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Comparative Evaluation of Three Markerless Motion Capture Solutions for Lower Limb Kinematics During Walking and Running

Feriel Drouiche, Junliang Cao, Théophile Cocquerez, Khalil Ben Mansour*

Laboratoire de Biomécanique et Bio-ingénierie - UMR 7338 CNRS UTC - Alliance Sorbonne Université - Centre d'Innovation, 60200 Compiègne
* Corresponding author: khalil.ben-mansour@utc.fr

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1. Introduction

In recent years, markerless motion capture solutions have emerged as a rapidly expanding alternative to traditional marker-based approaches for the biomechanical analysis of human movement. Thanks to advances in computer vision, these methods enable automatic detection of anatomical landmarks from standard video data. A common approach is to use multi-view triangulation to reconstruct the 3D positions of key points, and then perform a kinematic analysis using biomechanical models (Kwak et al., 2026). However, the reliability of these systems must be evaluated by comparison with established gold standard methods using markers.

This study compared three 3D markerless solutions. MoCap-IA is an in-house software based on RTMPose (Coco-Whole Body V1.0) for the 2D definition of 27 anatomical key points (MMPose, 2020). Pose2Sim combines 2D pose estimation (RTMPose in this study) with the Stanford LSTM model and inverse kinematics to estimate the position of 47 virtual markers compatible with OpenSim (Pagnon et al., 2021). SAM3D Body uses the Momentum Human RIG framework to directly estimate 3D human poses from a single camera, allowing the detection of 70 anatomical Key points (Nicolas et al., 2025).

2. Methods

2.1 Experimental protocol

A 24-year-old male volunteer (185cm, 74kg) took part in the experiment. He was instructed to walk at 2 and 6 km/h and run at 10km/h on a treadmill, with 15 seconds recorded for each speed. Four synchronised RGB cameras (C_i:1→4 / GoPro HERO 12B) recording at 30 Hz were mounted at approximately 2 m above ground level and 3.5 m to the treadmill (C_1 rear left, C_2 front left, C_3 front right, and C_4 rear right). Reference kinematics were obtained using a full-body model based on 55 reflective markers (Vicon Motion Systems) sampled at 120 Hz.

2.2 Data processing

Following intrinsic calibration, a chessboard was used to triangulate the four views, generating the MoCap-IA and Pose2Sim3D datasets with a 1.4 cm reprojection error. Sam3D then enables direct 3D reconstruction from each camera.

In this study, the analysis was focused on lower-limb step length and joint angles in the sagittal plane. Joint angles were computed using a geometric approach. First, the sagittal plane was defined. The X axis was established using Lhip and Rhip, while the Z axis was defined from the Hip (mid-point of Lhip and Rhip) to the Trunk (mid-point of Lshoulder-Rshoulder). The Y axis was then obtained through matrix multiplication, allowing the definition of the sagittal plane (YZ). For each joint angle, two vectors were constructed: for the Lhip angle, the first vector is Trunk-Lhip and the second is Lhip-Lknee. These vectors were then projected onto the sagittal plane, and the joint angles were calculated from the angle between the projected vectors using four-quadrant inverse tangent (atan2).

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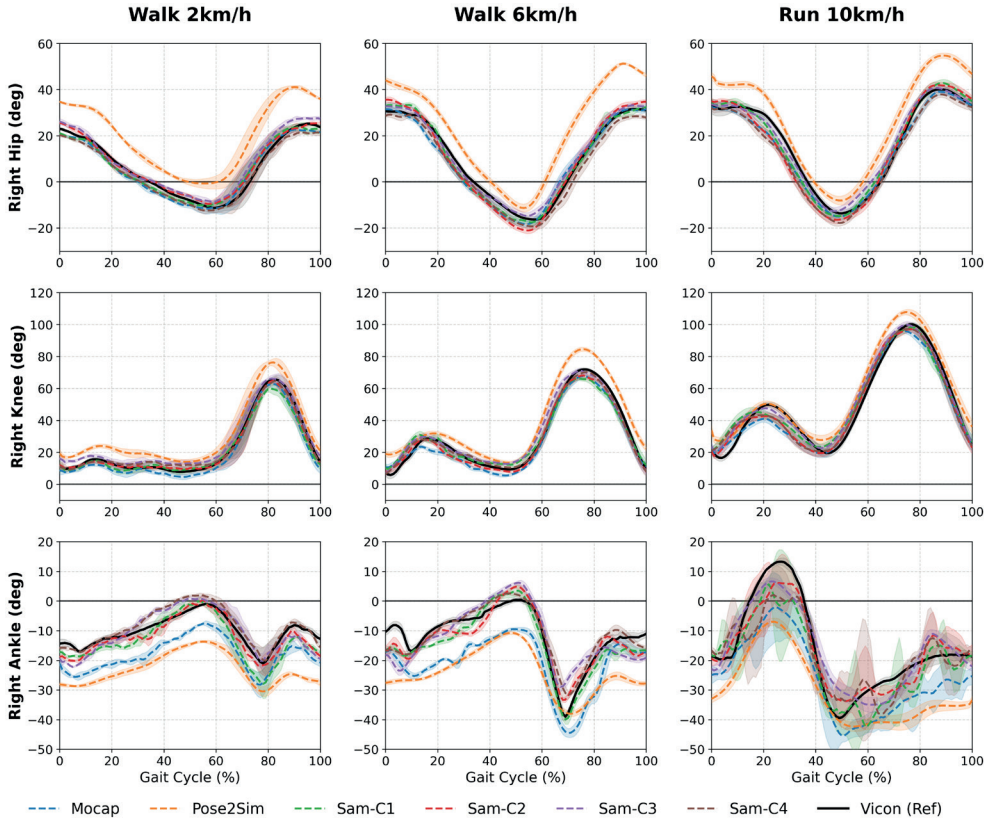

Figure 1. Right hip, knee and ankle angles during walking and running at different speeds using marker-based and markerless systems.

Table 1. RMSE±SD (°) of Lower limb joint angles between the reference system and MoCap-IA (M), Pose2Sim (P), and SAM3D ($SC_{i:1\to4}$).

Input	Walk 2Km/h	Walk 6Km/h	Run 10Km/h
r_hip	M: 2.5 ±2 P: 13.5 ±2 SC_i: 2.5 ±2; 2 ±2; 3 ±2; 2 ±1.5	M: 3.5 ±1.5 P: 14 ±1.5 SC_i: 2 ±1.5; 3.5 ±1.5; 2 ±1.5; 3.5 ±2	M: 5±1.5 P: 11.5±2 SC_i: 4 ±2; 5.5 ±2; 4 ±2; 5.5 ±2
l_hip	M: 2.5 ±2 P: 13.5 ±2 SC_i: 2 ±1; 4 ±1.5; 2 ±2; 2 ±1.5	M: 3 ±1 P: 15 ±1.5 SC_i: 3 ±1.5; 2.5 ±1; 3 ±1.5; 2 ±1.5	M: 5.5 ±2 P: 13.5 ±2 SC_i: 4 ±2; 5 ±2; 6.5 ±2; 6.5 ±2
r_knee	M: 5.5 ±3 P: 8.5 ±3 SC_i: 5 ±3; 4 ±3; 5 ±3; 5.5 ±2.5	M: 5 ±2 P: 9 ±1.5 SC_i: 5±2; 4.5 ±1.5; 4 ±2; 2.5 ±2	M: 7.5 ±2.5 P: 9±3 SC_i: 6 ±3.5; 7 ±3; 7 ±3; 5.5 ±3
l_knee	M: 5.5 ±2 P: 9 ±2.5 SC_i: 5 ±2; 6 ±2; 5.5 ±1.5; 6.5 ±2.5	M: 4.5 ±2 P: 11.5 ±2 SC_i: 4 ±2; 4 ±2; 4.5 ±2; 6.5 ±2.5	M: 8 ±2.5 P: 11.5 ±2 SC_i:6.5 ±3; 8.5 ±2.5; 9 ±3; 9.5 ±2
r_ankle	M: 8 ±1.5 P: 13±1 SC_i: 4.5 ±2; 3 ±1.5; 3.5 ±1.5;3.5±1.5	M: 10.5 ±1.5 P: 12 ±1 SC_i: 4 ±1.5; 4.5 ±1.5; 6 ±1.5; 4 ±1.5	M: 9.5 ±3 P: 13.5 ±2 SC_i: 5.5 ±2.5; 5.5 ±2.5; 6 ±2.5; 6 ±2.5
l_ankle	M: 8.5 ±1 P: 14 ±1 SC_i: 4.5±1; 5 ±1.5; 3.5 ±1.5; 3 ±1.5	M: 9 ±1 P: 12.5 ±1 SC_i: 3.5 ±1.5; 4.5 ±1; 4 ±1; 4 ±1.5	M: 5.5 ±2 P: 13.5 ±2 SC_i: 8 ±2; 6.5 ±2; 7.5 ±2; 7.5 ±2

Markerless and marker-based results were time-synchronised. The performance of the markerless methods was evaluated against a marker-based reference, using RMSE and Bland-Altman analysis.

Using an Intel i9-14900k CPU and NVIDIA RTX 4090 GPU, processing times per trial averaged 4–5 minutes for MoCap-IA and 5–7 minutes for Pose2Sim. In comparison, Sam3D required significantly more resources, taking 20-30 minutes to process a 15-second trial for a single camera.

3. Results and discussion

Figure 1 illustrates the right hip, knee, and ankle flexion-extension angles across all conditions. While the ranges and overall curve profiles are comparable to those reported by Verheul et al. (2026), Pose2Sim exhibits a consistent offset relative to the reference system. Bland–Altman analysis was used to assess agreement between each markerless system and the reference system. For all solutions, 95% of the differences fell within the limits of agreement (LoA), demonstrating good overall consistency between the methods.

As shown in Table 1, SAM3D generally outperformed MoCap-IA in joint angle estimation, achieving an error below 10° in 100% of cases and below 5° in 63.9% of cases. Performance remained consistent across all camera views, with no substantial differences observed between them.

By contrast, MoCap-IA achieved 40% of values within a 5° error range and 94.4% of values within a 10° error range. Pose2Sim exhibited larger deviations from the reference system but maintained good consistency across trial speeds. While SAM3D bypasses the need for prior calibration, its computation time is approximately three times longer. In contrast, MoCap-IA relies on a four-camera setup and a dedicated calibration process. Regarding spatial parameters, SAM3D's accuracy is constrained by the lack of subject-specific scaling, a limitation clearly reflected in the underestimation of step length across all markerless approaches. However, MoCap-IA and Pose2Sim demonstrated the highest accuracy (errors of -1 to -3 cm), outperforming SAM3D (-2 to -5 cm).

4. Conclusions

This study demonstrates a good level of agreement between markerless and marker-based motion capture systems during treadmill walking and running. Sam3D provided the most accurate joint angle estimations, despite operating with a single camera setup. All models produced consistent and reproducible results despite a systematic offset relative to the reference system. This suggests that these approaches are well-suited for longitudinal or trend-based assessments where reproducibility is critical, even if absolute accuracy is limited. Future work will aim to undertake a more comprehensive evaluation of the disparate systems and to identify their optimal domains of application.

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Conflict of Interest Statement

The authors hereby declare that there is no conflict of interest.

Contributor Roles

Feriel DROUICHE: definition of the protocol, acquisition and processing of data, acquisition and post-processing; Junliang CAO: Implementation of software, acquisition and processing of data from the markerless solution; Théophile COCQUEREZ: Acquisition and post-processing of motion capture data from a marker-based system (Vicon); Khalil BEN MANSOUR: Designing the project, securing funding, Validation, reviewing and editing.

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