Journal of Biomechanics 121 (2021) 110422

Contents lists available at ScienceDirect

Journal of Biomechanics

journal homepage: www.elsevier.com/locate/jbiomech
www.JBiomech.com

Inter-session repeatability of markerless motion capture gait kinematics

Robert M. Kanko [a,*], Elise Laende [a], W. Scott Selbie [b], Kevin J. Deluzio [a]

[a] Mechanical and Materials Engineering, Queen's University, Canada
[b] Theia Markerless Inc, Kingston, Canada

ARTICLE INFO

Article history:
Accepted 29 March 2021

Keywords:
Markerless motion capture
Gait analysis
Kinematics
Repeatability
Deep learning

ABSTRACT

The clinical uptake and influence of gait analysis has been hindered by inherent limitations of marker-based motion capture systems, which have long been the standard method for the collection of gait data including kinematics. Markerless motion capture offers an alternative method for the collection of gait kinematics that presents several practical benefits over marker-based systems. This work aimed to determine the reliability of lower limb gait kinematics from video based markerless motion capture using an established experimental protocol for testing reliability. Eight healthy adult participants performed three sessions of five over-ground walking trials in their own self-selected clothing, separated by an average of 8.5 days, while eight synchronized and calibrated cameras recorded video. Three-dimensional pose estimates from the video data were used to compute lower limb joint angles. Inter-session variability, inter-trial variability, and the variability ratio were used to assess the reliability of the gait kinematics. Compared to repeatability studies based on marker-based motion capture, inter-trial variability was slightly greater than previously reported for some angles, with an average across all joint angles of 2.5°. Inter-session variability was smaller on average than all previously reported values, with an average across all joint angles of 2.8°. Variability ratios were all smaller than those previously reported with an average of 1.1, indicating that the multi-session protocol increased the total variability of joint angles by 10% of the inter-trial variability. These results indicate that gait kinematics can be reliably measured using markerless motion capture.

1. Introduction

Three-dimensional (3D) human movement analysis is a widely used tool in clinical and research biomechanics to provide comprehensive 3D representations and quantification of individuals' movement patterns, particularly gait. This tool allows comparisons to be made within and between individuals and groups on a singular or longitudinal basis, providing quantified measures of functional musculoskeletal health. These data have typically been collected using marker-based motion capture, and have the potential to help monitor disease progression, improve physical therapy, and aid in surgical decision-making (Astephen et al., 2008; Crowell and Davis, 2011; Haim et al., 2012; Smania et al., 2011; Wren et al., 2011). However, the clinical uptake and influence of gait analysis has been hindered by the practical limitations of marker-based motion capture systems due to their reliance on skin-mounted markers. These markers are placed on the surface of the subject's skin by an expert operator to represent the position of bony anatomical landmarks and are tracked in 3D by an infrared camera system. Thus, these systems require highly skilled operators to accurately place markers, a dedicated laboratory space with controlled infrared light levels, non-negligible subject preparation time for marker placement, and the sacrifice of subject or patient comfort as a result of the minimal and skin-tight clothing that must be worn while collecting data.

Markerless motion capture is a quickly evolving technology that offers an alternative to measure human movement with fewer practical limitations. These systems often use arrays of two-dimensional (2D) video cameras or depth sensors in combination with machine learning algorithms to estimate human pose during physical tasks and have been implemented to varying levels of success (Mathis et al., 2020; 2018). With recent advances in computer vision techniques and the increased availability of computational power, markerless motion capture systems have undergone significant improvements in processing time and accuracy and are now available as commercial products. *Theia3D* (Theia Markerless Inc., Kingston, ON) is one example of a machine learning-based markerless motion capture software that uses 2D video data from an array

* Corresponding author at: Human Mobility Research Laboratory, Hotel Dieu Hospital, 166 Brock St, Kingston, ON K7L 5G2, Canada.

E-mail address: r.kanko@queensu.ca (R.M. Kanko).

https://doi.org/10.1016/j.jbiomech.2021.110422
0021-9290/

of standard video cameras to perform 3D pose estimation on human subjects. Since the motion capture system does not rely on skin-based markers, subjects are not required to wear minimal and skin-tight clothing, and instead wear their own clothing. Thus, subjects may be more comfortable and able to perform physical tasks more naturally, leading to more ecological data. Furthermore, the markerless system is not limited to use in laboratory spaces, allowing data to be collected in real-world environments which cannot be replicated in the laboratory. Finally, since the markerless system is not reliant on markers that can be placed inaccurately or inconsistently, there may be less variability introduced to kinematic measurements across sessions, operators, or facilities.

The objective of this work was to determine the reliability, in the form of test–retest repeatability, of over-ground gait kinematics measured using the *Theia3D* markerless motion capture system and compare those to previously reported values for field-accepted marker-based motion capture systems. We hypothesized that the markerless motion capture system would have lower variability in joint kinematics between repeated visits compared to marker-based systems.

2. Methods

2.1. Theia3D markerless motion capture

Theia3D is a deep learning algorithm-based approach to markerless motion capture which uses deep convolutional neural networks for object recognition (humans and human segments) within 2D camera views (Mathis et al., 2020). The neural networks were trained on over 500,000 publicly available digital images of humans in the wild. A total of 51 features, including joint locations and other identifiable anatomical features in the images were manually labelled by highly trained annotators and controlled for quality by a minimum of one additional expert labeller. These training images consisted of humans in a wide array of settings, clothing, and performing various activities. Deconvolutional layers were used to produce spatial probability densities for each image, representing the likelihood that an anatomical feature is in a particular location. During training with labeled data, the weights were iteratively adjusted. For a given image, the network assigned high probabilities to labeled anatomical feature locations and low probabilities elsewhere. This learning that occurred during training enables the application of "rules" for identifying the learned features within a new image.

When using *Theia3D* for markerless motion capture, the user provides newly collected video data from multiple synchronized and calibrated video cameras that capture one or more subjects performing a physical task. The time required to collect data is largely dependent on the task of interest and can take less than five minutes for the collection of ten walking trials, for example. From the collected videos, *Theia3D* extracts the 2D positions of its learned features within all frames of all of the videos, which are then transformed to 3D space based on the computed position and orientation of the cameras. These 3D features are distributed over the body, providing at least three noncollinear features on each segment from which anatomical reference frames (local coordinate systems) are constructed. These reference frames are constructed with their origin at the segment proximal joint, their z-axis aligned with a vector from the segment distal joint to the segment proximal joint, and one off-axis feature is used to orient the coordinate system about this axis (e.g. for the thigh, the lateral knee is used). Finally, an articulated multi-body model is scaled to fit the subject-specific landmark positions in 3D space, and a multi-body optimization approach (inverse kinematic (IK)) is used to estimate the 3D pose of the subject throughout the physical task. By default, the lower body kinematic chain has six degrees-of-freedom (DOF) at the pelvis, three DOF at the hip, three DOF at the knee, and three DOF at the ankle. If so inclined, the user may opt to remove the translation constraints to allow six DOF (6DOF) at the ankle. As a result of the hierarchical nature of the IK solution which uses 6DOF to define the pelvis pose, from which the thigh, shank, and foot segment poses are each defined in turn by 3DOF joints, the greatest difference between the default IK model and the 6DOF ankle model would be seen at the ankle joint. This markerless system has been shown to be able to measure similar gait kinematics to marker-based motion capture and accurately measure spatiotemporal gait parameters (Kanko et al., 2020b; 2020a).

2.2. Participants

A convenience sample of eight healthy, recreationally active adults (2 female/6 male, mean (SD) age: 30.3 (14.1) years, height: 173.8 (9.0) cm, mass: 69.0 (12.4) kg) were recruited to participate in this multi-session study at the Human Mobility Research Laboratory (Kingston, ON). Participants gave written informed consent and this study was approved by the institutional ethics board. Exclusion criteria included having any neuromuscular or musculoskeletal impairments that could prevent their performance of walking. Participants were given no prior instruction for what clothing to wear and participated wearing the clothing in which they arrived, and either their personal running shoes or were provided with a pair of running shoes. Participants returned for a total of three sessions, which were separated by an average of 8.5 (2.0) days. A composite image of the clothing worn by participants during each session is shown in Fig. 1.

2.3. Experimental setup and data collection procedure

Eight Sony RX0 II cameras (Sony Corporation, Minato, Japan) were connected and synchronized using a Sony Camera Control Box and were arranged around a capture volume approximately 12 m long by 5 m wide by 2.5 m tall within a large indoor laboratory space. The camera positions were minimally repositioned between the collection sessions and were recalibrated before each session. Red tape lines were placed on the ground ten metres apart and were used as walkway start/finish lines. At every session, participants performed five over-ground walking trials between the red start/finish lines at their comfortable walking speed, alternating direction for each trial, while synchronized 2D video data were collected at 60 Hz.

2.4. Data analysis

Video data were processed twice using *Theia3D* software to obtain 3D pose estimates of the subjects using the default IK solution and the 6DOF ankle option. In both cases, the 3D pose estimates for each body segment were exported as 4x4 pose matrices for each frame of data for further analysis in Visual3D (C-Motion Inc., Germantown, MD). A built-in Visual3D model designed for use with *Theia3D* output data was applied to all trials, which included toe and heel landmarks based on *Theia3D* estimates of their location. These landmarks were used with the method described by Zeni *et al.* to determine heel-strike and toe-off gait events throughout each trial (Zeni et al., 2008). Lower limb joint angles were calculated using the standard Cardan rotation sequence (X-Y-Z), equivalent to the joint coordinate system (Grood and Suntay, 1983), and time-normalized to the gait cycle using the heel-strike events. Using the first left and right gait cycle that occurred within the central five-meter portion of the walkway, average time-normalized joint angles were obtained for each trial and each joint and were exported for further analysis in MATLAB (The MathWorks Inc., Natick, MA).

Fig. 1. Composite image of participants and their clothing, with three images per participant (one per session). Participants were given no specific instructions regarding the clothing they should wear during the data collections.

Repeatability of measured kinematics was assessed using the method described by Schwartz *et al.* which measures subjects' inter-session variability, inter-trial variability, and the ratio between them (Schwartz et al., 2004). The inter-trial variability captures the stride-to-stride variation that exists within each kinematic measure due to intrinsic subject variability including the effects of varying gait speed, and any systematic noise that may be present between successive trials. The inter-session variability captures any variation that arises due to the repeated sessions methodology in addition to inter-trial variation. The variability ratio gives the proportion of inter-session variability that is accounted for by the inter-trial variability. The term "variability" is used in this work in place of "error", as used by Schwartz *et al.* when describing the measure obtained from the standard deviation of the inter-trial, inter-session, and inter-operator deviations, as error implies a difference from a ground truth measurement, which in general cannot be assessed for motion capture systems.

2.5. Data comparison

The repeatability measures were compared to those in existing literature that utilized marker-based motion capture systems and the Schwartz *et al.* method (Caravaggi et al., 2011; Kaufman et al., 2016; Manca et al., 2010; Schwartz et al., 2004). Three of these studies (Caravaggi et al., 2011; Manca et al., 2010; Schwartz et al., 2004) followed the same data collection protocol, in which four examiners each collected three separate sessions for each subject, with five trials per session. These studies then reported inter-trial, inter-session, and inter-examiner variability. The data collected for the fourth study (Kaufman et al., 2016) varied slightly, where one examiner at three separate laboratories collected three separate sessions for each subject, with five trials per session and the subjects travelling between laboratories. This study then reported inter-trial, inter-session, and inter-laboratory variability. The inter-laboratory variability reported by Kaufman *et al.*, which includes inter-examiner variability, was more similar in magnitude to the inter-examiner variability from the first three studies than the inter-session variability reported by Kaufman *et al.* As such, in this study we compared our inter-session repeatability values to the inter-examiner values of the first three studies and to the inter-laboratory (also inter-examiner) values of the fourth study, since markerless motion capture data can be collected by different examiners with no inter-examiner effects.

Among the included studies, one used a modified version of the Conventional Gait Model (Kainz et al., 2017) and three used 6DOF biomechanical models (Caravaggi et al., 2011; Kaufman et al., 2016; Manca et al., 2010). Since IK techniques have been shown to reduce measurement variability (Charlton et al., 2004; Kainz et al., 2017), we performed our analyses using both the default IK model and the optional 6DOF ankle model implemented in *Theia3D*. While the differences in model constraints are limited to allowing or disallowing translation at the ankle joint, this represents the greatest difference that would be seen when comparing the IK model to a full 6DOF model due to the feet being the most distal segments from the origin of the kinematic chain, which has 6DOF at the pelvis and 3DOF at the hip, knee, and ankle joints.

3. Results

Using markerless motion capture, the time required for each session, including subject initiation and data collection, was typically between five and ten minutes. The average standard deviation in gait speed for all eight subjects across all three collection sessions was 0.054 m/s, indicating their self-selected over-ground walking speed varied little across sessions.

Repeatability measures obtained from markerless motion capture using the IK model and the 6DOF ankle model minimally differed, with the greatest differences in both the inter-trial and inter-session variability being 0.1° (Fig. 4). On average, the inter-trial variability of the IK model was 0.1° smaller than that of the 6DOF model, and the inter-session variability of both models was identical. Subsequent results mentioned will be those of the default IK model.

Session-average joint angle waveforms for one representative subject using the default IK model are presented in Fig. 2. The variability seen in each joint angle in Fig. 2 is reflected in the inter-trial variability, inter-session variability, and variability ratio measures shown for the IK model results in Fig. 3 and summarized using the averages across all subjects for each joint angle in Fig. 4.

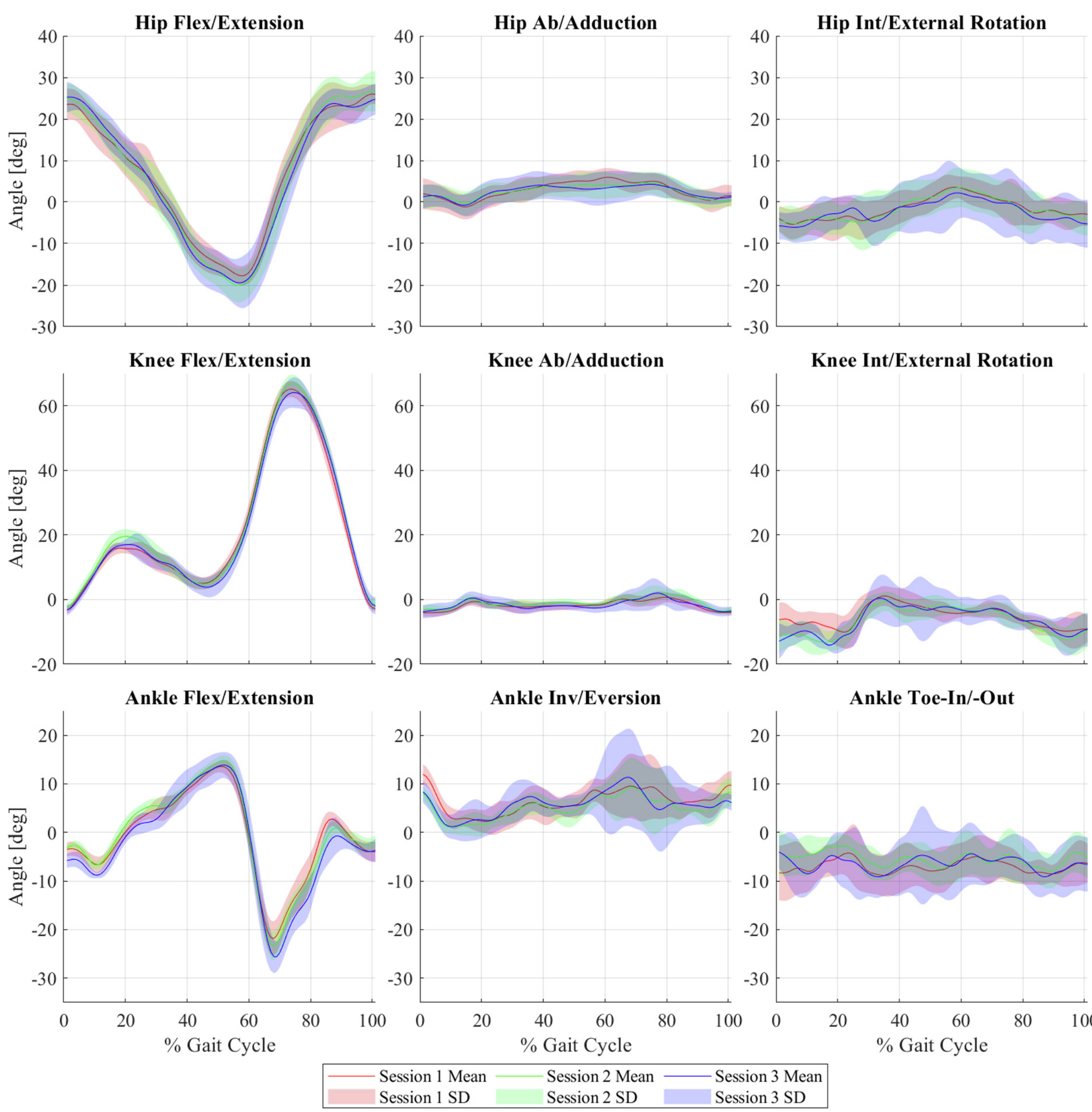

Fig. 2. Lower limb joint angle patterns measured using the *Theia3D* default IK model throughout the gait cycle, for all three sessions from one representative subject. Mean ± SD for session 1 (red), session 2 (green), and session 3 (blue) are shown. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

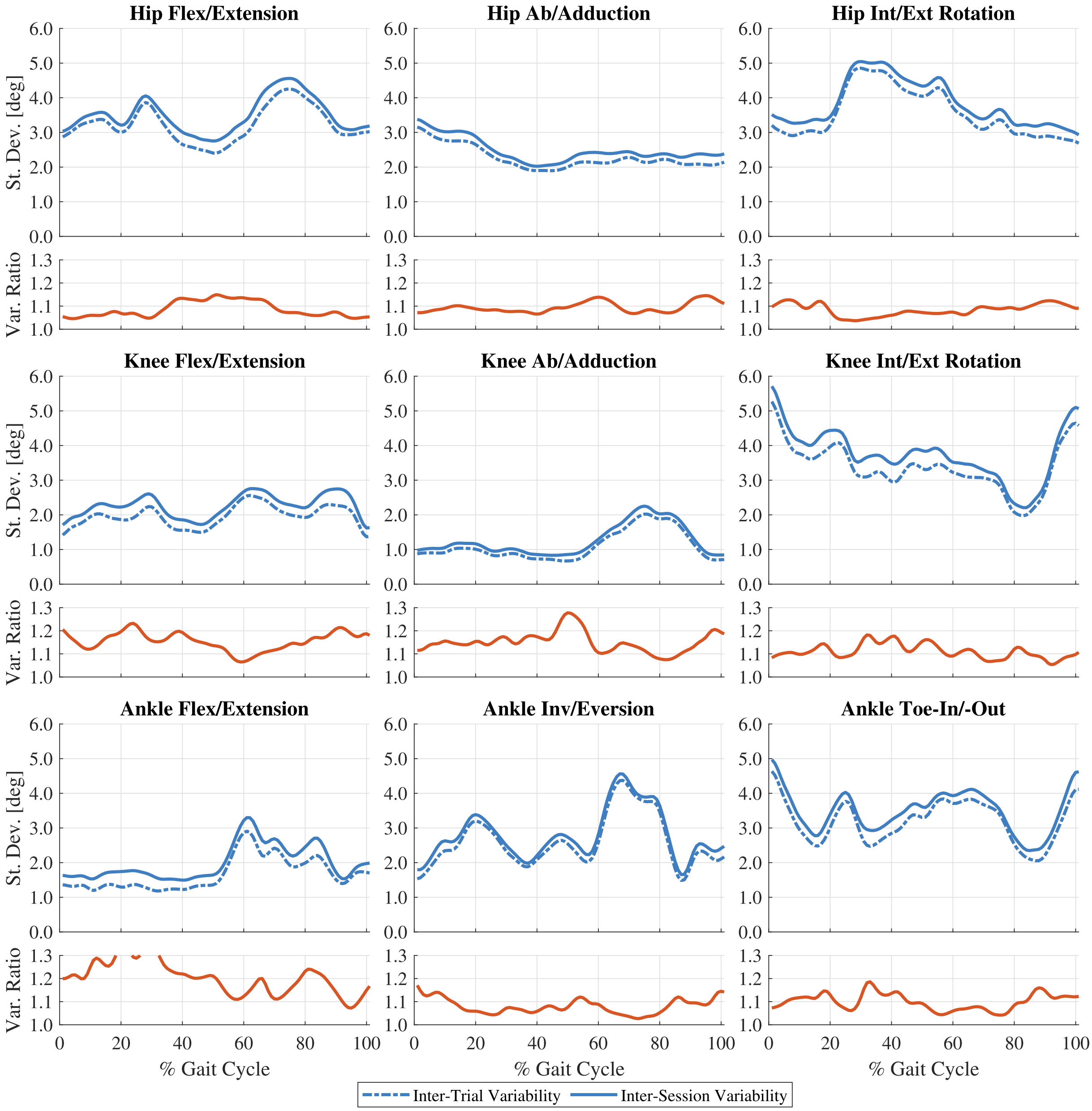

Fig. 3. Average patterns of inter-trial variability (dashed lines) and inter-session variability (solid lines) expressed as standard deviations (St. Dev.) in degrees, plotted throughout the gait cycle for the lower limb angles of all subjects from the *Theia3D* default IK model. The ratio of inter-session to inter-trial variability is included in the panel below each plot (Var. Ratio).

The inter-trial and inter-session variability estimates were found to be very similar across the gait cycle for all measures, with the inter-session variability being larger than the inter-trial variability but with little difference between them (Fig. 3). The inter-trial and inter-session variability measures were mostly below 5° except for some momentary peaks in hip internal/external rotation, knee internal/external rotation, and ankle toe-in/toe-out. The small differences between the inter-session and inter-trial variability are exhibited in the variability ratio, which is relatively constant and has an average of 1.1 or 1.2 for all measures (Fig. 3, Fig. 4C). Average inter-trial variation measures for the markerless kinematics were the largest among the compared studies for ankle inv/eversion and toe-in/-out, and all three hip joint angles. The average inter-trial variability across all joints and planes was 2.5°, the largest by a margin of 0.1° (Fig. 4A). Inter-session variability measures for the markerless kinematics were similar or slightly smaller than those from the included studies for most joint angles. Inter-session variation for ankle inv/eversion, hip flex/extension, and hip ab/adduction were the largest or tied for the largest, while ankle flex/extension, knee flex/extension, knee int/external rotation, and hip int/external rotation were the smallest or tied for the smallest among the included studies. The average inter-session variability across all joint angles was 2.8°, the smallest by a margin of 0.2° (Fig. 4B). Average variability ratios for the markerless kinematics were the smallest among the included studies for all joint angles, with an average of 1.1. This average variability ratio indicates that performing multiple separate sessions increased the total variability of subjects' measured kinematics by 10% on average.

4. Discussion

The use of markerless motion capture to measure joint kinematics removed the reliance on skin-mounted markers, thereby

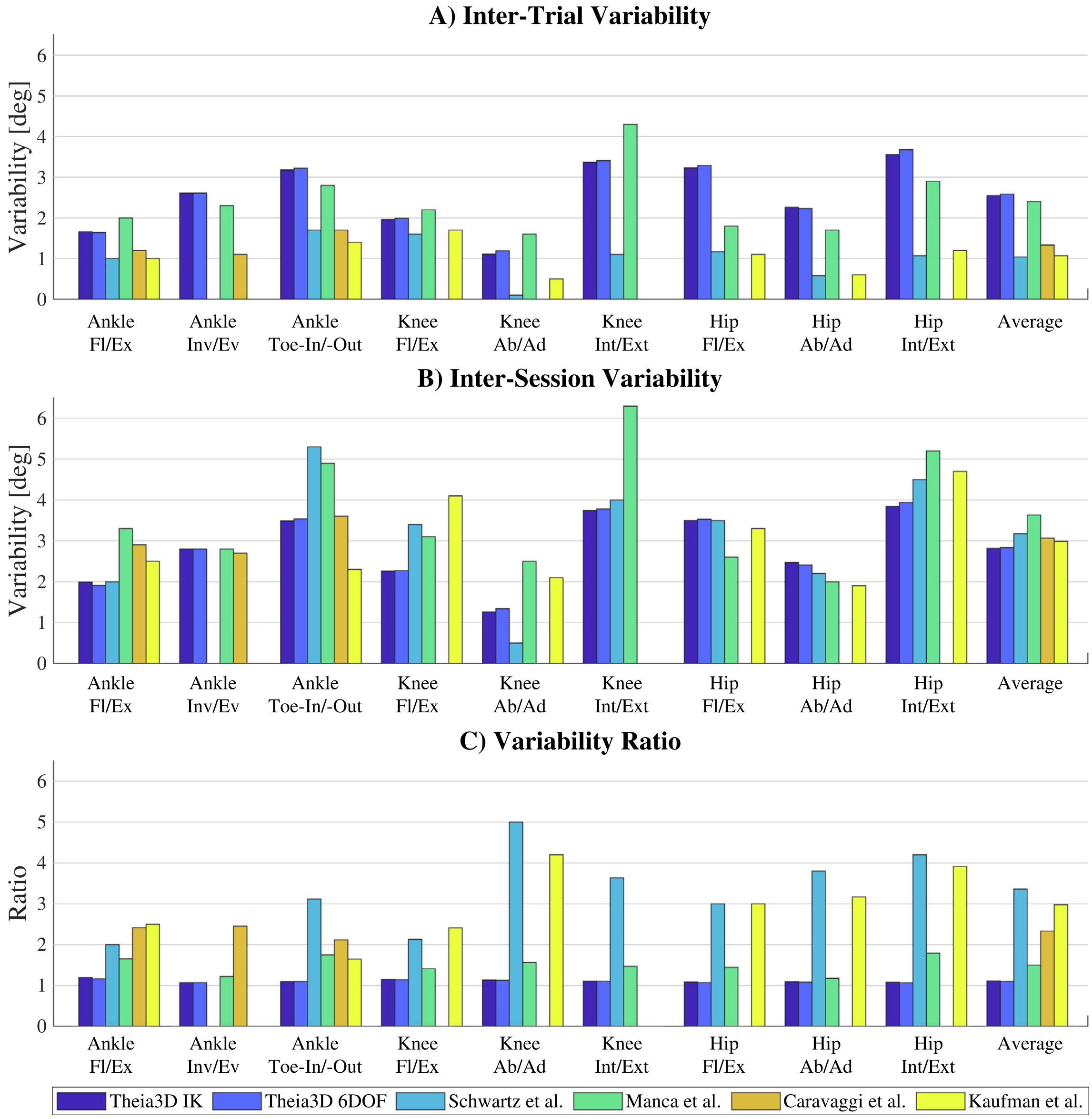

Fig. 4. (A) Average inter-trial variability, (B) average inter-session variability, and (C) average variability ratio obtained in this study using the 6DOF model and IK model, and that from studies by Schwartz *et al.* (Schwartz et al., 2004), Manca *et al.* (Manca et al., 2010), Caravaggi *et al.* (Caravaggi et al., 2011), and Kaufman *et al.* (Kaufman et al., 2016). The first three studies utilized data consisting of (four examiners) × (three sessions) × (five trials) = 60 trials/subject, and the "inter-session" values here are rather inter-examiner values. The fourth study utilized data consisting of (three laboratories) × (one examiner per laboratory) × (three sessions) × (five trials) = 45 trials/subject, and the "inter-session" values here are rather inter-laboratory values.

removing the need for an experienced examiner to identify anatomical landmarks and accurately place markers and a dedicated laboratory, reduced the total data collection time, allowed subjects to wear the clothing of their choice, and resulted in kinematic data that was reliable between sessions on separate days.

Inter-trial variability was generally larger in this study (average = 2.5°) than those previously reported (1.0°-2.4°), but by relatively small margins of 0.1°-1.5° and subjects' session mean waveforms were found to be consistent between sessions despite the greater inter-trial variability (Caravaggi et al., 2011; Kaufman et al., 2016; Manca et al., 2010; Schwartz et al., 2004). The average inter-session variability measured in this study (2.8°) was the smallest across all other studies (3.0–3.6°), indicating that measuring gait kinematics across multiple sessions using markerless motion capture introduces less variability compared to marker-based motion capture systems. Furthermore, in a systematic review of the reliability of 3D kinematic gait measurements, McGinley *et al.* stated that errors of between 2° and 5° are likely to be regarded as reasonable but may require consideration in data interpretation, which is a category that all studies in this work fall under (McGinley et al., 2009). The variability ratios measured here were smaller than those in all included studies for all examined joint angles, with the largest in the present study (1.2) being equal to the smallest reported value among the other studies (Manca et al., 2010). The small variability ratios obtained were due to the combined effect of somewhat larger inter-trial variability and somewhat smaller inter-session variability than those previously reported.

Repeatability measures obtained from the markerless kinematics were found to minimally differ when using the default IK and 6DOF ankle models, most notably for the ankle joint angles where the joint constraints differed between models. Although the difference between these models was limited to allowing translation at the ankle joint, this change would show the greatest differences that would exist between the IK model and a full 6DOF model due to the feet being the most distal segment from the origin of the kinematic chain, situated at the pelvis. Thus, any differences that would be seen by additionally implementing 6DOF knee and hip joints would be less than those found for the ankle joint. These findings indicate that the use of an IK approach to determine subject pose did not play a significant role in enabling the markerless system to measure repeatable gait kinematics, despite IK techniques having been shown in some studies to reduce the variability of kinematic measurements compared to alternative approaches (Charlton et al., 2004; Kainz et al., 2017; Mantovani and Lamontagne, 2017). We believe instead that the markerless system was able to measure repeatable gait kinematics due to the markerless tracking method itself. Furthermore, other studies have shown similar reliability between IK and other widely accepted modelling techniques (Horsak et al., 2018; Mentiplay and Clark, 2018).

Given that our subject sample was made up of healthy adults with no neurological or musculoskeletal impairments, it is more likely that the greater inter-trial variability was a result of increased measurement noise within and between successive trials as opposed to greater subject gait variability. This higher level of inter-trial noise may be a result of the markerless motion capture algorithm which uses a frame-by-frame approach to track subject movement. While this method has benefits such as not prescribing any expected movement patterns allowing it to track a wide variety of movements, it has the downside of potentially introducing greater noise to measurements.

There are some limitations to this work that warrant consideration. We did not directly compare markerless and marker-based motion capture kinematics during the same trials because we wanted to perform the markerless data collections on unrestricted attire, and we have separately performed and reported on such a comparison (Kanko et al., 2020a). Despite being provided no instruction regarding attire, the participants wore mostly dark clothing during the data collection sessions, which is thought to provide a greater challenge in the accurate identification of anatomical features for the markerless system due to reduced contrast but has not been studied in depth. We also acknowledge that in order to perform lower limb kinematics, both legs must be visible and so this approach does have some limitations in terms of clothing, excluding, for example, full-length coats or skirts. Also, while markerless motion capture does not rely on skin-mounted markers and is therefore not affected by the inconsistent placement of markers between operators, it may instead be affected by systematic anatomical landmark calibration errors that could arise through the training of its neural networks. However, the accuracy of the anatomical labels within the training dataset cannot be benchmarked as there is no ground truth available for this data. Furthermore, while the markerless motion capture system is largely unrestricted with regards to the data collection environment, the data used in this study were collected in a laboratory space. Finally, the makeup of people included in the training images has not been fully documented and may contain biases with respect to various subject appearance characteristics. Thus, further work should be done to determine the sensitivity of gait kinematics to the collection environment, subject appearance and attire, and capture volume size, since these factors may differ in collected video data compared to the training dataset.

The findings presented here demonstrate that gait kinematics measured using *Theia3D* markerless motion capture are somewhat less affected by the use of multi-session protocols as indicated by the lower inter-session variability and lower variability ratios compared to those previously reported for marker-based methods. The slight increase in inter-trial variability in combination with the decreased inter-session variability and ease of data collection is an acceptable compromise because of the potential for substantially more accessible data collections and adequately reliable gait kinematic measurements.

Declaration of Competing Interest

Scott Selbie is the CEO of Theia Markerless Inc. (Kingston, Ontario), the developers of *Theia3D*.

Acknowledgements

This work was supported by an NSERC Canadian Graduate Scholarship (Master's). We thank the members of the Human Mobility Research Laboratory for their assistance with participant recruitment, data collection, and data processing.

References

Astephen, J.L., Deluzio, K.J., Caldwell, G.E., Dunbar, M.J., 2008. Biomechanical changes at the hip, knee, and ankle joints during gait are associated with knee osteoarthritis severity. J. Orthop. Res. 26, 332–341. https://doi.org/10.1002/jor.20496.

Caravaggi, P., Benedetti, M.G., Berti, L., Leardini, A., 2011. Repeatability of a multi-segment foot protocol in adult subjects. Gait Posture 33, 133–135. https://doi.org/10.1016/j.gaitpost.2010.08.013.

Charlton, I.W., Tate, P., Smyth, P., Roren, L., 2004. Repeatability of an optimised lower body model. Gait Posture 20, 213–221. https://doi.org/10.1016/j.gaitpost.2003.09.004.

Crowell, H.P., Davis, I.S., 2011. Gait retraining to reduce lower extremity loading in runners. Clin. Biomech. 26, 78–83. https://doi.org/10.1016/j.clinbiomech.2010.09.003.

Grood, E.S., Suntay, W.J., 1983. A joint coordinate system for the clinical description of three-dimensional motions: application to the knee. J. Biomech. Eng. 105, 136–144. https://doi.org/10.1115/1.3138397.

Haim, A., Rubin, G., Rozen, N., Goryachev, Y., Wolf, A., 2012. Reduction in knee adduction moment via non-invasive biomechanical training: a longitudinal gait analysis study. J. Biomech. 45, 41–45. https://doi.org/10.1016/j.jbiomech.2011.10.017.

Horsak, B., Pobatschnig, B., Schwab, C., Baca, A., Kranzl, A., Kainz, H., 2018. Reliability of joint kinematic calculations based on direct kinematic and inverse kinematic models in obese children. Gait Posture 66, 201–207. https://doi.org/10.1016/j.gaitpost.2018.08.027.

Kainz, H., Graham, D., Edwards, J., Walsh, H.P.J., Maine, S., Boyd, R.N., Lloyd, D.G., Modenese, L., Carty, C.P., 2017. Reliability of four models for clinical gait analysis. Gait Posture 54, 325–331. https://doi.org/10.1016/j.gaitpost.2017.04.001.

Kanko, R., Laende, E., Davis, E., Selbie, W.S., Deluzio, K.J., 2020a. Concurrent assessment of gait kinematics using marker-based and markerless motion capture. bioRxiv 2020.12.10.420075. https://doi.org/10.1101/2020.12.10.420075.

Kanko, R., Strutzenberger, G., Brown, M., Selbie, S., Deluzio, K., 2020b. Assessment of spatiotemporal gait parameters using a deep learning algorithm-based markerless motion capture system. https://doi.org/10.31224/osf.io/j4rbg.

Kaufman, K., Miller, E., Kingsbury, T., Russell Esposito, E., Wolf, E., Wilken, J., Wyatt, M., 2016. Reliability of 3D gait data across multiple laboratories. Gait Posture 49, 375–381. https://doi.org/10.1016/j.gaitpost.2016.07.075.

Manca, M., Leardini, A., Cavazza, S., Ferraresi, G., Marchi, P., Zanaga, E., Benedetti, M. G., 2010. Repeatability of a new protocol for gait analysis in adult subjects. Gait Posture 32, 282–284. https://doi.org/10.1016/j.gaitpost.2010.05.011.

Mantovani, G., Lamontagne, M., 2017. How different marker sets affect joint angles in inverse kinematics framework. J. Biomech. Eng. 139. https://doi.org/10.1115/1.4034708.

Mathis, A., Mamidanna, P., Cury, K.M., Abe, T., Murthy, V.N., Mathis, M.W., Bethge, M., 2018. DeepLabCut: markerless pose estimation of user-defined body parts with deep learning. Nat. Neurosci. 21, 1281. https://doi.org/10.1038/s41593-018-0209-y.

Mathis, A., Schneider, S., Lauer, J., Mathis, M.W., 2020. A primer on motion capture with deep learning: principles, pitfalls, and perspectives. Neuron 108, 44–65. https://doi.org/10.1016/j.neuron.2020.09.017.

McGinley, J.L., Baker, R., Wolfe, R., Morris, M.E., 2009. The reliability of three-dimensional kinematic gait measurements: a systematic review. Gait Posture 29, 360–369. https://doi.org/10.1016/j.gaitpost.2008.09.003.

Mentiplay, B.F., Clark, R.A., 2018. Modified conventional gait model versus cluster tracking: test-retest reliability, agreement and impact of inverse kinematics with joint constraints on kinematic and kinetic data. Gait Posture 64, 75–83. https://doi.org/10.1016/j.gaitpost.2018.05.033.

Schwartz, M.H., Trost, J.P., Wervey, R.A., 2004. Measurement and management of errors in quantitative gait data. Gait Posture 20, 196–203. https://doi.org/10.1016/j.gaitpost.2003.09.011.

Smania, N., Bonetti, P., Gandolfi, M., Cosentino, A., Waldner, A., Hesse, S., Werner, C., Bisoffi, G., Geroin, C., Munari, D., 2011. Improved gait after repetitive locomotor training in children with cerebral palsy. Am. J. Phys. Med. Rehabil. 90, 137. https://doi.org/10.1097/PHM.0b013e318201741e.
Wren, T.A.L., Otsuka, N.Y., Bowen, R.E., Scaduto, A.A., Chan, L.S., Sheng, M., Hara, R., Kay, R.M., 2011. Influence of gait analysis on decision-making for lower extremity orthopaedic surgery: baseline data from a randomized controlled trial. Gait Posture 34, 364–369. https://doi.org/10.1016/j.gaitpost.2011.06.002.
Zeni, J.A., Richards, J.G., Higginson, J.S., 2008. Two simple methods for determining gait events during treadmill and overground walking using kinematic data. Gait Posture 27, 710–714. https://doi.org/10.1016/j.gaitpost.2007.07.007.