Journal of Information Organization

DLINE JOURNALS

Print ISSN : 2278 – 6503
Online ISSN: 2278 – 6511

JIO 2025: 15 (4)
https://doi.org/10.6025/jio/2025/15/4/179-186

A multi–Feature–based 3D Model for Personalized Teaching in Higher Education

Wei Yue
Physical Education Department of Henan University of Urban Construction
Pingdingshan, Henan, 467036, China
18637591599@163.com

ABSTRACT

The paper titled "Table Tennis Teaching 3D Model Based on Hierarchical Clustering Intelligent Algorithm" by Wei Zeng proposes an innovative approach to enhance university level table tennis instruction by leveraging a hierarchical clustering intelligent algorithm. Recognizing the limitations of traditional teaching methods particularly their inability to accommodate students' diverse skill levels the study introduces a data driven, layered teaching model. The algorithm preprocesses player movement data using background-difference and shadow removal techniques, then extracts features via Radon transformation and wavelet analysis. A multi feature fusion strategy enables precise posture recognition. The core of the method involves a two layer hierarchical clustering process that separates data points by density, removes outliers (~10% of low density points), and organizes the remaining data into cohesive clusters, improving classification accuracy. Experimental results from a PDCA cycle based teaching intervention show that this approach outperforms traditional algorithms like k-means++, CURE, and CBDP especially in handling complex, non-spherical cluster shapes. The study concludes that hierarchical clustering not only enhances teaching personalization and student engagement but also offers a robust framework for skill assessment and instructional design in physical education, particularly for sports like table tennis that require fine motor control and rapid decision making. This intelligent model supports adaptive, student centered pedagogy and paves the way for technology integrated sports education reforms

Keywords: Hierarchical Clustering, Table Tennis Teaching, 3D Model, Intelligent Algorithm, Posture Recognition, Layered Teaching, PDCA Cycle

Received: 25 July 2025, Revised 15 October 2025, Accepted 27 October 2025

1. Introduction

The sport known as "national ball," or table tennis, is immensely popular in China. It serves not only as a source of enjoyment but also as a means of enhancing muscle strength. In universities, it has been established as a mandatory physical education course, helping students improve their competitive skills and fostering awareness of team collaboration. Currently, numerous higher education institutions provide table tennis classes, yet the quality of instruction often falls short of expectations. Several factors contribute to this issue, with the most significant being the inability to cater to students' varying skill levels and the shortcomings of conventional teaching approaches, which hinder their ability to benefit from lessons and gradually diminish their passion for the sport. To better understand and address students' diverse characteristics, researching and implementing multidimensional clustering methods in university table tennis settings is particularly essential [1]. Utilizing a hierarchical clustering intelligent algorithm allows for more tailored physical education instruction, thereby achieving improved outcomes in table tennis teaching. This approach can not only enhance the class's engagement but also facilitate more focused quality management, consequently boosting the overall effectiveness of the educational process [2]. This procedure encompasses establishing quality objectives and executing these steps, which typically involve the repeated use of hierarchical clustering techniques. This methodology can be utilized not only in quality control systems but also across various sequential processes [3]. With the advancement of science and technology, there is an increasing emphasis on improving individual health standards and the ease of reading, comprehending, and observing information. Consequently, there has been a growing interest in the editing, segmentation, and organization of sports content. This research area is gaining significant importance. Presently, new video compression techniques, such as MPEG-2 and H.263, are being employed to minimize content data size. These methods exhibit low computational redundancy, stable overall performance, and superior efficiency in comparison to H.263 [4].

2. Early Studies

Mastering table tennis skills is quite intricate, demanding both rapid reflexes and muscular endurance. Crucially, the rules and tempo of the game are pretty rigid. All players must grasp the essential knowledge of the sport, including proper playing techniques, a well developed sense of rhythm, and refined skills. Jiang W estimated the trajectory of table tennis using a physical simulation that closely resembles real world conditions tennis ball and provided flight equations. Upon encountering a surface, these parameters are utilized to compute the ball's speed and construct a collision simulation based on that data. Wang laid the groundwork for accurately predicting table tennis trajectories by examining the local weighted linear regression algorithm in detail. The precision and dependability of this technique are effectively assured. As a result, it not only significantly reduces reliance on experimental methods but also yields more precise outcomes. The benefit of this approach is its ability to eliminate the steps required to construct dynamic simulations. However, it does come with some drawbacks: it requires sufficient data, and accurately assessing the movement state in table tennis is challenging, which affects the final accuracy of predictions. To enhance training guidance, trainers must be able to comprehend and clearly perceive their techniques. Nonetheless, previous training approaches have faced challenges, preventing trainers from accurately perceiving their techniques [6]. With technological advancements, posture recognition technology for table tennis players has gained recognition among a growing number of experts and researchers [7]. This technology not only aids in accurately identifying athletes' body positions but also enhances the safety and precision of competitions, leading to its broader application in the sports arena [8]. WeiZ and Li B both explored the use of the hidden Markov model for detecting the posture of table tennis athletes. Li B's technique is more adaptable and can more precisely identify the athlete's dynamics and statics. In contrast, WeiZ emphasizes extracting valuable information from both static and dynamic perspectives to detect the athlete's posture more accurately. Although the technology for recognizing table tennis athletes' posture based on human silhouette algorithms can satisfy most requirements, its excellent applicability and high efficiency make it one of the most sought-after technologies today. This technology is capable of capturing the body and hand positions of table tennis players from various angles, allowing for precise detection of their body and hands. While it demonstrates good robustness, it also presents certain computational challenges [9]. To address this issue, we devised a novel hierarchical clustering intelligent algorithm. This algorithm can autonomously identify the characteristics of table tennis players and adjust its reference values accordingly [10]. We initially preprocess the movement posture of the players using background difference methods and shadow removal techniques, followed by employing Radon transformation and wavelet analysis to extract these features, and finally utilizing a multi-feature fusion algorithm to combine them for more accurate recognition. Using the multi-feature fusion algorithm, we can precisely detect table tennis players' postures.

3. Layered Clustering Intelligent Algorithm

3.1 The Core Concept of the Layer Algorithm is Layering

By using a hierarchical algorithm, we can achieve an effective hierarchical structure in a special environment by calculating the values of k classes. This algorithm can effectively improve the accuracy and reliability of the model, while also avoiding conflicts between models. If we reconstruct this sentence: we can write it this way: we need to optimize the dataset of D and partition its various layers. We need to remove isolated values, noise values, and relatively scattered values from P, and then select S as our optimization set. After two layers of clustering, we found that S has strong hierarchical nature, so we chose a more effective way to implement the set. Firstly, based on the relationship between P and P, we classify them by distance and similarity, then assign them to the group to which S belongs, thereby ordering the set. We have also introduced a new type of dense hierarchical technology that can effectively solve various complex set problems.

By improving the algorithm, we can achieve the following goals: (1) By introducing a new algorithm, we can better evaluate the similarity between classes. This algorithm makes the relationship between two classes closer, so they can achieve better results by using nearest neighbor points. (2) By introducing a more flexible algorithm, noise, loneliness, and sparser values can be effectively suppressed, thereby improving the accuracy of the model. This algorithm effectively removes 10% of the sparse values and, for these values only, uses Hierarchical clustering to suppress noise interference. After repeated measurement, we got 10% of the sample size, which can effectively eliminate all Confounding, while retaining certain Outlier. (3) By using density-layered clustering, we can effectively divide data points into different layers, thereby improving the quality and efficiency of clustering. This method can effectively split data points into smaller classes, thereby improving classification accuracy. To better identify a class's features, we should separate the data points with the lowest density into a layer and place them along the class's boundary to more accurately identify its contour. In this way, we can more clearly identify the features of the class, thereby better clustering. By clustering two layers of data points, we can clearly divide the center and edge of the class, thus establishing a complete class structure, and can eliminate any irrelevant data points through Hierarchical clustering. (4) By layering the original data, we find that the number of clusters of k will lead to the distance between classes being less than the distance within a class. To solve this problem, we suggest setting q above $2k$, which can effectively increase the inter class distance and reduce the intra-class distance. (5) After investigation, 10% of the data points with the lowest density belong to deviation points, so it is impossible to form a complete new class. Therefore, Hierarchical clustering cannot be carried out alone; it must be divided into k nearest classes.

3.2 Adopting New Methods to Optimize the Implementation Process of the Algorithm

By improving the algorithm, we can remove 10% of the points with lower density from the dataset and cluster the remaining points into two layers: the highest and lowest density clusters. This allows us to extract more similarities and classify them into more closely related categories, thereby achieving more effective clustering. According to Figure 1, the known dataset has k classes and N data points.

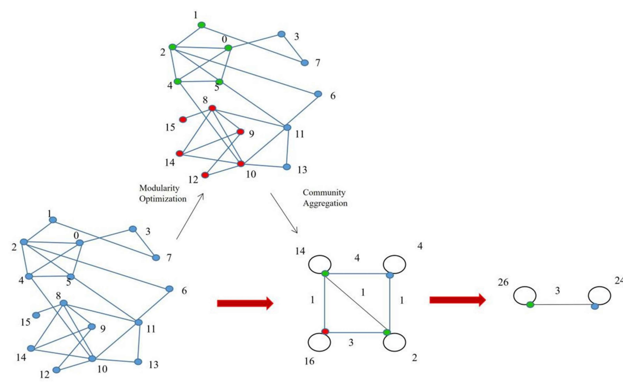

Figure 1. Implementation process of the intelligent algorithm using hierarchical clustering technology

(1) By calculation, determine the relative density of each node in the dataset D.

Density represents the number of specific points in a certain area, and the following formula can represent its definition:

$$\rho_i = \sum_{j \in D} \chi \left(d_{ij} - d_c \right) \qquad (1)$$

In this statement, "d" represents the demarcation line between two values "i" and "j". To determine the position of the demarcation line, we usually set it to 1% to 3% of the average value of the two values. For a dataset of about 1000, we usually set the average value as 10. In addition, we will consider the demarcation line between the two values, namely their average. (2) Extract 10% of the data points from the dataset D to build a dataset *Đ*, and then combine the other data points to build a dataset S. The density of these data points is lower than the cut off density pc, therefore, we need to constantly adjust the cut off density p to determine the positions of these points. According to the given cut off density p, we can calculate the number of points lower than p, n, and the specific calculation method is as follows:

$$\mathrm{n} = \sum_{\mathrm{i} \in \mathrm{D}} \chi \left(\rho_{\mathrm{i}} - \rho_{\mathrm{c}} \right) \qquad (2)$$

If n is greater than n>0.12N, adjust the intercept density top. =0.8pc; if n is less than n<0.08N, adjust the intercept density top. =1.2P, update p, and then count the number of points n. Continue to adjust p until the number of points n reaches 0.08N≤n≤0.12N, at this time p, is the final intercept density. By finding the last p, it can be determined which points in the dataset D have a density lower than the intercept density, thereby determining the bias points and forming the dataset P.

(3) The dataset S density is the maximum density of about 25% of the points constitute the dataset B, according to the cohesive hierarchical clustering method of the dataset B according to the cohesive hierarchical clustering method roughly clustered into about 2k classes. Finding dataset B is similar to the process of finding deviation points, where the green points constitute dataset B. Finding class tips for dataset B belongs to cohesive

hierarchical clustering, that is, at the beginning, each point within *B* is regarded as an individual class of categories, and then continuously combines the categories that have the smallest interclass distances, until there are only 8 classes left in *B*. Assuming that *i, j* are not the same data points, the distance between the two class clusters *u, p* is defined as follows:

$$d_{up} = \min_{i \in u, j \in p} d_{ij} \qquad (3)$$

(4) The two points with the lowest density of about 25% of the dataset S constitute the dataset *L*. The dataset *L* is roughly aggregated into 2k classes using a cohesive hierarchical clustering method. The aggregation process of dataset *L* is the same as the aggregation process of set *B*, which is first to regard each data point as a class, and then merge the two classes with the smallest distance between them consecutively and with the same distance between the two classes until the number of aggregation reaches 8. (5) Taking the three and four step hierarchical clustering method as a basis, the whole dataset *S* is aggregated to approximately k classes according to cohesive hierarchical clustering method. After each layer clustering method will be the density of the largest layer and the smallest layer of the two layers for clustering, the number of clustering classes have been: the density of the smallest layer clustering 8 classes, the density of the largest layer of point set clustering 8 classes, the density of the median layer of the median of the individual data points for an independent class (about 0.4*N* class). In the data set *S* (8+ 8+0.4*N*) of the clusters constantly class combination (the distance between the two classes is the smallest when the two classes are combined into a class), until the number of clusters to reach 4. (6) Finally, the deviation points within the data set *D* each into the closest to the *sk* classes, so that is the completion of the entire data set *D* categorization work.

4. Experimental Design and Result Analysis

4.1 Experimental Design

This study takes the experimental study of table tennis teaching 3D model in physical education college table tennis elective course teaching under the hierarchical clustering intelligent algorithm as the research object. Comprehensive literature review is conducted to understand the current scientific research status of basic theoretical and practical teaching in other colleges and universities, which provides reference for the design of experimental questions, detection objectives, experimental process, etc. Interviewing experts from the Small Ball Teaching and Research Department of Chengdu Sports College, discussing the influence on all aspects of classroom teaching and the current status and future direction of teaching methods, provides the theoretical and experimental basis for this article. The basic idea of the study: carry out experiments on three techniques of forehand attack, left push and right attack, and rub the under spin ball in the table tennis professional teaching course in university through the PDCA cycle. By setting control experiments, the students of the experimental class are taken as A (teaching with the PDCA cycle) and the students of the control class are taken as B (conventional classroom teaching). Obtain the standardized assessment data and skill assessment scores before and after the experiment, and compare the results of the two groups of experiments using the statistical software SPSS19.0. Explore whether the application of the PDCA cycle in table tennis skills teaching can provide references for the application in physical education skills teaching.

4.2 Analysis of Experimental Results

Through a comparative experiment, we can evaluate the clustering performance of different algorithms, and we can judge their pros and cons from the high and low of the results. The *k*-means++ algorithm uses a division based method, while the CBDP algorithm uses a dense peak algorithm. Both of these algorithms can effectively solve complex data analysis problems and can effectively reduce the difficulty of analysis complexity. This algorithm assumes that the set density of a specific set will peak in certain specific areas. The following is a detailed analysis of the results of the two groups of experiments.

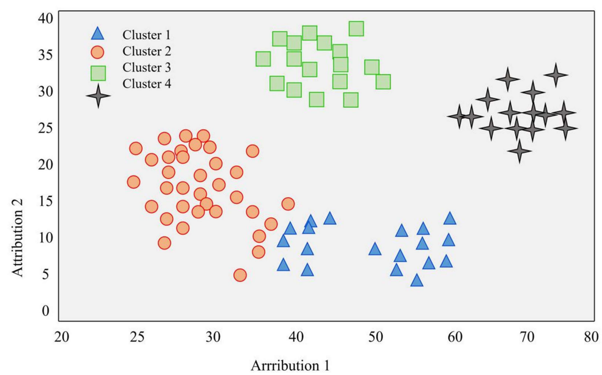

Figure 2. Comparison of four algorithms in the three circle dataset

According to Figure 2, when the density difference is significant, the clustering performance of k-means++ algorithm and CBDP algorithm is relatively poor. However, in contrast, the performance of CURE algorithm and the improved algorithm is outstanding. Through the comparison of three algorithms, the combination of k-means++ algorithm, CURE algorithm, CBDP algorithm, and the improved algorithm of this study can effectively solve various complex clusters such as spherical clusters, non spherical clusters, hollow clusters, and spiral clusters. In this way, they can more accurately capture the features of various clusters and effectively perform advanced analysis, thereby improving the algorithm's accuracy and flexibility. Through systematic training and demonstrations, learners are helped to become familiar with and use all basic skills, especially for high level learners, their basic skills will become very familiar. In class, we will focus on practical operations. The teacher will introduce challenging techniques and provide practical experience to help them deepen their understanding through class activities and ultimately achieve good results. When evaluating an algorithm's clustering performance, we should focus not only on its accuracy but also on its efficiency. The advantage of the K-means++ algorithm is that it adopts a partitioning method. The benefit of this method is that it can identify the target group more quickly and accurately, thereby improving the overall performance of the algorithm. According to Figure 3, we can see that the CURE algorithm and other optimization algorithms can effectively fuse the information in three different datasets.

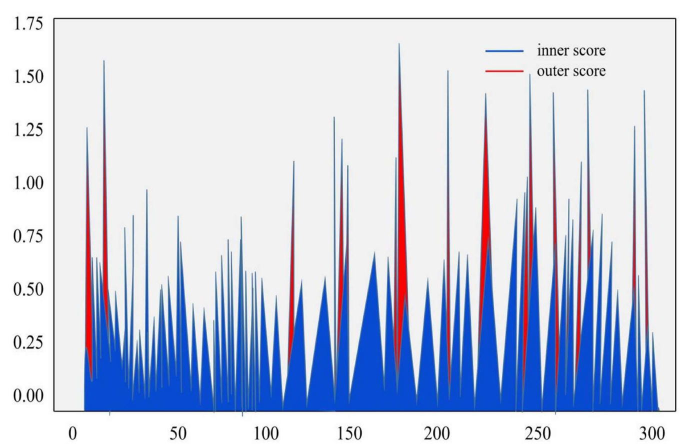

Figure 3. Clustering process of two different algorithms on multidimensional datasets

Both Iris and breast datasets are 4-dimensional and 9-dimensional, respectively, but the former's algorithm is more efficient at clustering than the latter's, while the latter's is less efficient. In addition, *wpbc* also belongs to a 33-dimensional dataset, but its algorithm is less efficient in completing clustering than the former's. Through the "layered" teaching method, we can clearly see that its purpose is to meet students' learning needs better. Therefore, the "layered" teaching method should be continuously reformed, starting from the initial teaching, gradually deepening until students reach a certain level, to meet the learning needs of students better better, prompt students to participate more actively in learning, thus better promoting the reform of teaching, and achieving the best teaching effect.

5. Conclusion

Implementing a layered teaching method can make the educational process more focused, allowing children to select various approaches based on their unique characteristics and interests, thereby providing them with an optimal learning experience. This can significantly boost students' enthusiasm for learning and enhance the quality of teaching. Following comprehensive research, we discovered that hierarchical clustering technology not only significantly improves the algorithm's performance but also produces more robust spherical and non spherical clusters, among other benefits. Compared with traditional algorithms such as k-means++, CURE, and CBDP, this technology's clustering results are more reliable. Through a thorough examination of the CURE algorithm, we observed that as the dataset's dimensionality increases, the algorithm's computational performance improves significantly. This approach can effectively address the limitations of traditional teaching methods and provide crucial support for advancing university table tennis programs.

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