PERVASIVE ALERT SYSTEM FOR FALL DETECTION BASED ON MOBILE PHONES

Kire Serafimov[1], Natasa Koceska[2,*]

[1]*Faculty of Computer Science, University Goce Delcev – Stip; kire.10470@student.ugd.edu.mk*
[2]*Faculty of Computer Science, University Goce Delcev – Stip; natasa.koceska@ugd.edu.mk**

Abstract: Falls are an everyday potential health hazards that all of us are exposed to. A fall can cause injuries or hurt people especially the elderly. Critical injuries provoked by falls are among the major causes of hospitalization in elderly persons, diminishing their quality of life and often resulting in a rapid decline in functionality or death. Rapid response can improve the patients outcome, but this is often lacking when the injured person lives alone and the nature of the injury complicates calling for help. This paper presents pervasive alert system for fall detection using common commercially available Android-based smart phone with an integrated tri-axial accelerometer. The focus of this research was developing the most successful algorithm for detecting falls and distinguishing them from non-falls. Hybrid algorithm concentrating on acceleration magnitude and angle change was developed for fall detection. We implement a prototype system on the Android phone and conduct experiments to evaluate its performances on real-world falls. Experimental results show that the system achieves strong detection performance and power efficiency.

Keywords: tri-axial accelerometer, acceleration magnitude, angle change, angular velocity, elderly.

1 Introduction

Fall is a major care and cost burden to the health and social services worldwide [1, 2]. Falls and fall-induces injury are more often among the elderly people due to their stability problems and fragile bones. Although most falls produce no serious consequence, 5–10% of community-dwelling older adults who fall each year do sustain serious injuries such as fractures, head injuries or serious laceration, that reduce mobility and increase the risk of premature death [3], [4]. Besides the physical injuries the falls can also elicit dramatic psychological consequences such as decreased independence [5] and increased fear of falling [6], [7]. This can lead to an avoidance of activity that can bring about a pattern of deterioration, social isolation and decreased quality of life [8], [9].

Treatment of the injuries and complications associated with falls costs the U.S. over 20 billion dollars annually [10]. This situation deteriorates as the elderly population surges. According to the scientific reports from the World Health Organization (WHO) during the next 3 to 4 decades, there will be a very significant increase (about 175%) in the number of elderly persons, particularly the older aged. Moreover, there will be large increases in the numbers of some very vulnerable groups, such as the oldest old living alone, especially women; elderly racial minorities living alone and with no living children; and unmarried elderly persons with no living children or siblings. With the population aging, both the number of falls and the costs to treat fall injuries are likely to increase.

Falls may be very risky or even fatal especially for old people living alone. Indeed, major concerns for these adults include the risks associated with falling and whether there will be someone there to help them in case of an emergency. There is therefore a demand and need for an automatic pervasive fall detection system in which a patient can summon help even if they are unconscious or unable to get up after the fall.

In order to find falls effectively and timely, many fall detection methods have been developed and shown their well performance [11], [12], [13], [14]. The current fall detection methods can be basically classified in three types: acoustic based, video based and wearable sensor based system. The acoustic based system means detecting a fall via the analyzing on the audio signals. This is achieved by having a device, usually implanted in the floor, monitor sound and other vibrations. In generally, this method is not very precise, and is used as an assistant way to the other methods [15], [16]. The video based system means capturing the images of human movement via one or several cameras, mounted in fixed locations, and then determining whether there is a fall occurred based on the variations of some image features [17], [18], [19], [20]. The wearable sensor based system means embedding some micro sensors into clothes, to monitor the human activities in realtime, and find the occurrence of a fall based on the changes of some movement parameters [21], [22], [23]. As long as a person wear such a clothes, he will be monitored anywhere.

The major problem with existing systems is that they require some application specific hardware or software design, which increases the cost and sometimes require a training period for the users. The main objective of this work is to design pervasive alert system for fall detection using common commercially available Android-based smart phone with an integrated tri-axial accelerometer. Our system eliminates the middle man call centre service and therefore the extra monthly fee. It offers a manual cancellation button in the event of a false alarm or minor fall that the user was able to recover from. Another advantage of our system is that it allows mobility beyond the range of the house. Our device also offers a wide range of selectable alert methods should the user be hearing-impaired, seeing-impaired or otherwise.

2 System design and architecture

To be able to detect falls, the device first has to be able to sense motion and the different measurable qualities involved with motion. Sensing in the device begins with a digital tri-axis accelerometer, which measures acceleration along the three coordinate axes. Using the data acquired, the algorithm should be able to distinguishing falls from non-falls.
Upon identifying a fall, the device initiates a continuous audible, tactile, and visual warning. The user is then given a window of time (20 seconds) in which to cancel the alert in the instance that the fall is not serious and the user is able to regain their composure on their own. If left un-cancelled, the fall is considered serious and an alert is sent out.
Accelerometer provides the acceleration readings in directions of x-, y-, and z-axis. Accelerations in these directions are represented by Ax, Ay and Az, respectively. For generality, we assume the directions of x-, y-, and z-axis decided by the posture of the phone. The x-axis has positive direction toward the right side of the device, the y-axis has positive direction toward the top of the device and the z-axis has positive direction toward the front of the device. Vector A_T represents the total acceleration of the phone body. Its amplitude can be obtained by Eq. 1.

$$|A_T| = \sqrt{|A_x|^2 + |A_y|^2 + |A_z|^2} \quad (1)$$

A mobile phone's orientation can be determined by yaw, pitch, roll values that are denoted as θx, θy and θz, respectively. We can further obtain the amplitude of Av, the acceleration at the absolute vertical direction, from Eq. 2.

$$|A_v| = |A_x * \sin\theta_z + A_y * \sin\theta_y - A_z * \cos\theta_y * \cos\theta_z| \quad (2)$$

We consider that a fall starts with a short free fall period, which is characterized by the acceleration magnitude (Eq. 1) decreasing significantly below the 1G threshold. The impact of the body on the ground causes a large spike in acceleration. The tests have shown that the minimum value for the upper threshold is around 2.6G. After the impact there is a period when the person may struggle to regain composure. After that, if the person is seriously injured in the fall he usually remains on the ground for a period of time. In this period of time the acceleration magnitude returns to a normal level. Also there is a notable change in the smartphone's orientation before and after the fall.

The algorithm monitors the acceleration magnitude of the mobile device to check if the acceleration magnitude breaks the predefined upper threshold, which is an indicator of a possible fall. If the upper threshold is broken, then the algorithm waits up to 20 seconds for the acceleration magnitude to return to a relatively normal level. If the magnitude doesn't return to normal after 20 seconds it is assumed that the large spike in acceleration was caused by some other daily activity, like jogging or biking. On the other side, if the magnitude returns to normal level in less than 20 seconds then it is assumed that the person has potentially stopped struggling and is immobilized after the fall. Then the algorithm checks to see if the person's orientation has changed. If that is true, then a fall is detected.

To determine the change in the person's position we are using the vectors of gravity. The algorithm uses two readings of the force of gravity: the vector of gravity recorded 1.5 seconds before the detection of a large spike in acceleration and the vector of gravity recorded after the fall, when the acceleration returns to normal level. The angle between these two vectors is calculated and if it's in the range between 0.98 and 1.87 radians then a fall is detected.

To determine the detection of falls, it has to circumvent the so-called false positives, which can range from a jump, going down/up stairs or even sitting in a chair. In order to circumvent these obstacles, the system was tested and evaluated under several situations. After detailed analysis of the collected data, the threshold value was defined.

This algorithm only uses the angle of change in the gravity regarding the phone's position, and not the actual position of the phone in the moment when the person lies on the ground after the fall. Because of this, there is no restriction for the phone to be in a certain orientation. The algorithm works well regardless of the smartphone's position, i.e. it doesn't matter whether the smartphone can is placed horizontally, vertically or in some other position in the pocket; with the screen towards the body or against, or even if it is placed upside down.

3 Experimental evaluation and results

To evaluate the proposed methodology we have developed an application called Fall Monitor (Figure 1 and 2).

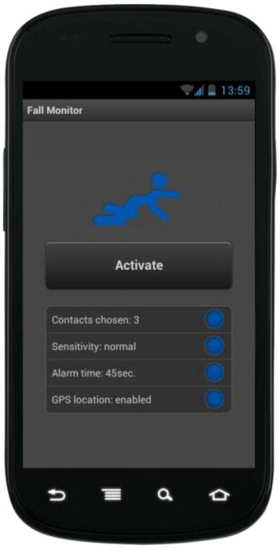

Figure 1 Main application interface

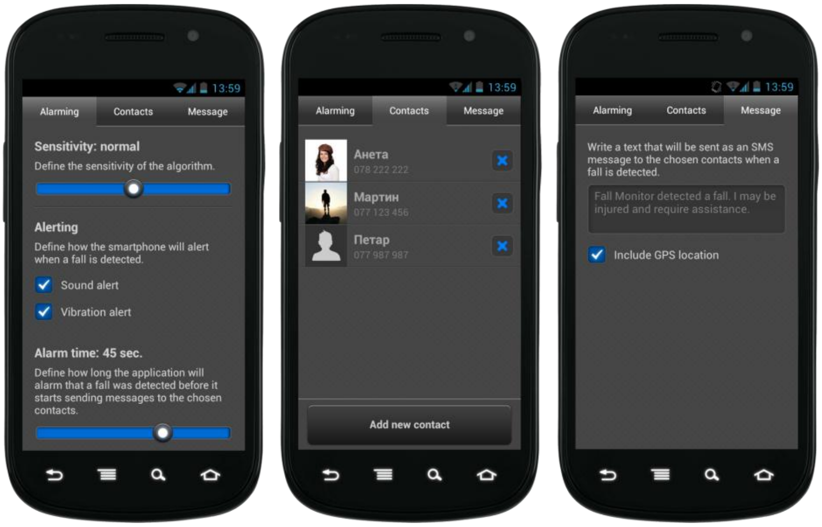

Figure 2 Screen of the application for alerting contacts, application settings and alerting message setting

For the evaluation purposes 20 persons aged between 24 and 37 were equipped with the mobile phone fixed with elastic band on their waist. They were asked to perform 20 times the following several activities: lying down, getting up (from the bed), sitting on chair, getting up from the chair, walking, running, climbing stairs, going down stairs. Each of the test subjects was asked to simulate 40 times various situations of falling (from stand position, pushed down, slipping, falling forward, falling backward, falling aside, from the chair etc.).

The overall results for each activity for all test subjects are presented in the Table 1.

Table 1 Results from the experimental fall detection using a confusion matrix with various activities

Activity	Fall detected		Number of trials	Percentage of correct action recognition
	Yes	**No**		
Falling	796	4	800	99,50%
Lying down on the bed	21	379	400	94,75%
Getting up from the bed	7	393	400	98,25%
Sitting on chair	9	391	400	97,75%
Getting up from the chair	2	398	400	99,50%
Walking	12	388	400	97,00%
Running	47	353	400	88,25%
Climbing stairs	22	378	400	94,50%
Going down stairs	23	377	400	94,25%

To make the application operable during a longer period of time, four steps are taken to reduce power consumption: (1) the monitoring daemon runs in the background while other components of the program halt; (2) the sampling frequency can be adjusted; (3) the pattern matching process is launched only after daemon-collected data exceeds the preset threshold; and (4) hardware such as the screen is activated only when necessary.

4 Conclusion

The main contributions of this paper are the following:

− We propose utilizing mobile phones as the platform for pervasive fall detection system development using mobile phones to integrate comprehensive fall detection and emergency communication.

− We design an algorithm for fall detection systems using mobile phones. It is an acceleration-based detection approach whose only requirement is that a mobile phone has an accelerometer.

− We design and implement a pervasive fall detection system, on the mobile phone-based platform to conduct fall detection. It has few false positives and false negatives; it is available in both indoor and outdoor environment; it is user-friendly, and it requires no extra hardware and service cost. It is also lightweight and power-efficient.

− We conduct experiments to evaluate detection accuracy. The experimental results show that our detection system achieves good performance in terms of low false negative and low false positive in fall detections.

This system is applicable not only to elderly but also to healthy individuals performing various activities walking, running, climbing, cycling, rolling, etc. experiencing falls due to various causes such as: unexpected health problems, inattention, dangerous environment, car accidents, attacks, etc.

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