Tennis Serve Correction using a Performance Improvement Platform

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***Abstract*—Technology based solutions for analyzing various metrics related to the game of tennis are becoming popular in market. But there is lack of a complete solution to track the effectiveness of training methods adopted for improvement. A platform to assess the effectiveness of these training routines is discussed in this paper. The platform consists of wireless measurement sensors which work in conjunction with software analysis modules. The sensors can measure kinetic parameters in real-time and are attached to the racket and to the player's body. The software module enables visualization of sensor data and evaluates performance. The platform has been made versatile and customizable to enable easy integration with any training procedure involved in performance improvement. In this paper, the proposed platform is utilized to monitor the effectiveness of drills involved in improvement of tennis serves. Methods adopted with inputs from trainers to compute numerical performance indices for tracking progress are discussed. Monitoring these indices computed over several training sessions helps in tracking the player's progress.**

Keywords—tennis training; performance evaluation; motion capture; inertial sensors; tennis serve

I. INTRODUCTION

Tennis is the fifth most widely played game in the world with major participation from Europe, America and Asia. Studies show that 6% of the UK population play tennis and more than 2 million people play it regularly. Latest research according to Tennis Industry Association (TIA) shows that overall tennis participation rose 1% to 17.9 million players in the US, in 2015 [1]. This Participation Study conducted by the Physical Activity Council (PAC) also shows a growth in the number of youth players interested in the game.

All professional sports demand regular and adequate training and qualified training personnel. With the steady increase in the number of incoming players every year, it has become difficult for intermediate tennis players to find qualified trainers. Those who manage to find such trainers usually end up congregated along with similar players. This limits attention given to each player and results in reduced quality of training. While this issue prevails, several technology based solutions surfaced in the market to provide players with detailed information relevant to their game [2].

These solutions employ sensors fixed to racket [3, 4] or camera based imaging methods [5, 6] or wearable sensors [7]. Various quantifiable parameters related to game are provided, using which players can understand their game. Measurement sensors developed by Sony, Zepp and Babolat that are attached to the racket, monitor swing patterns and identify the type of stroke that the player has played. They also estimate kinetic parameters like racket swing speed, ball speed and the location of impact on the racket string bed [8]. A summary of the match session is provided in a comprehensive manner for the players to gain insights and incorporate corrective measures by themselves. Camera based analysis systems use multiple cameras placed on the court to capture player's movements and track game events. These game events include line calls, faults and scoring patterns in addition to those offered by racket sensors. PlaySight [9] is one such tennis analytics technology system that employs 6 high definition cameras to draw out information about the game. Full body motion capture systems such as Pivot by TuringSense [10] gather information about the orientation of body parts with which actions performed by the whole body can be reconstructed. This eliminates the need for a multi camera system to capture 3-dimensional body movements.

Measurement sensors provide only metrics about the game and do not help in observing and correcting actions which are crucial for overall improvement. Camera based systems overcome this limitation capturing player's actions in addition to those parameters offered by measurement sensors. But such systems require an extensive infrastructure and rely on complex post processing and video analysis by domain experts to provide intuitive analysis. This limits the potential users of such solutions to sponsored players. Wearable sensor based motion capture systems simplify this problem by providing the benefits of camera based systems at a lower budget. However, these systems provide only a tool for detailed visualization of motion without focus on improvement tracking. Performance enhancement requires a variety of carefully designed training routines and methods to ensure adherence and tracking. None of the solutions listed above incorporate such distinct procedures to improve performance.

This paper introduces a sophisticated training technology platform to aid trainers provide players with effective training. The platform combines the advantages of all existing solutions mentioned above and is built for efficiency and performance improvement. It helps players adopt several training routines recommended by their trainers and monitors the effectiveness of the adopted routines. The technology consists of wireless sensors attached to the racket and to the body to measure kinetic and movement data in real-time. Analysis on these data is carried out by observing characteristic features specific to a routine that are identified by the trainer. The results are quantified with

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numerical indications and extended analysis over a period helps in tracking incremental progress that is usually unperceived. The platform is versatile and can be applied to various levels of players who incorporate different methods for training.

One such method discussed in the paper is the drill routine adopted for serve correction. Serves in tennis are crucial for the game [11] and perfecting them requires individual efforts. An ideal serve is achieved through repeated drill routines that help develop muscle memory. The effectiveness of such drills adopted by a player is enhanced by the platform under discussion and its implementation is elaborated in the upcoming sections of this paper.

II. Performance Improvement Platform

A. System Overview

Analyzing a game requires continuous motion capture, measurement of kinetic metrics and tools for computation of desired results. Finally, a vivid presentation of the computed results is essential to deliver insights to players and trainers. Therefore, the platform being discussed primarily consists of a network of devices that measure kinetic aspects of motion. An associated software enables computation and comprehensive visualization of measured parameters and derivation of meaningful results from those measurements. A block diagram of the platform is illustrated in Fig. 1.

Inertial Measurement Units (IMUs) are devices that can measure acceleration, angular velocity and magnetic field strength along multiple axes. These measurements along with sophisticated sensor fusion algorithms can yield absolute orientation of objects. IMUs, being the fundamental blocks of the platform, are employed to capture motion accurately thereby eliminating the need for camera based motion capture techniques. This substantially brings down the cost of training without compromising on the requisites for performance improvement. The architecture of the proposed system is illustrated in Fig. 2. Hardware comprising of IMUs are attached to the sports equipment (tennis racket) and to the body of the player to measure kinetic parameters of the racket and movement of the body respectively. These data are streamed to a host computer using a Bluetooth gateway node.

Drill routines instructed by the trainer and their outcomes are translated to the platform's software. The outcomes are indicated as numerical scores which directly relate to performance of the player. The hardware is consistent across

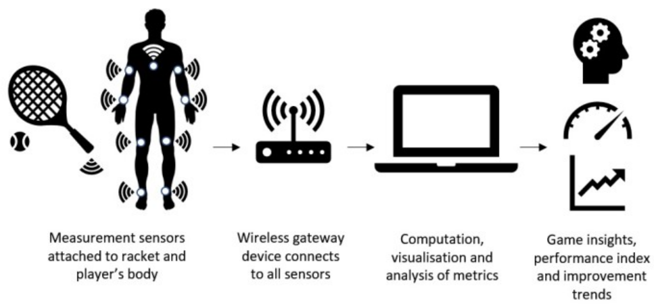

Fig. 1. System Block Diagram

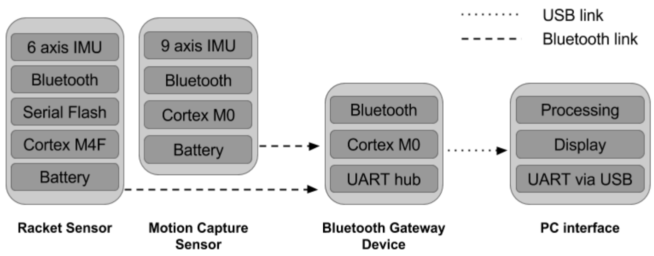

Fig. 2. Hardware Architecture

various drill practices and the software can be customized to be drill specific. This enables players with different requirements to adopt the same platform for game improvement. A typical drill routine consists of a specific set of tasks (that are usually a part of training) for the player and the system continually monitors his activity to translate them into metrics. Both the trainer and the players can review the results to follow the trends in the progress. Details relevant to hardware, software and analysis are furnished below.

B. System Hardware

A Micro-Electro-Mechanical Systems (MEMS) based Inertial Measurement Unit (IMU) sensor, comprising of a tri-axial accelerometer and a tri-axial gyroscope, is attached to the base of the handle of the racket. It captures the vibrations and kinetic parameters of the racket such as angular velocity and net acceleration during strokes. This sensor (referred to as racket sensor henceforth) can acquire 6 axis measurement data at the rate of 1000 samples per second with 16-bit resolution. The accelerometer has range of measurement up to ±32g in all its 3 axes whereas the gyroscope can measure tri-axial angular velocities up to ±4000 degrees per second. It is also equipped with a Bluetooth Low Energy (BLE) wireless module to enable connectivity to smartphones and other Bluetooth gateway nodes. An ARM Cortex M4F Micro-Controller Unit (MCU) on the device can implement real-time signal processing algorithms to carry out onboard analysis if required. It also has a 128 MB flash memory to accumulate data and store results of onboard analysis for several sessions. The device is equipped with an 80mAh battery to keep it powered for 4 hours of continuous operation. Fig. 3(a) shows the hardware and enclosure for the racket sensor.

Motion capture is accomplished by using an 9-axis IMU comprising of an accelerometer with ±16g range of measurement, a gyroscope with ±2000 degrees per second range of measurement and a magnetometer with a range of ±1300µT (X and Y axes) and ±2500µT (Z axis). This 9-axis IMU setup enables measurement of absolute orientation of the body part it is attached to. The motion capture device has an ARM Cortex M0 MCU to acquire 9 axis measurement data at the rate of 100 samples per second and calculate real-time orientation. Orientation information is represented in the form of Quaternions, a convenient 4-dimensional representation of an object's orientation in 3-dimensional space. Powered by an 80mAh battery, the motion capture device can run for 3 hours of continuous operation. The device is enabled by BLE wireless connectivity to stream data to a host computer through a Bluetooth gateway node. Multiple motion capture devices are

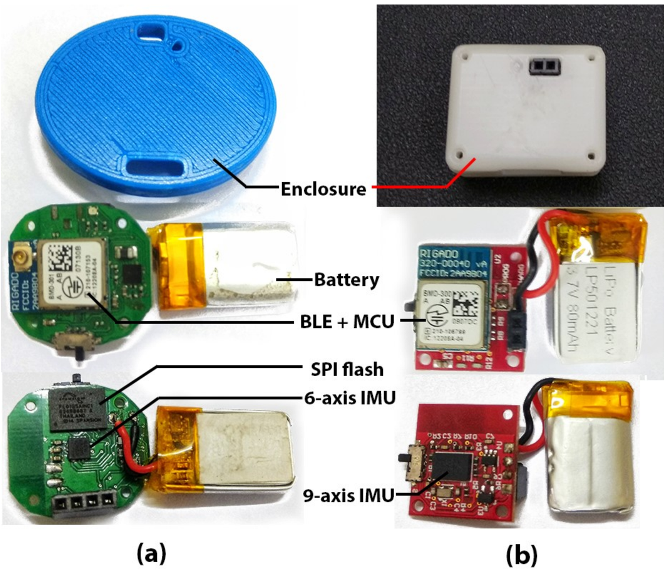

Fig. 3. Hardware prototype (a) Enclosure, top and bottom view of the racket sensor (b) Enclosure, top and bottom view of the motion capture sensor

attached on the body of the player, depending on the routine involved. Fig. 3(b) depicts the hardware and enclosure for the motion capture sensor.

A Bluetooth gateway device, consisting of BLE hardware, can connect to multiple sensor devices simultaneously and acts as a common interface between them and a host computer. Connection between several motion capture devices and the racket sensor is established with the gateway device through Bluetooth links. The gateway sends all the received measurement data to a host computer using Universal Asynchronous Receive Transmit (UART) interface. Data from devices are transmitted through BLE as 16-byte packets following a predefined packet structure for communication.

C. *Software and Analysis*

Computations and visualization are done in a real-time graphical user interface application created using *Processing*, an open-source graphical programming tool. Fig. 4 illustrates the graphical application interface built using *Processing*. Data from the racket sensor are worked upon by proprietary algorithms to

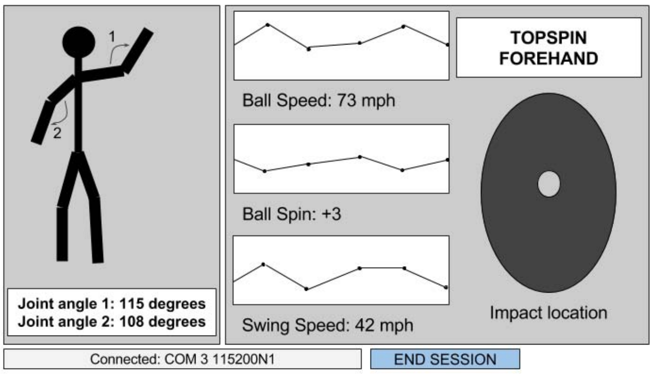

Fig. 4. Software user interface showing measured parameters derived from racket sensor data and motion capture data

compute various kinetic parameters including ball speed, ball spin, ball impact location on the racket and racket swing speed. Data from the motion capture devices, that can functionally replace a multi-camera system, are used to represent movements in a 3-dimensional space for visualization. These data are used for identifying inconsistencies or flaws and obtain issue pertinent results as described below.

1) Problem Identification: A 3-dimensional avatar of the player is reconstructed using the data streamed from the motion capture devices. The actions can be recorded and reviewed in slow motion to observe minute details. This observation is usually performed by the trainer and helps in narrowing down to the cause of the problem in a given action. Issues in actions are because of inconsistencies or flaws and in either of these cases, the exact cause that needs improvement is identified. These causes are translated into technical terms that are representable by the platform. For example, if a player commits a flaw during a shot by twisting his racket too much than normal, the twist of the wrist can be identified as a cause. This cause is translated to the platform as the angle of rotation of the wrist along the length of the arm. Complicated issues that affect the performance of players usually occur due to a combination of such causes. Under such circumstances, the improvement in correction routines are monitored by comparing the causes between the desired and the incorrect actions.

2) Template Matching: Causes for complex issues are identified and translated into a tuple of platform quantifiable values. The ability to characterize such causes has already been established in [12]. For the platform being discussed, the trainer identifies a set of repetitions from the player's drill as ideal ways of doing the action. These actions are marked by the platform as desired and are assigned as targets for a generic template matching algorithm. The algorithm runs a proprietary gesture recognition engine based on Dynamic Time Warping (DTW)

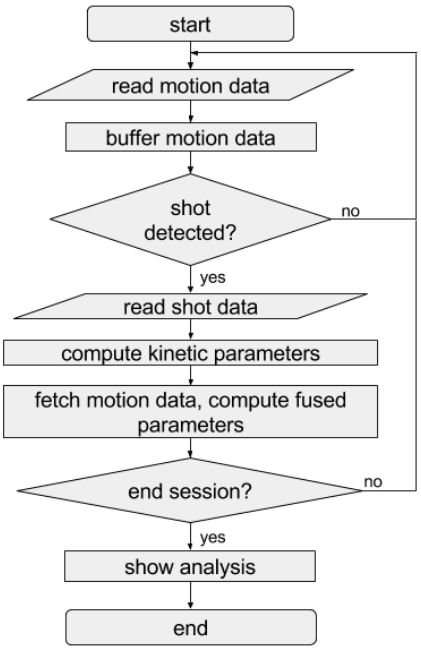

Fig. 5. Sample of flow chart for analysis

technique and can illustrate the amount of relevance between two given actions. Given a set of repetitions from a routine and the target, the algorithm determines the closeness of each of the repetitions to the target action. The closeness is quantified by a Relevance Index which directly relates to the amount of improvement in the adopted routine towards the desired action.

The flowchart depicting the sequence of operations carried out to perform analysis with qualitative scores is given illustrated in Fig. 5. Routines that employ motion capture sensors also make use of the racket sensor to detect valid shots. A trigger signal is provided by the racket sensor upon detection of a valid tennis stroke. The racket sensor runs algorithms onboard in real time to detect the exact shot type. Valid strokes fall into any of these categories – forehand, backhand, serve, slice, volley and smash. This triggering methodology enables efficient running of algorithms on the host computer in addition to identifying actions that resulted in faulty shots. The succeeding section discusses in detail on implementation of these procedures to observe improvement trends for serve correction.

III. Improving the Performance of a Tennis Serve

A generic analysis on various phases of a serve to provide corrective feedback is discussed in [13]. However, tracking effectiveness of the correction methodologies, being the only reliable way of observing improvement trends, remains unaddressed. The proposed platform is applied to a scenario where a trainer seeks to improve the serve of a player.

Conventional routines recommended by the trainer for serve improvement were chosen and necessary tools required for detailed observation were selected from the platform. According to training professionals, serves, being the most dominant element of a tennis game, helps in scoring aces against the opponent and gain a winning edge. Serve is the only type of shot where the player has complete control over various parameters such as placement of the ball on the other side of the court, amount of spin imparted on the ball and its speed, which collectively, in turn contribute to a proper serve. The key to get serves right fundamentally depends on three components, the toss, the swing and the jump. For a player to commit less faults during a serve, persistence in carrying out these three components is necessary. This is usually achieved by undertaking repetitive drill routines instructed by a trainer. Given a set of trainer-recommended routines for serve improvement, the tools are employed to continuously monitor the player's correctness that directly correlates to his performance during serves. Any motion capture system requires for calibration on the field before usage. Therefore, it is essential to calibrate the wearable motion capture sensors before being used by the player. An elaborate one-time calibration procedure is carried out on the court to standardize the accelerometer, gyroscope and magnetometer measurements. This ensures that the onboard sensor fusion algorithm provides a consistent absolute orientation across several sessions.

With the inputs from a qualified trainer, the serve correction setup has been piloted at his training academy in Chennai, Tamil Nadu, India. An All India Tennis Association (AITA) registered national level player under the trainer adopted the serve correction platform to tweak his serves for performance enhancement. The work done towards observing the relevant components and arriving at a Performance Index to assess his improvement is discussed as follows.

A. Toss Rectification

Toss is one of the most vital components of the serve in tennis and contributes towards getting further elements of the serve sequence right. Consistency and accuracy in serves are achieved only by maintaining reproducibility of a precise toss. Tossing the ball is usually done by moving the palm of the non dominant hand straight up from below the hip level without bending the elbow.

1) Problem Identification: For the scenario under consideration, the trainer insisted on the player to start his toss from near the knee level as shown in Fig. 6(b) and to keep his arm aligned to the baseline as depicted in Fig. 6(a). This ensured that the player always tossed the ball straight up so that it lands vertically above his head as shown in 6(c). Fig. 6(d) and Fig. 6(e) show the starting positions in the natural action of the player that resulted in the deviations of the ball from the vertical line along the length of his body as in Fig. 6(f). According to the trainer, since the player's racket meets the ball way off from this vertical line, he tends to bend his torso towards the side of the non dominant hand. This in turn reduces his ability to coil forward thereby reducing the effective power imparted to the ball. In short, the player has to put extra effort which is otherwise not required in getting the serve right. The player also maintains less consistency in the tossing action across repetitions in a drill

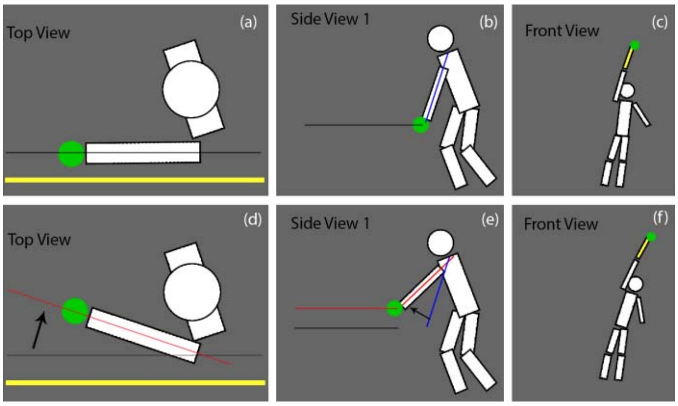

Fig. 6. Toss problem identification. Ideal toss demonstrated from (a) top view, (b) side view and (c) front view. Toss requiring correction demonstrated from (d) top view, (e) side view and (f) front view

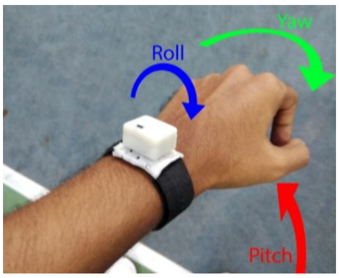

Fig. 7. Motion capture sensor worn by the player on his non dominant hand

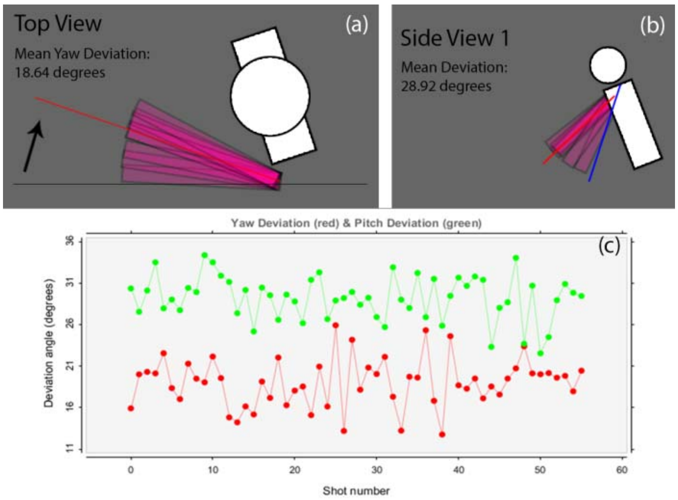

Fig. 8. Comprehensive summary for toss correction (a) yaw deviation for various repetitions (b) pitch deviation for various repetitions (c) variation of yaw deviation and pitch deviation over a drill session

routine. Therefore, his precision in placement of ball on the other side of the court during serves is cut down.

2) Performance Index for Yaw: The degree to which these deviations occur can be quantified accurately using motion capture sensors discussed in the proposed platform. Fig. 7 shows the motion capture sensors worn on the non dominant wrist of the player and the notations adopted by the setup. Yaw angle for any repetition is measured from the reference (black) line as indicated in Fig. 8(a). The desired way of tossing is to bring the tossing hand up keeping it aligned along the reference line. Doing this can effectively enhance forward coiling thereby reducing extra effort that are unnecessary. The yaw angle measured for a repetition when the tossing hand is horizontal to the ground is called as yaw deviation and is denoted by γ_{dev}. It provides a direct measure of the deviation that is responsible for improper tossing. For a session containing *N* tossing repetitions, this difference is built up as performance index for yaw and is denoted by

$$P_{yaw} = 1 - \frac{1}{N\,\gamma_{max}} \sum_{n=1}^{N} abs(\gamma_{n,dev})$$

where, γ_{max} is the worst-case yaw deviation identified for a given player during the problem identification stage. P_{yaw} varies from 0 to 1 and tossing routine is advised until it reaches a threshold fixed by the trainer. Fig. 8 shows a comprehensive summary containing information relevant to a drill session.

Pitch deviation for a repetition is defined as the difference between its starting pitch angle and the desired starting pitch angle. The position of the hand corresponding to the desired starting pitch angle is indicated by a blue line in Fig. 8(b). Performance index for pitch angles can be computed in a way similar to computations involved with yaw angles. According to the trainer, variation in the starting pitch angle does not heavily affect the performance of the player but reduces his serve consistency. Consistency of serves depend on repeatability of tossing action to which the starting pitch angle has a significant contribution.

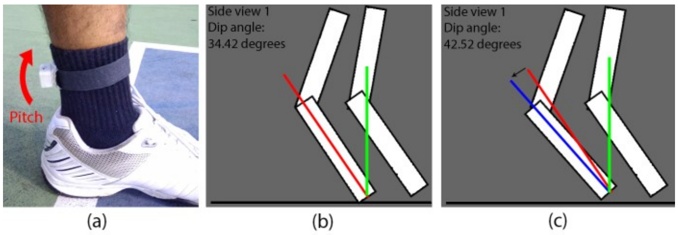

Fig. 9. Motion capture sensor (a) setup worn by the player on his lower leg (b) player's knee bending (c) preferred knee bending

3) Performance Index for Consistency: Enforcing corrective measures and observing the course of betterment helps to gain and retain consistency in the tossing action. A recommended tossing action (T_{action}) is set which involves desired yaw angle and starting position of the hand for a toss. Consistency among several repetitions ($\mathrm{T}_{repetition}$) can be observed if the correlation factor between them and the target tossing action is high. This correlation factor is taken as a target performance index for consistency in action and is denoted by P_{action}. A template matching algorithm, discussed in the preceding section, estimates this index that varies from 0 to 1. It is a direct measure of nearness of the player's current toss to the defined target.

B. Jump Rectification

1) Problem Identification: Coordinating footwork with swings during the game play of tennis is essential to achieve better results. Several works have been done to analyze timing characteristics of foot movements while playing shots [14]. But, timing of jumps during serves is an underestimated factor while considering effectiveness in the output. According to tennis professionals, jumping while serving enables the player to meet the ball at a higher point thereby providing steeper angle of shoot into the other side of the court. To improve the effectiveness of the serve, the trainer preferred the player to have bent his knees more to maximize the potential to jump higher.

2) Sensor Setup: To quantify the knee bending accurately a motion capture sensor is attached to the player's lower leg. A suitable place just above the ankle where the amount of muscle is less will reduce artifacts in captured signals due to muscle contractions. The data from this motion capture sensor are streamed to the host computer and synchronization between data from multiple motion capture sensors is done by the software. Trigger is provided by the racket sensor upon detection of a valid shot and the angle of knee bend during the toss is computed. For the toss correction scenario, a serve is considered as valid shot by the racket sensor. The sensor monitors the pitch angle illustrated in Fig. 9(b) and Fig. 9(c). The player steadies his body momentarily before tossing the ball and this instant is detected automatically by the algorithm. The amount of maximum dip in the pitch angle after this instant is measured.

3) Performance Index for Jumps: Measurement of dip in the pitch angle is a direct indication of the amount of knee bend which in turn reflects on the ability to jump high. Unlike setting target for toss correction, the degree to which a player jumps is

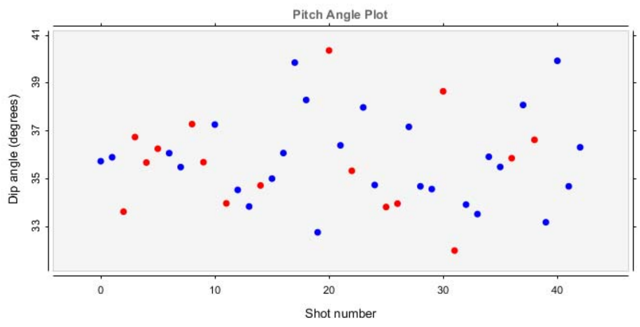

Fig. 10. Comprehensive summary for jump rectification - blue and red dots signify knee dip angles for shots that did and did not hit the sweet spot respectively.

not driven by setting an objective directly on the pitch angle, but on the overall outcome of the serve instead.

To provide reliable indications on the outcome, one of the parameters computed using the racket sensor that shows if the ball was met on the sweet spot of the racket is used as a target metric. A sweet spot is an optimal location on the string bed of the racket to contact the ball. Fig. 10 shows a summary where knee bends are clustered as two categories of markers, one belonging to a group of knee bends that resulted in meeting the ball at the sweet spot and the other group that did not result in meeting the ball at the sweet spot.

Improvement is measured as the ability to attain improved angles of dip (as indicated by blue line in Fig. 9(c)) without missing to hit the ball at sweet spot thereby minimizing the hits at non sweet spot locations. Analytically, from the plot shown in Fig. 10, this translates to a condition of increasing the dip angle with a simultaneous increase in the ratio of the number of blue dots to the total number of dots.

This condition is used to formulate the performance index for jumps (P_{jump}) that relates to the dip in the pitch angle (β_{dip}) as follows.

$$\mathrm{P}_{jump} = \frac{N_{true}}{\beta_{tar}\,(N_{total})^2} \sum_{n=1}^{N_{total}} \beta_{n,dip}$$

where, $N_{total} = N_{true} + N_{false}$, is the total number of shots played during a session. N_{true} and N_{false} are the number of shots that did and did not hit the sweet spot respectively. β_{tar} is the desired angle of dip suggested by the trainer as a target. Both β_{tar} and β_{dip} are measured from the reference for pitch angle (indicated by green lines in Fig. 9). P_{jump} is a quantitative index varying from 0 to 1 and it directly relates the contribution of jumps towards the effectiveness of serves.

IV. Results & Discussion

With the help of tools for serve correction, γ_{max} for the player was observed to be 26.7 degrees during problem identification. P_{yaw} was found to be 0.30 for a serve drill session containing 56 repetitions (Fig. 8). This implies that the player is 30% close towards the target suggested by the trainer. A set of 3 actions identified as desired ones by the trainer were labelled as target actions (T_{action}) and matched against the rest ($\mathrm{T}_{repetition}$) to find the consistency among shots. The performance index for consistency (P_{action}) was found to be 0.49 and this implies that the average relevance of all actions with the desired action is 49%. The tools helped the trainer to identify that, this consistency index must lie between 87-93% for repeatability of serves.

The desired dip angle for jumps was identified as 45 degrees for the player. A session containing 43 repetitions was carried out by the player to practice jumps for serves (Fig. 10). With the use of tools for jump rectification, P_{jump} was computed as 0.50 and a target of 0.70 was set by the trainer to achieve steeper angles of serving the ball.

The platform tools used for serve correction aided the player to quantify his performance, set targets and achieve them through feedback given by the platform. It enabled his trainer to easily visualize minute details in the actions that needed correction. Visualization provided were minimal and sufficient for the trainer and the player to gain comprehensive insights on training sessions. The analysis offered for serve correction proved the platform's potential to help the player enhance his toss consistency and perfect his serve.

Training procedures in tennis involves repetitions to develop muscle memory for the activities being instructed by the trainer. The outcome of such activities can be ranked only qualitatively through observation over a period of time. There are not many solutions to monitor the course of improving quality and quantify the same. The proposed performance improvement platform provides a complete analysis solution for players focused on improvement. The platform is being piloted at 3 coaching centers in Chennai, Tamil Nadu, India as a part of the pilot deployment to measure basic parameters such as ball speed and type of shots. The overall outcome of the pilot is out of the scope of this paper.

V. Conclusion

With a steady increase in the number of incoming players aspiring to ace in the game of tennis, the need for a skilled trainer is important to keep the demands met. Using appropriate technology for sports training, the effectiveness of training delivered to players could be increased significantly as shown by the potential of the results. Budding players are adopting innovative techniques and advocating them to play by the standards might hamper the performance as the techniques are constitutional to each player's ability. In such scenarios, rather than shifting their techniques to traditional methods, understanding the underlying mechanism of the techniques and tweaking them to maximize performance is most preferred. The platform and the tools provided can be tailored to meet the requirements of the applications upon taking inputs from a trainer. This ensures that a perfect blend of technology based training and intuition driven coaching is delivered to the player.

Extending the work done for toss correction by including monitoring of swing patterns and perfection of postures will provide a completely furnished solution to trainers and players. The platform has potential applications for analyzing the overall trends of the game play by observing several parameters such as ball speed and swing speed of the racket, efficiency of swings, consistency of hitting at sweet spots during groundstrokes and stability analysis of postures during rallies. Development work is being carried out to combine these parameters appropriately to provide reliable metrics to track progress.

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