Assessment of spatiotemporal gait parameters using a deep learning algorithm-based markerless motion capture system

Robert Kanko[1]*, Gerda Strutzenberger[2], Marcus Brown[3], Scott Selbie[3], Kevin Deluzio[1]

[1]Department of Mechanical & Materials Engineering, Queen's University, Kingston, Canada
[2]Department of Sport and Exercise Science, University of Salzburg, Salzburg, Austria
[3]Theia Markerless Inc., Kingston, Canada

*Correspondence: r.kanko@queensu.ca

Abstract
Spatiotemporal parameters can characterize the gait patterns of individuals, allowing assessment of their health status and detection of clinically meaningful changes in their gait. Video-based markerless motion capture is a user-friendly, inexpensive, and widely applicable technology that could reduce the barriers to measuring spatiotemporal gait parameters in clinical and more diverse settings. The aim of this work was to determine whether spatiotemporal gait parameters measured using *Theia3D* markerless motion capture demonstrate concurrent validity with those measured using marker-based motion capture. Thirty healthy adult participants performed treadmill walking at self-selected speeds while 2D video and marker-based motion capture data were collected simultaneously. Kinematic-based gait events were used to measure nine spatiotemporal gait parameters from both systems independently. The parameters were compared using their group means, Bland-Altman methods, Pearson correlation coefficients, paired-samples *t*-tests, and intraclass correlation coefficients ($ICC_{(A-1)}$ and $ICC_{(C-1)}$). Group means between systems were indistinguishable across all nine gait parameters, and the Bland-Altman plots showed no systematic biases or clinically meaningful differences between the systems. Pearson coefficients indicated near-perfect correlations ($r \geq 0.96$) between systems for all but two parameters, which had strong correlations (double-limb support time, r=0.87; swing time, r=0.88). T-tests indicated differences in stance, swing, and double-limb support time parameters, but strong correlations were found for all ICCs, the lowest being 0.84 for both double-limb support time and swing time. The measurements made by the *Theia3D* markerless motion capture system demonstrated concurrent validity with those from the marker-based system, indicating sufficient accuracy for research, clinical, and other uses.

Keywords: markerless motion capture; spatiotemporal parameters; gait analysis; deep learning.

1. Introduction

Gait analysis is a useful tool for assessing and comparing human movement patterns to gain insight into a variety of health-related factors. Spatiotemporal gait parameters are one form of data obtained through gait analysis that have been shown to be useful clinical measures that can detect 'negative' changes in individuals' gait patterns due to pathology (Elbaz et al., 2014; Givon et al., 2009; Lemke et al., 2000; Morris et al., 2001) or aging (Hollman et al., 2011), and 'positive' changes due to rehabilitation (Fung et al., 2006; Patterson et al., 2008) or locomotor training (Abd El-Kafy and El-Basatiny, 2014; Smania et al., 2011; Vitale et al., 2012). They have been implemented to study the gait patterns of children (Alderson et al., 2019), older adults (Vallabhajosula et al., 2019), individuals with Parkinson's disease (Mondal et al., 2019), dementia (Darweesh et al., 2019), multiple sclerosis (Novotna et al., 2019), and post-stroke patients (Cleland et al., 2019) as a few examples. However, it is crucial that they are obtained using objective techniques to ensure adequate accuracy and repeatability (Toro et al., 2003).

Marker-based optoelectronic motion capture has often been considered the 'gold standard' for gait analysis, but its high cost and requirements for experienced operators and dedicated laboratory space have prompted the development and validation of alternative technologies that can measure spatiotemporal gait parameters. In particular, the current trend towards collecting data in more realistic environments requires such alternative technologies. Some examples of alternative technologies include instrumented walkways (Bilney et al., 2003), depth sensors (Dolatabadi et al., 2016), photoelectric cell systems (Gomez Bernal. et al., 2016), inertial measurement units (Trojaniello et al., 2014), and in-shoe pressure sensors (Braun et al., 2015), each of which has its own advantages and disadvantages. However, some of these technologies still require expensive equipment, may have limited options for deployment, and provide minimal data compared to motion capture systems. Automated two-dimensional (2D) video-based markerless motion capture is an emerging technology that has the potential to quantify human movement using spatiotemporal parameters and other types of data (e.g. joint kinematics), without the need to place markers or sensors on the individuals and manually track points of interest. Several different approaches to 2D video-based markerless motion capture have been developed and implemented to varying levels of success, feature recognition being one such approach (Mathis et al., 2018b, 2018a; Mathis and Mathis, 2020). Feature recognition employs deep learning techniques such as neural networks to identify and track the movement of specific anatomical landmarks in single or successive photographic images. This process allows the pose of human subjects to be estimated based on the positions of the tracked anatomical landmarks. The feature recognition approach to 2D video-based markerless motion capture has several benefits over depth sensor-based approaches such as the Microsoft Kinect™ (Microsoft Corporation, Redmond, WA) or video-based surface registration approaches, two alternative approaches to markerless motion capture. Some benefits include there being no need for specific technology, no need to separate or subtract the background of the image from the subject, and the ability to make pose estimates despite occlusion of the subject. Feature recognition has been implemented in *Theia3D* software (Theia Markerless Inc., Kingston, ON) which uses an array of synchronized and calibrated 2D video cameras and a deep convolutional neural network to estimate human pose in three-dimensions (3D). *Theia3D* can estimate the pose of humans with minimal restrictions on the activity performed, the clothing worn, and the collection environment, which could increase the ease of and opportunities for collecting human movement data. As these possibilities bear promising potential for clinical use, the accuracy of this approach needs to be validated against the current gold standard for healthy and impaired gait.

Therefore, the aim of this work was to determine if standard spatiotemporal gait parameter measurements obtained by using the *Theia3D* markerless motion capture system were equivalent to those from a field-accepted marker-based motion capture system during healthy treadmill walking gait.

2. Methods

2.1 Theia3D *Markerless Motion Capture*

Theia3D is a markerless motion capture software that performs 3D pose estimation using artificial intelligence, specifically deep learning. Cameras are placed to establish a 3D volume captured by their 2D views and calibrated using an object of known dimensions to determine their position and orientation in 3D space. The calibrated cameras synchronously record video data while the subject performs a task in the capture volume. Given these synchronized video data, Theia3D performs feature extraction on the 2D images to identify and locate anatomical landmarks and joint positions in 3D space. This feature detection is performed using deep convolutional neural networks that are trained on a dataset of over 500,000 images, which included images from a proprietary dataset and Microsoft COCO (Lin et al., 2015). These images, which show humans in a wide array of settings, clothing, and performing various activities, had their anatomical landmarks and joint positions manually labelled by highly trained annotators. Quality assurance was performed on all labelled points by a second individual. The visual features that correspond to these keypoints were learned by the algorithm, and once learned can be applied to any image. Given an input image and the known camera locations, the algorithm detects and locates the keypoints in 3D, then applies an articulated multi-body model from which the motion of the subject is measured.

2.2 Participants

Thirty healthy, recreationally active individuals (15 male/15 female, mean (SD) age: 23.0 (3.5) years, height: 1.76 (0.09) m, weight: 69.2 (11.4) kg) were convenience-recruited to participate in this study at the Human Mobility Research Laboratory in Kingston, Ontario. Participants gave written informed consent and this study was approved by the institutional ethics committee. Exclusion criteria included having suffered any lower-limb injuries in the previous 9 months, having any neuromuscular, musculoskeletal or metabolic impairments that could prevent their performance of walking, running, or jumping tasks, or currently taking medication for any neurological, cardiovascular, or metabolic disorders.

2.3 Experimental Setup

Two camera systems, consisting of seven Qualisys 3+ cameras (Qualisys AB, Gothenburg, Sweden) which recorded marker trajectories and eight Qualisys Miqus cameras which recorded 2D videos were simultaneously used to record the movement of subjects while they walked on a treadmill. These cameras were temporally synchronized by connecting them to a single instance of Qualisys Track Manager and were calibrated simultaneously resulting in one shared global reference frame. Both camera systems recorded at 85 Hz. Treadmill walking was selected to maximize the video image quality by keeping participants within the cameras' focal range. While treadmill walking has been shown to reduce the variability of gait patterns compared to over-ground walking, subject mean spatiotemporal gait parameters do not change between the two conditions (Hollman et al., 2016).

2.4 Experimental Procedure

Participants wore minimal, tightly fitting clothing typical of marker-based motion capture methods, and their personal running shoes. Retroreflective markers were affixed bilaterally on the first, fifth, and between the second and third metatarsal heads, on the calcaneus, medial and lateral malleoli, tibial tuberosity, fibular head, medial and lateral femoral epicondyles, anterior superior and posterior superior iliac spines, lateral iliac crest, suprasternal notch, C7 vertebrae, superior acromion, lateral humeral head, medial and lateral humeral epicondyles, radial and ulnar styloid processes, and the third metacarpus. Rigid clusters of retroreflective markers were affixed to the shanks and thighs, and a headband with a central anterior marker, two lateral anterior markers, and two lateral posterior markers was worn by subjects. Starting at an initial speed of 1.2 m/s, participants walked on the treadmill and provided feedback to determine their comfortable walking speed. An acclimatization period of two minutes was used to allow subjects to become comfortable with the treadmill. This acclimatization period is shorter than is recommended for treadmill gait studies (Meyer et al., 2019), however, since the purpose of this study was simply to compare the measurements of the two systems, the data did not need to reflect the subjects' steady-state gait. Following the acclimatization period, ten consecutive four-second trials were collected to ensure that at least ten separate gait cycles were recorded.

2.5 Data Analysis

Marker-based motion capture data were tracked in Qualisys Track Manager and the 2D video data for markerless motion capture were processed in *Theia3D* to obtain 3D pose estimates of each body segment. The tracked marker data and the markerless 3D pose estimates, which were exported as 4x4 pose matrices, were both analyzed further using Visual3D.

In Visual3D, two skeletal models (one for marker-based and one for markerless) with homologous segments were defined from a static posture such that their segment local coordinate systems were identical in this static posture. These two models used independent tracking data; one tracked the 3D marker trajectories (marker-based), while the other tracked the 4x4 pose matrices (markerless). These models were generated for every participant and applied to all trials collected from the respective participant.

Independent, kinematically-defined gait events were generated for the marker-based and markerless models using the method described by Zeni *et. al.* (Zeni et al., 2008). This method detects heel-strike and toe-off events using kinematic data of the metatarsal head and heel markers and was used to demonstrate that force-based gait events are not required to measure spatiotemporal gait parameters using either system. This would give the markerless system further independence and support its use in measuring spatiotemporal gait parameters in non-laboratory settings. In order to determine these events using the markerless motion capture system, virtual markers were added to the markerless model at the same positions as the metatarsal head and heel markers in the static posture, but which tracked the motion of the markerless model's feet. If this method were to be used without the presence of markers, the landmarks identified by the markerless system could be used to generate the virtual markers instead. The independent gait events were used to measure the time- and distance-based spatiotemporal gait parameters of each participant from both motion capture systems separately. The gait parameters were measured for all strides within the ten four-second trials and a mean of both sides of the body was obtained for each subject. The parameters compared in this work were gait speed, cadence, step time, stance time, swing time, double-limb support time, step length, stride length, and stride width, and are described in further details Table 1. Parameters were computed in Visual3D and exported to MATLAB (MathWorks, Natick, MA) for further analysis.

Table 1: Descriptions of the included spatiotemporal gait parameters.

Gait Parameter	Description
Gait Speed	Distance covered per second, calculated as the measured stride length divided by the measured stride time, reported in meters per second [m/s].
Cadence	Rate of leg turnover, calculated as 60 seconds divided by the measured step time, reported in steps per minute [steps/min].
Step Time	Time elapsed between heel-strike of the contralateral foot and the successive heel-strike of the ipsilateral foot, reported in seconds [s].
Stance Time	Time elapsed between heel-strike of the ipsilateral foot and the successive toe-off of the same foot, reported in seconds [s].
Swing Time	Time elapsed between toe-off of the ipsilateral foot and the successive heel-strike of the same foot, reported in seconds [s].
Double-Limb Support Time	Time elapsed while both feet are in contact with the ground and taken as the sum of the two instances of double-limb support during one gait cycle, reported in seconds [s].
Step Length	Distance from the position of the proximal contralateral foot (ankle joint) at the previous contralateral heel-strike to the position of the proximal ipsilateral foot (ankle joint) at the ipsilateral heel-strike taken in the direction of progression, reported in centimeters [cm].
Stride Length	Distance from the position of the proximal ipsilateral foot (ankle joint) at ipsilateral heel-strike to the position of the proximal ipsilateral foot (ankle joint) at the successive ipsilateral heel-strike taken in the direction of progression, reported in centimeters [cm].
Stride Width	Perpendicular distance between the position of the proximal contralateral foot (ankle joint) at contralateral heel-strike to the vector between positions of the proximal ipsilateral foot (ankle joint) at successive ipsilateral heel-strikes, reported in centimeters [cm].

2.6 Statistical Analysis

Means and standard deviations for each gait parameter were calculated for each subject and across all subjects. Bland-Altman methods were used to compare the measurements taken by both systems on each subject by plotting the difference between the two measurements made on each subject against the average of the two measurements, providing insight into the bias and variability in the differences between the systems (Bland and Altman, 1986). Limits of agreement (LoA) were included to show the range of differences between measurements that could be expected from the two systems, and 95% confidence intervals were used to show the possible range over which the LoA could have been found (Carkeet, 2015). Pearson's correlation coefficient (r) was calculated to assess the correlation between the markerless and marker-based systems and paired-samples *t*-tests were used to detect significant differences between the sample means. Intraclass correlation coefficients (ICC) of the form

(C-1) and (A-1) were calculated to assess consistency between measurement systems and agreement within subjects, respectively (McGraw and Wong, 1996).

3. Results

The independent kinematic gait events determined from the marker-based and markerless models were found to have high agreement across all subjects, with greater than 80% of all events detected within two frames of each other (time difference <0.024 seconds) and only 3% of events detected more than four frames apart (0.047 seconds). The distributions of the differences between the gait events obtained from the marker-based and markerless models are shown in Figure 1.

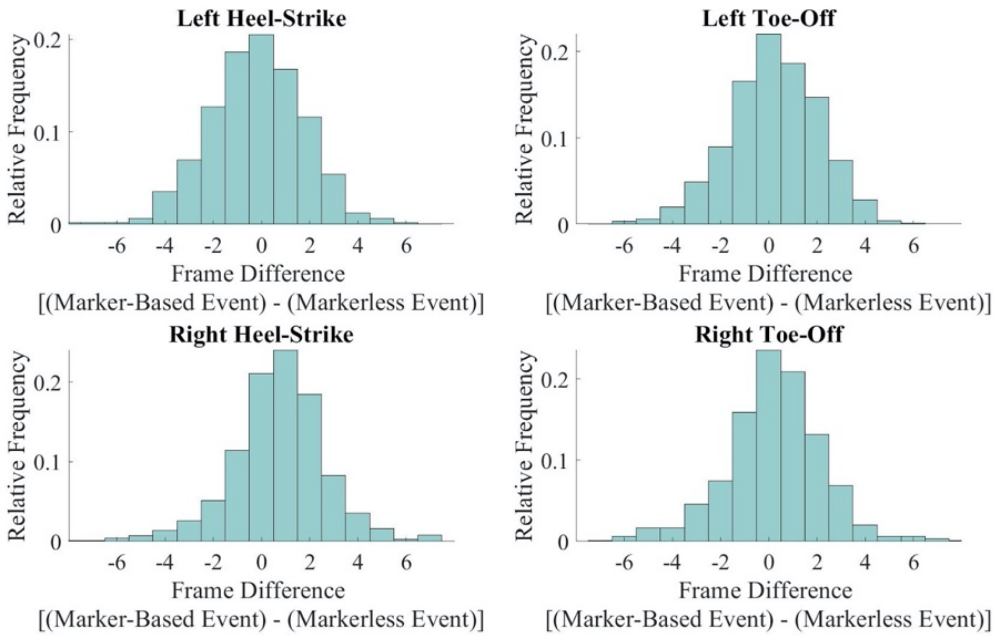

Figure 1: Relative frequency distributions of the difference between independent kinematic gait events detected based on the marker-based and markerless models, where the difference is calculated as (marker-based event frame number) - (markerless event frame number).

Means and standard deviations across all 30 subjects for the nine spatiotemporal gait parameters included were found to be nearly identical when measured by the marker-based and markerless motion capture systems (Table 2, Figures 2-5). Mean gait speed was 1.41 m/s for both the marker-based and markerless systems, compared to 1.40 m/s calculated using the actual treadmill belt speed. The sample means measured by both systems were identical for cadence, step time, stance time, swing time, and stride length, and varied minimally for mean double-limb support time, step length, and stride width. Violin and Bland-Altman plots for gait speed, cadence, step length, and step time are included as examples in Figures 2 through 5; the remaining gait parameter figures are included in the Supplementary Material.

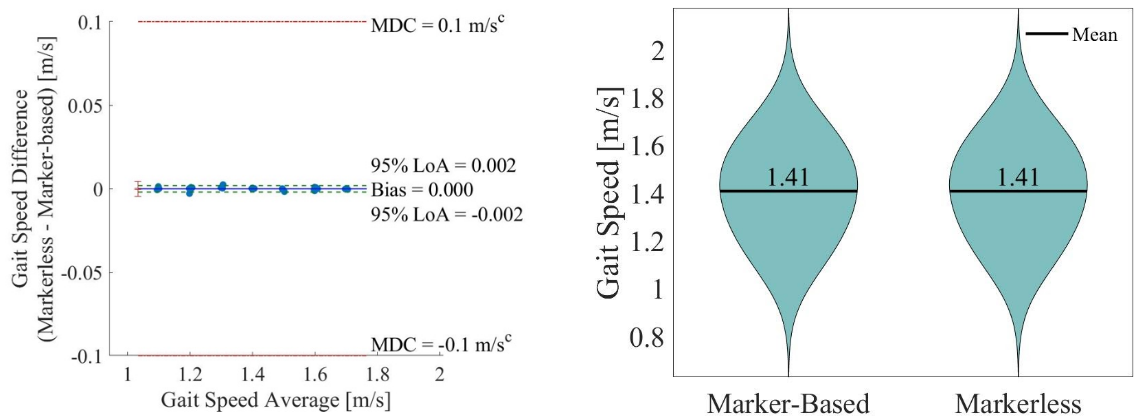

Figure 2: A) Violin plots of gait speed measurements, showing the distribution of the marker-based and markerless cadence measurements for all thirty subjects. B) Bland-Altman plot of gait speed measurements, showing the difference between the marker-based and markerless measurements against the average of the marker-based and markerless measurements. MDC values used are from (Wittwer et al., 2013).

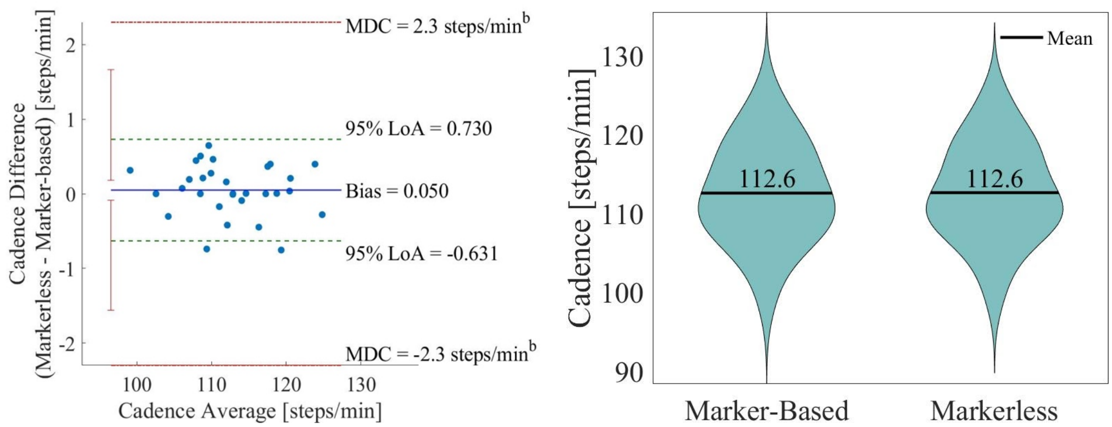

Figure 3: A) Violin plots of cadence measurements, showing the distribution of the marker-based and markerless cadence measurements for all thirty subjects. B) Bland-Altman plot of cadence measurements, showing the difference between the marker-based and markerless measurements against the average of the marker-based and markerless measurements. MDC values used are from (Wittwer et al., 2013).

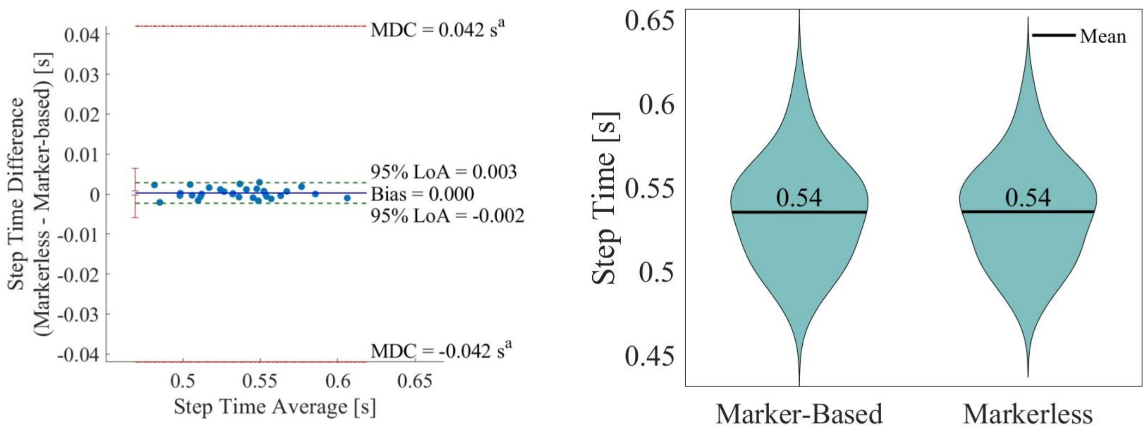

Figure 4: A) Violin plots of step length measurements, showing the distribution of the marker-based and markerless step length measurements for all thirty subjects. B) Bland-Altman plot of step length measurements, showing the difference between the marker-based and markerless measurements against the average of the marker-based and markerless measurements. MDC values used are from (Bohannon and Glenney, 2014).

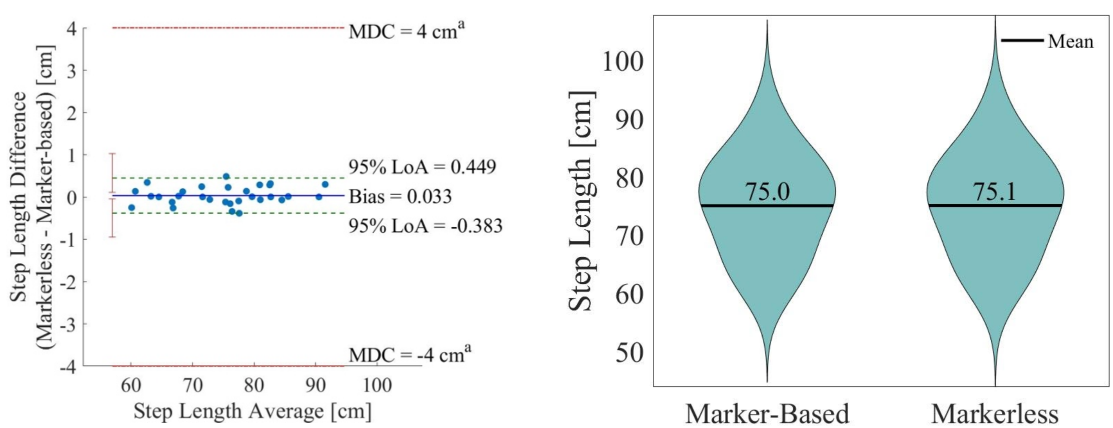

Figure 5: A) Violin plots of step time measurements, showing the distribution of the marker-based and markerless step length measurements for all thirty subjects. B) Bland-Altman plot of step time measurements, showing the difference between the marker-based and markerless measurements against the average of the marker-based and markerless measurements. MDC values used are from (Almarwani et al., 2016).

Differences in the gait parameters measured by the marker-based and markerless motion capture systems were very small and randomly distributed for all parameters as demonstrated by the Bland-Altman plots (Figures 2-5, Supplementary Materials). No relationships between the level of difference and the average measurement were visually observed, indicating there is no proportionality bias between the two systems. The biases between system measurements were very small for all gait parameters, with several parameters demonstrating no bias. The 95% limits of agreement were generally distributed equally on either side of the bias. The 95% confidence intervals on the limits of agreement were within minimal detectable change (MDC) values of 0.1 m/s for gait speed (Wittwer et al., 2013), 2.3 steps/min for cadence (Wittwer et al., 2013), 4 cm for step length (Bohannon and Glenney, 2014), 0.042 seconds for step time (Almarwani et al., 2016), 0.53 seconds for double-limb support time (Nair et al., 2012), 3.1 cm for stride length (Wittwer et al., 2013), and 8.3 cm for stride width (Wittwer et al., 2013). The positive and negative stance time confidence intervals and the positive swing time confidence interval extended slightly beyond the MDC of 0.028 seconds for stance time (Almarwani et al., 2016) and 0.044 seconds for swing time (Almarwani et al., 2016), indicating there is a possibility that those limits of agreement could have been found slightly outside of the MDC range.

The sample distributions from the marker-based and markerless motion capture systems shown in the violin plots were nearly indistinguishable for all included parameters (Figures 2-5, Supplementary Materials). The Pearson correlation coefficients indicated perfect correlation between the marker-based and markerless motion capture systems' measurements of gait speed, cadence, step time, step length, and stride length (Table 2). Stance time and stride length also demonstrated very high correlation between systems, while swing time and double-limb support time had the lowest correlation coefficients of 0.88 and 0.87, still indicating excellent agreement (ICC > 0.75) between the markerless and marker-based systems for all gait parameters (Table 2)(Cicchetti, 1995). No significant differences between the marker-based and markerless measurements of gait speed, cadence, step time, step length, stride length, and stride width were found based on paired-samples *t*-tests (Table 2).

Table 2: Comparison of spatiotemporal gait parameter measurements obtained from the marker-based and markerless motion capture systems, including means, standard deviations, Bland-Altman biases and limits of agreement, paired samples t-test p-values, Pearson's correlation coefficients (r), and intraclass correlation coefficients (ICCs) for consistency and agreement between measurement systems.

Gait Parameter	Marker-Based Mean (SD)	Markerless Mean (SD)	B-A Bias (95% LoA)	*P*-value	*r*	Consistency ICC (C-1)	Agreement ICC (A-1)
Gait Speed [m/s]	1.41 (0.19)	1.41 (0.19)	0.00 (-0.002, 0.002)	0.52	1.00	1.00	1.00
Cadence [steps/minute]	112.6 (4.1)	112.6 (5.0)	0.05 (-0.63, 0.73)	0.44	1.00	1.00	1.00
Step Time [s]	0.54 (0.02)	0.54 (0.02)	0.00 (-0.002, 0.003)	0.28	1.00	1.00	1.00
Stance Time [s]	0.70 (0.02)	0.70 (0.03)	-0.005 (-0.02, 0.01)	0.001	0.98	0.98	0.98
Swing Time [s]	0.37 (0.02)	0.37 (0.02)	0.006 (-0.01, 0.02)	0.001	0.88	0.88	0.84
Double-Limb Support Time [s]	0.33 (0.04)	0.32 (0.04)	-0.01 (-0.05, 0.02)	0.003	0.87	0.87	0.84
Step Length [cm]	75.0 (3.1)	75.1 (3.6)	0.033 (-0.38, 0.45)	0.40	1.00	1.00	1.00

Stride Length [cm]	150.1 (3.6)	150.1 (3.8)	0.02 (-0.75, 0.79)	0.77	1.00	1.00	1.00
Stride Width [cm]	14.1 (1.4)	14.1 (1.5)	0.2 (-1.2, 1.2)	0.86	0.96	0.96	0.96

4. Discussion

Spatiotemporal parameters are simple measures that effectively characterize gait patterns, allowing overall health status to be monitored and clinically meaningful changes to be detected (Givon et al., 2009; Hollman et al., 2011). For this reason, researchers and clinicians have sought to incorporate them into clinical practice. The aim of this work was to determine if spatiotemporal gait parameters for healthy gait measured using a markerless motion capture system were equivalent to those from the current gold standard marker-based motion capture system. If demonstrated with healthy gait and subsequently with impaired gait, this system could increase the clinical use and impact of spatiotemporal gait measurements by allowing these data to be collected without the placement of markers or sensors, and in more environments. The findings presented here showed that spatiotemporal gait parameters from both systems demonstrated excellent agreement for healthy gait.

Marker-based motion capture is a widely accepted technology that can accurately measure spatiotemporal gait parameters; however, these systems are expensive, require dedicated laboratory space and experienced operators, and are time intensive to use. Currently, there are a wide variety of alternative technologies also suitable for clinical applications that have demonstrated the ability to accurately and reliably measure spatiotemporal gait parameters (Braun et al., 2015; Gomez Bernal. et al., 2016; McDonough et al., 2001; Washabaugh et al., 2017). Of the alternative technologies, pressure-sensitive walkways have had perhaps the greatest success in translation to clinical use due to their simplicity, ease of use, and low cost. Despite the many benefits of these systems, they are limited to being used in straight, over-ground walking scenarios with their smooth, padded surface as the walking surface. These characteristics of the data collection conditions differ significantly from real-world walking, the majority of which is performed on inconsistent, rough surfaces with obstacles and turns to negotiate. Depth sensor-based technologies such as the Microsoft Kinect™ present another solution to collecting spatiotemporal gait data in clinical settings, and their validity has been demonstrated for several scenarios including over-ground walking (Müller et al., 2017), treadmill walking (Eltoukhy et al., 2017), and stair ambulation (Oh et al., 2018). However, depth sensors have a relatively short range of 3.5m and their ability to handle occlusions is limited, reducing the environments in which they can be used (Clark et al., 2013; Sarsfield et al., 2019).

Automated video-based markerless motion capture technology represents a simple and relatively inexpensive technology that has a high potential for gait analysis given its lack of requirements of the walking surface, environment, or path. Previous work has been done towards using markerless motion capture technology for gait analysis (Ceseracciu et al., 2014; Chakraborty et al., 2020; Clark et al., 2013; Sandau et al., 2014), but this work is the first to validate spatiotemporal gait parameter measurements from a video-based markerless motion capture system against those from a current gold standard measurement system for treadmill walking. The *Theia3D* markerless motion capture system does not require a specialized camera or walkway system and is not limited by the collection environment or walking surface, reducing some of the restrictions associated with collecting spatiotemporal gait data.

We found that the two methods were indistinguishable for a variety of spatiotemporal gait parameters between the *Theia3D* markerless motion capture software and the marker-based motion capture system. The parameters with the lowest agreement and correlation were time-based measures whose differences were on scales similar to the duration of one camera frame (0.012 seconds). Considering the use of imperfect kinematic-based gait event detection methods that allowed independent events to be used for the two systems, the scale of the differences and the parameters in which they were observed are unsurprising. Any timing differences in the detection of gait events would affect the measurement of spatiotemporal gait parameters and increase the differences in measurements between the two systems, particularly for time-based parameters. Thus, it is reasonable to assume that the differences between the markerless and marker-based spatial gait parameters would decrease when paired with force-detected gait events, however this work has demonstrated their similarity even without force-based event detection.

Despite the high level of agreement between spatiotemporal gait parameters measured using the marker-based and markerless motion capture systems, there are limitations to the present findings. The sample was composed of healthy, active, young individuals which is not representative of the typically older, injured, or pathological population for which gait analysis is often used. In addition, the data collection was performed with participants walking on a treadmill which has been shown to reduce movement pattern variability; however, mean gait parameters such as those measured here are not affected (Hollman et al., 2016)**.** Furthermore, since the markerless motion capture system is a purely image-based approach, its measurement of walking patterns is theoretically independent of the subject's health status and appearance, the collection environment, and whether they are walking over-ground or on a treadmill. However, the lack of sensitivity of the markerless system to these changes has yet to be confirmed. Subsequent work will investigate these factors and test the ability of markerless motion capture to measure spatiotemporal gait parameters in wider applications.

Based on the results presented here, the *Theia3D* markerless motion capture system is capable of accurately measuring spatiotemporal gait parameters of healthy adults during treadmill walking. This initial demonstration of its accuracy should prompt further investigation of this system's capability in measuring spatiotemporal gait parameters in impaired gait.

Conflict of Interest Statement

Scott Selbie is the President and Marcus Brown is the Director of Technology of Theia Markerless Inc. (Kingston, Ontario), the developers of *Theia3D*.

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