Novel Fall Detection Algorithm based on Multi-Threshold Fall Model

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***Abstract*—This paper elucidates an advanced, multi-threshold-based human fall detection algorithm, employing acceleration sensor data to revolutionize fall risk management in high-risk populations such as the elderly and mobility-impaired individuals. The data procured is meticulously analyzed and pre-processed, with various indicators employed in selecting appropriate parameters for data management. A key innovation of this study is the application of multiple thresholds, an enhancement leading to increased accuracy and reliability in distinguishing real falls from non-fall activities. Optimal thresholds were determined using a boxplot, facilitating a more precise fall detection system. Impressively, this approach achieved 95.45% fall detection accuracy, indicating its potential for practical integration. This research substantially contributes to the safety of individuals prone to falls.**

Keywords*—*fall detection algorithm, wearable sensor, threshold, triaxial accelerometer

I. Introduction

According to data from the International Database of the United States Census Bureau, the average proportion of the population aged 17 and older in developed countries such as the United States, Japan, and Germany was 2015%. It is projected to reach 2050% by 2030 due to declining birth rates and extended life expectancy. Population aging is a common phenomenon in many countries, particularly in developing and developed countries [1]. Falls among older adults pose a public health problem and a threat, which can impact quality of life and lead to severe disability affecting independent living [2,3]. Falls among individuals who are helpless at home are more severe than those who receive help within 12 hours [4]. There is a positive correlation between mortality rate and waiting time for rescue [4,5]. Non-fatal falls, in addition to causing disability or functional impairment, also have psychological and social impacts [6]. Fear of falling again leads to a loss of walking safety confidence in older adults, limiting activities of daily living (ADLs) [7].

To improve the quality of home healthcare services, two strategies have been proposed to address falls: falls prevention and falls detection [8]. Falls prevention strategies analyze risk factors and then provide targeted interventions to mitigate the occurrence of falls [9,10]. Environmental factors include obstacles, poor lighting, loose carpets, lack of safety equipment, and weather; the most common physiological causes of falls are balance impairment, history of falling, functional and cognitive impairments, medication use, orthostatic hypotension, muscle weakness, and visual impairment [7,11]. Existing methods for preventing falls include muscle strength and balance training, and creating a preventive checklist to minimize the risk of falling in hazardous environments. Unfortunately, falls cannot be completely prevented, making fall detection systems crucial for older adults.

Fall detection systems are considered assistive systems designed to send alerts when a fall event occurs. There are two types of fall detection systems, including user manual and automatic systems. User manual fall detection systems aim to send emergency messages through user operations. However, such systems cannot provide assistance to fallers when they lose consciousness. Alternatively, automatic fall detection systems are recommended to detect falls without any user operation when fallers lose consciousness. Automatic fall detection systems can be categorized into two major types based on their sensor types: environment-based fall detection systems and wearable device-based fall detection systems [12,13]. Environment-based devices are installed in smart environments, which include cameras [14], infrared sensors, acoustic sensors, vibration sensors, and pressure sensors [15]. These environment-based devices perform well in controlled environments such as living rooms, bathrooms, or laboratories. However, these devices are not practical in uncontrolled environments. In contrast, wearable sensor-based fall detection systems can detect falls anytime and anywhere when users wear the sensors. Lin et al. proposed a wearable mercury switch integrated with optical sensors to enhance fall detection rates of wearable devices [16]. Chen et al. used a three-axis accelerometer attached to the waist to detect falls, and fixed wireless networks to locate victims [17]. Bourke and Lyons used only a dual-axis gyroscope mounted on the trunk to detect falls [18]. In this work, the proposed fall detection algorithm aims to automatically detect severe falls, which are defined as "an event in which a person unintentionally comes to rest on the ground, floor, or lower level due to the following reasons: receiving a violent blow, losing consciousness, suddenly paralyzed, such as from stroke or seizure," considering that the patient cannot call for help on their own.

Fall detection algorithms play a crucial role in automatic fall detection systems. To provide reliable fall detection algorithms, two common technical issues and challenges should be addressed. First is variability as falls can occur suddenly and involuntarily in various forms and directions in daily life. Falls can happen during walking, standing, and frequently occur during transitional activities, such as getting out of bed or a chair . The second is ambiguity as certain characteristics of falls may resemble those of ADLs, which can confuse fall detection systems. For example, severe fall events can result in strong impact forces and energy similar to jumping or running in daily life. Additionally, the occurrence of minor falls has a smaller impact and energy compared to severe fall events, but minor falls may resemble lying down in daily life. These technical issues and challenges may hinder the adequacy of most fall detection algorithms for automatic fall detection systems when considering specific events such as impact, posture after a fall, and changes in speed during falls. Some prominent studies have proposed a multi-stage fall model that provides more granular observations of fall events for automatic fall detection systems, separating falls into different stages, such as four stages (pre-fall, impact, post-fall, and recovery stages), and five stages (pre-fall, fall, impact, rest, and recovery stages). For example, activities after a fall and before a fall can greatly influence the impact signal. Therefore, multiphase fall models have the potential to address the aforementioned technical challenges and provide more detailed information for fall detection systems.

This study aims to accurately detect falls during activities of daily living using wearable sensors. We propose a new multi-threshold fall detection algorithm, which includes a method based on multiple thresholds to detect fall events. First, a set of thresholds is established to identify absolute falls and ADLs using a threshold-based method. The advantage of the threshold-based approach is its low computational complexity and ease of implementation. However, it is challenging to set appropriate thresholds due to the overlap in peak acceleration values generated by falls and ADLs. This issue is addressed by selecting multiple thresholds.

The rest of this work is organized as follows: In Section 2, we briefly extend related work on fall detection, such as threshold-based fall detection algorithms. Section 3 introduces the proposed multi-threshold fall detection algorithm, including a method based on threshold knowledge, and performance evaluation. Detailed results analysis and discussion are provided in Section 4. Finally, conclusions from the proposed multi-threshold fall detection algorithm are summarized in Section 5.

II. Related Work

A. Fall Detection Algorithm

Sensor placement is a key issue in developing fall detection algorithms based on wearable sensors. The most common wearing positions are the waist, wrist, trunk, thigh, back, ankle, foot, neck, and head. The waist and trunk are close to the body's center of mass, and the neck maintains balance of the head during ADLs, so sensors attached to the waist, trunk, or head can detect larger accelerations when the body lands.

Fall detection algorithms for wearable sensor-based fall detection systems primarily fall into two categories: threshold-based fall detection algorithms [12,24]. Some studies aim to assess the effectiveness of different wearing positions and detection algorithms, as shown in Table I.

TABLE I. Threshold-Based Fall Detection Algorithm Literature

Article (Year)	Sensor (s)	Position	Fall and ADL Types	Results
Chao et al. (2009) [35]	Tri-axial accelerometer	Chest Waist	Falls: 8 ADLs: 13	Sn 2: 98.2% (Chest) Sp 2: 92.4% (Chest) Sn 2: 98.2% (Waist) Sp 2: 89.9% (Waist)
Huynh et al. (2015) [38]	Tri-axial accelerometer	Chest	Falls: 4 ADLs: 6	Sn 2: 96.55% Sp 2: 89.50%
Palmeri ni et al. (2015) [39]	Tri-axial accelerometer	Lower back	Falls: 5 ADLs: --	Sn 2: 90% Sp 2: 89.7%

B. Threshold-Based Fall Detection Algorithms

Threshold-based fall detection methods distinguish between falls and ADLs when the peak is below or above a threshold. The advantage of threshold-based techniques is their low computational complexity, making them easy to implement in wearable sensors. However, threshold-based techniques are not suitable for detecting different types of falls, as thresholds are designed based on the body's experience during the fall process, and fixed thresholds cannot meet the various individual activity habits in daily life.

Bourke et al. used a single threshold, either a fall threshold related to the peak impact force during the fall process, or a fall threshold related to the acceleration before ground contact, to detect falls through three accelerometer sensors installed on the trunk and thigh. The results showed that the fall threshold of 3.52 g (1g = 9.81 m/s^2) of the trunk had the highest specificity, indicating that the trunk is the best wearing position for the fall sensor. Kangas et al. used a single-threshold-based fall detection algorithm, performed postural detection after a fall, and studied the location of the fall detection sensor by installing a tri-axial accelerometer at the waist, wrist, or head. The results showed that the head-mounted accelerometer provided perfect results, and the authors believed that the head is a reasonable wearing position for fall detection. Kangas et al. designed a more complex algorithm than the single-threshold-based fall detection algorithm and used accelerometers installed at the waist, wrist, and head to evaluate different low-complexity fall detection algorithms. The results ultimately demonstrated that effective sensor positions are the waist and head. The sensor at the head level had the highest accuracy, but usability, and user acceptance, i.e., ergonomics, should be considered in more detail. In summary, an accelerometer worn at the waist may be the best choice for wearable sensor-based fall detection algorithms.

III. Materials and Methods

To develop the algorithm of the proposed model, the Sisfall public dataset is used. The Sisfall dataset contains 15 falls and 19 ADLs, performed by 38 subjects, with sensors fixed to the waist. Among other public domain datasets, Sisfall is distinctive because it has prefabricated falls and activities of daily living (ADL) for older adults, and ADL activities in the Sisfall dataset include walking, jogging, sitting, standing, and more. Whereas fall activities are 15 activities, including falling forward, falling backward, falling while walking, etc. The dataset is in CSV file format. We summarize the important characteristics of the Sisfall dataset in Table II.

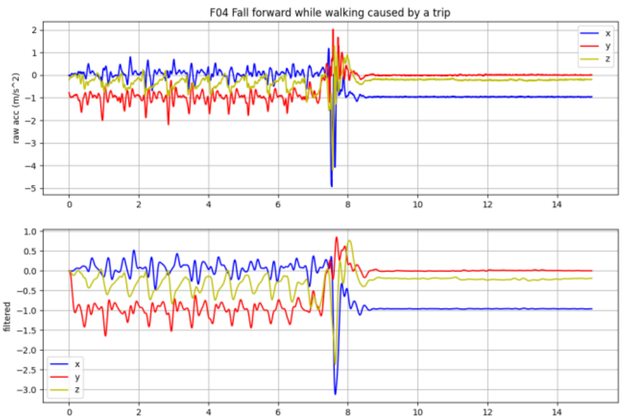
TABLE II. THE KEY CHARACTERISTICS OF THE SISFALL DATASET.

Characteristics	**Sisfall dataset**
Sampling frequency	200Hz
Number of subjects	38 subjects
Number of ADLs	19
Number of falls	15
Subjects age	19-75
Sensors used	accelerometer
Position of sensor	Waist

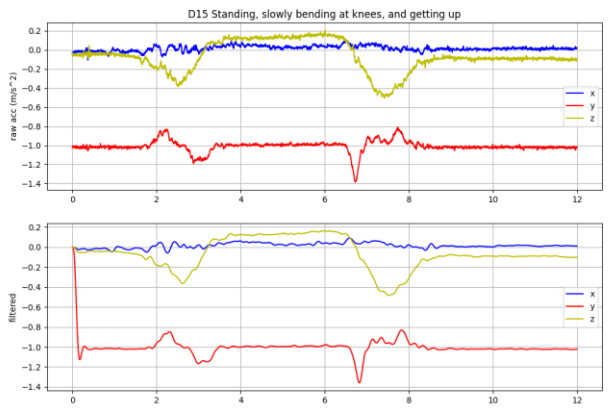
The main processes used in this study for fall and ADLs identification are detailed in the study. This approach is mainly applied to the Sisfall dataset. Figure 1 shows a flowchart of the steps performed in this study to predict falls and ADLs events to form accelerometer sensor data. Flowchart of the model presented in this study.

A. Data analysis and preprocessing

Since the accelerometer data results will seriously affect the recognition quality, the accelerometer data is selected for analysis and preprocessing during data processing. Fig. 1 shows an example of the fall and 3-axis acceleration curves of the ADL recorded in the Sisfall dataset. Fig. 1(a) is the fall acceleration data, and Figure 1(b) is the daily life acceleration data.



(a)



(b)

Fig 1. Fall and ADL acceleration data

In order to analyze and determine the cutoff frequency and the best filter selection criteria, I selected multiple metrics to determine, the selection of metrics is shown in Table III, and the final preprocessing stage consists of a fourth-order Butterworth low-pass filter with a cutoff frequency of 5 Hz.

TABLE III. THE KEY CHARACTERISTICS OF THE SISFALL DATASET.

Metrics	**Mathematical formulas**
PCA	$\mathrm{CP}_k = \dfrac{\sum_{i=1}^{k} \lambda_i}{\sum_{i=1}^{n} \lambda_i}$
SNR	$10\log\left[\dfrac{\sum_{n=mj-M+1}^{mj} a(n)^2}{\sum_{n=mj-M+1}^{mj} [a(n)-\widehat{a(n)}]^2}\right]$
MSE	$\dfrac{1}{N}\sum_{i=1}^{N}(y-\hat{y})^2$
R-squared	$1-\dfrac{\sum(y_i-\hat{y}_i)^2}{\sum(y_i-\bar{y}_i)^2}$
Energy ratio	$\dfrac{\sum_{i=0}^{k} x[i]^2}{\sum_{i=0}^{N-1} x[i]^2}$
MAPE	$\dfrac{1}{N}\sum_{i=1}^{N}\left\lvert\dfrac{y_i-\hat{y}_i}{y_i}\right\rvert$
MAE	$\dfrac{1}{N}\sum_{i=1}^{N}\lvert y_i-\hat{y}_i\rvert$

After comparing and analyzing multiple criteria, this paper selects the energy ratio as the best indicator for selecting the cutoff frequency, as shown in the following fig. 2:

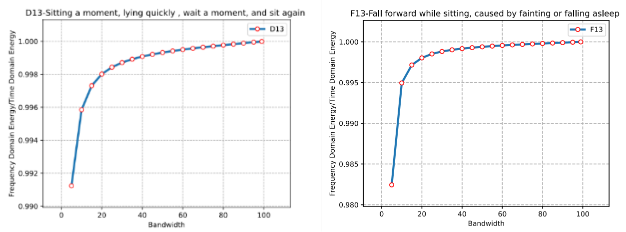


Fig 2. The curve graph of the energy ratio of 'Fall' and 'ADL'

The curve graph of the energy ratio of 'Fall' and 'ADL' shows that the greatest data increase is within the 0-20Hz bandwidth. We have refined the bandwidth, as shown in Fig. 3.

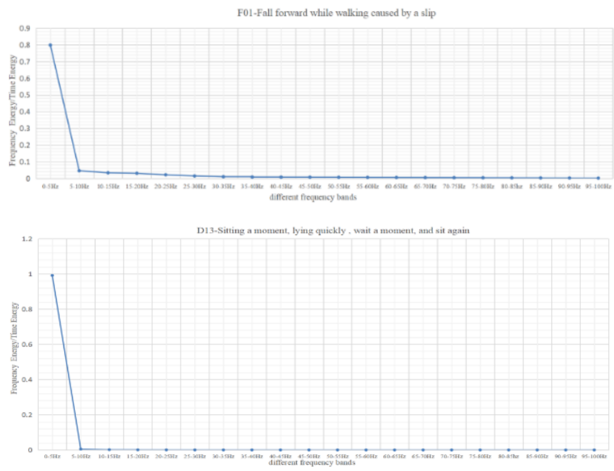


Fig 3. The curve graph of the energy ratio of 'Fall' and 'ADL' in different frequency bands

Fig. 3 shows a line chart of the energy ratio under the different frequency bands of ADL and Fall, with the abscissa representing the frequency band. Energy is displayed by frequency band. As can be seen from the figure, the energy in the 0-5Hz frequency range accounts for almost the entire proportion. The visible range of human activity is in the 0-5Hz range, so we can set the cutoff frequency of the low-pass filter to 5Hz.

At the same time, the choice of our filter is also very important, in digital signal processing, especially accelerometer data processing there are multiple filters for us to choose from, such as Bessel, Chebyshev and Butterworth filters, and the order of the filter also affects the quality of the filtered data. After testing, we select MSE indicators, signal-to-noise ratio and energy indicators to select the type and order of filters.

From Fig. 4 and Fig. 5, we can see that the Butterworth filter is always optimal under different metrics and different parameters. So we chose the Butterworth filter as the best filter for the data preprocessing stage.

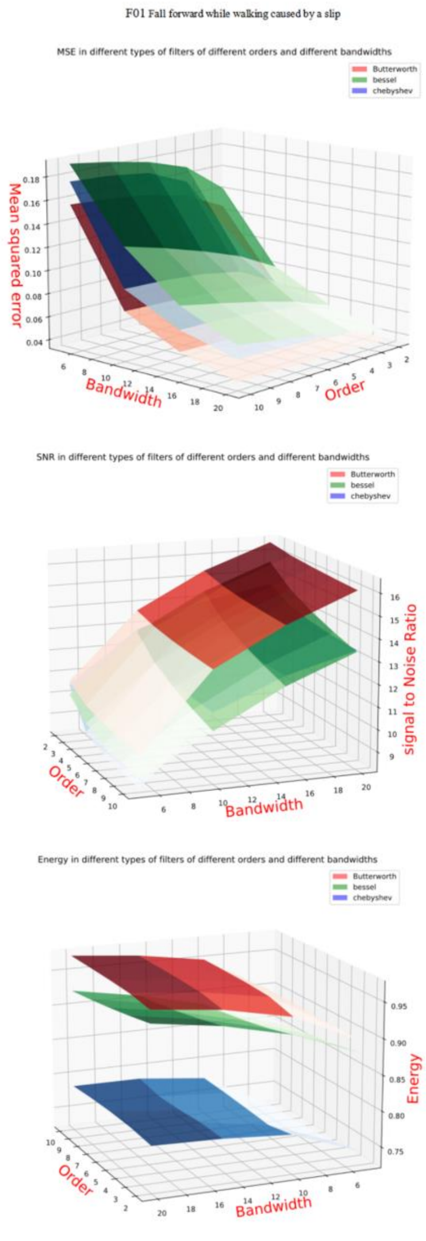


Fig 4. Comparison of different metrics of different filters under different orders and different bandwidths of Fall.

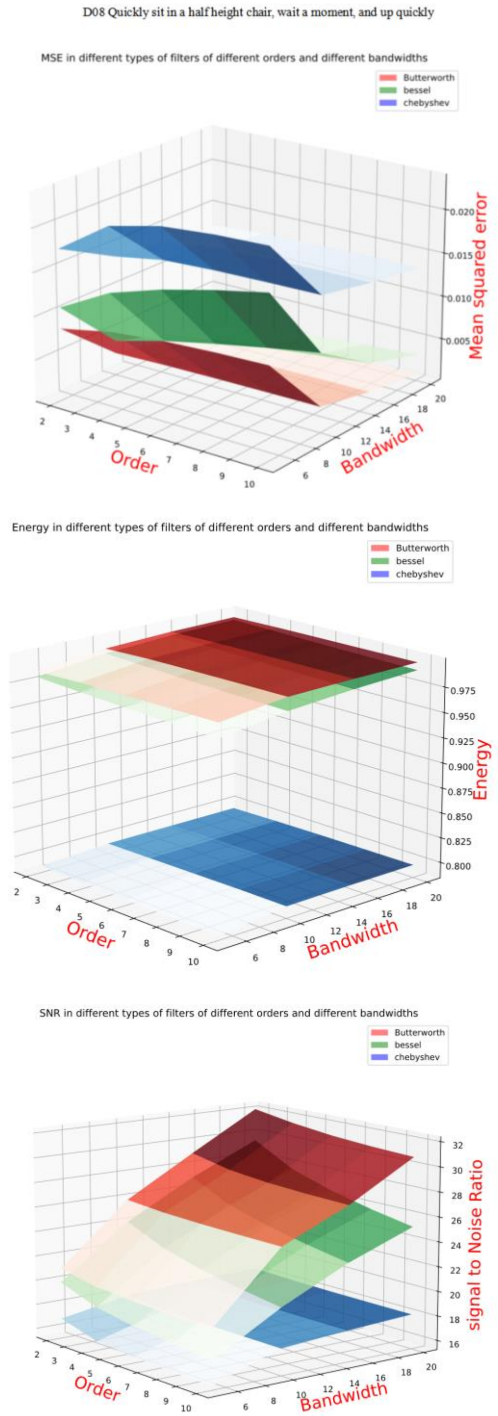


Fig 5. Comparison of different metrics of different filters under different orders and different bandwidths of ADLs.

B. Multi-threshold fall detection algorithm

This article takes a suitable approach to finding thresholds, using multiple thresholds to accurately identify falls and ADL activity. The threshold determination method used in this paper is based on the threshold selection method of Boxplot.

A boxplot, or box-and-whisker plot, is a standardized way of displaying the distribution of data based on a five-number summary: the minimum, the first quartile (Q1), the median (Q2), the third quartile (Q3), and the maximum. It provides a visual representation of the central tendency, variability, skewness, and outliers of the data set. One common method for threshold selection involves using the maximum value of the boxplot. This is especially useful when trying to identify and handle outliers in your data set.

The Interquartile Range (IQR), which measures statistical dispersion, is calculated as the difference between the upper quartile (Q3) and the lower quartile (Q1). An outlier is any value that lies more than one and a half times the IQR above the third quartile or below the first quartile.

The mathematical formula to calculate the boxplot's maximum value is as follows:

$$Maximum = Q3 + 1.5 \times IQR \tag{1}$$

The use of boxplot maximum values as a threshold selection method offers a robust and efficient strategy for managing large datasets. This technique allows for the identification and handling of outliers, ensuring the integrity of our data analysis.

Table IV shows the feature extraction features used to test the proposed dataset.

TABLE IV. THE FEATURE EXTRACTION FEATURES USED TO TEST THE PROPOSED DATASET.

Type	Code	Feature	Mathematical formulas
Amplitude	C1	Sum vector magnitude	$\mathrm{Norm}_{xyz} = \sqrt{a_x^2 + a_y^2 + a_z^2}$
	C2	Sum vector magnitude on horizontal plane	$\mathrm{Norm}_{hori} = \sqrt{a_y^2 + a_z^2}$
	C3	The value of the maximum ADLs sum vector magnitude	$T_{fall}^{Normxyz} = maximum\ \mathrm{Norm}_{xyz}\ of\ ADLs$
	C4	The value of the minimum falls sum vector magnitude	$T_{ADL}^{Normxyz} = minmum\ \mathrm{Norm}_{xyz}\ of$ Fall
	C5	The value of the maximum ADLs sum vector magnitude on horizontal plane	$T_{fall}^{Normhori} = maximum\ \mathrm{Norm}_{hor}\ of$ ADLs
	C6	The value of the minimum Fall sum vector magnitude on horizontal plane	$T_{ADL}^{Normhori} = minmum\ \mathrm{Norm}_{hor}\ of\ Fall$
	C7	Angle between z-axis and vertical	$Angle_z = atan2(\sqrt{a_x^2 + a_z^2} - a_y)$

As shown in Fig. 6 and Fig. 7, the thresholds are shown by Boxplot, we can easily get the threshold from the data of Boxplot.

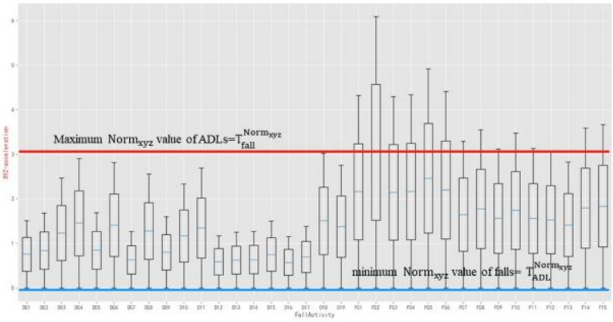


Fig 6. The threshold selection for $Normxyz$

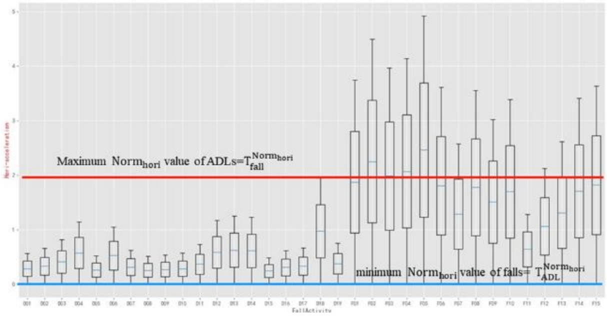


Fig 7. The threshold selection for $Normhori$

C. . Performance Evaluation Criteria

The result of fall detection is either fall or ADL, which belongs to the binary classification. In the performance evaluation criteria of the binary classification test, a positive condition means that the subject falls, and a negative condition means that the subject performed an ADL. Based on the detected result, a fall alarm belongs to the positive test outcome, and an ADL is the result of a negative test outcome. There are four situations in fall detection, including true positive (TP), false positive (FP), true negative (TN), and false negative (FN) . The fall detection system should avoid getting FP and FN results. Sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and accuracy are the common performance evaluation criteria for the binary classification test, and many studies adopted those criteria to show the results of fall detection Sensitivity (or recall) is the capability of detecting falls, and the PPV (or precision) is the quality of detecting exact falls. Sensitivity, specificity, precision, and accuracy show more effective evaluation of human activity classification for the imbalanced dataset The sensitivity, specificity, and precision are computed by Equations (2)–(3), respectively. Accuracy is the proportion of the truth test outcome in the total results, whose calculation follows Equation (4). The higher values of sensitivity, specificity, precision, and accuracy, the higher the performance the system provides.

$$\text{Sensitivity} = \frac{TP}{TP + FN}, \tag{2}$$

$$\text{Specificity} = \frac{TN}{FP + TN}, \tag{3}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}. \tag{4}$$

IV. Results and Discussion

In this paper, we used the SisFall dataset. It consisted of up to 34 activities (falls and ADL) performed by 38 participants using a wearable device fixed to the waist. One of the participants was an elderly person who simulated ADL and falls.

The SisFall dataset contains more actors, activities, and record types than any other publicly available dataset. It consisted of 2706 ADLs and 1798 falls, including data from 15 healthy independent older adults. The advantage of the dataset is that it has a large age span and includes both young and old people..

A. Combinations of thresholds

In the multi-threshold-based fall detection algorithm, threshold-based classification is utilized to identify absolute falls or ADLs and reduce computational complexity. We use Equal Error Rate to select the best threshold without features.

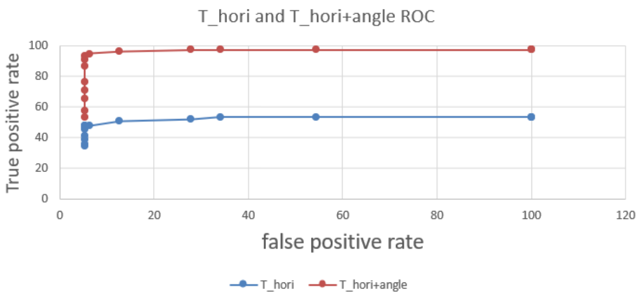


Fig 8. Comparison between T_hori threshold and T_hori + Angle threshold

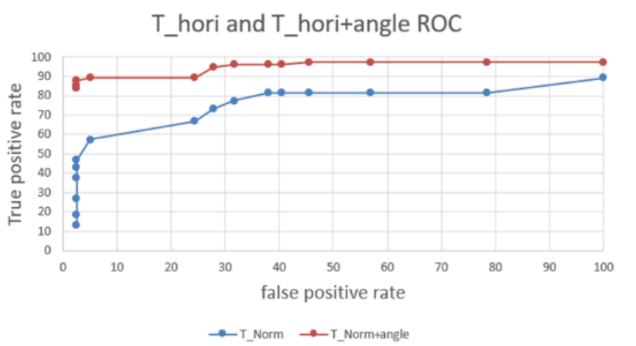


Fig 9. Comparison between T_Norm threshold and T_Norm + Angle threshold

As can be seen from Figures 9 and 10, the effect of a single threshold is much lower than that of a combination of two thresholds

B. Multiple threshold combinations

We combine multiple thresholds to determine the success of predicting fall, as shown in Table V. We can see in the table that Norm_hori + Norm_xyz + angle effect is optimal, and the Sensitivity, specificity, and accuracy are 93.33%, 97.46%, and 95.45%, respectively.

V. Conclusions

The problems arising from fall accidents are an important issue for aging and aging societies. Timely resuscitation of victims not only reduces injuries from falls, but also increases the confidence of older adults to undergo ADL.

TABLE V. Recognition success rate at different thresholds.

	Sensitivity	specificity	accuracy
Norm_hori	88%	97.46%	92.85%
Norm_xyz	53.33%	97.46%	75.97%
Norm_hori + Norm_xyz	48%	97.46%	73.37%
Norm_hori + angle	88%	97.46%	92.85%
Norm_xyz + angle	53.33%	97.46%	75.97%
$Norm_{hori}$ Norm_xyz + angle	93.33%	97.46%	95.45%

The data visualized is shown in Figure 10.

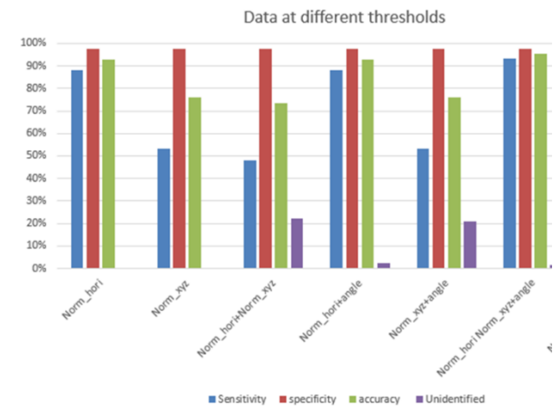


Fig 10. Accuracy at different thresholds

Rapid fall detection systems have the opportunity to provide real-time emergency alerts and services to improve safety and health-related quality of life. In this work, we propose a novel multi-threshold fall detection algorithm to detect fall events by using multiple threshold fall models. The overall performance of sensitivity, specificity and accuracy of the algorithm was 93.33%, 97.46% and 95.45%, respectively. Compared with single-threshold or double-threshold algorithms, algorithms using multiple thresholds have much better overall performance in terms of sensitivity, specificity, precision, and accuracy, respectively. In future work, we plan to improve the fall detection system for continuous monitoring and evaluate it in an out-of-laboratory environment.

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