Fall Detection System for the Elderly

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***Abstract*—According with the World Health Organization, Falls are the second leading cause of accidental or unintentional injury deaths worldwide. Adults older than 65 suffer the greatest number of fatal falls. Therefore, the quality of life of older people can be improved by using automatic fall detection systems. This paper presents a fall detection system that monitors in real-time an older adult. The system defines two major components: a wearable device and a cell phone. The wearable has the capability of communicating with a cell phone can be located in a 100ft radius. Once, the wearable device detects a fall, it sends an alert to the cell phone; then the cell phone alerts to the emergency contacts defined by the user. The main idea is to avoid the need of carrying the cell phone every time. In addition, our system has a panic button that can be used in order to alert the emergency contacts in the event that the user feels that a fall may happen.**

***Index Terms*—Fall detection, elderly, Health Systems**

I. Introduction

Falls are the second leading cause of death by accidental or unintentional injuries. Worldwide, 424, 000 people die due to fall related injuries. Out of this number, the ones who suffer fatal falls more often are the elderly people over 65 years old [1]. But how can we know if an elder has fallen? Nowadays, most elderly people have in their possession cellphones in case of emergency. However with the constant evolution of technology some senior citizens face hurdles in adopting new technologies [2]–[4]. Therefore, how can we design a solution involving technology when most elderly people have problems adapting to such technologies?

This paper presents a fall detection system for the elderly. The system defines two major components: a wearable device that detects, using an accelerometer and a gyroscope, if the user has suffered a fall, and a mobile application that automatically calls a predetermined number in case of emergency. The main advantage of the proposed system is that it does not require the person carry the cell phone everywhere since the fall detection is carry out in the wearable device. Therefore, the mobile phone can be located in any place in a house.

The wearable device has the capability of detecting a fall sensing an accelerometer and a gyroscope. The available literature states that measuring a person acceleration and orientation allows a electronic device to detect a fall [5]. Therefore, this project measures the acceleration in 3-axis as well as the angular position of the pendant. If the acceleration achieves a defined threshold, the angular position is measured. Then, if a position threshold is achieved, a fall has been detected and the emergency protocol is activated. The emergency protocol includes a phone call contacts that have been selected by the user previously.

A functional prototype was implemented and tested for this project. This prototype includes the wearable device acting as a pendant, and an Android application to activate the emergency protocol which includes an alerting call and a text message. In addition, our system allows the user to activate the emergency protocol when required, pressing a panic button as well as to cancel a call using a button in order to avoid false alerts. The experimental results shows that backward falls achieves the highest accuracy with 92% as well as side way falls.

The rest of the paper includes the related work followed by a description of the proposed system. The following sections include the experimental setup and results. Finally, the conclusions and future work are presented at the end of this paper.

II. Related Work

In this section we describe some of most relevant work on fall detection. Usually fall detection systems are based on one of the following approaches: wearable sensors, computer vision, and ambient-fusion. However, in the paper we focus just on methods based on wearable sensors, and in particular on treasure-based approaches.

Most of the fall detection systems using mobile devices use accelerometers as the primary sensor. Accelometry is a useful mechanism to measure the acceleration of different parts of the human body, and thus a useful tool for fall detection [6], and in general for human activity recognition [7]–[10].

Threshold-based methods are one the most popular techniques for fall detection using wearable sensors. Here, a fall is reported when the acceleration goes beyond a pre-defined thresholds. A typical problem with this approach is the difficulty of generalizing results for diverse populations (e.g., height and weight). Thereby, these methods need a set of predefine parameters that should be adjusted according to the target population. Research on this category include the work of De La Hoz *et al.* [11]. In this work the authors use the smartphones built-in sensors (accelerometer, gyroscope) to identify the location of the cellphone in the users body (chest, pocket, holster, etc), and to find known patterns associated with falls. An overall accuracy of 81.3% was reached, with top three locations to detect a fall: texting with a 95.8% fall detection accuracy, pants side pocket with an 87.5% accuracy, and shirt chests pocket with an 83.3% accuracy.

Following similar approach, Kangas *et al.* [12] used specific locations in the user's body to compute different thresholds with data collected from a three-axes accelerometer, and gyroscope. Sensor locations with the greatest fall recognition accuracy included places such as the users waist and head. In addition, the study found that the features with significant contribution for fall recognition were the sum vector, dynamic sum vector, vertical acceleration, and maximum and minimum values.

Finally, *et al.* [13] presents a fall detection system based on accelerometry. Here, the sensor is located in the user's pelvis. The solution is based on scenarios, namely stand still, sit to stand, stand to sit, walking, walking backwards, stoop, jump and lie on the bed. Fall detection is then carry out in the context of this scenarios. The following features were extracted from motion data: sum vector, magnitude of acceleration, acceleration on the horizontal plane and reference velocity. By using these feature the system was able to infer spatial changes of the acceleration while falling. Results showed a high level of fall recognition using this treasure-based approach.

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A different category of wearable sensor approaches for fall detection includes the systems based on machine learning techniques. The general architecture of these systems include a data collection module for gathering motion data; a feature extraction module that selects the most relevant characteristics from the motion that are useful for fall prediction; and an inference learning module that finds relationships from the extracted features to come up with a descriptive model for fall detection. Figure 1 sketches the stages of a typical fall detection system based on machine learning techniques. Projects on this category include the work of Vallejo *et al.* [14] who proposes a method based on artificial neural networks. The system uses an accelerometer on the user's waist, a microcontroller, and ZigBee module. The neural network is able learn falling events. In a similar work, but this time using decision trees Bianchi *et al.* [15] used a method that combines acceleration and air pressure. The air pressure data was collected from a wearable sensor located in the user's waist, these two input signals, namely acceleration, and air pressure were used to build a decision tree for fall detection.

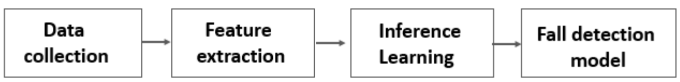

Fig. 1. General machine learning model for fall detection

III. The Proposed System

The system defines two main components. The first component is a wearable device acting as a pendant, and the other one is a mobile application running on a cell phone. These two items will communicate with one another via Bluetooth as showing on Figure 2. The pendant has a motion sensor for the fall detection. When a person falls, the pendant sends an alert to the cell phone. Then, the cell phone calls and messages a person of interest informing the location of the event.

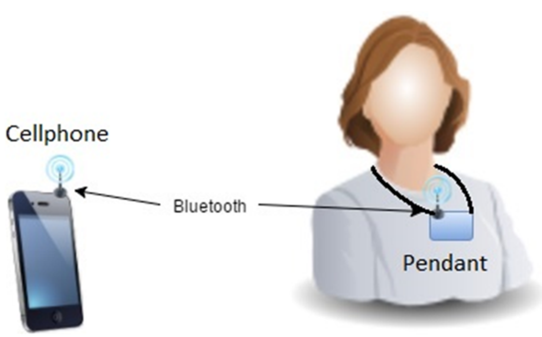

Fig. 2. The concept

A. General algorithm

Figure 3 depicts the system general algorithm. The first step is to connect the mobile application and the wearable device. Then, the wearable device runs the fall detection algorithm. Once a fall is detected, the wearable devices sends an alert message the mobile application. The mobile application has a 30 *seconds* timer in order to allow the user to cancel an emergency call. If the person does not cancel the call, the emergency protocol is started which includes a call, and SMS messages to predetermined contacts.

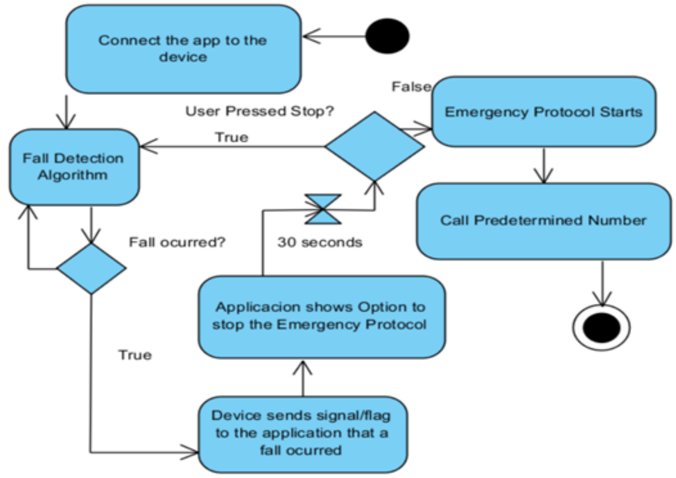

Fig. 3. Main Algorithm

B. System Architecture

Figure 4 shows the system architecture in detail.

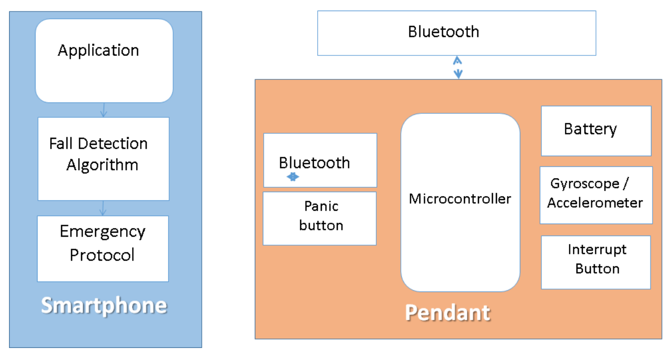

Fig. 4. System architecture.

1) The pendant: The pendant contains a Bluetooth module for communication with the application, a Battery, a giro/accel sensor for the axial movement measurements, a Panic button for normal emergencies and an Interrupt Button for Stopping the application to make the call in case of a false alarm.

Once the Application is started in the cell phone, the pendant connects to it. The microprocessor, using a gyroscope and an accelerometer, detects when a fall occurred, and sends a signal to the application as showed on Figure 3.

2) Mobile application: Figure 5 presents the application. Once the start button is pressed (1), the user is able to select the emergency contact information from the phone directory (2). Then, pressing the *Setup* button the mobile application start to listen to the wearable device (3). Once the mobile application receives a request for call from the pendant indicating a fall detected (4), it dials or messages to the emergency contacts indicating that the person has fall, or she is asking for help (5).

In the case in which the person cancel the emergency call pressing the *Stop* button in step (4), the application returns to the *listening* state (3).

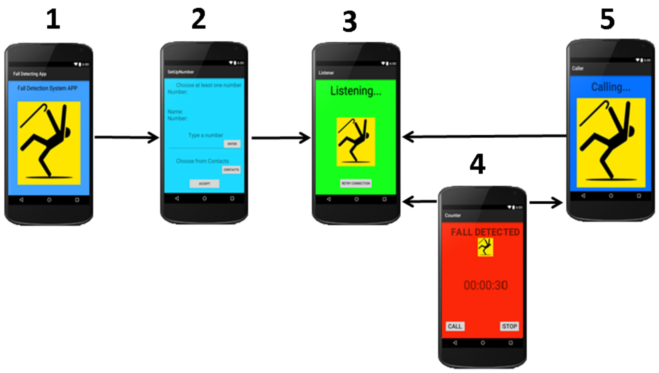

Fig. 5. Mobile application.

C. Fall detection algorithm

Algorithm 16 presents the fall detection algorithm defines in this project. Once the pendant is started and connected to the mobile application, it measures the accelerometer and gyroscope. If the acceleration exceeds a threshold, the device checks the gyroscope variation. If the position variation in any direction exceeds the defined threshold, then a 3 *seconds* timer is started. Once it expires, the position variation is checked again. If it exceeds the threshold, a fall has been detected. Then a 30 *seconds* timer is started, at this moment the person might cancel the emergency protocol. If not, the pendant sends a alert message to the mobile application.

Algorithm 1 Fall detection algorithm

```
Initialize
while True do
  Measure Accelerometer and gyroscope
  if Acceleration > threshold then
    if Position variation > threshold then
      Wait 3 Seconds
      if Position variation > threshold then
        Wait 30 Seconds
        if !(Stop button pressed) then
          Fall detected
          Start emergency protocol
        end if
      end if
    end if
  end if
end while
```

D. Use case

For the Solution Several roles were created to design the Use case of the project. The first one being the Cellphone owner. The owner must Activate the application for the system to begin to work, he must set the number that the phone will call when it detects a fall and he must activate and pair the Bluetooth module to the cell phones Bluetooth connection.

The second role of the project is the Wearer. As a wearer he must wear the pendant for the system to be completed. The wearer must push the stop button if he wished to stop the emergency protocol if he suffered a fall and he does not need help and if he feels ill, the wearer must push the panic button to activate the emergency protocol automatically.

Figure 6 shows the user case diagram, here you can see how the activities interact with each other depending on which case it is implementing.

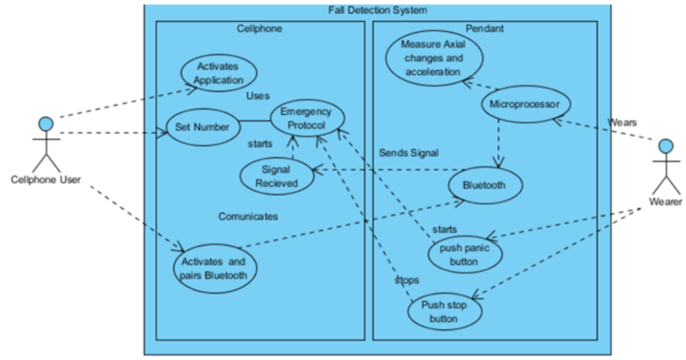

Fig. 6. User case diagram

IV. Experiments and Results

This section presents the experimental setup and the results of this project.

A. The prototype

The proposed system was prototyped using a Samsung Galaxy S5 running Android 4.4 KitKat. The pendant was implemented using a Teensy 3.1 Microprocessor, a MPU 6050 Gyroscope/Accelerometer, and a BlueSmirf Gold Bluetooth Module with a range up to 100 meters. The MPU 6050 is a 16-bits accelerator/ gyroscope that reports the 3-axis acceleration measures (i.e., ax, ay, az), and the 3-axis angular rate. The proposes algorithm computes the compound acceleration as $\sqrt{(ax)^2 + (ay)^2 + (az)^2}$. Figure 7 shows the compound acceleration resulting from a fall.

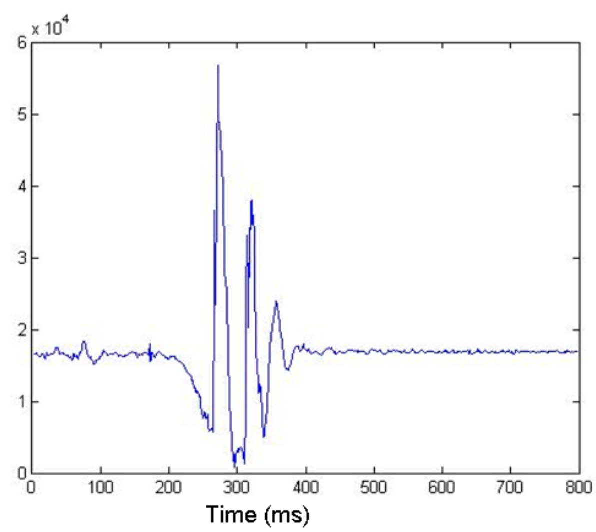

Fig. 7. Fall acceleration example.

On the other hand, Figure 8 shows an angle variation on time product of a fall.

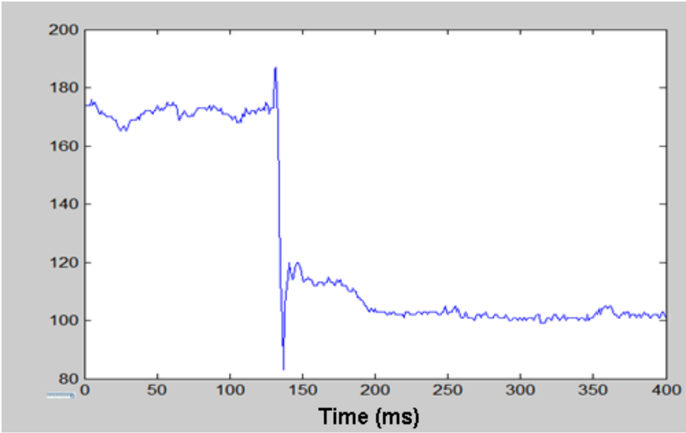

Fig. 8. Position example.

TABLE I
EXPERIMENTAL RESULTS

Test	Backwards	Right side	Left side	Diagonal (left)	Diagonal (Right)
1	Yes	Yes	Yes	Yes	Yes
2	Yes	Yes	Yes	Yes	Yes
3	Yes	No	Yes	Yes	Yes
4	Yes	Yes	Yes	No	Yes
5	Yes	Yes	Yes	Yes	Yes
6	Yes	Yes	Yes	Yes	Yes
7	No	Yes	Yes	Yes	No
8	Yes	Yes	Yes	Yes	Yes
9	Yes	Yes	Yes	Yes	Yes
10	Yes	No	Yes	No	Yes
11	Yes	Yes	No	Yes	No
12	Yes	Yes	Yes	Yes	Yes
Accuracy	**92%**	**83%**	**92%**	**83%**	**83%**

B. *Experimental results*

Table I presents the accuracy achieved using the prototype described on section IV-A. The experiments included several fall types: backwards, right side, left side, diagonal towards left, diagonal towards right. The higher accuracy, 92%, is achieved backwards, and left sided fall. Other situations achieve over a 83%. Falls to the front were not considered in these experiments due to safety reasons.

V. Conclusion and Future work

The fall detection system for the elderly has been developed to the point where the system can detect backward falls with an accuracy of 92%,Sideway falls with 92% accuracy for the left side and 83% for the right side. Future work considers detection of frontal falls. The application has been made to allow the user to call two different numbers but if the cellphone has an error it can make more than two calls on the last phone number. However, the entire application works properly. The Bluetooth service can connect the application if needed.

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