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Research of HMM-Based Fall Detection System for Elderly

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Abstract. With the aging of the deepening of the world, the fall accident of elder has been taken great attention by more and more people. This paper is committed to invent a set of automatic fall detection device, so as to reduce the damage for elder caused by fall accident and apply timely assistance. Therefore, we install a Tri-axial G-sensor on chest to acquire acceleration information, and establish a fall detection algorithm based on hidden Markov model. First the device can extract data features, then learn fall process to form a Markov fall model, finally, detect real-time data through the model to judge fall accidents from all the daily behavior. Experimental results show that the wearable device can effectively identify a simple fall process with high accuracy.

Keywords: fall detection, hidden Markov model, wearable device, G-sensor

1 Introduction

With the aging of society as a whole the deepening security issues concern the elderly, there is more than one-third of people aged over 65 fall accidents occur every year, accounting for 40% of injury death [1]. Elderly fall accident happened to bring them the degree of injury and rescue effect is largely dependent on the time they get relief. According to statistics, if the elderly fell to the ground for a long time (Long-lie), that is, after the fall of involuntary kept lying on the ground for more than an hour will be the death of about 50% within six months [2]. After the fall in order to allow the elderly to get timely medical care, to minimize the damage caused by a fall, automatic fall detection has become the focus of social health. More and more different types of fall detection device based on kinematic information is designed invented. Currently, the research of non-domestic and foreign users since the launch of the major fall detection method can be roughly divided into three [3]: 1. Based on video detection by image analysis, image analysis grab the body is falling; 2. Based on the environment device (pressure sensors, sound sensors, etc.), by analyzing human body has fallen and the sensor data; 3. Based on the wearable device, the posture of the human body is detected. Detection Algorithm based on the screen already international studies [4, 6], using an image analysis algorithm design variety and the indoor environment in a simple target human behavior judgment more accurate, but it is difficult to be widely adopted outdoors as well as under the condition with complex visual environment. In addition, the privacy of users is easily violated. With the limitation, this algorithm can fit the elder who live alone better. Detection methodology based on environment sensors accounts for less proportion among current studies, because errors are likely to come out in noisy environment (such as equipped with carpets or wood floors and so on) with complex crews when adopting sound sensors and vibration sensors. The behavior judgments of targeted objects are more likely to be incorrect with the narrow scope. The development of wearable

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devices for fall detection is relatively faster compared with the other two detection devices, which is based on the analysis of human dynamics and owns several merits like portable, without violating personal privacy, target at monitoring single object, easier algorithm, and controllable costs [5]. The algorithm based on wearable devices is designed to identify falling by equipping two simple G-sensors on waist. This algorithm is easy and practical, and identifies whether falling down or not by detecting the slope of curves. However it only makes sense when targeting at the slowly moving objects [7]. Phone built-in sensors are adopted to collect linear acceleration speed and angular velocity. After comparing data with obtained daily data, it can be identified whether falling down or not using threshold detection algorithm, as well as sending notice to colleagues. However, in order to use this algorithm mobile phones have to be equipped near chest. In addition, the threshold of various falling types is distinct. So this methodology is not applicable for falling down with phone in hands. Wearable detecting devices own merits of small, lightweight, user friendly, low cost, wide range of application, and so on. But high rates of detection, low false rates, and long-term robustness must be assured in actual use. Currently accelerometer, gyroscope, or both are adopted in studies at home and abroad to set the threshold of acceleration speed and angular velocity for detecting and predicting falling behavior and identifying falling down.

This thesis designed the wearable device to automatically detect falling down based on hidden Markov model. Two sensors were used to detect data of human moving information. Through real-time storage data, the data characteristics were extracted to analyze moving status based on the hidden Markov model. Furthermore the assessment rate of normalized probability was established to evaluate risks of falling down and judge whether falling down or not as well as sending warning messages.

2 Falling Recognition Algorithm Based on HMM

Due to the complexity and randomness of human motions in daily life, various motions can be regarded as the combination of various motion statuses in certain sequences. Similar motion during each state transition probabilities and each state is detected between the sensor information with a certain probability of occurrence regularity [7]. The behavior of falling down can be classified as an unexpected status of human normal behaviors. Compared with normal daily behavior, the status of falling down relates with daily behaviors and can be represented by transition probabilities after analyzing data.

2.1 First Order Hidden Markov Models

The classic theory of Hidden Markov Models (HMM) was put forward by Baum and others in the late 1960s [9]. As a widely-used statistics model, HMM has already been an important tool in the areas of speech recognition, image processing and signal processing, ecology, cryptanalysis, associate genetic analysis and gene identification, target tracking, and gait recognition. HMM was developed from the basis of Markov Chain and consisted of two stochastic processes, one is implicit state transition sequence, which corresponds to a simple Markov process; and the other is implicit state of observation sequence. The relationship between implicit and observation sequences is indicated by the probability of observed value. In both series, the hidden state transition sequence is unobservable and can only be inferred by observing another output sequence.

HMM can be described by the group of five factors: $\lambda = (M, N, \pi, A, B)$ and each factor can be defined as follows:

(1) M: Number of hidden states of Markov Chain, the finite set of status is defined as $U = \{u_1, u_2, \cdots, u_M\}$.

(2) N: The number of possible values of the random process of observation, the finite set of observations is defined as $V = \{v_1, v_2, \ldots, v_N\}$.

(3) π : The probability distribution of initial state, describes the probability of u_i in initial hidden state. π is a vector and defined as $\pi = \{\pi_1, \pi_2, \cdots, \pi_M\}$. Specifically $\pi_i = P(Q_t = u_i)$, $i = 1, 2, \cdots, M$.

(4) A: The transfer matrix of Markov Chain hidden status in HMM, defined as $A = \{a_{ij}\}_{M \times M}$, a_{ij} indicates the Markov Chain hidden status is u_i at the moment of t, while u_j at the moment of t+1.

Namely,

$$a_{ij} = P\left(Q_{t+1} = u_j \mid Q_t = u_i\right), i, j = 1, 2, \cdots, M \quad \textbf{(1)}$$

(5) B : Output matrix, indicates the probability matrix of the observed value in implicit state. Defined as $B = \left\{b_{ij}\right\}_{M \times N}$, specifically：

$$b_{jk} = P\left(O_t = v_k \mid Q_t = u_j\right), k = 1, 2, \cdots, N. j = 1, 2, \cdots, M \quad \textbf{(2)}$$

In some time-related problems, a process carried out over time, the process consists of a sequence of state constitutes a series, and a sequence corresponding to the current time t and the previous state only one time $t-1$ sequence corresponding to the state of related to the state sequence can be called a first-order Markov process.

Using an HMM for problem handling time, the three main issues to consider are: assessment, decoding and learning. The application of the HMM recognition problems and human behavior, you need to obtain a sequence of several acts of observation, HMM by learning a reasonable model, and then evaluate the real-time observation sequences obtained by judging whether the probability of the occurrence of falls. In this article, it is judged to fall process involves a sequence of observations by the feature extraction to extract human motion data obtained.

2.2 Extraction of Features of Falling Down

In order to accurately detect human fall process requires the extraction behavior and other acts fall comparative information has a strong difference in nature. Timing analysis (statistical method known as process) processed data is dynamic. Any perpetrator is the process of sex, hence the timing analysis method can better describe the characteristics of the process of human behavior. For universality, we use human torso acceleration information to better identify the fall.

In order to study the process of some motion parameters fall, fall quantification process, first define the coordinates of the various parts of the body and steering. Different parts of the body acceleration and the angular velocity information is not the same, in order to improve the accuracy of fall detection, the selection of a proper location of the trunk acceleration data acquisition is very important. Wearing position can be considered by the body’s objectivity has arms, wrists, waist, chest, thigh, ankle. According to the study showed that: the acceleration information upper torso of the body more than the lower body torso indicate the state of the body’s movement and body posture. Upper torso, arm and wrist motion state data because the conversion often too complex, so does not apply to obtain acceleration information to determine whether the fall. Because the body’s neck is relatively weak position, taking into account the wear on the neck wearable devices could fall during the course of the neck injury caused by unpredictable, so this measurement data is selected torso chest. For general data, take a human chest as the origin point, establish a Cartesian coordinate system $Oxyz$, wherein the z-axis perpendicular to the ground, x-axis pointing straight ahead, level with the ground, y-axis points to the right, and also the ground horizontal, as shown in Fig. 1

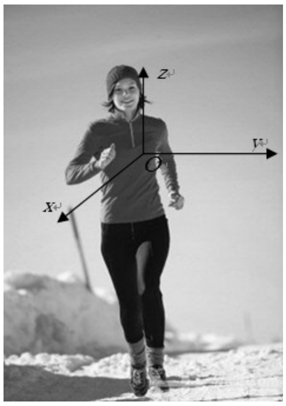


Fig. 1. The Cartesian coordinate system $Oxyz$

In real life, fall is a random event, you can't pre-judge the direction of fall, difficult only uniaxial accelerometer data from the analysis of whether the person wearing the device has been falling, but the direction is not judged necessary conditions of fall. Therefore, the experiment data used in the analysis refers to the resultant acceleration ($a=\sqrt{a_x{}^2+a_y{}^2+a_z{}^2}$) and combined angular velocity ($\omega=\sqrt{\omega_1{}^2+\omega_2{}^2}$) to simplify the calculation.

For the combined value of the sequence of acceleration combined acceleration value tri-axial accelerometer data acquisition system of values obtained constituted calculated (Acceleration Data Series, ADS), can be expressed in detail the status of human movement. Sequence acceleration time series (Acceleration Time Series, ATS) for the characterization of a certain period of time the body motion acceleration information elements characteristic chronological formed. The period of ATS was defined as Ts, the length of sequence was n, namely included n chronological acceleration information elements $\{c_j\}$ ($i=1,\ldots,n$), specifically each element in the characterization of the corresponding period of Ts on the body trunk motion characteristics.

The period of ADS was known as $T=10ms$. Describe the motion characteristics of the acceleration time series ATS by getting the torso movement with sliding time window, the step length of sliding window is Ts, the length keeps n. Assume $Ts=n\times T$, namely during the time of Ts, m groups of tri-axle acceleration values can be collected to get m combined acceleration speeds $a=\sqrt{a_x^2+a_y^2+a_z^2}$ and extract characteristics to get the new c_i. M values relate with useful information and timeliness, through experiments this thesis chosen m as 4. Correspondence between ATS and ADS is shown in the Fig. 2.

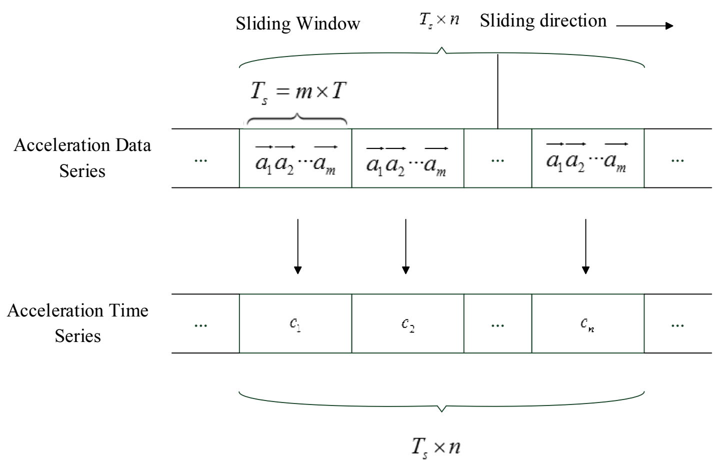


Fig. 2 The conversion chart of ADS and ATS

The extraction process of ATS includes:

(1) The method of maximum distance calculated the characteristics information a_c of combined acceleration during the time of Ts. According to the knowledge of life, the range of combined acceleration is relatively narrow when normal human sitting, lying and other relatively static action. To simplify the description, define the range as $[S_1,S_2]$, define the moment of t, the combined acceleration of a, and the distance of S: $S(\mathrm{a})=|a-S_1|+|a-S_2|$. The more intense the state of motion, the greater the distance of co-acceleration deviation. Let the characteristics information of combined acceleration during the time period of Ts be $a_c=a_j$. When $S(a_j)=\max[S(a_i)]$, $\forall i=1,2,\cdots,m$.

(2) a_c range segment symbols generated elements of acceleration time series c. Human fall acceleration process can reach a large value, the range of a_c can be large, a_c as non-segmented symbolic, led the number of element $\{c_j\}$ be very large, while let a_c as segmented symbolic can reduce the element number of $\{c_j\}$ to simplify the calculation. Acceleration range of human activities is generally

within the range of less than $S_h = 30m/s^2$. However when falling down, the body acceleration has a large peak value. To satisfy the demand, a_c can be separated as N parts, each range indicates elements $\{1\ldots N\}$ within $\{c\}$, which will be discussed in the following part.

2.3 HMM Based Falling Detection Model

A sliding window is used to acquire ATS: $\{c_j\} = \{c_1, c_2, \ldots, c_n\}$, The observation sequence $O = \{O_1, O_2, \cdots, O_n\}$ describes person falling process, where $O_t = c_t$, $1 \le t \le n$. And the corresponding hidden status sequence to the observation sequence is $Q = \{Q_1, Q_2, \ldots, Q_n\}$, describing the body's state.

If an HMM $\lambda = (M, N, \pi, A, B)$ is used to describe the falling process, each factor can be defined as follows:

(1) M: Number of hidden states of Markov Chain, the finite set of person statuses are defined as $U = \{u_1, u_2, \cdots, u_M\}$. In this paper, $M = 4$, four statuses are Balance, imbalance, impact the state, the stationary state after the fall.

(2) N: The number of acceleration observations, i.e. the number of ATS $\{c\}$ elements, the finite set of observations is defined as $V = \{v_1, v_2, \ldots, v_N\}$

(3) π: The probability distribution of initial state, describes the probability of u_i in initial hidden state. π is a vector and defined as $\pi = \{\pi_1, \pi_2, \cdots, \pi_M\}$. Specifically $\pi_i = P(Q_t = u_i), i = 1, 2, \cdots, M$

(4) A: The transfer matrix of HMM based falling detection model, defined as $A = \{a_{ij}\}_{M\times M}$, a_{ij} indicates the status of person is u_i at the moment of t, while u_j at the moment of $t+1$. Namely,

$$a_{ij} = P\left(Q_{t+1} = u_j \mid Q_t = u_i\right), i, j = 1, 2, \cdots, M \tag{3}$$

(5) B: Output matrix, indicates the probability matrix of the observed value in implicit state. Defined as $B = \{b_{ij}\}_{M\times N}$, specifically：

$$b_{jk} = P\left(O_t = v_k \mid Q_t = u_j\right), k = 1, 2, \cdots, N. j = 1, 2, \cdots, M \tag{4}$$

b_{jk} represents the probability when the body is in status u_j, and the observation probability value is v_k.

Because the falling activities are irreversible, we have adopted a left - right chain model [11], that is, each state will shift down to next a state or maintained in its current state.

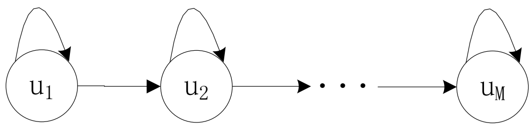


Fig. 3. The HMM left - right chain model

In order to make the falling HMM could adequately describe falling, we need to collect J sets of typical falling data. It's easily to turn ADS into ATS as a training sequence on HMM. According to the daily human behavior analysis of experimental data and the person status collection $U = \{u_1, u_2, \cdots, u_M\}$, we designed corresponding state sequences. Known observations (ATS), hidden status (state sequence), $N = 8$ and $M = 4$, the model parameter $\lambda_i = (\pi_i, A_i, B_i), i = 1, \cdots, J$ could be learnt from sample data. Each sample data's contribution to the falling models λ_m is equal. So the average of ten models' parameters contributes to final falling model based on HMM, which combines all the features of ten samples. The falling model based on HMM is:

$$\lambda_m = (\pi, A, B) = \frac{1}{J}\sum_{i=1}^{J}\lambda_i \tag{5}$$

HMM based falling detection model establishing flowchart is shown in Fig. 4.

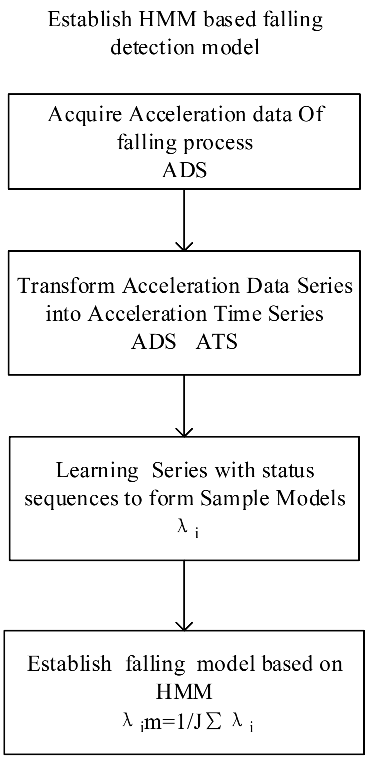


Fig. 4. HMM based falling detection model establishing flowchart

2.4 HMM Based Falling Detection Algorithm

Acceleration of the falling process will reach a larger peak value, so the international employment of a G-sensor usually takes an acceleration threshold detection employment to detect falling. Some scholar take multiple axis acceleration thresholds for determination, and some scholar take resultant acceleration threshold for determination. The main step is to compare a plurality of single-axis acceleration value or the resultant acceleration value or the differential acceleration, in real time, with a threshold value. Exceeding the threshold value, or the time exceeding the threshold value is longer than a certain length of time, then algorithm determines the people fallen [12]. Single-stage threshold detection algorithm refers only to a set of data is compared with a fixed or dynamic threshold value, in chronological order. When the data is determined to satisfy the threshold condition, the setting event occurs. Such algorithms have an advantage with a low computational complexity and easy to understand. But its drawback comes the large false positive rate. When vigorous movements happened, it’s difficult to recognize whether people fall or run [5]. When the threshold range set by single-stage threshold algorithm is large, algorithm can detect almost all kinds of simple falling, but it is easy to determine some non falling like strenuous exercise to falling, what means large false positive rate, and the undetected-rate is small. However, when the threshold range is small, the detected events are almost correct which means false positive rate is small, in contrast, the undetected-rate is large.

HMM based falling detection algorithm, obtains the HMM falling model λ_m by training, and match it with the unrecognized acceleration time sequence ATS. The higher degree of matching, the more possibility of falling. Therefore, By calculating the output probability $P(ATS \mid \lambda_m)$, and compare it with the threshold probability PH, we can distinguish between the falling and daily behavior.

Main procedures of the algorithm are as follows:

(1) Sensors acquire the information of the human motion acceleration, and obtain the resultant acceleration by calculation.

(2) Extract ADS sequence by sliding time window and translate them into ATS sequence, then recorded as observation sequence O.

(3) Calculate $P(O|\lambda_m)$ through model λ_m, and compare it with threshold probability PH.

(4) If $P(O|\lambda_m) > P_H$, then algorithm determines falling, otherwise determines not falling, continue determining, until the end.

The flow chart of HMM based falling detection algorithm is as shown in Fig. 5:

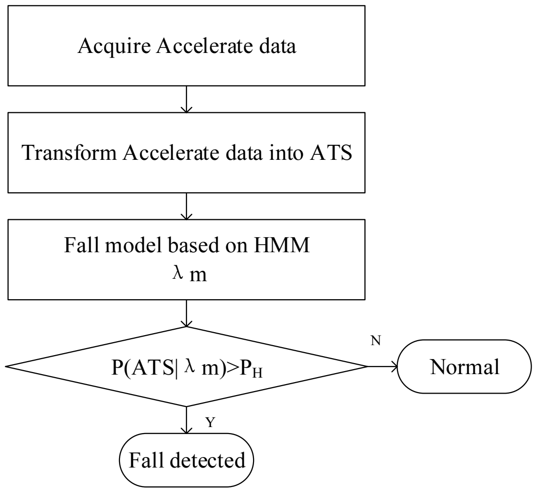


Fig. 5. The flow chart of HMM based falling detection algorithm

3 System Verification of Fall Detection

3.1 Hardware Design Of Data Acquisition System

According to the theoretical analysis and the requirement of experiment, a small portable device that could program, acquire and store 3-axis acceleration information of the human body movement process should be designed and implemented.

Based on all requirement, the data acquisition system we designed adopt STM32F103 MCU have which stable performance and richly functional interface. Hardware module is mainly composed of the acceleration acquisition module, the angular rate acquisition module, the memory module, and each module chip all choose the same power supply voltage range.

The MMA8452Q, a smart low-power, three-axis, capacitive micro-machined accelerometer with 12 bits of resolution, which designed by Freescale Semiconductor, was chosen to the data acquisition system. MMA8452Q's output data rates (ODR) from 1.56 Hz to 800 Hz, and support I^2C digital output interface. Capacitive accelerometer could sense the acceleration and vibration movements in different directions by travel mechanism using the mechanical properties of silicon. The mechanism mainly includes two groups of silicon fingers, one fixed, another group move with target's movement. The former is equivalent to a fixed electrode, and the function of the latter is a movable electrode. While movable silicon fingers' displacement happens, capacitance value will change proportional to the displacement, and the interface chip will output voltage values according to the change of capacitance value.

The L3G4200D manufacture by STMicroelectronics is a low-power three-axis angular rate sensor able to provide unprecedented stability of zero rate level and sensitivity over temperature and time. The sensing element of it is manufactured using a dedicated micro-machining process developed by STMicroelectronics to produce inertial sensors and actuators on silicon wafers. The L3G4200D support I^2C/SPI digital output interface, 16 bit-rate value data output, scale of ±250/±500/ ±2000 dps.

The memory module connected to Micro SD card (SanDisk, 4G) by SDIO interface, which has the characteristics of small size, fast storage.

Circuit board of the data acquisition system with 3.1cm×3.4cm size is shown in Fig. 6, and system's power supply can use 3V battery directly.

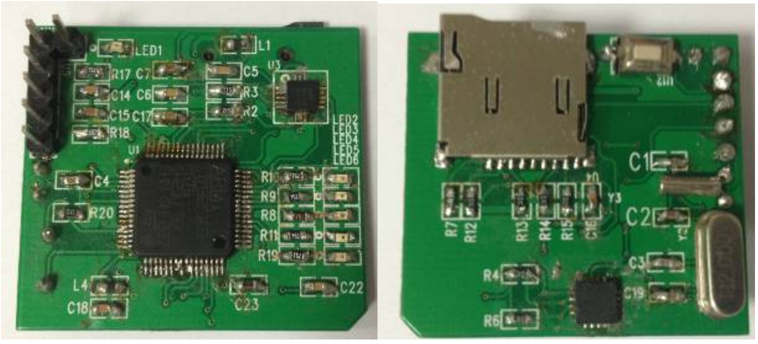


Fig. 6. The data acquisition system hardware

The circuit board can be fixed in the bosom and appressed body by elastic cord. After initialization, the system will acquire and store acceleration data automatically in the storage card. The system analyzes and calculates the data, judge the wearer's possibility of fall. If wearer falls, the system will issued a warning.

3.2 Software Design Of Data Acquisition System

With the Keil4 development environment and C language program design, based on the STM32 latest version 3.5.0 peripheral device library and device driver we designed, this paper program in user application code layer to acquire acceleration and angular rate data under specific frequency. After that, the system store the data to Micro SD card and analysis the data to judge if a fall happens. Software block diagram of the system is shown in Fig. 7.

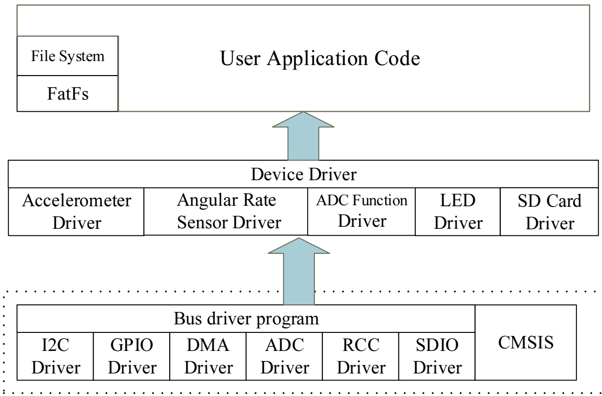


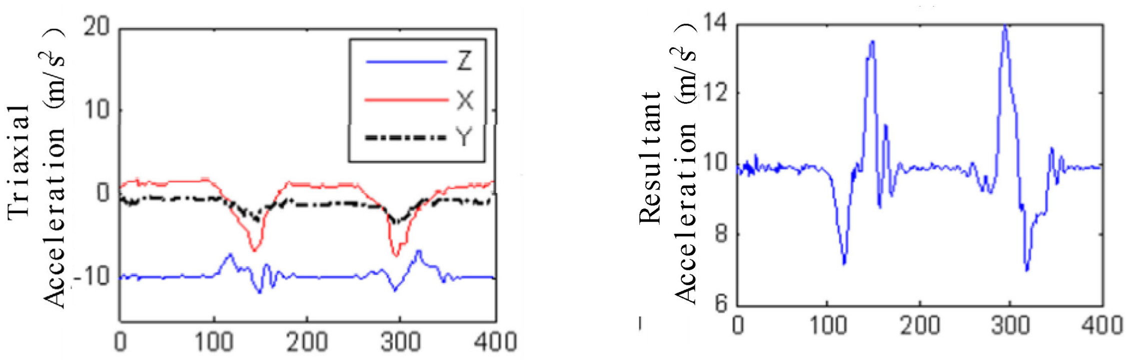
Fig. 7. The software block diagram of the data acquisition system

In system, STM32F103 MCU connect to sensors by I^2C bus, and acquire real-time acceleration and angular rate data by read corresponding register. The sampling frequency of system is 100Hz, which meet the demands of Nyquist-Shannon sampling theorem. The time series of MCU reading acceleration data from MMA8452Q is that firstly send 8bit command 0x38 which includes device address (7bit, 001110B) and write command (1bit, Write: 0, Read: 1), secondly after received ACK send register address of acceleration data, thirdly after received ACK sending 8bit command 0x39 which includes device address and read command, finally read 8bit acceleration data after received ACK. The registers address of x, y, z three-axis acceleration data are 0x01 ~ 0x06. The time series of L3G4200D I^2C operation is similar.

4 Experimental Results and Analysis

Fixing a circuit board design in Section 3 on the body of volunteer, it makes the circuit board flat on the chest. Pressed the initialization button, acceleration data could be collected. Once acceleration data obtained, it will calculate the resultant acceleration. All volunteers are young students (including boys and girls, body weight 45*kg*-70*kg*). Part of the daily behavior data as well as falls data do as shown in Fig. 8, Fig. 9, Fig. 10.

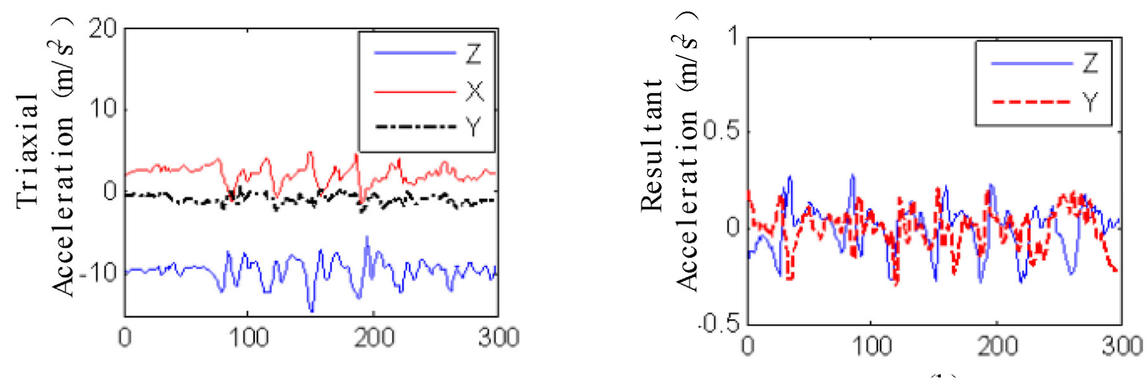
Fig. 8 shows a process of sitting down and standing up. Volunteer sat down slowly, then stood up peacefully while the middle section is relatively static state. Fig. 8(a) shows tri-axial acceleration of the process, and the data performance symmetrically. Although a slight angle deviation exists during fixing the board, the vertical gravitational acceleration g coincides with z axis substantially. Negative indicates the direction of acceleration downward and acceleration magnitude $a = 10\ m/s^2$ during stationary. Acceleration at z axis decreases at first as well as decreases then, however leaning forward gets acceleration more at x axis rather than y axis. Resultant acceleration describes the movement much more simply. Fig. 8(b) shows the resultant acceleration of the whole process distinctly. The acceleration first decreases and then increases, finally still which represents a complete process of sitting down. Analysis of standing up is similar to sitting down but acts as an opposite process. The peak resultant acceleration of both of the movements two is close to $15\,m/s^2$.



(a) (b)

Fig. 8. Sit - Standup process (Sampling period $T = 10ms$)

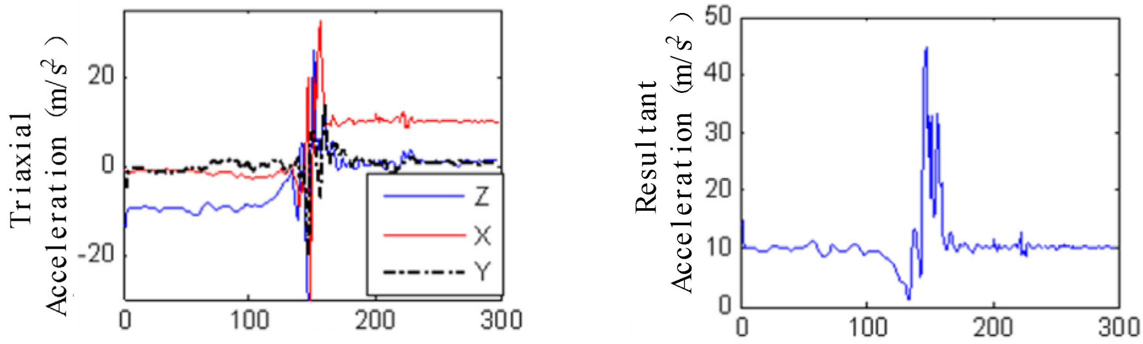
Fig. 9 shows a process of walking. Fig. 9(a) indicates tri-axial acceleration of walking, and Fig. 9(b) indicates the resultant acceleration of walking clearly. Shown in three gait cycle, the visible size of the acceleration during walking is uncertain, but displays a periodic characteristic to some extent. The acceleration increases first, then decreases. The peak resultant acceleration of walking is s close to 15 m/s^2 as well as sitting-standing up.



(a) (b)

Fig. 9. Walking process (Sampling period $T = 10ms$)

Fig. 10 shows a simple falling process. Fig. 10(a) indicates tri-axial acceleration of falling, and Fig. 10 (b) indicates the resultant acceleration of falling briefly. Tri-axial acceleration is more difficult to analyze because of the uncertainty of falling. Shown in the Fig. 10(b), its biggest resultant acceleration already exceeds 40 m/s^2, whose value is much larger than the normal daily behavior, such as sitting and walking. However by detecting a variety of behaviors, the body's acceleration can also easily reach 35 m/s^2 or more when jogging. Besides acceleration even could achieve 120 m/s^2 [13], when falling accidently. In a word, falling can hardly be judged by a threshold accurately.



(b)

(a) (b)

Fig. 10. Falling process (Sampling period $T = 10ms$)

Adopting HMM algorithm to detect falling requires to collect some typical falling sample data for training so that the falling model can adequately describe the typical fall process. According to the daily human behavior analysis of experimental data we acquired, this paper takes a relatively static daily behavior acceleration range $[S_1, S_2] = [8\,m/s^2,\ 12\,m/s^2]$ and splits range of a_c into $N = 8$ segments. In other words, turning the range of a_c into symbolic segments makes $\{c\} = \{1, 2, \ldots, 8\}$. A typical falling experiment including 10 groups collected falling acceleration data. On the platform of MATLAB, we extracted the ADS data and turned it into ATS data as training falling samples based on HMM. According to the human status $U = \{u_1, u_2, ..., u_4\}$ in section 1.3, 10 corresponding state sequences were designed. Known observations (ATS), hidden status (state sequence), no. of observations $N = 8$ and no. of hidden statuses $M = 4$, the model parameter $\lambda_i = (\pi_i, A_i, B_i)$, $i = 1, \cdots, 10$, could be learnt from sample data. Each sample data's contribution to the falling models λ_m is equal. So the average of ten models' parameters contributes to final falling model based on HMM, which combines all the features of ten samples. The falling model based on HMM is:

$$\lambda_m = (\pi, A, B) = \frac{1}{10}\sum_{i=1}^{10}\lambda_i \tag{6}$$

Through falling model λ_m to detect falling process from human motion behavior, the output probability of an ATS should be compared with probability threshold $\mathrm{P_H}$. It's obviously that the probability threshold $\mathrm{P_H}$ is very affective to the accuracy of the identification of falling. In this paper, the probability threshold $\mathrm{P_H}$ is determined with statistical methods, i.e. we use some falling sample data O_i^f (ATS) to calculate the falling output probability $P_i^f(\mathrm{O}_i^f \mid \lambda_m)$, and also calculate some other daily activities O_j^o output probability $P_j^o(\mathrm{O}_j^o \mid \lambda_m)$, then take the mean value $\overline{P}_i^f$ and $\overline{P}_j^o$ respectively, on the basis of the difference between the two averages $\Delta = \overline{P}_i^f - \overline{P}_j^o$, we take probability threshold $\mathrm{P_H}$ as $\mathrm{P_H} = \overline{P}_i^f - \varepsilon\Delta$. to obtain the final threshold probability. The output falling probability is a normalized value. It grows with the probability of falling growing. When an ATS's output probability $P(\mathrm{ATS} \mid \lambda_m) > \mathrm{P}_H$, the device believes the body has been fallen, while an ATS's output probability $P(\mathrm{ATS} \mid \lambda_m) \le \mathrm{P}_H$, he device believes the body didn't fall.

We use the wearable device to detects a sets of data that including some regular movements and falling process. Every movements contain 10 different sample which came from 10 different volunteers. If the movements contained falling, falling detecting device detect falling correctly with alarm light on which means accurate result. If the movements didn't contain falling, alarm light off means accurate result. The experimental results of falling detection based on HMM falling model in Table 1.

Table 1. Experimental Results

Behavior	Falling	Fall detected/Sum	Accuracy
Walking	N	0/10	100%
Sit-Standup	N	0/10	100%
Up-Downstairs	N	0/10	100%
Jogging	N	1/10	90%
Falling'	Y	9/10	90%

As show in the Table 1 the HMM based fall detection device recognize falling process with a high accuracy. It proves the HMM based falling detecting algorithm feasible. The algorithm distinguished falling upon all the test movements effectively. But there's still some errors because of a similar trend exists jogging with falling acceleration. Sometimes the HMM model can't find out the difference when its output probability higher than the output probability threshold.

5 Conclusion

An HMM based falling detection algorithm and system has been put forward in this paper. The system achieves an efficient, high recognition accuracy rate of falling process. The complexity of human behavior determines that detecting falling is difficult to achieve one hundred percent accuracy rate combined with acceleration time series alone. But for different groups, with different behavioral characteristics, especially for the elderly, a large part of human behavior can be ignored. Most of regular strenuous exercise do not happen. In this way, HMM based fall detection model is suitable for the elderly population.

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