# Fall Detection Enhancement In Android Platform

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**Abstract— Health care technology presents daily use devices that predict fall in elderly and save their lives due to the embedded accelerometer sensor in the cellphone. The accelerometer signal has shown unexpected ripples that could disturb any adaptive algorithm because of the noise generated. To eliminate the drift in accelerometer signals, a moving average with window size 4 utilized. In this study, we hypothesized that there is a difference in the signal of a phone call response accelerometer and a body fall signal. The ability to discriminate between falls and Activity of Daily Life (ADL) tested in MATLAB R2017a. We present a new method to find peak values based on the best line approximation slope. A Linear classifier on 79 observations and 2 response classes, Fall (direct forward fall, fall towards the bed, and falling while jumping) and ADL (answer a phone call, frontal and sagittal speed, walking, and climbing stair), gave 83% sensitivity and 97% specificity with 88% accuracy. The second part of the study performed the Android gesture detection listener, in which the caregiver get the appropriate alert within the range of home and provide action call service in case of no response and hearing aid housing.**

Index Terms - Accelerometer, Activity of Daily Life, Android platform, Fall detection, Slope detection, Signal orientation, Linear Discriminate Analysis.

## 1. INTRODUCTION

The activity of daily living for elder people is a major concern for public health and aging society. The fall is underestimated when one deals with aging society studies. A different study demonstrated that over one-third of the population over the age of 65 falls at least once a year [1]. Fall can vary from accidental fall like transportation accidents to a fall because of sickness like the epileptic seizure that denies from outside living activity. Fall could occur also in bathrooms by slipping and tripping [2]. However, fall detection approaches can appear in different methods. For instance, In-shoe wearable sensor can detect a fall or walk speed by measuring the differences in pressure, or in piezoelectric sensors. Then, the embed device delivers the observed results over the smartphone and Bluetooth communication [3]. Inertial measurement unit (IMU) that comprises 3 to 6-dimensional gyroscopes and accelerometer could indicate a more accurate reading than in-shoe pressure sensors to obtain a fall signal [4]. Another type of fall detection conservative approach is to classify human fall based on data observed from a visual camera and applied neural network classifiers [5]. This approach is useful to distinguish real falls from a fall taken as an action. For instance, studies followed the category of fall from stairs, fall from a higher than 1 meter or a fall towards a bed. These types of fall mechanisms are self-initiated and differ from sudden falls. A one cannot hide the fact that most of the fall detection techniques are prototypes and for research laboratory purposes. We can conclude that there are three types of detecting a fall: Fall detection using an accelerometer. For instance, the detector system can wear over the chest or placed in a pouch on a belt to utilize the triaxial accelerometer [6]. Second, the combined systems contain triaxial accelerometer along with physical devices that receive the signal over Bluetooth Communication and send to a cell phone for emergency aid. For instance, MiiLink [7, 8] dials a phone line to establish verbal communication to call for aid. The last but not the least attempted to use loud sound to determine a fall and its location from the ground [9]. Another different method used the monocular vision system to determine the velocity of the leg [10]. In this paper, we describe a new method of identifying peak threshold that discriminates between falls and activity of daily living. The signal would have peak values during a fall, which is unique from the one predicted by normal ADL. Hence, Local maxima and lower minima are the simplest methods to detect peaks. The signal first has filtered and classified from a non-fall event to identify the sensitivity and specificity using classifier linear app in MATLAB R2017a. Android smartphone will detect the fall signal and use Arduino Uno to indicate the aid from the regular assistance, i.e., drinking water or walking to the bathroom.

## 2. METHODS AND MATERIALS

### 2.1 Hardware part

The system designed for Android KitKat LG D105 with 1.0 GHz Dual Core performance and 3.0” QVGA Display. The Android smartphone performs long-running services that can start and continue running in the background even if the user switches to a different activity. For example, we can utilize system services to derive data from the accelerometer sensors and gesture listener events. The cell phone is connected to Bluetooth HC-05, Arduino Uno, Relay 60Hz and flashing light to broadcast the indicated messages of the fall.

### 2.2 Software part

The application software used Java open source in Android Studio IDE. The framework of the fall detection algorithm, illustrated in **Error! Reference source not found.** 1, mainly divided into two stages. First, the phone used OnSensorChanged Method for Android accelerometer and applied (1) to find the length of the three axes in Cartesian Coordinates of the signal.

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

$$Sh = \sqrt{Ax^2 + Az^2} \qquad (2)$$

Where the sum of the all three axial accelerations is $(Sa)$, $(Sh)$ finds the frontal and sagittal acceleration components. Different falls and ADL trials were tested to find the threshold points [11]. Values taken from Android accelerometer application in this study showed falls towards a bed, occurs with lower minima values between 0.8 to 6.2g, free fall can occur at zero to 1.8 gravity, while the fall velocity estimated between 2 to 2.2 m/s. For ADL event: answer a phone call, the log showed magnitude between 7.7 to 14g.

### 2.3 Method

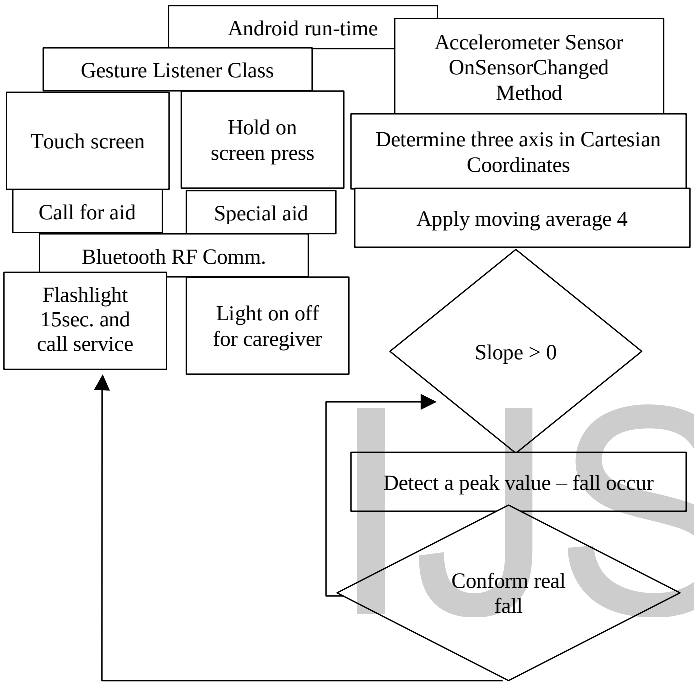


Fig. 1. System framework

Equation vector (1) has a noise that makes an obstacle to find peak values. The threshold peaks are used to discriminate between falls and rise the phone towards a subject's ear. For the related study, Kangas, Maarit [12] used low pass filter (LPF) to determine the impact data points and utilize the ability of LPF to find the fall phases' algorithms (Impact+Posture, Start of Fall+Impact+Posture, and Start of Velocity+Impact+Posture). Moving Average in Fig. 2 is a simple method in forex analysis and defines the direction of trend marketing. We have applied moving average with window size-4 to eliminate noise and reduce aliasing. The method is to simulate a fall out of the bed and extract the data for MATLAB analysis. The second procedure is to find peak values of the signal that indicates the fall. The processed signal used slope algorithm that compares two adjacent points and determines the differences if it equals to zero. The slope derivative will describe the best linear approximation of the function at a given point and it depends on how the function curve changes in several directions at once. The slope is determined:

$$m = \frac{y_2 - y_1}{x_2 - x_1} \qquad (3)$$

Where $y_2 - y_1$ the slope magnitude between two points and $x_2 - x_1$ is the slope index value

$m > 0$ The signal goes up from left to right

$m < 0$ The signal goes down from left to right

$m = 0$ The signal is horizontal and has a possible peak value.

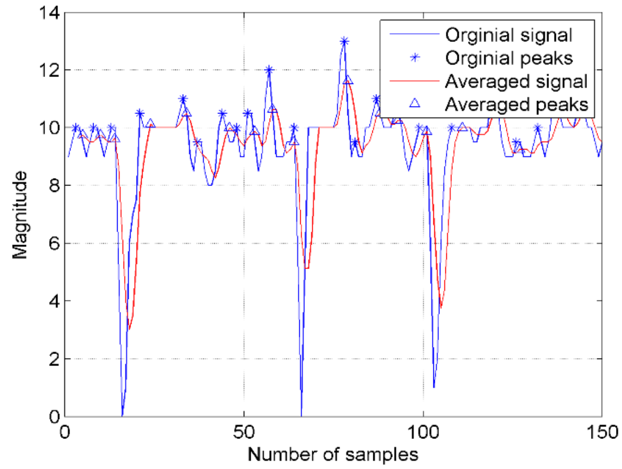


Fig. 2. Perform a fall towards a bed with/out averaging-4.

The slope detection method, in Fig. 1, was compared in MATLAB2011a using local maxima peaks function in [3].

Once a peak signal detected, a possible valley occurred beforehand. This indicates a real fall needs a quick response from the phone. We have given the user more control functionality to revoke permission to access phone contact for a call. The Android will take care of this by calling the ContextCompat.checkSelfPermission() method and passing back the user response with the same request code through onRequestPermissionsResult() method. The life cycle occurs once at the fall example. Hence, the Android runs in limited access resources, the application must ask for permissions outside its sandbox.

Most of the falls, caused by slips and trips attempt to mimic the real fall [13, 14]. However, the fall assumed in this study performed: forward fall, fall from the bed, fall while jumping, in which they compared with the most critical overlap signal: answer a phone call and climbing stairs.

The data collected from three young male subjects with average age 22±21 BMI. Each subject instructed to perform intentional fall and ADL activity in a home environment while the phone is in his pocket. The application is designed to collect fall and ADL data in short period of test with an event-based trigger and sample frequency 25Hz. The collected data from the phone buffer is transmitted to a laptop for further research.

## 3. Result

The resultant data is short-listed for Pearson correlation coefficient. With $\propto = 0.5$ and 33 samples, the obtained results in table.1 showed the multiple correlation relationships between their measurements. We state there is a significant relationship between direct forward fall and the fall towards a bed, and no relationship between raising the hand to answer a phone call event with the both direct

Table 1. Pearson correlations with α = 0.5

| | | Fall directly | Fall Towards Bed | Answer phone call | Climbing stair |
|---|---|---|---|---|---|
| Fall directly | Pearson Correlation | 1 | -.199 | -.098 | -.115 |
| | Sig. (2-tailed) | | .267 | .587 | .525 |
| | N | 33 | 33 | 33 | 33 |
| Fall Towards Bed | Pearson Correlation | -.199 | 1 | .091 | -.009 |
| | Sig. (2-tailed) | .267 | | .614 | .958 |
| | N | 33 | 33 | 33 | 33 |
| Answer phone call | Pearson Correlation | -.098 | .091 | 1 | .138 |
| | Sig. (2-tailed) | .587 | .614 | | .444 |
| | N | 33 | 33 | 33 | 33 |
| Climbing stair | Pearson Correlation | -.115 | -.009 | .138 | 1 |
| | Sig. (2-tailed) | .525 | .958 | .444 | |
| | N | 33 | 33 | 33 | 33 |

fall and fall towards a bed. However, the phases between falls from bed with answer a phone call event illustrated in Fig. 3. One can notice that they may have similar amplitude, but at each valley occurs, a high peak amplitude obtained during fall events. The fall peaks impacts shown in Fig. 3 were lower than 3g as discussed in section 2.2. In addition, Linear Discriminate Analysis, in MATLAB 2017a, was applied with 79 observations and 2 categories: Fall and ADL. The trained data-set obtained area under the curve (ROC) with 0.9, while the confusion matrix, evaluates how many falls fall on the true positive area from those who fall on the false negative, gave 83% sensitivity and 97% specificity with accuracy 88%. The second stage of the study used the gesture listener class GestureDetector.OnGestureListener() to notify the user with different motion events [15]. In order to react to the events of gestures, we have override two objects. OnDown() is an override method that notified when the user touches the screen at once-would toggle the Arduino Uno to turn the light on for an aid. In the case of no response, the application will access phone contacts for a call. The second method is OnLongPress() method, the user will hold press the screen of the application will toggle the Arduino, through Bluetooth, for special assistance as in Fig. 4



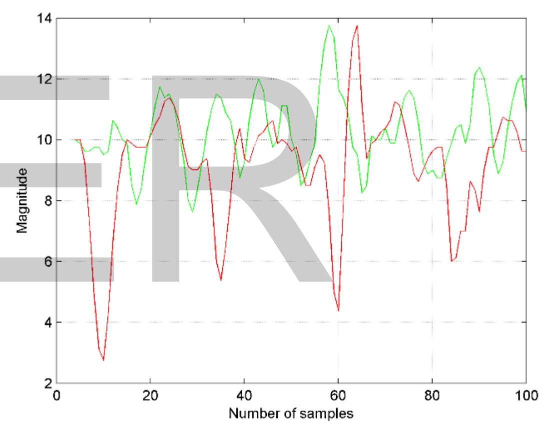


Fig 3 Comparison of a fall towards bed (red signal), with an answer a phone call event (green signal).

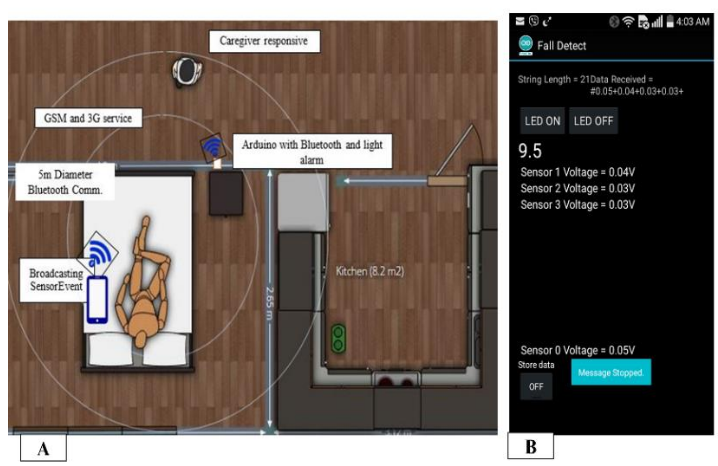


Fig 4. (A). System simulation. (B). Android design

## 4. Discussion

The application in this study tends to use the orientation changes of the signal based on the human body movement. We assume that the tilt degree of the body plays significant roles to detect a fall, but most of the non-fall events may overlap with the simulated real fall. We need a larger dataset from different fall events and different subjects. It is hard to instruct a subject to perform over 4 fall examples. Therefore, a different method could involve a fall from a dummy subject to perform falls onto different real-life surfaces. The future development of this study is to build a portable unit that is capable of monitoring fall and call for aid.

## 5. CONCLUSION

The challenge in this study was to obtain accurate readings from unobtrusive devices. The study can distinguish between Activity of Daily Living (ADL) and real fall from 88 trials. The application used the embedded accelerometer sensors provided from the Android phone. Accelerometer signals were processed and applied the slope method to find peak values that considered threshold points. Different activities measured and applied the linear classifier to obtain 83% sensitivity and 97% specificity with accuracy 88%. We have focused mostly on jumping events since the signal overlapped with the fall that may cause falsely measurements. The application is capable of alerting caregivers about their clients' activity through two options: Either by the motions (falling, ADL) or by the gesture listener class. The systematic research was limited to Bluetooth LE within the range of home. Although, the application implemented to use call service method through GSM and 3G communication in case of no response. However, the simplicity overwhelmed the application to serve countries with low incomes and high aging society.



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