A Falling Recognition Algorithm based on Threshold and Peak of Accelerometer

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Abstract

At present, the aggravation of population aging has brought great pressure to health care and society. Falling recognition algorithm has become a hot research topic. In this paper, a method based on threshold and peak is proposed to identify the fall motion, which is based on the problem that the recognition algorithm is not simple. In this algorithm, we judge the threshold first. And if it is larger than the set threshold, it will continue to judge the direction of the fall. By analyzing the size of the peak, it will identify the direction of the fall, including forward falls, backward falls and lateral fall. Finally, the recognition degree of the algorithm is verified experimentally. The experimental platform is the inertial measurement unit of the laboratory. Through the experiments of 9 testers, the algorithm can be more accurate to achieve the tester's fall detection, and can accurately identify the direction of the fall.

Keywords

Accelerometer, Threshold, Peak, Fall Detection

1. Introduction

With the continuous improvement of the level of science and technology, people's average age is increasing. Although the state has taken some policies, the current population aging has brought tremendous pressure for the health care and society [1,2]. In this case, there is an urgent need for a technique that can accurately detect the falls. At the same time, it would issue a warning to the pedestrian call for help, thus reducing the medical expenses and social costs. There are two main methods to the fall detection. One is based on image analysis, and the other is based on the accelerometer. The method based on image analysis has high requirements on equipment and limited to specific occasions [3]. The method based on acceleration can provide an objective and quantitative information on human activities. With its small size, low power consumption and high sensitivity, it is widely used in the falls detection [4,5,6]. In [7], researchers used multiple accelerometers combining thresholds to detect falls. Jantaraprim P et al proposed a time window based SVM dual threshold decision method to detect human fall, and the algorithm is simple and effective [8]. In [9], researchers through Kinect to obtain data of the human head and shoulder center and other skeleton joints of the spatial position, design fall recognition characteristics. The fall detection algorithm in the paper used the support vector machine technology. Khan A M et al put MEMS accelerometers in different parts of the body clothes pockets to monitor the activities of the elderly [10]. The program is easy to implement, but the system reliability is not high.

2. The framework of algorithm

According to statistics, in most time the bodies are in an upright state. In general, the cause of the fall are caused by slipping or the uncontrolled body [11]. According to the direction of the fall, falls can be divided into three categories, forward falls backward fall and lateral fall. And lateral fall contains fall to the left and fall to the right. This paper analyzes the falls. The waist belongs to the body of the trunk part, and is located in the center of the human body, which can represent most of the movement of the human body and collects more comprehensive information. In this paper, we fix the micro inertial measurement unit at the waist. In this paper, we identifies the forward fall, backward fall and lateral fall by analyzing the accelerometer threshold and the size of the peak. We also analyze the daily behaviors, including running and downstairs and other actions, to improve the accuracy of the fall detection algorithm in complex environment. The algorithm of the fall detection algorithm is shown in the following Fig.1.

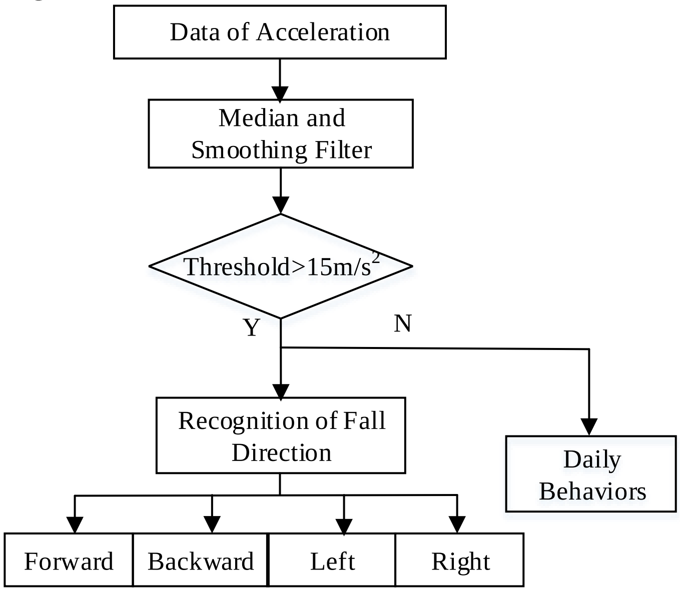

Fig.1 Block diagram of the algorithm

Based on the block diagram of the detection algorithm of the fall detection, we can collect the data of the accelerometer through the micro-inertial measurement unit integrated in the laboratory, and carry out the median and smooth filtering process on the collected sensor data. We identify the fall motion through the acceleration of the threshold. If the acceleration data is less than the set threshold, we consider the motion is a non-fall motion. If the threshold value is greater than the set threshold value, the recognition result is output based on the data size of the accelerometer X-axis and Y-axis, including forward, backward, left, and right falls.

3. Fall detection algorithm

3.1 Data preprocessing.

The accelerometer signal collected by the micro inertia measurement unit includes not only the motion data to be recognized but also the noise signal generated by the involuntary movement of the body and the sensor itself. In order to reduce the influence of noise signal on subsequent feature extraction and classification and recognition, it is necessary to preprocess the data before extracting the feature of the micro inertial sensor data, remove the noise signal and keep the data of human motion as much as possible. In this paper, median filtering and smoothing filter are used to preprocess the data. A median filter is performed every 5 data points. Assuming $x_1, x_2, \cdots, x_n$ is a sample of the sensor data, the mathematical model of smoothing is as shown in Equation (1).

$$x_i = 0.01x_{i-2} + 0.01x_{i-1} + 0.9x_i + 0.03x_{i+1} + 0.05x_{i+2} \tag{1}$$

The simulation of the data before and after the simulation shown in Fig.2.

As can be seen from the figure, the unfiltered acceleration signal contains more noise signal, the acceleration signal is not smooth. After filtering, the noise signal is basically eliminated. The smoothness of the acceleration signal is obviously improved, showing obvious and regular gait characteristics, which is suitable for extracting the time domain characteristics of the motion sensor.

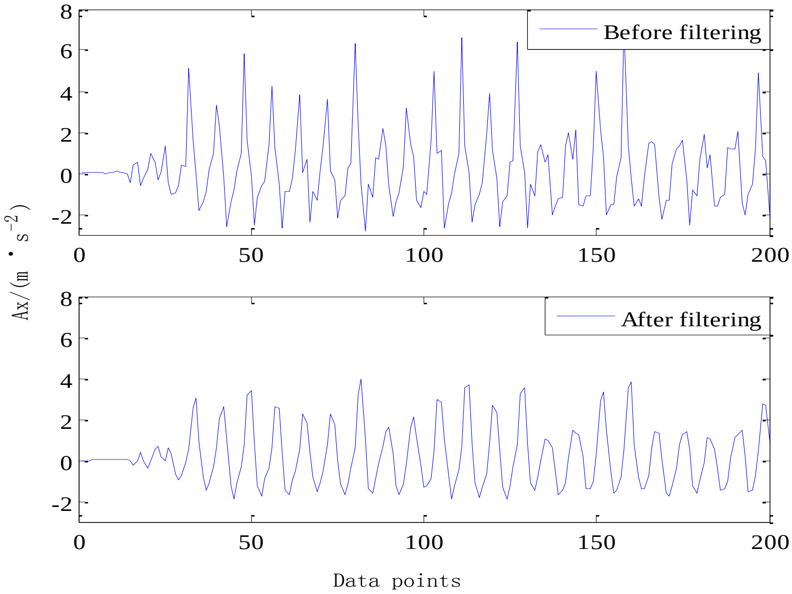

Fig2. Simulation comparison chart of data

3.2 Feature Extraction of Abnormal Behavior Based on Threshold.

Through the analysis of the data of several simulated fall movements, the instantaneous acceleration of the fall action will change drastically, which is much higher than the peak of the daily acceleration. The acceleration formula is expressed by the following Equation (2).

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

where Acc is the combined acceleration of the three-axis acceleration. a_x, a_y, a_z are the accelerometer tri-axial data, respectively. Processing data by window segmentation is easy to extract the action information. However, if the characteristics information of falls are divided into two windows, it will weak the characteristics information, which will result the phenomenon of missing detection. In this paper, we don’t take the window to capture the fall signal, thus avoiding the phenomenon of missing detection.

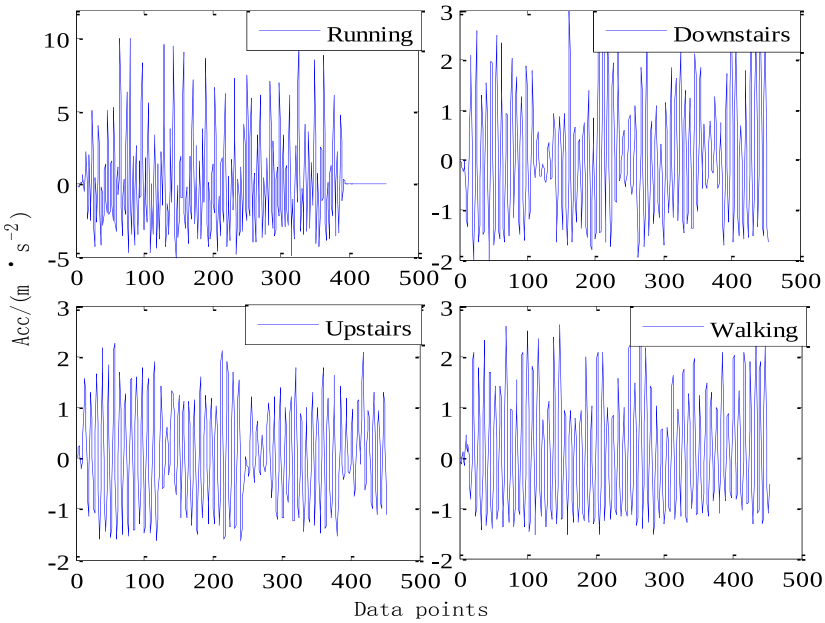

Fig.3 Acceleration simulation in daily behaviors

In this paper, we analyze the threshold of the acceleration in the daily patterns. The acceleration simulation in the daily behaviors is shown in Fig.3. The abscissa is the data point and the ordinate is the value of the acceleration. The acceleration values of the daily behaviors are between -2 $m \cdot s^{-2}$ to 3 $m \cdot s^{-2}$, which are walking, upstairs and downstairs. The acceleration value of run is between -5 $m \cdot s^{-2}$ to 10 $m \cdot s^{-2}$. The acceleration simulation in the falling behaviors is shown in Fig.4. For the falling moment, the acceleration will be produce a great change. The value of the acceleration will be achieve 20 $m \cdot s^{-2}$, which is much larger than the daily behaviors.

After comparing and analyzing, this paper sets the acceleration value of 15 $m \cdot s^{-2}$ to identify the fall behaviors. When the acceleration value is less than 15 $m \cdot s^{-2}$, the behaviors will be recognized as daily behavior. If the acceleration value is greater than 15, it continues to judge the next acceleration value size. If the three consecutive acceleration values are greater than 15, we recognize this behavior as a fall. By judging the number of consecutive data beyond the acceleration threshold, it is possible to reduce the misrecognition due to the cause of the accelerometer.

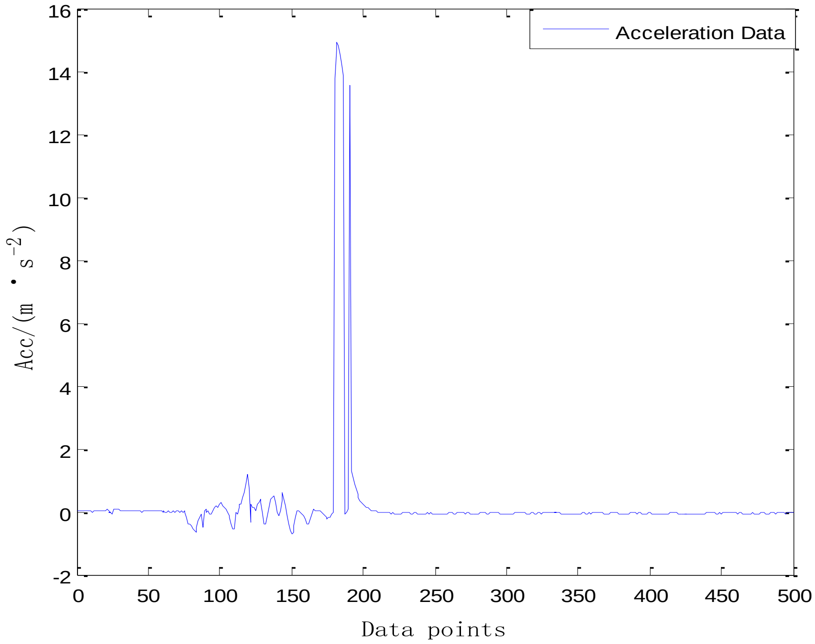

Fig.4 Acceleration simulation in falling behaviors

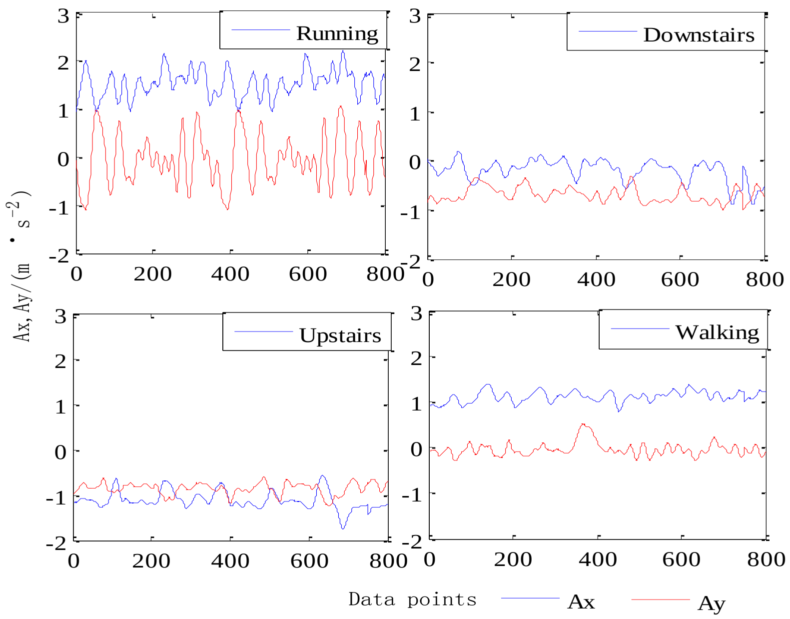

Fig.5 Acceleration data of the X-axis and Y-axis in the daily behaviors

3.2 Falls Recognition based on Peak of Acceleration Data.

In this paper, the micro-inertial measurement unit is placed in the waist. The Z-axis of the sensor is perpendicular to the ground. The X-axis points to the direction of movement of the human body. The Y-axis is parallel to the ground, which conforms to the right-hand Cartesian coordinate system. Under normal circumstances, the acceleration data of X-axis and Y-axis are almost 0. In the sudden falls, the acceleration data of X-axis and Y-axis will suddenly increase.

The acceleration data of the X-axis and Y-axis in the daily behaviors are shown in Fig.5. The abscissa is the data point and the ordinate are the values of the X-axis and Y-axis. The acceleration data of the X-axis and Y-axis of the daily behaviors are between -2 $m \cdot s^{-2}$ to 3 $m \cdot s^{-2}$, which are running, walking, upstairs and downstairs.

On the basis of predicting the fall behaviors, we select the peak of the acceleration data of X-axis as the characteristic vector to identify the forward and backward fall. The peak change of X-axis in the forward fall is about 9.8 $m \cdot s^{-2}$. We set the identifying threshold for the forward fall is greater than 5 $m \cdot s^{-2}$. The peak change of X-axis in the backward fall is about -9.8 $m \cdot s^{-2}$. We set the identifying threshold for the backward fall is less than -5 $m \cdot s^{-2}$. The peak distribution of the forward and backward fall are shown in Fig.6.

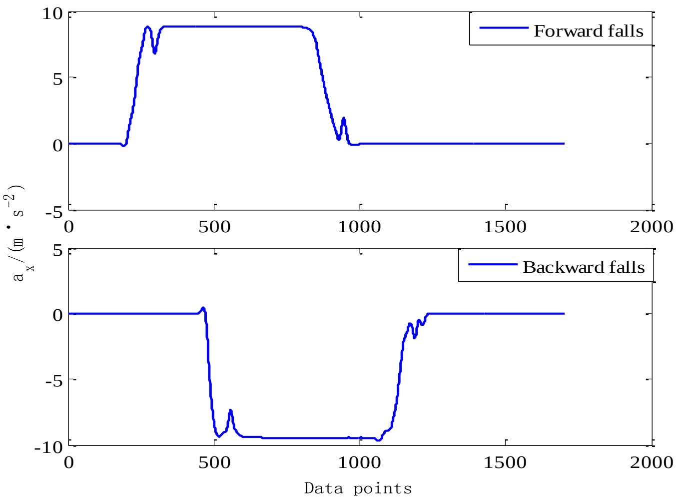

Fig.6 Acceleration simulation of the forward and backward fall

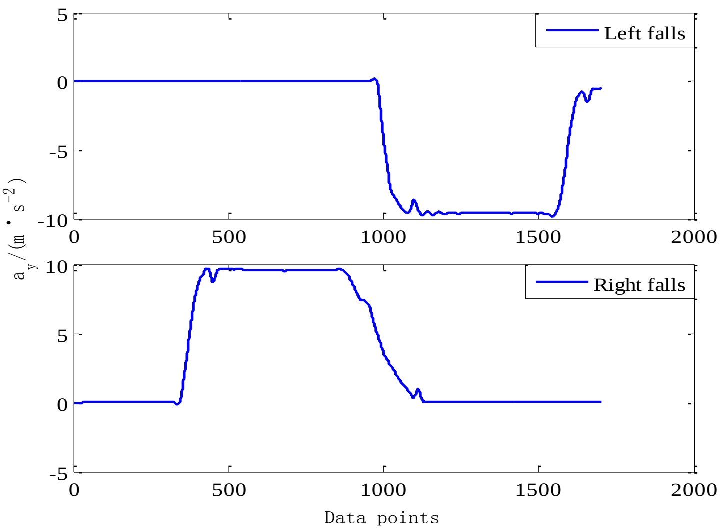

Fig.7 Acceleration simulation of the left and right falls

We select the peak of the acceleration data of Y-axis as the characteristic vector to identify the left and right falls. The peak change of Y-axis in the left falls is about 9.8 $m \cdot s^{-2}$. We set the identifying threshold for the left fall is greater than 5 $m \cdot s^{-2}$. The peak change of Y-axis in the right falls is about -9.8 $m \cdot s^{-2}$. We set the identifying threshold for the right fall is less than -5 $m \cdot s^{-2}$. The peak distribution of the left and right fall are shown in Fig.7.

4. Experiments and Analysis

In order to verify the feasibility and accuracy of the proposed algorithm, we invite 10 testers in this experiment, including 7 males and 3 females, which are experimentally verified by the laboratory independent integrated micro inertial measurement unit. Each tester simulates the elderly's fall in the lab. Each fall is simulated 10 times, including the forward, backward and lateral falls. The recognition rate is defined as follows.

Recognition rate = (Number of measurements / Number of measurements) ×100%

Table.1 The results of experiments

Fall behaviors	Forward fall	Backward fall	Left falls	Right falls
Number of measurements	100	100	100	100
Number of measurements	95	92	93	92
Number of missing	2	5	5	6
Number of misidentification	3	3	2	2
Recognition rate (%)	95	92	93	92

The results of the fall behaviors are shown in Table 1. For the fall behaviors, misidentification of the situation is confused with running. The recognition accuracy of the forward fall is higher than the other behaviors, and the average recognition accuracy of the fall detection is 93%.

5. Conclusion

In this paper, we proposed a recognition algorithm to identify the fall behaviors based on the threshold and peak of acceleration data. In this algorithm, we judge the threshold first. And if it is larger than the set threshold, it will continue to judge the direction of the fall. By analyzing the size of the peak, it will identify the direction of the fall, including forward falls, backward falls and lateral fall. Finally, the recognition degree of the algorithm is verified experimentally. The average recognition accuracy of the fall detection is 93%. It also can identify the direction of the fall.

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