Fall Detection Monitoring System Based on MEMS Sensor

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Abstract. In order to get timely treatment after the elderly fall, this paper proposes a wearable device to monitor the fall of the elderly. The device includes a data acquisition module, a data processing module, and a wireless communication module. With the elderly wear the device at the waist, the human body posture data will be collected by data acquisition module, and will be processed by data processing module, and combines the random forest algorithm to distinguish between daily activities and fall behaviors. When the fall occurs, the device alarms by sound and light. At the same time, the transparent cloud platform matched with the wireless communication module can monitor the position and status of the elderly in real time. When a fall occurs, the emergency contact will be notified through WeChat and email, and the real-time alarm will be realized, and the old man will get timely treatment after the fall.

1. Introduction
As the problem of population aging increases, more and more elderly people increase. Since the physical functions, reaction speed and body balance of the elderly are relatively poor, they cannot protect themselves well when facing unexpected situations [1]. For example, when faced with a fall, it is extremely easy to cause fatal accidental injuries to the elderly [2]. In order to be able to receive timely treatment after the fall of the elderly, the health monitoring of the elderly is of great economic and social significance [3]. In recent years, many countries have launched research on this. There are three main research methods:

(1) Video image recognition. Through the installation of camera in the area where the elderly often move, and then collect human motion images, and afterwards apply image processing algorithm to detect whether the elderly fall [4].
(2) Vibration analysis. By installing sensors on the floor, when the human body falls, the sensors detect the corresponding waveform to determine whether the elderly fall [5].
(3) Wearable device. Since the wearable device is worn on the relevant parts of the human body, and then the relevant data collected by the internal sensor of the wearable device is combined with the algorithm analysis to determine whether the elderly fall [6].

The above three methods have their own advantages and disadvantages. The video monitoring will violate personal privacy, and the vibration analysis depends on space [7]. Both methods are only suitable for small-scale monitoring. For the third method, the wearable device only depends on the device itself and has a wider application range [8]. It only needs human body to wear the device and does not depend on the range of human activities. Therefore, it has more advantages and larger application scenarios.
In traditional wearable devices, Bluetooth, WiFi, ZigBee and other communication modes are commonly used, which limits the range of human motion. Narrow Band Internet of Technology (NB-IoT) can just solve the problem of limited communication distance. Therefore, in this paper, a wearable device is designed to monitor the fall state of the elderly, using NB-IoT communication to transmit data, to achieve real-time monitoring of the elderly's movement state and alarm the elderly's abnormal state.

2. **Design of monitoring system based on MEMS sensor**

2.1. **System structure**

The system structure is shown in Figure 1. The human body wears the hardware system of the lower system. The lower system collects the relevant data of the human body and sends it to the upper system for receiving. The upper system displays the received data. The upper system calls the algorithm model to judge the human body posture.

![Figure 1. System architecture diagram.](image1)

2.2. **Hardware system**

The structure diagram of the whole hardware is shown in Figure 2. MEMS inertial sensor obtains acceleration, angular velocity through accelerometers and gyroscopes, and obtains attitude angle through attitude fusion. The sensor communicates through I²C protocol with the main control chip. The main control chip processes the collected acceleration and angular velocity data, and sends the processed data to the transparent cloud platform (platform used with NB-IoT module). The transparent cloud platform can monitor the collected data in real time and give it location. The upper system uses random forest algorithm to detect whether the data falls. When a fall is detected, the upper system sends information to the NB-IoT, and the main control obtains information to control the alarm circuit to remind people around to take measures. At the same time, by adding triggers, the transparent cloud platform can set that when the data is over a certain value, the contact can be notified through we-chat and SMS alarm.

The hardware system is mainly composed of three modules, reset circuit and sound and light alarm circuit. Three modules are: data acquisition module, data processing module, wireless communication module.

![Figure 2. Hardware structure diagram.](image2)
Data acquisition module. In order to facilitate the carrying and installation of hardware circuits and saving cost, this system adopts MPU6050 produced by InvenSense company. MPU6050 integrates 3-axis acceleration, 3-axis gyroscope and digital motion processor (DMP), which can be directly connected to the main controller STM32 through I2C [9]. Without additional ADC circuit, the current output of the sensor can be read directly through the digital interface. MPU6050 integrates a triaxial gyroscope with angular velocity sensing range of ±250, ±500, ±2000°/sec (DPS). MPU6050 integrated triaxial accelerometer, the sensing range of acceleration is ±2g, ±4g, ±8g and ±16g. The package size is 4mm × 4mm × 0.9mm, using QFN package. Small volume, low noise, high performance, which meet the requirements of portable equipment.

Data processing module. Since STM32 processor is convenient for user development and low cost, this system chooses STM32F103RET6 as the main control chip. The main frequency of STM32F103RET6 is 72MHz, which can meet the requirements of real-time data acquisition, processing and fusion. LQFP64 package is small and able to meet the requirements of small system. I2C bus can be used to control MEMS inertial sensor. It communicates with NB-iot through UART and transmits data to NB-iot. An alarm circuit is connected with the module. When receiving the relevant instructions sent by the upper system, the alarm circuit is triggered to realize the alarm [10].

Wireless communication module. At present, many wearable devices use bluetooth, wifi, ZigBee and other communication methods to transmit data. These communication methods are short distance communication technology. In order to solve this problem, this paper proposes a fall down device based on NB-iot narrowband Internet of things. Narrow Band Internet of Technology (NB-iot) is a new generation of Internet of things communication technology, which is built on cellular network. Compared with 4G network, ZigBee and other short-distance communication technologies, NB-iot technology has the characteristics of large capacity, wide coverage, deep penetration, low cost, low power consumption and so on. Data can be transmitted to the PC platform without cable connection. The application of this module can reduce the cost of the whole system, and the low power consumption of the product can extend the standby time of the whole module. When the platform at the PC has processed the data and detected a fall, it can notify the emergency contact through SMS, email and we-chat to realize alarm processing.

3. Experiment and Algorithm Design

3.1. Fall detection algorithm based on random forest

In recent years, in order to reduce the further injury to the elderly caused by accidental falls, it has become a research hotspot of universal health technology to detect and alarm the fall behavior accurately and in real time with the help of commonly used mobile intelligent terminals and currently emerging wearable devices. Most of these studies use the time series, statistical domain or transform domain features of acceleration or gyroscope data, and use time series curve method, or machine learning related algorithms, such as SVM, decision tree, etc., to detect falls. Based on the time series curve method, the fall detection is based on the weightlessness, overweight and time thresholds of acceleration time series data in turn during the fall process. However, due to the difference between body and equipment, it often leads to the difficulty in determining the curve threshold with a wide range of application, which affects the accuracy and robustness of fall detection. In addition, some scholars apply SVM to fall detection, mining the parameter characteristics of acceleration sample data statistical domain and transformation domain. The obtained classifiers are used to classify and evaluate falls and other behaviors based on off-line training of classifiers. Their performance is greatly improved compared with the fall detection method based on time series curve threshold. As the existing fall algorithm research has not yet formed a universally recognized test data set, most of the research work is to use young people's simulation to collect experimental data set for testing. This kind of data is small in scale and not representative, which often leads to over fitting of classifiers and low accuracy and robustness of fall detection.
In order to obtain accurate and robust fall detection results, and to solve the problems of over fitting and insufficient adaptability caused by the lack of real fall samples for the elderly and the small scale of simulated fall samples for the young, this paper uses fall detection algorithm based on a random forest.

Random forest is an integrated classifier composed of a series of decision trees, and its learning results are determined by voting on the classification results of its basic unit decision tree. Decision tree is a kind of tree structure widely used in the field of classification and prediction, and it is also the basic unit of random forest. It is simple and intuitive and can realize visualization, which is helpful for the subsequent analysis and decision-making of data. The theoretical basis of decision tree is classification function approach, which is widely used in all aspects of machine learning. There are many advantages, such as small amount of calculation, easy to understand rules and so on. At the same time, there are some shortcomings, such as lack of scalability and insensitivity to noise data. A large number of scholars have proved that the random forest algorithm has a good prediction accuracy, a good resistance to noise, and a good robustness. Because the bagging method is used to construct random forest, which can eliminate the internal relationship between different decision trees, and can effectively avoid the shortcomings of over fitting and local optimization of decision trees. Random forest algorithm can show better anti-noise and anti-multipath fading ability.

Random forest algorithm is used to distinguish daily actions (including downstairs, running, walking, bending, etc.) from falls (including forward falls, backward falls, left falls, right falls). The acceleration and angular velocity collected by MEMS sensor and the DMP in MPU6050 are used for attitude fusion to obtain the attitude angle, we can judge the fall state and improve the accuracy of judgment. This algorithm solves the problem of over fitting of single decision tree, and its classification performance is better than that of single classifier. In this paper, the random forest classification algorithm is applied to fall detection and non-fall behavior detection, and good classification results are obtained.

When constructing a random forest tree, each node is divided according to the Gini of the property. In the classification problem, if there are k classes and the probability of sample points belonging to class k is P(k), the Gini of probability distribution is defined as:

\[ Gini(p) = \sum_{k=1}^{K} P_k (1 - P_k) = 1 - \sum_{k=1}^{K} P_k^2 \]  

(1)

If the sample set D is divided into two parts: D1 and D2 according to a certain feature A, then under the condition of feature A, the Gini of set D is defined as:

\[ Gini(D, A) = \frac{|D1|}{D} Gini(D1) + \frac{|D2|}{D} Gini(D2) \]  

(2)

Gini represents the uncertainty of data set D in different groups of feature A. The larger the Gini is, the greater the uncertainty of the set you will get. Therefore, the Gini can be used to determine the best partition point of a feature, which is the basic rule of CART tree as classifier.

Each tree of a random forest is a CART tree. For an input sample, N trees will have N classification results. The whole random forest inherits all the classification voting results, and specifies the category with the most voting times as the output of the final classifier.

The basic steps of the algorithm are:

1. In this experiment, firstly, volunteers wear the device on their waists, and perform walking, running, sitting standing, standing, going up, going down, front down, left down, back down, right down and so on. The collected acceleration is calculated by calculating the acceleration within 1-2s. The maximum value, minimum value, median value, mean value, tangent tail mean value, variance, kurtosis, skewness, coefficient of variation, 9 characteristics A set of data is tagged to label the output.
The normal action is 1 and the fall is 0. Sampling techniques are used to extract K training samples from the dataset and form K sample data sets. Use these samples to train the cart decision tree.

(2) For each sample data set, m features (m < 9) are randomly selected from nine input features. Each time the tree is split, the Gini index is calculated, and the one with the smallest Gini index is selected as the optimal split feature and split point. The training data set is allocated to two sub nodes, and each tree is not pruned. Repeat the process until the stop condition is met.

(3) Train the decision tree model with K sample data sets in the way of 2, and combine all the generated decision trees into a random forest model.

(4) The final result is output by means of mode voting, and the result is a binary result, the output result is 1 or 0.

The flow chart is shown in the Figure 3:

Figure 3. Algorithm flowchart.

3.2. Experimental process and result analysis

In order to distinguish falls from daily actions, volunteers wear the device on the waist, and make the X-axis of the sensor point to the Y-axis of the human body, and the Y-axis point to the Z-axis of the human body, that is, the attitude angle of human body forward and backward is represented by roll angle, and the left and right tilt angles are represented by yaw angle. The wearing method is shown in Figure 4. The daily activities of the head, chest, big arm, wrist and other parts of the human body are more frequent, which is not conducive to the analysis of motion data. The waist is the center of gravity of the human body, so the sensor data worn in the waist can accurately reflect all kinds of movement changes of the human body, and the interference to the daily behavior of the human body is relatively small.

Figure 4. Wearing position.
When the human body wears the device, the upper system receives the basic data (acceleration, angular velocity, attitude angle) sent by the device and displays it in the data display area. As is shown in Figure 5.

![Figure 5. Data receiving display diagram.](image)

Input the received basic data into the trained random forest model, and the upper system will give tips according to the different state of human body. Judge the state of human body through the alarm of circuit. The daily actions (walking, running, sitting standing, standing sitting, going upstairs and downstairs) and falling actions (forward, left, back and right) of human body were experimented, each action was 100 times. The experimental statistical results are shown in table 1.

| Number | Activity Sample size | Missing result |
|--------|----------------------|----------------|
| 1      | walking              | 100            | 4              |
| 2      | running              | 100            | 7              |
| 3      | Sit-to-stand, stand-to-sit | 200          | 10             |
| 4      | Upstairs, downstairs | 200            | 12             |
| 5      | left-fall            | 100            | 5              |
| 6      | right-fall           | 100            | 4              |
| 7      | forward-fall         | 100            | 5              |
| 8      | backward-fall        | 100            | 4              |

In order to verify the effectiveness and performance of the algorithm, threshold, decision tree algorithm and random forest algorithm are used to detect each group of data in the data set. The accuracy, missed judgment rate and time of each group of experiments are recorded. The average value is calculated according to the results. The performance comparison of the three algorithms is shown in the table 2.

| Evaluation parameter | Random forest | Decision tree | Threshold |
|----------------------|---------------|---------------|-----------|
| Average accuracy     | 0.949         | 0.935         | 0.916     |
| Average miss rate    | 0.051         | 0.065         | 0.084     |
| Average time/s       | 0.84          | 1.43          | 0.64      |

Table 2 lists the performance comparison of the three algorithms in detail. According to the experimental results, the random forest algorithm is superior to the other two algorithms in accuracy rate and slightly slower in execution time than the threshold value. However, it has a significant improvement in the rate of missed judgment, which is obviously superior to the other two algorithms.
4. Conclusion
This paper proposes to design a wearable device to monitor the fall status of the elderly, to monitor the movement status of the elderly in real time and to monitor the abnormal state of the elderly and to handle the alarm. By wearing the device on the waist of the elderly, it can measure the acceleration and angular velocity through MEMS sensor, and get the angle through attitude fusion. Through the random forest algorithm, it can detect the elderly's falling state, when there is an exception, it can alarm. In this experiment, for the sake of safety, 10 young people about 24 years old were used to simulate the movement of the elderly. In practical application, it may be necessary to adjust the relevant parameters of the model according to individual differences to meet the needs of different individuals.

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