Design and Evaluation of a Fall Detection Algorithm on Mobile Phone Platform

Manuel Silva, Pedro M. Teixeira, Filipe Abrantes, and Filipe Sousa

Fraunhofer Portugal AICOS
Rua do Campo Alegre 1021
4169-007 Porto, Portugal
{manuel.silva,pedro.teixeira,filipe.abrantes,filipe.sousa}@fraunhofer.pt

Abstract. The increasingly aging population will pose a severe burden to the health services. Falls are a major health risk that diminishes the quality of life among the elderly people and increases the health services cost. Reliable fall detection and notification is essential to improve the post-fall medical outcome which is largely dependent upon the response and rescue time. In this paper, we analyze mobile phones as a platform for developing a fall detection system. The feasibility of such platform is assessed by running an acceleration based fall detection algorithm on the phone. The algorithm was implemented for the Android OS and tested on several HTC models, which included a MEMS accelerometer. Extensive simulations of fall events as well as activities of daily life were conducted on a lab environment to evaluate the system performance. Experimental results of our system, which we still consider as work in progress, are encouraging making us optimistic regarding the feasibility of a highly reliable phone-based fall detector.

Keywords: Fall-detection, Algorithm, Accelerometer, Activities of Daily Living.

1 Introduction

Falls are dangerous, prevalent and costly. The frequency of falling is considerably higher among elderly. Nearly one third of the people aged over 65 fall every year [1]. Approximately 3% of all fallers lie for more than 20 minutes without external support [2]. The need of assistance in the case of unconsciousness or extreme injury are the main reasons why elders leave the comfort and privacy of their own home to live in an assisted-care environment (40 % of nursing home admissions are due to falls [3]). According to the world population prospects by the United Nations, the median age of the population rose from 23.9 in 1950 to 28.1 in 2005, and is forecast to rise to 37.8 by 2050 [4]. This will pose a severe burden to the health services. The financial exertion and physical requirements necessary to provide the current level of care to such a large forecast population are far too great to be feasible. Various ideas need to be produced to provide an appropriate level of care in a more efficient manner by taking advantage

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of current technologies. Reliable fall detection and notification is essential in independent living facilities and in ambulatory systems for elders or patients. The objective is to improve the medical outcome which is largely dependent upon the response and rescue time. Immediate reporting to caregivers after fall event detection can certainly improve the health outcome due to faster caregiver response and appropriate medical care.

1.1 Why a Mobile Phone

Recently, technical advances in Micro Electro Mechanical System (MEMS) sensors, microprocessors and wireless communication technologies have been the driving factors to facilitate telemonitoring of people's physical activities [5]. Smaller in size, lighter in weight and relatively low cost, sensors are designed into a kind of body-attached or wearable system. The sensors collect kinetic parameters of human body and analyze data to monitor the physical activities without disturbing the wearer's daily life. A typical fall detection system has two major functional components: the fall detection component (used by the user) and the help communication component (installed indoors). The maximum distance between the sensor and the communication base is limited. Utilizing mobile phones as a fall detection system combines the detection and communication components as they present a mature hardware and software environment. They are more convenient and highly portable, enabling an outdoor fall detection system. The only prerequisite is the presence of an accelerometer to sense the user's activity. The popularity of mobile phones is likely to continuously increase in the near future due to decreasing prices, thus projecting an overall acceptance regarding it as a fall detection platform.

1.2 Major Differences When Doing It on a Mobile Phone

Carrying a mobile phone implies the user choice of its place. This in turn increases the difficulty of fall detection. The sensor location on the body relatively to the point of impact modifies the pattern of the recorded acceleration signal [6]. Besides position variability, some chaotic environments like a loose pocket might increase the turbulence of the mobile phone sensor. Another problem is the lack of a fixed referential for simpler approaches such as tilt analysis. Under static conditions a three axis accelerometer can be used to find the direction of the gravity vector, which can be used to find the tilt angle of a person relative to the gravity vector. Unfortunately, human movements are far from being static and even small motions can cause high accelerometer readings. For this reason, they are only really good for gross measurements like the analysis of intense acceleration magnitudes due to fall impacts.

1.3 Objectives

The objective of our work is threefold. Firstly, we aim at assessing the feasibility of a fall detector on a mobile phone. Is the processing speed of such devices sufficient to run the algorithm? Do the public APIs of the device grant us with the required functionality? Secondly, we want to have an idea of the order of magnitude of the accuracy that one might achieve with a phone-based fall detector. Typically, dedicated-hardware fall-detectors are positioned and fixed in certain parts of the body whereas a mobile phone is handled freely by its user and its position in the body is unknown to the fall detection application. Finally, this work has the objective of understanding the difficulties and limitations of developing a mass-market fall detection application for real handsets. Different devices will have different characteristics, from CPU speed to accelerometer accuracy. This initial approach give us a insight on the barriers one will have to overcome to achieve this goal.

1.4 Structure

The paper is organized as follows: Section 2 presents related work in the field of fall detection. In Section 3 we describe the implementation of our fall detection algorithm for the Android platform and in Section 4 we detail the specificity and sensitivity results achieved in the lab. Finally, in Section 5 we conclude the paper.

2 State of the Art and Related Work

In the past 15-20 years there have been many commercial solutions and academic developments aimed at detecting falls. The most simple and popular solutions are community alarm systems (e.g. Vivatec's Wrist Care [9]) which are based on alarm buttons located on a wrist watch or fixed in a stationary location. The main problem with those solutions is that the button is often unreachable after the fall specially when the person is unconscious [10].

Lindemann [11] created a fall detector system based on accelerometers placed into a hearing-aid housing fixed behind the ears. The sensitivity of the fall detection was assessed by acceleration patterns of the head.

The human horizontal and vertical velocity were found to be discriminatory parameters used to distinguish fall movements from normal activities [7]. During the descending phase of the fall, usually about 300 - 400 ms before the fall impact on the ground, a threshold of 1.0 ms^{-1} was identified experimentally. However it has been argued by Bourke [8] that thresholding of the vertical velocity of the trunk alone, is sufficient for fall detection, found experimentally as 1.3 ms^{-1} with 100% sensitivity and 100% specificity.

Zhang [12] placed a tri-axial accelerometer in a mobile-phone, and monitored the following sequence of events: a daily activity, fall and then person remaining motionless. In [13] was also proposed a pervasive fall detection system implemented on mobile phones.

Besides wearable sensors, image processing of video signals can also be used to detect a fall by either identifying the lying posture using scene analysis or by detecting abrupt movements. While these techniques are well established in controlled environments (laboratory, scene), they must be modified in uncontrolled environments where one controls neither the lighting nor the framing [14]. These techniques are becoming feasible, both technically and financially, thanks to the emergence of low cost cameras (web cams), the possibility to wirelessly transmit images over short distances and the availability of the required algorithms. Nevertheless the acceptance of this technology poses a major problem, as it requires the placement of video cameras in the person's living space, and in particular in the bedroom and the bathroom, with consequent concerns of privacy.

3 Mobile Phone Fall Detection

Detecting user falls on a mobile phone is significantly more difficult than doing so with dedicated fixed equipment. The mobile phone is handled freely by the user, therefore the sensor orientation is also variable, invalidating its analysis for the purpose of user position. Besides this, the MEMS accelerometer technology embedded in current mobile phones has limited accuracy and suffers from value drifting depending on the phone orientation. Finally, if one aims at developing a truly global solution, one that works across different mobile phone models, or even different operating systems, there is one extra layer of complexity that needs to be handled. Different phones will have different hardware specifications and operating system configurations, thus fall detection algorithms running on different phone models will have to deal with accelerometer data with variable precision and polling frequency. Before any data analysis can be carried out by the algorithm, it is crucial that all these effects are taken into account and that the data is normalized to the reference implementation.

3.1 The Algorithm

The fall detection algorithm was designed as a state machine, which is a simplified version of the algorithm proposed by [16]. The behavior model is composed by five finite states: *normal*, *fall*, *impact*, *recovery* and *unconscious* states as illustrated in Fig. 1. Transitions between states are done by inspecting the acceleration values and by analyzing its symbolic sequences. The states can be divided into two distinct phases, the pre-fall phase and post-fall phase.

Beginning at the *normal* state (pre-fall phase), if a "free-fall" acceleration profile is reached by reading acceleration values below a minimum threshold, the *fall* state is reached. Once in the *fall* state, the algorithm will record the minimum reached acceleration value and an inversion of acceleration polarity with high magnitude values are monitored within a time frame to check if a person suffers an impact. If the maximum acceleration value exceeds a threshold value, the *impact* state is reached otherwise it returns to the *normal* state. Once in the *impact* state, the algorithm will check if the difference of maximum and minimum acceleration values exceeds a threshold in order to confirm the fall event or to discriminate it as an ADL (Activities of Daily Living). If the threshold is not exceeded the algorithm moves directly to the *recovery* state and enters the post-fall phase otherwise it returns to the *normal* state. During the *recovery*

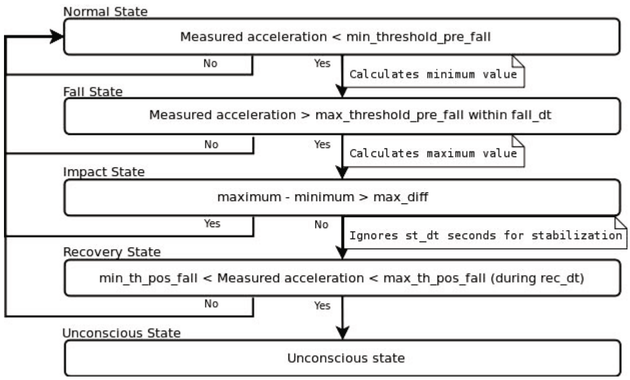

Fig. 1. Fall detection algorithm

Table 1. Threshold values and units of the different parameters for the fall-detection algorithm

Threshold	Value	Unit
min_threshold_pre_fall	8.00	m/s^2
max_threshold_pre_fall	13.42	m/s^2
max_diff	12.00	m/s^2
fall_dt	2000	ms
st_dt	7500	ms
min_th_pos_fall	9.35	m/s^2
max_th_pos_fall	10.45	m/s^2
rec_dt	5000	ms

phase it will check for user inactivity by monitoring if the acceleration values exceeds the vicinity of the passive acceleration profile value (1G) by a certain small threshold. If it does, the algorithm assumes the user has recovered from the fall and returns to the *normal* state. However, if the acceleration values do not leave the vicinity of the reference value, it is assumed that the user was unable to recover from the fall and the algorithm enters the *unconscious* state, triggering an alarm which consists in sending an SMS and Email to some predefined emergency contact.

The threshold values used in the fall-detection algorithm resulted from the analysis of a set of 120 recorded simulated falls and non fall activities on a lab environment and are presented in Table 1.

3.2 Implementation

The algorithm was implemented for the Android platform and tested on 5 different phone models: HTC G1, Samsung i7500, HTC Desire, HTC Desire HD and the Google Nexus 1. The fall detection function was embedded in a broader activity monitoring application called 'Mover' that is available on the Android Market. The application is composed by 3 modules:

– **Background Service** a long-standing process running in the background responsible for collecting data from the accelerometer and processing it,
– **Application User Interface** an Android activity that shows a summary of the user activity throughout the day,
– **Application Preferences** an Android preference activity that allows the user to toggle the fall-detection function as well as to configure the SMS and e-mail emergency contacts.

More interesting perhaps, are our findings regarding the accelerometer data capture on these devices. We found out that the polling frequency can vary from approximately 20 to 40 ms on the HTC models and it is never a fixed interval. On the Samsung model we were unable to reduce the accelerometer polling frequency below an average of 250 ms. Furthermore, we observed that the reference acceleration value while the phone was resting on a table would vary significantly depending on the phone orientation (horizontal versus vertical); we observed the reference acceleration value to vary between approximately 9.4 and 10.1 ms^{-2}.

4 Results of Fall Detection Algorithm

We performed the final experiment using a HTC Desire HD mobile phone running the fall detection algorithm. As the goal is to distinguish fall events from other safe daily activities, we analyzed the algorithm performance on both activities.

4.1 Evaluation Method

The algorithm performance was measured through a series of specific activity tests proposed as evaluation of fall detectors [15]. It contains 20 test scenarios for the evaluation of fall sensors, with 50% "negative" and 50% "positive" fall activities. The algorithm was tested in a laboratory environment performing falls onto a crash mat and normal activities in order to evaluate its performance. At the beginning of the trial, a mobile phone running the algorithm was placed in the pocket of each subject at the thigh position. The subjects were 10 young (<30 years) healthy males. The mean±standard deviation age, height and mass of the subjects were 26,2±3,04 years, 1,776±0,052m, and 78,3±5,3kg respectively. Each activity was performed 3 times for each subject obtaining an amount of 600 activity tests.

4.2 Data Analysis

An activity result is binary and need statistical analysis on a series of tests. There exists four possible situations:

- True positive (TP): a fall occurs and the device detects it.
- False positive (FP): the device announces a fall, but it did not occur.
- True negative (TN): a normal (no fall) movement is performed, the device does not declare a fall.
- False Negative (FN): a fall occurs but the device does not detect it.

In [15] was also proposed a classification and evaluation of fall detectors. Two criteria were proposed to evaluate the response to these four situations. Sensitivity (the capacity to detect a fall, Eq. (1)) and specificity (the ability to detect only a fall, Eq. (2)).

$$sensitivity = \frac{TP}{TP + FN} \tag{1}$$

$$specificity = \frac{TN}{TN + FP} \tag{2}$$

Results have shown that falls can be distinguished from normal activities with a sensitivity of 92.67% and a specificity of 72.67%. Poorer fall detection precision was achieved on falls ending on the knees (33,33% not detected) and the activity with highest amount of false positives was lying down as it was on a bed and then rising up (60% of false alarms).

5 Conclusion and Future Work

In this paper we have designed, implemented and evaluated a fall detection algorithm for mobile phones. Despite other similar experiments [13] within the past year and the fact that fall-detection has been a topic of research for almost a decade, we believe that fall-detection through a mobile phone is a research topic that is still in its infancy. We regard our work as an initial approach to the problem and our main objective with this experiment is to assess the overall feasibility of such system, both in terms of implementation on real hardware and software as well as expectable performance.

The results we have obtained are encouraging. We were able to implement a fall-detection algorithm on real hardware and observed that the processing power of current phones is more than sufficient to process the accelerometer data in real-time. At the same time the lab results showed that our algorithm was able to distinguish falls from normal activities with a sensitivity of 92.67% and a specificity of 72.67%.

Our implementation effort also provided us with insight on the practical hurdles of developing a phone-based fall detector. We learned that the accelerometer polling frequency as well as its reference values vary from model to model, something that has to be taken into account in the algorithm design.

In summary, the findings described in this paper provide us the ground for future refining of our phone-based fall detection algorithm and expect they do so also for others in the research community.

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