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Research on Fall Detection During Elderly Exercise Activities Under the Background of Healthy China Initiative

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Abstract:
For the elderly are easy to fall and cause accident frequently in sports, fall detection is of much importance. this paper presents a method of detecting movement fall, based on the acceleration signals and attitude angle of human activity t acquired from a triaxial accelerometer sensor MPU6050 module, and protect the elderly from the second injury after the fall. By extracting the characteristics of the acceleration signal amplitude vector SMA and the deflection angle θ. This algorithm divides the movement state of the elderly into three categories, recurrent physical exercise and short-term daily activities and post-exercise rest state, using Signal Magnitude Vector Sliding Average (SVMLS) to distinguish fast running and jumping, and studying the program to detect the fall of the elderly after the exercising. immediately after exercise to avoid casualties after the fall. The major advantage of this method is that it can detect the violent fall and slow fall and its applicability is strong. Experiments show that the accurate alarm rate of the device is 95%, meet the fall detection accuracy.

Keywords: tri-axial accelerometer; fall detection for the elderly; Signal Magnitude Vector SMA; attitude angle

1. Introduction

In 2016, China launched the "Outline of Healthy China 2030", aiming to promote the construction of a healthy China. The plan emphasizes the need to "address the health issues of women, children, the elderly, disabled individuals, migrant populations, and low-income groups" [1]. Among these, addressing the health concerns of the elderly is a critical component in the realization of a Healthy China.

According to the "Statistical Communiqué of the People’s Republic of China on the 2022 National Economic and Social Development" released by the National Bureau of Statistics, the population aged 60 and above reached 280.04 million, accounting for 19.8% of the total population. The population aged 65 and above numbered 209.78 million, or 14.9% of the total population. Based on the World Health Organization’s criteria for an aging society, China’s population aging level has already far exceeded the WHO’s threshold. Research suggests that by 2025, China’s elderly population will reach 330 million, and by 2040, this number will increase to 460 million [2]. The accelerating aging process and the growing size of the elderly population pose significant long-term social challenges for China, both now and in the future. Data from the former Ministry of Health indicates that 76.2% of chronic disease patients are aged 60 or older, and the rapid aging trend will exert tremendous pressure on the country’s healthcare system and economy. Therefore, addressing the health needs of the elderly will be a major challenge in the construction of a Healthy China, representing a critical factor in determining the success or failure of this initiative.

Studies have shown that regular physical exercise not only helps the elderly to strengthen their bodies, enhance immunity, and reduce the risk of various chronic diseases, but also enriches their quality of life. It is evident that elderly participation in physical activities is an effective approach to achieving healthy aging and is a key measure for the construction of a Healthy China, which will yield positive social and economic outcomes.

According to relevant surveys and studies, the exercise routines of elderly individuals are relatively fixed, with the majority engaging in physical activities in the morning and evening, and fewer in the late morning or afternoon. The duration of each exercise session typically ranges from 31 to 60 minutes, followed by 61 to 90 minutes. Regarding exercise frequency, most elderly individuals exercise 3 to 7 times per week [3-5]. The types of exercise include both individual and group activities. Individual activities predominantly involve walking or light jogging, while group activities often consist of square dancing and traditional martial arts. The common exercise venues are parks, sports fields in residential areas, public squares, roadsides, and open spaces in residential neighborhoods. Moreover, the vast majority of elderly individuals engage in self-directed physical exercise [6-7]. However, if the exercise intensity is too high, the exercise method is inappropriate, or there is a recurrence of physical ailments, elderly individuals are at an increased risk of falls. Additionally, if the ground is slippery, the risk of falling is further heightened. According to data from the World Health Organization, 28% of individuals aged 65 and above experience a fall each year, with the likelihood of falling increasing with age. In China, elderly individuals experience 2-3 falls per person annually, with falls often resulting in fractures, soft tissue contusions, and in some cases, triggering cardiovascular events such as cerebral hemorrhages. In severe cases, falls can lead to unconsciousness, loss of awareness, and pose a life-threatening risk. Falls in elderly individuals during physical exercise generally occur either during the exercise itself or during rest periods following exercise. Over 30% of elderly individuals aged 65 and above in China have experienced falls during physical activity [8-9].

Given the exercise habits and environment of the elderly, places like open parks or quiet areas in the early morning or late evening lack essential safety measures. Moreover, if an elderly person falls and no one is nearby to assist, or if the person is unable to move or loses consciousness, timely rescue efforts may be delayed. This can result in missing the critical window for emergency treatment, leading to further injury or even death. Therefore, early detection of falls during exercise is a crucial protective measure for elderly safety and an indispensable part of ensuring safety in the construction of a Healthy China.

Currently, fall monitoring for elderly individuals primarily relies on video surveillance [10-11] and wearable device detection methods [12-15]. In references [10-11], surveillance cameras are installed in the activity areas of elderly individuals, and differential comparison is made between adjacent frames to extract areas of motion. The system then determines whether the elderly person is in a falling state based on the extracted motion regions. This method offers high accuracy; however, its effectiveness depends on the density of camera installation. Areas with blind spots in the surveillance system cannot be monitored, making it suitable only for relatively fixed, small-scale areas where the elderly are active. References [12-13] describe a method based on a three-axis accelerometer to obtain the body's movement acceleration. By setting threshold values for relevant variables, the system identifies falling actions. This method is not limited by the elderly person's location and meets the requirements for real-time monitoring. However, relying solely on acceleration as a variable for detection may lead to misinterpretations, such as categorizing activities like running or jumping as falls, which can compromise the accuracy of the detection system.

References [14-15] improve the accuracy of detection by additionally monitoring the vertical speed of the body's center of mass and the angle in the vertical direction, based on the elderly person's movement acceleration. While this approach enhances detection accuracy, it cannot be used for identifying slow falls caused by dizziness or other discomforts during rest periods after exercise.

This paper proposes a fall detection algorithm for elderly individuals based on a three-axis accelerometer sensor. The algorithm utilizes three-axis accelerometer data and the attitude angle in the vertical direction for dual-fusion detection to identify falls during both physical activity and resting phases. An experimental device was constructed using the MPU6050 three-axis accelerometer sensor and the Intel Edison core module as the main components. This study employs the movement acceleration magnitude SVM with the smoothed average (SVMSA) and the movement acceleration vector area (SMA) to describe the motion state, eliminating common daily activities of elderly individuals. The trunk attitude angle in the vertical direction is used to distinguish between activity-induced falls and fainting during rest periods after physical activity. Through experimental validation and comparison, the proposed fall detection method demonstrates strong applicability and high accuracy.

2. Experimental Setup

The CPU of the experimental setup utilizes the Intel Edison computer module, which operates in low-power mode with a power consumption of 250 mW. The system runs on the Linux operating system, and data collection programs are developed using the Eclipse C/C++ Integrated Development Environment, with C language programming and GCC compilation for debugging. The MPU6050 sensor module collects the three-axis accelerometer data and attitude angle information from the test subject, with acceleration value stability reaching 0.01g and attitude angle stability reaching 2°. Given the noise interference in movement data, low-pass and median filters are applied. Test data is uploaded via the serial port to a computer and stored in the 1GB memory of the Intel Edison module. Additionally, the experimental device is equipped with a 2.4 GHz Wi-Fi module, which allows direct data transmission to a computer when a wireless network is available in the test environment, as shown in Figure 1.

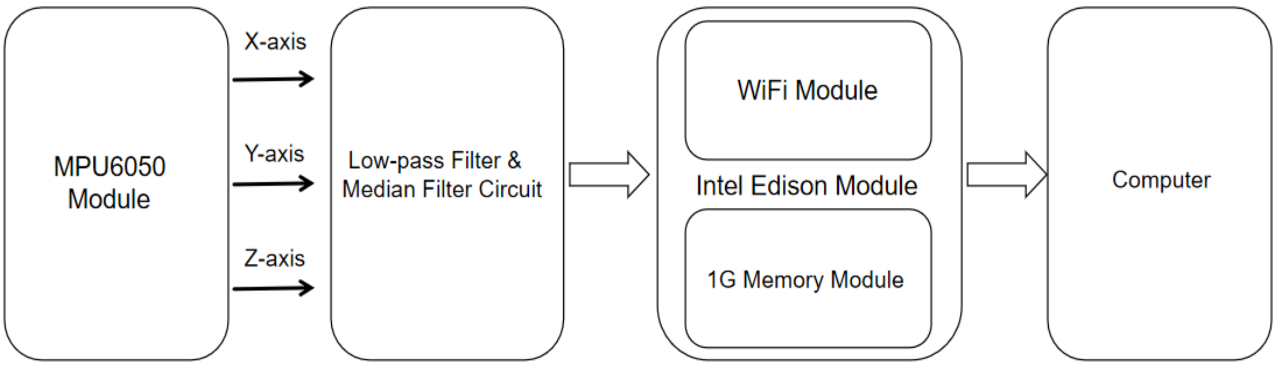

Figure 1: System Architecture Diagram of the Hardware Setup

3. Three-Axis Accelerometer and the Principle of Fall Detection

The physical activities of elderly individuals encompass not only fitness exercises such as walking, running, and jumping, but also daily activities such as sitting, lying down, and taking elevators. These movements can interfere with the detection of falls during fitness activities. During physical exercise, elderly individuals experience variations in force and acceleration in the forward-backward, left-right, and up-down directions of their bodies. Different types of movements result in different forms of acceleration change. Therefore, by using a three-axis accelerometer to collect acceleration data from the elderly during physical activity, it is possible to analyze and identify various movement states such as falls and running.

3.1 Establishing the Coordinate System

To analyze the dynamic parameters of the fall process in elderly individuals, a three-dimensional coordinate system for the human body is first established. Since the waist is closest to the body's center of mass and can more accurately reflect the human body's movement acceleration signals, the center of the three-dimensional coordinate system is chosen to be at the waist level, as shown in Figure 1. A three-dimensional rectangular coordinate system (O-xyz) is established, with the following orientations: the X-axis points toward the front of the body, the Y-axis points to the left of the body, and the Z-axis aligns with the direction of the torso, vertically upward. The coordinate system moves with the body during activity.

Carlin et al. [11] found that during light movements such as walking, the body's center of mass acceleration ranges from 0.5g to 4.1g, while during vigorous activities such as running, the acceleration remains below 7g. The three-axis accelerometer used in this study is the MPU6050 module, with an acceleration measurement range set to ±8g. According to [12], the frequency of human motion acceleration signals is typically below 20 Hz. In accordance with the Nyquist sampling theorem, the sampling frequency for this study is set to 40 Hz.

3.2 Acceleration Data Preprocessing

During physical activity, it is necessary to collect motion acceleration data along the three axes of the elderly individuals' bodies. This data is susceptible to system noise and external environmental noise [12], which need to be filtered out. This study applies two preprocessing techniques: low-pass filtering and median filtering.

3.2.1 Low-Pass Filtering

Due to the effect of gravity on the human body, the acceleration value along the Z-axis remains at 0.98g when the body is at rest. Therefore, it is essential to separate the gravitational acceleration from the movement acceleration. A 3rd-order IIR filter with a cutoff frequency of 0.25 Hz is used to isolate the movement acceleration values, while a 40 Hz low-pass filter is employed to remove external noise.

3.2.2 Median Filtering

During exercise, the body of elderly individuals may experience shaking, and the acceleration data along the three axes may contain significant pulse noise. A 3rd-order median filter is used to eliminate this system noise.

As shown in Figures 2 and 3, after processing, the acceleration signal curves become smooth.

3.3 Motion Process Features

During a fall, elderly individuals may experience a variety of scenarios, including falling to the left, right, forward, or backward, or even fainting. Since the direction of the fall is uncertain, it is difficult to predict which spatial direction will exhibit the most significant change in acceleration. Therefore, using motion signals from a single axis as the sole criterion for detection is not advisable. Research has shown that during relatively intense movements such as falls, elderly individuals experience significant changes in acceleration magnitude (SVM), vector area (SMA), and the attitude angle along the Z-axis [13]. This study uses both the acceleration magnitude SVM and the vector area SMA to represent the combined changes in the three-axis accelerations, which can be used as criteria for identifying intense physical activities in elderly individuals.

3.3.1 Acceleration Magnitude SVM

The acceleration magnitude SVM represents the intensity of human movement and is defined as shown in Equation (1-1):

$$\mathrm{SVM} = \sqrt{(x_i^2 + y_i^2 + z_i^2)} \quad (1\text{-}1)$$

Where x_i, y_i, and z_i are the acceleration values along the X, Y, and Z axes at the i-time point, respectively. As shown in Equation (1-1), SVM reflects the intensity of movement at time i. The more intense the elderly person's movement, the larger the value of SVM.

3.3.2 Acceleration Vector Area SMA

The acceleration vector area SMA reflects the rate of change in acceleration, indicating the degree of intensity in the body's state of motion. It is defined as shown in Equation (1-2):

$$\mathrm{SMA} = \frac{1}{\Delta t}\left(\int_{t_1}^{t_2} |x(t)|dt + \int_{t_1}^{t_2} |y(t)|dt + \int_{t_1}^{t_2} |y(t)|dt\right) \quad (1\text{-}2)$$

In Equation (1-2), $\Delta t = t_2 - t_1$, x(t), y(t), and z(t) represent the components of acceleration along the X, Y, and Z axes during the time interval Δt. When Δt is set between 0.8s and 1.2s, the SMA shows the optimal discrete effect [14]. In this study, Δt = 1.1s is used. As shown in Equation (1-2), SMA can describe the intensity of motion over a period of time, allowing differentiation between the elderly individual being in motion or in a post-exercise resting state.

3.3.3 Vertical Attitude Angle θ

The variation in the vertical attitude angle θ of the body can indicate the degree of body tilt. As shown in Figure 4, θ represents the attitude angle of the body along the Z-axis at time i. The greater the body tilts, the larger the value of θ. Therefore, θ can be used to determine whether an elderly individual has fallen

4. Fall Detection Algorithm

The daily physical activities of elderly individuals are complex and include both non-sportive movements driven by daily needs and sportive exercises aimed at fitness [15]. Non-sportive movements encompass actions such as sitting, squatting, standing, bending, and going up or down stairs, while sportive exercises include activities such as jumping, slow walking, brisk walking, and running. It is evident that non-sportive movements tend to be of short duration with low repetition, leaning toward brief actions, meaning elderly individuals are unlikely to repeat the same activity frequently. In contrast, sportive movements tend to have longer durations and higher repetition, favoring cyclical actions, meaning elderly individuals will continue performing the same motion repeatedly. Although jumping is a brief action, elderly individuals often engage in jumping movements during exercise, where the repetitive nature qualifies it as a sportive activity. Slow walking, on the other hand, fits both as a sportive and non-sportive activity.

5. Detection of Falls During Non-Sportive Activities

5.1 First Layer: Detection of Motion Intensity

Research has shown that the duration of a fall for elderly individuals typically lasts between 1-2 seconds, which is considered a brief action. At the moment of the fall, the elderly person loses their balance, and their body moves downward with an impact. A specific part of the body collides with the ground or a low-lying object, causing a noticeable change in the downward acceleration. This results in a sudden increase in the SVM value, as shown in Figure 5, where the SVM exceeds 2.5g. Statistical studies have found that during non-sportive activities of the elderly, the SVM value when sitting down is approximately 1.72g, while quickly sitting down is around 1.8-2.1g. The SVM value during squatting is about 1.61g, while standing up is approximately 1.56g. When climbing stairs, the SVM value is about 1.63g, and when descending stairs, it is approximately 1.83g. During the process of standing up and bending down, the SVM value ranges from 1.73g to 2.2g. Most non-sportive activities have an SVM value below 2g, which is consistent with findings in the literature [11]. Therefore, setting the SVM threshold svmth0 at 2g can effectively exclude most non-sportive activity movements.

5.2 Second Layer: Detection of Attitude angle

Generally, compared to younger individuals, elderly people tend to perform the transition from standing to sitting more slowly, with an SVM value around 1.72g. However, during a rapid sitting motion, the entire process is more intense, with a larger range of movement, resulting in an SVM value of approximately 1.8-2.2g. The same holds true for bending movements, where the SVM value ranges from about 1.5-2.1g, all of which can exceed 2g.

By analyzing the specific steps involved in these actions, the rapid sitting movement includes standing posture, knee bending and sitting down, followed by straightening the body while sitting. The bending motion includes standing posture, bending forward or bending the knees and bending forward, and then returning to an upright position. After completing either of these actions, the elderly person's body typically returns to an upright state. In contrast, after a fall, elderly individuals generally remain lying on the ground or on a low object, making it difficult for the body to return to an upright position in the brief moment following the fall. Therefore, attitude angle data in the vertical direction can help exclude movements like bending or rapid sitting, which are short-lived but intense. Research has found that the duration of a rapid sitting or bending action is approximately 1.5-2 seconds. In this study, the attitude angle at the moment 2.5 seconds after the SVM value exceeds the threshold is used as the determining criterion.
Jumping is also considered a brief action. As shown in Figure 6, the SVM value during a jump also exceeds 2g, which can easily be misinterpreted as a fall. However, studies have shown that during the upward phase of a jump, the elderly person's center of gravity gradually rises. At this time, the body's own gravity is performing negative work, causing the fluctuations in the SVM value to be relatively smooth. To address this, this study employs the smoothed discrete SVM sequence, denoted as SVMLS, as a variable for analysis.
From Figures 7 and 8, it can be observed that during the elderly person's jumping phase, the SVMLS sequence value gradually increases. When it reaches its peak, the difference between adjacent discrete points is less than 0.4g. In contrast, during a fall, the difference between adjacent SVMLS sequence points is much greater than 0.4g. Therefore, the difference sequence of SVMLS, denoted as DSVMLS, can be used to distinguish between a jump and a fall.

6. Exclusion of Sportive Activities

6.1 First Layer: Detection of Motion Cyclicity

In sportive activities, elderly individuals engage in continuous, repetitive motions, primarily including walking, fast walking, running, and jumping, with the goal of fitness. Research has shown that during slow walking, the SVM value is approximately 1.53g, and during fast walking, it ranges from 1.73g to 2.3g. As shown in Figures 9-10, during running, the SVM value is about 2.5g, and during jumping, it is around 3.1g. Both values exceed 2g, which could mistakenly be interpreted as a fall when the SVM threshold svmth0 is used. Studies have found that during fast walking, running, and jumping, the SVM values often experience multiple peak values within a certain period, where the SVM exceeds 2.0g repeatedly. This is because all three activities are cyclic in nature. In contrast, during a fall, the SVM value after 1.1 seconds drops well below 2.0g, as the body moves with smaller amplitude after hitting the ground or a low-lying object, and the motion becomes less intense. The body's acceleration decreases rapidly. Therefore, the motion acceleration vector area value, SMA, which reflects the degree of change in the elderly person's motion state over a given period, can be used to distinguish between a fall and a cyclic sportive activity.
To analyze the entire process of the fall in elderly individuals, it is necessary to determine the observation time for the discrete SMA sequence. During a fall, it is assumed that the elderly person's vertical velocity is zero, and the center of mass undergoes free fall.

Considering that the center of mass for an elderly person with a stooped posture is in the range of 0.7 to 0.9 meters, and with gravitational acceleration $g=9.8\ m/s^2$, the fall duration is approximately 530–620ms. Given that the observation time for the SMA is $\Delta t = 1.1s$, this is sufficient to fully capture the entire fall process. As shown in Figures 10 and 11, during a fall, only one discrete point of the SMA value exceeds 2.0g, with the adjacent points showing values below 2.0g, and the difference from the peak value being significant. In contrast, during running, the discrete SMA sequence values repeatedly exceed 2.0g, with the adjacent values also being greater than 2.0g, and the difference from the peak value is smaller. Therefore, the threshold for SMA is set as smath1, and when two or more consecutive discrete points exceed smath1, it is classified as a sportive cyclic activity, indicating a non-fall action. At this point, the elderly individual is considered to be in a state of motion.

6.2 Second Layer: Attitude angle Detection

To improve the detection accuracy, the first layer of fall detection is supplemented with attitude angle assistance, which helps determine whether the elderly person is in a lying position. If the vertical attitude angle exceeds a threshold of 85° continuously for a period of time, the incident is classified as a fall.

Research has shown that at the moment of a fall, an elderly person first loses balance, followed by the body tilting and falling towards the ground or a low-lying object. During this brief period, the elderly person's body transitions from an upright, standing position to a prone or lying position on the ground or another low object. The attitude angle in the vertical direction changes significantly. As shown in Figure 12, after a fall, the Z-axis attitude angle θ fluctuates greatly, increasing by more than 85° and remaining around 85° for a period of time. Therefore, in this study, the vertical attitude angle threshold angth is set at 85°. When 15 consecutive values of θ exceed 85°, the system classifies the situation as a fall.

6.3 Detection of Slow-Type Falls After Exercise

During exercise, elderly individuals may fall due to slippery floors and improper movements. Additionally, after exercise, they may faint due to overexertion or lack of oxygen, or the fall may be triggered by pre-existing chronic conditions such as cardiovascular or cerebrovascular diseases. Before such falls or fainting events occur, elderly individuals often feel unwell, stop exercising, and enter a resting or recovery phase, such as sitting or squatting. As their physical condition weakens further, they may faint and fall to the ground or onto a low object like a chair. The movement involved in these falls is typically slow and gentle, with smaller fluctuations in SVA and SMA values, making the event prone to being overlooked or misjudged. Furthermore, during daily activities, when elderly individuals lie on a sofa or rest in bed, the attitude angle θ\thetaθ may also exceed 85°, potentially leading to false positives.

To accurately detect fainting during the recovery phase after exercise, this study considers two factors for judgment.

6.4 First Layer: Attitude angle Detection

When elderly individuals faint, their bodies are in a prone position, and the vertical attitude angle undergoes significant changes. The threshold for θ is still set at 85°. If 15 consecutive values of θ exceed this threshold, the system classifies the posture as prone and excludes non-prone postures.

6.5 Second Layer: Detection of Previous Motion State

According to research [16-17], fainting or loss of balance often occurs within 5 minutes after exercise. Under normal conditions, due to severe ischemia in myocardial cells after exercise, increased respiratory rate, and significantly higher systolic blood pressure and heart rate compared to the resting state, elderly individuals will not typically choose a prone or lateral resting position within 5 minutes after exercise. Therefore, the system detects a motion flag to check the elderly person's previous motion state, including both "exercised" and "non-exercised" states. If the elderly individual is in a lying posture immediately after exercise, the system classifies it as a post-exercise fall. Otherwise, the system classifies it as a normal lying/resting state. The "stopped exercise time" is measured from when the individual stops moving. Here, the motion flag is marked: "1" for after exercise, and "0" for before exercise. The stop time is marked as t2, and the post-exercise fainting detection threshold ftime is set to 4 minutes.

By combining the conditions in (1) and (2), when the flag equals 1, and during the time period from t2~t2+240s, if 15 consecutive values of θ exceed the threshold angth, the system judges it as a post-exercise fainting event.

Based on the above analysis, the elderly fall detection process, using SVM, SMA signals, and attitude angle θ, is illustrated in Figure 13.

6.6 Experimental Results and Analysis

To verify the effectiveness and accuracy of the fall detection algorithm proposed in this study, we compared it with an existing fall detection algorithm based solely on acceleration signal thresholds. Both algorithms were tested under the same conditions in simulation experiments. As shown in Figure 10, the experimental device was worn on the waist of the subjects. The simulation experiment included 12 action categories, such as falls and running, to simulate different motion scenarios. To avoid injury to elderly individuals during the fall simulations, the participants in the experiment were 12 healthy young adults, aged 21 to 28 years, with heights ranging from 1.6 to 1.9 meters. The subjects were instructed to fall onto a 15 cm thick cushioning mat and a 40 cm high sofa to simulate falls onto the ground and onto low objects. This arrangement ensured the validity of the experiment while minimizing the risk of injury. Running and other physical activities were conducted on a 400-meter-long rubber track. After the experiment, the running speed was measured at 2.51 m/s, and the walking speed was measured at 1.35 m/s, which are consistent with the physical activity characteristics of elderly individuals [18]. The experimental results are shown in Table 1.

Experiment Item	Test Count	False Alarm Count (Comparison Algorithm)	False Alarm Count (Proposed Algorithm)
Slow Walking	24	0	0
Fast Walking	24	0	0
Sitting Down	24	0	0
Lying Down	36	0	0
Squatting	36	0	0
Bending Over	36	0	0
Elevator Up/Down	36	0	0
Jogging	48	0	0
Sprinting	48	0	1
Jumping	24	18	1
Fainting After Exercise	24	0	23
Fall During Exercise	60	57	57

Table 1 shows that when detecting daily activities of elderly individuals, such as sitting down or squatting, both the proposed algorithm and the comparison algorithm achieved the same accuracy, reaching 100%. However, when detecting brief and intense movements, such as falls during exercise, jumping, or sprinting, the performance of the proposed algorithm was superior. This improvement is attributed to the use of the discrete sequence SVMLS from SVM to distinguish between jumping and falling motions, as well as the introduction of vertical attitude angles as auxiliary indicators, which enhanced the overall accuracy. Furthermore, the proposed algorithm specifically addresses the detection of faint or slow falls during the rest phase of exercise, incorporating attitude angle features to effectively identify slow fall events.

In the experiment, there were 3 instances of falls during exercise that were not detected. This was due to the falls being too mild, with SVM values lower than 2g, leading to misclassification as daily activities. One instance of a faint fall during the rest phase was missed because the subject was reclining on a sofa and the vertical θ angle remained below 85°. Additionally, there were 2 instances of false alarms during jumping exercises, as the device attached to the waist tilted during intense jumping, misclassifying the action as a reclining state with the vertical θ angle exceeding 85°.

7. Conclusion

This paper addresses the critical issue of exercise-related falls that endanger the safety of elderly individuals, proposing a dual-fusion detection method based on three-axis acceleration and attitude angle. This method is designed to detect both falls during physical activity and those occurring during the rest phase. First, we investigate fall detection during physical activity, where motion intensity and cyclicity are used to exclude non-sportive and sportive movements.

Next, we focus on detecting fainting during the post-exercise rest phase, using lying posture and the previous motion state to filter out daily resting actions. This detection algorithm not only applies to fall detection during elderly individuals' physical exercise but also effectively identifies fainting episodes during the post-exercise rest period, addressing the gap in detecting fainting during rest. The method demonstrates strong applicability and comprehensiveness, and experimental results validate the effectiveness and accuracy of the proposed detection algorithm.

Disclosure

Author's contribution

This article is designed and written by Yongsen Liu and Bin Ji. Mufan Zhang is responsible for literature collection and organization. Meanwhile, Bin Ji is the project manager and has approved the author and corresponding author of this study.

All authors have read and agreed with the published version of the manuscript.

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