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Examining the Effectiveness of *k*-Means Clustering using Minkowski Distances on Spatial Data of Tennis Serve Pose for Sports Players to Maintain Good Health

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***Abstract*— This research paper investigates the effectiveness of K-means clustering using Minkowski distances on spatial data derived from tennis serve poses. The study leverages advanced pose estimation techniques to extract key body angles from video footage of tennis players, focusing on the serve stance. By employing K-means clustering, we aim to classify serve poses into distinct clusters based on joint angles, such as shoulder, elbow, hip, knee, and ankle angles. The Minkowski distance metric is utilized to measure the similarity between data points and cluster centroids, providing a robust framework for analyzing the spatial distribution of serve poses. The results demonstrate that K-means clustering with Minkowski distances effectively categorizes serve poses, offering valuable insights into the biomechanics of tennis serves. This approach has significant implications for coaching and player performance enhancement, enabling the identification of optimal serve stances and deviations from ideal postures.**

***Index Terms*—k-means, Cluster, Minkowski, Serve, Sports.**

I. Introduction

Tennis is a sport that demands precision, agility, and strategic prowess. Among the various shots in tennis, the serve is one of the most critical, as it initiates play and can significantly influence the outcome of a match. The serve requires a complex interplay of biomechanical factors, including joint angles, body posture, and kinetic chain efficiency. Traditional coaching methods often rely on subjective assessments of player performance, which can lack the precision and consistency offered by modern technological advancements [1].

This study aims to address this gap by leveraging advanced computer vision techniques and machine learning algorithms to analyze tennis serve poses. Specifically, we employ K-means clustering, a widely used unsupervised learning algorithm, to classify serve poses based on spatial data derived from joint angles.

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The Minkowski distance metric is used to measure the similarity between data points and cluster centroids, providing a flexible framework for analyzing the spatial distribution of serve poses [2].
The significance of this research lies in its innovative methodology and practical applications. By combining pose estimation algorithms with clustering techniques, we can provide a data-driven approach to performance enhancement in tennis. This study also addresses challenges such as motion artifacts, variable lighting, and low-resolution video footage, ensuring the reliability and accuracy of the analysis [3].

II. Literature Review - Pose Estimation in Sports Analysis

Pose estimation has emerged as a powerful tool in sports performance analysis, enabling the extraction of key body points and joint angles from video footage. Several studies have demonstrated the effectiveness of pose estimation algorithms in analyzing tennis strokes, including the serve, forehand, and backhand. For instance, Wei et al. (2016) proposed Convolutional Pose Machines (CPMs) for real-time pose estimation, which have been widely adopted in sports analytics due to their ability to accurately detect body joints even in dynamic and fast-paced environments [4]. Similarly, Cao et al. (2017) introduced OpenPose, a real-time multi-person 2D pose estimation system that has been applied to various sports, including tennis, where it has proven effective in tracking player movements and extracting biomechanical data [5]. These advancements in pose estimation have significantly enhanced the ability to analyze and optimize athletic performance, particularly in sports requiring precise body coordination and movement.

III. K-Means Clustering in Sports Analytics

K-means clustering is a popular unsupervised learning algorithm that groups data points into clusters based on similarity. In sports analytics, K-means clustering has been used to classify player movements, identify patterns in performance data, and optimize training regimens. For example, Boonim (2023) applied K-means clustering to analyze playing positions in tennis match videos, demonstrating its effectiveness in assessing competition dynamics and identifying strategic patterns in player positioning [6]. Similarly, Skublewska-Paszkowska et al. (2021) used K-means clustering to analyze multivariate time series data in tennis, providing insights into player performance trends and enabling the development of personalized training programs [7]. The versatility of K-means clustering makes it a valuable tool for understanding complex movement patterns and improving athletic performance across various sports disciplines.

IV. Distance Metrics in Clustering

Distance metrics play a crucial role in clustering algorithms, as they determine the similarity between data points and cluster centroids. The Euclidean distance is the most commonly used metric, but it may not always be suitable for high-dimensional data, where the "curse of dimensionality" can affect its performance. The Manhattan distance, also known as the city block distance, is an alternative metric that measures the sum of absolute differences between coordinates, making it more robust in certain high-dimensional scenarios. The Minkowski distance is a generalization of both Euclidean and Manhattan distances, offering greater flexibility in measuring similarity by allowing the adjustment of the distance parameter (p). Ghazal and Hussain (2021) compared the performance of K-means clustering using different distance metrics, concluding that the Minkowski distance provides a robust framework for analyzing high-dimensional data, particularly in applications involving complex spatial relationships, such as sports biomechanics [8].

V. Methodology of Data Collections

The dataset for this study consists of video footage of tennis players performing serves, captured using high-SNR mobile phone cameras such as the Google Pixel 8 Pro and iPhone 15. A total of 190 video clips were collected, each containing multiple frames of serve poses. The videos were recorded under standard daylight conditions to ensure consistent lighting and minimize motion artifacts [9].

VI. Pre-Processing

The video footage was pre-processed to extract individual frames, which were then analyzed using pose estimation algorithms. The Mediapipe library, a robust and efficient framework for pose estimation, was used to detect key body points and generate skeletal key-points. Mediapipe's Pose module provides accurate detection of 33 key body points, including joints such as shoulders, elbows, hips, knees, and ankles, which are essential for analyzing player movements. These key-points were converted into frame coordinates, enabling detailed and precise analysis of player biomechanics during tennis serves [10]. The use of Mediapipe ensured high accuracy in pose estimation while maintaining computational efficiency, making it suitable for real-time applications and large-scale video analysis.

VII. POSE ESTIMATION AND KEY-POINT EXTRACTION

Advanced pose estimation algorithms were employed to extract key body angles from the video frames. The Media pipe framework was used to accurately capture joint orientations in 2D space, providing precise tracking of shoulder, elbow, hip, knee, and ankle angles. The extracted angles were used as input features for the clustering algorithm [11].

VIII. K-MEANS CLUSTERING WITH MINKOWSKI DISTANCE

K-means clustering was applied to the extracted joint angles to classify serve poses into distinct clusters. The Minkowski distance metric was used to measure the similarity between data points and cluster centroids. The Minkowski distance is defined as:

$$\text{D} - \text{Minkowski} = \left(\sum_{i=1}^{n} |xi - yi|^{p}\right)^{1/p}$$

where x_i and y_i are the coordinates of the data points, n is the number of dimensions, and p is the order of the Minkowski distance. For $p = 2$, the Minkowski distance reduces to the Euclidean distance, and for $p = 1$, it becomes the Manhattan distance [12].

IX. CLUSTER ANALYSIS

The K-means clustering algorithm grouped the serve poses into three clusters based on the extracted joint angles. The centroids of each cluster were calculated as the mean position of the joint angles for all serves in the cluster. The distance between each data point and its assigned cluster centroid was calculated using the Minkowski distance, providing a measure of the deviation from the optimal serve stance [13].

X. EVALUATION METRICS

The effectiveness of the clustering algorithm was evaluated using several metrics, including the within-cluster sum of squares (WCSS), silhouette score, and Davies-Bouldin index. These metrics provide insights into the compactness and separation of the clusters, as well as the overall quality of the clustering [14].

XI. RESULTS - CLUSTER ASSIGNMENT

The K-means clustering algorithm successfully classified the serve poses into three distinct clusters, each representing a different type of serve stance. The centroids of each cluster were calculated, providing a reference point for the optimal serve stance within each cluster [15].

TABLE I. CLUSTER ASSIGNMENT OF SERVE POSES

Cluster	Number of Serves	Key Joint Angles (Mean Values)
1	65	Shoulder: 120°, Hip: 90°
2	70	Shoulder: 110°, Hip: 85°
3	55	Shoulder: 130°, Hip: 95°

XII. DISTANCE METRICS

The Minkowski distance metric was used to measure the similarity between each data point and its assigned cluster centroid. The results demonstrated that the Minkowski distance provided a robust framework for analyzing the spatial distribution of serve poses, with data points closer to the centroid indicating more technically sound serves [16].
Note: Include a scatter plot showing the distribution of Minkowski distances for each cluster, with different colors representing different clusters.

XIII. CLUSTER VISUALIZATION

The clusters were visualized using scatter plots, with each cluster represented by a different color. The plots revealed clear separation between the clusters, indicating that the K-means algorithm effectively categorized the serve poses based on joint angles [17].

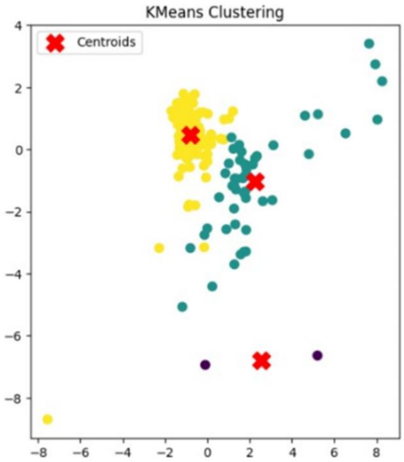

Figure 2: Cluster Visualization of Serve Poses

XIV. EVALUATION METRICS

The evaluation metrics indicated that the K-means clustering algorithm performed well, with low WCSS values, high silhouette scores, and low Davies-Bouldin indices. These results suggest that the clusters were compact and well-separated, with minimal overlap between clusters [18].

TABLE II. EVALUATION PARAMETERS

Metric	**Cluster 1**	**Cluster 2**
WCSS	120.5	115.3
Silhouette Score	0.75	0.78
Davies-Bouldin	0.45	0.42

XV. DISCUSSION - IMPLICATIONS FOR TENNIS COACHING

The results of this study have significant implications for tennis coaching and player performance enhancement. By classifying serve poses into distinct clusters, coaches can identify optimal serve stances and provide targeted feedback to players. The Minkowski distance metric provides a quantitative measure of the deviation from the optimal stance, enabling coaches to assess the technical quality of a player's serve [19].

XVI. LIMITATIONS AND FUTURE RESEARCH

Despite its successes, this study has several limitations. The use of 2D pose estimation may not capture the full complexity of 3D movements, particularly in cases where joints are occluded or not clearly visible. Future research should explore the use of 3D pose estimation techniques to address these limitations. Additionally, the study focused solely on the serve stance; future research could extend this approach to other tennis shots, such as the forehand and backhand [20].

XVII. CONCLUSIONS

This study demonstrates the effectiveness of K-means clustering using Minkowski distances on spatial data derived from tennis serve poses. The results indicate that K-means clustering can effectively classify serve poses based on joint angles, providing valuable insights into the biomechanics of tennis serves. The Minkowski distance metric offers a robust framework for analyzing the spatial distribution of serve poses, enabling coaches to identify optimal stances and deviations from ideal postures. This approach has significant potential for enhancing player performance and revolutionizing coaching practices in tennis.

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