COMPARISON OF MARKERLESS AND MARKER-BASED MOTION CAPTURE FOR ESTIMATING EXTERNAL MECHANICAL WORK IN TENNIS: A PILOT STUDY

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This pilot study assessed the accuracy of markerless motion capture to estimate the external mechanical work performed during tennis serves. One tennis player performed 9 serves whilst motion data were captured concurrently with a criterion marker-based and a custom markerless system (utilising HRNet and OpenPose). Centre of mass kinetic and potential energy were calculated and used to compute external mechanical work for all 3 approaches. Markerless methods yielded differences of 2-3% (HRNet) and 6-9% (OpenPose) for external work compared to the criterion measure, with the former regarded as a high level of agreement. Our markerless system, paired with HRNet, shows promise for accurately estimating external work during the tennis serve and has potential to provide players and coaches with a non-invasive tool for monitoring training 'load' in the field.

KEYWORDS: computer vision, training load, racket sport

INTRODUCTION: Tennis is a physically demanding sport involving repetitive high-intensity movements. It is often associated with high injury rates and demanding competition schedules (Reid et al., 2016). Monitoring training 'load' (a concept referring to the training stimuli experienced by an athlete) is an important component of planning training and competition schedules, which is done with the aims of optimising performance and reducing the risks of injury, illness and overtraining. There are many metrics used to quantify training 'load', but no single marker has been validated (Impellizzeri et al., 2022). This study will focus on mechanical work which has the advantages of taking into account all the movements of the entire body and accounting for the high energetic cost of accelerations and changes in direction (Peyre-Tartaruga et al., 2021), which are neglected by other common metrics. Mechanical work can be split into external (work done to accelerate and raise body centre of mass (CoM)) and internal (work done to accelerate segments in relation to CoM) components. Mechanical work is not yet used in sport as a metric for quantifying training 'load', perhaps due to the requirement for accurate measurement of full-body kinematics outside of the laboratory, in normal training and competition settings. This is now becoming a possibility due to advancements in deep learning-based pose estimation, although it's not currently known if such approaches are capable of accurately quantifying full-body 3D kinematics and subsequently quantifying mechanical work.
The development of a markerless motion capture system for automatic player tracking in tennis has the potential to provide an accessible and non-invasive tool for player 'workload' monitoring. This pilot study initially aims to quantify the external mechanical work done during a tennis serve using markerless motion analysis approaches and to compare the outputs against the criterion measure of marker-based motion capture.

METHODS: One female participant (1.76 m, 72.1 kg) provided written informed consent. The participant performed nine tennis serve motions, with a racket but no ball, in a biomechanics laboratory. Motion data were captured concurrently with a criterion 15-camera marker-based motion capture system (Oqus, Qualisys AB, Gothenburg, Sweden) and a custom 9-camera markerless motion capture system (JAI sp5000c, JAI ltd, Denmark) for the duration of the entire serve movement. The systems were spatially aligned and time-synchronised with a frame locked sampling frequency of 200 Hz to ensure that all frames were captured simultaneously. The Qualisys system was calibrated according to manufacturer's specifications and the markerless system was calibrated using observations of a binary dot matrix. For the criterion system, a full-body marker set consisted of 42 individual markers, two clusters for each lower limb and four clusters for each upper limb, allowing for bilateral thighs, shanks, feet, forefeet, upper arms, forearms and hands, and head, thorax and pelvis segments. Three additional markers allowed the racket to be tracked. Marker trajectories were labelled and gap-filled in Qualisys Track Manager. The processing of the markerless data followed the workflow presented by Needham et al. (2022). Pose estimation was performed for each camera view to find 2D sparse body keypoint locations, with two different algorithms: OpenPose ('body_25' model) (Cao et al., 2019) and HRNet (Sun et al., 2019) with the inclusion of foot and hand keypoints. For these approaches, the racket was assumed to be fixed to the hand. Detections were associated between viewpoints and reconstructed in 3D space, before a bidirectional Kalman filter was applied to the trajectories. Marker trajectories from both systems were used to drive motion of constrained rigid body models in OpenSim. First, the model was scaled to the participant using a static calibration trial and segment mass and inertia properties were assigned based on de Leva (1996). Inverse kinematics (IK) calculations were then performed for each frame of motion to find a global optimisation of pose. The resulting joint angles were filtered using a low-pass 4th order Butterworth filter, with a cut-off frequency of 6 Hz. CoM kinematics were calculated in OpenSim and exported for analysis in Python 3.6. External mechanical work was calculated in line with the methods of Pavei et al. (2017). Total mechanical (kinetic and potential) energy of the CoM was calculated at each timepoint during a trial and increments and decrements across this energy time-course were summed to respectively give the total positive and negative mechanical work. External mechanical work and CoM energies for nine serve trials were compared between the marker-based and two markerless methods. As the energies are calculated from CoM position data, additional CoM metrics (total displacement and peak resultant velocity) were also calculated. Differences were evaluated using effect sizes (ES) ± 90% confidence intervals (CI), with ES between 0.2 and 0.6, between 0.6 and 1.2 and between 1.2 and 2.0 considered to be small, moderate and large differences respectively (Hopkins et al., 2009). A root mean squared difference (RMSD) in energy was calculated between marker-based and markerless methods across the duration of the trials.

RESULTS: For calculating the external mechanical work done during a tennis serve, the HRNet method performed better than OpenPose, demonstrating 2.4% and 2.8% differences to the criterion marker-based approach for positive and negative work respectively, compared to 9.2% and 6.2% for OpenPose. The ESs associated with these values were small for HRNet and moderate for OpenPose (Table 1). However, mean RMSDs for CoM energies were higher for HRNet (Figure 1), as was the mean ES across the total energy trace (1.41 for HRNet and 1.00 for OpenPose). The markerless methods showed small to moderate ES for these, with the exception of peak velocity for OpenPose which was very large (Table 1).

Table 1: Mean (±SD) of discrete metrics across nine serve trials for marker-based and two markerless methods. Effect sizes (ES) ± 90% confidence intervals comparing each markerless to marker-based method are given.

Method	Positive External Work (J)	Negative External Work (J)	CoM Total Displacement (m)	CoM Peak Velocity ($m \cdot s^{-1}$)
Markers	311.9 ± 18.1	-338.1 ± 17.7	1.03 ± 0.05	1.71 ± 0.06
OpenPose	283.1 ± 24.3 [ES = 1.13 ± 0.20]	-317.2 ± 22.4 [ES = 0.93 ± 0.21]	1.01 ± 0.05 [ES = 0.54 ± 0.24]	1.60 ± 0.05 [ES = 2.02 ± 0.34]
HRNet	319.2 ± 28.0 [ES = 0.31 ± 0.37]	-347.4 ± 28.5 [ES = 0.40 ± 0.39]	1.08 ± 0.07 [ES = 0.76 ± 0.31]	1.65 ± 0.09 [ES = 0.65 ± 0.41]

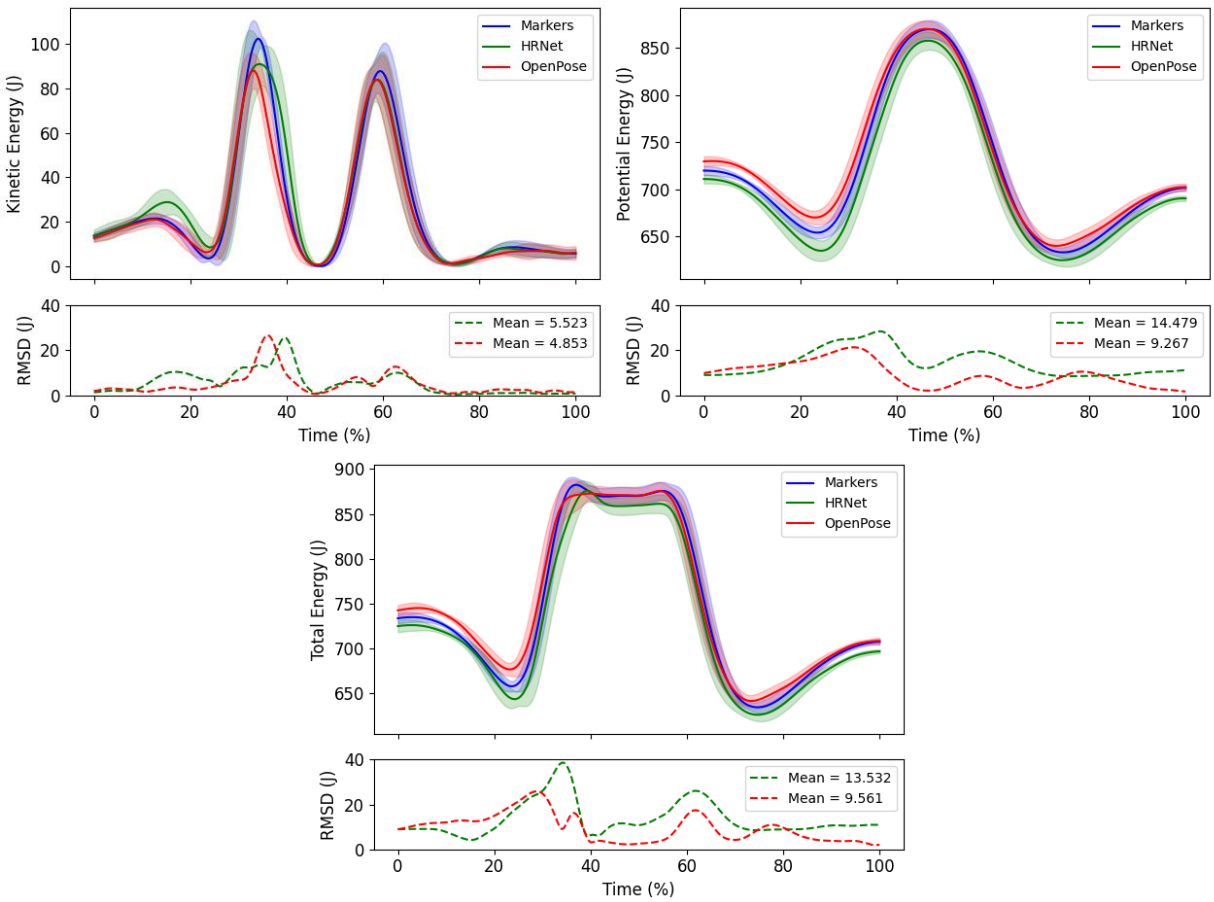

Figure 1: Upper pane – Mean (±SD) of kinetic, potential and total energy across nine serve trials for marker-based and two markerless methods. Lower pane – RMSD between marker-based and each markerless methods. Trials normalised by peaks in CoM vertical position trace.

DISCUSSION: This study aimed to compare the performance of a markerless motion capture system (utilising two different pose estimation algorithms) against a criterion marker-based motion capture system for estimating external mechanical work done during tennis serves. For HRNet, the average positive and negative external work differed from the marker-based approach by only 7.3 J and 9.3 J respectively, whereas the differences were much greater for OpenPose (Table 1). This movement lasts only a couple of seconds and so the differences would be far greater over a whole training session or match. For context, during one Grand Slam it was reported that male players hit an average of 106 serves per match (Reid et al., 2016), translating to a total positive external work of ~33,000 J, for just this one component. Whilst the error may therefore be ~1000J, we consider 2-3% differences in the external work to show a high level of agreement between HRNet and the criterion measure. Differences in external work of over 10% have previously been reported between marker-based motion capture and a 'gold-standard' force plate approach for different gaits (Pavei et al., 2017). Our differences fall well within this known uncertainty of the criterion measure.

Interestingly, the better performance of HRNet for estimating external work compared to OpenPose is not observed in the instantaneous energy traces from which the work was calculated. OpenPose demonstrates a better overall fit and lower RSMD values, with mean RMSDs of less than 10 J. Variations in the shape of the total energy trace will contribute to the larger discrepancies in work. Conversely, the shape of the HRNet energy trace is a very close match to that of the marker-based approach, but with a systematic offset which appears to stem from CoM vertical position. This causes higher RMSDs for the energy traces but does not influence the calculation of work. Therefore, as mechanical work is our primary metric, we consider HRNet to outperform OpenPose in this particular application.

The results of this initial pilot study are promising and demonstrate the potential for markerless motion capture to be used by players and coaches for estimating the external mechanical work done during tennis serves. However, more work is needed to overcome some of the current challenges faced by markerless methods. Keypoint 'jitter' is a common source of error when pose estimation is applied independently to video frames. This is observed for our data, with increased 'jitter' for OpenPose. The processing pipeline aimed to address this through the use of the Kalman filter, IK and finally the Butterworth filter, however some 'jitter' remains. Another challenge is encountered during the IK optimisation, which is relying on a sparse model consisting mostly of joint centres. This means that all segments do not have 6DoF. Joint constraints were applied to the OpenSim model and the inclusion of foot (both methods) and hand (HRNet only) keypoints helped to infer limb longitudinal rotations. Despite this, certain segments (e.g., pelvis and upper limbs) are visibly unstable after the IK step. The inclusion of additional off-axis keypoints would improve the IK results. Large open-access datasets on which many pose estimation algorithms have been trained, typically lack off-axis keypoints and also do not possess the level of anatomical accuracy required for biomechanics applications. Ultimately, the performance of markerless motion capture will be limited by these training datasets. The next step for this work is to extend this case study to incorporate a range of tennis-specific movements to better represent the demands of playing tennis. Future work should also evaluate the limitations of mechanical work as a measure of training 'load'.

CONCLUSION: Our markerless motion capture approach utilising HRNet can estimate the external mechanical work done during tennis serves with good agreement to a criterion marker-based approach. Currently this has been limited to one movement in a lab-based setting, and using a system that is not yet widely accessible. Future work will aim to validate the markerless approach for additional tennis-specific movements with a larger sample of players, and eventually progress this to a real-world environment. These initial results show promise for estimating external mechanical work in tennis, and subsequently the utilisation of this approach as a 'workload' monitoring tool to be employed by players and coaches.

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