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Clustering Mining Method of College Students' Physical Exercise Behavior Characteristics based on Ant Colony Algorithm

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ABSTRACT

'Physical exercise is essential for the sustainable self-cultivation of college students and is an indispensable part of higher education. However, most college students lack systematic knowledge of physical exercise, making it challenging to exercise scientifically. Therefore, this paper introduces the ant colony algorithm into the model for extracting characteristics of college students' physical exercise behavior to improve the effectiveness of behavior recognition and clustering. Furthermore, the model's performance is enhanced through optimization of the ant colony algorithm. The experimental results demonstrate that the clustering model of college students' physical exercise behavior, based on the ant colony algorithm, effectively reduces the error rate and maintains good accuracy as the sample size increases, indicating good stability and reliability. Additionally, for different physical exercise behaviors, the clustering F-measure standard values of the model all exceed 0.8, indicating a better clustering effect.

Keywords: Ant Colony Algorithm, Physical Exercise, Behavior Characteristics, Clustering Mining

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1. Introduction

Physical fitness is crucial for the sustainable development of individuals and society; cultivating physical fitness has always been essential to contemporary education. Compared with high school students, college students have more freedom in time allocation, and teachers mainly play a guiding role. Therefore, without compulsory exercise requirements and intense supervision, many college students exhibit significant differences in time allocation between studying and engaging in physical exercise. The exercise time and intensity may not meet the needs of college students' physical fitness development. According to relevant surveys, although most college students recognize that physical exercise can improve their physical fitness, they find it challenging to control the amount of exercise scientifically due to a lack of systematic cognition and training during the exercise process. At the same time, many college students' exercise behaviors are incorrect, leading to potential physical injuries and failing to achieve the goal of adequate exercise.

To enhance the accuracy of college students' physical exercise behavior and facilitate their receipt of scientific feedback during the exercise process, information technology, big data, and artificial intelligence have been widely applied in physical exercise behavior research. Monitoring and feedback systems for college students' physical exercise have been developed, enabling students to adjust their exercise behaviour promptly based on the feedback information and ensure the accuracy of their sports behaviour. As college students' physical exercise behavior is dynamic, there are significant difficulties in recognizing exercise behavior, and different recognition methods have considerable differences in accuracy. Moreover, it is challenging to adapt to the recognition of different exercise behavior characteristics, resulting in a relatively narrow scope of application. Additionally, some algorithms in behavior clustering analysis, which is based on behavior characteristics, suffer from issues such as lengthy processing times, significant errors, and high dependence on manually set conditions, resulting in insufficient precision in obtaining results. Therefore, this paper introduces the ant colony algorithm into the model for extracting college students' physical exercise behavior characteristics, aiming to find the optimal clustering path using the ant colony algorithm to enhance the effectiveness and efficiency of behavior feature clustering. It aims to achieve a better purpose by clustering analysis and mining college students' physical exercise behaviour characteristics.

2. Identification and Analysis of Physical Exercise Behavior

As people pay increasing attention to physical exercise, many scholars have identified issues such as improper movements, excessive exercise, and physical injuries that can occur during the exercise process. Not only does this fail to achieve the goal of exercising the body, but it also causes particular harm to the body and mind [4]. Additionally, college students exhibit two distinct trends in physical exercise. Due to age, personality, and other reasons, some students prefer adventurous sports, while others engage in minimal or avoid physical exercise. According to relevant surveys, many college students have reported injuries during physical exercise, primarily due to a lack of professional guidance and a limited understanding of scientific principles [5]. In response to this problem, some scholars have utilized digital and mobile devices to record exercisers' behavior and provide guidance and corrections by professionals based on the recorded videos [6]. However, this method suffers from a time delay, as exercisers cannot correct their movements promptly. To address this issue, some scholars have built a physical exercise behavior error detection system based on neural networks, utilizing convolutional neural networks to recognize and compare physical exercise movements and provide timely feedback to exercisers [7]. However, this model has a relatively high computational complexity and lacks application stability, necessitating further optimization. Other scholars have utilized computer vision technology to recognize the behavior of physical exercisers and provide timely feedback through intelligent algorithms [8]. Additionally, some researchers have developed aggregation behavior recognition models for group sports, utilizing the ant colony algorithm to identify and recognize group sports behavior, and provide corresponding feedback based on evaluation criteria [9]. Currently, there is still a significant amount of error in identifying physical exercise behavior, particularly in dynamic movements, resulting in relatively poor accuracy. Further optimization and research are needed in this regard.

3. Ant Colony Algorithm-based Clustering Mining Model for College Students' Physical Exercise Behavior

3.1 Construction of the College Students' Physical Exercise Behavior Model

As the human body exhibits high flexibility and experiences changes in position and velocity in different directions during movement [10], their body can be viewed as a whole to study better the changes in college students' body movements during physical exercise. By examining the changes in the centroid position and the velocities generated in different directions, it is possible to a large extent reflect the characteristics of college students' physical exercise behavior. Assuming the college student's body is the centroid, it will undergo movements in the horizontal and vertical directions during the exercise process. At the same time, movements in different directions can be decomposed into horizontal and vertical motion components based on their respective speeds. Based on Formula (1), the corresponding binary description image matrix can be obtained:

$$h_{m,n} = \sum_{x=1}^{i}\sum_{y=1}^{j} x^m x^n f(x,y) \tag{1}$$

Wherein the description of the order moment is h, and the corresponding numbers are m and n, respectively. The corresponding coordinates of the different order moment numbers on the abscissa of $m$are x, and the description of the Binary image is $f\ (x, y)$.

According to the above formula, we can analyse the change in the centroid position of college students in their physical exercise behaviour. If the centroid coordinate in the Binary image with the sequence number G is expressed as (x, y), we can describe the position change of the centroid in the horizontal and vertical directions in the following image through the corresponding calculation formula, as shown in Formula (2):

$$\begin{cases} K_s = \left| x_{g+1} - x_g \right| \\ K_c = \left| y_{g+1} - y_g \right| \end{cases} \tag{2}$$

When collecting images, there is a time interval between each video frame and every other image frame. If the time interval is considered, the velocity of the centroid motion in the horizontal and vertical directions is described by formula (3):

$$\begin{cases} v_s = \dfrac{25K_s}{2} \\ v_c = \dfrac{25K_c}{2} \end{cases} \tag{3}$$

Based on the expressions described above, the images of college students' physical exercise must be collected from the initial video sequence and then undergo real-time normalization processing to obtain the corresponding image sequence dataset. Subsequently, the respective images can be subjected to binary mode processing to extract the corresponding local histogram features. Additionally, corresponding sets of feature vectors are generated based on the decomposition of the centroid motion of college students in the horizontal and vertical directions.

3.2 Ant Colony Algorithm-based Behavior Feature Clustering and Mining Model

The ant colony algorithm is derived from the natural process of ants searching for food. When searching for the same food, ants leave corresponding pheromones along the paths they pass through, and the concentration of pheromones gradually decreases over time. This means that longer-distance paths have relatively lower pheromone levels, reducing the probability that other ants will choose those paths. When more ants choose the same path, the concentration of pheromones on that path will continue to increase, and typically, this path represents the shortest route between the ants and the food. Based on this idea, if the feature vectors of college students' physical exercise behaviors are considered as the targets for the ant colony to search for, and the search area is divided into a two-dimensional grid space, with a single feature vector in each different grid, the ant colony will search for the target feature vectors according to the objectives. When ants randomly walk in a two-dimensional grid and encounter a feature vector representing physical exercise behavior, they evaluate the probability of taking that target based on the similarity between the target and the neighboring feature vectors in the grid. The ant will move randomly to another grid if the probability does not meet the requirements. To avoid missing some feature vectors, this study sets the likelihood of the ant colony and the movement of feature vectors within the grid. When ants carrying the feature vectors of college students' physical exercise behaviors encounter empty grids or grids with high consistency between the feature vectors they carry and those in the neighboring grids, they can place the feature vectors according to the probability related to the type density of the feature vectors. The likelihood of identifying the feature vector is positively correlated with its density. If the calculated density does not meet the requirements, the ant will continue to carry the feature vector. The Euclidean distance can describe the consistency between two feature vectors, where a result of 0 indicates high consistency and 1 indicates low consistency. Based on the calculated results of the Euclidean distance, a two-dimensional consistency matrix can be obtained, and based on this matrix, the local density can be calculated, as shown in Formula (4):

$$f(w_m) = \frac{\sum w_m \left(l + \frac{d(w_m, w_n)}{2}\right)}{2} \tag{4}$$

Among them, the neighborhood edge length of lattice r is l, and the area is $l * l$.

Assuming that the probability of the feature vector of college students' physical exercise behavior during ant movement is F, and the corresponding likelihood of dropping it is $F(W)$, the calculation formula is shown in (5):

$$\begin{cases} F_p(w_m) = \left(\dfrac{A_1}{A_1 + f(w_m)}\right)^2 \\ F_d(w_n) = \begin{cases} 2f(w_m) & f(w_m) < A_2 \\ 1 & f(w_m) \geq A_2 \end{cases} \end{cases} \tag{5}$$

The threshold constant is represented as A.

Because the Ant colony optimization algorithms in practical application will produce problems such as high difficulty of data to be processed at the initial stage of the algorithm, poor convergence efficiency, and high probability of stagnation in the solution process, which will affect the clustering results of the characteristic vectors of college students' physical exercise behavior, this paper has carried out corresponding optimization for the problem of Ant colony optimization algorithms. The optimization is mainly carried out in two aspects: the Pheromone update mode and the ant selection path mode. To avoid or reduce the problem that the optimal path is ignored when the ant colony searches for the path initially, a random perturbation strategy is added in the Pheromone update, that is, when any ant in the ant colony divides any feature vector into a category, the corresponding path Pheromone concentration will increase and make corresponding marks. At this time, other ants will be affected by the ant's pheromone, and the concentration of Pheromone on the corresponding path will also increase. In the process, different ants in the ant colony constantly search for the optimal path each time, and the Pheromone on other paths is in a dynamic state. After all ants have finished exploring, the Pheromone increment on different paths is calculated, and the selection range of the optimal path is obtained based on this result.

4. Experimental Results of the Ant Colony Algorithm-based College Students' Physical Exercise Behavior Feature Clustering and Mining Model

The performance of clustering and mining algorithm models is critical for their practical application. Therefore, this study selected two other clustering algorithms and the optimized Ant Colony Algorithm-based behavior feature clustering and mining model for comparison. Two datasets, namely Iris and Robot Navigation, were selected for experimentation to better verify the adaptability of the clustering algorithm models across different datasets. The experimental results are shown in Figure 1. The two datasets used in the experiments are Iris and Robotnavigation, with the latter having more samples than the former. Figure (a) shows that the F-measure values of the two other clustering algorithm models are closer to each other, and there is a specific error compared to the F-measure value of this study's algorithm model. The overall fluctuation amplitude is also higher for the other two models. On the other hand, the F-measure value of this study's algorithm model has a relatively small fluctuation amplitude, indicating better model stability. Figure (b) shows that the F-measure values of the other two clustering algorithm models have decreased to a certain extent. In contrast, the F-measure value of this study's algorithm model remains relatively unchanged compared to Figure (a). This is mainly because the increase in the number of samples in this dataset has increased the error rate of the other two clustering algorithm models, resulting in a noticeable decrease in their F-measure values. In contrast, the clustering algorithm model in this study has a clear purpose, and even with an increase in sample data, it does not lead to an increase in the fluctuation of its error rate. Therefore, the F-measure value of this study's model remains stable in both datasets. This indicates that this study's algorithm model has higher reliability and stability than the other two algorithm models. Additionally, considering the results from both datasets, it can be seen that although the algorithm model in this study does not show a significant advantage in F-measure values when the dataset is relatively small, it converges faster than the other two algorithms.

To better verify the practical effectiveness of the Ant Colony Algorithm-based college students' physical exercise behaviour feature clustering and mining model, this study conducted separate clustering for common behaviours and physical exercise movements among college students. The results are presented in Figs. 2 and 3. As shown in Fig. 2, the clustering F-measure values for all common physical exercise behaviors exceed 0.8, while the F-measure values for other behaviors are not lower than 0.9. In Fig. 3, the F-measure values for slow running and fast walking, among other physical exercise behaviors, are slightly higher than 0.8, and the F-measure values for different physical exercise behaviors exceed 0.9. This is mainly because running and walking behaviors in physical exercise are similar, resulting in relatively lower recognition accuracy. However, overall, the clustering effect of this study's algorithm model is good and can help avoid algorithm stagnation by preventing it from getting stuck in local optimal solutions. It also enhances the accuracy of recognizing and clustering college students' physical exercise behaviour, yielding better clustering results.

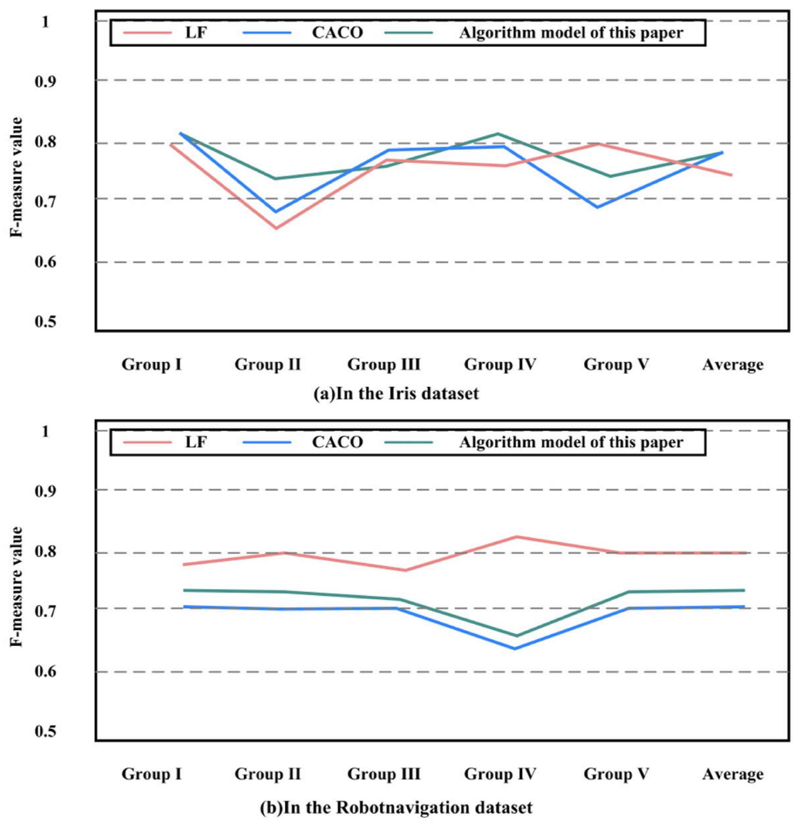

Figure 1. Comparison of F-measure values of three algorithms in two different datasets

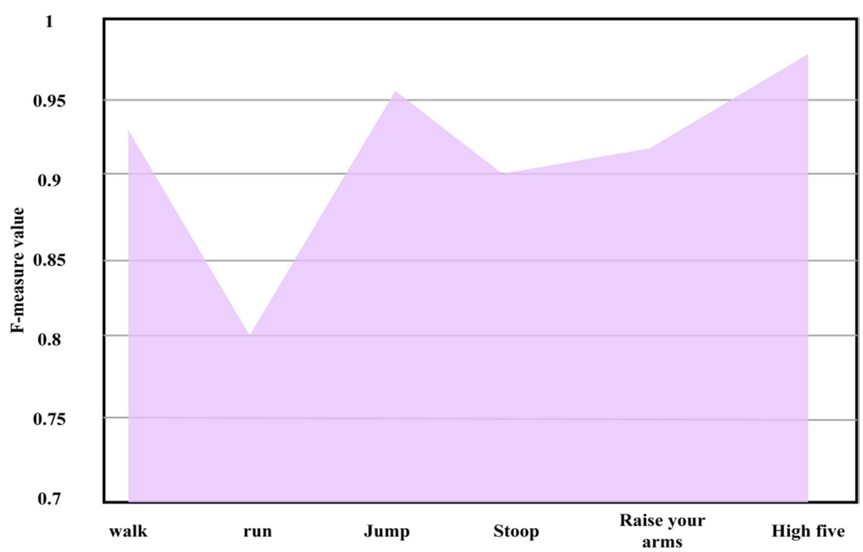

Figure 2. Clustering effect of common physical exercise behaviors in college students

In conclusion, the Ant Colony Algorithm-based model for clustering and mining college students' physical exercise behavior features can adapt to various scenarios and dataset types. It exhibits a high convergence speed, and the error rate remains stable regardless of the sample dataset size, demonstrating good stability and reliability. Moreover, it effectively avoids the problem of getting stuck in local optima and improves the accuracy of behavior recognition and clustering, resulting in more effective clustering in practical applications.

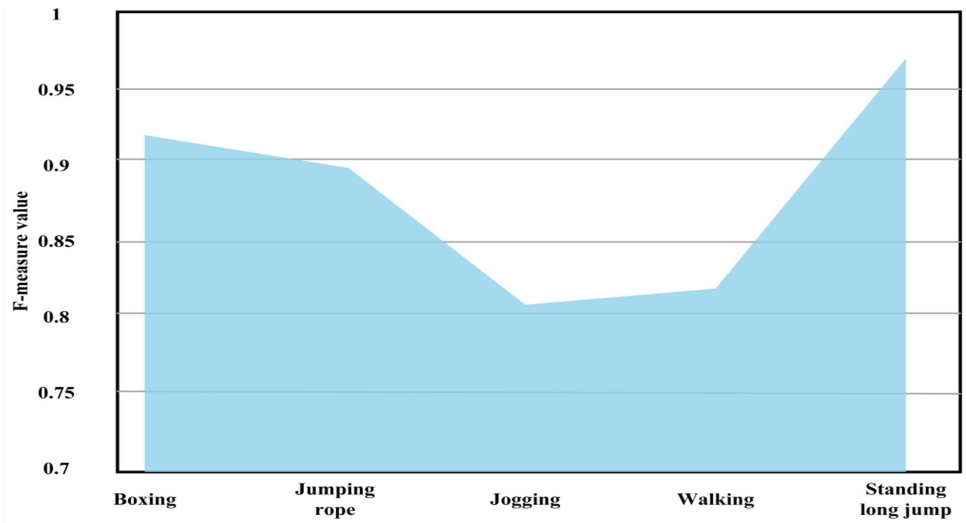

Figure 3. Clustering effect of physical exercise movements in college students

5. Conclusion

College students' physical exercise is an essential part of their self-cultivation and an indispensable guarantee for achieving self-worth and self-improvement as future talents. However, due to the lack of systematic and professional knowledge and skills in physical exercise, many college students cannot make correct judgments about their exercise behavior and have difficulty managing exercise intensity. Therefore, this study constructed a model for extracting the features of college students' physical exercise behavior and introduced the Ant Colony Algorithm for behavior clustering. To achieve better clustering results, optimizations were made to the ant colony algorithm regarding information pheromone concentration updates and ant path selection. The experimental results showed that the Ant Colony Algorithm-based model for clustering and mining college students' physical exercise behavior features exhibited sound and stable clustering effects across different datasets. Its accuracy does not decrease with an increase in dataset samples, demonstrating excellent stability and reliability. Overall, this algorithm model can achieve good clustering results for various physical exercise behaviors, although further optimization is needed to enhance the clustering effect for running and walking behaviors.

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