Analysis of Playing Positions in Tennis Match Videos to Assess Competition Using a Centroid Clustering Heatmap Prediction Technique

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***Abstract*—This research aimed to use clustered heatmap positioning analytical techniques in tennis in order to be able to analyze the positions of tennis players. A heatmap represents the cumulative frequency of tennis players' movements in each zone of the tennis court. The performance testing of centroid clustering heatmap position analysis was achieved on selected men's doubles tennis matches during the SINGHA CLASSIC 2019 competition. The research was done by collecting the cumulative frequency data and replacing it with intensity of color space. The process started with, firstly, cutting videos for each match based on the area of the court that could be seen clearly by the cameras in the field. Secondly, the video was converted into binary images. Thirdly, noise reduction was performed using morphological techniques. Fourthly, the centroid position was identified using a connected component and blob analysis. Fifthly, clustering data with k-mine was used to predict new tracks by Kalman filter. Finally, the percentage of player position in the three zones of the tennis court was calculated with the percent yield formula. The experimental results clearly showed the cumulative frequency of the players' movement with the intensity of color space, allowing coaches and players to easily understand and use the data in planning for the next practice or competition.**

***Keywords*—video analysis, heatmap technique, centroid clustering, cluster analysis, heatmap regression model, playing pattern analysis**

I. Introduction

Match analysis is significant in strategizing, planning and assessment of sports competitions [1−4]. In sports, match analysis assists by providing data on playing patterns, and physiological and psychological pressure of the performers.

Previous work on sports video analysis and the state-of-the-art techniques has included object detection, action recognition, highlight detection, event recognition, contextual inference, and semantic analysis, as summarized and categorized in Fig. 1 [5]. Sports video analysis has been widely used in sports such as soccer, baseball, tennis, and American football, while other sports, such as golf, hockey, racing, boxing, badminton, sumo, table tennis, and volleyball, have not concentrated as much on this type of analysis, which relies on the use of visual features for content analysis, captions and text, playfields, camera motion, ball positions, player position, and replays.

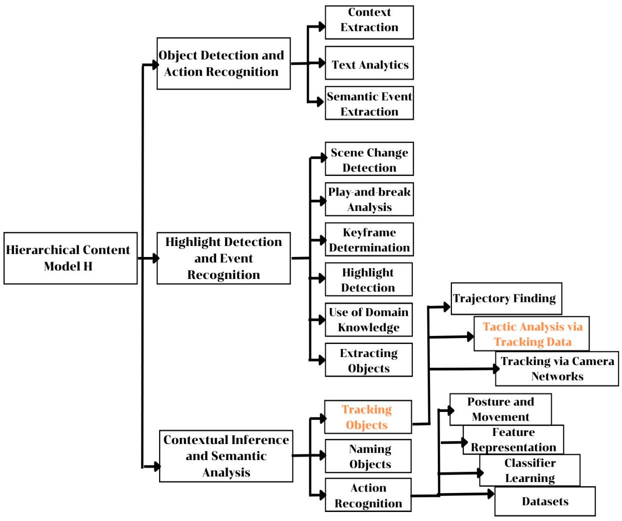

Figure 1. Categorization of surveyed sports video analysis techniques [5].

The work was done in the space of sports analysis, which integrated a variety of approaches related to Music Analysis, Retrieval and Synthesis for Audio Signal (MARSYAS), Support Vector Machine (SVM), entropy-based movement analysis, homoscedastic error model, radial basic function, support vector regression, and a combination of domain-independent global and model-based filtering methods with domain-specific and object-level assessment for goals, faults, volleys, silence, overhead swings, left-right swings, and action recognition, all of which can be applied to recognize goals in soccer, faults, volleys, scores, misses, and free-kicks. In other words, prior research has developed methods that effectively utilize tools such as video division, occasion location, synopsis, full of feeling examination, feature positioning, video perusing, and activity acknowledgment.

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Playing position analysis [6−12] has been applied in previous work to support vector regression with tennis for effective analysis, and highlight ranking and action recognition.

Clustering relies on a number of techniques and methods; the k-mean clustering algorithm is used because of its simplicity and rapid convergence. According to one study [13], compiling the clustering method and the main objectives involves performing grouping with big data, but there are a number of commonly used clustering techniques for identifying data formats and performing analysis of sample data.

Based on a review of previous work, it does not appear that there has been research to propose athlete position analysis using the heatmap technique. Therefore, in this study, researchers are interested in using the heatmap technique for this type of analysis, which relies on centroid calculation to find the data group's representative values. A heatmap is then generated to represent the cumulative frequency of tennis players' movements in each zone of the tennis court in order to be able to analyze the positions of the tennis players. Our framework can calculate the percentage of movement density of the players in different positions on the court, which is displayed as a percentage of the playing position in 3 zones on the court, allowing coaches and players to understand and evaluate the match easily, and to use the data to plan for the next practice or competition.

This paper is organized as follows. Section II provides a brief overview of the literature related to sports video and playing pattern analysis, as well as centroid use and contour object base tracking. Section III elaborates the elements and details of the proposed method. In Section IV, researchers assess the performance of the proposed test and its experimental results. Finally, Section V presents the conclusions of the experiment.

II. Literature Review

Researchers reviewed prior studies in sports video investigation as indicated by three progressive layers of the flow research routine, which are low-level, mid-level and high-level analysis. To recognize the work from other related studies, researchers additionally examined human conduct acknowledgment in the transmission of sports video and the effects on both semantic and viable video.

A. Sport Video Analysis and Playing Pattern Analysis

Most of the previous sports video analyses have analyzed well-known sports such as football, baseball, basketball, American football, and tennis [6−12]. Furthermore, the occasion model is normally associated with scoring objectives with the utilization of procedures. Examples include feature identification and extraction, occasion location and acknowledgment, Sports Vector Machine (SVM), and Hidden Markov Models (HMM). A Support Vector Machine (SVM) was used to classify normal and abnormal images using the Leave-One-out Cross-Validation Method (LOOM) [14].

B. Heatmap Technique

A heatmap [15−19] technique utilizes liabilities, which are determined by the Markov-chain Model (MMM). It was proposed in this work by examination of Principal Component Analysis (PCA), Independent Components Analysis (ICA), and Non-negative Matrix Factorization (NMF). Heatmaps and Wi-Fi, as displayed, (heat map-based Wi-Fi fingerprinting: HMF) can further develop existing Wi-Fi fingerprinting plans like Radar and Horus [17]. This work concentrates on heat map-based time-varying data, visualization technique, and highlighting an intelligent instrument in order to show significant information and time ensures for shape fitting sizes of heatmap and spotlight on significant information things or time steps.

C. Contour Based Object Tracking

Contour based object tracking can track objects in both images and videos. The most important task in contour-based object tracking is fi0nding the contours. Using these contours, researchers can detect the centroids of the objects; these centroids will represent the object, allowing the researcher to easily follow its movement path. This contour-based object tracking can be utilized in a few computer vision applications as well [20].

The following section will zero in on how the proposed strategy presents an anticipated centroid grouping heatmap for investigation of tennis playing positions based on video of tennis matches. Numerous calculations are used, including point Tracking algorithms such as Kalman Filter, Kernel tracking, Mean shift, KLT tracker, various silhouette tracking methods, and condensation. These algorithms track the objects based on different principles. A few foundations are deducted with techniques that are likewise utilized for this item catching the video with the webcam or any video recording gear [20].

III. Proposed Approach

The goal of this research is to analyze athletes' positions by heatmap technique with centroid clustering. This analysis is intended for the benefit of trainers and coaches to facilitate analysis and prediction, as well as to enhance the ability to plan the athletes' movements during competition. In each match, the movements of athletes between the zones of the playing court are calculated in percentages in order to facilitate the training plan for the next competition. In this part, the researcher has provided an outline of the proposed structure for anticipating the centroid bunching heatmap. The following segments examine the subtleties of our proposed strategy:

A. Overview of the Framework

Our proposed framework is a Centroid Clustering Heatmap Prediction technique. Fig. 2 shows the conceptual framework and principles of the proposed method. The first step is to remove the superfluous parts from the tennis video. For example, periods of time when a player is very still during preparation would be removed.

After this is done, the remaining video content is converted into a parallel picture; this progression will seem to be commotion on the item. Researchers utilized a morphological strategy to dispense with commotion. Following this step, a calculation is used to identify centroid bunching, as displayed in Fig. 3. Each video has a centroid recorded as x- and y-coordinates; then, at that point, the heatmap is utilized to show the thickness of the competitor's position. The final step is to calculate the percentage of time spent by each player positioned in each of three zones on the court, providing valuable information that can be used by coaches and players in developing training plans and playing strategies.

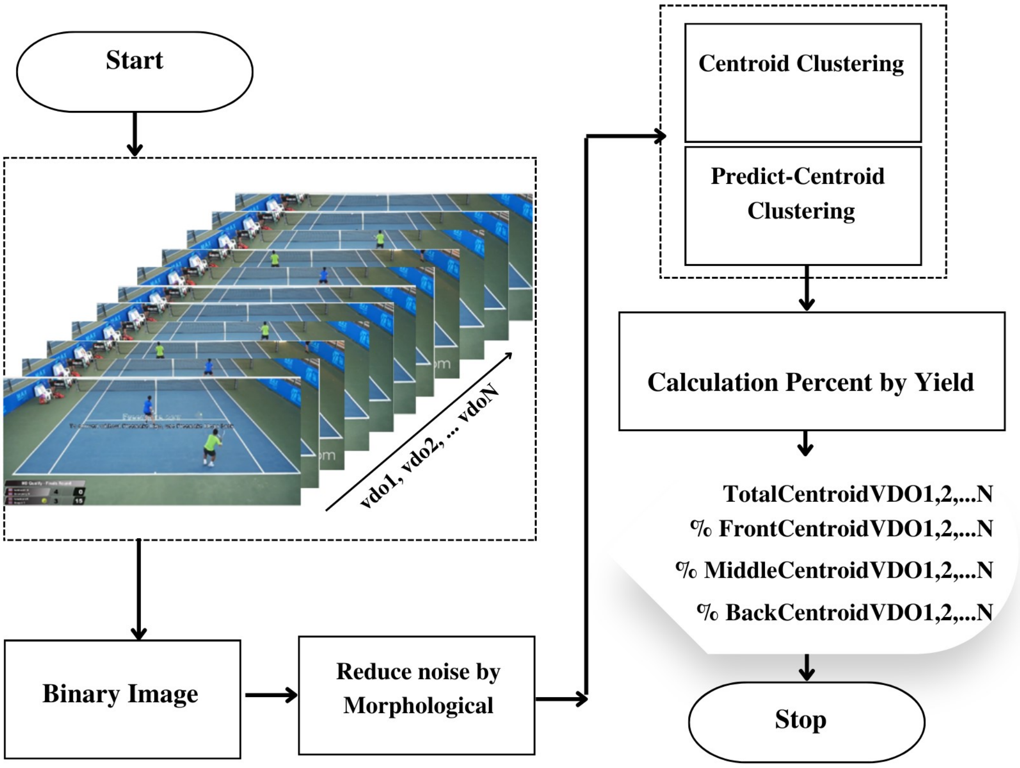


Figure 2. Conceptual framework of our propose.

Figure 3. Centroid clustering heatmap.

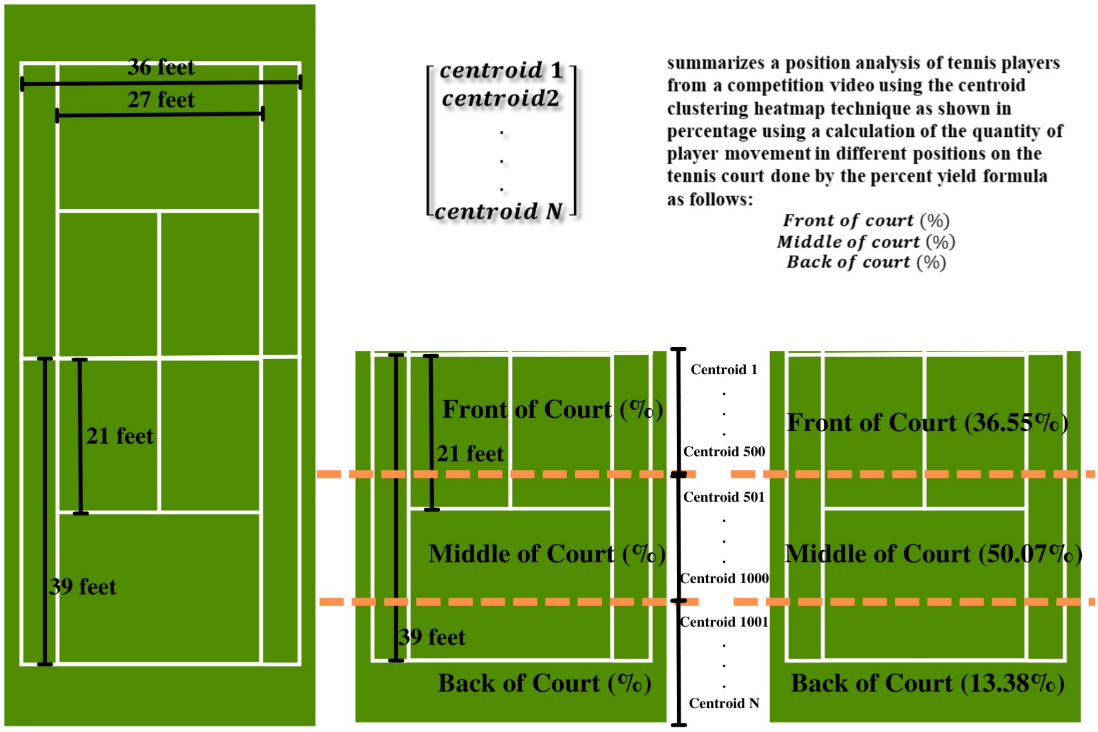


Figure 4. Data density percentage calculation (a) tennis court (b) position in court part of 3 zones (c) percentage of position in 3 zones.

B. Centroid Clustering Heatmap

For our framework, finding a centroid is done by inputting a binary image in which pixel=1 (white color) or pixel=0 (black color). Then, each connected component is labeled. The output is the centroid position (x, y). This step is done by blob analysis. Blobs help to separate multiple objects that are contiguous and come together in the frame. Area and position values for each object are displayed. Thus, the width of each object can be calculated.

The focus of mass of the area is returned as a 1-by-Q vector. The first element of the centroid is the x-coordinate (the horizontal) of the center of the mass. The second element is the y-coordinate (the vertical). All other elements of the centroid are in order of dimension (matwork.com).

Fig. 3 shows the centroid clustering heatmap. Inside the figure the sign * represented by M is centroid clustering. Then, the coordinates of the centroid can be determined as follows [21]:

$$x = (M[m10]/M[m00]) \quad (1)$$

$$x = (M[m01]/M[m00]) \quad (2)$$

Fig. 4(a) shows the layout of a tennis court. Fig 4(b) illustrates the segmentation of one side of the tennis court into 3 parts, namely the front, middle, and back, which are used to identify the position of the players on the court. Fig. 4(c) presents the results of the calculation of the quantity of movement in each position of the tennis court as percentages. This information can be used to plan training and set strategy for the next match.

Algorithm 1: The Proposed Centroid Clustering Heatmap Technique approach

Input: binary image **X** and **Y, K**
Output: Total Centroid (**D***i: n*, **K***i: n*)
Initialize **X***i*, **Y***i*, Di,**K***i* , i, n
while not converge **do**
    Label Connect Component **I***i*,
    Centroid (**X***i*, **Y***i*); blob analysis [22];
    predict new location;
    i=i+1;
  TotalCentroid (**D***i*, **K***i*)
end while
return Total Centroid (**X***1: n*, **Y***1: n*)

C. Cluster Analysis by K-mean

K-means clustering of Nonhierarchical Cluster Analysis must be a part of the data or object, and is represented by the average of the group instead of the centroid. The Euclidean formula is as follows.

$$dist = \sqrt{\sum_{k=1}^{n}(p_k - q_k)^2} \quad (3)$$

D. Data Density Percentage Calculation

Calculation of the quantity of player movement in different positions on the tennis court is done by the percent yield formula. The actual yield is divided by the theoretical yield in moles, and multiplied by 100%, as follows [23].

$$\%\ Of\ Front = (Front/(Front+Middle+Back))\times 100 \quad (4)$$

$$\%\ Of\ Middle = (Middle/(\ Front+Middle+Back))\times 100 \quad (5)$$

$$\%Of\ Back = (Back/(\ Front+Middle+Back))\times 100 \quad (6)$$

TABLE I. PERFORMANCE TESTING OF CENTROID CLUSTERED AND HEATMAP POSITIONING TECHNIQUES IN TENNIS SPORT VIDEO

Video	Tennis Court Areas (%)			Total
	Front	Middle	Back	
1	39.60	41.62	18.78	100.00
2	38.71	41.09	20.20	100.00
3	46.36	43.06	10.58	100.00
4	28.37	60.96	10.67	100.00
5	34.02	48.42	17.56	100.00
6	34.49	54.45	11.06	100.00
7	42.40	43.30	14.30	100.00
8	30.00	55.36	14.64	100.00
9	39.89	52.93	7.18	100.00
10	28.92	66.04	5.05	100.00
11	39.36	43.51	17.13	100.00
$\overline{X}$	36.55	50.07	13.38	100.00

Table I summarizes a position analysis of tennis players from a competition video using the centroid clustering heatmap technique, which shows the most common playing position to be in the middle of the tennis court. Therefore, the middle zone of the tennis court has a higher percentage of movement than the other two positions.

IV. EXPERIMENTS AND RESULTS

In order to demonstrate the effectiveness of the proposed approach, we carried out experiments on tennis match videos recorded from live broadcast television programs. The data for the tennis games were captured from the matches of men's doubles tennis matches in the SINGHA CLASSIC 2019 competition. The videos were compressed into MPEG-4 standard with a 25-frame rate per second, with a frame width of 1280 and frame height of 720. To evaluate our proposal, we tested our algorithm with 11 men's doubles tennis matches recorded during the SINGHA CLASSIC 2019 competition. The important results of our framework show the quantity of movement in all 3 zones of the court, with heatmaps to facilitate evaluation of the athletes. In our proposal, we use a centroid clustering heatmap prediction technique in order to work efficiently.

The results in Table I show the amount of movement of tennis players in the 3 zones of the court. The overall percentages of movement were found to be 36.55% in the front, 50.07% in the center of the court, and 13.38% in the back for the tennis players in this tournament. Fig. 5 compares the percentages of athletes' positions in 3 zones of tennis courts in all 11 matches, while Fig. 6 displays snapshots that present our technique. The left figure (a) displays the predicted centroid clustering heatmap, and the right figure displays the amount of player movement in 3 zones of the tennis court (%) of 11 matches. The left figure comprises 11 heatmaps and the right figure (c) displays the centroid of each of the 11 matches. Standard equipment can be used to perform the 3 steps of the working process. Regarding the experiment results from our proposal, they confirm the accuracy of our application and achievement

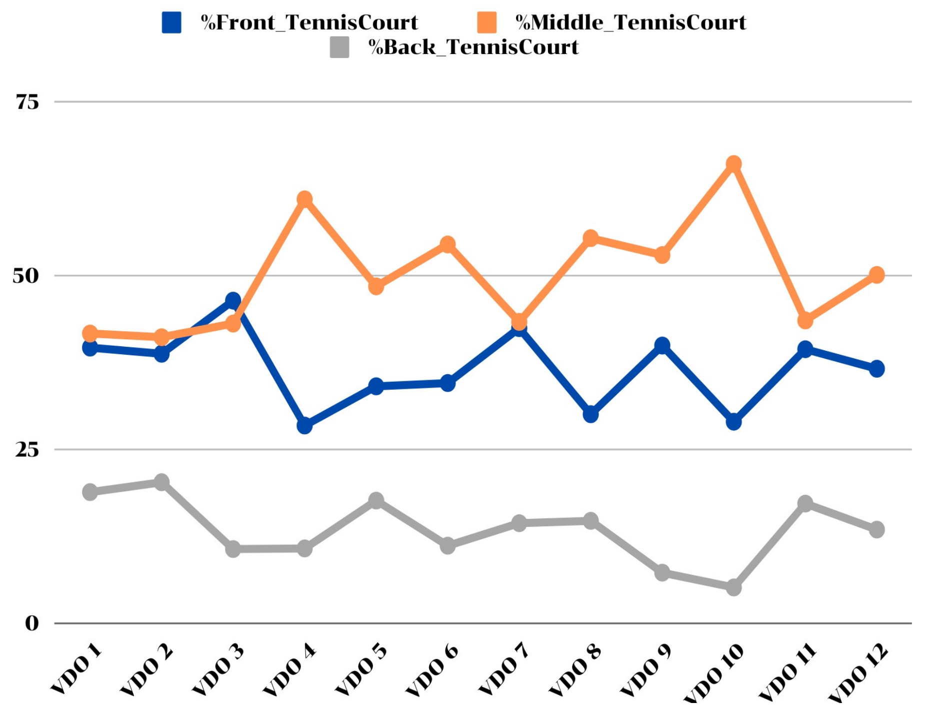
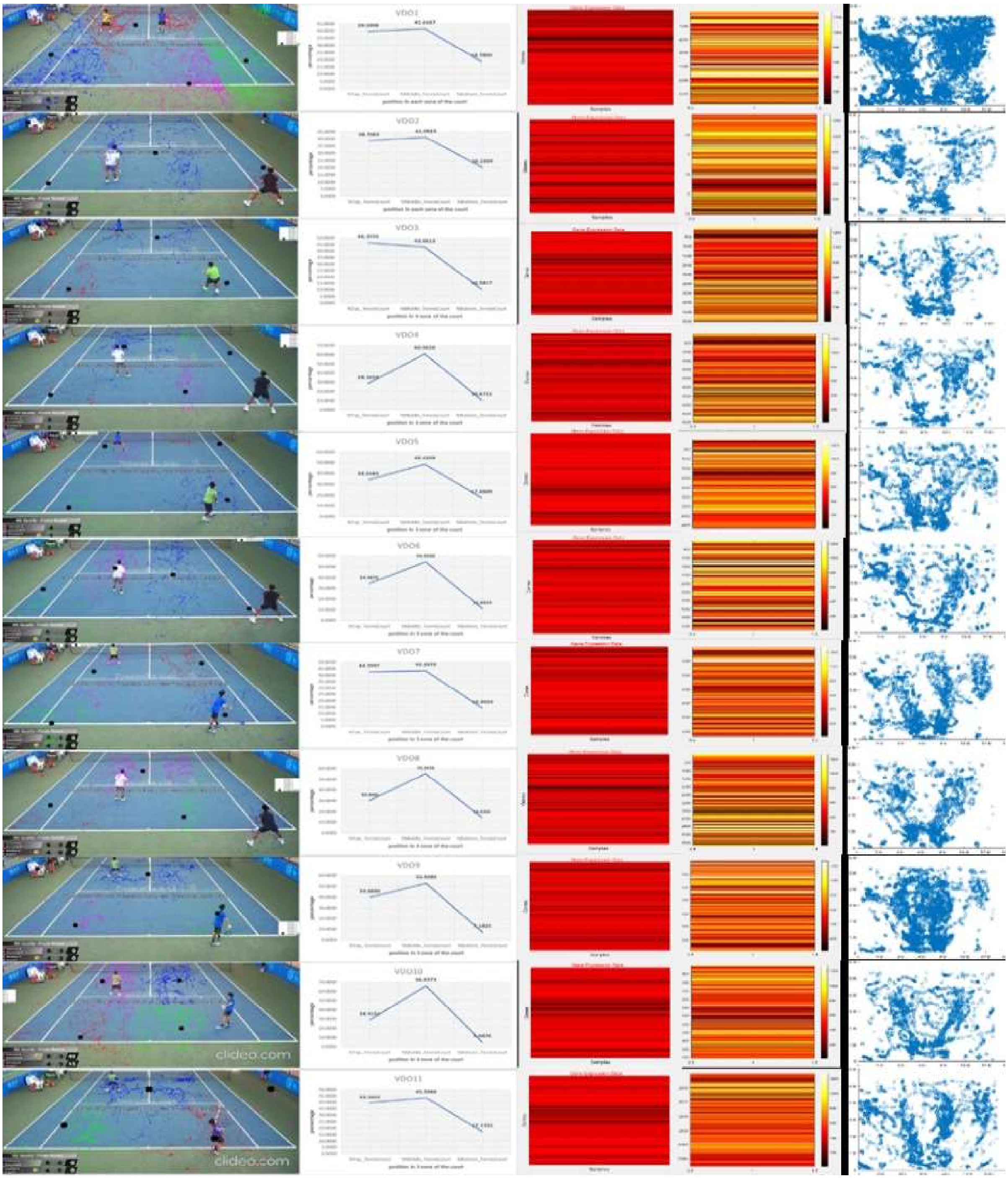


Figure 5. Comparison between the percentage of athlete's movement positions in 3 zones of tennis courts from competition video all 11 matches.

As can be seen in the graph in Fig. 5, position analysis of tennis athletes from competition video using the centroid clustering heatmap technique shows that, with only one exception (VDO3) the orange line (middle of the tennis court) consistently represents a higher percentage of cumulative movement than the gray or blue line lines (back and front of court, respectively).

The study compares the percentage of athletes' movement positions in 3 zones of tennis courts from the competition video of all 11 matches. Judging from videos 4 and 10, the cumulative movement of tennis players is higher than in other matches with a cumulative moving average of 60.9620% and 66.0373 % respectively.

In Fig. 6, The snapshot presents our technique. (a) displays centroid clustering heatmap. (b) displays the amount of the player movement in 3 zones of a tennis court as a percentage of 11 matches, and (c) the snapshot presents our technique as a heatmap and the centroid of the 11 tennis matches.



(a) (b) (c)

Figure 6. (a) Centroid CLUSTERING heatmap (b) graph of centroid clustering heatmap (c) represents heatmap of centroid.

V. Conclusion

The data calculation of the centroid technique can be done using a simple technique to achieve an effective result. Finding centroids for group data can help to predict the new location of data. A heatmap is generated to represent the cumulative frequency of tennis players' movement in each zone of the tennis court. For video analysis, one consideration is the enormous size of the data file, which should be dealt with. A large file requires a long processing time. Moreover, to prevent any processing mistakes, each match video should be checked before processing. It is also important to reduce the video size by cutting irrelevant parts of the video, such as pre-match training, breaks, and time requests in order to prevent any problems in creating the heatmap. In this paper, the researchers propose the use of centroid grouping heatmaps in analysis of playing positions based on videos of tennis matches. Information clustered by k-mean is used to make the heatmap. Our algorithm then calculates the percentage of movement density of players' different positions on the court. This technique is useful for coaches in designing training and planning strategies the next match. In future work, we are committed to adopting this algorithm into real-time video processing for the convenience and timeliness of each competition.

Conflict of Interest

The authors declare no conflict of interest.

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