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Reliability and concurrent validity of spatiotemporal stride characteristics measured with an ankle-worn sensor among older individuals

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Abstract

Background: Wearable inertial sensors have been shown to provide valid mean gait characteristics assessments, however, assessment of variability is less convincingly established.

Research question: What level of concurrent validity, and session-to-session reliability does an ankle-worn inertial measurement unit (IMU)-based gait assessment with a novel angular velocity-based gait event detection algorithm have among older adults?

Methods: Twenty seven (women N = 17) participants volunteered (age 74.4 (SD 4.3) years, body mass 74.5 (12.0) kg, height 165.9 (9.9) cm). Right leg stance, swing, and stride duration and stride length, and stride velocity were concurrently assessed with motion capture and with an IMU from a 3 min self-paced walk up and back a 14 m track repeated twice a week apart. Gait variability was assessed as the SD of all of the registered strides.

Results: Significant difference was observed between methods for many of the mean stride characteristics and stride variability (all $p < 0.05$), fair to excellent agreement was observed for mean values of all of the five stride characteristics evaluated (intra-class correlation coefficient [ICC] from 0.43 to 1.00). However, poor agreement was observed for the SD of all of the evaluated stride characteristics (ICC from -0.25 to 0.00). Both methods indicated excellent session to session reliability for all of the five stride characteristics evaluated (ICC from 0.84 to 0.98, $CV\%_{RMS}$ from 1.6% to 3.6%), whereas the variability characteristics exhibited poor to good reliability (ICC from 0.0 to 0.69, $CV\%_{RMS}$ from 18.0% to 34.4%)

Significance: Excellent concurrent validity and reliability was observed for mean spatiotemporal stride characteristics, however, gait variability exhibited poor concurrent validity and reliability.

Although IMUs and the presented algorithm could be used to assess mean spatiotemporal stride characteristics among older individuals, either a more reliable gait event detection algorithm or alternative analytical approaches should be used for gait variability.

Keywords: wearable; gait; accelerometer; motion capture; variability;

1. Introduction

Gait characteristics of older people reflect their health status, and deviations from normal gait patterns also predict future adverse health events [1,2]. Spatiotemporal characteristics, such as average stride length, cadence or velocity are often used to describe gait in older populations [3]. Additional insight into the functional status of an individual may be gained by exploring the step-to-step or stride-to-stride variation (gait variability) [3,4], which may be an even more sensitive prognostic indicator of future health outcomes than the mean stride characteristics [5,6].

There are several methods that capture spatiotemporal gait characteristics. Arguably, the golden standards would include motion capture for spatial information (e.g. stride length), and force plates and instrumented walkways for temporal characteristics (e.g. stride duration). However, these are laboratory-bound methods and limit the number of captured strides in overground walking to only the instrumented part/capture volume. Accordingly, much recent effort has been devoted to affordable wearable inertial measurement units (IMU) [7–13], which capture strides independent of a pre-determined capture area [5,6,14,15]. Most of the validation studies of IMU-based gait assessments have been conducted for mean gait characteristics. For example, foot-worn sensors show excellent concurrent validity when compared to motion capture, force plate and instrumented walkways [7–13]. For session-to-session reliability of mean spatiotemporal characteristics, many wear-locations (trunk, shank, foot), have shown good results [7,8,16,17]. However, the concurrent validity and reliability of IMU-based gait variability characterisations have rarely been reported.

IMUs have exhibited the best concurrent validity when foot-worn sensors have been utilised [11,12]. However, mounting a sensor on the foot is somewhat cumbersome particularly if extended monitoring is desired. Participants have indicated a preference for an ankle worn device if given a choice [18]. Hip-worn sensors, while convenient, produce suboptimal results, particularly when attempting to identify stride length or gait velocity [19] and therefore, an ankle/shank-worn unit might be considered the preferred wear-location. While the validity and reliability of ankle/shank-worn IMUs for spatiotemporal gait characteristics assessments have been established among young healthy adults [11,12], data among older people is still missing. This is problematic because older people walk slower than younger people [20], and the validity and reliability of some IMU-based gait characteristics depend on gait speed [7]. Consequently, the validity and reliability of IMUs should be evaluated also among older people.

The purpose of the present study was to assess the concurrent validity and session-to-session reliability of ankle-worn IMU-based spatiotemporal gait characteristic assessments among healthy older adults aged 70 years and older. Numerous alternatives for gait event identification have been reported in the literature but no golden standard algorithm has yet emerged. Therefore, a novel algorithm based on prior art [21] was developed and evaluated in the present study.

2. Methods

A convenience sample of N = 27 healthy men (N = 10) and women (N = 17) were recruited from the University of the Third Age meetings at the University of Jyväskylä, and through word of mouth. The mean age, height and body mass of the women were 74.8 (SD 44) years, 160 (6) cm, and 68.8 (9.5) kg, and the respective values for men were 73.7 (4.1) years, 176 (7) cm, and 84.2 (9.4) kg. The inclusion criteria included age 70 years or older, and the ability to walk continuously for three minutes without assistive devices. The exclusion criteria included acute or unstable chronic cardiovascular disease. The study was conducted in agreement with the Helsinki declaration, informed written consent was obtained from all participants, and the study was approved by The Ethical Committee of the University of Jyväskylä (April 5th, 2018).

2.1. Protocol

The participants attended two measurement sessions a week apart at the University of Jyväskylä biomechanics laboratory. The participant was prepared for 3D motion capture (sampled at 200 Hz, Vicon T40, Oxford, UK) by taping on 2 spherical light-weight retroreflective markers on the right foot (the 2nd metatarsal head and the heel). The participant was also asked to wear an inertial measurement unit (3-dimensional accelerations ±16 g, rotations ±2000 °/s and magnetic field ±1300 μT recorded at 400 Hz, 400 Hz and 20 Hz sample rates, respectively. NGIMU, x-io Technologies, Bristol, UK) on the right leg strapped on with an elastic Velcro belt just above the lateral malleolus. After instrumentation the participants were asked to walk up and back a 14 m track continuously for three minutes at their preferred pace with the motion capture volume covering the central 3 m portion of the track. The continuous 3 min walk was concurrently recorded with the inertial measurement unit and the motion capture system. The measurement devices were synchronised with a 1.5 V square pulse applied concurrently to the auxiliary channel of the respective devices.

2.2. Numerical analysis

Motion capture

Following the rationale presented by Zeni and colleagues [22], we identified strides from the marker trajectories. Flat foot phases were first identified based on the difference between the vertical position of the heel and the 2nd metatarsal head marker signal. We calculated the variance of the vertical position difference of the markers using a sliding 0.15 s epoch. Troughs of at least 0.2 s with variance less than 0.5 mm were defined as parts of the flat foot phase, and the instant with minimum variation within a given flat foot phase was used to identify a flat foot instant. The preceding heel-strike and the subsequent toe-off were then identified surrounding each flat foot instant. The preceding heel-strike instant was defined as the last instant prior to the flat foot instant when the distance from the flat foot instant coordinates was less than 2 cm. The subsequent toe-off was defined as the first instant last instant after the flat foot instant with distance less than 1 cm from the flat foot instant coordinates (Figure 1). To handle possible false flat foot phases and missing flat foot phases the heel-strike and toe-off instances were merged, sorted and then any heel-strikes not followed by a toe-off or toe-offs not followed by a heel-strike were eliminated. Subsequently any strides (defined as heel-strike to the next heel-strike) with duration not within 1.25 ratio of the median of all identified strides duration were eliminated. This approach resulted in identifying 41 to 63 strides (mean 51.1) from the 3 min walking trial. We defined stride length as the distance between successive heel-strikes in the horizontal plane.

Inertial measurement unit (IMU)

We developed a gyroscope-based algorithm for the present study based on recent investigations regarding the optimal algorithms for heel-strike and toe-off event detection based on IMU recordings [21]. Pacini Panebianco reported that sagittal plane angular velocity and basing event detection on more than just a single datum resulted in the best reliability out of the approaches they reviewed and tested [21]. Our approach in the present study included identifying the swing-phases based on sagittal plane angular velocity. The angular velocity around the Z-axis of the sensor recorded by the IMU was used to represent sagittal plane angular velocity. The shank rotates counter clockwise during most of the swing phase and therefore the bell-shaped segments with positive angular velocity were identified (Figure 1). A parabola was fit onto each of the continuous positive angular velocity epochs, and the residuals between the fit and the measured angular velocity were calculated. Subsequently the fits were extrapolated until the residual reached more than 1.5 times the median of the residuals within the positive angular velocity epochs. The instant of the residual reaching the 1.5 times median cut-off prior to the positive angular velocity epoch was defined as a toe-off event and the instant after the epoch was defined as a heel-strike event. Subsequently the toe-off and heel-strike events were handled using the approach used for motion capture events. That is, the events were merged, events in incorrect order were discarded, and any strides with duration more than 1.25 from the median were eliminated. This approach identified a total of 117 to 199 (mean 158.6) strides from the 3 min trial. Some of the identified strides had occurred outside of the motion capture volume. From 38 to 61 strides started within 0.2 s of the strides identified based on motion capture, and only these matched strides, which occurred on the straight path, were used to calculate the reported outcome for both the motion capture and the IMU-based analyses for temporal characteristics.

*** FIGURE 1 ***

We evaluated stride length and stride velocity following the rationale presented by Hamacher and colleagues [8] based on orientation corrected horizontal accelerations. The manufacturer of the IMU used in the present study provides orientation correction on the sensor [23] which we used. The horizontal accelerations were integrated twice with respect to time from current stride flat foot instant to the next stride flat foot instant. Due to the sensor being located above the ankle it was known *a priori* that the velocity of the sensor was never actually zero and therefore an optimisation procedure was applied to evaluate the initial antero-posterior and medio-lateral velocities for the integration. Initial antero-posterior and medio-lateral velocities were set to 0 m/s to start the integral initial velocity optimisation and non-linearly optimised to minimise the difference between the initial and final velocities over the integration period. Stride length was defined as the distance from start of the integration to the end of the integration. The number of strides included in stride length and stride velocity analysis was further reduced by excluding strides where stride length estimate differed by more than 1.25 from the median of all stride lengths. Consequently, the concurrent strides included in the stride length and stride velocity analysis varied from 31 to 63 (mean 49.0) strides. Most of the excluded strides were caused by intermittent breaks in the inertial measurement unit recording caused by device failure, which caused excessive integration drift to accumulate.

We report the mean of the stance duration, swing duration, stride duration, stride length and stride velocity as mean gait characteristics. Gait variability of the aforementioned five characteristics are represented by the standard deviation of all of the strides of a participant within a measurement session.

2.3. Statistical analysis

Mean and standard deviation (SD) are reported where applicable. The sample size of 27 individuals measured twice provides a reasonable width of the confidence interval for reliability of repeated measurements [24]. Concurrent validity is evaluated with similar statistical methods as reliability, and therefore the same reasoning applies to evaluating concurrent validity as well. The concurrent validity of the IMU-derived spatiotemporal gait characteristics was evaluated based on the first measurement session by using motion capture-derived characteristics as the comparison. Mean difference (bias) evaluated with paired t-test, 95% limits of agreement (95% LoA), Pearson correlation coefficient (r), root mean squared coefficient of variation percentage ($CV\%_{RMS}$), and intra-class correlation coefficient (calculated for absolute agreement, ICC) are reported to indicate validity. ICCs were used to indicate whether the agreement was poor (<0.40), fair (0.40 to < 0.60), good (0.60 to 0.75) or excellent (≥ 0.75) [25]. Bland Altman plots were used to visualise the agreement between the methods, and the reliability of repeated measures. Reliability was evaluated using paired t-tests, r, $CV\%_{RMS}$, and ICC calculated for absolute agreement. Statistical analysis was conducted using project R (version 2018-12-18 r75863, https://www.R-project.org/) and the significance level was set at $p \leq 0.05$.

3. Results

The mean values of the stride characteristics measured with both the motion capture-based and IMU-based methods and on both measurement sessions are given in Table 1.

*** TABLE 1 ***

Significant difference (mean bias calculated as motion capture minus IMU) was observed between methods in stride length (3 cm), stride velocity (2 cm/s), stance duration SD (-4.5 ms), swing duration SD (-10.7 ms), stride length SD (-3.1 cm), and stride velocity SD (-2.4 cm/s) (all $p < 0.05$). Fair to excellent agreement was observed for mean values of all of the five stride characteristics evaluated (ICC from 0.43 to 1.00), whereas poor agreement was observed for the SD of all of the evaluated stride characteristics (ICC from -0.25 to 0.00) (Table 2).

*** TABLE 2 ***

Both the motion capture-based and IMU-based methods indicated excellent session to session reliability for all of the five stride characteristics evaluated (ICC from 0.84 to 0.98, $CV\%_{RMS}$ from 1.6% to 3.6%), whereas the SD of the stride characteristics exhibited poor to good reliability (ICC from 0.0 to 0.69, $CV\%_{RMS}$ from 18.0% to 34.4%) (Figures 2 & 3).

*** FIGURE 2 & 3 ***

Sensitivity of the results to heteroscedasticity was explored using Kendall's Tau (τ) between the mean and the norm of the difference between methods or between measurement sessions. If τ was > 0.2 the values were base 10 log-transformed prior to re-evaluating concurrent validity or reliability. All variability results were consequently re-evaluated, log-transform brought τ to below 0.2, but this had no noteworthy effects on the concurrent validity or reliability findings.

4. Discussion

The primary findings of the present study were 1) that, apart from swing duration, IMU-evaluated mean stride characteristics exhibited excellent concurrent validity to corresponding motion-capture-evaluated values and 2) that both methods exhibited excellent reliability for mean stride characteristics. However, IMU-based stride variability characteristics exhibited poor concurrent validity to motion capture. Notably, both the motion capture and the IMU-based characterisation exhibited poor to good reliability for stride variability. The mean gait characteristics results are in line with the literature, where excellent concurrent validity, and session-to-session reliability has been previously reported [7–13]. The poor to good reliability of the variability results is in line with walkway-based gait assessment which have indicated that while the mean spatiotemporal stride characteristics can be validly captured with 10 to 20 strides, a relatively large number of strides are required in evaluating variability to even a moderate reliability level [26].

Temporal parameter evaluation based on IMU-recordings is an easier task compared to spatial parameter evaluation due to the fact that a double integration with respect to time is required to derive displacement from the recorded accelerations, which leads into significant integration drift and consequent unpredictable error [8,13]. With a foot-worn sensor the integration drift issue is handled by identifying the foot flat phase of the strides, and always resetting the velocities to zero during the foot flat phase [8,13]. This approach is not appropriate with an ankle or shank worn sensor because the sensor is factually continuously moving [27]. The optimisation procedure to set the velocities to an optimised initial and final value for each stride at the foot flat phase developed in the present study was appropriate to handle this issue. Noting the systematic bias, the present stride length and velocity results exhibited excellent congruency with motion capture, and excellent session-to-session reliability. As regards to the temporal characteristics, it has been pointed out that the exact timing of heel-strike and toe-off events based on IMU-recordings tend to be off by several milliseconds compared to force plates [28]. Moreover, while valid and reliable stride duration can be obtained based on IMU-recordings, the validity and reliability of stance phase and swing phase durations has been found to be weaker [21] as was found to be the case in the present study as well. Taken together the present results indicated that the mean stance and stride duration characteristics could be used interchangeably between the methods utilised in the present study if one were, for example, to pool results from different studies, but that the IMU-based method produced a consistent under estimate of the mean stride length and stride velocity characteristics and would require calibration to be combined with motion capture-based results. Mean swing duration results were found to be incongruent between the methods and should not be pooled between the methods nor can a calibration be used to align the results.

We observed poor congruence between the motion capture and IMU-based stride variability measures. This is attributable to the algorithms used to detect the gait events. For the sake of argument we will assume that the motion capture-based values correspond to the true event instants. The IMU-based algorithm led into random fluctuation of the event with respect to the motion capture-defined event on occasions where the bell-shaped part of the angular velocity signal was not smooth, and explains why the variability calculated from the matched concurrently registered strides is incongruent (the reader may refer to Figure 1 for a visualisation of the issue). Furthermore, the reliability of both methods was poor to good with IMU-based results actually consistently exhibiting better reliability compared to the motion capture-based results. Concurrent validity of IMU-based stride variability measures has been scarcely reported in the literature but our findings on suboptimal reliability independent of the method is well in line with previous literature based on other assessment methods, and quantifications of variability [26,29]. That is, it seems that extended gait samples of more than a 100 strides are required for even moderately reliable stride variability characterisation [26,29]. Based on the lack of reliability found in the present study, and in the past literature [26,29], it may be preferable to utilise alternative methods to quantify gait variability with IMUs. That is, Riva and colleagues [29] showed that the number of strides required for e.g. reliable multiscale entropy analyses based on acceleration time-series was lower than that required for SD or coefficient of variation analyses.

The present study has some limitations that should be considered. Firstly, we had a sample of healthy community-dwelling older adults who chose to volunteer to the study, and thus the results may not apply to other populations. Secondly, the number of concurrently registered strides varied from 31 to 63 in the present study, which may have been too few to evaluate variability reliably [29]. However, the present findings were very consistent in indicating that motion capture-based variability estimates do not agree with IMU-based variability estimates. Thirdly, we evaluated stride length with direct integration of the accelerations. Although, this led into excellent concurrent validity, it is worth noting that individual strides may have produced markedly erroneous results. Finally, measurements were conducted on a level floor. Incline and decline may affect the validity of IMU-based gait assessments [30] and although excellent concurrent validity and reliability were observed for mean stride characteristics it remains to be established whether these characteristics could be assessed e.g. utilising prolonged monitoring in the habitual environment.

In conclusion, excellent concurrent validity and reliability was observed for mean spatiotemporal stride characteristics among community-dwelling older adults aged 70-years-of-age or older. However, gait variability exhibited poor concurrent validity and reliability. Taken together this indicates that ankle-worn inertial measurement unit can be used to assess mean spatiotemporal stride characteristics among older individuals. On the other hand, either a more reliable gait event detection algorithm with more strides included needs to be utilised or gait variability quantifications that do not depend on gait event detection, such as multiscale sample entropy [29], should be explored for IMU-based variability assessments. The benefit of being able to assess gait characteristics with a wearable sensors include prolonged measurements in the habitual environment.

Conflict of interest statement

None of the authors have conflicts of interests to report.

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FIGURE LEGENDS

Figure 1. Visualisation of the signals used in determining heel strike and toe-off events from motion capture (top pane) and inertial measurement unit (IMU) recording (bottom pane). Top pane; vertical position of the heel (solid black line) and the 2nd metatarsal head (dashed gray line) markers. Dashed black vertical line indicates heel-strike based on motion capture, dash-dot gray line toe-off. Black circle indicates heel-strike based on IMU recordings and gray asterisk toe-off. Dotted gray line in the bottom pane shows the fitted parabola used to define heel strike and toe-off events based on the IMU recordings. Sample strides chosen to highlight where the discrepancy between methods likely arises. Note the variation in IMU-defined toe-off instant with respect to the stride cycle at around 92.5 s versus 93.5 and 94.5 s.

Figure 2. Bland-Altman plots of temporal stride characteristics assessed a week apart with an ankle-worn inertial measurement units (IMU).

ICC = intra-class correlation coefficient;

Figure 3. Bland-Altman plots of spatial stride characteristics assessed a week apart with an ankle-worn inertial measurement units (IMU).

ICC = intra-class correlation coefficient;

TABLES

Table 1. Stride characteristics measured in the first and the second measurement session a week apart with the two methods. Reliability values given in text.

	Motion capture			Inertial measurement unit		
	Session 1	Session 2	difference (95% CI)	Session 1	Session 2	difference (95% CI)
Stance duration [ms]	621 (73)	610 (71)	10 (0 to 21)	634 (74)	626 (77)	8 (-1 to 17)
Swing duration [ms]	427 (38)	429 (39)	-1 (-10 to 7)	410 (48)	409 (48)	1 (-5 to 6)
Stride duration [ms]	1040 (100)	1030 (100)	10 (0 to 20)	1040 (100)	1030 (100)	10 (0 to 20)
Stride length [m]	1.33 (0.14)	1.33 (0.13)	0 (-0.02 to 0.01)	1.3 (0.14)	1.31 (0.14)	-0.01 (-0.02 to 0.01)
Stride velocity [m/s]	1.29 (0.19)	1.3 (0.19)	-0.01 (-0.03 to 0.01)	1.26 (0.19)	1.28 (0.19)	-0.02 (-0.04 to 0.01)
Stance duration SD [ms]	20 (5.5)	17.7 (6.6)	2.3 (-0.7 to 5.4)	24.6 (8.2)	24 (7.2)	0.6 (-2 to 3.1)
Swing duration SD [ms]	11.3 (6.2)	13 (7.8)	-1.7 (-5.2 to 1.8)	22 (11.1)	21.3 (9.2)	0.6 (-2.6 to 3.9)
Stride duration SD [ms]	23.9 (7.3)	23 (9.9)	0.9 (-3.6 to 5.5)	26.3 (9.3)	25 (8.5)	1.3 (-2.7 to 5.2)
Stride length SD [m]	0.0345 (0.0114)	0.0313 (0.0082)	0.0033 (-0.0014 to 0.0079)	0.0653 (0.0267)	0.0631 (0.0273)	0.0022 (-0.0092 to 0.0135)
Stride velocity SD [m/s]	0.0492 (0.0149)	0.0447 (0.0106)	0.0046 (-0.0031 to 0.0122)	0.073 (0.0263)	0.0711 (0.0249)	0.0019 (-0.0097 to 0.0134)

CI = confidence interval; SD = standard deviation;

Table 2. Concurrent validity of the stride characteristics measured with the two methods (session 1).

	Motion capture	Inertial measurement unit	Bias (95% CI)	$CV\%_{RMS}$	ICC (95% CI)	r^2
Stance duration [ms]	621 (73)	634 (74)	-14 (-31 to 4)	5.1	0.81 (0.64 to 0.91)	0.68
Swing duration [ms]	427 (38)	410 (48)	17 (0 to 35)	8.1	0.43 (0.07 to 0.69)	0.24
Stride duration [ms]	1040 (100)	1040 (100)	0 (0 to 0)	0.2	1.00 (1.00 to 1.00)	1.00
Stride length [m]	1.33 (0.14)	1.3 (0.14)	0.03 (0.02 to 0.04)***	2.1	0.96 (0.92 to 0.98)	0.96
Stride velocity [m/s]	1.29 (0.19)	1.26 (0.19)	0.02 (0.01 to 0.03)***	1.9	0.98 (0.96 to 0.99)	0.98
Stance duration SD [ms]	20 (5.5)	24.6 (8.2)	-4.5 (-8.4 to -0.7)*	30.8	-0.05 (-0.41 to 0.33)	0.00
Swing duration SD [ms]	11.3 (6.2)	22 (11.1)	-10.7 (-15.8 to -5.6)***	56.2	-0.25 (-0.57 to 0.13)	0.00
Stride duration SD [ms]	23.9 (7.3)	26.3 (9.3)	-2.4 (-7.1 to 2.4)	31.9	0.00 (-0.37 to 0.37)	0.00
Stride length SD [m]	0.0345 (0.0114)	0.0653 (0.0267)	-0.0308 (-0.0411 to -0.0204)***	47.0	-0.23 (-0.55 to 0.16)	0.07
Stride velocity SD [m/s]	0.0492 (0.0149)	0.073 (0.0263)	-0.0238 (-0.0342 to -0.0133)***	35.6	-0.05 (-0.41 to 0.33)	0.07

CI = confidence interval, $CV\%_{RMS}$ = root-mean-squared coefficient of variation percentage. ICC = intra-class correlation coefficient calculated for absolute agreement; SD = standard deviation; * = $p < 0.05$; *** = $p < 0.001$;