Monitoring System for Elderly Care with Smartwatch and Smartphone

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Abstract. In recent years, mobile devices, such as Smartphones and Smartwatches, have increasingly been used as personal healthcare gadgets. This work presents the development of a monitoring system based on a software application over Android OS for mobile devices. The main goal is to use it as tool for monitoring and tracking elderly people. The proposed application allows to: detect falls to the ground of the users; monitor the heart rate; count the number of steps that the users perform during the day and also track their position on a map. Despite the presence of several cases of possible false positives (e.g. answer a call or sending a message could trigger a wrong detection of fall or increase the steps counters.), the results obtained show that it is possible, by using current mobile devices in the market, to supervise and track the user's activities.

Keywords: elderly care, mobile applications; wearable; Android.

1 Introduction

Currently, there are more than two billion Smartphones (SmP) around the world and it is expected that, by 2019, 36% of the population will have one [1]. This exponential growth, added to the higher performance computing, sensing and communication capabilities that current devices present [2], have aroused the interest of different research groups and companies. Current research efforts are focused on the development of functionalities that could assist in the daily life of persons in order to monitor or provide data about: 1) User falls [3]; 2) Heart rate [4]; 3) Number of steps [5] and 4) Location of users [6] among other parameter useful in healthcare.

Cardiovascular diseases (CVD) are the leading cause of death in the worldwide, in 2012 it is estimated that 17.5 million people have suffered some type of CVD. Real time supervision of users' heart rate could detect irregularities [7] in the normal cardiovascular system functioning, that may help to avoid these types of accidents more frequently.

Falls are the second world's leading cause of death from accidental or unintentional injuries, it has been estimated that 424,000 people in the world die every year from this cause. People over sixty-five years-old suffer most fatalities. There are 37.3 million non-fatal falls per year that need medical attention [8]. For these reasons, in this age-group, the supervision and reporting of falls is an important improvement of the quality of life.

It has been estimated that 24 million people in the world are suffering from Alzheimer's disease and that by the year 2040, this number will reach 81 million. The most affected regions are those that are more densely populated [9]. People who suffer from this disease are prone to disorientation, so it may be desirable to track the movements made by this type of users through their geolocation.

Currently six out of ten people do not perform adequate physical activity according to the World Health Organization (WHO). This can lead to diseases such as obesity and diabetes According to WHO, a sedentary lifestyle causes 2 million deaths per year. Children, adults and the elderly do not perform enough exercise and instead occupy their time with sedentary activities related to video games, cell phones, television and computer use [10]. For these reasons, providing information about the number of steps and the distance traveled would help users to know how many calories they burn per day, in this way users would be encouraged to overcome daily goals imposed by themselves in order to maintain a healthy state.

This work presents a monitoring system in order to provide information about the described variables of interest, based on the use of Smartphone and Smartwatch mobile devices, in order to be used, for example, in residential elderly. The paper is organized as follows: Section 2 describes the system architecture and the functionalities to be implemented. Section 3 presents a description of the algorithms used. Then, in section 4, the obtained experimental results are shown, and finally, in section 5 the conclusions of the work are given.

2 Monitoring and tracking system

The global architecture of the proposed system is shown in Fig. 1. The SmP device reports the data collected to a central server. Smartwatches (SmW) are used to provide data that is transmitted to the SmP as shown in Fig. 2 such that it is processed and sent to the server. The SmP not only sends information by this mean, in special cases, like in the fall detection, it sends a report by a text message, with the location and time at which the event occurred. The connection between the SmP and SmW is established through Bluetooth. Depending on the functionality, the SmW sends the data on demand to the SmP, as it is done in the Heart Rate report, but for example, the Step Counter functionality reports whenever the SmW needs it and not when the phone requires it.

2.1 Selection of mobile devices

According to the specifications of parameters to be supervised, mobile devices must have the following sensors: accelerometer and pedometer on both devices and at least GPS on the SmP. Also, a heart rate sensor must be available in the SmW. In order to develop the software application, Android Operating System has been selected, since it is the most used in the world with 82.8% for the second quarter of 2015 [11]. This OS offers many resources to develop software, and most of the applications available in the literature for the detection of falls were developed on this platform [12]. In the current market, different models of SmP are available. In this case, due to their availability, the following devices have been used:

1. Samsung Galaxy S4
   a. OS: Android Lollipop
   b. Processor Exynos 5 Octa-core 1.6Ghz
2. Samsung Galaxy S6
   a. OS: Android Marshmallow
   b. Processor: Exynos 7420 CPU Cortex A53 cores 4 1.50 GHz GPU Mali T760 CPU Cortex A57 4 cores 2.10 Ghz
3. Samsung Galaxy S7
   a. OS: Android Nougat
   b. Processor: Exynos 8 Octa 8890 8 cores 2,3 GHz

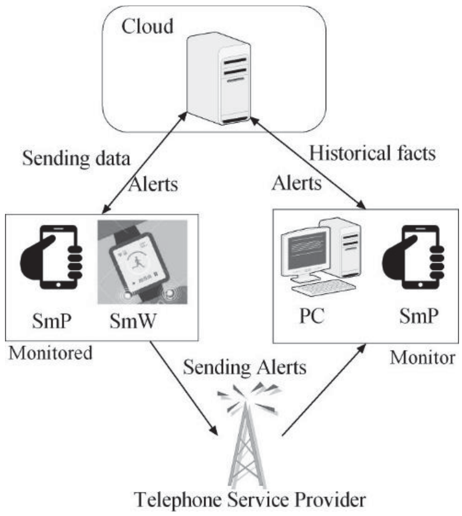

Fig. 1 Architecture of monitoring system for supervising elderly people.

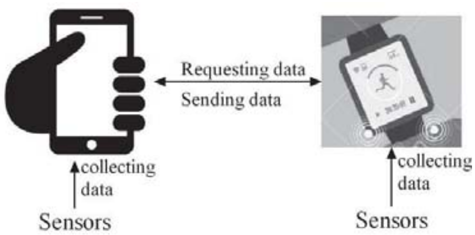

Fig. 2. Communication and gathering of information among mobile devices.

3 Algorithms for measuring parameters of interest

3.1 Pedometer

The pedometer functionality has been designed to detect the steps that the user performs in their daily life. Thus, taking into account the weight and the distance traveled, an approximation of the burned calories is calculated. To perform this function both devices, SmW and SmP, report their data. These devices have the sensor called "Step counter". This sensor provides step information and the period of time in which those occurred (time intervals). According to this, the highest step value computed between both devices is selected and reported to the server. In addition to the steps count, the distance traveled and the burned calories are computed.

3.2 Heart beat

The heart rate measurements are automatically performed every hour or when the user sends a request using the graphical interface. It also displays the historical data of the day and the evolution of the current measurement. The heart rate sensor is located in the SmW, but the control and storage of the data occur on the Smartphone, each device has a service that performs the actions outside of the main thread, keeping constant communication, ensuring the sending of requests and reception of data.

3.3 Georeferencing

This function has been designed to detect the user's location every 100 meters and/or at intervals of twenty minutes. In this way, with the data provided by the GPS, markers are deployed on a map, allowing drawing a path between them and leaving a record of the displacement activity. In this case, the mobile network can also be used to detect the location, but since it was decided to use a fine coarse detection, only the GPS sensor is used. Once the data is obtained, it is saved in the SmP, and the algorithm establishes a connection with the central server to send the information. At that moment, all previously unsent data is transferred, and already sent data is deleted from the local storage, preventing it from filling up and keeping the memory usage by the application at a minimum.

3.4 Fall detection

A fall is an event that can be divided into 5 stages [13] (see Fig. 3) in the following way:

1. *Pre-fall*: Activity of daily life performed by the person.
2. *Free fall*: The free fall of the subject to the ground caused by the loss of balance.
3. *Impact:* When the subject hits the ground.

4.*Post impact:* When the person is on the ground and remains inactive by the impact.

5. *Recovery:* When the subject stands or tries to do so.

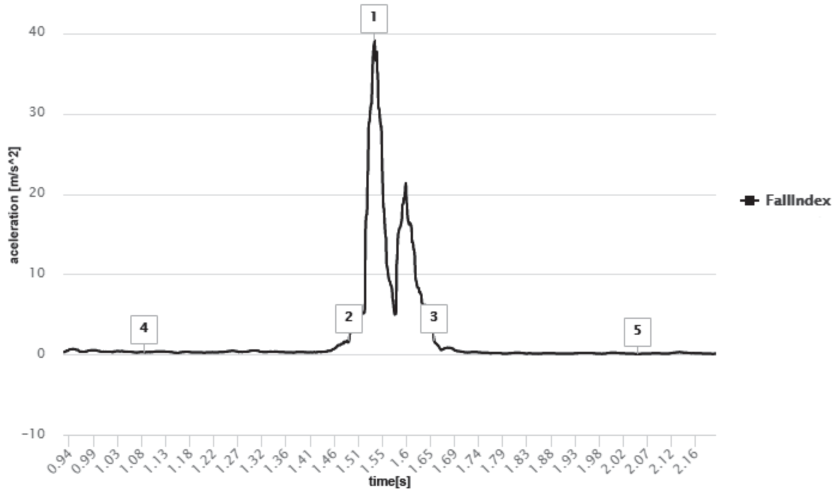

Fig. 3. Acceleration functions of a fall obtained by (1) and his characterization.

Figure 3 shows the fall index expressed in m /s^2 as a function of time in seconds. The falling index is obtained according to (1). As it depends on adjacent data, it is necessary to have a high sampling rate for efficient results.

$$FI_i = \sqrt{\sum_{k=x,y,z} \sum_{i-j}^{i} ((A_k)_i - (A_k)_{i-1})^2} \quad (1)$$

where A_k is the acceleration in the axis k, $k \in \{x,y,z\}$, i is the index of samples $k \in \{1, 2, \cdots, j\}$and j is the size of the window to be used to analyze de data.

The fall detection algorithm is performed in real time and is divided into the following three phases: 1) Smartphone Acceleration Threshold; 2) Smartphone Pattern Recognition; 3) Smartwatch Threshold and Pattern Recognition.

Smartphone Acceleration Threshold (fixed threshold). This is the first stage because it has the lowest computational cost. It consists of calculating the fall index taking a window of 20 measurements. The highest value in this window that also exceeds 24 m/s^2 is selected as a candidate and the next step is carried out.

Smartwatch Threshold and Pattern Recognition. The last step is to check if the SmW also detected a fall. The procedure on this device is the same, only that the size of the window is 5 measurements for the calculation of the fall index, since the sampling rate is much lower than the one obtained in the SmP. When a fall detection takes place on both devices, a message is sent to the designated emergency contact, along with the heartbeat and the recorded time&location data of the fall event. Additionally, all this information is sent to the server. Table 1 summarizes the values of the parameters for the detection of limits exceedance and the recognition of the acceleration pattern in both devices.

Table 1. Threshold values of the characterization parameters of a fall.

Value	Smartphone	Smartwatch
Peak of acceleration	24 m/s^2	2.10 m/s^2
Distance between point 2 and 3	1.95 Milliseconds	4.63 Milliseconds
Average of pre-fall	1.8 m/s^2	0.183 m/s^2
Average Post impact	0.9 m/s^2	0.16 m/s^2

The values in the table above were obtained from the analysis of the tests discriminated by type of fall (see section 4.3).

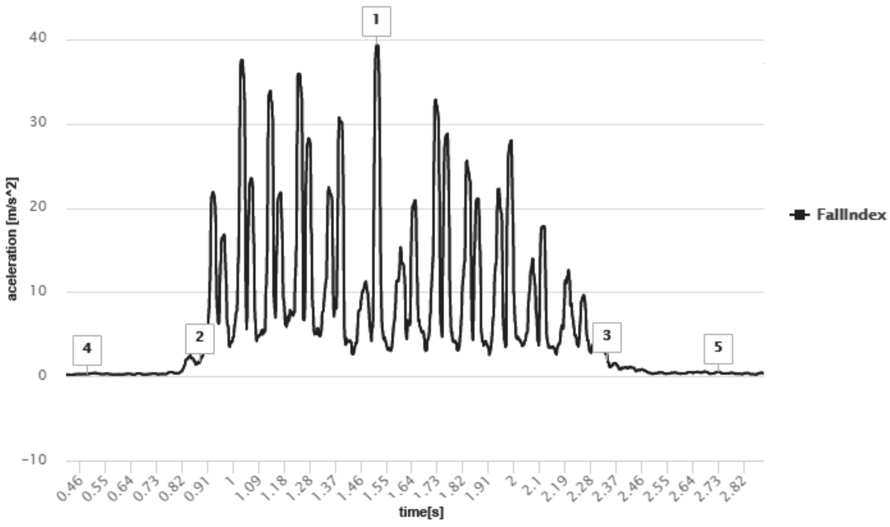

Fig. 4. Acceleration function of going down the stairs and his characterization.

Figure 4 shows the fall index of going down the stairs. Although it complies with the first part of the algorithm (point 1, the peak of acceleration greater than 24m /s^2) the distance between point 2 and 3 is not correct, thus it does not meet the pattern and is not detected as a fall.

4 Performance evaluation of the system

4.1 Step Counter

Tests were made using our developed application, and contrasted against Google Fit.

For Google Fit the following tests were carried out:

1. The first test consisted of walking alone with the SmP resulting in a value of 1604 steps. Then it was synchronized with the SmW, which had not registered steps, and obtained a final value of 1604 steps.
2. The second test consisted of walking alone with the SmW resulting in a value of 2064 steps. Then it was synchronized with the SmP that had recorded steps from the first test and got a final value of 1604 steps. With the obtaining of this result, it was verified that the SmP disregards the results obtained by the SmW.

The same tests were carried out in our software, and the following results were obtained:

Table 2. Step count on each device for each test

Type	Smartphone	Smartwatch	Smartphone/ Smartwatch
Test 1	0	1150	1150
Test 2	1500	1150	1500

As shown, the algorithm always keeps the greatest number of detected steps, regardless of their origin.

4.2 Location detection

It was decided to make a journey of no more than 20 km of distance in which the application was marking the route made. As can be seen in Fig. 5 the path was delimited with the markers and red lines to obtain an estimate of the user's travel path. The application has obtained 6 different positions in which the device had a good signal quality to perform the marking of the place. After carrying out several tests of this type, it was concluded that the device was taking the information correctly.

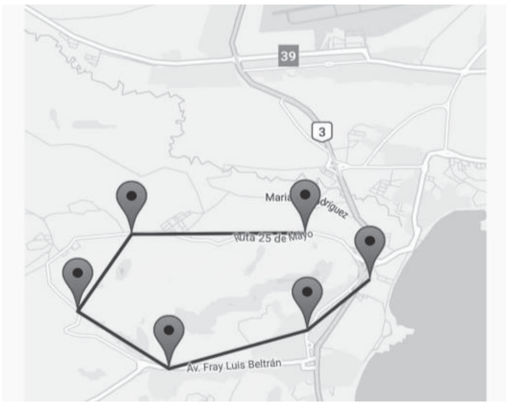

Fig. 5. Location detection interface.

4.3 Fall detection tests

In order to define the values used in the detection algorithms, a system was developed. This system records the acceleration in the devices and then sends them to a server for analysis. For that, 270 tests were performed, each one had associated the type of fall and the values 1 to 5 necessary for the detection algorithms (see 3.4), then the ranges of each parameter, according to the type of test, were analyzed resulting in those mentioned in table 1, these gave us the best percentage of detection for the tests performed.

Table 3 shows the values of fall detections according to the type of test and device that gives us the following result in percentages:

- Smartphone:
  - 96% of fall detections.
  - 0.47% false positives.
- Smartwatch:
  - 91,6% fall detections.
  - 3.8% false positives.

Those numbers must be interpreted as number of detection trials, e.g. in the test “falling forward” 29 of 30 trials were successfully detected as a fall in the SmP.

Table 3. Fall detection chart by type of test

Type	Smartphone	Smartwatch
walking 10 mts	0/30	0/30
Turning around	0/30	0/30
Tying shoes	0/30	0/30
Running	0/30	0/30
Stairs	0/30	0/30
Sit down slowly	0/30	1/30
Sit down quickly	1/30	7/30
Falling forward	29/30	26/30
Falling backward	29/30	29/30

5 Conclusions and future work

Mobile devices are widely used in daily human life and could be used to supervise people by means of GPS, pedometer, accelerometer, among other useful sensors. They also have the ability to send information by different communications ways such as text messages and calls over mobile data or Wi-Fi networks. In terms of detection of steps, mobile devices are very useful, although the sensors could be improved. Currently, the mere fact of moving the phone with the hand could detect false steps. This could be avoided with the use of other sensors working together, for example, GPS. Regarding the heart rate detection functionality, the sensors included in the SmW Moto 360 that we used for the tests work satisfactorily. A blood oxygen level detector could be added to further improve functionality. Regarding the detection of falls, the tests carried out show that by using the data from both a SmP and a SmW, the fall detection algorithm reduces the probability of a false positive event to a minimum. However, being a multipurpose gadget, sudden actions like taking the phone out of pocket or leaving it on a table might trigger an unwanted fall detection. This problem is further accentuated in the SmW since the wrist is not the ideal position to represent the stability of the person, as it is a device that is located in the torso or hip. That is why the ideal target group is the elderly or persons with reduced mobility, not only because of their health monitoring needs but also because of current device limitations.

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References

1. Number of smartphone users worldwide from 2014 to 2020, https://www.statista.com/aboutus/
2. X. Su, H. Tong and P. Ji, "Activity recognition with smartphone sensors," in Tsinghua Science and Technology, vol. 19, no. 3, pp. 235-249, (2014).
3. Abbate, S., Avvenuti, M., Bonatesta, F., Cola, G., Corsini, P., & Vecchio, A. (2012). A smartphone-based fall detection system. Pervasive and Mobile Computing, 8(6), 883-899.
4. Tapia, E. M., Intille, S. S., Haskell, W., Larson, K., Wright, J., King, A., & Friedman, R. (2007, October). Real-time recognition of physical activities and their intensities using wireless accelerometers and a heart rate monitor. In Wearable Computers, 2007 11th IEEE International Symposium on (pp. 37-40). IEEE.
5. Butte, N. F., Ekelund, U., & Westerterp, K. R. (2012). Assessing physical activity using wearable monitors: measures of physical activity. Medicine & Science in Sports & Exercise, 44(1S), S5-S12.
6. Chon, John, and Hojung Cha. "Lifemap: A smartphone-based context provider for location-based services." *IEEE Pervasive Computing* 10.2 (2011): 58-67.
7. OMS Enfermedades cardiovasculares, http://www.who.int/mediacentre/factsheets/fs317/es/
8. OMS | Caidas, http://www.who.int/mediacentre/factsheets/fs344/es/
9. El Alzheimer en el mundo, http://www.alzheimers-support.com/es/alzheimers.html
10. OMS, http://expansion.mx/salud/2012/04/07/seis-de-cada-10-personas-no-tienen-suficiente-actividad-fisica-oms
11. IDC: Smartphone OS market share 2016, 2015, http://www.idc.com/promo/smartphone-market-share/os
12. MDPI AG, http://www.mdpi.com/1424-8220/15/8/17827/htm*/
13. N. Noury, P. Rumeau, a. K. Bourke, G. OLaighin, and J. E. Lundy: A proposal for the classification and evaluation of fall detectors, *Irbm*, vol. 29, no. 6, pp. 340–349 (2008).