WEARABLE MOTION SENSOR BASED PHASIC ANALYSIS OF TENNIS SERVE FOR PERFORMANCE FEEDBACK

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ABSTRACT

Recent trends show that wearable devices embedded with high-range sensors play a significant role in tracking health and fitness, including sports activities. For crucial analysis of tennis as a sport, this paper describes a serve analytics engine that provides feedback to players for enhancing their serve performance while preventing potential injuries. By utilizing the information of inertial sensors from the wrist of a player and using serve kinetics, the engine segregates sensor signals into various serve keypoints: start, trophy pose, cocking position, impact and finish. Motion between these keypoints constitutes serve phases like backswing, pronation, follow-through, which are compared against corresponding phases of professionals or related statistics in biomechanical studies. Such comparisons using machine learning techniques enable us to provide players with insights into their playing styles and corrective feedback.

***Index Terms*—** Tennis Serve, Wearable Sensors, Feedback, Backswing, Follow-through

1. INTRODUCTION

Increased penetration of miniaturized sensors into wearable devices has led to a rise in the number of health & fitness analytics solutions. For swing based games like tennis, golf, baseball, various commercial solutions have been developed that keep track of a player's game. However, no solution provides the essential qualitative analytics related to game performance enhancement and injury prevention. In tennis, it has been established that serve is one of the most important techniques and its perfection is imperative for success in the sport [1]. In this paper, we propose a comprehensive analysis of serve based on the sequential segmentation of the serve swing. The data is captured using motion sensors embedded in a wrist-worn wearable. We develop an approach to identify serve keypoints and based on them, prime phases of serve like backswing, pronation, follow-through are studied for an in-depth analysis. Backswing type, backswing consistency and correctness of follow-through are benchmarked against professionals, to suggest recommendations for improvement and injury prevention. We also examine pronation during impact, which is an important contributor in serve speed, and speed has been shown as the most correlated variable with the tennis performance level [2].

Earlier, in [11], we had discussed a system for shot detection and classification in tennis. The system detects and classifies tennis shots (including serves) with high accuracy. In an attempt to address the missing analytics related to qualitative performance, this paper discusses phasic analysis of tennis serve, using only sensors on wrist. This also eliminates the need of any expensive device or setup for this purpose. We provide insights to players for improving their serve technique and game performance.

2. RELATED WORK

Researchers have primarily adopted two distinct approaches for tennis serve analysis. The first approach is modeling and detailed study of anatomical motions of body in serve kinematics and injury prevention. In a series of publications [3, 4, 5, 6, 7], key contributor segments to mean linear velocity of racquet head were identified through videography and electromyography analysis. In [8], Kovacks et al. studied sequential segmental rotations in serve kinetic chain, and proposed an 8-stage partitioning for tennis serve that could better explain potential areas of injury. Elliott et al. [9] did analysis on serve actions with full and abbreviated backswings and claimed that the full backswing technique should be preferred because it involves applying lesser loads on shoulder.

Another approach has been to correlate data derived from camera or inertial sensors to comment on skill level of serve. In [10], Ahmadi proposes a method for assessment and acquisition of skill for athletes by measuring rotations of key contributor segments between point of maximum knee flexion and impact during first serve. Another study by Sogut [2] showed significant and positive relationships between serve speed and International Tennis Number (ITN) in males (Pearson's correlation coefficient r = 0.678)

In this paper, we propose a novel framework based on the combination of above two approaches. Utilizing studies of serve kinematics modeling, we present phasic analysis of serve data obtained from just wrist-worn inertial sensors, which helps in enhancing player performance. Continuing from our previous work in [11], we first develop an algorithm to identify serve keypoints as suggested in [8]. Then, based on stages within serve, salient performance features like backswing type, pronation score, follow-through score and backswing consistency are analyzed.

3. EXPERIMENTAL SETUP

We have used Samsung smart watch Gear S2 to capture and store inertial sensor data, and a 30Hz video recorder to record the video of tennis sessions. The wearable has 3-axes accelerometer with dynamic range of $\pm 8g\ m/s^2$ and 3-axes gyroscope with range of $\pm 2293.62 degrees/s$ as shown in Fig.1. The sampling rate is 100Hz. Data of 1844 serves were collected from 49 players of tennis academies (mix of professionals, amateurs, children and girl players). Serves were tagged in data using a video sync tool built in-house. The videos and the sensor data are synced in time and further utilized for validating correctness of the subsequently developed algorithms.

4. SERVE STAGES

As serve involves a series of kinetically linked actions of multiple body segments, it is divided into stages which are then studied in

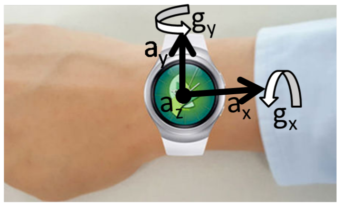
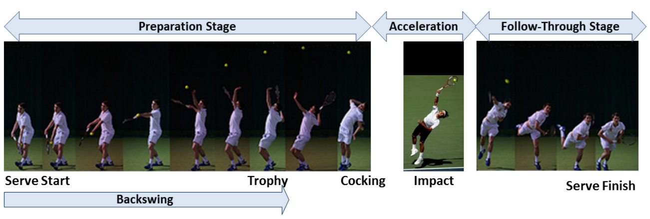


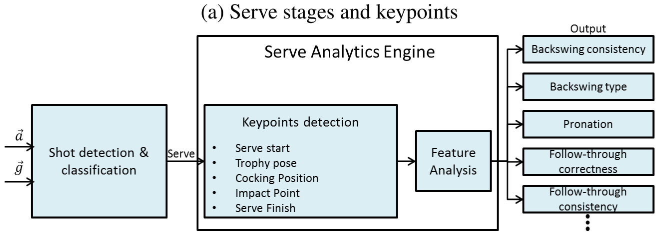
Fig. 1: Axes in the wearable device

detail. Tennis serve is partitioned into three broad stages - Preparation, Acceleration and Follow-Through [8] as shown in Fig. 2a. The preparation stage is defined from the start of hand movement of a player during serve until the maximum external rotation of the shoulder. Within this stage, the segment between serve start and trophy pose is called backswing. Next stage is the acceleration stage, which ends at ball impact. The last is the follow-through stage, post ball-impact until the serve motion ends. These stages are further partitioned into - start, release, loading and cocking (preparation stage), acceleration and impact (acceleration stage), deceleration and finish (follow-through stage) [8]. In-depth analysis of the player's actions in these stages is necessary to enhance serve performance and to avoid potential causes of injury.

The system design of serve analytics engine is shown in Fig. 2b. The shot detection and classfication developed in [11] utilize the 3-axes accelerometer (a_x, a_y, a_z) and gyroscope (g_x, g_y, g_z) data from a wrist-worn wearable, to detect a shot region and classify it as serve, forehand or backhand. For serve analysis, the detected serve region from the sensor data is used in the keypoints detection module. Using these keypoints, prime performance features in the various phases are studied and recommendations are output.



(a) Serve stages and keypoints

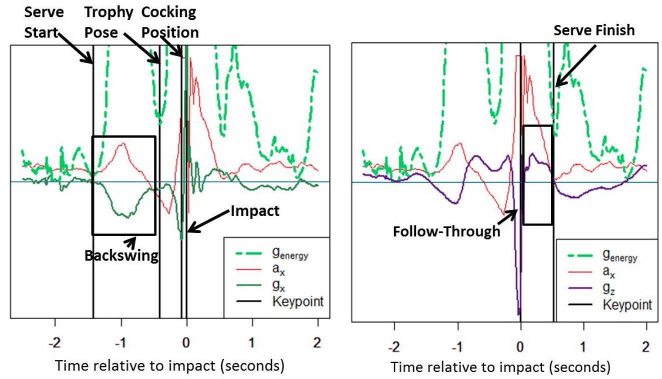


(b) System Design

Fig. 2: Serve analytics engine for analyzing serve stages

5. KEYPOINTS DETECTION

In order to perform analysis of the player's serves, it is important to first identify the start and end of the aforementioned phases in the sensor signals of detected serves, as shown in Fig. 3. The following subsections explain the behaviour of sensor signals for detecting different keypoints - serve start, trophy pose, cocking position, impact point and serve finish, and the algorithms followed to obtain them.



(a) Backswing phase and keypoints (b) Follow-through phase and finish

Fig. 3: Signals with identified serve keypoints and phases

5.1. Impact Point

For serve analysis, we begin by determining the impact point in the signal as it helps us to set empirical windows relative to the impact position for detecting other keypoints. It is observed that the impact point is characterized by a sudden jerk in the high values of accelerometer and gyroscope signals. This jerk is seen because hitting the ball at a high speed for a momentary time duration(5-6 ms) [12] transfers impulse on the racquet and ultimately to the wrist. To utilize jerk for calculation of impact point, we define:

$$\begin{aligned} &J_{a_{axis}}(i) = |a_{axis}(i+1) - a_{axis}(i)| \\ &\forall i \in [1 : length(serve\ signal) - 1], axis \in \{x, y, z\} \end{aligned} \tag{1}$$

Another observation from the video sync tool is that for most of the shots, maximum jerk occurs at (or very close to) the impact point. But often, multiple high-magnitude jerk peaks characterize impact region as the jerk sustains after impact and then dies quickly. It was found using video sync tool that the first such high jerk point is the actual impact. Hence, we reduce *impact point search window* to $0.5s$ before and $0.4s$ after the point of maximum a_x (extending from [11]), and utilize effective jerk function $\mathscr{J}$ (defined in equation 2). There are two advantages of using $\mathscr{J}$, firstly it emphasizes the start of jerk and suppresses the immediate following jerks and secondly, J_{sum}, which is the sum of jerks is weighed equally at high jerk values (due to clipping) to obtain candidate points for impact. For the calculation of $\mathscr{J}$, only a_y and a_z are considered for the entire sequence if a_x is clipped beyond $8g$ (dynamic range of sensor)

$$\begin{aligned} &\mathscr{J}(i) = \\ &|J_{sum}(i)| * |J_{sum}(i) - J_{sum}(i-1)| * |J_{sum}(i) - J_{sum}(i-2)| \\ &where, J_{sum}(i) = min(norm(J_{a_x}(i) + J_{a_y}(i) + J_{a_z}(i)), 0.5) \\ &\forall i \in \textit{impact point search window}; \text{normalisation is done in [0,1]} \end{aligned} \tag{2}$$

The following Algorithm 1 applies a fuzzy logic over candidate points (3 points considered) to find the impact point in the signal. We validated the correctness of calculated impact point index against the observed impact point index from the video sync tool, and the average error was found to be 22ms.

5.2. Serve Start

The start of a serve is marked by disturbance in the signal stability due to the beginning of backswing. Outwards rotation of the forearm

Algorithm 1 Impact Point Index

procedure IMPACTPOINTINDEX
    $p, q, r \leftarrow$ Indices of first 3 maximum in $\mathscr{J}$ ▷ p,q,r are in chronological order
    $max\_jerk \leftarrow max(\mathscr{J}(p), \mathscr{J}(q), \mathscr{J}(r))$
    for `i in` $\{p, q, r\}$ **do**
        if $\mathscr{J}(i) >= 0.8 * max\_jerk$ **then** ▷ For a jerk to be considered for impact point, the $\mathscr{J}$ value should be significantly high (at least 80%) compared to the max_jerk
            $impactIndex \leftarrow i$
            `break`

(supination) causes a negative rise in g_x and centripetal acceleration causes a positive rise in a_x. A negative lobe is generally visible in g_x which terminates at the trophy pose. This part of serve motion is called backswing (Fig. 3a). Preceding the backswing, a dip followed by steep rise in square magnitude of gyroscope signals ($g_x^2 + g_y^2 + g_z^2$), hereafter called as g_{energy}, is also a good indicator of serve start.

By utilizing the described determinants in the sensor values and an empirical time offset from the impact point, the Algorithm 2 and Algorithm 3 are used to fix the serve start in the signal.

Algorithm 2 Backswing Lobe Index

procedure BACKSWINGLOBEINDEX
    $g_{xlimited} \leftarrow g_x[backswingLobeSearchWindow]$
    for `all i in` $1 : len(g_{xlimited})$ **do**
        $g_{xMvgAvg}(i) \leftarrow moving\_average(g_{xlimited}(i))$ ▷ moving average of 21-points, centered at i
        $A(i) \leftarrow g_{xMvgAvg}(i) * g_x(i) * signum(g_x(i))$
    $backswingLobeIndex \leftarrow$ *index of minimum*(A)
    $backswingLobeWeight \leftarrow A[backswingLobeIndex]$

Algorithm 3 Serve Start Index

procedure SERVESTARTINDEX
    $backswingLobeIndex \leftarrow$ BackswingLobeIndex()
    $serveStart \leftarrow (impactIndex - 80ms)$ ▷ Empirical
    if $backswingLobeWeight < -40000$ **then**
        $serveStart \leftarrow backswingLobeIndex - 20ms$
    $serveStart \leftarrow$ first local minima of g_{energy}, within a window of 200ms before $serveStart$ index with magnitude less than 15000

5.3. Trophy Pose

The end of the backswing is marked by the L-position or trophy pose as shown in Fig. 2a. The value of a_x in this position falls close to 0 because of negative acceleration along $x - axis$ due to gravity and reduced centripetal acceleration. A local minima in the g_{energy} and also in g_x is observed due to the decreased rotational velocity.

As the trophy pose occurs roughly around the mid of serve start and impact, we find a window in the signal where a_x is in the range of $[-7, -2]m/s^2$ (empirically determined). The trophy pose is shown to be at the index where low-passed g_{energy} attains a minima in this window, as seen in Fig. 3a.

5.4. Cocking Position

After reaching the trophy pose, the arm starts extending outwards in order to generate racquet speed and the point of maximum shoulder external rotation is the cocking position or backscratching position. During this motion, the centripetal acceleration and the angular acceleration decreases along a_x and g_x respectively (outwards radius of curvature). From this position, the player starts accelerating and pronating on the racquet which causes a sudden increase in angular velocity along g_x. Utilizing this characteristic in a pre-defined window (60 to 200 ms before impact), the point of local minima in g_x, which also has the highest rate of change in g_x, is shown to be the cocking position in the sensor signal.

5.5. Serve Finish

After the ball impact, the pronation persists and dies down slowly along with the centripetal acceleration and rotational energy. This phase is called the follow-through. The serve finish is at the end of follow-through where there exists a momentary pause in the motion and the rotational velocity in g_z is very low, as shown in Fig. 3b.

The empirically determined serve finish time is generally 0.3 to 0.7 sec beyond the impact point. In this window, the point where a_x value is below a pre-defined threshold ($16m/s^2$) and g_z is close to 0 or is minimum in a window starting from this point and ending 200ms later, is identified as the serve finish.

6. FEATURE ANALYSIS AND RECOMMENDATIONS

For a set of serves by a player, we define key performance features in the different serve phases to provide basic insights and suggest recommendations for improving the serve.

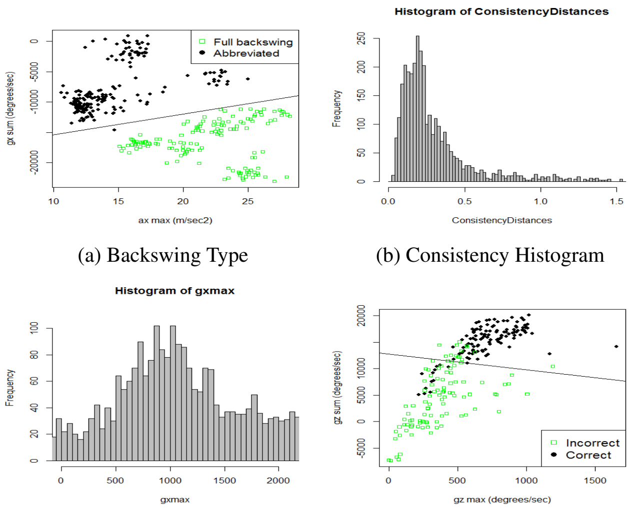
6.1. Backswing type

Backswing styles have been broadly characterized into two classes - full and abbreviated. Full backswing is the classical method for backswing where the forearm is extended outwards and back, involving full rotation of shoulder joint. In abbreviated, the racquet is lifted vertically during early backswing. In order to generate more power and from loading perspective, full backswing is a preferred technique [9], whereas coaches recommend abbreviated backswing if a player has problem in delivering consistent serves. The classification of a player's backswing is thus useful in suggesting appropriate recommendations or simply provide information to the player.

6.1.1. Backswing Classifier

For analysis of backswing, 341 tagged serves from 10 players (2 professionals and 8 average players) are used. Observing the signals in the backswing region shown in Fig.3a, statistical features of the 3-axes accelerometer and gyroscope signals along with backswing times are studied to develop a linear model using SVMs. Training data includes 8 players' data (containing 80% of serves).

It is found that only 2 features $a_{x_{max}}$ and $g_{x_{sum}}$ (maximum value of a_x and sum of g_x) are sufficient to distinguish the two classes (Fig. 4a), mainly because more shoulder joint rotation($g_{x_{sum}}$) and longer backswing path in full backswing leads to higher centripetal acceleration ($a_{x_{max}}$). The testing data consisted of remaining 20% players' serves. The classification accuracy is 100% on training set and 98.3% on testing set.



(a) Backswing Type

(b) Consistency Histogram

(c) Pronation Histogram

(d) Follow-through correctness

Fig. 4: Serve analysis in identified phases

6.2. Backswing consistency

The concept of swing consistency is same as in [13]. We utilize it for analysis of serve backswing using a modified approach. Having consistency in the backswing helps a player deliver more confident serves. It is also an indicator of inconsistency in ball toss height, as inconsistent ball tosses induce backswing inconsistencies.

6.2.1. Consistency Calculation

The wrist movement of players during the backswing can be captured well in the changing orientation of the wrist, represented by quaternions. Thus we calculate quaternions using gyroscope values, for the backswing region of a serve as explained in [13]. This calculation is performed for all the backswings, and to generate equally spaced representation of wrist orientation, the quaternions are down sampled to 25 points using slerp interpolation [14]. Downsampled quaternions capture the rotation information required for consistency equally well and reduce the processing time for further calculations.

Utilizing the fact that for consistent serves, majority of the swings should be close/similar to the medoid, we use distances of backswings from the medoid backswing to measure consistency. The similarity measure used for distance calculation is given in equation 3, where $quatDist(quat1, quat2)$ is the quaternion distance measure, d_q from [15]. To provide a quantitative measure to backswing performance of a player, consistency score is calculated.

$$distance(i,j) = \sum_{k=1}^{25} quatDist(backswing_i[k], backswing_j[k])$$
$$\forall i,j \in [1 : length(InputBackswings)] \tag{3}$$

6.2.2. Scoring Methodology

Data of 1844 serves from 49 players are used to generate a distribution of distances of serve backswings' quaternion series. For each player, distances of his/her backswings from his/her medoid backswing are calculated, thus giving us 1844 distances. For the scoring mechanism, we generate 100 equally probable bins of distance range, which can represent scoring bins. As the data collected are mostly from better-than-average players, the distribution is slightly skewed and does not represent universal player set. To overcome this, the values higher than the median distance were duplicated to generate synthetic data for scoring bins (Histogram in Fig. 4b).

For a set of backswings of a new player, medoid and the distances of all the backswings from the medoid are calculated. To make sure that processing does not take too much time for large sets, we take a random sample of atmost 50 serves. Accounting for the errors in any of the pipeline stages, including keypoints calculation, we remove 10% backswings with the highest distances as outliers. For the remaining, depending on the bin number in which the average distance lies, consistency score is provided from 1 to 100.

6.3. Forearm Pronation

Sprigings et al. [6] showed that forearm pronation has 15% contribution in racquet head speed at impact, hence making it a key contributor in determining serve speeds, and indirectly game performance.

The amount of pronation is directly correlated to the internal rotation of forearm near ball impact which is captured in g_x. In order to provide a pronation score to the players, the maximum value of g_x is used in a pre-defined window of 50ms (to account for error in impact point calculation (5.1)) around the impact point. The scoring methodology used is same as in 6.2.2, where the distribution is of maximum g_x values. Using histogram from 1844 shots (Fig.4c), 100 equi-probabale bins are made, and a score from 1 to 100 is provided to the player. Good player has higher value for $g_{x_{max}}$.

6.4. Follow-through Correctness

After hitting the ball, the racquet is still moving at a high speed and a proper follow-through gives longer distance for racquet to slow down. This reduces the strain on the player's arm, eventually lowering chances of injury [16]. Thus, feedback is provided to players by classifying their follow-through as being correctly performed or not.

6.4.1. Follow-through Classifier

In order to differentiate the follow-through action of a player, we use 226 tagged serves from 8 players. Observing the videos, the follow-throughs are manually tagged for their correctness and validation is done against these tags. We developed a logistic regression model for classification using the training data of 80% of tagged serves. The region of interest starts 60ms after impact (as the high intensity motion ceases), ending at the serve finish. The features used for classification are $g_{z_{max}}$,$g_{z_{sum}}$ and $settlingTime$ (which is the time from impact to serve finish), as g_z captures the deviation in trajectory of racquet arm in follow-through phase. Feature-space difference between two classes can be seen in Fig. 4d. The testing data consisted of remaining 20% of serves. The classification accuracy was 86.6% on training and 87.4% on testing set.

7. CONCLUSION

We developed a mechanism to partition serve into key phases, proposed features that can be derived out of phasic analysis of inertial sensor data like backswing type, consistency, pronation, follow-through; and provided relevant feedback subjectively or through score to the player. We delved into biomechanical aspects of serve that could help a player recognize key areas of improvement, or identify potential causes of injury, thus impacting performance. The current work can be extended to analyze other features like classify slice/kick serves, determining racquet grip or determining power generation from racquet drop. The proposed analysis can be extended to other sports like baseball pitching [17], and volleyball [18] which have a similar kinetic chain modeling as tennis serve.

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