Original Article

Objectifying clinical gait assessment: using a single-point wearable sensor to quantify the spatiotemporal gait metrics of people with lumbar spinal stenosis

Callum Betteridge[1,2,3,4], Ralph J. Mobbs[1,2,3,4], R. Dineth Fonseka[1,2,3,4], Pragadesh Natarajan[1,2,3,4], Daniel Ho[1,2,3,4], Wen Jie Choy[1,2,3,4], Luke W. Sy[2,3,4,5], Nina Pell[2,3,4]

[1]Faculty of Medicine, University of New South Wales, Sydney, Australia; [2]NeuroSpine Surgery Research Group, Sydney, Australia; [3]NeuroSpine Clinic, Prince of Wales Private Hospital, Randwick, Australia; [4]Wearables and Gait Assessment Group, Sydney, Australia; [5]School of Biomechanics, University of New South Wales, Sydney, Australia

Contributions: (I) Conception and design: RJ Mobbs; (II) Administrative support: RJ Mobbs; (III) Provision of study material or patients: RJ Mobbs, LW Sy, C Betteridge; (IV) Collection and assembly of data: C Betteridge, RD Fonseka; (V) Data analysis and interpretation: C Betteridge, RD Fonseka; (VI) Manuscript writing: All authors; (VII) Final approval of manuscript: All authors.

Correspondence to: Ralph J. Mobbs. Suite 7, Level 7 Prince of Wales Private Hospital, Barker Street, Randwick, New South Wales 2031, Australia. Email: ralphmobbs@hotmail.com.

Background: Wearable accelerometer-containing devices have become a mainstay in clinical studies which attempt to classify the gait patterns in various diseases. A gait profile for lumbar spinal stenosis (LSS) has not been developed, and no study has validated a simple wearable system for the clinical assessment of gait in lumbar stenosis. This study identifies the changes to gait patterns that occur in LSS to create a preliminary disease-specific gait profile. In addition, this study compares a chest-based wearable sensor, the MetaMotionC© device and inertial measurement unit python script (MMC/IMUPY) system, against a reference-standard, videography, to preliminarily assess its accuracy in measuring the gait features of patients with LSS.

Methods: We conduct a cross-sectional observational study examining the walking patterns of 25 LSS patients and 33 healthy controls. To construct a preliminary disease-specific gait profile for LSS, the gait patterns of the 25 LSS patients and 25 healthy controls with similar ages were compared. To assess the accuracy of the MMC/IMUPY system in measuring the gait features of patients with LSS, its results were compared with videography for the 21 LSS and 33 healthy controls whose walking bouts exceeded 30 m.

Results: Patients suffering from LSS walked significantly slower, with shorter, less frequent steps and higher asymmetry compared to healthy controls. The MMC/IMUPY system had >90% agreement with videography for all spatiotemporal gait metrics that both methods could measure.

Conclusions: The MMC/IMUPY system is a simple and feasible system for the construction of a preliminary disease-specific gait profile for LSS. Before clinical application in everyday living conditions is possible, further studies involving the construction of a more detailed disease-specific gait profile for LSS by disease severity, and the validation of the MMC/IMUPY system in the home environment, are required.

Keywords: Lumbar spinal stenosis (LSS); wearable; gait; accelerometry

Submitted Feb 13, 2021. Accepted for publication Jun 25, 2021.
doi: 10.21037/jss-21-16
View this article at: https://dx.doi.org/10.21037/jss-21-16

Introduction

Neurological and musculoskeletal diseases often impact walking (1). These diseases affect the kinematics and dynamics of movement, directly by reducing joint range of motion, muscle strength and endurance (2); semi-directly by impairing movement speed and conscious control (3); and indirectly by causing pain and numbness which drive compensatory maladaptive walking patterns (4,5). In this way, diseases may present with a unique disease-specific gait pattern (DSGP) which describes the walking patterns of a typical patient with the disease (6). Some well-known DSGPs are the shuffling gait in Parkinsonism (7) and the Duchenne limp of hip osteoarthritis (8). In a clinical setting, a practitioner can match their patient's unique gait profile to a DSGP, which may help to confirm or reject a preliminary diagnosis (9). Physicians can also monitor a patient's disease status by identifying if any features of the unique gait profile are improving or worsening (10,11), and compare pre- and post-intervention gait profiles to assess intervention efficacy (12,13).

Gait analysis has evolved with advancements in technology. Historically, gait evaluation has been performed by the clinician directly observing a walking bout and making empirical observations regarding the patient's gait (14). However, this method is entirely subjective, has high inter-observer and test-retest variability, and lacks usefulness in long-term disease monitoring (15). As they could not directly measure or quantify changes to gait features like step length or step frequency, comprehensive DSGPs could not be developed using these techniques. These shortcomings have stimulated interest in more objective gait analysis techniques: 3D-motion capture systems, and wearable devices which contain accelerometers, gyroscopes, and magnetometers, so-called inertial measurement units (IMUs) (16-18). Both techniques are capable of quantifying various gait features, including spatiotemporal, balance-, smoothness-, and symmetry-related features. While the former technique is the gold-standard for accuracy, it requires dedicated laboratories and technicians which limit its clinical viability (19). Additionally, the unfamiliar setting increases the Hawthorne effect (20), where subjects consciously alter their walking when being observed. IMUs on the other hand are smaller, cheaper and do not require an operator (18). Moreover, IMUs can record several walking bouts and be taken home by a patient, giving the clinician insight into 'free-living' gait, which avoids the Hawthorne effect (20). A meta-analysis assessing the accuracy and test-retest reliability of IMU devices in assessing gait of healthy adults showed that the devices accurately measured all spatiotemporal gait parameters when compared to gold-standards (21). As such, IMUs have become a mainstay in clinical studies which perform gait assessment (18).

Although IMUs have been used to develop DSGPs in various neurological diseases such as Parkinson's disease (22), stroke (23), multiple sclerosis (24) and cerebral palsy (25), there are few studies which use IMUs in the assessment of lumbar spinal stenosis (LSS) and its gait alterations. As the stenosis worsens, the cross-sectional area of open spaces within the spine is reduced, resulting in compression and tension of nerves (20) (*Figure 1*). Consequently, the patient's capacity to walk long distances is compromised (20,26), and results in changes to walking patterns. Patients will adjust the position of their pelvis, torso and legs to alleviate pain, or compensate for weakness (27), which would be detected by IMUs. The studies that compare the gait between patients with LSS and healthy controls have shown that LSS patients have a decreased gait velocity, step length, and step duration with a more variable gait pattern compared to healthy controls (20,28-33). However, these studies have only considered 2–5 gait metrics each (34), with significant overlap. These gaps in knowledge preclude the adoption of IMUs for gait analysis in clinical assessment and management of LSS. The present study is a cross-sectional observational study to compare the gait characteristics of patients suffering from symptomatic LSS with those of healthy controls using the MetaMotion C sensor and a comprehensive battery of gait metrics. With this, we aim to contribute towards the development of a preliminary DSGP for LSS and simultaneously highlight the potential for the uptake of wearable technology in the clinical evaluation of patients with disorders of the lumbar spine.

We present the following article in accordance with the STROBE reporting checklist (available at https://dx.doi.org/10.21037/jss-21-16).

Methods

Study population

The study was conducted in accordance with the Declaration of Helsinki (as revised in 2013). Ethics approval for this study was obtained from the South Eastern Sydney Local Health District Ethics Committee, with reference code 17/184. Informed consent was taken from

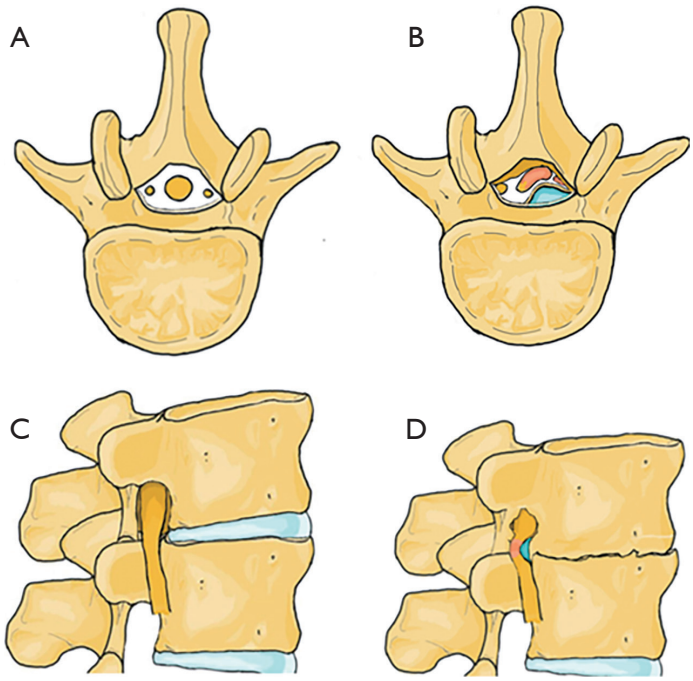

Figure 1 Pathological processes in spinal stenosis. (A) Transverse section showing typical vertebral morphology with spinal cord/cauda equina running through patent central canal and traversing nerve roots (left and right) in the lateral recesses. (B) Vertebral canal stenosis with disc prolapse (blue) causing right lateral recess and partial central canal stenosis and ligamentum flavum (yellow) hypertrophy contributing to central stenosis. (C) Sagittal section showing typical vertebral morphology with nerve root exiting the right neural foramen. (D) Foraminal stenosis with disc prolapse (blue), loss of disc space, spondylolisthesis and osteophyte formation causing compression of exiting nerve root.

all patients. For the construction of a preliminary DSGP for LSS, patients presenting to a single neurosurgery clinic (NeuroSpineClinic, Suite 7, Level 7, Prince of Wales Private Hospital) between February and August 2020 were screened for eligibility. Inclusion and exclusion criteria are detailed in *Table 1*. After accounting for Bluetooth™ connectivity issues or IMUGait application bugs which caused a loss of data, and discarding trials which required intervention by an investigator, data were available from 25 LSS patients (*Table 2*). 47 healthy participants were recruited with verbal outreach from Prince of Wales Private Hospital. Of these, 25 with similar demographic characteristics to the LSS cohort (*Table 2*) were used as healthy controls to investigate the gait of LSS patients. To test the accuracy of the MMC device, the 21 LSS patients and 33 healthy individuals whose walking bouts were recorded by both the MMC and a reference standard (videography), and exceeded 30 m, (as approximations made by videography would have a greater margin of uncertainty for shorter walking bouts) were used.

Wearable device

The IMU device used in this study was the MetaMotionC© (MMC) device developed by Mbientlab Inc. which was placed on the skin immediately overlying the sternal angle during all walking bouts (*Figure 2*). The MMC contains a 100 Hz triaxial accelerometer for detection of linear acceleration, a 100 Hz triaxial gyroscope for detection of angular acceleration and a 25 Hz triaxial magnetometer for orientation to Earth's magnetic field. The data captured by the MMC was stored as a matrix of the values captured by the three sensors at each time point. This data was transmitted via Bluetooth™ to a device running the IMUGait application developed for this study where a modified version of the GaitPY program (35) was used to interpret the data (*Figure 3*). The sensor was placed on the skin overlying the sternal angle. Gait metrics obtained by the sensor are defined in *Table 3*. Configuration files, setup instructions, detailed descriptions and calculations of gait metrics can be accessed via Appendix 1.

Table 1 Eligibility criteria for lumbar spinal stenosis cohort

Inclusion criteria
Present with complaint of neurogenic claudication. We defined neurogenic claudication as pain, numbness, and/or fatigue below the gluteal line with or without back pain (if back pain is present, leg pain is greater than back pain) that is precipitated by walking and alleviated by sitting down or lumbar flexion
Clinical diagnosis of lumbar spinal stenosis
Aged greater than 18
Exclusion criteria
Women who are pregnant
Serious spinal pathology including cancer, infection, cauda equina syndrome, spinal fracture, inflammatory arthritis
Present with active Paget's disease of the spine
Previous lumbar spinal surgery
Presence of known or demonstrated peripheral vascular disease-causing vascular claudication, i.e., claudication accompanied by absent foot pulse or vascular insufficiency detected with Doppler ultrasound or CT angiography
Presence of significant lumbar scoliosis (Cobb angle >25°) or other spinal deformities
Meyerding classification grade 2 or greater spondylolisthesis
Symptomatic hip disease with symptoms reproduced with external or internal rotation of the hip joint
Inability to walk independently without the use of a walking aid or investigator assistance
Cognitive impairment or inadequate English language skills that interfere with patient's ability to give fully informed consent or complete the baseline or follow-up assessments

Table 2 Demographic features of the healthy control and lumbar spinal stenosis patients included in the analysis of gait for the construction of a preliminary disease-specific gait profile for lumbar spinal stenosis

Demographic variables	Healthy controls (n=25)	Lumbar spinal stenosis (n=25)
Continuous {mean [range, (SD)]}		
Age (years)	55.1 [37–94, (15.5)]	59.4 [32–92, (16.7)]
BMI (kg/m^2)	24.8 [19.5–39.1, (4.16)]	28.1 [19.0–37.7, (5.37)]
Height (m)	1.71 [1.55–1.86, (0.0872)]	1.73 [1.54–1.90, (0.102)]
Categorical [n, (% of total)]		
Gender		
Male	13 [52]	17 [68]
Female	12 [48]	8 [32]
Smokes regularly	0 [0]	2 [8]
Diabetic	2 [8]	2 [8]
Fall in previous year	1 [4]	7 [28]

BMI, body mass index; n = number of data entries for the respective category.

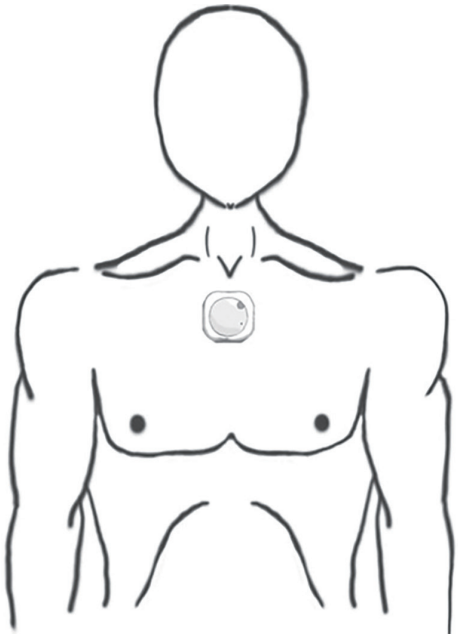

Figure 2 Frontal view of male subject showing where the MetaMotionC wearable device was placed. Device was placed on the skin immediately overlying the sternal angle for gait analysis of both healthy controls and lumbar spinal stenosis patients.

Procedural details

Participants were consented and underwent a structured interview to gather demographic information. The MMC device was attached to the chest and connected to the IMUGait application. After a 3-second pause to orient the MMC while the participant stood upright, participants walked at a comfortable pace along an unobstructed corridor (spanning 60 m) for a self-selected distance of at least 5 meters and a maximum distance of 120 m.

To investigate the gait of LSS patients, gait was measured by the MMC for the 25 LSS patients and compared to 25 healthy controls with similar ages. To investigate the accuracy of the MMC, both the MMC and videography were used to analyse the walking bouts of an additional 32 healthy controls regarding the number of steps and time taken, which were used to calculate gait velocity, step length, stride length, cadence, step time and stride time. For the walking bouts measured using videography, a handheld camera was used, with specifications including a wide-angle f/1.8 aperture, telephoto f/2.4 aperture, six-element lens, and 2436-by-1125-pixel resolution at 458 ppi. The video was assessed by 2 independent reviewers (CB and DH) to determine the total number of steps and strides during the walking bout (with discrepancies being resolved by a third reviewer, NP), and a surveyor's wheel was used to measure the total distance travelled during that walking bout. The relevant gait metrics were subsequently manually calculated as below:

Gait velocity = (Distance travelled)/(Time taken),
Step length = (Distance travelled)/(Steps taken),
Strides taken = (Steps taken)/2,
Stride length = (Distance travelled)/(Strides taken),
Step time = (Steps taken)/(Time taken)
Cadence =60/(Step time), and
Stride time = (Strides taken)/(Time taken).

Statistical analyses

To investigate the gait of LSS patients compared to controls, normality for each gait parameter measured by the MMC was assessed using the Shapiro-Wilk tests. The groups were then compared using two-sided Welch's *t*-tests at 5% significance to determine which metrics were altered in the LSS cohort. To investigate the accuracy of the MMC against a videography using a sample of healthy individuals, methods were compared by visually inspecting for normality of the inter-method difference using a histogram. Bland-Altman plots with 95% confidence intervals and limits of agreement were then used to estimate consistency and average inter-method difference. The methods were also examined using the intraclass correlation coefficient to determine the consistency of the inter-method agreement. This was done in accordance with the reporting standards for Bland-Altman testing (36). All statistical analyses were conducted using R studio version 1.3.959.

Results

Demographic characteristics

The demographic features of the LSS cohort differed slightly from their healthy controls (*Table 2*). In particular, the LSS cohort had a higher BMI (28.1 kg/m^2) than their healthy controls (24.8 kg/m^2), despite there being a negligible height difference between the groups. In addition, the LSS cohort had a slightly higher mean age (59.4 years) compared to their healthy controls (55.1 years). The LSS cohort had a male predominance, while there was a more even gender distribution amongst the healthy controls. Furthermore, 7 subjects in the LSS cohort had fallen in the previous year, compared to 1 subject out of the healthy controls.

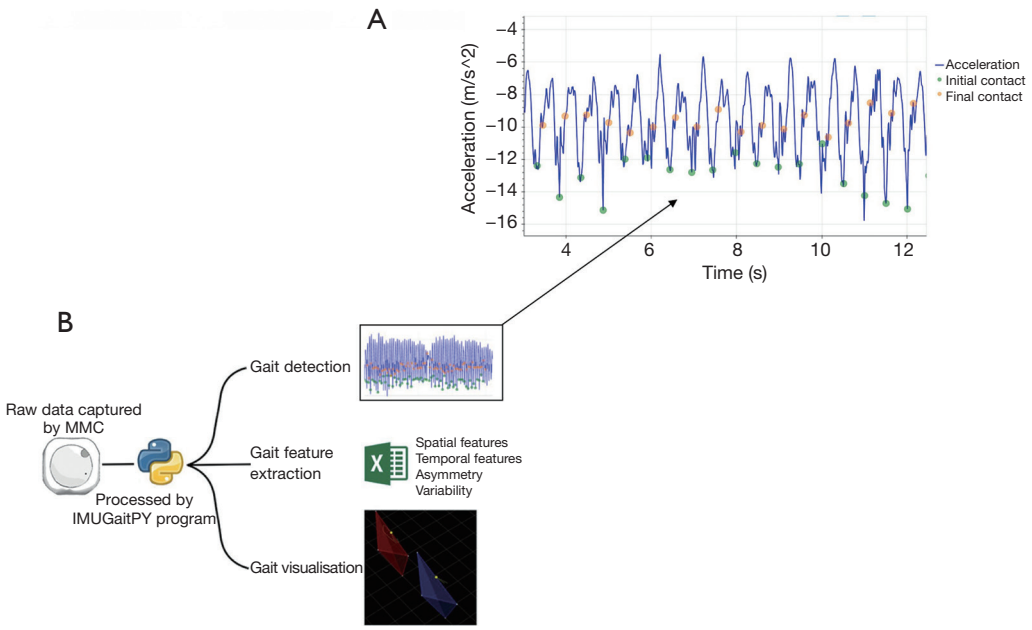

Figure 3 Summary of data collection, processing, and outputs from the MetaMotionC sensor and IMUGaitPY program for gait analysis used in this study. (A) First output is a .html file which documents the vertical acceleration measured by the sensor (y-axis) against time (x-axis) during the walk done by the participant. Green circles represent the initial foot contact with the ground, usually the 'heel strike' phase of gait and orange circles represent the final foot contact with the ground, usually the 'toe-off' phase of gait. (B) The IMUGaitPY program uses the gait cycle events detected in image a to identify when gait cycles begin and end, and thus creates a .csv file with the values of each gait parameter displayed per gait cycle and for the bout overall. For calculations see Appendix 1. Additionally, a .c3d file is created which can be viewed using Mokka, an open source platform, and the configuration file in Appendix 1. This creates a visual recreation of the gait using the accelerometry data. WORM, walking orientation randomness metric; MMC, MetaMotionC sensor from Mbient Labs, used to measure gait in the present study.

Gait differences between spinal stenosis patients and controls

There was a significant difference between LSS patients and healthy controls in most gait metrics measured by the MMC (*Table 4*). Compared to the healthy cohort, the LSS cohort had a more asymmetrical gait, with a 67.9% and 153% increase in step length and step time asymmetry, respectively. Furthermore, their temporal features (stride time, step time, and cadence) were approximately 12–16% slower and spatial features (stride length and step length) approximately 12–15% shorter than healthy controls, resulting in a 23.1% reduction in gait velocity. However, there was no statistically significant difference between the irregularity of gait between LSS patients and healthy controls, measured using the variability of gait metrics, notably, gait speed, step time, and step length variability. Together, these findings allow the construction of a preliminary disease-specific gait pattern for LSS (*Figure 4*).

The MMC accurately estimated gait metrics in spinal stenosis patients and healthy controls

Results for the accuracy analysis were available for 54 trials (21 LSS patients, and 33 healthy controls). There was greater than 90% agreement between the methods for all spatiotemporal features across both cohorts (*Tables 5,6*). There was no significant inter-method disagreement for temporal metrics (stride time, cadence, and step time). Additionally, high intraclass coefficients and narrow limits of agreement on Bland-Altman plots (Appendix 2) indicated low inter-method variability for these metrics. However, for distance related metrics (gait velocity, stride length, step length), the sensor underestimated the true value by approximately 7–8%. Visual inspection of Bland-Altman plots (Appendix 2) revealed a trend whereby non-temporal

Table 3 Definitions of each gait metric captured by the wearable system used in the present study

Simple metric	Definition	Type[4]	Units	Derivative metrics[3]	Definition (unit)	Type[4]
Steps[1]	The number of steps taken over the entire walking bout	N/A	N/A	N/A	N/A	N/A
Gait velocity[1]	Average distance travelled in the ambulant direction per second	Combined spatiotemporal	Meters per second (m/s)	Gait speed variability[2]	Step-to-step variability of gait velocity	Smoothness -related
Stride time[1]	Average amount of time between two consecutive contacts of the same foot with the ground	Temporal	Seconds (s)	Stride time variability[2]	Step-to-step variability of stride time	Smoothness -related
Step time[1]	Average amount of time between two consecutive contacts of any foot with the ground	Temporal	Seconds (s)	Cadence[1]	Frequency of steps (steps/minute)	Temporal
				Step time variability[2]	Step-to-step variability of step time	Smoothness -related
				Step time asymmetry	Average of difference in time taken between successive steps on left and right foot (s)	Symmetry -related
Stride length[1]	Average distance between two consecutive contacts of the same foot with the ground	Spatial	Meters (m)	Stride length variability[2]	Step-to-step variability of stride length	Smoothness -related
Step length[1]	Average distance between two consecutive contacts of any foot with the ground	Spatial	Meters (m)	Step length variability[2]	Step-to-step variability of step length	Smoothness -related
				Step length asymmetry	Average of difference in length of successive steps on left and right foot (m)	Symmetry -related

For calculations see Appendix 1. [1], these metrics can be estimated using both videography and the MMC/IMUPY device; [2], all variability metrics are defined in this paper as the coefficient of variation of the set of values taken from each step or stride of the walking bout i.e., stride length variability is the coefficient of variation of the set of stride lengths from the first to the last stride; [3], derivative metrics refers to metrics that are, in some way, calculated using the values from their simple base metric; [4], Temporal = time-related, spatial = distance related, combined spatiotemporal = dependent on both spatial and temporal features, balance-related = related to postural instability, asymmetry-related = related to differences between steps on left and right feet, smoothness-related = related to the regularity or consistency of the movement.

parameters were overestimated at lower magnitudes and underestimated at higher magnitudes. Additionally, there was moderate inter-method variability for these metrics.

Discussion

In this study, we found significant differences between the gait of LSS patients and healthy controls using a single-point chest-based wearable sensor, facilitating the construction of a preliminary disease-specific gait pattern for LSS. This provides the groundwork upon which future studies can construct more refined gait profiles for LSS, adjusted for LSS severity and patient characteristics such as age and sex. In addition, the MMC and IMUPY gait analysis system (MMC/IMUPY) had high agreement with videography for all spatiotemporal gait metrics that both methods were able to measure. Together, these findings allude to the possibility of a future where wearable sensors are routinely used in clinical practice for the diagnosis and monitoring of gait-altering medical conditions such as LSS.

Gait profile of LSS

By comparing spatiotemporal gait metrics between LSS

Table 4 Comparison of gait metrics between cohorts of lumbar spinal stenosis patients and healthy controls during a walking bout

Gait metrics	Healthy controls (n=25)	LSS (n=25)	Mean difference		95% CI of mean difference		P value
	Mean (SD)	Mean (SD)	LSS – control	% of control	Lower	Upper	
Gait velocity (m/s)	1.35 (0.254)	1.03 (0.277)	–0.311	–23.1	–0.462	–0.160	<0.001*
Gait speed variability	0.0921 (0.0426)	0.0909 (0.0619)	–0.00127	–1.38	–0.0315	0.0289	0.933
Cadence (steps/min)	116 (10.3)	102 (12.6)	–14.0	–12.0	–20.6	–7.44	<0.001*
Stride time (s)	1.05 (0.0850)	1.21 (0.191)	0.166	15.9	0.0808	0.251	<0.001*
Step time (s)	0.524 (0.0430)	0.606 (0.0972)	0.0822	15.7	0.0390	0.125	<0.001*
Step time asymmetry (s)	0.0346 (0.0206)	0.0877 (0.0886)	0.0531	153	0.0166	0.0897	0.005*
Step time variability	0.0949 (0.0654)	0.105 (0.0709)	0.00972	10.2	–0.0291	0.0485	0.617
Stride length (m)	1.383 (0.254)	1.214 (0.251)	–0.168	–12.1	–0.312	–0.0245	0.023*
Step length (m)	0.706 (0.107)	0.606 (0.128)	–0.0997	–14.1	–0.167	–0.0327	0.004*
Step length asymmetry (m)	0.056 (0.03)	0.093 (0.07)	0.038	67.9	0.0113	0.0756	0.01*
Step length variability	0.0973 (0.0346)	0.144 (0.120)	0.0464	47.7	–0.00472	0.0975	0.0740

*P values less than 0.05, which indicates a significant difference between the cohorts for that metric. Welch's *t*-tests were used for stride time, step time, step time asymmetry, step length asymmetry, and step length variability due to these metrics having unequal variances between population groups, while Independent *t*-tests were performed for all other metrics. n, number of data entries for the respective category; SD, standard deviation; 95% CI, 95% confidence intervals; (m), measured in meters; (s), measured in seconds; (m/s), measured in meters per second.

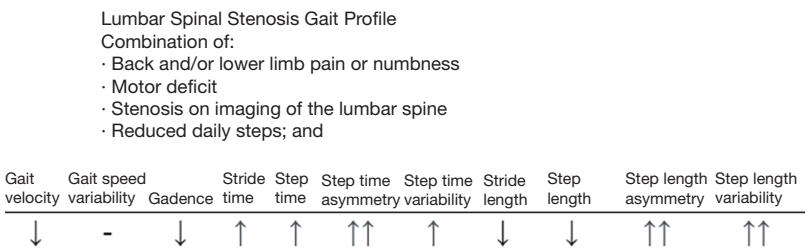

Figure 4 Preliminary gait profile describing the differences between the gait patterns of lumbar spinal stenosis patients compared to the baseline gait patterns of healthy controls that were identified in the present study. Upward arrows (↑) represent an increase in the value of the metric in lumbar spinal stenosis patients compared to healthy controls. Downward arrows (↓) represent a decrease in the value of the metric in lumbar spinal stenosis patients compared to healthy controls. Dashes (-) represent a negligible difference (<5%) in the value of the metric in lumbar spinal stenosis patients compared to healthy controls. Double arrows represent a change of high magnitude (>40%).

patients and healthy controls, we constructed a preliminary disease-specific gait pattern for LSS, summarized in *Figure 4*. This study largely agrees with other studies which have examined the gait of patients with LSS, whilst offering additional information surrounding the impact of the disease on symmetry and variability.

Pertaining to the spatial and temporal gait patterns of LSS patients, studies (17,20,29,32,37) found that patients took strides of 0.96–1.1 m in length, at a rate of 96–114 steps/minute. The same is true for gait velocity, where most studies of LSS patients (17,32,37) found values of 1.02–1.09 m/s. However, Perring *et al.* (20) found a lower average gait velocity for LSS patients at 0.80 m/s. Additionally, while Conrad *et al.* (29) found that male LSS patients walked at 1.02 m/s, the female cohort walked much slower, at 0.75 m/s. Notably, the average age of the LSS

Table 5 Results of Bland-Altman plots and intraclass correlation coefficient analysis measuring the inter-method agreement between gold-standard (videography) and MetaMotionC sensor estimation of gait parameters captured during walking bouts of 30 meters and over in healthy controls

Metrics	Healthy controls (n=33)							
	Video	Sensor	Mean difference (video-sensor)	95% CI		Accuracy (%)	ICC	P value
	Mean (SD)	Mean (SD)		Lower	Upper			
Steps	236 (98.7)	236 (97.5)	0.030	–1.13	1.19	100	1.00	<0.001
Gait velocity* (m/s)	1.29 (0.173)	1.38 (0.224)	–0.0923	–0.130	–0.0543	93.3	0.875	<0.001
Cadence (steps/min)	111 (8.13)	111 (7.43)	–0.291	–0961	0.379	99.7	0.985	<0.001
Stride time (s)	1.09 (0.0804)	1.09 (0.0710)	0.00194	–0.00530	0.00920	99.8	0.982	<0.001
Step time (s)	0.545 (0.0402)	0.545 (0.0359)	0.000600	–0.00290	0.00410	99.9	0.984	<0.001
Stride length* (m)	1.40 (0.168)	1.50 (0.241)	–0.0987	–0.141	–0.0567	93.4	0.862	<0.001
Step length* (m)	0.707 (.08)	0.759 (.11)	–0.0491	–0.0701	–0.0281	93.5	0.862	<0.001

Metrics with an asterisk * have a statistically significant (P<0.05) mean inter-method difference between sensor device and reference-standard. Accuracy is measured as 100 minus the absolute mean difference as a percentage of the reference-standard estimated value. The P value shown is for the correlation analysis using the ICC, bolded values imply significant correlation. N, number of data entries for the respective category; SD, standard deviation; 95% CI, 95% confidence interval; ICC, intraclass correlation coefficient; (m), measured in meters; (s), measured in seconds; (m/s), measured in meters per second.

Table 6 Results of Bland-Altman plots and intraclass correlation coefficient analysis measuring the inter-method agreement between reference standard (videography) and MetaMotionC sensor estimation of gait parameters captured during walking bouts of 30 meters and over in lumbar spinal stenosis patients

Metrics	Lumbar spinal stenosis patients (n=21)							
	Video	Sensor	Mean difference (video-sensor)	95% CI		Accuracy (%)	ICC	P value
	Mean (SD)	Mean (SD)		Lower	Upper			
Steps	267 (96.2)	266 (95.4)	0.333	–2.04	2.71	99.9	0.999	<0.001#
Gait velocity* (m/s)	1.02 (0.233)	1.10 (0.245)	–0.0790	–0.131	–0.0275	92.8	0.917	<0.001#
Cadence (steps/min)	105 (10.9)	106 (9.91)	–0.302	–1.49	0.883	99.7	0.985	<0.001#
Stride time (s)	1.155 (0.141)	1.155 (0.130)	0.0000300	–0.0127	0.0128	100	0.990	<0.001#
Step time (s)	0.575 (0.0724)	0.579 (0.0646)	–0.00270	–0.0115	0.00610	99.5	0.980	<0.001#
Stride length* (m)	1.15 (0.218)	1.25 (0.245)	–0.0989	–0.158	–0.0402	92.1	0.877	<0.001#
Step length* (m)	0.575 (0.109)	0.625 (0.123)	–0.0492	–0.0786	–0.0198	92.1	0.877	<0.001#

Metrics with an asterisk * have a statistically significant (P<0.05) inter-method difference between sensor device and reference-standard. Accuracy is measured as 100 minus the absolute mean difference as a percentage of the reference-standard estimated value. #, the P value shown is for the correlation analysis using the ICC, imply significant correlation. n, number of data entries for the respective category; SD, standard deviation; 95% CI, 95% confidence interval; ICC, intraclass correlation coefficient; (m), measured in meters; (s), measured in seconds; (m/s), measured in meters per second.

cohort in Perring *et al.* (20), and female patients in Conrad *et al.* (29) were 5–15 years above the SSRGA cohort used in this study, and age over 65 is known to correlate with slow walking speed (38).

However, our study did not demonstrate significant differences in gait variability between LSS patients and healthy controls. The only other study to examine gait variability in LSS patients (28) also found that LSS patients exhibit more variable gait than healthy controls. A follow-up study by the same author group also demonstrated that the

variability was reduced following operative intervention (12). However, these authors measured the variability of the patients' gait as a whole using a differential entropy algorithm, while we measured the variability of individual gait metrics using their coefficient of variance. In addition, despite not reaching statistical significance, our findings demonstrated that the step time of LSS patients was 10.2% more variable than controls, and the step length 47.7% more variable. It is possible that these results may reach statistical significance with a larger study population. Overall, it is likely that LSS leads to a more variable gait pattern compared to healthy individuals, lending credence to the role of gait variability in pre- and post-intervention assessment.

The present study is the first to compare the gait symmetry of LSS patients and healthy controls. The findings suggest that asymmetry of step length and time are features of the DSGP of spinal stenosis. In addition, observational studies of LSS patients have identified that gait asymmetry improves following surgical intervention and is associated with a greater degree of disability (16,37,39). This is in accordance with empirical observations, where a limp is a well-documented feature of the gait pattern in LSS (39).

Due to a limited sample size, the present study did not perform regression analysis controlling for several possible covariates which may influence gait, including age, gender, disease severity, and height, constituting a limitation of our study. While the age and height of LSS and healthy controls in our gait analysis were comparable, there were 4 more males in our LSS cohort than amongst our healthy controls. Age-matched men and women have been found in some instances to have differences in spatiotemporal gait metrics. For example, Cho, Park & Kwon (40) found that women had a shorter stride length (and hence step length), and narrower step width, although other gait metrics such as cadence and gait velocity were not significantly different between sexes. Meanwhile, in a study (41) involving men and women with osteoarthritis of the knee, there was no significant difference in walking speed, cadence, and step length between sexes, while differences were found in other gait characteristics such as swing phase and toe-out angle. Although it is possible that the inconsistency in sexes between the groups in our study may introduce differences between LSS patients and healthy controls that may not explicitly be due to the presence of LSS, the expected direction of this difference would be favouring shorter spatial parameters and slower temporal parameters amongst women. In our study, we were still able to find shorter spatial parameters and slower temporal parameters amongst our predominantly male LSS cohort, supporting the use of these metrics in our gait profile for LSS. Finally, the present study did not compare the gait of subcategories of LSS (LSS with unilateral predominance, LSS with bilateral predominance) to identify if the syndromes had unique DSGPs. This is likely to be the case, as it is known that the presence of a limp and therefore gait asymmetry factors, is more common in unilateral LSS (6). Furthermore, the present study did not characterize its LSS cohort based on radiological severity, where patients with radiologically more severe LSS would be expected to demonstrate more significantly altered gait patterns compared to controls.

Future studies should endeavour to collect a larger cohort of symptomatic individuals, ideally no less than 30 per subcategory of LSS, perform regression analysis accounting for possible cofactors and compare the gait patterns occurring in spinal pathology at different anatomical locations and with differing levels of radiological severity. This would provide a more rigorous DSGP for LSS and provide greater discriminative power to IMU-based gait profiling for LSS, improving clinical utility. Future studies could construct disease-specific gait profiles for other lumbar spine pathologies which commonly present to spine clinics, such as lumbar disc herniation, or mechanical low back pain. Building upon this, it is interesting to speculate whether single-point IMUs would be able to routinely partake in differentiating (using DSGPs) between lumbar spine pathologies to aid clinicians in their decision-making process. In addition, the potential for IMUs to be worn by patients in everyday living conditions indicates that IMUs could be useful in the long-term remote monitoring of patients with gait-altering disease states. For example, in a recent case report by Mobbs, Katsinas, Choy, Rooke and Maharaj, a sudden decrease in daily step count and gait velocity measured using an Apple Watch allowed for the detection of a recurrent disc herniation on day 57 postoperatively, which was later confirmed with a lumbar MRI (42). This demonstrates how continuous objective data streamed remotely to clinicians can facilitate the early detection of post-operative complications—one of the many potential applications of long-term continuous monitoring.

MMC/IMUPY accuracy

The findings from the present study demonstrate that the MMC/IMUPY has good (>90%) agreement with videography for each gait metric that both methods could

estimate. Thus, a system like the MMC/IMUPY can capture the gait features of SSRGA patients in a single walking bout over 30 m with reasonable accuracy.

While there is no consistent bias for estimation of temporal features, the system underestimated the true value of non-temporal gait features by 7–9% on average, however this bias was proportional to the value of the parameter. Thus, the MMC/IMUPY should adjust its estimations of spatial metrics using a linear transformation rather than a fixed value correction which is more optimal for a consistent error (43). This better approximates the gait features for clinical use and allows results to be compared between this method and others. However, clinicians should still consider the adjusted estimation of non-temporal gait features by the MMC/IMUPY to be within 10% of the true value on account of the inconsistency when estimating these metrics. This may prevent our gait analysis system from detecting minor or early signs of gait-altering disease, detracting from its current clinical utility.

The results are similar to those found in studies examining healthy subjects using comparable devices (21,44-47) which suggested that single and multi-point IMU devices provide excellent estimations of temporal features of gait, but poorer and less reliable estimations of spatial features. There was evidence of a similar proportional error for spatial parameters in the IMU used by Washabaugh *et al.* (48). However, studies which utilised single (49) and multi-point (50) IMU devices in patients with various upper motor neuron diseases found that the devices had 5–10% inaccuracy when estimating the true values of both spatial and temporal features of gait. Given that IMU devices rely on acceleration signals from gait cycle events like heel-strike and toe-off, the signal can be made to detect false gait cycle events or fail to detect true gait cycle events. False negatives often occur in Parkinson's disease due to low foot clearance, or hemiplegia due to irregularity of foot placement, while spastic movements in Huntington's disease cause "noisy" acceleration signals and therefore false positives (51). Thus, the conditions examined in these studies may cause over- or under-estimation of the true step count, resulting in imperfect estimation of temporal characteristics. This does not happen in LSS patients as they often experience localised dysfunction (52) or fine motor impairments(s) (53) but rarely present with difficulty initiating and controlling coarse movements of the limbs.

While our results may suggest that the chest-based MMC/IMUPY system has poor reliability for spatial metrics, the present study did not examine test-retest reliability and therefore cannot confirm this result. Additionally, while the present study did not examine the accuracy of IMU estimation of variability, or asymmetry, it has been shown that similar devices have lower accuracy for these variables (21,54-56). Finally, videography could not be used for trials under 30 m. While it is unlikely that the MMC/IMUPY device has lower accuracies for shorter walking bouts, this assumption cannot be confirmed by the present study. Future studies should test the accuracy of this system for shorter walking bouts, especially as it is unlikely that elderly patients or patients with balance issues will be undergoing continuous walking bouts exceeding 30 m whilst in their home environment. We were also unable to test the surrounding environment for ferrous interference, which could distort the Earth's magnetic field and thereby disturb the magnetometer of our MMC sensor (57). Nonetheless, our sensor still demonstrated good agreement for gait metrics that both methods could estimate, suggesting that there was no significant effect of ferrous interference. Future studies using this system should assess test-retest reliability in addition to accuracy analysis. They should also attempt to validate results from the MMC/IMUPY pertaining to symmetry and variability against more complex gold-standard techniques like 3D motion capture, or gait mats, which can also capture shorter gait cycles without compromising accuracy. They could also test for ferrous interference.

Although most studies performing gait analysis using wearable sensors rely on positioning at the thighs, ankles, knees, or wrists (18), our use of a chest-based sensor is not a new approach. For instance, a systematic review investigating the measurement of gait in Parkinson's disease using wearable sensors found that 9 out of 36 papers used chest-based sensors, which together cumulatively measured various metrics including those in the present study (58). However, no study in the review used a single-point chest-based sensor alone as we did, and there are a limited number of studies in the literature which do so. Nazarahari & Rouhani (59) found that a single-point chest-based triaxial accelerometer measured step count and walking speed with an accuracy over 80% when compared to a 3D motion capture system (gold-standard). Meanwhile, Hashmi, Riaz, Zeehsan, Shahzad & Fraz (60) performed measurements of gait metrics (notably, step and stride length, and step and stride time) using a smartphone (containing a built-in IMU) attached to the participant's chest. However, no accuracy analysis was performed. Another study by Del Din *et al.* measured the accuracy of an IMU system when placed at

the chest, compared to its accuracy when placed at the lower back for which it was developed. The system demonstrated high agreement of mean spatiotemporal gait features (such as step length, and step time, with intraclass correlation coefficient values exceeding 0.88) but showed less agreement when measuring variability and asymmetry (61). Overall, studies have shown that single-point chest-based sensors have potential for the measurement of spatiotemporal gait metrics, while more research is required to assess the use of chest-based sensors for the measurement of gait asymmetry and variability. In addition, placement of IMUs at the chest have the advantage of detecting less "noise", compared to ankle- or wrist-based wearables where sensors frequently change orientation due to the degree of freedom of the upper and lower extremities (60). Furthermore, the flat bony surface of the sternum enables repeatable sensor attachment by even unskilled users (59), which is important for future possibilities of being used by patients in everyday living conditions. Therefore, there is a need to perform additional investigations into the use of single-point chest-based wearables for the measurement of gait metrics.

The clinical utility of IMUs relies on their potential to be taken home to measure gait in everyday living conditions away from the Hawthorne effect (20), unlike more sophisticated methods of gait analysis such as 3D motion capture or gait mats. While IMUs focussing on the measurement of physical activity (most notably, step counts) can be easily shown to operate in everyday living conditions such as with the widely used Fitbit fitness trackers (62,63), there is limited evidence to demonstrate the same for IMUs that measure advanced spatiotemporal gait metrics (such as step and stride length and time, and variability and asymmetry measures). Even the sensor used in the present study is only designed to measure walking bouts with a duration up to 30 minutes due to limitations on data storage capacity. This restricted data collection to a corridor outside the neurosurgery clinic, which constitutes an unfamiliar environment for patients that may cause them to inadvertently alter their walking patterns in accordance with the Hawthorne effect. In addition, our accuracy analysis was conducted using a long, straight unobstructed pathway, which is dissimilar to a typical home environment. It is unlikely that patients in their home environment would routinely walk at least 30 m in a straight line, unless outdoors, which is unlikely for patients with relatively severe forms of LSS, and patients living in cold climates. Technological advancements are required to overcome limitations on battery life, allowing for IMUs to be validated in home environments in future studies. A possible solution is for IMUs to operate on a reasonable threshold, for instance, by only operating at high frequencies of data capture once 10 steps have occurred, or once 10 seconds of activity has elapsed. This would facilitate operation during longer walking bouts by eliminating battery usage during relatively inactive segments of daily life. Another potential solution is for IMUs to, during periods of activity, perform several short episodes of data capture rather than measure gait metrics continuously throughout the entire period of activity. This would conserve processer and battery resources, but further studies are required to explore the accuracy of this approach. To demonstrate the clinical feasibility of gait analysis using IMUs, future studies measuring spatiotemporal gait parameters are required in everyday conditions.

Conclusions

This study has constructed a preliminary disease-specific gait profile for LSS. A unique gait profile taken by the MMC/IMUPY or a similar device may be compared to the DSGP from this study to aid in the diagnosis of LSS. Additionally, the present study demonstrated that the chest-based MMC/IMUPY device has a high agreement with videography when measuring spatiotemporal gait metrics. While promising, further studies are required before this or a similar system can have clinical applications in the patient's home environment—particularly pertaining to the development of a more nuanced disease-specific gait profile for LSS, and the validation of the system in the home environment.

Acknowledgments

The authors would like to thank Dr. Matthew Brodie for assisting with project conceptualisation and Jessie Ding for providing artwork. Additionally, I would like to personally thank Professor Boaz Shulruf and Dr. Greg Smith for assistance with statistical analysis and manuscript preparation, respectively. Finally, I would like to thank Associate Professor Stephen Redmond and Scientia Professor Nigel Lovell for their help in recruiting Dr. Luke W. Sy for engineering assistance.
Funding: None.

Footnote

Reporting Checklist: The authors have completed the STROBE reporting checklist. Available at https://dx.doi.org/10.21037/jss-21-16

Data Sharing Statement: Available at https://dx.doi.org/10.21037/jss-21-16

Peer Review File: Available at https://dx.doi.org/10.21037/jss-21-16

Conflicts of Interest: All authors have completed the ICMJE uniform disclosure form (available at https://dx.doi.org/10.21037/jss-21-16). RJM serves as the Editor-in-Chief of *Journal of Spine Surgery*. The other authors have no conflicts of interest to declare.

Ethical Statement: The authors are accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved. The study was conducted in accordance with the Declaration of Helsinki (as revised in 2013). Ethics approval for this study was obtained from the South Eastern Sydney Local Health District Ethics Committee, with reference code 17/184. Informed consent was taken from all patients.

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Cite this article as: Betteridge C, Mobbs RJ, Fonseka RD, Natarajan P, Ho D, Choy WJ, Sy LW, Pell N. Objectifying clinical gait assessment: using a single-point wearable sensor to quantify the spatiotemporal gait metrics of people with lumbar spinal stenosis. J Spine Surg 2021;7(3):254-268. doi: 10.21037/jss-21-16

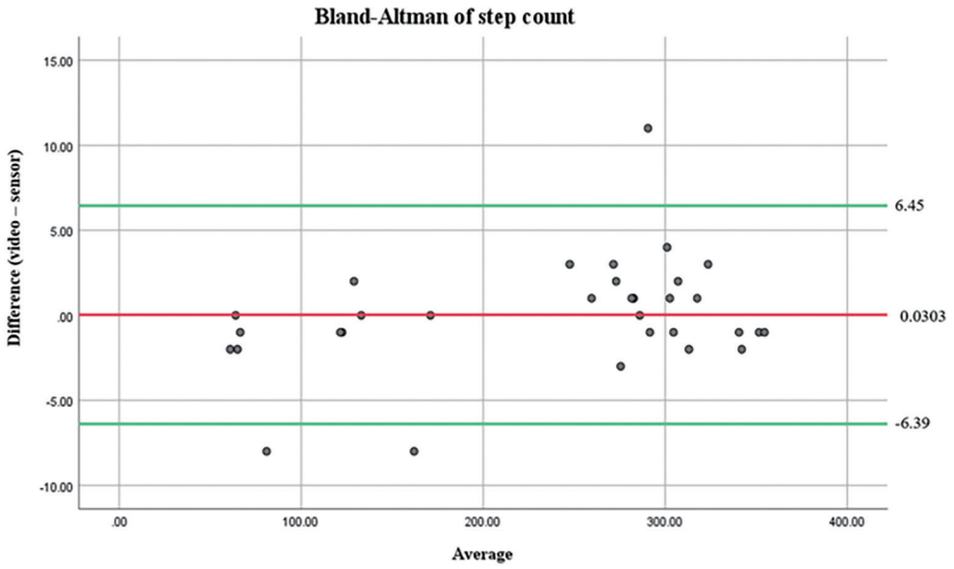
Supplementary

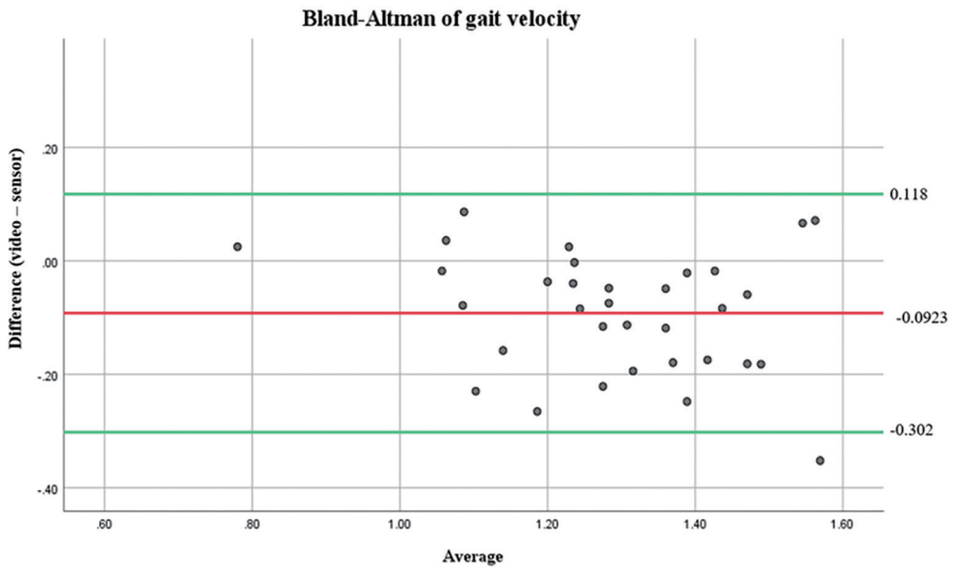
Appendix 1: Link to more information on the MetaMotionC/IMUPY system

The following link will take you to a Github.io webpage which has detailed set-up instructions, configuration files and data explanations.
https://lsy3.gitlab.io/IMUGaitPy/index.html

Appendix 2: Bland-Altman plots when comparing the MetaMotionC/IMUPY system with videography

Green lines indicate 95% limits of agreement. The red line indicates the mean difference.
Healthy controls





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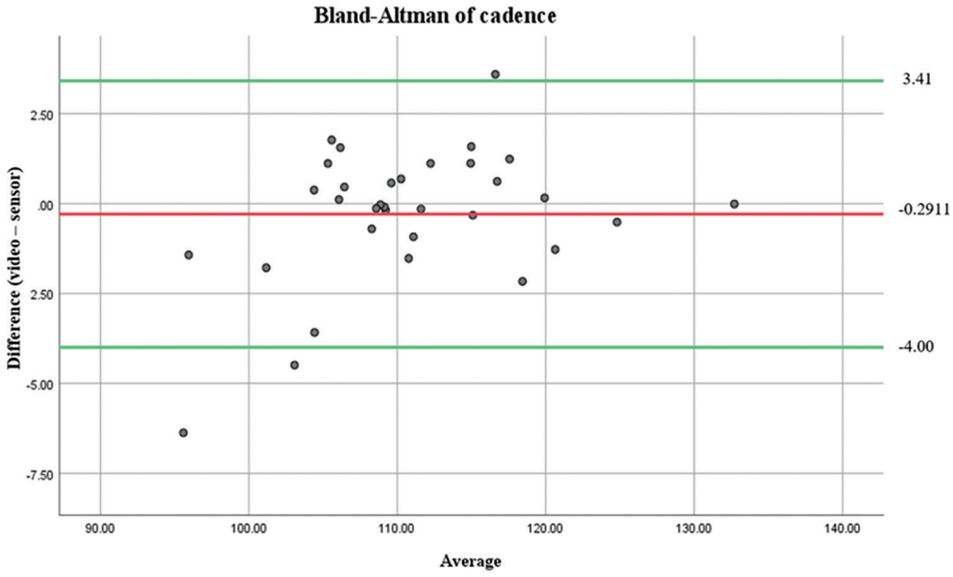

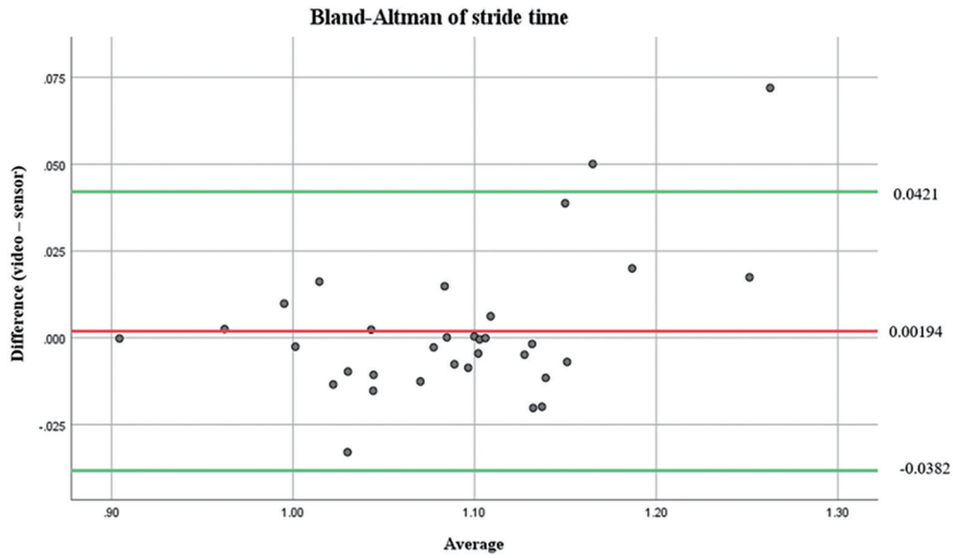

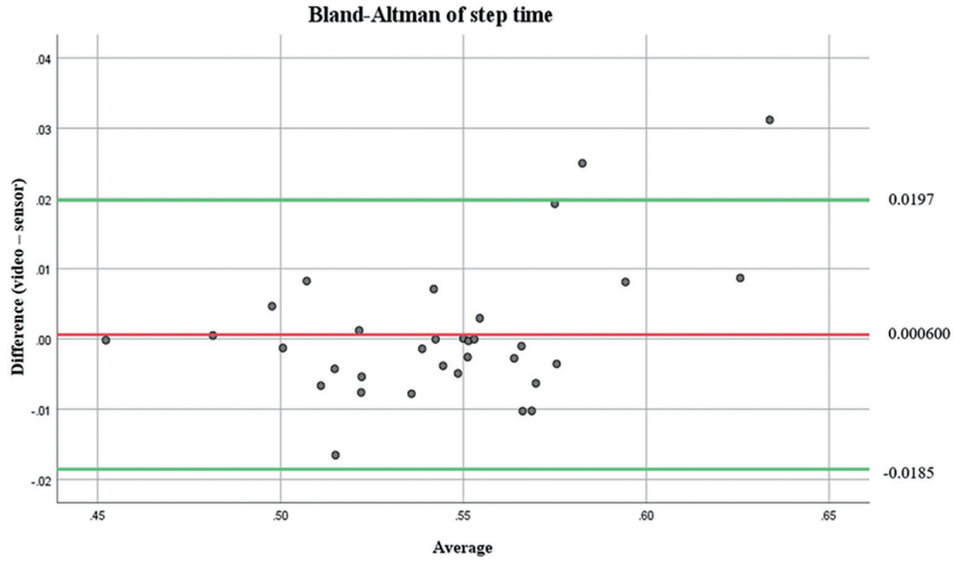

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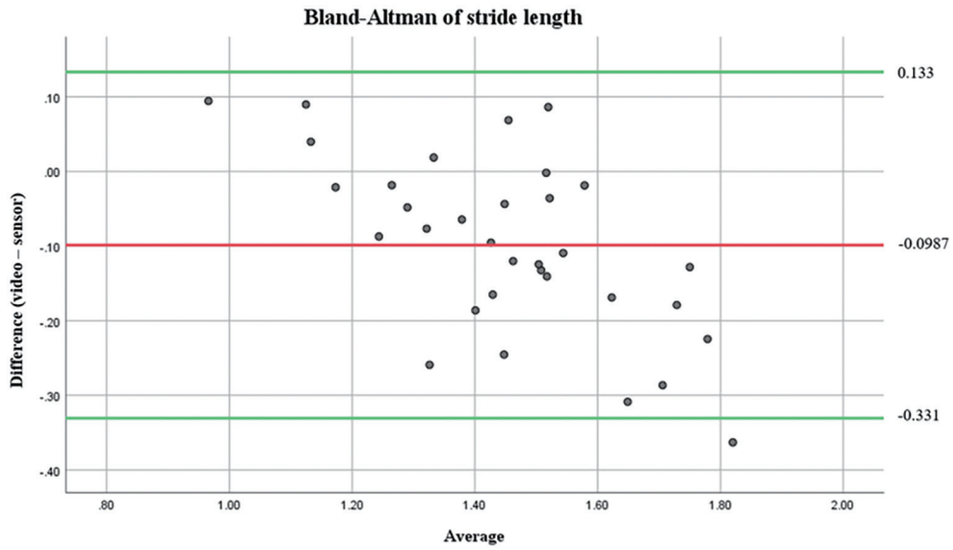
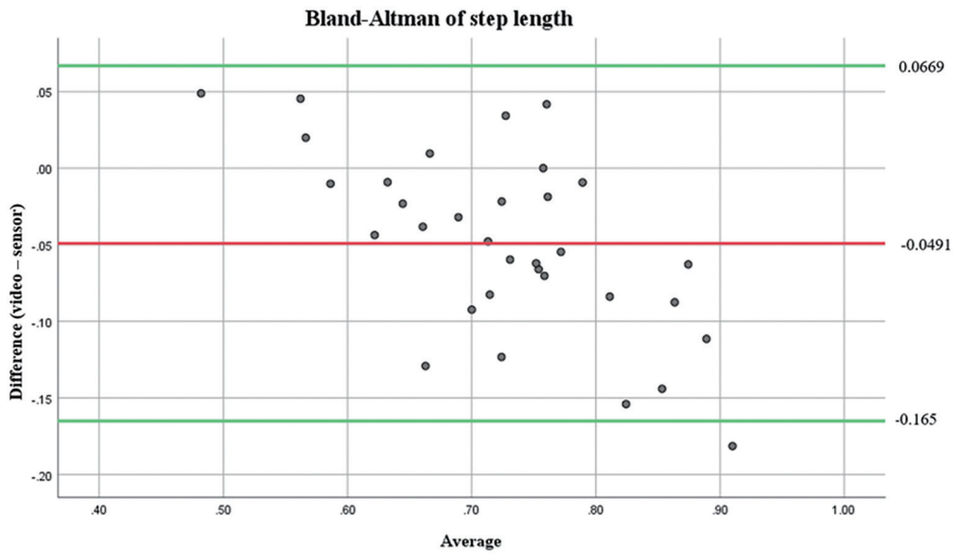
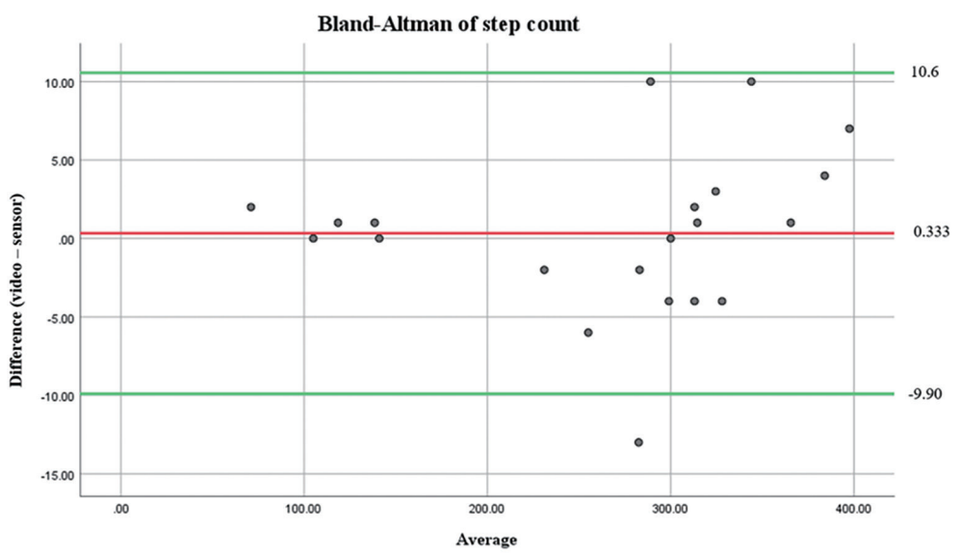
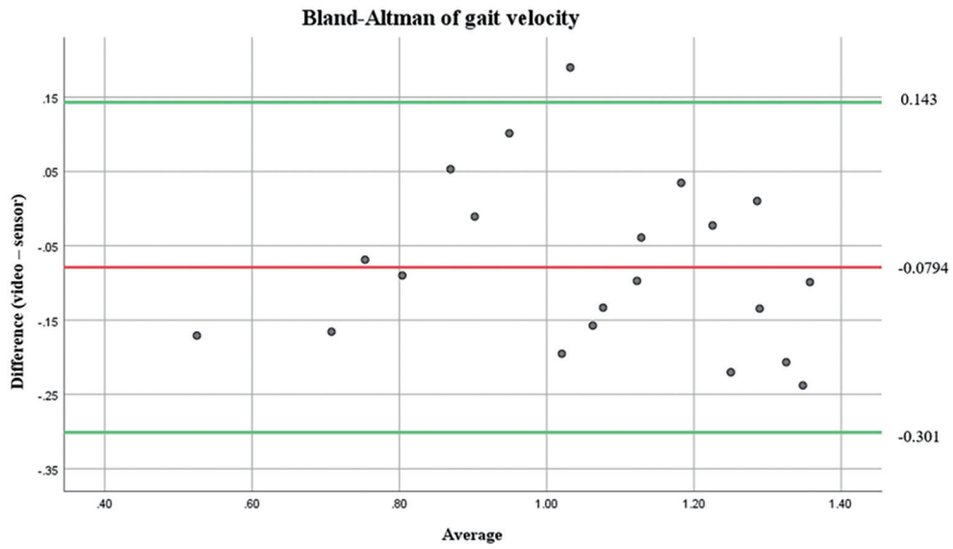


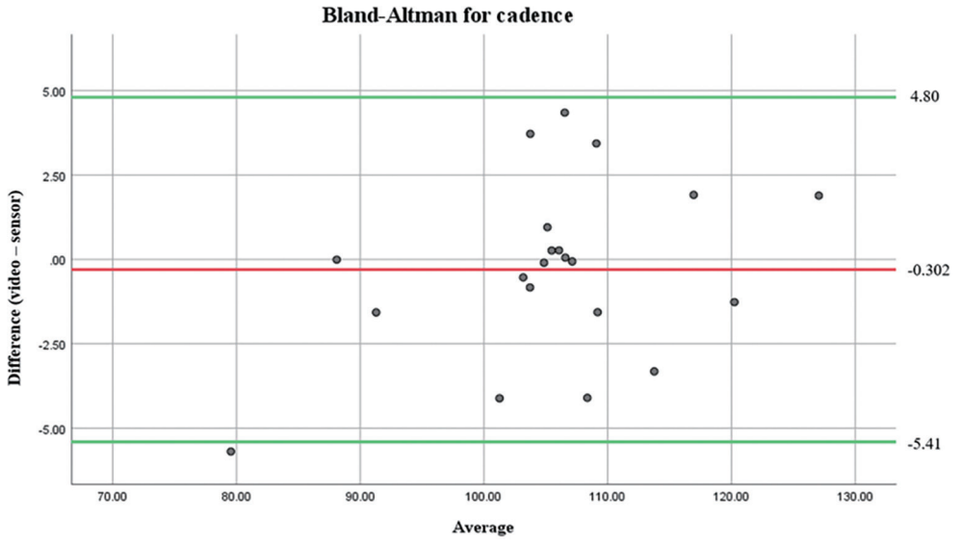


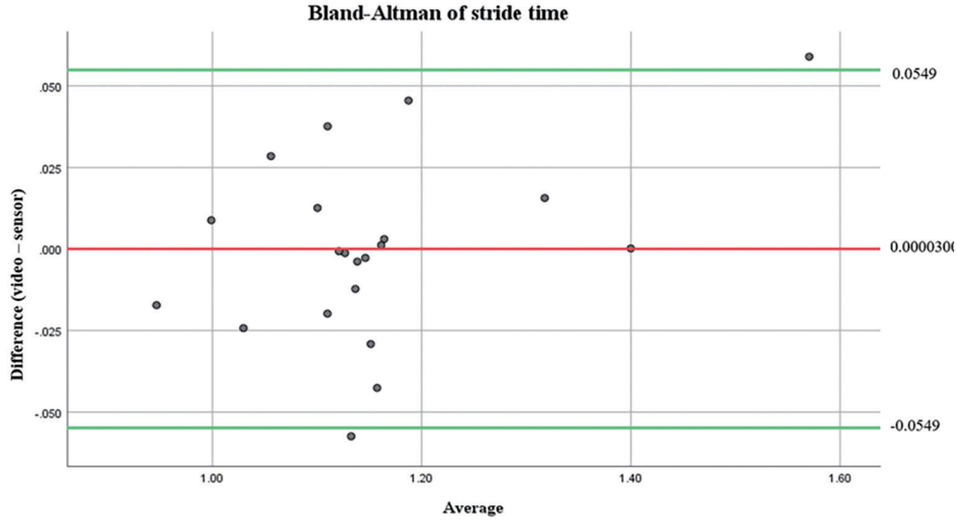
Lumbar spinal stenosis cohort



https://dx.doi.org/10.21037/jss-21-16







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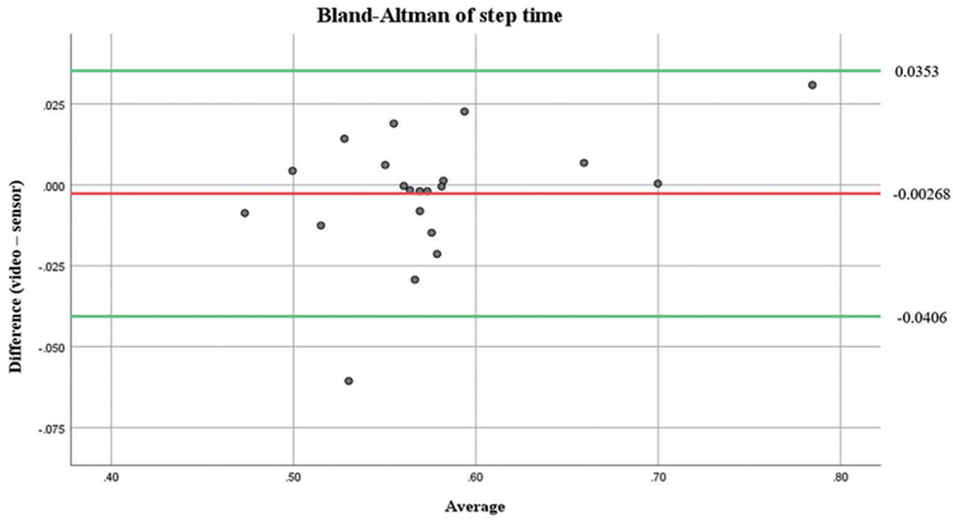

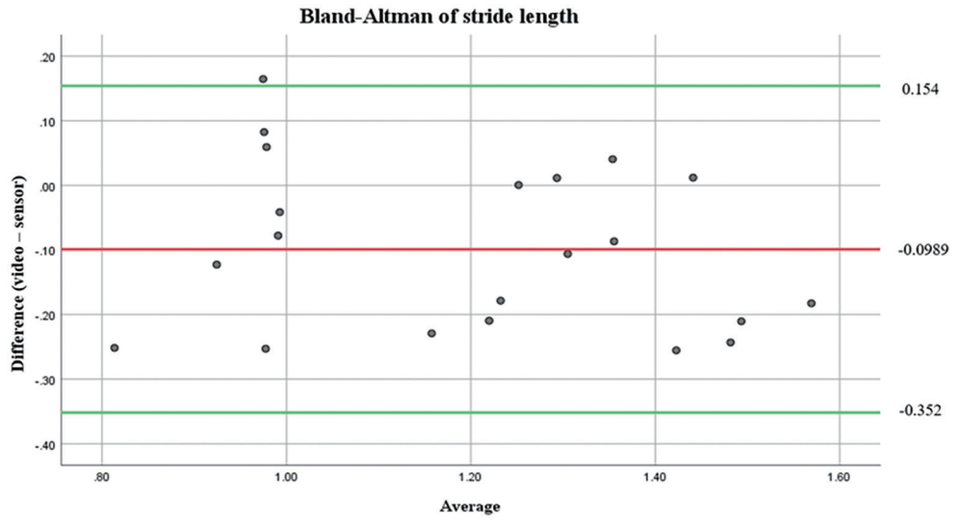

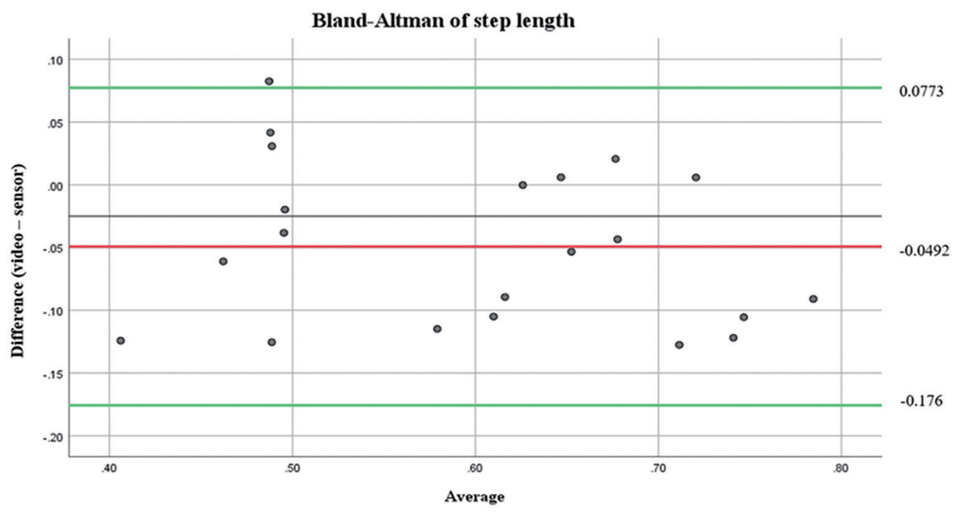

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