A Wrist -Worn Fall Detection System using Accelerometers and Gyroscopes

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***Abstract*—This paper presents a system that utilizes wrist-worn motion sensing devices to detect falls. The sensing device consists of a tri-axis accelerometer and a three-axis gyroscope. The user wears two devices, one on each wrist. The device transmits collected data to the computer through Zigbee. The system then analyses the collected data and determines if a fall event has occurred. The system can rule out the non-fall events such as clapping, lying down, jumping, and clapping during jumping, and will not misrecognize them as fall events. Compared to other devices worn on the head or the chest, the sensing devices are worn on the wrists, and hence will not drop off easily. This also saves the user from the trouble of taking them down and then putting them on again when the user changes clothes. According to the experimental results, the average sensitivity and specificity of the detection system reached 95% and 96.7%, respectively. It performed better than another wrist-worn fall detection mechanism.**

Keywords—fall detection; wrist-worn device; gyroscope

I. INTRODUCTION

Due to the technological and medical progress, the population of seniors keeps growing in human society. Several researches indicated that when a fall accident occurs, many of them are incapable of moving their bodies or, even worse, in an unconscious state, and thus they can only lie on the ground and wait for help. As researchers also note, the longer they wait, the longer the recovery time is. Thus, it is very important that the medical treatment be provided in time.

Due to the advance of technology and popularity of MEMS sensors such as accelerometers, gyroscopes, etc., many researchers [1]-[5] have developed detection systems by utilizing the sensors to detect fall events. When a fall is detected, medical treatment can then be provided in time, reducing the level of injuries that might have been higher if the treatment had been delayed.

The accelerometer is one of the most popular sensors used to detect the body motion. Chen et al. [6] placed an accelerometer on the user's waist to detect falls. The signal vector magnitude (*SVM*) and the change in orientation are calculated and used for detection. Although falls can be detected by their device, some human motions such as sitting down and lying down may lead to false alarms.

The gyroscope is another popular sensor used to detect body motions. Nyan Tay et al. [7] used a two-axis gyroscope and attached it to the user's chest, waist, and right arm. They detected falls by analyzing the body angel speed and the thigh angel speed. Their approach produced good experimental results on detecting falls. However, they did not consider some normal motions such as sitting down and lying down, and therefore, the practicability of the approach is still uncertain.

Over the years, smartphones have become very popular. Because they are equipped with accelerometers and gyroscopes, some researchers adopted smartphones as sensing devices. Yi He et al. [8] placed a smartphone on the waist to sense the human motion, detect the impact, and compute the angel change of human body. Since many people carry their smartphones by placing them in the pockets of the clothes or pants, or even in bags, it is not very realistic to ask the users to place their smartphones on the waist. The smarphone approach may generate false alarms when the users place their smartphones somewhere other than on the waist.

Recently, smartphone manufacturers Sony [9] and Samsung [10] further announced smartwatches that can be paired with the smartphones, letting the user conduct calls or browse SMS messages directly from the watches. There is no doubt that, in the foreseeable future, MEMS components will be embedded into wrist-worn devices such as smartwatches to provide more applications such as motion detection.

The paper presents a fall detection system paired with wrist-worn devices consisting of accelerometers and gyroscopes. The data collected from the gyroscopes are used to rule out most of the non-fall motions. The data from the accelerometers are then used to make the final judgment. By utilizing the data from two kinds of motion sensors, the system can detect fall events effectively.

II. RELATED WORK

Wearable devices can be placed on several positions, such as heads, ears, waists, and wrists. When they are mounted over the heads, or worn on the ears [11], fall detection can be very easy. Normally, the motions of the human head are usually minor. However, when a fall occurs, the motion will be very large and the data from the motion sensors will change dramatically. Although heads or ears seem to be good positions, head-worn devices are usually big and unbecoming, and ear-worn devices may be uncomfortable and can drop off easily.

Placing the device on the chests [12] or the waists [13] has the same position benefit. Fall detection can be very easy because chest or waist motions of the human body are also minor. The problem with the positions is that it may cause inconvenience when people change clothes because the devices have to be taken off and then put back on again.

A wrist-worn device looks like a regular watch. It does not have the drawbacks mentioned above. It can be small and will not drop off easily. It does not have to be taken off when people change clothes. Therefore, wrists are the best positions for people that need to wear sensing devices. However, wrists are the most unsteady positions because people use hands very frequently.

T. Degen et al. [14] designed a wrist-worn detector called SPEEDY, which has a two-axis accelerometer. They utilized the maximum accelerating speed, the current speed, and the vertical speed to detect falls. However, some hand motions, such as wrist turning and clapping, may produce big impacts, which may be recognized as falls if only accelerometers alone are used to detect falls. To reduce false alarms, one possible way is to add other motion sensors like gyroscopes to the device to collect another kind of data for better judgment.

III. RELATED BACKGROUND

A. Accelerometers

When the accelerometer is in a steady state, the absolute value in the vertical axis is $9.81 m/s^2$, which is equal to $1G$ (Gravity). Figure 1 shows the values from an accelerometer collected before, during, and after a fall. Area *A* shows the values before the fall. The vertical axis is *Y*, whose values are around $-1G$. The values collected during the fall are in Area *B*. All the values of the three axes fluctuate heavily. Area *C* contains the values acquired after the fall; the vertical axis is *X*, whose values are around $-1G$.

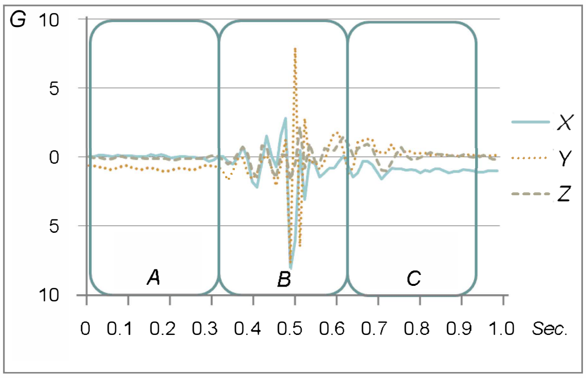


Fig. 1. The values collected before, during, and after a fall.

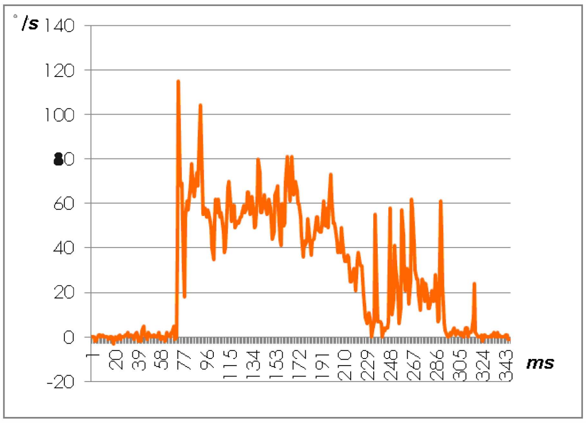


Fig. 2. The values of a gyroscope spinning 90 degrees

B. Gyroscopes

The gyroscope measures the angular velocity of an object on which it is mounted. Figure 2 shows the values of a gyroscope spinning 90 degrees with the frequency 100*Hz*. The total angular distance can be obtained by multiplying the summation of angular speed by the sampling time. For example, if the summation of angular speed is 9820 °/*s*, and the sampling time is 10 *ms*, then the total angel distance is 98.2 °.

IV. THE PROPOSED SYSTEM

As Fig. 3 shows, the system uses two sensing devices worn around both wrists. Each device has a three-axis accelerometer, a three-axis gyroscope, and a Zigbee module for data transmission. The sensitivity of the accelerometer is set to $4G$. The frequency for the sensors to collect data is set to 50*Hz*; that is, data are collected every 20 *ms*.

The three directions of the accelerometer are shown in Fig. 4. On the left hand side, the *X* axis is vertical and points down; the Y axis is horizontal and points to the front; the *Z* axis is horizontal and points to the left. On the right hand side, the *X* axis is vertical and points down; the Y axis is horizontal and points to the back; the *Z* axis is horizontal and points to the right. The directions of the three axes of the gyroscope are defined in the same manner.

Fig. 3. Sensing devices' positions

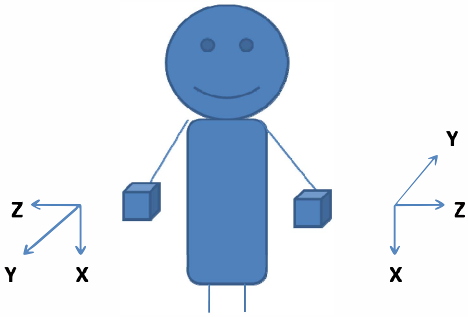


Fig. 4. The directions of the 3-axis

In our daily life, many kinds of movements (e.g., turning the wrist) can greatly affect the values in the X axis. However, the relationship between wrist turning and falls is insignificant. Therefore, our system ignores the values in the X axis and utilizes values from the Y and Z axes of the gyroscope, and those from the three axes of the accelerometer.

The following are some definitions and equations used in our system.

- *SVM*: The value directly reflects the movement of hands and the impact of a fall.

$$SVM(t_i) = \sqrt{A_x^2(t_i) + A_y^2(t_i) + A_z^2(t_i)}\,, \qquad (1)$$

where $A_x(t_i)$, $A_y(t_i)$, and $A_z(t_i)$ represent the accelerating speeds of the X, Y, and Z axes in time t_i respectively. According to our experiment, an impact or large movement can be detected by setting the threshold to $6G$, which can therefore be used to detect falls. U. Lindemann, et al. [11] also mentioned that most non-fall movements can be eliminated by setting the *SVM* to $6G$. Figure 5 shows the *SVM* values during an arm movement and a fall respectively. As can be seen in the figure, when *SVM* is greater than $6G$, the standard deviations are 1.07 and 1.69 for the arm movement and the fall respectively. The values are different and can be used to distinguish a fall from an arm movement. According to our experiment, the threshold of the standard deviation is set to $1.5G$.

- *GS*: The value directly represents a hand (or arm) swing or turning.

$$GS(t_i) = \sqrt{G_y^2(t_i) + G_z^2(t_i)}\,, \qquad (2)$$

where $G_y(t_i)$ and $G_y(t_i)$ represent the values from the Y axis and Z axis of the gyroscope respectively. Figure 6 shows the *GS* values during rotation of an arm. As the figure shows, the peak values of *GS* are close to or greater than $400^{\circ}/s$ during continuous arm rotations. Our experimental results showed that the peak *GS* values were higher than $350^{\circ}/s$ during a fall event.

- *SMA*: The value has a positive relation to the momentum resulting from body motions.

$$SMA = \sum_{i=1}^{N} [\,|A_x(i)| + |A_y(i)| + |A_z(i)|\,]\,, \qquad (3)$$

where $A_x(t_i)$, $A_y(t_i)$, and $A_z(t_i)$ represent the accelerating speeds of the X, Y, and Z axis in time t_i respectively, and N is the total sample number. The *SMA* can be used to judge whether the body is in a moving state or a stationary state. As Fig. 7 shows, the *SMA* values resulting from sitting down and lying down are all smaller than hand clapping, arm rotation, and clapping during jumping. According to our experiment, *SMA* is greater than $200G$ when the body is in motion.

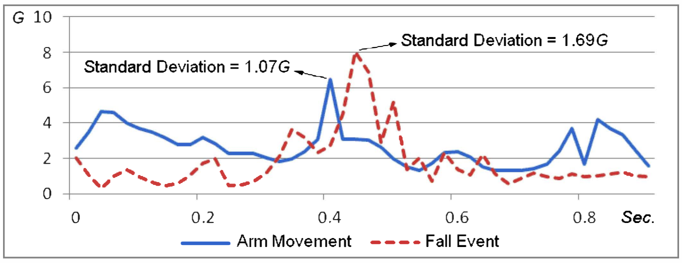


Fig. 5. The *SVM* values of an arm movement and a fall event

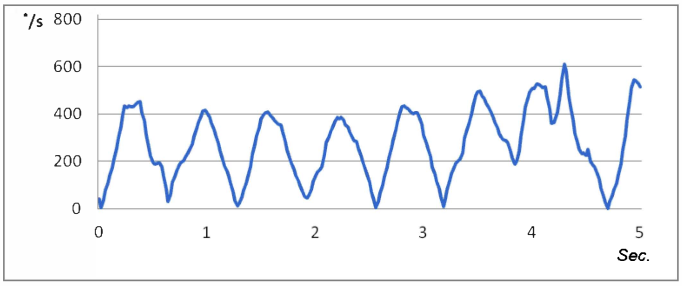


Fig. 6. The GS values during arm roatations

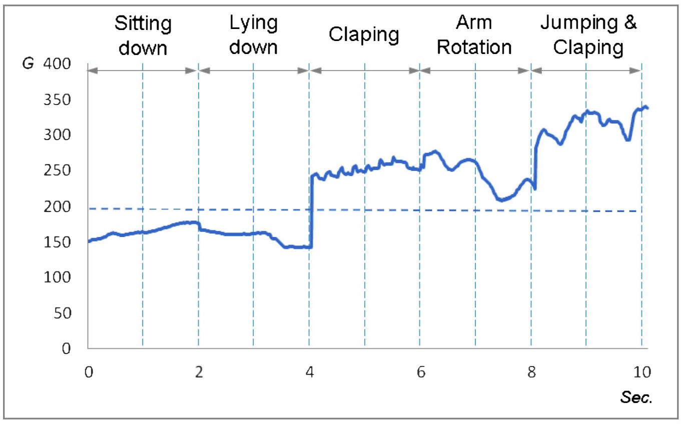


Fig. 7. The SMA values under different movement

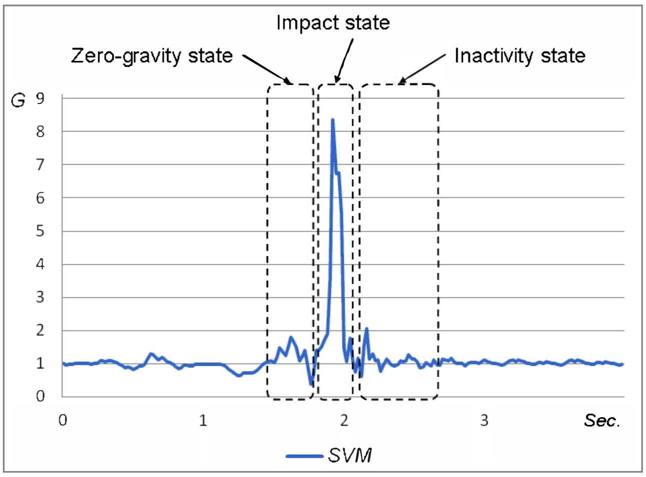


Fig. 8. The three states of a fall event

There are three states during a fall (see Fig. 8), which are the zero-gravity state, the impact state, and the inactivity state. In the zero-gravity state, the body falls down toward the ground. The relative accelerating speed decreases because the accelerating direction and the gravity direction are the same; thus, the *SVM* value will be smaller than 1*G*. In the impact state, the *SVM* value changes dramatically because of the massive change of the accelerating speed. In the inactivity state, because of unconsciousness or incapability of movement, the person is nearly stationary on the ground and hence the accelerometer values change slightly. According to our experimental results, the time period from the zero-gravity state to the impact state is no longer than 40 *ms*.

The proposed system works as follows (see Fig. 9). First, the system computes the *GS* value to see if the value is greater than $350^{o}/s$. If so, it next calculates the *SVM* values in the following 0.4 seconds. If one of the values is larger than 6*G*, then it is possibly a fall impact or a jump. The system then calculates the standard deviations within the 0.4 seconds before and after the maximum *SVM* value. If none of them are less than 1.5*G*, the system calculates the *SMA* value for the next two seconds. Finally, if the value is less than 200, the system can therefore confirm a fall event has occurred.

V. EXPERIMENTAL RESULT

Experiments were conducted to demonstrate the effectiveness of the proposed system. Another detector, SPEEDY [14], was also implemented for comparison. Three male volunteers were asked to conduct fall and non-fall activities. The experiments to detect falls were performed 20 times in each of the four directions: forward, backward, left, and right (Fig. 10). Non-fall activities include sitting down, lying down, walking, running, jumping, clapping, wrist twisting, arm rotation, and clapping during jumping.

Sensitivity (defined in (4)) is used to measure the ability to detect real falls.

$$\text{Sensitivity} = TP\,/\,(TP + FN) * 100\,\%, \qquad (4)$$

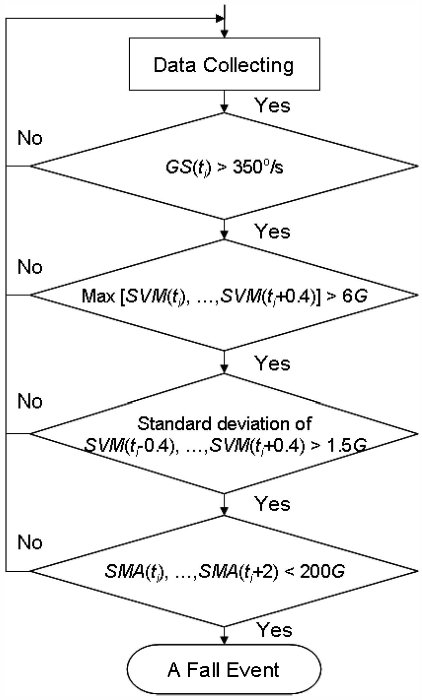


Fig. 9. The flowcahrt of the proposed system

where *TP* (True Positive) represents the number of times the system correctly detected real falls, and *FN* (False Negative) is the number of times the system failed to do so. The experimental results in Table 1 indicate that the abilities of both schemes to detect real falls are almost the same.

Moreover, specificity (defined in (5)) is used to measure the ability not to recognize non-fall activities as falls.

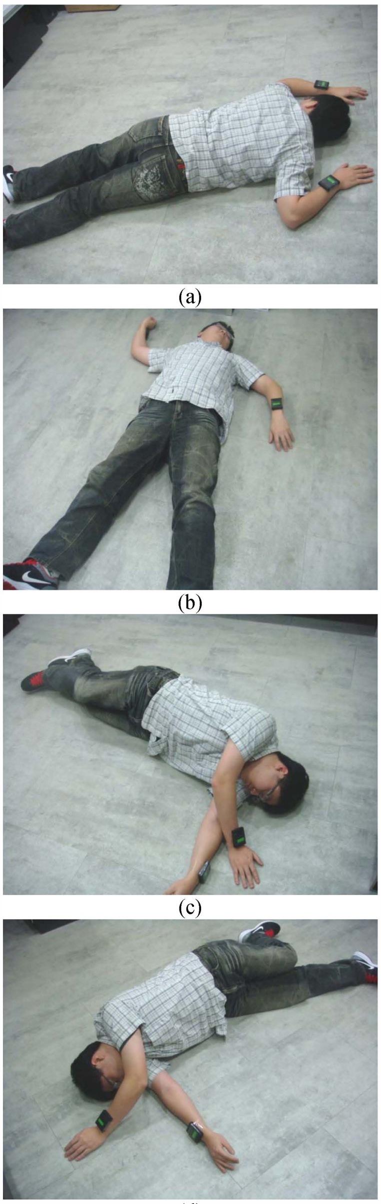
$$\text{Specificity} = TN\,/\,(TN + FP) * 100\%, \qquad (5)$$

where *TN* (True Negative) represents the number of times the system did not recognize non-fall activities as falls, and *FP* (False Positive) is the number of times for misrecognition. The experimental results in Table 2 clearly show that our scheme outperforms SPEEDY for hand related activities.

VI. CONCLUSION

The paper presented a detection system that can detect fall events effectively. The user wears the sensing devices on both hands. The system then detects the fall events according to the data gathered from the accelerometers and the gyroscopes in the devices. Moreover, the proposed system will not false alarms caused by non-fall motions such as clapping, lying down, jumping, jumping and clapping, etc. According to the experimental results, the proposed scheme obtained better performance than another wrist-worn fall detection system. This proves the effectiveness of the proposed system.

It is, however, cumbersome to wear two sensing devices on both hands. We are currently putting effort into exploring the possibility of utilizing only one device for fall detection.



(a) (b) (c) (d)

Fig. 10. Four directions of falls: (a) forward; (b) backward; (c) left; (d) right

TABLE I. SPECIFICITY

	Forward		Backward		Left		Right	
	○	□	○	□	○	□	○	□
Total Number of Times	20	20	20	20	20	20	20	20
Number of Misses	0	1	1	1	1	1	2	2
Sensitivity (%)	100	95	95	95	95	95	90	90

○: Ours △: SPEEDY

TABLE II. SPECIFICITY

(A) NORMAL ACTIVITIES

Activity	Sitting Down		Lying Down		Walking		Running		Jumping	
Scheme	○	□	○	□	○	□	○	□	○	□
Times of Misrecognition	0	2	1	5	0	0	1	1	1	8
Specificity (%)	100	90	95	75	100	100	95	95	95	60

(B) HAND-RELATED ACTIVITIES

Activity	Clapping		Wrist Turning		Arm Rotation		Clapping during Jumping	
Scheme	○	□	○	□	○	□	○	□
Times of Misrecognition	1	4	0	10	1	9	1	10
Specificity (%)	95	80	100	50	95	55	95	50

○: Ours □: SPEEDY

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