AI-BASED MARKERLESS SINGLE-CAMERA MOTION ANALYSIS FOR ESTIMATING KNEE AND HIP JOINT KINEMATICS DURING GAIT

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This study aimed to pilot-test a markerless motion analysis approach (i.e., SMARTGAIT) for estimating knee and hip joint kinematics in the sagittal and frontal plane during overground walking. One person (age 24 years) walked four times over an 8-meter distance. Joint kinematics were measured using SMARTGAIT (single RGB smartphone camera) and Vicon (reference system). Angle trajectories of sixteen gait cycles were used for the analysis. Agreement between SMARTGAIT and Vicon angle trajectories was greater in the sagittal plane (hip: Pearson's r=0.989; knee: r=0.990; root mean square error [RMSE] ≤2.6 deg) compared to the frontal plane (hip: r=0.789; knee: r=0.793; RMSE ≤3.9 deg). These initial results show the potential of SMARTGAIT for measuring lower extremity joint kinematics. The camera perspective may influence the accuracy of SMARTGAIT.

KEYWORDS: markerless motion analysis, gait, joint kinematics

INTRODUCTION: Gait analysis is an important tool in prevention and rehabilitation and for quantifying functional decline. Joint kinematics refers to the variables that describe the spatial movement between segments, such as joint angular motion during walking measured in degrees (deg). Most motion during normal walking occurs in the sagittal plane, providing useful information, e.g. for quantifying neurologic disease status (Balaban & Tok, 2014). In general, kinematics in clinical gait analysis is calculated in the sagittal plane. For the hip and the knee joint, joint ankles are also often reported for the frontal plane (Sandau et al. 2014).
To date, joint kinematics are typically measured via marker-based gait analysis (e.g. Vicon system). Inertial measurement units (IMU) can accurately estimate kinematics, but commercially available sensors remain expensive and time-consuming to don and doff (Uhlrich et al. 2023). To enhance the feasibility of measurement, especially in clinical environments, markerless gait analysis using low-cost equipment like RGB cameras (e.g., embedded into Smartphones) proves more practical. Recently, Horsak et al. (2023) validated a markerless motion capture system (OpenCap) utilizing two smartphone cameras and reported RMSE values of ≤5.7 deg for knee flexion, hip flexion, and hip abduction. The authors concluded that their approach had approximately comparable accuracy to IMU-based approaches. However, errors were still above the clinically desirable thresholds of two to five deg (McGinley et al. 2009). This paper introduces a novel approach (i.e., SMARTGAIT) utilizing cutting-edge computer vision algorithms to track 3D joint coordinates of persons from a single RGB camera (Barzyk et al., 2023). The SMARTGAIT trajectory reconstruction technique is based on a multi-stage convolutional neural network estimating the 3D joint coordinates. This study aimed to gather initial validity evidence of the SMARTGAIT motion analysis for quantifying hip and knee joint angular trajectories in the sagittal and frontal plane during overground walking.

METHODS: The sample comprised one healthy adult aged 24 years (height: 174 cm; weight: 66 kg) without gait abnormality. Gait measurements were taken simultaneously using the marker-based Vicon (reference system) and the SMARTGAIT system. SMARTGAIT videos were recorded at 60 frames per second using a single smartphone (Google Pixel 6a). Four gait trials at normal pace were taken on a straight stretch of eight meters. The subject walked barefoot and always in the same direction. The Vicon cameras were located around the room on the ceiling. Regarding the SMARTGAIT system, the smartphone camera was used to capture footage from the side of the Vicon measuring area (Figure 1). A total of 16 gait cycles from four walks were used for analysis. The synchronization was performed by first determining the timestamps of the foot contacts during the first gait cycle within the measurement area for both systems, afterwards a least-squares fit was used to determine the temporal offset. Agreement between the SMARTGAIT system and Vicon system for measuring angular trajectories in the sagittal plane (i.e., hip flex./ext., knee flex./ext.) and frontal plane (i.e., hip abd./add., knee var./val.) was quantified using Pearson correlations (r), root mean square error (RMSE), relative root mean square error (RRMSE, i.e., RMSE divided by the target variable range), mean absolute error (MAE), maximum error (Max_err, i.e., average error of the maximum angle), minimum error (Min_err, i.e., average error of the minimum angle), and statistical parametric mapping (SPM). SPM is a method for hypothesis testing on statistical processes that are continuous functions in space or time. In our case, we tested for a statistically significant agreement between the time-continuous measurements of the two systems using a t-test metric with a target of $p<0.05$.

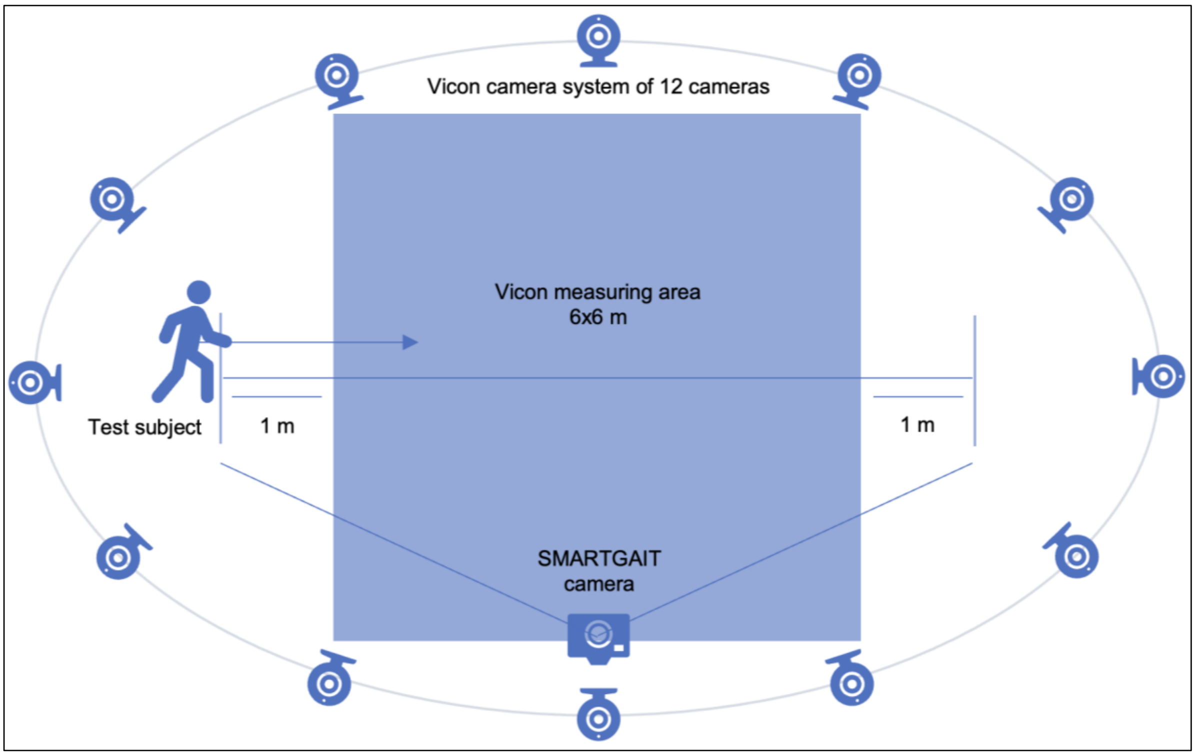

Figure 1: Laboratory setting of the validation study including position of the Vicon cameras and SMARTGAIT camera.

RESULTS: Correlations between Vicon and SMARTGAIT were greater in the sagittal plane (≥0.989) as compared to the frontal plane (≥0.789) for hip and knee angle kinematics (Table 1). The lowest RMSE (2.4 deg) and MAE (1.7 deg) were found for hip flex./ext. and the highest for knee var./val. (3.9 deg, 2.5 deg). RRMSE was substantially lower for joint kinematics measured in the sagittal plane (≤4.1%) compared to the frontal plane (≤19.1%). Max_err and Min_err ranged 0.2-2.6 deg. SPM analysis showed significant correlations between VICON and SMARTGAIT for all angle trajectories (Table 1, Figure 2A-D), except for the knee var./val. at the end of the gait cycle (Figure 2C).

Plane	**Move-ment**	**r**	**RMSE (deg)**	**RRMSE (%)**	**MAE (deg)**	**Max_ err (deg)**	**Min_ err (deg)**	**SPM mean (p-value)**	**SPM max (p-value)**
Sagittal	**Hip**	0.989	2.4	4.1	1.7	2.2	1.4	0.007	0.039

	flex./ext.								
	Knee flex./ext.	0.990	2.6	4.0	1.9	1.8	0.2	0.007	0.040
Frontal	**Hip abd./add.**	0.789	2.7	19.1	2.0	0.4	2.6	0.008	0.029
	Knee var./val.	0.793	3.9	18.9	2.5	2.3	0.8	0.020	0.085

Table 1: Agreement between the SMARTGAIT system and Vicon system quantified by Pearson correlations (r), root mean square error (RMSE), relative root mean square error (RRMSE), mean absolute error (MAE), maximum error (Max_err), minimum error (Min_err), and statistical parametric mapping (SPM).

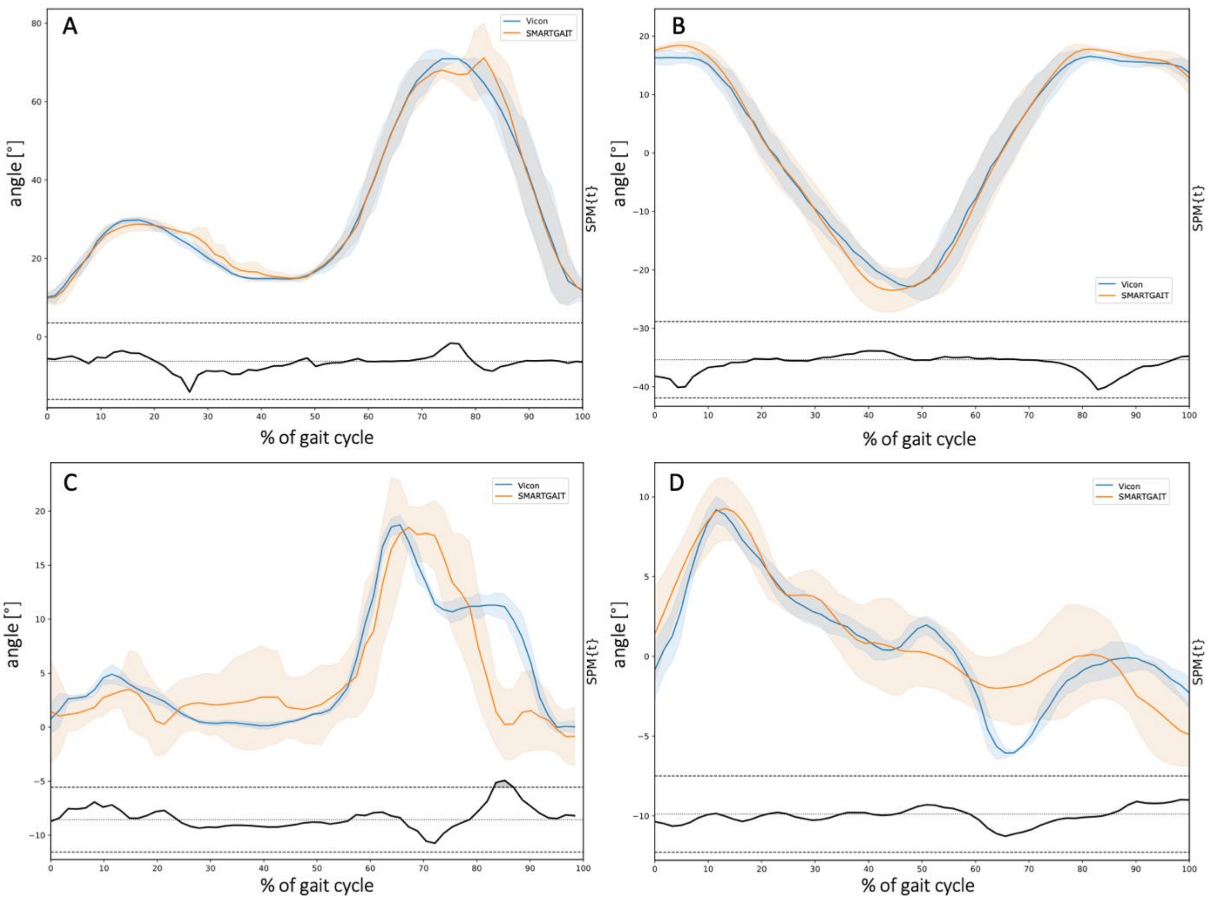

Figure 2: Sample plots of kinematics are shown for the angle trajectories in the sagittal plane of movement (A knee joint; B hip joint) and in the frontal plane of movement (C knee joint; D hip joint). Data are plotted as a gait cycle (data from 16 gait cycles). Results for Vicon are shown in blue, whereas results for SMARTGAIT are displayed in orange. The shaded areas around each graph indicate the 2-sigma confidence intervals for the respective system. Results for SPM are shown at the bottom of each graph as the corresponding t-test statistics about the critical threshold (black dashed lines; p = .05).

DISCUSSION: This pilot study compared the joint kinematics recorded concurrently using a marker-based and a markerless motion capture system. The findings demonstrate the proof-of-concept of SMARTGAIT for measuring hip and knee joint kinematics during gait. The correlations found between both systems may suggest that SMARTGAIT has the potential to measure hip and knee angle trajectories during gait cycles with an accuracy that is sufficient for clinical gait analysis, particularly in the sagittal plane. This is supported by RMSEs ≤3.9

deg. On the same note, caution is required in interpreting our findings given that the testing involved a healthy individual.

McGinley et al. (2009) suggested that in most common clinical situations errors of two deg or less are highly likely to be widely considered acceptable, as such errors are probably too small to require explicit consideration during data interpretation. Errors of between 2-5 deg are also likely to be regarded as reasonable but may require consideration in data interpretation. The errors observed in our study are within this 2-5 deg window, suggesting that SMARTGAIT may have value for clinical gait analysis, but caution is required when interpreting values. The measurement errors found in our study are particularly significant in the frontal plane, where only minor angular changes occur during walking. This results in higher RRMSE values.

In contrast to the SMARTGAIT one-camera approach, Ota et al. (2021) validated a markerless dual-camera-based gait analysis algorithm while subjects walked on a treadmill. They found smaller correlations for the hip flexion/extension (r=0.79/0.80) and knee flexion/extension (r=0.20/0.32) as compared to our study.

Horsak et al. (2023) used two smartphone cameras and OpenCap markerless gait analysis. They reported greater RMSE values for hip flexion (5.4 deg), knee flexion angle (5.7 deg), and hip abduction (3.7 deg) as compared to our study. These findings may suggest that the pose estimation algorithms embedded into SMARTGAIT result in higher correlation and lower error rates during marker-based motion capturing than previous approaches, despite using fewer cameras (i.e., one vs two cameras). One can speculate that the “end-to-end” modelling of the 3D reconstruction within the deep learning model of SMARTGAIT is more robust than the retrospective reconstruction of multiple 2D views of OpenCap. On the same note, our findings are limited to data captured on one subject (16 gait cycles) and are not directly comparable to Horsak et al’s study measuring gait in 21 subjects.

Finally, the lower RMSE and MAE values for the hip angle compared to the knee angle found in our study may suggest that the SMARTGAIT system may be more sensitive to hip kinematics than knee kinematics.

CONCLUSION: Overall, the results of this study demonstrate the potential of the SMARTGAIT system as a tool for markerless gait analysis. Further analyses are needed to demonstrate the validity of SMARTGAIT in larger samples and the transferability of the positive findings to clinical populations. Accuracy needs to be estimated for other joints relevant to gait analysis (e.g. ankle joint). The present results are an initial step towards a markerless gait analysis approach based on a single RGB camera.

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