

Mini Review: Technology-Driven Bridging of Biomechanics and Pedagogy: Translating Forehand EMG Data into Intelligent Coaching Strategies

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ABSTRACT- Tennis forehand is a tricky activity that employs practically all parts of a body. The legs and the trunk are important as well as the arm and the wrist, as they determine the speed with which the racket attains movement, and influence the mastery that the player is going to have over the ball when it strikes and is entered. Surface electromyography (sEMG) is a non-invasive method of recording muscle switching on and the intensity of the work. Kinematic and wearable-sensor data provide an addition of a picture of the joint motion in the body segments. This article gathers previously known biomechanical evidence of the forehand as well as extending it into a technology-centered paradigm of AI-assisted coaching. Recent studies indicate that not all players who activate their muscles more are necessarily stronger. It seems to be their benefit of a superior timing and improved alignment of the segments, as well as the accelerated movement of the swing. The suggested paradigm begins with the combination of sEMG and inertial or kinematic measurements. Signals are initially cleansed. Attributes are subsequently obtained and fed through machine-learning algorithms that identify movement patterns. The last steps are error identification and personalized coaching feedback. What this might imply to practical teaching (core-centered movement instruction and control of excessive co-contraction) is also given due consideration in the article. The concepts of the wrist and forearm control and ground reaction force awareness are also discussed. The framework is theoretical and not clinically or performance validated. Annotated multimodal data sets should be built in future work and contrasting machine-learning models should be compared. It will also need to evaluate their generalization between players and skill levels, and whether AI-generated feedback does indeed positively affect the measurable tennis results.

KEYWORDS- Artificial Intelligence, Tennis Forehand, Surface Electromyography, Biomechanics, Machine Learning, Intelligent Coaching

I. INTRODUCTION

In competitive tennis the forehand is one of the principal baseline strokes and it has received a lot of biomechanical interest. The forehand is not a good thing because of a strong arm. It relies on the flow of energy within the body through a smooth sequence of body parts. Biomechanical studies have been emphasizing that sequencing and timing and the manner of loading of the body determine performance and injury management [1]. Surface electromyography (sEMG) has provided a neuromuscular overlay to this image, due to its ability to allow scientists to observe muscle discharge and the degree of discharge. Technology has since taken this type of testing out of the laboratory. Motion capture currently has the ability to be integrated with the inertial measurement unit (IMU) and other wearable sensors (in 3D). The recordings are then subjected to computational analysis to convert them into massive data sets on joint motions, muscle activities, racket velocity and movement times. One study (2026) compared 3-D motion capture with sEMG, which compared high-performance and intermediate players [8]. The differences in performance were principally attributed to finer coordination among segments. The superior players also had a faster rate of movement of their legs and distal parts, and had localized activation in their elbow muscles, as opposed to an increased activation of the whole upper limb. This is important to smart coaching. It implies that an AI system must seek timing and coordination patterns and needs not merely demand increased muscle activity.

These multidimensional measurements can be transformed into classification, prediction and decision-support systems using artificial intelligence (AI) and machine learning (ML). According to the recent reviews, there is an increase in the use of AI in sports biomechanics. Common applications include wearable sensing and motion tracking, performance measurements and work-related injuries [16]. The same is the case with tennis literature. There, machine learning and computer vision is applied, as well as tracking technology and performance analysis based on data [17]. The question that this article poses is how an AI-assisted coaching pipeline could be fed on EMG and biomechanical

information. It attempts to maintain a fixed set of evidence quite distinctly, and what is merely suggested.

The key novelty of this mini-review is a technology-based conceptual framework. It links multimodal forehand biomechanics with AI-assisted movement analysis and with teaching feedback. Biomechanical measurement and coaching are perceived to be two different jobs. The framework is a description of a single pathway. It begins with sensor capture and preprocessing of the signal and proceeds to inferring movement patterns. The mistakes are then determined in an explainable manner which is then followed by an individualized coaching intervention. The contribution is theoretical. It attempts to describe an architecture which is testable and a research agenda to accompany it. It makes no mention of a newly trained AI model

II. REVIEW METHODOLOGY

This paper is a conceptual framework paper, a focused narrative mini-review. It is neither systematic review, nor an experimental validation study. The sources were categorized as four themes. The former deals with tennis forehand biomechanics and kinetic-chain sequencing. The second deals with sEMG and neuromuscular evaluation. The third one examines machine learning, AI and wearable technologies to analyze human movements and the fourth one analyzes the way in which quantitative movement data can be converted into coaching feedback. Recent work which was technology focused was prioritized 2018-2026 and studies on the foundations of tennis-biomechanics were retained with this.

The search words were composite phrases that included: tennis forehand, surface EMG, electromyography, biomechanics, machine learning, artificial intelligence, wearable sensors, motion analysis and intelligent coaching. A source was considered to be relevant when it addressed directly either tennis movement or sEMG or kinematic measurement. Research on machine-learning animal motion analysis or A.I.-based sports evaluation also was eligible. This is a narrative mini-review; hence no risk-of-bias assessment was performed. None of the effect sizes were pooled and no attempt was made to perform a meta-analysis. How the review does not declare PRISMA level systematic screening. It does not intend a technical implementation of AI-assisted coaching architecture but rather bridges the known biomechanical results with it.

A. Search Strategy and Selection Criteria

Combinations of the following terms were used to search scholarly databases and academic sources to identify relevant studies: “tennis forehand,” “surface EMG,” “electromyography,” “biomechanics,” “machine learning,” “artificial intelligence,” “wearable sensors,” “motion analysis,” and “intelligent coaching.” The review mainly considered studies that were published between 2018 and 2026. Previous studies were also included if relevant background on tennis biomechanics, muscle activation, or forehand mechanics could be found. Studies were included when they were related to tennis movement and forehand biomechanics, sEMG and neuromuscular assessment, kinematic or wearable-sensor measurements, or the application of machine learning and artificial intelligence to human movement and sports analysis. We also looked at

research from the broader fields of sports biomechanics and AI-based movement analysis, if it provided useful methodological or technological context. The final references were selected based on their relevance to the topics and discussions presented in this mini-review.

These details are provided to ensure transparency and reproducibility and include: the databases or search sources, the period or date the search occurred and the basic inclusion criteria. They fail to transform the article into a PRISMA-style systematic review.

References were selected based on the arguments that they claim. In the case of stroke biomechanics, muscle activation or tennis movement, tennis- and forehand-specific studies are utilized. Wider research on machine learning, wearable sensing and sEMG methodology can back only general methodological claims or technology related claims. Some of the studies mentioned relate to an associated tennis movement, as opposed to the forehand itself. Their findings are made available in the form of contextual evidence rather than as direct forehand evidence.

III. BIOMECHANICAL FOUNDATIONS OF THE TENNIS FOREHAND

A. Professional Proximal-to-Distal Sequencing

In forehand the power generation begins with ground reaction forces. It en route travels along the pelvis and trunk and on to the shoulder, elbow, forearm and the wrist [1]. A kinetic-chain perspective does not consider the arm as a source of power itself. It poses the question of how the energy and the angular momentum are passed to the next segment. Previous biomechanical research emphasized the view of multisegment coordination and rotation of the trunk, coupled with timing, as determinants of efficient stroke production [1], [2]. The reviews of tennis groundstrokes confirm the same [9], [12].

EMG experiments have also served to elucidate the way time organization of muscle activity proceeds. Nonetheless, it should not be understood that activation is a mere fetish in place of performance. Results of Pedro et al. [8] in their comparison of high and intermediate players indicated that, in general, the EMG patterns in most of the muscles were similar. The differences between the two were very huge but were limited to some activation periods of the biceps and triceps. This helps to make the coaching objective more accurate. The challenge is to identify meaningful activation windows and coordination relationships and not to think that greater activation is necessarily better. The former EMG studies of tennis players involved studying the activation of the elbow, trunk and upper-limb muscles during tennis actions [3], [4], [5], [6].

B. Skill-Level Differences and Kinematic Coordination

Intermediate and leisurely players can display a weaker heterogeneity amongst pieces. They also have a higher tendency of compensation using their upper limb. These trends can influence the speed of the rackets and stability of the shots, and can also cause fatigue. Nonetheless, they are more of tendencies than general traits. Technique depends upon playing style and the task demands, and also on handedness, racket set-up and skill.

Recently recorded 3-D motion-capture and sEMG have demonstrated that top-performing players are able to attain higher racket, shoulder, elbow and wrist speeds toward the end of the forward swing [8]. They also had more hip and knee angular velocities and localized activation increases in the elbow muscles. This provides an AI system with an empirically motivated temporal model of signal coordination among multiple signals. There are still limited evidence of the players and conditions that were tested. Additional background information to interpret these differences is found in wearable motion-analysis studies and studies into skill-related muscle activation [13], [14].

C. Shoulder, Forearm, Wrist Control.

Shoulder complex is involved in stabilization and quick rotation. The wrist and the shape of the forearm determine the direction of the racketing and the way the impact is absorbed, as well as assist in shock absorption. The studies of EMG and upper-extremity kinematics in tennis confirm the usefulness of coordinated muscle activity and optimal timing [10], [11]. Too much co-contraction or distal activity can reduce the efficiency of movements. The extent of that effect and its causes is likely to be dependent on the task and the player. Another effect of grip on the extent to which the upper limb provides racket-head velocity is pertinent in assessing technique at the distal end [7].

IV. AI-ASSISTED EMG AND KINEMATIC ANALYSIS

A. Multimodal Data Acquisition

A practical intelligent coaching system may be able to integrate sEMG, with IMUs, and video-based pose estimation. Optional force or pressure measurements are possible, as are racket or inertial sensors. The sEMG is used to record the neuromuscular activity. IMUs and motion-analysis systems provide data of joint orientation, angular velocity, and acceleration, and the timing of segments. Wearable sensors, including both EMG and IMUs, have recently been highlighted as important tools to assess individual movement in a personalized way for use in AI-based movement assessment [16]. In recent tennis research it has been also demonstrated that 3-D kinematics and sEMG can be used simultaneously during the forehand [8]. This technology-based approach is further supported by the work done with machine-learning in tennis and

machine-learning practice in human-movement biomechanics, respectively [15, 18].

B. Signals Preprocessing and Feature Extraction

Raw sEMG is very sensitive to disturbance. Typical problems include power-line interference, differences between sessions, motion artefact and displacement of the electrodes. Therefore, before any model is trained, a signal should be filtered, normalised and segmented using a computational pipeline to ensure it has undergone quality control. Methods for sEMG analysis, such as frequency-domain analysis, are discussed in recent literature [21]. There are two features of sEMG, which are considered to be candidates for introducing in the procedure, namely mean absolute value and root-mean-square amplitude. Waveform length, zero crossings, median frequency and activation-onset timing are other options. Kinematic characteristics may relate to joint angles and angular velocities, as well as the timing between segments, racket velocity and coordination between segments. Recently, it was demonstrated that machine-learning models are able to automatically retrieve the timing of sEMG activation. It also demonstrates that the results of the classification heavily depend on the types of features and models used [19].

C. Machine-Learning Models

There are a number of families of models that might be appropriate for an intelligent coaching pipeline. Fairly interpretable classification on engineered features is provided by support vector machines and random forests. Gradient-boosting models can learn several measurements' nonlinear relationships. Convolutional neural networks operate on structured representations of signals, while a recurrent or temporal model can be used to represent sequences of movements. This decision should be made on a practical basis based on a well-defined data set and evaluation process. No model should be presumed, in advance, to be better. Wider applications of learned models for the neuromuscular signals have been examined with deep-learning techniques to estimate hand-wrist forces from surface EMG [20]. The proposed AI-based forehand analysis pipeline is summarized in Table 1. Each stage is associated with what it is commonly used as an input, and what it computes in addition to its output. The pipeline starts with the multimodal data acquisition, then preprocessing and feature extraction, and finally AI analysis. It then moves on to error interpretation, coaching feedback and re-measurement.

Table 1: Proposed AI-Assisted Forehand Analysis Pipeline

Pipeline Stage	Typical Input	Computational Operation	Output
Data acquisition	sEMG, IMU, video, racket/pressure sensors	Synchronized multimodal recording	Raw multimodal signals
Preprocessing	Raw sEMG/kinematics	Filtering, normalization, segmentation, quality control	Clean synchronized signals
Feature extraction	sEMG and kinematic signals	RMS, MAV, median frequency, onset timing, joint/racket velocity	Feature vector/time series
AI analysis	Features and temporal sequences	RF/SVM/boosting/CNN/temporal models	Movement-pattern estimate
Error interpretation	Model output + player baseline	Temporal comparison, feature importance, explainability	Interpretable movement deviation

Coaching feedback	Deviation + task context	Expert-reviewed rules/pedagogical mapping	Player-specific coaching cue
Re-measurement	New practice session	Within-player comparison	Progress/feedback update

D. AI for the Human Brain: Explainable AI and Movement-Error Interpretation

Accuracy is not sufficient when coaching. Coaches should understand the reasons for flagging a movement pattern. Explainable AI techniques can demonstrate the contribution of EMG amplitude to a model's output and vice versa, the contribution of activation timing to a model's output, the contribution of joint velocity to a model's output, or the contribution of racket kinematics or racket timing between segments to a model's output. There are other methods like feature-importance methods that can work alongside classification (such as SHAP). The same may be achieved through temporal attention mechanisms or clear/rule-based models. These outputs should be provided to the system as information for making decisions and should continue to maintain the oversight of the experts. The statistical deviations should not be interpreted directly as diagnoses or forcing certain changes in technique.

E. Introduces the Classification Knowledge and How it is used to make Coaching Recommendations.

The proposed system should not be confined to making a distinction between a “professional” and an “amateur” stroke. A better design identifies the specific deviation in movement and/or neuromuscular function and connects that deviation to an evidence-based coaching action. Assume that lower body rotation is delayed with respect to trunk acceleration. The system could then provide a signal as to initiating the lower body sooner. Too much co-contraction can result in a relaxation exercise. Wrist kinematics may be inconsistent which could result in a controlled mini-tennis progression. These are rules offered for coaching, and have not been experimentally validated. They should be viewed by experts at the beginning of deployment.

V. TECHNOLOGY-DRIVEN COACHING FRAMEWORK

Proposed framework has 4 phases (see figure 1). Multimodal data acquisition and biomechanical measurement is the first of these. The second includes signal preprocessing and feature extraction, as well as analysis of the neuromuscular and kinematic patterns using an artificial intelligence. In the third, movement errors are presented in an understandable manner and they are translated into pedagogical concepts. The fourth is an individualized coaching experience with re-measurement. The concept of the framework. It should be used in an experimental fashion prior to use in clinical settings or for making high-stakes decisions.

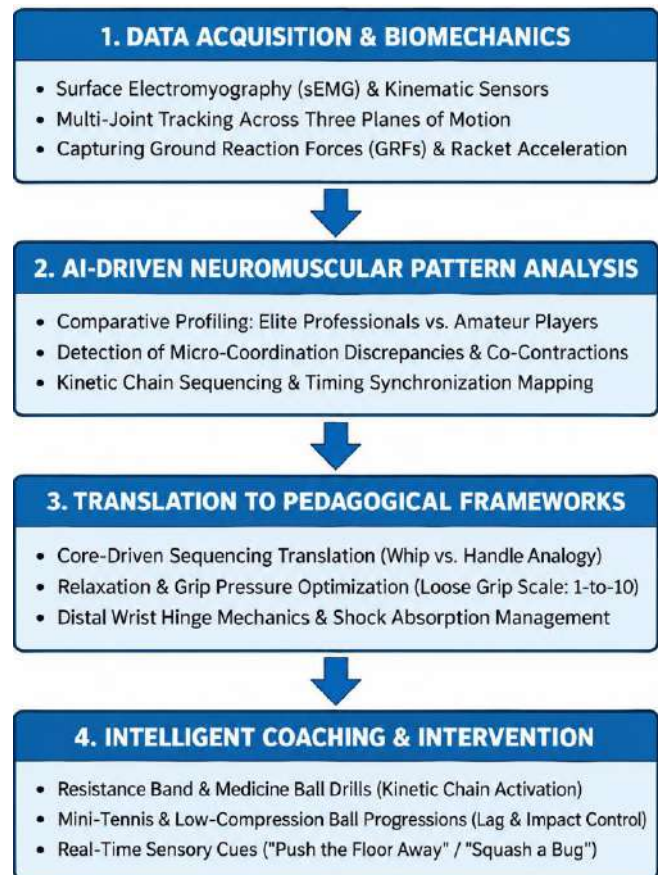


Figure 1: Proposed AI-assisted technological and pedagogical framework linking sEMG/kinematic acquisition, signal processing, AI-based pattern analysis, movement-error identification, and personalized coaching feedback

The overall framework is presented in Figure 1. Stage 1 is the collection of the multimodal biomechanical data. In Stage 2, the AI analysis of the neuromuscular and kinematic patterns is performed. In Stage 3, the characteristics of the movement are converted into pedagogical ideas. Stage 4 takes these findings and translates them into individual coaching interventions, then re-measures.

A. Core-Centric Movement Strategy

This is a core-centric movement strategy. This is a strategy for moving around using the core. The terms used in Figure 1 are used to illustrate the proposed framework. Included within it are terms such as micro-coordination discrepancies and co-contraction, core-driven sequencing, grip-pressure optimization and distal wrist-hinge mechanics. They are to be considered as ideas for analysis or coaching. These are not actual experimental criteria. The wording is consistent with those on the interpretation of movement errors and the core-centric movement strategy. It is also comparable with other tasks involving co-contraction and relaxation, and wrist and forearm control. The timing relationship between lower body, trunk

and upper limb signals can be compared using an AI system. It can then filter and determine if the pattern captured is consistent with the desired kinetic-chain sequence. It is not clear to the player when you say “use the core.” Rather, the system might provide a particular hint related to measurable timing differences. A unit turn drill with a resistance band or a medicine ball rotation drill with control might follow. The recommendation should be considered coaching support, not as a diagnosis.

B. Co-Contraction and Relaxation Strategy

Synchronized EMG channels can be used to look at excessive simultaneous activation of opposing muscles. Co-contraction indices could be calculated on selected phases of the swing within the system. It could then highlight numbers that are above an average for that player. Feedback may focus on relaxation and progressive grip control exercises. Co-contraction may also be used to help stabilize a joint. The algorithm should therefore check the signal for task demands, and not mark every occurrence as an error.

C. Wrist and Forearm Control

A combination of forearm EMG and wrist and racket kinematics can provide some information about distal control. A fixed wrist action is not to be recommended for all players. The system could alternatively pick up on an inconsistent racket face position or too much deviation. Bad timing of the activation could also be marked. Thereafter, progressive drills can be suggested. The intention is to reduce the unnecessary manipulation without losing the player's own technique. Ground Reaction Force and Lower Body Awareness (D.Ground-Reaction-Force and Lower-Body Awareness

D. Ground-Reaction-Force and Lower-Body Awareness

Wearables could be useful in the field—either inertial or pressure. These measurements can be used to assess if loading and transferring into the lower body occurs before the actual acceleration phase of the upper body. This provides a cue-sheet version of the well-known “push from the ground” instruction. It also does not presume a player may have one correct timing pattern.

E. Personalized Feedback Loop

A deployment should be treated as a closed loop feedback system. It starts with a measurement, then to analysis, and then to a coaching cue, practice and re-measurement. Previous sessions could give each player a reference of his/her own, and the system would be able to identify important changes within the player. In recent times, the feasibility of personalized and real-time evaluation in sports biomechanics has been highlighted, underscoring the promise of AI and wearable technologies. In addition, it stresses the need for reliable databases and models that can be interpreted [16].

VI. RESEARCH GAPS AND FUTURE DIRECTIONS

There are a few constraints remaining for the proposed framework to be a validated coaching product. Firstly, public tennis data available with synchronized sEMG and 3-D kinematics is limited. Very few of them also have racket data, skill level and expert coaching labels for

players. C2, secondly, EMG signals will vary significantly between players and between recording. Third, AI models must be evaluated with regard to meaningful coaching outcomes and not just the classification. Fourth, errors in the measurement or occlusion (occlusion effect) might be introduced by markerless motion capture or wearable sensing. There is the risk of sampling limits. All of these can have a negative impact on the performance of the downstream models [22].

Future studies should develop multi-modal datasets that are split into participant-level train/validation/test sets. They should compare explainable ML models to deep temporal architectures and measure the importance of features. The generalisation of the cross player should be checked. It also should be evaluated if there's any evidence that using AI feedback results in better increases in racket velocity or consistency, or in improving movement timing or workload. Explainable AI techniques should also be evaluated to determine which of the temporal, kinematic or EMG features caused the deviation to be detected, which the coach can then use to check. The possibilities of computer-vision methods and markerless motion capture seem to be promising alternative technologies to be used in racket-sport analysis. However, current evidence suggests that there are a number of limitations in the current video sampling and pose-estimation accuracy [22]. Finally, recent studies in the field of tennis science have pointed to another research axis related to AI and related technologies in tennis [17] that is emerging.

VII. CONCLUSION

The forehand should be viewed as a series of movements of many segments. The timing and sequencing of the neuromuscular activation of segments seems to be as important as the size of the individual muscle's activation. Combined kinematic and sEMG measurements have recently demonstrated that better performance may be linked to finer coordination and more specifically, to differences in the activation of muscles [8]. The results provide a basis for the proposed AI-assisted coaching framework. It integrates wearable sensing and signal processing, machine learning and explainable pattern analysis, with expert informed pedagogical feedback.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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