Fall Detection with Three-Axis Accelerometer and Magnetometer in a Smartphone

Soo-Young Hwang[1], Mun-Ho Ryu[2,3], Yoon-Seok Yang[2,3] and Nak-Bum Lee[4]

[1]Department of Healthcare Engineering, Chonbuk National University, 567 Baekje-daero, Deokjin-gu, Jeonju-si, Jeollabuk-do 561-756 Republic of Korea
[2]Division of Biomedical Engineering, Chonbuk National University, 567 Baekje-daero, Deokjin-gu, Jeonju-si, Jeollabuk-do 561-756 Republic of Korea
[3]Center for Healthcare Technology Development, Chonbuk National University, 567 Baekje-daero, Deokjin-gu, Jeonju-si, Jeollabuk-do 561-756 Republic of Korea
[4]Technology Licensing Center, Industrial-Academic Cooperation Foundation, Chonbuk National University, Korea
{hexion, mhryu, ysyangg, biomecca}@jbnu.ac.kr

Abstract. As an aging society approaches, the issue of injuries from falls by the elderly has emerged anew. Because of the dangers involved, research has recently been conducted on various types of falls; in particular, considerable research has been carried out on the detection and prevention of falls. We design an algorithm for the detection of falls using smartphones equipped with three-axis accelerometers and magnetometers. We propose a method of fall detection that recognizes a fall if the magnitudes of acceleration and angular displacement exceed given thresholds. Experiments to detect falls are performed in four directions: forward, backward, left, and right. Based on data from 200 experimental falls, obtained by fastening a smartphone to a belt worn around the waist, an overall detection rate of 95% was achieved, corresponding to direction-specific rates of 94% for forward falls, 100% for backward falls, 94% for leftward falls and 92% for rightward falls.

Keywords: Fall Detection, Smartphone, Three-axis Accelerometer, Magnetometer

1. Introduction

As the quality of life increases, medical technology advances, and life expectancy for the elderly rises, the size of the aged population is growing rapidly. As an aging society approaches, the issue of injuries from falls among the elderly is rising afresh. In fact, one third of the elderly older than age 75 suffer fall injuries at least once per year, and one quarter of those suffer serious injuries [1]. Moreover, the fear of injuries from falling limits the everyday activities of the elderly and increases the obstacles they face to maintaining independent lives [2, 3]. For these reasons, there has been steady research into the detection and prevention of falls.

There are two ways to detect falls: through visual observation or through an accelerator sensor. Fall detection through visual observation limits the scope of activity for the person being observed because it is primarily appropriate indoors and privacy may be compromised. While this approach can provide accurate information, the required equipment is expensive [4]. As for fall detection through an accelerometer, the scope of activity is relatively unrestricted; the device may be easily attached to the human body, and the cost of equipment is low. These factors explain why research using accelerometers has increased. Most research using accelerometers is focused on determining whether the magnitude of acceleration, sensed through the shock to the accelerometer, exceeds a definite threshold [5]. For long-term fall detection, Nyan et al. attached microelectromechanical system (MEMS) accelerometers to the shoulders for a relatively wide scope of motion and comfort than pertains to attachment to other parts of the body, and they identified falls by fixing a threshold based on a peak value of acceleration [6]. Bourke et al. judged whether the magnitude of acceleration exceeded a threshold by fastening three-axis accelerometers on the chest and thighs, respectively, in order to distinguish falls from activities of daily living (ADL). Their approach demonstrated greater accuracy when the accelerometers were attached to the chest [7]. Nevertheless, such studies entail the inconvenience of having to attach separate accelerometers on different parts of the human body. Dai et al. designed a fall detection system called PerFallD, and applied the platform to smartphones. They identified falls by measuring the magnitude of acceleration in the vertical direction through a built-in accelerometer in the device and comparing the difference between the maximum and minimum values for triggering the time window to a peak value. [4]. However, one of the inherent weaknesses in such research is the difficulty of obtaining naturalistic data from experimental subjects performing intentional falls, which are different from ordinary falls that occur when balance has been lost unintentionally.

In the present study, to address the aforementioned problems, we designed a fall detection algorithm using a smartphone with a three-axis accelerometer and a magnetometer built in to the device. While users are uncomfortable when separate accelerometers are attached to different parts of the body, smartphones do not require multiple devices and may be used freely anywhere, both indoors and outdoors. In addition, we gained naturalistic data by inducing unintentional falls in subjects placed standing on a pneumatic mattress. Our fall detection algorithm validates a fall when the magnitudes of acceleration and angular displacement exceed thresholds generated from ADL.

2. Method

2.1. Program Design and Hardware

The experiment used a smartphone (SHW-M110S, Samsung Electronics, South Korea) running on the Android 2.3.3 operating system. The smartphone contained a 1 GHz CPU (Samsung S5PC110), 512 MB RAM, and 16 GB built-in memory, along with a three-axis accelerometer and a magnetometer. We programmed an application to obtain sensor data using Eclipse (indigo release), an integrated development environment. The system recorded 100 Hz bandwidth signals from the three-axis acceleration sensor into external memory. The saved data were processed to detect falls using Matlab 7.0 (www.mathworks.com) on a PC, and results were secured using a low-pass filter with a 10 Hz cutoff frequency.

2.2. Experiment Protocol

To evaluate the fall detection system designed for this study, we proceeded with the experimental protocol described below. First, an experimental subject performed motions of ADL and falling after inserting the smartphone into its case and attaching it to the belt around the waist, as illustrated in Figure 1(a). The X, Y, and Z axes of the three-axis accelerometer and magnetometer in the smartphone produced positive (+) values in the directions to the right, top, and front of the screen, respectively, as shown in Figure 1(b).

(a) (b

Fig. 1. (a) The direction in which the smartphone is inserted into its case and the position of its attachment on the body of the subject. (b) The direction of each axis on the smartphone.

In order to generate a threshold based on ADL, data were gathered from six ADL scenarios in order of priority, including walking, jogging, sitting down, standing up, ascending stairs, and descending stairs. For falling motions, data were gathered in four directions: forward, backward, left, and right. We selected five healthy males (average age: 25.5; average height: 173±5.3 cm) for the group of experimental subjects. Next, a total of 40 attempted falls, with 10 attempts in each of the four directions, were carried out on the pneumatic mattress that was manufactured for the experiment. In total, we obtained 200 data points from the five experimental subjects. In order to generate the data for acquisition, falls were induced by moving the mattress at a random moment so that the subject standing on the mattress would fall unintentionally.

2.3. Program Algorithm and Fall Detection Algorithm

We programmed a smartphone application to collect the data for fall detection. The data saved on the smartphone in the course of the experiment consisted of raw data representing three-axis acceleration and angular data converted through programming. First, raw data representing acceleration were saved using the sensor manager object. Next, angular data were saved and various calculations were performed to determine the angles. The data from the accelerometer and the magnetometer were first read and then used to populate a [3 × 3] rotation matrix, of the form in Eq. (1), through functions related to sensor events.

$$R = \begin{bmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ r_{31} & r_{32} & r_{33} \end{bmatrix} \quad (1)$$

Then, elements of the rotation matrix were substituted in Eqs. (3) and (4) for calculation and a quaternion, Q, as in Eq. (2), was induced.

$$Q = (q_0, q_1, q_2, q_3) \quad (2)$$

$$q_0 = \frac{1}{2}\sqrt{1 + r_{11} + r_{22} + r_{33}} \quad (3)$$

$$\begin{bmatrix} q_1 \\ q_2 \\ q_3 \end{bmatrix} = \frac{1}{4q_0}\begin{bmatrix} r_{32} - r_{23} \\ r_{13} - r_{31} \\ r_{21} - r_{12} \end{bmatrix} \quad (4)$$

Finally, the obtained quaternion elements were processed, as shown in Eq. (5), to calculate the angle of rotation centered on each axis.

$$\begin{aligned} \theta &= 2\arccos(q_0) \\ \theta_x &= 180 \times q_1 \times \theta / \pi \sin\frac{\theta}{2} \\ \theta_y &= 180 \times q_2 \times \theta / \pi \sin\frac{\theta}{2} \\ \theta_z &= 180 \times q_3 \times \theta / \pi \sin\frac{\theta}{2} \end{aligned} \quad (5)$$

The acceleration data and angular data obtained in this way were saved into the smartphone, and an algorithm for fall detection was designed using Matlab.

It is necessary to set a threshold for the magnitude of acceleration to identify falls accurately. Thus, we calculated the signal vector magnitude (SVM) of the acceleration due to the shock of a fall, shown in Eq. (6), using the data collected by the three-axis accelerometer.

$$||A|| = \sqrt{(A_X)^2 + (A_Y)^2 + (A_Z)^2} \quad (6)$$

If ||A|| exceeds the designated threshold, the first condition for acknowledging a fall is established. Next, angular data are analyzed for comparison of the angular displacements of each axis. Because the smartphone is affixed to the human body, there is no considerable angular displacement in the direction of the vertical Y axis. Therefore, if the magnitudes of angular displacements along the other two axes exceed the threshold, the second condition for a fall is constituted. The process of calculating the magnitude of angular displacement is shown in Eq. (7).

$$||\theta_{xz}|| = \sqrt{(\theta_x)^2 + (\theta_z)^2} \quad (7)$$

A fall is judged as certain only if both the conditions are satisfied.

3. Results

Based on the experimental results of ADL, conducted in order to set criterion values for a fall, the threshold for acceleration was established at 2.2 g and the threshold for angular displacement was set at 50°.
Experimental results confirmed that average acceleration for falls exceeded the 2.2 g threshold in all four directions; average angular displacement exceeded the 50° threshold in all four directions, as well. The graph in Figure 2 illustrates the detection results of forward falls. The results of backward, leftward, and rightward falls were similar.
Although the ADL jogging scenario generated angular displacement with an experimental magnitude of 80.8317°, exceeding the threshold of 50°, the acceleration magnitude of 1.9268 g was smaller than the threshold of 2.2 g, distinguishing it from falls. Based on these results, we confirmed the need to apply both the acceleration and angular displacement thresholds to distinguish a fall from an ADL.

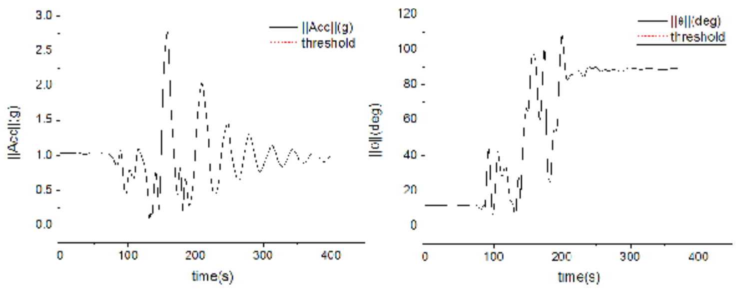

Fig. 2. Results of forward falls.

As a result, 190 out of a total of 200 falls were identified, thereby achieving 95% accuracy. With respect to the 5% that were not detected, we inferred that the subjects instinctively touched the ground with their hands or knees to protect the body while falling, preventing accurate data collection. This inference is supported by the fact that backward falls returned 100% accuracy, which we attribute to the difficulty of protecting the body while falling backwards.

4. Conclusion

This study describes experiments in fall detection conducted using smartphones in an algorithm designed by the authors. The study established the first condition of fall detection by setting the threshold of acceleration SVM at 2.2 g, and established the second condition by setting the threshold of angular displacement at 50°. When both conditions were fulfilled, falls were identified accurately. After a total of 200 experimental falls were tested, an average accuracy rate of 95% in fall detection was achieved.

Future research building on these results could involve long-term monitoring of the elderly and the development of a real-time fall detection system to cope flexibly with emergencies from falls, based on additional research into smartphone-based algorithms.

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