smartphone were compared with those obtained by a conventional accelerometer.

Subjects and Methods

SUBJECTS

Students at Kyoto University were recruited as subjects for this study. 17 men and 13 women volunteered, none of whom reported present or previous diseases or injuries associated with gait and/or balance impairments. Informed consent was obtained from all subjects prior to their participation, in accordance with the guidelines approved by the Kyoto University Graduate School of Medicine (approval number E1095) and the Declaration of Human Rights, Helsinki, 1975.

TEST PROCEDURES

The subjects were instructed to walk on a 25-m smooth, horizontal walkway, with a 2.5-m space at each end of the walkway for acceleration and deceleration. Thus, measurements were performed over a distance of 20 m. Subjects walked the length of this walkway three times at their preferred speeds, wearing shoes that did not influence their gait.

APPARATUS

We used two kinds of acceleration measurement terminals: One equipped with a smartphone (Xperia SO-01B, Android™ operating system version 2.1, 139 g, 119×60×13.1 mm, Sony Ericsson Co., Japan) and the other equipped with a tri-axial accelerometer (model WAA-006, 17 g, 38×39×10 mm, ATR-Promotions Co., Japan). The smartphone and the tri-axial accelerometer were taped together. With the method used by Moe-Nilssen and Helbostad,[10] the terminals were secured over the L3 region, which is close to where the body's center of mass is believed to be located during quiet standing. We developed a gait analysis application and installed it in the smartphone to measure the acceleration of the terminal. This application measured the acceleration of an Android smartphone and immediately displayed the gait analysis results on the smartphone's screen. In our gait analysis, the sampling rate of acceleration measurement for the smartphone was set at SENSOR_DELAY_FASTEST, which is the highest mode listed in the specifications for an Android smartphone. Because the sampling rate was not constant, we adjusted the sampling rate of the acceleration measurement in the smartphone to 0.03 s during interpolation. In total, 256 samples (7.68 s) of acceleration data were obtained from each measurement terminal and analyzed. For the same reasons as above, the sampling rate of the tri-axial accelerometer was set to 0.03 s.

DATA PROCESSING

We selected the following gait parameters, according to previous studies: peak frequency (PF),[11] root mean square (RMS),[10] autocorrelation peak (AC),[11,12] and the coefficient of variance (CV) of the acceleration peak intervals.[13,14]

The PF value indicates the gait cycle, which is the time taken for one step. The RMS value indicates the degree of gait instability; thus, a higher RMS value indicates a lower degree of stability. The AC value indicates the degree of gait balance, so a higher AC value indicates a greater degree of balance. The CV value indicates the degree of gait variability (i.e., the variability in the elapsed time between the first contacts of two consecutive footfalls). To calculate the gait parameters, we used the absolute values of the tri-axial acceleration data to decrease the influence of the measurement terminal posture. Let $a_{t_1:t_n} = a_{t_1}, a_{t_2}, \ldots, a_{t_n}$ denote the set of all acceleration absolute values acquired from time t_1 to t_n, for $t_1 \leq t_n$. Let a_t and n, respectively, denote the acceleration absolute value at time t and the number of all acceleration absolute values acquired from time t_1 to t_n.

PF DETECTION PROCEDURE

The PF f_p of acceleration data $a_{t_1:t_n}$ was detected with high accuracy based on the PF candidate f_p', which was detected from the smoothed acceleration data in order to decrease the influence of the high-frequency measurement noise that accompanied PF detection. The PF detection procedure is shown in *Figure 1*. First, acceleration data $a_{t_1:t_n}$ were smoothed using a low-pass filter. Second, the PF candidate, f_p', was detected where the power spectrum at frequency f_p' was the highest peak in the frequency space to which the smoothed acceleration data were converted by fast Fourier transformation. Finally, PF f_p was detected in the frequency space to which acceleration data $a_{t_1:t_n}$ were converted, where the power spectrum of PF f_p had the highest peak around PF candidate f_p'.

PROCEDURE FOR CALCULATION OF RMS

The RMS of acceleration data $a_{t_1:t_n}$ was calculated as follows:

$$RMS = \left(\frac{\int_{t_1}^{t_n} a(t)^2 dt}{t_n - t_1} \right)^{\frac{1}{2}}$$

Here, let t_1 and t_n, respectively, denote the start time and the stop time of our gait analysis measurement.

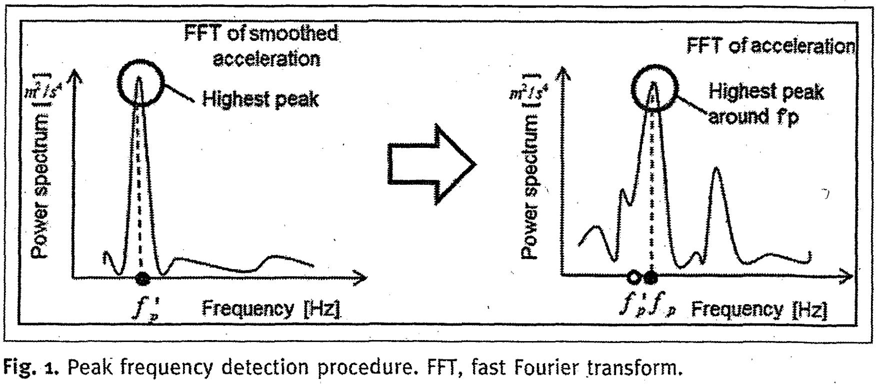

Fig. 1. Peak frequency detection procedure. FFT, fast Fourier transform.

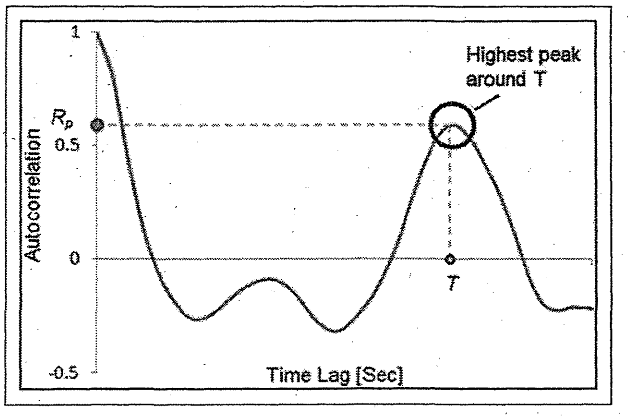

Fig. 2. Autocorrelation peak detection procedure.

PROCEDURE FOR DETECTION OF AC

The procedure for detection of AC is shown in *Figure 2*. AC R_p from the autocorrelation function was detected by using PF f_p. This allowed us to detect AC R_p with a high degree of accuracy, based on the hypothesis that the gait cycle is related to the time lag of when AC detection.[10] The AC detection method was follows. First, the autocorrelation function was calculated from the acceleration data. $a_{t_1:t_n}$. The autocorrelation function was represented by the sequence of the following autocorrelation coefficients $R_{xx}(k)$ over increasing time lags k:

$$R_{xx}(k) = \frac{1}{n-k} \sum_{i=1}^{n-k} x_{t_i} x_{t_{i+k}}$$

Here, let x_t denote the normalized acceleration data, which was calculated by both the mean a_{MEAN} and standard deviation a_{SD} of the acceleration data $a_{t_1:t_n}$; that is,

$$x(t) = \frac{a(t) - a_{\mathrm{MEAN}}}{a_{\mathrm{SD}}}$$

Let n denote the number of acceleration data samples in our gait analysis. Finally, AC R_p was detected as the highest peak around the lag related to gait cycle $T\,(=1/f_p)$.

PROCEDURE FOR CALCULATION OF CV

The CV was calculated by using the group of positive peak time candidates detected in the smoothed acceleration data. This reduced the influence of the high-frequency measurement noise that accompanied positive peak detection. Here, the positive peak indicated the acceleration data with a positive convex shape on the acceleration waveform. First, acceleration data $a_{t_1:t_n}$ were smoothed using a low-pass filter. Second, each positive peak on the smoothed acceleration waveform was detected as a group of positive peak candidates. These measured times were extracted as a group of positive peak time candidates. Third, each positive peak of acceleration data $a_{t_1:t_n}$ was detected where each peak was the highest around each positive peak time candidate on the acceleration waveform. The time intervals between the neighboring positive peaks were then calculated. Finally, the CV was calculated from the mean t_{MEAN} and standard deviation t_{SD} of time intervals, as follows:

$$\frac{t_{\mathrm{SD}}}{t_{\mathrm{MEAN}}}$$

STATISTICAL ANALYSIS

The test–retest reliability of the gait analysis performed using the smartphone was assessed using the ICCs ($\mathrm{ICC}_{1,1}$) of the values of the gait parameters obtained by the smartphone (PF, RMS, AC, and CV). The criterion-related validity was determined by evaluating the correlation between the gait parameters obtained by the smartphone and the tri-axial accelerometer using Spearman's correlation coefficient r. Data were recorded and analyzed using the Statistical Package for the Social Sciences (Windows version 19.0). Statistical significance was considered at $p<0.01$.

Results

SUBJECT CHARACTERISTICS

The subjects were between 18 and 27 years old, with a mean age of 20.9 ± 2.1 years. The mean height and weight were 167.3 ± 7.8 cm and 60.4 ± 7.7 kg, respectively. The mean gait speed and cadence were 1.41 ± 0.03 m/s and 121.03 ± 1.35 steps/min, respectively.

TEST–RETEST RELIABILITY

Remarkable consistency was observed in the test–retest reliability of all the gait parameter results obtained by the smartphone ($p<0.001$): PF $\mathrm{ICC}_{1,1}=0.906$, 95% confidence interval (CI) 0.83–0.95; RMS $\mathrm{ICC}_{1,1}=0.902$, 95% CI 0.82–0.95; AC $\mathrm{ICC}_{1,1}=0.752$, 95% CI 0.55–0.87; and CV $\mathrm{ICC}_{1,1}=0.777$, 95% CI 0.59–0.89.

CRITERION-RELATED VALIDITY

The acceleration waveforms of the smartphone and tri-axial accelerometer are shown in *Figure 3*. All gait parameter results obtained by the smartphone showed considerable and statistically significant correlations with those obtained by the tri-axial accelerometer ($p<0.01$) (*Table 1*).

Discussion

The results of this study indicate that the gait parameters obtained by the smartphone are reliable. Furthermore, the smartphone and the tri-axial accelerometer showed similar acceleration waveforms (*Fig. 3*). The parameters obtained by the smartphone were considerably correlated with those obtained by the tri-axial accelerometer. Thus, the smartphone with gait analysis application used in this study offers high test–retest reliability and has the capacity to quantify gait parameters as

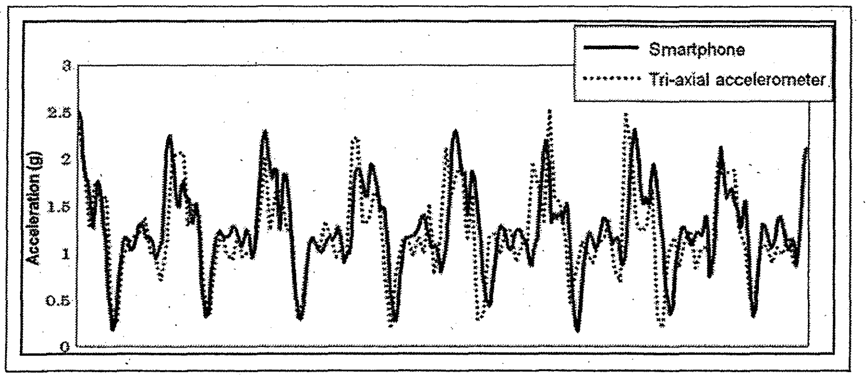

Fig. 3. Acceleration waveforms of the smartphone and tri-axial accelerometer.

accurately as a tri-axial accelerometer. The gait parameters used in this study (PF, RMS, AC, and CV) can be used to assess gait patterns from different perspectives.[10–14] The PF indicates the gait cycle. The RMS indicates the degree of gait instability; the higher the RMS, the lower is the degree of stability. The AC indicates the degree of gait balance; the higher AC, the greater is the degree of balance. The CV indicates the degree of gait variability. It is possible that accidental falls in elderly people could be predicted using these parameters.[13,15] This indicates that smartphones have the potential to assess the risk of fall and can be used as a new tool for fall prevention in the future.

Smartphones offer several important advantages that are useful for a potential portable medical device.[8,9] First, smartphones are now ubiquitous devices, and they are less expensive than the conventional accelerometers. Second, they can process and save large amounts of data and convey gait data via both wireless transmission and e-mail. This enables us to assess gait patterns easily in daily life. Third, smartphones are equipped with applications that are flexible and that can be easily improved. For these reasons, a smartphone is more advantageous than a conventional accelerometer for gait analysis. However, this application appears difficult to manipulate and needs to be improved for greater ease of use. Recently, some researchers have studied the use of smartphones as a self-monitoring or management tool, for example, in cardiac and pulmonary rehabilitation.[16,17] We consider that such applications can be used for the promotion of public health. In this context, there is a need to develop smartphones equipped with applications such as the one used in this study. Such new medical devices could then be used not only for young people but also for the elderly to prevent falls, to enable self-monitoring activities of orthopedic patients, etc.

Table 1. Correlation Between All Gait Parameter Results Obtained by Smartphone and Tri-axial Accelerometer

	SMARTPHONE	TRI-AXIAL ACCELEROMETER	SPEARMAN'S R
PF (Hz)	2.08 (1.82–2.21)	2.08 (1.82–2.21)	0.99*
RMS (g)	10.86 (10.48–12.62)	11.23 (10.89–12.37)	0.89*
AC	0.81 (0.61–0.91)	0.87 (0.71–0.95)	0.82*
CV	0.092 (0.04–0.18)	0.064 (0.02–0.15)	0.85*

Data are median (range) values.

*$p<0.01$ is statistically significant.

AC, autocorrelation peak; CV, coefficient of variance; PF, peak frequency; RMS, root mean square; Spearman's r, Spearman's correlation coefficient.

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Disclosure Statement

Tatsuaki Ito, Shinyo Muto, and Tatsuya Ishihara are employees of NTT Cyber Solutions Laboratories. All the other authors have no conflict of interest.

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Concept Software Based on Kinect for Assessing Dual-Task Ability of Elderly People

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Abstract

Objective: Assessment of fall risk of elderly people is a critical issue. Dual-task (DT) ability is a criterion for risk assessment. We developed new concept software based on Microsoft (Redmond, WA) Kinect™ for assessing DT ability. The software is named "Dual-Task Tai Chi" (DTTC) and includes Tai Chi and number place (Sudoku) components. The purpose of this study is to validate the DTTC test for assessment of DT ability.
Subjects and Methods: Forty-five community-dwelling elderly (mean age, 74.1 ± 6.6 years) individuals participated in this study. They performed DTTC, locomotive, cognitive, and DT tests. DT ability was evaluated with a 10-m walk under a cognitive-task condition and a 10-m walk under a manual-task condition. The correlation between the time taken to complete the DTTC test and each function test was determined using Pearson correlation coefficients. Stepwise multiple regression analysis was conducted to assess the relationship between the DTTC test results and results of the other tests.
Results: The time taken to complete the DTTC test was correlated with DT ability, locomotive functioning, and cognitive functioning. Results of stepwise multiple regression analysis confirmed that DT, balance, and cognitive ability are statistically significant. No statistically significant association was found for the other variables.
Conclusions: The DTTC test quantitatively evaluates a compound function including DT, balance, and cognitive abilities.

Introduction

Falls among older adults are a serious problem in countries with large populations of older people. It has been estimated that 32% of community-dwelling individuals ≥75 years old will fall at least once during a 1-year interval and that 24 percent of them will sustain serious injuries.[1,2] Falling is, therefore, a common problem in the growing population of elderly people. The cost of treating fall-related injuries is substantial.[3]

Many researchers have studied the risk of falls in older people and countermeasures to prevent them. Motor functions (e.g., muscle force, balance ability, and gait performance) are an important factor known by the public. The next most important risk factor is reported to be cognitive impairment.[4–6] Dual-task (DT) activity (i.e., performance of simultaneous locomotive and cognitive tasks) has recently become more important for assessment of fall risk.[7] Improving DT performance can also help prevent falls in older people.[8,9]

While evaluating the locomotive, cognitive, and DT skills of the elderly and providing active intervention, it is vital to quantify these skills. There are many assessment methods and exercises for improving locomotive and cognitive performance to prevent falls,[4–6] but there are few methods for evaluating simultaneous locomotive and cognitive performance (DT activity). We think that a more accessible measure of DT performance will facilitate interventions that are more effective for preventing falls in older people.

Commercial videogames such as the Nintendo (Redmond, WA) "Wii™ Fit" have generated much interest because of their promotion of health[10] and rehabilitation.[11] We previously reported that the scoring of a Nintendo "Wii Fit" program was associated with fall risk in community-dwelling older adults.[12] We also developed a smartphone application for assessment of fall risk.[13] However, motion-tracking controllers such as the Nintendo Wiimote are not sensitive enough to accurately interpret the user's movements, and the smartphone tool is limited to assessing the motion of only one body segment.

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The Kinect™ sensor (Microsoft, Redmond) does not require the user to hold an interface device. The sensor is a low-cost, depth-sensing camera (produced by the Israeli company PrimeSense® [Tel Aviv]) that captures the user's full-body movements in three-dimensional space and incorporates them in the game. The user's body, operating in three-dimensional space, replaces traditional handheld controllers. The Kinect camera can be connected to a personal computer. The Kinect system is flexible and commercially available.

We developed a new concept device to assess DT ability and named it the "Dual-Task Tai Chi" (DTTC) test.[14] To quantify DT skill, we developed this system using Kinect, a motion-capture device. We chose Tai Chi as a locomotive task and Sudoku as a cognitive task. In the input and convert module of the game system, Kinect translates positional data of the user and objects located in front of the system into an animated stick figure, which is displayed on a screen. A Sudoku is simultaneously displayed on a screen.

A reason for combining Tai Chi exercises with Sudoku is that we can change the level of difficulty and guide the subject's movements by changing the position of empty boxes in the Sudoku puzzle. Additionally, Tai Chi is a valid locomotive task based on full-body motion, and Tai Chi training is useful for preventing falls in elderly people.[15] Sudoku is a useful tool for assessing cognitive ability. Sudoku exercises improve cognitive performance (specifically, reaction time and number of correct and missing answers) of people with Parkinson's disease, as measured by the Stroop test.[6] The purpose of this study was to validate this new concept device as an assessment tool.

Subjects and Methods

Participants

Forty-five community-dwelling, elderly subjects participated in this study. They were recruited by means of an advertisement in the local press. The following selection criteria were used: age ≥ 60 years, community-dwelling, independent ambulation, willingness to participate in the measurement of physical fitness, and minimal hearing and vision impairments. Exclusion criteria were as follows: inability to complete the tasks because of reduced cognitive function; severe cardiac, pulmonary, or musculoskeletal disorders; pathologies associated with increased risk of falls, such as Parkinson's disease or stroke; osteoporosis; and use of psychotropic drugs. We obtained informed consent from each participant. This study was approved (protocol approval E-880) by the Ethical Review Board of Kyoto University Graduate School of Medicine, Kyoto, Japan.

Measurement device

The DTTC test requires users to solve a number place problem (Sudoku) by controlling a stick figure with movement of their entire body. The user's full-body motion is captured using Kinect, a motion-capture device, and is translated into movements of a stick figure on a screen. The cognitive task is to fill in three boxes chosen randomly from a 4×4 grid with digits ranging from 1 to 4. The user selects a digit using his or her right hand and left foot and points to a box with his or her left hand. In addition, the user must move his or her right hand to the left hand to fill the pointed box with the selected digit. As such, a full-body motion similar to Tai Chi Chuan movements is required. We recorded the time taken to fill in all three boxes; this was our evaluation index.

To begin with, the user stands 3 m in front of the Kinect sensor with his or her right foot in front of the sensor (Fig. 1). The following instructions were provided (Fig. 2):

1. Reach a digit you need to answer with your right hand.
2. Step 50 cm laterally with your left leg to grip a number in your right hand.
3. Select a blank you want to answer with your left hand, and move your right hand to your left one.

A pilot experiment indicated that the test–retest reliability for completion time was considerably high (inter-trial correlation coefficient, 0.94; 95% confidence interval, 0.86–0.97; $P < 0.001$).[14]

Cognitive status measures

Cognitive function was evaluated with the Rapid Dementia Screening Test (RDST),[16] trail-making test (TMT),[17] and verbal fluency test (VFT).[18–20] The TMT is a well-established psychomotor test originally developed as part of the Army Individual Test Battery[17] and has been widely used in clinical evaluations to assess deficits in executive cognitive function. The VFT has a letter fluency component and a category fluency component.[17] Participants were asked to think of as many animal names as possible in 1 minute (category fluency).[19] Verbal fluency is an evaluation of expressive language ability and executive function.[18–20] The score was the number of successful words (except for some proper nouns).

Physical performance measures

Locomotive function was evaluated as 10-m walking time under standard conditions (ST walking),[21] 10-m maximum walking time (10-m MAX) (see DT performance measures), functional reach (FR),[22] timed up-and-go test (TUG),[23] one-leg standing (OLS) test,[24] and five-chair stand (5-CS) test.[25] In the ST walking test, participants were asked to walk 15 m at a speed that was comfortable to them, and the time taken to

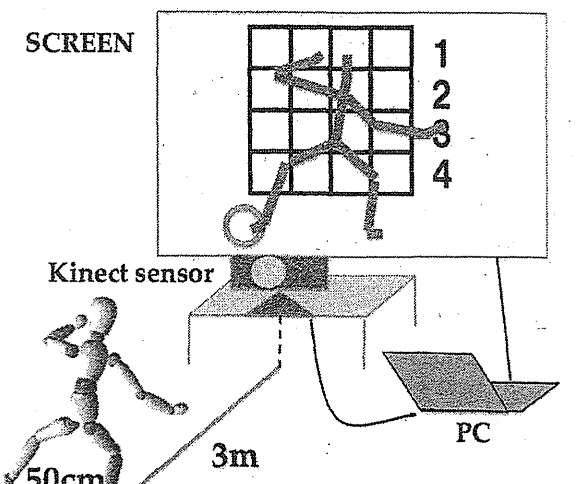

FIG. 1. Big-picture view of Dual-Task Tai Chi test. Color images available online at www.liebertonline.com/g4h

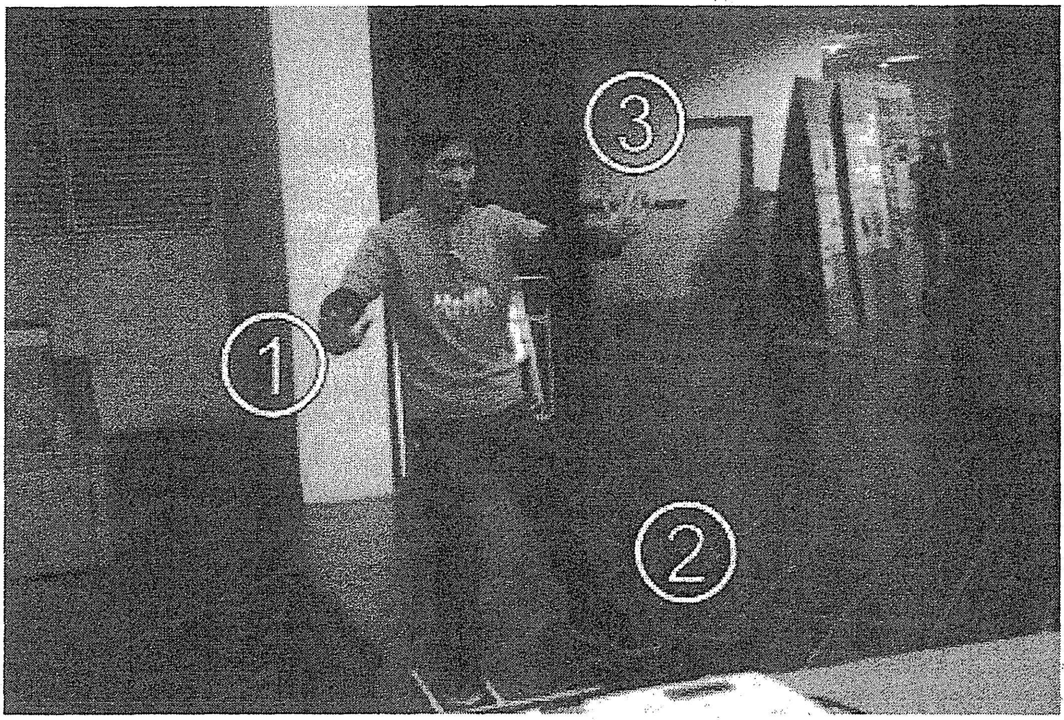

FIG. 2. Numbered instructions for the Dual-Task Tai Chi test (see text). Color images available online at www.liebertonline.com/g4h

walk 10 m during this walk was measured using a stopwatch. The ST walking score was the average time recorded for two trials. In the FR test, each participant was positioned next to a wall, with one arm raised at 90° and fingers extended. A yardstick was mounted on the wall at shoulder height. The distance the participant could reach while extending forward from an initial upright posture to the maximal anterior leaning posture without moving or lifting the feet was visually measured in centimeters as the third fingertip position against the mounted yardstick. The distances measured in two trials were averaged to obtain the FR score. In the TUG test, participants were asked to stand up from a standard chair with a seat height of 40 cm, walk a distance of 3 m at a normal pace, turn, walk back to the chair, and sit down. The time recorded in two trials was averaged to obtain the TUG score. In the OLS test, participants were instructed to start from a position with a comfortable base as support, with eyes open and arms along the side of the trunk. They were then instructed to stand unassisted on either leg. The OLS time was the number of seconds from when one foot was lifted from the floor to when it touched the floor again or the standing leg. In the 5-CS test, participants were asked to stand up and sit down five times as quickly as possible. They were timed from the initial sitting position to the final standing position, at the end of the fifth stand.

DT performance measures

A 10-m walk under a cognitive-task condition (CT walking) and a 10-m walk under a manual-task condition (MT walking) were used to evaluate DT function.[8,9] The method for measuring 10-m MAX, CT walking, and MT walking is roughly the same as the method for the ST walking test. For 10-m MAX, we asked participants to walk as fast as possible. For CT walking, we asked them to walk at the most comfortable speed while counting down from 100. For MT walking, we asked them to carry a ball (7 cm in diameter, 150 g) on a tray (17 cm in diameter, 50 g) while walking at the most comfortable speed.

Statistical analysis

The correlation between the time taken to complete the DTTC and functional tests was determined using Pearson correlation coefficient. Additionally, we evaluated the association between DTTC time and other test results using stepwise multiple regression analysis. We included DTTC time as the dependent variable and age, ST walking, MT walking, TUG, FR, OLS, 5-CS, TMT-B, RDST, and VFT as independent variables. We considered multicollinearities among tests when we chose these variables. A value of $P < 0.05$ was considered statistically significant for all analyses.

Results

Subject characteristics

The 45 subjects were 60–91 years old, with a mean age of 74.1 ± 6.6 years; many subjects were in their 70s. The male-to-female ratio was 1:4. All the participants completed the DTTC program. The mean time taken to complete the DTTC test was 50.2 ± 27.1 seconds.

Correlation analysis

Table 1 shows the Pearson correlation coefficients for time to complete the DTTC program and other functional tests for

TABLE 1. PEARSON CORRELATION COEFFICIENTS OF THE TIME TAKEN TO COMPLETE THE "DUAL-TASK TAI CHI"

	Mean ± SD	*Correlation coefficient*	P *value*
Age (years)	74.1 ± 6.6	0.581	
Locomotive task			< 0.01**
ST walking	7.3 ± 1.3	0.433	< 0.01**
10-m MAX	5.7 ± 0.9	0.477	< 0.01**
TUG	6.9 ± 1.5	0.447	< 0.01**
FR	28.2 ± 6.1	−0.531	< 0.01**
OLS	34.8 ± 22.7	−0.568	< 0.01**
5-CS	8.8 ± 3.1	0.256	0.075
Cognitive task			
RDST	9.6 ± 2.2	−0.347	0.018*
TMT-A	72.9 ± 24.8	0.616	< 0.01**
TMT-B	115.4 ± 49.7	0.537	< 0.01**
VFT	13.7 ± 4.7	−0.244	0.098
Dual-task			
DT(MT) walking	7.9 ± 2.1	0.534	< 0.01**
DT(CT) walking	8.9 ± 3.1	0.420	< 0.01**

*$P < 0.05$, significant difference; **$P < 0.01$, highly significant difference.

5-CS, five-chair stand test; 10-m MAX = 10-m maximal walking time; DT(CT) walking, 10-m walk under a cognitive-task condition; DT(MT) walking, 10-m walk under a manual-task condition; FR, functional reach; OLS, one-leg standings; RDST, Rapid Dementia Screening Test; ST walking, 10-m walking time under standard conditions; TMT, trail-making test; TUG, timed up-and-go test; VFT, verbal fluency test.

DT, locomotive, and cognitive performance. Time was strongly correlated not only with the DT function test but also with locomotive function and cognitive function tests ($P < 0.05$).

Results of stepwise multiple regression analysis confirmed that MT walking, FR, OLS, and TMT-B were statistically significant ($P < 0.05$). No statistically significant association was found for the other variables (Table 2).

Discussion

This study has two main components. First, the purpose of the new device is to evaluate DT ability, comprising a cognitive task and a locomotive task. It is difficult to quantify locomotive skill. In general, locomotive function is evaluated using devices to capture motion and measure ground reaction forces and triaxial acceleration.[26] The next task was to combine quantifications of locomotive and cognitive skills.

TABLE 2. STEPWISE MULTIPLE REGRESSION ANALYSIS FOR THE TIME TAKEN TO COMPLETE THE "DUAL-TASK TAI CHI"

Independent variable	*β estimates*	P *value*
OLS	−0.392	< 0.01**
FR	−0.302	< 0.01**
DT(MT) walking	0.276	0.049*
TMT-B	0.269	0.046*
ST walking	—	—
TUG	—	—
5-CS	—	—
RDST	—	—
VFT	—	—

*$P < 0.05$, significant difference; **$P < 0.01$, highly significant difference.

5-CS, five-chair stand test; DT(MT) walking, 10-m walk under a manual-task condition; FR, functional reach; OLS, one-leg standings; RDST, Rapid Dementia Screening Test; ST walking, 10-m walking time under standard conditions; TMT, trail-making test; TUG, timed up-and-go test; VFT, verbal fluency test.

We required a motion-capture device capable of accurately capturing full-body motions. Kinect is an innovative motion-capture device, and its software development kit enabled us to capture a user's motions while the user performed a cognitive task in real time. We designed the DTTC to mimic Tai Chi Chuan movements (a motor task) and to include Sudoku number place problems (a cognitive task). It is difficult to fill the boxes by full-body motions while balancing, let alone while solving Sudoku. Because the degree of difficulty of the locomotive, cognitive, and dual tasks was moderate, we were able to obtain results. The strong correlation between DTTC time and the practical assessment of DT suggests that the DTTC is a useful device for assessing DT ability. A great advantage of Kinect is that there is no need to use controllers or markers. Therefore, movement is not restricted, and the exercise is quite exciting. Kinect holds promise not only for promoting health but also for rehabilitation of older adults.

Second, Kinect is a promising augmented-reality game system. This technology opens up new possibilities. For instance, it has been used to train surgeons by providing three-dimensional information, and now it is being used for rehabilitation.[27,28] Commercial augmented-reality game "Wii Fit" (Nintendo) software has already been used for rehabilitation.[10–12] Adaptability to acute environmental change is a major health issue for elderly Japanese individuals, as it involves locomotive and cognitive function. Some individuals may isolate themselves, withdrawing from social activity, because they cannot adapt to environmental changes. They confuse real and virtual space. Augmented-reality technology will continue to develop and mix real and virtual space for our amusement or to make our daily life easier, but this could be chaotic for some elderly people. We hope that new augmented-reality devices like the DTTC will be used to help elderly people improve physical function and adaptability and will motivate them to remain socially active.

The current study has several limitations. First, the number of participants was small, and physical ability varied greatly according to age and according to the individual. Second, this study showed the accuracy of the DTTC test as an assessment of DT ability. The main purpose of this system is to assess fall risk. A large cross-sectional or longitudinal study is required to evaluate the reliability and effectiveness of the DTTC test. Moreover, an intervention study is required to determine the usefulness of DTTC for preventing falls. DTTC may be a promising game system for promoting health.

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Author Disclosure Statement

No competing financial interests exist.

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A novel infrared laser device that measures multilateral parameters of stepping performance for assessment of fall risk in elderly individuals

Running head: Step-Tracking Device Applying LRF for Fall Risk Assessment

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Abstract

[Background and Aims]

Avoiding falls requires fast and appropriate step responses in real-life situations. We developed a step-tracking device that uses an infrared laser sensor for convenient assessment of stepping performance, including concurrent assessment of temporal and spatial parameters. In the present study, we created a new index for assessment of fall risk that uses step speed and accuracy measurements. The purpose of this study was to determine whether the new index could discriminate between elderly individuals with different risks of falling.

[Methods]

152 community-dwelling elderly individuals (73.9 ± 4.6 years) participated and performed stepping tasks as quickly as possible on a plus-shaped mat in response to optical cues. The step-tracking device with the infrared sensor detected the motion and position of both legs in the step field. The device recorded temporal and spatial parameters, foot-off and foot-contact time, step length, and the percentage of correctly executed steps. We used the coefficients of a logistic regression model to develop “Stepping-response score” based on the weighted sum of these temporal and spatial parameters.

[Results]

The faller group had significantly worse stepping-response score than the non-faller group ($p < 0.001$). A stepwise logistic regression analysis demonstrated that stepping-response score was independently associated with falling (odds ratio = 0.15; $p < 0.001$). The ROC curve had a moderate AUC

(0.73) for stepping-response score (sensitivity 73.0%; specificity 69.7%).

[Conclusions]

This study indicates that the stepping-response score calculated from measurements obtained using the new step-tracking device can identify elderly individuals who are at a risk of falling.

[Key words]

Falls, Elderly, Stepping performance, Step-tracking device, Laser range finder

1. Introduction

One-third of community-dwelling elderly individuals aged over 75 years will experience at least 1 fall each year (1). Falling occurs in various situations of daily life and generally results from an interaction of multiple and diverse risk factors (2, 3). Falling is a common problem in the aging population; hence, more effective and convenient tools, than those currently available, are required for the assessment of fall risk, to enable better identification of people who are more likely to fall and who need preventive interventions.

Avoiding falls requires fast and appropriate step responses in real-life situations. Falls can arise from external perturbations (e.g. slips, trips, and collisions), but are also frequently a consequence of self-induced perturbation during volitional movement (e.g. turing, bending, and reaching). Voluntary stepping reaction time can identify elderly individuals who are at a risk of falling (4-8). The step responses for avoiding a fall are composed of several components, including motor and cognitive functions and visuospatial skills. Previous studies indicate that decreased reaction time (9, 10), reduced step length (11), and step accuracy (4, 12) affect balance control or are important indicators of fall risk. However, previous step-response tests made use of relatively fixed and specialized laboratory equipment (i.e. force platform) or assessed only step speed as the indicator of fall risk in elderly individuals.

In order to add some knowledge with regard to new objectively measured parameters, we developed a method to easily quantify stepping performance in terms of step speed, length, and accuracy. Our new device, which uses an infrared laser sensor (laser range finder [LRF]), can assess stepping performance conveniently. The device consists of only a LRF and a computer, and it can detect the motion of both legs. It measures temporal and spatial parameters of steps by measuring the distance and angle of the legs using the infrared laser sensor. In the present study, we took advantage of our device's ability to concurrently measure temporal and spatial parameters automatically to create a new index for assessment of fall risk that uses step speed and accuracy measurements. Measuring multilateral parameters of stepping performance seems more important for assessment of fall risk than measuring a single function.

The aim of this study was to determine whether the new index developed using the LRF device can discriminate between elderly individuals with different fall risks. We hypothesized that an index integrating temporal and spatial measurements, rather than traditional clinical measures, may help more successfully discriminate between elderly individuals with different fall risks.

2. Materials and Methods

2.1. Participants

We recruited participants through advertisements in the local press requesting for healthy community-dwelling volunteers. In total, 152 Japanese participants living in Kyoto city who were 65 years and older (mean age, 73.9 ± 4.6 years) participated in this study. Participants were excluded if they had any of the following symptoms: (a) serious visual impairment (including cataracts, glaucoma, or color blindness), (b) inability to ambulate independently (those requiring the assistance of a walker were excluded), (c) a score of less than 5 on the rapid dementia screening test (RDST) (13), (d) symptomatic cardiovascular disease, (e) neurological and orthopedic disorders, (f) peripheral neuropathy of the lower extremities, or (g) severe arthritis. Written informed consent was obtained from each participant in accordance with the guidelines approved by the Kyoto University Graduate School of Medicine (approval number E-880).

Each participant was categorized as either faller group (F) or non-faller group (NF), based on self-reports of the occurrence of at least 1 fall within the past 1 year. Using a standardized questionnaire, a fall was retrospectively defined as an event that results in a person unintentionally coming to rest on the ground or any other lower level with or without injury or loss of consciousness (14).

2.2. Experimental Protocol

Five 30 cm × 30 cm squares were arranged in a plus shape and participants started by standing upright in the center square. In the stepping performance task (see Figure 1), participants were instructed to step as quickly as possible into 1 of the 4 squares arranged around the starting position after receiving a visual cue indicating in which of the 4 directions they should step. Participants were instructed to step fully into the indicated square, with one foot followed by the other, and then to return to the center square. The direction participants were to step (forward, backward, right, or left), was indicated by an arrow on a computer monitor. The computer monitor was placed 1 m in front of the participants. Participants were instructed to gaze at the computer monitor while awaiting the cue, but were allowed to look at the mat prior to stepping. The stepping performance task consisted of 2 trials in each of the 4 stepping directions, for 8 consecutive trials. The entire task required a few minutes to complete. Visual cues, indicating the stepping direction, were presented in random order.

All participants also underwent 3 clinical measurements of motor function in the presence of an experienced physiotherapist; a 10-m walking test (WT) (15), timed up and go test (TUG) (16), and a 5-chair stand test (5CS) (17). To evaluate cognitive function, we administered the RDST and evaluated participant performance on a verbal fluency task. Both tests are very sensitive and economical psychometric screening tools for identifying patients with cognitive impairment (13, 18, 19). For the verbal fluency task, participants were instructed to name as many animals as possible in 1 minute. The score for this task was the number of animals the participants were able to name.

2.3. Data Collection and Analysis

The temporal and spatial raw data obtained during the stepping performance task were collected with a step-tracking device (Murata Machinery, Ltd., Kyoto, Japan) of our own design that consisted of a LRF and a computer. To calibrate the device, the center position and angle of the stepping field were calculated geometrically by the LRF so that the stepping field can be coordinated. The LRF measured the distance and angle of the legs using the infrared laser sensor, and detected the motion of both legs. We used the leg detection algorithm proposed in a previous study (20). Although the conventional leg detection algorithm measured only the position of the center of the legs, our step-tracking device is capable of measuring both the position of the center of the legs and that of each leg. The time of movement initiation and step completion were obtained from the leg position and step velocity data. The foot-off time was defined as the time that the velocity of the leg movement started to increase and the foot-contact time was defined as the time that the velocity of the leg movement was less than the threshold. The computer extracted the temporal and spatial parameters using a program written in Microsoft Visual C+ (Microsoft Japan Co., Ltd., Tokyo, Japan). The details of the data analysis algorithms used in this system are described in our previous study (Matsumura et al., unpublished data).

The following temporal parameters were measured: (a) foot-off time of the leading leg (reaction time), defined as the time from the cue to the movement initiation of the leading leg and (b) foot-contact time of the trailing leg (stepping time), defined as the time from the cue to the completed second step. Step length was calculated as the difference of the center of both legs between the positional information of the starting position and that of the position after the second step. To assess the accuracy of reaction choices, we classified the stepping performance of each trial as correct, hesitant, or wrong. Correct stepping was defined as stepping with both legs in the correct direction. Hesitant stepping was defined as initially stepping with the leading leg in an incorrect direction, followed by stepping with both legs in the correct direction. Wrong stepping was defined as stepping with both legs in an incorrect direction. The computer program, based on spatial data, automatically classified the stepping performance of each trial. Correct stepping was scored as 1, hesitant stepping as 0.5, and wrong stepping as 0. The percentage of correctly executed steps was calculated from the average score of 8 trials.

Our previous study indicated that this stepping performance device had high test-retest reliability (inter-trial correlation coefficient (ICC) foot-off time = 0.810; foot-contact time = 0.831; $p < 0.001$), and had the capacity to measure foot-off and foot-contact time that were highly correlated with those measured using a force platform (foot-off time: $r = 0.997$; foot-contact time: $r = 0.879$; $p < 0.001$) (Matsumura et al., unpublished data).

2.4. Statistical Analysis

Before analyzing stepping parameters (reaction time, stepping time, and step length), we removed the 11 steps that were classified as wrong stepping. In order to create a "Stepping-response score", a series of nested regression models was preliminarily used to determine which combination of parameters in a model provided a significantly better fitting regression than those in other candidate models. A model that included 3 parameters (age, reaction time, and the percentage of correctly executed steps) provided the best fit of other models, and we calculated a multiple logistic regression model that included these parameters. Based on the coefficients from this model, we developed the "Stepping-response score" that used a weighted sum of the following step assessment parameters: age, reaction time, and the percentage of correctly executed steps. To calculate the stepping-response score, the antilog of the coefficient associated with each predictor was multiplied by the predictor. The stepping-response score was calculated as follows: stepping-response score = -{- 3.051 + (0.071 × age) + (2.521 × reaction time) + (- 0.054 × percentage of correctly executed steps)}. As the domain of stepping-response score, we grouped reaction time of all directions together because the directional specificity of the stepping performance task was not shown in the preliminary analysis.

We used Student's *t* test for independent measures to evaluate differences between the stepping performance parameters of F and NF. A multivariate logistic regression analysis using a stepwise method was performed to determine whether these measurements were independently associated with falling. For this analysis, F and NF were the dependent variables and those measurements that were significantly different between groups were the independent variables. For the independent variables that remained in the final step of the regression model, odds ratios (ORs) with 95% confidence intervals (CI) were presented. We then calculated the area under the receiver operating characteristic (ROC) for the independent variables that remained in the final step of the regression model. The sensitivity and specificity of these variables were also calculated based on the ROC curve.

Data were analyzed using the Statistical Package for the Social Sciences (SPSS, Windows version 20.0, SPSS Inc., Chicago, IL, USA). *P*-values less than 0.05 were considered statistically significant.

3. Results

3.1. Participant Characteristics

A total of 41 F and 111 NF elderly individuals participated in the study. The demographic and performance characteristics of participants in both groups are shown in Table 1. Participants in the F group were significantly older those in the NF group. F participants took significantly longer to complete the WT, TUG, and 5CS tests than NF participants. There were no significant differences in other variables between groups.

3.2. Group Comparisons

The stepping performance parameters of both groups are shown in Table 2. F participants had significantly lower (worse) stepping-response score than NF participants ($p < 0.001$). F participants had significantly longer reaction time and stepping time than NF participants, whereas there were no significant differences in step length and percentage of correctly executed steps between groups.

3.3. Logistic Regression and ROC Analysis

In the analysis, the measurements that were significantly different between groups (the stepping-response score, age, WT, TUG, 5CS, reaction time, and stepping time) were employed as independent variables. Stepwise logistic regression analysis indicated that the stepping-response score (OR = 0.15; 95% CI = 0.12– 0.51; $p < 0.001$) and 5CS (OR = 1.23; 95% CI = 1.04 – 1.45; p = 0.015) were the independent variables that remained in the final step of the regression model and were therefore considered to be independently associated with falling (Table 3). The ROC curve had a moderate area under the curve (AUC) for stepping-response score (0.73) and a low AUC for 5CS (0.65). The sensitivity of the stepping-response score was 73.0%, and the specificity was