Research on the Falling Detection System for Elderly-assistant and Walking-assistant Robot

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Abstract. With the development of living standards, the problems caused by aging population have become more and more serious. At the same time, with the growth of age, the body function of the elderly is degenerating and the body flexibility is reducing, which leads to frequently occurring of falling in elderly. The research data shows that falls are the most common and unpredictable problem for old people, which are even life-threatening. Therefore, a falling detection system used in the walking-assistant robot is proposed to make the walking-assistant robot better service during the outdoor walking. Firstly, a general design plan of the falling detection for old people, which is used in walking-assistant robot, is introduced through the analysis of falling mechanism of elderly. Then, an acceleration sensor ADXL345 and the detection module of touch pressure sensors are used to collect data of acceleration and hand touch force of users. Next, the feature extraction is carried out on the above data, and the falling detection is delivered by time domain feature representation and recognition algorithm. At last, the test system is built for test verification, and the results show that the falling detection system has a stable and reliable performance and high detection accuracy rate, reaching 99.05%. It can detect the falling of elderly effectively.

1. Introduction
With the coming of aging population, the fall has become one of the main causes of disability and death of old people. The World Health Organization reports that more than 400000 people worldwide died from falls in 2002, where in people aged 60 and above accounts more than 50% and people aged 70 and above accounts 40% [1]. Therefore, it is rather important to take measures to provide assistance for old people. That is to take scientific measures to detect the falling of the elderly, and then to reduce the injuries caused by falls. In this lab, a safe and reliable walking-assistant robot with full function and comfortable structure has been studied. The motion analysis of the robot and the human-computer interaction control method based on tactile are also studied [2-3]. Although there are plenty of researches on walking-assistant robot worldwide. However, there is little research on the falling of old people with walking-assistant robot. So, the safety of the elderly is not guaranteed. This paper focuses on solving the problem of falling detection and prediction through the relevant theory exploration of information obtaining, so to improve the accuracy and timeliness of the detection. So, in this paper, an experimental platform that aims to detect the falling identification and sensing information of old people has been built to research the falling detection. Within the experimental samples, this paper has proposed an identification method for body falling based on the time series analysis of human motion state.

2. The Overall System Design of Falling Detection System for Elderly
A walking-assistant robot is a walking assistance robot system guided by walking intention and driven by power. It aims to provide body support and walking assistance to old people with walking problems,
and to satisfy the old people’s needs of autonomic walking, friendly use, maintaining of walking ability and ability of self-living[4]. In this paper, a sensor ADXL345 is used to collect the three-dimensional acceleration value of the upper body to calculate the body inclination, and a pressure sensor is used to measure the hand pressure so to calculate the change of the hand pressure.

And, the probability of human fall is evaluated on this basis. Then, the single chip microcomputer is used as the falling data processing module to analyze and handle fusion process of these data. When abnormal falls are detected, the falling trend will be sent to the main controller DSP2812 by wireless communication. Once the main controller DSP2812 detects the fall, it will control the alarm module to alarm. If the user does not cancel the alarm within a certain time, the main controller will control the SMS module SIM800A remote alarm. The whole system block diagram is shown in figure 1.

**Figure 1.** Falling detection system block diagram of walking–assistant robot.

### 3. Design of Falling Detection System for Old People

In this paper, the acceleration sensor and the pressure sensor are adopted in combination. The acceleration sensor ADXL345 is used to calculate the inclination of the body relative to the horizontal plane and to analyze the movement mode. And the film pressure sensor FSR402 on the handler is used to measure the hand pressure. The pressure applied on the thin film area of the sensor can be converted into the change of resistance, which enables the sensor to obtain the pressure data. The acceleration sensor ADXL345 can measure the acceleration of X-axis, Y-axis and Z-axis. It can judge the falling posture with the collected three dimension data, and then calculate the acceleration of the whole human body. When it works, the acceleration signal is firstly induced in real time by the front-end sensing device of the module, then the acceleration signal is converted into an internal identifiable analog signal through the internal inductor of the sensor. And there is an analog-to-digital converter integrated within the module, which can convert analog signals into digital signals. The pressure sensor FSR402 obtains the pressure values indirectly, that is by measuring the resistance value and then converting the resistance value into pressure value. The resistance value is obtained by the voltage ratio of the known resistance. The AD module in DSP2812 is mainly used to collect the array signal for the pressure sensor. SIM800A SMS module mainly concludes power supply circuit and card connection circuit. The power supply circuit supplies stable power to the whole module unit. The single chip microcomputer is connected with the communication module of SIM800A by sending and receiving data through serial port, thus the data transmission is finished. SIM800A SMS module is connected to SIM card by SIM card interface circuit. The single chip microcomputer sends out the control command to start SIM800A, and then the remote communication of the data is realized.

### 4. Algorithm of Falling Detection

In this paper, the threshold falling detection algorithm based on human motion time series analysis is used to judge falls.
4.1. Threshold of Resultant Acceleration

The three dimension resultant acceleration is usually used in common falling detection algorithms based on threshold, that is Signal Magnitude Vector (SMV), which is defined as following:

\[ SMV = a = \sqrt{a_x^2 + a_y^2 + a_z^2} \]  

(1)

\( a_x \) --acceleration amplitude of x-axis /g; \( a_y \) --acceleration amplitude of y-axis /g; \( a_z \) --acceleration amplitude of z-axis /g; \( a \) --amplitude of resultant acceleration /g. According to the judgment of TJ1( threshold of resultant acceleration), the body movement can be divided into strenuous actions, including jumping and running, and small actions, including sitting down and standing up. TJ1 is not enough to judge the fall. The falling behavior to be judged in this paper is a strenuous action. So, it needs to distinguish strenuous actions from falling, which belongs a kind of momentary behavior.

4.2. Threshold of Mean Resultant Acceleration

The common strenuous actions for old people covers only a few behaviors, such as jumping and running. Wherein, running is a behavior with strong regularity. That is because the body moves repeatedly during running. Therefore, the mean value of the resultant acceleration \( A_{SMV} \) is introduced to distinguish the falling behavior from running behavior, which is defined as follows:

\[ A_{SMV} = \frac{1}{n} \sum_{i=1}^{n} SMV_i \]  

(2)

\( N \) refers to the number of resultant acceleration. \( A_{SMV} \) reflects the range of human movement. Small \( A_{SMV} \) indicates small range of human movement and large indicates large range of human movement. The human body has large movement range during strenuous activities, such as running, which belongs to activities with large range of movement in a period. So, falls can be distinguished from strenuous activities by selecting appropriate threshold of acceleration mean value (TJ2).

4.3. Threshold of Inclination

According to the judgment of TJ1 and TJ2, falls can be removed from most ADL(Activities of Daily Living). However, there are still some activities such as jumping, which cannot be distinguished successfully by the system. It can be found from the comparison of jumping and falling that their human postures are quite different. So the falls can be judged by the detection of human inclination.

A three dimension human coordinate model is built, as shown in figure 2-(a). Where, the front and behind directions are taken as the X axis, the left and right directions as the Y axis, and the upper and lower directions as the Z axis. As shown in figure 2-(b), the inclination is introduced:

\[ \theta = \arccos \left( \frac{a_x}{\sqrt{a_x^2 + a_y^2 + a_z^2}} \right) \]  

(3)

(a) Human three dimension coordinate model       (b) Human inclination model

Figure 2. Human coordinate model.
The inclination can indicate the body gesture. When human body falls, the inclination angle will generally keep within 30°, conversely, the inclination will be more than 60° during strenuous activities such as jumping. So, strenuous activities such as jumping can be distinguished from falls by setting appropriate inclination threshold TJ3. In conclusion, the fall can be judged by setting appropriate values for TJ1, TJ2 and TJ3. The working flow of the algorithm is as below: 1) Sensor collects acceleration signals in real time and calculates SMV values; 2) To judge whether the resultant acceleration value is more than TJ1. If so, continue to the next step; if not, back to the first step; 3) To judge whether the resultant acceleration value is less than TJ2. If not, continue to the next step; if not, back to the first step; 4) To judge whether the inclination value is less than TJ3. If so, the fall occurs; if not, back to the first step.

4.4. Determination of the Threshold

Determination of the resultant acceleration threshold. ADL (Activities of Daily Living) and Fall are tested separately; and the peaks of resultant acceleration are recorded, as shown in table 1 and table 2. The SMV peaks of ADL and Fall in table 1 and table 2 can be further analyzed and extracted, as shown in table 3. To sum up, it is found that the minimum SMV value is 1.78 g when the human body falls. As the limit SMV value of slow activities is 1.5 g, the resultant acceleration threshold YJ1 in this paper is set to be 1.64 g to distinguish ADL from Falls. TJ1 is smaller than any SMV values generated during falling, which can make sure that there is no false negative occurring on the judgement of falling in the system.

| Code | Stand | Rise | Jog | Walk | Sit | Upstairs | Downstairs | Squat | Jump |
|------|-------|------|-----|------|-----|-----------|------------|-------|------|
| 1    | 1.13  | 1.42 | 2.60| 1.48 | 1.41| 1.29      | 1.42       | 1.49  | 3.28 |
| 2    | 1.08  | 1.38 | 2.46| 1.38 | 1.35| 1.27      | 1.39       | 1.40  | 3.26 |
| 3    | 1.08  | 1.35 | 2.66| 1.42 | 1.38| 1.29      | 1.42       | 1.48  | 3.28 |
| 4    | 1.09  | 1.43 | 2.38| 1.46 | 1.37| 1.26      | 1.35       | 1.38  | 3.18 |
| 5    | 1.06  | 1.29 | 2.49| 1.37 | 1.33| 1.35      | 1.41       | 1.49  | 3.08 |

| Code | Fall frontward | Fall backward | Fall to the left | Fall to the right |
|------|---------------|---------------|------------------|-------------------|
| 1    | 2.14          | 2.16          | 1.89             | 1.88              |
| 2    | 2.23          | 2.01          | 1.89             | 1.90              |
| 3    | 2.11          | 2.11          | 2.00             | 1.99              |
| 4    | 2.13          | 2.15          | 2.01             | 2.00              |
| 5    | 2.05          | 2.06          | 1.89             | 1.89              |

| SMV  | ADL and Fall  |
|------|----------------|
| SMV<1.5g | Stand, Rise, Walk, Sit, upstairs, Squat |
| SMV>2g   | Jog, Jump, Fall |

4.4.1. Determination of the mean resultant acceleration threshold. When SMV values are not more than TJ1, no falls will occur. And, when SMV values are more than TJ1, falls or strenuous activities may happen. Therefore, falls and strenuous activities need to be further distinguished. Here, the mean values of resultant acceleration are recorded, which are shown in table 4.
Table 4. Mean value of resultant acceleration (g).

| Code | Jog  | Jump | Fall frontward | Fall backward | Fall to the left | Fall to the right |
|------|------|------|----------------|---------------|-----------------|------------------|
| 1    | 1.75 | 1.11 | 1.08          | 1.09          | 1.10            | 1.08             |
| 2    | 1.67 | 1.13 | 1.12          | 1.10          | 1.08            | 1.09             |
| 3    | 1.80 | 1.08 | 1.06          | 1.08          | 1.07            | 1.11             |
| 4    | 1.60 | 1.06 | 1.08          | 1.07          | 1.06            | 1.08             |
| 5    | 1.66 | 1.08 | 1.10          | 1.06          | 1.09            | 1.07             |

It can be found from the analysis of table 4 that the mean value of the resultant acceleration during jogging is relatively larger, which is more than 1.5 g. And the mean value of the resultant acceleration during falling and jumping fluctuates around 1.1 g, which is mainly due to the fact that the human body does not move much after falling or jumping. In summery, jogging of ADL can be picked out from strenuous activities by setting appropriate thresholds TJ2 for threshold of mean resultant acceleration. Then, falls can be distinguished as long as jumping can be picked out from strenuous activities. So, the selection of TJ2 can distinguish falls from strenuous activities. Therefore, TJ2 is set to be 1.20g in this paper, which removes jogging from falls.

4.4.2. Determination of the inclination threshold. With the comparison of TJ1 and TJ2, most of the ADL have been distinguished from the fall. However, there still exists false judgement on jumping and some other activities. Thus, the human inclination during jumping and falling is recorded as below. The data are shown in tables 5.

Table 5. Human inclination angle (°).

| Code | Jump  | Fall frontward | Fall backward | Fall to the left | Fall to the right |
|------|-------|----------------|---------------|-----------------|------------------|
| 1    | 79.5  | 15.6          | 16.2          | 17.8            | 19.2             |
| 2    | 82.3  | 18.4          | 17.9          | 19.2            | 21.6             |
| 3    | 76.5  | 21.1          | 19.7          | 23.0            | 17.4             |
| 4    | 80.2  | 18.6          | 17.8          | 20.9            | 21.7             |
| 5    | 83.6  | 22.4          | 23.0          | 18.6            | 17.5             |

It can be seen from table 5 that the maximum human inclination generated during falling is 23.0°, which is much smaller than that produced during ADL. So it only needs to set an inclination angle larger than 23.0°to judge the fall. Thus, the inclination threshold TJ3 is set to be 30°, which can ensure that there is no false negative on the falls. In conclusion, the fall is judged by using the threshold falling detection algorithm with the selected three different thresholds, wherein, the threshold of resultant acceleration TJ1=1.64g, the threshold of mean resultant acceleration TJ2=1.2g, and the human inclination threshold TJ3=30°.

5. Test Verification and Results Analysis

Two groups of experiments have been arranged for ADL and Fall. ADL mainly simulates walking, sitting, squatting or going upstairs and downstairs, while Fall mainly simulates the falls, taking human body as the baseline, in four different directions: front, behind, left and right. Firstly, nine groups of ADL are simulated, each of which is simulated 50 times. So, there are totally 450 times. The test data is shown in table 6. Secondly, four kinds of falls are simulated, each of which is stimulated for 50 times. So, there are totally 200 times of simulation data have been collected for comparison and analysis. The test data is shown in table 7. Through the analysis of the data, it is found that the alarm accuracy of the fall reaches 99% when the system detects the falls, in which the miss-alarm radio of the falls is only 1%. In the same way, the alarm accuracy of the fall reaches 99.1% during the ADL indication, in which the false alarm rate is only 0.9%. Therefore, it is considered that the system can accurately alarm for the falling of old people.
Table 6. ADL test data.

| ADL         | Number of test | Number of alarm | Accuracy radio |
|-------------|----------------|-----------------|----------------|
| Stand       | 50             | 0               | 100%           |
| Rise        | 50             | 0               | 100%           |
| Sit         | 50             | 0               | 100%           |
| Up stairs   | 50             | 1               | 98%            |
| Down stairs | 50             | 1               | 98%            |
| Walk        | 50             | 0               | 100%           |
| Jog         | 50             | 1               | 98%            |
| Jump        | 50             | 0               | 100%           |
| Squat       | 50             | 1               | 98%            |
| Sum         | 450            | 4               | 99.1%          |

Table 7. Test data of Fall.

| Fall            | Number of test | Number of alarm | Accuracy radio |
|-----------------|----------------|-----------------|----------------|
| Fall frontward  | 50             | 50              | 100%           |
| Fall backward   | 50             | 50              | 100%           |
| Fall to the left| 50             | 49              | 98%            |
| Fall to the right| 50           | 49              | 98%            |
| Sum             | 200            | 198             | 99%            |

Table 8. Total data of falling detection system.

| Human activities | Times | Comprehensive accuracy | False-alarm | Miss-alarm |
|------------------|-------|------------------------|--------------|------------|
| ADL and FALL     | 650   | 99.05%                 | 0.9%         | 1%         |

It can be seen from table 8 that accuracy rate, false alarm rate and miss alarm rate are taken as the standards of falling detection. The accuracy rate is the detection probability of the happened falls; the false alarm rate refers to the alarm probability on the falls which do not occur actually; and the false alarm rate means the alarm probability on the falls that occur without alarm. Thus, totally 650 tests have been carried out, in which the comprehensive accuracy rate reaches 99.05%, the false-alarm rate is 0.9% and the miss-alarm rate is 1%. So, it shows that although there exists certain false alarm rate and miss-alarm rate for the threshold falling detection algorithm during the falling detection, its accuracy rate for falling detection is very high. Therefore, this algorithm can be used to detect the falls of the elderly.

6. Conclusion

In this paper, a falling detection system for old people used for walking-assistant robot is designed, including the design of falling data collection system, feature extraction and identification of falling data for falling detection. Firstly, an acceleration sensor ADXL345 and a tactile sensor are used to collect real-time data of acceleration and hand touch force of bodies to process. Then, the threshold falling detection algorithm is applied to judge if a fall has occurred. And, it will alarm in remote with the wireless communication module SIM800A. At last, the threshold falling detection algorithm is verified. And the test data reflects that the accuracy rate of the threshold fall detection algorithm has reached 99.05%, which shows that the threshold falling detection algorithm can judge the falls and achieves the desired effect.

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