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

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The purpose of this study was to compare the performance of a 2D 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 were collected simultaneously via a marker-based (Oqus) and a 2D video-based motion capture system (Miqus, both: Qualisys AB, Gothenburg, Sweden). The 2D video data was further processed using *Theia3D* (Theia Markerless Inc.), both sets of data were analysed concurrently in *Visual3D* (C-motion, Inc). Excellent agreement between systems with ICCs >0.988 exists for Jump height (mean average error of 0.35 cm) and ankle and knee sagittal plane angles (RMS differences < 5°). The hip joint showed higher differences with an average RMSD of 16.9° but maintained a strong correlation of 0.885.

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

INTRODUCTION: In performance and rehabilitation diagnostics assessing 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 images. This process allows the pose of human subjects to be estimated based on the positions of the tracked anatomical landmarks throughout a movement. *Theia3D* (Theia Markerless Inc., Kingston, ON) is one such software that uses feature recognition to perform 3D pose estimation. 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 (13♀, 10♂, 21.1±1.9 yrs, 1.78 ± 0.09 m 71.2 ± 11.2 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) installed in a treadmill (due to setup reasons including gait &running tasks, which all were collected in the same volume), while motion capture data were collected synchronously at 85 Hz using a seven-camera marker-based system (Qualisys 3+, Qualisys AB, Gothenburg, Sweden) and an eight-camera 2D video-based system (Miqus, Qualisys AB, Gothenburg, Sweden). The trajectories of the retroreflective markers placed on relevant anatomical landmarks of the subjects' body were tracked using Qualisys Track Manager and exported for further analysis in *Visual3D* (C-Motion Inc., Germantown, MD). The 2D video data were processed by *Theia3D* (Theia Markerless, Inc., Kingston, Ontario), a software that uses deep convolutional neural networks to perform feature recognition on 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 in a wide variety of settings, clothing, and performing various activities. The 3D pose estimates of each body segment were exported as 4x4 pose matrices from *Theia3D* for further analysis in *Visual3D*. 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. The following events were detected throughout the duration of each CMJ trial: standing (first 0.5 s of trial), start (first downwards movement of the centre of mass), deepest squat (minimum height of right hip joint centre) and landing (force > 20 N). The jump height achieved during each trial 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. For each participant the CMJ trial with the highest jump was taken for further analysis. Jump height, lower limb flexion angles, and the distance between the corresponding lower limb joint centre positions were compared between the marker-based and markerless systems. Bland-Altman and violin plots were used to compare jump height measurements and knee flexion angle measurements at the deepest squat event, from both systems. The difference between the lower limb joint position estimates from both systems was measured using the root-mean-square of the 3D distance (RMSD) between the corresponding joints across the jump task (beginning of the counter movement to landing), and the mean RMSD was calculated across all subjects. The lower limb joint 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}) between the angles from the two systems throughout the duration of each jump.

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 0.35 cm and an ICC of 0.996 (Figure 1A). No relationship was visually observed between the mean of the jump height measurements and the difference in jump height measurements. The violin plot shows the sample distribution of jump heights measured by both systems, demonstrating the visually identical sample distributions and median jump heights for both systems (Figure 1A).

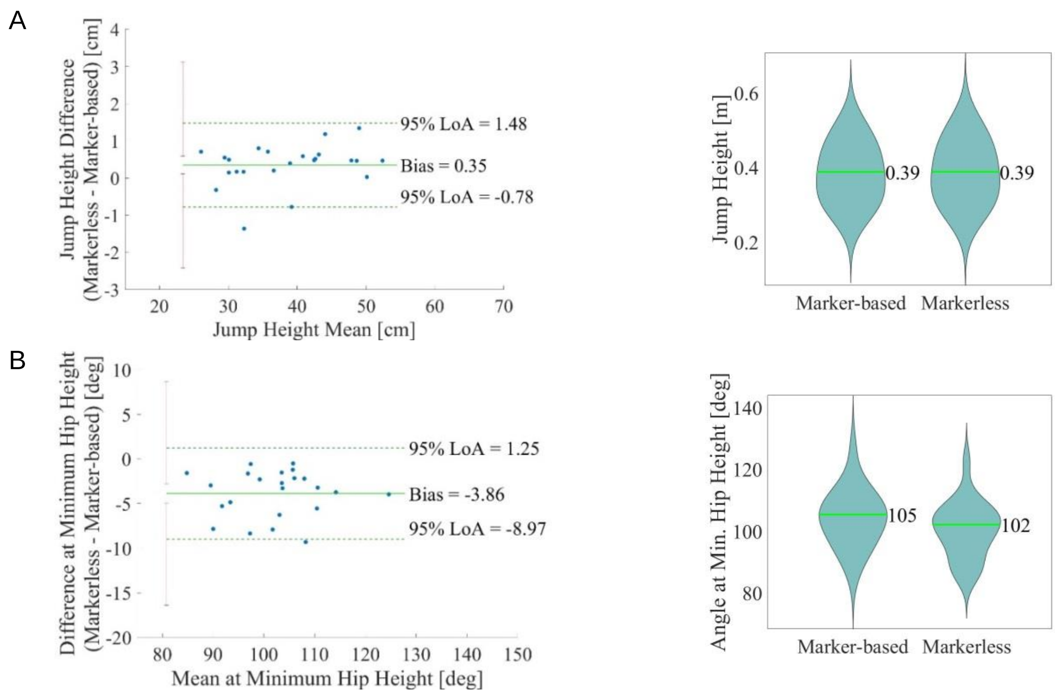

Figure 1: System differences via Bland-Altman plots and sample distributions via violin plots (green line: median) for (A) jump height, and (B) knee flexion angle at minimum hip joint height, measured by both motion capture systems.

The knee flexion angles measured by both systems at the deepest squat event were found to differ by less than 4° on average, as indicated by the bias of -3.86° (Figure 1B). The violin plots of the measured knee flexion angle at this event from both systems show that the markerless system measured a visually less normal sample distribution, with a slightly more flexed knee angle position of 3° between the sample medians. The differences in the lower limb joint position estimates between both systems were measured as the RMSD between corresponding joint centres. 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).

Table 1: Mean 3D joint position estimate RMSD during jumping task across all 23 subjects.

	3D Joint Position RMSD [cm, mean (std)]	Joint Flexion Angle	
		RMSD [deg, mean (std)]	ICC_{A-1}
Ankle	3.03 (0.01)	4.04 (1.61)	0.988
Knee	1.95 (0.01)	5.26 (1.72)	0.988
Hip	3.05 (0.01)	16.9 (4.77)	0.885

The differences in the ankle and knee flexion angles were found to be approximately 5° or lower throughout the jump task for all subjects. The hip joint flexion angle was found to have a significantly higher average difference of nearly 17°.

DISCUSSION: This is the first study to evaluate an automatic 2D video-based markerless motion capture approach using a convolutional neural network for the dynamic movement task represented by a CMJ. The CMJ places high demands on the algorithm, 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 position. 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 >0.885) between the marker-based and markerless approach for the jump height and the flexion angles of the hip, knee and ankle averaged over the jump. The jump heights measured using the markerless system were on average 0.35 cm higher than those from the marker-based system, and the joint flexion angles were found to differ by <5.3° at the knee and <4° at the ankle over the course of the CMJ task. The hip angle measurements were found to have an average RMSD of 17° yet a strong average ICC of 0.885, which possibly indicate that the hip joint angles may measure similar hip flexion patterns but have isolated differences peaks or relatively constant offsets between systems. Therefore, the current iteration of the pelvis segment definition in the markerless system was identified as currently inadequate to measure the pelvis movement during a CMJ. This issue is currently being addressed by Theia Markerless Inc., with an imminent new release that promises to improve the pelvis pose estimation. The identified joint centres differ in 3D space including all movement directions by less than 3.1 cm for the hip and ankle joints, and 2.0 cm for the knee joint. These joint position estimate differences directly affect the other kinematic measures compared in this work, yet the close agreement of those measures indicate their effect is limited. These 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, 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. The pelvis pose estimation resulted in higher differences in the hip flexion angle, an issue that is currently being addressed. These results generally seem promising for the measurement 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

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

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CONFLICT OF INTEREST: Scott Selbie is the president of Theia Markereless Inc.