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Original Article

Reliability of Bluetooth inertial sensors for assessing lower limb segment angles and stride length during gait

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Abstract. [Purpose] To assess the agreement between our custom Bluetooth IS system and the gold standard MOCAP system during gait. Bluetooth inertial movement sensors (IS) allow for real-time movement analysis with fewer restrictions than optoelectrical motion capture systems (MOCAP) and more accessibility than wireless IS systems. [Participants and Methods] We collected simultaneous Bluetooth IS and MOCAP data for 16 young participants walking at a self-selected speed. Sensors were placed on the right thigh and shank. Segment angles and stride length were calculated and compared between systems using Pearson's correlation coefficients (R), intra-class correlation coefficients (ICC), root mean square errors (RMSE), limits of agreement (LOA), and Bland-Altman plots. [Results] R values ranged from 0.371–0.715; ICC values ranged from 0.263–0.770. RMSE was 0.369 m for stride length and ranged from 6.85–13.07° in segment angles. Limits of agreement were −0.01–0.66 m for stride length and ranged from −27.71–20.53° in segment angles. [Conclusion] The Bluetooth IS system showed moderate agreement with MOCAP. Bluetooth IS could be used for reliable gait analysis with fewer space requirements and more portability than wireless IS or MOCAP systems. Bluetooth IS could be used outside of the clinic for real-time monitoring of gait during daily life.

Key words: Inertial sensors, Gait analysis, Bluetooth

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INTRODUCTION

Inertial movement sensors (IS) are commercially available devices capable of recording human movement through integration of accelerometer, gyroscope, and magnetometer[1)]. IS can be used to calculate kinematic variables of interest such as gait speed and movement of the center of mass (COM)[2, 3)], thereby offering an alternative method for analyzing movement compared to the 'gold standard' method of motion analysis: optoelectronic motion capture (MOCAP)[4)]. Although MOCAP allows for thorough movement analysis during gait and postural tasks[5, 6)], it is limited by lengthy set-up and post-processing, high cost, and lack of portability[7, 8)]. Therefore, MOCAP is primarily used for motion analysis in research settings and is not implemented into clinical practice due to time and space restrictions[4)].

Clinical gait analysis involves the observation and analysis of gait (e.g., speed, symmetry, variability) to identify functional limitations and underlying impairments, monitor rehabilitation progress, and quantify fall risk[9, 10)]. Functional performance assessments (e.g., ten-meter walk test, dynamic gait index) are commonly used by clinicians to rapidly assess overall gait performance and stability[11, 12)]; however, unlike IS and MOCAP, these assessments are not capable of quantifying objective kinematic measures (e.g., joint angles, step length, variability in gait parameters) which can indicate subtle underlying impairments and changes to fall risk[10, 13)]. Due to their portability, relatively low cost, and immediate feedback, IS could be a

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feasible tool for clinicians to rapidly assess gait kinematics with more complexity than functional performance assessments, yet fewer resource requirements than MOCAP[8].

Many researchers have implemented IS to analyze gait kinematics[14–16], yet fewer studies have assessed the validity of IS systems compared to MOCAP systems. Overall, existing studies have found moderate to high agreement between commercially-available IS (XSens) and MOCAP during gait, slipping and tripping, and stair climbing[17, 18], indicating that IS can accurately analyze human movement. However, these studies examined only commercial IS that connect to a monitoring device (PC) via wireless connection (station or USB dongle)[19]. Thus, commercial IS systems are limiting because they are not completely wearable and the system takes up space, restricting the locations in which IS can be used (i.e., inside of the clinic or domestic settings). Additionally, commercial IS are still costly, even though they are relatively more affordable than MOCAP systems. Wearable IS may be important to monitor movement during day-to-day activities in order to accurately assess gait, given that individuals can alter their gait during clinical assessment compared to daily living[20].

Bluetooth IS improve the accessibility of gait analysis, allowing for monitoring in virtually any location with the presence of a Bluetooth-connected monitoring device. Although previous studies have implemented Bluetooth IS to evaluate gait[21, 22], there is limited information about the validity of Bluetooth IS. Bolink et al. found Bluetooth IS to accurately compare to MOCAP, however this was only a single sensor attached to the lower back to measure pelvic angles during gait[23]. It has been reported that wireless connections like Bluetooth may introduce occasional loss of data packets and timing errors in wireless sensor networks might lead to unacceptable joint angle errors[24, 25], especially for multiple Bluetooth connections[26]. Hence, the accuracy of multi-sensor Bluetooth IS in reporting gait parameters still deserves to be verified.

The purpose of this study was to assess the agreement between a multi-sensor custom-designed Bluetooth IS system and MOCAP system when calculating segment angles and stride length during gait. This study will help to determine the validity of Bluetooth IS during gait analysis, which could allow for real-life gait monitoring both in and out of the clinic.

PARTICIPANTS AND METHODS

Previously collected data from 16 participants were used for this secondary study (9 female, 7 male; 27.8 ± 3.8 y; 70.3 ± 11.5 kg; 162.3 ± 16.5 cm; presented as Mean ± SD). These data have not previously been published in any papers. Participants responded to a general health questionnaire to ascertain their health status. Exclusionary criteria included neurological, musculoskeletal, cardiopulmonary, or any other system disorders. This study was approved by the Institutional Review Board at the University of Illinois at Chicago (2017-1069). All participants provided informed consent.

Kinematic data were collected simultaneously from MOCAP and IS systems. For MOCAP, data were collected using an 8-camera MOCAP system (Qualisys Motion Capture, Goteberg, Sweden) (Sampling Frequency: 120 Hz). Twenty-six reflective markers were placed on the participant using a modified full-body Helen Hayes marker set. Four reflective markers were placed on the overground walkway. For IS, we developed a custom IS-based motion analysis system (FRATS) using IMU sensors (Wit-Motion Shenzhen Co., Ltd., Shenzhen, China) connected to an Android tablet via Bluetooth. The IMU sensor could measure 3-axis angle, angular velocity, acceleration, and magnetic field. Two sensors were placed on the right side thigh and shank, and the FRATS system collected the angular data with a sampling frequency of 40 Hz.

Participants were instructed to walk at a self-selected speed over a 7-meter overground walkway. Participants wore a safety fall-arrest harness connected to an overhead trolley for precaution. Each participant completed 8 walking trials over the overground walkway. Each trial lasted approximately 8 seconds, depending on individual walking speed. In between trials, participants were given as much time as necessary to walk back to the beginning of the walkway.

Individual MOCAP markers were initially identified and gap-filled using Qualisys software (Qualisys Motion Capture). Marker data were then analyzed using a custom MATLAB code (MathWorks, Natick, MA, USA) to generate thigh and shank segment angles on the right side for MOCAP system. The thigh angle was calculated as the angle between the horizontal line and the line connecting hip marker and knee marker in sagittal plane, and the shank angle was calculated as the angle between the horizontal line and the line connecting knee marker and ankle marker. For IS system, these segment angles were directly generated from the IMU sensors. Segment angles for both systems were calculated at the fourth right touchdown (RTD) and subsequent right liftoff (RLO); the fourth step was selected to avoid the gait acceleration phase. For MOCAP, these gait events were detected automatically by loading and unloading of time-synchronized bilateral force plates embedded in the overground walkway (AMTI; sampling frequency: 600 Hz). As MOCAP and IS recording systems were both started manually, there was not exact time synchronization between the two systems. Therefore, IS gait events were identified separately, and the key variables were compared on the same gait events between these two systems. For IS, segment angles were used to generate a stick figure of the right leg and gait events were determined through visual identification of the fourth RTD and subsequent liftoff. Segment angle trajectories were compared between IS and MOCAP to visually confirm that segment angle trajectories were similar and gait events were nearly identical (see Fig. 1 for example of segment angle trajectory plot). Stride length was calculated as the swing distance of right heel marker in anterior-posterior direction from RTD to the following right touchdown (RTD2) for MOCAP system. For IS system, the hip to ankle distance was first calculated at RTD and RTD2 based on thigh angle and shank angle, and their sum was defined as the stride length from RTD to RTD2.

Each trial was considered as the fourth RTD (RTD) to the fifth RTD (RTD2) (i.e., one gait cycle). We identified data loss

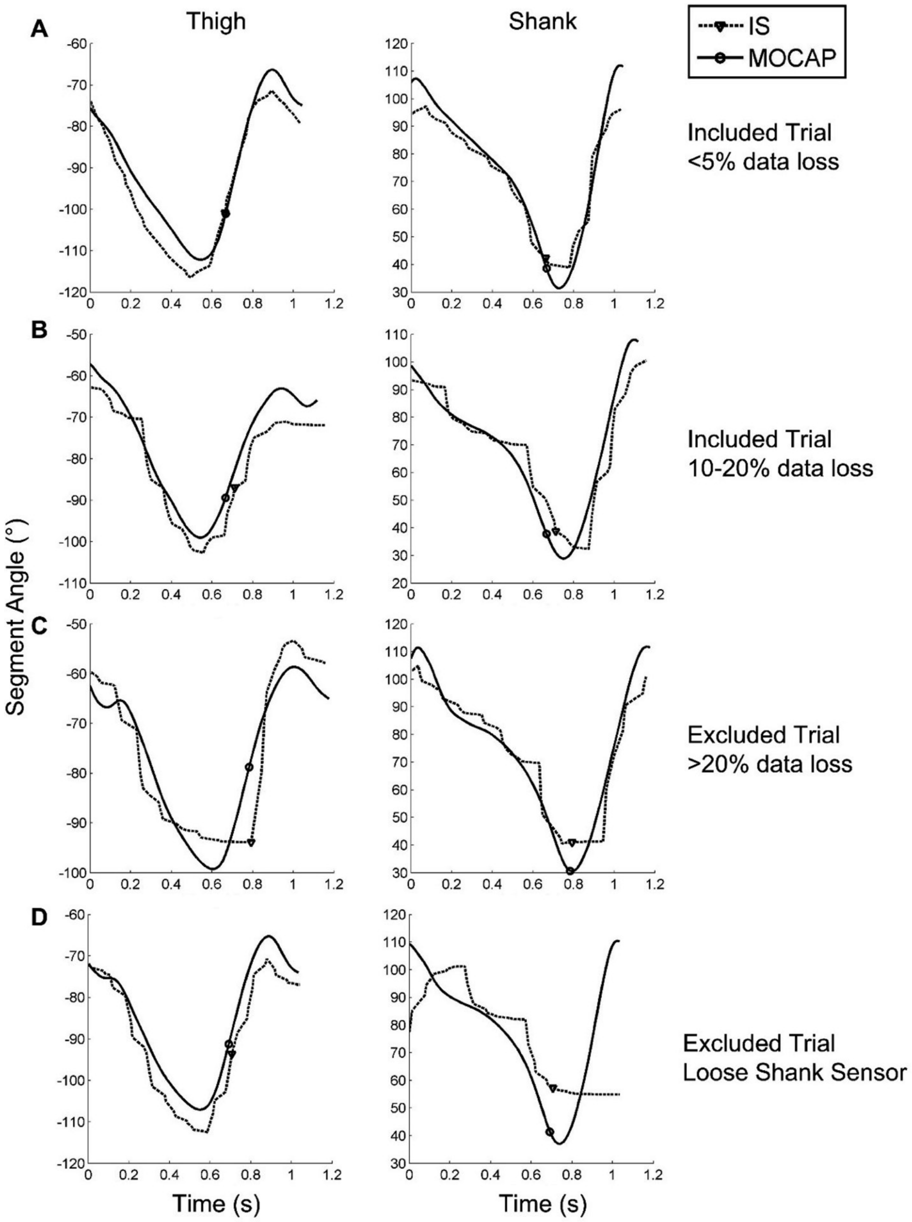

Fig. 1. Representative segment angle tracings of the right thigh and shank for individual walking trials over one gait cycle compared between inertial sensor (IS) and motion capture (MOCAP) systems. The percentage of data loss was calculated for each trial and trials were excluded from reliability analysis if they had >20% data loss or if segment trajectory angles indicated an error in data collection (e.g., loose sensor). **A**: Included trial with <5% data loss in both thigh and shank sensor. **B**: Included trial with 10–20% data loss in thigh and shank sensor that does not affect trajectory shape. **C**: Excluded trial due to >20% data loss. **D**: Excluded trial due to loose shank sensor that affected trajectory shape. Dashed lines and solid lines represent IS and MOCAP data, respectively. Triangular and circular markers indicate right lift off (RLO). The start of the trial (i.e., 0 s) indicates right touchdown (RTD); the end of the segment trajectory indicates the following right touchdown (RTD2).

in each trial by identifying any repeated segment angle value in subsequent frames, as the IS system gap-filled lost frames of data by auto-filling that frame with the last valid value. The overall percentage of data loss was calculated for each trial as the number of frames with data loss out of the total number of frames. We also calculated the largest data loss gap for each sensor in each trial by identifying the largest number of subsequent frames with repeated segment angle values. We excluded trials from data analysis if they had more than 20% of overall data loss. One hundred and twenty-eight trials were initially assessed. Eighteen trials were excluded from analysis due to having >20% IS data loss during the trial (Fig. 1C). Eighteen trials were additionally excluded when the segment trajectory angles in IS output indicated an error in collection, such as a loose sensor or low battery (Fig. 1D). Trials were included in the reliability analysis if they had <20% of overall data loss and the segment angle trajectories did not indicate any data collection errors (i.e., IS trajectories matched MOCAP trajectories) (Fig. 1A, 1B). Ninety-two trials were included in the final analysis.

Pearson's correlation coefficient (R) and intra-class correlations (ICC) were used to assess the agreement between IS and MOCAP segment angles and stride length. Root mean square error (RMSE) and Limits of Agreement (LOA) were additionally calculated. Bland Altman plots were created by calculating the bias between IS and MOCAP as the average difference between IS and MOCAP outcomes. To determine the significance of R and ICC, the alpha level was set at 0.05. All statistical analyses were conducted using SPSS (IBM Corporation, Endicott, NY, USA).

RESULTS

R values indicated a moderate to strong significant correlation between IS and MOCAP for all segment angles and stride length (0.434–0.715; all p's<0.01), except for the shank at RTD (r=0.371; p<0.01). ICC values also indicated fair to good significant agreement between systems for all segment angles (0.351–0.770; all p's<0.01), but the ICC value was lower for stride length (ICC=0.263, p<0.001). RMSE ranged from 6.85–13.07° for segment angles; RMSE was 0.369 m for stride length. R, ICC, and RMSE values and LOA can be found in Table 1. Bland–Altman plots can be found in Fig. 2. The bias between systems was generally positive (Thigh RTD: 4.64° (−0.72, 17.01), Thigh RLO: 3.82° (−7.42, 15.05), Shank RLO: 5.72° (−9.10, 20.53), stride length: 0.33 m (0.00, 0.66); presented as bias (lower LOA, upper LOA)) except for the shank at RTD (−8.95° (−27.71, 9.81)).

Overall data loss ranged from 0–19.5% of the trial in the thigh sensor and 0–18.2% of the trial in the shank sensor. Most trials had some percentage of data loss. There was only one trial with no data loss in either sensor. In the thigh sensor, 48 trials had 0–5% data loss; 28 trials had 6–10% data loss; 10 trials had 11–15% data loss; 6 trials had 16–20% data loss. In the shank sensor, 58 trials had 0–5% data loss; 28 trials had 6–10% data loss; 6 trials had 11–15% data loss; 0 trials had 16–20% data loss trials (Fig. 3). The average data loss was 8.0 ± 7.6% of the trial in the thigh sensor and 6.4 ± 6.9% of the trial in the shank sensor. The largest individual gap of data loss (i.e., continuous frames of data loss) was 5.0 ± 4.6% of the trial in the thigh and 5.0 ± 4.5% of the trial in the shank.

DISCUSSION

This paper assessed the reliability of a custom-designed Bluetooth IS system to determine joint angles and stride length during gait compared to the well-established MOCAP system. We showed that the IS system could provide accurate segment angles and stride length, generally in moderate agreement with the MOCAP system.

Bluetooth IS systems could be used for real-time gait monitoring with fewer limitations than other methods of gait analysis (i.e., functional performance tests, MOCAP systems, commercially-available IS systems). Gait analysis allows clinicians to identify functional limitations and underlying impairments, monitor rehabilitation progress, and quantify fall risk[27, 28]. MOCAP and commercially-available IS allow for in-depth assessment of kinematic parameters such as stride length and lower-limb joint angles, which can indicate subtle underlying impairments and differentiate fall risk[10, 13]. However, MOCAP is still primarily used only in research settings due to its space and equipment requirements[4]. Likewise, commercially available IS can be limiting because they rely on a wireless connection to a monitoring device (via base system or USB) to record data. Thus, commercially-available IS are not completely portable/wearable and do not allow for set-up outside of clinical or domestic locations.

This study showed that Bluetooth IS systems can provide kinematic outputs in good agreement with MOCAP systems. Previous studies have shown that commercially-available IS systems can reliably provide kinematic variables in high agreement with MOCAP systems[17, 18], however fewer studies have examined the reliability of Bluetooth IS. The benefit to using Bluetooth IS systems is the increased portability of the system. Bluetooth IS systems can be used virtually anywhere if there

Table 1. Reliability comparison between inertial sensor (IS) system and motion capture (MOCAP) system using Pearson's correlation coefficient (R), intra-class correlations (ICC) and 95% confidence intervals (CI), root mean square error (RMSE), and limits of agreement (LOA)

Outcome	R	ICC	ICC 95% CI	RMSE	LOA
Thigh: RTD	0.434*	0.501**	0.087, 0.711	7.84°	−7.82–17.09°
Shank: RTD	0.371*	0.351*	−0.095, 0.610	13.07°	−27.71–9.81°
Thigh: RLO	0.715*	0.770**	0.466, 0.882	6.85°	−7.42–15.05°
Shank: RLO	0.589*	0.641**	0.203, 0.814	9.44°	−9.10–20.53°
Stride length	0.507*	0.263**	−0.164, 0.594	0.369 m	−0.01–0.66 m

Ninety-two walking trials were used to compare thigh and shank joint angles at right touchdown (RTD) and liftoff (RLO) and stride length between IS and MOCAP.
*p<0.01, **p<0.001.

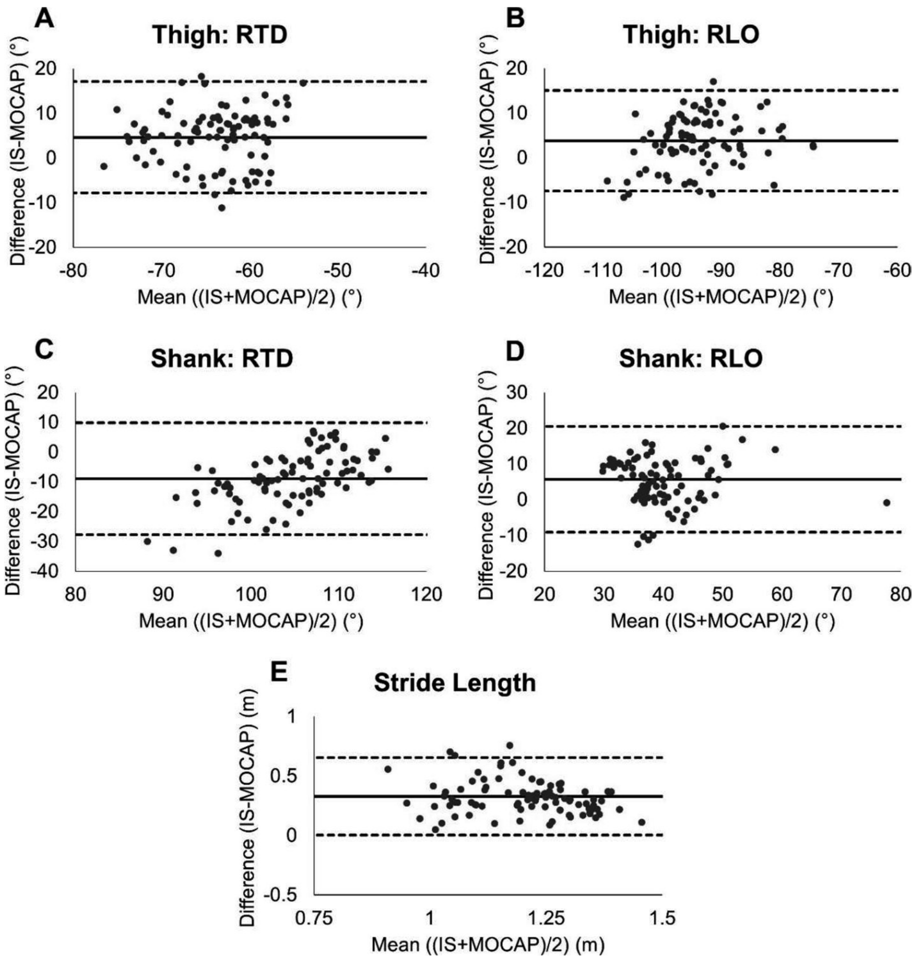

Fig. 2. Bland–Altman Plots for inertial sensor (IS) and motion capture (MOCAP) system comparisons for segment angles of the thigh at right touchdown (RTD) (A) and right liftoff (RLO) (B), shank at RTD (C) and RLO (D), and stride length (E). Solid lines indicate the mean difference between IS and MOCAP outcomes; dashed lines indicate the mean difference ± 1.96*standard deviation between IS and MOCAP outcomes.

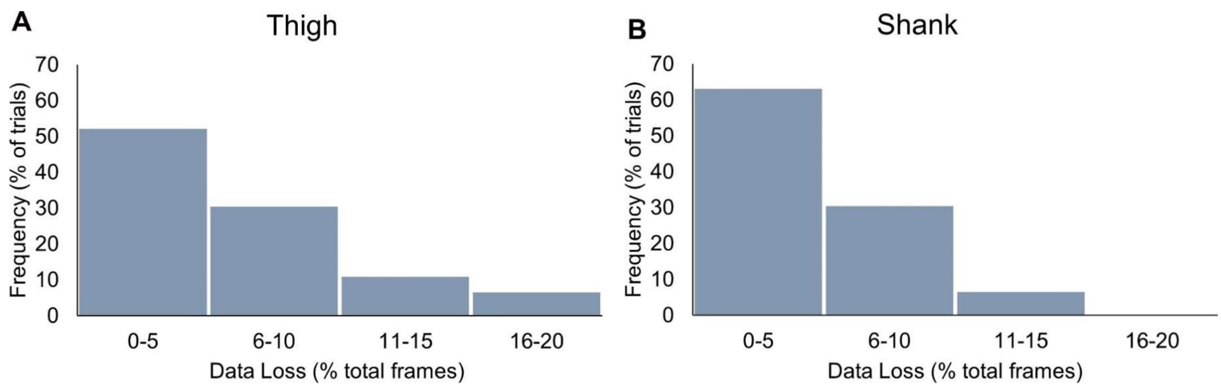

Fig. 3. Frequency of data loss for the inertial sensor (IS) system in the thigh (A) and shank (B) sensors. This figure presents the percentage of walking trials (out of 92 included trials) which had 0–5% data loss, 6–10% data loss, 11–15% data loss, and 16–20% data loss. Percent data loss was calculated by the number of data loss frames divided by the total number of frames during one gait cycle. Trials with >20% data loss were excluded.

is a Bluetooth connection to a monitoring device (e.g., tablet, smartphone), which broadens the scope of gait monitoring beyond clinical and domestic settings. Portability is crucial for accurate gait analysis as individuals can change their gait patterns (i.e., gait speed, cadence, step time variability) during clinical assessments from their normal gait pattern[29, 30]. Brodie et al. reported that while daily-life gait assessments could distinguish between fallers and non-fallers, performance on clinical gait assessments was not indicative of fall status[20]. This may be because individuals will walk with an "optimal" gait in clinical assessments which does not reflect their "usual" gait during activities of daily living[20]. Therefore, longer-term gait monitoring during activities of daily living, especially in situations where individuals may change their gait (e.g., walking quickly while running late), may be necessary to accurately assess gait and comprehensively understand gait impairments and fall risk. Additionally, portable Bluetooth IS systems allow for the option of individuals self-recording their movement so that clinicians can remotely monitor progress over the duration of home-based exercise or rehabilitation programs with less need for in-person assessments.

Previous studies have used Bluetooth IS systems to monitor gait parameters[31–34], although these studies used either a single sensor[31, 34] or sole-embedded sensors in the shoe[32, 33] that were not capable of recording segment angles. We found that our custom Bluetooth IS system could calculate segment angles and stride length with moderate to strong correlation and fair to good ICC agreement. The shank at RTD and the stride length had slightly lower values for correlation coefficient and ICC, respectively. However, these correlation coefficient and ICC values were still significant. The IS system had the largest bias in the shank, which was negative at RTD (−8.95°), and positive at RLO (5.72°). It is possible that this bias occurred because the IS system underestimates peak range of motion values. RTD occurs when the knee is extended and shank angle is around its peak maximum value. The IS system underestimated shank angle at this time point by almost 9° (i.e., negative bias). Further, the knee is flexing at RLO and shank angle is around its peak minimum value. At this time point, the IS system also underestimated the peak minimum shank angle (i.e., positive bias). This bias could occur in the shank because the shank has a larger range of motion from RTD to RLO than the thigh. Therefore, future reliability analyses of IS systems may want to further examine IS system biases, especially for motion analysis during movements with large ranges of joint motion. On examination of the segment angle trajectories, we found that the IS system and the MOCAP system had very similar segment angle trajectory paths, even if the absolute values of segment angles were 5–10° different (e.g., Fig. 2B). The difference in absolute segment angles may be the reason why we found moderate, rather than strong, agreement between the IS and MOCAP systems and larger biases. Additionally, as segment angles were extrapolated to calculate stride length, this could explain why the ICC value for stride length was lower than expected. Our results indicated that this IS system could reliably record segment angle trajectories and stride length; however, it was still not as accurate as the well-established MOCAP system. Therefore, IS might not be a replacement for MOCAP until the reliability of the system could be improved, especially when precise measurements of gait parameters or segment angles are required, such as in research settings. However, the IS system but could still be used for more gross analysis of gait patterns to benefit gait analysis in clinical settings. For example, this IS system could potentially be used to monitor segment angles over the course of rehabilitation to provide information to clinicians about changes in gait patterns over time. In this case, changes in general gait patterns could be monitored, rather than absolute segment angles. Future studies would also be needed to assess the test-retest reliability between days of this Bluetooth IS system; however, we expect this system would be reliable as previous studies have found moderate to excellent test-retest reliability of IS systems[35, 36], one of which was Bluetooth connected[35].

One concern for the reliability of Bluetooth IS is the issue of data loss, which is common in the wireless system[24, 25]. Our study confirmed the common occurrence of data loss, as only one out of 92 trials had no data loss. All other trials had at least one frame of data loss in either sensor. Our data indicated that although data loss was common, it did not occur in a large percentage of trial frames. There was less than 5% overall data loss in 52% of trials in the thigh sensor and 63% of trials in shank sensor (Fig. 3). Additionally, the largest continuous gap of data loss (i.e., subsequent frames of data loss) was on average only 5% of the whole trial in both thigh and shank sensors. Our results indicate that even with packets of data loss, the IS data was still reliable. We found good agreement between IS and MOCAP systems even when trials with up to 20% data loss were included. Likely, this is because the occasional loss of data does not interfere with the overall segment angle trajectory (such as in Fig. 1B). Although we found good agreement between IS and MOCAP, the reliability of the IS system could be improved by implementing a better gap-filling method to virtually fill frames of data loss. This IS system auto-filled frames of data loss by replicating the last collected segment angle value until the Bluetooth connection was re-established. This method has no computational complexity and is easy to apply in real time; however, it also affects the accuracy of the collected data. In the future, developers may consider implementing a post-collection gap-filling method that closer mimics the anticipated segment angle trajectory, such as polynomial interpolation, which is a standard gap filling procedure that usually works well for small gaps (<0.2 s)[37]. Additionally, algorithms based on principal component analysis have proved to be a simple and robust method for gap-filling[38]. These modifications to gap-filling method could likely improve the reliability of Bluetooth IS systems in the future. Furthermore, data loss issue was related to a larger packet size and data transmission frequency, and a previous study has reported that lowered transmission frequency and data bundling could reduce the data loss to less than 1%[39].

This study had some limitations. Primarily, many trials were excluded from data analysis due to errors in data collection or data loss. We excluded 18 trials from the reliability analysis because they had many frames of data loss (>20% of the trial) (Fig. 1C). This amount of data loss can affect the accuracy of segment angle outputs, as it is likely that at least one gait event of interest will occur during a packet of data loss. However, we found that trials with large amounts of data loss could easily be identified through visual inspection of the segment angle trajectories. Thus, even if large amounts of data loss occur during a trial being recorded for clinical gait analysis, the monitoring clinician could immediately note this and recollect the trial without reporting faulty outputs and affecting gait analysis. We also excluded 18 trials because the IS segment angle trajectory clearly indicated a data collection error, such as a loose sensor (Fig. 1D). Similarly, these trials are easily identified through visual inspection and a clinician could identify the faulty sensor and fix it before continuing with data collection or exclude these trials from gait analysis if they are not actively monitoring the data collection. As this was a feasibility study and the first time collecting data with these sensors, it was logical for some data collection errors to occur which could be given more attention in the future. Additionally, as discussed above, data loss in wireless sensors was expected and did not interfere with the reliability of the IS system. Another limitation of this study is that only joint angles of the right side were assessed. However, as the sample in this study was young adults with symmetrical gait, we assume that joint angles and stride length recorded on the left side would be equally as reliable as the right side. Some readers may want to consider that this paper was a secondary research study and primary study outcomes were calculated using the gold-standard MOCAP system. However, we do not feel like there were any limitations to using these data because this reliability analysis was carefully executed. Considering this was a secondary study, future larger planned studies should validate these results.

Overall, this paper demonstrated that our custom Bluetooth IS system could reliably provide gait parameters, compared to the accurate and precise MOCAP system. This IS system requires fewer space, time, and monetary resources than MOCAP and commercially-available IS systems, and thus could be used by clinicians to expand gait monitoring beyond the clinic itself, such as during activities of daily living or to monitor progress throughout home-based rehabilitation programs. Increased accessibility to gait analysis technologies could help expand the early identification of underlying motor or cognitive impairments and improve fall-risk identification. Validation of Bluetooth IS systems will provide assurance to clinicians that this technology is a reliable resource to improve the ease, speed, and accessibility of movement analysis.

Funding and Conflict of interest

There is no funding or conflict of interest to declare.

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