# ASSESSMENT OF KINEMATIC CMJ DATA USING A DEEP LEARNING ALGORITHM-BASED MARKERLESS MOTION CAPTURE SYSTEM

**Gerda Strutzenberger[1,2], Robert Kanko[3], Scott Selbie[4], Hermann Schwameder[1] Kevin Deluzio[3]**

**Department of Sport and Exercise Science, University of Salzburg, Austria[1]**
**Sports Medical Research Group, Department of Orthopaedics, Balgrist University Hospital, University of Zurich, Switzerland[2]**
**Department of Mechanical & Materials Engineering, Queen's University, Kingston, Canada[2]**
**Theia Markerless Inc, Kingston, Canada[3]**

The purpose of this study was to compare the performance of a video-based markerless motion capture system to a conventional marker-based approach during a counter movement jump (CMJ). Twenty-three healthy participants performed CMJ while data was collected simultaneously via a marker-based (Oqus) and a 2D video-based motion capture system (Miqus, both: Qualisys). The video data was further processed to 3D-data using *Theia3D* (Theia Markerless Inc.). Excellent agreement between systems with ICCs >0.99 exists for jump height (mean average error of -0.27 cm) and sagittal ankle and knee plane angles (RMSD < 5°). The hip joint showed an average RMSD of 21° with a strong correlation of 0.80. As such the markerless system is capable of detecting jump height, sagittal ankle and knee joint angles and 3D joint positions of a CMJ to a high accuracy.

**KEYWORDS:** markerless motion capture, error assessment, joint kinematics.

**INTRODUCTION:** In performance and rehabilitation diagnostics the assessment of dynamic movements such as jumps (e.g. counter-movement jumps (CMJ), drop jumps), squats, or running can provide important information for clinicians, coaches and athletes. Parameters of interest can vary from basic performance variables such as jump height or running speed, up to detailed analysis of kinetic and kinematic variables using motion capture to assess technique and performance. The most common method for accurate measurement of three-dimensional movement is marker-based motion capture. While these systems are referred to as the current gold standard, they are equipment- and cost-intensive, require laboratory set-up, operator expertise and markers being attached to the participant (e.g. Mundermann, Corazza, & Andriacchi, 2006).

Attaching the markers to the participants however might interfere with the natural movement of participant or is sometimes not possible (e.g. during competition). Therefore, markerless approaches to measure human movement have been developed and include manual tracking of joint positions of two-dimensional (2D) video data, shape recognition, visual hull detection, and depth sensor-based hull detection. However, these approaches are time-consuming and might be operator dependent (e.g. manual tracking), and information on the validity of the latter two systems during dynamic tasks is limited (e.g. Kotsifaki, Whiteley, & Hansen, 2018; Stone et al., 2013).

Several different approaches to automated 2D video-based markerless motion capture have been developed and implemented to varying levels of success, with one such approach being feature recognition (Cronin, Rantalainen, Ahtiainen, Hynynen, & Waller, 2019). Feature recognition employs deep learning techniques such as neural networks to identify and track specific anatomical landmarks in single or successive photographic 2D images. This process allows the 3D pose of human subjects to be estimated based on the positions of the tracked landmarks throughout a movement. *Theia3D* (Theia Markerless Inc., Kingston, ON) is one such software that uses 2D video data of multiple camera views for feature recognition and further 3D pose estimation (Kanko, Laede, Strutzenberger, Brown, Selbie, dePaul, Scott, S. & Deluzio (2021). However, the performance of this system relative to a marker-based system in estimating 3D pose during dynamic functional tasks has yet to be tested. Therefore, the aim of this study was to compare the performance measures of a countermovement jump (CMJ) when measured using the markerless and marker-based motion capture systems.

**METHODS:** Twenty-three recreationally active participants (12♀, 15♂, 21±2 yrs, 1.76 ± 0.09 m 70.6 ± 11.1 kg) performed a test battery consisting of gait, CMJ, single- and double-legged DJ, squats, and jogging. This paper will focus on the CMJ. Participants performed three maximal effort CMJ on a force plate (AMTI Inc., Watertown, MA), while motion capture data were collected synchronously using two camera systems, both operating at 85 Hz and an eight-camera 2D video-based system (Miqus, Qualisys AB, Gothenburg, Sweden).
Marker-based system: The trajectories of the retroreflective markers placed on relevant anatomical landmarks of the subjects' body were tracked using a seven-camera marker-based system (Qualisys 3+, Qualisys AB, Gothenburg, Sweden). Markers were labelled in Qualisys Track Manager and exported for further analysis in *Visual3D* (C-Motion Inc., Germantown, MD). Markers were filterd using a lowpass Butterworthtfilter of 10Hz
Marker-less system: The 2D video data was collected using eight-camera 2D video-based system (Miqus, Qualisys AB, Gothenburg, Sweden) and further was processed by *Theia3D* (v2020.6.0.1106, Theia Markerless, Inc., Kingston, Ontario), a software that uses deep convolutional neural networks to perform feature recognition on 2D photographic images in order to identify anatomical landmarks and estimate human pose in 3D. The neural networks are trained on a dataset of over 500,000 images sourced from a proprietary dataset and the Microsoft COCO dataset (Lin et al., 2014), and include images of humans performing various activities in a wide variety of settings and clothing. The 3D pose estimates of each body segment were exported as 4x4 pose matrices (providing the position and orientation of a segment) from *Theia3D* for further analysis in *Visual3D*.
Comparison: In *Visual3D*, two skeletal models with identically-defined body segments and inverse kinematic constraints (knee 2 DoF: extension/flexion, varus/valgus) were created which independently tracked human motion using either the labelled marker trajectories (marker-based system) or the 4x4 body segment pose matrices (markerless system). These models were applied to all CMJ trials from all participants, for further analysis the CMJ trial with the highest jump was taken for further analysis. The jump phase was time normalized from start CMJ (first downwards movement of the centre of mass) to take-off (force > 20N) Additionally the timepoint of the deepest counter movement position was defined (minimum height of right hip joint centre).
<u>Parameters:</u> The jump height was calculated as the difference in the vertical position of the marker-based hip joint centre between standing and its maximum vertical position during the jump. Bland-Altman plots were used to compare jump height and knee flexion angle of the right and left limb at the deepest counter movement position, from both systems. The difference between the ankle, knee and hip joint position estimates from both systems was measured using the root-mean-square of the 3D distance (RMSD) across the jump phase. The mean RMSD was further calculated across all subjects. The differences between the lower limb joint 3D position and flexion angles measured by the two systems were compared using the root-mean-square of the difference (RMSD) and the intraclass correlation coefficient ($ICC_{A-1}$) throughout the duration of each jump. Right ankle, knee and hip flexion angles, and the distance between the respective joint centre positions during the jump phase were compared between the systems using SPM

**RESULTS:** The jump heights measured independently by the marker-based and markerless motion capture systems were found to have a very high level of agreement, with a mean average error of -0.27(±0.58) cm and an ICC of 0.997 (Figure 1A). The differences and correlations in the ankle, knee, and hip flexion angles between the systems throughout the jump task and across all subjects are summarized using the RMSD and $ICC_{A-1}$ (Table 1).

Time series of the sagittal ankle, knee and hip flexion angles show between the two systems similar angle curves over large parts of the counter movement phase. The very high ICC

agreement exists with an ICC of 0.97 in the ankle angle. Over the entire jump phase, a RMSD of 4.96° exists, with significantly less plantarflexion during the take-off phase for the markerless analysis as demonstrated by the SPM. Additionally, a narrower bandwidth of the sagittal ankle flexion data can be observed in the markerless data. The time series of the knee joint angle show a very high agreement with an ICC of 0.99, with significant differences over large parts of the entire jump with RMSD of 4.44°. The hip joint angles show an ICC agreement of 0.80. The SPM shows significant differences between the markerbased and markerless calculation with an offset of 20.5° (RMSD) indicated by the RMSD (Figure 1, Table 1).
The knee flexion angles measured by both systems at the deepest counter movement position were found to differ by less than 2° (± 2.0°) on average, as indicated by the bias of -1.53° (Figure 1B).

**Table 1: Mean 3D joint position estimate RMSD during jumping task across all 27 subjects.**

| | 3D Joint Position RMSD [cm, mean (std)] | Joint Flexion Angle RMSD [deg, mean (std)] | Joint Flexion Angle $ICC_{A-1}$ |
|---|---|---|---|
| Ankle | 2.8 (0.5) | 4.96 (1.85) | 0.97 |
| Knee | 2.0 (0.5) | 4.44 (1.20) | 0.99 |
| Hip | 3.0 (0.8) | 20.60 (5.22) | 0.80 |

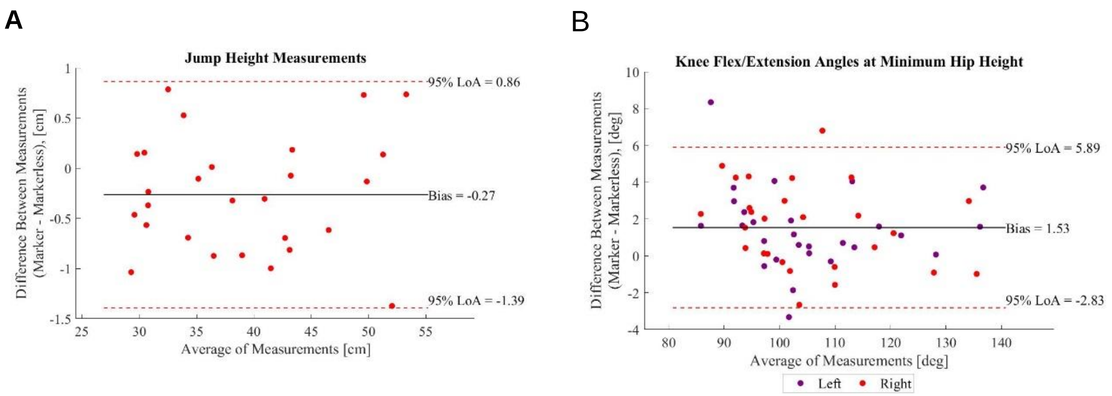


**Figure 1: System differences via Bland-Altman plots for (A) jump height, and (B) knee flexion angle at deepest squat position, measured by both motion capture systems.**

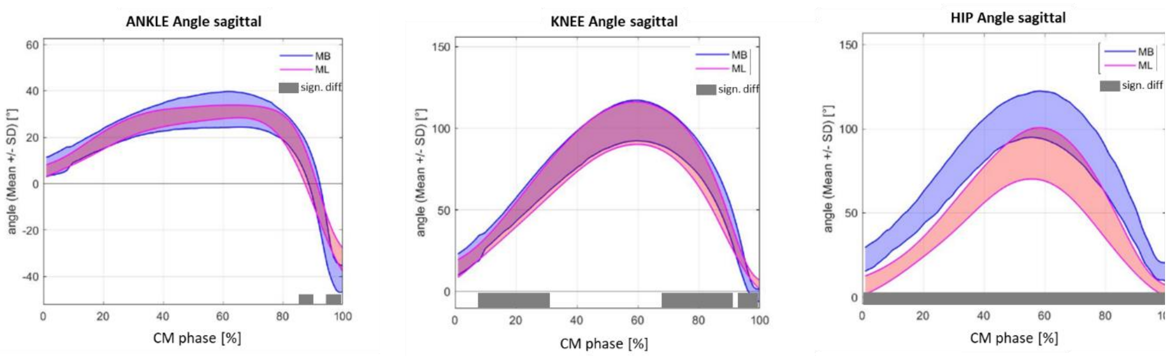


**Figure 2: Shade plot (Mean±SD) of time series of the sagittal ankle knee and hip angle of the right foot, calculated with markerbased (MB) and markerlss (ML) approach. Grey bars indicate a significant difference between the systems.**

**DISCUSSION:** The CMJ places high demands on the algorithm of the convolutional neural network, as 1) in the position where the jump height is calculated the person is in an almost fully extended position, which increases the difficulty for the algorithm to detect the features needed for foot, shank and thigh segments identification and 2) the counter movement itself, where occlusions of especially the hip occur due to the forward lean of the trunk and crouching. Therefore the aim of this paper was to compare the ability of a markerless system using feature recognition to the conventional marker-based system for this task. Comparison to the reliability of similar measures from other markerless systems is difficult due to the novelty of the approach, the limited amount of studies using a dynamic jump task and the evaluation of different parameters in other studies. From the field of depth-sensors Kotsifaki et al. (2018) reported ICC values above 0.80 for the sagittal shin and thigh segment angles, 0.38 for the ankle, with a bias of 6.9° [limits of agreement -3.3 – 17.1] for the hip flexion and -2.6° [limits of agreement -9.2-4.4] for knee flexion during a modified CMJ using a dual Kinetic system. Stone et al. (2013) investigated vertical drop jumps using the Kinect system and reported ICCs above 0.7 for valgus and frontal plane knee kinematics. The ICCs of this study demonstrate excellent agreement correlations (ICC >0.97) between the marker-based and markerless approach for the jump height as well as for the flexion angles of the ankle and knee averaged over the jump. The jump heights measured using the markerless system were on average 0.27 cm lower than those from the marker-based system, and the joint flexion angles were found to differ by <4.5° at the knee and <5° at the ankle over the course of the CMJ task. For the hip flexion angles an ICC of 0.80 shows better outcome than the before reported systems, however a considerable offset of 21° exist. This indicates that the tracking of the orientation of the pelvis system yet is not comparable to marker-based measurements of the pelvis movement during a CMJ and subject of further improvement. The effects including frontal plane movements are currently being examined in greater depth.

**CONCLUSION:** This study indicates that this markerless motion capture system can measure jump height, sagittal ankle and knee flexion angles, and lower limb joint positions during a dynamic CMJ with high agreement to an accepted marker-based system. The current version of this software provides flexion angles that differ by less than 5.3° at the knee and ankle. While the estimates of the hip joint center show differences of less than 3 cm, the pelvis pose estimation resulted in higher differences in the hip flexion angle, an issue that is currently not solved. These results generally seem promising for the measurement for ankle knee flexion as well as jump height identification of CMJ parameters without the need of marker placement.

**REFERENCES**

Cronin, N.J., Rantalainen, T., Ahtiainen, J.P., Hynynen, E., & Waller, B. (2019). Markerless 2D kinematic analysis of underwater running: A deep learning approach. *J Biomech, 87*, 75-82. doi: 10.1016/j.jbiomech.2019.02.021

Kanko, R., Laede, El., Strutzenberger, G., Brown, M., Selbie, S., dePaul, V., Scott, S., Deluzio, K. (2021). Assessment of spatiotemporal gait parameters using a deep learning algorithm-based markerless motion capture system, Journal of Biomechanics, 122:110414. doi: 10.1016/j.jbiomech.2021.110414

Kotsifaki, A., Whiteley, R., & Hansen, C. (2018). Dual Kinect v2 system can capture lower limb kinematics reasonably well in a clinical setting: concurrent validity of a dual camera markerless motion capture system in professional football players. *BMJ Open Sport Exerc Med, 4*(1), e000441. doi: 10.1136/bmjsem-2018-000441

Lin, T.-Y., Maire, M., Belongie, S., Bourdev, L., Girshick, J., Ross , Hays, J., et al. (2014). Microsoft COCO: Common Objects in Context. *CoRR, abs/1405.0312*.

Mundermann, L., Corazza, S., & Andriacchi, T.P. (2006). The evolution of methods for the capture of human movement leading to markerless motion capture for biomechanical applications. *J Neuroeng Rehabil, 3*, 6. doi: 10.1186/1743-0003-3-6

Stone, E.E., Butler, M., McRuer, A., Gray, A., Marks, J., & Skubic, M. (2013). Evaluation of the Microsoft Kinect for screening ACL injury. *Conf Proc IEEE Eng Med Biol Soc, 2013*, 4152-4155. doi: 10.1109/EMBC.2013.6610459

**ACKNOWLEDGEMENTS:** This work was supported by NSERC and the ISBS Developing Researcher Mobility Grant. We thank the members of the Human Mobility Research Laboratory for their assistance with participant recruitment and data collection.

CONFLICT OF INTEREST**:** Scott Selbie is the CEO of Theia Markerless Inc.