Efficient Characterization of Tennis Shots and Game Analysis using Wearable Sensors Data

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***Abstract*— Recent trends show that wearable devices with high-range inertial sensors are actively being used for outdoor activities. The paper describes our developed sports analytics engine used for self-learning and/or coach-assisted training for swing-based games like tennis, golf, etc. by utilizing rich set of data collected from these wearable sensors. The sports analytics engine for tennis uses techniques based on modified Pan-Tompkins algorithm for detecting the shot and then uses time-warping based hierarchical shot classifier which uses Dynamic Time Warping (DTW) at first level (forehand, backhand and serve) and Quaternion Dynamic Time Warping (QDTW) at second level (slice and non-slice). Major challenges included distinguishing shots from noise in sensor data, classifying the shots based on information only from wrist of player and capturing the various playing styles across different players. Based on efficacy of the developed engine, we foresee wider usages of the proposed techniques in developing learning applications for swing-based sports.**

I. INTRODUCTION

With latest wearables having embedded inertial sensors, for gaining insights into swing-based games (like tennis, golf etc.), it is critical to develop methods that capture intricacies of hand movement for distinguishing each shot type(eg. Forehand Slice, Serve etc.). We have developed an analytics engine for tennis which processes(detects and classifies shots) sensor data from a wrist-worn wearable, provides game statistics, assesses player's performance and suggests areas of improvement for self-learning and/or coach-assisted training. Shots were detected with 99% accuracy using modified Pan Tompkin's algorithm [1]. We emphasize that Quaternions based Dynamic Time Warping (QDTW) [2] technique provides an efficient means for characterizing different shot/swing types and have achieved 90% classification accuracy. Approaches to derive game features like racquet speed (PS Application No. 3927/CHE/2015), trajectory, consistency etc. are proposed using information from shot detection and classification modules. Based on characterization of a player's shots and comparing them with professional's, we define the concept of consistency in shots and provide recommendations on inconsistent areas and wrist rotation. Such game analysis provides insights into his/her playing style and helps the player improve his/her game strategy.

A. Related Work

Recent trends show that inertial sensor data from wearables are being used for sports application [3], [4]. The work reported in [5] discusses detection of tennis shots based on peaks in accelerometer data and classification into forehand, backhand and serves using machine learning on sensor data from wrist. Various techniques for activity recognition for sports applications etc. using inertial sensors are discussed in [6]. In [7], techniques for detecting incorrect parts in a tennis/squash swing based on machine learning have been discussed. Other work on training a player in tennis include [8], [9], [10], where the authors discuss using multiple sensors or video analysis for recommending improvements in a player's game. Our proposed approach differs from them as we perform sub-classification of tennis shots (along with forehand, backhand and serve classification) and extract game features based on sensors attached only to the wrist of a player.

II. EFFICIENT CHARACTERIZATION OF TENNIS SHOTS

The system design of sports analytics engine is shown in Fig. 1. The 3-dimensional accelerometer(a_x, a_y, a_z) and gyroscope data were collected from inertial sensors embedded in a wearable worn on wrist. The shot detection, identifies the shot region from the sensor data, which is then used in traininig/classifying shot types as well as for game analysis.

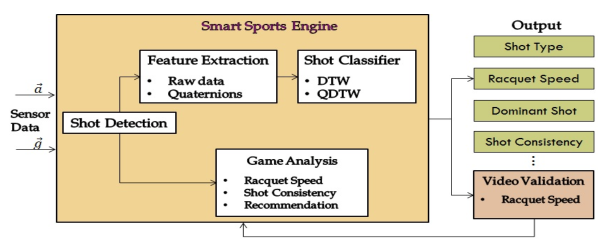

Fig. 1. System Design

III. SHOT DETECTION

The gyroscope and accelerometer data collected from the players have shot patterns as well as noise due to sensor disturbance and player movements. Pan Tomkin's algorithm [1] better suits to isolate shot signal from noise. As shown in Fig. 2, accelerometer signal consists of a sudden spike during a shot.

The x-axis accelerometer data is differentiated and then squared to magnify the output. Subsequently, we perform moving window integration with window size of three times the sampling rate and identify potential shot impact region using thresholding. Impact point of the shot region is extracted by finding global maxima. The start point and end

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point are detected using minima search in backward and forward directions of buffer window, respectively. Since the buffer is processed only if the potential shot impacts were detected, this method is much faster than windowed pattern matching.

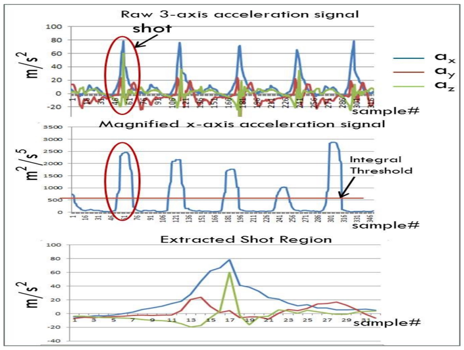

Fig. 2. Shot Detection Steps

IV. Tennis Shot Classifier

The different shot types in tennis are forehand, backhand and serve, categorized further into sub-shot types - flat, topspin and slice. We utilized inertial sensor data to create ideal models/templates for the different shot types and sub-shot types. We then use these templates in our classifier, called QDTW classifier [11], for classifying test shots. It is a two level hierarchical classifier where at first level, classical DTW is applied on accelerometer and gyroscope signals to classify a shot as a forehand, backhand or serve. At second level, we have different templates for sub-types within forehand and backhand and QDTW is applied on quaternion time series calculated for test shots to classify them into sub-shot type.

A. Orientation Estimation using Gyroscope Output

Quaternion (4-dimensional vector{q0, q1, q2, q3}) corresponding to the first sample of the shot is taken as the reference quaternion with values (1, 0, 0, 0). We calculate unit quaternions for complete shot by utilizing gyroscope values and timestamps [12].

Fig. 3 shows the quaternion values for forehand flat and slice.

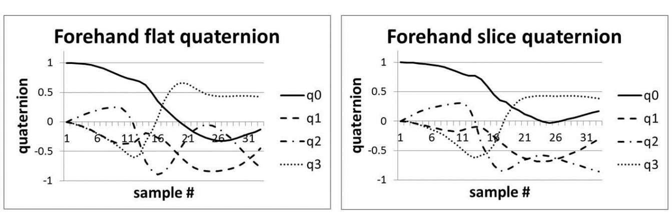

Fig. 3. Quaternions for a forehand flat shot and forehand slice shot of a professional. As it can be seen that the differences in the quaternion values for sub-shot types are minor, we use QDTW rather than classical DTW to capture these subtle differences in the quaternions. domain.

B. QDTW classifier training module

Input to the trainer consists of sets of shots (sensor data and timestamps) labeled with their shot types. To obtain templates for the first level, accelerometer and gyroscope data are normalized based on maximum absolute value found in respective axes data respectively. For the second level, quaternions are calculated for all input shots. The steps followed to obtain template(s) corresponding to each shot type at the two classifier levels are:

1) For the first and second level, DTW costs based on Manhattan distance for all sensor axes individually and QDTW costs [2] are calculated among all shots of a shot type. We have termed *the final cost when QDTW is performed between two shots as* **Q-distance**.
2) K-median clustering is performed for respective levels on magnitude of all gyroscope axes costs and QDTW costs. Medians of only those clusters containing at least 40% or more of total shots of a shot type are used as templates and corresponding cluster radius is used as threshold for classification.

C. QDTW classifier validation module

A shot detected from the detection module is input to the validation module. First, DTW is performed between the shot and the templates at the first level to classify a shot as forehand, backhand or serve. In case of forehand or backhand shot, this output is passed to second level where QDTW is performed between shot and existing sub-type templates at second level to decide flat, topspin or slice. The resultant shot type is determined based on the minimum cost obtained among all costs lying within thresholds, otherwise it is determined based on minimum cost among all calculated costs.

V. Game Analysis

Based on data received from sensors, we aim to summarize player's game. It is challenging to derive key aspects like spin, speed and trajectory of serve using only wrist-worn sensor data. Further, serve and return-shot are also an important part while competing against each other.

For a single player data, each session is segregated into a series of rallies. Rally is detected as a set of shots played between two successful serves. Details of last shot of each rally help the player to learn differentiating factors which may have led him/her or opponent to gain points. We summarize the session into key performance parameters e.g. total number of shots, shot type distribution, number of serves and second serves, speed range, dominant shot type, total playing time, longest rally etc.

Table I summarizes a game played with opponent for 7 min and 24 secs. Both players played 68 shots. Key performance indicators are summarized in the table.

For each session, we define key parameters that provide basic insights to a player and suggest recommendations for improving the game.

A. Racquet Speed

Racquet head speed is calculated using gyroscope data from wearable. It is assumed that while playing a shot, hand and racquet behaves like a rigid body and rotates with

TABLE I : GAME STATISTICS

Parameters	Values/Types
Total Play Time	444.56 sec
Active Time	221.34 Sec
Resting Time	223.22 Sec
Total Shots	68
No of Rallies	7
Longest Rally	45.11 Sec (13 Shots)
First Serves	4
Second Serves	3
Dominant First Serve	Topspin
Dominant Second Serve	Flat
Dominant return	Forehand Topspin
Max Shot Speed	62.56 mph
Average Shot Speed	43.82 mph
Min Shot Speed	28.21 mph
Shot Rate	18 shots/min
Dominant Shot	Backhand Slice

same angular velocity. We model this system (racquet and hand) as a rigid body rotating around shoulder joint of the player (Fig. 4(a)). We estimate angle between upper arm and forearm(θ_1), and angle between forearm and racquet(θ_2) (Fig. 4(b)). For different type of shots, θ_1 and θ_2 range between [130°, 180°] and [100°, 180°] respectively based on experimental observations.

Racquet head speed is estimated as follows:

$$A' = \frac{A}{2\sqrt{2(1-cos(\theta_1))}}; \alpha = cos^{-1}(\frac{A'}{A})$$

$$R' = \sqrt{R^2 + A'^2 - 2RA' cos(\theta_2 - \alpha)}$$

where A is arm length; R is racquet length; A' is effective arm length; R' is effective radius of rotation and ω is angular rotation rate about shoulder joint.

Using effective radius of rotation, angular velocity around impact point is converted to racquet head speed (Fig. 4).

$$\omega = \sqrt{{g_y}^2 + {g_z}^2}$$

$$V = \omega * R'$$

where g_y is angular rate about local y-axis, g_z is angular rate about local z-axis, and V is racquet head speed.

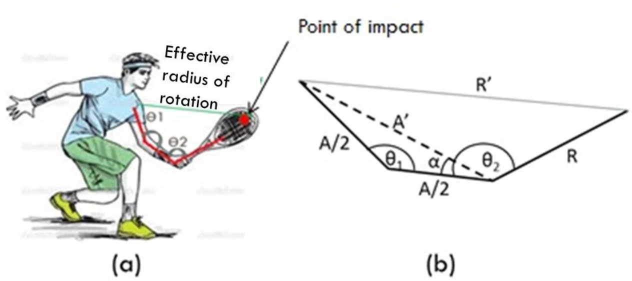

Fig. 4. (a) Estimated Rigid Body Model, (b) Swing Model

Considering ranges of θ_1 and θ_2, this estimation comes within limit of ±5mph.

B. Insights on Shot Consistency

We provide 2 means of ascertaining consistency of a shot-type: 1. Q-distance and 2. Shot-deviation.

1) Q-distance based: If a player plays all his shots of the same shot-type in a very similar way, player's shots are said to be consistent, whereas if a player plays shots of the same shot type with the wrist movement being different for every other shot, the player's shots are said to be inconsistent. Charts as in Fig. 5 are called **consistency plots**. We perform k-median clustering for all shots of a shot type of a player with k = 1 and find the median shot. The center of the consistency plot represents this median shot and all other shots are then plotted in the chart at their corresponding Q-distance from the median shot.

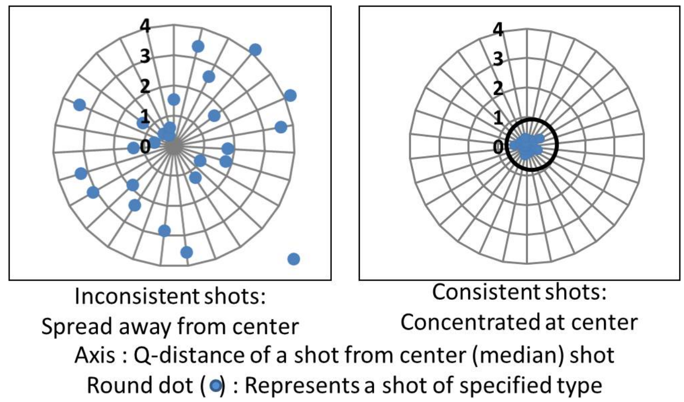

Fig. 5. Q-Distance based Consistency of a Shot-type

2) Shot-Deviation Based: The standard deviation plot derived from gyroscope sequences of all shots of a specific type provides visual cues on determining overall consistency of the shot with that of a professional player. As the impact causes jerks in sensor values, we visualize a spike at the center of the plot and comparatively low deviation values at all other points when a player is consistent in his shots, as shown in Fig. 6. Multiple spikes or multiple positions of spikes indicate inconsistency in where a player is impacting the ball during the course of his swing. On similar lines, a higher deviation in the follow-through region implies inconsistency in follow-through. Recommendations for improvement can be provided to a player based on these insights.

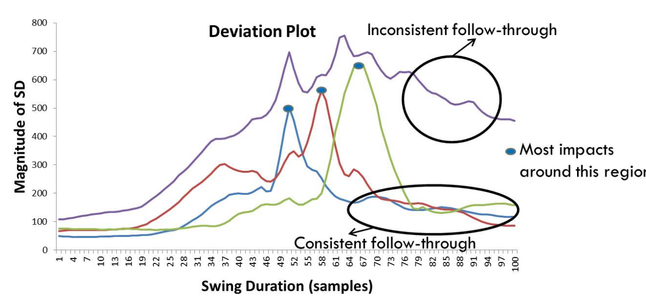

Fig. 6. Consistency of a shot type based on Deviation from Ideal-Shots

C. Recommendation on wrist rotation

The optimal matching path calculated between a test shot and the template which classified the shot at second level is also used to suggest certain recommendations to a player. As QDTW is a time warping technique, it matches paths with different speeds also and this fact is used for recommendations. From Fig. 7, it can be visualized that the region marked in green is the QDTW matching path between two shots – professional's shot samples along vertical axis and subject player's shot samples along the horizontal axis and the various regions in a professional's shot are also marked. A horizontal region of the matching path represents that the subject player is slower in a region, whereas the vertical region shows that the subject is faster and a diagonal region shows exact matching to the professional's change in wrist orientation during the shot. Such insights may also help the player to look into how to vary his wrist orientation as the shot progresses.

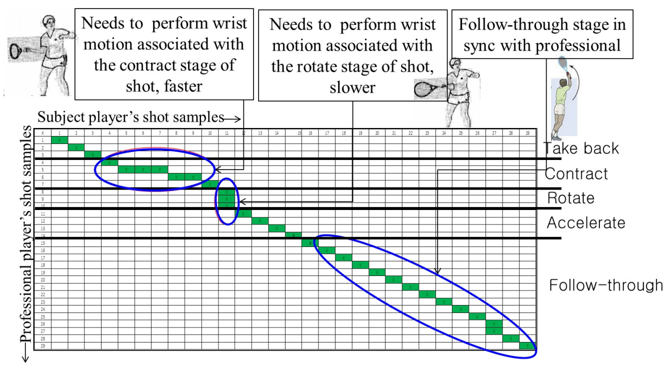

Fig. 7. Q-distance Matrix: Insights for Improvement

VI. Experimental Setup and Results

We have used Samsung smart watch Gear S to capture and store sensor values during tennis sessions. The analysis of this data was done on a smartphone which receives streamed sensor data from the Gear S. The wearable has 3-axes accelerometer with range of $\pm$8g and 3-axes gyroscope with range of $\pm$2000 degrees/s. The sampling rate of the sensors was 25 Hz. Tennis professionals and novice players were requested to play a fixed number of shots of each shot type for training and testing purpose.

The average accuracy of Shot Detection module is $>$99%. The details are shown in Table II for players with varying skill levels.

TABLE II : Shot Detection Accuracy

Player Type	# shots played	# shots detected	Accuracy (%)
Professionals	2676	2665	99.58
Novice	1060	1049	98.96
Total	3736	3714	99.41

To test the classifier, we input X test shots of a shot type x and look at the true positives, say Y reported by the classifier and define accuracy as, $accuracy = (Y/X) * 100$.

TABLE III : QDTW Classifier Accuracy

Classifier Levels	Professional players	Novice Players
First Level(DTW)	99.6	99.3
Second Level(QDTW)	90.7	86.2

The average accuracy at two levels of the classifier - first level (Forehand, Backhand, and Serve) and second level (Non-slice i.e. flat and topspin and Slice shots) for professional and novice players is given in Table III. The accuracy is based on $\sim$1000 number of shots used in the training set (from 5 professional players) and $\sim$1800 number of shots (from 9 subject players) used for testing purposes. We are continuously adding new data to our datasets.

VII. Conclusion

We have described the techniques for efficient detection of tennis shots and their classification into various shot types based on sensors embedded in wrist-worn wearable. Further, we have proposed a novel approach for calculating the racquet speed around ball impact using only inertial sensor data from wrist. We also analyzed player's game and provided basic recommendations for improvement. If opponent data is also available in real time, additional features like return shot type and time-line can be derived using statistical analysis of synchronized sensor data from wearables of both players. This can help the player to analyze game against opponent with specific playing style or skill level. Trends of this analysis over a few sessions can be useful in building strategies and improving game in different playing environments. In the future we plan to provide complete self-learning and/or coach-assisted training by extending our recommendation system and also providing a collaborative learning environment based on ranking etc. among groups of tennis players.

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