

Survey and Evaluation of Real-Time Fall Detection Approaches

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Abstract- As we grow old, our desire for independence does not diminish; yet our health increasingly needs to be monitored. Injuries such as falling can be a serious problem for the elderly. If a person falls and is not able to get assistance within an hour, casualties arising from that fall can result in fatalities as early as 6 months later [1]. It would seem then that a choice between safety and independence must be made.

Fortunately, as health care technology advances, simple devices can be made to detect or even predict falls in the elderly, which could easily save lives without too much intrusion on their independence. Much research has been done on the topic of fall detection and fall prediction. Some have attempted to detect falls using a variety of sensors such as: cameras, accelerometers, gyroscopes, microphones, or a combination of the like. This paper is aimed at reporting which existing methods have been found effective by others, as well as documenting the findings of our own experiments. The combination of which will assist in the progression towards a safe, unobtrusive monitoring system for independent seniors.

I. Introduction

Miniaturization of computing devices and advances in wireless communication have fueled interest in the development of new and innovative applications in many fields, including medicine for diagnosis, monitoring, and therapeutic applications. Although medical instruments have benefited a great deal from the technological advances in past decades, many practices and day-to-day activities in medical environments remain virtually unchanged. Due to concerns about security and reliability of new technologies, penetration of IT advancements into the medical domain remains a challenge. This paper discusses real-time monitoring systems for the elderly with mobility issues.

Mobility is a key issue for maintaining independence for the elderly. Falls can drastically affect the activeness of the elderly and also pose a major health risk. Even the fear of falling, can lead to decreased activity and mobility [11][12][13]. For this

reason many researchers have developed methods to detect and monitor falls.

In this paper, we give a survey of fall detection approaches in the literature in Section 2. After the survey of previous methods, the paper reports the results of additional experiments performed Section 3. Finally, concluding remarks are given in Section 4.

II. Methods of Real-Time Fall Detection

The first function of this paper is to provide a survey of different fall-detection methods. The most common methods of fall detection can be grouped into three categories: methods that measure only acceleration, methods that measure acceleration combined with other methods, and methods that do not measure acceleration.

A. Acceleration-Only Sensors

In [3] an Australian group developed a movement classification algorithm based on the acceleration data generated from 2-axis accelerometers. The device they used was placed in a pouch on a belt, which they attached to the waist of patients. Once attached, the device was positioned so that the measurements in line with the vertical axis and anterior-posterior axis. Since, for this experiment, measurements were only done in 2 axes, side falls were very difficult to detect.

Their test study involved separate sensors for fifteen elderly patients labeled as having a high risk of falling. The study lasted for 309 patient days, and the average amount of time the sensor was worn by a patient was 18 days. Four falls were recorded.

Because of the low number of falls, patient data was insufficient to create a reliable fall-detection algorithm. Simulated falls were done by a healthy younger volunteer after observing recordings of different types of falls typically done by the elderly. Two observations found about falls were found. First, every fall had a negative peak in the acceleration data. Only the vertical axis was used to determine the fall threshold. The second observation was that falls always had an acceleration change from a positive value to a negative value, and the speed of this change was important for fall detection.

The results of this study showed that some types of falls are easier to detect than others (falling

forward from a standing position versus a falling to the side off of a chair) fall detection based on acceleration magnitude alone was not significantly useful, while detection based on acceleration magnitude and the speed of the sign change proved to be much more reliable.

In a study by U. Lindemann (et al.) in [10], seven types of falling and five types of daily activities were detected and distinguished using a system with two accelerometers placed in hearing aid housing. Integration period to obtain velocity from acceleration is set to empirical value of 1.5 seconds. This paper suggests using dynamically determined period of integration for better suiting the system for distinguishing widely different types of falls and daily activities. Data obtained from accelerometers were sampled at 200 Hz. X-axis of the sensor corresponds to frontal side, Y-axis to the vertical side, and Z-axis to the sagittal side.

In [5], Chia-Chi Wang expanded on the method of [10] by finding the sum of all the three axial acceleration components S_a and the sum of frontal and sagittal acceleration components S_h are used to determine additional parameters in the algorithm used to detect falls. These parameters are used to determine significant points of time in the falling process, find velocity of the subject during impact, and identify lying condition. The following equations were used.

$$S_a = \sqrt{a_x^2 + a_y^2 + a_z^2}$$

$$S_h = \sqrt{a_x^2 + a_z^2}$$

$$V_{\max} = \int_{T_{rs}}^{T_{ic}} [S_a(t) - 1] dt \Big|_{\max}$$

For normal falls, S_a exceeds 6g and S_h remains below 2g. A fall is detected when the values are above this threshold limits. If, however, S_a does not exceed the threshold but S_h does, additional calculations determines if it is a fall. T_{rs} , defined as timestamp when subject is at rest, and T_{ic} , defined as timestamp when subject is in initial contact to ground, are used to calculate velocity during the impact. T_{ic} set to the time when S_h exceeds threshold. T_{rs} set to the time when S_a is back to 1g and subsequent 60 samples of S_a is the same. These two timestamps defines the interval of integration while finding maximum velocity during the impact. A velocity of 2 m/s or more is regarded as threshold for fall detection.

The system was tested with seven types of daily activities – standing, sitting down, lying down, walking, jumping, going up and down the stairs, and jogging; and with eight types of fall – falling while standing straight, falling during standing up, falling

while sitting down, falling while walking forward, falling while walking backward, falling while bending 90 degrees, falling while jumping, and falling while laying down on a bed. Five volunteers (three males and two females) performed 21 falls each during the experiment. All of the falls and all of the daily activities were detected correctly by the system. Parameters measured during the experiments were below the threshold for fall during the daily activities.

The group in [6] describes development of the fall detector system worn over the chest that utilizes a tri-axial accelerometer. From studies referenced by the author, it is known that there exists a number of fall detection system based on accelerometers, optical motion capture systems, or gyroscopes. Those systems utilize velocity profiles of trunk of the subject in detecting and predicting the fall [6].

The system described in [6] uses accelerometer based sensor worn over chest using custom harness made from elastic and Velcro straps. Accelerometer signal is converted to physical measurements using method outlined in [7]. Velocity is calculated from acceleration using the formula:

$$v = \int \left(\sqrt{x^2 + y^2 + z^2} - 9.81 \text{ m/s}^2 \right) dt$$

Numerical integration is performed according to the method by [9]. In order to eliminate drift due to noise in accelerometer signals, a 2nd order Butterworth filter is applied with high pass and low pass cutoff frequencies at 0.15 Hz and 15 Hz respectively.

Three variance of 1-second window of accelerometer data is used to compute static activity. A static activity is characterized by variance of such signals below 1.

Experiment is performed by enacting 4 types of falls and 6 types of daily activities as naturally as possible by 5 young healthy male subjects less than 30 years of age. Data from accelerometer as well as data from an optical motion capture system is recorded during the experiment. Coefficient of Multiple Correlation (CMC) between the two sets of data was computed using MATLAB software.

The results from the experiment indicated high correlation coefficients and low error rates for activities of daily living. Due to the nature of vigorous movement during fall, error rates during fall were higher than that for ADLs. However, a relatively strong CMC was observed. Analysis of all

activities concluded a threshold of -1.3m/s vertical velocity of trunk can be used to distinguish ADL with 100% specificity and 100% sensitivity.

B. Combination of Sensor Detection

A French Research group developed a Waist-mounted rechargeable Triaxial Accelerometer for detection and prevention of falls for the Elderly [1]. Their device is known as the "PreventFall ambulatory monitor" (PFAM). But the PFAM is more than just a monitor - it also is able to provide the user with self-administrable tests for fall risk assessment. With both of these features PFAM is aimed to provide tracking of fall risk parameters and use them to for early identification of increased fall risk.

This system mentioned in [1] contains 2 major physical devices, the worn PFAM device and the stationary receiver device named "MiiLink". The two devices communicate using Blue-tooth radio. In the case of an emergency, the MiiLink can access the phone lines to dial for an emergency response while also establishing verbal communication with the User and the Emergency Response personnel. Based on the severity of the fall the MiiLink calls appropriate personnel (example: less severe if user is able to stand up; call family member).

The user is expected to start a "directed routine" with the push of a button on a daily basis. This routine includes such activities as: timed sitting/standing repetitions, and measuring reaction time. The tests are designed to be short, yet effective for evaluation. All of the data (including activity of daily living) is stored on an SD device located on the MiiLink and Uploaded to an off site location for remote processing.

Though [1] only tested their device for 1 individual, the ability for the PFAM to detect falls autonomously while also allowing the User to provide input and self-testing produces a robust yet simple method for fall detection and prevention.

An International Research group from both Italy and the USA developed a framework for High-Reliability detection of falls in [2]. They developed an integrated prototype which used three different sensors: a 3D time-of-flight range camera, a wearable Zigbee MEMS accelerometer and a microphone - all of which were connected with custom interfaces circuits to a central PC to collect and process the data.

The camera uses a people-detection and tracking algorithm. With this tracking the centroid height of the person is determined. If the height is below a threshold, then the person is in a "fallen" state.

The Accelerometer detects fall events in which the acceleration peaks and then has a short period of little movement; these fall events are detected

separately for each axis. For the accelerometer 3 different thresholds were used, each generating 3 different levels of alarms - for the most part the medium level threshold was preferred.

The microphone detected acoustic sounds in attempt to find the "sound of a fall". The threshold was based off of the 'acoustic weight' of the sound generated. The microphone alone was not even 60% reliable at its best - this is because doors slamming generated similar sounds to a person falling.

The combination of each of these sensors was not yet developed in [2], but it is expected that they will compliment each other and provide much more reliable results when used in tandem compared to separately.

A study done in France by Noury [4] discusses the psychological consequences of a fall. The worst case scenario is one in which the elderly person falls unconscious and is unable to call for help. The goal of their designed fall detector is to assure elderly that help will arrive shortly after a fall, motivating them to stay more active and continue a healthy lifestyle.

The device created combines three sensors to create an "actimeter". The actimeter measures vertical acceleration, body orientation, and surface vibrations through an accelerometer, position tilt switch, and a vibration sensor, respectively. Each of these three sensors generates a Boolean value, and the three values generated are then used to determine whether a person has fallen. Each time one of the three values changes, the actimeter sends a packet of information containing all three values to a nearby computer. The device uses a low power RF transceiver for communicating with the local computer, making monitoring of patients far away (i.e. outside of the home) not viable. The battery life of the 3V battery used to supply power to the device is not discussed.

The algorithm used to determine a fall is: if vibrations, then check if the vertical movement is over the threshold and if the person is horizontal. If all three of these checks are true, then the device considers the action a fall.

A healthy younger male was used to test five types of falls, as well as seven activities of daily living (ADL) to determine if only actual falls were being detected as falls. Each type of fall and ADL was tested five times. Fall detection of actual falls varied significantly depending on the type of fall, from detecting all five of the tests, to detecting only one. ADL were detected as falls (false positives) in every situation tested at least once.

C. Non-Acceleration Methods

In [18] they developed a method of fall detection, based on an array of acoustic sensors.

They attempted to determine if a loud sound (a fall) was heard. They were also able to determine whether the sound was located high or close to the ground. Combining the sound and the height of that sound they attempted to determine if it was a fall. They were able to adjust their device to have 0 false alarms, but unfortunately it was only able to detect 70% of the falls. They were also able to adjust the device to detect 100% of the falls, but then it had 5 false alarms every hour.

In [19] they developed a different method to track mobility using a Monocular Vision System. This device was attached to an elderly person’s walker. The camera detected the positioning of the user’s legs over several frames to determine the velocity. This velocity was used to determine if the user was losing mobility over time. Unfortunately the results were prone to high error rates, but the paper does admit that they have “much room for improvement.”

D. Comparison and Discussion

For the most part, it appears that methods measuring acceleration are good at detecting falls. These results have low error rates as well as high detection rates. In [14] it was determined that good placement of the accelerometers can make the data even more reliable. Another method [15] was able to improve the readings by filtering out extraneous data collected by the accelerometers. Others such as [16] were able to remove false positives by determining the angle between the vertical axes of a tri-axel accelerometer sensor.

Though Combination methods are not devoid of errors, for the most part it seems that combining other sensors with accelerometers provides a more robust and reliable detector. Though it should be recognized that simply adding sensors will not guarantee better results, sometimes the added sensors provide more beneficial features besides simply fall detection, such as [17] which included a heart-rate detection circuit. The data from the heart-rate detection circuit was also able to provide some insight into whether the patient was in a state of increased anxiety (such as after a fall). Additional sensors therefore, may provide a way to boost the detection rate as well as reduce errors – or simply provide additional useful data.

Analysis of previous works suggests that acceleration is a critical role in elderly mobility monitoring, and should be used in fall detection. Compared to visual and acoustic sensors, accelerometers consume less energy and much easier to integrate into wearable mobility monitoring devices. For these reason, the next section will

involve experimental data that utilized accelerometers.

III. Experimental Study

A. Configuration

An experimental study was conducted to verify whether falls can be detected among various events of activity in daily life (ADL). These events were recorded using an accelerometer based device (Fig 1a). BioMOBIUS v1 [20] from software (Fig. 1b) developed by TRIL Centre (TRIL Centre) was used to collect the data (Fig. 1c) from the experiment. Using MS Excel (Fig. 1d), the data was analyzed, visualized and classified as either an ADL or a fall in a post-processing stage (Fig 1e). The software involved in acquiring, transferring and storing event data were all available in open source domain with corresponding applicable copyright notices. The experiments were conducted by two male subjects in a lab setting performing each event as naturally as humanly possible. For fall experiments, an air bed was used as a cushion to prevent fall related injuries to the subjects.

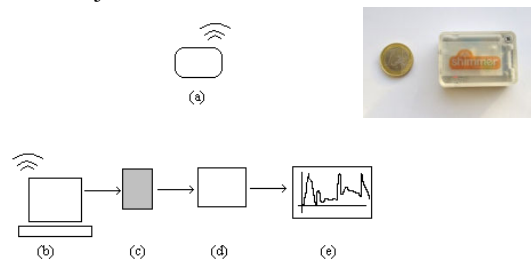


Figure 1. Architecture of the experimental system

The device (image inset) [21] used in the experiment was acquired from Shimmer-Research Inc. Shimmer is an extremely compact platform for long-term wearable sensing in both connected and disconnected settings. Having small form factor with an accelerometer sensor and communication module integrated into the hardware platform was the main reason for selecting this device among various other contenders with similar features in the market. The code running in the shimmer device was obtained via TinyOS source code repository [22].

The sensor was placed on a small pouch and secured to the subject during the experiment on his right hip using a belt. Positive X axis of the sensor device is directed towards the bottom along the vertical axis; positive Y axis is directed to the front

outward along the sagittal plane; and the Z axis is directed to the right outward along the coronal plane.

B. Methods

Algorithms used in analyzing daily events work on time based data obtained from the accelerometer. Analog signal produced by the accelerometer is converted into digital signals by digitizer unit of the processor. This signal is converted to physical units according to the sensors' hardware datasheets available at [21].

These physical data are used as inputs to an algorithm that detects peaks in acceleration signal over a threshold determined empirically from preliminary experiments. The methods below describe algorithms used in this experiment.

- The first method was done by utilizing accelerometer data only to detect falls among various events. The accelerometer signals are compared to determine if it is over a threshold of 3g. If so, 100 samples following it are checked for peaks and noise. Such closely spaced peaks in time should be counted as single event of impact to prevent the problem of multiple counting.
- The next method was done with the utilization of accelerometer and gyroscope data together to detect falls. Together the accelerometer and gyroscope are both sampled to obtain different aspects of an event. Since a gyroscope gives rate of angular displacement, a threshold value was used to check against values related to a fall. A confirmation of high angular rates was used to validate fall detection via accelerometer data.
- The last method was done with a combination of acceleration data, gyroscope data, and static orientation data to detect falls. The additional parameter, static orientation, is calculated from the accelerometer signal of a patient at rest. The static component of gravity is detected in the vertically oriented axis of the device regardless of the orientation of the device. The difference between the initial and final orientation is used to determine the change in position of the patient after an event.

C. Results

Below are the graphical representations of our findings. Ax, Ay, Az are vector components of acceleration data. A is the vector sum computed from

the component vectors. Gx and Gy are rate of angular displacement around X and Y axis. Whenever a fall is detected, the 'Fall' value is raised to 1.

Overall sensitivity was measured to be 80% and specificity was measured to be 89%. Falls that landed on left showed lesser sensitivity than falls on the right (Fig. 2a). Most of the jump events were falsely detected as falls due to the higher peaks in the signal than the threshold for fall. However, the detection of other activities is quite accurate according to the results in Fig. 2b.

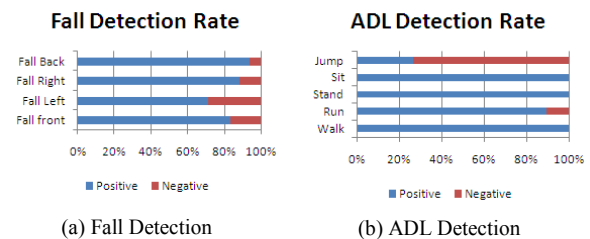


Figure 2. Summary of experiments

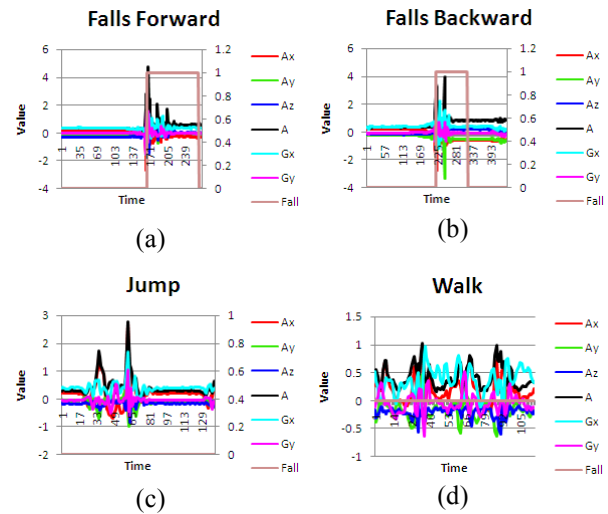


Figure 3. Features of fall and other ADLs

- Falling face down onto on an airbed cushion.
- Falling on a back onto an airbed cushion.
- Jumping while standing.
- Normal walk.

IV. Conclusion

Over the broad spectrum of previous works used in fall detection, acceleration detection was a vital part in generating accurate analysis. Some methods expanded on the acceleration-only methods which was able to increase the accuracy and reduce false alarms. Consequently methods that did not use acceleration were found to be less accurate and often have many false alarms.

The experimental study done at the University of Nebraska at Omaha used acceleration methods to detect falls. The findings showed MEMS accelerometer was able to detect falls with 80% sensitivity and 88% specificity. Using accelerometer to detect fall events is possible with relatively higher accuracy. Parameters extracted from accelerometer, e.g. static orientation, etc, can also be used to further increase accuracy of detection. Additional motion sensors, e.g. gyroscope, can further fine tune the classification of events as fall or ADL, thus increasing accuracy furthermore.

Based on the research done by previous works and the experiments mentioned in this paper, detecting falls are best done with the use of accelerometers. Simple reasoning tells us that the acceleration from gravity is a major component to falling; thus a measurement of our acceleration is vital in fall detection.

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