Inertial gait analysis measurement system for large-scale health checkups

Amir Mukhriz AZMAN*, Chikara NAGAI*, Koichi SAGAWA*, Yuichi HIRAKAWA**
and Kaori SAWADA***

* Graduate School of Science and Technology, Hirosaki University
3 Bunkyo-cho, Hirosaki-shi, Aomori 036-8561, Japan
E-mail: h17ds201@hirosaki-u.ac.jp
** Graduate School of Health Science, Hirosaki University
66-1 Hon-cho, Hirosaki-shi, Aomori 036-8564, Japan
*** Graduate School of Medicine, Hirosaki University
5 Zaifu-cho, Hirosaki-shi, Aomori 036-8562, Japan

Received: 17 June 2019; Revised: 16 August 2019; Accepted: 24 September 2019

Abstract
An inertial measurement system for estimating gait parameters indicating cognitive impairment is developed for use during large-scale health checkups. Current health checkups conduct a 10 m fastest gait examination to assess signs of cognitive impairment and physical performance. Earlier methods require examiners to follow a subject and measure the gait time using a stopwatch. The method proposed herein reduces burdens on examiners. Several gait parameters in addition to the gait time of many subjects can be measured simultaneously and quantitatively from three-dimensional foot movements estimated using inertial sensors comprising two accelerometers and two gyroscopes with different measurement range attached to both feet. Gait parameters derived from the inertial sensor are gait time, stride length, gait cycle, gait velocity, toe angle, toe height, and the percentage of swing phase. The gait condition, such as walking or running, is distinguished from the moment of toe off and heel contact of both feet. In all, 1406 subjects with ages of 19-93 years old were given instructions to walk at their highest velocity on a straight 16-m-long walking course. Mini-Mental State Examination (MMSE) is conducted on subjects. The score is used as a reference valuation of the cognitive impairment level. Experimental results show that the proposed measurement system provides equal performance to that obtained using a stopwatch and improves correlation between the MMSE score and the fastest 10 m gait time of subjects who did not run. Furthermore, it is confirmed that the proposed measurement system using inertial sensors can quantitatively provide spatiotemporal gait parameters to evaluate the physical performance in a short time during the large-scale health checkups.

Keywords: Cognitive impairment, Gait parameter, Health examination, Inertial sensor, Mini-mental state examination, Motion analysis

1. Introduction

Dementia is the loss of cognitive functioning such as thinking, memory, and reasoning as well as behavioral capabilities to such an extent that it interferes with daily life activities. Dementia is usually regarded as a predominantly cognitive disorder. However, aside from cognitive decline, discussion has been made on neurocognitive function as related with physical activity (Kramer et al., 2005). Recently reported evidence suggests that gait abnormalities can also be found in early stages of the disease (Ijmker and Lamoth, 2012). Gait abnormalities include decreased walking speed, step length, step frequency, and increased gait variation (Lamoth et al., 2011; Manckoundia et al., 2006; Sheridan et al., 2003). People with risk of dementia also tend to walk shorter distances, which can be caused by declining physical function (Abbott et al., 2004). These gait disturbances are greater than the gait impairments that can be expected to result...
from normal aging process (Beauchet et al., 2008). Current evidence suggests that walking is related closely to executive function. Impaired executive function has been related to decreased walking speed, increased stride time variation, increased incidence of falls, and decreased performance of complex motor tasks (Allali et al., 2008; Persad et al., 2008; Yogev et al., 2008). Although fall risk and gait have often been the object of investigations in adults with dementia, few studies have yet investigated the relation between executive function and measures of gait variation and stability, which are associated with fall risk (Barnes et al., 2003; Hausdorff et al., 2008; Lamoth et al., 2010; Lockhart and Liu, 2008; Yaffe et al., 2001). A clearer picture of the relation between gait parameter and executive function can be of great clinical relevance with respect to the diagnosis of dementia and the early detection of increased fall risk in this population.

The School of Medicine of Hirosaki University has conducted health examinations for approximately 1000 citizens of Hirosaki city in Japan per year since 2005 as part of a cohort study. This project has been conducted to raise the health level of residents in the city and to extend the average healthy lifespan. The 10 m fastest gait examination has been conducted to investigate signs of cognitive impairment by measuring the gait time, which is known as an indicator of predicting dementia (Vergheese et al., 2014). However, the earlier method requires that numerous staff members measure the gait time with a stopwatch by following subjects back and forth throughout a walking course (Esser et al., 2011). Moreover, some subjects may run during the examination for good results, which leads to incorrect diagnostic results. It is difficult to visually judge whether they are walking or running. Therefore, movement of both feet for every step must be investigated to predict the deterioration of neurocognitive functions, such as that related to dementia, and to detect other disease precursors.

Gait parameters are obtainable from analysis of foot kinematics. Although spatiotemporal gait analysis is conducted using an optical motion capture system (MCS), such a system is unsuitable when measuring numerous subjects in a short time as with a large-scale health checkup because it requires a dedicated laboratory and appropriate clothing of subjects. Ambulatory measurement devices using body-worn inertial sensors can overcome some of these limitations and enables analyze gait kinematics. Use of inertial sensors in physical activity monitoring have gained popularity (Ohtaki et al., 2004; Chen and Bassett, 2005; Khan et al., 2011; Ibata et al., 2013) because more accurate, more inexpensive, and smaller sensors are available with the advancement of MEMS technology. Many systems are proposed to classify various physical activities such as walking, running, sitting, standing, walking upstairs or downstairs, and cycling by placing sensors on human body (Bao and Intille, 2004; Maurer et al., 2006; Ermes et al., 2008; Arif et al., 2014). Activity monitoring systems using accelerometer can also be applied to identify different gait parameters and walking pattern classification (Lee et al., 2010) and abnormal gait detection (Yu et al., 2010). However, the inertial measurement system is hardly used for quantitative evaluation in medical field because measurement method using accelerometer and gyroscope are adversely affected by measurement errors and integration drifts. Furthermore, many researchers have worked on quantitative analysis of normal velocity movement utilizing inertial sensor to overcome shortcoming of the inertial sensor extensively (Mariani et al., 2010; Ojeda and Borenstein, 2007; Sagawa and Ohkubo, 2015; Yang and Li, 2012). However, few researches deal with quantitative measurement of high-speed movement like the 10 m fastest gait examination because amplitudes of acceleration and angular velocity measured are so large that they exceed the measurement range of the inertial sensors commonly used.

In this paper, the authors propose the inertial measurement system for 10 m fastest gait examination at large-scale health checkups, where numerous subjects take the examination simultaneously. The sensor system consists of two accelerometers and gyroscopes with a wide measurement range to investigate the movement of one foot during fast walking precisely (Azman et al., 2017, 2019; Kuga and Sagawa, 2015). The sensor unit is useful to measure several kinds of spatiotemporal gait parameters. Measurement error from numerical integration of inertial data can be corrected periodically by assuming null velocity of the foot during the stance phase. Because the 10 m fastest gait examination must be performed while walk, not run, two sensor units are used to identify the gait condition by mounting them on both feet. Gait parameters derived from the inertial sensor are gait time, stride length, gait cycle, gait velocity, toe angle, maximum toe clearance, and the percentage of swing phase. The gait time of 10 m fastest gait examination is estimated using the displacement of both feet and is compared with that measured by a stopwatch. Then the practicality of the system in place of the stopwatch is confirmed. Moreover, correlation coefficient between gait parameters estimated and the MMSE is investigated to find an indicator to evaluate cognitive impairment. Characteristics of estimated gait parameters by age are investigated and utilization of inertial sensor to measure the gait parameters in large-scale health checkups is discussed.
2. Theory

2.1 Foot movement estimation

The walking velocity is derived by integrating three-dimensional (3D) acceleration data of the toe of the foot. Further integration derives the 3D trajectory of the toe. The trajectory during gait is calculated step-by-step to minimize effects of drift from the inertial sensor. This calculation is achieved by integrating the translational acceleration of the toe during each swing phase. During integration, 3D acceleration based on the sensor-fixed coordinate system is transformed into acceleration based on the earth coordinate system by defining the sensor coordinate system orientation.

Let a three-by-three orientation matrix (OM) representing the sensor orientation with respect to the earth coordinate system be $E(t)$, where $i, j,$ and $k$ are three-by-one orthogonal unit vectors as shown in Fig. 1 (Sagawa and Ohkubo, 2015). The acceleration and angular velocity based on the earth coordinate system $a_E(t)$ and $\omega_E(t)$ are calculated from the acceleration and angular velocity based on the sensor-fixed coordinate system $a_S(t)$ and $\omega_S(t)$ using the following equations.

$$a_E(t) = E(t)a_S(t) \quad (1)$$
$$\omega_E(t) = E(t)\omega_S(t) \quad (2)$$

In this study, the temporal change in the sensor orientation with respect to the earth coordinate system during walking is estimated by time-integrating the angular velocity of the sensor from the foot-flat time. The sensor orientation is updated at every sampling period $\Delta t$ in the integration section as shown below.

$$E(t + \Delta t) = R(t)E(t). \quad (3)$$

where $R(t)$ stands for a rotation matrix, which rotates the OM $E(t)$ around $\omega_E(t)$ by an angle $\Delta t\|\omega_E(t)\|$.

In this study, toe acceleration $a_E(t)$ is time-integrated from the time that the foot starts moving ($t_0$) to the time that the foot movement stops ($t_{\text{end}}$) during one stride. At this time, because the integral error accumulates as a result of drifting, sensor noise, sensor system misalignment and wrong estimation of OM caused by sensor vibration, the estimated velocity of the sensor at $t_{\text{end}}$ rarely becomes zero. However, it is difficult to measure and remove these errors. On the other hand, the velocity of foot at $t_{\text{end}}$ becomes zero. Therefore, assuming that the integral error accumulates linearly with time between $t_0$ and $t_{\text{end}}$, and setting that the estimated velocity at $t_{\text{end}}$ is $v_e$, the toe velocity $v(t)$ during one stride is modified by subtracting error which increases linearly between zero and $v_e$ from the time-integrated acceleration. The toe velocity $v(t)$ is calculated as shown below.

$$v(t) = \int_{t_0}^{t} a_E(t)dt - \frac{t - t_0}{t_{\text{end}} - t_0}v_e \quad (4)$$

Applying this modification method, the toe velocity reaches zero at $t_{\text{end}}$ in every step.
The 3D trajectory of the toe $P(t) = [P_x(t) P_y(t) P_z(t)]$ is obtained by further integration of velocity $v(t)$. Because no slope exists on the walking surface, the vertical displacement of the sensor at $t_{\text{end}}$ must be zero. However, integration result of the vertical velocity rarely becomes zero because the assumption that integration error of the acceleration accumulates linearly is applied and the effect of sensor error remains still. Therefore, similar to the modification of the toe velocity, the vertical toe displacement $P_z(t)$ between $t_0$ and $t_{\text{end}}$ is modified by subtracting integration error of vertical velocity from the time-integrated vertical velocity. When the result of integrating vertical toe velocity is $p_{ez}$ at $t_{\text{end}}$, $P_z(t)$ is calculated as shown below.

$$P_z(t) = \int_{t_0}^{t} v(\tau) d\tau - \frac{t - t_0}{t_{\text{end}} - t_0} p_{ez} \tag{5}$$

The time trajectory of horizontal displacement of the toe $D_e(t)$ from the start location of gait ($t = 0$) to the stop location is calculated as shown below.

$$D_e(t) = \sqrt{(P_x(t))^2 + (P_y(t))^2} \tag{6}$$

However, $D_e(t)$ fundamentally includes integration error and differs from the actual displacement with which the subject walked. Therefore, $D_e(t)$ is modified linearly so that the estimated displacement with which the subject stopped agrees with the actual displacement. When the total walking time estimated by the waveform measured from the inertia sensor is $t_w$ and the actual displacement obtained by reading the scale on the floor where the subject has stopped is $D_a$, the modified horizontal displacement $D(t)$ can be recalculated as shown below.

$$D(t) = D_e(t) - \frac{t}{t_w} (D_e(t_w) - D_a) \tag{7}$$

### 2.2 Gait parameter

In the experiment, subjects are asked to walk on 16 m walking course and gait parameters are obtained from 10 m section between 3 m point and 13 m point. Gait parameters derived in this paper are the 10 m gait time (GT), stride length (SL), gait cycle (GC), gait velocity (GV), maximum toe angle ($\theta_{\text{max}}$), minimum toe angle ($\theta_{\text{min}}$), maximum toe clearance (TC), and percentage of swing phase ($S_p$). These are calculated off-line based on measured sensor data. Gait parameters obtained during one gait cycle are shown in Fig. 2.

The GT is derived by first calculating $D(t)$. Of those variables, $D(t)$ of the right and left toe are calculated separately. Then the time at which the horizontal displacement of both toes reached 3 m and 13 m earlier are defined as $t_{3m}$ and $t_{13m}$. Eventually, GT can be calculated as presented below.

$$\text{GT} = t_{13m} - t_{3m} \tag{8}$$
foot. Assuming the times of TO and HC of the \( n \)th stride as \( t_{TO}(n) \) and \( t_{HC}(n) \), respectively, then SL of the \( n \)th stride is obtained as shown below.

\[
SL(n) = \left( P_x(t_{HC}(n)) - P_x(t_{TO}(n)) \right)^2 + \left( P_y(t_{HC}(n)) - P_y(t_{TO}(n)) \right)^2
\]

(9)

The GC is the elapsed time from one HC on \( t_{HC}(n-1) \) to the next HC of the ipsilateral leg on \( t_{HC}(n) \). The gait cycle of the \( n \)th stride is calculated as

\[
GC(n) = t_{HC}(n) - t_{HC}(n-1)
\]

(10)

The GC is divisible into a stance phase and a swing phase. The stance phase refers to the period from the HC to the TO. The foot is in contact with the support surface in this period. The swing phase refers to the duration between the TO and the following HC. The foot is not in contact with the ground during this period. The TO time is ascertained from the synthesized angular velocity. The HC time is found from the synthesized angular acceleration, which is obtained by differentiating three axis of angular velocity and then synthesizing the results. The synthesized angular velocity reaches a peak at TO, which marks the end of the stance phase and the beginning of the swing phase. The synthesized angular acceleration reaches a peak at HC, which marks the end of the swing phase and the beginning of the stance phase (Tanaka and Sagawa, 2010).

The GV of the \( n \)th stride is obtained as shown below.

\[
GV(n) = \frac{SL(n)}{GC(n)}
\]

(11)

During one gait cycle, which starts with a HC and ends with the successive HC, the maximum toe clearance TC can be found from the peak of the vertical foot displacement \( P_z(t) \).

The toe angle is the amplitude of the angle of the toe direction from the floor. The inertial sensor is attached on the toe tip. Therefore, the toe angle is derived using the elevation angle of the unit vector \( \mathbf{i} \) in \( O\mathbf{M} \). Assuming the vertical component of \( \mathbf{i} \) during the swing phase and that of the stance phase as \( i_{sw} \) and \( i_{st} \), the toe angle \( \theta \) is calculated as presented below.

\[
\theta = \sin^{-1}i_{sw} - \sin^{-1}i_{st}
\]

(12)

Maximum and minimum toe angles \( \theta_{\text{max}} \) and \( \theta_{\text{min}} \) are obtained at every swing phase.

Also, \( S_p \) is a ratio of the duration of the swing phase to the duration of one gait cycle. The time of TO within the \( n \)th gait cycle is \( t_{TO}(n) \). Therefore, \( S_p \) of the \( n \)th step is defined as shown below.

\[
S_p(n) = \frac{t_{HC}(n) - t_{TO}(n)}{GC(n)}
\]

(13)

2.3 Detection of running

Subjects are asked to walk as fast as possible through 10 m gait time measurement. However, running accidentally or intentionally occurs, causing inappropriate evaluation of the health checkup. Therefore, the measured data evaluated as a running condition must be removed from the experimentally obtained results. Running technically requires both feet to be off the ground during a stride, although walking always has at least one foot touching the ground. The gait condition is ascertained by the HC and TO time of both feet. During walking, TO of one foot occurs after the HC of the other foot, meaning at least one foot always touches the ground. During running, TO of one foot occurs before the HC of the other foot, meaning both feet leave the ground simultaneously.

3. Experimental equipment and methods

A wearable inertial measurement system is developed as the measurement tool of gait parameters in health checkup. Figure 3 portrays a block diagram of the sensor unit; Fig. 4 presents an overview of the sensor system. The sensor unit consists of a 16-bit microprocessor unit (MPU, dsPIC33FJ128GP802; Microchip Technology Inc.), an accelerometer and
gyroscope with high sensitivity (±16 g, ±2000 deg/s, MPU-6050; InvenSense Inc.), a low sensitivity accelerometer (±200 g, ADXL375; Analog Devices Inc.), two low sensitivity gyroscopes (±6000 deg/s, LPY4150AL; STMicroelectronics), LEDs for information display, a microSD card, and a USB connector with a charging function to a lithium ion battery (400mAh). This sensor unit can be operated from on-board switches or a wireless communication module (XBee, MaxStream; Digi International Inc.). At the checkup site of the 10 m fastest gait measurement, several subjects wear sensor systems and wait in a row for the start of the measurement. The examiner turns on the power switch of two sensors attached on both feet before measurement starts. Then the examiner begins recording inertial data using a wireless controller to synchronize the start time of two sensors exactly (Fig. 5). However, sensors are turned off using the on-board switch because powering off wirelessly might cause other sensors used during measurements to stop. Data were sampled at 100 Hz and were stored into a microSD card.

Large-scale health checkups have been conducted by Hirosaki University, Japan, since 2005. About 1000 subjects receive health checkup every year. This study used measured data of 1406 people (604 men, 52.3 ± 15.4 years old; 802 women, 53.5 ± 15.2 years old) who had taken the 10 m fastest gait examination in 2016 and 2017. Figure 6 shows the number of subjects and their age distribution. The health checkup was approved by Hirosaki University Ethics Committee. Informed consent was obtained from all subjects.

Figure 7 portrays a schematic diagram of the experiment. If a subject wears shoes that are unsuitable for the measurement such as loose shoes, slippers and sandals, the prepared exercise shoes are used. Inertial sensors were fixed on the toe tips of both feet of the subject using adhesive tape so that the $i$ axis of the sensor unit coincides with the toe direction. The subjects were asked to move to the start line and then to walk on a 16 m walking course as fast as possible but were cautioned to avoid running. The 3 m and 13 m points on the walking course were marked with cones and adhesive tape pasted on the floor as a sign of 10 m distance. The examiner who walked along with the subject measured the 10 m gait time using a stopwatch and the actual walking distance by reading the scale at which the subjects stopped, as portrayed in Fig. 7. The subjects conducted the fastest gait three times, in which the first gait was for training. Data were recorded for the last two turns. Because the subjects were asked to walk with their fastest velocity, some were unable to stop on the 16 m line and passed the line. Measurements of the actual walking distance are necessary to compensate for the distance pasted in advance.
for the estimated gait time using the inertial sensors. After measurements, sensors are removed, and data recorded on the microSD card are copied to the computer and are analyzed.

To measure the level of cognitive impairment, MMSE has been used extensively in clinical and research settings. MMSE is a 30-point test that includes simple questions and problems from several areas such as the recognition of time and place, repeating lists of words, arithmetic, language use and comprehension, and basic motor skills. A score of 24 or more indicates a normal cognition. A score of 23 or less indicates a possibility of mild (18-23) and severe (0-17) cognitive impairment. The MMSE consists of two sections that, together, contain 11 tasks of cognition. The first section involves verbal responses and addresses orientation, memory, and attention. The second section involves the ability to respond to verbal and written commands, such as to write a sentence and copy a polygon figure. Time to administer the screening ranges from 5 to 10 minutes, and to complete the test successfully subjects must have adequate hearing and vision and they must demonstrate sufficient musculoskeletal function to be able to write with a pencil or pen (Pangman et al., 2000, Tombaugh and McIntyre, 1992). A salient benefit of MMSE is that it requires no special equipment or training and that it has both validity and reliability for the diagnosis of dementia. Because the administration period is short and easy to use, MMSE is useful for cognitive assessment in the clinician's office space or at the bedside (Harrell et al., 2000). The feasibility of the inertial measurement system as a measurement tool of physical performance in health checkup is investigated. Gait parameters showing high correlation with MMSE are derived.

4. Results

The time taken for the whole measurement process was about two to three min per subject. The time taken for analyzing raw inertial data to obtain gait parameters was about 9 s per subject using programming software (MATLAB; Mathworks Inc.). Figure 8 presents an example of experimental results of horizontal displacement for both toes and gait parameters estimated for a subject (woman, 44 years old; MMSE score 30) using an inertial measurement system. From top left to lower right, horizontal displacement of both feet, stride length (SL), gait cycle (GC), gait velocity (GV), maximum toe angle ($\theta_{\text{max}}$), minimum toe angle ($\theta_{\text{min}}$), maximum toe clearance (TC), and percentage of swing phase ($S_p$) are depicted. The red lines indicate the 3 m and 13 m points and is obtained from the horizontal displacement of both feet. Circles and triangles are places where the stance phase occurred. In this example, the actual walking distance was 14.9 m; the estimated distance was 14.5 m. Applying equation (7) for modification of the horizontal displacement,

![Fig. 6 Relation of the number of subjects by age.](image)

![Fig. 7 Schematic diagram of the experiment. Distance walked is recorded where the subject stopped from the scale on the floor. For example, when the front foot stopped as in the figure, the total length walked is recorded as 13.5 m.](image)
the right foot passed the 3 m line and 13 m line at 13.93 s and 17.61 s, and the left foot passed the 3 m line and the 13 m line at 13.69 s and 17.84 s, respectively. Eventually the 10 m fastest gait time was estimated as 3.92 s. The gait time measured using the stopwatch is 4.00 s. The estimation error is $-0.08$ s. It is readily apparent that SL, GC, GV, TC, and $S_p$ reached the highest value in the middle of the 10 m section and that they began to decrease before arrival at 13 m line. From these results, it is confirmed that the gait parameters of each step can be analyzed.

The horizontal displacement of each subject can be measured by reading the scale where the subject stopped on the walking course. It is regarded as the reference displacement. The displacement estimated using the inertial measurement system is modified linearly to match the reference displacement using equation (7). The 10 m gait time is recalculated and then compared with time recorded using a stopwatch, which is the reference time. The relation between the actual gait time $G_{T_{SW}}$ and the estimated gait time $G_{T_{IS}}$ using inertial measurement system of all subjects is shown in Fig. 9. The average and standard deviation of $G_{T_{SW}}$ and $G_{T_{IS}}$ are $3.58 \pm 0.85$ s and $3.56 \pm 0.84$ s, respectively, and root mean square error is 0.24 s. The correlation coefficient is 0.96, which is sufficiently high. When no modification is applied to the estimated horizontal displacement, the correlation coefficient is reduced to 0.91 as shown by red circles.
and a line in Fig. 9. This indicates the effectiveness of the compensation of the gait time using the actual displacement. The newly estimated gait time $G_{t}^{IS}$ is useful as a gait parameter for use instead of the stopwatch. Figure 10 depicts the relation between running incidence rate (RIR) and the number of measurements of all subjects. The RIR is the ratio of the number of steps ran to the number of total steps during one measurement and is derived from the temporal relation of the TO and the HC of both feet. When a subject runs three steps and the total number of steps taken is ten during the measurement, RIR is 0.3, for example. The total number of measurements is 2814, and it is confirmed that 1944 measurements (69.1 %) resulted in almost no running with RIR of 0.2 or less and 97 measurements (3.5 %) were almost running with RIR of 0.8 or more across the entire 10 m section. In this paper, RIR of 0.2 or less is treated as walking, otherwise it is treated as running.

The relation between ages of all subjects with gait parameters and MMSE score is presented in Fig. 11. It is readily apparent that the gait parameters deteriorate as the subjects become older. The changes in $G_{t}^{IS}$, GC, and GV over the age of 60 are especially remarkable. Change ratios between the age of 20 and 80 of these gait parameters are 58.9 %, −22.6 % and −22.55 %, respectively. The average MMSE score also drops as age increased and the change ratio results in −5.5 %. From these results, it is suggested that the gait time is the most sensitive to the decline in physical performance with age.

Next, we leave the calculation of gait parameters and move to investigation of correlation between MMSE and gait parameters. Figure 12 represents the absolute values of correlation coefficient $|R|$ between MMSE with gait parameters. The correlation coefficient with the gait time measured by a stopwatch $G_{t}^{SW}$ is also illustrated as the reference. Note that $G_{t}^{IS}$ is obtained using gait time without running data and $G_{t}^{SW}$ involves running data. The $G_{t}^{IS}$ shows the highest correlation with MMSE, with $|R|$ value of 0.34, which indicates weak correlation. However, the $G_{t}^{SW}$ shows a slightly reduced correlation ($R = 0.31$) with MMSE compared to $G_{t}^{IS}$. Moreover, $G_{t}^{IS}$ including the running data shows $|R|$ value of 0.31, which is the same value of $G_{t}^{SW}$. The inclusion of running data in the 10 m fastest gait time measurement may lead to incorrect diagnostic results. Detection and rejection of running data are necessary for the precise evaluation of the relation between gait performance and cognitive impairment. The GC provides the second highest correlation among the gait parameters obtained from the inertial measurement system. However, little relation is observed between SL and MMSE. Therefore, it is suggested that the prolonged gait time causing a decrease in MMSE score results from the extension of GC rather than the shortening of SL.

5. Discussion

This paper presents a proposal for utilization of the inertial measurement system as a measurement tool of physical performance in the large-scale health checkup and the use of the fastest gait time as an indication to predict the possibility of mild cognitive impairment. The subject’s gait was measured using two inertial sensors, which allowed us to obtain diverse information related to gait parameters. Results show that the gait measurement is fast and easy and that it imparts a minimal burden on subjects in addition to the examiner. Calculating the gait parameters also takes short time. The results can be presented on the spot when requested.
We use MMSE results as an index of the subject’s cognitive impairment level. From the 10 m fastest gait experiment, we confirmed that $GT_{IS}$ shows the highest correlation with the MMSE score. Moreover, removal of the running data improves the correlation coefficient. Reportedly, the increase in GT results from the extension of GC. Ijmker and Lamoth (2012) conducted a gait experiment by classifying the study sample into three groups: dementia patients, healthy elderly people, and younger elderly people. The report described that dementia patients scored significantly lower on MMSE and gait speed than the other groups, which supports our result. The difference is that dementia patients were not joined to our measurement. The MMSE score was high in this study.

The inertial sensor estimation accuracy has been verified by comparing estimated data with data using MCS (Azman et al., 2017). Error in estimation for the toe angle amplitude, toe height, and stride length are, respectively, $-6.9 \pm 3.7$ deg, $7.4 \pm 20.2$ mm, and $-15.14 \pm 26.1$ mm. The system can estimate gait parameters with reasonable accuracy. An earlier report (Sagawa et al., 2018) described that the estimation precision of total gait distance has improved from $-5.23 \pm 5.64\%$ to $-0.81 \pm 5.40\%$ and that the estimation precision of 10 m gait time has improved from $7.81 \pm 29.33\%$ to $1.27 \pm 8.60\%$. In this study, to improve the accuracy of the gait parameters for medical use, the estimated gait displacement was adjusted to match the measured displacement. The gait trajectory was recalculated. The modified estimated 10 m gait time shows preferable correlation with the reference time, as shown in Fig. 9. If the walking displacement of all subjects

![Fig. 11 Relation between age of subjects with gait parameters and MMSE score.](image-url)
Acknowledgements

A part of this study was supported by JSPS KAKENHI Grant Number 25350663. The authors wish to express our gratitude to Dr. Shigeyuki Nakaji for his acceptance of our sensor system at the City of Hirosaki’s Iwaki Health Promotion Project.

References

Abbott, R. D., White, L. R., Ross, G. W., Masaki, K. H., Curb, J. D. and Petrovitch, H., Walking and dementia in...
physically capable elderly men, JAMA, Vol.292, No. 12 (2004), pp.1447–1453.

Allali, G., Assal, F., Kressig, R. W., Dubost, V., Herrmann, F. R. and Beauchet, O., Impact of impaired executive function on gait stability, Dement Geriatr Cogn Disord, Vol.26 (2008), pp.364–369.

Arif, M., Bilal, M., Kattan, A. and Ahamed, S. I., Better physical activity classification using smartphone acceleration sensor, J Med Syst, Vol.38:95 (2014), DOI: 10.1007/s10916-014-0095-0

Azman, A. M., Kuga, H., Sagawa, K. and Nagai, C., Fastest gait parameters estimation precision comparison using high-sensitivity and low-sensitivity inertial sensor, IFMBE Proceedings (2017), Vol.67, pp.79–84. DOI: 10.1007/978-981-10-7554-4_13

Azman, A. M., Nagai, C., Sagawa, K., Hirakawa, Y. and Sawada, K., Predicting possibility of mild cognitive impairment from gait parameter measured using inertial sensor, Conference on Information, Intelligence, and Precision Equipment, 1B03 (2019).

Bao, L. and Intille, S. S., Activity recognition from user-annotated acceleration data, Pervasive computing (2004), pp.1–17.

Barnes, D. E., Yaffe, K., Satariano, W. A. and Tager, I. B., A longitudinal study of cardiorespiratory fitness and cognitive function in healthy older adults, J Am Geriatr Soc, Vol.51 (2003), pp.459–465.

Beauchet, O., Allali, G., Berrut, G., Hommet, C., Dubost, V. and Assal, F., Gait analysis in demented subjects: interests and perspectives, Neuropsychiatr Dis Treat, Vol.4 (2008), pp.155–160.

Chen, K. Y., and Bassett, D. R., The technology of accelerometry-based activity monitors: current and future, Medicine and science in sports and exercise, Vol.37, No.11 (2005), S490, DOI: 10.1249/01.mss.0000185571.49104.82

Ermes, M., Pärkkä, J., Mäntyjärv, J. and Korhonen, I., Detection of daily activities and sports with wearable sensors in controlled and uncontrolled conditions. IEEE Transactions on Information Technology in Biomedicine, Vol.12, No.1 (2008), pp.20–26.

Esser, P., Dawes, H., Collett J., Feltham, M. G. and Howells, K., Assessment of spatiotemporal gait parameters using inertial measurement units in neurological populations, Gait & Posture, Vol.34 (2011), pp.558–560.

Harrell, L. E., Marson, D., Chatterjee, A. and Parrish, J. A., The Severe Mini-Mental Status Examination: A New Neuropsychologic Instrument for the Bedside Assessment of Severely Impaired with Alzheimer's Disease, Alzheimer Disease and Associated Disorders, Vol.14 No.3 (2000) 168–175.

Hausdorff, J. M., Schweiger, A., Herman, T., Yogev-Seligmann, G. and Giladi, N., Dual-task decrements in gait: contributing factors among healthy older adults, J Gerontol A Biol Sci Med Sci, Vol.63 (2008), pp.1335–1343.

Ibata, Y., Kitamura, S., Motoi, K. and Sagawa K., Measurement of three-dimensional posture and trajectory of lower body during standing long jumping utilizing body-mounted sensors, 2013 35th Annual International Conference of the IEEE (2013), pp.4891–4894.

Ijmker, T. and Lamoth, C. J., Gait and cognition: The relationship between gait stability and variability with executive function in persons with and without dementia, Gait & Posture, Vol.35 (2012), pp.126–130.

Khan, M., Ahamed, S. I., Rahman, M. and Smith, R. O., A feature extraction method for realtime human activity recognition on cell phones, Proceedings of 3rd International Symposium on Quality of Life Technology (2011).

Kramer, A. F., Colcombe, S. J., McAuley, E., Scaf, P. E. and Erickson, K. I., Fitness, aging and neurocognitive function. Neurobiology of Aging, Vol.26, Issue 1, Supplement, (2005), pp.124–127.

Kuga, H. and Sagawa, K., Estimation of walking distance of 10 meter fastest walk using tiptoe-mounted inertial sensor, Proceedings of International Conference on Mechatronics and Information Technology (ICMIT2015), (2015), pp.201–205.

Lamoth, C. J., Ainsworth, E., Polomski, W. and Houdijk, H., Variability and stability analysis of walking of transfemoral amputees, Med Eng Phys, Vol.32 (2010), pp.1009–1014.

Lamoth, C. J., Deudekom, F. J., Van Campen, J. P., Appels, B., De Vries, O. J. and Pijnappels, M., Gait stability and variability measures show effects of impaired cognition and dual tasking in frail people, J Neuroeng Rehabil, Vol.8 (2011), p.2

Lee, J. A., Cho, S. H., Lee, Y. J., Yang, H. Y. and Lee, J. W., Portable Activity Monitoring System for Temporal Parameters of Gait Cycles, Journal of Medical Systems, Vol.34, No.5 (2010), pp.959–966.

Lockhart, T. E. and Liu, J., Differentiating fall-prone and healthy adults using local dynamic stability, Ergonomics, Vol.51 (2008), pp.1860–1872.

Manckoundia, P., Pfiftenmeyer, P., d’Athis, P., Dubost, V. and Mourey, F., Impact of cognitive task on the posture of
elderly subjects with Alzheimer’s disease compared to healthy elderly subjects, Mov Disord, Vol.21 (2006), pp.236–241.

Mariani, B., Hoskovec, C., Rochat, S., Bülə, C., Penders, J. and Aminian, K., 3D gait assessment in young and elderly subjects using foot-worn inertial sensors, Journal of Biomechanics, Vol.43, Issue 15, 16 (2010), pp.2999–3006.

Maurer, U., Smailagic, A., Siewiorek, D. P. and Deisher, M., Activity recognition and monitoring using multiple sensors on different body positions, International Workshop on Wearable and Implantable Body Sensor Networks, (2006).

DOI: 10.1109/BSN.2006.6

Ohtaki, Y., Inooka, H., Sagawa, K., Suzuki, A., Xiumin, Z., Okutsu, M. and Nagatomi, R., Recognition of daily ambulatory movements utilizing accelerometer and barometer, Proceedings of the Second IASTED International Conference BIOMECHANICS (2004), pp.18-21.

Ojeda, L. and Borenstein, J., Non-GPS navigation for security personnel and first responders, J Navig, Vol.60 No. 3 (2007), pp.391–407.

Pangman, V. C., Sloan, J. and Guse, L., An Examination of Psychometric Properties of the Mini-Mental Status Examination and the Standardized Mini-Mental Status Examination: Implications for Clinical Practice, Applied Nursing Research, Vol.13, No.4 (2000), pp.209–213.

Persad, C. C., Jones, J. L., Ashton-Miller, J. A., Alexander, N. B., and Giordani, B., Executive function and gait in older adults with cognitive impairment, J Gerontol A Biol Sci Med Sci, Vol.63 (2008), pp.1350–1355.

Sagawa, K. and Ohkubo, K., 2D trajectory estimation during free walking using a tip-toe-mounted inertial sensor, J. Biomech, Vol.48 No. 10 (2015), pp.2054–2059.

Sagawa, K., Kuga, H., Azman, A. M., Nagai, C., Nakaji, S. and Kurauchi, S., Improvement of measurement precision of wearable gait evaluation system used in large scale health checkup, Conference on Information, Intelligence, and Precision Equipment, 1B16 (2018) (in Japanese).

Sheridan, P. L., Solomont, J., Kowall, N. and Hausdorff, J. M., Influence of executive function on locomotor function: divided attention increases gait variability in Alzheimer’s disease, J Am Geriatr Soc, Vol.51 (2003), pp.1633–1637.

Tanaka, H. and Sagawa, K., Judgement of the stance phase using tip-toe-mounted sensor, The Society of Instrument and Control Engineers Tohoku Chapter 258th Research Meeting, 258-8 (2010) (in Japanese).

Tombaugh, T. N. and McIntyre, N. J., The mini-mental Status Examination: A comprehensive Review, Journal of the American Geriatrics Society, Vol.40, No.9 (1992), pp.922–935, DOI: 10.1111/j.1532-5415.1992.tb01992.x

Verghese, J., Ayers, E., Barzilai, N., Bennett, D. A., Buchman, A. S., Holtzer, R., Katz, M. J., Lipton, R. B. and Wang, C., Motoric cognitive risk syndrome: multicountry prevalence and dementia risk, Neurology, Vol.83 No.8 (2014), pp.718–726.

Yaffe, K., Barnes, D., Nevitt, M., Lui, L. Y. and Covinsky, K., A prospective study of physical activity and cognitive decline in elderly women, Arch Inter Med, Vol.161 (2001), pp.1703–1708.

Yang, S. and Li, Q., Inertial sensor-based methods in walking speed estimation: a systematic review, Sensors (Basel), Vol.12 No.5 (2012), pp.6102–6116.

Yogev-Seligmann, G., Hausdorff, J. M. and Giladi, N., The role of executive function and attention in gait, Mov Disord, Vol.23 (2008), pp.329–342.

Yu, M., Piao, Y. J., Eun, H. I., Kim, D. W., Ryu, M. H. and Kim, N. G., Development of Abnormal Gait Detection and Vibratory Stimulation System on Lower Limbs to Improve Gait Stability, Journal of Medical Systems, Vol.34, No.5 (2019), pp.787–797.