Recognition of Human Fall Events Based on Single Tri-axial Gyroscope

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***Abstract*—Falls are a critical public health issue that requires continuous monitoring, especially for the elders. This paper proposed a method based on a tri-axial gyroscope for fall events recognition. A tri-axial gyroscope is placed at the user's waist to collect tri-axial angular velocity information. In order to facilitate data processing and extract features, real-time data are divided into a set of consecutive and partially overlapping windows. Three time-domain features that reflect the differences between the falls and other movements in our daily lives are extracted from these consecutive data windows. Then, each of these windows is classified as representing either a fall or a non–fall event by using a trained machine learning classifier. Decision Tree is chosen as the classifier because of its low algorithm complexity and easy implementation on embedded systems. Experimental results have shown that our proposed method can effectively differentiate the fall events from other human daily activities in spite of their high similarity in some cases, with the Accuracy of 99.52%, Precision of 0.993, Recall of 0.995 and F-measure of 0.994.**

Keywords—fall detection; tri-axial gyroscope; angular velocity; machine learning algorithm; Decision Tree

I. INTRODUCTION

Falls are a major cause of fatal injury and lead to significant disabilities that may be prohibitive for independent living, particularly for the elders [1]. As people get older, their body becomes more fragile, and more prone to fall, caused by the multiple physical changes [2]. More than 33% of the elders aged above 65 years have experienced falls only due to physical deterioration, which costs thousands of millions of dollars every year [3]. Fall risk is also high for people with special occupations like fire fighting [4]. To solve these problems, automatic fall detection is considered a very significant research area in human activity recognition field [5]. With the technological development, new methods are being applied to fall events recognition field. At present, the technologies for fall detection are generally classified into 3 categories: 1) wearable technologies, 2) ambient technologies and 3) combination of wearable and ambient technologies. Ambient sensor-based methods are limited to the location, as they rely on equipment installed in patient's home/room; conversely, by using wearable sensors and wireless connections, the assisted living can be monitored in mobility without location constraints [1]. In addition, the cost of wearable sensors is the lowest among the aforementioned methods and they can be attached to different parts of the human body. Therefore, in recent years, some wearable sensors-based systems for fall detection have been developed [1-4].

The identification of fall events based on wearable sensors can mainly be divided into two steps: feature extraction and event identification through classification algorithm [10]. The quality of the feature extraction determines the upper limit of the accuracy of the classification, and good features can facilitate the process of subsequent classification. In general, the methods of extracting features of three-axis acceleration and angular velocity signal fall into the following three categories: time domain analysis, frequency domain analysis, and time-frequency analysis. Human Activity Recognition (HAR) based on motion sensor mainly includes threshold method [11] and machine learning algorithm [12]. The threshold method is widely used because its algorithm is simple and the threshold can be obtained from a large number of experiments. But owing to its strong subjectivity, it can lead to misdetections [13]. HAR is typically performed with supervised learning algorithm, with great amount of training data, which is more objective and scientific than the threshold method.

Most of wearable sensor-based methods for HAR are accelerometer-based or accelerometer and gyroscope-based. Furthermore, the angle errors calculated from discrete data from tri-axial accelerometers lead to the misdetection of fall events [14]. The sensor information fusion based on both accelerometers and gyroscopes can effectively eliminate those errors, but it is not easy to implement in embedded devices due to its high calculation complexity. Hence, in this paper, we propose a tri-axial gyroscope-based method to detect human falls, which has lower computational complexity and better performance on falls detection.

The rest of the paper is organized as follows: in Section II some important related works are introduced. Section III covers the system design and proposed methods. Section IV sets up the experiments and analyses the results. Finally, section V concludes the paper and presents some future directions.

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II. RELATED WORK

Human falls detection has been a hot topic in many areas. The technologies for falls detection can be classified into three categories: 1) wearable technologies, 2) ambient technologies and 3) combination of wearable and ambient technologies. In this section, we review recently-developed approaches in fall events detection domain using these three technologies.

Wearable technologies: Bourke et al. [17] used a bi-axial gyroscope to detect fall events. However, the bi-axial angular velocity cannot fulfill the sensing information required to describe human motion. Fortino et al. [26] proposed Fall-MobileGuard, a fall detection and alarm notification system that is based on a wearable accelerometer node worn at the waist and capable of distinguishing multiple severity levels of fall events; their detection method consists of two main processing blocks: a threshold-based monitor is executed on the wearable sensor and triggers a posture classification block operating on the mobile device to greatly reduce false-positive fall detections. Wang et al. [15] utilize an accelerometer, cardiotachometer and smart sensors to gather information of human body and the impacts of falls can be distinguished from normal daily activities. But this system can only operate in a limited place.

Ambient technologies: Li et at. [21] presented an acoustic fall detection system called acoustic-FAD, which consists of a circular microphone array that captures the sounds in a room. When a sound is detected, acoustic-FADE locates the source, enhances the signal, and classifies it as "fall" or "nonfall." Stone et at. [16] presented a method for detecting falls in the homes of older adults using the Microsoft Kinect and a two-stage fall detection system. The first stage of this system is to characterizes a user's vertical state and then segments on ground events from the vertical state time series. The second stage uses the decision tree algorithm to compute a confidence value of a fall event. Bian et at. [4] proposed a camera-based fall detection method by analyzing the tracked key joints of the human body. In their scheme, a pose-invariant randomized decision tree algorithm is used for the key joint extraction and the support vector machine classifier is employed to determine the fall event.

Combination of wearable and ambient technologies: Bianchi et at. [23] used a barometric pressure sensor as a surrogate measure of altitude, to assist in discriminating real fall events from normal activities of daily living. Moreover, the acceleration and air pressure data are recorded using a wearable device attached to the subject's waist and analyzed offline. Liu et at. [5] developed and validated a new fall detection algorithm using 3-D information (3-D orientation, 3-D acceleration, and 3-D angular velocity), which is able to detect slip-induced backward falls prior to impact with high sensitivity and specificity.

Compared with previous literature, we introduce a human falls detection method based on a tri-axial gyroscope, which is more computationally lightweight and no place limitation. The gyroscope is utilized to collect the tri-axial angular velocity information. Then, a machine learning classifier is utilized to detect human falls.

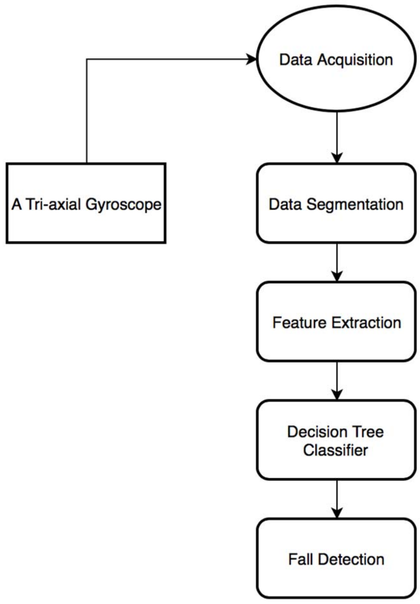


Fig. 1. The workflow of our proposed method

III. METHODS AND SYSTEM SET UP

As shown in Fig. 1, to study the relationship between human fall process and angular velocity time series (AVTS), a tri-axial gyroscope based system was built to collect data of angular velocity during human fall processes and other daily life activities. By data segmentation and feature extracting, AVTS was extracted to describe the whole fall process and other movements. Then, they were used as training samples to train a ID3 Decision Tree, a lightweight algorithm in machine learning field that can be easily implemented in wearable embedded devices.

A. System Design

The system board is designed with a STM32f103 microprocessor, a 12-bit ADC, a USB interface, and a SD memory card, powered by a 9V battery. The sensor chosen is the MEMS tri-axial gyroscope MPU3050 produced by InvenSense. With a package size of 4cm×4cm×1cm, it can be easily placed to the human body's and can be worn comfortably without disturbing the wearer's daily life.

B. Sensor Location

As the human activity data varies in different parts of the body during movements, the location of the wearable device on human body surface should truly reflect the key features of human fall process. As shown in [17], the arm, wrist, hip and leg are not suitable positions for the gyroscope based devices due to their high movement frequency and complexity, although they may be the more comfortable place in terms of wearability. As the waist is the human body's geometric center of gravity [18], we attached the sensor to the waist of the subject in order to reflect overall human movements. The *x*-axis, *y*-axis and *z*-axis of the sensor correspond to horizontal

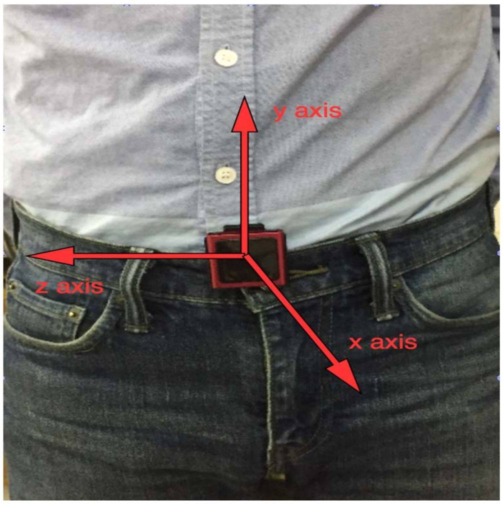


Fig. 2. A MEMS sensor tagged on the subject's waist

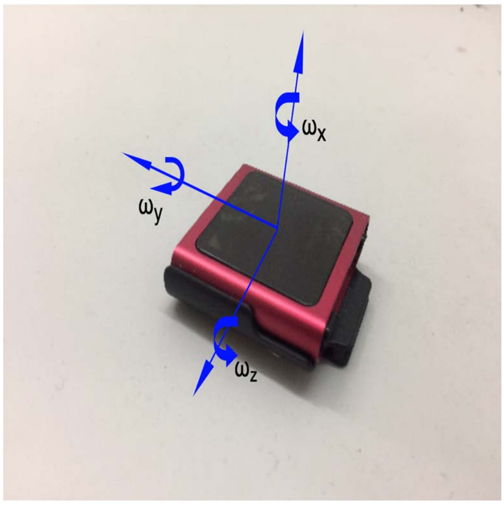


Fig. 3. Tri-axial gyroscope for the experimental setup.

(transverse rotation), median (axial rotation) and lateral (sagittal rotation) of human body, respectively (as shown in Figs. 2-3).

C. Data Preprocessing

Each sampling point of the collected raw data is: $w_r = (w_{rx}, w_{ry}, w_{rz})$. According to (1), we preprocess the raw data and obtain every sample point: $w = (w_x, w_y, w_z)$. $k_{\omega x}, k_{\omega y}, k_{\omega z}$ are the sensitivity coefficients of three axes. $b_{\omega x}, b_{\omega y}, b_{\omega z}$ are their zero drift values. Because the zero drift values are small, we ignore their negligible impact on our study.

$$\begin{cases} \omega_x = \omega_{rx} / k_{\omega x} + b_{\omega x} \\ \omega_y = \omega_{ry} / k_{\omega y} + b_{\omega y} \\ \omega_z = \omega_{rz} / k_{\omega z} + b_{\omega z} \end{cases} \tag{1}$$

Due to the large amount of data, data set is segmented into small units in order to facilitate the study and analysis. T seconds is sampling time of a data unit (T is 1 second in our study). The sampling frequency f is set to 50Hz in order to meet the characteristic of its low frequency of daily activities of human body. Therefore, the k-th data units: $\mathrm{W_k} = \{\omega_n, \omega_{n+1}, \omega_{n+2}, \dots, \omega_{n+48}, \omega_{n+49}\}, 1 \le k \le M$, where M is the total number of data units. According to a large number of experiments, the fall process is about 300ms [19]. In order not to cut off the data of fall process, each data window has 50% overlapping with the previous window. Thus, we set $n = 25 \times (k-1)$.

D. Feature Extraction

In order to accurately recognize the fall movement with less computational complexity, we should select less features which can truly reflect the differences between the fall process and other movements in our daily lives.

1) Resultant angle change (RAC): The most obvious difference between fall process and other movement is the considerable angular change during a short period. The RAC can be represented as follows:

$$W_T = \sqrt{{W_X}^2 + {W_Y}^2 + {W_Z}^2} \tag{2}$$

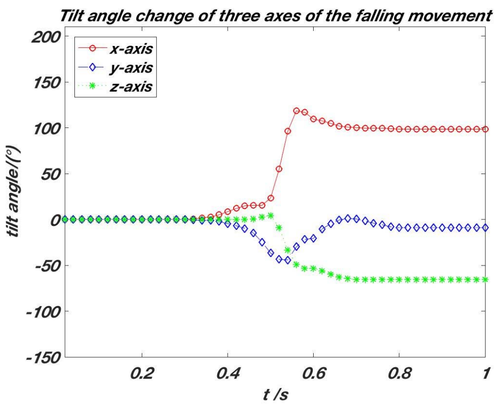
where W_X, W_Y, and W_Z are tri-axial angle changes on a data unit, which can be calculated as (3). The tri-axial angular velocity is integrated by the trapezoidal integral method because the collected data are discrete.

$$\begin{cases} W_X = \int_{\frac{f^2 \times T}{2}\times(k-1)}^{\frac{f^2 \times T}{2}\times(k+1)} \omega_x dt = \frac{f}{2} \sum_{n=\frac{f\times T}{2}\times(k-1)}^{\frac{f\times T}{2}\times(k+1)-1} (\omega_{x_n} + \omega_{x_{n+1}}) \\ W_Y = \int_{\frac{f^2 \times T}{2}\times(k-1)}^{\frac{f^2 \times T}{2}\times(k+1)} \omega_y dt = \frac{f}{2} \sum_{n=\frac{f\times T}{2}\times(k-1)}^{\frac{f\times T}{2}\times(k+1)-1} (\omega_{y_n} + \omega_{y_{n+1}}) \\ W_Z = \int_{\frac{f^2 \times T}{2}\times(k-1)}^{\frac{f^2 \times T}{2}\times(k+1)} \omega_z dt = \frac{f}{2} \sum_{n=\frac{f\times T}{2}\times(k-1)}^{\frac{f\times T}{2}\times(k+1)-1} (\omega_{z_n} + \omega_{z_{n+1}}) \end{cases} \tag{3}$$

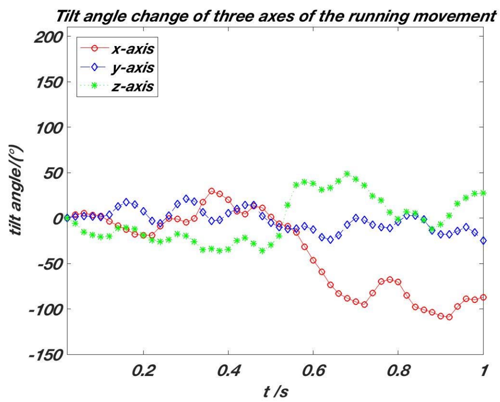
where k is the sequence number of the current data unit.

2) Maximum resultant angular acceleration (MRAA): Since there are many movements (such as lying down, bending and getting up) with large body tilt angle change within a short period, a high error is inevitable only using the RAC to detect the fall event. The instant of the impact of collision against the ground is extremely short, resulting that the body bears a great force in the opposite direction to the angular velocity. The MRAA can be represented as follows:

$$\omega_{\max} = \max_{\frac{f\times T}{2}\times(k-1) \le n \le \frac{f\times T}{2}\times(k+1)-1} \left\{ \left| \sqrt{{\omega_{x_{n+1}}}^2 + {\omega_{y_{n+1}}}^2 + {\omega_{z_{n+1}}}^2} - \sqrt{{\omega_{x_n}}^2 + {\omega_{y_n}}^2 + {\omega_{z_n}}^2} \right| \right\} \tag{4}$$



(a)



(b)

Fig. 4. Tilt angle change of three axes of two different movements: (a) falling, (b) running

3) Fluctuation frequency (FF): The sensor will shake relative to the body in the case of strenuous exercises according to several experimental results. RAC will be distorted while exercising strenuously. As shown in Fig. 4, the trapezoidal integration curve of the three-axis angular velocity of the running movement greatly fluctuates during the period T, while during the fall movement is much smoother. Strenuous exercises may be misclassified as the fall event. The FF can be represented as follows:

$$d = d_x + d_y + d_z \quad (5)$$

where d_x, d_y, d_z are the frequency of direction change of the tri-axial angular acceleration, which can be calculated as (6).

$$\begin{cases} d_x = \sum_{n=\frac{f\times T}{2}\times(k-1)}^{\frac{f\times T}{2}\times(k+1)-2} \left| \frac{|\omega_{x_{n+2}} - \omega_{x_{n+1}}|}{2\times(\omega_{x_{n+2}} - \omega_{x_{n+1}})} - \frac{|\omega_{x_{n+1}} - \omega_{x_n}|}{2\times(\omega_{x_{n+1}} - \omega_{x_n})} \right| \\ d_y = \sum_{n=\frac{f\times T}{2}\times(k-1)}^{\frac{f\times T}{2}\times(k+1)-2} \left| \frac{|\omega_{y_{n+2}} - \omega_{y_{n+1}}|}{2\times(\omega_{y_{n+2}} - \omega_{y_{n+1}})} - \frac{|\omega_{y_{n+1}} - \omega_{y_n}|}{2\times(\omega_{y_{n+1}} - \omega_{y_n})} \right| \\ d_z = \sum_{n=\frac{f\times T}{2}\times(k-1)}^{\frac{f\times T}{2}\times(k+1)-2} \left| \frac{|\omega_{z_{n+2}} - \omega_{z_{n+1}}|}{2\times(\omega_{z_{n+2}} - \omega_{z_{n+1}})} - \frac{|\omega_{z_{n+1}} - \omega_{z_n}|}{2\times(\omega_{z_{n+1}} - \omega_{z_n})} \right| \end{cases} \quad (6)$$

E. Classification Method

Studies have shown that machine learning approaches [20-25] play an important role in HAR field with satisfactory accuracy [6]. In this paper, a supervised learning algorithm called Decision Tree is used as the classifier to recognize the fall events due to its low computational complexity and easy implementation on embedded system.

Decision Tree [4] is a common machine learning algorithm. It is a Tree-like structure in which each internal node represents a "test" on an attribute, each branch represents the outcome of the test, and each leaf node represents a class label (decision taken after computing all attributes). The paths from root to leaf represent classification rules. The learning phase of Decision Tree is to produce a "Tree" with strong generalization ability that can accurately classify new instances and it follows the simple and intuitive strategy called divide-and-conquer [24]. The algorithm of learning phase is summarized as follows:

Input: Training Data set $D = \{(x_1, y_1), (x_2, y_2), \dots, (x_m, y_m)\}$;
Attribute set $A = \{a_1, a_2, \dots, a_d\}$.
Function: TreeGenerate (D, A):
1. Generate node
2. **if** all samples in D belong to the same subclass C **then**
3. Mark node as the C-type leaf node
4. **return**
5. **end if**
6. **if** $A = \emptyset$ **OR** the samples in D have the same value on A **then**
7. Mark node as a leaf node and the category is labeled as the class with the largest number of samples in D;
8. **return**
9. **end if**
10. $a_* = arg\max_{a\in A} Gain(D, a)$
11. Choose the best partitioned attribute a_* from A
12. **for** a_*^v **in** a_*
13. Generate a branch for node
14. Let D_V denote a subset of samples in D that take the value of a_*^v on a_*
15. **if** $D_V = \emptyset$ **then**
16. Mark node as a leaf node and the category is labeled as the class with the largest number of samples in D
17. **return**
18. **else**
19. Mark TreeGenerate $(D_V, A\backslash\{a_*\})$ as a node of the branch
end if
20. **end for**
21. **Output**: a decision tree with the node as the root node

$Gain(D, a)$ represents the "information gain" obtained by dividing set D in terms of a, which is defined as follows:

$$Gain(D, a) = Ent(D) - \sum_{v=1}^{V} \frac{|D^v|}{|D|} Ent(D^v) \quad (7)$$

where $Ent(D)$ (Information entropy) [25] is the most commonly used measure of sample collection purity. Let us assume that the proportion of the kth sample in the current sample set D is p_k. Then, $Ent(D)$ can be calculated as follows:

$$Ent(D) = -\sum_{k=1}^{|y|} p_k log_2 p_k \quad (8)$$

TABLE I. FALLS DETECTION PERFORMANCE EVALUATION RESULTS OF PROPOSED METHOD

Accuracy	Precision	Recall	F-measure	MBT
99.52%	0.993	0.995	0.994	0.44s

The Decision Tree can be trained utilizing the pre-collected data set. Therefore, after training phase, the Decision Tree can be used to classify new instances into fall events or non-fall events.

IV. EXPERIMENTS

A. Data collection

Five subjects were randomly selected for data collection (Three males and two females, aging from 20 to 25, with heights between 150cm and 172cm, and weights between 39kg and 80kg). Each subject was asked to perform two types of activities: long-term activities and short-term activities. Long term activities include: sitting still (STS), walking (WK), going upstairs (GU), going downstairs (GD), running (RN) and jumping (JP). The subjects sat indoors, walked and jumped on the playground, ran on the playground at the speed of 2.5m/s, ascended and descended stairs in a four-floor school building, and felt on a safety cushion. The short-term activities include: lying down (LD), sitting down (SD), bending over (BD), Squat (SQ), falling forward, falling backward (FB), falling to the left (FL) and falling to the right (FR). The subjects sat down on a wooden chair, lay down in the bedroom, bent over and squatted indoors and felt on a safety cushion. Each type of the long-term activity was carried out 20 times (20 ten-minute samples) and that of the short-term activity was carried out 50 times (50 one-second samples) for each subject. In this work, 10-fold cross validation was used to separate the training from the test set. The classifier models were obviously trained using the training set, while, in the test step, the estimated classes were compared to the true classes in order to compute the classification accuracy. All the data sets were preprocessed and extracted the features as referred to before.

B. Classification Performance on the collected data set

In this study, our goal is to recognize two human activity states: fall state and non-fall state. The Decision Tree was trained using the training samples, then, in order to verify the performance of our method, since the data set of fall events is much smaller than the non-fall events, five relevant metrics (Accuracy, Precision, Recall, F-measure, Model Build Time (MBT)) have been computed.

The Accuracy measures the proportion of correctly classified examples. In the case of binary classification, the Accuracy is defined as follows:

$$Accuracy = \frac{T_p+T_n}{T_p+T_n+F_p+F_n} \tag{9}$$

where T_p are the correct classifications of fall events; T_n are the correct classifications of non-fall events; F_p are the non-fall events incorrectly classified as fall events; F_n are the fall events incorrectly classified as non-fall events.

In order to accurately and comprehensively evaluate the classifiers, Precision, Recall and F-measure of the test data set have been computed to compare the classification performance. F-measure represents the overall accuracy that is the combination of Precision and Recall. The formulas of these three metrics can be expressed as follows:

$$Precision = \frac{T_p}{T_p + F_p} \tag{10}$$

$$Recall = \frac{T_p}{T_p + F_n} \tag{11}$$

$$F\_measure = \frac{2 \times Recall \times Precision}{Recall + Precision} \tag{12}$$

Table 1 summaries the performance of our proposed method on the test data set, with the Accuracy of 99.52%, Precision of 0.993, Recall of 0.995, F-measure of 0.994. The experimental results show that our proposed method can accurately distinguish fall events and other daily life activities effectively, with high Accuracy value (99.52%). Precision value (0.993), Recall value (0.995) and F-measure value (0.994) indicate the low missing rate and the low false rate of the fall detection which guarantee the stability of our proposed method, even though the dataset includes amount of short-term activity data that have great similarity with fall events. It is lightweight and easy to implement in embedded devices since the value of MBT is 0.44s.

C. Comparison of the Proposed Method with Previous Studies

In this study, we compared the types of sensors for fall detection and the difficulty of implementing the algorithm, respectively, with the literature [9, 17, 22]. Purwar et al. [22] used a tri-axial accelerometer to set thresholds of acceleration and orientation of trunk through experiments to detect falls. Their proposed method is not accurate, with the accuracy of 81%, due to its overly simple algorithm and subjective threshold setting. Bourke et al. [17] used a bi-axial gyroscope to detect fall events. With this approach, falls and daily life activities can be fully identified. However, the bi-axial angular velocity can not fulfill the sensing information required to describe human motion. It has great impact on identifying the movements that have high similarity to fall processes. Pierleoni et al. [9] proposed a HMM-based fall detection method using tri-axial accelerometer, with the ability to predict the fall events 200–400ms ahead the occurrence of collisions. But the limitation in determining the lying status based on tri-axial acceleration information influences the accuracy while predicting the fall events. Differently from the methods from above literature, the tri-axial gyroscope used in our study can provide the required sensing information in human fall processes. Furthermore, the classification method (Decision Tree) has low computational complexity and is highly objective because it was trained by the pre-collected data set.

V. CONCLUSION

Fall detection is essential for the health care, especially for the elders, which makes the real time automatic recognition of fall events (with the ability to accurately differentiate them from other daily activities) truly crucial. Therefore, this paper proposed a fall detection method using body-worn tri-axial gyroscope. In order to collect users' angular velocity information, a tri-axial gyroscope is utilized and placed at user's waist. Data are divided into a set of consecutive and partially overlapping windows. Three features truly reflecting the differences between the fall process and other movements in our daily lives are extracted from these consecutive data windows. Then, each of these windows is classified as representing either a fall or a non–fall event by means of a machine learning approach. Decision Tree has been chosen as the classifier to detect the fall events in our study. The experimental results showed that the proposed method can effectively distinguish fall events from other daily life activities with the Accuracy of 99.52%, Precision of 0.993, Recall of 0.995, and F-measure of 0.994.

In our future work we plan to apply multi-sensor fusion techniques [20] to better detect physical states and using deep learning methods to identify more complicated abnormal behaviors, which can put solid ground for the design and implementation of a real system for real-time physical abnormal state detection.

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