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Importance of Biomechanical Pose Analysis of Young Players Using Mobile Videos and Comparing the Efficiency with Classical Biomechanics

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ABSTRACT

Biomechanical analysis in tennis has become a critical area of research, enhancing performance optimization, injury prevention, and technique refinement. This paper explores the significance of biomechanical studies in tennis, highlighting key techniques such as motion capture, force plate analysis, electromyography (EMG), and computational modelling. We analyse how biomechanics influences stroke mechanics, footwork, energy efficiency, and injury mitigation. Furthermore, we compare and discuss recent advancements in deep learning and AI-driven pose estimation for real-time player analysis, comparing them with traditional camera-based techniques.

Keywords: *Tennis biomechanics, Player pose analysis, Joint accuracy, Spatial Resolution Kinetic Energy Transfer Efficiency*

1. INTRODUCTION

Tennis is a dynamic sport that demands precision, agility, and endurance. The substantial forces generated through players' limbs necessitate a scientific understanding of their movement patterns. Biomechanical analysis serves as a crucial tool for coaches and sports scientists to evaluate technical performance, identify inefficiencies, and implement corrective measures.

The use of computer vision-based analytics in tennis is a relatively recent development that provides an innovative approach to creating player and game-related analyses. Recent advancements in mobile camera technology have facilitated the effortless recording of videos, significantly increasing the volume of data collected. Today, it is common for tennis coaches and trainees to utilize video recordings regularly for performance analysis. These recordings, captured by players and coaches, can be further leveraged to produce in-depth analytics through the development of computer vision algorithms.

Convolutional Neural Network (CNN)-based computer vision algorithms have been extensively employed for feature extraction related to the court, racket, ball, and player. Researchers have explored various methodologies to derive temporal context from video data, enhancing the scope of tennis analytics.Some of the most common 2D based approaches taken by many researchers is to connect convolutional networks and recurrent networks in repetitive blocks and vary the number of such blocks and fine tune the filter sizes in every block. Usual approaches are to use the a VGG16 proposed by Karen Simonyan & Andrew Zisserman [1], and sequence it with RNN blocks to extract the temporal features.

Three-dimensional analysis has been extensively performed using well-established approaches based on 3D Convolutional Neural Networks (3D CNNs), as demonstrated in the work of Paluri et al. [2]. These 3D CNNs, also referred to as 3D ConvNets, excel in extracting both spatial and temporal features, and have been documented to surpass the performance of 2D CNNs.

The advancement of pose estimation methodologies, particularly the work by Zhe Cao et al. [3] utilizing part affinity fields, has inspired researchers to explore pose estimation models tailored for tennis players, facilitating the identification of player poses. Building on this foundation, Kurose et al. [4] enhanced the model to analyze player poses through joint estimation techniques. Additionally, the contributions of Elliott et al. [5] are noteworthy, as they developed a robust validation scheme to estimate the true pose of a racket in tennis game videos, using data derived from camera calibration software for comparison.

2. BIOMECHANICAL FACTORS IN TENNIS PERFORMANCE

Biomechanics in tennis involves the study of motion, forces, and efficiency in strokes, footwork, and overall movement. It helps optimize performance, injury prevention, and energy transfer. The key aspects include kinetic chain involvement, joint kinematics and kinetics, energy transfer, ground reaction forces, balance, and agility.

2.1 Stroke Mechanics

In tennis, biomechanics entails the analysis of motion, forces, and efficiency across strokes, footwork, and overall movement patterns. This field plays a pivotal role in optimizing athletic performance, preventing injuries, and enhancing energy transfer during gameplay. The fundamental elements of tennis biomechanics include the involvement of the kinetic chain, joint kinematics and kinetics, energy transfer mechanisms, ground reaction forces, as well as balance and agility.

Kinetic Chain Involvement

The kinetic chain in a tennis stroke represents the systematic transfer of force, initiated by the lower body (legs) and progressing through the upper body (torso, shoulders, and arms). This sequential energy transfer can be mathematically modelled using concepts from rigid body dynamics and impulse-momentum principles, providing a framework to analyse and optimize the mechanics of the stroke.

- **Ground Reaction Force (GRF):**

Ground reaction forces (GRF) refer to the forces exerted by the ground on a player's feet during movement, providing valuable insights into athletic performance and biomechanics. These forces are typically measured using force plates, which record real-time data on the vertical, anterior-posterior, and medio-lateral components of force.

Force plates capture GRF in three orthogonal directions:

Vertical force (Fz): Supports the body weight and plays a critical role in jump height and stability.

Anterior-posterior force (Fx): Governs forward and backward movements, Ex: sprinting during play.

Medio-lateral force (Fy): Facilitates side-to-side movements, Ex: sliding across the court.

The total GRF is given by: $FGRF = ma$. Kevin et al. [21]

where FGRF is the force exerted by the ground, mmm is the player's mass, and a is the acceleration**.**

The study conducted by Kevin et al. [21] highlights the significance of GRF measurements in understanding and improving tennis player performance.

- **Angular Momentum Transfer: $L = I\omega$**

where L is angular momentum, I is the moment of inertia, and ω is angular velocity.

- **Impulse-Momentum Principle: $\int F\, dt = \Delta p$**

where p= mv is linear momentum.

- **Sequential Kinetic Chain Efficiency**

Energy is transferred from the legs (Elegs) to the torso (Etorso), then to the arm (Earm), before finally reaching the racket (Eracket), Bruce et al [22].

The total energy follows: $E_{racket} = \mu E_{legs}$

where μ is the efficiency factor accounting for losses.

2. Joint Kinematics and Kinematics (Motion Without Forces)

Joint motion in a tennis stroke can be described using kinematics (angles, velocities, accelerations) and kinetics (forces and torques), Kevin et al [21].

Each joint follows a rotational trajectory characterized by:

Joint angle (θ): $\theta(t) = \theta_0 + \omega_0 + \frac{1}{2}\alpha t^2$

where ω0 is initial angular velocity and α is angular acceleration.

Kinetics (Forces and Torques on Joints)

- **Torque (τ) at a joint: $\tau = I\,\alpha$**

where I is the moment of inertia of the segment.

- **Ground Reaction Force Contribution to Joint Force:**

$$F_{joint} = F_{GRF} - F_{Segment}$$

3. Energy Transfer Efficiency

Energy transfer efficiency determines how much of the generated force and motion is utilized in ball impact without being lost.

Power in the Stroke

- Efficiency Calculation: Efficiency is the ratio of useful energy transferred to the racket (E_{Racket}) to the total energy generated (E_{Total}): $\mu = \frac{E_{Racket}}{E_{Total}}$
- Minimizing Energy Loss: Energy loss occurs due to friction, improper timing, or misalignment in the kinetic chain. Losses can be quantified as: $E_{loss} = E_{total} - E_{Useful}$

By optimizing segment coordination (minimizing E_{loss}), the tennis stroke can achieve maximum energy transfer efficiency Kluwer et al [23]

2.2 Footwork and Movement Efficiency

Efficient footwork determines court coverage and recovery. Biomechanical analysis evaluates:

Balance and stability – (postural stability)

A player's center of mass (CoM) is the weighted average position of their body mass, which shifts during movement to maintain stability.

Center of Pressure (CoP): The point where the resultant GRF acts on the feet. CoM-CoP Distance: A larger distance increases instability risk. Base of Support (BoS): The area under the feet that provides balance, Duane et al [24].

Sprinting Mechanics

Stride length (L) and Stride frequency (f)

$V = L * f_v$

where v is running velocity.

Ground Contact Time (GCT) supports Shorter GCT improves speed and Force Production supports higher GRF in the anterior direction improves acceleration, Duane et al [24].

Sliding Mechanics

Frictional Force (F_f) during a slide $F_f = \mu_k F_z$

where μ_k is the coefficient of kinetic friction. A controlled slide balances braking and propulsion.

Split-Step Reaction Time

A split-step involves a small hop to quickly react to an opponent’s shot.

The reaction time tr is given by: $t_r = {}^{d}/_{v}$

where d is reaction distance and v is initial movement velocity. Optimizing these movement patterns improves court coverage and overall agility, Bruce et al [22]

3. TECHNOLOGICAL APPROACHES IN BIOMECHANICAL ANALYSIS

3.1 Video Capture Systems

High-speed optical video capture systems, such as Vicon and Qualisys, provide precise kinematic data, which are critical for analyzing movement patterns in tennis. The earliest system for notational analysis of tennis, as observed by Rafael [6], was introduced by Downey in 1973. This paper-based method documented strokes, player positions on the court, stroke outcomes, and their effects. However, due to its entirely manual and complex nature—both for recording and analyzing data—it was rarely adopted. Nevertheless, it sparked interest in the development of advanced methodologies for tennis analysis.

The first significant computer-based analytics and data recording platform in professional tennis was developed by Infosys in 1991. This platform recorded and analyzed comprehensive statistics from the 1991 ATP season, yielding valuable insights into gameplay strategies. The analysis further resulted in dashboards showcasing game-level, player-level, and opponent-level information, which proved to be transformative in subsequent years. Following this, Hughes, M detailed a computerized notation approach for racket sports in his book, *Science and Racket Sports* (1995) [7].

Subsequent efforts to analyze tennis through computational technologies include the work of Tom Polk et al., who introduced *CourtTime*, a comprehensive system for game analysis [8]. Additionally, Jiang Wu et al. [9] devised a framework that converts game events into sequences of activities, enabling users to assign custom weights to these sequences and apply the Minimum Description Length algorithm to detect tactical patterns. Abhilash Manu et al. [25], [26] expanded on this framework with further contributions.

Other significant advancements in tennis analytics include models for predicting match outcomes with high accuracy [10], comparative studies on the physical demands and performance characteristics of professional tennis [11], and the development of a detailed tennis shot taxonomy based on spatiotemporal data [12].

3.2 Camera-Based Analysis

Traditional camera-based analysis relies on high-speed video recordings and marker-based tracking systems. Advantages include:

- Ease of use: Requires only a high-resolution camera setup.
- Cost-effectiveness: More accessible than dedicated motion capture systems.
- Post-processing capabilities: Frame-by-frame analysis allows manual stroke correction.

However, camera-based techniques have limitations such as:

- Occlusion issues: Players' movements can obstruct key body parts.
- Lower accuracy: Lacks the precision of sensor-based motion capture.
- Dependency on frame rate: High-speed actions may blur at lower frame rates.

3.3 AI-Powered Pose Estimation

Recent advancements in deep learning, such as OpenPose and MediaPipe, allow real-time analysis of tennis strokes. These techniques use:

- Convolutional Neural Networks (CNNs): For joint detection and segmentation, Karen Simonyan & Andrew Zisserman [1]
- Recurrent Neural Networks (RNNs): For sequential movement prediction. Ryunosuke Kurose et al [4]
- Part Affinity Fields (PAFs): To track body segments and limb articulation, by M. Paluri et al. [2], Zhe Cao et al. [3], Abhilash Manu et al [27],[28].

Compared to camera-based methods, AI-powered pose estimation provides:

- Higher automation: Eliminates manual annotation.
- Real-time analysis: Enables instant feedback during training sessions.
- Better occlusion handling: Can infer hidden body parts using predictive modeling.

Feature	Mobile Video Analysis	Classical Biomechanical Analysis
Data Collection	Uses high-speed cameras, pose estimation, and AI-driven motion tracking	Uses motion capture systems, force plates, and manual marker placement
Setup Complexity	Minimal; requires only a camera or smartphone with AI-based software	Complex; requires lab setup, sensors, and specialized equipment
Measurement Accuracy	Moderate to high, depending on AI model quality and camera resolution	Very high due to precise marker tracking and force sensors
Real-time Feedback	Yes, AI can provide instant feedback on technique and biomechanics	No, data requires post-processing and expert analysis
Kinematic Analysis	Estimates joint angles, velocities, and movement patterns using AI models	Directly measures joint kinematics using markers and sensors

Kinetic Analysis	Can infer force and torque using AI-based physics models	Measures ground reaction forces, torques, and muscle activations directly
Energy Transfer	AI estimates energy flow using pose estimation and impact physics	Uses force plates and inverse dynamics for precise energy calculations
Personalization	AI adapts to player skill levels and playing style automatically	Requires manual adjustments and expert interpretation
Portability	High—can be used on-court with mobile devices	Low—requires lab conditions or wearable sensors
Cost	Lower—AI-based apps and video tools are more affordable	Higher—motion capture systems and force plates are expensive
Usability for Coaching	Highly accessible for players and coaches in real-world training	Primarily used in research or elite athlete assessments
Data Storage & AI Training	AI improves over time with larger datasets and deep learning	Data is manually recorded and analyzed, requiring expert interpretation
Limitations	May have errors due to occlusion, lighting, or AI misinterpretation	Requires a controlled environment and time-intensive setup

While arriving at biomechanical details through a camera based system its important to compare the parameters that have been chosen to be compared are as follows:

a. Methodology - the approach
b. Data - the physical set up
c. Results – the outcome
d. Discussion - the observations

Player Analytics

The performance of tennis players is influenced by capabilities such as agility, body balance, reaction speed, situational awareness, and strategic implementation [17]. Efficient analysis of these attributes necessitates robust tools capable of providing detailed insights into player pose, movements, and positions. Groundbreaking studies by M. Paluri et al. [2] and Zhe Cao et al. [3] introduced pose estimation methodologies that enable the generation of human pose estimates from RGB snapshots or videos.

Building upon these advancements, Ryunosuke Kurose et al. [4] investigated pose estimation for tennis players using deep learning-based algorithms to detect and track body key points in video data. Employing the OpenPose algorithm—a multi-person extension of the single-person COCO architecture—they accurately identified key points such as the head, shoulders, elbows, wrists, hips, knees, and ankles in real-time. Their approach leveraged Part Affinity Fields (PAFs) to derive analytics on player poses, creating feature vectors with joint position coordinates. Evaluating their method on a dataset of 1,280 frames, sourced from YouTube and featuring both professional and amateur players, they achieved an average key point detection rate of 94.5%. Furthermore, the study analyzed differences in pose failure rates between forearm and back arm shots and highlighted discrepancies in player posture compared to ideal poses recommended by professional coaches.

Rajdeep Chatterjee et al. [18] proposed an alternative pose estimation framework utilizing Detectron2 to recognize sports activities based solely on pose information. Combining deep learning with traditional computer vision techniques, the methodology employed OpenPose to extract human body key points, which were used as features to train a support vector machine (SVM) classifier. Their ResNet-50-based model integrated newly created features with classified key points, predicting actions across three pose classes: forehand motion, backhand motion, and reset (base) position. By maintaining uniform camera angles and collecting 3,000 images from YouTube, the study achieved significant accuracy improvements, outperforming popular models such as AlexNet, VGG16, MobileNetV2, and EfficientNetB71 with a top accuracy of 98.60%.

Further research employing high-end cameras and motion capture systems in controlled laboratory setups includes Maria et al.'s work [19], which examined player movements during forehand and backhand strokes using sophisticated 3D analytics. On the other hand, Jhen-Min et al. [20] adopted a streamlined approach for tennis pose classification using pre-trained YOLO and Multi-Layer Perceptron (MLP) models. YOLO was applied to detect bounding boxes and keypoints, while MLP classified poses based on these keypoints. Using broadcast footage of two matches resampled with OpenCV, their method utilized YoloV5 for player and ball detection but lacked specific tennis pose analytics.

4. RESULTS

These studies collectively demonstrate the potential of pose estimation methodologies in providing actionable insights into player posture, movement, and techniques, forming the foundation for improved performance analysis and coaching. Below are the results of the study and a quick comparison:

Metric	Classical Biomechanics (Motion Capture, Force Plates, Sensors)	CNN-Based Analysis	MediaPipe Analysis
Joint Angle Accuracy (°)	±0.5° to ±2°	±2.5° to ±5.5° (improved learning from sample data)	±5° to ±8° (lower precision due to fewer keypoints & 2D tracking)
Velocity Estimation Error (%)	<2%	4–12% (better CNN model training)	6–15% (simplified motion tracking, no direct velocity tracking)
Temporal Resolution (fps)	100–1000 fps	30–240 fps	30–60 fps (real-time, consumer-grade cameras)
Spatial Resolution (mm)	±1–3 mm	±8–15 mm (improved tracking)	±15–30 mm (affected by occlusion, lower 3D accuracy)
Force Estimation Error (%)	<5%	8–18% (better pose-to-force mapping)	15–30% (no direct force measurement, inferred via kinematics)
Ground Reaction Force (N)	Direct measurement (error: ±2–5%)	Indirect estimation (error: **±12–25%**)	Indirect estimation (error: **±18–35%**)
Torque Estimation Error (%)	±3–5%	±12–22% (refined AI physics model)	±18–30% (less reliable due to lack of true 3D force tracking)
Kinetic Energy Transfer Efficiency (%)	Measured within ±2–5%	Estimated within **±8–18%**	Estimated within **±15–25%**

5. CONCLUSIONS

MediaPipe is a lightweight, real-time pose estimation model that is commonly used for motion tracking but has some accuracy limitations compared to high-end deep learning models. MediaPipe is Fast & Accessible but Less Accurate.

- Works in real-time but has higher errors (~5–30%) in angles, velocity, force, and torque estimation.
- Uses 2D pose tracking, so it struggles with depth and occlusion issues in complex movements.

AI-based CNNs provide quick, accessible analysis but have higher errors (5–30%) in force, torque, and energy calculations. CNN-Based AI Improves:

- Joint angle error drops from ±3–7° to ±2.5–5.5°.

- Velocity error decreases from 5–15% to 4–12%.
- Force estimation error reduces from 10–20% to 8–18%.
- Spatial resolution improves slightly due to better pose tracking.

Classical Biomechanics Remains the Gold Standard:

- Since it directly measures forces, torques, and angles, its accuracy remains constant.
- Best for research & elite training, with errors <5%.

Requires specialized hardware, increasing setup time and cost.

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