Gait and Balance Analysis for Patients With Alzheimer's Disease Using an Inertial-Sensor-Based Wearable Instrument

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***Abstract*—Despite patients with Alzheimer's disease (AD) were reported of revealing gait disorders and balance problems, there is still lack of objective quantitative measurement of gait patterns and balance capability of AD patients. Based on an inertial-sensor-based wearable device, this paper develops gait and balance analyzing algorithms to obtain quantitative measurements and explores the essential indicators from the measurements for AD diagnosis. The gait analyzing algorithm is composed of stride detection followed by gait cycle decomposition so that gait parameters are developed from the decomposed gait details. On the other hand, the balance is measured by the sway speed in anterior-posterior (AP) and medial-lateral (ML) directions of the projection path of body's center of mass (COM). These devised gait and balance parameters were explored on twenty-one AD patients and fifty healthy controls (HCs). Special evaluation procedure including single-task and dual-task walking experiments for observing the cognitive function and attention is also devised for the comparison of AD and HC groups. Experimental results show that the wearable instrument with the designed gait and balance analyzing system is a promising tool for automatically analyzing gait information and balance ability, serving as assistant indicators for early diagnosis of AD.**

***Index Terms*—Alzheimer's disease (AD), balance, balance analyzing algorithm, gait, gait analyzing algorithm, inertial sensor.**

I. Introduction

WITH the coming of the aging society, Alzheimer's disease (AD) and related dementias are becoming the major diseases of the elderly. For patients with AD and related dementias, gait disorders, balance problems, cognitive frailty, and memory impairments will increasingly become more obvious with patients' condition worsening [1], [2]. Gait disorders and balance problems are common in AD patients, which can decrease their mobility and increase the risk of falling [2]. These symptoms can cause severe consequences such as fractures, worsened mobility, loss of independence, and increased cardiovascular morbidity and mortality [3].

Recently, clinical reports have generally indicated that gait abnormalities and variability are not only clinical AD syndromes, but also independent predictors for potential AD diagnosis [4]. A number of studies have also investigated the relationship between gait abnormalities and cognitive function for AD. For example, Nadkarni *et al.* [5] compared gait parameters between 40 early AD patients and 34 healthy controls (HCs), and the participants were asked to walk at their comfortable speed on a level ground. The findings were that AD patients had slower velocity, slower cadence, and shorter stride length than HCs. Muir *et al.* [6] demanded participants to perform three dual-task walking tests which consist of naming animals, counting down from 100 by ones, and counting down from 100 by sevens. Both AD patients and mild cognitive impairment (MCI) subjects showed significant differences in lower stride velocity, longer stride time, and greater stride time variability than HCs. To record gait information of the elderly as well as AD patients, many researchers have focused on developing and employing various instruments for their clinical experiments. To name a few, Nakamura *et al.* [7] studied the relationship between falls and stride length variability in AD, by videotaping ten consecutive walking patterns of the patients. Webster *et al.* [8] used the GAITRite walkway system (CIR Systems, Inc., 60 Garlor Drive Havertown, PA, USA), which is an electronic mat consisting of pressure-activated sensors arranged in grid formation, to record subjects' spatial and temporal gait information at their self-selected slow, preferred, and fast speeds.

Over the past two decades, many clinical balance examines have been developed for evaluating human balance ability. For example, the Berg Balance Scale (BBS) [1], [2], the Timed Up and GO Test (TUGT) [1], [2], and the Short Physical Performance Battery (SPPB) [9]. Recently, the abovementioned examines were further used to probe into the relationship between balance ability and cognitive function. Pettersson *et al.* [2] utilized the frenchay activities index (FAI), BBS, TUGT, TUG manual (diffTUGT), Talking While Walking (TWW), and Tinetti balance tests for the evaluation of the activity level and motor function of the subjects with no cognition impairment, MCI, AD, and other dementia. The results suggested that the motor function seems to be affected in very mild AD but not in MCI subjects and the AD subjects had difficulties in performing a cognitive task during walking. Alexander *et al.*

Manuscript received June 6, 2013; revised May 5, 2014 and March 27, 2014; accepted May 8, 2014. Date of publication June 2, 2014; date of current version November 3, 2014. This work was supported by the National Science Council of the Republic of China, Taiwan, under a Sino-Franco jointed project under Grant NSC 99-2923-E-006-001-MY3.

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Digital Object Identifier 10.1109/JBHI.2014.2325413

[10] used an optoelectronic camera system to compare body motion and force output at the feet in AD subjects with those in healthy elderly while they were asked to stand on a force plane. The literature concluded that AD subjects had poor balance ability.

Based on the abovementioned literature review, despite that gait and balance analysis have already commonly adopted in the diagnosis of AD patients, there is lack of a reliable wearable device which can be used for measuring the gait and balance parameters. Traditional methods with camera, footswitches, or electronic mats are constrained to a laboratory environment. In this paper, we developed and explored the capability of an inertial-sensor-based wearable device composed of a triaxial accelerometer and two gyroscopes. Embedded with the device are automatic gait and balance analyzing algorithms to analyze gait patterns and balance ability for AD patients. The automatic gait analyzing algorithm consists of stride detection followed by gait cycle decomposition to decompose a gait cycle into stance and swing periods and acquire several sophisticated gait parameters. On the other hand, the automatic balance analyzing algorithm applies the center of mass (COM) analysis to acquire the sway speed of body in anterior-posterior (AP) and medial-lateral (ML) directions. The experiments suggest the high possibility of using solely inertial sensors for AD patient gait and balance analysis and therefore, a truly wearable device used for clinics and AD daily evaluation should be further developed. Based on the descriptions, one of the main contributions of the paper is the proposal of an inertial-sensor-based wearable device along with automatic gait and balance analyzing algorithms for AD patients. Intensive evaluations of the device were performed showing its potential as an alternative to other devices commonly used in clinics for gait and balance analyzing, while gives much higher portability. Furthermore, this paper also discovers the proposed gait and balance parameters as the assistive indicators of AD patients.

The rest of this paper is organized as follows. In Section II, the demographics and participant characteristics, neuropsychological assessment, apparatus, and procedures are described in detail. The automatic gait analyzing algorithm and automatic balance analyzing algorithm are presented in Sections III and IV, respectively. The results and discussions are presented in Section V. Finally, the conclusions are presented in Section VI.

II. Experimental Setup

A. Participants

In this study, for gait analysis tests, all 71 participants were referred from the Department of Neurology at National Cheng Kung University Hospital, with 21 AD patients and 50 HCs according to the professional diagnosis. In addition, for balance analysis tests, all 50 participants chosen from the 71 participants were referred from the Department of Neurology at National Cheng Kung University Hospital, with 21 AD patients and 29 HCs. In this paper, we used two common neuropsychological tests, which are the Mini-Mental State Examination (MMSE) and the Cognitive Assessment Screening Instrument (CASI) to evaluate cognitive dysfunction and memory impairment in all participants. All the statistical tests were performed with SPSS 16.0 software. The significant differences of all the statistical results between each group were performed by using analysis of variance (ANOVA) test. A significant difference between AD and HC is concluded when the p-value < 0.05. Subjects were excluded from participants in this paper if their body mass index (BMI) scores > 35, reported pain sufficient to affect their walking, were unable to walk at least 50 m without assistance, cannot follow the instructions, had neurological disorders (e.g., Parkinson's disease), history of stroke, history of falls in the past year, or orthopedic surgery in the past year.

TABLE I
Participants' Characteristics for Gait Analysis Tests

Parameters	AD (N = 21)	HC (N = 50)	p-value
Men/women (n)	10/11	20/30	0.560
Height (cm)	159.05 ± 7.61	161.90 ± 7.41	0.165
Weight (kg)	63.22 ± 9.35	60.50 ± 10.28	0.383
BMI ($\mathrm{kg/m^2}$)	24.90 ± 2.29	23.30 ± 3.17	0.082
Age (years)	61.48 ± 4.85	59.86 ± 4.62	0.189
CASI	77.93 ± 11.23	95.33 ± 3.60	<0.001***
MMSE	23.00 ± 3.23	28.38 ± 1.55	<0.001***

$*p < 0.05$, $**p < 0.01$, $***p < 0.001$

TABLE II
Participants' Characteristics for Balance Analysis Tests

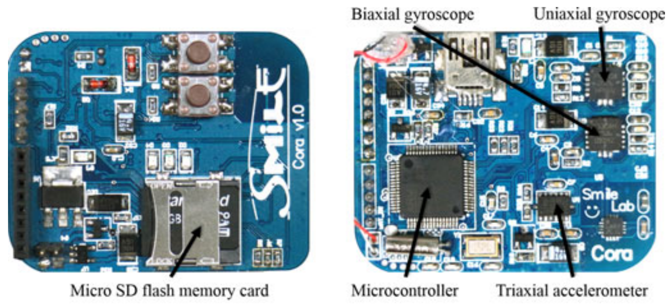
Parameters	AD (N = 21)	HC (N = 29)	p-value
Men/women (n)	10/11	10/19	0.650
Height (cm)	159.05 ± 7.61	159.41 ± 5.82	0.342
Weight (kg)	63.22 ± 9.35	63.42 ± 12.97	0.672
BMI ($\mathrm{kg/m^2}$)	24.90 ± 2.29	24.78 ± 3.23	0.053
Age (years)	61.48 ± 4.85	58.07 ± 5.85	0.056
CASI	77.93 ± 11.23	96.35 ± 2.92	<0.001***
MMSE	23.00 ± 3.23	28.48 ± 1.25	<0.001***

$*p < 0.05$, $**p < 0.01$, $***p < 0.001$

The demographics of the participants for the gait and balance analysis tests are summarized in Tables I and II, respectively. Informed consent has been obtained from all subjects, complying with an approved by National Cheng Kung University Hospital's institutional review board (IRB). Both the AD patients and the HCs underwent the MMSE and CASI tests to evaluate their cognitive functions. Both results showed that the AD patients had significantly lower scores than the HCs did on both tests, which is consistent with previous clinical findings.

B. Apparatus

The wearable device we have designed for gait and balance measurement was composed of a triaxial accelerometer (ADXL345), a uniaxial gyroscope (LY530ALH), a biaxial gyroscope (LPR530AL), a microcontroller (STM32F103), and a micro-SD flash memory card. The ADXL345 senses the acceleration signals of walking and balance motions. The LY530ALH measures the yaw-rate of the wearable device and the LPR530AL measures the roll- and pitch-rates of the wearable device. The sensitivity of the ADXL345 was set from −4g



(a) (b)

Fig. 1. Inertial-sensor-based wearable hardware device. (a) Front view of the circuit. (b) Back view of the circuit.

(a) (b)

Fig. 2. (a) Feet mounted the inertial-sensor-based wearable devices for gait analysis. (b) Waist mounted the inertial-sensor-based wearable device for balance analysis.

to +4g in this study. Furthermore, the STM32F103 is used to collect the inertial signals measured from the accelerometer and gyroscopes, and store the data to SD card. The output signals of the accelerometer and gyroscopes are all sampled at 100 Hz by a 12-bit analog to digital converter (ADC). The power consumption of the wearable hardware device is 30 mA at 3.7 V. The size of the board is 45 mm $\times$ 32 mm $\times$ 8 mm as shown in Fig. 1. The wearable device satisfies the following fundamental requirements: lightness and sensing capability.

C. Procedure of Experiments

1) Gait Analysis: The proposed inertial-sensor-based wearable devices were mounted on participants' feet as shown in Fig. 2(a). The participants were demanded to walk along two straight lines of 40 m on National Cheng Kung University Hospital campus, one for single-task walking and the other for dual-task walking. The aim of the experimental design is to investigate differences in the relationship between executive function and gait variability during single-task and dual-task walking when more cognitive capacity and attention loading are required. In single-task walking, the participants were demanded to walk at normal speed. In dual-task walking, they were asked to also walk at normal speed while simultaneously count down from 100 to 1. During the walks, all subjects were accompanied by a researcher to minimize the risk of falls. The researcher must remain out of the subjects' sight to avoid the interferences resulted from his or her presence to the walking test, causing unnecessary cues for the subjects' movement.

2) Balance Analysis: An inertial-sensor-based wearable device is mounted on the participants' waists as shown in Fig. 2(b). Then the participants are requested to maintain body balance and perform eight balance ability tests, which are:

1) side-by-side stand with open eyes;
2) side-by-side stand with close eyes;
3) left foot tandem stand, a stand with the heel of left foot in front of and touching the toes of the right foot, with open eyes;
4) left foot tandem stand with eyes closed;
5) right foot tandem stand with open eyes;
6) right foot tandem stand with eyes closed;
7) stand on left foot with open eyes; and
8) stand on right foot with open eyes.

The tests 1, 3, and 5 are based on the SPPB for assessing lower extremity function [9]. In addition, the literatures indicated that vision functions proprioceptively as an integral component of the control system in standing [11]. Hence, the tests 2, 4, and 6 are utilized to evaluate this phenomenon. The tests 7 and 8 are used due to the assertion that the poor ability of one-leg standing had a positively correlation with cognitive impairment [12].

III. Automatic Gait Analyzing Algorithm

This section introduces the automatic gait analyzing algorithm which has been developed to automatically acquire gait information from the acceleration and the angular velocity signals measured by the accelerometer and gyroscopes embedded in the wearable device. The automatic gait analyzing algorithm is composed of the following steps.

A. Signal Preprocessing

The signal preprocessing consists of calibration and low-pass filter. First, the calibration process is used to reduce the drift errors and offsets from the raw inertial signals. Second, a moving average filter is used to reduce the high-frequency noise of the calibrated inertial signals from the inertial sensors. A detailed signal preprocessing procedure can be found in [13].

B. Stride Detection

A stride detection algorithm has been developed to automatically acquire gait information of each gait cycle from the filtered acceleration and angular velocity signals generated from walking motions during the single-task and dual-task walking. The proposed stride detection algorithm is composed of the steps described as follows.

Step 1: Calculation of signal vector magnitude (SVM): Let SVM represents a measure of the degree of movement intensity of walking motions in this study. The SVMs of the acceleration and angular velocity signals, respectively, are calculated as follows:

$$\mathrm{SVM_{acc}}\,(k) = \sqrt{a_x^2\,(k) + a_y^2\,(k) + a_z^2\,(k)} \tag{1}$$

$$\mathrm{SVM_{gyro}}\,(k) = \sqrt{\omega_x^2\,(k) + \omega_y^2\,(k) + \omega_z^2\,(k)} \tag{2}$$

where k is the time step, $a_x(k)$, $a_y(k)$, and $a_z(k)$ are the filtered accelerations of *x*-, *y*-, and *z*-axis of the triaxial accelerometer, respectively. $\omega_x(k)$, $\omega_y(k)$, and $\omega_z(k)$ are the filtered angular velocities of *x*-, *y*-, and *z*-axis of the gyroscopes, respectively.

Step 2: Windowing: The SVMs of the acceleration and angular velocity signals are segmented into windows of three sample points (0.03 s) without overlapping, respectively. Then, the variances of the SVMs of the acceleration and angular velocity signals in each window can be calculated, respectively.

Step 3: Finding start points of strides: Initially a start flag *Fs* is set and the signal is scanned from the starting, window by window. Once the variances of the SVMs of the acceleration and angular velocity signals of a window are higher than $\mathrm{TH}_1 = 0.001$ and $\mathrm{TH}_2 = 0.1$, respectively, this window is considered one starting window of stride and the first sample point of this window is determined as the start point of a dynamic interval within a gait cycle. Once a start point of a stride is detected, the *Fs* is reset to allow the following step (Step 4) to find the end point of the stride.

Step 4: Finding end points of strides: This step is conducted when *Fs* is reset. If the variances of the SVMs of the acceleration and angular velocity signals of a window are lower than $\mathrm{TH}_3 = 0.0005$ and $\mathrm{TH}_4 = 0.0005$, respectively, this window is considered one ending window and the first sample point of this window is determined as the end point of a dynamic interval within a gait cycle. Once an ending point of a stride is found, the *Fs* is set again to allow Step 3 to search the start point of the subsequent step.

Fig. 3(a) and (b) shows the filtered acceleration and angular velocity signals, respectively. Fig. 3(c) shows the SVMs obtained from the filtered acceleration and angular velocity signals. The obtained static and dynamic intervals of the gaits are also illustrated in Fig. 3. Once the static and dynamic intervals have been determined, we further calculate six gait parameters, including: 1) number of strides, 2) walking time, 3) mean stride length, 4) mean stride frequency, 5) mean stride speed, and 6) mean stride cadence. Definitions of these six parameters can be found from our earlier work [14].

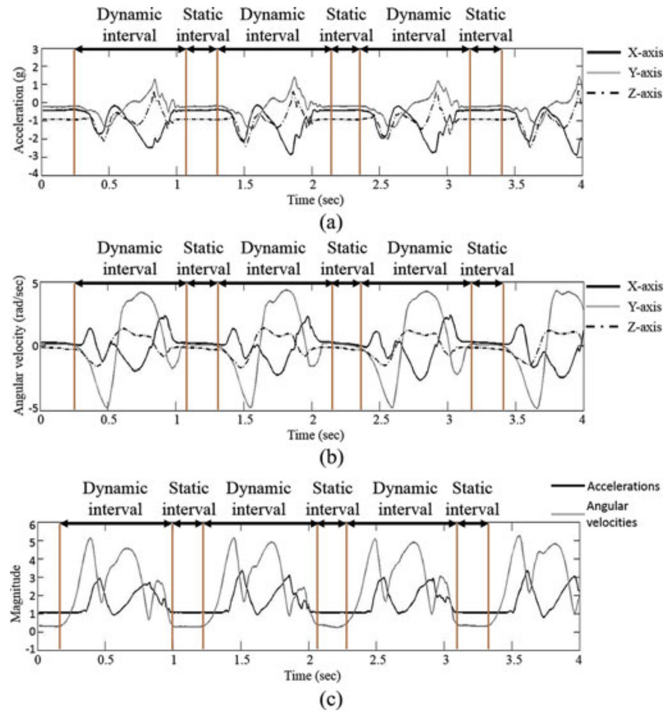


Fig. 3. Partition of dynamic intervals and static intervals divided by using the proposed stride detection algorithm. (a) Filtered accelerations. (b) Filtered angular velocities. (c) SVMs of the filtered accelerations and angular velocities; black color: SVM of the filtered accelerations (*g*); gray color: SVM of the filtered angular velocities (rad/s.).

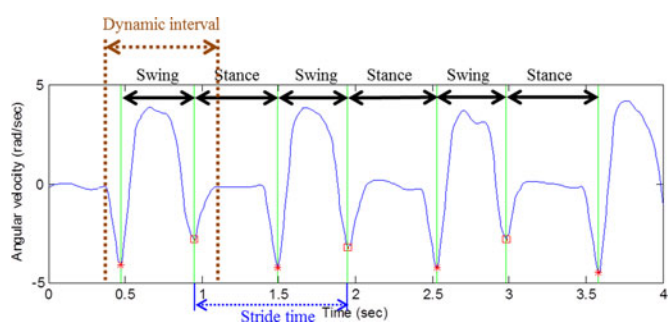


Fig. 4. Partition of stance periods and swing periods decomposed by using the y-axis angular velocity signals of the gyroscope. Star shape: toe-off points. Square shape: heel-strike points.

C. Gait Cycle Decomposition

Once each stride is detected through the abovementioned stride detection algorithm, we can further detect the points of toe-off and heel-strike within the dynamic intervals by using y-axis angular velocity signals of the gyroscope. An approach to find out the toe-off and heel-strike points by detecting the first and second local minimums/maximums of the angular velocity in the gait cycle, proposed by [15], is adopted in this paper. From Fig. 4, the first and the second local minimums within each dynamic interval are defined as the toe-off and heel-strike points, respectively. Once the toe-off and heel-strike points of each gait cycle can be found, we can obtain the stance and swing periods within each gait cycle. Then, we can calculate ten gait parameters to represent the pace, rhythm, and variability factors. The gait parameters will be described as follows:

1) *Stride time:* The time interval from the heel strike point to the next heel strike point.
2) *Stance time:* The time interval from the heel strike point to the toe off point within each gait cycle.
3) *Swing time:* The time interval from the toe off point to the heel strike point within each gait cycle.
4) *Coefficient of variation (CV) of stride time:* The ratio of the standard deviation of the stride time to the mean as a percentage, which can indicate the variability of the stride time.
5) *CV of stance time:* The ratio of the standard deviation of the stance time to the mean as a percentage, which can indicate the variability of the stance time.

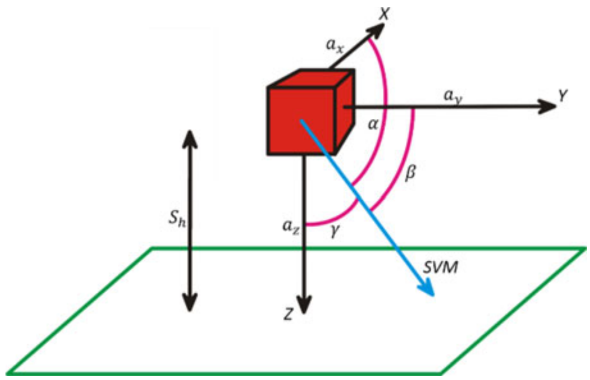


Fig. 5. Projection path of body's COM.

6) *CV of swing time:* The ratio of the standard deviation of the swing time to the mean as a percentage, which can indicate the variability of the swing time.
7) *Percentage of the stance period in the gait cycle (stance period):* The ratio of the stance time to the stride time as a percentage of gait cycle.
8) *Percentage of the swing period in the gait cycle (swing period):* The ratio of the swing time to the stride time as a percentage of gait cycle.
9) *CV in the percentage of the stance period in the gait cycle (CV of stance period):* The ratio of the standard deviation of the percentage of the stance period in the gait cycle to the mean as a percentage, which can indicate the variability in the percentage of the stance period in the gait cycle.
10) *CV in the percentage of the swing period in the gait cycle (CV of swing period):* The ratio of the standard deviation of the percentage of the swing period in the gait cycle to the mean as a percentage, which can indicate the variability in the percentage of the swing period in the gait cycle.

IV. Automatic Balance Analyzing Algorithm

Since the wearable device was mounted on participants' waists, the accelerations of the triaxial accelerometer embedded in wearable device can be regarded as the acceleration signals at the approximate level of the COM [16]. Once we obtain the filtered acceleration signals through the signal preprocessing procedure as that used in gait analysis, the average sway speed rate in AP and ML directions of the projection path of body's COM can be calculated as follows.

Step 1: Calculate the SVM of the filtered acceleration signals generated from the wearable device mounted on participants' waist at each time step (k).

Step 2: Calculate the directional cosines of the SVM of the accelerometer signals [16], as shown in Fig. 5

$$\cos\alpha(k) = \frac{a_x(k)}{\mathrm{SVM}_{\mathrm{acc}}(k)} \tag{3}$$

$$\cos\beta(k) = \frac{a_y(k)}{\mathrm{SVM}_{\mathrm{acc}}(k)} \tag{4}$$

$$\cos\gamma(k) = \frac{a_z(k)}{\mathrm{SVM}_{\mathrm{acc}}(k)} \tag{5}$$

where $\alpha(k)$, $\beta(k)$, and $\gamma(k)$ represent the directional angle between the SVM and the x-, y-, and z-axis, respectively, of the accelerometer at time step (k).

Step 3: Calculate the distance (D) between the wearable device and ground at each time step (k) [16]

$$D(k) = \frac{S_h}{\cos\gamma(k)} \tag{6}$$

where S_h represents the partial height of the participant from the waist to the floor. According to [17], S_h can be estimated as 0.618 multiplied by the height of the participant.

Step 4: Calculate the projection displacement of each time step (k) from original point in the X coordinate $(d_x(k))$ [16]

$$d_x(k) = D(k)\cos\alpha(k). \tag{7}$$

This can also be regarded as the displacement of each time step in the AP direction.

Step 5: Calculate the average sway speed in AP direction of the projection path of COM S_{AP}

$$S_{\mathrm{AP}} = \frac{P_{\mathrm{AP}}}{T} = \frac{\sum_{k=1}^{T} |d_x(k) - d_x(k-1)|}{T} \tag{8}$$

where P_{AP} is the sum of the projection displacement of the sampling points in the X coordinate, and T is the total execution time steps.

Step 6: Calculate the projection displacement of each time step (k) from original point in the Y coordinate $(d_y(k))$

$$d_y(k) = D(k)\cos\beta(k). \tag{9}$$

This can also be regarded as the displacement of each time step in the ML direction.

Step 7: Calculate the average sway speed in ML direction of the projection path of COM (S_{ML})

$$S_{\mathrm{ML}} = \frac{P_{\mathrm{ML}}}{T} = \frac{\sum_{k=1}^{T} |d_y(k) - d_y(k-1)|}{T} \tag{10}$$

where P_{ML} is the sum of the projection displacements of the sampling points in the Y coordinate.

V. Results and Discussion

A. Single-Task Walking Test

Table III summarizes the spatiotemporal gait parameters for each of the AD and HC groups when walking at self-selected speeds in single-task walking test. The statistical results of gait parameters showed significant differences (p-value < 0.05) between the AD and HC groups. Obviously, the AD patients take more stride counts and time than the HCs did to complete the 40 m test. The AD patients presented significantly shorter stride length, slower stride speed, longer stance time, higher percentage of stance period, lower percentage of swing period, greater CV of stand period, and greater CV of swing period in comparison with the HCs. The findings in some previous studies also indicated that the AD patients demonstrated a shorter stride length and a slower stride speed compared with the HCs when

TABLE III
GAIT PARAMETERS OF AD AND HC GROUPS IN SINGLE-TASK WALKING TEST

Parameters	AD (N = 21)	HC (N = 50)	p-value
No. of strides (count)	31.14 ± 2.69	29.26 ± 2.92	0.013*
Walking time (s)	32.54 ± 4.45	29.27 ± 3.58	0.002**
Stride length (m)	1.29 ± 0.11	1.38 ± 0.14	0.011*
Stride frequency (Hz)	0.97 ± 0.09	1.00 ± 0.08	0.087
Stride speed (m/s)	1.25 ± 0.16	1.38 ± 0.17	0.003**
Stride cadence (stride/min)	58.00 ± 5.55	60.30 ± 4.58	0.074
Stride time (s)	1.05 ± 0.10	1.00 ± 0.08	0.073
Stance time (s)	0.59 ± 0.08	0.55 ± 0.06	0.025*
Swing time (s)	0.46 ± 0.03	0.45 ± 0.03	0.613
CV of stride time (%)	2.31 ± 0.66	2.02 ± 0.78	0.147
CV of stance time (%)	3.31 ± 0.84	3.13 ± 1.07	0.480
CV of swing time (%)	2.67 ± 0.69	2.47 ± 0.64	0.230
Stance period (% gait cycle)	56.00 ± 2.25	54.70 ± 2.04	0.021*
Swing period (% gait cycle)	44.00 ± 2.25	45.30 ± 2.04	0.021*
CV of stance period (%)	4.78 ± 5.48	1.80 ± 0.47	0.004**
CV of swing period (%)	5.74 ± 7.80	2.17 ± 0.58	0.009**

$*p < 0.05$, $**p < 0.01$, $***p < 0.001$

TABLE IV
GAIT PARAMETERS OF AD AND HC GROUPS IN DUAL-TASK WALKING TEST

Parameters	AD (N = 21)	HC (N = 50)	p-value
No. of strides (count)	34.71 ± 5.62	30.96 ± 4.98	0.007**
Walking time (s)	74.01 ± 47.35	40.81 ± 15.30	<0.001***
Stride length (m)	1.18 ± 0.18	1.32 ± 0.17	0.003**
Stride frequency (Hz)	0.75 ± 0.19	0.85 ± 0.10	0.006**
Stride speed (m/s)	0.90 ± 0.31	1.12 ± 0.20	0.001**
Stride cadence (stride/min)	36.21 ± 15.33	47.78 ± 8.37	<0.001***
Stride time (s)	2.07 ± 1.03	1.32 ± 0.29	<0.001***
Stance time (s)	1.37 ± 0.80	0.76 ± 0.20	<0.001***
Swing time (s)	0.70 ± 0.26	0.56 ± 0.10	0.002**
CV of stride time (%)	31.31 ± 26.83	14.38 ± 18.37	0.003**
CV of stance time (%)	43.31 ± 37.32	19.47 ± 27.40	0.004**
CV of swing time (%)	17.24 ± 12.99	10.23 ± 8.77	0.010*
Stance period (% gait cycle)	63.70 ± 6.90	57.26 ± 2.96	<0.001***
Swing period (% gait cycle)	36.30 ± 6.90	42.74 ± 2.96	<0.001***
CV of stance period (%)	12.30 ± 10.18	5.07 ± 4.08	<0.001***
CV of swing period (%)	18.95 ± 15.09	6.88 ± 5.91	<0.001***

$*p < 0.05$, $**p < 0.01$, $***p < 0.001$

walking at similar speeds [5], [10], [18]. Another finding in the single-task walking is that the AD patients spent more time in the stance phase, higher percentage of stance period, and lower percentage of swing period within the gait cycle compared with the HCs in this paper, which could be explained by the inference that AD patients needed more standing time in each gait cycle to maintain balance. This notable phenomenon presumably indicates that the increased time for standing was the compensation for the decreased of their balance so as to control stability between steps [19]. In addition, the CVs of stance and swing periods of the AD patients were slightly greater than that of the HCs with both about 3%.

B. Dual-Task Walking Test

Table IV summarizes the results of the AD and HC groups in dual-task walking test. AD group differed significantly from the HC group on number of strides, walking time, stride length, stride speed, stance time, stance period, swing period, CV of

TABLE V
COMPARISON OF THE GAIT PARAMETERS DURING THE SINGLE AND DUAL TASKS IN THE AD GROUP

Parameters	Difference	p-value
No. of strides (count)	3.57 ± 5.45	0.012*
Walking time (s)	41.47 ± 46.74	<0.001***
Stride length (m)	-0.11 ± 0.17	0.020*
Stride frequency (Hz)	-0.21 ± 0.16	<0.001***
Stride speed (m/s)	-0.34 ± 0.26	<0.001***
Stride cadence (stride/min)	-21.78 ± 13.30	<0.001***
Stride time (s)	1.02 ± 1.00	<0.001***
Stance time (s)	0.78 ± 0.78	<0.001***
Swing time (s)	0.24 ± 0.24	<0.001***
CV of stride time (%)	29.00 ± 26.54	<0.001***
CV of stance time (%)	40.00 ± 36.96	<0.001***
CV of swing time (%)	14.57 ± 12.82	<0.001***
Stance period (% gait cycle)	7.70 ± 6.21	<0.001***
Swing period (% gait cycle)	-7.70 ± 6.21	<0.001***
CV of stance period (%)	7.51 ± 20.18	0.007**
CV of swing period (%)	13.21 ± 15.15	0.002**

$*p < 0.05$, $**p < 0.01$, $***p < 0.001$

stand period, and CV of swing period under the dual-task condition. Additionally, the stride frequency, stride cadence, stride time, swing time, CV of stride time, CV of stance time, and CV of swing time had significant differences between the AD patients and HCs, whereas this gait profiles showed no significant differences in the single-task walking. It indicated that the countdown motion is related to the cognitive function and attention [20], so the AD patients performed worse in those gait parameters than the HCs in dual-task walking. Some previous literatures also reported that the gait speed, stride length, stride frequency, and stride regularity revealed significant differences in a dual-task walking in AD subjects [21], [22]. The findings in some previous studies indicated that the AD patients demonstrated a longer stride time and a greater CV of stride speed compared with the HCs when walking at self-selected speeds [23]. In addition, these findings are consistent with those reported for the influences on gait variability in dual-task walking in some previous studies [24]. This phenomenon strengthens the growing evidence of the linkage between gait variability and cognitive decline. During the dual-task walking, the AD patients also spent more time in the stance phase, higher percentage of stance period, and lower percentage of swing period within the gait cycle compared with the HCs for maintaining their balance. The CVs of stance and swing periods of the AD patients were greater than those of the HCs with about 7% and 12%, respectively.

C. Comparison of the Gait Parameters during Single-Task and Dual-Task Walking Tests

The calculated differences between the gait parameters of the AD and HC groups in the single-task and dual-task walking are shown in Tables V and VI. Both in the AD and HC groups, performing an additional cognitive task causes a significant difference in all gait parameters. Hence, all gait parameters presented in this paper are more or less influenced by attention loading. Obviously, from the results, to perform an additional

TABLE VI
COMPARISON OF THE GAIT PARAMETERS DURING THE SINGLE AND DUAL TASKS IN THE HC GROUP

Parameters	Difference	p-value
No. of strides (count)	$1.70 \pm .3.60$	0.040$*$
Walking time (s)	11.54 ± 14.72	$<$0.001$***$
Stride length (m)	-0.06 ± 0.10	0.042$*$
Stride frequency (Hz)	-0.15 ± 0.10	$<$0.001$***$
Stride speed (m/s)	-0.26 ± 0.16	$<$0.001$***$
Stride cadence (stride/min)	-12.52 ± 8.93	$<$0.001$***$
Stride time (s)	0.31 ± 0.29	$<$0.001$***$
Stance time (s)	0.21 ± 0.20	$<$0.001$***$
Swing time (s)	0.10 ± 0.10	$<$0.001$***$
CV of stride time (%)	12.35 ± 18.56	$<$0.001$***$
CV of stance time (%)	16.34 ± 27.66	$<$0.001$***$
CV of swing time (%)	7.76 ± 8.90	$<$0.001$***$
Stance period (% gait cycle)	2.56 ± 2.96	$<$0.001$***$
Swing period (% gait cycle)	-2.56 ± 2.96	$<$0.001$***$
CV of stance period (%)	2.64 ± 3.83	0.001$**$
CV of swing period (%)	3.81 ± 5.63	0.001$**$

$*p < 0.05$, $**p < 0.01$, $***p < 0.001$

TABLE VII
STATISTICAL ANALYSIS FOR AP DIRECTION (CM/S)

Balance Ability Tests	AD	HC	p-value
Side by side stand with open eye	4.39 ± 1.65	4.06 ± 0.16	0.491
Side by side stand with close eye	4.39 ± 1.70	4.07 ± 1.94	0.396
Left foot tandem stand with open eye	11.32 ± 6.27	9.95 ± 5.47	0.283
Left foot tandem stand with close eye	20.36 ± 10.58	15.90 ± 9.86	0.128
Right foot tandem stand with open eye	13.47 ± 12.86	9.17 ± 4.60	0.101
Right foot tandem stand with close eye	19.08 ± 12.32	14.02 ± 10.92	0.130
Stand on left foot	20.95 ± 12.77	16.07 ± 9.99	0.132
Stand on right foot	19.32 ± 11.20	14.47 ± 10.28	0.115

$*p < 0.05$, $**p < 0.01$, $***p < 0.001$

cognitive task leads to that the AD patients presented a significantly greater difference of the gait parameters between single-task and dual-task than the HC group. In previous studies, we found that cognitive loading increase gait variability in AD patients [6], [22]. This phenomenon adds to the growing evidence of the linkage between gait variability and cognitive decline, which may help to explain why AD patients fall more frequently than cognitively normal people among elderly.

D. Balance Test

The parameters extracted from the signal for balance evaluation are the sway speed in AP direction (S_{AP}) and ML direction (S_{ML}), respectively. Tables VII and VIII show the statistical analysis for S_{AP} and S_{ML}, respectively. As can be seen, for ML direction, the results of independent samples *T* test showed a significant difference between AD and HC in right foot tandem stand with close eye and stand on right foot activities. Although the rest parameters did not present a significant difference between AD and HC, it can still be observed that AD patients presented larger average sway speed in all of the rest parameters. These imply that AD may have poor standing balance than HCs, especially in one-leg standing and foot tandem stand with close eyes standing postures. These findings are in line with previous studies. Rolland *et al.* [12] indicated that an abnormal one-leg balance test was a marker of more advanced dementia and predicts a higher rate of cognitive decline. Chong *et al.* [11] pointed out that although AD patients were able to maintain their balance when standing in normal posture (side-by-side standing) with eyes either open or close, AD patients had a trouble to maintain balance when standing in incongruent surface with eyes closed. It is worth to mention that with the inertial sensors and the analyzing algorithm, the balance abilities of the AD and HC can be quantitative measured, which cannot be achieved in the abovementioned studies.

TABLE VIII
STATISTICAL ANALYSIS FOR ML DIRECTION (CM/S)

Balance Ability Tests	AD	HC	p-value
Side by side stand with open eye	5.25 ± 1.40	4.91 ± 0.75	0.330
Side by side stand with close eye	5.28 ± 1.17	5.00 ± 1.67	0.595
Left foot tandem stand with open eye	9.79 ± 6.80	8.87 ± 5.41	0.154
Left foot tandem stand with close eye	16.91 ± 9.96	12.77 ± 7.75	0.101
Right foot tandem stand with open eye	12.22 ± 15.24	8.02 ± 3.28	0.214
Right foot tandem stand with close eye	15.68 ± 9.80	9.97 ± 6.07	0.015$*$
Stand on left foot	18.85 ± 15.99	13.39 ± 9.25	0.132
Stand on right foot	17.78 ± 15.76	11.05 ± 6.13	0.040$*$

$*p < 0.05$, $**p < 0.01$, $***p < 0.001$

VI. CONCLUSION

AD patients were reported of having different walking patterns. Traditionally, this is conducted using optical or camera sensors. In our study, we attempt to answer the question whether it is possible to use solely the inertial-sensor-based wearable device with gait and balance analyzing algorithms for the evaluation of gait parameters and balance ability of AD patients. Through our experiments, the proposed wearable device demonstrated its effectiveness as a tool to estimate strides of the subjects, to measure spatial and temporal gait parameters, and to assess balance capability. Experimental results indicated that to perform an additional cognitive task requiring much more cognitive and attention functions leads to that the AD patients presented a significantly greater difference of the gait parameters between single-task and dual-task than the HC group. In the balance ability tests, AD patients also presented a significant larger average sway speed in ML direction compared with the HCs during right foot tandem stand with close eye and stand on right foot. The abovementioned phenomena add to the growing evidence of the linkage between gait variability, balance ability, and cognitive decline, which may help to explain why AD patients fall more frequently than cognitively normal people among elderly. The results obtained from this paper suggest that the inertial-sensor-based wearable device reveals promising potential for gait and balance capability analysis and is worth of further in-depth research to identify gait and balance parameters in mild AD patients, so as to be served as indicators for early diagnosis of AD, and also as predictive clinical factors of progression towards dementia in this population.

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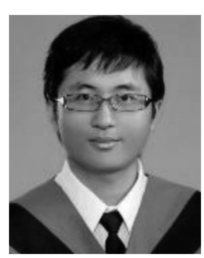

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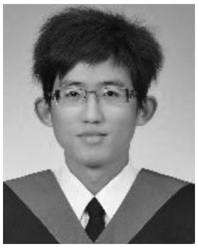

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