ON-COURT MECHANICAL WORK MEASURED USING MARKERLESS MOTION CAPTURE IS ASSOCIATED WITH ACUTE FATIGUE IN TENNIS

Julie Emmerson[1,2], Laurie Needham[1,2,3], Murray Evans[1,4], Sean Williams[2] & Steffi Colyer[1,2]

Centre for the Analysis of Motion, Entertainment Research and Applications, University of Bath, UK[1]
Department for Health, University of Bath, UK[2]
Seiko Timing Systems, UK[3]
Department of Computer Science, University of Bath, UK[4]

Measurement of mechanical work with a markerless motion capture system was assessed for the application of training 'load' monitoring. Four tennis players completed an on-court fatiguing protocol interspersed with sprint tests, with relationships between reduction in sprint velocity and internal and external mechanical work done tested. Repeated measures correlations for total and external mechanical work, and external mechanical work estimated from centre of mass proxies (pelvis and mid-hip) were comparable and ranged from -0.89 to -0.86. Whilst the calculated work done varied greatly between the methods (~42% for pelvis), all showed a strong relationship with fatigue and could provide insight into a player's training 'load', despite the absolute values being inaccurate. This promising tool could be implemented for non-invasive, on-court training 'load' monitoring in the field.

KEYWORDS: computer vision, training load, racket sport

INTRODUCTION: Monitoring training 'load' (a concept referring to the training stimuli experienced by an athlete) is an important component of planning and adjusting training and competition schedules in many sports. This certainly applies for tennis, which is a physically demanding sport, characterised by repetitive high-intensity movements such as multi-directional sprints, changes of direction and explosive racket strokes. The demanding nature and the high injury rates, particularly during tournaments, emphasise the need for training 'load' monitoring in tennis (Pluim et al., 2006). Previously, we have shown that mechanical work can be accurately measured using markerless motion capture (Emmerson et al., 2023). Whilst there are many metrics used to quantify training 'load', mechanical work has the advantages of considering movements of the entire body and the high energetic cost of accelerations and changes in direction (Peyré-Tartaruga et al., 2021), which are neglected by other common metrics. Mechanical work can be split into external (W_{ext}) (work done to accelerate and raise body centre of mass (CoM)) and internal (W_{int}) (work done to accelerate segments in relation to CoM) components and requires measurement of full-body kinematics. Measuring mechanical work with markerless motion capture potentially offers a new approach to monitoring training 'load' in a way that is completely non-invasive to players, as opposed to more commonly used wearable technology (e.g. accelerometry). However, the utility of our system in the field has not yet been tested. It is also not currently known whether measurement of full-body kinematics is indeed required or if a simpler approximation could be sufficient. Using a simpler approach would reduce data processing times and allow for a more accessible system. This could lead to a video-based tool becoming available to a far wider pool of players than is reached by current 'load' monitoring technology, with the potential to be used during match-play and eventually operating in real-time.

The first aim of this study is to assess whether our custom markerless motion capture system, which has been used successfully in a controlled lab environment, is a suitable tool for monitoring training 'load' in an applied setting. This will be addressed by using the system to measure mechanical work done during a tennis-specific on-court fatiguing protocol and associating the work done with a measure of fatigue. The subsequent aim is to determine if measuring total mechanical work (W_{tot}) is necessary or if a simpler, more computationally efficient approach is sufficient for this application. The effects of neglecting the internal component of mechanical work and of using a fixed point as a proxy for CoM will be investigated.

METHODS: Four tennis players (1.77 ± 0.06 m, 75.4 ± 3.6 kg, 3 male and 1 female) from a university tennis team provided written informed consent. They completed an on-court fatiguing protocol whilst video data were captured with a custom markerless motion capture system. A cycle consisted of three sets of one serve and eight groundstrokes, alternating between forehand and backhand sides, with balls dropped into target zones (1.25 m forward from the baseline and 1 or 1.5 m in from the tramlines for males or females respectively) at a set frequency (one ball every 2 s for males and 2.5 s for females). Between sets, 20 s rest was given, which was reduced by 5 s after the fifth and tenth cycles. The third set was immediately followed by a maximum effort sprint back-and-forth along the baseline and up the tramline to the net. This cycle was repeated with 1-minute rest in-between until players reached volitional fatigue. The sprint test was also performed prior to the protocol for a baseline velocity measure. Players wore a heart rate (HR) monitor (Polar H10, Polar Electro Oy, Finland) for the duration of the protocol. Training impulse (TRIMP) was calculated from HR data using Edwards' method (Edwards, 1993). A high-definition 8-camera system (JAI sp5000c, JAI ltd, Denmark) was used to capture the third set only (including sprint) of every cycle due to excessive data saving times. The work done in each of the first two sets was assumed to be sufficiently similar to that of the captured third set. The system was calibrated using observations of a binary dot matrix and the processing of the markerless data followed the workflow presented by Needham et al. (2022). Pose estimation with HRNet (Sun et al., 2019) (trained on the COCO-WholeBody dataset) was performed for each camera view to find 2D sparse body keypoint locations. Detections were associated between viewpoints and reconstructed in 3D space, before a bidirectional Kalman smoother was applied to the trajectories. Keypoint trajectories were used to drive the motion of a constrained rigid body model 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. Segment kinematics and CoM were calculated in OpenSim and exported for analysis in Python 3.10. 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 and increments and decrements across this energy time-course were summed to give the total positive and negative W_{ext} respectively. This was repeated using both the pelvis segment (after the IK step) (W_{pelvis}) and the midpoint of the hip keypoints (after the 3D reconstruction and smoothing) (W_{hips}) as proxies for CoM, to give approximations for W_{ext}. W_{int} was calculated using the same approach for the energy time-courses of each limb, which were found by taking the total kinetic (rotational and translational) energies of segments relative to CoM and summing within limbs. The work done by each limb were summed to give W_{int}. The reduction in the maximum forward CoM velocity reached during each sprint to the net was taken as a measure of fatigue. This maximum velocity (as a percentage of the player's overall maximum) was correlated (Pearson's coefficient) against variations of the mechanical work done, as well as the TRIMP, that the player had accumulated up until that point of the protocol. Repeated measures correlations, with 95% confidence intervals (CI), were calculated across the players.

RESULTS: The players completed 7.8 ± 3.0 cycles of the fatiguing protocol. Maximum CoM forward velocities in the baseline sprint test were 6.2 ± 0.3 $m \cdot s^{-1}$ with reductions of 1.2 ± 0.2 $m \cdot s^{-1}$ across the protocol. Repeated measures correlation between maximum sprint velocity of each cycle and the cumulative work done was -0.89 (95% CI: -0.94, -0.78) when considering just W_{ext} and -0.88 [-0.94, -0.77] when internal work was included, while using the pelvis segment origin and the midpoint of the hip keypoints as CoM proxies yielded values of -0.89 [-0.94, -0.78] and -0.86 [-0.93, -0.72] respectively (Figure 1). For TRIMP, the correlation with sprint velocity reduction was -0.86 [-0.93, -0.74]. Results for negative mechanical work were almost identical so have been omitted.

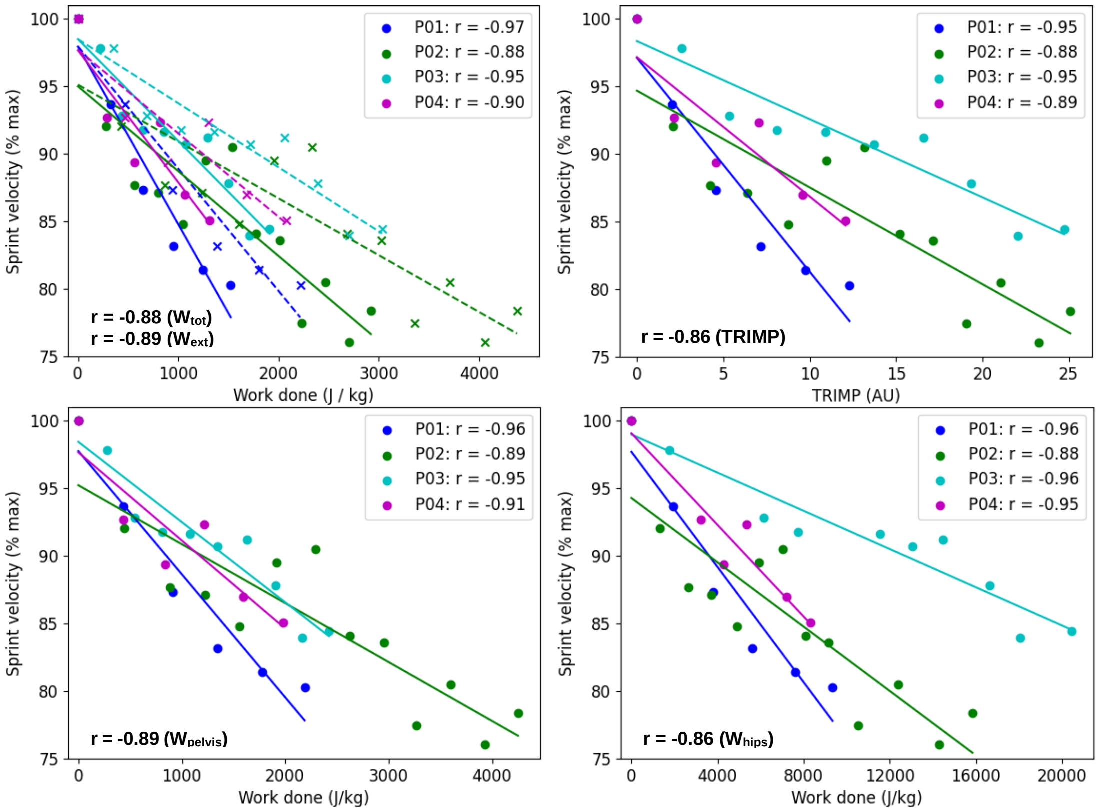

Figure 1: Maximum sprint velocity of each cycle against cumulative 'load' for each player (with Pearson's r). Repeated measures correlation in bottom left corner. Upper left – Positive W_{tot} (crosses and dashed lines) and positive W_{ext} only (circles and solid lines) (correlations the same for both). Upper right – Edwards' TRIMP. Lower left – positive W_{pelvis}. Lower right – Positive W_{hips}.

DISCUSSION: During the fatiguing protocol, the positive W_{tot} done by players showed a strong association with reductions in maximum-effort sprint velocity. This relationship is comparable to the one observed for Edwards' TRIMP, a well-established measure of internal 'load', which showed a slightly weaker correlation (Figure 1). This would suggest that mechanical work measured with our custom markerless motion capture system is an appropriate indicator of fatigue and as such could be implemented as a method for monitoring training 'load'. As a 'load' monitoring tool, this has the key advantage of being completely non-invasive to players. Calculating W_{tot} requires kinematics of all body segments and is computationally heavy in comparison to other possible metrics, such as distance covered or time in velocity zones. Therefore, we sought to determine if a simpler approach to estimating mechanical work could be sufficient. The first potential simplification was to use only W_{ext}. Full-body pose estimation is still required to accurately estimate CoM location, but energies only need to be calculated for CoM and not for every segment. In this study, W_{int} accounted for approximately a third of W_{tot} so it cannot be neglected if an accurate measurement of mechanical work is required. However, the similar correlation when using only W_{ext} suggests that this is still enough to provide an estimate of player fatigue (Figure 1) and for the application of monitoring training 'load', W_{ext} therefore appears sufficient. From a practical perspective, it is also more relatable to commonly used metrics and is more understandable to coaches and players.
If using W_{ext} only is sufficient, the next simplification was to use a fixed point as a proxy for CoM, to negate the need for the full markerless processing pipeline used in this work. The midpoint of the hip keypoints obtained from pose estimation (after 3D reconstruction and smoothing) represents a simpler point to track and could represent CoM close enough for this application. Whilst the correlation between sprint velocity and cumulative W_{hips} is still strong (r = -0.86), the W_{hips} values are an average of six times greater than W_{ext} (Figure 1). This is due to very noisy trajectories of the reconstructed hip keypoints, which highlights the importance of the IK step in the markerless pipeline and the current limitations of the 2D pose estimator. Until the accuracy of sparse point pose estimation improves, this will continue to be a challenge.

An alternative CoM proxy examined in this study was the pelvis segment origin (after IK). While this still requires the full markerless pipeline, it has been used in this work to represent a generic fixed point that could be tracked using other means. The values of W_{pelvis} also overestimate W_{ext} (although considerably more accurate than W_{hips}), with similar values to W_{tot} (Figure 1). Using a fixed point on the body is not a good approximation of CoM due to the dynamic and irregular movements performed during tennis. However, this appears to be a consistent overestimate, with the correlations observed between sprint velocity and W_{pelvis} comparable to those reported for W_{ext} and W_{tot}. This could still be considered an appropriate indicator of training 'load' with the acknowledgment that the values of work are not an accurate measurement of the work done by the CoM. This would greatly simplify the tracking process, with pose estimation no longer required. Future work should explore alternative computer vision techniques to track a fixed point on the player.
A limitation to this study is the controlled and repeated nature of the protocol, with players repeating the same drill, and hence doing approximately the same amount of work, during each cycle. The standardised protocol was necessary to handle data capture constraints of the markerless motion capture system, with long saving times making it impossible to capture the whole protocol without unfeasibly long rest periods. The compromise was to only capture the third set of each cycle, with the assumption that the work done in each of the three sets would be sufficiently similar. In order to comprehensively determine if the simplifications of neglecting W_{int} and using a CoM proxy for W_{ext} are acceptable, this investigation needs to be repeated during open play to allow for a greater variety of movements and intensities.

CONCLUSION: Markerless motion capture can be implemented as a tool for monitoring training 'load' in tennis, with mechanical work providing a suitable metric that is very strongly associated with fatigue. Neglecting the internal work and using a fixed point as a proxy for CoM can still allow for an acceptable indication of 'load', although this should be verified in open play. This would allow for simpler data processing compared to the pipeline presented here, without the need for pose estimation and inverse kinematics, which would greatly reduce data processing times and increase accessibility. A tool of this nature would allow for non-invasive 'load' monitoring from video data and could be implemented in a range of settings, from training to competition. It is also possible that this could eventually be achieved in real-time and even from broadcast footage, opening up additional entertainment opportunities.

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