Self-Adaptive Fall-Detection Apparatus Embedded in Glasses

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Abstract* - Fall injury is already a major problem in elderly health care. This work develops a self-adaptive fall-detection apparatus which is embedded in glasses for users easily to put on. The proposed system adopts a 9-axis sensing module of a triaxial magnetometer, accelerometer and gyroscope. First, the magnetometer is to filter out some normal events like head rotating, based on variations of rotation angles which are modeled by the Gaussian mixture model. Second, the sensed signals from a triaxial accelerometer are computed to obtain differential acceleration values at three directions, which are integrated and then compared with a threshold. Here, the threshold is determined by the Gaussian mixture model and optimized thresholding technique. Our system can update an adequate threshold on the fly. Third, when a fall occurs, its direction is identified using an accelerometer and a gyroscope. The experimental results reveal that the proposed system achieves accuracy rate of 92.1%, a specificity of 98.7%, and a sensitivity of 81.7%. As compared to the conventional fall-detection systems, the proposed system not only shows fairly good performance but also provides convenient, comfortable and non-intrusive wearing. Therefore, the system proposed herein can be widely spread in various head-mounted devices for health care applications.

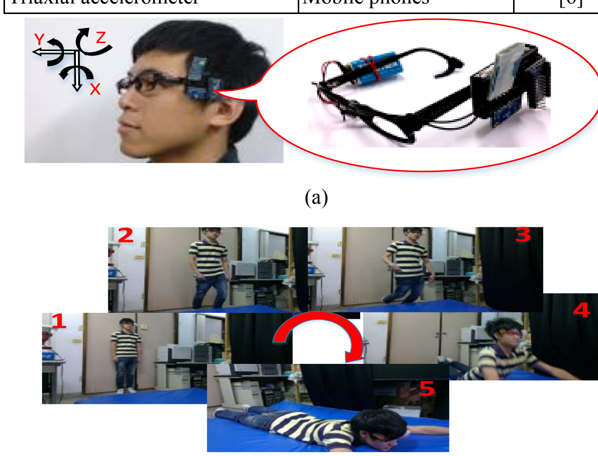
I. INTRODUCTION

Unexpected fall accidents account for a major cause of death in the elderly. Nowadays, fall detection is realized by using sensors worn on the body to detect activities of daily living issues, as illustrated in Table I. Regarding to sensors, the majority of studies adopt triaxial accelerometers as the primary measurement tool, supplemented with other sensors, like a gyroscope or a barometric pressure sensor [1], [2]. To determine the occurrence of a fall or not, a specific threshold is used as the criterion of acceleration or angular velocity, which does not adapt to different user's behaviors or conditions, likely resulting in a miscarriage of justice occurred frequently. Furthermore, when considering the positions of sensors disposed on the body, such as waist, wrist and head [3], [4], or on portable devices such as shoes [5] and mobile phones [6], the acceleration values associated with the same posture activities vary with sensors' locations. With multiple sensors placed throughout the body, the comfort of wearing the devices need be considered. With view of these, the sensors built on the glasses can bring a user convenient, comfortable and non-intrusive. Additionally, the accuracy of fall detection can be raised when the adaptive mechanism is employed to learn users' behaviors. Such an approach can increase a user's motivation to wear glasses with a fall-detection function.

This work is to investigate daily activities which are classified into normal and abnormal states. From the abnormal state, a fall and its direction are identified based on a triaxial accelerometer and gyroscope. Additionally, the magnetometer is used to remove some normal events which are easily misjudged as fall events. Owing to three sensors located at glasses, some actions of sneezing, coughing and other head movements are easily modeled to exclude themselves from training and identification. Notable, the optimized thresholding technique is employed to attain the optimized threshold under the Gaussian mixture model [7]. From the experimental results, the proposed self-adaptive fall-detection system can reach an accuracy rate of 92.1% in average. Therefore, the fall-detection system proposed herein can yield fairly good recognition rate and make a user conveniently, comfortably, and non-intrusively wearing glasses.

TABLE I. SENSORS AND THEIR POSITIONS OF FALL DETECTION SYSTEMS.

Sensors	Positions	References
Triaxial accelerometer and gyroscope	Chest and leg	[1]
Triaxial accelerometer and a barometric pressure sensor	Waist	[2]
Triaxial accelerometer	Waist and chest	[3]
Triaxial accelerometer	Waist, wrist and head	[4]
Triaxial accelerometer	Shoes	[5]
Triaxial accelerometer	Mobile phones	[6]



(a)

(b)

Fig. 1. Proposed fall-detection apparatus. (a) Fall-detection board on glasses. (b) Subject with glasses participating in the experiment.

II. PROPOSED FALL-DETECTION SYSTEM

A. System Architecture

The main purpose of this work is to develop a wearable headset fall-detection apparatus. Such an apparatus can be integrated with glasses to reach convenient, comfortable and non-intrusive utilization. Fig. 1 shows glasses with the proposed fall-detection board which includes a 9-axis sensing module, an A/D converter, an AVR microprocessor and a

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Bluetooth module. Here, the Bluetooth module can be replaced by a WiFi module or GSM module for calling a help. In addition to sensing, converting, computing and communication units, a small button and an alarm device, which are employed for interaction with a user, are designed in this board. Fig. 1(b) depicts that the subject wearing glasses conducts a fall experiment.

B. Fall-Detection Sensors

The fall-detection apparatus proposed in this work adopts a nine-axis sensing module (GY-80) that contains a triaxial magnetometer, accelerometer and gyroscope. A triaxial magnetometer capturing a horizontal rotation up to 360 degrees is used to find out fast head rotations which are removed from the recognition process in order to increase accuracy and reliability of fall detection. A triaxial accelerometer can immediately response *X*, *Y* and *Z*-axis acceleration values under a unit of *g*, gravity, where the sensing range is ± 16g. The sensed acceleration values on *X*, *Y* and *Z* axes can be applied to determine whether a fall occurs, and the corresponding fall direction. A triaxial gyroscope can yield instant angular velocities and directions where each axis has a sensing range of ± 2000°/S. With aid of this triaxial gyroscope, sensitivity associated with a fall is apparently enhanced.

C. Database Establishment

A database associated with various types of falls was established for Gaussian model training. Table II lists actions fulfilled by all subjects who participated in the experiments. This database is built from 50 healthy volunteer subjects, including 43 males and seven females, with an average age of 20.5 years, an average height of 1.7m, and an average weight of 60.5kg. The output values of the 9-axis sensing module associated with 18 kinds of actions on falls and daily activities are recorded where all actions are classified into three categories according to their characteristics. The category (I) has a total of 350 tests associated with fall actions whereas categories (II) and (III) include 550 tests for normal actions. Notably, the category (II) that likely has a large activity is easily misjudged as the category (I). Accordingly, the categories (I) and (III) can be fairly and precisely determined. In addition to classifying action events into three categories, the category (I) is further partitioned into *F*, *B*, *R* and *L* in terms of forward, backward, right and left falls, respectively.

TABLE II. ACTION TASKS FULLFILLED BY EACH SUBJECT.

Types	Activities	Categories	Directions	Fall/Non-fall
F1	Front kneeling	(I)	F	fall
F2	Forward fall	(I)	F	fall
F3	Stumble	(I)	F	fall
F4	Backward fall	(I)	B	fall
F5	Sitting-immediately fall	(I)	B	fall
F6	Right fall	(I)	R	fall
F7	Left fall	(I)	L	fall
A8	Bending over to pick up something	(II)		normal
A9	Jumping	(II)		normal
A10	Coughing	(II)		normal
A11	Sneezing	(II)		normal
A12	Jogging	(II)		normal
A13	Standing	(III)		normal
A14	Walking	(III)		normal
A15	Sitting down	(III)		normal
A16	Standing up	(III)		normal
A17	Going up stairs	(III)		normal
A18	Going down stairs	(III)		normal

D. Self-Adaptive Fall-Detection System

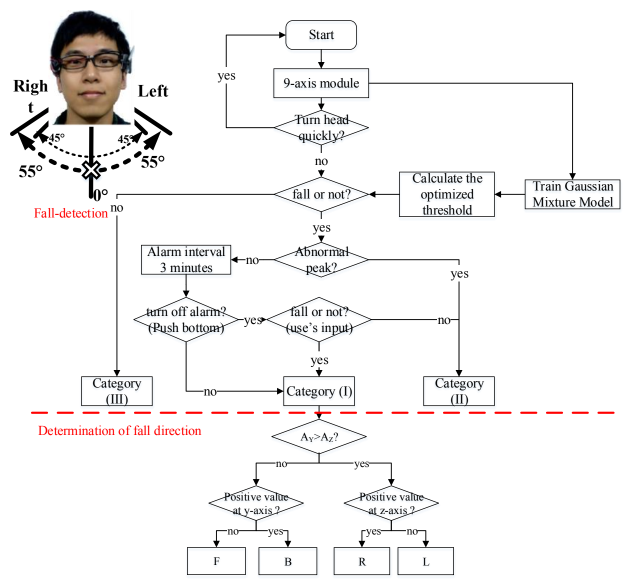


Fig. 2. Proposed self-adaptive fall-detection system.

Fig. 2 shows the proposed self-adaptive fall-detection system where output signals from the 9-axis sensing module are recorded regarding to daily activities. Before determining a fall event, the magnetometer is used to filter out normal events associated with head rotations. According to medical reports, angles of comfortable rotations are within 45°. When a rotation angle is larger than 55° at a short instant, this activity event is likely a rapid rotation or swinging between left and right. Based on this concept, the Gaussian mixture model is adopted to learn the events below 45° and above 55°. Afterwards, the optimized threshold is determined and then used for rotation detection where the determination of the optimized threshold is illustrated in the next section.

Triaxial accelerometer and gyroscope are to collect real-time signals associated with daily activities. Acceleration value and angular velocity value are calculated to obtain whether a fall occurs. When there is a fall, the corresponding acceleration value or angular velocity value tend to be large. Based on this physical phenomenon, we can build a judgment model associated with falls. First, the time-variant characteristics of acceleration values are derived as $|a_x(i) - a_x(i-1)| = A_x$. Similarly, absolute differential acceleration values of A_y and A_z at Y-axis, and Z-axis are straightforwardly obtained, respectively. Afterwards, the integrated absolute differential acceleration value is $L = \sqrt{{A_x}^2 + {A_y}^2 + {A_z}^2}$. Simultaneously, time-variant characteristics of angular velocity values are also considered. Restated, the integrated absolute differential value associated with angular velocity values at three axes is computed.

These data are further computed to update the Gaussian mixture model and then to yield the updated threshold. Based on the updated threshold, T, whether an action event belongs to a fall is determined. If the computed L is less than T, the action events are recognized as the normal ones in category (III). Otherwise, the cases of multiple peaks above the threshold are identified as the category (II). If no multiple peaks exist, the system will give an alarm. The user has to push the bottom and then turn off it in three minutes. If not, the GSM module will call out for help. On the other hand, if the user switches off the alarm, he/she needs to provide a feedback to verify his/her action event. Afterwards, our system can classify this event as the category (I) or (II). When a fall occurs, its direction is further understood in this work. Fig. 2 depicts the flowchart of determining fall directions which include forward F, backward B, left L and right R. The fall direction is estimated based on an accelerometer and a gyroscope. The acceleration values from Y-axis and Z-axis are compared to obtain a larger one on which polarities (positive or negative) of Y-axis and Z-axis angular velocities are identified to determine a fall direction.

III. Proposed Self-Adaptive Fall Detection Scheme

This work proposes a fall detection scheme which is mainly used to distinguish normal activities of daily life and fall events. Additionally, an initially optimized threshold is determined according to the database which includes normal and fall events. The proposed self-adaptive fall detection scheme is composed of four phases as shown in Fig. 3. The first phase is to calculate triaxial magnetic, acceleration and gyro values by using a 9-axis sensing module which records event activities of a user. The sensed signals from the magnetometer are to compute variations of rotation angles, based on which we can remove some normal events, like head rotating. The following phases will adopt the sensed signals from accelerometer and gyroscope.

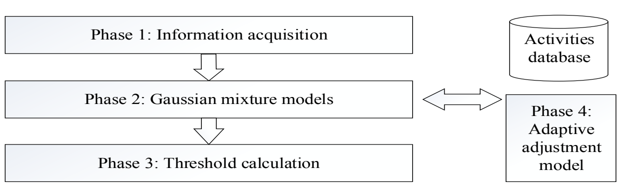
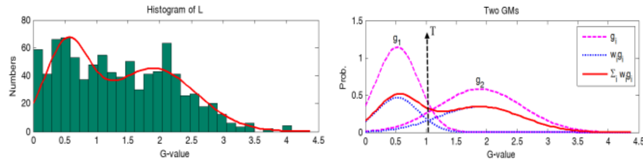


Fig. 3. Proposed self-adaptive fall-detection scheme

A. Gaussian Mixture Models

The second phase is to establish adequate thresholds which are criteria to determine whether a head rotation and a fall occur or not. For example, the experimental tests of normal events (550 tests) and fall events (350 tests) are adopted to get integrated absolute differential acceleration values which are characterized by two Gaussian Models (GMs) in fall detection. Fig. 4(a) depicts the histogram of integrated absolute differential acceleration values, L, which has two peaks. Usually, normal and fall events likely have small and large values of L, respectively. Accordingly, two GMs of g_1 and g_2 can be employed to model the normal and fall events, respectively, as shown in Fig. 4(b). The superposition of two Gaussian distributions is used to represent the original histogram. Restated, we need find out two optimized Gaussian distributions which are added together to yield the distribution close to the original one. Based on these two Gaussian distributions, the optimized threshold, T, can be determined.



(a) (b)

Fig. 4. Histogram of L characterized by Gaussian mixture model. (a) Histogram of L. (b) Two GMs denoting normal and fall events.

B. Threshold Calculation

After creating GMs, the third phase is to determine an adequate threshold which will be located between two peaks of Gaussian distributions. Here, the optimized thresholding technique is used to compute the threshold, T, based on two GMs. Since the distributions from two GMs associated with normal and fall events are overlapped to some extent, the binary threshold, T, need be chosen to minimize the classification error.

The mixture probability density function of two GMs is defined as Eq. (1), where W_1 and W_2 are weighting values of which summation equals to one ($W_1 + W_2 = 1$).

$$g(x) = W_1 g_1(x) + W_2 g_2(x) = \frac{W_1}{\sqrt{2\pi}\sigma_1} exp\left[-\frac{(x-\mu_1)^2}{2{\sigma_1}^2}\right] + \frac{W_2}{\sqrt{2\pi}\sigma_2} exp\left[-\frac{(x-\mu_2)^2}{2{\sigma_2}^2}\right]. \quad (1)$$

μ_1 and σ_1 are the mean and standard deviation of GM associated with normal events, respectively. Additionally, μ_2 and σ_2 are the mean and standard deviation of GM associated with fall events, respectively. According to Fig. 4(b), the probability of a fall event misclassified as a normal one is to integrate the GM, g_2, from 0 to T,

$$E_1(T) = \int_0^T g_2(x)dx. \quad (2)$$

Similarly, the probability of a normal event misclassified as a fall one is to take the integration of the GM, g_1, from T to ∞,

$$E_2(T) = \int_T^\infty g_1(x)dx. \quad (3)$$

The total probability associated with misjudgment is

$$E(T) = W_2 E_1(T) + W_1 E_2(T). \quad (4)$$

Differentiating Eq. (4) with respect to T, and setting to 0, yield

$$W_1 g_1(T) = W_2 g_2(T). \quad (5)$$

Taking a logarithmic function of Eq. (5), and after simplification, we attain $AT^2 + BT + C = 0$, where $A = {\sigma_1}^2 - {\sigma_2}^2$, $B = 2(\mu_1{\sigma_2}^2 - \mu_2{\sigma_1}^2)$ and $C = {\sigma_1}^2{\mu_2}^2 - {\sigma_2}^2{\mu_1}^2 + 2{\sigma_1}^2{\sigma_2}^2 \ln[\sigma_2 W_1/\sigma_1 W_2]$. Finally, the optimized threshold is derived as

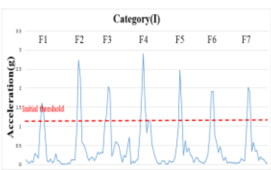
$$T = \frac{-B \pm \sqrt{B^2 - 4AC}}{2A}. \quad (6)$$

C. Self-Adaptive Mechanism

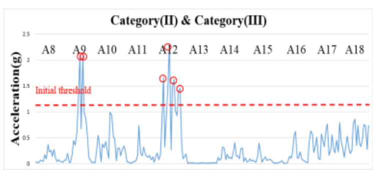
The fourth phase is to automatically adjust the threshold, T, to make our detection system adaptive to different users who may have much different amounts of L at the same action events. Since each person has different action behaviors, the fixed threshold may not be a fair criterion to determine a fall or not. Therefore, to improve accuracy, we propose a self-adaptive mechanism to collect daily activities and find a proper threshold which can match the activity characteristics of user's behaviors.

IV. Experimental Results

900 tests fulfilled by 50 subjects are used to examine the proposed system. Fig. 5 shows the integrated absolute differential acceleration values, L, associated with 18 actions where T is initially set to 1.093. The category (I) as depicted in Fig. 5(a) has an apparent peak which is easily discovered by using an adequate threshold, T. In Fig. 5(b), the category (II) of A8 to A12 does not have consistent characteristics. However, the cases of A9 (jumping) and A12 (jogging) have multiple peaks above the threshold, T. They can be filtered out based on this phenomenon. The other cases in the category (II) are prone to have amplitudes smaller than T. The category (III) of A13 to A18, as displayed in Fig. 5(b), has relatively small amplitude of L which can be precisely judged as the normal event by using T.



(a)



(b)

Fig. 5. L under 18 actions. (a) Category (I). (b) Categories (II) & (III).

Table III lists the accuracy of the proposed self-adaptive fall-detection system which performs the experiments under 900 tests. The accuracy of recognizing normal events is up to 98.7% whereas the accuracy of identifying fall events is around 81.7%. More than half of errors from distinguishing fall events come from the case of F1 (front kneeling), which has slight L. The reason is that our 9-axis sensor module mounted at glasses may not easily capture motion activities only on legs and thighs. Table IV lists accuracy, specificity, and sensitivity of the proposed system with and without self-adaptive mechanism. The accuracy, specificity and sensitivity can be fairly enhanced by using adaptation. Overall, the proposed self-adaptive mechanism is beneficial to the fall-detection system.

When fall events in category (I) is identified, their directions are further recognized from sensed signals of accelerometer and gyroscope. The experimental results reveal that the accuracy of left (86.0%) and right (84.0%) detections is better than that of forward (77.3%) and backward (67.0%) detections. This is that user's hands and arms will help to release movements, especially in falling forward and backward, from subconscious reactions. The overall average accuracy rate of identifying directions can reach 76.5%.

TABLE III. Accuracy of the Proposed System.

Events		**Predicted Cases**	
		fall	normal
Actual Cases	fall	286(81.7%)	64(18.3%)
	normal	7(1.3%)	543(98.7%)
Accuracy	92.1%(829/900)		

TABLE IV. Accuracy, Specificity, and Sensitivity of the Proposed System with/without Adaptation.

Performance	**Without adaptation**	**With adaptation**
Accuracy (%)	90.7%	92.1%
Specificity (%)	97.7%	98.7%
Sensitivity (%)	79.8%	81.7%

V. Conclusion

In this work, we propose a self-adaptive fall-detection system realized in glasses. Our system includes a 9-axis sensing module of magnetometer, accelerometer and gyroscope. First, the magnetic sensor aids to get rid of some normal events, like head rotating. Second, the triaxial accelerometer is to find fall events where the optimized threshold is calculated. Additionally, the self-adaptive mechanism is employed to update the threshold which can fit to different users. Notably, some normal events like jumping and jogging are effectively recognized. Third, accelerometer and gyroscope are used together to determine directions of fall events. Experimental results demonstrate that proposed system can yield the accuracy rate of 92.1% in average. Moreover, the proposed adaptive approach can fairly improve the accuracy, specificity and sensitivity. The proposed system also provides good performance on detecting fall directions. Therefore, the proposed system can be widely used in various head-mounted devices, especially in Google glasses, to provide comfortable, convenient and non-intrusive wearing.

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