Stroke Comparison between Professional Tennis Players and Amateur Players using Advanced Computer Vision

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Abstract: In this paper, we created a method to find how professional and amateur tennis serves differ from each other. We collected videos from online and from our own recordings and turned those videos into frames. From those frames, we manually selected ones appropriate for our study and ran those through a pose estimation system, which turned those frames into simple stick figures of the players including all the x and y coordinates of the player. By normalizing all data, we were able to calculate the Euclidean distance between two compared players' joints and analyze their consistency in their serves. Our results from our t-tests showed that there was a significant difference between the amateur's consistency and the pro's consistency and body parts like both shoulders showed a significant difference.

1 INTRODUCTION

Tennis is a popular competitive and leisure sport that is played in a one-on-one or two-on-two format. The sport is largely composed of various "strokes" to keep the ball in play, such as the forehand and backhand strokes during a rally and a serve to start the game. Of those strokes, the serve plays a critical role, as it has been shown to be one of the two most important shots along with the return in determining wins (O'Donoghue and Brown, 2008). It is also a shot with high variance, with variability in power, ball speed, accuracy, ball impact location and angular velocities (Whiteside, et al. 2014, Martin, et al. 2016,). Given the serve's significance and variance, amateur players often observe professional players who compete at international tournaments like Wimbledon and the US Open to emulate the form of those top players and improve their own serve. However, simply watching them play is not nearly sufficient if the goal is to understand the real differences between an amateur and a professional.

Today, computer vision is a rapidly growing technology within the broader fields of computer science and artificial intelligence (Arai and Kapoor 2019; Shavit and Ferens 2019). It is both fairly new and has a wide range of applications. It can take in images from videos or photos and provide numerical evaluations. From those outputs, we can analyze data more specifically and efficiently and derive compelling results. Applications of computer vision in the field of sports include but are not limited to analysis and evaluation of tennis players (Mukai, Asano, Hara, 2011), highlight detection (Ren, Jose, 2009) and support decision making (Owens, Harris, Stennett, 2003).

We propose using computer vision to analyze tennis shots, and potentially provide amateur players with the level of specificity and data necessary to help them improve. Although tennis includes many types of strokes, we chose to focus on one of the most important: the serve (O'Donoghue and Brown, 2008). Although the serve does not require much movement, as the shot is hit in one stationary location, the way the serves are hit varies between players, thus making it difficult to improve just by watching professionals' play. With a computer vision algorithm, recognizing what is different and how it is different from professionals to amateurs will become clearer.

We first split the collected videos into frames and then used an accurate pose estimation system to simplify the frames into a stick representation of the player. After normalizing all data into the same size and making it comparable, we were able to analyze the similarities and differences between professional

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and amateur players, leading to the conclusion that not only were the patterns between the professionals and amateurs different, but that specific body part positioning showed a significant divergence.

2 RELATED WORK

A survey of what has been already published in this area revealed a range of existing publications that agreed on the importance of analyzing the serve in greater detail along with other strokes, but chose to focus on different components.

In Whiteside et al. (2014), the researchers focused on the tossing component of the serve and how important the consistency of it is to the resulting serve. From their research, they were able to recognize that while professionals were not consistent in the horizontal placement of the ball, they were consistently tossing the ball at the same height. This paper's main topic was about the serve but it differs from our paper, as they focused mainly on the toss of the ball, rather than focusing on the whole serving motion.

Chow et al. (2007) focused on how the activation of the muscles varied before and after the impact in the tennis volley, as many players are concerned about the after effect, potentially leading to severe injuries on the wrist. They collected data by placing electrodes on the players' bodies. This data collection was conducted with several controls, such as the tennis string and racket type. From the EMG data, they were able to conclude that the oversize tennis balls "do not significantly increase upper extremity muscle activation compared to regular size balls during a tennis volley". While this paper focused primarily on volleys and not the serve, the level of detail it went into showing how even miniscule changes in one's form can lead to drastically different physiological impacts in the long run reinforced how important our research is when it comes to a stroke that covers a much wider range of motion than volleys.

This importance is corroborated by Chow et al. (2009) which looked into how different types of serves affect the players' conditions. They included 3 types of serves - flat, topspin, and slice, and examined how those shots activate the middle and lower trunk muscles. For each subject, their two highest rated EMG and kinematic data, which are coordinate data extracted from their raw videos, were used to analyze the differences. Even though there were no significant effects for the serve type on muscle activation, they found that on average, the largest EMG levels were observed in the "descending windup or acceleration phases". While this does identify certain components of the serve that hold significant weight, our research hopes to add data and detail to those components in order to better understand the angles and stroke lengths that separate the professional player from the amateur.

Baily and Nguyen (2018) developed a method to classify different tennis strokes based on an armband that measures data from its accelerometer, gyroscope, quaternion, and EMG. The authors use a supervised learning model, a Support Vector Machine (SVM), to determine the correct tennis shot based solely data from the armband.

3 PROPOSED METHOD

In this section we describe our proposed method we used to analyze differences in player serves. We first collected sample serve videos from both amateurs and professionals from the Internet and our own recordings. We manually looked through each video and identified the sets of frames that capture the serve motion. A pose estimation algorithm is used to reconstruct the poses of each player appearing in those frames, and the result is put through a pose tracking system to label each person with an integer identifier. We then manually labelled the result with the player name, ID number, and whether they are left-handed or not. The labelled pose data is then normalized to account for the difference in body size, position in image and left-handedness. Finally, we calculated the Euclidean distance between the same limbs in all pairs of serve clips collected and made observations based on statistical analysis. This is visually represented in Figure 1 below.

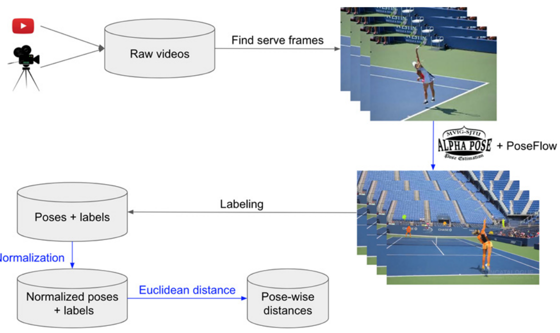

Figure 1: Our data pipeline. Black arrows denote manual steps, and blue arrows denote steps done using computer programs.

Essential to standardizing our results was the algorithm used for pose estimation, which has been one of the major challenges in computer vision since its introduction. In pose estimation, an algorithm attempts to determine the positions and the poses of the humans in a given digital image and helps to ensure that the data collected is comparable. In this case, a human pose is defined as a set of points describing the important body joints. For our problem, we used the pose estimation algorithm proposed by Fang, et al. (2017). The framework, named *Alpha Pose*, first detects all human locations in an image. Each location is treated as a single-person image and fed to a Symmetric Spatial Transformer Network (Jaderberg et al., 2015) to find the region of interest, continued to a Single Person Pose Estimator (Newell, et al., 2016) to estimate the pose in local image and finally through a Spatial De-Transformer Network to remap the estimated human pose back to the original coordinate. The estimated poses are then refined through the use of parametric Pose Non-Max Suppression (Fang et al., 2018) to obtain the final human poses. We used the Alpha Pose authors' official implementation available on GitHub (Machine Vision and Intelligence Group, 2017), which outputs human poses in the Microsoft COCO (Lin et al., 2015) format[1].

One of the common concerns in pose estimation is that in a 2D image, very often some of the important body joints are not visible. Alpha Pose addresses this by representing a joint using 3 numbers: x-coordinate, y-coordinate and a confidence score. The third number ranges from 0 to 1, with lower values assigned to less visible joints. Even when a joint is completely invisible, unless it lies outside of the image, the model does a good job predicting its position and assigning a confidence score. Our videos were chosen so that the main player is always completely visible in most of the frames, so missing data wasn't a big concern. Also, for the sake of simplicity, we didn't use the confidence score in our analysis.

The pose estimation step is repeated for all frames we wanted to analyze. Note that this analysis is done in 2 dimensions and not 3, and because we are analyzing each frame, we compare sets of static poses of the players, not their overall motion. Since there can be multiple people in a frame, we needed to accurately identify the main player in all frames. We did this by running the pose estimation results through a pose tracking system, which analyzed the connectivity of the poses between consecutive frames and assigned an identifier to each human, then manually reviewed the results and recorded the IDs of the main players as well as whether they're left-handed or not. The tracking system used is *Pose Flow* (Xiu, et al, 2018), which is available as an open source project on GitHub (Machine Vision and Intelligence Group, 2018). In this system, the pose estimation result is fed to an optimization framework to build the association of cross-frame poses and form pose flows, then to a pose flow non-maximum suppression to robustly reduce redundant pose flows and re-link temporal disjoint ones. The result of this step is a database of poses in MS COCO format with player name, tracking ID, video link and handedness.

3.1 Data Processing

Serve videos of 4 professionals and 3 amateurs were used to conduct this research. 3 out of the 4 professionals' data were collected via the internet and the rest of the videos were collected on our own. In the data collection, we used videos including 4~13 serves per player and as a control, all of the videos were captured from the back angle of the player. With the videos, we turned them all into frames, thus making the data manipulation easier. All of the videos were at 30 frames per second. We manually cut the frames into smaller sections, with only one full stroke per section. To keep the frame number per cut equal, we set a constant of 72 frames. This resulted in each player having 4~13 serve videos, each consisting of 72 frames, and the number for professionals and amateurs were roughly equivalent, which makes the comparison more accurate. To further simplify and make the analysis accurate, we selected 21 frames from those 72 frames, including the contact point of the serve and 10 frames before and after. We selected those specific frames because the time at which a player takes before and after their contact point of the ball during a serve is different and only selecting frames around the contact point reduces variation between players during analysis.

In Figure 2, the image highlighted in yellow is the "contact point" frame, which is the point at which the player makes contact with the ball at the maximum height. By adding on 10 frames before and after, the images capture the serve motion around the ball hit of the serve for a total of 21 frames.

[1] https://cocodataset.org/#format-data

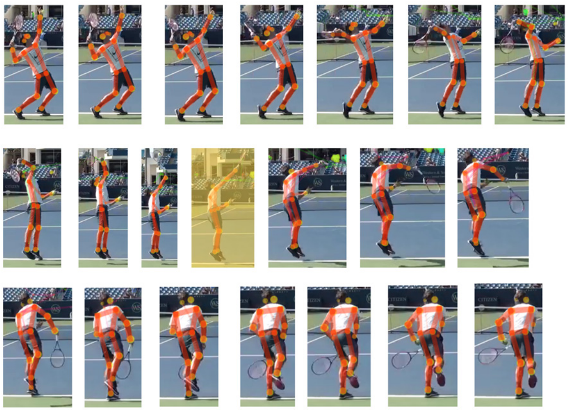

Figure 2: One of the professional's 21 frames, the contact point frame and 10 frames before and after.

We then ran the Alpha Pose system on all those frames we manually collected and the output includes a stick figure of the players with 17 important points on the player's body.

In Figure 3 and 4, we display the output of the Alpha Pose detection so that one can see the lines and key points drawn on the player's body, representing the simple outline of a human body in one frame.

Figure 3: A female professional player before and after Alpha Pose detection.

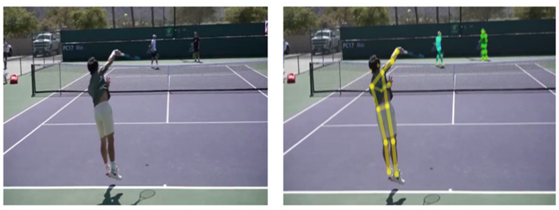

Figure 4: A male professional player before and after Alpha Pose detection.

Even though all of the videos were taken from the back of the player, the distance between the player and the camera varied throughout different videos so normalizing the scales of the players became essential. It is clear in Figure 5 that because the scaling is not applied, the poses do not overlap or match well to each other.

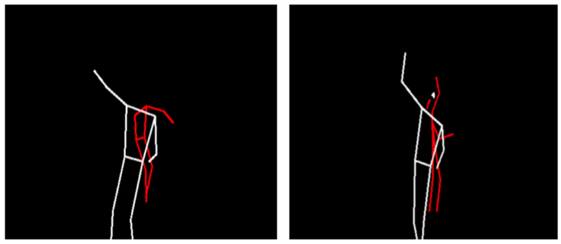

Figure 5: Comparison of two players (one left-handed which is the white stick figure and the other right-handed with the red stick figure) initially without any scaling or shifting.

We created separate scales for the x axis and the y axis. To find the right scales for the x coordinates, we looked through all of the poses' x coordinates of the left and right shoulder and found the distance between them. We repeated this process for the y coordinates, the left and right hip, and we selected the greatest values of both the x and y to create the scale. These scaling factors were then normalized to a set width and height. After finding the scaling factors we applied it to all frames and finally shifted the poses, in order for them to overlap with each other. With the scaling and shifting, the poses now are comparable, as shown in Figure 6.

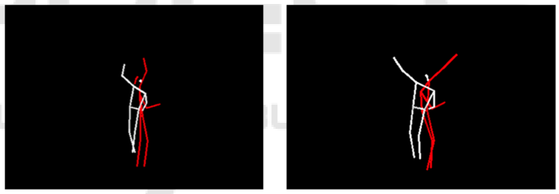

Figure 6: The same players from Figure 5 but scaled and shifted.

To further improve the comparison, we also flipped left-handed players so that their data can be analyzed as well with the right-handed players, which is displayed in Figure 7 below.

Figure 7: Final output with scaling, shifting, and flipping (for left-handed players only).

3.2 Comparison

As shown in Figure 8, we first collected the data, then manually selected the important frames and put those images through pose estimation.

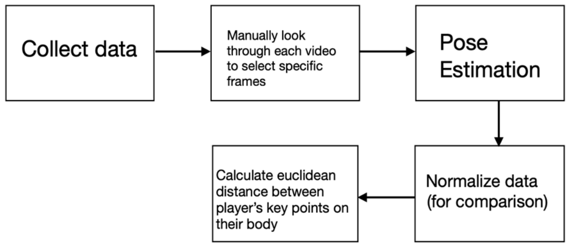

Figure 8: Flow diagram of the comparison process.

Then with the normalization completed, we analyzed the data by taking the Euclidean distance between each of the 17 points on the two players for all of the frames. We calculated the Euclidean distance between the same joints of two players by using the equation $\sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$. Each player has 17 key points detected from the pose estimation and for each of the key points, the same point on the other player's pose estimation was compared, using the equation above. We repeated this process for all 17 points and summed up the distances for us to compare.

To further analyze the differences between players, we used t-tests to compare the distributions of the data sets. The t-test data are specifically for the player's differences with themselves at their contact point. Because we were aware that the variances between each of the players were different, we used a Welch's t-test, which can be used on datasets with varying standard deviations or heteroscedasticity. Also, we used this type of test because the number of samples were different for each player.

4 EXPERIMENTAL SETTING

To start off, we gathered videos from several angles of one player hitting overhead serves. Those videos were 10 to 30 minutes of a player practicing the serve. The first couple of serves, around 4 to 5, were ignored as they showed significant differences with the following serves and were likely warm-ups, so we collected 5 to 10 strokes of each player after their warm-ups. To get a wider variety of players, we collected data from the Internet where there are plenty of professional players' practice videos. In total we gathered 4 professionals, 3 amateurs, and within those players, only one player was left-handed. Similar to the data collection method for the first player, we ignored the first couple of serves and took the next 5 to 10 serves, making sure that we collected their real serving style. The point of this research is to compare pros to pros, amateurs to amateurs, and amateurs to pros to see whether the consistency amongst those data sets are significantly different.

5 RESULTS

In this section, we will discuss the results collected from our data. We first looked at 2 boxplots, side by side, of the sums of the Euclidean distances between limbs for amateurs and pros.

The results in Figure 9 clearly show that the distribution for the amateurs was more spread out when compared to the pros implying a greater variance in the data. The median, as well as the interquartile range of the data, for amateurs are greater than that for the pros. Knowing that there are clear distinctions between the distributions of the pros and amateurs, we looked more closely to where exactly those differences arise by creating histograms specific for each player.

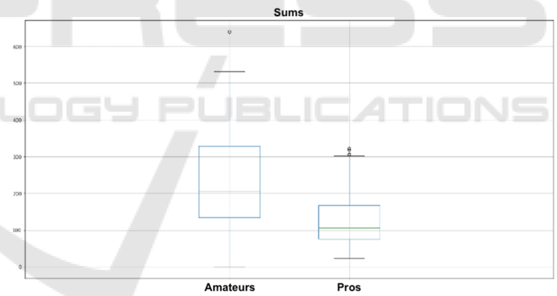

Figure 9: Boxplot of the distributions of the sums of the Euclidean distances between limbs for the amateur and pro category.

In Figure 10, Figure 11 and Figure 12, the x axis represents a normalized Euclidean distance between each of the players, and the y axis represents the frequency of those distances occurring. Figure 10 compares Amateurs to other Amateurs, Figure 11 compares Professionals to Professionals while Figure 12 compares Professionals to Amateurs. There is a clear distinction between the distributions of professionals and amateurs. The professionals' histograms are more tightly distributed and mostly skewed to the right, meaning the differences between their serves were not very large. However, the histograms of the amateur players have larger ranges and their distributions are not as skewed compared to the professionals. This shows how amateur players were not consistently making similar movements, thus shifting the distribution towards larger values. In Figure 12, it shows a histogram with pros and amateurs being compared to each other. Compared to Figure 10 and 11, there are no distinct features that stand out when comparing pros to amateurs.

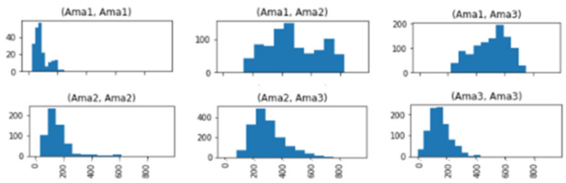

Figure 10: Histograms of the distributions of the sums of Euclidean distances between limbs comparing Amateurs to Amateurs.

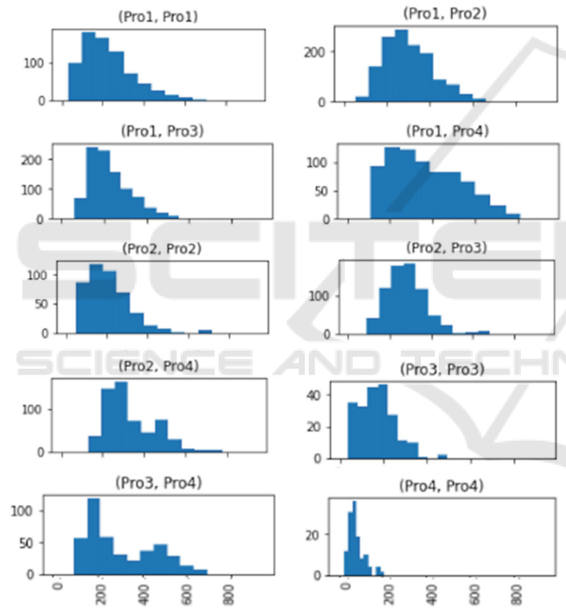

Figure 11: Histograms of the distributions of the sums of Euclidean distances between limbs comparing Pro to Pro.

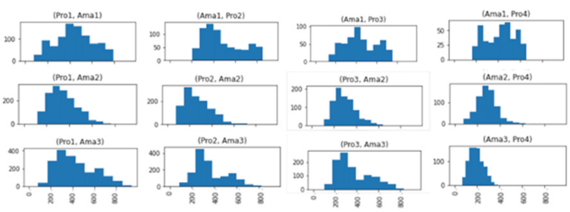

Figure 12: Histograms of the distributions of the sums of Euclidean distances between limbs comparing Pro to Amateur.

Because the histograms only provide qualitative data, we then used Welch's unequal variance t-test, a type of statistical analysis to determine whether there is a significant difference between the means of two groups. This test showed a similar result when testing for significant differences between professional and amateur players.

We conducted a Welch's t-test between the professionals' sums of distances and the amateurs' sums of distances and the resulting p-value was 0.0036. From this, we were able to conclude that there is, in fact, a significant difference between the means of the two groups, the professionals' sum and the amateurs' sum.

To further analyze where exactly those differences were, we conducted several t-tests, shown in Table 1, each for the key points on the player's body, and found that, while neither of the right wrist nor left hip were significant, there were significant differences in the rest of the body points analyzed (all p-values less than 5%). The p-values for the shoulder comparisons were most significant. With this, it is evident that one of the most consistent differences between amateurs and professionals is in the shoulders.

In Figures 13, 14, 15, where we plot the distribution of differences in left shoulder locations across different player types, it is clear that the differences between the distributions for the professional and amateur players are significant. For instance, Figure 14 shows that Professionals compared to other different Professionals have a significantly right skewed distribution while the Amateurs compared to other different Amateurs (Figure 13) or Amateurs compared to Professionals (Figure 15) have a significantly less right skewed distribution and in some cases are almost symmetrically distributed.

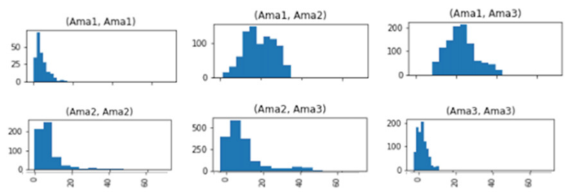

Figure 13: Histograms of the distributions of the sums of Euclidean distances between the left shoulder comparing Amateurs to Amateurs (only left shoulder).

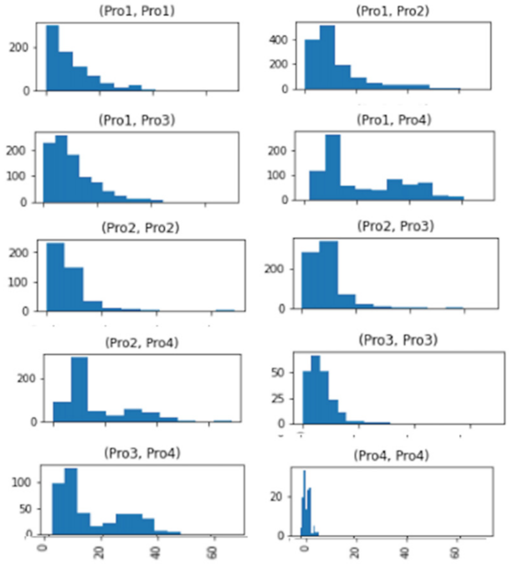

Figure 14: Histograms of the distributions of the sums of Euclidean distances between the left shoulder comparing Pro to Pro (only left shoulder).

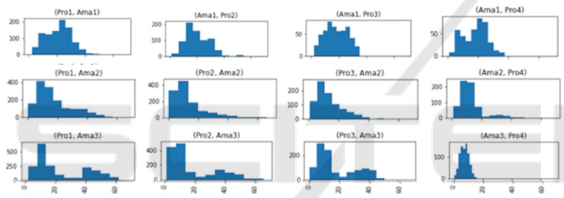

Figure 15: Histograms of the distributions of the sums of Euclidean distances between the left shoulder comparing Amateur to Pro (only left shoulder).

We conducted another test to see if there are clear distinctions between the distributions of differences of professional player serves compared to other professional players and the differences of amateur player serves compared to other amateur players. In other words, we are comparing the difference in the pro distribution versus the amateur distribution. From this we were able to conclude that those two groups are, in fact, significantly different from each other, with respect to intra-group differences, with a p-value of 2.735×10^{-6}. In contrast, there was no significant difference in amateur distribution to the distribution of pro vs amateur differences.

Although we only focused on some of the p-value results, the numbers in Table 1 shows all of our results and although some values are not significant, others show a significant value, like the pro-to-pro to pro-to-amateur.

Table 1: All of the collected p-value results for different types of distributions.

Compared Distributions	P-values
Pro Sum to Amateur Sum	0.0036
Pro Right-Sum to Amateur Right-Sum	0.0532
Pro Left-Sum to Amateur Left-Sum	0.00463
Pro Upper-Sum to Amateur Upper-Sum	0.021998
Pro Left-Elbow to Amateur Left-Elbow	0.02279
Pro Right-Elbow to Amateur Right-Elbow	0.003554
Pro Right-Shoulder to Amateur Right-Shoulder	3.729×10^{-6}
Pro Left-Shoulder to Amateur Left-Shoulder	1.21×10^{-6}
Pro Right-Wrist to Amateur Right-Wrist	0.9789
Pro Left-Wrist to Amateur Left-Wrist	0.0346
Pro Right-Hip to Amateur Right-Hip	2.324×10^{-6}
Pro Left-Hip to Amateur Left-Hip	0.0857
Pro-to-Pro to Amateur-to-Amateur	2.735×10^{-13}
Pro-to-Pro to Pro-to-Amateur	3.083×10^{-26}
Amateur-to-Amateur to Pro-to-Amateur	0.3798

6 DISCUSSION

In this section, we will discuss some possible explanations and implications of our results and will evaluate the strengths and weaknesses of our research.

To start off, not only have we confirmed the obvious result that professional body movements during serves are significantly different to amateurs in terms of consistency. We have also shown that professionals are more consistent among each other as a group then amateurs. Our main result however is our ability to narrow down the differences to each limb area and do so with only a simple single recording of the player without the need for special set ups. Indeed, nearly half of our analyzed player videos came from publicly available videos.

Among our limb differences, while most limb areas showed significant differences from pros to amateurs, the right wrist and left hip were not significantly different, in fact the right wrist was significantly similar. Given that we analyzed serves frames around the ball contact point, this implies most players, professional and amateurs alike, can manage to position their racket to an optimal contact point with the ball, even if the rest of their body and footwork is dissimilar or suboptimal. Although, the left hip and leg is where most players are often taught to keep their weight during a serve, the p-values seem to indicate there isn't a significant difference in how pros and amateurs position this limb even if there might be some small variations. This may imply that most players, even amateurs, reach a good level of consistency with this limb.

Our findings are definitely informative to tennis players. This gives players points they can focus on improving and points where they may not need to spend as much effort, rather than watching professionals and not knowing where to pay attention. It allows amateur players to have an objective understanding in their performance consistency, compared to other professionals and other amateur players. This data can be helpful to tennis coaches, as it gives them a focus point in their lessons. Our data is applicable to a wide range of players in a wide range of situations because of our normalization methods we applied on all stroke data and the minimal requirements for the analysis videos, limited to only their shooting angle, without need for special preparation.

However, the drawbacks are that we had to manually select the 21 frames (1 contact point frame, 10 frames before and after), which we would ideally like to automate. Additionally, because we looked into each video by frames, this means that we only considered a series of static poses, not a time evolution and that is one limitation our research has. The static poses are adequate enough for the research but it also means that the overall flow of the strokes are disregarded, meaning we could have been overlooking important parts regarding the overall movements of the player's strokes. Another weak point of our research is that our analysis was only in 2 dimensions, not 3 dimensions. This is a limitation as even though the player's movements are in 3 dimensions, we are only looking at the x and y coordinates. However, because we are focusing on analyzing players from only a single camera angle, 3-dimensional analysis poses significant challenges that require dedicated testing with a multiple camera setup to adequately address. Finally, we conducted our research with only 7 athletes, which included 3 amateur and 4 professional players, and that is considerably a low number of data points. In our future work, the research can be further developed by collecting more data for different players to ensure more diversity in our collection.

7 CONCLUSIONS

In this paper, we collected videos of both amateur and professional tennis players, and through the use of pose estimation and tracking, we were able to simplify frame images from videos into stick figures. With the given data, we analyzed the differences between players' key points on their body, such as their shoulders and elbows. This led us to understand better how the consistency between pros and amateurs differ and where the biggest differences lie. For example, in our P-value table, we found significant differences in both shoulders while the right wrist showed little difference between professionals and amateurs. In future works, we look to further identify differences between professionals and amateurs looking at differences in limb position and also body dynamics. Through our t-tests, we were able to conclude that the distributions of overall Euclidean distance between limbs as well as specific limbs such as the left shoulder, right shoulder, and right hip, for professionals and amateurs were significantly different.

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