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Effects of walking speed and age on the directional stride regularity and gait variability in treadmill walking †

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Abstract

In Inertial measurement unit (IMU) based gait analysis systems, the shoe-type sensor is not commonly used, unlike trunk attached sensors. The purpose of this study was to assess the directional Stride regularity (SR) and Gait variability (GV) of data from shoe-type IMU sensors during leveled treadmill walking. The other aim was to investigate the effects of walking speed and age on directional SR and GV in an attempt to find the directional preference associated with gait stability. The DynaStab™ (IMU based gait analysis system) including Smart Balance® (shoe-type data logger) was used to collect normal gait data from forty-four subjects in their 20s (n = 20), 40s (n = 13), and 60s (n = 11). Four different walking speeds (3, 4, 5 and 6 km/h, respectively) on a treadmill were applied for one-minute of continuous leveled walking. Three linear accelerations and three angular velocities were measured with shoe-type IMU sensors. The SR (autocorrelation) and CV of ensemble data (coefficient of variation) on directional kinematics were calculated and compared with different walking speeds and ages. The results indicated that the lateral kinematics (mediolateral acceleration and yawing and rolling angular velocities) had lower stride regularity and higher gait variability than the anteroposterior and vertical kinematics across all walking speeds and ages. Significant interactions on the SRs and GVs from walking speed and age were found for only mediolateral acceleration and rolling angular velocity. Conclusively, the shoe-type IMU sensor system assessed directional SR and GV during walking conveniently. People should be careful with lateral kinematics since it is very sensitive to walking speed and age from the perspective of gait stability.

Keywords: Gait stability; Inertial sensor; Regularity; Variability

1. Introduction

In daily life, walking is one of the most important fundamental motor skills of human beings because it enables free locomotion. While walking, people tend to shift their Center of mass (CM) from one leg to the other, resulting in rhythmical lateral and vertical movements with forward translation. This dynamic stability while walking has been interpreted in terms of stride or step regularity and variability of spatio-temporal gait parameters [1-3]. These parameters are also used for overall quality assessments of normal gait [1, 4]. Gait variability has been represented by temporal parameters of stride time and swing time and spatial parameters such as step length and step width [5, 6]. Stride regularity is obtained with the use of unbiased autocorrelation procedures on acceleration data [7, 8].

Recently, gait assessments using IMU sensors on the waist, trunk, shank, heel, and top of the foot have been tested [9-12]. Conventionally, optical motion capturing systems that enable two-dimensional or three-dimensional analyses have been a standard tool in gait study. This system provides precise measurements of spatio-temporal parameters and joint kinematics, but it has disadvantages of high cost, huge space, long post-processing time, and the necessity of a skilled technician to operate it efficiently. Therefore, the IMU-based sensor is considered an alternative option because it can quantify spatial (e.g., step and stride length) and temporal gait parameters (e.g., stance time, double support times, and cadence) conveniently with low cost [14]. The IMU-based gait analysis system is known to be valid and reliable for the analysis of gait parameters [14-16].

The variability of trunk movement (or lower trunk acceleration) is considered a reasonable indicator of gait variability and stability with the help of the IMU sensor [7, 17]. Nonetheless, the initial contact segment on the ground is the foot. The variability and regularity of feet movements are considered to be a factor in stabilizing balance during gait due to the manipulation of the center of mass [18]. Even though results of gait assessment with shoes-type IMU sensors agreed with the results of optical motion capturing systems [19, 20], the direc-

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Table 1. Demographic data for subjects.

		N	Height (cm)	Mass (kg)	Age (yr)
20s	M	10	173±2.7	68.4±5.2	23.6±1.0
	F	10	161±5.2	55.3±5.7	21.8±2.7
40s	M	6	172±5.5	73.4±3.2	46.0±3.0
	F	7	161±2.2	56.4±5.4	43.1±5.6
60s	M	5	169±3.7	65.8±6.7	64.6±4.3
	F	6	157±6.4	60.5±8.8	64.7±4.3
Total			166±7.7	62.8±9.7	39.6±17.7

tional kinematics associated with gait stability, assessed through shoe-type IMU sensors, has not been well established. Thus, the primary purpose of this study was to assess the directional stride regularity and gait variability in terms of shoe-type IMU sensors.

Aging is the process of deterioration of physiological and cognitional functions as people get old. Many elderly people develop a geriatric gait profile due to frailty [21]. One of characteristics of a geriatric gait profile is the increased fall risk [22]. Many studies have focused on the control of balancing and gait parameters in anteroposterior (A-P) direction, but there is growing evidence that elderly people may be vulnerable to dynamic instability of the frontal plane [23-25].

Therefore, the other purpose of this study was to investigate the effects of walking speed and age on the directional stride regularity and gait variability of data from shoes-type IMU sensors. We hypothesized that the stride regularity and gait variability would be different from the direction of 3D motions. Moreover, it was hypothesized that the stride regularity would decrease and the gait variability would increase with increases in walking speed and age.

2. Methods

2.1 Subjects

Forty-four adults in their 20s, 40s and 60s voluntarily participated in this study. The detailed demographic data for the subjects are shown as Table 1. They had no neuromuscular diseases during the last six months and no physical restrictions to walking on a treadmill. Written informed consent forms were obtained from all subjects. All procedures in this study were in accordance with the Declaration of Helsinki.

2.2 Equipment and data acquisition

Gait data were collected with the DynaStab^{TM} (JEIOS, Powell, OH, USA), an IMU sensor-based gait analysis system. The DynaStab^{TM} consists of the Smart Balance SB-1$^{®}$ (data-logger of shoes-type IMU sensors), a treadmill, and a data collecting computer (Fig. 1). The SB-1$^{®}$ with IMU sensors (IMU-3000^{TM}, Inven Sense, San Jose, CA, USA) can measure three-axial accelerations (up to ±6 g) and three-axial angular velocities (up to ±500°/s) in three orthogonal axes. The IMU

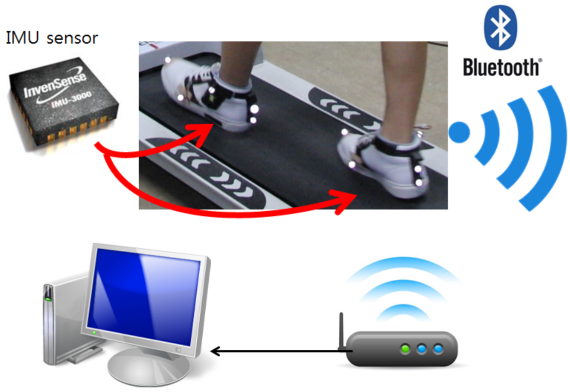

Fig. 1. Shoe-type IMU sensor gait system and experimental set-up for data communication.

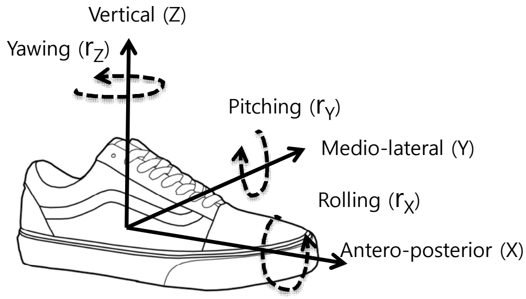

Fig. 2. Directional definitions of six directional kinematic data for normal gait.

sensors were inserted in both out-soles of the shoes. The local axis of the IMU sensor was aligned with the usual orientation of the gait such as the anteroposterior (AP) (X-axis), mediolateral (ML) (Y-axis), and vertical (Z-axis) directions, respectively (Fig. 2). Raw data from sensors were sampled at 100 Hz, filtered at 17 Hz with a low-pass Butterworth filter, and wirelessly transmitted in real time to a computer through a Bluetooth$^{®}$ receiver (Fig. 1). Three differently sized shoes (i.e., 235, 255 and 275 mm) were used for fitting differently sized individuals' feet.

2.3 Procedures

When subjects came to the lab, they were allowed to perform as much warm-up and stretching as they desired. After warm-up, subjects wore the SB-1$^{®}$ shoes and walked on a treadmill at four different speeds of 3, 4, 5 and 6 km/h (0.83, 1.11, 1.38 and 1.66 m/s), respectively. Data for one-minute continuous and steady walking were collected at each designated treadmill speed when subjects felt comfortable and verbally expressed a steady state condition in the middle of treadmill walking. It took less than 5 minutes to reach a steady state at each designated speed. The order of treadmill speeds was determined using the counter-balanced design. A three-minute resting interval between different speed conditions was given to remove the effect of fatigue.

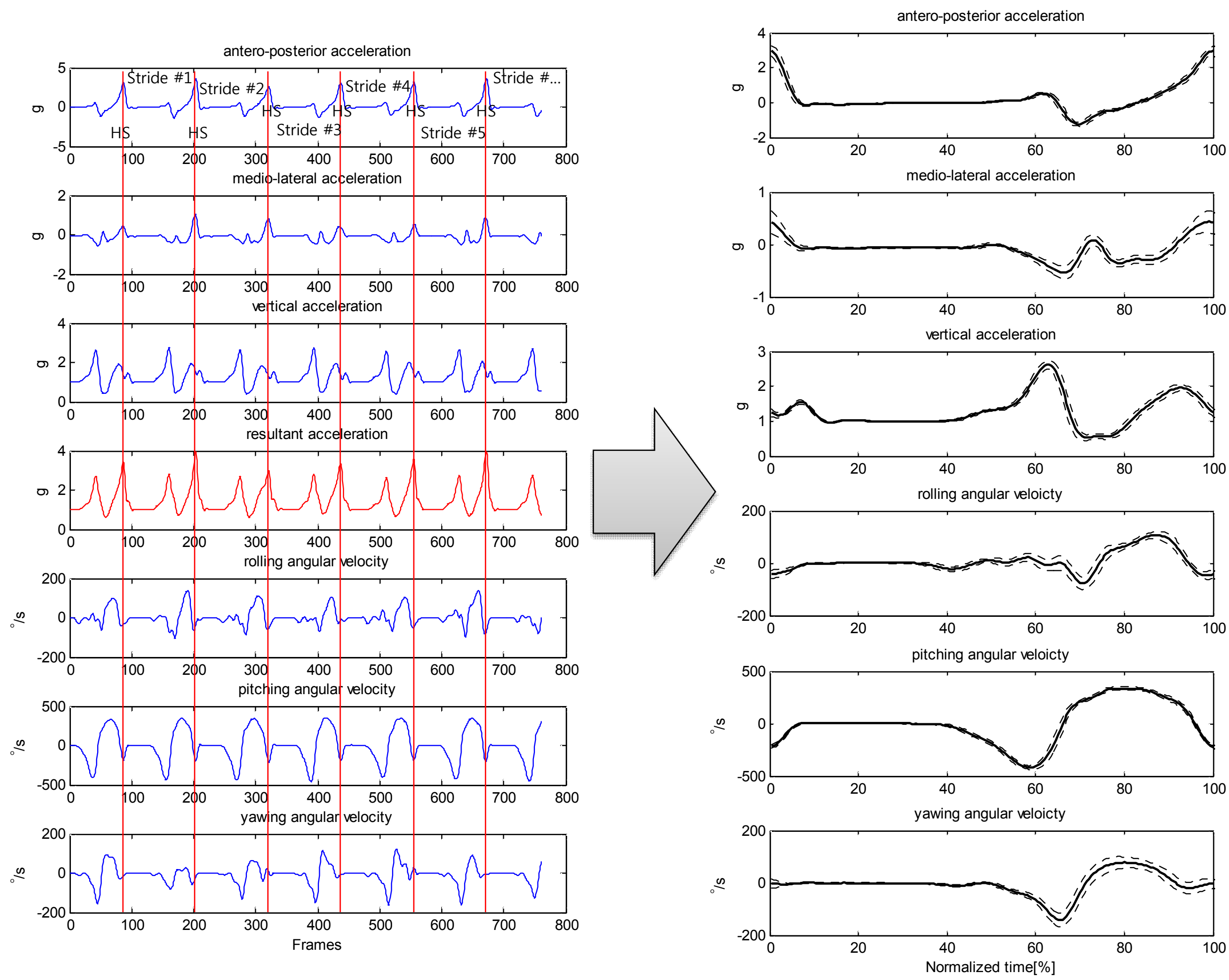

Fig. 3. Examples of filtered data for six components (up to 800 frames) and their ensemble averages in normalized gait time. Heel strike (HS) events (solid vertical lines in graphs) separate the continuous data into discrete strides during one-minute continuous walking.

2.4 Data analysis

The local minimums and maximums of linear accelerations and angular velocity of pitching were used to determine the temporal features of gait, such as the stride time and the stance time [12, 26, 27]. By using temporal features, recorded continuous gait data for six components (i.e., three accelerations and three axial angular velocities) during one-minute of continuous walking were dissected and normalized to the gait cycle (heel-strike to next ipsilateral heel-strike) (Fig. 3). The linear drift problem was corrected periodically by assuming null velocity of the foot during the stance phase.

Stride regularity (SR) is calculated using unbiased autocorrelation procedures. The Pearson product correlation coefficient (r) between two adjacent cycles was calculated first. The mean value of correlation coefficients of repeated cycles during one-minute walk was defined as SR [7, 28].

Gait variability (GV) was determined by the average standard deviation of spatio-temporal parameters across the gait cycle [1]. Normalized ensemble gait data were investigated by 0.5% normalized time interval (a total of 200 points in normalized time interval). At each time frame, the mean (m) and standard deviation (σ) were calculated. Then variability at each time frame, the Coefficient of variation (CV), was expressed as σ/m. GV was defined as the mean value of CV across the entire normalized time frames.

$$\mathrm{SR} = \frac{\sum_{i=1}^{n-1} r_i}{n-1}, \quad \mathrm{GV} = \frac{\sum_{k=1}^{200} CV_k}{200}$$

where n = the total number of gait cycles during one-minute of continuous walking, i = the serial number of individual Pearson product correlations, and k = the serial number of 0.5% time step.

2.5 Statistical analysis

For the six components data, SR and GV were calculated. There were two factors, namely walking speed on a treadmill (repeated measures) and the subjects' ages (independent measures). Walking speeds had four levels (3, 4, 5 and 6 km/h) and the subjects' ages had three group levels (20s, 40s

Table 2. Changes in cadence and step length according to walking speed and age.

		Walking speed			
		3 km/h	4 km/h	5 km/h	6 km/h
Cadence (bpm)	20s	90.4±7.5	102.7±7.0	112.9±9.0	122.8±9.3
	40s	97.7±10	108.4±7.1	118.9±8.1	127.6±7.8
	60s	102.0±8.7	112.3±8.2	121.9±7.2	131.8±7.9
Step length (m)	20s	0.55±0.05	0.65±0.06	0.72±0.09	0.80±0.07
	40s	0.51±0.06	0.59±0.04	0.70±0.06	0.78±0.05
	60s	0.49±0.08	0.61±0.06	0.66±0.07	0.74±0.06

and 60s).

Two-way mixed analysis of variance (ANOVA) was performed with commercial statistics software (SPSS, ver, 18.0, Chicago, IL, USA). The significance level was set to .05. When significant interaction or main effect was detected between groups, Bonferroni's multiple comparison was applied as a post-hoc test to determine the cause of interaction or main effect.

3. Results

3.1 Cadence and step length

Means and standard deviations of cadence and step length are listed according to walking speed and age in Table 2. There were significant monotonic increases in cadence and step length with increases in walking speed (p < .05). Even though there was no main effect from age, a significant mean difference by age was only found between the 20s and 60s age groups (p < .05). The results for the 60s age group demonstrated higher cadence values than those for the 20s age group across all walking speeds. The 60s age group showed significantly shorter step lengths than the 20s age group (p < .05). There was no significant interaction from walking speed and age.

3.2 Directional SR and GV

Table 3 summarizes the overall results for directional SR and GV. For the linear acceleration components, A-P acceleration had the highest SR (0.970±0.029) and the lowest GV (0.028±0.033) while M-L acceleration had the lowest SR (0.893±0.075) and the highest GV (0.085±0.074). For the angular velocity components, pitching velocity had the highest SR (0.985±0.013) and the lowest GV (0.017±0.016) while yawing velocity had the lowest SR (0.852±0.079) and the highest GV (0.142±0.088).

3.3 Effects of walking speed and age on SR in normal gait

The radar charts for the SRs of six direction components (linear accelerations and angular velocities) are provided in Fig. 4. Regarding the linear accelerations, M-L components demonstrated worse SRs across all ages and walking speeds compared with AP and vertical components (Fig. 4). As for SRs of angular velocities, the pitching component (dorsi-/plantar flexion) had excellent SR and was followed by the rolling component (inversion/eversion) and the yawing component (ab-/adduction).

Two-ways repeated measures mixed ANOVA found significant interactions with age and walking speed for only M-L acceleration (F = 2.48, p = .027) and rolling angular velocity

Table 3. Directional SR and GV including all walking speeds and ages.

			Score	F	p
Stride regularity (SR)	Linear	AP	0.970±0.029	274	<.01 (AP > V > ML)
		ML	0.893±0.075		
		V	0.959±0.035		
	Angular	R	0.919±0.053	419	<.01 (P > R > Y)
		P	0.985±0.013		
		Y	0.852±0.079		
Gait variability (GV)	Linear	AP	0.028±0.033	137	<.01 (ML > V > AP)
		ML	0.085±0.074		
		V	0.048±0.049		
	Angular	R	0.061±0.049	339	<.01 (Y > R > P)
		P	0.017±0.016		
		Y	0.142±0.088		

AP : Anteroposterior, ML : Mediolateral, V : Vertical, R : Rolling, P : Pitching, Y : Yawing

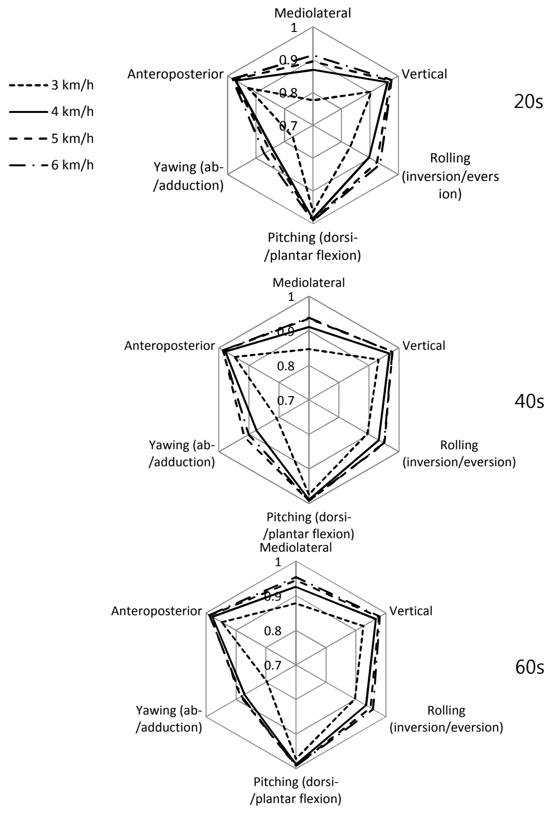

Fig. 4. SRs for six directional components according to age and walking speed. Larger numbers indicate excellent SR.

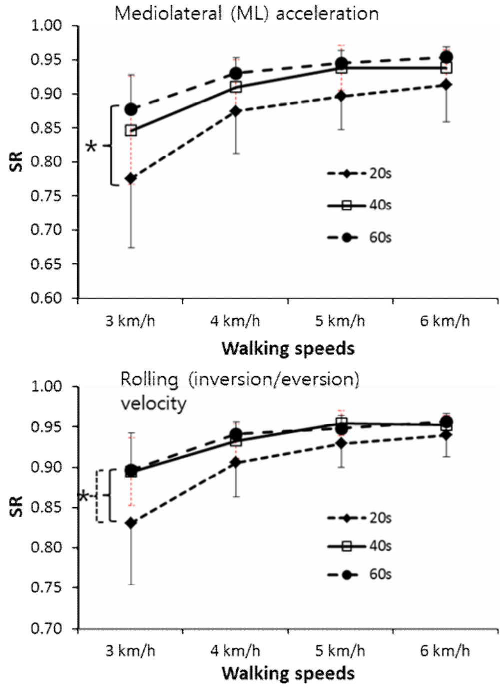

Fig. 5. Changes in SRs for M-L acceleration and rolling angular velocity according to age and walking speed. * indicates significant mean differences between groups.

(F = 3.80, p = .002, Fig. 5). In M-L acceleration, post-hoc analysis revealed that the significant difference of SRs between the 20s (0.776±0.101) and 60s (0.878±0.051) age groups at 3 km/h significantly decreased at 6 km/h (p < .05). In addition, the mean SR for the 60s age group (0.927±0.027) was significantly higher than that for the 20s age group (0.865±0.067, p = .006).

Regarding rolling velocity, significantly lowered SR for the 20s age group at 3 km/h (0.831±0.077) compared to the 40s (0.895±0.042) and 60s (0.897±0.046) age groups produced a significant interaction for age and walking speed. The SR for the 20s age group (0.902±0.044) was significantly lower than for the 40s (0.934±0.023) and 60s age groups (0.936±0.022) (p = .019).

There were significant main effects from walking speed across all ages (p < .05). Faster walking speed improved SR. The older subjects showed a tendency to have better SR, but there was no significant difference except in M-L acceleration and rolling velocity.

3.4 Effects of walking speed and age on GV in normal gait

The radar charts of GVs for six directional components (linear accelerations and angular velocities) demonstrated different patterns according to the walking speed (p < .05) and age (Fig. 6). The GVs of yawing angular velocity were high and the GVs of pitching angular velocity were relatively small across all ages and walking speeds.

Statistical analysis detected significant interactions with

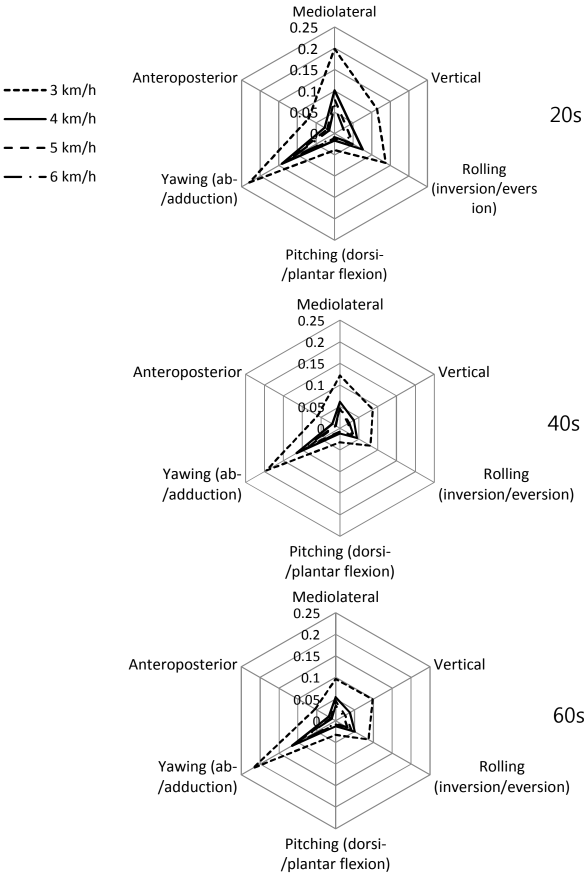

Fig. 6. GVs for six directional components according to age and walking speed. Higher values indicate higher GV.

GVs from age and walking speed in M-L acceleration (F = 2.42, p = .031) and rolling angular velocity (F = 2.65, p = .019, Fig. 7). In M-L acceleration, GVs were reduced by increased walking speeds. Post-hoc analysis demonstrated significant main effects from walking speed (F = 66.8, p < .01) and age (F = 36.0, p < .05). The M-L acceleration GV for the 20s (0.110±0.091) age group was significantly higher than those for the 40s (0.068±0.051, p = .018) and 60s age groups (0.056±0.038, p = .005). Regarding rolling velocity, main effects from walking speed and age were detected as well. The GV for the 20s (0.074±0.060) age group was significantly higher than those for the 40s (0.048±0.029, p = .013) and 60s (0.051±0.036, p = .037) age groups.

4. Discussion

Recent studies have focused on the use of trunk- (or pelvic-) type IMU sensors in an attempt to compute step-to-step (or stride-to-stride) regularity and variability as a method for assessing gait stability [7, 13-16]. The shoe-type IMU sensor is not well established for this purpose. This study assessed the directional SR and GV of data from shoe-type IMU sensors and investigated the effects of walking speed and age on those variables because the SR and GV are closely associated with

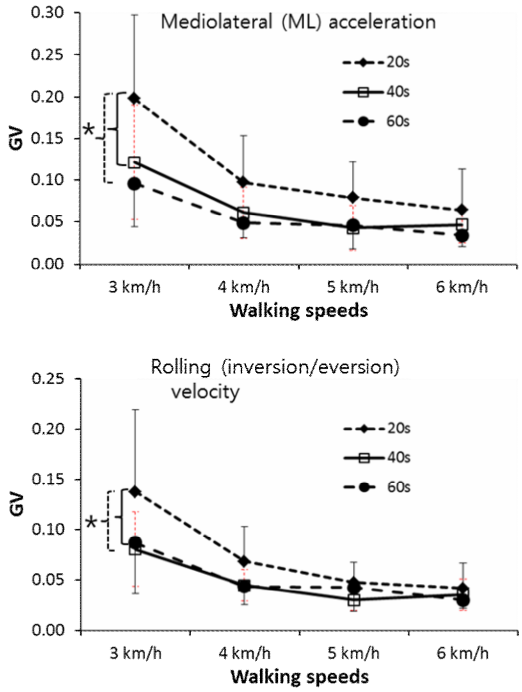

Fig. 7. GVs for M-L acceleration and rolling angular velocity according to age and walking speed. * indicates significant mean differences between groups.

gait stability [3, 7, 9].

The first hypothesis was well supported by the results of the current study. The lateral SR and GV, represented by M-L acceleration, yawing angular velocity (abduction/adduction), and rolling angular velocity (inversion/eversion), were worse than the A-P acceleration and pitching angular velocity. Specifically, the SRs were lower and the GVs were higher in lateral kinematics. For maintaining gait stability, higher SR and lower GV are necessary. The current results for directional dependency on stride-to-stride regularity and variability were well supported by previous studies [18, 29, 30].

There are a few reasons why lateral stability is weak compared to fore-aft stability during walking. It is reported that the fore-aft dynamics of walking is likely to be controlled passively by gravity and the subcortical system [29, 30], since there is a large linear momentum in the fore-aft direction because of higher directional velocity. The lateral dynamics, however, is actively controlled by the neuromuscular system. Therefore, it requires more consideration and is sensitive to external perturbations [29, 30]. Another reason is partially attributed to the fact that the yawing motion of the foot is coupled with a rolling motion [30]. Anatomically, the ankle joint provides coupled motions of inversion/adduction and eversion/abduction, which tend to induce motions in the frontal and transverse planes simultaneously. Mechanically the displacement and the velocity of the Center of mass (CM) must be regulated with respect to the base of support defined by the feet in order to maintain postural stability [31, 32]. The A-P base of support, represented by the step length, is larger than the M-L base of support represented by the step width. Therefore, the SRs and GVs in lateral kinematics are relatively worse than the SRs and GVs in A-P kinematics.

Regarding the effects of walking speed and age, significant interactions from walking speed and age were found with only lateral SRs and GVs (i.e., M-L acceleration and rolling angular velocity). There was no significant interaction in A-P and vertical kinematics, which indicated insensitivity to walking speeds and ages. The primary cause of interaction with lateral kinematics was attributed to differences in SRs and GVs between the 20s and 60s age groups. These differences were very large at 3 km/h but were significantly reduced at 5 km/h and 6 km/h.

These results gave rise to a couple of neuromechanical related speculations. First, the difference in preferred walking speed according to different ages would contribute to the lateral SRs and GVs significantly [33, 34]. Brach et al.'s [33] study identified a preferred speed of 3.6 km/h (1 m/s) for elderly subjects while Sekiya et al. [34] reported 4.99 km/h (≈ 5 km/h) for young male subjects. These were very similar to our results. The elderly subjects (the 60s age group) have a lower preferred speed that would induce stable gait characteristics at lower speed, while the young subjects (the 20s age group) would have struggle with controlling rhythmic motions when moving slowly because they are more comfortable with faster preferred speed [33, 34]. Secondly, the adapted linear gait parameters (e. g., shorter step length and faster step rate for the elder) for different ages would determine their stable range of walking speeds [35]. According to the results, the elderly subjects (the 40s and 60s age groups) showed a small drop in GV from 3 to 4 km/h and their GVs were relatively maintained regardless of increased speed up to 6 km/h.

Interestingly, a local minimum for GVs was only detected in the 40s age group at 5 km/h. Sekiya et al. [35] demonstrated that GV has a U-shaped profile with a function of walking speed and a local minimum at the preferred walking speed. In addition, this was partially interpreted by previous frequency domain analysis. Yack and Berger [36] showed gait variability in terms of frequency domain and insisted that slow walking is less stable unless harmonic ratios are controlled for walking speed.

Biomechanically, the lateral SR and GV are closely associated with fall risk [6, 22, 23]. Brach et al. [6] noted that variability in step width is valuable for predicting fall risk, and suggested the avoidance of step width variability that is too high at or near the normal speed for older persons. In addition, Hilliard et al. [23] pointed out that among many predictors of fall risk, the lateral balance stability is very important as it is a neuromusculoskeletal factor. Therefore, we need to pay more attention to the lateral SRs and GVs of gait for general gait stability.

5. Conclusions

This study illustrated that shoe-type IMU sensors assessed directional SR and GV while walking. The walking speed and age significantly affected the lateral SRs and GVs while walking in comparison with A-P and vertical kinematics. Since lateral stability is well associated with fall risk and gait problems, people need to pay more attention to the lateral dynamics of normal gait.

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Conflict of interest

None of the authors had financial and personal relationships with other people or organizations that could inappropriately influence their work.

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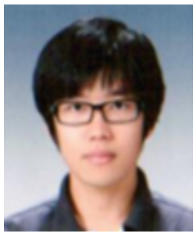

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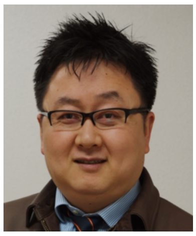

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