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Discrimination of Fall and Fall-like ADL Using Tri-axial Accelerometer and Bi-axial Gyroscope

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Abstract

A threshold-based fall recognition algorithm using a tri-axial accelerometer and a bi-axial gyroscope mounted on the skin above the upper sternum was proposed to recognize fall-like activities of daily living (ADL) events. The output signals from the tri-axial accelerometer and bi-axial gyroscope were obtained during eight falls and eleven ADL action sequences. The thresholds of signal vector magnitude (SVM_Acc), angular velocity (ω_{res}), and angular variation (θ_{res}) were calculated using MATLAB. When the measured values of SVM_Acc, ω_{res}, and θ_{res} were compared to the threshold values (TH1, TH2, and TH3), fall-like ADL events could be distinguished from a fall. When *SVM_Acc* was larger than 2.5 g (TH1), ω_{res} was larger than 1.75 rad/s (TH2), and θ_{res} was larger than 0.385 rad (TH3), eight falls and eleven ADL action sequences were recognized as falls. When at least one of these three conditions was not satisfied, the action sequences were recognized as ADL. Fall-like ADL events such as jogging and jumping up (or down) have posed a problem in distinguishing ADL events from an actual fall. When the measured values of SVM_Acc, ω_{res}, and θ_{res} were applied to the sequential processing algorithm proposed in this study, the sensitivity was determined to be 100% for the eight fall action sequences and the specificity was determined to be 100% for the eleven ADL action sequences.

Keywords: Fall recognition, Activities of daily living (ADL), Fall-like ADL, Tri-axial accelerometer, Bi-axial gyroscope

1. ITRODUCTION

Falls and unstable balance rank high among serious clinical problems faced by older adults [1]. A fall is a common and devastating clinical problem faced by the elderly, resulting in injury, physical disability, high rates of skilled nursing home placement, expensive medical costs, and loss of patient confidence leading to voluntary restriction of activity [2]. Falls may cause damage to soft tissues, joints, bone fracture, and can even lead to death [3]. In addition, traumatic experiences from falls can induce fear and anxiety, leading to a loss of self-confidence and depression. In order to overcome these problems, researches have been actively undertaken to monitor walking patterns and postural changes during activities of daily living (ADL: routine activities such as eating, bathing , dressing, toiling, transferring (walking) and continence that people tend to do every day without needing assistance) and falls. Several fall detection methods using video and acoustic sensors [3-5], accelerometers [6,7], and gyroscopes [8,9] have been performed. Among them, a tri-axial accelerometer and a bi-axial gyroscope have been widely used owing to their good performance in terms of high accuracy and reproducibility, despite a relatively low price. Najafi et al. attached sensors to different parts of the body to monitor falls and ADL events of the elderly [10]. A postural change detection sensor module (PCDSM) was developed to investigate postural changes and movement patterns in ADL events and falls [11]. Bourke et al. and Kangas et al. studied the effect of the position of tri-axial accelerometer on the accuracy of fall-recognition. Bourke et al. announced the chest to be the best position for attaching the tri-axial accelerometer [12], whereas Kangas et al. reported the waist to be the best position [13]. Other researchers too suggested the chest (or trunk) to be a suitable position for attaching fall-detection sensors [14]. Although these researches have been conducted extensively, actions involving rapid motion with a large impact, such as jogging and jumping up (or down), have not been accurately discriminated as ADL by fall recognition sensors yet.

In this study, a threshold-based fall recognition algorithm using

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a tri-axial accelerometer and a bi-axial gyroscope mounted on the skin above the upper sternum was proposed to recognize fall-like ADL events without false alarms. When the measured values of *SVM_Acc*, ω_{res}, and θ_{res} were compared with the thresholds (TH1, TH2, and TH3), fall-like ADL events could be distinguished from fall events. In addition, when the measured values of *SVM_Acc*, ω_{res}, and θ_{res} were applied to the sequential processing algorithm, the sensitivity was determined to be 100% for eight fall action sequences and the specificity was determined to be 100% for eleven ADL (including three fall-like ADL) action sequences.

2. EXPERIMENTAL

2.1 Signal vector magnitude

The signal vector magnitude (*SVM_Acc*) is obtained by summing the signal vectors acquired from the tri-axial accelerometer. The parameter *SVM_Acc* is effective in detecting actions, such as a fall, accompanied by a large impact. When an object hits the floor or an obstacle during the fall, a large impact is generated upon collision.

Karantonis et al. proposed the *SVM* for detecting a fall according to the following formula [15]:

$$\mathrm{SVM} = \sqrt{x_i^2 + y_i^2 + z_i^2}\,, \tag{1}$$

where x_i denotes the acceleration signal in the front/back direction, y_i denotes the acceleration signal in the left/right direction, and z_i denotes the acceleration signal in the upper/lower direction.

2.2 Angular velocity and angular variation

The average angular velocity (ω) of the body in a time interval of $\Delta t = t_2 - t_1$ is defined as the time ratio of the angular displacement $\Delta_\theta = \theta_2 - \theta_1$ to Δt

$$\omega_p = \frac{d\theta_p}{dt} \text{ and } \omega_r = \frac{d\theta_r}{dt}\,, \tag{2}$$

where ω_p is the angular velocity of the pitch signal generated in the front/back direction and ω_r is the angular velocity of the roll signal generated in the left/right direction.

The resultant vector of the angular velocity (ω_{res}) is derived by obtaining the root-sum-of-squares of ω_p and ω_r according to the following formula.

$$\omega_{res} = \sqrt{\omega_p^2 + \omega_r^2} \tag{3}$$

The rotational angles (θ_p, θ_r) in the pitch and roll directions can be obtained by integrating the angular velocity along the pitch and roll axes. Thus, θ_p and θ_r are expressed as follows.

$$\theta_p = \int \omega_p \,\mathrm{dt} \text{ and } \theta_r = \int \omega_r \,\mathrm{dt} \tag{4}$$

The resultant angle variation (θ_{res}) of a rotating body can be expressed as

$$\theta_{res} = \sqrt{\theta_p^2 + \theta_r^2}\,, \tag{5}$$

The resultant maximum angle of rotation can be represented as

$$\theta_{Max} = \mathrm{Max}\left(\theta_{res}\Big|_{t_1=-0.5\mathrm{s}}^{t_2=+0.5\mathrm{s}}\right), \tag{6}$$

where t_1 is -0.5 s and t_2 is +0.5 s before and after the fall, respectively.

2.3 Fall and ADL recognition algorithm

Falls and ADL action sequences can be distinguished by sequentially comparing the mean ± SD of *SVM_Acc*, ω_{res}, and θ_{res} with the thresholds (TH1, TH2, and TH3), respectively. Fig. 1 shows the fall and ADL recognition algorithm proposed in this experiment. The thresholds of *SVM_Acc*, ω_{res}, and θ_{res} were set to 2.50 g, 1.75 rad/s, and 0.385 rad, respectively [16]. The thresholds were obtained by attaining the average of the minimum values of falls and the maximum values of ADL events [17]. The fall and ADL recognition algorithm is described as follows. First, when *SVM_Acc* is larger than TH1 (2.50 g), ω_{res} is larger than TH2 (1.75 rad/s), and θ_{res} is larger than TH3 (0.385 rad), eight falls and eleven ADL action sequences are recognized as falls. Second,

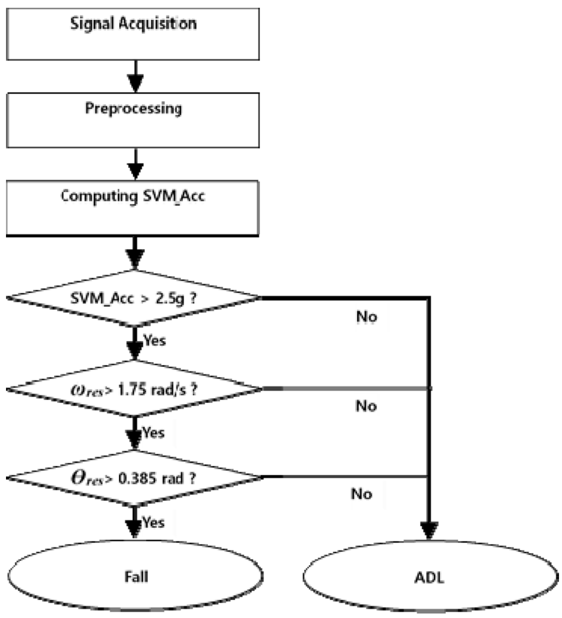


Fig. 1. Flowchart of a sequential processing algorithm proposed for fall and ADL recognition.

when *SVM_Acc* is smaller than TH1 (2.50 g), ω_{res} is smaller than TH2 (1.75 rad/s), and θ_{res} is smaller than TH3 (0.385 rad), these action events are recognized as ADL events. Third, when *SVM_Acc*, ω_{res}, and θ_{res} values are larger or smaller than the thresholds (TH1, TH2, and TH3), respectively, these action events are recognized as falls or ADL events according to a sequential processing algorithm

2.4 Experimental protocol

Table 1 shows the experimental protocol proposed in this study. The experimental protocol can be divided into two categories: falls and ADL.

2.5 Sensitivity and specificity

The fall detection sensitivity was measured for eight fall types separately, resulting in 200 samples. In order to measure the fall detection specificity, ADL samples were combined, resulting in 275 samples. The sensitivity represents the percentage of correctly detected fall events among the total number of events. The specificity represents the percentage of correctly detected ADL events among the total number of events. Using these definitions,

Table 1. Experimental protocol of falls and ADL action sequences

Protocol	Action Sequence	Abbreviation
Fall	Walking_right falls	W_RF
	Walking_left falls	W_LF
	Walking_forward falls	W_FF
	Walking_backward falls	W_BF
	Standing_right falls	S_RF
	Standing_left falls	S_LF
	Standing_forward falls	S_FF
	Standing_backward falls	S_BF
ADL	Standing_sit on the floor_standing	S_sOF_S
	Sitting_lying on the floor_sitting	s_LOF_s
	Standing_lying on the bed_standing	S_LOB_S
	Standing_sit on the chair_standing	S_sOC_S
	Standing_slow walking (60 - 70 step/min.)_standing	S_SW_S
	Standing_normal walking (80 - 90 step/min.)_standing	S_NW_S
	Standing_walking using cane (40 - 50 step/min.)_standing	S_WC_S
	Standing_jogging (5 ~ 6 step/s)_ standing	S_Jo_S
	Standing_jump up (25 ~ 30 cm)_standing	S_Ju_S
	Standing_jump down (40 ~ 45 cm)_standing	S_Jd_S
	Standing_up stairs_down stairs_standing	S_US_DS_S

the sensitivity and specificity can be expressed as follows [18]:

$$\text{Sensitivity} = \frac{TP}{TP+FN} \times 100\,, \tag{7}$$

$$\text{Specificity} = \frac{TN}{TN+FP} \times 100\,, \tag{8}$$

where TP is a true positive (fall action events recognized as a fall), FN is a false negative (fall action events misrecognized as ADL), TN is a true negative (ADL action events recognized as ADL), and FP is a false positive (ADL action events misrecognized as a fall).

2.6 Subjects

In order to evaluate the validity of the fall and ADL recognition sequential algorithm presented in Fig. 1, experiments were carried out repeatedly after establishing the experimental protocol described in Table 1. The subjects were five healthy males with an average age of 27.5 (±2.5 years), average height of 173 cm (±3.2 cm), and average weight of 75 kg (±4.1 kg). It is important to distinguish between fall and fall-like ADL for the elderly. However, it is dangerous for the elderly to fall actually. So young subjects performed simulated fall and fall-like ADL action sequences on thick mattress instead. The purpose and experimental method of the study was fully explained to the subjects before the experiment, and informed written consents were obtained from each subject.

Each subject performed eight fall action sequences on thick mattress and each fall was repeated five times; thus, each subject performed 40 falls. Fig. 2 (a) shows the 3-axis acceleration and 2-axis gyroscope mounted on the sternum. Fig. 2 (b) shows the fall state in which a subject fell down in the backward from the standing position on the mattress. Since there were five subjects, fall recognition experiments were all carried out 200 times. Furthermore, ADL experiments were executed repeatedly. Each subject performed eleven ADL action sequences on thick mattress,

(a) (b)

Fig. 2. (a) Tri-axial accelerometer and bi-axial gyroscope attached to the sternum. (b) Simulated fall (backward) action sequence performed by young subject on mattress.

and each ADL was repeated five times; thus, each subject performed 55 ADL sequences. Since five subjects participated in the experiment, ADL action event experiments were performed 275 times.

3. RESULT AND DISCUSSION

3.1 SVM_Acc parameter

After attaching a tri-axial accelerometer to the skin above the sternum, experiments were conducted according to the experimental protocol described in Table 1. The values of *SVM_Acc* were obtained by substituting the data acquired from the tri-axial accelerometer into Eq. (1). The threshold (TH1) for distinguishing eight falls and eleven ADL events was set to 2.50 g. Fig. 3 shows the mean ± SD of *SVM_Acc* for eight falls and eleven ADL actions. The sensitivity was determined to be 100% for eight falls. However, the tri-axial accelerometer on the sternum could not accurately discriminate five ADL actions - S_LOB_S, S_sOC_S, S_Jo_S, S_Ju_S, and S_Jd_S. These five action sequences were misrecognized as falls because they produced a large *SVM_Acc* accompanying an instantaneous impact exceeding TH1 (2.50 g). Thus, five of the eleven action sequences were misrecognized as falls (i.e., with a specificity of 54.54%).

Fig. 4 shows the measured signals of *SVM_Acc* exceeding TH1 (2.5 g) for five ADL actions, which were misrecognized as falls in Fig. 3. When sitting or lying on an elastic surface, such as a bed, a fall-like event is unlikely to be produced. However, in certain circumstances, peak acceleration can occur because the body has relatively high kinetic energy. After initial contact with the surface, kinetic energy is dissipated very slowly, resulting in several smooth peaks along the acceleration trace graph. As

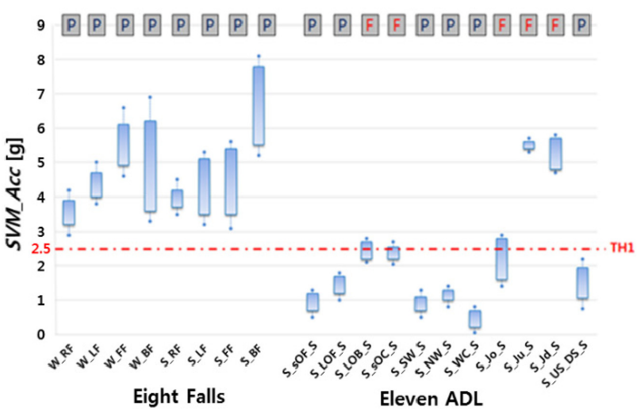


Fig. 3. Mean ± SD of *SVM_Acc* for eight falls and eleven ADL action sequences.

shown in Fig. 4 (a), there is a peak higher than 2.5 g followed by several oscillations. A similar pattern of oscillation can be observed in the case of soft surfaces, such as a chair. In this case,

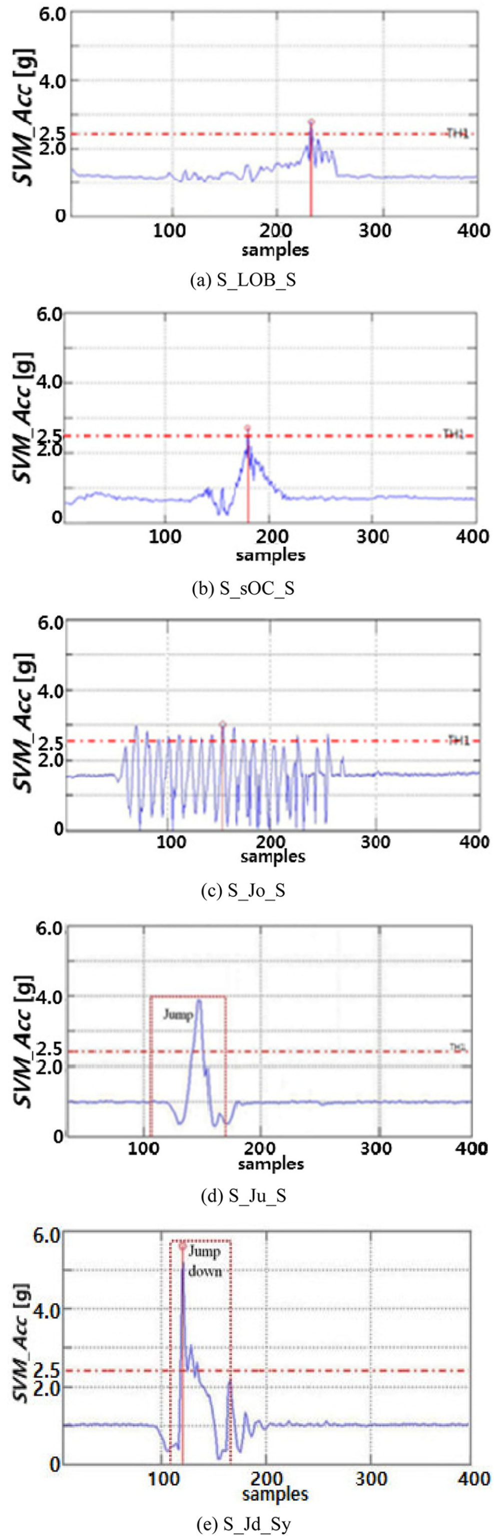


Fig. 4. Measured signals of SVM_Acc (g) for five ADL actions misrecognized as falls in Fig 3: (a) S_LOB_S, (b) S_sOC_S, (c) S_Jo_S, (d) and (e) S_Ju_S and S_Jd_S.

the first peak is generally very smooth, subsequently followed by smaller peaks. In contrast, Fig. 4 (b) shows that sitting on a hard surface like a chair often produces a fall-like event. When the subject sits or lies down on elastic/soft surfaces, the acceleration magnitude stabilizes with slow oscillations. In contrast, when the subject sits or lies down on hard surfaces, the acceleration magnitude quickly stabilizes with a few oscillations. As illustrated in Fig. 4 (c), jogging can be modeled as small jump. When free phases between steps are shorter, landing peaks are often made of two or more overlapped sub-peaks owing to the landing foot starting a new leap [19]. As shown in Figs. 4 (d-e), jumping up and down leads to a relatively high peak acceleration exceeding TH1 (2.5 g). The jumping motion is accompanied by a distinctive acceleration pattern that can be easily identified. As illustrated in Fig. 4 (d), the acceleration magnitude was smaller than 1 g when the subject leaped to execute the jumping up motion. When the subject reached the ground after jumping, the magnitude of acceleration increased to approximately 4 g. This was subsequently followed by oscillations, as the body stabilized itself. As shown in Fig. 4 (e), the acceleration magnitude was decreased to smaller than 1 g when the subject drew back to execute the jumping down motion. When the subject landed on the ground, the magnitude of acceleration was greatly increased (5.7 g) owing to high kinetic energy. The motion was followed by subsequent oscillations as the body stabilized itself.

3.2 Angular velocity and angle variation

Fig. 5 shows the mean ± SD of ω_{res} for eight falls and eleven ADL actions. The values were obtained by applying the data acquired from the bi-axial gyroscope to Eq. (3). The threshold (TH2) of ω_{res} for differentiating between falls and ADL events was set to 1.75 rad/s. The sensitivity was 100% for eight falls. On the other hand, ω_{res} could not accurately discriminate four ADL actions - s_LOF_s, S_Jo_S, S_Ju_S, and S_Jd_S - among the eleven ADL action sequences. Accordingly, these four ADL actions were misrecognized as falls, resulting in a specificity of 63.64%. Action sequences such as s_LOF_s produced a momentary rotational motion exceeding TH2 (1.75 rad/s).The actions S_Jo_S, S_Ju_S, and S_Jd_S were misrecognized as falls owing to the instantaneous angular velocity despite small rotational motions.

Fig. 6 shows the measured signal values of ω_{res} exceeding TH2 (1.75 rad/s) for four ADL action sequences, which were misrecognized as falls in Fig. 5. In Fig. 6 (a), when the glute region of subject touched the floor, a large angular velocity exceeding TH2 was generated, which in turn generated a

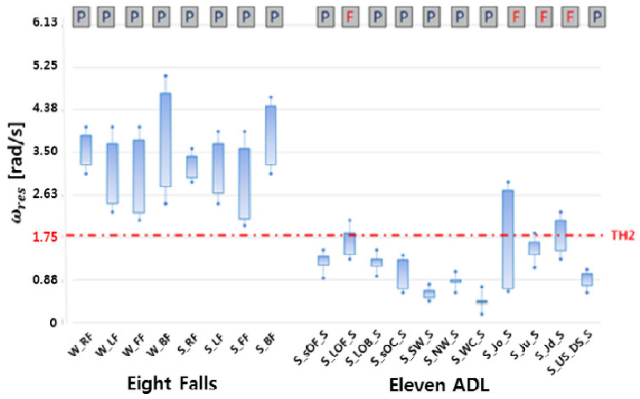
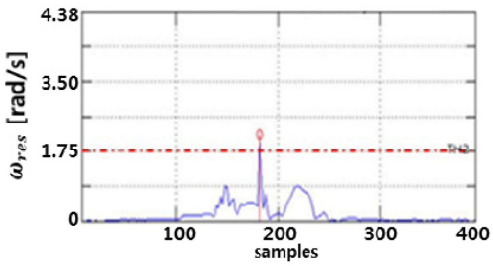


Fig. 5. Mean ± SD of ω_{res} for eight falls and ADL action sequences.

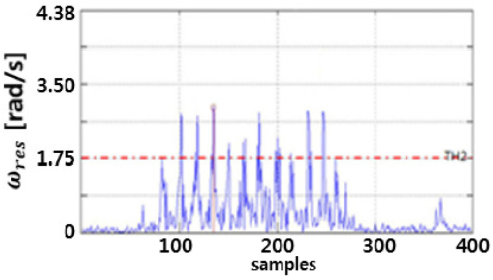
rotational motion. In Fig. 6 (b), during jogging, large angular velocities exceeding TH2 were repeatedly generated whenever the feet touched the ground. After executing the jumping up motion in Fig. 6 (c), a small angular velocity was generated when the forefeet touched the ground, whereas a large angular velocity was generated when the heels touched the surface. After executing the movement, the body subsequently stabilized itself, resulting in a low and wide angular velocity trace. After executing the jumping down motion in Fig. 6 (d), a small angular velocity (0.88 rad/s) was generated when the forefeet touched the ground. When the feet were completely in contact with the ground, they caused a large angular velocity exceeding TH3. The peak angular velocity caused by the jumping down was higher compared to that caused by the jumping up because jumping down from a high position (40 - 45 cm) increased the rotational kinetic energy as the subject touched the ground. In addition, the peak angular velocity shown in Fig. 6 (d) was broader than that shown in Fig. 6 (c) because the human body attempts to minimize the force of impact by reacting flexibly and increasing the contact time with the surface. Subsequently, movement was caused as the body stabilized itself.

Fig. 7 shows the mean ± SD of θ_{res} for eight falls and eleven ADL action events. The data from a bi-axial gyroscope was substituted into Eq. (5) in order to acquire these values. The threshold (TH3) of θ_{res} for differentiating between falls and ADL actions was set to 0.385 rad. The sensitivity was determined to be 100% for eight falls. ADL actions such as s_LOF_s and S_LOB_S were misrecognized as falls (with a specificity of 81.82%), since these action sequences were accompanied by a large angular motion. However, when θ_{res} was compared to TH3 (0.385 rad), S_Jo_S, S_Ju_S, and S_Jd_S action sequences, which were reported to be indistinguishable from a fall [17, 19], were correctly recognized as ADL events.

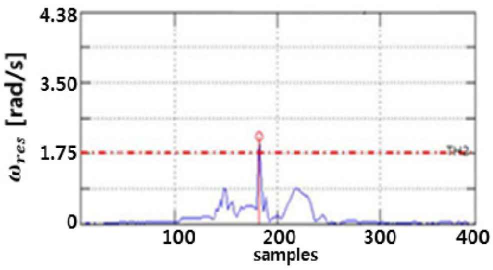
Fig. 8 shows the measured signal values of θ_{res} - exceeding TH3



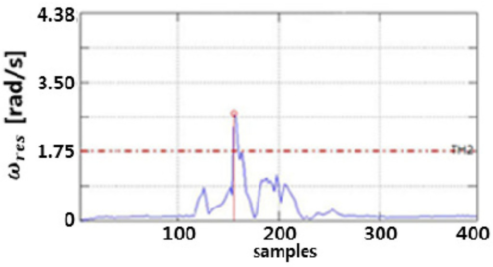
(a) s_LOF_s



(b) S_Jo_S



(c) S_Ju_S



(d) S_Jd_S.

Fig. 6. Measured signals of ω_{res} for four action sequences misrecognized as falls in Fig. 5: (a) s_LOF_s, (b) S_Jo_S, (c) S_Ju_S, and (d) S_Jd_S.

(0.385 rad) for the action sequences s_LOF_s and S_LOB_S misrecognized as falls in Fig. 7. Fig. 8 (a) shows θ_{res} of the body as the subject lies down on the floor from a sitting position. The large change in θ_{res} was caused in a relatively short time was caused by the rotational motion with a small range. The parameter θ_{res} was almost matained at a constant value after the subject reached the maximum angle. Fig. 8 (b) shows θ_{res} of the body as the subject lies down on a bed from a standing position. The large change in θ_{res} in a relatively long time period was caused by the rotational motion with a large range. After reaching the maximum

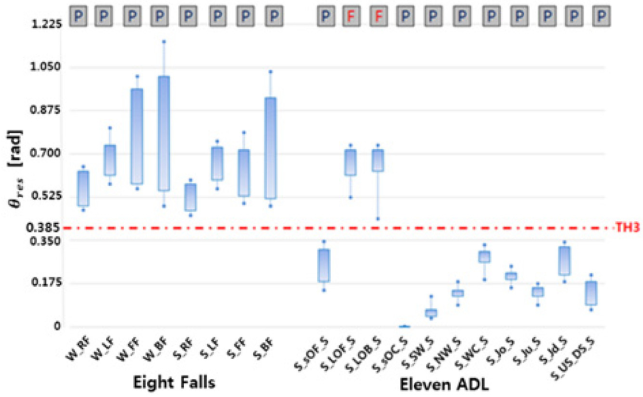
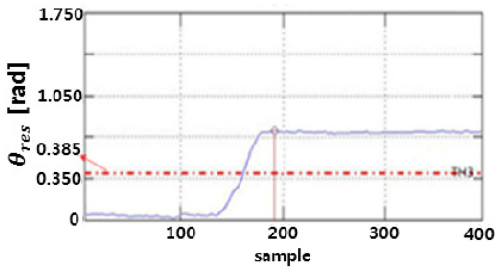
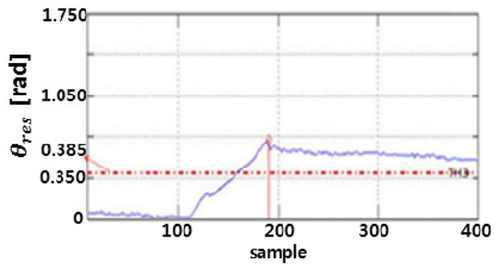


Fig. 7. Mean ± SD of θ_{res} for eight falls and eleven ADL action events.



(a) s_LOF_s



(b) S_LOB_S

Fig. 8. Measured signal values of θ_{res} for two action sequences misrecognized as falls in Fig. 7: (a) s_LOF_s and (b) S_LOB_S.

angle, θ_{res} gradually decreased, accompanied by oscillations.

When a tri-axial accelerometer and a bi-axial gyroscope were simultaneously used for discriminating between falls and ADL events, some of the eleven ADL action sequences were misrecognized as falls. For example, when *SVM_Acc* values were compared with TH1, the action sequences S_LOB_S, S_sOC_S, S_Jo_S, S_Ju_S, and S_Jd_S were misrecognized as falls. When ω_{res} values were compared with TH2, the action sequences S_LOF_s, S_Jo_S, S_Ju_S, and S_Jd_S were misrecognized as falls. When θ_{res} values were compared with TH3, the action sequences S_LOF_s and S_LOB_S were misrecognized as falls.

In order to recognize these action sequences accurately, the proposed fall and ADL recognition algorithm (Fig. 1) was applied to the experimental protocol (Table 1). Table 2 shows the experimental results for eight falls and eleven ADL action sequences. For the eight fall action sequences, P (pass) indicates that the value of *SVM_Acc* is larger than TH1 (2.50 g), the value of ω_{res} is larger than TH2 (1.75 rad/s), and the value of θ_{res} is larger than TH3 (0.385 rad). When at least one of these values is lower than the corresponding threshold value, this action sequence is denoted as F (false). On the other hand, for the eleven ADL action sequences, P (pass) indicates that the value of *SVM_Acc* is lower than TH1 (2.50 g), the value of ω_{res} value is lower than TH2 (1.75 rad/s), and the value of θ_{res} is lower than TH3 (0.385 rad). When at least one of these values is larger than the corresponding threshold value, this action sequence is denoted as F (false).

The description of Table 2 is as follows.

First, when the values of *SVM_Acc*, ω_{res}, and θ_{res} for eight falls action sequences were compared with the thresholds (TH1, TH2, and TH3), respectively, the eight fall action sequences were recognized as falls.

Second, when the values of *SVM_Acc* for the eleven ADL action sequences were compared with TH1, the action sequences S_LOB_S, S_sOC_S, S_Jo_S, S_Ju_S, and S_Jd_S were misrecognized as falls. However, when the value of ω_{res} for these five actions were compared with TH2, the action sequences S_LOB_S and S_sOC_S were correctly recognized as ADL events. In addition, when the values of θ_{res} for the action sequences S_Jo_S, S_Ju_S, and S_Jd_S were compared with TH3, these actions were correctly recognized as ADL events.

Third, when the values of ω_{res} for the eleven ADL action sequences were compared with TH2, the action sequences S_LOF_s, S_Jo_S, S_Ju_S, and S_Jd_S were misrecognized as falls. However, when the value of *SVM_Acc* for the action sequence S_LOF_s was compared with TH1, this action was recognized as ADL. When the values of θ_{res} for the action sequences S_Jo_S, S_Ju_S, and S_Jd_S were compared with TH3, these actions were recognized as ADL.

Fourthly, when the value of θ_{res} for the eleven ADL action sequences were compared with TH3, the action sequences S_LOF_s and S_LOB_S were misrecognized as falls. However, S_LOF_S was recognized as ADL by *SVM_Acc* and S_LOB_S was recognized as ADL by ω_{res}.

When the values of *SVM_Acc*, ω_{res}, and θ_{res} values for the eight falls and eleven ADL action sequences were sequentially applied to the algorithm in Fig. 1, the sensitivity and the specificity of these actions were determined as follows. When *SVM_Acc* was compared with TH1, the sensitivity was 100% for the eight fall action sequences and the specificity was 54.54% for the eleven ADL action sequences. When ω_{res} was compared with TH2, the sensitivity was 100% for the eight fall actions and the specificity was 63.63% for the eleven ADL actions. When θ_{res} was compared with TH3, the sensitivity was 100% for the eight fall types and the specificity was 81.81% for the eleven ADL types. However, when *SVM_Acc*, ω_{res}, and θ_{res} were applied sequentially to the thresholds (TH1, TH2, and TH3) according to the sequential processing algorithm proposed in this study, the sensitivity for the eight falls and the specificity for the eleven ADL events were both 100%.

Table 2. Experimental results when the fall and ADL recognition algorithm in Fig. 1 was applied to the experimental protocol in Table 1.

	Action Sequences	*SVM_Acc*	ω_{res}	θ_{res}	Results of SPA
Falls	W_RF	P	P	P	P
	W-LF	P	P	P	P
	W_FF	P	P	P	P
	W_BF	P	P	P	P
	S_RF	P	P	P	P
	S_LF	P	P	P	P
	S_FF	P	P	P	P
	S_BF	P	P	P	P
ADLs	S_sOF_S	P	P	P	P
	S_LOF_s	P	F	F	P
	S_LOB_S	F	P	F	P
	S_sOC_S	F	P	P	P
	S_SW_S	P	P	P	P
	S_NW_S	P	P	P	P
	S_WC_S	P	P	P	P
	S_Jo_S	F	F	P	P
	S_Ju_S	F	F	P	P
	S_Jd_S	F	F	P	P
	S_US_DS_S	P	P	P	P

-SPA: Sequential Processing Algorithm

4. CONCLUSIONS

In order to distinguish between falls and ADL events, many researches have been actively undertaken to monitor the walking patterns and postural changes in ADL events and falls. Several fall detection methods using video and acoustic sensors, tri-axial accelerometer, bi/tri-axial gyroscope, a combined sensor module with tri-axial accelerometer and bi/tri-axial gyroscope, and a fall recognition algorithm have been studied so far. Despite these studies, fall-like ADL events, such as jogging and jumping up (or down), have not been accurately distinguished from real falls.

In this study, a threshold-based fall recognition algorithm using a tri-axial accelerometer and a bi-axial gyroscope mounted on the skin above the upper sternum was proposed to recognize fall-like ADL events without false alarms. When the measured values of SVM_Acc, ω_{res}, and θ_{res} were compared with the thresholds (TH1, TH2, and TH3), fall-like ADL events could be distinguished from fall events. In particular, when the measured values of SVM_Acc, ω_{res}, and θ_{res} were applied to the sequential processing algorithm, the sensitivity was determined to be 100% for the eight fall action sequences and the specificity was determined to be 100% for eleven ADL (including three fall-like ADL) action sequences.

The limitation of this study is as follows. When performing fall and fall-like ADL action sequences, the elderly could pose a risk. So young subjects performed simulated action sequences on mat instead. However, the elderly cannot control their own body flexibly due to the aging of the body's musculoskeletal system, so the data may be significantly different when the elderly perform fall and fall-like ADL action sequences than the young do. In the future, it will be possible to obtain more fall-related data similar to the actual situation if the experiment is conducted safely for the elderly.

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