Project Title: Tennis Like the Tennis Pros (Forehand Swing)

Group Members: Eric Li

Abstract

While tennis research and analytics is a developing field, it has yet to penetrate the professional world in a way that is noticeable to the everyday fan nor is it easily accessible to the recreational player. This project uses available open-source software, such as OpenPose, for the purpose of tracking movement of various tennis professionals during play. While the proposal includes features such as court movement and shot selection, this project focuses on forehand arm angle as a proof of concept. Thereafter, recreational users can be matched with a professional that the user's play is most similar to in order to provide the user a better frame of reference for which professional the user should study further. This project hopes to better bridge the gap between recreational players and their favorite professional players as well as provide an avenue for the growth in tennis analytics.

Keywords: tennis, forehand, pose estimation, computer vision, analytics

Introduction and Related Works

Tennis research has existed for decades, but the analytical tools have not been able to penetrate the sport at the professional level effectively, let alone the amateur and recreational levels. One reason for this is due to the relative decentralization of tournament organization at the professional level, where promoters of tennis events, such as the International Tennis Federation, the Grand Slam Board, the ATP Tour, and the WTA, may not be incentivized to allow for data collection, sharing, and analysis during their respective tournaments [1]. Tennis lags behind sports such as baseball in entering the *Moneyball* analytical era. However, this is not for lack of effort in the academic world. Tennis is a sport that can capitalize on the growth of computer vision. For example, with video analysis and sensors, researchers have investigated the contribution of shoulder and elbow joints during forehands using pose estimation technology as well as movement paths during play using computer tracking [2, 3]. It is also not for lack of tools available on the market. For example, software such as those provided by Dartfish, TennisAnalytics, and PlaySight allow for players at all levels to capture and upload videos and capture key analytics during their play, such as service locations, winning shots, pose estimations, and other key performance indicators [4, 5, 6]. These tools are certainly robust, yet notably require a premium account to access these reports. While this paper does not suggest a method to surpass these excellent tools, we do seek to increase the approachability of analytical tools at the recreational level by providing recreational players a method to analyze their own videos and compare this with a database of professional players. This project hopes to better bridge the gap between recreational players and their favorite professional players by helping the recreational player better understand to whom their style of play best emulates and in parallel provide an avenue for the further growth of analytics in the sport of tennis.

Project Description

The goal of this project is to use readily available open-source software to identify and track the pose of tennis professionals during play and thereafter allow recreational users to compare their own play with these professionals. The recreational user would be able to see which professional player his or her style of play best emulates to allow the recreational player a basis for future study. A primary example for the motivation of this project is that recreational players may be fans of specific players such as Roger Federer but may not be able to effectively recognize that their tennis swings and/or movement does not match Roger Federer's. His or her technique may match Novak Djokovic's better for example. This initial premise is nebulous since there are many different components to a player’s profile, such as court movement, posture, contact angle, shot selection, serve analysis, among other details. Therefore, for this initial proof of concept portion of the project, we chose to first analyze professional and recreational players’ forehand arm angle. The analysis should provide a database of professional players’ forehand arm angles, allow for a recreational user to upload a video of themselves performing a forehand swing, and provide the user with whom the user’s forehand swing is most similar to.

Design Process and Preliminary Evaluation

This project necessitates available software to detect human body keypoints from video sources. To accomplish this, researchers at CMU developed the OpenPose software [7]. We can process .mp4 files with the software, and OpenPose will return a mapping of humans in the video to various pose keypoints for every frame. Figure 1 shows the set of OpenPose keypoints.

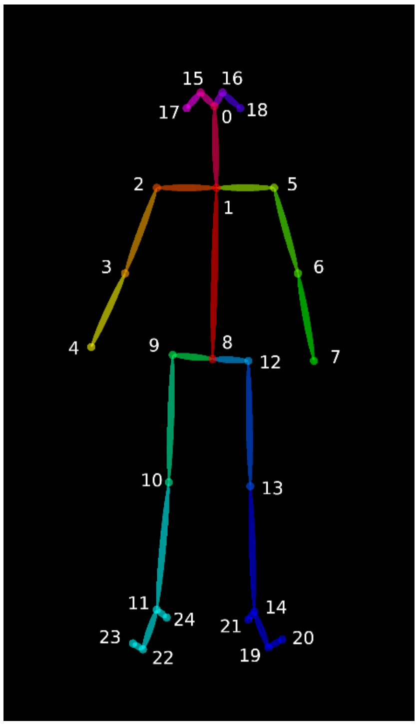

Figure 1. OpenPose Pose Keypoints [7].

Thereafter, we identified at least two professional players with enough of a discrepancy of forehand arm angles for proof of concept. Tennis players primarily have two forehand techniques: the straight arm forehand and the bent arm forehand. The bent arm forehand is more prevalent in the professional world with players such as Novak Djokovic, Andy Murray, Stan Wawrinka, Pete Sampras, Serena Williams, and Maria Sharapova leveraging this technique [8]. That said, there are still top-level players that leverage the straight arm forehand, such as Roger Federer, Rafael Nadal, and Juan Martín del Potro [8]. The bent arm forehand technique, shown in Figure 2 allows for a closer point of contact with respect to the core. This allows for more control and flexibility and therefore a greater margin for error [8]. The straight arm forehand, shown in Figure 3, allows for a higher peak speed as it is further away from the body but does necessitate better movement, positioning, and timing to use effectively [8]. Therefore, we decided that Roger Federer and Novak Djokovic were two excellent candidates for this project.

Figure 2. Bent Arm Forehand [8].

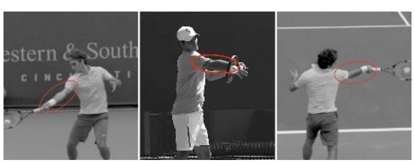

Figure 3. Straight Arm Forehand [8].

Next, we identified various YouTube videos of Roger Federer and Novak Djokovic with a court level view centered on their back. From these videos, we selected five 1-2 second clips for each player’s forehand swings. We processed these clips in OpenPose, which will provide a clip with the identified keypoints overlaying the players and the coordinates of each of the keypoints. Figures 4 and 5 show examples of the OpenPose output. Due to the robustness of OpenPose, many bystanders in the videos were captured and at times it was difficult to isolte the professional player. This can also be exacerbated when the clip is 60 frames per second instead of 30 frames per second as it will produce more extraneous data points over the 120 frames for a 2 second clip. We iteratively selected the ten most promising clips based on how effective it was to manually isolate coordinates of the primary player from the videos.

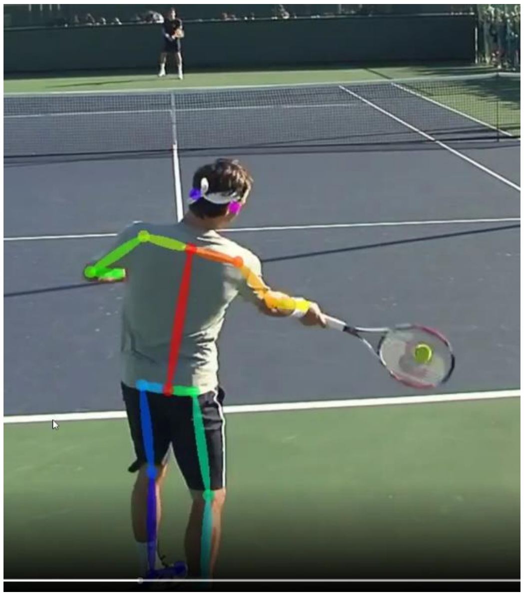

Figure 4. OpenPose output for Roger Federer.

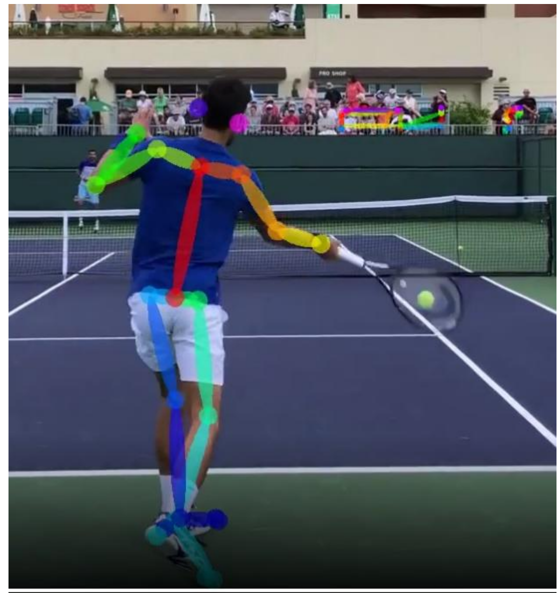

Figure 5. OpenPose output for Novak Djokovic.

To isolate the player, we iteratively shrunk the capture region to the region of interest. That is, the bystanders are typically on the periphery of the clip. Additionally, any players not of primary interest in the clip typically do not have as many keypoints captured as the person of interest. In conjunction with this effort, we can isolate the 2nd, 3rd, and 4th keypoints (see Figure 1 for reference) to isolate the player's forehand for every frame. If any frame could not isolate any of one those keypoints or if the player's wrist is no longer extended further outward as compared to the player's shoulder, then that frame was not used for the analysis. We then calculated the arm angle by taken the arccosine of the dot product of the vector between keypoint 2 and keypoint 3 and the vector between keypoint 3 and keypoint 4. The progression of a player's arm angle through the frames can be seen in Figure 6. Figure 6 shows a successful iteration since the number of frames captured (22) was less than the total number of frames in the video (60), suggesting that we have captured the forehand arm motion as well as excluded other humans in the video from the data for this clip.

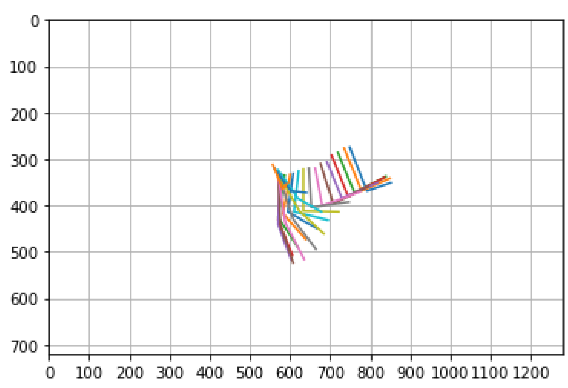

Figure 6. Example progression of a player's arm angle. Each new angle is a different frame. Axes are video coordinates.

Finally, we used the same methodology on a video captured of a recreational player. We likewise calculated the arm angle of the recreational player in the clip and compared this arm angle with the professional player database of Roger Federer and Novak Djokovic to see who the recreational player's forehand is more similar to.

Findings and Discussion

With the compilation of arm angle per frame for each of the ten clips chosen, we can assess each players' peak arm angle during his forehand. Figure 7 shows the arm angle progression for Roger Federer for each of his clips. Figure 8 shows the arm angle progression for Novak Djokovic for each of his clips. Roger Federer, with a known straight arm forehand technique, has a notable peak when performing his forehand. Novak Djokovic, with a known bent arm forehand technique, has a less pronounced peak when completing his forehand. Due to the variance in clip length and frames per second, the most comparable point of interest is the peak arm angle for each of the frames during the player's forehand. When averaged together, Roger Federer has a mean peak arm angle of 165 degrees, while Novak Djokovic has a mean peak arm angle of 151 degrees. These values confirm our understanding of each player's forehand technique, discussed earlier.

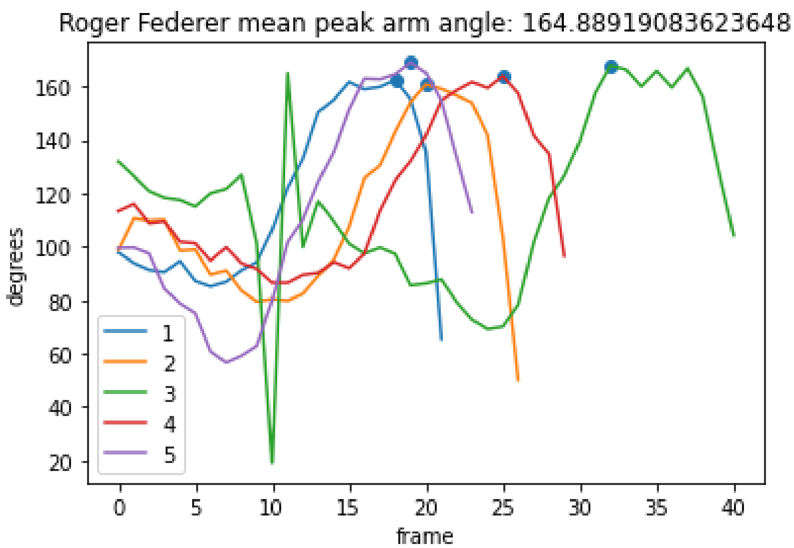

Figure 7. Roger Federer: Arm Angle Progression per Clip

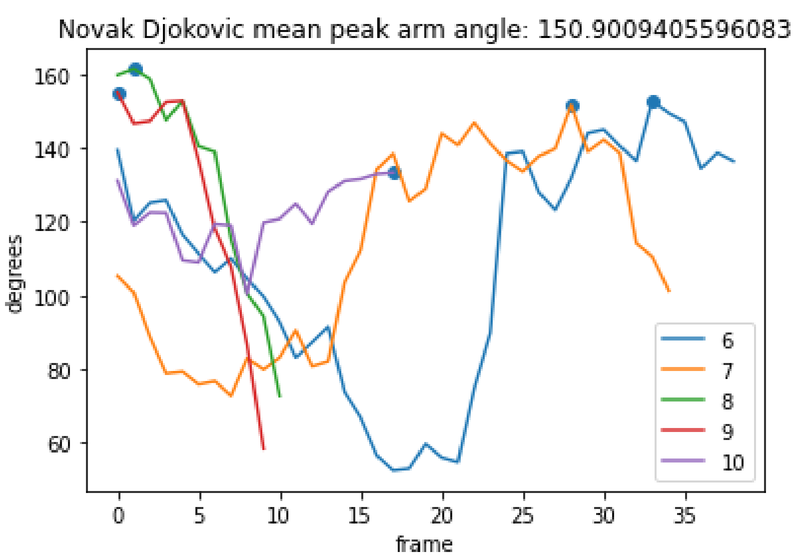

Figure 8. Novak Djokovic: Arm Angle Progression per Clip

Finally, we compare the arm angle progression for the novice recreational player to match the recreational player to a professional player. Figure 9 shows the arm angle progression for the recreational player. This player's mean peak arm angle was 146 degrees. Therefore, we would conclude that this player has a bent arm forehand technique that more closely matches Novak Djokovic's 151 degree mean peak arm angle as compared to Roger Federer's 165 degree mean peak arm angle. The player can leverage this information from this analysis by studying more of Novak Djokovic's forehand rather than focus on Roger Federer's different technique.

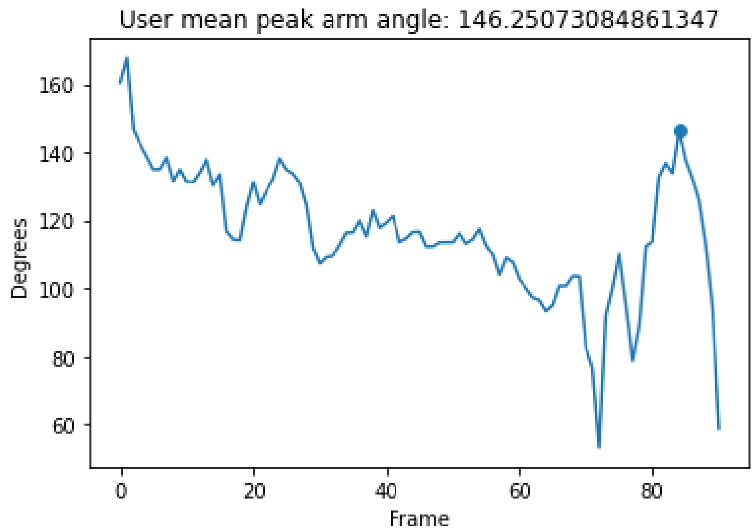

Figure 9. Recreation player's arm angle progression.

Conclusions, Limitations, and Future Work

This project exemplifies the use of free and available software that allows recreational players to better connect with professional players. From this initial analysis, we could determine that a recreational user's forehand arm technique better emulated Novak Djokovic's as compared to Roger Federer's. These recreational players can then leverage this information to identify who they can learn from the most when watching the sport and provide a basis on which to study further. This project also allows recreational players to begin using analytics, which provide further progress at all levels of tennis to better embrace the analytical revolution in sports.

As an isolated proof of concept, this project did have noteworthy limitations. The design methodology required manual work to isolate the player of interest in the clips. To improve on this limitation, we would spend more time on developing stronger heuristics to allow for more automatic capture of the person of interest. Similarly, we needed to manually distinguish the players' arm during their forehand swing from the rest of the player's pose. To improve on this limitation, we would include ball tracking into the methodology to better capture the time of contact with the ball. Next, the professional player database only included two professional players. While these two players were chosen for their difference in arm angle, a larger database would be more helpful for recreational users. Similarly, we would improve upon the user interactivity and usability of such a software to allow users to upload videos and, as necessary, clip the video themselves. Finally, in line with the project premise, this project should be expanded to include other components of a player's profile, such as movement, posture, contact angle, shot selection, and serve mechanics, to better match the recreational player with an appropriate professional player.

References

1. Kovalchik, S., 2021. Why Tennis Is Still Not Ready to Play Moneyball. *Issue 3.1, Winter 2021*.
2. Kurose, R., Hayashi, M., Ishii, T. and Aoki, Y., 2018. Player pose analysis in tennis video based on pose estimation. *2018 International Workshop on Advanced Image Technology (IWAIT)*.
3. Pedro, B., João, F., Lara, J., Cabral, S., Carvalho, J. and Veloso, A., 2022. Evaluation of Upper Limb Joint Contribution to Racket Head Speed in Elite Tennis Players Using IMU Sensors: Comparison between the Cross-Court and Inside-Out Attacking Forehand Drive. *Sensors*, 22(3), p.1283.
4. Dartfish.com. 2022. *Dartfish |Video Performance and Data Analysis Solutions*. [online] Available at: <https://www.dartfish.com/> [Accessed 7 June 2022].
5. Tennis Analytics. 2022. *Tennis Analytics | Tennis Match Reporting & Video Analysis*. [online] Available at: <https://www.tennisanalytics.net/> [Accessed 7 June 2022].
6. PlaySight. 2022. *Tennis SmartCourt - PlaySight*. [online] Available at: <https://playsight.com/our-sports/tennis/> [Accessed 7 June 2022].
7. Cmu-perceptual-computing-lab.github.io. 2022. *OpenPose: OpenPose Doc - Output*. [online] Available at: <https://cmu-perceptual-computing-lab.github.io/openpose/web/html/doc/md_doc_02_output.html> [Accessed 7 June 2022].
8. Pat Cash Tennis. 2022. Tennis Forehand Technique: Straight Arm vs Bent Arm | Pat Cash Tennis. [online] Available at: <https://www.patcash.co.uk/2019/04/tennis-forehand-technique-straight-arm-vs-bent-arm/> [Accessed 7 June 2022].