Scholar Publishing Group
International Journal of Multimedia Computing
https://doi.org/10.38007/IJMC.2020.010206
ISSN 2789-7168 Vol. 1, Issue 2: 62-78

Motion Fall Detection System for the Elderly Based on Multi-feature Fusion Robot

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Keywords: Multi-Feature Fusion, Fall Detection, Acceleration, Support Vector Machine, Android Platform

Abstract: With the improvement of people's living standards, countries around the world are facing the serious problem of aging in their own countries. Unexpected events such as falls in the elderly have a serious and inestimable impact on the health of the elderly. The purpose of this paper is to study the elderly fall detection system based on multi-feature fusion robot. This article first introduces a fall detection algorithm. Second, it improves the way of feature fusion. It uses feature weighted kernel functions to achieve the weighted fusion of acceleration and angular velocity features to build a fall recognition model based on support vector machines. Then, it analyzes the key parts of the fall recognition model. To verify the generalization performance of the algorithm. Finally, a fall detection system based on the recognition model constructed in this paper is implemented on the Android phone platform, and the practical application effect of the fall detection algorithm is verified. The experiments show that the feature fusion fall monitoring algorithm constructed in this paper has a sensitivity of 90.67%, a specificity of 92.96%, and an accuracy of 92.14%, which verifies the detection performance of the detection algorithm constructed in this paper. The robustness and stability of the drop detection software based on the Android platform.

1. Introduction

Fall is one of the main accidental injuries common to the elderly, especially in the social environment of aging and family empty nests, it is more difficult to get timely assistance after a fall. With the growth of the population and the development of science and technology, the aging trend in our country is becoming more and more obvious. The number of elderly people aged 65 and over has reached 150 million. Even if only based on the 30% fall rate, it occurs at least once a year More than 40 million elderly people have fallen. It has brought great inconvenience to the lives of the elderly, making them unable to live alone and go out. At the same time, it also increases household medical expenditures and the country's economic burden. Under current economic development conditions, adopting a home-based pension is still the main trend. Among them, family pensions accounted for 90%, community pensions accounted for 7%, and only 3% existed in nursing homes. Therefore, the research on fall recognition technology can greatly reduce the burden of family care for the elderly and increase the family's happiness index. In recent years, elderly people have fallen on the street repeatedly, and at the same time, it has triggered public discussion on morality. Fall detection, protection, and intervention measures have developed and matured against this background. If you can promptly report to the police and ask for help after a fall, you will reduce the damage caused by the fall and avoid accidental secondary injuries.

In fact, a fall does not directly cause many serious consequences. Faced with the problem of falling among the elderly, in addition to strengthening precautions in advance, such as mobile safety education and environmental safety. When a fall occurs, the most important thing is to send the elderly to the nearby hospital for ambulance at the fastest speed, which can reduce more injuries. Therefore, designing an accurate and effective fall detection device is very necessary for this problem. At present, high-tech such as artificial intelligence and robots have been widely used in many fields, but their contribution to improving the services of the elderly and vulnerable people is still small. This article hopes to be able to design a fall detection system through artificial intelligence and robot technology. The system can detect and determine the fall event of the human body, accurately obtain the fall position, and automatically send a text message for help through a mobile phone. In order to rescue and deal with these users in time and avoid serious consequences. In order that the size of the fall detector will not greatly affect the daily activities of the elderly, it is designed to be worn on the body. Doing so not only allows the elderly to be more comfortable with outdoor activities, it is no longer necessary to go out because of fear of falling, and it can also reduce the pressure on society and children.

Li Y and his team made full use of the synchronized phasor provided by the GPS-based Wide Area Measurement System (WAMS) and proposed a new method of VBpMKL-based transient stability assessment (TSA) through multi-feature fusion. First, a set of classification characteristics reflecting the transient stability characteristics of the power system are extracted from the synchronized phasors, and they are divided into three non-overlapping subsets according to the different stages of the disturbance process. Then by combining the feature spaces corresponding to each feature subset, a multi-feature fusion is used to build a VBpMKL-based TSA model. Finally, the application of this model in IEEE 39 bus system and real-world power system is proved. The novel method is that it improves the accuracy and reliability of TSA classification by using multi-feature fusion technology with synchronous phasors. Although the algorithm has accuracy and reliability, it needs to be improved in speed [1]. Kianoush S and his team believe that the fall detection and positioning of people in the work space is a major issue in ensuring a safe working environment. The disturbance of radio frequency (RF) signals, which are commonly used in wireless communications, can also be used as a sensing tool for deviceless human motion detection. RF-free human-sensing applications range from unlabeled human positioning to detection and surveillance of human well-being (e-Health). They proposed a real-time system for human motion sensing, focusing on joint body positioning and fall detection. The proposed system continuously monitors and processes RF signals from industry-standard radios operating in the 2.4 GHz ISM band and supporting machine-to-machine communication. For fall detection, a hidden Markov model is used to identify the different postures of the operator, and the track of the received signal intensity indicator is tracked. To detect security-related events. The fall detection performance has been confirmed by extensive experimental measurement results in different environments. In addition, they have proposed a sensor fusion tool that can integrate device-based RF-free sensing systems into the industrial image sensor framework. The preliminary results obtained during the measurement in the field test confirmed the effectiveness of the method in terms of positioning accuracy and sensitivity / specificity to correctly detect a fall event from the posture before the impact [2]. Abdiansah A. His team considers support vector machines (SVM) to be one of the machine learning methods that can be used to perform classification tasks. Many researchers use the SVM library to accelerate their research and development. Using such a library will save them time and avoid writing code from scratch. LibSVM is one of the SVM libraries and has been widely used by researchers to solve their problems. The library is also integrated into WEKA, one of the popular data mining tools. Contains work results related to the complexity analysis of support vector machines. Their work focuses on the SVM algorithm and its implementation in LibSVM. They also used two popular programming languages (ie C ++ and Java) and three different datasets to test their analysis and experiments. They found that the complexity of the SVM (LibSVM) is O (n_3), and the time complexity indicates that C ++ is faster than Java in training and testing. In addition, data growth will be affected and increase time [3].

This article first introduces a fall detection algorithm. Second, it improves the way of feature fusion. It uses feature weighted kernel functions to achieve the weighted fusion of acceleration and angular velocity features to build a fall recognition model based on support vector machines. Then, it analyzes the key parts of the fall recognition model. To verify the generalization performance of the algorithm. Finally, a fall detection system based on the recognition model constructed in this paper is implemented on the Android phone platform, and the practical application effect of the fall detection algorithm is verified.

2. Proposed Method

2.1. Fall Detection Algorithm

(1) Algorithm based on threshold judgment

Acceleration and angular velocity can be used as feature quantities to distinguish fall behavior from daily behavior activity [4-5]. The maximum acceleration and maximum angular velocity produced during the fall are quite different from the corresponding values of daily behavioral activities. Therefore, a simple idea is to set an acceleration or angular velocity threshold, and determine whether a behavior is a fall behavior by comparing the collected sensor data with the magnitude of the threshold [6-7].

Let the selected feature amount be x, the threshold of this feature amount is TH_x, $Bool(x)$ is a Boolean function of x, the value is 1 to judge the fall behavior, and the value is 0 to judge the non-fall behavior. The model is shown in equation (1):

$$Bool(x) = \begin{cases} 1, x > TH_x \\ 0, x \le TH_x \end{cases} \tag{1}$$

(2) Algorithm based on pattern recognition

The purpose of pattern recognition is to achieve the correct classification of a specific thing [8]. Statistics-based recognition is a major method for pattern recognition [9]. In statistical pattern recognition methods, data preprocessing and feature extraction are the focus of research in the entire method.

1) Classifier based on Bayes decision theory

In the Bayesian decision theory classifier, its theoretical basis is the Bayesian rule in probability theory, which is the following formula:

$$p(w_i \mid x) = \frac{p(x \mid w_i)\, p(w_i)}{p(x)} \tag{2}$$

In formula (2), w_i represents the i-th type action sequence, that is, fall or ADL. x represents the value of the sample point, that is, the eigenvector composed of eigenvalues such as acceleration and angular velocity during the fall. According to the definition of probability, $p(w_i \mid x)$ means that when the value of the sample is x, the sample belongs to the conditional probability of w_i, that is, when the acceleration of the sample is $35m/s^2$, it is the probability of falling activity. The $p(x \mid w_i)$ indicates that when a sample is known from the action sequence, the value of the sample is x, that is, the probability that the sample is a fall activity sequence and the acceleration of the sample is w_i. $35m/s^2$ represents the probability that a sample belongs to $p(w_i)$ when other conditions are not considered. Similarly, $p(x)$ represents the probability that a sample feature vector is x when other conditions are not considered.

The advantage of using the Bayesian decision theory classifier is that the calculation is small and fast, but the disadvantages are also obvious [10]. Several probability distributions of the fall sample data are not easy to obtain.The main reason is that it is impossible to collect a large amount of real fall sample data.The data obtained under the experimental conditions may have a phenomenon that cannot reflect the real situation and thus the obtained probability distribution is biased. And then make the algorithm invalid [11-12].

2) Decision tree

Decision tree, also called classification tree, is a common method in pattern recognition [13-14]. As a method of multi-process decision-making, decision tree has an obvious difference from other pattern recognition methods: decision-trees examine different indicators at different decision-making levels. Generally, other algorithms use feature indicators as a whole. The principle of decision tree is shown in Figure 1.

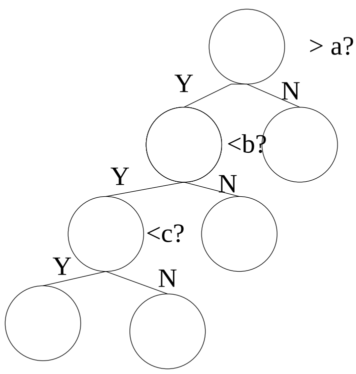

Figure 1. Principle of decision tree

If the simple decision tree in Figure 1 is applied to a fall detection algorithm, its algorithm idea is mainly: the nodes at different levels in the decision tree effectively distinguish the feature quantities from falls and ADL. Therefore, the top-level node may first examine whether the maximum combined acceleration exceeds a certain threshold, and if it does not exceed, it is classified as ADL activity; if it exceeds, it enters the middle-level node for further investigation, at this time, the middle-level node may investigate the angular velocity [15-16]. A layer of judgment is used to determine whether the sample has fallen.

3) K nearest neighbors

K-nearest neighbor algorithm is a simple and mature machine learning algorithm, and its geometric meaning is very intuitive [17-18]. Applied to the fall detection algorithm, the main idea of K-nearest neighbor is that one fall sample data can be regarded as a point in space, that is, if acceleration and angular velocity are selected as the feature variables to distinguish between falls and daily behavior activities, then a two-dimensional the vector can represent a sample, so a one-to-one mapping from the fall experiment sample to a point on the two-dimensional space is formed [19-20].

K nearest neighbor discrimination has the advantages of being intuitive and easy to implement, but it also has some disadvantages. Doing a lot of calculations and making judgments after the sample enters is likely to reduce the sensitivity of the fall alarm response. Each time, the distance between each new sample point and the test sample point needs to be calculated, and the nearest K sample points belong to the number of each category. High battery.

4) Support Vector Machine

The classification model of support vector machine is shown in equation (3).

$$y = sign(\omega \cdot x + b) = \begin{cases} 1, \omega \cdot x + b > 0 \\ -1, \omega \cdot x + b < 0 \end{cases} \tag{3}$$

In the formula, $sign(\cdot)$ is a symbolic function, x is a feature quantity or a feature vector composed of multiple feature quantities, and ω, b is a parameter of a support vector machine, which needs to be obtained by training on sample data. Basic process of fall recognition based on support vector machine:

First, classify the sample data of each movement behavior process of the human body into two categories that do not intersect each other, that is, the set of fall data samples and the set of daily behavior activities;

Then train the sample set to obtain the SVM classification model, that is, the parameter (3) is determined;

Secondly, the collected feature values are substituted into equation (3) for judgment. It is important to note that the support vector machine method using a single feature, the classification model is shown in equation (4), and the threshold method model in equation (1) is essentially equivalent.

$$y = \begin{cases} 1, x > -\dfrac{b}{\omega} \\ -1, x < -\dfrac{b}{\omega} \end{cases} \tag{4}$$

The method based on support vector machine is used to improve the recognition efficiency of the algorithm to a certain extent. In the fall recognition, support vector machine method has a good classification performance for small sample data, so the fall recognition method based on support vector machine is widely used.

2.2. Multi-Feature Fusion

The ultimate goal of information fusion technology is to realize the automatic analysis and classification of data from multiple information sources. It is a multi-level and multi-angle data processing and analysis process, which mainly implements the detection, analysis, combination and optimization of data.

(1) Information fusion based on data layer

The data layer-based fusion method is the lowest-level information fusion technology. Its basic idea is to directly analyze the original data and achieve fusion, that is, the data without preprocessing, then, extract features, construct classifiers and implement data classification [21-22]. The method based on the data layer has very obvious advantages, that is, the original information is less lost and the data is more accurate. However, the amount of data it processes is large, the recognition efficiency is low, and the generalization performance is poor.

(2) Information fusion based on feature layer

The fusion of the feature layer first preprocesses the original data, then comprehensively analyzes the extracted features and realizes the information fusion, which belongs to the information fusion technology of the intermediate layer [23-24]. It achieves a better compression and combination of data features and improves the efficiency of classification and recognition. The fusion of target feature information is essentially the process of pattern recognition. Common methods include neural networks, K-nearest neighbors, and clustering. From the perspective of feature fusion strategy, it mainly includes multiplicative fusion strategy and additive fusion strategy. Additive fusion is widely used. Its main idea is to use observation probability weighted estimation to estimate the likelihood of a sample.

(3) Information fusion based on decision-making layer

Decision-level information fusion is the highest-level fusion technology. Its basic idea is to construct multiple classifiers to complete preliminary classification and recognition through pre-processing of the previous data, and finally fuse the recognition results of each classifier [25-26].

In the fall recognition, most of them use a single feature or a simple fusion of acceleration and angular velocity features. Each feature has its own unique attributes, but it cannot fully describe all the information of the human motion process. The multi-feature fusion recognition method can make full use of the advantages of various features to improve the performance of fall recognition, and how to use multiple features to build an efficient multi-classifier model is the key problem to be solved [27-28]. Multi-feature uses decision-level fusion with high recognition efficiency.It is mostly used in image recognition or video surveillance.Its shortcomings are also obvious.It needs to train multiple classifiers.The complexity of the algorithm is high and the operating efficiency is low. Research on detection technology. Although feature-level fusion has a relatively low recognition accuracy, it has a simple structure and is easier to implement. At the same time, because only one classifier is used, the real-time performance of the algorithm is greatly improved [29-30].

2.3. Support Vector Machine

(1) Linearly separable case

Suppose the sample set $(x_i, y_i), i = 1,2,...,n \quad x_i \in R^d$ is linearly separable, where $y \in \{1,-1\}$ stands for sample label. In the d-dimensional feature space, it is assumed that $\omega \cdot x + b = 0$ represents the classification hyperplane, that is, the above classification hyperplane can divide the sample set into two categories, then the classification discriminant function (that is, the classification model) corresponding to the classification hyperplane is as follows:

$$y = sign(\omega \cdot x + b) = \begin{cases} 1, \omega \cdot x + b > 0 \\ -1, \omega \cdot x + b < 0 \end{cases} \tag{5}$$

In the formula, $sign(\cdot)$ is a symbolic function.

From the relevant mathematical analysis, it is known that solving the optimal classification hyperplane is the optimal solution of the following problems:

$$\min \frac{1}{2}\|\omega\|^2 \, s.t. y_i sign(\omega \cdot x_i + b) \geq 1, i = 1,2,...,n \tag{6}$$

Define formula (7) as a Lagrange function:

$$L(\omega, b, a) = \frac{1}{2}\|\omega\|^2 - \sum_{i=1}^{n} \alpha_i \{y_i[(\omega \cdot x_i) + b] - 1\} \tag{7}$$

In the formula, $\alpha = (\alpha_1, \alpha_2, ..., \alpha_n), \alpha_i > 0$ is called Lagrange coefficient vector.

The problem of solving the optimal hyperplane is transformed into solving the minimum value of the Lagrange function for ω, b. Partial differentiation of ω, b in the Lagrange function gives the following formula:

$$\begin{cases} \dfrac{\partial L(\omega, b, a)}{\partial b} = \omega - \sum_{i=1}^{n} y_i \alpha_i x_i = 0 \\ \dfrac{\partial L(\omega, b, a)}{\partial \omega} = \sum_{i=1}^{n} y_i \alpha_i = 0 \end{cases} \tag{8}$$

Then, substitute equation (8) into equation (7) and use equation (8) to get the dual problem of equation (9):

$$\begin{cases} \max_{\alpha} (\sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j (x_i \cdot x_j)) \\ s.t \quad \sum_{i=1}^{n} y_i \alpha_i = 0, \alpha_i \geq 0, i = 1,2,...,n \end{cases} \tag{9}$$

If α_i^* is the optimal solution, then

$$\begin{cases} \omega^* = \sum_{i=1}^{n} \alpha_i^* y_i x_i \\ b^* = y_i - \sum_{i=1}^{n} y_i \alpha_i^* (y_i \cdot x_i) \end{cases} \tag{10}$$

(2) Linear inseparable case

For non-linear training samples, equation (6) cannot be satisfied, and there will be no solution. Add a relaxation term and a penalty parameter C (C> 0) to the formula.These two parameters represent the degree of acceptance of the misclassification and the degree of emphasis on the misclassification, and the optimization problem becomes

$$\begin{cases}\min_{\omega} \frac{1}{2}\|\omega\|^2 + C\left(\sum_{i=1}^{n}\xi_i\right) \\ s.t. \quad y_i(\omega \cdot x_i + b) \geq 1-\xi, i=1,2,...,n\end{cases} \tag{11}$$

The Lagrange function is constructed, and the optimization problem of equation (11) is transformed into its dual problem equation (12).

$$\begin{cases}\max_{\alpha}(\sum_{i=1}^{n}\alpha_i - \frac{1}{2}\sum_{i,j=1}^{n}\alpha_i\alpha_j y_i y_j (x_i \cdot x_j)) \\ s.t \quad \sum_{i=1}^{n} y_i\alpha_i = 0, C \geq \alpha_i \geq 0, i=1,2,...,n\end{cases} \tag{12}$$

The above theoretical analysis shows that the nonlinear classification problem and the linear classification problem of the optimal classification hyperplane are basically the same. The Lagrange function is constructed, transformed into a dual problem, and the minimum value is solved under certain constraints.

2.4. Fall Recognition Model Based on Feature Weighted Fusion of Support Vector Machines

(1) Fusion of triaxial acceleration and triaxial angular velocity features

Aiming at the limitation of single feature and multiple features simple fusion method recognition, this paper improves the feature fusion method and adopts multi-feature weighted fusion method to build a fall recognition model based on support vector machine. Its main idea is to jointly build a classification and recognition model of fusion features according to the recognition weight of each feature model.

Let the total sample number be N and $NumC_i$ be the total sample number belonging to the C_i category, then $N = \sum NumC_i$ and $n_1 = n_2 = ... = n_n = N$ are satisfied.

The definition probability $P_{ij} = \frac{n_{ij}}{NumC_i}$ represents the accuracy of identifying the label as C_i under the feature A_j.

Define probability $P_i = \frac{NumC_i}{N}$, where P_i represents the proportion of category label C_i to the total number of samples.

Define $M_{ij} = Min(n_{ij}, NumC_i)$, that is, M_{ij} is the exact number of class labels C_i under the feature A_j.

$$P_j = \frac{\sum_{i=1}^{k} Min(n_{ij}, NumC_i)}{N}, j=1,2,..,m \tag{13}$$

Where P_j represents the accuracy of sample recognition under a single feature A_j.

Assuming the sample set is M, if there are k different category labels in the sample, the entropy of the sample set M relative to the k different category labels is defined as:

$$Entropy(M) = -\sum_{i=1}^{k} P_i \log_2 P_i \tag{14}$$

According to the definition of entropy, the information HC contained in the feature category in the above contingency table, the information contained in the feature H_A, and the weighted information sum of each feature value of the feature A_j can be obtained according to the following formula.

$$\begin{aligned} &Hc = -\sum_{i=1}^{k} P_i \log_2 P_i, H_A = -\sum_{i=1}^{k} P_i \log_2 P_i \\ &H_{C/Aj} = -\sum_{j=1}^{m} P_j \sum_{i=1}^{k} P_{ij} \log_2 P_{ij} \end{aligned} \tag{15}$$

Define the information gain of feature A_j as:

$$H_{IG} = H_C - H_{C/A} \tag{16}$$

The meaning of H_{IG} is the information about the value of the objective function obtained from the value of the characteristic A_j. The greater the information gain of the feature, the greater the degree of discrimination of the classification results, and the more important the feature is. This article uses the information gain as the weighted value of the feature.

(2) Construction process of fall behavior recognition model

The process of establishing a fall behavior recognition model is mainly divided into three major modules, namely training support vector machine model, finding the optimal classification surface, and test sample prediction. When it is applied to fall detection, firstly, human motion data is obtained from sensor nodes and training samples are selected. Then, the preprocessed sample data is processed to construct an SVM classifier based on acceleration and angular velocity weighting. After the classifier is trained, the optimal classification hyperplane and the optimal classification function for identifying fall behavior and daily activity behavior are fixed. At this time, the model is provided with similar test data, and the most likely classification of the set of data can be obtained. The construction process is shown in Figure 2.

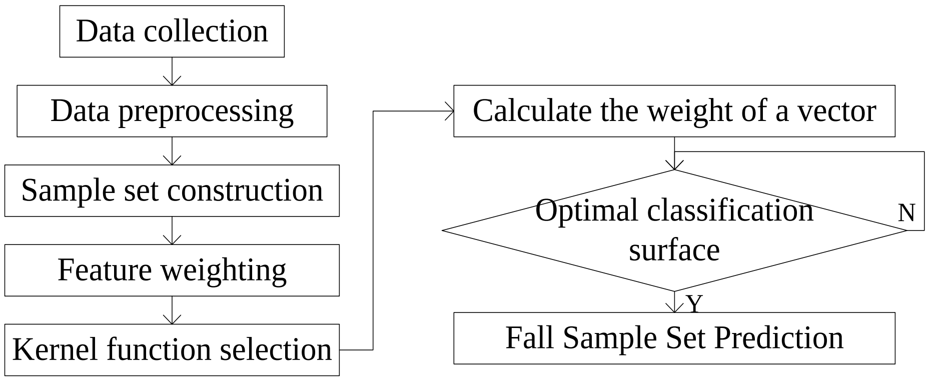

Figure 2. Construction process

3. Experiments

3.1. Data Collection

This article mainly selects healthy young people as the research object, and allows them to complete a series of fall actions unprepared according to the experimentally designed actions under the protection of similar sponge pads, so as to ensure the reliability of the experimental data research value. In this experimental study, we have 8 volunteers.

3.2. Experimental Environment

The sports fall detection system in this article uses Myeclipse development tools.Myeclipse is a powerful integrated development environment mainly for Java development.Myeclipse provides functions such as intelligent code completion, code checking, real-time errors, and fast repair. It not only supports Java, but also supports JavaScript, SQL, HTML / CSS. It is very convenient to use in system development. The Java language is mainly used to write the algorithm of this system. The database used in this system is SQLserver2008. The operating environment is shown in Table 1.

Table 1. Operating environment

Type	Andriod version	Processor	RAM	Resolution
EMUI	9.0	Kirin 970	Java	9.0

3.3. System Design

This article divides the software into the following three modules when designing the software:

(1) Data processing module: Mainly performs data collection, preprocessing, and fall detection.

(2) Alarm processing module: When a fall is detected, the alarm processing module will be triggered to start working.

(3) Basic parameter setting module: At the beginning of system startup, set basic information, emergency contacts, alarm SMS content.

Figure 3 shows the software functional module design.

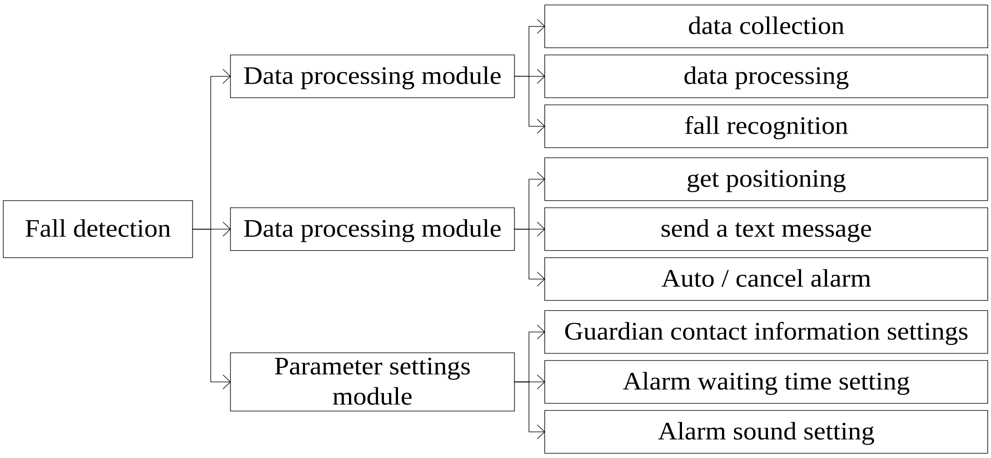

Figure 3. Overall design architecture diagram

3.4. Verification Index

A fall detection system may have the following four situations in fall detection: (1) TP: A fall action occurs, and the fall detection algorithm correctly recognizes a fall as a fall. (2) FP: A daily non-fall activity. The fall detection algorithm recognizes that a fall has occurred. (3) TN: A daily non-fall activity. The fall detection algorithm does not recognize a fall. (4) FN: A fall occurred, and the fall detection algorithm did not recognize the fall. Therefore, this article defines three indicators of sensitivity, specificity and accuracy to detect the effectiveness of the fall detection system. The definition and formula of the three indicators are as follows:

Sensitivity reflects the proportion of all fall events that are correctly identified by the fall detection system, that is, the detection rate of all fall actions.The formula is defined as follows:

$$SE = \frac{TP}{TP + FN} \tag{17}$$

The specificity reflects the proportion of all daily non-fall events of the fall detection system that are correctly identified, that is, the detection rate of all daily activities.The formula is defined as follows:

$$SP = \frac{TN}{TN + FP} \tag{18}$$

The accuracy reflects the proportion of all events that are correctly detected, that is, the detection rate of all actions.The formula is defined as follows:

$$AC = \frac{TP + TN}{TP + FN + TN + FP} \tag{19}$$

4. Discussion

4.1. System Function Module

(1) Fall detection module

The fall detection module is the core part of the system, which mainly includes three functions: acquisition of exercise data, processing of exercise data, and judging whether a fall has occurred. This module first collects the X-axis, Y-axis, and Z-axis acceleration values generated by human motion in real time through the built-in sensors of the Android phone; then processes these motion data to calculate the various discriminative thresholds; finally, according to the calculated multiple thresholds and falls The detection algorithm process detects whether a fall has occurred. The fall detection module is shown in Figure 4.

As shown in Figure 4, the function interface displays the motion acceleration value and whether the current behavior is normal in real time. Click the “Exit” button to exit the motion monitoring interface. Once the system detects a fall, it will send an alarm for help.

(2) Alarm processing module

Alarm processing is an important module of this system, which is related to whether elderly people can be treated in time after a fall, including functions such as beeping alarms, obtaining location information, sending help text messages, and canceling alarms. When the system detects that the user has fallen, it will continue to beep for local help, and obtain the current fall location information through positioning technology. During the alarm waiting time, if the user cancels the alarm by himself, the system will consider the fall as a false alarm or there is no need for an alarm, so the beep will be canceled and the program will return to the program entrance to continue the fall monitoring; if the waiting time is over, the user does not Any operation, the system determines that this is a real fall event, and will send the current location of the fall person to a designated contact for help. The alarm processing module is shown in Figure 5.

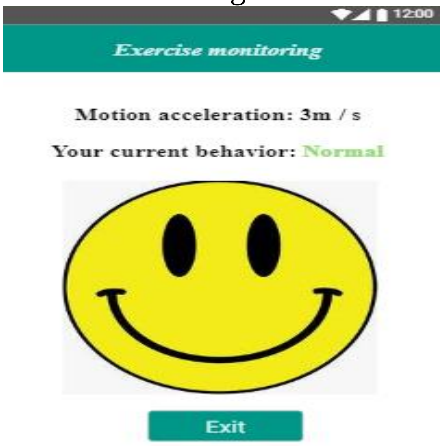

Figure 4. Fall detection module

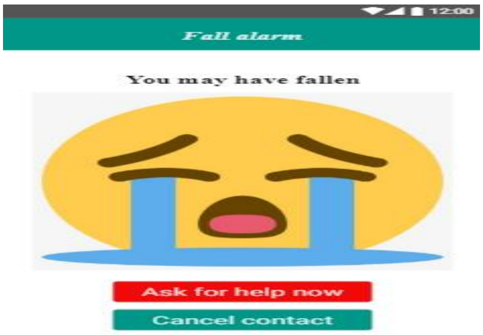

Figure 5. Alarm processing module

As shown in Figure 5, the function interface will display the delay time set by the user in the format of a countdown. If the countdown ends without the user doing anything or clicking the "Help Now" button before the end, the system will send a contact for help SMS; if the user does not feel the need to ask for help, click the "Cancel Contact" button to terminate the alarm and restart the motion monitoring.

4.2. System Performance Verification

(1) Experimental analysis of fall with irregular posture

In the irregular posture fall group, the fall posture is divided into five types of falls: forward fall, backward fall, left fall, right fall, and fall on the wall. The main records in the experiment are the actions, the number of experiments, the number of alarms, and the accuracy rate., The number of false negatives, and the false negative rate of five experimental data. The experimental results of the irregular posture fall group are shown in Table 2 and Figure 6.

Table 2. Experimental results of the random posture fall group

Action	Number of experiments	Number of alarms	Accuracy	Underreports	Underreport rate
Forward fall	30	28	93.33	2	6.67
Fall backward	30	29	96.67	1	3.37
Fall left	30	28	93.33	2	6.67
Fall right	30	29	96.67	1	3.37
Fall on the wall	30	22	73.33	8	26.67

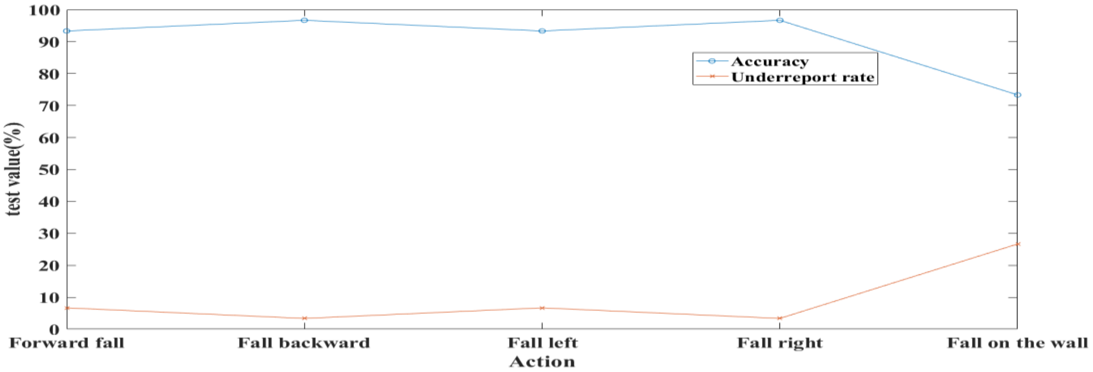

Figure 6. Experimental results of the fall posture group

As shown in Table 2 and Figure 6, in the fall test group, we can find that the system has a good recognition rate for the other four types of fall behaviors except the fall of the supporting wall, which verifies the effectiveness of the fall model and fall detection software constructed in this paper. Sex. However, in the fall group experiment, the falling wall fall accuracy rate is low. The reason for this phenomenon may be that the system software design uses 60 sampling points as the fall detection window. In the fall wall fall, the continuous action of the fall has a certain buffer. As a result, no valid fall data was collected. In response to this similar fall situation, this article has set up a “one-click help button” and the fall detection result cancellation mechanism in the software system, because the elderly will maintain a certain sobriety when this situation falls. If you are in a real fall, you can choose one-click help for alarm. If it is a false alarm, you can cancel the alarm. This will not only reduce the false alarm rate, but also allow the elderly to get timely assistance when they fall.

(2) Non-falling experimental analysis of daily activities

In the daily activities of the non-falling group, the fall test mainly tests daily activities such as walking, jogging, going up stairs, going down stairs, quickly sitting down, lying down, sitting upright, squatting upright, and using the mobile phone normally. It mainly records five experimental data of action, number of experiments, number of alarms, accuracy rate, and false alarm rate. The results of daily activities non-fall test are shown in Table 3 and Figure 7.

As shown in Table 3 and Figure 7 are the experimental results of the daily activities of the non-falling group. According to the data in the table, the mobile phone has the highest false alarm rate in daily activities.Because mobile phones are more complex in daily activities, it is difficult to distinguish them in the algorithm. This reflects the shortcomings of the algorithm. In order to make up for the shortcomings of the algorithm, software mechanisms can be used in the fall detection system to improve the accuracy of the algorithm and reduce the false alarm rate of the algorithm. At the same time, the "cancel alarm" and "automatic alarm" can be designed in the fall detection system the function strives to minimize the impact of false alarm rates. At the same time, it also points out a direction for future algorithm research, the recognition of falls in continuous action sequences, that is, the recognition of falls based on the context of the action.

Table 3. Analysis of non-fall test results of daily activities

Action	Number of experiments	Number of alarms	Accuracy	False alarm rate
Normal walking	30	1	96.67	3.33
Jogging	30	1	96.67	3.33
Down stairs	30	2	93.33	6.67
Sit down quickly	30	3	90	10
Lie down	30	1	96.67	3.33
Stand up	30	0	100	0
Mobile phone daily use	30	10	66.67	33.33

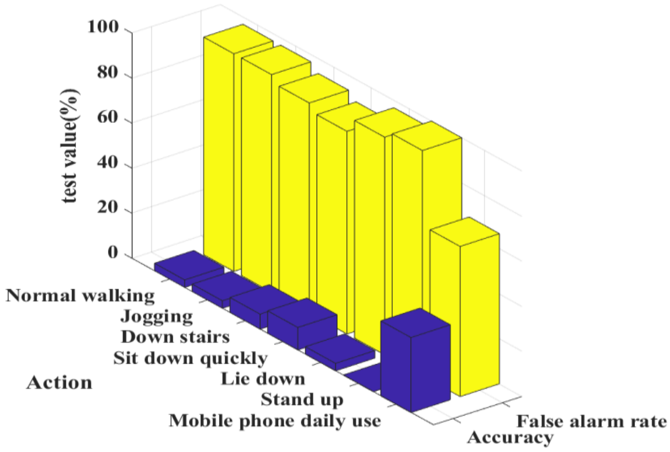

Figure 7. Analysis of non-fall test results of daily activities

5. Conclusion

(1) This article mainly introduces the basic theory of support vector machines, and then introduces the data fusion method. By comparing the structure and implementation of data fusion at different levels, the feature level fusion method is used in fall detection. Then the method of weight selection for feature weighted fusion is detailed. After feature weighting, similar data is more closely clustered and easier to classify. Finally, a multi-feature weighted fusion-based fall recognition model based on support vector machine is proposed, and a construction process of multi-feature weighted fusion-based fall detection model based on support vector machine is also given.

(2) This article describes the implementation process of the fall detection system based on the Android platform, and introduces the process of the data processing module and the alarm processing module. Then design the realization of the irregular fall group and the daily activity fall group. After preliminary experiments, the sensitivity of the system is 90.67%, the specificity is

92.96%, and the accuracy is 92.14%, which verifies the feasibility and effectiveness of the system.

(3) Although the human body motion recognition model based on the Android platform studied in this paper can effectively recognize some daily behaviors, and the proposed fall algorithm and developed fall detection system can identify most of the fall behaviors, but because of time, There are still some deficiencies and shortcomings due to the limitation of ability and experimental environment, which need to be further improved and perfected in the subsequent work.

Funding

This article is not supported by any foundation.

Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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