The difference between leisure and competitive squash

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ABSTRACT

One can easily tell about an ongoing squash game whether it is played as a leisure activity or a tournament is going on. Although it seems trivial by the look of it, it is hard to quantify the differences between the two ways of playing squash. In this paper we present our preliminary findings on squash analytics that we performed on large-scale data obtained from a smart squash court. Our results show that indeed one can distinguish leisure and competitive squash based on the positions and speed of the players, the location of front-wall ball impacts, etc. In this paper we present our data collection framework, the applied data analytics methodology and our results.

Keywords

sports analytics, squash, amateur, professional, sensor, video

1. INTRODUCTION

There is a saying: "Sports are the most important of unimportant things". With the advent of information society the way people follow sports events has changed dramatically. Instead of watching matches on linear television, one can enjoy the extended feature set of on-demand pausing and replaying, zooming in, and on-screen statistics. This evolution does not stop here: technology is available to bring experience to a whole new level with 3D imaging, integrated in-game commenting on social network platforms, etc.

Indeed, sports are getting ever more important, not only from the fans' perspective: fantasy sports and gambling are a key economic factor of the games. Both benefiting of sport statistics and prediction. Data analytics related to sports is gaining steam: with novel means of collecting data, creative data mining methods and the rise of big data technologies, the complexity and importance of sports analytics, especially in team sports, are steeply increasing. Tracking technology and big data have opened up new avenues in this field: even the simplest, least sophisticated statistics that have been around for some years provide interesting insights for the the viewers, not to mention the more sophisticated ones that can be helpful to the players and to their coaches.

In several high stakes sports, technical advantage can often decide the outcome of matches and this is exactly why sports analytics are on the rise. While decisions are still made by human intuition data analytics plays a huge role in decision support. While data analytics is already part of the rules and game strategies in popular sports like rugby or tennis, economically less interesting sports have not even been investigated by the scientific community. One of these undeservedly sidelined sports is squash. While not an Olympic sport yet, Squash has an estimated player base of 15-25 million worldwide, playing on over 50.000 courts.

In this paper our goal is twofold. First, we approach the popular field of sports analytics with scientific rigor and with an engineering mindset, and present a simple quantitative analysis of squash. Second, we demonstrate the potential of our findings for further study which in the end may help deriving novel practical squash key performance indicators, describing and predicting player dynamics, and characterizing key motifs of success and failure for the player. Our contribution can be dissected in 3 layers: a preliminary comparison of leisure and competitive squash from the perspective of players' movements, location of front-wall ball impacts and the stroke attributes.

The paper is organized as follows. In Sec. 2 we briefly describe the data collection and analytics methods that we apply, and we dig into the prior art touching upon squash analytics, or similar. In Sec. 3 we summarize our findings on figures and provide some analytical insights. Finally we conclude the paper in Sec. 4 with the potential of the presented work as the basis of future advancement.

2. DATA COLLECTION AND ANALYSIS

In this section we describe the data types we collect on a squash court, the methods we apply in order to derive our analytical results, and we briefly discuss related work.

2.1 Data sources

A squash court is of size 6.4m by 9.75m with a minimum height of 5m. The court is enclosed between four walls. The front wall has a 4.57m height, while the back wall is only 2.13m high [3]. A rather small court compared to tennis. The front wall impacts are invalid below 0.5m, while all other walls can be played down to the floor. In a venue, there are typically multiple courts. We equipped a court with the required cameras and networking to gather sports data.

Squash is played in a similar manner as tennis: players have to hit the ball alternately, before it bounces two times on the floor. Aside the closed space, the main difference is in scoring, and in the order of serving.

We used wall-mounted cameras and racquet-mounted motion sensors in order to track the squash games.

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2.1.1 Cameras

While walls at tournaments are transparent, most courts have three concrete walls, usually shared by neighboring courts, making it difficult to install camera systems that can capture players from different perspectives. The low intensity of artificial lighting, and the close space calls for expensive wide-angled lenses and sensitive image sensors. In our court we installed a bird-eye-view camera above the center of the field, and two front facing cameras, one to observe the front wall, and another to capture the players.

We captured 1280x960@30FPS videos with standard RPi camera modules connected to Raspberry Pis for ball impact, and a 640x480@30FPS video with a similar camera retrofitted with wide angle lenses to detect the players' movements. All Raspberry Pis were linked to the compute server via a switch, videos were streamed using VLC, and processed with dedicated OpenCV scripts.

2.1.2 Racquet sensor

A tennis ball has a weight of 58.5g. Squash balls weigh 24g. The lightest tennis rackets weigh 255g compared to the 135g weight of an average squash racquet. Hence a tennis racket can accommodate a sensor more easily, and hitting the ball causes more distinct acceleration and vibration patterns. An other main aspect of the squash ball is its rebound. A squash ball at game temperature is required to bounce back 35% of the drop height (a tennis ball needs to do 58%), and the ball can bounce off the walls several times and still count for a legal strike. On the other hand a direct front-wall rebound can be intercepted mid-air. This wide spectrum of scenarios calls for a wide range of strikes that cannot always be classified as forehands or backhands. To meet player's requirements, we had to integrate our motion sensors (InvenSense MPU-6050) inside a very light racquet. We managed to keep the overall weight under 140g, with a battery lasting 10 hours of continuous capture.

2.2 Data analysis

We collected the top and back camera feed for hundreds of hours of amateur, leisure-purpose matches, and tens of hours of competitive games at local tournaments. We applied video processing tools to distill player positions and to detect front-wall ball impacts at a frequency as high as we could attain. In terms of the racquet sensor, we developed a stroke-detection method that has proven very reliable in all types of strokes, no matter the force of them. Besides the fact a stroke happened, our method can decide whether it was a forehand or backhand, and also gives an estimate about its force, based on Newton's laws.

2.3 Related work

Automating sport event data gathering includes video based player detection, tracking and interaction recognition. Challenges of tracking players on video feeds are discussed by Gerke [7] and by Liu [8], such as player identification and interaction detection on dozens of players at a time.

The other extremity of the range is tennis, another career sport that attracts huge audiences. In tennis, there is no physical interaction between the players. Event detection is easier, as serving players have to stand behind the baseline, and shots go back and forth from there. Video processing has been used extensively in the last decade [9]. While research focuses on player tracking and motion detection [10], rules now incorporate HawkEye [1], a ball tracking and trajectory estimation system. An optical beacon-based motion tracking system: Ubitag [6], has been evaluated for detecting players' movements and motions. The tennis racket has been another source of data [5], now commercialized by several manufacturers [2, 4].

Till this day there are no publications or products addressing this sport to the best of our knowledge. As squash is more popular among amateurs than among sport fans and gamblers, we aimed at designing a system that appeals to the masses, helping hobbyist and amateur players in their workout and training. This system was the source of that data that we have derived our preliminary results from, to be presented in the next section.

3. RESULTS

We analyzed 174 hours of video and tens of hours of racquet data from amateur game plays where players were using our prepared racquets. To compare leisure with competitive sessions, we processed 22 hours of video captured at a tournament (for 35+ years old), organized on our venue. On all of our figures we summarize data from all game sessions.

3.1 Player position analysis

"Keep your friends close, but your enemies closer." The most significant difference between leisure and competitive sessions is the distance the players keep from each other: when playing for fun, players split the court and rarely get in each other's way; while in a competitive scenario both players want to occupy strategically superior positions and get in as close as the rules permit, avoiding let and stroke situations. This explains the steeper curve at lower distances for "professional" players in Fig. 1.

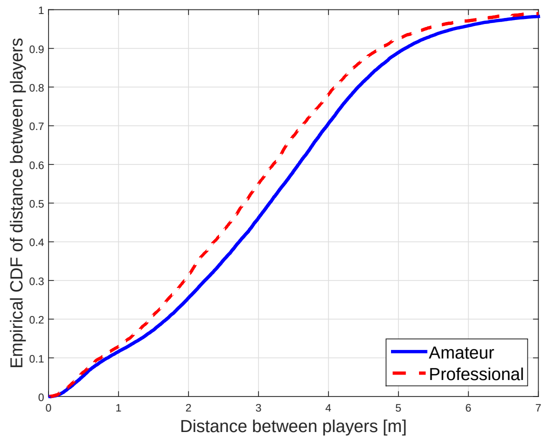


Figure 1: Measured distances between players during games

Based on the position data, we calculated the players' instantaneous speed with 30 Hz frequency. The distribution of the observations are summarized in Fig. 2: surprisingly amateurs tend to move slightly faster than professionals, but the difference does not seem to be characteristic.

Heat maps of player positions in Fig. 3 show that leisure players (Fig. 3a) have no lateral preference and tend to use the front of the court more often than competitive players (the top of the plot represents the front of the court, close to the front wall), shown in Fig. 3b. This can be explained

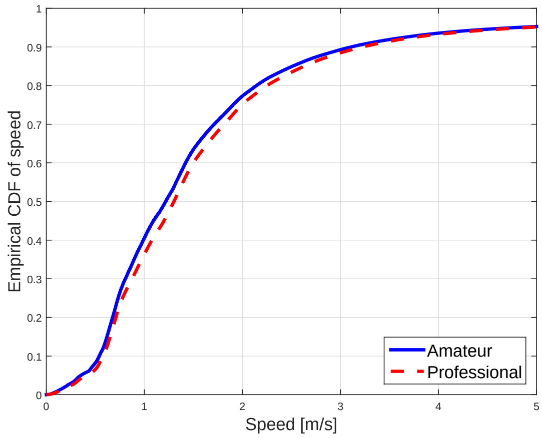


Figure 2: Empirical distribution of amateur and professional squash players' speed during games

first by the bounce of the ball: for an amateur it is hard to hit a strike at the back wall that bounces back all the way, resulting in a less skewed position distribution between the front- and the back walls. Whereas more experienced players have no trouble delivering the ball from the back to any point of the court; second, in a competition it is strategically beneficial to keep the opponent in the back. Frequenting the left side of the court is also the trait of professional players, as it forces the opponent to return the ball with backhand, which in turn causes her a disadvantage.

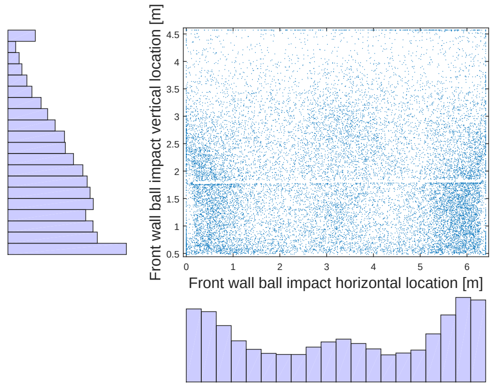
Typical velocity vectors, i.e., the superposition of measured instantaneous velocities, at meter-by-meter areas of the court also show differences between leisure (Fig. 3c) and competitive (Fig. 3d) players. While both types of players tend to rush to spots near the walls to reach difficult balls, a relatively smaller, but a constant trend can be seen in velocities in the top half of the court for amateur players but not in competitive players' velocity patterns. This tells us that amateur players tend to run towards the front wall to reach short balls more often than professional players.

3.2 Ball impact analysis

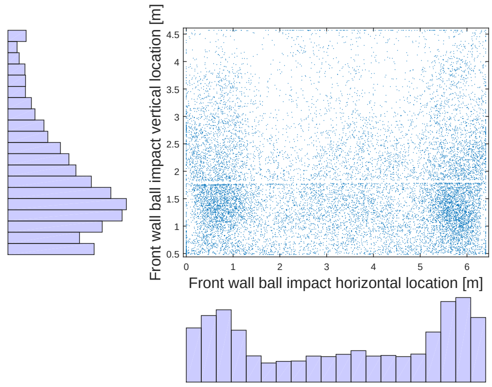
Front wall ball impacts are shown on Fig. 4, for leisure (displayed as "amateur") and competitive (denoted by "professional" tag) matches. While competitive players target their hits below the service line (marked by missing impacts resulting from an artifact of the visual impact detection), leisure players' hits show less skewed distribution for vertical positions. It is interesting to note that while competitive players play below the service line, the hits are concentrated in the upper-middle of the region. These are usually powerful shots intended to force the opponent back. Meanwhile leisure players have a tendency to score points hitting low and slow balls, targeting the bottom of the front wall. Both groups favor the horizontal extremities, but an accented center area can be observed among leisure players. This might be the result of the players standing in their respective halves of the court and passing the ball to each other as warm-up or to catch their breath after a faster rally.

3.3 Stroke analysis

Due to the reluctance of professional players to play with our smart racquet we have managed to collect data on stroke



(a) Amateur players



(b) Professional players

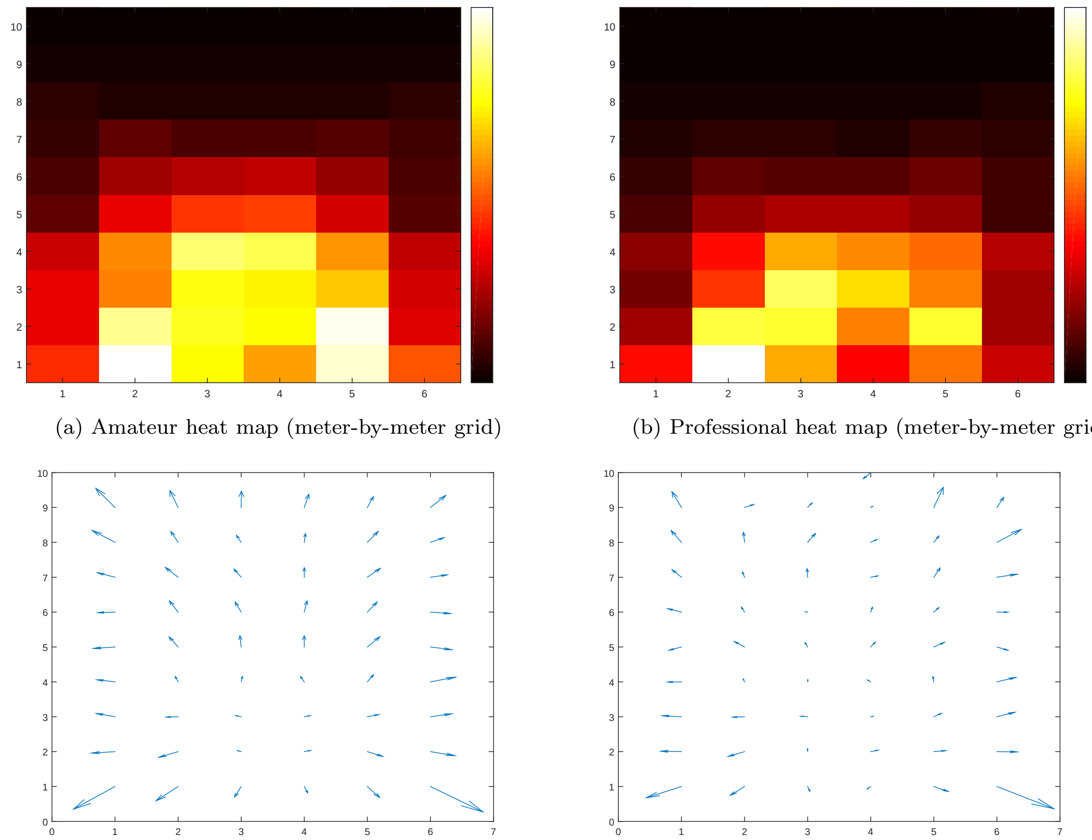
Figure 4: Empirical distribution of front wall ball impacts

attributes only from amateur matches. The first main result is that the recorded split between forehand and backhand strokes is 55% vs. 45%. It is commonly known that beginners might have problems with their backhand technique, and therefore might hesitate to apply backhand and forehand equally.

In Fig. 5 we show the distribution of stroke forces that we estimate based on the 6-axis sensor's data; both for the total data set (on the vertical histogram on the left) and for a minute-by-minute split (time series of 95-, 75-, and 50-percentiles for the minutes at the bottom subfigure). We expected that as time goes by amateur players tend to hit with less and less force during a game. Surprisingly there is no such general trend that we could have found, on the other hand the fraction of low-force strokes is strikingly high.

4. CONCLUSIONS

Analyzing squash has its many challenges, from camera placement to ball size, its fast pace and often chaotic movement patterns. However preliminary results are promising. Comparing leisure and competitive games we were able to identify some key aspects of the captured dataset. The three presented data sources need improvement, but with the smart squash court already in place we are continuously gathering data and working together with professional players and trainers to gain better understanding of the underlying mechanisms.



(a) Amateur heat map (meter-by-meter grid) (b) Professional heat map (meter-by-meter grid)

(c) Amateur speed vectors (meter-by-meter grid) (d) Professional speed vectors (meter-by-meter grid)

Figure 3: Typical positions and movements during amateur and professional squash games

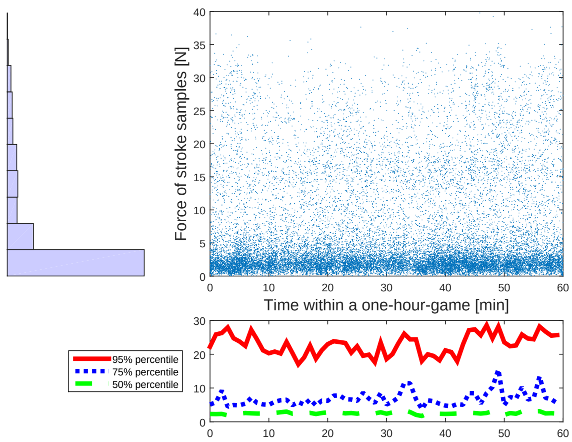


Figure 5: Distribution of stroke force measurements at amateur players during 1-hour games

5. ACKNOWLEDGMENTS

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6. REFERENCES

[1] Hawk-eye ball tracking. http://www.hawkeyeinnovations.co.uk.

[2] Smart Tennis Sensor for Tennis Rackets. http://www.sony.com/electronics/smart-devices/sse-tn1w.

[3] Specifications for Squash Courts. http://www.worldsquash.org/ws/wp-content/uploads/2014/10/130115_Court-Specs1.pdf.

[4] Zepp tennis | analyze & improve your serve & stroke. http://www.zepp.com/en-us/tennis/.

[5] D. Connaghan et al. Multi-sensor classification of tennis strokes. pages 1437–1440. IEEE Sensors, 2011.

[6] K. Conroy et al. Enrichment of raw sensor data to enable high-level queries. In *Database and Expert Systems Applications*, pages 462–469. Springer, 2010.

[7] S. Gerke and K. Mueller. Identifying Soccer Players using Spatial Constellation. In *KDD Large-scale sports analytics Workshop, 2015*.

[8] T.-Y. Liu et al. Effective feature extraction for play detection in american football video. In *Multimedia Modeling Conference*, pages 164–171. IEEE, 2005.

[9] R. Martin Nieto and J. M. Martinez Sanchez. An automatic system for sports analytics in multi-camera tennis videos. In *Advanced Video and Signal Based Surveillance*, pages 438–442. IEEE, 2013.

[10] X. Wei et al. Predicting Shot Locations in Tennis Using Spatiotemporal Data. pages 1–8. IEEE, 2013.