Wearable Gait Analysis in Adult with and without Stroke: System, Reliability and Validity Evaluation

Abstract

Background: Monitoring changes in gait provides valuable insights into the health of an aging population and individuals with chronic conditions. These insights can be leveraged by clinicians to tailor treatment. Smart-insoles, portable technology for gait monitoring, are emerging in consumer markets. Clinicians should be provided quantitative information on this technology. Research Question: To quantify the validity and reliability of a commercially available smart-insole, SENNOTECH. Further, to examine its ability to capture differences in gait between individuals with and without stroke. Methods: The SENNOTECH smart-insole was first validated against Vicon Motion Capture using Pearson's correlation. Second, older adults and individuals with stroke were recruited to wear the smart-insoles on two days while completing clinical assessments: two minute walk, and self-paced and fast paced 10 meter walks. Gait parameters were captured for the left and right sides. We examined if gait parameters differed between older adults and adults with stroke. Finally, reliability was analyzed using a coefficient of variance (CoV) to examine the consistency of measurement within and across days. Results: Comparing smart-insole data with Vicon Motion Capture data revealed low to very high correlations (0.42-0.96). The CoV within a day for gait parameters during self-paced 10 meter walks ranged from 2.29-9.12 for older adults and 4.08-19.58 for adults with stroke. The CoV for the fast paced 10 meter walks ranged from 2.19-14.66 for older adults and 3.24-15.14 for adults with stroke. Comparing CoV between days, there is no significant difference between days for almost all of the gait parameters for both cohorts. Significance: The majority of the findings were positive. The SENNOTECH smart-insoles are capable of identifying kinematic differences in gait and demonstrate reliability in measurements within and across days. This technology can enhance gait quantification practices in clinical as well as ecological settings.

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Keywords: Smart-Insoles, gait monitoring, aging, stroke, rehabilitation

1. Introduction

Monitoring gait in older adults and individuals with chronic conditions such as stroke can provide information on their state of well-being [1, 2]. A direct correlation exists between gait and performance of activities of daily living (ADLs) [3]. Gait monitoring also provides insight into muscle strength [4], endurance [5] and potential for successful independent community dwelling [1]. Deteriorating gait is associated with a higher risk of falls [6] and hospitalization [7]. Relatively small changes in gait speed are meaningful. An increase of 0.05 m/s in walking speed is an indication of meaningful improvement [8]. On the other hand, a reduction of 0.01 m/s in walking speed indicates deterioration of health [9]. Increased variability of stride and swing duration in a six minute walk has been associated with falls in older adults [10]. With such valuable information associated with gait, it is advantageous to examine multiple aspects of gait.

Following stroke there is asymmetry in gait that has been shown to increase with time [11, 12, 13]. Temporal asymmetry in gait following stroke is positively correlated with impairment [12], repetitive musculoskeletal injury [14], increased energy expenditure [15] and diminished balance [16]. Asymmetry has not consistently been correlated to gait speed post stroke [11, 12]. This suggests measuring and tracking both gait speed and asymmetry is important to fully assess recovery and design tailored rehabilitation programs.

Gait analysis methods such as stereophotogrammetic system are expensive and requires technical skills to operate. Low tech assessment method are labor-intensive and may not be completely indicative of their day-to-day performance. Wearable gait analysis solutions have the potential to enhance physical rehabilitation. But there is no rigorous study using most of the wearables in gait analysis to obtain medical-grade data.

This study aimed to test the validity and reliability of a commercially available insole, SENNOTECH smart-insoles (Figure 1, SENNOTECH smart-insoles, SENNOTECH Inc., Shenzhen, China), for gait analysis during common clinical assessments. We selected the SENNOTECH smart-insoles based on price ($300 US), ease of use and range of parameters captured during gait. The SENNOTECH microchip calculates the gait parameters according to the formulas described in Table 1. The SENNOTECH smart-insoles fit comfortably inside a typical shoe. To use the insoles, the individual removes the insole of their shoe and slips the smart insoles into their shoes. The SENNOTECH smart-insole comes with an app that shows selected gait parameters instantaneously to the user. To test the validity and reliability of the smart-insoles, we conducted experiments with three different cohorts including young adults, older adults and individuals with stroke.

This study was approved by the University at Buffalo Institutional Review Board and all participants provided informed consent to participate in the study, participants were recruited from the university and from the larger community of Erie County through flyers in public spaces and clinical offices.

The objectives of this work were to:

1. Conduct a validation study of SENNOTECH smart-insole data compared to stereophotogrammetric system (Vicon) data for the gait of young adults.
2. Examine whether the SENNOTECH smart-insoles are able to distinguish differences in gait kinematics between older adults and adults with stroke.
3. Examine the reliability of SENNOTECH smart-insoles to consistently measure the gait of older adults and adults with stroke at self-selected pace and fast pace.

2. Related Work

Objective clinical assessments frequently focus on measuring average gait speed (e.g., ten meter walk [8]), or the distance traveled in a set time (e.g., two- or six-minute walk [17, 18]). Low tech tools, such as a stopwatch and tape measure, are used during these assessments. These assessments provide coarse-grained quantitative data. Detailed gait analysis can be acquired from stereophotogrammetic systems such as VICON (Vicon Motion Systems Ltd., United Kingdom) and pressure mats such as GAITRite (GAITRite, CIR Systems Inc., New Jersey). Low adoption of these systems in clinical settings may be due to the expense or technical skills needed to correctly operate the system and analyze the data. An inexpensive low tech, but labor-intensive assessment of gait parameters is also possible. Individuals wear ink-soaked moleskin patches on the soles of their shoes while they walk on white paper, a tape measure is used to measure the imprints and speed and stride and/or step length calculated[19]. The need to perform these detailed analyses in a gait lab or clinic is limiting. They collect a snapshot of the individual's performance that may not be completely indicative of their day-to-day performance. An individual may perform worse if s/he has test anxiety or better if s/he is motivated by clinicians[20, 21]. Ideally, it would be best to monitor gait with minimal set up time, at multiple time points, and in environments in which the individual normally walks, e.g., their home or community.

Technology-based solutions are entering pervasive gait analysis in the form of wearable smartinsoles. For example GaitUp Gait Analysis suite of products [22], Lechal Fitness Tracking Insoles [23], Pedar In-shoe Dynamic Pressure Measuring System [24], and SENNOTECH InsoleX [25] have been introduced. These portable technologies have the potential to enhance physical rehabilitation. However, to be used in rehabilitation, conformance to ground-truth and high reliability is important, yet there is little research publicly available.

3. System Overview

In this section, we analysis the system framework of SENNOTECH smart-insole. It mainly consists of three parts: smart-insole hardware, smart-insole app, and cloud analysis. The hardware of the smart insole detects the gait data and transmits it to the mobile app. The mobile app records this data and send it to the cloud server for analysis.

3.1. Hardware

Each SENNOTECH smart-insole has an inertial measurement unit (IMU) located approximately below the inner arch of the foot. Using the readings of the accelerometer and gyroscope located inside the IMU, the SENNOTECH smart-insoles report gait parameters as the participant walks. A total of 42 gait parameters for each limb can be captured for each gait cycle.

3.2. Software

Gait parameters are calculated instantaneously after each gait cycle, and shown on the corresponding SENNOTECH app installed on the individual's smartphone, along with an animation of how both feet moved during each gait cycle in the recording session. At the end of each data recording session, the average values of select measured gait parameters are calculated and displayed with the smartphone app. The raw data, i.e., the gait parameters files are automatically uploaded by the app to the cloud for easy online access. For this study, the .csv files on the cloud were downloaded onto a computer and assessed using MATLAB (ver. 2018a, Natick, MA), Python (ver.3), Microsoft Excel (ver. 2016, Redmond, WA), and IBM SPSS (ver. 24, Chicago, IL). For cohort 1, MATLAB was used to analyze the smart insole data and the Vicon system data. For cohorts 2 and 3, Python was used to extract gait parameter values from the already segmented gait cycles available in the raw .csv files and also create and populate new .xlsx formatted files for easy import into SPSS for statistics.

3.3. Cloud Statistical Analysis

For each participant and with each system, the average for each gait parameter was extracted for each of the assessments. Pearson's correlation coefficient was calculated to establish the validity of parameters from the SENNOTECH smart-insole compared to data from the Vicon motion analysis system. An independent sample's t-test was conducted to examine differences in gait parameters between older adults and adults with stroke. When Levene's test for equality of variances was significant, equal variances were not assumed and the t-scores and degrees of freedom were adjusted accordingly. To measure the reliability of the SENNOTECH smart-insole, we calculated the coefficient of variation (CoV) for older adults and adults with stroke on the gait parameters for the 10 meter walks on day one and day two. The CoV is calculated using the formula $CoV = (standard\ deviation)/(mean)$ for both older adults and adults with stroke. The mean of all individual participants' CoV was reported for each cohort. We also examined if there was a difference in mean CoVs between days using a paired t-test.

4. Validity and Reliability Study

In this section we examine whether the SENNOTECH smart-insoles are able to distinguish differences in gait kinematics between older adults and adults with stroke, and examine the reliability of SENNOTECH smart-insoles to consistently measure the gait of older adults and adults with stroke at self-selected pace and fast pace.

4.1. Setup

Two cohort of participants were recruited. Cohort 1 included 11 older adults (5 males; average age: 73.8yrs $\pm$ 7.62 SD) and cohort 2 consisted of 8 adults with stroke (5 males; average age:71.1yrs $\pm$ 11.95 SD). In cohort 2, four individuals had right hemiplegia and the other four had left hemiplegia. Two of the adults with stroke used assistive walking devices during the gait assessments.

Cohort 1 and cohort 2 participants came to the lab twice within one week for testing sessions.During the first session they completed standard clinical assessments consisting of the two minute walk and the 10-meter walk at two different paces. To examine if the insoles are able to distinguish the differences in gait kinematics between different cohorts, we compared gait data from older adults to adults with stroke. Both cohorts first performed the two-minute walk, rested and then did a total of six 10-meter walks at their normal self-selected pace and six 10-meter walks at a fast pace. "Fast" was described as "walking as quickly as you can without feeling like you will fall". Rest breaks were given between clinical assessments. Length of the breaks were based on the participant's preference.

For the 10 meter walk, in a clinical setting, the clinician would time the participant's gait from the two meter to the eight meter mark. This provides the time for six meters of steady walking and eliminates the acceleration and deceleration phases of gait[26]. Since it is difficult to fairly account for the acceleration and deceleration phases with data from the smart insoles over a short distance, we considered the full 10 meter walk. For the two-minute walk, the clinical measurement assessed is total distance walked. For this test, we captured the total distance and then analyzed gait using the middle 80% of the obtained gait cycles to evaluate steady state gait.

The gait parameters from the SENNOTECH smart-insoles that we chose to analyze were: cycle duration, maximum swing velocity, stance duration, step height, step length, and swing duration for both the right and the left limbs individually. The cycle duration is the time taken in seconds from initial contact of a limb to the following initial contact of the same limb. The maximum swing velocity is the maximum value of the velocity measured by the IMU in any of the initial, mid or terminal phases of the limb swing. The stance duration is the time in seconds wherein the limb is in absolute contact to the ground from heal-strike event to the corresponding toe-off event. The step height is the height in meters measuring the distance of the limb from the ground during each gait cycle. The step length is the distance in meters from toe-off to the heel-strike of the contralateral limb. Finally, the swing duration is the time in seconds for the initial, mid and terminal phases of the swing to occur in every cycle of a limb.

4.2. Result

Differences between cohorts was examined. In the two minute walk, the average distance traversed by the older adults is 263.97m±41.91 SD and adults with stroke is 81.15m± 51.36 SD ($t_{17} = 8.54, p < 0.001$). Independent sample's t-test conducted on all six gait parameters between older adults and adults with stroke on the two minute walk test reveal a statistical difference of $p < .05$ in almost all parameters (Table 3(a)). The 10 meter walk test also shows a statistically significant difference of the gait parameters between older adults and adults with stroke (Table 3(b)). The average time taken to complete the 10 meter walk at a normal self-selected pace by older adults during day one was 16.49s±1.65 SD, whereas it was 29.56s±20.48 SD for adults with stroke (t15 = -3.00, p = .008).

Performance on the 10 meter walk tests, both self-selected and fast paced, were used to examine consistency in measurement for the SENNOTECH smart-insoles. In the self-selected pace 10 meter walk, the average time for older adults on day one is 16.49s±1.65 SD and day two is 15.48s±1.52 SD (paired-t10 = 1.90, p = .08). The average time taken for the self-selected pace by adults with stroke on day one is 29.56s±20.48 SD and day two is 31.13s±18.95 SD (paired-t9 = -.62, p = .55). Demonstrating that neither cohort had a significant difference in time across days. The mean CoV and the standard deviation of the CoV within days one and two reveal that the SENNOTECH insoles reliably measured the gait parameters of both cohorts (Tables 4(a-d)). Tables 4(e-f) show the paired t-test results for differences in CoV between days for the self selected and the fast- pace, respectively

5. Performance

In this section we conduct a validation study of SENNOTECH smart-insole data compared to stereophotogrammetric system (Vicon) data for the gait of young adults.

5.1. Setup

Cohort 3 consisted of seven young adults (4 males; average age: 25.6y rs3.87 SD). they completed the testing in the University at Buffalo SMART Motion Lab using the Vicon motion capture system. Reflective markers were placed on the left and right thigh, left and right knee, left and right tibia, left and right ankle, left and right heel, and left and right toe, to allow for use of the commonly used Plug-in Gait lower body model, while the participants walked wearing the smart insoles in their shoes. Participants followed a designed track (see Figure 2) for five repetitions. They were instructed to walk at their normal pace. From the five repetitions, 10 straight walking paths were extracted. Gait parameters were obtained from the reflective markers using standard Vicon data extraction procedures and parameters including stride count, stride length, stride speed, stride duration, and stance duration were obtained for both the left and right sides.

5.2. Result

Table 1 provides the results of the correlation analysis between the extracted parameters for the Vicon system and the SENNOTECH smart-insoles. Correlation analysis reveals low to very high correlations (0.42 - 0.88) for the five gait parameters measured.

6. Discussion

Gait velocity has been referred to as the sixth vital sign[1] by clinicians because of the wealth of information it infers about an individual. As products become available for pervasive gait analysis, it is necessary to evaluate their capacity to measure gait, as well as consider price point and portability. In assessment of reliability, the majority of gait parameters examined have a very high correlation, above .90, between measurements with Vicon and the SENNOTECH insoles. Two parameters, step speed right (.60) and swing speed left (.58), have a moderate correlation (.50-.70) and two parameters have a low correlation (less than .50) – step length right (.47) and step speed right (.42). When we examined swing duration, the parameter with the lowest correlation, there was reasonable symmetry between limbs for the insole measurements (average right=.402, average left=.411) and Vicon (average right=.41, average left=.399). It is possible that the insole slightly understated the parameter on some of the 10 meter walks and overstated on others. While the amount may be small, this would result in a point cloud of data that does not have a strong trend and therefore a lower correlation.

In clinical settings, it is necessary to analyze gait of individuals with normal and abnormal gait patterns and be able to differentiate between these individuals. The SENNOTECH smart-insoles demonstrate the ability to identify kinematic differences in gait between individuals with and with stroke. Furthermore, the insoles demonstrate reliability in measurements within and across days for both groups. Tables 4(a-d) indicate that the data collected has low CoV within a day. A mean CoV value below 10 is considered good in human gait analysis[27]. Tables 4(e-f) show minimal statistical difference between days. We anticipated that most gait parameters would be stable since there is no intervention between testing sessions. Reliable tracking of data across days opens the doors for gait analysis with portable insoles to be an acceptable outcome measure that can be used across recovery in chronic conditions. The insoles have the capacity to enhance common standardized assessments in rehabilitation such as the two minute walk and the 10 meter walk by providing more in-depth information about gait. The importance of using standardized assessments has been acknowledged as a means to compare outcomes across time and across facilities[28, 29]. Healthcare is moving towards value-based payment in which documented benefit to the patient is paramount. The Improving Medicare Post-Acute Transformation Act of 2014 requires providers in post-acute settings including: skilled nursing facilities, inpatient rehabilitation facilities, long-term care hospitals and home health agencies to report patient assessment data[30]. Standardized gait analysis with smart insoles helps to address this requirement.

This study included gait analysis of young and older adults and individuals with stroke. The SENNOTECH smart-insoles were able to analyze gait in this diverse population. This technology has the capacity to assess populations with any chronic condition. Monitoring gait across the lifespan has the potential to assist individuals with progressive pathologies such as Parkinson's disease or multiple sclerosis. Clinicians monitoring gait have valuable information to better manage their healthcare[31]. As the price of the smart insoles decreases, it becomes more likely that they are utilized outside of lab and clinical settings. This allows for gait assessment in environments that are more ecologically valid for the individual. It also opens the possibility of using smart insoles in home programs to provide individuals with quantitative feedback on their gait. Providing quantitative feedback on gait has been effective in positively impacting gait performance[32, 33].

The results generated in this study involved some manual data processing. The SENNOTECH smart-insoles software allowed for this customized assessment of data. In collaborative research, this feature can provide a multitude of opportunities for assessment. Alternatively, manual data processing can pose a limitation in clinical settings. It will be necessary to refine software to have the technology more usable for clinicians and caregivers.

7. Conclusion

In this work, we examined SENNOTECH smart-insoles as a viable technology to accurately record gait analyses in young adults, older adults and adults with stroke. This insole was selected in part due to its low price point, open software and portability. We conclude that the SENNOTECH smart-insoles capture differences in gait between populations with and without gait abnormalities and consistently measure gait parameters across time. Portable gait analysis systems have the potential to improve documentation of recovery, assist in tailoring treatment programs and provide quantitative feedback on progress to the user. Continued work to refine these systems for clinical use is merited.

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Table 1: Gait Parameters and their associated formula as implemented in SENNOTECH Insole X.

Features	**Formula**
Cycle Duration	$T_{hs'} - T_{hs}$ hs and hs' are two consecutive heel strikes. T_X is the timestamp of an event X (e.g., heel strike).
Stance Duration	$T_{to} - T_{hs}$ to and hs are a toe off and a heel strike within the same gait cycle.
Swing Duration	$D_{gc} – D_{st}$
Maximum Swing Velocity	$\int_{T_{hs}}^{T_{hs'}} \sqrt{\left(a_x^w\right)^2 + \left(a_y^w\right)^2 + \left(a_z^w\right)^2}\ dT$ $a_x^w, a_y^w\ and\ a_z^w$ are the world frame tri-axis accelerations converted from IMU data.
Step Height	$\iint_{T_{hs}}^{T_{hs'}} (a_z^w)\ dT$
Step Length	$\iint_{T_{hs}}^{T_{hs'}} \sqrt{\left(a_x^w\right)^2 + \left(a_y^w\right)^2}\ dT$
Step Speed	(Step Length) / (Swing Duration)

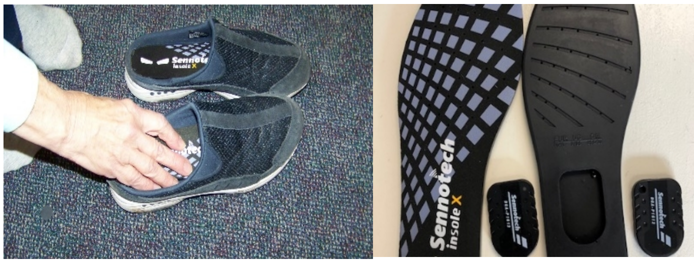

Figure 1: SENNOTECH insoles being put into a shoe.

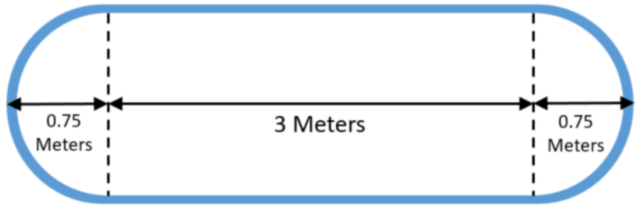

Figure 2: Experimental Setup to validate SENNOTECH insoles with VICON system.

Table 2: Pearson's correlation coefficients for VICON compared to SENNOTECH insoles.

Parameter	Correlation	Vicon Avg (SD)	Smart Insole Avg (SD)
step length left	0.88	0.932 (0.122)	0.914 (0.138)
step speed left	0.86	2.365 (0.347)	2.156 (0.261)
step duration left	0.96	1.607 (0.165)	1.607 (0.216)
stance duration left	0.93	1.208 (0.162)	1.196 (0.194)
swing duration left	0.58	0.399 (0.030)	0.411 (0.037)
step length right	0.47	0.906 (0.121)	0.866 (0.127)
step speed right	0.60	2.327 (0.390)	2.088 (0.344)
step duration right	0.96	1.463 (0.176)	1.467 (0.200)
stance duration right	0.95	1.053 (0.182)	1.066 (0.183)
swing duration right	0.42	0.410 (0.064)	0.402 (0.027)

Table 3(a): Summary of 2-minute walk test.

Parameter (units)	Mean		SD		t-test
	OA	ST	OA	ST	
left.cycleDuration (s)	1.07	1.63	.06	.85	$t_{7.06}$ = -1.86, p = .104
right.cycleDuration (s)	1.07	1.76	.07	1.04	$t_{7.05}$ = -1.88, p = .101
left.maxSwingVel (m/s)	4.09	2.50	.46	1.21	t_{17} = 3.97, p = .001
right.maxSwingVel (m/s)	4.13	2.90	.46	1.09	$t_{8.89}$ = 3.01, p = .015
left.stanceDuration (s)	.70	1.18	.06	.78	$t_{7.07}$ = -1.72, p = .129
right.stanceDuration (s)	.70	1.36	.06	1.04	$t_{7.03}$ = -1.79, p = .115
left.stepHeight (m)	.24	.16	.05	.06	t_{17} = 2.88, p = .010
right.stepHeight (m)	.19	.14	.03	.05	t_{17} = 2.43, p = .026
left.stepLength (m)	1.23	.79	.15	.35	$t_{8.97}$ = 3.32, p = .009
right.stepLength (m)	1.24	.89	.15	.35	$t_{8.95}$ = 2.61, p = .028
left.swingDuration (s)	.36	.45	.02	.13	$t_{7.43}$ = -1.81, p = .110
right.swingDuration (s)	.36	.45	.02	.09	t_{17} = -1.08, p = .295

Table 3(b): Summary of self-selected 10m walk test (on day1).

Parameter (units)	Mean		SD		t-test
	OA	ST	OA	ST	
left.cycleDuration (s)	1.07	1.63	.03	.08	t_7 = -1.91, p = .009
right.cycleDuration (s)	1.06	1.74	.03	.11	t_7 = -1.94, p = .009
left.maxSwingVel (m/s)	3.50	2.36	.19	.17	t_9 = 3.31 , p = .008
right.maxSwingVel (m/s)	3.56	2.43	.17	.14	t_{10} = 3.56 , p = .005
left.stanceDuration (s)	.70	1.22	.02	.08	t_7 = -1.90, p = .097
right.stanceDuration (s)	.70	1.31	.03	.10	t_7 = -1.73, p = .125
left.stepHeight (m)	.21	.15	.01	.02	t_{14} = 2.63, p = .019
right.stepHeight (m)	.17	.14	.01	.01	t_{12} = 2.02 , p = .065
left.stepLength (m)	1.06	.76	.03	.06	t_{10} = 3.35 , p = .007
right.stepLength (m)	1.07	.75	.04	.05	t_9 = 3.23 , p = .010
left.swingDuration (s)	.36	.40	.00	.02	t_8 = -1.52, p = .165
right.swingDuration (s)	.36	.43	.00	.02	t_8 = -1.61, p = .145

Table 4(a): Self-selected Pace (within day 1).

Parameter (units)	Mean CoV		SD CoV		Range CoV		t-test
	OA	ST	OA	ST	OA	ST	
left.cycleDuration (s)	3.41	4.08	1.34	2.74	1.48 – 6.75	1.04 – 10.19	t_{17} = -.70, p = .493
right.cycleDuration (s)	3.28	5.47	1.04	3.21	1.98 – 5.47	1.68 – 9.75	$t_{8.07}$ = -1.85, p = .100
left.maxSwingVel (m/s)	5.68	8.31	1.54	6.65	2.95 – 7.86	3.93 – 23.95	t_{17} = -1.28, p = .218
right.maxSwingVel (m/s)	4.93	6.02	1.72	1.56	1.69 – 7.17	4.16 – 8.38	t_{17} = -1.42, p = .174
left.stanceDuration (s)	4.16	5.33	2.03	3.52	2.30 – 9.62	1.37 – 13.07	t_{17} = -.91, p = .371
right.stanceDuration (s)	4.32	7.00	1.06	3.67	2.68 – 6.45	3.15 – 13.48	$t_{7.85}$ = -1.99, p = .082
left.stepHeight (m)	9.12	16.47	3.57	23.43	4.24 – 16.30	2.71 – 72.33	$t_{7.23}$ = .87, p = .408
right.stepHeight (m)	9.10	13.70	3.54	16.00	3.43 – 17.11	3.14 – 51.60	$t_{7.50}$ = -.79, p = .449
left.stepLength (m)	3.83	10.23	1.33	12.93	1.41 – 6.25	2.12 – 41.52	$t_{7.10}$ = -1.39, p = .205
right.stepLength (m)	3.94	7.92	1.41	3.65	2.33 – 6.31	3.77 – 15.04	$t_{8.53}$ = -2.92, p = .018
left.swingDuration (s)	2.61	5.53	.58	7.98	1.61 – 3.33	1.33 – 25.07	$t_{7.05}$ = -1.03, p = .337
right.swingDuration (s)	2.44	5.26	.66	4.06	1.52 – 3.72	1.42 – 11.76	$t_{7.27}$ = -1.94, p = .092

Table 4(b): Self-selected Pace (within day 2).

Parameter (units)	Mean CoV		SD CoV		Range CoV		t-test
	OA	ST	OA	ST	OA	ST	
left.cycleDuration (s)	2.73	4.81	1.02	2.96	1.12 – 4.06	1.10 – 10.59	$t_{8.22}$ = -1.89, p = .093
right.cycleDuration (s)	2.72	6.58	.97	5.11	1.54 – 4.12	1.02 – 17.64	$t_{7.37}$ = -2.10, p = .072
left.maxSwingVel (m/s)	4.04	13.66	1.26	23.88	1.53 – 6.57	2.10 – 72.52	$t_{7.02}$ = -1.13, p = .292
right.maxSwingVel (m/s)	4.16	8.53	1.28	10.21	2.84 – 6.08	2.51 – 32.96	$t_{7.16}$ = -1.20, p = .267
left.stanceDuration (s)	3.14	6.19	1.34	4.57	1.47 – 4.90	1.62 – 15.64	$t_{7.88}$ = -1.82, p = .106
right.stanceDuration (s)	3.35	8.01	1.24	5.56	1.35 – 5.14	1.79 – 19.05	$t_{7.51}$ = -2.32, p = .050
left.stepHeight (m)	8.58	13.70	4.00	20.48	3.57 – 17.73	.71 – 63.04	t_{17} = -.81, p = .426
right.stepHeight (m)	8.22	11.70	5.39	11.27	1.20 – 19.87	2.64 – 37.27	t_{17} = -.89, p = .381
left.stepLength (m)	2.82	19.58	1.10	38.78	1.44 – 4.88	2.26 – 115.47	$t_{7.00}$ = -1.22, p = .261
right.stepLength (m)	3.38	14.44	1.01	24.42	2.12 – 5.19	2.10 – 74.19	$t_{7.01}$ = -1.28, p = .241
left.swingDuration (s)	2.36	5.43	.66	4.86	1.19 – 3.40	.98 – 16.64	$t_{7.19}$ = -1.77, p = .118
right.swingDuration (s)	2.29	5.38	.92	7.59	.80 – 3.91	.98 – 23.49	$t_{7.15}$ = -1.14, p = .289

Table 4(c): Fast Pace (within day 1).

Parameter (units)	Mean CoV		SD CoV		Range CoV		t-test
	OA	ST	OA	ST	OA	ST	
left.cycleDuration (s)	3.86	6.43	3.89	5.88	.81 – 11.84	1.52 – 19.22	t_{17} = -1.15, p = .266
right.cycleDuration (s)	3.83	7.18	4.40	6.40	.97 – 13.62	1.77 – 19.32	t_{17} = -1.35, p = .193
left.maxSwingVel (m/s)	4.49	7.87	3.50	7.11	1.37 – 13.71	2.55 – 24.53	t_{17} = -1.37, p = .188
right.maxSwingVel (m/s)	4.75	4.71	3.41	1.91	2.30 – 13.24	2.63 – 7.12	t_{17} = .28, p = .978
left.stanceDuration (s)	5.14	5.08	5.02	2.96	.92 – 17.12	2.42 – 11.19	t_{17} = .03, p = .975
right.stanceDuration (s)	4.95	10.40	5.87	9.80	1.29 – 19.20	2.65 – 30.36	t_{17} = -1.51, p = .148
left.stepHeight (m)	8.45	13.87	3.73	16.60	3.73 – 17.23	1.9 – 53.37	t_{17} = -1.05, p = .305
right.stepHeight (m)	14.66	9.78	9.25	5.43	7.08 – 33.59	3.64 – 18.99	t_{17} = 1.32, p = .202
left.stepLength (m)	3.39	15.14	1.96	30.68	1.47 – 8.38	1.56 – 90.95	$t_{7.04}$ = -1.08, p = .315
right.stepLength (m)	3.77	7.01	2.44	4.00	1.33 – 8.35	2.45 – 13.61	t_{17} = -2.19, p = .042
left.swingDuration (s)	3.06	13.78	2.07	16.55	1.04 – 9.02	1.20 – 42.75	$t_{7.16}$ = -1.82, p = .111
right.swingDuration (s)	2.85	6.48	1.86	7.43	1.28 – 7.92	1.56 – 23.34	$t_{7.64}$ = -1.35, p = .215

Table 4(d): Fast Pace (within day 2).

Parameter (units)	Mean CoV		SD CoV		Range CoV		t-test
	OA	ST	ST	OA	ST	OA	
left.cycleDuration (s)	3.17	3.24	2.92	1.52	1.09 – 11.31	1.88 – 6.06	t_{17} = -.05, p = .956
right.cycleDuration (s)	3.62	4.89	2.92	4.36	1.05 – 9.29	1.80 – 14.34	t_{17} = -.76, p = .456
left.maxSwingVel (m/s)	2.99	8.93	1.86	10.66	.94 – 8.06	.81 – 34.34	$t_{7.31}$ = -1.55, p = .161
right.maxSwingVel (m/s)	3.39	5.13	1.44	2.05	1.35 – 6.70	2.37 – 7.58	t_{17} = -2.16, p = .045
left.stanceDuration (s)	4.18	3.95	4.62	1.86	1.12 – 17.45	2.26 – 7.85	t_{17} = .13, p = .896
right.stanceDuration (s)	5.11	6.89	4.63	6.57	1.58 – 15.03	2.26 – 21.95	t_{17} = -.69, p = .497
left.stepHeight (m)	7.93	14.70	3.66	16.58	3.00 – 14.18	4.55 – 54.67	t_{17} = -1.32, p = .203
right.stepHeight (m)	10.86	12.02	5.93	13.50	2.72 – 20.47	1.46 – 42.09	t_{17} = -.25, p = .802
left.stepLength (m)	2.19	13.33	1.26	24.39	.79 – 5.44	1.86 – 73.33	$t_{7.02}$ = -1.29, p = .238
right.stepLength (m)	2.47	5.35	1.08	3.42	.92 – 4.61	.94 – 10.78	$t_{8.03}$ = -2.29, p = .051
left.swingDuration (s)	2.35	4.97	.73	5.33	1.14 – 3.27	1.29 – 17.85	$t_{7.19}$ = -1.38, p = .209
right.swingDuration (s)	2.54	6.56	1.00	9.07	1.71 – 4.76	1.18 – 28.51	$t_{7.12}$ = -1.24, p = .252

Table 4(e): Paired t-test results for differences between days (self-pace).

Parameter (units)	Paired t-test statistics	
	OA	ST
left.cycleDuration (s)	t_{10} = 1.16, p = .27	t_7 = -.49, p = .63
right.cycleDuration (s)	t_{10} = 1.21, p = .25	t_7 = -.77, p = .46
left.maxSwingVel (m/s)	t_{10} = 2.40, p = .03	t_7 = -.85, p = .42
right.maxSwingVel (m/s)	t_{10} = 1.16, p = .27	t_7 = -.66, p = .52
left.stanceDuration (s)	t_{10} = 1.17, p = .26	t_7 = .40, p = .70
right.stanceDuration (s)	t_{10} = 2.01, p = .07	t_7 = .72, p = .48
left.stepHeight (m)	t_{10} = .30, p = .77	t_7 = 1.41, p = .20
right.stepHeight (m)	t_{10} = .76, p = .46	t_7 = 1.10, p = .30
left.stepLength (m)	t_{10} = 2.05, p = .06	t_7 = -1.00, p = .34
right.stepLength (m)	t_{10} = 1.05, p = .31	t_7 = -.73, p = .48
left.swingDuration (s)	t_{10} = 1.31, p = .21	t_7 = .07, p = .94
right.swingDuration (s)	t_{10} = .35, p = .73	t_7 = -.05, p = .95

Table 4(f): Paired t-test results for differences between days (fast-pace).

Parameter (units)	Paired t-test statistics	
	OA	ST
left.cycleDuration (s)	t_{10} = .47, p = .64	t_7 = 1.47, p = .18
right.cycleDuration (s)	t_{10} = .14, p = .89	t_7 = 1.21, p = .26
left.maxSwingVel (m/s)	t_{10} = 1.96, p = .07	t_7 = -.64, p = .53
right.maxSwingVel (m/s)	t_{10} = 1.56, p = .14	t_7 = -.44, p = .67
left.stanceDuration (s)	t_{10} = .47, p = .64	t_7 = .99, p = .35
right.stanceDuration (s)	t_{10} = .07, p = .94	t_7 = 1.22, p = .26
left.stepHeight (m)	t_{10} = .47, p = .64	t_7 = 1.89, p = .62
right.stepHeight (m)	t_{10} = 1.36, p = .20	t_7 = -.58, p = .57
left.stepLength (m)	t_{10} = 2.31, p = .04	t_7 = .71, p = .49
right.stepLength (m)	t_{10} = 1.83, p = .09	t_7 = 1.14, p = .29
left.swingDuration (s)	t_{10} = 1.16, p = .26	t_7 = 1.59, p = .15
right.swingDuration (s)	t_{10} = .61, p = .55	t_7 = -.05, p = .95