P-ISSN 2586-9000
E-ISSN 2586-9027
Homepage : *https://tci-thaijo.org/index.php/SciTechAsia* **Science & Technology Asia**
Vol.25 No.2 April - June 2020 Page: [36-46]

Original research article

An Application of a Cumulative-Sum Control Chart for Elderly Fall Detection using Smartphone Accelerometers

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Received 13 June 2019; Received in revised form 1 November 2019
Accepted 18 November 2019; Available online 29 June 2020

ABSTRACT

The objective of this work is to apply a cusum control chart to detect elderly falls using accelerometers in a smartphone. A violent fall, for example, is that the subject is unconscious due to acute stroke. If the subject is helped in time, he/she can be remedied and gotten back to normal. The cusum control chart is selected because it is a simple tool for calculation which saves resources and provides a fast response. The smartphone including accelerometer sensors is appropriate for this work because it is comfortably and widely used and the cost is affordable. The smartphone is attached at the chest level. For each volunteer, the smartphone records the signals of the five falls (collapsed fall, front fall, left fall, right fall, and back fall) and eight activities of daily life (walking, running, jumping, bending down, kneeling, sitting on the floor, sitting on a chair, and lying down). There are 40 volunteers (10 normal weight volunteers of each gender and 10 overweight volunteers of each gender) less than 50 years old, who performed as elderly people using the elderly simulation kit. Two replications of each activity are done by each volunteer. The first is for threshold development for detection and the second is for verification. Using the cusum, any fall is detected when the values of the magnitude of the positive shift and the nonzero period are more than their own threshold values developed for each target group. The overall sensitivity and the specificity are 96.00% and 93.44%, respectively.

Keywords: Fall detection; Cumulative-sum (cusum) control chart; Accelerometer; Smartphone

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1. Introduction

Falling is a main problem for elderly people. Willems et al. [1] states that several thousands of elderly people experience falling accidents each year. Particularly, over one third of people over 75 years old had at least one falling experience. In the same population, falling is also the main cause of injuries like hip fracture and impacts awareness of fear of falling in performing activities of daily life (ADL). Therefore, there have been several developments relative to algorithms based on accelerometers for inclination detection utilizing in portable fall-detection devices.
Lindemann et al. [2] developed an algorithm for a fall detector based on accelerometers to distinguish between ADLs and falls and recommended that it be placed at the head level. The development was onlyapplied to a young volunteer for both fall and ADL studies. The threshold in terms of acceleration in all x-, y-, and z-directions was > 6g. Bourke et al. [3] also developed a fall-detection algorithm based on tri-axial accelerometer, and suggested that it be mounted on the trunk or thigh. The development was applied to 10 young volunteers for the fall study and 10 elderly subjects for the ADL study. Simultaneously using both upper and lower thresholds, the fall-detection thresholds of the algorithm were > 3.52g for the upper threshold and < 0.36g for the lower threshold. In addition, Jantaraprim et al. [4] evaluated the elderly fall-detection threshold using a tri-axial accelerometer mounted on the user's trunk, obtaining > 1.9g. The number of the volunteers for the experiments was 10 adults for the fall study and 10 elders for the ADL study. Using the same experiment, Jantaraprim et al. [5] improved the accuracy of a fall-detection algorithm, obtaining ≥ 1.75g and ≤ 0.75g for the upper and lower thresholds, respectivelyor more complex methods, Shin et al. [6] developed a fall-detection algorithm based on Short-Time Fourier Transform (STFT). Forty male volunteers participated, but were not classified. Using 3-axis accelerations, the sensor was attached to the middle of the splines. In Palmerini et al. [7], Wavelet Transform (WT) was used for fall detection with 29 real-world falls from nine people recorded by the sensing unit from community-dwelling patients. The sensor, the tri-axial acceleration, was held by a belt at the lower back of the subjects.

The works mentioned above applied to the groups of the volunteers that did not classify any personal characteristics like gender, age, or, body mass index (BMI). These characteristics may be a factor sensitive to a fall-detection threshold. Furthermore, the stated works developed their own devices applied to tri-axial accelerometers. Users had to mount or attach the device to their body for utilization. Possibly, the users, particularly elders, may forget to mount or charge the battery or feel uncomfortable. However, the current technology of smartphones mostly includes an accelerometer sensor for inclination measurements. Therefore, the developed fall-detection algorithms can also be applied using accelerometers on any smartphone. There also are several advantages for using a smartphone to detect falls. For example, it is comfortably and widely used, only one device to carry, the cost is affordable, and only software development is needed.

In this work, we developed a novel algorithm for fall detection using accelerometers in any smartphone. The thresholds for detections were obtained from classified dataset from different groups of volunteers to suitably utilize with each user. The algorithm applied a cusum control chart to detect elderly falls when 2 conditions are true.

2. Materials and Methods

A smartphone applied in this work was Samsung GALAXY S5 which already had a built-in accelerometer sensor. It was attached at the chest level and used to record the acceleration of each activity. The operating system (OS) was Android. An application to record accelerations was Accelerometer Analyzer which is an open-source software available on Android Market or Play Store. A camera was also used to record the motional experiments. Six rubber mats were used to support falls. Five formats of falls were considered: collapsed fall, front fall, left fall, right fall, and back fall. Eight formats of ADLs were also considered: walking, running, jumping, bending down, kneeling, sitting on the floor, sitting on a chair, and lying down. There were 40 volunteers, 20 men and 20 women. The personal data were also recorded such as gender, age, height, weight, BMI, waist, and occupation. Twenty volunteers in each gender were grouped as 10 for normal weight (BMI ≤ 25) and 10 for overweight (BMI > 25). For the male group with BMI ≤ 25 kg/m^2, the averages of age, waist, height, weight, and BMI were 27.00 years, 32.00 inches, 65.00 kilograms, 1.75 meters, and 21.22 kg/m^2, respectively. For the male group with BMI > 25 kg/m^2, the averages of age, waist, height, weight, and BMI were 30.60 years, 40.25 inches, 90.00 kilograms, 1.72 meters, and 30.41 kg/m^2, respectively. For the female group with BMI ≤ 25 kg/m^2, the averages of age, waist, height, weight, and BMI were 24.80 years, 26.60 inches, 46.20 kilograms, 1.58 meters, and 18.48 kg/m^2, respectively. For the female group with BMI > 25 kg/m^2, the averages of age, waist, height, weight, and BMI were 28.80 years, 32.80 inches, 70.40 kilograms, 1.58 meters, and 28.05 kg/m^2, respectively. All 40 volunteers performed as elderly subjects using the elderly simulation kit shown in Fig. 1. The kit consisted of a weight vest, 2 angle weights, 2 wrist weights, 2 elbow restraints and 2 knee restraints. Two replications of each fall and ADL were done by each volunteer. The first was for threshold development for detection and the second was for verification.

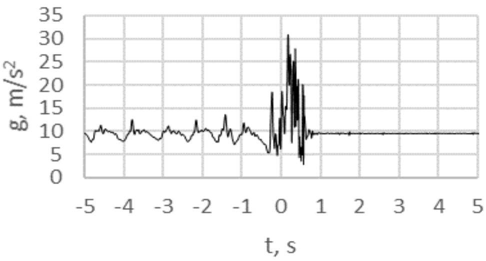
Fig. 1. The elderly simulation kit.

An accelerometer is a means of acceleration measurement and is installed in general smartphones to measure their inclination. While the accelerometer is measuring the inclination, an application running on the phone processes its data according to its logical conditions. For example, when the phone is alternatively turned in a vertical or horizontal direction, the screen will rotate in a portrait or landscape direction, respectively. The accelerometers may be made from a piezoelectric, capacitive, or micro-electromechanical system (MEMS) device. It functions to transform physical properties into electrical signals and then the application calculates the acceleration against the gravity (g) in meter per second square (m/s^2) using equation (2.1), the sum vector magnitude of accelerations (SVMa) equation. Currently, general smartphones consist of three-axis (x, y, and z) accelerometers. Fig. 2 represents the frontal (x), sagittal (y), and vertical (z) directions of the smartphone relative to the three-axis accelerometers.

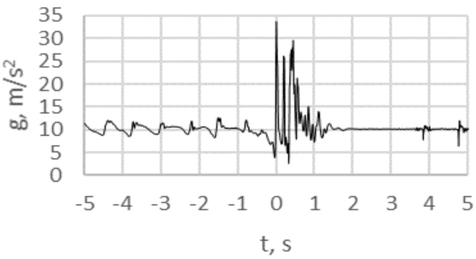
$$g = SVM_a = \sqrt{a_x^2 + a_y^2 + a_z^2}\,, \tag{2.1}$$

Fig. 2. Inclination directions relative to tri-axial accelerometers in a smartphone.

Any movement with only gravitational force has stable acceleration which is approximately 9.8 m/s^2. Therefore, g = 9.8 m/s^2 was applied as the target (μ) of Equation 2.1 and any activity acceleration was expected to vary around the g value. Fig. 3 illustrates examples of fall signals and Fig. 4 illustrates examples of ADL signals. The acceleration of the activities in the figures obviously varied around 9.8 m/s^2.



(a)



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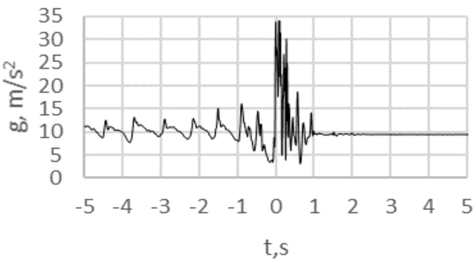

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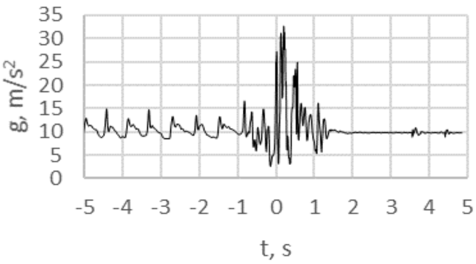

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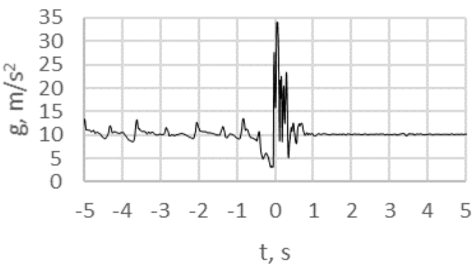

(e)

Fig. 3. Examples of fall signals; (a) collapsed fall, (b) front fall, (c) left fall, (d) right fall, and (e) back fall.

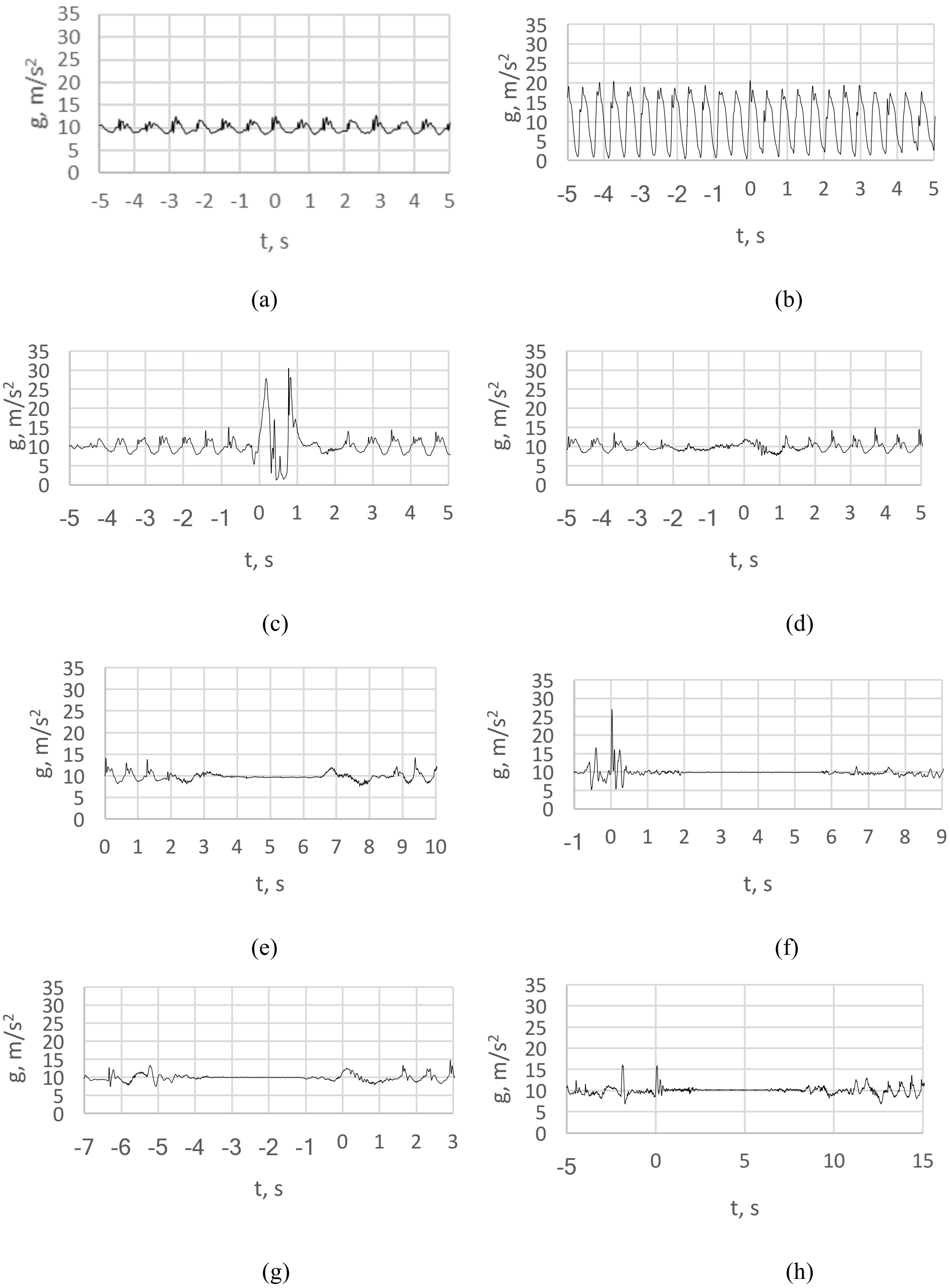

Fig. 4. Examples of ADL signals; (a) walking, (b) running, (c) jumping, (d) bending down, (e) kneeling, (f) sitting on the ground, (g) sitting on the chair, and (h) lying down.

From the literature reviews earlier, each work applies one or two thresholds for the fall-detection process. Industrially, the detection is just like a process-control procedure for production or service by using control charts in quality control. Because any fall is an abrupt accident in a very short period of time, general control charts for monitoring the process known as variables control charts such as $\overline{X}$ and R charts cannot appropriately detect a fall or a so-called out-of-control event. However, the alternate control chart that is very effective for detecting small process shifts is the cumulative-sum (cusum) control chart [8]. The representation of the cusums mostly applies the tabular form although the V-mask form is also applicable. Using data from Montgomery [8], Fig. 5 is an example of a tabular cusum control chart for monitoring to detect out-of-control signals.

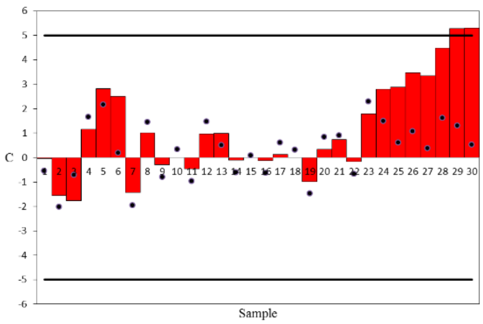

Fig. 5. An example of a tabular cusum control chart.

Normally, we expect the observed values (x) from the samples equal to the target value (x = μ), but practically the cumulative sum will increase when x > μ and the cumulative sum will decrease when x < μ. If the values (x) tend to fall in one side, the process is indicating problems or needs a remedy. Fig. 5 illustrates that the first 20 values vary around the target (μ = 10) and the last 10 values fall in the positive side. Therefore, the process is shifting up and needs an adjustment.

Tabular cusum is the cumulative sum of positive changes from the target and the cumulative sum of negative changes from the target as mathematically described in equations (2.2) and (2.3), respectively. For example, Table 1 numerically shows the tabular cusum and Fig. 5 graphically illustrates the tabular cusum.

$$C_i^+ = \max\left[0, x_i - (\mu_0 + K) + C_{i-1}^+\right], \quad (2.2)$$

$$C_i^- = \max\left[0, (\mu_0 - K) - x_i + C_{i-1}^-\right], \quad (2.3)$$

where $K = \dfrac{\sigma}{2}$.

Notice C+ and C- cumulate the deviation from the target that is more than K; otherwise, they are zero. If the cumulative sum of C+ or C- is more than the threshold (H), the process is out-of-control. H = 4.77σ or approximately 5σ is recommended in general [8]. Obviously, the cusum control chart is quite simple and powerful to detect the small change. The fall detection app on the smartphone needs a simple tool for calculation to save resources and to provide a fast response.

Table 1. Tabular Cusum.

i	x	x-10	C	a			b		
				x_i-10.5	C_i^+	N^+	9.5-x_i	C_i^-	N^-
1	9.45	-0.55	-0.55	-1.05	0.00	0	0.05	0.05	1
2	7.99	-2.01	-2.56	-2.51	0.00	0	1.51	1.56	2
3	9.29	-0.71	-3.27	-1.21	0.00	0	0.21	1.77	3
4	11.66	1.66	-1.61	1.16	1.16	1	-2.16	0.00	0
5	12.16	2.16	0.55	1.66	2.82	2	-2.66	0.00	0
6	10.18	0.18	0.73	-0.32	2.50	3	-0.68	0.00	0
7	8.04	-1.96	-1.23	-2.46	0.04	4	1.46	1.46	1
8	11.46	1.46	0.23	0.96	1.00	5	-1.96	0.00	0
9	9.20	-0.80	-0.57	-1.30	0.00	0	0.30	0.30	1
10	10.34	0.34	-0.23	-0.16	0.00	0	-0.84	0.00	0
11	9.03	-0.97	-1.20	-1.47	0.00	0	0.47	0.47	1
12	11.47	1.47	0.27	0.97	0.97	1	-1.97	0.00	0
13	10.51	0.51	0.78	0.01	0.98	2	-1.01	0.00	0
14	9.40	-0.60	0.18	-1.10	0.00	0	0.10	0.10	1
15	10.08	0.08	0.26	-0.42	0.00	0	-0.58	0.00	0
16	9.37	-0.63	-0.37	-1.13	0.00	0	0.13	0.13	1
17	10.62	0.62	0.25	0.12	0.12	1	-1.12	0.00	0
18	10.31	0.31	0.56	-0.19	0.00	0	-0.81	0.00	0
19	8.52	-1.48	-0.92	-1.98	0.00	0	0.98	0.98	1
20	10.84	0.84	-0.08	0.34	0.34	1	-1.34	0.00	0
21	10.90	0.90	0.82	0.40	0.74	2	-1.40	0.00	0
22	9.33	-0.67	0.15	-1.17	0.00	0	0.17	0.17	1
23	12.29	2.29	2.44	1.79	1.79	1	-2.79	0.00	0
24	11.50	1.50	3.94	1.00	2.79	2	-2.00	0.00	0
25	10.60	0.60	4.54	0.10	2.89	3	-1.10	0.00	0
26	11.08	1.08	5.62	0.58	3.47	4	-1.58	0.00	0
27	10.38	0.38	6.00	-0.12	3.35	5	-0.88	0.00	0
28	11.62	1.62	7.62	1.12	4.47	6	-2.12	0.00	0
29	11.31	1.31	8.93	0.81	5.28	7	-1.81	0.00	0
30	10.52	0.52	9.45	0.02	5.30	8	-1.02	0.00	0

3. Results and Discussion

Fig. 3 shows the five fall signal examples from an elderly-male volunteer with BMI > 25 kg/m^2. Each signal consists of five steps of walking at the beginning and then a fall of each format followed by unconsciousness on the floor. From the figure, notice the acceleration signals vary about 9.8 m/s^2 for walking, then suddenly changes up to almost 35 m/s^2 for falling, and lastly get back to vary at 9.8 m/s^2 for unconsciousness. Fig. 4 shows the eight ADL signal examples from the same volunteer. The signals from walking, bending down, kneeling, sitting on the floor, sitting on a chair, and lying down vary about 5 – 15 m/s^2 which are obviously different from falling. In terms of running and jumping, the signals vary about 0 – 35 m/s^2 which are quite close to falling. These results similarly take place with all three groups of each volunteer. Fig. 6 shows graphically the tabular cusum of the fall signals obtained from the same volunteer. From the figure, notice each magnitude of the positive shift (MPS) from zero is rather high in a short period of time and then gradually gets back to zero, the nonzero period (NZP). Fig. 7 shows graphically the tabular cusum of the ADL signals obtained from the same volunteer. From the figure, notice running and jumping have MPS and NZP higher than other activities. Comparing between the falls and the ADLs, these two values are obviously different. Therefore, if the tabular cusum of any activity has both MPS > its average and NZP > its average, that activity is considered as a fall.

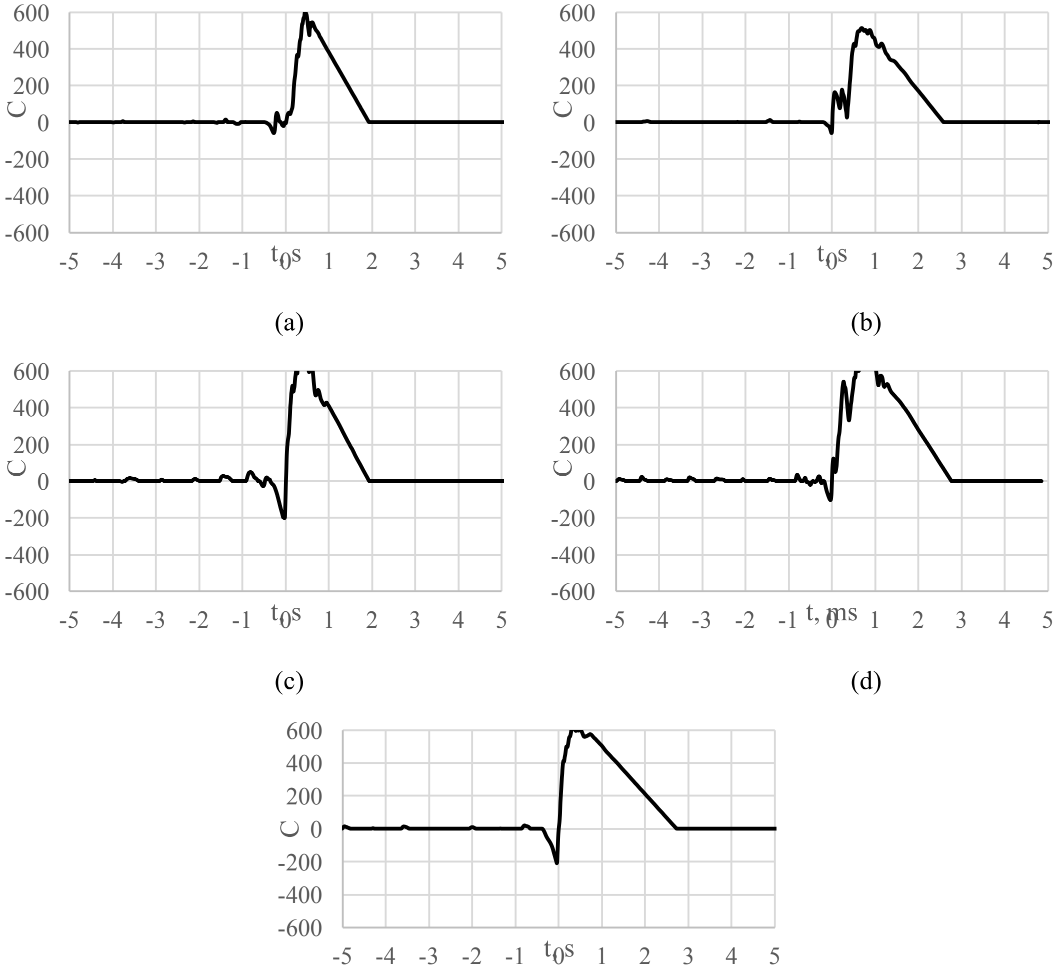

Fig. 6. Examples of tabular cusum of fall signals; (a) collapsed fall, (b) front fall, (c) left fall, (d) right fall, and (e) back fall.

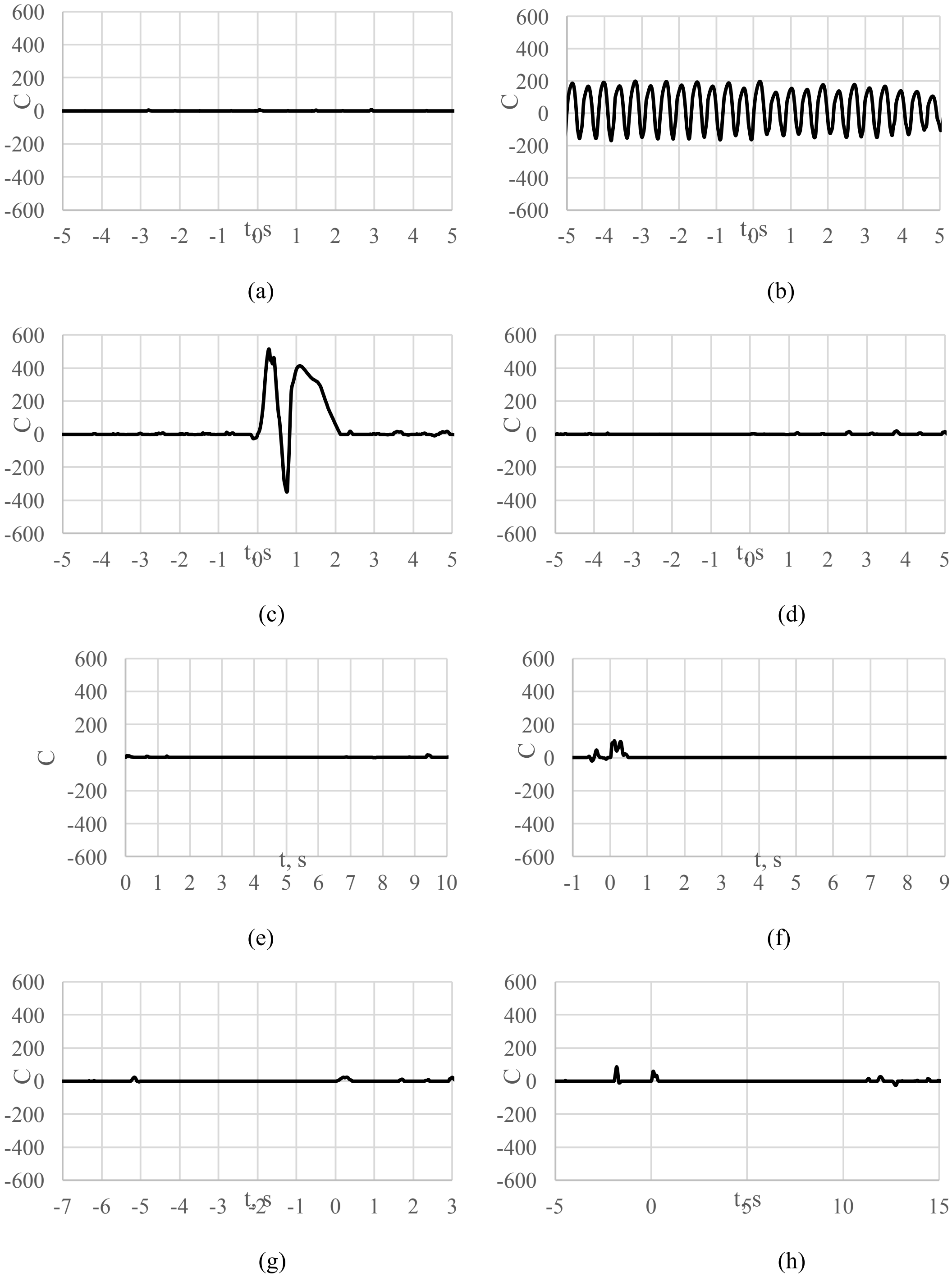

Fig. 7. Examples of tabular cusum of ADL signals; (a) walking, (b) running, (c) jumping, (d) bending down, (e) kneeling, (f) sitting on the ground, (g) sitting on the chair, and (h) lying down.

For the group of 10 elderly-male volunteers with BMI ≤ 25 kg/m^2, the average MPS for running and NZP for jumping are 249.75 and 640.95 ms, respectively. For the group of 10 elderly-male volunteers with BMI > 25 kg/m^2, the average MPS for running and NZP for jumping are 224.88 and 429.00 ms, respectively. For the group of 10 elderly-female volunteers with BMI ≤ 25 kg/m^2, the average of MPS for running and NZP for jumping are 266.54 and 501.20 ms, respectively. For the group of 10 elderly-female volunteers with BMI > 25 kg/m^2, the average of MPS for running and NZP for jumping are 255.35 and 546.80 ms, respectively.

For verification, the sensitivity and the specificity are applied to the data from the second replication. The sensitivity is applied to verify the correction of the fall detection and the specificity is applied to verify the error of the ADL detection as a fall. For the group of 10 elderly-male volunteers with BMI ≤ 25 kg/m^2, the sensitivity and the specificity are 98.00% and 91.25%, respectively. For the group of 10 elderly-male volunteers with BMI > 25 kg/m^2, the sensitivity and the specificity are 94.00% and 95.00%, respectively. For both groups of 10 elderly-female volunteers with BMI ≤ 25 kg/m^2 and BMI > 25 kg/m^2, the sensitivity and the specificity are the same which are 96.00% and 93.75%, respectively. As a result, the overall sensitivity and the specificity are overall 96.00% and 93.44%, respectively.

Comparing to the other works, Shin et al. [6] claims their fall-detection algorithm based on STFT with the 96.90% sensitivity and 97.10% specificity. The claims are not so different from this work, but their method is more complex and the subjects are not classified. Also, only 3 types of falls and 4 types of ADLs are applied. The application may not suitably sense falls with a variety of users. Comparing to the algorithm of Palmerini et al. [7] using WT with 29 real-world falls from nine people, the sensitivity and the specificity are 90.00% and 89.74%, respectively, which are obviously lower than this work.

4. Conclusion

We developed a cusum control chart to detect elderly falls using accelerometers in a smartphone. Based on the tabular cusum, any fall is detected when both values of the magnitude of the positive shift and the nonzero period exceed their own threshold values developed for each target group. Comparing to other developments, this method is another option for fall detection which is simple and saves resources in terms of time and energy. For future work, this algorithm may be applied to wristbands which is currently a popular device to monitor user's healthcare. However, fall-detection developers using accelerometers need to manage an arm-swing signal during walking.

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