Estimating cognitive function in elderly people using information from outdoor walking

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Abstract

The rapid increase in the aging population of Japan is becoming a serious social concern, and the number of elderly individuals with dementia is also increasing. The Ministry of Health, Labour and Welfare of Japan has reported that the elderly account for 4.62 million individuals, of which approximately 4 million have mild cognitive impairment (MCI). However, monofunctional disorders, such as those in individuals with MCI, can be treated, with patients recovering 44% of their abilities 2 years after treatment, thereby suggesting that early detection and treatment of dementia is important. It has been reported that individuals who walk slowly or have experienced a significant decline in walking speed with age have a higher risk of developing dementia. In this study, to study movement in individuals aged ≥ 60 years, we focused on walking, a basic activity of daily living. We proposed and evaluated novel methods to estimate cognitive function. Acceleration and angular velocity sensors were attached to the waists of 20 elderly participants who were asked to walk outdoors ordinarily for 5–10 min, during which acceleration and angular velocity were measured. The similarity, standard deviation, and period of the stride were determined from the acceleration waveform and angular velocity waveform during walking. These were used as independent variables, and multiple regression analysis was performed using the Mini-Mental State Examination (MMSE) score as a dependent variable. An MMSE score estimation equation was constructed. The relationship between the estimation formula and the actual test value was $R^2 = 0.773$ ($P < 0.01$), which was good. As a result of cross-validation, the root mean square (RMS) error is low and the error is neither fixed nor proportional. Using the body acceleration and angular velocity information when walking outdoors, we built a very accurate formula for estimating the MMSE score.

Keywords: Dementia, Walking, Elderly, Mild cognitive impairment (MCI), Motoric cognitive risk (MCR), Mini-Mental State Examination(MMSE)

1. Introduction

The rapid increase in the aging population of Japan is becoming a serious social concern, and the number of elderly individuals with dementia is also increasing. The Ministry of Health, Labour and Welfare has reported that the elderly comprise 4.62 million individuals, of which approximately 4 million have mild cognitive impairment (MCI). The prevalence of dementia among individuals aged ≥ 65 years is estimated to be 15.0% (approximately one in seven individuals develops dementia). The primary symptoms of dementia include memory disorders, disorientation, and dysfunctional behaviors. Examples of the behavioral and psychological symptoms of dementia include wandering, depression, hallucinations, and insomnia. However, monofunctional disorders, such as those in individuals with MCI, can be treated, with patients recovering 44% of their abilities within 2 years after treatment. Thus, early detection and treatment of dementia is important. In a recent study focusing on the motor functions of patients with dementia, Verghese et al. (2014) investigated the association between the prevalence of motoric cognitive risk (MCR) syndrome and the risk of dementia using the data of 26, 802 adults aged ≥ 60 years. They found that MCR syndrome was prevalent in 9.7% of individuals in the target group. In addition, these studies have found MCR syndrome to be an initial symptom of declining cognitive function. Moreover, in a longitudinal study of 3,932 individuals aged ≥ 60 years, Hackett et al. (2018) found that individuals with a slow or a significant decline in walking speed with age had a high risk of developing dementia. In addition, Trienke et al. (2012) conducted a study on dual task gait. They reported that elderly with dementia observed irregular patterns with varying stride length and time for each stride compared to healthy elderly.

In recent years, inexpensive inertial sensors (acceleration and angular velocity) have been installed in smartphones using MEMS (Micro Electro Mechanical Systems) technology and are becoming popular as wearable sensors. By using inertial sensors (acceleration and angular velocity), it is possible to estimate the walking speed and stride using the acceleration standard deviation and stride period as parameters (Akihiro et al. 2011). For walking variability, the waveform similarity of acceleration and angular velocity during walking can be used. Therefore, if the cognitive function can be estimated from the walking information of the elderly using an inertial sensor, it can be used as a new function of the health care system, leading to the early detection of dementia. In this study, we evaluated novel methods for estimating cognitive function in individuals aged ≥ 60 years by focusing on walking, a basic movement for the activities of daily living.

2. Modeling to estimate the cognitive function

To estimate cognitive function from observations of the gait in the elderly, we used acceleration and angular velocity sensors attached to the waist to determine the waveform similarity, standard deviation, and stride cycle during walking. We then used these parameters to estimate cognitive function using the following equation involving the Mini-Mental State Examination (MMSE) score, which is a screening test for assessing dementia impairment.

$$\text{MMSE Score} = \alpha_0 \cdot \gamma_a + \alpha_1 \cdot \gamma_\omega + \alpha_2 \cdot \sigma_a + \alpha_3 \cdot \sigma_\omega + \beta_0 \cdot T + \beta_1 \quad (1)$$

where γ_a is the acceleration waveform vector similarity, γ_ω is the angular velocity waveform vector similarity, σ_a (G) is the acceleration waveform vector standard deviation, σ_ω (degrees/s) is the angular velocity waveform vector standard deviation, and T (s) is the stride period. The coefficients (α_n , β_n) were determined by conducting multiple regression analysis using experimental data, with the MMSE score as the dependent variable and each parameter as the independent variable. The independent variable is a vector value (with three components in the X, Y, and Z directions) that excludes the stride period and has 13 types [γ_a (3types), γ_ω (3types), σ_a (3types), σ_ω (3types), and T (1type)]; it is then selected and optimized such that the degree-of-freedom adjusted coefficient of determination is maximized. IBM SPSS Statistics Ver. 23 for Windows was used for this analysis.

The method of calculating the cognitive function estimation parameter in Equation (1) is shown. Since acceleration and angular velocity data include offset components and high-frequency noise, smoothing and offset components are first removed using a bandpass filter (IIR Butterworth BPF with 0.1 – 40 Hz pass band). The similarity of the waveform is a measure of the acceleration waveform or angular velocity waveform of one step as an evaluation of walking stability. Figure 2 shows the vertical acceleration of the acceleration sensor attached to the waist during walking. Because one peak value appears per step due to heel-contact when walking, the waveform of one stride was cut out. The average in

Fig. 1 Experimental scene and direction of sensor axis

Fig. 2 Acceleration in the vertical direction during walking

the walking section of this peak interval was considered as one stride cycle. The extracted stride waveform W_j [Equation (2)] was linearly interpolated to comprise 100 points. The cross-correlation coefficient γ_j [Equation (4)] between this and the average waveform W_{mean} [Equation (3)] was obtained. j is the stride number ($j = 1, 2, \dots, m$), and s is the s th data string ($s = 1, 2, \dots, 100$). In this study, this cross-correlation coefficient was used as the walking waveform similarity. In addition, because acceleration in the horizontal and front-back direction was small and multiple peak values appeared in one stride, one stride waveform was extracted based on the peak position of the acceleration waveform in the vertical direction, and the waveform similarity was calculated. As for the angular velocity waveform, one stride waveform was extracted based on the peak position of the vertical acceleration waveform, and the waveform similarity was calculated.

$$\{W_j(s) | s = 1, 2, \dots, 100\} \quad (2)$$

$$W_{mean}(s) = \frac{1}{m} \sum_{j=1}^m W_j(s) \quad (3)$$

$$\gamma_j = \frac{(W_j, W_{mean})}{|W_j| \cdot |W_{mean}|} \quad (4)$$

3. Experiment

3.1 Subjects

The Subjects included 20 healthy elderly individuals (4 men and 16 women) with a mean age of 76 (63–82) years who could independently walk without using walking aids. The median MMSE score was 27 (range, 23–30; Table 1). This study was approved by the National Institute of Technology, Ichinoseki College Ethics Committee. Signed informed consent was obtained from each subject (and family members, where applicable) after detailed information about the study was provided.

3.2 Experimental method

A wireless motion sensor (GPS+9-axis wireless motion sensor, SPORTS SENSING Co. Ltd, Japan, Table 2) affixed to a waist belt was attached to the waist at the third lumbar vertebra, which is considered to reflect the acceleration of the center of gravity the most (Osaka et al. 2011), to measure the walking state of the participant (Figure 1). The waist belt can be in close contact with the body, and measurement data errors due to clothing displacement can be prevented. Triaxial acceleration and triaxial angular velocity were measured. The walking speed was that of free walking, and each participant was instructed to walk at a normal pace. Immediately after the start of walking, the muscles and joints were considered to be hard; thus, 3 min after the start of walking, linear walking data over a 20-s-period was extracted and used for analysis. Positional information during walking was acquired using GPS, and acceleration and angular velocity were simultaneously measured. The walking route was confirmed on a map, and the straight walking section was

Table 1 Subject specification

Subject	Age	Gender	MMSE Score
Subject 1	66	Female	29
Subject 2	75	Female	25
Subject 3	77	Female	23
Subject 4	78	Female	26
Subject 5	71	Female	30
Subject 6	63	Female	27
Subject 7	72	Female	28
Subject 8	77	Female	29
Subject 9	82	Female	28
Subject 10	76	Female	29
Subject 11	74	Female	27
Subject 12	76	Male	30
Subject 13	82	Male	23
Subject 14	76	Male	30
Subject 15	82	Female	29
Subject 16	74	Female	27
Subject 17	70	Male	27
Subject 18	67	Female	26
Subject 19	69	Female	25
Subject 20	78	Female	25
Median	76		27
Range	63–82		23–30

Table 2 Sensor specification

Size		40 mm (W) × 20 mm (H) × 30 mm (D)
Detection range	Acceleration	±16 G
	Angular velocity	±1500 degrees/s
Quantization bit rate		16 bit
Manufacturer		SPORTS SENSING Co.,Ltd.(Japan)
Sampling frequency	Acceleration	100 Hz
	Angular velocity	
	GPS	1 Hz

extracted. From the measured triaxial acceleration and triaxial angular velocity data, the waveform similarity, standard deviation, and stride cycle were obtained and used as parameters for analyzing cognitive function. As shown in Figure 1, the sensor's axial directions are the x-axis in the vertical direction, the y-axis in the left–right direction, and the z-axis in the front–rear direction. The subjects in this experiment were healthy elderly people, and none of the lumbar segment axes were tilted due to senile round back. Therefore, each axis is not corrected to the absolute coordinate system based on gravity.

We also measured the cognitive function of the participants using the MMSE, which was developed by Folstein et al. (1975). The MMSE is composed of 11 questions related to orientation, calculation, language, figure reproduction, etc., and evaluates cognitive function with a maximum score of 30. The lower the total score, the more likely it is that the patient has dementia. MMSE scores of 26–29 denote suspected dementia, 21–25 denote mild dementia, 11–20 denote moderate dementia, and 0–10 denote severe dementia (Perneczky R et al., 2006). The median MMSE score of the participants assessed in this study was 27 (23–30) (Table 1), and the group comprised individuals with suspected-to-mild dementia.

4. Result and Discussion

Table 3 shows the average, standard deviation, and maximum and minimum values for the cognitive function estimation parameters calculated from the experimental results. Multiple regression analysis was performed with the MMSE score as the dependent variable and each cognitive function estimation parameter as the independent variables. The MMSE estimation formula shown in Equation (5) was obtained. The variable $\gamma_{\omega y}$ in Equation (5) is the angular velocity waveform similarity around the y-axis, σ_{ax} and σ_{az} are the acceleration standard deviations in the x- and z-

Table 3 The measured parameters for estimating the cognitive function of the participants

		Mean	SD	Min	Max
Similarity of walking acceleration waveform	x	0.923	0.070	0.986	0.754
	y	0.814	0.186	0.964	0.342
	z	0.877	0.098	0.977	0.638
Similarity of walking angular velocity waveform	x	0.630	0.102	0.879	0.491
	y	0.430	0.165	0.820	0.232
	z	0.484	0.169	0.845	0.230
Standard deviation of walking acceleration waveform (G)	x	0.263	0.062	0.368	0.172
	y	0.187	0.069	0.363	0.103
	z	0.226	0.059	0.323	0.142
Standard deviation of walking angular velocity waveform (degree/s)	x	15.394	3.977	27.787	9.350
	y	18.613	13.215	43.031	6.348
	z	13.068	4.733	23.823	6.329
Stride cycle (s)		1.050	0.155	1.482	0.867

Fig. 4 Relationship between MMSE_{mes} and MMSE_{est}

Table 4 Coefficients of Equation (5)

	Coefficient	Standardized coefficient	p value	VIF
(Constant)	18.603	—	0.000	—
Similarity of angular velocity $y: \gamma_{\omega y}$	7.884	0.596	0.002	1.316
SD of acceleration $x: \sigma_{ax}$	29.079	0.821	0.005	3.383
SD of acceleration $z: \sigma_{az}$	-60.586	-1.632	0.000	5.689
SD of angular velocity $x: \sigma_{\omega x}$	0.166	0.303	0.043	1.045
SD of angular velocity $y: \sigma_{\omega y}$	0.228	1.381	0.000	2.899
Stride cycle: T	4.172	0.295	0.100	1.590

Fig. 5 Bland and Altman analysis showing the precision of cognitive function estimation by equation (5).

Table 5 Coefficient of determination of Equation (5)

R	R ²	Adjusted R ²
0.879	0.773	0.669

axes, $\sigma_{\omega x}$ and $\sigma_{\omega y}$ are the angular velocity standard deviations around the x- and y-axes, and T indicates the stride period. Table 4 shows the coefficients and standardized coefficients of Equation (5), and Table 5 details the coefficients of determination and coefficients of adjustment with adjusted degrees of freedom. Figure 4 indicates the relationship between the MMSE score estimated by Equation (5) ($MMSE_{est}$) and the MMSE score measured by the schooling test ($MMSE_{mes}$).

$$MMSE \text{ Score} = 7.884\gamma_{\omega y} + 29.079\sigma_{ax} - 60.586\sigma_{az} + 0.166\sigma_{\omega x} + 0.228\sigma_{\omega y} + 4.172T + 18.603 \quad (5)$$

As shown in Figure 4, the relationship between the estimation formula and the actual test value was $R^2 = 0.773$ ($P < 0.01$), which was good. However, cross-validation was performed using leave-one-out (LOO) cross-validation to verify the generalization of the estimation equation (Zanconato et al., 1991). Using LOO, one participant's data are extracted from all participants' data for test data and the rest are treated as training data. Then, using the test data extracted in advance, the estimation model constructed from training data is verified, and the verification method is repeated for the number of participants while exchanging training and test data. As a result of verification, the root mean square error was 1.01. This was associated with the resolution of the MMSE scores; it was then confirmed that Equation (5) had generalization performance. Next, error analysis was conducted using the derived Equation (5) using Bland and Altman analysis (Bland et al., 1986). A Bland and Altman plot is shown in Figure 5. Here the vertical axis is the difference between the estimated MMSE value obtained from Equation (5) and the examined MMSE value. The horizontal axis is the average of the estimated and determined MMSE values. Using the data from Figure 5, it was confirmed that all the difference values were within the range of the mean value ± 2 SD. In addition, no average offset and no fixed bias were observed. Furthermore, the correlation coefficient of the difference between the estimated value, obtained and average values was as small as 0.262, and the p value was 0.264. Thus, no significance and no proportional bias were observed.

The standardized coefficients of the MMSE estimation formula (5), as shown in Table 4, are the coefficients of the multiple regression model calculated from the standardized values of the independent and dependent variables. This is an index that indicates the magnitude of the influence of each variable in the estimation formula. As shown in Table 4, the standardization coefficients for σ_{az} (standard deviation of the z-axis acceleration) and $\sigma_{\omega y}$ (standard deviation of the y-axis angular velocity) are large. This demonstrated that cognitive function decreased as the amount of change in the acceleration of the front–rear direction in one step increases (the standardization coefficient is negative), and the angular velocity around the axes of the left–right direction in one step decreased. This coincides with the fact that dementia causes gait disturbances such as brachybasia and walking with a shuffle (Kenichi Sugawara, 2013).

5. Conclusion

In this study, a model for estimating cognitive function based on walking information obtained from elderly individuals was derived and verified using multiple regression analysis. As a result, a cognitive function estimation formula with a high coefficient of determination was developed. This makes it possible to confirm the decline in cognitive function from walking behavior during activities of daily living and may assist in the early detection and treatment of dementia.

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