J. Phys. Ther. Sci. 34: 320–326, 2022

The Journal of Physical Therapy Science

Original Article

Identification of the cause of fall during the pre-impact fall period

Sho Sasaki[1)*], Hiroaki Yamamoto, RPT[1, 2)], Kodai Kitagawa[1)], Chikamune Wada, PhD[1)]

[1)] *Graduate School of Life Science and Systems Engineering, Kyushu Institute of Technology: 2-4 Hibikino, Wakamatsu-ku, Kitakyushu-shi, Fukuoka, Japan*
[2)] *Department of Physical Therapy, Fukuoka Tenjin Medical Rehabilitation Academy, Japan*

Abstract. [Purpose] This study aimed to develop and validate a method for identifying factors that may cause a fall during the pre-impact fall period using wearable sensors. [Participants and Methods] The participants were 23 young people from the public data set (mean age, 23.4 years). Acceleration and angular velocity information obtained from sensors attached to the participant's waist was used to generate the pre-impact fall. The cause of the fall (slip, trip, fainting, get up, sit down) was then classified with and without the addition of activity of daily living data using three different support vector machine. In addition, we investigated the influence of lead time (0–2.0s) on accuracy. [Results] The quadratic and cubic support vector machine identified the activity of daily living and fall patterns more accurately than the linear support vector machine, and the cubic support vector machine was better for classification, although the difference was slight. The greatest accuracy for predicting the cause of the fall (87.9%) was obtained when the cubic support vector machine was used, activity of daily living was factored into the analysis, and the lead time was 0.25 sec. [Conclusion] Support vector machine can identify the cause of the fall during the pre-impact fall period. Appropriate individualized interventions may be designed based on the most likely cause of fall as identified by this analysis method.

Key words: Preimpact fall, Cause of fall, Lead time

(This article was submitted Dec. 10, 2021, and was accepted Jan. 25, 2022)

INTRODUCTION

Because the severity of injuries due to falls increases with age, they pose a major health threat to older individuals and can sometimes lead to death[1)]. Thus, it is important to prevent falls because they have a significant effect on an individual's mobility and independence[2)]. Understanding various information related to the risk of falls is necessary to prevent them. Previous studies using assessment sheets[3)] and walking tests[4, 5)] did not measure the movements involved in a fall and could determine only the potential fall risk. A number of studies have measured actual fall situations, and wearable sensors have been used to identify the occurrence of a fall[6–8)]. The purpose of those studies was to detect the impact on the floor (i.e., after the person had fallen down on the floor) and to inform the caregiver that the individual required help, with the aim of reducing the amount of time the person remained lying with loss of unconsciousness. However, those previous studies were unable to provide information that could help avoid the injury, because the fall had already occurred. Therefore, to prevent falls, research should focus on the detection of factors related to falling in the period before floor impact. Bourke et al.[9)] defined a preimpact fall as the movement that occurs before floor impact and predicted a fall occurrence during a preimpact fall period. In addition to detecting the presence of a fall during the preimpact fall period, Wu et al.[10)] classified the direction of the fall. Although there have been studies determining the presence and direction of falls before impact, none of these studies have been able to determine the reason for the fall, such as tripping or fainting.

*Corresponding author. Sho Sasaki (E-mail: sasaki.sho260@mail.kyutech.jp)

To take more effective action to prevent falls, it is necessary to determine the detailed factors that cause falls. If these factors are understood, it might be possible to take appropriate action to reduce fall risk. In research conducted by Robinovitch et al.[11], 25% of indoor falls due to tripping were caused by the individual's getting his or her feet caught on a leg of a chair or table, and it was concluded that improvements in environmental planning and furniture design were necessary. Thus, determining the factors that cause falls is expected to improve the quality of care by providing an appropriate care plan, such as improving the living environment.

Therefore, there is a need for a system that can identify the factors contributing to falls during the preimpact fall period by measuring body movement in a real-time operation. Generally, wearable sensors or nonwearable devices can be used to measure body motion related to fall detection and prevention. Nonwearable devices mostly measure motion using vision-based techniques, such as video cameras, or ambience-based techniques such as pressure and thermal sensors[12]. However, nonwearable devices have only a limited measurement area and are considered to be difficult to use in daily life. In contrast, wearable sensors are often used to measure body motion because of they are smallness, lightweight, and low cost. In addition, as long as the sensor is worn, the measured data can be acquired without any restriction of location, which is suitable for this research. For this reason, in this study, we selected a wearable sensor that includes an accelerometer and gyroscope, as this is the most widely used sensor combination for detecting falls before impact[10].

Machine learning has been widely used in research on fall detection systems because of its high accuracy in identifying falls as compared with threshold-based algorithms. Among a variety of machine learning techniques, the support vector machine (SVM) is the most commonly used[13]. The SVM can effectively handle high-dimensional data such as fall detection without the risk of overtraining. This SVM is better at discriminating distinct matters between falls and activities of daily livings, because its principle ensures a wide margin for the class to be classified. The SVM has also good memory efficiency and is suitable for wearable usage. Therefore, we decided to use the SVM as the algorithm in this study.

The purpose of this study was to develop and validate a method for identifying factors during the preimpact fall period using wearable sensors. Specifically, we set the period of preimpact fall to allow adequate time to distinguish falls/ADLs based on motion data. Here, we define the impact point as the time at which the body contacts the floor, and the preimpact fall period does not include the impact point. Based on the features extracted from the motion data during the preimpact fall period, we used the SVM to correctly classify ADLs and patterns of fall and estimate the fall factors. Furthermore, the change in the discrimination rate of fall factors according to the length of the preimpact fall period will clarify the necessary time before the impact point.

PARTICIPANTS AND METHODS

The proposed method classifies fall situations by machine learning using acceleration and angular velocity obtained from an inertial sensor (Fig. 1). In this study, we analyzed the open data set from Sucerquia et al. (SisFall Dataset)[14] to investigate whether falls/ADLs could be classified by using inertial sensor data of body motion before the impact point. The experiment for this dataset was approved by the Bioethics Committee of the Faculty of Medicine of the University of Antioquia UDEA (Medellin, Colombia), approval number 005 April 9, 2015. We chose this data set for the following reasons:

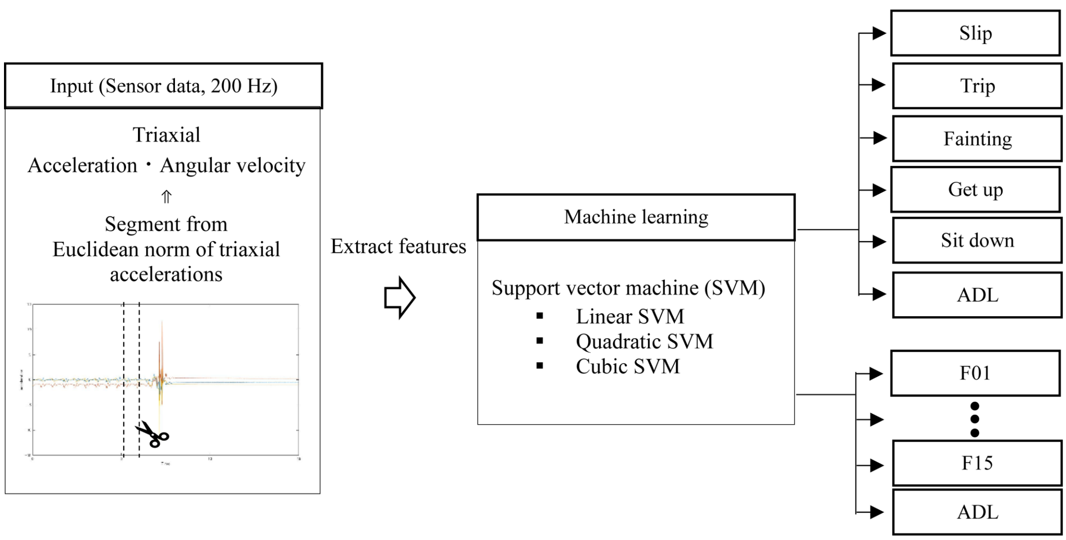

Fig. 1. Overview of the classification of fall causes.
ADL: activity of daily living.

• This data set was cited in a recent review article on the comprehensive analysis of open data sets used for wearable fall detection systems[15].
• The data were obtained from a sensor mounted on the waist, which was considered to be the optimal sensor position[16].
• This data set included the most variety of fall patterns in the review article.
• This data set also included information on fall factors.

The data set consisted of 15 fall patterns and 19 patterns of ADLs collected from a waist-mounted accelerometer (Analog Devices, Norwood, MA, USA) and gyroscope (Texas Instruments, Dallas, TX, USA). Data were collected from 23 young people and 15 older people. In this data set, fall data were obtained by emulating young people, and older individuals did not emulate a fall. Therefore, in this study, we did not use the data from the older participants but only data from the younger individuals (11 males, 12 females, age 23.4 ± 3.3 years, height 165.4 ± 10.0 cm, weight 59.5 ± 11.4 kg). A total of 1,723 falls and 1,809 ADLs were included. Table 1 presents the details of the included falls and ADLs. The sampling rate was 200 Hz, and both acceleration and angular velocity data were used as the input for machine learning. Table 2 shows the two patterns of falls to be classified: 15 defined in the data sets and 5 defined in this study according to the cause of the fall.

Because the raw data from the data set contained the impact point, we needed to segment the data to obtain preimpact information. The raw data consisted of temporal data on three axes on acceleration/angular velocity. After calculating the

Table 1. Types of falls and activities of daily living (ADLs) in SisFall dataset[14]

Code	Activity of fall
F01	Fall forward while walking caused by a slip
F02	Fall backward while walking caused by a slip
F03	Lateral fall while walking caused by a slip
F04	Fall forward while walking caused by a trip
F05	Fall forward while jogging caused by a trip
F06	Vertical fall while walking caused by fainting
F07	Fall while walking, with use of hands in a table to dampen fall, caused by fainting
F08	Fall forward when trying to get up
F09	Lateral fall when trying to get up
F10	Fall forward when trying to sit down
F11	Fall backward when trying to sit down
F12	Lateral fall when trying to sit down
F13	Fall forward while sitting, caused by fainting or falling asleep
F14	Fall backward while sitting, caused by fainting or falling asleep
F15	Lateral fall while sitting, caused by fainting or falling asleep
Code	**Activity of ADL**
DO01	Walking slowly
DO02	Walking quickly
DO03	Jogging slowly
DO04	Jogging quickly
DO05	Walking upstairs and downstairs slowly
DO06	Walking upstairs and downstairs quickly
DO07	Slowly sit in a half height chair, wait a moment, and up slowly
DO08	Quickly sit in a half height chair, wait a moment, and up quickly
DO09	Slowly sit in a low height chair, wait a moment, and up slowly
DO10	Quickly sit in a low height chair, wait a moment, and up quickly
DO11	Sitting a moment, trying to get up, and collapse into a chair
DO12	Sitting a moment, lying slowly, wait a moment, and sit again
DO13	Sitting a moment, lying quickly, wait a moment, and sit again
DO14	Being on one's back change to lateral position, wait a moment, and change to one's back
DO15	Standing, slowly bending at knees, and getting up
DO16	Standing, slowly bending without bending knees, and getting up
DO17	Standing, get into a car, remain seated and get out of the car
DO18	Stumble while walking
DO19	Gently jump without falling (trying to reach a high object)

norm of the acceleration in the three axes, the maximum norm value was set to be the impact point. A point before the impact point was defined as the cut point, and the time window containing the data before the cut point was defined as W_1 (Fig. 2). The interval between the cut point and the impact point (hereafter called the lead time) was varied in 0.25-sec steps between 0.0 sec and 2.0 sec to compare the accuracy of the classification. W_1 was set to a fixed length of 1.5 sec, which was the suitable window size for fall detection[17]. When segmenting, if there were no data and the window size was not adequate, the data were excluded. There was no impact point for ADLs. ADL data were segmented into fixed lengths of 1.5 seconds, similar to falls, at random locations. The purpose of feature extraction was to collect information that could correctly classify falls and ADLs. Thirteen types of features were extracted[17]: mean, variance, standard deviation, maximum, minimum, median absolute deviation, range, median, number of local maximum values, number of local minimum values, skewness, kurtosis, and sum. The features were extracted from the acceleration and angular velocity of the three axes. Subsequently, 78 features were used in total. The SVM was used as a machine learning model, and its accuracy was compared with that of the linear, quadratic, and cubic SVMs. These models differ in the way of drawing boundaries for classification. They use a kernel function[18] to set the boundary, and the order of the function is first, second, and third order, respectively. Since it is impossible to find out which of these bounds is suitable without training, we compared the accuracy of the three models.

The accuracy was evaluated using a k-fold cross-validation approach, where k=10. This approach uses one of the 10 randomly divided groups for test data and the rest for training. The analysis was evaluated in two types of models: one model included only falls in the training and test data, and the other model included falls and ADLs. All work was conducted in MATLAB2018 (MathWorks, Natick, MA, USA).

RESULTS

In this study, we evaluated the performance of 23 young participants in terms of the accuracy in the patterns using only falls data (Table 3), adding ADL data to those patterns (Table 4), and accuracy focusing only on falls when ADL was added (Table 5). With or without ADL data, the quadratic and cubic SVMs gave better results than the linear SVM did. They also showed similar results when ADL data were added. These results suggest that quadratic and cubic SVMs were suitable for detecting the risk of falling in the preimpact period. In the case of the five types of classification without ADL, the best performance was 83.0% for the cubic SVM with a lead time of 0.50 sec and 87.9% with 0.25 sec when ADL was added. Regardless of the models, the accuracy of the classification tended to decrease as the lead time increased. The cubic SVM achieved approximately 80% classification accuracy when dealing only with falls in the range of 0.25 to 0.50 sec, except for 0.0 sec, which included the impact point. When the lead time was less than 0.50 sec, the addition of ADL resulted in a small number of the misclassification of fall causes, and the proposed method was able to reliably discriminate between falls and ADL.

DISCUSSION

In this study, data regarding falls were cut before the impact point to create a simulated preimpact fall period. We investigated whether the preimpact fall period could be classified according to the cause of the fall and whether the period could also be classified when ADLs were added. From the experimental results, it was possible to identify each fall factor during

Table 2. Types of causes of falls defined in this study[14)]

Type of fall	Code
Slip	F01–F03
Trip	F04, F05
Faiting	F06, F07, F13–F15
Get up	F08, F09
Sit down	F10–F12

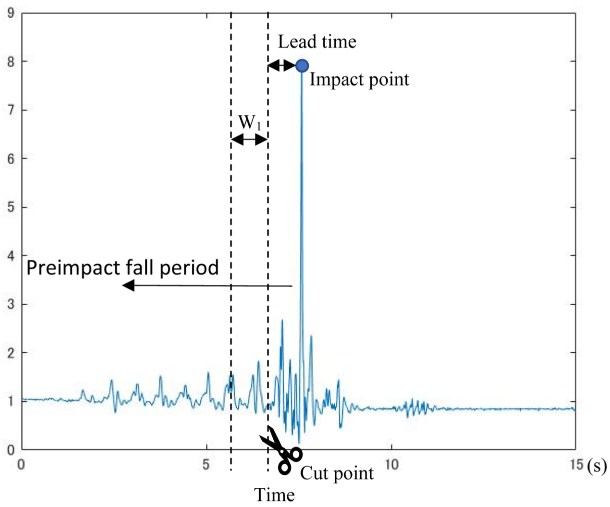

Fig. 2. Segment of the window in the preimpact fall state.

Table 3. The accuracy using only falls data (unit: %)

Lead time (sec)	5 type			15 type		
	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
0	71.8	78.9	79.2	68.9	75.2	76.7
0.25	73.2	80.3	82.9	66.6	74.5	76.1
0.5	75.6	82.8	83.0	64.8	73.3	74.3
0.75	74.8	80.4	82.6	59.2	67.9	67.9
1	74.1	79.9	81.0	56.2	61.1	63.1
1.25	73.8	77.5	79.0	52.0	58.9	61.1
1.5	72.2	77.4	78.7	50.0	56.0	58.4
1.75	68.1	75.5	77.0	46.8	52.8	54.9
2	64.3	71.3	74.0	41.3	48.5	50.4

Linear, Quadratic, and Cubic are the kernel type of support vector machine (SVM).

Table 4. The accuracy with activity of daily living (ADL) added (unit: %)

Lead time (sec)	5 type+ADL			15 type+ADL		
	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
0	85.4	89.5	90.0	84.3	87.5	88.4
0.25	77.9	87.4	87.9	77.8	84.3	85.4
0.5	74.7	83.7	84.8	72.2	79.7	80.0
0.75	74.0	80.3	81.9	68.9	76.3	76.8
1	72.0	79.4	79.9	65.9	71.7	72.7
1.25	71.6	77.2	78.2	63.2	70.0	71.3
1.5	70.6	75.6	76.8	61.2	68.8	70.1
1.75	68.3	73.9	75.3	59.5	65.7	67.0
2	66.8	71.3	72.7	57.8	64.2	65.2

Linear, Quadratic, and Cubic are the kernel type of support vector machine (SVM).

Table 5. The accuracy focusing only on falls (unit: %)

Lead time (sec)	5 type+ADL			15 type+ADL		
	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
0	71.3	78.7	80.0	68.6	74.9	76.8
0.25	62.5	78.3	79.6	59.3	70.7	73.6
0.5	60.0	74.9	79.5	49.6	64.3	66.2
0.75	58.1	71.1	74.3	43.3	58.9	60.7
1	53.8	69.0	70.7	36.1	50.5	53.6
1.25	53.0	64.7	68.2	30.2	46.4	50.1
1.5	52.2	61.6	65.8	25.3	44.0	48.5
1.75	48.3	59.3	63.6	20.6	37.4	41.9
2	44.1	54.1	59.4	15.0	32.7	37.7

Linear, Quadratic, and Cubic are the kernel type of support vector machine (SVM).
ADL: activity of daily living.

the preimpact fall period, with an accuracy of approximately 80% between 0.25 and 0.50 sec of lead time. The fact that the quadratic and cubic SVMs performed better than the linear SVM suggests that it was difficult to classify fall factors using a simple linear approach. The reason for this was that it was not possible to distinguish falls from ADL in a linear fashion, and it was desirable to set the boundaries of the classification in a higher dimension using a second- or third-order kernel function. Although the difference between the quadratic and cubic SVM was only a few percentage points, it could be said that the cubic SVM was a more suitable model for classification with the addition of ADL. Performance identifying only the fall data with a lead time of 0.25–1.0 sec was generally the same or better than performance with data including the impact point (lead time=0 sec). The classification was possible only in the window of the preimpact state (the impact point was not included). We believe there were differences in each factor, such as tripping or slipping, in that state. Therefore, even if an older person loses his or her balance and does not impact against the floor because of recovery actions, our method can detect and identify the cause of the preimpact fall.

In a previous study of preimpact detection, Wu et al.[10] proposed a system consisting of two sensors on the waist and thigh to classify three categories: nonfall, backward fall, and forward fall. In addition, using the Kinect, the preimpact fall detection system proposed by Xu et al. achieved 75% accuracy with a lead time of 333 msec[19]. Because these methods have limitations such as uncomfortableness and coverage area resulting from the use of multiple sensors, we believe that the proposed method has an advantage of having fewer limitations. The proposed method is more practical because it takes more fall patterns into account. However, because falls can lead to death, we believe that effective prevention requires a system with a reliability of 90% or greater[17], and the performance in this study was not enough for actual use in the care field. By detecting the differences in each factor leading to a fall and improving the accuracy of the classification, a care plan that suits the patient can be provided. In this study, we used the raw data of angular velocity and acceleration in each of the three axes as inputs. To discriminate the classification of falls with higher accuracy, it is necessary to increase the number of inputs. For example, inputs such as derivatives and norms, as well as additional features, are necessary. As the lead time became larger, the performance decreased when ADL was added. This result was similar to a previous study that compared the accuracy of preimpact falls[10]. This was due to the fact that as the cut point moved away from the impact point, the motion of the body became closer to ADL rather than a dangerous motion that caused a fall.

One limitation of this study is that we conducted the analysis using emulated falls, not actual falls. Therefore, the data might be different from that of an actual state of the preimpact fall. However, it has been shown that sensor data from real-life falls have similar characteristics to those from intentional falls[20], and these data are important for training machine learning models. Another limitation is that the participants in the data set used in this study were young. However, it is ethically difficult to conduct an experiment using actual falls in people who need care or in older adults. A model trained on healthy young people may not be suitable for them. Therefore, there remains a need for future investigations on the effect on classification accuracy using real-life data.

Our study showed that it is possible to classify falls by cause in preimpact falls. By improving the accuracy of the data, we believe that a monitoring system could be developed for individuals who require long-term care. By using the research results, the system identifies the causes of falls. Then, it will be possible to provide appropriate interventions to help those who need nursing care in order to avoid falls. For example, when the monitoring system based on our results notices a person is tripping frequently, a medical staff can instruct the person to improve foot clearance[21] or can suggest to change living environment and furniture design[11] such as no doorsill. We expect that, in the future, the risk of falls in a patient's life will be monitored, and from this information, appropriate care strategies will be provided to each individual.

Conference presentation

Part of this research was presented at 9th International Joint Symposium on Applied Engineering and Sciences (SAES2021).

Funding and Conflicts of interest

There are no conflicts of interest to be disclosed in this study.

REFERENCES

1) James MK, Victor MC, Saghir SM, et al.: Characterization of fall patients: does age matter? J Safety Res, 2018, 64: 83–92. [Medline] [CrossRef]
2) King MB, Tinetti ME: Falls in community-dwelling older persons. J Am Geriatr Soc, 1995, 43: 1146–1154. [Medline] [CrossRef]
3) Tamura S, Kobayashi M, Saito Y, et al. NS: Fall prediction using decision tree analysis in acute care units. J Phys Ther Sci, 2020, 32: 722–728. [Medline] [CrossRef]
4) Masuda S, Suganuma K, Kaneko C, et al.: Prediction of falls using a 3-m Zigzag Walk Test. J Phys Ther Sci, 2013, 25: 1051–1054. [Medline] [CrossRef]
5) Hachiya M, Murata S, Otao H, et al.: Usefulness of a 50-meter round walking test for fall prediction in the elderly requiring long-term care. J Phys Ther Sci, 2015, 27: 3663–3666. [Medline] [CrossRef]
6) Bourke AK, O'Brien JV, Lyons GM: Evaluation of a threshold-based tri-axial accelerometer fall detection algorithm. Gait Posture, 2007, 26: 194–199. [Medline] [CrossRef]
7) Özdemir AT, Barshan B: Detecting falls with wearable sensors using machine learning techniques. Sensors (Basel), 2014, 14: 10691–10708. [Medline] [CrossRef]
8) Khojasteh SB, Villar JR, Chira C, et al.: Improving fall detection using an on-wrist wearable accelerometer. Sensors (Basel), 2018, 18: 1350. [Medline] [CrossRef]
9) Bourke AK, O'Donovan KJ, Ólaighin G: The identification of vertical velocity profiles using an inertial sensor to investigate pre-impact detection of falls. Med Eng Phys, 2008, 30: 937–946. [Medline] [CrossRef]
10) Wu Y, Su Y, Feng R, et al.: Wearable-sensor-based pre-impact fall detection system with a hierarchical classifier. Measurement, 2019, 140: 283–292. [CrossRef]
11) Robinovitch SN, Feldman F, Yang Y, et al.: Video capture of the circumstances of falls in elderly people residing in long-term care: an observational study.

Lancet, 2013, 381: 47–54. [Medline] [CrossRef]
12) Mubashir M, Shao L, Seed L: A survey on fall detection: principles and approaches. Neurocomputing, 2013, 100: 144–152. [CrossRef]
13) Usmani S, Saboor A, Haris M, et al.: Latest research trends in fall detection and prevention using machine learning: a systematic review. Sensors (Basel), 2021, 21: 5134. [Medline] [CrossRef]
14) Sucerquia A, López JD, Vargas-Bonilla JF: SisFall: a fall and movement dataset. Sensors (Basel), 2017, 17: 198. [Medline] [CrossRef]
15) Casilari E, Santoyo-Ramón JA, Cano-García JM: Analysis of public datasets for wearable fall detection systems. Sensors (Basel), 2017, 17: 1513. [Medline] [CrossRef]
16) Özdemir AT: An analysis on sensor locations of the human body for wearable fall detection devices: principles and practice. Sensors (Basel), 2016, 16: 1161. [Medline] [CrossRef]
17) Liu K, Hsieh C, Huang H, et al.: An analysis of segmentation approaches and window sizes in wearable-based critical fall detection systems with machine learning models. IEEE Sens J, 2020, 20: 3303–3313. [CrossRef]
18) Amari S, Wu S: Improving support vector machine classifiers by modifying kernel functions. Neural Netw, 1999, 12: 783–789. [Medline] [CrossRef]
19) Xu T, Yun Z: Fall prediction based on biomechanics equilibrium using kinect. Urban Study, 2017, (April): 2366–2382.
20) Kangas M, Vikman I, Nyberg L, et al.: Comparison of real-life accidental falls in older people with experimental falls in middle-aged test subjects. Gait Posture, 2012, 35: 500–505. [Medline] [CrossRef]
21) Barrett RS, Mills PM, Begg RK: A systematic review of the effect of ageing and falls history on minimum foot clearance characteristics during level walking. Gait Posture, 2010, 32: 429–435. [Medline] [CrossRef]