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Research paper

Deepracket: AI powered player performance evaluation in racket sports

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Abstract

The project, "Qualitative Racket Player Analysis" is to analyse the player performance in a professional racket sport match using advanced video analysis techniques. It is predictive of the most common angles to opposite floor locations. A thorough analysis like court line detection using image processing to determine accurate boundaries of courts, player recognition and motion tracking during matches via particle filter algorithms for human activity measurement, action moment in games by replay frame in Convolutional Neural Networks (CNN), or possing the posture and body behavior from skeleton key points estimation with OpenPose library built-in function followed task-driven multisigmoid models — as well classification testing stroke accuracy could potentially make it into modern automated systems. These methods are combined to provide an in-depth qualitative understanding into racket sports players which can aid gameplay, enhance coaching strategies, increase performance and engage with fans.

Keywords: *Badminton; Player Analysis; Video Analysis; Court Line Detection; Particle Filter; Player Tracking; Convolutional Neural Networks (CNN); Replay Frame Detection; Pose Estimation (Openpose) Stroke Detection Machine Learning Computer Vision Sports Analytics.*

1. Introduction

The Badminton Analysis project is a fantastic example of how computer vision techniques can be utilized in creative new ways to improve the analysis process when it comes to badminton matches. At the heart of the initiative is advanced machine learning, enabling real-time player and shuttlecock detection within video. The adoption of this automated mechanism for the in-game segment, brings unprecedented understanding into gameplay that benefits strategy building as well performance analysis and coaching decisions. The project aims to simplify and improve the analytics workflow in comparison with traditional manual procedures using object detection methods.
For badminton, identifying these key components during a game requires advanced algorithms to handle the game's high rate of play. Accurately tracking the motion of players and a shuttlecocks allows for instant feedback ontecnique position, moves, tactics — to coaches as well as player themselves. This leads to better They have to collect a dataset for training the model or creating an image and video from badminton matches. We usually split such datasets into a training set and validation/test set, so that the model generalizes well to unseen data as possible. Annotations are essential in dataset generation by marking the location of players and shuttlecock for each frame This annotation process is key in the creation of accurate and reliable detection models.
This project uses several techniques to make it work. The Hough Line Transform technique is used to detect court boundaries. It is important exercises for assessing the position of players in relation to where they are on the court. As a result, Particle Filters track movement across the court to allow the system to capture complex motion traces of players. The project provides an analysis of the dynamics of players during games due to this combination.
Convolutional Neural Networks (CNNs) play a crucial role in the classification of goodminton smashes, clears and drops during performance analyis. This more detailed classification of shots provides increased understanding about player performance to help athletes assess their personal skill range and the potential need for development. Additionally, integrating OpenPose for pose detection enables the system to assess players' techniques and stances, thereby providing recommendations to perfect their form and elevate their gameplay.

2. Overview of domain

This project leverages machine learning and computer vision to analyze racket sports, with the objective of predicting the landing positions of shots and monitoring player movements during matches. Techniques such as the Hough Line Transform are utilized to identify court boundaries, while Particle Filters are employed to track players' movements on the court.

Convolutional Neural Networks (CNNs) aid in categorizing various shot types, and OpenPose is used to analyze player movements for technique assessment. Collectively, these methodologies create a comprehensive system for performance evaluation, enabling players to gain insights into areas for enhancement and strategy refinement.

3. Literature review

The use purposely designed physical simulation models and high speed video analysis to improve tennis skills. Conclusions the presented methodology validates the simulation approach for skill acquisition using broadcast videos. However, this study is limited to tennis and may not be widely generalizable amongst other sports. Furthermore, the performance of the simulation largely depends on its accuracy implying an unexplored research aspect regarding how reliable are these simulations models (Learning Physically Simulated Tennis Skills from Broadcast Videos 2023).[1]

This study explores tactic-based visual analytics applying simulation techniques tailored to table tennis. It brings the viewers a very important point of view on strategies and tactics used in table tennis demonstrated by video simulations. Nevertheless, it serves only a single sport and remains questionable for other racket sports because of its focus on more accurate simulations (Tac-Simur: Tactic-Based Simulative Visual Analytics of Table Tennis 2020). [2]

In this study, we develop a deep reinforcement learning framework for improving player decisions in soccer by obtaining and executing strategies to enhance in-game performances. While it was effective for soccer decision making, whether a similar AX strategy would work in other sports remained to be seen. A further substantial limitation is its reliance on significant amounts of labeled training data, which poses an important challenge (Beyond Action Valuation: A Deep Reinforcement Learning Framework for Optimising Player Decisions in Soccer 2022). [3]

This paper provides a detailed survey of what methods, and datasets that exist for video action recognition in sports. It also focuses on the evolution of action recognition tech — particularly in sports. While the comprehensive nature of this survey is beneficial, it may limit its detail within specific implementations and outlines practical application gaps in research (A Survey on Video Action Recognition in Sports: Datasets, Methods, and Applications 2024). [4]

In this regard, a more detailed article that has recently been published discusses the progress made in using AI to analyze basketball shooting techniques. It creates new scoring features designed to improve metrics for shooting ability (like basketball). But, this article just focused on shooting techniques and ignored other aspects of the game (Review of Basketball Shooting Analysis Based on Artificial Intelligence, 2023). [5]

The study explains the use of visual analytics for understanding evolving racket sport strategy. Thanks to analytics, it also offers interesting views into how tactics keep changing and evolving over time. However, the study mostly focused on visual analytics and might have failed to address other important aspects of tactic performance assessment (TacticFlow: Visual Analytics of Ever-Changing Tactics in Racket Sports, 2022). [6]

The research employed two-dimensional human pose estimation for a few reasons: first, to enable fast and efficient recognition of table tennis strokes; next building 3D models from relatively sparse data can be challenging compared mapping into the spatial dimensions in an image frame. Still, this methodology proficiently classify different table tennis strokes and it is interesting to see how well the algorithm performs when we take into account that his study focuses uniquely on table tennis as a whole (Reference: Table Tennis Stroke Recognition Using Two-Dimensional Human Pose Estimation, 2023). [7].

4. Architecture

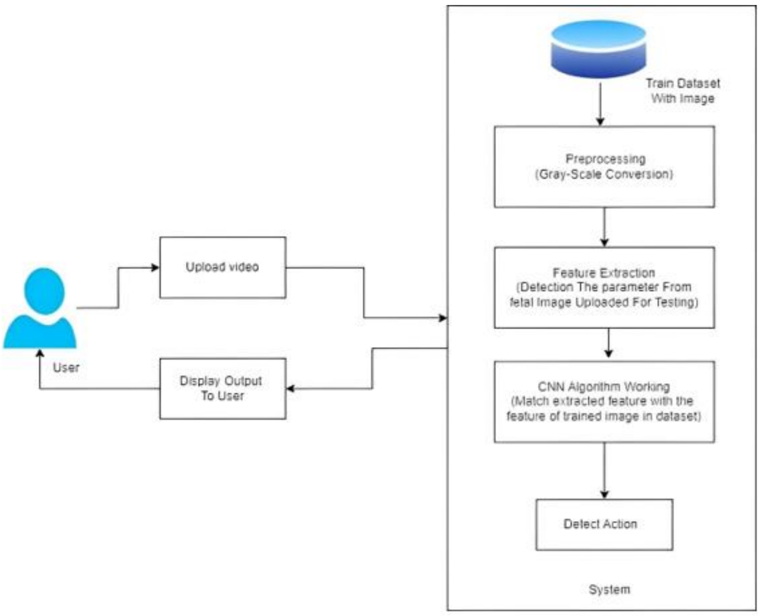

Fig. 1: Sports Analytics System.

5. Proposed method

4.1. Court line detection

It goal is to accurately locate the court limits and the corner coordinates. This leads to all future processing and predictions being on the relative positions of players on court than individual frame itself. This is because not all badminton tournaments capture the same camera angles, and comparatively inconsistently positioned players (on-court) are arguably in a single position, leading to unfair results.

- Binary Threshold Image is used for an Intensity Transformation to highlight the white lines on the court and mask out distractions.
- All edges go through Hough Lines then, only vertical and horizontal lines come out. We then define a specific function that extracts the lines needed based on length. Tuning this parameter is very important for every new tournament to get the right border lines.
- Detection of the point intersections in view using determinants.
- K-Means clustering is used to put the points into 4 bins which are >= each of the four corners in court. This aims to tackle the issues of multiple cross boundary lines detected by Hough Lines filter.

4.2. Player detection

One of the most important things to determine in predicting shot direction is, as mentioned earlier, where players are on court. And this parameter is very much useful in future use. Result Till now we have gone through few techniques for detection of objects and the three methods are as follows:-

- Particle Filter: ideal speed/accuracy compromise It is good at sensing where the players are on a court.
- YoloV3: Yolov3 is a very accurate and strong object detection method. But it is rather slow compared to other techniques.
- Video Frame Difference: This technique can employ to detect tiny movements like outside the playing court. You can do that to spot player positions during the game. Our goal is to detect the position of a player in such a manner that will help us predict the direction of shot accurately, so we have applied following methods.

4.2.1. Automatic color detection

The method which the Particle Filter performs is by tracking the RGB values of a pixel that we chose. In each game, we automated the process of detection using binarization techniques into unique colors during target color identification for accurate recognition.

- Top Half of the Court Frames —Lower Play Classification for Individual Players • Gathered top or bottom frames to identify specific parts of a court collected data by shot types for individuals.
- Used court boundary coordinates to create a mask for the outer region of court.
- Picked out the most common colors in these two sub-frames and eliminated: black (representing outside of court), green for mat color on the court, border color of course.

4.2.2. Replay detection using CNN

As we were working on improvements to our particle filter script, a very important problem emerged: the entire thing crashes when it starts trying out some of those close-up replay frames the kind that shows something about midcourt approaching from overhead as nothing but pixels [excludes many kinds]. Hence, we implemented a CNN model to predict either 'play' or 'non-play' through the frames. The Ids of non-play frames> are stored in a text file that is mentioned to be passed from section 2.3 of the algorithm Below are visuals that demonstrate side by each 'non-play' and "play" frames.

4.2.3. Particle filter

- Allocation of distinctive sets of particles, while one set is intended for each player.
- The particles representing the lower player are scattered in a trapezoidal formation reinforcing our earlier image, as shown on Figure X. In contrast, the particles associated with upper player spread over a rectangle area (which slightly exceeds court borders see physical human presence)
- Draw solid black vertical lines that extend for the entire height of a video frame along both edges of the court to limit clumping near borders since player jersey is similar in color.
- Then check if for this frame ID, it has been marked as a playback Frame per frame If yes, then the particles are reset and object tracking is momentarily stopped until another 'play' frame occurs again.

4.3. Player stroke detection

In this project, another crucial element involves predicting the type of stroke or shot executed by the players. Three main shot types, namely, 'net-drop return', 'smash', and 'defense', are considered for illustrative purposes. To predict these shots accurately, we manually gathered training data by isolating frames corresponding to these shots and assigning labels to them. Subsequently, the labeled training data undergoes classification through a multi-class classifier, and stroke identification is conducted using a sophisticated Artificial Neural Network model such as CNN.

4.4. Player pose estimation using openpose library

Details of 19 specific body parts, with associated interconnections After this a pre-designed TensorFlow model is used to train on the input image which results in an output of lines and points, outlining every connection between joints The figure below provides an example of the process.

6. Research gap

The Qualitative Racket Player Analysis project sets out a practical and user-friendly solution to analyze racket sports matches based on computer vision technologies. It seamlessly integrates a number of different approaches, such as court line detection, player tracking via particle filters and shot prediction based on each players location in the court. By studying video inputs, the mechanism even predicts where a player or team is most likely to shoot long on any given point in time — automatically spotting patterns and trends (and then adjusting those as new data comes along).

The achievements include the project being able to adapt cameras with different angles and detect court boundaries accurately, along with tracking player motion using algorithms like particle filters and YOLOv3. Additionally, the project uses CNN replay frame filtration by which only gameplay frames are being analyzed keeping distractions away from replays. Shot prediction mechanisms (e.g., smash, net drop) are included to enable the system provide real-time forecasts of player movements through both position and action.

By making advanced racket analytics available to aspiring players and coaches, this project meets an important demand: providing a way for people who play the sport or help others improve at it to learn about how they are doing. However, Better dice control by human can also be obtained using techniques from advanced player assessment [33], such as reinforcement learning to evaluate not only intended behaviors but in the context of an overall game strategy.

7. Conclusion

The project “Qualitative Racket Player Analysis” presents an efficient method to study racket sports using a computer vision approach. This includes building a court line, player tracking using a particle filter and YOLOv3, and player action recognition based on their location in the video. The system shows the reliability of the court line recognition from different camera views and the ability to eliminate the replay frames with the help of CNNs. Besides, it works unreliably at predicting shot types such as smash or net drop before they happen.

Due to its efficiency and utility, this system is expected to change how players and coaches perform their racket analysis as well as their game strategies in their day to day activities. In the future, it is expected that the system could be refined further on through the application of reinforcement learning in the task of assessing different actions for optimality.

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