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Reliability and Validity Study of Inertial Sensor-Based Application for Static Balance Measurement

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Objective: To investigate the reliability and validity of static balance measurements using an acceleration sensor and a gyroscope sensor in smart phone inertial sensors.

Design: Equivalent control group pretest-posttest.

Methods: Subjects were forty five healthy adults aged twenty to fifty-years-old who had no disease that could affect the experiment. After pre-test, all participants wore a waist band with smart phone, and conducted six static balance measurements on the force plate twice for 35 seconds each. To investigate the test-retest reliability of both smart phone inertial sensors, we compared the intra-correlation coefficient (ICC 3, 1) between primary and secondary measurements with the calculated root mean scale-total data. To determine the validity of the two sensors, it was measured simultaneously with force plate, and the comparision was done by Pearson's correlation.

Results: The test-retest reliability showed excellent correlation for acceleration sensor, and it also showed excellent to good correlation for gyroscope sensor($p < 0.05$). The concurrent validity of smartphone inertial sensors showed a mostly poor to fair correlation for tandem-stance and one-leg-stance ($p < 0.05$) and unacceptable correlation for the other postures ($p > 0.05$). The gyroscope sensor showed a fair correlation for most of the RMS-Total data, and the other data also showed poor to fair correlation ($p < 0.05$).

Conclusions: The result indicates that both acceleration sensor and gyroscope sensor has good reliability, and that compared to force plate, acceleration sensor has unacceptable or poor correlation, and gyroscope sensor has mostly fair correlation.

Key Words: Telemedicine, Wearable Technology, Postural Balance, Smartphones

Introduction

Fall refers to falling to a lower position or floor than an individual's intention during daily life [1] and falls due to loss of balance can cause serious complications such as trauma and fractures [2]. In particular, aging causes functional loss and degeneration of all organs and tissues. Also, it increases instability in everyday life [3]. According to the Korea Ministry of Health and Welfare survey of senior citizens aged 65 and older, the rate of falling is about 15.9% per year, and the rate of hospitalization is about 64.9% [4].

Balance is the ability to maintain the center of gravity (COG) of the body in the basal plane [5], and is an essential component of functional activity during daily life [2]. The body requires delicate interactions of the motor and sensory systems to maintain balance [6], however, it is reduced by aging-induced muscle strength, impaired proprioceptive sense, vestibular and visual impairment, and delayed response time, as a result, increases the risk of falls [7, 8].

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Currently, various examination methods are being tried for balance evaluations. Romberg test can be applied conveniently without any space constraints and is still widely used today as an easy method. Although such a highly utilized evaluation method, it has the disadvantage that quantitative measurement is difficult [9]. Clinics use a lot of equipment to measure center of pressure (COP) in force plate and insole, but it is expensive and requires a large space and expertise [10, 11]. On the other hand, smartphones have less space-time constraints, and frequency collection using acceleration sensors shows high potential for static balance evaluation [12].

Recently, in preparation for the prolonged COVID-19 pandemic, the government has made efforts to make non-face-to-face medical care a regular medical service [13], which has highlighted the importance of tele-rehabilitation. However, there are challenges for clinicians in understanding and technology to evaluate and manage patients remotely [14].

Smartphones are easily accessible and have high potential in tele-rehabilitation for neurological patients, and are actually studying various rehabilitation possibilities using smartphones [15-17]. An inertial measurement unit (IMU), which is key to various rehabilitation studies using smartphones, is a device that measures the speed, direction, gravity, and acceleration of moving objects, consisting of acceleration sensors, geomagnetic sensors, and gyroscope sensors [18]. Various studies have been conducted clinically to develop a smartphone-based balance assessment system by attaching acceleration sensors and gyroscope sensors to the body [17-20].

However, due to the lack of studies that evaluate the reliability of measuring postural sway through two sensors mounted on smartphones while verifying their validity against other balance equipment, it is somewhat difficult to utilize the two sensors in clinical setting.

Therefore, we would like to utilize acceleration sensors and gyroscope sensors to evaluate their balance abilities, verify their reliability and validity, and propose a new balance evaluation methods that can be conveniently used without space-time constraints.

Method

1. Participants

52 healthy adults aged 20 to 50 in the K hospital in Seoul were selected as subjects based on their agreement. Five people who did not meet the pre-experimental criteria were excluded, and two were eliminated during the experiment. Thus, 45 subjects were finally selected. After collecting general features including gender, age, weight, and height. The pre-test was measured with the dominant foot kicking the ball through a ball kick [21] (Table 1). Exclusion criteria were those who had fallen in their daily lives, those who had nervous system, musculoskeletal system disease or damage, and those who had exercised excessively within the past week. This study was reviewed by the Institutional Review Board of Sahmyook University, Seoul. The serial number for the review is 2-1040781-A-N-012021015HR.

2. Measures

The participants of this study wore their smartphones as a belt around their waist (Sacrum 2) and performed the six static balance tests; Shoulder-width-stance with eye open (SWS-EO), Shoulder-width-stance with eye closed (SWS-EC), Feet-together-stance (FTS), Semi-tandem-stance (STS), Tandem-stance (TS), and One-leg stance (OLS)

Table 1. General characteristics of participations (N=45)

	Mean±SD
Gender(M/F)	22/23
Age (year)	34.64±8.33
Heights (cm)	167.42±7.73
Weight (kg)	62.27±11.22
Dominant Foot (R/L)	40/5

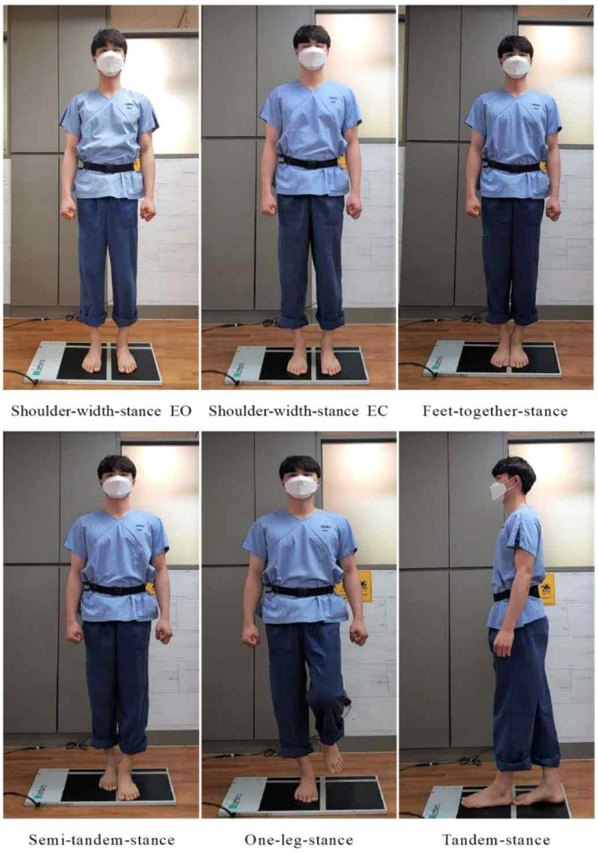

Figure 1. Static Balance Measurement Postures

[20, 22] (Figure 1). In order to verify the concurrent validity, all posture measurements were made on the force plate, and simultaneously through an application that records the smartphone inertial sensors. They were repeated twice for 35 seconds. When tests were completed, results were repeated a day later (24 hours) with the same postures and methods in order to identify the test-retest reliability [19]. A Galaxy S20 (SM-G981N, Samsung, Korea) mounted with an inertial sensor (LSM6DSO MEMS, STMicroelectronics, Switzerland) was used to measure the static balance tests. The smartphone was set to horizontal mode and fixed with a belt to the subject's waist (Sacrum 2), and Sensor kinetics pro (Sensor kinetics pro ver.3,1.2, Innovations Inc., US) was run simultaneously with the start of the experiment to measure acceleration data and gyroscope data.

Acceleration data

The acceleration data was based on the Z-axis movement as Accelerometer root mean scale anteroposterior (ARMS-AP) and the Y-axis movement as Accelerometer root mean scale mediolateral (ARMS-ML), and the values obtained through the square root of the Z-axis and Y-axis was normalized to the accelerometer root mean scale total (ARMS-Total).

Gyroscope data

Gyroscope data was the gyroscope root mean scale pitch (GRMS-Pitch) for the movement of the pitch and the gyroscope root mean scale roll (GRMS-Roll) for the movement of the roll, and the gyroscope root mean scale total (GRMS- Total).The data calculated by the gyroscope sensor was multiplied by $180 \div \pi$ to the calculated data value to change the unit from rad/s to degree/s [20] (Figure 2).

Force plate data

The data of the force plate measured by the movement of COG was normalized to the following three data; Center of pressure velocity anteroposterior

(COPV-AP), Center of pressure velocity mediolateral (COPV-ML), and Mean sway velocity (MSV) obtained through the square roots of the X-axis and Y-axis.

$$\mathrm{RMS} = \sqrt{\frac{\sum_{i=1}^{n}(S_i)^2}{N}} \quad \mathrm{S} = \text{sequence},$$

N = total number of units,

$i = 1, 2, \cdots, N$ [22]

Figure 2. Detailed Data Conversion Equations

3. Data analysis

SPSS software (SPSS ver.20.0, IBM SPSS Statistics, USA) was used for all operations and statistics, and descriptive statistics were used for general characteristics. In order to confirm the reliability of the acceleration data and gyroscope data measured in the first and second trials, each data was analyzed as an intra-class correlation coefficient (ICC 3,1). Pearson's correlation analysis was used to verify the validity of the smartphone inertial sensor-based application. A significance level was set at a p-value of <0.05.

Result

1. Test–retest reliability of smartphone inertial sensors

The reliability of the acceleration sensor showed a very high correlation (ICC > 0.90) in all postures ($p < 0.001$). The reliability of the gyroscope sensor showed a very high (ICC > 0.90) or high correlation (ICC > 0.75) in all postures ($p < 0.001$), which can be shown as below (Table 2).

2. Concurrent validity of smartphone inertial sensors and force plate

Most of tandem-stance and one-leg-stance showed a poor to fair correlation ($0.3 < r < 0.7$) and were significant ($p < 0.01$), and the other four postures showed negligible correlation ($r < 0.3$) and not significant ($p > 0.05$) in a comparison of the acceleration sensor correlation with the force plate (Table 3, Figure 3). However, fair correlation ($0.5 < r < 0.7$) was shown in all values except tandem-stance in the comparison of the RMS-Total of the gyroscope and the MSV of the force plate ($p < 0.01$). In addition, in the comparison values of GRMS-Pitch and COPV-AP, GRMS-Roll and COPV-ML, all showed a significant correlation of poor to fair ($0.3 < r < 0.7$) (Table 4, Figure 4).

Table 2. Reliability of smartphone inertial sensors (N = 45)

Sensor	Postures	[a] ICC	[b] 95% CI
Acceleration	SWS-EO	0.978**	0.960–0.988
	SWS-EC	0.915**	0.846–0.953
	FTS	0.958**	0.924–0.977
	STS	0.962**	0.931–0.979
	TS	0.916**	0.847–0.953
	OLS	0.949**	0.908–0.971
Gyroscope	SWS-EO	0.885**	0.791–0.937
	SWS-EC	0.902**	0.822–0.946
	FTS	0.840**	0.709–0.912
	STS	0.786**	0.610–0.882
	TS	0.760**	0.564–0.868
	OLS	0.903**	0.824–0.947

[a] Intra-class correlation coefficient (ICC 3,1).
[b] 95% Confidence Interval.

Table 3. Validity of acceleration sensor and force plate (N = 45)

Postures	ARMS/FP COPV	[a] PCC (p)	[b] 95% CI
SWS-EO	AP	0.013 (0.937)	−0.347～0.533
	ML	0.130 (0.419)	−0.341～402
	Total/MSV	0.157 (0.328)	−0.290~0.569
SWS-EC	AP	0.015 (0.549	−0.160～0.394
	ML	0.096 (0.548)	−0.160～0.394
	Total/MSV	0.104 (0.516)	−0.167～0.431
FTS	AP	−0.089 (0.604)	−0.261～0.124
	ML	0.143 (0.371)	−0.057～0.419
	Total/MSV	0.004 (0.981	−0.160～0.204
STS	AP	0.028 (0.862)	−0.245～0.337
	ML	0.102 (0.524)	−0.071～0.464
	Total/MSV	0.121 (0.452)	−0.092～0.373
TS	AP	0.405 (0.009)**	−0.151～0.719
	ML	0.289 (0.067)	−0.006～0.564
	Total/MSV	0.408 (0.008)**	−0.016～0.681
OLS	AP	0.299 (0.057)	−0.101～0.590
	ML	0.556 (0.000)**	0.291～0.749
	Total/MSV	0.542 (0.000)**	0.303～0.725

[a] Pearson's correlation coefficient.
[b] 95% Confidence Interval.

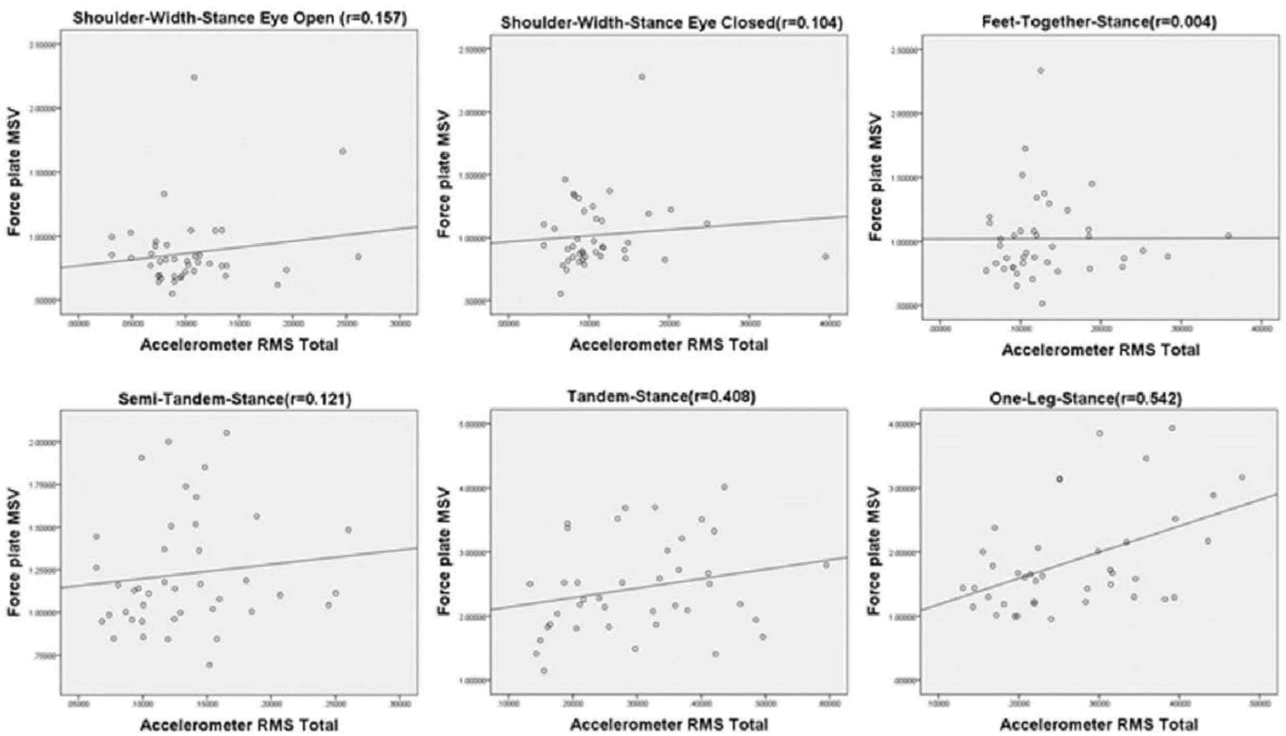

Figure 3. Validity of acceleration sensor and force plate

Table 4. Validity of gyroscope sensor and force plate (N = 45)

Postures	GRMS/FP COPV	[a] PCC (p)	[b] 95% CI
	Pitch/AP	0.470 (0.009)**	0.068～0.711
SWS-EO	Roll/ML	0.427 (0.019)*	0.015～0.683
	Total/MSV	0.623 (0.000)**	0.277～0.811
	Pitch/AP	0.470 (0.009)**	0.144～0.734
SWS-EC	Roll/ML	0.560 (0.001)**	0.255～0.771
	Total/MSV	0.661 (0.000)**	0.385～0.839
	Pitch/AP	0.709 (0.000)**	0.519～0.842
FTS	Roll/ML	0.413 (0.023)*	0.049～0.664
	Total/MSV	0.684 (0.000)**	0.466～0.829
	Pitch/AP	0.645 (0.000)**	0.385～0.839
STS	Roll/ML	0.474 (0.008)**	0.110～0.791
	Total/MSV	0.623 (0.000)**	0.300～0.849
	Pitch/AP	0.364 (0.019)*	0.079～0.629
TS	Roll/ML	0.636 (0.000)**	0.381～0.822
	Total/MSV	0.450 (0.003)**	0.074～0.719
	Pitch/AP	0.559 (0.001)**	0.358～0.740
OLS	Roll/ML	0.663 (0.000)**	0.443～0.829
	Total/MSV	0.640 (0.000)**	0.440～0.799

[a] Pearson's correlation coefficient.

[b] 95% Confidence Interval.

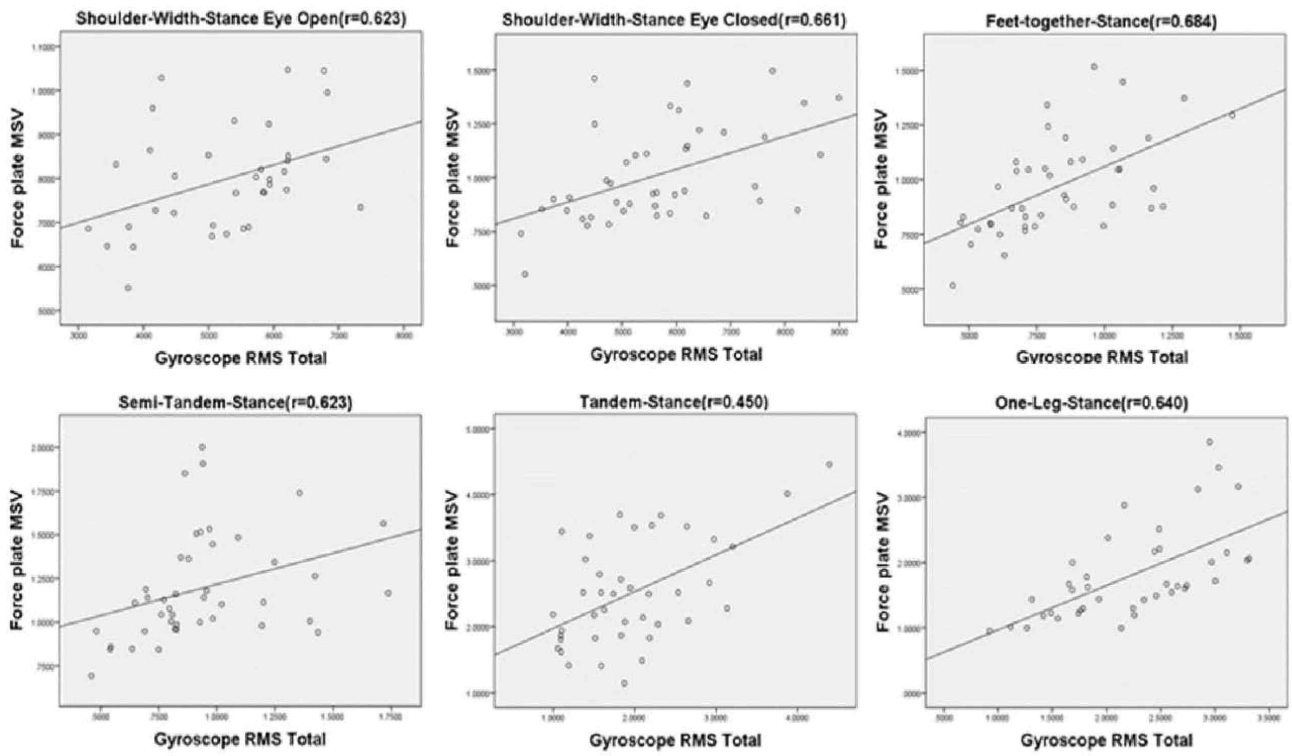

Figure 4. Validity of gyroscope sensor and force plate

Discussion

Deterioration in the ability to maintain posture is the cause of falls, and restoration of balance becomes a key goal in the rehabilitation process. Thus, objective evaluation of balance is clinically an important indicator in tracking disease or performing therapeutic interventions [24]. Since the force plate measures the movement of the COP, it measures the velocity on the ground. As activities to increase body stability in both feet increase, the values proportionately increase. On the other hand, the smartphone inertial sensor measures the value of acceleration and angular velocity through the movement of COM from the body. As the body's activity increases, these values become larger [23] Therefore, two signals differ slightly in the movement position, so the relationship cannot be expressed as completely linear [19]. However, because both variables show body sway in proportion to the numerical value and the inertial measurement technologies have the potential to be a reliable alternative compared to the balance evaluation of the force plate [25], many studies have compared simultaneous validity through analysis between the two signals [19, 23, 26, 27]. Therefore, this study tried to verify that the acceleration sensor and gyroscope sensor mounted in smartphones have reliability and validity in measuring the static balance abilities.

First, it was found that both sensors have high reliability when measuring six static balance tests. The studies of Hou et al. [20] and Lee. D. H et al. [28] showed similar results to this study that both sensors have high reliability, and supports the results of this study. On the other hands, the reliability of this study was higher than the study of De Groote et al. [19], which reported that the smartphone acceleration sensor has moderate-high reliability. The reason is that this study used a smartphone equipped with an LSM6DSO sensor with improved accuracy than the LSM6DS3 sensor used in De Groote's research. In addition, the study was analyzed through the RMS values of the Z-axis and Y-axis data, respectively, however, in this study, the mechanical error was corrected by analyzing the total RMS obtained through the square of the two axes, and the reliability value could be increased. Therefore, it is believed that the smartphone acceleration sensor and gyroscope sensor can measure the static balance consistently and reliably.

Second, this study found that it has a higher validity when measuring balance abilities with the gyroscope sensor than with the acceleration sensor. It shows similar results to the studies of De Groote et al. [20] and Han Seul-gi et al. [29] that there was negligible correlation when performing balance tasks with low difficulty level, and that there was a fair or higher correlation when performing balance tasks with higher difficulty level. O'Sullivan et al. [30] reported that acceleration data can be measured in more difficult balance tasks, which supports this study. The reason is that, in the bipodal postures, only minute postural fluctuations occur in the ankle with a wide BOS, so it is not recorded as acceleration data measuring instantaneous postural fluctuations. However, in the tandem stance and one leg stance, the movements of the ML and AP axes appear as large fluctuations due to the narrowed left and right BOS, and are recorded in the acceleration sensor. On the other hand, the reason that the correlation of this study was lower than that of Ruopeng Sun et al. [25] is because the subjects of this study were healthy adults with superior balance ability than those with multiple sclerosis. Thus, it was judged that it was difficult to measure minute postural fluctuations in the easy postures with acceleration data representing strong body movements. A similar study by Koller et al. [31] reported that the acceleration sensor was unable to distinguish between mild multiple sclerosis patients and healthy adults in a low-difficulty static balance postures.

Also, most of the previous static balance measurements only studied the correlation between the acceleration sensor and the force plate [32-34]. However, in this study, the correlation between the gyroscope sensor and the force plate was compared, and it was confirmed that there was poor to fair correlations ($0.3 < r < 0.7$) in all postures ($p < 0.05$). In the study of Hou et al. [20], it reported that acceleration data did not correlate with Berg Balance Scale (BBS) ($p < 0.05$), but gyroscope data had strong negative correlations with it ($-0.694 < r < -0.805$). In addition, in another study by Hou et al. [35] comparing chronic stroke patients, there was no significant correlation between smartphone acceleration sensor and BBS in static balance measurements ($p > 0.05$). However, the data measured with the gyroscope sensor showed a significant correlation with it ($p < 0.05$). These results are consistent with the results of this study that most of the acceleration sensor data had no correlation, but the gyroscope data had poor to moderate correlations. Among the two sensors measured by the smartphone application, the acceleration sensor is easy to measure static balance tests in difficult postures, and the gyroscope sensor is expected to be used to measure most static balance tests. The reason for the difference in correlation between the two devices is that acceleration data can represent strong body movements, whereas gyroscope data represents the degree of how much postural sway appears. As a result, acceleration data is mainly used to analyze the direction and speed of body movement, while gyroscope data analyzes how much the body moves while performing the task in rotational movement and amplitude. Thus, it is necessary to appropriately sum the values obtained through the acceleration sensors and the gyroscope sensors, and correct the error. Therefore, the combination of the two inertial sensors by using additional algorithms such as Kalman filter or Complementary filter could better measure the balance abilities [35]. Park, D, S. et al. [36] reported that there are needs for balance evaluation equipment that can be used immediately and can be evaluated at low cost, instead of existing expensive balance equipment. In this study, we confirmed the possibility of using a smartphone as a method to measure static balance tests as a low cost and easy method in an environment where setting of large equipment is difficult, though measuring the static balance abilities through a smartphone may be less sensitive than measuring the balance using a force plate [19]. Therefore, this study is meaningful as a study that first considered the possibility that a smartphone gyroscope sensor can be used as a new balance evaluation tool in a period of expanding tele-rehabilitation.

There are several limitations in this study. First, this study fixed the smartphone to sacrum two. However, the result values can differ depending on the location of the smartphone attachment because the movements of the ankle, knee, and hip joint may appear as different balance strategies. Therefore, efforts are required to try to quantitatively measure balance tests in various body parts. Second, the sample in the study was homogeneous, consisting of healthy adults aged 20 to 50. In future studies, it will be necessary to conduct studies on various groups, such as patients with difficulty in balance and elderly people with high risk of falling. Third, the test interval was short, so the learning effect was likely to be involved. In future studies, it is necessary to verify the reliability in various aspects. Finally, it took a lot of time to organize a large amount of data because Sensor kinetics pro used to derive inertial data is not a system developed solely to measure balance. In future studies, it will be necessary to develop an application that can calculate data and implement it with an easy quantitative measurement methods.

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