Human Fall Detection Algorithm Design Based on Multi-Threshold Comprehensive Judgment

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**Abstract:** Using a single method of acceleration threshold discriminator cannot fully characterize the change in human fall behavior and is easy to result in misjudgment. This paper proposes a human fall detection algorithm that combines the human posture, support vector machine and quadratic threshold decision. Firstly, a large number of human posture data are collected through the six-axis inertial measurement module (MPU6050). A fall detection model is established through filtering preprocessing, eigenvalues extraction, classification, and SVM training. Secondly, a first-level threshold determination is performed through the wearable wristband device. When a suspected fall occurs, six eigenvalues will be captured and uploaded to the cloud platform to trigger the second-level SVM fall judgments. By matching the eigenvalues with the fall detection model, it can be accurately determined whether or not a fall has taken place. The experimental results show that the fall detection wristband has a recognition rate of 92.2%, a false rate of 3.593%, and missing rate of 2.187%, which can better distinguish other non-falling actions.

**Keywords:** fall detection; eigenvalues; support vector; SVM fall model

1. Introduction

The fall detection systems can be classified into three types respectively, based on video images, physical environment and wearable devices [1]. The video image-based system can achieve accurate fall detection and recognition, but it requires to be fixed the camera in the room, thus limiting the user's activities. In addition, this system is mostly not accepted by the users because of personal privacy. Fall detection system based on the physical environment fits indoor use only, such as the plantar pressure sensor, infrared sensor, etc. Considering the limited monitoring range and high installation cost, it’s only used on specific scenarios thus not being accepted by the public. However, the fall detection system based on wearable devices has the advantage that it can be applied both indoors and outdoors [2], with no limit on the user's behaviors and no inference on privacy. Its alarm mode is relatively flexible, and the low price is more suitable for widespread promotion, but the recognition rate of fall behavior is not high enough, and corresponding fall detection algorithms need to be designed for different devices.

This paper proposes a human fall detection algorithm based on multiple thresholds comprehensive judgment, and designs a fall detection wearable device with STM32 as a hardware platform, MPU6050 as a sampler, and SIM808 as a communication positioning module, equipped with a fall detection bracelet with a WeChat public account. It has the advantages of small size, simple and stable operation and has a large market [3].

2. System design of fall detection bracelet

2.1. Overall design of the system

The scheme consists of three parts: a wearable device, a cloud platform and a WeChat public account. The overall design of the system is shown in Figure 1.

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**Figure 1.** Overall design of the system

The wearable device collects posture information of the human body and conducts first-level fall detection, uploads Global Positioning System (GPS) positioning information to the cloud platform periodically. Meanwhile, the guardian can monitor the user's current location and historical trajectory through the WeChat. When the fall is detected, the buzzer on the bracelet will alarm immediately and a user's suspected fall message will be sent to the guardian. At the same time, the secondary fall detection with Support Vector Machine (SVM) will be triggered. The platform judges the fall accurately by comparing the fall detection model. If it is true, the platform sends a confirming message to the wearable device. It sends a confirmation message and dials to the guardian's phone or emergency center, so that the user will have medical treatment in time [4]. During the wearable device alarm, the user can cancel the alarm by pressing the canceling button.

2.2. The hardware design

The hardware part of the fall detection bracelet is mainly composed of STM32F103 master controller module (MCU), MPU6050 six-axis inertial sensor module, SIM808 communication positioning module, button module, power management module and buzzer. The frame is shown in Figure 2.

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**Figure 2.** Hardware design block diagram

2.3. The software design

The software of fall detection system can be divided into three functional modules: fall detection, fall alarm, and remote monitoring, relying on functional requirement. The system software flow chart is shown in Figure 3.

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**Figure 3.** Software design flow chart

2.4. WeChat public account design

WeChat was developed by Tencent Holdings as a lightweight messaging platform. As it grew quickly to become the most popular messaging app in China, it added a range of products and services that sat on top that were designed to appeal to a broad range of consumers and businesses. Official accounts, WeChat payment, and online to offline features expanded its reach.

The old man or child can't find a way home because of memory impairment, guardian can monitor them from WeChat remotely. The fall detection bracelet can upload GPS positioning information to the cloud platform at regular intervals. The positioning information and historical track will be displayed on the WeChat, enabling the guardians to monitor the user position accurately in real time [5]. The current position and the history track is shown in Figure 4.

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| 图片4   1. The query interface showing the current position | 图片5   1. The query interface presenting the historical route |

**Figure 4.** The query interface showing the current position and the historical route

3. Research on human fall behavior

Human activity patterns can be divided into two categories. One type is daily activities, such as standing, sitting, walking, sitting, underarm, etc., while the other is falling behaviors, such as falling forwards, falling backwards, falling to the left and falling to the right [6]. The classification of human activity patterns is shown in Figure 5.

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**Figure 5.** Classifications of human activity patterns

3.1. Fall behavior

Falling behavior can be simply understood as the human body is affected by physiology, disease, environment, etc. The body suddenly falls to the ground or a low plane with non-autonomous. The fall behavior can be divided into three phases from the beginning to the end, namely the unbalance phase, the weight loss phase, and the collision phase [7].

The first phase is termed as unbalance. The body is out of balance, and there is a fall tendency from a stable state to an unstable state. Because the human body has not made any large movement, it is difficult to detect with posture sensor. The second stage is the weight loss. The body will tilt and lose weight from the loss of balance to the collision between the body and the ground. The angular velocity changes because of the tilt, the change of resultant acceleration caused by the weight loss, and the effective time period is an important factor in the fall detection from standing to falling. The third stage is the collision phase. The human body collides with the ground and has a great energy change, which can be retrieved from the resultant acceleration. The degree change reflects the behavior of the human body at that time. The extracted corresponding eigenvalues in the collision phase can be also used to judge the fall.

3.2. Analysis of fall model

In this paper, the wearable device is used for fall detection, so the energy change of the human body, the angle change of the body, and the change of the movement of the arm are all important reference factors. Establishing a suitable and accurate human posture model is the basis for the analysis of the fall behavior of the human body. The three-dimensional model of the human body is shown in Figure 6. If the human body is standing in the scene, the front and back of the human body are set to the x-axis, the sides of the human body are the y-axis, and the direction perpendicular to the human body is set to the z-axis.

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| 图片7 |

**Figure 6.** Three-dimensional model of the human body

When the body falls, the most obvious change takes place in the weight loss phase and the collision phase. During this period, the human body's energy will change greatly due to weightlessness or violent collision with the ground. Referring to the human body's three-dimensional coordinate model, we set the lost energy to be.It can be represented by the sum of the absolute values in the three-axis direction of the x-axis, y-axis and the z-axis. The energy loss is calculated as:

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| --- | --- |
| , | (1) |

In the formula (1), ,,represent the magnitude of the different component forces in the x-axis, y-axis, and z-axis directions respectively in the weight loss phase or the collision phase, while T is time from the unbalance phase to the completion of the collision phase. According to Newton's second law of motion, the magnitude of the acceleration of the object is proportional to the force, inversely proportional to the mass of the object, and proportional to the reciprocal of the mass of the object. The direction of the acceleration is the same as the direction of the force [8]. If the force is F, the acceleration is a, and the mass of the object is m, the Newton's second law of motion can be expressed as:

|  |  |
| --- | --- |
| , | (2) |

Expanded from the x-axis, y-axis, and z-axis respectively, it can be expressed as:

|  |  |
| --- | --- |
| , | (3) |

It can be inferred from formula (1) and (3), the energy loss is proportional to the amount of triaxial acceleration change during the fall, namely,

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| --- | --- |
| , | (4) |

It is inferred from the above theory that the fall behavior can be transformed into the collection, analysis and judgment of the special amount produced by the body change. The three-axis acceleration and the three-axis angular velocity are collected by the sensor module MPU6050 [9]. By analyzing and extracting the original data, the changes of the human body energy and angle can be obtained during the fall, so as to judge fall behavior accurately.

In this paper, the square root of the added up triaxial accelerations is set to the judgment unit to eliminate the influence of the direction uncertainty [10]. With the set as a resultant acceleration, the expression is as follows,

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| , | (5) |

where,,, represent the acceleration data of x-axis, y-axis and z-axis respectively, and the data are collected by the six-axis inertial measurement module MPU6050. is termed as resultant acceleration. So, data can be used for the analysis of human daily activities and fall behavior.

3.3. Data analysis of typical behaviors

The resultant acceleration and human activities are inseparable, according to the analysis of the fall model. With the resultant acceleration as a basis for determination, researchers can accurately distinguish between normal movements and the fall behavior. Two boys and one girl with different heights and weights were selected in the experiment and the acceleration data of typical human activities were collected. Typical activity behaviors include walking slowly, standing still, sitting down, lying down, going up and down stairs, falling and so on. In the experiment, the three-axis acceleration data is collected by the MPU6050, the three-axis acceleration data is processed into the resultant acceleration and output by the serial port assistant. The typical activity behaviors of the MATLAB simulation are shown in Figures 7.

|  |  |
| --- | --- |
| 1   1. Resultant acceleration curve under the static standing state | 行走.png   1. Curve of resultant acceleration of walking |
| 站立到坐下   1. Resultant acceleration curve of standing to sitting | 站立到躺下.png   1. Resultant acceleration curve of standing to lying down |
| 站立到蹲下.png   1. Resultant acceleration curve of standing to squatting | 站立   1. Resultant acceleration curve of standing up |
| 上楼.png   1. Resultant acceleration curve under the state of going upstairs | 下楼.png   1. Resultant acceleration curve under the state of going downstairs |
| 向前跌倒.png   1. Resultant acceleration curve of falling forwards | 向后跌倒.png   1. Resultant acceleration curve of falling backwards |
| 向左跌倒.png   1. Resultant acceleration curve of falling to the left | 向右摔倒.png   1. Resultant acceleration curve of falling to the right |

**Figure 7.** Simulation diagram of typical activity behaviors

3.4. Analysis of fall behavior feature

Unlike the traditional fall detection device fixed on the head, waist and back, the wrist-type fall detection device can focus on the tilt angle of the human body and the angular velocity of the three axes. Therefore, the eigenvalue and feature vector should be chosen and further analyzed. The following six signal characteristics are chosen as the fall detection.

1. Acceleration intensity vector(Signal Magnitude Vector, SMV)

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| --- | --- |
| , | (6) |

The SMV is actually the resultant acceleration. The maximum and minimum values of  are the eigenvalues of the fall detection.

In the process of human fall, from the unbalanced phase to the weightlessness period, the human body loses balance and the body is in a free fall stage. The resultant acceleration of the human body will have a decreasing change, and the minimum resultant acceleration is set to .

The third stage of the fall behavior is the collision stage. In this stage, the human body will have a strong impact with the ground. When the human body hits the ground, the speed of the human body is zero, and the maximum acceleration of the body is set to .It reflects the violent degree of impact between the human body and the ground, and is selected as the second eigenvalue of the behavior.

1. Signal amplitude area(SMA)

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| --- | --- |
| , | (7) |

In the formula (7), T represents the time from the start of the weight loss phase to the end of the collision phase.

The SMA is calculated by the absolute value of the triaxial acceleration as a basic parameter, which can intuitively reflect the intensity of the human motion state, and is selected as the third eigenvalue of the behavior.

1. Gyro resultant angular velocity(Gry)

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| --- | --- |
| , | (8) |

In equation (8),、、 represent the angular velocities of the x-axis, y-axis, and z-axis, respectively, and can be acquired by the gyro sensor of the MPU6050 sensor module. Resultant angular velocity (Gry) can reflect the severity of the wrist or body rotation when the human body is active [11]. However, the angular velocity avoids the complexity of different axial directions effectively. Gry is selected as the fourth eigenvalue of the behavior.

1. Time Of Weightlessness(TWL)

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| --- | --- |
| , | (9) |

TWL is defined as the time from the unbalance phase to the end of the weight loss phase.  is the first point time when the free fall begins.  is the last point time in the free fall movement. The weight loss duration is selected as the fifth eigenvalue of the behavior.

1. Time Of Impact(TIM)

|  |  |
| --- | --- |
| , | (10) |

TIM is defined as the period from the start of the impact phase to the end of the impact phase. It is selected as the sixth eigenvalue.

4. Fall detection algorithm based on quadratic decision

In this paper, the SVM classifier method is used to obtain the suspected fall signal data from the First Input First Output (FIFO), and six of the eigenvalues are extracted. By matching with the fall detection model [12], an accurate second judgment result can be obtained.

Firstly, a large number of human posture data needs to be acquired through the MPU6050 sensor module. The data are saved after preprocessing and eigenvalues processing, and then the six eigenvalues were edited into a file according to the input format of the SVM, made into corresponding training sets and finally, the fall detection model is trained. Human posture data such as standing, walking, standing up, sitting down, squatting, going up and down the stairs, falling forwards, falling backwards, falling to the left, and falling to the right, are collected before being labeled as daily activity behavior labels or fall behavior.

Secondly, the bracelet needs to realize the judgment of suspected fall. When the detected resultant acceleration is larger than the threshold value, the suspected fall is determined. At the same time, the secondary SVM fall detection will be triggered, which requires the bracelet to upload the data carrying fall feature to the platform, and then through comparison with the fall detection model, an accurate determination can be made.

Algorithm detection steps are as follows.

1. Suspected fall determination. The wristband detects the magnitude of the human body resultant acceleration in real time. When the detected acceleration is greater than the set one-level threshold acceleration, it is determined that a suspected fall occurs.
2. Extract eigenvalues. Six eigenvalues are extracted from the suspected fall signal segment.
3. Second fall determination. Compared the calculated feature vector with the fall detection model vector, if it is determined to be a fall, the fall is confirmed. Otherwise, it is determined to be a false alarm.

Figure 8 demonstrates the algorithm flow.

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**Figure 8.** Flow chart of the fall detection algorithm

5. Experiment and analysis

The fall detection bracelet prototype, with a diameter of 80mm, is shown in Figure 9. The wearing method is shown in Figure 10.

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| 图片21 |

**Figure 9.** Fall detection bracelet prototype

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| 图片22 |

**Figure 10.** Man wearing a fall detection bracelet

5.1. Threshold selection experiment

One male and one female were selected to contribute 10 sets of fall behavior data and 20 groups of normal movement respectively. The test results are shown in Table 1.

**Table 1.**Comparisonof the first-level and second-level thresholds

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **First-level threshold determination** | | **Second-level SVM determination** | |  |
| **Threshold setting** | **Determining normal behavior** | **Determining the fall behavior** | **Determining daily behavior** | **Determining the fall behavior** | **Number of missing falls** |
| 2.8g | 16 | 14 | 2 | 12 | 0 |
| 3.0g | 15 | 15 | 3 | 12 | 0 |
| 3.2g | 18 | 12 | 3 | 9 | 1 |
| 3.4g | 18 | 12 | 1 | 11 | 0 |
| 3.6g | 19 | 11 | 0 | 11 | 0 |
| 3.8g | 21 | 9 | 0 | 9 | 1 |
| 4.0g | 23 | 7 | 2 | 5 | 5 |
| 4.2g | 23 | 7 | 0 | 7 | 3 |
| 4.4g | 24 | 6 | 0 | 6 | 4 |

From the above table, ensuring a lower missing rate, 3.2g is selected in this experiment as the first-level decision threshold.

5.2. Experiment on the effectiveness of algorithm

After selecting the first-level threshold values, this section will use the sample data set collected by the experiment to evaluate the effectiveness of the fall detection algorithm completely through three indicators, namely the recognition rate (CR), missing rate (MR) and false rate (FR).

Suppose n experiments are performed, in which the normal behaviors are performed a times and the fall behavior is n-a times. The first-level threshold algorithm determines that the number of occurrences of the suspected fall alarm and triggers the SVM secondary fall determination is p, and the number of times the SVM accurately identifies the fall and the secondary acknowledgement alarm is q.

Recognition rate (or): The fall detection bracelet can correctly distinguish the probability of normal behavior and the fall behavior. The recognition rate for normal behavior is, while that for the falling is.

Missing rate (): The probability that a fall behavior that is not recognized by the first-level threshold algorithm occurs.

False rate (): The probability that a primary threshold algorithm misinterprets daily activity as a fall behavior.

In a fall detection system, the missing rate should be reduced to 0 as much as possible to better ensure the safety of the user groups. At the same time, the higher the recognition rate is, the higher the effectiveness of the fall detection algorithm will be. In addition to a comparatively low false rate, the user will have a satisfactory experience with the product.

In the experiment to verify validity, eight experimenters respectively simulated ten groups of eight normal behaviors including standing, walking, sitting down, lying down, squatting, standing up, going up stairs, and going down stairs, and participated in a fall detection experiment. In the normal behavior testing, the recognition rate and false rate were used as the evaluation criteria. Results are shown in Table 2.

**Table 2.**Experimental evaluation of normal behaviors

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Event** | **Number of experiments** | **Number of the alarm at the first level** | **Actual number of alarms** | **Recognition rate** | **False rate** |
| Standing | 80 | 0 | 0 | 100% | 0 |
| Walking | 80 | 3 | 1 | 98.75% | 3.75% |
| Sitting down | 80 | 5 | 3 | 96.25% | 6.25% |
| Lying down | 80 | 2 | 0 | 100% | 2.5% |
| Squatting | 80 | 8 | 6 | 92.5% | 10% |
| Standing up | 80 | 3 | 2 | 97.5% | 3.75% |
| Going up the stairs | 80 | 0 | 0 | 100% | 0 |
| Going down the stairs | 80 | 2 | 2 | 97.5% | 2.5% |
| Sum | 640 | 23 | 14 | 97.8125% | 3.59375% |

The same group of experimenters simulated ten groups of falling, including falling forwards, falling backwards, falling to the left and falling to the right. The experiment results based on the criteria of recognition rate and missed rate are shown in Table 3.

**Table 3.**Experimental evaluation of fall behavior

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Event** | **Number of experiments** | **Number of the alarm at the first level** | **Actual number of alarms** | **Recognition rate** | **False rate** |
| Falling forwards | 80 | 78 | 73 | 91.25% | 2.5% |
| Falling backwards | 80 | 80 | 78 | 97.5% | 0 |
| Fall to the left | 80 | 75 | 70 | 87.5% | 6.25% |
| Fall to the Right | 80 | 80 | 75 | 93.75% | 0 |
| Sum | 320 | 313 | 296 | 92.5% | 2.1875% |

From Table 2 and 3, it can be seen that in the normal behavior detection, the fall detection bracelet has a recognition rate of 97.8125% and a false rate of 3.59375%. In the fall behavior detection, the system recognition rate reaches 92.5%, and the missing rate is at 2.1875%. The reason for the high missing rate of leftward fall is that the wristband is worn on the right side of the tester, and the left hand has a buffering action to push the body up over the ground, which reduces the acceleration. The missing report of the forward fall lies in the reduced acceleration caused by the experimenters’ knee-buffering action.

6. Conclusions

This paper presents a human fall detection algorithm that combines human posture, support vector machine and quadratic threshold decision. A fall detection model is established, and a fall detection bracelet has been designed to realize fall detection, fall alarm, remote monitoring and other functions. The experimental results show that the fall detection bracelet, with a recognition rate of 92.2%, a false rate of 3.593%, and an under reporting rate of 2.187%, can well distinguish falls from other non-falling actions.

**Funding:** This research was funded by [International Cooperation and Exchange Program of Shaanxi Province ] grant number [2018KW-026],[Natural Science Foundation of Shaanxi Province] grant number [2018JM6120],and [Major Science and Technology Projects of Xian Yang Bureau] grant number [2017k01-25-12],[Graduate Innovation Fund of Xi’an University of Posts & Telecommunications] grant number [CXJJ2017012,CXJJ2017028, CXJJ2017056].

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