Towards in-situ analysis of serving performance in tennis: A video-based method for 3D reconstruction of the ball and racket

Simon Ozan, Loïc Fourel, Pierre Touzard, Kaïes Deghaies, Louis Arles, Caroline Martin, Richard Kulpa

2025-2 | 50th congress of the Société de Biomécanique
27-29 October 2025, Marseille, France

Multidisciplinary Biomechanics Journal

Towards in-situ analysis of serving performance in tennis: A video-based method for 3D reconstruction of the ball and racket

Simon Ozan*, Loïc Fourel, Pierre Touzard, Kaïes Deghaies, Louis Arles, Caroline Martin, Richard Kulpa

Univ Rennes, Université Rennes 2, Inria, M2S, 35000, Rennes, France
* Corresponding author: simon.ozan@univ-rennes2.fr

Received date: 04/04/2025
Accepted date: 27/06/2025
Publication date: 27/10/2025

Keywords: Tennis Serve, Markerless, Deep Neural Network, Kinematics, Tennis racket

1. Introduction

The holy grail of biomechanical analyses in tennis serve is to measure players motions during real matches (Lester et al., 2023) thus monitoring the effects of fatigue or pressure induced by stressful points. To this day, tennis biomechanical investigations were mostly confined in the laboratory using a 3D motion capture (MoCap) system based on markers placed on players skin, racket and ball. Marker positions are used to extract performance indicators like ball speed, impact height and racket head velocity to assess serve effectiveness (Fourel et al., 2024). If this tool is still considered the most accurate, it is clearly not suited for in-situ assessment. Instead, markerless MoCap, a recent MoCap system based on video and artificial intelligence, offers the enticing possibility to measure people motions in ecological situations. But most of the available 3D Markerless MoCap cannot be easily adapted to reconstruct objects in 3D such as the ball and racket. The aim of this study is to develop a method based on DeepLabCut (DLC), an open-source pose estimator of user-defined key points (Mathis et al., 2018), to track and reconstruct racket and ball in 3D from videos of a tennis serve and to compare it to the reference MoCap system.

2. Methods

2.1 Participants and task

Thirteen right-handed tennis players (6 women and 7 men, age: 31.5±11.4yr, height: 173.9±9.3cm, mass: 69:1±11.7kg) performed 42 serves on the deuce and advantage sides.

2.2 Experimental set-up

A motion capture system with 10 optoelectronic cameras (Arqus A12, 300Hz, Qualisys AB, Göteborg, Sweden) recorded the trajectories of five markers placed on the racket (Fourel et al., 2024) and four markers positioned on the outer surface of the ball. Simultaneously, a markerless system consisting of 10 video cameras (Miqus Video, 540p resolution, 300Hz, Qualisys AB, Göteborg, Sweden) recorded each serve.

2.3 Markerless Model

Following (Torvinen et al., 2024), one DLC model was trained for each of the 10 points of view. One serve from each subject on each side (deuce and advantage) was randomly selected to train the DLC models. From each video, 20 frames were extracted using k-means method. This amounts to a total of 520 labelled images for each point of view (only ~0.2% of all the frames recorded). On each image, nine racket key points were manually labelled (handle-shaft junction, shaft-frame junctions, and 6 points equally distributed around the frame) and one was placed on the ball centre. Each of the 10 DLC models was fine-tuned using a ResNet50 architecture with a 95-5 train-test split and trained for 500,000 iterations. The average test error over the 10 models was 3.8 pixels.

To cite this article: S. Ozan, L. Fourel, P. Touzard, K. Deghaies, L. Arles, C. Martin, R. Kulpa, Towards in-situ analysis of serving performance in tennis: A video-based method for 3D reconstruction of the ball and racket, *Multidisciplinary Biomechanics Journal*, 2025, vol. 2, p. 29–31, DOI: 10.46298/mbj.16198.

Table 1. Bland-Altmann biases, LoA and reference values from the marker-based system.

		Bias	95% LoA	Mean values measured by the marker-based system [minimum; maximum]	
Impact location (mm)	Medio-lateral axis	-1.1	[-40.3; 38.0]	195.3	[-1418.9; 1700.8]
	Antero-posterior axis	9.4	[-21.3; 40.1]	347.0	[-401.6; 991.0]
	Height	-1.8	[-29.3; 25.8]	2507.7	[1932.2; 2799.6]
Ball velocity (km.h^{-1})		0.7	[-9.6; 10.9]	111.5	[18.7; 182.1]
Racket orientation (°)	Medio-lateral axis	2.9	[0.0; 5.8]	6.4	[-14.8; 27.6]
	Antero-posterior axis	0.8	[-2.3; 4.0]	-12.5	[-50.2; 30.8]
	Longitudinal axis	1.7	[-8.1; 11.5]	9.1	[-20.7; 39.5]
Racket head velocity (m.s^{-1})		-0.2	[-4.3; 3.8]	28.0	[14.2; 45.2]

The Weighted Direct Linear Transform was used to make the 3D reconstruction of each point (Pagnon, Domalain, & Reveret, 2021). A rigid body racket model was then fitted to the 3D points to ensure the absence of racket deformation.

2.4 Statistical Analysis

From both systems, ball location at impact, ball speed (computed over 5 frames), racket orientations and racket head linear velocity at impact were extracted and compared using Bland-Altman analysis. The Euclidean distances of the ball at impact between both MoCap systems was computed. Impact in the marker-based system was identified as the frame where the ball was closest to the racket plane.

3. Results and discussion

The mean Euclidean distance of the ball at impact between the two systems was 29.0±9.5 mm, approximately half of the diameter of the ball (65 mm). This result was expected, as the markers were placed on the outer surface of the ball, and only one of the four markers was tracked by the marker-based system. Consequently, the amplitude of the limits of agreement (LoA) for the impact location in all axes is within the range of the ball's diameter (Table 1). For the ball velocity, the large LoA could be explained by the movement of the tracked marker from one side to the opposite side of the ball (through the ball's rotation), which can result in a 14 km.h^{-1} difference from the ball's centre velocity. Regarding the racket orientation at impact, the biases were relatively small across all axes. However, the high LoA observed along the longitudinal axis could be attributed to the fact that this rotation is mostly defined by the medio-lateral axis of the racket, which is shorter than the longitudinal axis. Consequently, an equal placement error on both axis results in a larger angular deviation along the longitudinal axis.

4. Conclusions

A markerless approach for reconstructing the ball and racket during a tennis serve was developed and validated. It demonstrated good agreement compared to marker-based system. Coupled to markerless MoCap, this method lays the foundations for tennis serves performances analyses during official tennis matches.

Acknowledgements

The authors would like to thank all the participants and the Betton Tennis Association (AT Betton) for hosting the experiments.

Conflict of Interest Statement

The authors declare no conflict of interest during this study.

Contributor Roles

SO: Conceptualization, Methodology, Investigation, Software, Formal analysis, Writing original draft; LF: Conceptualization, Methodology, Investigation, Software, Writing-review & editing; PT: Conceptualization, Methodology, Investigation, Writing-review & editing; KD: Investigation; LA: Investigation; CM: Conceptualization, Methodology, Funding acquisition, Supervision, Writing-review & editing; RK: Conceptualization, Methodology, Funding acquisition, Supervision, Writing-review & editing.

Funding

This work was supported by French government funding managed by the National Research Agency under the Investments for the Future program in France 2030 with the grants ANR-18-EURE-0022 (DIGISPORT) and ANR-21-ESRE-0030 (CONTINUUM).

References

Fourel, L., Touzard, P., Fadier, M., Arles, L., Deghaies, K., Ozan, S., & Martin, C. (2024). Relationships between force-time curve variables and tennis serve performance in competitive tennis players. *Journal of Strength and Conditioning Research*, *38*(9), 1667–1674. https://doi.org/10.1519/JSC.0000000000004848

Lester, M., Peeling, P., Girard, O., Murphy, A., Armstrong, C., & Reid, M. (2023). From the ground up : expert perceptions of lower limb activity monitoring in tennis. *Journal of Sports Science & Medicine*, *22*(1), 133–141. https://doi.org/10.52082/jssm.2023.133

Mathis, A., Mamidanna, P., Cury, K. M., Abe, T., Murthy, V. N., Mathis, M. W., & Bethge, M. (2018). DeepLabCut : Markerless pose estimation of user-defined body parts with deep learning. *Nature Neuroscience*, *21*(9), 1281–1289. https://doi.org/10.1038/s41593-018-0209-y

Pagnon, D., Domalain, M., & Reveret, L. (2021). Pose2Sim: An end-to-end Workflow for 3D markerless sports kinematics—Part 1: Robustness. *Sensors (Basel)*, *21*(19), 6530. https://doi.org/10.3390/s21196530

Torvinen, P., Ruotsalainen, K. S., Zhao, S., Cronin, N., Ohtonen, O., & Linnamo, V. (2024). Evaluation of 3D markerless motion capture system accuracy during skate skiing on a treadmill. *Bioengineering*, *11*(2), 136. https://doi.org/10.3390/bioengineering11020136