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Human Fall Detection using Accelerometer and Gyroscope Sensors in Unconstrained Smartphone Positions

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Abstract*: This study explored several methods for detecting body falls based on the data captured by the sensors (accelerometer and gyroscope) built in a smartphone carried by a person. The data for this study were collected by recording many sample units from each of the following human activity categories: stand-fall, walk-fall, stand-jump, stand-sit, stand, and walk. Several time-series data captured by the sensors were used as human motion features. One of the challenges of this study was the existence of human body motions whose features resembled those of body falls. In addition, unfixed smartphone positioning made human body falls harder to detect and can lead to high rate of misclassification (not detected as fall). This incident can caused serious bone fracture or even death if the person not handled as immediately as possible because of misclassification. To address this problem, we modified Resultant Acceleration and ∠ Y formulas to address the problem of unconstrained smartphone positions. We proposed to combine five methods such as AGVeSR, Alim, ∠ α, GyroReDi, and AGPeak to build a robust detector model to reduce the misclassification. The experiment results showed that the accuracy of the combination of both sensors (accelerometer and gyroscope) outperformed the accuracy of accelerometer only by more than 15%. The decision fusion that used voting involving five methods could boost the accuracy rate by up to 4.15%.

***Keywords* : accelerometer, gyroscope, human fall detection, unconstrained smartphone positions.**

I. INTRODUCTION

Everybody wants to live independently in their preferred environments, including the elderly and people taking special treatments [1]. The increase of the elderly population in the "baby boomers" era can cause social problems, one of which is health issues that occur when they fall [2, 3]. The estimations of percentage of the elderly population potentially fall based on the data of the World Health Organization/WHO - 2007 are 28—35% for people aged 65 and up to 42% for those aged over 70 [4]. Fall incident can cause major health problems for the elderly and people taking special treatments (those with diabetes, stroke, early stage of dementia, or heart failure) [2, 5]. If the incident is not handled as immediately as possible, serious bone fracture, head injury, or even death may be caused [2, 5, 6, 7].

In the past two decades, there have been many studies proposing various methods for minimizing post-fall incident problems. One of the methods is fall detection [3, 7]. Human fall detection typically has two components, namely the component for detecting falls and that for communication. Smartphone is the best candidate for fall detection because it already has those components, is portable, and is already accepted by the elderly [8, 9, 10]. A smartphone has sensors (accelerometer, gyroscope, GPS, etc.) that can be pushed past their limits to detect human activities, and it can be used as a communication device [2, 10].

The advent of smartphone technology has inspired many researchers to use the various sensors available in a smartphone to detect body fall. Although many methods have been proposed, to the best of our knowledge, the previous methods set out a premise that the position of the smartphone used should be defined, and people will normally place their smartphones in any positions as they want [6]. Therefore, the aim of this study was to detect body fall using the sensors of a smartphone, which is not attached to a fixed location of the human body, under a monitor.

In this study, we proposed a fall detection method comprising of five methods which run in a parallel manner, namely: Accelerometer Gyroscope Vector Signal Resultant (AGVeSR), Alim, Alpha Degree (∠α), Gyroscope Resultant Distance (GyroReDi), and Accelerometer Gyroscope Peak (AGPeak). We made use of the existing method for Alim, but ∠α method was modified from ∠Y, and the other three methods AGVeSR, GyroReDi, and AGPeak were the enhancement of accelerometer-based methods (Accelerometer Amplitude, Resultant Acceleration, and Signal Vector Magnitude (SVM)) for the purpose of accommodating unconstrained smartphone positions [3, 7, 11].

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Receiver Operating Characteristic (ROC) curves were used to distinguish between the results of AGVeSR method that used two sensors (accelerometer and gyroscope) and those of the other methods that used accelerometer sensor only [4]. Accelerometer-gyroscope (AGVeSR) ROC curve had better results than accelerometer ROC curve. The combination of two sensors (accelerometer and gyroscope) and the five proposed methods could increase the accuracy rate better than a single sensor (accelerometer).

II. LITERATURE REVIEW

Fall detection methods can be divided into three main methods, namely: acoustic/vibration-based method, image-based method, and carried/ wearable-sensor-based method [7]. Each method will analyze fall patterns informed by each specific sensor provided.

A. Acoustic/Vibration-Based Method

A piezoelectric sensor is placed on the floor to detect sound or vibration patterns [12, 13]. The purpose of placing this sensor on the floor is to detect the vibration caused when someone falls [12, 13, 14]. The patterns recognized are monitored to detect vibration patterns caused by falls because usually these patterns are different from those of other human activities and the fall of objects [12, 13, 16]. Since this method does not require the use of a wearable device, people do not need to remember to wear this device when they want to do their daily activities [13, 15]. The downsides of this method are that fall cannot be detected if it occurs in an uncovered area and that the sensors are not readily movable to any place 12, 13, 14].

B. Image-Based Method

A camera (or video camera) is usually used as a sensor, and it is installed on a wall in a fixed position. This method is targeted to detect movements in a given period of time [13, 17, 18, 19, 20, 21, 22]. If the image-processing algorithm detects that a certain object does not move for more than a certain period of time, or if it identifies some unusual activities, it means that the object (human) has fallen [13]. The advantage of image-based method is that there is no need to encourage people to wear pendants with call buttons [17]. The disadvantages of this method are similar with those of acoustic/vibration-based method, and people will usually be skeptical and have the feeling of being spied, watched, or monitored [13].

C. Carried/Wearable-Sensor-Based Method

Accelerometer and gyroscope sensors are typically used in carried- or wearable-sensor method [3, 23, 24, 25, 26, 27, 28, 29]. Sensors can detect the force caused by falls. The downside of this method is that the sensor can only detect when its position has been defined before. Some methods that are based on a threshold used in the detection of fall are Accelerometer Amplitude, Resultant Acceleration, and Signal Vector Magnitude methods [3, 7, 11].

Resultant Acceleration, Accelerometer Amplitude, and Signal Vector Magnitude methods basically have very similar formulas [3, 7, 11]:

$$Asum = \sqrt{\left(AX^2 + AY^2 + AZ^2\right)} \qquad (1)$$

Equation (1) is the formula of Resultant Acceleration method, where AX, AY, and AZ represent the acceleration on the X, Y, and Z axes in accelerometer sensor. This method can detect fall in the form of accelerometer signals because it can detect significant changes if a fall occurs. If the peak value of (1) exceeds the threshold, it means that a human has fallen.

Smartphone can be categorized as a wearable device because it can be placed by the user in their pocket, smartphone armband, or bag [7, 8]. Wearable-sensor method usually depends on accelerometer or gyroscope sensor equipped in a device [2, 7, 8, 10]. Occam's razor rule is perfect to be implemented due to the limitation of smartphone hardware because simple computation is needed to detect fall using the smartphone's sensors [30]. As a result, decision tree for human fall detection can be formed when fall detection method is combined with Occam's razor.

D. Previous Research

The method used to detect fall can be divided into two areas, namely threshold-based detection and pattern recognition. Threshold-based detection focuses on the mathematical calculation of thresholding, while pattern recognition can be done by implementing machine learning [4, 8, 11]. Threshold-based detection tends to be used for human fall detection more widely because its computation process can be done relatively fast, and this is evidenced by its wide use in smartphones. This computation does not require hardware with high specification, and it is faster and easier to implement compared to pattern recognition. The downsides of threshold-based detection are that its accuracy tends to be lower than that of pattern recognition and that there is a need for recalculation in the threshold-based detection if a new dataset is provided. Accelerometer-based methods (Accelerometer Amplitude, Resultant Acceleration, and Signal Vector Magnitude (SVM)) are widely used for human detection in conjunction with threshold-based detection because they have quite good accuracy for some specific datasets, and they do not need any complex computation process to detect fall.

III. METHOD

Accelerometer and gyroscope will respond if a movement occurs. Based on Fig. 1, both accelerometer and gyroscope respond based on fall (green rectangles). By the time this research was conducted, Resultant Acceleration method had been implemented only for accelerometer sensor. We proposed gyroscope sensor to be used along with accelerometer to increase the accuracy rate of human fall detection.

Data are collected using an Android smartphone to capture accelerometer and gyroscope signals when human does some activities. Human falls are detected and the data are compared to a threshold, and this was modified by the researchers to be used as pattern recognition for recognizing fall patterns based on the given features (Soh, 2017).

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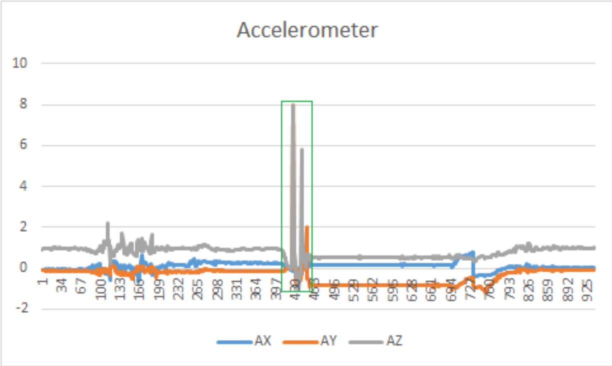

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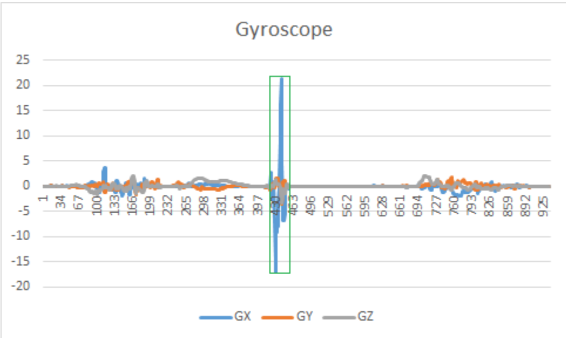

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Fig. 1. Signal comparison when doing stand-fall activity in a face-up position: (a) accelerometer and (b) gyroscope

A. Accelerometer Gyroscope Vector Signal Resultant (AGVeSR)

By using the Resultant Acceleration formula, the accelerometer sensor, which has X, Y, and Z axes (AX, AY, and AZ), calculates based on the signals that pass some thresholds to detect fall. As a result, the three accelerometer axes - AX, AY, and AZ - become one feature. The implementation of ROC curve in a threshold-based Resultant Acceleration accelerometer sensor is represented in Fig. 2(a). This ROC curve has a unique characteristic because if the threshold is set too low or too high, the threshold will either accept or reject both True Positive (TP) and False Positive (FP).

Table- I: Resultant Acceleration for stand-fall data sample: face-down position

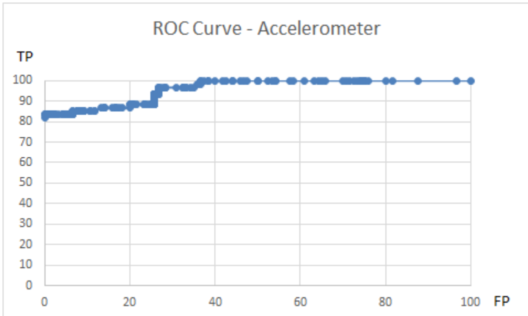
AX	AY	AZ	Resultant Acceleration
-0.016	0.024	-0.019	0.035
-8.000	2.079	-8.000	11.503
-2.785	1.107	0.168	3.002
-0.039	-0.011	-0.036	0.054
0.047	-0.771	0.027	0.773

Sometimes accelerometer sensor is not sufficient for fall detection. We combined accelerometer and gyroscope sensors on the grounds that in the preliminary research, the accuracy of fall detection increased when both sensors were combined. A new method called AGVeSR (2) was proposed to capture human movement when they fall or do other activities in their daily life. Resultant Acceleration method was modified, and gyroscope data were added to yield better results. AGVeSR combines both accelerometer and gyroscope sensors, and a total of six values are extracted from each axis.

$$AGVeSR = \sqrt{\left((|AX|+GX)^2 + (|AY|+GY)^2 + (|AZ|+GZ)^2\right)} \quad (2)$$

AX, AY, and AZ represent acceleration on the X, Y, and Z axes in accelerometer, and GX, GY, and GZ represent acceleration on the X, Y, and Z axes in gyroscope. The benefit of the implementation of this formula is that it does not detect fall based on specific orientations as it applies absolute notation. If a certain axis has a negative value, the value will be converted into positive thanks to the application of absolute notation. An absolute value will allow for the calculation of smartphone sensor's data and allow the sensor to detect human activities in various (unconstrained) smartphone positions.

ROC represents the performance metric or the characteristic of the method. This research aimed to reach 100% TP and minimum FP value as fall risk that can be misclassified is more crucial than non-fall. An FP value that is too high (more than 10%) will irritate the user of this method because the sensor misclassifies non-fall actions too often. An ideal ROC system characteristic is achieved if the TP value is near 100 and the FP value is near 0. The results of the observation, experiment, and comparison of ROC presented in Fig. 2(b) showed that the combination of accelerometer and gyroscope sensors (AGVeSR) had better results (FP values being near 0 and higher TP values) than those of accelerometer sensor only.



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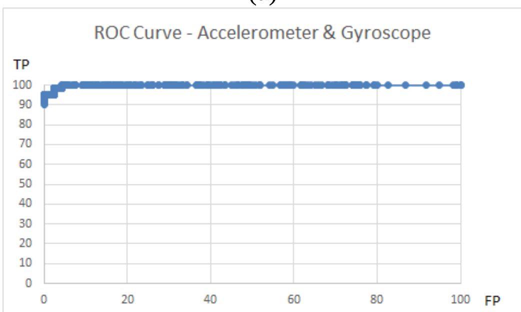

(b)

Fig. 2. Signal comparison when doing stand-fall activity in a face-up position: (a) accelerometer and (b) gyroscope

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B. Linear Acceleration (Ali) and Sum Vector of Linear Acceleration (Alim)

To distinguish between fall and non-fall actions, a sum vector value that excludes the gravity vector should be calculated to count linear acceleration (Ali) and sum vector of it (Alim) [23]. AX, AY, and AZ are the acceleration on the X, Y, and Z axes in accelerometer. GX, GY, and GZ represent the acceleration on the X, Y, and Z axes in gyroscope. We implemented Ali (3) and Alim (4) to accommodate our research problem without depending on smartphone positions.

$$Ali = \left[\left(AX - GX \right), \left(AY - GY \right), \left(AZ - GZ \right) \right] \quad (3)$$

$$Alim = | Ali | \quad (4)$$

C. Alpha Degree (∠α)

Since body posture will change when fall occurs, the smartphone angle needs to be measured using ∠Y (5) [31]. This formula is based on the acceleration on the X, Y, and Z axes in accelerometer (AX, AY, and AZ). The inclination between the person who carries the smartphone when falling and the ground plane can be computed with the help of the accelerometer sensor [31]. The corresponding window from the 25th and the 1st data (0.5 second gap) will be compared to determine the tilting angle. If the angle calculated has a value of more than the specified threshold (60°), it means that a fall has occurred.

$$\angle Y = \tan^{-1} \left(\frac{AY}{\sqrt{AX^2 + AZ^2}} \right) \quad (5)$$

Because the smartphone position is not fixed, (5) needs to be customized depending on the smartphone orientation. Equation (6) and Table II represent our customized formula based on the accelerometer axes and orientations. Before calculating ∠α, the algorithm should have determined the highest axis absolute value of the accelerometer. To validate the value, the values of all accelerometer axes should be converted into hundred value (e.g. 0.053 is converted into 5.3). If the absolute value of X is higher than those of Y and Z, it will goes to α notation, Y to β, and Z goes to γ. For more (6) legends, please refer to Table II.

$$\angle \alpha = \tan^{-1} \left(\frac{A\alpha}{\sqrt{A\beta^2 + A\gamma^2}} \right) \quad (6)$$

Table- II: Resultant Acceleration for stand-fall data sample: face-down position

Highest Axis Value	α	β	γ
|X|	X	Y	Z
|Y|	Y	X	Z
|Z|	Z	X	Y

D. Gyroscope Resultant Distance (GyroReDi)

Gyroscope signals have a sudden high spike when a fall occurs (Fig. 1(b)). This spike can be used in the fall detection method because it can indicate the sudden movement caused when someone falls. The orientation of the smartphone will not be counted because the method should work in unconstrained smartphone positions.

$$GyroRe = \sqrt{\left(GX^2 + GY^2 + GZ^2 \right)} \quad (7)$$

$$GyroReDi = \frac{\left(GyroRe(n) - GyroRe(n-2) \right) + \left(GyroRe(n-2) - GyroRe(n-4) \right)}{2} \quad (8)$$

GyroRe (7) is based on X, Y, and Z axes in gyroscope (GX, GY, and GZ). GyroReDi (8) method counts the average gyroscope resultant distance from a specific timeline (n). Timeframes n, n-2, and n-4 are chosen based on the signal characteristic. There is 0.08 second of latency since the method needs to check the surrounding timelines, and in this case, four previous timeframes need to be checked when the method is executed. If the GyroReDi exceeds the specific threshold, it means that a fall has occurred, and the specific timeline will be marked with fall.

E. Accelerometer Gyroscope Peak (AGPeak)

The high spike in accelerometer when a fall occurs usually corresponds to the high spike in gyroscope (Fig. 1(a) and Fig. 1(b)). The AGPeak formula computes the sum of the signal vector of each sensor to be compared with each threshold. Ac notation (9) is used for counting and comparing the vector magnitude of accelerometer sensor with Tha (the threshold of accelerometer). Gy (10) indicates the summation of gyroscope vector magnitude and compares it with Thg (gyroscope's threshold). If Ac and Gy are similar (both have a spike), AGPeak method will detect it as a fall action.

$$Ac = \sum_{i=1}^{n} \sqrt{\left(AX^2 + AY^2 + AZ^2 \right) i} > Tha \quad (9)$$

$$Gy = \sum_{i=1}^{n} \sqrt{\left(GX^2 + GY^2 + GZ^2 \right) i} > Thg \quad (10)$$

F. Fall Detection Method

The proposed method for detecting fall comprises of five methods which run in a parallel manner, namely: AGVeSR, Alim, ∠α, GyroReDi, and AGPeak. Each method is in fact able to detect fall by using a threshold. To increase the accuracy of each method, decision fusion using voting is used for fall detection. If the majority of the methods (at least three methods) detect the data as a fall, the action is classified as a fall. The process block of fall detection method is represented in Fig. 3.

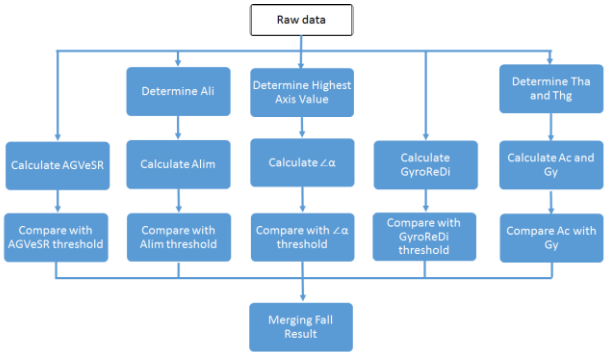


Fig. 3. Block diagram of fall detection method

Due to smartphone's hardware limitation, these features are specially handcrafted to have a simple process and to be able to run fast on the smartphone. The implementation of the five methods for fall detection will not trade the ability of the smartphone's hardware to process other tasks because the cost to combine all methods are not too high.

IV. RESULT AND DISCUSSION

The experiment conducted was divided in two steps, namely: model development (training) and model verification (testing). Generally, each step started with reading the raw data from accelerometer and gyroscope sensors, followed by calculating the values obtained using five methods (Fig. 4): AGVeSR – Alim – ∠α – GyroReDi – AGPeak, categorizing the action as a fall if the values obtained exceeded the threshold, and calculating the accuracy.

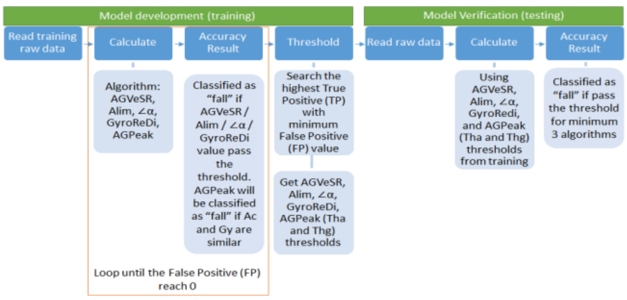


Fig. 4.Experimental flow

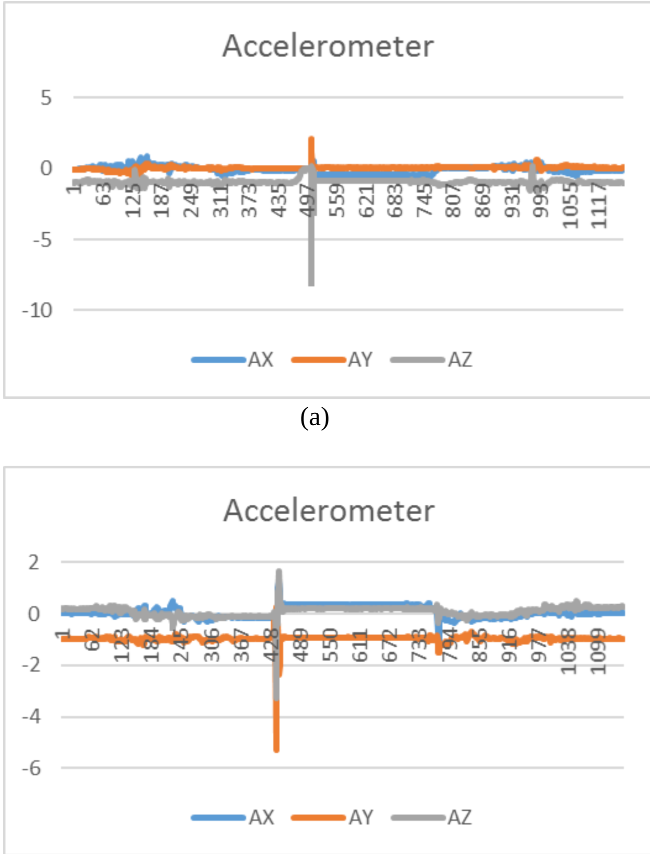
A. Data

Time-series raw data from accelerometer and gyroscope sensors were captured using a smartphone. Each sensor has X, Y, and Z axes, making up six axes in total (AX, AY, AZ, GX, GY, and GZ), where A indicates accelerometer and G indicates gyroscope (Table III).

Table- III: Stand-fall sample data in face-down position

AX	AY	AZ	GX	GY	GZ
-0.016	0.024	-0.019	0.663	1.247	-0.197
-8.000	2.079	-8.000	0.613	0.839	-0.188
-2.785	1.107	0.168	-3.264	7.592	-2.380
-0.039	-0.011	-0.036	0.340	1.261	-0.216
0.047	-0.771	0.027	0.69	0.395	-0.033

The data were classified and labelled into two classes, namely fall and non-fall. There were 84 data for fall (stand-fall and walk-fall) and 168 data for non-fall (stand-jump, stand-sit-stand, stand, and walk). Each activity was captured in six different smartphone positions: face-up, face-down, vertical-bottom, vertical-left, vertical-right, and vertical-top.



(a)

(b)

Fig. 5.Accelerometer – stand-fall: (a) face-down position and (b) vertical-down position

B. Experimental Design

The experiment was conducted indoor. The data of the two classes of activities — non-fall and fall — were captured using an Android smartphone in six different smartphone positions: if the smartphone was in a face-up position, it faced upwards; if it was in a face-down position, it faced downwards; if it was in a vertical-bottom position, it was on a standing position; if it was in vertical-left position, it was left-landscape-oriented (i.e. the home button on the left side of the smartphone); if it was in the vertical-right position, it was right-landscape-oriented; and if it was in the vertical-top position, it was in the upside down, standing position. Non-fall activities included stand-jump, stand-sit-stand, stand, and walk, and fall activities included stand-fall and walk-fall. The respondents were from both genders: male and female and aged 25-35. A mattress was used for safety reason.

The training-testing data were chosen randomly, and leave-one-out cross-validation was used for this experiment.

As many as 180 training data (60 fall data, 120 non-fall data) and 72 testing data (24 fall data, 48 non-fall data) were used.

C. Model Implementation - Fall Detection Model

Six different smartphone positions of each activity were tested using AGVeSR, Alim, ∠α, GyroReDi, and AGPeak methods. AGVeSR method played a big role in fall detection in unconstrained smartphone positions. The results obtained by using the the AGVeSR method were compared one to another to accurately identify whether there was any difference between the smartphone positions. Vertical positions were very difficult to measure because each sensor did not have the same reaction as pre- and post-smartphone positions were not always in the same. Face-up and face-down positions were more stable than vertical positions. Since the sensors would react differently depending on the smartphone positions (Table IV), AGVeSR method would neutralize the occurring anomaly because it implements absolute notation. As a result, positive resultant values were obtained when AGVeSR method was used.

Table- IV: Smartphone sensor reaction when fall occurred

Smartphone Positions	AX	AY	AZ	GX	GY	GZ
face-up	no	no	+	no	+	no
face-down	no	no	-	+	no	no
vertical-bottom	-	-	-	no	+ / -	+ / -
vertical-left	no	no	-	+ / -	-	+
vertical-right	no	+ / -	+	+ / -	+	-
vertical-top	no	+	+	+	+	-

Legends: no means no movement in sensor, + means sensor value moves to positive (going up), – means sensor value moves to negative (going down), +/- means sensor value moves to positive and negative (can be both ways: up and down)

D. Accuracy Results

There were 84 fall data and 168 non-fall data for testing the accuracy of human fall detection method. One-leave-out cross-validation was used, and the data were divided into training data (60 fall data, 120 non-fall data) and testing data (24 fall data, 48 non-fall data). Testing data were randomly chosen. The threshold for fall detection was chosen carefully based on the ROC curve for forming the decision tree. Because the accuracy of fall detection is more crucial than non-fall detection, the fall detection threshold was picked based on the highest TP value and the lowest FP value. When the data were tested using accelerometer-based method (Resultant Acceleration) with only one sensor (accelerometer), the resulted accuracy was 76.67%. When the method was enhanced, and the accelerator sensor was combined with gyroscope sensor in AGVeSR, the accuracy increased by more than 15%. When the proposed method consisting of five methods was used, a better result was obtained, and the accuracy rate could reach up to 95.82% (Table V). Stand-jump and stand-sit-stand were two actions that were most frequently misclassified since the signals of both actions had a spike similar to those of fall, but not as high.

Table- V: Accuracy results of fall detection methods

Resultant Acceleration	AGVeSR	Five Methods
76.67%	91.67%	95.82%

V. CONCLUSION

Fall detection for the elderly and people taking special treatments is needed since it can minimize post-fall incident problems. Smartphone with accelerometer and gyroscope sensors is a perfect device for human fall detection because they have already been accepted by most people. A human fall detection comprising of five methods: AGVeSR, Alim, ∠α, GyroReDi, and AGPeak can help detect human falls using smartphone sensors when the falls occur and solve the problem if people use their smartphones in many positions. The formula in each method uses absolute notation or power to neutralize negative values and generates resultant for accelerometer and gyroscope axes. In this research, ∠α method was modified from ∠Y, and the other three methods: AGVeSR, GyroReDi, and AGPeak, were inspired by Resultant Acceleration formula for accommodating the problem of unconstrained smartphone positions. The combination of two sensors (accelerometer and gyroscope) can increase the accuracy by more than 15%, which is better than the accuracy of a single sensor (accelerometer). The decision fusion using voting for five methods used for decision making to detect fall could boost the accuracy by up to 4.15%.

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