Pre-Impact Fall Detection Based on Wearable Device Using Dynamic Threshold Model

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***Abstract*—Falling accidents, including slipping, tripping and falling, are the primary reason of injury related to death not only for elderly, but for young people or worker happening at workplace also. If falling accident can be early detected in pre-fall or critical fall phase, called pre-impact fall detection, it will be very useful such as conducting airbag inflation. Furthermore, various detection methods, with an uncomplicated threshold detection method, do maximizing the true positive prediction values but the lead-time, time before subject impacts to the floor, will likely increases the chance of false alarms. Consequently the researcher found that the using of adaptive threshold may reduce false alarms. In this paper, the dynamic threshold method, automatically adjustable threshold for pre-impact fall detection in wearable device, has been proposed and experimented. For our evaluation, 192 instances of several kinds of activity of daily living and falling, were captured. All activities were performed by 6 different young healthy volunteers, 4 males and 2 females, aged between 19 and 21. The several experiments were conducted for performance evaluation including sensitivity, specificity and accuracy measurements. The results of proposed method can detect the pre-impact fall from normal activities of daily living with 99.48% sensitivity, 95.31% specificity and 97.40% accuracy with 365.12 msec of lead time. The results confirm that our proposed method with automatically adjustable threshold based on motion history, is suitable for using in pre-impact fall detection system than fixed threshold based method.**

Keywords—Pre-impact fall detection; elderly fall; Pre-fall detection; Dynamic threshold

I. Introduction

According to most country have become edging society [1], one of the primary reason of injury related death for elderly is falling accidents increasingly and continually. Moreover, falling accidents included slip trip and fall not over happen in elderly, but in young people or workers also [2]. The frequently falling happen areas in workplaces are food service area, building entrances, bathroom and patient room etc. To create a fall detection hierarchical methods, researchers had explained existing fall detection approaches and categorized as three different classes that consisted of wearable device, ambience sensor and camera or vision based. In addition of researchers in [3, 4] who have defined fall event as four phases included pre-fall, critical-fall, post-fall, and recovery fall phases. Firstly the pre-fall phase means subject performs activities of daily living (ADL) such as sitting or walking that different from falling. Secondly, the critical phase means subject performs of body movement toward the floor and ending with impaction, approximately time 300 - 500 msec. Thirdly the post fall phase means subject lying on the floor and deceleration. Lastly the recovery phase means subject sit or stand up by themselves or helped by other. That means if falling accidents are early detected in pre-fall or critical fall phase, it will be very useful to protecting them. Additionally, lead time between beginning of fall until impact to the floor most importantly that were used for early detection [5, 6] and protection such as using wearable airbag.

II. Related Work

The major concern [7] in protecting or decreasing of risk in slip, trip, and fall accidents is pre-impact fall detection in early fall phase before impact to the ground. Thus several groups of researchers have demonstrated pre-impact fall detections such as [7, 8, 9, 10, and 11].

As table 1, the comparison of pre-impact fall detection methods, most of researchers using wearable devices for pre-impact falls detection by thresholding velocity and acceleration features in horizontal and vertical direction of subject movement. Nyan et al. [10] shown that falls could be detected with an average longest lead-time of 700 msec in pre-impact fall detection, with 100 % specificity (no false alarms) and 95.2% a lowest sensitivity (falling occurs but fails to detect it in 4.8%). Moreover the researcher found that the use of dynamic threshold may reduce false alarms. While fixed threshold based method is set too low, the probability of number of fall occurring that correctly detected or true positive will be increased. At the same time, false positive number, fall did not occur in fact but system defines as a fall, will be increased simultaneously. On the other hand, if a fixed threshold based method is set too high, not only the possibility of false positive number will be decreased but true positive number also will be decreased. It confirms explanation of [12] as all detection methods do, with an uncomplicated threshold detection method, maximizing the true positive prediction value but the lead-time will increase the chance of false alarms in vise versa.

There are several fix threshold based methods using wearable devices for pre-impact fall detection [5, 8, 11, 12,

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13, 14, and 15]. However fixed threshold value cannot perform well for all falls detection equally due to each people has quite different characteristics and behaviors in their movements. Therefore, it is a major problem to obtain a suitable threshold value in designing a pre-fall detection algorithm. In this paper, the dynamic threshold method to solving that problem has been proposed.

TABLE I. THE COMPARISON OF FALL DETECTION METHODS

	Ref.	Sensors, Methods & Basic principles	Sensi-tivity (%)	Speci-ficity (%)	Lead time (msec)
1	Wu, G. (2000) [11]	Vision, 3 markers Threshold based, Velocity characteristics	97.8	100	300 – 400
2	Nyan (2006) [13]	Vision & Gyroscopes Threshold based	100	94.6	200
3	Wu and Xue (2008) [11]	Tri-axial accelerometers Threshold based on a vertical velocity	100	N/A	70 ~ 375
4	Bourke (2008) [8]	Tri-axial accelerometers and tri-axial gyro Threshold based on a vertical velocity	100	100	314
5	Nyan (2008) [10]	Tri-axial accelerometers and bi-axial gyro Threshold based	95.20	100	700
6	Shan and Yuan (2010) [15]	Tri-axial accelerometers Support vector machine classifier	100	100	203
7	Tong (2013) [16]	Tri-axial accelerometers hidden Markov model (HMM)-based method	100	88.75	323
8	Lee (2015) [5]	Tri-axial accelerometers and gyroscope Threshold based	100	99.4	200 – 400

III. PROPOSED METHOD

A. Dynamic Threshold Model (DTM)

Youm et al., [17] and Dimou et al., [18] achieved a novel scene change detection method. Their work defines an automated dynamic threshold model which is useful for tagging scene changes. As the dynamic threshold method [6, 17, 18], variable parameters are utilized to change the threshold dynamically. The dynamic threshold can scale up and down depending on previous scene change that suitable for separate fall from not fall occurrences. Moreover, the results indicate that DTM has shown low computation requirement and robustness against false alarms. Wu [12], proposed the use of velocity characteristics (vertical and horizontal velocity) in a coordinate system using wearable markers to separate falls from normal activities.

B. Hardware

Fall activities can be separated from normal activities using appropriate dynamic thresholds based method on velocity and acceleration of the chest position. All subjects are attached by MetaTracker [19] at the chest position for tracking velocity and acceleration characteristics. It is the tracking platform and comes with light, pressure, humidity and motion sensors. Furthermore it comes in a coin cell and 3 axis accelerometer. The board is powered by a CR2450 coin-cell battery and based on the nRF51822 SOC from Nordic built around an ARM® Cortex™ M0 CPU, Bluetooth Low Energy, and 2MB of FLASH memory.

C. Software

Fall detection using DTM are computed in real-time. For data analyzing, all acceleration data sent via Bluetooth to smartphone for data storing. In the fall detection process, the smartphone continuously real-time monitor the sensing data from the embedded 3 axis accelerometer that usually provide the acceleration readings in directions of x, y, and z axis. The directions of acceleration are represented by A_x, A_y and A_z successively. Generally, the directions of *x, y,* and *z* axis are supposed by the posture of device. The amount of acceleration is represented by vector ADL_{acc} that amplitude can be calculated by equation (1).

$$|ADL_{acc}| = \sqrt{|A_x - A_{x-1}|^2 + \left|A_y - A_{y-1}\right|^2 + |A_z - A_{z-1}|^2} \quad ..(1)$$

The velocity of activities of daily living (ADL) between frames can be calculated from the following formulas

$$\bar{X}_{adl} = \frac{1}{n}\sum_{i=1}^{n} ADL_{acc_i} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2), and$$

$$SD_{adl} = \frac{1}{n-1}\sqrt{\sum_{i=1}^{n}(ADL_{acc_i} - \bar{\bar{X}}_{adl})^2} \quad \ldots\ldots\ldots(3),$$

with $\bar{X}_{adl}$ being the ADL acceleration mean value, *n* being the frame number of ADL as 10,000 data frames approximately by using equation (2) and SD_{adl} being the standard deviation of ADL acceleration that calculated by using equation (3). Kalman filtering method has been used for noise reduction in preprocessing phase. Because of proposed method is combined from fixed value and dynamic threshold based value, that fixed value was calculated by mean values of ADL acceleration added by its standard deviation as equation (4).

$$FT = \bar{X}_{adl} + SD_{adl} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

Then the dynamic threshold value for pre-impact fall detection can be calculated by the following formulas

$$\bar{X}_{rt} = \frac{1}{n}\sum_{i=1}^{n} RT_{acc_i} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(5),$$

$$SD_{rt} = \frac{1}{n-1}\sqrt{\sum_{i=1}^{n}(RT_{acc_i} - \bar{X}_{rt})^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (6), and$$

$$DTM = FT + SD_{rt} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(7)$$

with *n* of (5) and (6) being the number of previous motion history frames in 1 second (40 frames) and with $\bar{X}_{rt}$ being the mean value of vertical acceleration and SD_{rt} being the standard deviation of motion history frames in 1 second also.

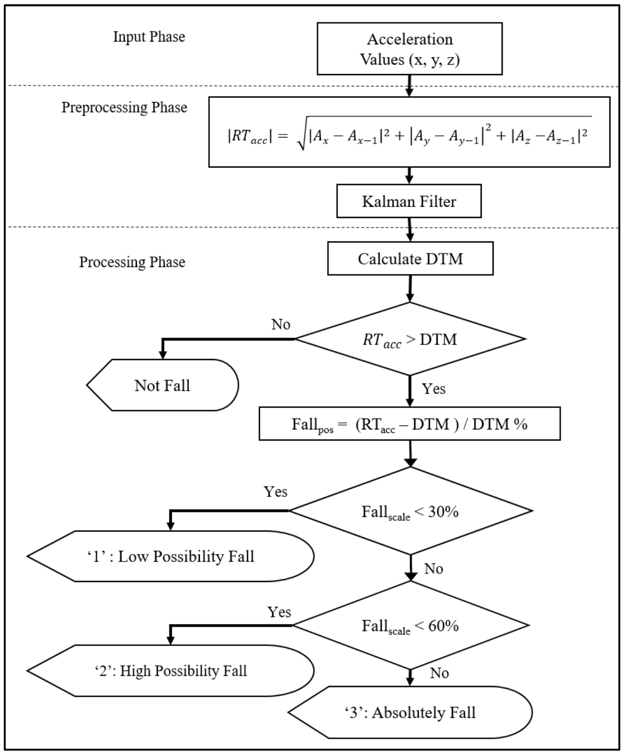

Fig. 1. Pre-impact fall detection diagram.

Thus the dynamic threshold model (DTM) is formulated by fixed value of ADL that calculated by equation (4) added by standard deviation (SD_{rt}) of real time motion history as represent in equation (7). The DTM of pre-impact fall detection algorithm is based on the values of *FT* and SD_{rt} that varies by difference of time. Finally the decision making for fall or not fall occurring in early fall phase or pre-impact fall detection can be detected by following formula

$$|RT_{acc}| = \sqrt{|A_x - A_{x-1}|^2 + |A_y - A_{y-1}|^2 + |A_z - A_{z-1}|^2} \quad (8)$$

with RT_{acc} being real time acceleration calculated by 3 dimension Euclidean distance. Then RT_{acc} is compared by DTM. If RT_{acc} higher than DTM it means falling has occurring. Moreover for increasing of fall alarm accuracy, 3 point rating scale has been used for fall alarm possibility by following formula

$$Fall_{pos} = (RT_{acc} - DTM) / DTM * 100 \quad \ldots\ldots\ldots\ldots\ldots(9)$$

with $Fall_{pos}$ being the percentage possibility of falling occurred. Then fall or not fall are decided by $Fall_{pos}$ rating scales, if $Fall_{pos}$ lower than 30 percentage let $Fall_{scale}$ as '1', if $Fall_{pos}$ higher or equal to 30 and lower or equal to 60 percentage let $Fall_{scale}$ as '2', and if $Fall_{pos}$ higher than 60 percentage let $Fall_{scale}$ as '3' as shown in figure 1 diagram. As 3 rating scales are used for decision making by '1' as low possibility, '2' as medium possibility and '3' as high possibility for falling occurred.

IV. Experimental Setup and Results

As Noury et al. [3] has claimed that although the goal of a fall detection is to detect the fall of elderly or young people, it is actually infeasible to experiment the fall situations with them. For our evaluation as figure 2, 192 instances of falls were captured that included: 48 frontward falls, 48 backward falls and 96 left side and right side falls on the floor. All activities performed by 6 different young healthy volunteers, 4 males and 2 females, age between 19 to 21. For safety reasons, all volunteers were performed the fall activities on 30 cm. thick mats and soapy water was poured on the mats for real scenario of falling. Thus the fall activities may be imitated by young healthy people and the activities of daily living may be experimented on elderly in the risk age group and worker in the risk places for falls. This demonstrates that a fall behavior is highly related to the acceleration data, resulting in a dramatically change and peak acceleration value. The training data are used to find the suitable dynamic threshold by using the overall acceleration.

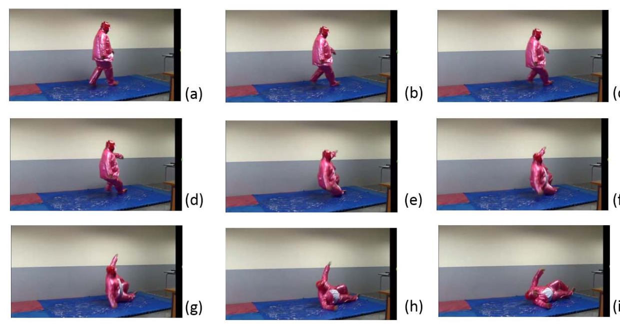

Fig. 2. Subjects perform falling activites.

The system compares performance in terms of the sensitivity and specificity. Generally, there are four conditions in fall detection [5]. True Positives (TP): Number of fall occurs that correctly detected. True Negatives (TN): Number of normal activities that correctly detected as ADL. False Positives (FP): Number of normal activities that incorrectly detected as fall occurs. False Negatives (FN): Number of fall occurs that incorrectly detected as fall not occurs. The sensitivity or true positive rate is the ratio of the correctly detected positive instances over the entire set of positive instances.

The specificity (SPC) or true negative rate is the proportion of the correctly detected instances as negative over the entire set of negative instances. The specificity (SPC) or true negative rate is the proportion of the correctly detected instances as negative over the entire set of negative instances. As figure 3 and table II, that represent the comparisons of detection results by different methods as fixed threshold (FT) values of 30, 40, 50, 60, 70 and proposed dynamic threshold method (DTM) continuously. This table shows that when the device was attached at the chest, the sensitivity of DTM is equal to FT 30 but higher than FT 40, 50, 60 and 70. The specificity of DTM is higher than FT 30, 40 and 50 but lower than FT 60 and 70. Thus the 97.40%

accuracy of DTM is higher than all of FTs about 15.10%, 6.25%, 3.13%, 14.06% and 29.69% respectively. Finally the lead time of DTM is 365.12 msec that higher than fixed threshold 50 about 100 msec as shown in table 2.

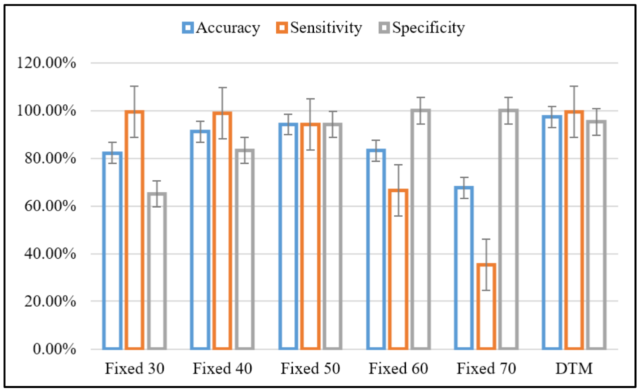

Fig. 3. Comparison of detection results by different methods.

TABLE II. THE COMPARISONS OF DETECTION AND LEAD TIME RESULTS

		Fixed 30	Fixed 40	Fixed 50	Fixed 60	Fixed 70	DTM
Accuracy (%)		82.29	91.15	94.27	83.33	67.71	97.40
Sensitivity (%)		99.48	98.96	94.27	66.67	35.42	99.48
Specificity (%)		65.10	83.33	94.27	100.00	100.00	95.31
lead time (msec.)	$\bar{X}$	451.33	361.11	263.12	209.82	157.75	365.12
	SD	191.48	179.71	172.74	155.92	102.88	173.23

V. CONCLUSION

Slipping, tripping and falling are the major health crisis, not only in elderly but in worker and young people also, related to deaths and symptoms after falls [2]. These experiments were designed and developed for pre-impact fall detection system based on wearable device using dynamic threshold model that can be adjusted automatically depending on motion history. The algorithm of dynamic threshold model was compared with various fixed values threshold based methods. The several experiments were conducted for performance evaluation including sensitivity, specificity and accuracy measurements. The results show that the proposed algorithm can detects the pre-impact falling from normal activities of daily living with 99.48% sensitivity, 95.31% specificity and 97.40% accuracy. Moreover the results confirm that our proposed method is suitable for using in pre-impact fall detection system than fixed threshold based methods with dynamic threshold model, automatically adjustable based on motion history.

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