Classification of Tennis Serve According to Players' Experience through Wearable Motion Capture Technology

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***Abstract*— Tennis is a sport that demands an outstanding level of hand-eye coordination, speed, flexibility, and practice. It contains numerous stroke techniques; however, serving is critical for an effective beginning to the game. To complete the action correctly, prevent injury, and give corrective feedback to players, it becomes essential to observe the players' body movements, as well as the joint angles involved in the movement. Analyzing the dominant arm's motions in the three-dimensional plane during the serve uncovers information about the stroke. In addition, since the movement occurs in a so short period, coaches may struggle to comprehend it from its location or point of view. Therefore, in this study, tennis serves performed by professional and beginner players were classified using various machine learning algorithms. Wearable motion capture technology was used to collect upper limb joint movements from 14 players, seven amateurs, and seven professionals. The upper extremity joints, including the wrist, elbow, and shoulder, had their range of motion calculated. Six classification algorithms including LDA, SVM, kNN, and EL were used to determine accuracy, recall, and precision. As a result, EL produced the best classifier with 96.3% accuracy. Additionally, the three-dimensional movements exhibited by the players in each joint were compared comprehensively. Wearable motion capture technology has accurately identified players based on their experience; thus, players can gather immensely useful feedback for objective evaluations.**

Keywords*— *biomechanics; human motion analysis; machine learning; tennis serve; wearable motion capture.

I. INTRODUCTION

Tennis is a sport that needs cerebral hand-eye coordination, as well as balanced and synchronized movement of the entire body [1]. Good coordination, endurance, flexibility, speed, and strength are all necessary for success in this sport. In addition, developing an effective stroke skill takes considerable practice. The stroke is the motion of swinging the racket to make contact with the tennis ball. A proper stroke technique not only leads to achievement in sports but also reduces the risk of injury [2]. The primary strokes are the backhand, forehand, smash, volley, and serve [3]. Examining the range of motion (RoM) and positions of the upper extremities of the body during the tennis stroke might provide helpful insights in determining whether the technique is correct [4].

The tennis serve, which begins the play and must be used in every game, is one of the most critical moves for getting the match off to its best possible start. This stroke method is impacted by the ball's speed as well as interdependent anthropometric, biomotoric, and biomechanical factors that comprise a complicated totality [5]. A coordinated movement takes place along three axes in the player's dominant arm, particularly at the shoulder joint. To hit the ball in the hand, the player rotates his arm rearward. At this point, shoulder rotation has a significant impact on a player's ability to generate force while hitting. When the ball reaches its highest position, the player fulfills the maximum flexion angle of the shoulder joint and shoots it with full effort. Following the serve, the arm and racket go to the front, where the balancing procedure for the subsequent move begins. Everything that happens culminates in a stroke technique that takes both skills and training [6].

Convenient training and a skilled coach may assist in enhancing serve technique to a high level [7]. Whether or not the stroke is performed satisfactorily by beginner tennis players is determined by the coach's observation of the movement without microscopic details. However, since the serve is performed swiftly and in a three-dimensional plane of motion, observation can be challenging and the movement may be evaluated subjectively [8]. The coach's perspective and position during the serve may also influence the player's evaluation. Therefore, a system that evaluates the player and identifies the best serving style may boost the feedback mechanism for players.

Nowadays, the motion of players regarding tennis serve may be monitored because sensor technologies that are lightweight and portable produce highly reliable results [9]. Wearable motion capture technology allows players to perform their moves without changing the nature of the serve. All of the player's motions can be reconstructed in the computer environment and modeled using a variety of computational techniques. However, interpreting and assessing the massive amounts of data generated by these sensor arrays requires in-

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depth analysis and strenuous effort. Hence, well-known machine learning algorithms can handle this issue.

Perri et al. implemented a machine learning that classifies forehand, backhand, and serve stroke techniques [10]. A motion capture sensor was mounted on each of the eight junior-elite tennis players to collect data. The prototype algorithm achieved an accuracy of 94% on the forehand, 74% on the backhand, and 98% on the serve. However, the use of only one sensor in the study makes it difficult to comprehend this highly intricate movement. They also indicated that improved approaches to classification were necessary in their studies. Ye et al. proposed a motion capture system for tennis serve training [11]. They installed three 9-degree-of-freedom (DoF) sensors, that can communicate via Bluetooth, to the ankle, wrist, and racket, but only collected data at a sample frequency of 30 Hz. They also captured the players' body motions using a high-speed industrial camera. Wrong serve strokes were classified using the convolutional neural network (CNN) method with 98.2% accuracy. They stated that the system they developed would provide quantitative tennis serve outcomes and training recommendations without being affected by environmental conditions. However, the system they use is not sufficient to measure the joint angles of the players and wrong serve prediction may not be accurate due to the small number of sensors and image-processing techniques. In another study, Li et al. attempted to estimate the best tennis serve stroke using video image processing [12]. In the study, the arm joints of 20 young elite male tennis players were colored and video records were acquired. A tennis serve model was created using the trajectory of the shoulder point and found the properties of the best ball-hitting point. They suggested that determining the stroke point could aid effective serve. However, approaches based on image processing allow for 2D analysis, which may result in more inaccuracies than three-dimensional methods. In another study by Sharma et al where they evaluated the tennis serve, a smartwatch, which has a 100 Hz sampling rate inertial measurement unit (IMU) sensor with 6 DoF, and a video camera were used [13]. Data were obtained from 49 tennis players, including professionals and amateurs, and the phases of the serve (start, trophy pose, cocking position, impact, and finish) were classified with the logistic regression method with 87.4% accuracy.

The motivation of this study is that there is no more comprehensive study on the joint movements of the players by classifying the upper extremity joint movements according to experience for the serve stroke. Another objective of the study is to identify the tennis serve in more depth using more sensors with high accuracy. For this reason, in this study, an appropriate stroke style was classified using machine learning algorithms and wearable motion capture technologies encompassing the entire body.

II. Materials & Methods

A. Data Acquisition

A total of 14 athletes were included in the study, consisting of 7 (5F, 2M) amateur tennis players and 7 (3F, 4M) pros, who did not have any health problems. Professional athletes have an average of 12 years of experience, whereas amateur athletes have an average of 1 year. Initially, the subjects' anthropometric measurements (body size) were obtained. These are the subjects' height, foot length, arm span, shoulder height, shoulder width, hip height, hip width, knee height, and forearm length. The measurements were taken by a single individual to ensure that they did not differ from one another.

One of the wearable motion capture technologies, Rokoko SmartSuit Pro (Copenhagen, Denmark), is a system made up of 19 IMU sensors that are hidden inside the suit [14]. These sensors have 9 DoF: 3-axis gyroscope, 3-axis magnetometer, and 3-axis accelerometer. These points, which are deliberately designated on the suit, have the ability to capture all joint ranges of motion and positions. Sensor locations are given in Fig. 1a. The suit is composed of flexible fabric with straps at the sensors' locations to avoid slippage during movement. Sensors within the suit are connected together by cables, which are then attached to the HUB. Thus, the control unit receives all sensor data and prepares it for transmission. The HUB operates with an external power bank, so there is no need to give the suit with wired electricity. In addition, this HUB connects using WIFI in the 5 GHz bandwidth and is capable of a sampling rate of 100 Hz. The obtained data is simultaneously transferred to Rokoko Studio (v1.20.5r, Copenhagen, Denmark) software, and simulated by a rigid body diagram (Fig. 1c), and mass data is recorded for later processing. Before beginning motion, anthropometric data were assigned to the Rokoko Studio software to ascertain that the sensor positions on the Rokoko SmartSuit Pro matched the rigid model generated.



Fig. 1. a) Layout of sensor locations of Rokoko SmartSuit Pro, b) Obtaining data from the volunteer while performing the serve-hitting, c) Modeling a tennis player in the software while performing the movement

The subjects were informed about the experiment and asked to serve once only. Rokoko Studio was used to calibrate the sensors prior to the measurements. During the calibration process, subjects were requested to remain straight and stick their hands to the body, for 3 seconds without moving. Software calibration resets potential sensor drifts and corrects faults in the initial locations. The subjects did not have any obstacles restricting movement, and any implants regarding limbs that would hamper movement. The data collected from the individuals was transferred to the MATLAB (v2023b, MathWorks, Massachusetts, USA) software for processing in CSV format.

10 of the 19 sensors' data were focused on since the movement occurred in the upper extremities. These are the hands, forearms, arms, shoulders, and spines for both the right and left sides of the body. From these sensor data, the duration

of the movements and the RoM of the shoulder, elbow, and wrist joints according to three axes were calculated in degrees. Also, the maximum, minimum, and range values of the motion were calculated. Since the major angle measurement exhibited by the joints in the serve is flexion-extension, the movement average and variances of all players throughout time were determined to identify deviations between players in this plane.

B. *Extracting Features*

Flexion extension (flex-ext), abduction-adduction (abd-add), external-internal rotation (exter-inter), ulnar-radial deviation, and pronation-supination (pron-sup) angulations for the joints were calculated. To extract features from these data, the duration of movement, maximum, minimum, average, median absolute deviation, standard deviation, variance, skewness, kurtosis, entropy, energy, interquartile range, and range of motion values were calculated in each plane [15]. A total of 218 features were obtained.

C. *Machine Learning Algorithms*

Features were exported to the MATLAB classification learner app and 10-fold cross-validation was applied. The classification performances of linear discriminant analysis (LDA), support vector machine (SVM), k-nearest neighbors (kNN), and ensemble learning (EL) were calculated [16]. In addition, the performance metrics computed for these classifiers are accuracy (ACC), the area under the ROC curve (AUC), recall (Rec), precision (Prec), and F1-Score [17].

III. Results

The maximum and minimum values of ROM in each anatomical plane during the movement are shown in Table I. The values in this table for beginning and professional players represent the average of all players in the group. A 5° difference was observed in pro players' maximum shoulder flexion movement compared to beginners. It has been determined that pro players serve at a wider angle. Similarly, pro players moved at higher angles in abd-add and exter-inter movements. In addition, it was found that beginner and pro players had a similar range for the flex-ext movement, but there was a significant difference of around 26° in the abd-add movement.

TABLE I. Mean Values of Motion Angles of the Shoulder Joint for Beginner and Professional Players According to Three Different Planes

Shoulder Joint		Max (°)	Min (°)	Range (°)
Flexion	Beginner	120.27	-23.82	144.09
Extension	Pro	125.43	-16.82	142.25
Abduction	Beginner	69.21	-29.92	99.13
Adduction	Pro	75.33	-50.44	125.77
External Internal	Beginner	64.21	-45.34	109.55
Rotation	Pro	70.21	-31.28	101.49

In the elbow flex-ext movement, pro players have approximately 8° differences at their maximum (Table II). In the pron-sup movement, however, pro players generated the largest difference of 28° when compared to beginners. The movements in both planes revealed a difference of roughly 9° and 24° between the RoMs.

TABLE II. Mean Values of Motion Angles of the Elbow Joint for Beginner and Professional Players According to Three Different Planes

Elbow Joint		Max (°)	Min (°)	Range (°)
Flexion	Beginner	103.59	4.30	99.29
Extension	Pro	111.49	2.57	108.92
Pronation	Beginner	24.28	-31.11	55.39
Supination	Pro	52.29	-27.17	79.46

In the wrist joint, beginner players have approximately 11° higher angles for the maximum on pron-sup movements (Table III). Also, there was a significant difference of 33° in the minimum of the same plane in favor of pro players. The players' movements in the other planes are quite comparable. However, pro players had a 4° better RoM in flex-ext.

TABLE III. Mean Values of Motion Angles of the Wrist Joint for Beginner and Professional Players According to Three Different Planes

Wrist Joint		Max (°)	Min (°)	Range (°)
Flexion	Beginner	71.86	-24.31	96.16
Extension	Pro	75.90	-24.41	100.31
Ulnar Radial	Beginner	28.26	-39.97	68.23
Deviation	Pro	27.83	-38.03	65.86
Pronation	Beginner	48.69	-21.56	70.25
Supination	Pro	37.05	-54.64	91.69

Fig. 2 illustrates the shoulder joint motion performed by choosing a beginner and a pro player to highlight the differences between the players. It was evident from the graph that the pro player stretched the shoulder better, around 170°, and executed the action more quickly.

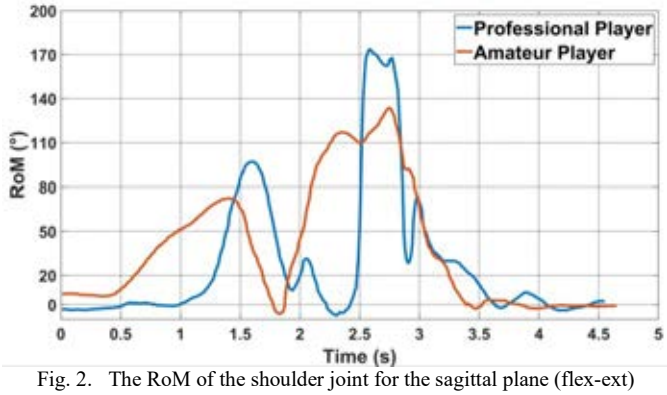


Fig. 2. The RoM of the shoulder joint for the sagittal plane (flex-ext) according to player experience

Furthermore, the variance and average graph that were computed for every player provide an improved overview of this difference. The variance is minimal because pro players' shoulder joint motions produce remarkably similar results, as indicated in Fig. 3. In addition, all pro players executed their moves around one in three times faster. Beginner players have a higher variance, which causes the graph to span a larger region.

All performance metrics of the classifiers are given in Table IV. EL attained the highest accuracy (96.3%) among the classifiers, whilst LDA had the lowest (88.9%). Although SVM and kNN give the same accuracy value (92.6%), there are differences in other performance metric results.

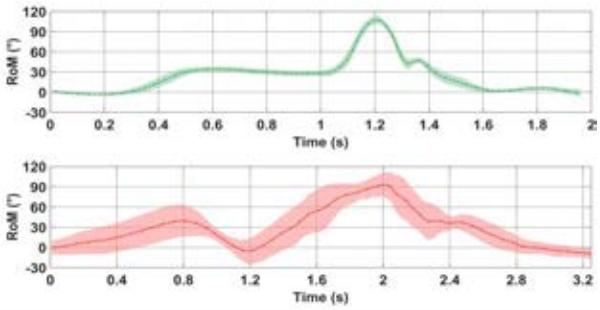


Fig. 3. Mean and variance of the motions of the shoulder joint in the sagittal plane for professional (green) and beginner (red) players, respectively

TABLE IV. PERFORMANCE METRICS OF CLASSIFIERS

Model	*ACC*	*AUC*	*Rec*	*Prec*	*F1*
LDA	**88.9**	0.89	1	0.77	0.87
SVM	**92.6**	0.99	0.87	1	0.93
kNN	**92.6**	0.98	0.92	0.92	0.92
EL	**96.3**	0.95	1	0.92	0.96

IV. DISCUSSION & CONCLUSION

Since tennis is a sport that relies substantially on the upper extremities, this study concentrated on shoulder, elbow, and wrist motions. The shoulder has the broadest range of motion, and the more it is stretched during the stroke, the quicker the ball moves, making it more difficult for the opponent to counter. This study revealed that pro players had high RoM values during shoulder flex-ext motions. Figures 2 and 3 demonstrated the difference more explicitly. On the other hand, there has been virtually no research on the issue. Especially the angles during serve provide good feedback for players and offer objective evaluation. The sensors' 9 DoF and lack of impediment to movement make them suitable for such studies. This technology can also generate a three-dimensional movement trajectory. In this study, the assessment was focused on angles, however, the number of features can be expanded by computing joint positions. Peri et al. classified tennis stroke techniques, they used a single sensor and achieved 98% accuracy [10]. However, since the stroke techniques are so distinct, they are simple to recognize. In our study, we performed a single-stroke style as the serve of players with different experiences. As a result, identifying between them becomes challenging since our movements are so similar. Despite this, a high performance of 96.3% was accomplished. In Ye et al.'s comprehensive tennis serve training system, they were able to recognize the wrong serve with a rate of 98.2% [11]. However, the performance of this study, which employs both the IMU and the camera system and concentrates on image processing, is outstanding. However, the study focused on wrong serve strokes rather than experience. The performance of the classifiers was assessed by collecting a motion dataset using Rokoko SmartSuit Pro, which hadn't previously been used for this purpose. EL exhibited considerably high performance; nevertheless, to further improve performance, alternative features or all sensors can be utilized instead of the 10 sensors used in this study. But this may increase the computational cost. This study offered highly beneficial outcomes for the development of a system that can deliver feedback to players. The feedback mechanism for players' serves can provide objective evaluation and a three-dimensional solution to this problem.

ACKNOWLEDGMENT

This study was supported by TÜBİTAK 2209-A research project support programme as project number 1919B012319790 for İnci Kanat's undergraduate research project.

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