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Fall Detection System for Elderly Based on Android Smartphone

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***Abstract*—Physical ability of elderly person will degrade as the aging process occurs, thereby increasing the potential for falls. Falls on the elderly will have serious impact such as injury or even death if they do not get help immediately. Aid can be given more quickly if the occurrence of falls can be immediately detected. This paper study the fall detection technique using Android smartphone. The proposed technique computes the total acceleration and tilt angle from accelerometer sensor in smartphone. Fall is detected based on total acceleration and sum of difference of total acceleration. The tilt angle is used to mark whether a forward fall, backward fall, fall to the left, or fall to the right. The results show that the proposed technique has a sensitivity of 90% and specificity of 94% in a total set of 490 movements.**

***Index Terms*—Elderly, accelerometer, total acceleration, sum of difference of total acceleration, tilt angle, Android.**

I. INTRODUCTION

Physical ability of elderly person will degrade as the aging process occurs, thereby increasing the potential for falls. Approximately 50% of nursing home residents fall at least once a years, while 40% of them fall more than once [1]. According to the research in [2] 28% to 35% of people, aged above 65, fall at least once a year. Another study stated that one of two people, aged 80 or over, have experienced falls [3]. Number of persons, aged 60 years and over was 841 millions in 2013 and it is estimated that nearly 2 billion of person aged 60 years and over in 2050 [4]. Thus, falls affect millions of people (especially the elderly) and may result in significant injuries.

The fall of the person can be described as uncontrolled movements from standing or sitting position to a lying or almost lying position [3]. Fall will certainly have a direct impact on health, such as increase of mortality, morbidity, disability, and frailty [5]. Therefore, a system that can detect the uncontrolled movement such as fall is needed.

Yu [6] categorizes methods of fall detection into three approaches: wearable device, ambiance device, and camera-based. Among three approaches, wearable device has a relatively low cost and ease to configure [6]. Wearable devices can be worn on clothes or part of certain body, or held by the user. Smartphone and microcontroller can be designed as a wearable devices, because they have a relatively small size and enough computational capability to process data.

Chen *et al.* use microcontroller as a processing unit to generate total acceleration and tilt angle on z-axis from accelerometer sensor [7]. The proposed system has sensitivity of 95% and specificity of 100%. Sensitivity is ability of system to identify fall. Specificity is ability of system to detect non fall activities. Falls detection technique using accelerometer sensors on smartphones have been done by previous works [8] [9] [10]. Feature extraction on acceleration of accelerometer sensor can use method Signal Magnitude Area (SMA), Signal Magnitude Vector (SVM), and Tilt Angle (TA). The results obtained from feature extraction are used as a parameter to detect fall [8]. Fang *et al.* [10] use the total and vertical accelerations to distinguish fall with normal activity. This method has a sensitivity of 72% and specificity of 73%. Dai *et al.* [9] use the same method with Fang, but they add time window. Referencing to the dynamic of free fall, velocity can be used as a parameter whether fall has occurred or not [11] [12].

This paper study the fall detection technique using Android smartphone. The proposed technique uses total acceleration, sum of difference of total acceleration, and tilt angle. Tilt angle consist of three, namely, tilt angle based on x-axis, y-axis, and z-axis. Tilt angles are used to mark the fall direction, whether a forward fall, backward fall, fall to the left, or fall to the right. All of parameters, such as total acceleration, sum of difference of total acceleration, and tilt angle are generated by accelerometer sensor in Android smartphone. This paper focus on developing methods for improving sensitivity and specificity based on Android smartphone.

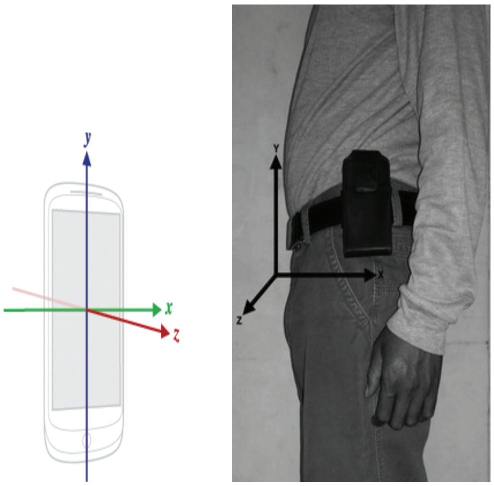
The remainder of this paper is organized as follows. Section II describes the design of the proposed system. The experimental results are represented in section III. Section IV concludes the paper.

II. SYSTEM DESIGN

A. System Overview

The proposed system uses a smartphone with Android operating system. The accelerometer sensor has three axis, namely x-axis, y-axis, and z-axis, which can create sensing data in three-dimentional space. The x-axis forms horizontal line, y-axis forms vertical line, and z-axis leads to front and back of screen device (see Fig. 1a). As shown in Fig. 1b, smartphone is attached on the left waist. The device has placed firmly on the belt, so that the position of device does not change during falls.

As shown in Fig. 2, there are three important parts of fall detection processes, namely total acceleration, sum of difference of total acceleration, and tilt angle. First, acceleration from sensor accelerometer is filtered by high pass filter. After that the total acceleration is calculated. Fall is detected by comparing the total acceleration, sum of difference total acceleration, and tilt angle with the threshold values.



(a) [13] (b)

Fig. 1: (a) X-axis, y-axis, z-axis on smartphone. (b) Smartphone attached on left waist.

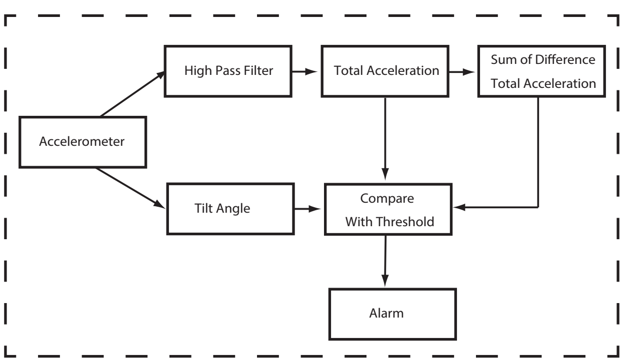


Fig. 2: Process of fall detection.

B. Algorithm of Fall Detection

Acceleration on accelerometer sensor is affected by mass of the device, force, and gravity. Fig. 3 shows that when the smartphone is placed horizontally, acceleration of x-axis, and y-axis is 0 m/s^2, while z-axis is 9.81 m/s^2.

To get the actual value of acceleration, the influence of gravity and noise can be removed by filtering. There are two filters that can be applied, namely high pass filter and low pass filter. Bylemans *et al.* [14] used two filters to reduce the effect of gravity and noise. However, this study only uses a high pass filter such as Eq. (1). Fig. 4 shows the results of a high pass filter, where the acceleration in the z-axis is close to zero when the smartphone is placed horizontally. In other words, the effect of gravity is reduced using filter.

$$\begin{aligned} ACCHPavg &= ACCnew * 0.1 + ACCHPavg * 0.9 \\ ACCHPFiltered &= ACCnew - ACCHPavg, \end{aligned} \tag{1}$$

where ACCnew is data obtained from each axis of accelerometer, ACCHPavg is acceleration that has been isolated from force of gravity, and ACCHPFiltered is result of high pass filter.

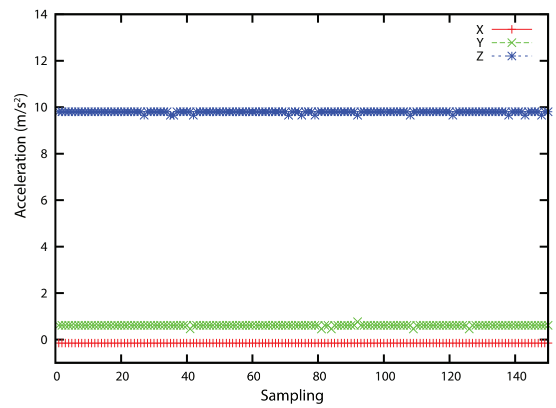


Fig. 3: Acceleration without filtering.

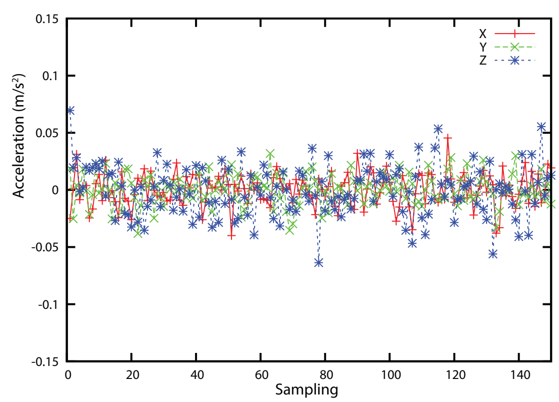


Fig. 4: Acceleration with filtering.

In the fall detection process, the accelerometer sensor continuously monitors acceleration of a smartphone along three axes. After filtering process, total acceleration (AT) is calculated using Eq. (2). As indicated in Eq. (2) A_x, A_y, and A_z, are the acceleration in the x, y, z axes, respectively. Generally, movements of fall are faster than normal activities, so that total acceleration caused by falls is higher than that of normal activities. As shown Fig. 5, total acceleration soars from normal activities (such as walking) to the position of the falls, and then decreased significantly when the body begins to lay. In addition, falls and normal activity are distinguished by using sum of difference of total acceleration SDif. It is calculated by Eq. (3). SDif is calculated if AT reaches a peak that is caused by a fall.

$$AT = \sqrt{A_{x^2} + A_{y^2} + A_{z^2}} \tag{2}$$

$$SDif = \sum_{i=0}^{6} AT_{i+1} - AT_i \tag{3}$$

Fall is an uncontrolled movement from a standing position to a lying position. The position of standing and lying can be differentiated by using tilt angle. The position of lying caused by falls is used to mark the direction of fall, such as forward fall, backward fall, fall to the left, or fall to the right. Each position of lying that caused by falls, has differences of tilt angle with others activities.

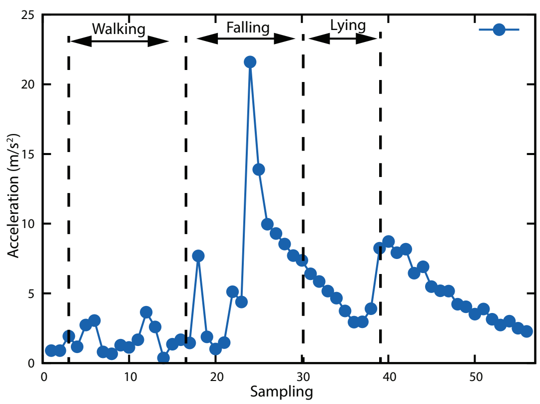


Fig. 5: Acceleration with filtering.

In this study, tilt angles are calculated based on acceleration that is generated by the accelerometer sensor on x-axis, y-axis, and z-axis. As indicated in Eq. (4)-(6), the tilt angles of three axes are denoted by TA_x, TA_y, TA_z and gravity is denoted by G. Chen *et al.* [7] used tilt angle to identify fall, but they only used single angle on z-axis.

$$TA_x = \arccos(A_{x/G}) \times (180/pi) \tag{4}$$

$$TA_y = \arccos(A_{y/G}) \times (180/pi) \tag{5}$$

$$TA_z = \arccos(A_{z/G}) \times (180/pi) \tag{6}$$

Tilt angles that are generated by sensor accelerometer depend on the position of smartphone. Fig. 6 shows the up position, left position, right position, back-up position, and front up position of smartphone. Tilt angles based on position of smartphone (see Fig. 6) are shown by Table I.

Normally, position of smartphone on standing position, lying face down, lying face up, lying on the left side, and lying on the right side, are shown in Fig. 6a-6e respectively. This condition applies if the smartphone is attached on the left

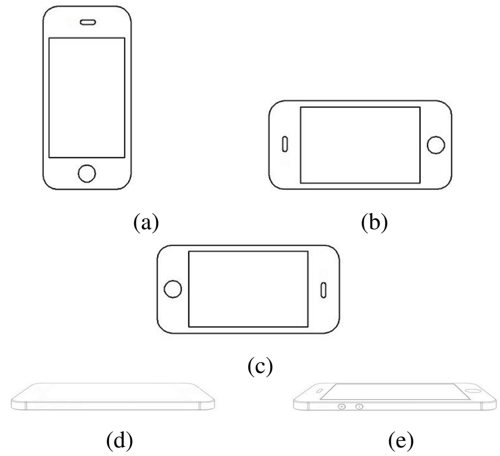


Fig. 6: (a) Up position. (b) Left position. (c) Right position. (d) Back-up position. (e) Front up position.

TABLE I: Tilt angle based on smartphone position

Position	TA_x	TA_y	TA_z
Up	90	0	90
Left	0	90	90
Right	180	90	90
Back-up	90	90	180
Front up	90	90	0

waist as shown Fig. 1. In reality, tilt angles of lying that are caused by fall are not always the same with the tilt angles that are shown Table I. However, it can be approached using the minimum and maximum values as shown in Table II.

TABLE II: Aproach of tilt angle

Position	TA_x		TA_y		TA_z	
	Min	Max	Min	Max	Min	Max
Lying face down	0	45	75	115	75	115
Lying face up	140	180	75	115	75	115
Lying on the left side	75	115	75	115	140	180
Lying on the right side	75	115	75	115	0	45

To determine threshold of total acceleration AT_{Th} and sum of difference of total acceleration $SDif_{Th}$, extensive experiments are performed (200 times). Since it is high risk to conduct the experiment on the elderly, the non-elderly is used as the subject of experiment. AT_{Th} of greater than or equal to 11 m/s^2 and $SDif_{Th}$ of less than or equal to -2 m/s^2 were based on experiments.

If the total acceleration is greater or equal to 11 m/s^2 in certain sample, it is marked as AT_0, and next samples are marked as AT_1 to AT_7 respectively, as shown in Fig. 7. Based on AT_0 to AT_7 the sum of difference of total acceleratioan can be calculated. When AT is greater or equal to AT_{th}, and SDif is greater or equal to $SDif_{th}$, tilt angles TA_x, TA_y, and TA_z are calculated, then they are observed along samples AT_0 to AT_7. If contains tilt angle as shown in Table II, it is can be categorized as fall.

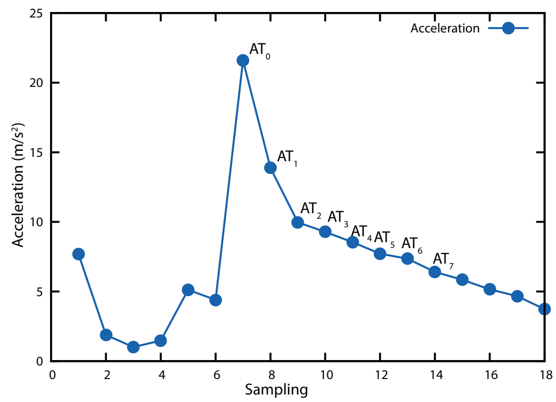


Fig. 7: Calculating SDif along AT_0 to AT_7.

III. Results

A. Experiment Design

Tests are carried out on three subject who have weight about 60-75 kg and height 170-180 cm. Mattress that is used in the experiments has high about 25 cm from floor. Table III shows the design of experiments.

TABLE III: Experiment Design

Category	Instruction
Forward fall	Ending Lying
	Ending Lateral Position
	With Recovery
	On the Knees
Backward fall	Ending Lying
	Ending Lateral Position
	Lateral Position
	With Recovery
Fall to the left	Ending Lying
	With Recovery
Fall to the right	Ending Lying
	With Recovery
Normal Activities	Sitting Down-Stand Up
	Lying Down-Rising Up
	Walking
	Bending Down-Rising Up
	Running

Performance of fall detection system can be measured by sensitivity and specificity. There are four parameter that are used in measuring the performance. True positive (TP), means that fall occurs, the system can correctly detects. False positive (FP), means that the system detects fall when no fall occurs. True negative (TN), means that system does not detect fall when no fall occurs. False negative (FN), means that the system does not detect fall but fall occurs.

$$Sensitivity = \frac{TP}{TP + FN} \tag{7}$$

$$Specificity = \frac{TN}{TN + FP} \tag{8}$$

B. Experiment Results

Experiments are conducted in 490 movements, which is categorized into fall by 365 movements, and normal activities by 125 movements. Since it is high risk to conduct the experiment on the elderly, the non-elderly is used as the subject of experiment. We also compare result without SDif and result with SDif. The results are shown in Table IV and V.

TABLE IV: Experiment results

Category	Times	Without SDif		With SDif	
		True	False	True	False
Forward fall	92	85	7	85	7
Backward fall	93	86	7	86	7
Fall to the left	90	83	7	83	7
Fall to the right	90	76	14	76	14

TABLE V: Experiment results in normal activities

Category	Times	Wihtout SDif		With SDif	
		True	False	True	False
Sitting Down-Stand Up	25	0	25	0	25
Lying Down-Rising Up	25	3	22	3	22
Walking	25	0	25	0	25
Bending Down-Rising Up	25	0	25	0	25
Running	25	4	21	4	21

Numbers of true positive (TP) and false positive (FP) are determined based on fall categories as shown in table IV, and true negative (TN) and false negative (FN) are determined based on normal activities as shown in Table V. Number each of parameter is shown in Table VI.

TABLE VI: Number of parameter

Parameters	Scheme without SDif	Scheme with SDif
True positive (TP)	330	330
True negative (TN)	118	118
False negative (FN)	7	7
False positive (FP)	35	35

TABLE VII: Comparing our scheme with previous work

Proposed	Sensitivity	Specificity
Previous work [10]	56.67%	66.39%
Scheme without SDif	90.41%	94.4%
Scheme with SDif	90.41%	94.4%

Based on the results as shown in Table VII, the proposed scheme with SDif and without SDif have sensitivity of 90.41% and specificity of 94.4%, which improves the performance of system compared to that of previous work [10]. Tilt angle based on x-axis, y-axis, and z-axis is one factor that caused the proposed scheme better sensitivity and specificity than previous work. There are no difference between proposed scheme with SDif and without SDif, this may be due to the sampling rate of the accelerometer in smartphone is low.

IV. Conclusions

In this paper, we have proposed technique uses total acceleration and sum of difference of total acceleration (SDif) to identify falls. We also use tilt angle to mark whether a forward fall, backward fall, fall to the left, or fall to the right.

The proposed technique with SDif and without SDIf have sensitivity of 90% and specificity of 94% from 180 movements. It is important to note that the combination of AT and SDif can only mark a drastic changes in acceleration that are caused by falls. Sometimes normal activities produce drastic changes in acceleration, so that they will be detected as a fall. Exploring the factors that influence the performance of the proposed scheme is left as our future work.

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