HMM-Based Human Fall Detection and Prediction Method Using Tri-Axial Accelerometer

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***Abstract*— Falls in the elderly have always been a serious medical and social problem. To detect and predict falls, a hidden Markov model (HMM)-based method using tri-axial accelerations of human body is proposed. A wearable motion detection device using tri-axial accelerometer is designed and realized, which can detect and predict falls based on tri-axial acceleration of human upper trunk. The acceleration time series (ATS) extracted from human motion processes are used to describe human motion features, and the ATS extracted from human fall courses but before the collision are used to train HMM so as to build a random process mathematical model. Thus, the outputs of HMM, which express the marching degrees of input ATS and HMM, can be used to evaluate the risks to fall. The experiment results show that fall events can be predicted 200–400 ms ahead the occurrence of collisions, and distinguished from other daily life activities with an accuracy of 100%.**

***Index Terms*— Accelerometer, acceleration time series (ATS), fall detection, fall prediction, hidden Markov model (HMM).**

I. Introduction

THE INCREASING aging population is one of the major social problems in 21st century worldwide. Among many other problems caused by aging, each year, approximately one third of adults over 65 years old fall, and the likelihood of falling increases substantially with advancing age [1]. Nearly half are recurrent falls, and nearly 10% of falls result in serious injuries. As the world aging process quickened, falls in the elderly have become a significant financial burden to family and society [2], [3]. Besides the extent of injury, the medication outcome of a fall may also largely depend upon the response and rescue time [4]. Hence, reliable fall prevention and detection are essential in independent living facilities: predict then prevent the heavy collision of a fall, or fall event detection followed by immediate notification to caregivers, and researches showed that the risk of hospitalization can be reduced by 26% and death by over 80% [5].

Recent years, technical advances in MEMS sensors, microprocessors and wireless communication have been the driving factors to facilitate telemonitoring of people's physical activities. As a result, some wearable automatic sensor based fall detectors have been developed [4]–[13]. Most of them utilize accelerometers, gyroscopes, or tilt sensors and set thresholds of their outputs to detect the large impact of body with ground or near horizontal orientation of trunk, or both. For instance, Purwar et al. [6] used a tri-axial accelerometer to set thresholds of acceleration and orientation of trunk through experiments to detect falls, which achieved an accuracy of 81%. By calculating trunk's angle, angle acceleration and set their thresholds, Bourke et al. [4] used a bi-axial gyroscope to detect fall events. With this approach, falls and daily life activities can be fully identified, but no mention has been given on its applications to fall prediction. Wen J Li's team [8], [9] developed an airbag system to protect hip when falling just like the application of airbags in car crash. To make sure that air was fully filled before a collision they applied a tri-axial accelerometer and gyroscope, then set accelerations and angular velocities thresholds using Support Vector Machine (SVM) methods to predict fall events. However, the accuracy and timeliness didn't been mentioned.

The angle errors calculated from tri-axial acceleration maybe one of the reasons for misdetection of accelerometer based detection system, since their outputs consist of not only body accelerations but also the gravity. And the acceleration information at one instance is not sufficient to describe human motions, since they are processes. As for gyroscope based detection system, it brings significant errors to the calculated angular acceleration and angular position through differential and integral operations, since those low-cost gyroscopes suffer from time-varying zero shift seriously. Although these errors can be compensated using magnetograph, it takes calculation too complex to be implanted on a single chip in real-time applications. Hence, it is expected that to predict and detect fall events accurately with thresholds methods, a tri-axial accelerometer and gyroscope are needed [7]–[10].

Therefore, to reduce the complexity of algorithm and improve fault tolerance, the accelerometer based methods without angle calculation is considered in this paper. In the process of human motion, the accelerations vary real-timely because of one's own movements, touching with other objects and also gravity, and then make up an acceleration time series (ATS). Different motion states constitute different

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motion processes through some kinds of turns, and generate different ATS. Although the acceleration at one single point can't fulfill the sensing information completeness to describe human motion, the ATS that consists of information of a period of time orderly can be used to describe the features of human motion process. Thus, identify human motion processes through ATS, and detect fall events before the collision of body with lower subjects is possible. HMM is a tool to build random process based mathematical model to distinguish different features of time series signals because of its good statistical properties [18]. This study made use of HMM to describe human fall process through analyzing the ATS during fall events. Different from most of the other researches, we build HMM to describe the course that before the collision of body with lower subjects in fall process here, so as to not only distinguish falls from other activities, but also predict falls.

This paper describes a reliable human fall detection and prediction method using HMM and tri-axial accelerometer, through analyzing the features of human motion series during fall processes. First, acquire tri-axial acceleration at human upper trunk from fall processes and other daily life activities. Second, extract features that describe the movements during a series of short time periods by turns to make up ATS, which characterize motion processes. Then, study the features of ATS from the course that before the collision of body with lower subjects in fall processes as training samples to build HMM, whose outputs express the marching degree of input ATS and HMM, thus it can be applied to evaluate the risks to fall. Finally, we set thresholds by compiling statistics of the outputs from different motion processes to detect and predict fall events. The experiment results show that this methods can predict falls in 200∼400 ms before the impact and can also distinguish fall events from other daily life activities accurately.

II. Methods and System Set Up

To study the relationship between human fall process and ATS, a tri-axial accelerometer based system was built to collect accelerations during human fall processes and other daily life activities. By feature extracting, ATS were extracted to describe fall process, especially up to the instant before the impact of collision. Then they were used as training samples to train HMM, a random process mathematical model to describe fall process before impact.

A. System Design

The system board is designed with a STM32 microprocessor, a 12-bit ADC, a USB interface, and an SD memory card etc., powered by a 9V battery. The sensor chosen is the MEMS tri-axis accelerometer MMA7260Q (± 6 g, 200 mV/g) produced by Freescale Semiconductors, which can be worn comfortably without disturbing the wearer's daily life. With a size of 9 cm × 5.5 cm × 2 cm, it can be mounted to human body's surface easily.

B. Sensor Location

As the acceleration varies in different parts of human body during movements, the location of device on human body surface is very important and should truly reflect the key features of human fall process. Indeed as shown in [4], [6], [11], the arm, wrist, hip and leg are not the suitable positions for the accelerometer, based devices due to their high movement frequency and complexity, although they may be the more comfortable place to wear. Studies show that the upper trunk, which is below the neck and above waist, is the most suitable feature region for distinguish falls from other movements using acceleration.

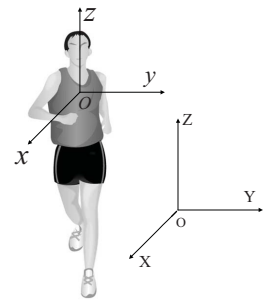

Fig. 1. Definition of coordinate systems.

Fig. 2. Photos of information acquisition procedures.

C. Information Acquisition

Define that the upper trunk Cartesian coordinate system $oxyz$, whose origin is located at the upright upper trunk of human body, and is parallel with the geodetic coordinate system $OXYZ$ as shown in Fig. 1. Accelerations along x, y, z axis are denoted as a_x, a_y, a_z respectively, and its norm (the resultant acceleration) is: $a = \sqrt{a_x^2 + a_y^2 + a_z^2}$.

To get data samples, the device mentioned above was used to acquire accelerations during both fall events and some daily life activities with a sampling period of $T = 10$ ms. Eight young healthy student volunteers (including male and female, aged 25 ± 3 years old and weight 61 ± 19 kg) performed simulated falls caused by dizziness or losing control of legs onto thick sponge mat as well as some other daily life activities (Fig. 2). The samples totally includes 80 times of falls (including 64 frontward falls and 16 sideway falls), and 40 times of each motion including standing (while talking), walking, sit-to-stand (on armchair), squat-to-stand and falling while walking frontward. And every subject performed the same amount of every kind of activities.

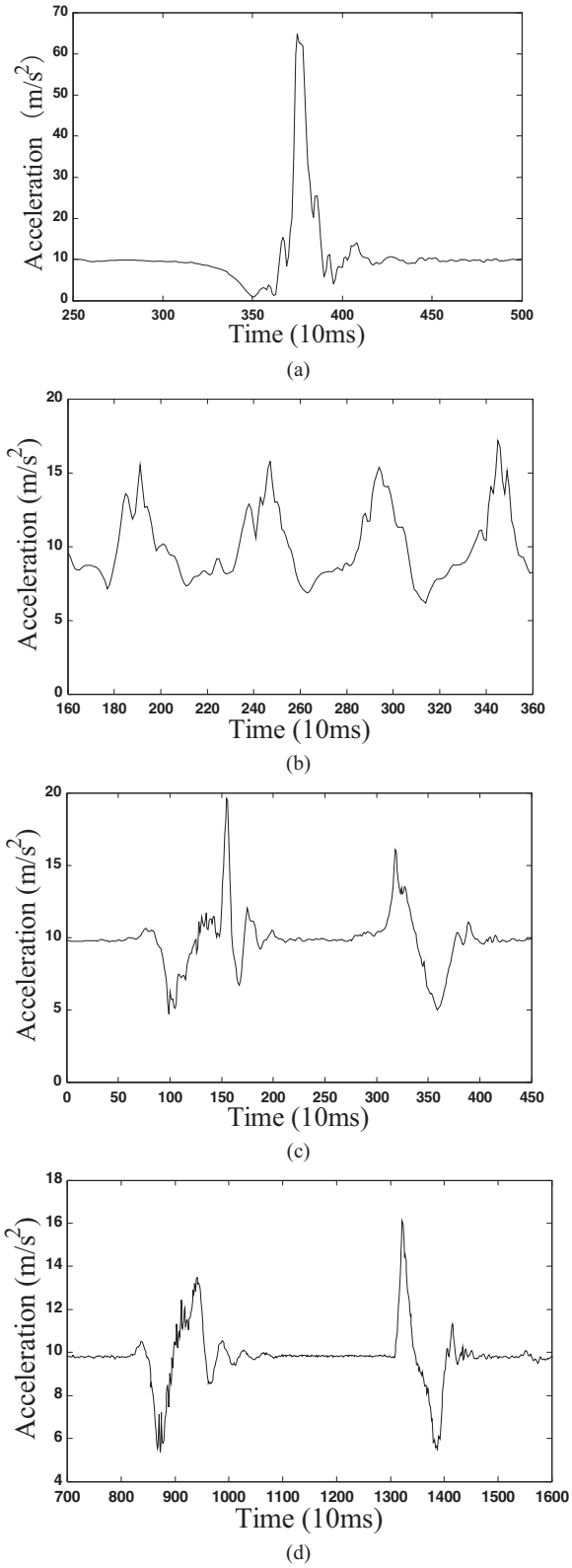

Fig. 3. Data examples (resultant acceleration) of some motion processes. (a) Process of fall frontward. (b) Process of walking. (c) Process of stand-to-sit-to-stand. (d) Process of stand-to-squat-to-stand.

Fig. 3 shows the resultant acceleration curves from each kind of motion process that indicates significant distinctions among them. For instance, the curve in (a) shows that the biggest impact during this fall has exceeded 6 G (Where G is gravity acceleration constant.) due to the collision between body and sponge mat; and (b) shows that the accelerations of normal walk show some periodic features.

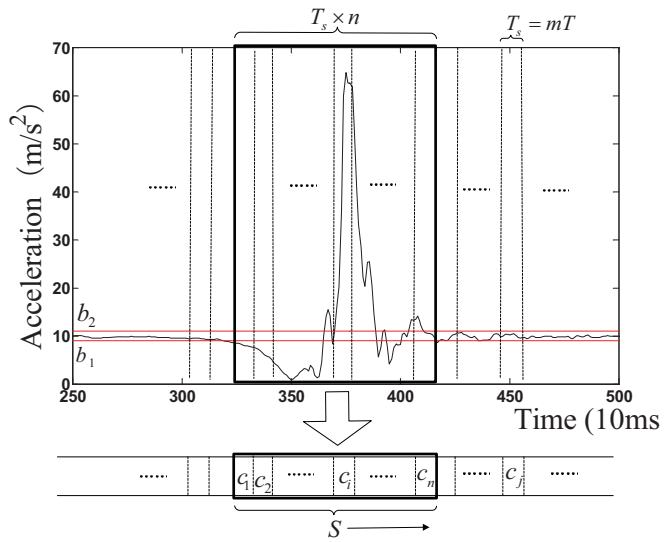

Fig. 4. Extract ATS by a sliding window (S). The resultant acceleration curve is about a fall process. Base area $B = [b_1, b_2]$ is defined in step 1 as follow.

D. Feature Extraction for ATS

An ATS consists of a series of elements by turns of time, where every element describes the acceleration features of movement during a time period. It can be produced by a sliding window (S), as who moves forward, new elements are generated, and also new ATS. Thus, an ATS and sliding window (S) have the same sampling period (T_S) and length (n), cover a time period of $T_S \times n$. There are n elements (c_i, $i = 1, \ldots, n$) in an ATS by turns of time, and every element describes the acceleration features of movement during T_S. The number of sensing data (a_x, a_y, a_z) acquired from accelerometer is denoted as $m(m \geq 1)$ during T_S, and also the number of resultant acceleration (a). The sampling period of sensor in our experiment is $T = 10$ ms, $n = 10$, $T_S = mT$.

The procedure of feature extraction is to extract one element (c_i) from m sets of sensing data during T_S, then n elements made up an ATS that describes the features of human motion during time period of $T_S \times n$. Hence, we can see that bigger m is set, the use efficiency of sensing data is lower, more useful information may be lost. And smaller m is set, more elements that describe a kind of motion process in an ATS are needed, makes the algorithm more complex. In our experiment, m = 4. Fig. 4 shows the relationship between resultant accelerations and sliding window (S).

To reduce the dimensions, the resultant acceleration (a) is used to describe the features of movement instead of vector (a_x, a_y, a_z). The method of getting elements (c_i) is by two steps:

Step1. Determine the resultant acceleration (a_F), which describes the features of movement during T_S.

TABLE I
SEGMENT METHOD IN THIS PAPER

Range	$[0, b_1)$	$[b_1, b_2]$	(b_2, θ_{K-1})	$[\theta_{K-1}, \theta_K)$
Segment method	Average	Be one segment	Average	Be one segment
Mount of segment	K_1	1	K_2	1

Here, $K = K_1 + K_2 + 2$

In static state, (a_x, a_y, a_z) varies in a small scale around $(0, 0, -G)$, due to the gravity, noise, and physiologic movements, such as human breath, etc. Thus the resultant acceleration (a) varies in a small scale around G, which can be defined as a base area: $B = [b_1, b_2]$, satisfying $b_1 < G < b_2$ (as shown in Fig. 4). Therefore, the farther the resultant acceleration from B, more dramatic body motion conclude. B can be determined statistically and is given by $B = [9\ \mathrm{m/s^2}, 11\ \mathrm{m/s^2}]$ in this study. Then a_F can be determined by considering maximum distance. Define the distance between acceleration (a) and B as

$$d(a, B) = |a - b_1| + |a - b_2|. \tag{1}$$

Then the maximum distance between resultant accelerations $\{a_i\}$ $(i = 1, 2, \ldots, m)$ during T_S and B is

$$\max[d(a_i, B) \mid i = 1, 2, \ldots, m] \tag{2}$$

If $d(a_j, B) = \max[d(a_i, B)]$, $\forall i, j = 1, 2, \ldots, m$, then $a_F = a_j$.

Step 2. Determine the elements $(c_i,\ i = 1 \ldots n)$ of sliding window (S) and ATS.

The range of a_F is recorded as $\boldsymbol{\theta}$, which is very large because the peak resultant acceleration during human fall processes can exceed $12G$ [11] due to the heavy collision. To make the algorithm simpler, a_F can't be the elements (c_i). Therefore, in this study, $\boldsymbol{\theta}$ is segmented and then a_F can be symbolized by introducing a finite set of symbols: $S = \{s_1, s_2, \ldots, s_K\}$, $K \geq 1$. That is:

$$\boldsymbol{\theta} = [\theta_0, \theta_1) \cup [\theta_1, \theta_2) \cup \ldots \cup [\theta_{K-1}, \theta_K),$$

where $\theta_0 = 0$, $\theta_K \to +\infty$
If $a_F \in [\theta_{j-1}, \theta_j)$, $j = 1, 2, \ldots, K$
then the symbolized result of the i-th element (c_i) in S is given by $c_i = s_j$.

The segmenting method of $\boldsymbol{\theta}$ can be determined according to the features of data samples. Since the resultant acceleration of upper trunk in daily life is less than 35 $\mathrm{m/s^2}$ most time [11], the experiment set $\theta_{K-1} = 35\ \mathrm{m/s^2}$, and base area $B = [b_1, b_2]$ is set as a segment, then the other two ranges are segmented by average method separately. The segment method in this paper is shown in Table I.

It can be revealed that bigger K is set, the use efficiency of sensing data is lower; and smaller K is set, more kinds of elements that ATS contains, makes the algorithm more complex. In this paper, the experiment set $K_1 = K_2 = 3$, $soK = 8$.

TABLE II
PARAMETRIC DESCRIPTION OF HMM FOR FALL PROCESS

Parameter	Description
The number of invisible states in human fall process: M	Finite set of motion states: $U = \{u_1, u_2, \ldots, u_M\}$; such as: balance state, losing balance state, impact state, et al.
The number of observation values after information fusion process: N	The same as the kinds of elements that ATS contains, $N = K$. Finite set of observation values (The elements of ATS): $V = \{v_1, v_2, \ldots, v_N\}$
Initial state distribution: $\pi = \{\pi_i\}$, $(i = 1, 2, \ldots, M)$	$\pi_i = P(Q_1 \mid u_i),\ \sum_{i=1}^{M} \pi_i = 1$
State transition matrix: $A = \{a_{ij}\}$, $(j = 1, 2, \ldots, M)$	Describe the transition probability between each motion state: $a_{ij} = P(Q_{t+1} = u_j \mid Q_t = u_i),\ \sum_{j=1}^{M} a_{ij} = 1$
Emission matrix: $B = \{b_{jk}\}$, $(k = 1, 2, \ldots, N)$	Describe the relationship between motion states and sensing data. $b_{jk} = P(O_t = v_k \mid Q_t = u_j)$£¬$\sum_{k=1}^{N} b_{jk} = 1$

E. HMM-Based Recognition Method

The special statistical properties of HMM has made it a tool for probability-based modeling to distinguish different features of a random signal sequence. In fact, it has been used in speech, handwriting recognition [14], [15] and some other areas successfully [16]. Although human motion is very complex dynamic process with many different features, the transition probabilities between motion states and the appearance probabilities of each state do show some interested characteristics such as regularities and similarities. In this study, by means of information fusion on falling acceleration signal acquired, we are able to find out the regularity of human falls and therefore further to acquire motion features for the short time interval just before the collision occurs. As a result of this, an HMM based system is built; it can not only detect the fall but also can predict it for the purpose of fall prevention using some other techniques such as airbag [9], etc.

An HMM is a double random process, composing of an invisible, finite, first-order Markov chain that describes the state transition, and a visible random process that describes the relationship between states and observation series, which can be acquired by sensors, etc. Hence, we can analyze the state transition indirectly through observation series. Thus, human motion state transition can be analyzed through ATS that extracted from sensing information. Define the observation series (an ATS from fall process) as: $O = \{O_1, O_2, \ldots, O_t, \ldots, O_L\}$, where L is length of O and O_t is the t-th element in ATS; then the invisible motion states correspond with O is denoted as $Q = \{Q_1, Q_2, \ldots, Q_t, \ldots, Q_L\}$. The HMM describes fall process is denoted as λ, and it can be expressed by a five item array: $\lambda = (M, N, \pi, A, B)$, whose parameters are defined in Table II.

Given the ATS acquired from human fall process (as the observation series of HMM): O, adjusting parameters of λ to

TABLE III
DESCRIPTION FOR DATA SAMPLES

Sample Sets	Sample Types			Sample Amount.
	Falls.	Fall while walking frontward	Standing, sit-to-stand, walking, squat-to-stand	
Φ_T:Training sample set	4 frontward falls and 1 sideway fall from every subject.	0	0	40
Φ_S: Statistical sample set	Other 4 frontward falls and 1 sideway fall from every subject.	0	5 samples of each activity from 4 subjects.	120
Φ_E: Experiment sample set	0	5 samples from every subject.	5 samples of every activity from the other 4 subjects.	120
Sample amount of each activity.	64 frontward falls and 16 sideway falls	40	40 samples of each activity.	——

get the conditional probability $P(O|\lambda)$ local maximum can be used to train an HMM (λ) that describes fall process. Then giving a trained HMM (λ) and a new observation series (O) acquired from any motion process, the conditional probability $P(O|\lambda)$ represents the marching degree of λ and O. To train λ and calculate $P(O|\lambda)$, standard Baum-Welch algorithm [18], [19] is utilized in this paper, which is a particular case of a generalized expectation maximization (GEM) algorithm. It can compute maximum likelihood estimates and posterior mode estimates for the parameters of an HMM. Its core idea is updating weights through recursion to get model parameters that can explain training sample series better, and the computation complexity is lower relatively.

Starting from balance state, a typical human fall usually experiences the transition of the following states: losing balance, impact with lower objects (some are multi-impact) and finally relatively steady state after the collision. Distinguish fall processes before the first impact from other daily life activities accurately is the key issue of establishing effective fall detection and prediction model. Hence, the ATS extracted from the states that before the collision of body with lower objects should be used as the training samples to train HMM using Baum-Welch algorithm [19]. The Markov chain in HMM contains 3 states: balance state, losing balance state, unbalance state, and a fall process should start from the balance state. The number of observation values is equal to the number of kinds of elements of ATS. Thus, the initialization condition used for HMM training is:

1) the number of invisible states: $M = 3$;
2) the number of observation values: $N = 8$;
3) initial state distribution: $\pi_1 = 1$, $\pi_i = 0$ ($i = 2,\ldots,M$);
4) state transition matrix (A): uniform distribution (General principle);
5) emission matrix (B): uniform distribution (General principle).

When $\lambda = (M, N, \pi, A, B)$ is trained, it can describe the features of the course before collision in fall process. Therefore, extract ATS from any motion that is under recognition, the output probability $P(ATS|\lambda)$ can express the marching degree (probability) between the course before collision in fall process and the motion process under recognition, so as can be used to evaluate the risks to fall in a manner of higher P gets, more risk to fall. This investigation indicates that it is feasible to predict falls before collision by means of setting thresholds on P properly to distinguish fall events from other daily life activities.

Therefore, the data samples got in the information acquisition part should be divided into 3 disjoint sets as showed in Table III. The training sample set Φ_T consists of half amount of fall process samples is used to train λ. The other fall process samples and half amount of daily life activity samples make up the statistical sample set Φ_S, which is used to compile statistics of $P(ATS|\lambda)$, so as to set thresholds on P. Since the "Fall while walking frontward" process is a kind of continuous action, which is nearer to real falls than the other kinds of fall samples, is used to test the method. Hence, the experimental sample set Φ_E consists of "Fall while walking frontward" samples and the other daily life activity samples. Every set contains 40 fall samples.

F. Fall Prediction and Detection Algorithm

The algorithm for detecting and predicting falls is based on taking the statistical sample set $\Phi_S$to set threshold on P. That is, basing on ATS extracted from all samples in Φ_S, calculate the matching degrees $P(ATS|\lambda)$ between every ATS and λ, then compile statistics of P to set thresholds.

The thresholds should take two demands into account, i.e., the prediction should be made as early as possible for taking protection; and the detection should identify the falls effectively to reduce false alarm. Therefore two threshold are needed: $P1$, for fall prediction, and $P2$ is for fall detection. First, set threshold $P1$, which is determined by Support Vector Machine (SVM), to make prediction in a time period (TP). An SVM can construct an optimal hyperplane or set of hyperplanes, which can be used for classification. Then, a good separation is achieved by the hyperplane that has the largest distance to the nearest training data points of any class, since in general the larger the margin the lower the generalization error of the classifier [18]. Here, we use SVM to separate the highest P values from daily life activity samples from lowest P values from fall samples. This is a one dimensional problem, so the optimal hyperplane can be a one-dimensional point, and that is the value $P1$ is set. Second, by setting the threshold at the lowest P value during the state while the body has lost balance we can detect falls, which is recorded as $P2$.

The fall detection and prediction algorithm is described by a flowchart in Fig. 5.

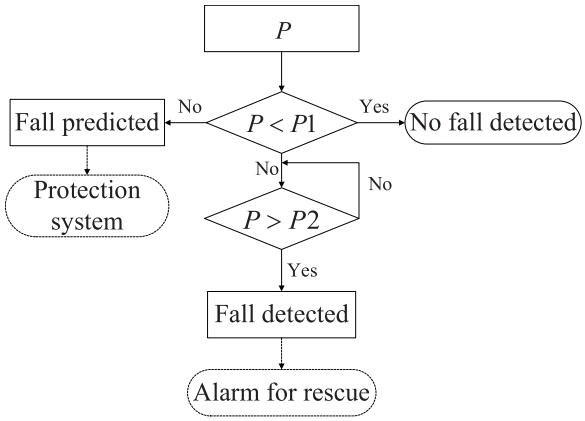

Fig. 5. Flowchart for fall detection and prediction method

1) First, if $P < P1$, no fall is detected, since the risk to fall is too slow. Or else a fall process is in progress, a fall event is predicted, and the fall protection system should be activated.
2) Second, if P rises and exceeds $P2$, it indicates that the body has lost its balance that a fall has happened definitely, so fall is detected and alarm for rescue is needed.

In the investigation, by means of normalization and statistical result of all P values, $P1 = 0.334\%$ and $P2 = 12.3\%$ were obtained.

If the application system is only used to predict or detect falls, just one threshold $P1$ or $P2$ above is enough. In this case only one rule, $P > P1$ or $P > P2$ is needed.

III. Experiments

Taking the set of experimental sample set (Φ_E) as mentioned before to test the method, in our algorithm justification, it turns out that:

1) In the prediction part, the results showed that falls can be predicted in a time period of $TP = 200\sim400$ ms priors to the collision of body with ground (thick sponge mat) with threshold $P1$, since the time span of each fall process varies. This time period is enough to permit the inflation of protective airbag used in cars [20] (about 20 ms). To predict more precisely, large sample statistics is needed. And threshold $P2$ can not be used to predict falls.
2) In the detection part, it turns out that the fall processes can be detected 100% without misdetection for daily life activities with threshold $P2$: 100% sensitivity and 100% specificity [17]; as for threshold $P1$, the detection result shows 100% sensitivity and 88.75% specificity. We can see that, compare to $P1$, $P2$ can reduce more false alarm, can be used for fall detection, while $P1$ not.

Some experiment results are shown in Fig. 6. In (a) and (b), the risks to fall (P values) are all very low in a range of [0, 0.1), no fall is predict or detect, the results are agree with the experimental samples. The acceleration curve in (c) is about an experimental motion process of falling frontward while walking, the risks to fall turn out different from others. In standing and walking process, the risks are very low that

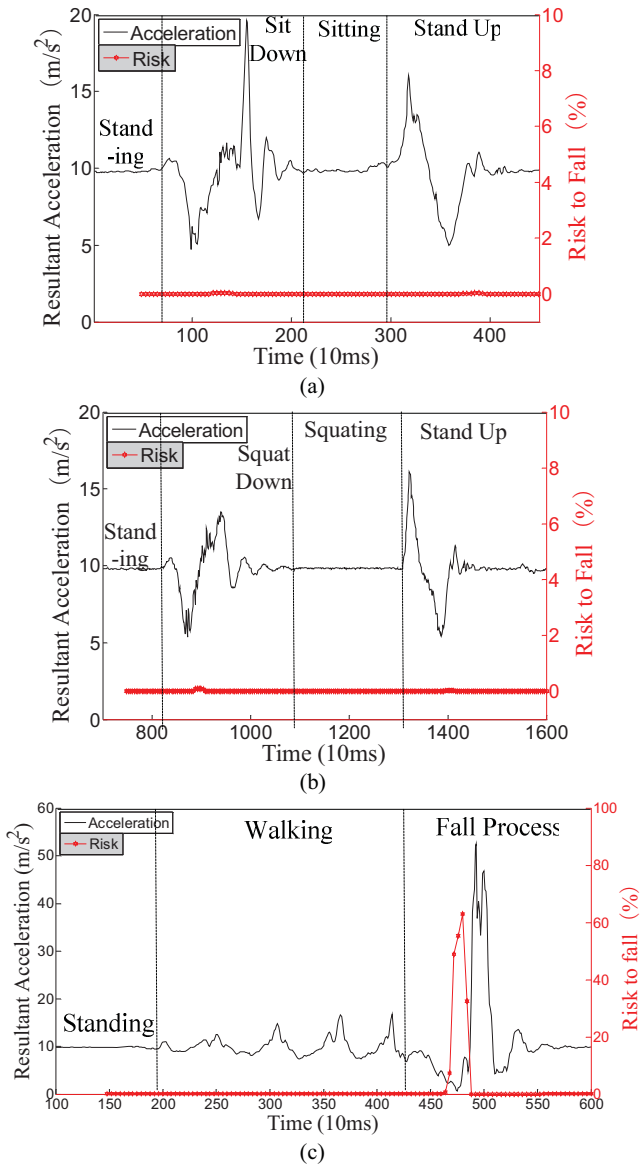

Fig. 6. Prediction result. (a) Fall risks during sit-to-stand process. (b) Fall risks during squat-to-stand process. (c) Fall risks during process of falling frontward while walking.

less than 0.001. Then from $t = 4640$ ms, the risk value rises up obviously, the acceleration curve is corresponding to the state of losing balance before the collision in this fall process, and the probability of fall down is rising. At $t = 4880$ ms, the risk gets down to near 0, when the acceleration curve shows the beginning of collision state, that is human body (except feet) has already touched the collision area, so the probability of falling in the next time period is low.

The contrastive analysis of Fig. 6 shows that our method can distinguish fall events and other daily life activities effectively. The risk values (P) are higher at losing balance state, therefore it can be used to predict falls before the collision of body with lower objects, too.

IV. Conclusion

Reliable fall prevention or notification after detection is essential in independent living facilities for the elders. This

paper proposed a reliable and low-cost human fall prediction and detection method using tri-axial accelerometer. To reduce the cost and complexity we utilize a tri-axial accelerometer placed at human upper trunk, and to fulfill the completeness of sensing information, the accelerations during a consequent time period are investigated as ATS instead of information at single time point. We extract ATS from fall processes and study the acceleration variation regularity before the collision of body with lower objects in fall processes, and then built a HMM (λ) to describe it. The risk to fall can be evaluated using the normalized output of λ to predict and detect fall processes. The experiment results show that the algorithm proposed can predict falls 200$\sim$400 ms before the collision, and can distinguish fall evens from other daily life activities with 100% sensitivity and 100% specificity.

In terms of timing performance, this method is able to complete evaluation in a very short time period and therefore to make the falling prediction priors to the collision of human body with lower objects. This makes it a reliable tool to be applied together with other protection equipments such as air-bags to prevent fall injury of elders. Compare with the thresholds method using accelerations at several single time points, our mathematical model in this paper is an effective method for human fall process recognition and has several advantages:

1) *Application:* The thresholds methods using tri-axial acceleration are mostly used to detect falls nowadays, but our method can applied to both fall detection and prediction. This study accomplished fall prediction and detection by using tri-axial accelerometer alone. As far as the authors' knowledge, besides this method, to predict and detect falls accurately, both tri-axial accelerometer and gyroscope are needed until now [7]–[10].
2) *Detection accuracy:* There are still misdetections in some experiments using thresholds method, such as [6] achieved an accuracy of 81%, [12] achieved sensitivity of 91% and specificity of 92%, [17] achieved sensitivity of 91% and specificity of 100%. The information completeness can be one of the reasons. Most thresholds methods use the results of sensing information at uncontinuous time points to detect falls, thus some misdetection may be caused by the incompleteness information. Our method analyzes the ATS during the whole course before the collision of human fall process, so more complete sensing information is used to study the features of human fall process and the transition of motion states, and also the experiment showed good results.

However, the HMM λ and thresholds in this paper, were set based on the data samples of young people's simulated activities, so the experiment results will be different in real-world practice [21]. In the application for the elders', this method must be tested on a variety of real-world falls, and the mathematical model and thresholds should be trained and reset based on the large real-world samples of the elders. That is our next work in plan.

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REFERENCES

[1] Centers for Disease Control and Prevention. (2007). *Injury Statistics Query and Reporting System (WISQARS)*, Waltham, MA, USA [Online]. Available: http://www.cdc.gov/injury/wisqars/index.html
[2] J. A. Stevens, P. S. Corso, E. A. Finkelstein, and T. R. Miller, "The costs of fatal and nonfatal falls among older adults," *Injury Prevent.*, vol. 12, no. 5, pp. 290–295, 2006.
[3] L. Corsinovi, M. Bo, N. R. Aimonino, R. Marinello, F. Gariglio, C. Marchetto, L. Gastaldi, L. Fissore, M. Zanocchi, and M. Molaschi, "Predictors of falls and hospitalization outcomes in elderly patients admitted to an acute geriatric unit," *Arch. Gerontol. Geriatrics*, vol. 49, no. 1, pp. 142–145, 2009.
[4] A. K. Bourke and G. M. Lyons, "A threshold-based fall-detection algorithm using a bi-axial gyroscope sensor," *Med. Eng. Phys.*, vol. 30, no. 1, pp. 84–90, Jan. 2008.
[5] N. Noury, P. Rumeau, A. K. Bourke, G. Ólaighin, and J. E. Lundy, "A proposal for the classification and evaluation of fall detectors," *Integr. River Basin Manage.*, vol. 29, no. 6, pp. 340–349, 2008.
[6] A. Purwar, D. U. Jeong, and W. Y. Chung, "Activity monitoring from real-time triaxial accelerometer data using sensor network," in *Proc. IEEE Int. Conf. Control, Autom. Syst.*, Oct. 2007, pp. 2402–2407.
[7] A. K. Bourke, K. J. O'Donovan, and G. Olaighin, "The identification of vertical velocity profiles using an inertial sensor to investigate pre-impact detection of falls," *Med. Eng. Phys.*, vol. 30, no. 7, pp. 937–946, 2008.
[8] G. Shi, C. S. Chan, Y. Luo, G. Zhang, W. J. Li, P. H. W. Leong, and K. S. Leung, "Development of a human airbag system for falling protection using MEMS motion sensing technology," in *Proc. IEEE Int. Conf. Intell. Robots Syst.*, Oct. 2006, pp. 4405–4410.
[9] G. Shi, C. S. Chan, W. J. Li, K.-S. Leung, Y. Zou, and Y. Jin, "Mobile human airbag system for fall protection using MEMS sensors and embedded SVM classifier," *IEEE Sensors J.*, vol. 9, no. 5, pp. 495–503, May 2009.
[10] M. N. Nyan, F. E. Tay, and E. Murugasu, "A wearable system for pre-impact fall detection," *J. Biomech.*, vol. 41, no. 16, pp. 3475–3481, 2008.
[11] L. Tong, W. Chen, Q. Song, and Y. Ge, "A research on automatic human fall detection method based on wearable inertial force information acquisition system," in *Proc. IEEE Int. Conf. Robot. Biomimetics*, 2009, pp. 949–953.
[12] Q. Li, J. A. Stankovic, M. A. Hanson, A. T. Barth, J. Lach, and G. Zhou, "Accurate, fast fall detection using gyroscopes and accelerometer-derived posture information," in *Proc. Body Sensor Netw.*, 2009, pp. 138–143
[13] G. C. Chen, C. N. Huang, C. Y. Chiang, C. J. Hsieh, and C. T. Chan, "A reliable fall detection system based on wearable sensor and signal magnitude area for elderly residents," in *Proc. 8th Int. Conf. Smart Homes Health Telematics Aging Friendly Technol. Health Independ.*, 2010, pp. 267–270.
[14] R. Gomez, T. Toda, H. Saruwatari, and K. Shikano, "Techniques in rapid unsupervised speaker adaptation based on HMM-sufficient statistics," *Speech Commun.*, vol. 51, no. 1, pp. 42–57, 2009.
[15] S. Günter and H. Bunke, "HMM-based handwritten word recognition: On the optimization of the number of states, training iterations and Gaussian components," *Pattern Recognit.*, vol. 37, no. 10, pp. 2069–2079, 2004.
[16] M. H. Cheng, M. F. Ho, and C. L. Huang, "Gait analysis for human identification through manifold learning and HMM," *Pattern Recognit.*, vol. 41, no. 8, pp. 2541–2553, 2008.
[17] M. Kangas, I. Vikman, J. Wiklander, P. Lindgren, L. Nyberg, and T. Jämsä, "Sensitivity and specificity of fall detection in people aged 40 years and over," *Gait Posture*, vol. 29, no. 4, pp. 571–574, 2009.
[18] R. O. Duda, P. E. Hart, and D. G. Stork, *Pattern Classification*, 2nd ed. New York, USA: Wiley, 2001.
[19] L. R. Rabiner, "A tutorial on hidden Markov models and selected applications in speech recognition," *Proc. IEEE*, vol. 77, no. 2, pp. 257–286, Feb. 1989.

[20] T. Matsunaga and M. Esashi, "Acceleration switch with extended holding time using squeeze film effect for side airbag systems," *Sens. Actuators A*, vol. 100, no. 1, pp. 10–17, 2002.

[21] J. Klenk, C. Becker, F. Lieken, S. Nicolai, W. Maetzler, W. Alt, W. Zijlstra, J. M. Hausdorff, R. C. van Lummel, L. Chiari, and U. Lindemann, "Comparison of acceleration signals of simulated and real-world backward falls," *Med. Eng. Phys.*, vol. 33, no. 3, pp. 368–373, 2011.

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