Then, techniques for sensor data fusion, synchronization and preprocessing are introduced. Next, the methodology for the both healthcare tasks is introduced. Finally, the experimental results achieved for both tasks are discussed.

2 Smartphone Implementation

An overview of the smartphone implementation is given in Figure 1.

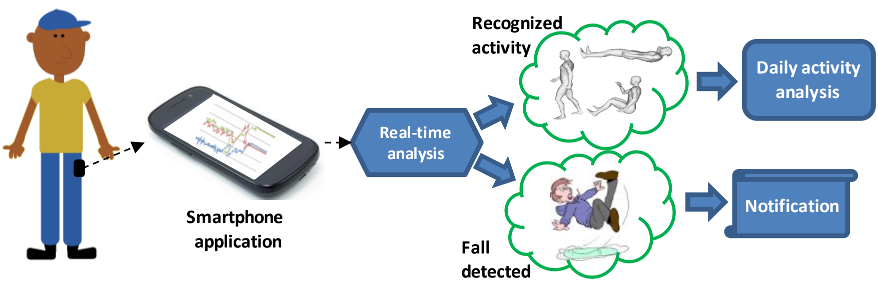

Figure 1. Smartphone implementation overview.

The implementation consists of a smartphone equipped with inertial sensor. A software application on a smartphone implements all the methods described in this paper. The application uses the inertial sensor's data from the smartphone as an input and in real-time outputs user's activity and detects fall events. If a fall is detected, an appropriate alarm notification can be triggered e.g. an SMS is sent to the user's predefined contacts. This is especially useful for elderly who live alone and could be, in the case of a fall, stranded for a long time. In the case of the activity recognition (AR), the recognized activities are logged during the whole day and can be later analyzed. The analysis may contain daily activity statistics, comparison between different days and therefore, detection of health-related anomalies.

3 Inertial Sensors

Inertial sensors detect and measure the inertial forces that influence them. When the sensors are attached on a human body, they measure forces of a particular body part. An inertial sensor consists of an accelerometer and a gyroscope. An accelerometer is a sensor that measures the acceleration applied to the sensor and also the constant Earth's gravity. When the accelerometer is at rest, only Earth's gravity is measured. Additionally velocity and sensor orientation can also be estimated. A gyroscope or a gyro is a device for determining or maintaining orientation. It measures the angular velocity and therefore allows more accurate recognition of movement than in devices with only an accelerometer, which was the only inertial sensor in older smartphones.

4 Preprocessing

The data from inertial sensors can contain many erroneous measurements due electromagnetic noise. To reduce the impact of the noise on the data, a band-pass filter (between the frequencies 0.1 to 20Hz) and a low-pass filter (with a cut-off frequency of 1Hz) are used [3]. The band-pass filter has two goals: (1) to eliminate the low-frequency acceleration (gravity) that captures information about the orientation of the sensor with respect to the ground and (2) to eliminate the high-frequency signal components generated by non-human motion and high-frequency noise, thus preserving the medium-frequency signal components generated by dynamic human motion. The band-pass filtered data is used for the extraction of features relevant for dynamic activities, such as walking, running and cycling. The low-pass filter has the opposite purpose: to eliminate most of the signal generated by dynamic human motion and preserve the low-frequency component, i.e., gravity. In this way the low-pass filtered data contains the sensor-orientation information, which is relevant for the recognition of the static activities (postures), such as lying, sitting, standing and kneeling. These filters provide two streams of filtered data which is further processed in order to extract appropriate features for AR or FD.

Finally, an overlapping sliding-window technique is applied. A window of fixed size (width) moves across the stream of data, advancing by half its length in each step. The data within each window is used in the AR described in the next section.

5 Methodology

Different methodology was used for each of the analyzed tasks. On one side, the method developed for the AR is mainly based on the machine learning and combining classification models with a multi-layer architecture. On the other side, the fall detection methodology is based on the recognized activity and additionally applies context-based reasoning rules to detect a fall situation. The methodology is briefly described in the following sections; more details can be obtained in the provided references.

5.1 Activity Recognition

To recognize the users' activity, the stream of data from the sensors is first segmented into 2-second time windows. We showed in prior work that 2-second windows are a reasonable trade-off between the overall recognition accuracy (increases with window length) and the ability to recognize very short activities (decreases with window length) [4]. To recognize an activity from sensor data three-layer architecture for the AR, i.e., TriLAR [5], is used. The TriLAR architecture consists of the following: (i) a bottom layer, where the data is passed to an arbitrary number of independent AR methods; (ii) a middle layer, where a hierarchical aggregator combines the predictions from the bottom-layer methods; and (iii) a top layer, where a hidden Markov model uses the temporal dependence of activities to remove the spurious transitions between them and produce the final activity.

5.2 Fall Detection

Because of the specificity of the fall detection task, a higher level reasoning about the user's situation is performed. The methodology is based on domain rules which are applied on already processed data in order to reason about the user's situation. In particular, we developed a CoFDILS (Context-based Fall Detection using Inertial and Location Sensors) reasoning schema [6], which uses the context information from the sensors to determine whether a fall has occurred. It exploits three context components: the user's activity, body accelerations and location information. Each of the components is obtained using a separate method. First, the user's activity is recognized using the TriLAR method, explained in the previous subsection. Next, the user's body accelerations are extracted using the changes in the acceleration signal during motion: Acceleration Vector Changes (AVC) [7]. This AVC sums up the differences between consecutive values of the lengths of the acceleration vector and normalizes them. By applying an empirically defined threshold to the AVC value, the movement of a sensor is detected. Finally, the user's location is determined using a location tag attached to the user. In general any technique that can detect the location of smartphone can be used as input in the method. In recent years several examples of successful indoor localization of smartphones were proposed. WIFARER [8] is a smartphone application that provides the location of the phone using the Wi-Fi signals. Another successful indoor localization for smartphones is the LocLizard platform [9] that provides API which can be used in the smartphone application.

To explain the basic principle of the context-based reasoning, let us consider the following example in which a user is lying down quickly on a bed, i.e., a non-fall situation. In this case, the body movement component recognizes a high acceleration. If this component reasons by itself, a wrong decision would be formed: a fall would be detected. If the activity of the user is additionally evaluated, the decision would still be wrong (a high acceleration and lying activity = a typical fast fall). However, when the location of the user is evaluated (the bed), the final decision is corrected into non-fall (quickly lying on the bed). In similar manner, several more rules that reason about the user situation and detect a fall are defined.

6 Experiments

The experiments were performed with wearable sensor equipment consisting of the same types of sensors as the ones included in the smartphones, i.e. inertial sensors.

Because the methods developed are general and can be reused for any type of inertial sensors, we are confident that the main findings are also valid for the smartphone implementation.

6.1 Activity Recognition

6.1.1 Experimental Scenario

A 90-minute, test scenario was designed in cooperation with a medical expert to capture the real-life conditions of a person's behavior, although it was recorded in a laboratory. The scenario was performed by ten volunteers. It was divided into three groups: exercising activities, elementary activities and everyday-life activities. The scenario included ten elementary activities (the percentage of instances per class): standing (16%), sitting (11%), lying (22%), on all fours (10%), kneeling (6%), bending (standing leaning) (3%), walking (15%), running (5%), cycling (10%) and transition (going down and standing up) (2%). These activities were selected as they are the most common elementary, everyday-life activities.

6.1.2 Results

To test the TriLAR architecture, we used the abovementioned dataset. The evaluation technique was leave-one-person-out cross validation. This technique constructs the training model on the data from all the people except one. The remaining person is used to evaluate the accuracy of the trained model. This procedure was repeated for each person (10 times) and the average performance was measured. In Figure 2 results of AR evaluated with the F-measure are shown. F-measure combines the precision and the recall (harmonic mean) of each activity.

Dynamic activities are better recognized than static activities, with two exceptions. The TriLAR architecture is successful at recognizing lying activity as the sensor's orientation is significantly different than with other activities, but has trouble recognizing the transitional activities as sensor's movement is similar to other static activities. The static activities, other than lying, are more difficult to recognize because the inertial sensor is not moving and sensor's position is similar between these activities.

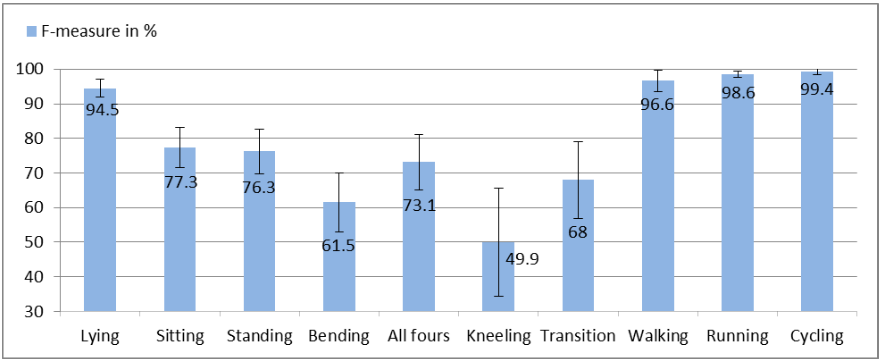

Figure 2. Activity recognition results among different activities.

6.2 Fall Detection

6.2.1 Experimental Scenario

A complex, 15-minute test scenario was specifically designed to investigate events that might be difficult to recognize as falls or non-falls. This scenario was created in consultation with a medical expert. The events in the scenario are listed in Table 1. Because typical fast falls are easy to detect due to high acceleration, only one such fall (1) was included. Three atypical falls not involving high acceleration (2, 3 and 4) were included to test the use of the contextual activity information, i.e., that a person is not expected to sit/lay on the ground (as opposed to the chair/bed). Furthermore, the two events 5 and 6 involve high acceleration and could thus be misclassified as falls by acceleration-based methods. However, the methods that use the activity and location as contextual information should be able to detect that these are non-fall events. An event (7) was included that involves voluntarily lying on the ground, which could mislead the methods that use information other than acceleration. The events 8, 9 and 10 are normal and were included to verify that all the methods work correctly during normal events.

The scenario was recorded by 11 young healthy volunteers (24–33 years, 7 males and 4 females). It was repeated 5 times by each person, resulting in 55 recordings and a total of 550 events for the FD. Testing elderly people was not feasible, because the scenario was too strenuous and risky for them, but the volunteers were advised how to act by the medical expert in order to mimic elderly. Additionally, the data for 3 more people was recorded for tuning the basic parameters, e.g., thresholds, preliminary tests and choosing the best algorithms.

6.2.2 Results

The results achieved by the inertial sensors only and their combination with the location information, are shown in Table 1. In the experiments the location was provided by additional sensor. Because the method requires only rough estimations of predefined locations, we are confident that the smartphone estimations provided by the LocLizard API [9], would be enough for achieving similar performance.

The results show that, if only inertial sensors are used half of the falls with high acceleration can be detected (1). However, the slow falls are almost impossible to be detected with inertial sensors only (2, 3 and 4). During the non-fall, but events with high acceleration (5 and 7), the acceleration is misleading and false alarm is raised. The normal events (8, 9 and 10) are recognized as non-fall events with high performance.

The location is really important for detection of complex fall situations (events from 1 to 4). Compared to the inertial sensors alone approach, the overall performance is improved by 41 percentage points when the location is included. The reason for this is that the inertial sensors are not enough for accurate FD especially not for events that do not include high accelerations (the events 2, 3 and 4). These types of events require additional user information, such as the location.

Table 1. FD results for each fall and non-fall event.

		Inertial		Inertial + Location	
		TR	**TL**	**TR**	**TL**
Fall Events	(1) Tripping – Quick falling	**53**	**45**	**100**	**100**
	(2) Fainting – Falling slowly	**3**	**0**	**95**	**96**
	(3) Falling from a chair slowly	**3**	**3**	**93**	**93**
	(4) Sliding from a chair	**5**	**4**	**91**	**93**
Non-Fall Fall-like Events	(5) Sit down quickly on a chair	**36**	**36**	**75**	**75**
	(6) Searching on the ground	**100**	**100**	**85**	**86**
	(7) Quickly lying down on a bed	**56**	**50**	**100**	**100**
Non-Fall Normal Events	(8) Sitting normally	**95**	**95**	**86**	**87**
	(9) Lying normally	**100**	**100**	**100**	**100**
	(10) Walking	**100**	**100**	**100**	**100**
	Overall F-measure in %	**42**	**40**	**93**	**93**

The analysis of the performance for the different sensor placements (left or right thigh) shows that there is no significant difference. Therefore, the user can simply choose the placement which is more appropriate to him/her without decreasing the FD performance.

7 Conclusion

The paper presented an idea of transforming a smartphone into a healthcare device capable of recognizing activities and detection of fall situations. Techniques for sensor data fusion, synchronization and preprocessing were introduced. Then, the proposed methodology for the both healthcare tasks was evaluated on two special comprehensive experimental scenarios. The results showed that it is possible to achieve satisfactory performance for the both tasks using only one inertial sensor embedded in a smartphone. In the future, we first plan to finalize the whole smartphone implementation, extensively test it in everyday usage and offer the application to everybody who needs it.

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For wider interest

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The intelligent use of these sensors is allowing many potential applications. Recent studies have shown that the body-worn inertial sensors give rich information about the user, which can be used in many healthcare applications: automatic recognition of daily activities, detection of alarming situations (fall), step counters, energy expenditure estimation, etc. The early studies in this area were made using intrusive body-worn sensors and were not applicable for everyday usage. When these sensors were introduced in the smartphones, a whole new era for practical usage was has started. By applying intelligent techniques such as the ones described in this study, any smartphone user can benefit from the rich information that his/hers smartphone sensors can provide.

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