An Alarm System Based on BP Neural Network Algorithm for the Detection of Falls to Elderly Person

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Abstract. With the increase in the elderly population, people pay more and more attention to the harm caused by falls. When people reach old age, various functions of the body will degrade to a certain extent. If the elderly fall down, it may endanger their physical and mental health. In view of the above problems, this system designed a elderly fall detection and alarm system based on the reverse neural network algorithm, specifically using MPU6050 sensor to detect human posture data, the control module using the algorithm for real-time judgment, if the fall behavior, the control alarm module to send alarm messages. This system can be used in nursing home health monitoring system, intelligent home system in the detection subsystem and other intelligent medical aspects, can be used in various aspects to protect the health of the elderly, reduce the risk of accidental injury.

Keywords: Falls in older people · BP neural network · MPU6050 sensor · Wisdom care

1 Introduction

With the improvement of life quality and medical progress, the average age of the elderly has been increased, and the aging of the population has become increasingly obvious. According to statistics, the number of people over 65 will account for about 30% of China's population by 2050 [1]. Accidental falls can cause great harm to the elderly and increase morbidity and mortality among the elderly. Therefore, it is of great significance to develop a system that can detect the daily activities of the elderly in real time and give a real-time alarm after a fall, so as to effectively guarantee the life safety of the elderly [2].

At present, there are two main techniques to detect falls: video image processing and accelerometer detection. Video image processing is the use of cameras to track the daily behavior of the elderly to obtain real-time images and uses a specific algorithm to detect whether there is a fall [3,4]. The technology can

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only be used in specific places, is computing-intensive and difficult to process, and the images taken can be a privacy risk.

The accelerometer method detects people's attitude changes in real-time through microsensors [5,6]. The system uses a fall detection algorithm to determine whether a fall has occurred. This technology has obvious advantages which it is not limited by space, low cost, and easy to carry. At present, the accelerometer detection method is generally the threshold detection method. For example, LIU Li, Design of MPU6050-based fall monitoring system for the elderly [11], this detection method determines whether a fall has occurred by detecting the acceleration of human body and setting the acceleration threshold of fall. This detection method is simple and easy to operate, but with low accuracy, high error detection rate and easy to make mistakes.

In this paper, we propose a fall alarm system for the elderly based on a neural network algorithm. We use the MPU6050 acceleration sensor to detect the real-time acceleration and attitude angle of human movement, then send the data to the master controller through serial communication and then use the fall recognition algorithm to process the data to get the result of whether the fall has occurred.

2 System Structure Design

The system is mainly composed of the data module, message module, and power module. The data module is composed of MPU6050 sensor and STM32F103 control chip. The message module is connected to the STM32F103 chip through a serial port. The power module is responsible for power supply, 5 V voltage 1 A current. The above modules are fixed and worn on the waist of the elderly for real-time detection. If the fall action is detected, an alarm message will be sent to the relatives or the hospital. The system structure diagram is shown in Fig. 1.

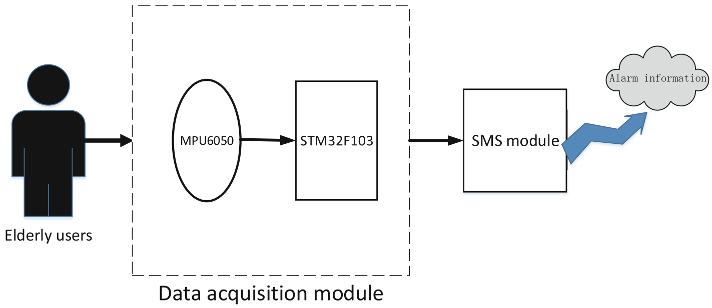

Fig. 1. System structure diagram.

2.1 MPU6050

MPU6050 is integrated with triaxial acceleration sensor and triaxial gyroscope sensor, and contains DMP and ADC module, which can effectively process detected data and transmit it to STM32F103 master controller through IIC bus [7]. Compared with the traditional acceleration sensor, MPU6050 has a strong anti-interference capability and can effectively remove the sensitivity between accelerator and gyroscope axis.

2.2 Controller, STM32F103

The controller is the STM32F103RCT6 chip, which is equipped with 48 KB SRAM, 256 KB FLASH,2 IIC, 5 serial ports, etc. The highest working frequency can reach 72MHz, and the working voltage is between 3.3 V–5 V. The chip has the characteristics of low power consumption and strong functions, which can meet the system design requirements

2.3 Short Message Module

The alarm module of this system adopts the SIM900A, supports RS232 serial port and LVTTL serial port, and has hardware flow control. It supports the ultra-wide working range of 5 V–24 V, and the working frequency band is dual-frequency 900/1800 MHz. It connects with the controller through serial communication, with low working power consumption and stable data transmission, which conforms to the alarm design requirements of this paper.

3 Algorithm of Fall Action Detection

3.1 Data Preprocessing and Network Feature Selection

The fall has abruptness, rapidity and acuteness, it is to fall on the ground that is lower than the human body commonly, produce a violent impact with the ground. In this case, the acceleration and angle of the human body will mutate [8]. Based on this feature, this paper designs an algorithm to distinguish falls from normal activities, such as walking, running, sitting, going up and down a building, etc., so as to detect falls of the elderly and give a timely alarm.

The data sources of this paper are mainly human motion acceleration and attitude angle. How to extract the data and how to process the data into the neural network after extraction is a major problem to be solved in this paper. As shown in Table 1, the part with the largest mass proportion of the human body in the trunk [9]. During normal movement, the activity frequency of the trunk position is small, and the movement data changes steadily. In the process of people fall, the trunk part instantly changes greatly, but after the fall, the data tends to be stable [10]. While in normal activities, legs or arms are frequently used, and the data changes are also very messy, which will make the detection results susceptible to interference and reduce the accuracy. In conclusion, we

Table 1. Proportion of the mass of each part of the human body

Name	The quality of (%) man	The quality of (%) woman
On the trunk	16.33	16.42
Under the trunk	26.27	25.98
Head	9.3	8.60
Arm	2.61	2.62
Hand	0.64	0.49
Thigh	14.00	14.28
Calf	4.00	4.55
Foot	1.50	1.38

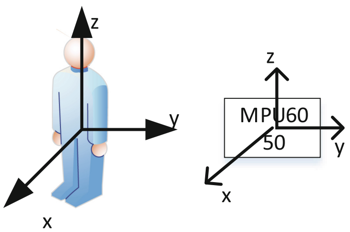

Fig. 2. Coordinate comparison diagram of human body and sensor attitude

put the system at the waist so that the correct data can be collected without affecting the normal activity of the person.

In order to collect correct sensor data, it is necessary to establish a three-dimensional coordinate system in which the human body is in a standing state and the sensor acquisition direction is consistent, as shown in Fig. 2. The MPU6050 sensor detects acceleration along the X, Y, and Z axes in the event of a violent fall. We define the acceleration as $a_x a_y a_z$. We define Ca as the magnitude of combined acceleration, which is an important parameter that distinguishes falling motions from normal motions. The larger the Ca, the more intense the movement. Ca will reach a peak when colliding with the ground when falling [11], so Ca can be used as a feature selection of the BP neural network.

$$Ca = \sqrt{a_x^2 + a_y^2 + a_z^2} \tag{1}$$

The angle of the human body during the fall is also very obvious. When a fall occurs, the body tends to fall forward, backward or to the left and right, that is, the angle changes on the X-axis and Y-axis are relatively obvious, while the angle changes on the Z-axis are not very obvious. Therefore, Pitch in the X-axis direction and Roll in the Y-axis direction is selected as the characteristics of the BP neural network. As shown in Fig. 3, the Pitch and Roll data are significantly changed during the fall. In Fig. 3, the X-axis represents the data length, and the Y-axis represents the angle value. In daily life, the elderly move slowly and the activity frequency is generally no more than 20 Hz. Therefore, the sampling frequency 30 Hz is used to collect data of Ca, Pitch and Roll, and the dynamic Kalman filter is used for denoising. Kalman filter is an optimized autoregressive data processing algorithm, which can well deal with the data noise brought by a real-time sensor[9].

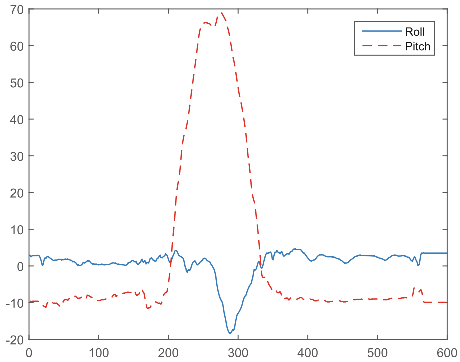

Fig. 3. Change curve of Pitch and Roll data during fall.

3.2 BP Neural Network Algorithm Implementation

Based on the above analysis, this paper designs a three-layer neural network for training sample data [8]. (1) For the input layer, based on feature selection and fall data changes, three neurons can be set on the input layer, namely, acceleration Ca, Pitch and Roll. (2) For the output layer, it only needs to show whether the human body falls, so a neuron is set as a fallen marker. (3) The hidden layer selects two neurons for weight correction. The results show that the model algorithm can train samples quickly with a low error detection rate and good robustness. Figure 4 shows the BP neural network model.

The working principle of this model is as follows.

1) The model is initialized with normal distribution with mean value of 0 and variance of 1.
2) Training samples were collected and divided into Ca, Pitch and Roll data for falls and normal activities, and normalized to make the model more sensitive to data.
3) Do the forward calculation. The induced local domain of the input layer is obtained as follows:

$$net_j^{(1)}(n) = \sum_{i=0}^{3} V_{ji}^{(1)}(n) X_i(n) \qquad j = 1, 2 \tag{2}$$

$X_i(n)$ represents the input layer eigenvalues. $V_{ji}(n)$ is the weight from i to j. The activation function selection is sigmoid function, so the input of the

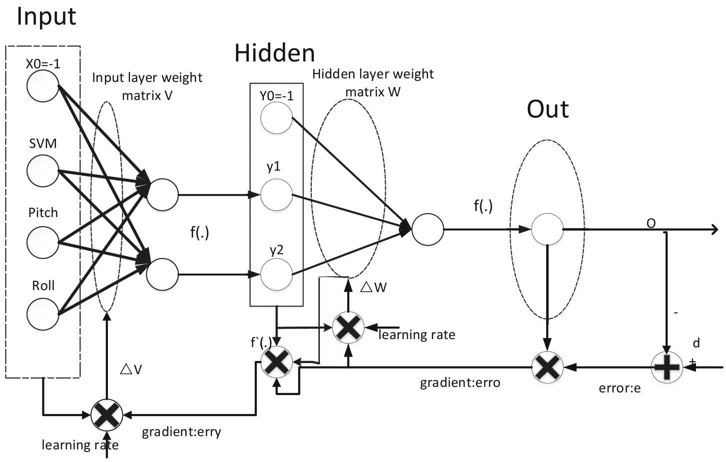

Fig. 4. BP neural network module

hidden layer can be calculated:

$$Y_j(n) = f(net_j^{(1)}(n)) = \frac{1}{1 + exp(-a * net_j^{(1)}(n))} \quad a > 0 \tag{3}$$

Similarly, the induced local domain of the hidden layer can be obtained:

$$net^{(2)}(n) = \sum_{j=0}^{2} W_{kj}^{(2)}(n) Y_j(n) \tag{4}$$

$W_{kj}(n)$ is the weight from j to k. Then the actual output is:

$$o(n) = f(net^{(2)}(n)) = \frac{1}{1 + exp(-a * net^{(2)}(n))} \tag{5}$$

Calculable error:

$$e(n) = d(n) - o(n) \tag{6}$$

After the forward calculation, we have set a threshold for the error. If the error is within the threshold range, we can say that training has been completed. If the error is greater than the threshold, the calculation is reversed to adjust the weights on the network for each layer. 4) Reverse training The gradient descent method is used to calculate the optimal weight to minimize the error, and the local gradient of the neural network can be obtained:

$$erro(n) = e(n) f'(net^{(2)}(n)) \tag{7}$$

$$erry(n) = f'(net_j^{(1)}(n)) erro(n) W_{kj}^{(2)}(n) \tag{8}$$

Using the rule, the weights of the hidden layer can be obtained:

$$W_{jk}(n+1) = W_{jk}(n) + \alpha W_{jk}(n) \tag{9}$$

$$\Delta W_{jk}(n) = \alpha[W_{jk}(n-1)] + \eta e(n) f'(net^{(2)}(n)) y_j \tag{10}$$

$$V_{ji}(n+1) = V_{ji}(n) + \delta V_{ji}(n) \tag{11}$$

$$\Delta V_{ji}(n) = \alpha[V_{ji}(n-1)] + \eta erro(n) f'(net^{(1)}(n)) x_i \tag{12}$$

Where is the learning rate parameter and is the momentum constant. 5) Iterative calculation After a round of weight adjustment, the forward calculation process is repeated in turn until the error is less than the range of convergence criteria. Then the next set of samples was trained until N samples were trained to detect falls in the body. After all the samples are trained, the overall modeling is completed.

The overall flow chart of the training process is shown in Fig. 5.

After training the samples with neural network algorithm, the weights are obtained, which can be applied to the system. The overall work flow chart of the system is shown in Fig. 6.

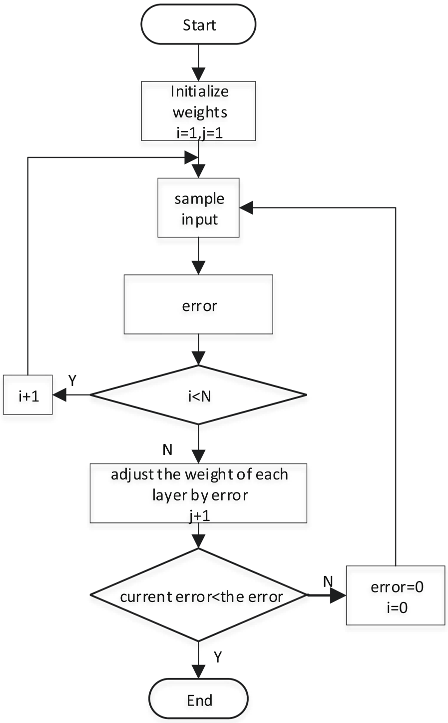

Fig. 5. Overall flow chart of the training process.

4 Experimental Analysis

We apply the above algorithm to this system and carry out a simulation experiment to verify the fall action of the elderly. In this experiment, 10 young students aged 22's–28's were selected to simulate the daily activities of the elderly (walking, jogging, sitting, going up and down the stairs) and falling (falling forward, backward, left and right). Each movement was performed in 50 groups. The experimental results are shown in the Table 2 and Table3.

Table 2. The success rate of fall behavior detection based on the BP neural network algorithm)

Fall of status	Fall times	Alarm times	Success rate
Forward	50	48	96%
Backward	50	50	100%
Left	50	48	96%
Right	50	49	98%

Table 3. The false rate of normal behavior detection based on the BP neural network algorithm

Status	Times	Alarm times	False detection rate
Walking	50	0	0%
Run	50	1	2%
Sit down	50	3	6%
Upstairs	50	2	4%
Go downstairs	50	2	4%

In order to verify the superiority of the system algorithm, we used the threshold based detection method to detect the actions. The experimental results are shown in Table 4 and Table 5.

The tested subjects wear the system for walking, sitting, lying down and falling, as shown in Fig. 7.

The experimental results were basically in line with expectations, and the correct rate of falls reached more than 95%, while the false detection rate of normal activities was around 5%. The fall accuracy rate of threshold comparison method is about 60%, and the false detection rate is about 20%, which is not very practical. This BP algorithm can distinguish the normal activities and fall actions of the elderly very well. As there is a similar place between sitting action and falling action, the range of the human body may be relatively large, so the

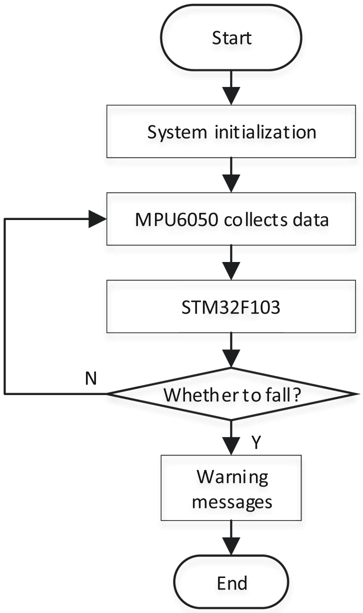

Fig. 6. Overall work flow chart.

Table 4. The success rate of fall behavior detection based on the threshold algorithm

Fall of status	Fall times	Alarm times	Success rate
Forward	50	30	60%
Backward	50	35	70%
Left	50	28	56%
Right	50	25	50%

Table 5. The false rate of normal behavior detection based on the threshold algorithm

Status	Times	Alarm times	False detection rate
Walking	50	8	16%
Run	50	5	10%
Sit down	50	15	30%
Upstairs	50	10	20%
Go downstairs	50	8	16%

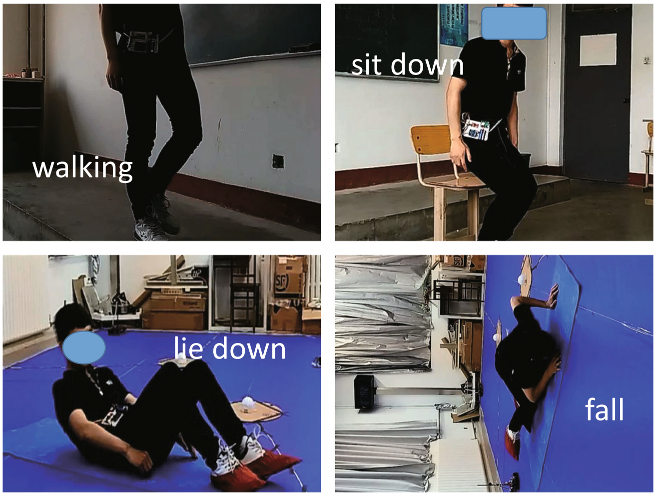

Fig. 7. Action test.

rate of false detection will be correspondingly higher. We set the acceleration threshold to detect lying down and falling action. Because the attitude Angle of lying down and falling is very similar, BP neural network will increase the error. We will continue to improve the system.

5 Conclusion

In this paper, we designed a wearable fall action detection system based on a neural network algorithm, which can more accurately judge fall actions by learning a lot of characteristic data of normal activities and fall actions from the neural network. Moreover, due to the wide source of feature data, the robustness of the system is improved, which is better than the system based on the simple threshold detection method. The experimental results verify the accuracy of the system. The system is simple in design and easy to wear. If the fall is detected, it can send an alarm message to inform the family or the hospital in time, so as to better protect the life and safety of the elderly.

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