A Hierarchical Teaching Mode of College Computer Basic Application Course Based on K-means and Improved PSO Algorithm

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***Abstract*—As different students have different basics in learning College Computer Basic Application Course, so uniform teaching methods and curriculum cannot satisfy the needs of all of the students. To address this problem, an algorithm of student clustering which can achieve hierarchical teaching is designed in this paper. After analyzing the disadvantages of slow convergence in the late processing and the local extreme of PSO, an improved Particle Swarm Optimization (i-PSO) algorithm based on granules and maximum distances is proposed. By adopting tactics of linearly decreasing weight and random distribution, adding the extremum disturbance operator, and optimizing the individual extremum of particles, the i-PSO algorithm can quickly converge to an optimal global solution. The i-PSO algorithm combined with the K-means algorithm can improve the poor clustering effect and instability of the K-means algorithm caused by random initial clustering center. Finally, the i-PSO and K-means algorithms are applied to the clustering. The results of simulation experiments show that this algorithm has higher accuracy, a faster convergence rate and greater stability, and can better help to realize layered teaching in College Computer Basic Application Course.**

***Index Terms*—College Computer Basic Application Course, hierarchical teaching, K-means clustering, improved PSO algorithm**

I. INTRODUCTION

To master computer knowledge and basic application is the basic requirement for college students, and it is also an important part of the training of students in colleges. The requirements of the College Computer Basic Application Course will change with the rapid development of information technology and the rapid popularization of the network. Currently, primary and secondary schools in China also offer computer and information technology courses, which demand higher requirements for the education of computer basic courses. Therefore, the contents and requirements of the College Computer Basic Application Courses must be changed as well; that is, the training of college students' computer application capability now has higher requirements [1-3].

Uneven economic development in various regions of China has resulted in an imbalance in computer education in primary and secondary schools. Although primary and secondary school information technology education already includes the contents of the computer basic education, many urban areas have carried out the computer basic education. But in many schools in poor conditions, the student does not even come into contact with a real computer, let alone enjoy the basic computer education [4-5].

Hierarchical teaching refers to the case where students are grouped according to their various levels of understanding of the basics, then accordingly determining different teaching objectives, contents and methods, following the principle of individualized teaching, to enhance each student's computer application capability [6-8].

It follows the people-oriented education principle, teaches students in accordance with their aptitude and basic knowledge and has a clear direction of educational development in hierarchical teaching mode. So, the hierarchical teaching mode requires different teaching materials for students of different levels. It is necessary to test the basic knowledge of and operational skills on the computer, and then cluster students according to their skills and scores.

The traditional classification method is only by ranking the students simply according to their scores. In students' stratification, the clustering method is more comprehensive, and the amount of information contained in the clustering is more [9-10].

According to the situation of the students in our schools, students are divided into three levels: students in level 1 can apply for exemption to the course and get the credit directly; students in level 2 can eventually pass the National Computer Rank Examination; students in level 3 must learn the course in detail.

In the following, a kind of hierarchical teaching mode based on the improved PSO (Particle Swarm Optimization) and K-means clustering algorithm is presented, which can reasonably cluster students and achieve the goal of optimizing the course curriculum and teaching.

II. RELATED ALGORITHMS

The algorithm proposed in this paper is based on the classical clustering algorithm K-means and the improved algorithm PSO. So the two algorithms will be introduced first.

A. K-means Algorithm

As a classical clustering algorithm, the K-means algorithm has been used in many practical applications because of its reliable theory and fast computation. K-means divides the data into K clusters according to the input parameter K. The advantage of the K-means algorithm is simplicity and convenience, producing good results [11-13].

Supposing the datasets are $X = \{X_i, i = 1, 2, \ldots n\}$, $X_i = \{x_{ij}, j = 1, 2, \ldots m\}$, C_k ($k = 1, 2, \ldots K$) these indicate K clusters, while $c_k = \{c_{kj}$ ($j = 1, 2, \ldots m$)$\}$ represents the initial cluster centers.

The clustering steps of the K-means algorithm are as follows:

Step 1: Select k initial clustering center, represented as $c_1, c_2, \ldots, c_k$;

Step 2: For the remaining samples, calculate their weight values according to (1), and then assign it to its nearest cluster. Weight constraints are shown in (2);

$$w_{ik} = \begin{cases} 1 & if \|x_i - c_k\| \le \|x_i - c_m\|, \forall m \ne k \\ 0 & otherwise \end{cases} \quad (1)$$

$$\sum_{i=1}^{K} w_{ji} = 1, \forall j = 1,2, \ldots N \quad (2)$$

Step 3: Calculate the value of the objective function according to (3)

$$J = \sum_{k=1}^{K} J_k = \sum_{k=1}^{K} \sum_{i=1}^{n} w_{ik} \|x_i - c_k\|^2 \quad (3)$$

J_k is the objective function of the k^{th} cluster, K is the number of clusters, xi_j is the i^{th} input vector, c_k is the k^{th} cluster center, and w_{ik} is the weight.

Step 4: Calculate the difference of the objective functions according to (4). If the objective function converges then finish clustering, otherwise update the cluster center based on (5), and then return to Step 2.

$$J_{n-1} - J_n \le \varepsilon \quad (4)$$

$$c_k = \frac{\sum_{i=1}^{n} w_{ik} x_i}{\sum_{i=1}^{n} w_{ik}} \quad (5)$$

Clustering results of K-means are calculated by iteration. The maximum number of iterations is set usually in order to avoid an infinite loop if the conditions of Step 4 are no met.

As shown in (6), the differences among the cluster centers indicates the distance between different clusters, and the greater the value, the better the clustering.

$$Q = \sum_{1 \le i < j \le K}^{K} \left\| c_i - c_j \right\|^2 \quad (6)$$

Eq. (7) is used to calculate the overall quality of the cluster, which is defined as the ratio of the difference between the inter cluster and the intra cluster.

$$e = J/Q \quad (7)$$

The goal of clustering is to make the data objects in the same cluster have more similarity; that is, the inter clusters difference is small. Meanwhile, the data objects of different clusters have less similarity; that is, the intra clusters difference is large. Therefore, the smaller the value of the evaluation function is, the better the clustering result is.

B. *Standard PSO Algorithm*

PSO is a kind of optimization algorithm based on iteration. Each particle in the PSO algorithm may be a potential solution to the optimization problem in the search space. The algorithm first generates a group of random particles, and then finds the optimal solution through iteration. In iteration, the particles adjust the flight velocity of the particles dynamically through their own and peer's flight experience, so that the whole group can fly to a better search area [14].

A group composed of m particles fly at a certain speed in d-dimensional search space. It is supposed that the position of the i^{th} particle in the d-dimension is represented by x_{id}, its flight speed is v_{id}, the current best point of the particle search history is p_{id}, and the optimal position of the whole particle swarm is p_{gd}. The basic particle swarm optimization algorithm for the speed and position update formula is as follows:

$$v_{id}^{t+1} = \omega v_{id}^{t} + c_1 r_1 (p_{id} - x_{id}^{t}) + c_2 r_2 (p_{gd} - x_{id}^{t}) \quad (8)$$

$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1} \quad (9)$$

In (8) and (9), t is the current number of iterations, ω is the inertia weight, c_1 and c_2 are learning factors, r_1 and r_2 are random numbers in [0,1]. The PSO algorithm will end when the maximum number of iterations has been achieved or the algorithm meets the requirements.

III. IMPROVED PSO ALGORITHM

A. *Simplified PSO Algorithm*

Because the evolutionary process of the PSO algorithm is not concerned with the particle velocity, the particle velocity can be removed, and the search process is controlled by the position vector. Thus, the simplified PSO algorithm is obtained. Taking into account the position of each particle in the iterative process, the simplified PSO algorithm is updated as (10).

$$x_{id}^{t+1} = \omega x_{id}^{t} + c_1 r_1 (p_{ad} - x_{id}^{t}) + c_2 r_2 (p_{ad} - x_{id}^{t}) \quad (10)$$

In (10), p_{ad} is the mean of all the individual optimal locations, as shown in (11).

$$p_{ad} = \frac{1}{m} \sum_{i=1}^{m} p_{id} \quad (11)$$

B. *Improved Inertia Weight*

Most PSO algorithms use the linear decreasing strategy to improve the inertia weight. In the initial stage of the iteration, the inertia weight is taken as a larger value in the global search, while in the later part of the iteration, and the inertia weight is smaller in the local search. If the global optimum cannot be found at the beginning of iteration, it is easy to fall into local extremum at the later stage of iteration.

By using the inertia weight value generated by the random distribution, the larger value can be obtained at the later stage of the search, which is beneficial to the local optimum. Therefore, by combining the inertia weight with the linear decrement, the random distribution is proposed, and the number of the evolutionary stagnation is adopted as the trigger condition. The inertia weight equation is shown in (12).

$$\begin{cases} \omega(t) = \omega_{max} - (\omega_{max} - \omega_{min}) * \frac{t}{t_{max}} \quad t_g \le T_g \\ \omega = \mu_{min} + (\mu_{max} - \mu_{min}) * rand(\ \ ) + \sigma * rand(\ \ ) t_g > T_g \end{cases} \quad (12)$$

In (12), t_g represents the stagnation step number of the global extremum, T_g indicates the threshold of stagnation steps of global extremum which needs to be perturbed, t is the number of iterations, t_{max} is the maximum number of iterations, ω_{max} and ω_{min} are inertia weights of the maximum and minimum values, μ_{max} and μ_{min} are the maximum and the minimum of the random inertia weight, and rand() is a random number which is distributed uniformly in [0,1]. σ (variance) is used to measure random inertia weight and expectations (means) between the degree of deviation. The item is to value the weight of error control. Stochastic inertia weight was conducive towards the direction of evolution of the expectations. The basis for doing so is that experimental error obeys normal distribution.

C. Changed learning factors

In the PSO algorithm, learning factors control the particle's self-learning and social learning ability.

Learning factors, which are always changing, can make particles with greater self-learning ability and lower social learning ability in the initial optimization, which can strengthen the ability of global development. And in the later optimization, learning factors have very high social learning ability and lower self-learning ability, which can accelerate the convergence.

$$c_1 = c_{1.max} + \frac{c_{1.max} - c_{1.min}}{t_{max}} * t \qquad (13)$$

$$c_2 = c_{2.min} + \frac{c_{2.max} - c_{2.min}}{t_{max}} * t \qquad (14)$$

In (13) and (14), $c_{2.min}$ and $c_{1.min}$ are the minimum values of c_1 and c_2, $c_{1.max}$ and $c_{2.max}$ are maximum values of c1 and c2; t_{max} is the maximum number of iterations; *t* is the current iteration number.

D. Extreme value perturbation operator

When PSO falls into local extreme value, p_{gd} has been around the high density search, and it is difficult to get out of the local extreme value and lead to the slow convergence of the later evolution. The number of stagnation steps is used as a trigger condition. The global extreme value p_{gd} is perturbed randomly, so that all particles fly to a new location, in order to start a new search path and field, to find a better solution. Perturbation operator is as follows:

$$P_{gd} = r^* P_{gd} \qquad (15)$$

$$r^* = \begin{cases} 1 & t_g \le T_g \\ U(0,1) & t_g > T_g \end{cases} \quad (16)$$

In (15) and (16), actor r* represents uniform random function with conditions. Thus, the equation of the PSO with the addition of the extreme value perturbation operator is shown as (17).

$$x_{id}^{t+1} = \omega x_{id}^t + c_1 r_1 (p_{ad} - x_{id}^t) + c_2 r_2 (r^* p_{gd} - x_{id}^t)$$
(17)

E. Improved particle swarm initialization stage

In the standard PSO algorithm, the initial population is selected randomly, which leads to poor performance of the iterative algorithm. This paper proposes the method of generating initial particle population based on the product of particle density and maximum distance, which can be expressed as:

Step 1: The S region consisting of high density particles is obtained by calculating the particle density, as well as the center of each particle in the region.

Step 2: The initial k center point is obtained by using the maximum distance product method. The largest density of the particle corresponding to the center is selected as the first cluster center c_1. The center which is the largest density particle and the largest distance from c_1 is selected as the second cluster center, denoted as c_2.

Step 3: The distance is computed from data object x_t in s to c1 and c2, denoted as $d(x_t, c_1)$ and $d(x_t, c_2)$. c_3 is the data object x_t which is max(d(xt,c1)*d(xt,c2)). c_k is the data object x_t which is $\max(d(x_t,c1)*d(x_t,c2)*\ldots*d(xt,c_{k-1}))$. Continuing in this manner, k initial cluster centers can be obtained.

Step 4: The k cluster centers are as the initialization of the first particle position coding, and then a sample is randomly selected from the first particle of each cluster center as the position of the second particles encoding. Repeated n-1 times, the initial particle swarm containing n particles is obtained.

F. fitness function

Each particle is a partition of the whole dataset. In order to determine the accuracy of clustering results, the sum of distance within the cluster is defined as the objective function, which is represented as f (c1, c2,...ck) and the smaller distance the better, as shown in (18).

$$f(c_1, c_2, \ldots c_k) = \sum_{j=1}^{k} \sum_{p \in C_j} \left| P - z_{ij} \right|^2$$
(18)

In (16), z_{ij} is the j-th center point of i-th particle cluster, C_j is the cluster where c_j is the center.

Fitness function is expressed as equation (19).

$$fitness = \frac{1}{f(c_1, c_2, \ldots c_k)} \qquad (19)$$

G. New cluster center

The new cluster center V_{ij} is nearest to the cluster center, which is expressed as:

$$v_{ij} = \left\{ x_t \middle| min_{t=1}^{n} x_i - z_{ij} \right\} (20)$$

In (20), i=1, 2,..., n, j=1, 2,... k, n represents the total number of samples; x_t represents the sample; z_{ij} represents the j-th dimensional clustering center of the i-th particle.

IV. ALGORITHM PROCEDURE OF COMBINED I-PSO AND K-MEANS

The flow of the algorithm based on improvement PSO and K-means is shown in Fig.1.

Step 1: The particle swarm is initialized according to the V section.

Step 2: The initial position of each particle is taken as the particle's optimal individual position p_{id}, and then the datasets are classified based on K-means algorithm.

Step 3: The fitness value of each particle is calculated by (18) and (19), to obtain the global optimal position p_{gd}. The fitness of each particle is compared with that of the optimal location p_{id}; if it is better, the current individual position is taken as the best position. The fitness of each particle is compared with that of the optimal location of overall situation p_{gd}; if it is better, the current particle is taken as the global optimal location.

Step 4: The position of the particle is updated based on (17), inertia weight is updated according to (12), and the learning factor is updated using (13) and (14).

Step 5: The new cluster center is calculated according to the latest position of each particle and (20).

Step 6: The clustering is finished if the end condition is met (the best position has been found or the maximum number of iterations has been reached), otherwise return to Step 3.

V. STUDENT CLUSTERING BASED ON K-MEANS AND I-PSO ALGORITHM

In order to verify the performance of this algorithm, the related software are used: operating system Microsoft 2010, Windows Visual C++6.0 as development tools, SPSS19.0 as a data mining tool, and MATLAB7.0 as a simulation tool.

The entrance test results of college computer basic course of the class of 2015 are used as the dataset to carry on the simulation experiment using the combined i-PSO and K-means algorithm.

The students are stratified by the clustering algorithm proposed in this paper, and the steps are shown in Fig.2.

Step 1: Integration of performance data

Data integration produces a scientific and rational combination dataset. Hierarchical teaching is not only based on the entrance exam results alone, but also should include the score rate of each item in order to make a more comprehensive classification of students.

Step 2: Data cleaning

Data cleaning is refilling the missing data. Student name, student ID and examination of the arrangement process and data which is not related to the data analysis is ignored.

Step 3: Data conversion

The process of data transformation is to standardize the data. The analysis of students' scores requires the integration of the score rate of each chapter and the total overall score, and standardize to the numerical values.

There are 2,772 samples of the dataset, and each sample has 7 attributes as shown in Table I.

Step 4: Algorithm implementation

The algorithm based on i-PSO and K-means implemention is displayed in Fig.1.

Step 5: Data analysis

The data shown in Tab.I is the initial dataset of the clustering algorithm, and then it is clustered and analyzed.

After many experiments, the parameters used are set as shown in Table II.

The results of data clustering and cluster centers using i-PSO K-means algorithm are shown in Table Ш.

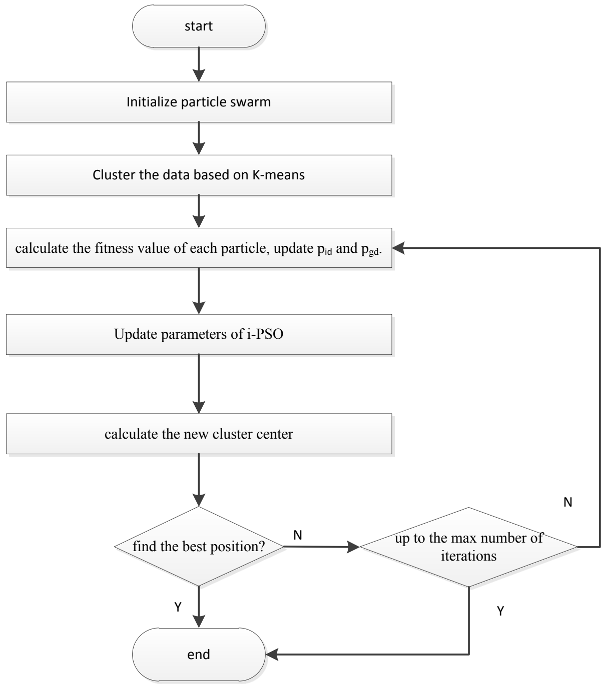

Figure 1. Flowchart of improvement algorithm

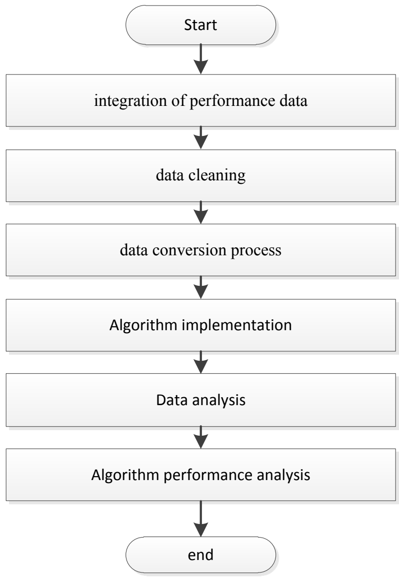

Figure 2. Process of data mining

TABLE I.
DATASET OF STUDENTS' SCORES

Total Score	**Score rate of each item**					
	Basic knowledge	***operation***				
		Win	***Network***	***MS Word***	***MS Excel***	***MS PPt***
79.8	0.35	0.7	0.38	0.8	0.15	0.1
59.4	0.35	1	1	0.9	0.75	0.75
83	0.45	0.9	1	1	0.4	0.65
86.9	0.5	0.7	0.5	1	0.6	0.75
64.3	0.35	0.8	0.88	1	0.45	0.75
71.8	0.4	0.8	0.83	0.75	0.55	0.2
63.5	0.6	0.89	0.5	1	0.6	0.75
81.8	0.6	0.9	0.83	0.85	0.65	0.2
…	…	…	…	…	…	…

TABLE II.
PARAMETERS OF EXPERIMENT

parameters	values
number of clusters	k = 3
maximum number of iterations	30
particle number	n = 20
inertia weight	ω_{max} =1.5, ω_{min} = 0.4
stochastic inertia weight	μ_{max} = 1.0, μ_{min} =0.5
learning factor	c1.max=2.0 , c2.max =2. 0 c1.min=2.0, c2.min = 0.2
disturbance threshold	T_g = 5

TABLE III.
CLUSTER CENTERS

Cluster	Scores centers
1	83.2764
2	67.5191
3	45.476

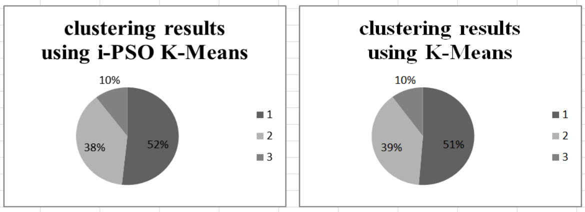

Figure 3. Clustering results

Figure 4. The results of data clustering with different algorithms are shown in Fig.3.

From the Tab.Ш and Fig.3, it can be seen that only about 10% of the students need more training, and more than half of the students have good capabilities with computers and basic knowledge. Comparing classification results using original K-means with that using i-PSO K-means reveals that classification is basically consistent. But because i-PSO K-means algorithm considers not only the total score but also includes the score of each item, the classification is more in line with the reality of students' actual computer-related capabilities and knowledge.

Step 6: Algorithm performance analysis

In order to verify the stability of the i-PSO K-means algorithm and to evaluate the clustering quality, five experiments were conducted using the original K-means and i-PSO K-means algorithms. The value of the evaluation function of each clustering is calculated as shown in Tab.IV.

Tab. IV shows that the evaluation function value of K-means algorithm is not the same for each experiment, and the evaluation function value of i-PSO K-means is always the same. This means that the i-PSO algorithm is more stable in optimizing initial cluster centers than the K-means algorithm's random selection method for initial cluster centers. In addition, it can be seen from Tab. IV that the evaluation function value of the combined i-PSO K-means is smaller than that of K-means alone, which shows that the clustering of i-PSO K-means is better than that of K-means.

Fitness and running time are also taken into account to evaluate the performance of the improved algorithm as shown in Fig.4 and Fig.5.

TABLE IV.
COMPARISON OF K-MEANS AND I-PSO K-MEANS CLUSTERING RESULTS

Number of experiments	Values of evaluation function	
	K-means	*i-PSO K-means*
1	1.53	1.30
2	1.79	1.30
3	1.50	1.30
4	1.81	1.30
5	1.76	1.30

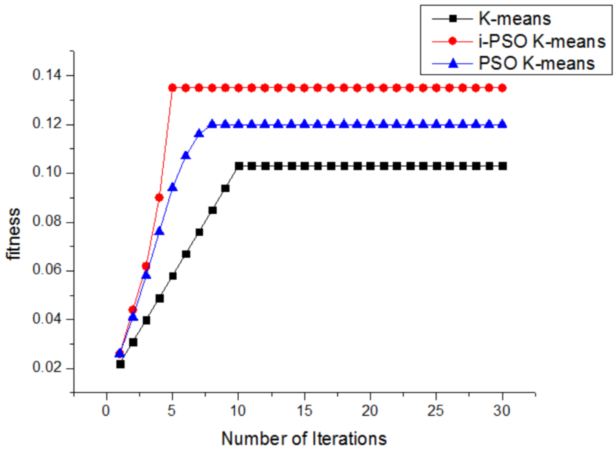

Figure 5. Comparison of the fitness of each algorithm

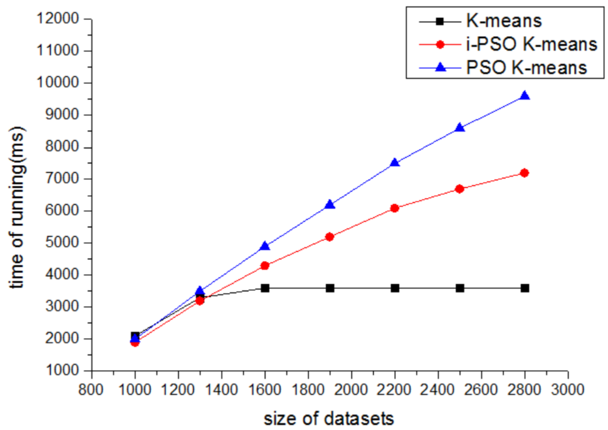

Figure 6. Comparison of running time of each algorithm

Fig.4 shows proof of the fast convergence of i-PSO K-means algorithm in this paper. The algorithm of i-PSO K-means finds the local extremum after approximately five times iteration. To achieve the global optimal, the algorithm is stable and smooth. In contrast, K-means and PSO K-means algorithms are convergent slower when functioning independently of each other, meeting convergence after more than ten times iteration.

It can be seen from Fig.5 that the running time of the three algorithms are basically the same when the size of dataset is between 1000 and 1500. But time consumed by i-PSO K-means algorithm and PSO K-means will be more than that of K-means algorithm when the size of the dataset is more than 1600, and its consumption time increases exponentially with dataset sizes increasing when running time of K-means algorithm becomes more slow. And the time consumed by i-PSO K-means algorithm is less than the PSO K-means algorithm, so it has a better performance.

VI. CONCLUSIONS

Hierarchical teaching methods of College Computer Basic Application Course can not only develop learning interests of students with different abilities, but also can identify students with greater potential and allow students with different majors to obtain the optimal education. In this paper, an improved PSO algorithm combined with K-means algorithm is designed for student stratification. In the algorithm, the initial particle swarm optimization method is presented, the structure of PSO is simplified, inertia weight value in the search process is optimized by using linear decreasing strategy combined with a random distribution, and rapid convergence to global optimum ability is further improved by improved learning factors and extreme perturbation operator. Finally, this algorithm is applied to the hierarchical teaching model of College Computer Basic Application Course. The results of experiments and simulations show that the improved mode has stronger convergence, and can be more accurate.

A hierarchical teaching mode of college computer application basic course, in practice, is very popular with the students. The method of hierarchical teaching is worth exploring deeply, and the practice of teaching at different levels is also worth exploring. Although we have realized an intelligent category of the object of education, there is still a long way to go to realize fully individualized education. Despite the large gap currently, we can help make progress toward this goal by having a correct teaching attitude, encouraging students, and treating students enthusiastically based on the correct clustering to enable students to establish self-confidence and to learn more skills and knowledge.

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