

Retraction

Retracted: Multiclass Interactive Martial Arts Teaching Optimization Method Based on Euclidean Distance

Security and Communication Networks

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] Z. Hu and Y. Wang, "Multiclass Interactive Martial Arts Teaching Optimization Method Based on Euclidean Distance," *Security and Communication Networks*, vol. 2022, Article ID 7272048, 10 pages, 2022.

Research Article

Multiclass Interactive Martial Arts Teaching Optimization Method Based on Euclidean Distance

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Aiming at the problems of low optimization accuracy, poor optimization effect, and long running time in current teaching optimization algorithms, a multiclass interactive martial arts teaching optimization method based on the Euclidean distance is proposed. Using the K-means algorithm, the initial population is divided into several subgroups based on the Euclidean distance, so as to effectively use the information of the population neighborhood and strengthen the local search ability of the algorithm. Imitating the school's selection of excellent teachers to guide students with poor performance, after the "teaching" stage, the worst individual in each subgroup will learn from the best individual in the population, and the information interaction in the evolutionary process will be enhanced, so that the poor individuals will quickly move closer to the best individuals. According to different learning levels and situations of students, different teaching stages and contents are divided, mainly by grade, supplemented by different types of learning groups in the form of random matching, so as to improve the learning ability of members with weak learning ability in each group, which effectively guarantees the diversity of the population and realizes multiclass interactive martial arts teaching optimization. Experimental results show that the optimization effect of the proposed method is better, which can effectively improve the accuracy of algorithm optimization and shorten the running time of the algorithm.

1. Introduction

With the development and progress of science, people are facing more and more problems, and the solutions to these problems are becoming more and more difficult. Many of them have become optimization problems [1–3]. People also put forward various optimization methods based on the phenomena in life, such as the gradient method, hill climbing method, linear programming method, simplex method, and so on. However, these traditional optimization algorithms show different defects in solving some complex optimization problems. Therefore, with the development of scientific research and the improvement of cognition level, many intelligent optimization algorithms with enlightening properties have appeared one after another [4–6].

As a population-based heuristic algorithm, teaching optimization algorithm simulates the process of teachers

teaching students in the class, so as to gradually improve the knowledge level of students in the class [7]. The algorithm is widely used in solving optimization problems because of its simplicity, easy understandability, less parameters and no specific information, fast optimization speed and strong convergence ability. The algorithm is very suitable for solving low-dimensional problems and high-dimensional single-peak optimization problems, but it is easy to lose the global optimal solution for high-dimensional multi-peak optimization problems. Therefore, scholars in related fields have studied the teaching optimization algorithm. Zhu et al. [8] proposed a multiobjective teaching optimization algorithm based on Pareto advantage theory. Based on Pareto dominance theory, external archives are used to guide the search direction of the population. The hybrid mechanism of teacher selection strategy, student stage, and evolutionary search of external file population is improved. This method

is effective. Zhang and Jin [9] proposed a group teaching optimization algorithm based on metaheuristic algorithm. According to the group teaching mechanism, this paper constructs a group teaching model composed of teacher distribution stage, ability grouping stage, teacher stage, and student stage. The solution quality of this method is good. However, the above methods still have the problems of poor optimization effect, low optimization accuracy, and long running time.

In view of the above problems, a multiclass interactive Wushu teaching optimization method based on Euclidean distance is proposed. Euclidean distance is a centralized method, which can divide students into several subgroups, select students with different grades according to the school, make the worst individual in each subgroup learn from the best individual of the population after the “teaching” stage, make the poor individual quickly approach the best individual, and optimize the effect of multiclass interactive Wushu teaching as a whole. The optimization effect of this method is good, It can effectively improve the optimization accuracy of the algorithm and shorten the running time of the algorithm.

2. Related Algorithms

2.1. Basic Teaching Optimization Algorithm. Teaching-learning-based optimization (TLBO) is a new intelligent optimization algorithm that simulates the teaching process [10–12]. TLBO algorithm is a group-based heuristic optimization algorithm, which does not need any specific parameters of the algorithm. The algorithm simulates the process of teachers teaching students. Teachers and students are equivalent to individuals in evolutionary algorithm, students' learning performance is fitness value, teachers are the individuals with the best fitness value, and each subject studied by students is equivalent to a decision variable. The algorithm has the advantages of simple algorithm and good convergence performance.

2.1.1. Basic Theory of TLBO Algorithm. The so-called optimization problem is to find a set of parameter values under certain constraints, so that certain optimality metrics can be satisfied, even if certain performance indicators of the system reach the best or minimum. Optimization problems can be divided into many categories according to their objective function, the nature of the constraint function, and the value of the optimization variable. Each type of optimization problem has a specific solution method according to its nature [13–15]. Without loss of generality, suppose the considered optimization problem is

$$\begin{aligned} z &= \min f(X) \\ \text{s.t. } X &\in S = \{X | g_j(X) \leq 0, j = 1, 2, \dots, d\}, \end{aligned} \quad (1)$$

where $z = \min f(X)$ is the objective function, $g_j(X)$ is the constraint function, S is the constraint domain, and X is the optimization variable. In order to use the TLBO algorithm to solve the optimization problem, the concepts in the

algorithm correspond to the parameters in the optimization problem. The search space in the optimization problem is the entire class in the algorithm, namely:

$$S = \{X | x_i^L \leq x_i \leq x_i^U, i = 1, 2, 3, \dots, d\}, \quad (2)$$

where $X = (x_1, x_2, \dots, x_d)$ is a student in the class in the algorithm, d is the number of subjects each student learns, that is, the number of decision variables corresponding to the feasible solution in the optimization problem, x_i^L and x_i^U are, respectively, the highest and lowest scores of each subject studied by the students, which are equivalent to the upper and lower limits of the feasible solution decision variables in each dimension of the optimization problem, and $f(X)$ is the objective function in the optimization problem, that is, the fitness value or evaluation function for evaluating student performance in the algorithm [16–18]. Suppose $X^j = (x_1^j, x_2^j, \dots, x_d^j)$, $j = 1, 2, \dots, NP$, is a point in the entire search space in the optimization problem, and x_i^j ($i = 1, 2, \dots, d$) is a decision variable at point X^j , that is, the learning subject in the algorithm. NP is the number of searches in the search space in the optimization problem, that is, the size of the population, which is equivalent to the number of students in the class in the algorithm. The optimization problem corresponds to the following mathematical model:

- (1) Class: in the TLBO algorithm, the set of all points in the search space is used as the entire class.
- (2) Student: at a certain point in the class, that is, a feasible solution in the search space, $X^j = (x_1^j, x_2^j, \dots, x_d^j)$ is a student, and d is the subject the student is studying.
- (3) Teacher: student X_i with the best performance in the class, that is, the student with the best fitness value, is called the teacher, denoted by X_{teacher} . Therefore, the matrix of a class can be expressed as

$$\begin{bmatrix} X^1 & f(X^1) \\ X^2 & f(X^2) \\ \vdots & \vdots \\ X^{NP} & f(X^{NP}) \end{bmatrix} = \begin{bmatrix} x_1^1 & x_2^1 & \cdots & x_d^1 | f(X^1) \\ x_1^2 & x_2^2 & \cdots & x_d^2 | f(X^2) \\ \vdots & \vdots & & \vdots \\ x_1^{NP} & x_2^{NP} & \cdots & x_d^{NP} | f(X^{NP}) \end{bmatrix}. \quad (3)$$

2.1.2. Basic Flow of TLBO Algorithm. Assuming that the distribution of students in a class conforms to the normal distribution, the distribution density function is as follows:

$$f(X) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}, \quad (4)$$

where σ is the standard deviation and μ is the mathematical expectation of X . The steps of the basic TLBO algorithm are as follows.

Initialize the performance of each student in the entire class and the main parameters of the algorithm. Each student

$X^j = (x_1^j, x_2^j, \dots, x_d^j)$, $j = 1, 2, \dots, NP$, in the class is randomly generated in the search space.

$$\begin{aligned} x_i^j &= x_i^L + \text{rand}(0, 1) \times (x_i^U - x_i^L), \\ j &= 1, 2, \dots, NP; i = 1, 2, \dots, d. \end{aligned} \quad (5)$$

- (1) “Teaching” stage: in the “teaching” stage of the TLBO algorithm, each student X^j ($j = 1, 2, \dots, NP$) in the class will learn according to the difference between the teacher X_{teacher} and the student’s average grade mean. The score distribution model of “teaching” stage is shown in Figure 1.

As shown in Figure 1, the average grade mean_A of the class at the beginning is at a low level, and the grades are widely distributed and scattered. After many “teaching” classes by the teacher, the average grade of the class gradually increased from the lower mean_A to the higher mean_B , and the distribution of grades became relatively concentrated. The “teaching” process in the TLBO algorithm can be expressed by the following formula:

$$X_{\text{new}}^i = X_{\text{old}}^i + \text{difference},$$

$$\text{difference} = r_i \times (X_{\text{teacher}} - TF_i \times \text{mean}), \quad (6)$$

$$\text{mean} = \frac{1}{NP} \sum_{i=1}^{NP} X_i,$$

where X_{old}^i and X_{new}^i are the values of the i th student before and after the teacher’s teaching, mean is the average of all students in the entire class, and $TF_i = \text{round}[1 + \text{rand}(0, 1)]$ and $r_i = \text{rand}(0, 1)$ are the teacher’s teaching factor and learning step length, respectively. After the “teaching” is over, update each student’s grades. According to the comparison between the results after study and the results before study, update each student:

$$X_{\text{old}}^i = X_{\text{new}}^i, \quad \text{if } f(X_{\text{new}}^i) > f(X_{\text{old}}^i). \quad (7)$$

- (2) “Learning” stage: for each student X^i ($i = 1, 2, \dots, NP$), randomly select a student in the class as the learning object X^j ($j = 1, 2, \dots, NP, j \neq i$), and student X^i makes learning adjustment after analyzing and understanding the differences of student X^j . The improved learning method is similar to the differential mutation operator in the difference algorithm. The difference is that the learning step r in the TLBO algorithm is different for each student [19–21]. Use the following formula to realize the student’s “learning” process:

$$\begin{aligned} X_{\text{new}}^i &= X_{\text{old}}^i + r_i \times (X^i - X^j), f(X^i) < f(X^j), \\ X_{\text{new}}^i &= X_{\text{old}}^i + r_i \times (X^j - X^i), f(X^j) < f(X^i), \end{aligned} \quad (8)$$

where $r_i = U(0, 1)$ represents the learning factor of the i th student, that is, the learning step length. Update student actions:

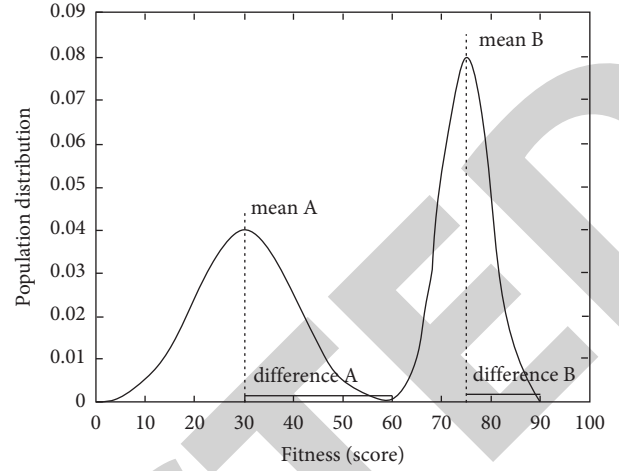


FIGURE 1: Achievement distribution model in “teaching” stage.

$$X_{\text{old}}^i = X_{\text{new}}^i, \quad \text{if } f(X_{\text{new}}^i) \leq f(X_{\text{old}}^i). \quad (9)$$

If the end conditions are met, the optimization process ends; otherwise, it jumps to the “teaching” stage to continue. The fitness function used by the TLBO algorithm is as follows:

- (1) Using Euclidean distance formula [22–24] for all class centers C_{ij} , the formula for calculating distance $d(z_p, v_{ij})$ is as follows:

$$d(z_p, v_i) = \sqrt{\sum_{j=1}^s (z_{jp} - v_{ji})^2}, \quad (10)$$

where z_{jp} is the j th attribute of z_p and v_{ji} is the j th attribute of v_i . Assign z_p to C_{ij} according to the following:

$$d(z_p, v_{ij}) = \min d(z_p, v_{ic}), \quad \forall c = 1, 2, \dots, C. \quad (11)$$

- (2) Calculate the fitness function and measure the quantization error formula of the candidate class center:

$$J_e = \frac{\sum_{j=1}^C \left[\sum_{z_p \in C_{ij}} d(z_p, v_{ij}) / |C_{ij}| \right]}{C}, \quad (12)$$

where $|C_{ij}|$ is the number of z_p contained in C_{ij} . The flow of the TLBO algorithm is shown in Figure 2.

It can be found from Figure 2 that the “teaching” stage of this algorithm is similar to the social search part of particle swarm optimization algorithm. When every student is learning knowledge from teachers, the whole class (i.e., population) is easy to get close to teachers, and the search speed is relatively fast. However, it affects the diversity of the whole population and is very easy to fall into local search, that is, what we find is the local optimal solution rather than the global optimal solution [25–27].

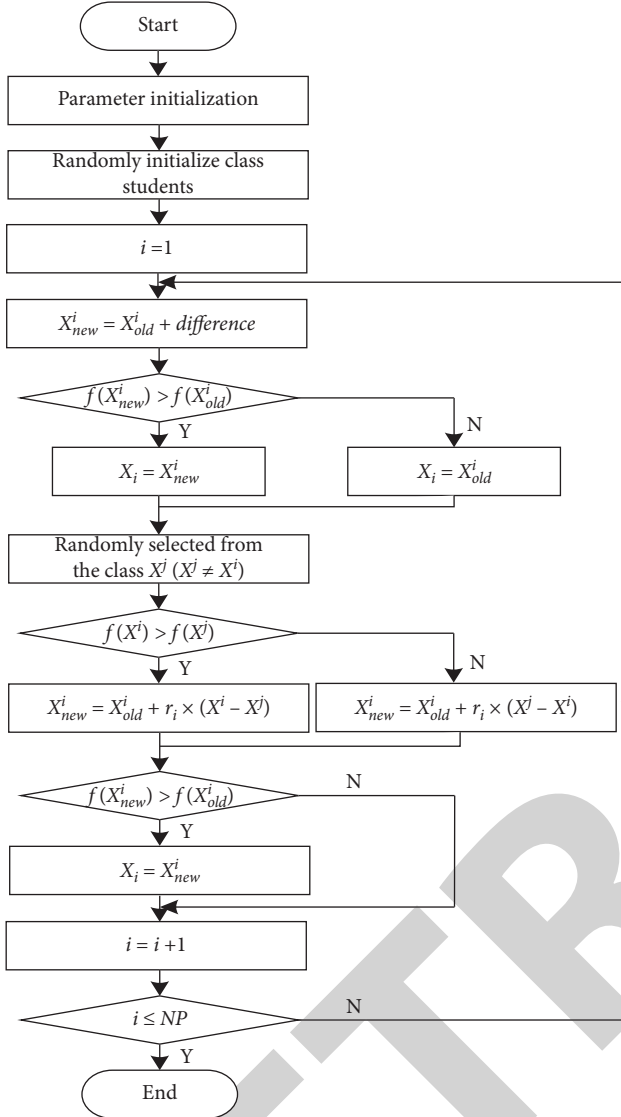


FIGURE 2: TLBO algorithm flowchart.

The “learning” stage among students is the exchange of learning between students, learning from each other, and improving each other’s achievements. At this stage, students learn from each other, so that the whole search will not prematurely approach the direction of the global best, so as to effectively maintain the diverse characteristics of the whole students, that is, individuals in the population, and ensure the global search ability of the algorithm in the whole search space.

2.2. K-Means Clustering Algorithm. The K-means algorithm realizes the overall adjustment and optimization of cluster centers by adjusting the minimum mean square error function corresponding to the optimized distance as the objective function [28–30]. The similarity measurement of K-means algorithm usually uses the Euclidean distance as the benchmark and uses the error square sum clustering criterion function J_c as the evaluation function [31–33], which is defined as

$$J_c = \sum_{i=1}^k \sum_{p \in c_j} \|p - V_i\|^2, \quad (13)$$

where V_i is the center of the i th class. The specific steps of the algorithm are as follows.

Step 1. Randomly select k sample data points from the dataset $X = \{x_1, x_2, \dots, x_n\} \subset R^d$ as the initial clustering center, denoted as $C = \{c_1, c_2, \dots, c_k\}$, and denote the cluster with c_j as the clustering center as w_j .

Step 2. Calculate the Euclidean distance $D(x_i, c_m)$, $i = 1, 2, \dots, n, m = 1, 2, \dots, k$, from each sample data object to the cluster center, if it satisfies

$$D(x_i, c_j) = \min\{D(x_i, c_m), m = 1, 2, \dots, k\}. \quad (14)$$

Then, divide the i th data into the j th cluster, namely, $x_i \in w_j$.

Step 3. Calculate the average value of all data objects in each cluster as the new cluster center c'_j . If the data in cluster w_j are $x_i^j, i = 1, 2, \dots, n_j, n_j$ is the number of data in cluster w_j , namely:

$$c'_j = \frac{1}{n} \sum_{i=1}^{n_j} x_i^j, \quad j = 1, 2, \dots, k. \quad (15)$$

Step 4. Calculate the error square sum clustering criterion objective function [34] J_c , namely:

$$J_c = \sum_{j=1}^k \sum_{i=1}^{n_j} \|x_i^j - c_j\|^2. \quad (16)$$

Step 5. Determine whether the criterion objective function J_c is convergent. If it converges, the algorithm ends and the clustering result is output; otherwise, go to Step 2 and continue the calculation.

3. Multiclass Interactive Martial Arts Teaching Optimization Method

In order to effectively improve the accuracy and stability of algorithm optimization, this paper proposes a multiclass interactive martial arts teaching optimization algorithm (multiclass interaction TLBO (MCITLBO)). First, the K-means algorithm is used to divide the initial population into several subgroups based on the Euclidean distance, so as to effectively use the information of the population neighborhood and strengthen the local search ability of the algorithm. Then, follow the example of the school by selecting excellent teachers to tutor students who have poor performance. After the “teaching” stage, make the worst individual of each subgroup learn from the best individual of the population, enhance the information interaction in the process of evolution, and quickly make the poor individual close to the best individual. Finally, according to students’

different learning levels and situations, at the end of the “learning” stage, different types of learning groups are divided according to their learning levels, and all learning members in the group are randomly matched to ensure the diversity of members in the group.

3.1. Multiclass Division. According to the K-means algorithm, the initial grade is divided into multiple classes based on the Euclidean distance. The specific steps are as follows.

Step 1. Generate an initial population and randomly generate a correlation point R in the search space.

Step 2. Find the closest individual x between R (i.e., the smallest Euclidean distance).

Step 3. Form a subgroup of x and the $M - 1$ closest individuals to x .

Step 4. Evaluate M individuals.

Step 5. Repeat Steps 1 to 4 until the initial population is divided into NP/M subgroups.

3.2. Communication between the Worst Students and the Best Teachers. In real life, in order to improve the performance of poor students, the school will organize the best teachers to provide after-school guidance. Based on this principle, after the “teaching” stage, select the worst individual in each subgroup to communicate with the best individual in the whole population and accelerate the poor individual to approach the best individual. The specific steps are as follows.

Step 1. For the k th iteration, find the best individual T_k in the population.

Step 2. Find the worst individual $x_i (i = 1 \sim M)$ in each subgroup.

Step 3. Let the worst individual learn from the best individual; the method is as follows:

$$x_{\text{new},i} = x_{\text{old},i} + \text{rand}(T_k - x_{\text{old},i}). \quad (17)$$

Step 4. If $x_{\text{new},i}$ is better than $x_{\text{old},i}$, then accept $x_{\text{new},i}$; otherwise, keep $x_{\text{old},i}$.

3.3. Students Learning from Each Other between Classes. In schools, students in different classes will flow to each other and have an impact. In order to strengthen the information interaction between different classes in the process of evolution and enhance the population diversity, after the “learning” stage, a random student in each class will communicate with the students in the other two classes. The specific steps are as follows.

Step 1. In the k th iteration, randomly select a student x_{M_1} from class M_1 .

Step 2. Randomly generate another two classes M_2 and M_3 and random students x_{M_2} and x_{M_3} in each class.

Step 3. Update x_{M_1} as follows:

$$\begin{cases} x_{\text{new},M_1} = x_{\text{old},M_1} + \text{rand}(x_{M_2} - x_{M_3}), & \text{if } f(x_{M_2}) < f(x_{M_3}), \\ x_{\text{new},M_1} = x_{\text{old},M_1} + \text{rand}(x_{M_3} - x_{M_2}), & \text{if } f(x_{M_3}) < f(x_{M_2}). \end{cases} \quad (18)$$

Step 4. If x_{new,M_1} is better than x_{old,M_1} , accept x_{new,M_1} ; otherwise, keep x_{old,M_1} .

3.4. Proof of Convergence of the Algorithm. Without loss of generality, it may as well set the global optimal value of the problem to be solved as $x_{g\text{best}}$. In the iterative process of the TLBO algorithm, the optimal solution of the current population can be set as $x_{\text{teacher}}(t)$, which is the individual teacher. If the TLBO algorithm is convergent, it should have

$$\lim_{t \rightarrow \infty} x_{\text{teacher}}(t) = x_{g\text{best}}. \quad (19)$$

After clustering, the original feasible region is divided into M subregions, denoted as $\Omega_1, \Omega_2, \dots, \Omega_M$, and the local optimal individual of Ω_i is set to $x_{i,\text{teacher}}(t)$, and then there should be

$$x_{\text{teacher}}(t) = \min\{x_{1,\text{teacher}}(t), x_{2,\text{teacher}}(t), \dots, x_{M,\text{teacher}}(t)\}. \quad (20)$$

Each class completes “teaching” and “learning” independently. Due to the convergence of the TLBO algorithm, after a certain number of iterations, each region must converge to the local optimum [35], that is, for the subregion Ω_i , there must be

$$\lim_{t \rightarrow \infty} x_{i,\text{teacher}}(t) = x_{i,g\text{best}}. \quad (21)$$

In the improved algorithm, the introduction of two learning methods establishes the individual communication between each subregion, makes each subgroup evolve synchronously, avoids the phenomenon of “lag” or “precocity,” and ensures the global convergence of the algorithm [36]. Therefore, after the algorithm meets a certain number of iterations, there must be

$$x_{g\text{best}} = \min\{x_{1,g\text{best}}, x_{2,g\text{best}}, \dots, x_{M,g\text{best}}\}. \quad (22)$$

To sum up, MCITLBO algorithm is convergent.

3.5. Diversity Measurement of Algorithm. Through the above description of the MCITLBO algorithm, the flow of the MCITLBO algorithm is shown in Figure 3.

In order to explain the performance of the MCITLBO algorithm in terms of population diversity more accurately,

population entropy is introduced to measure the diversity of the algorithm. If the t th generation population has Q subsets $S_1^t, S_2^t, \dots, S_Q^t$, the number contained in each subset is recorded as

$$\begin{aligned} & |S_1^t|, |S_2^t|, \dots, |S_Q^t|, (Q \leq N), \\ & S_p^t \cap S_q^t = \emptyset, \\ & \bigcup_{q=1}^Q S_q^t = A^t, \end{aligned} \quad (23)$$

where $p, q \in \{1, 2, \dots, Q\}$ and A^t represent the set of the t th generation population, and the entropy of the t th generation population is defined as

$$E = - \sum_{j=1}^Q p_j \lg(p_j), \quad (24)$$

where Q is the population size and $p_j = |S_j|/N$. It can be seen from the definition that when all individuals in the population have the same fitness value, the entropy takes the minimum value $E = 0$. The larger the individual fitness value, the more uniform the individual distribution and the larger the entropy value.

4. Experimental Analysis

In order to verify the effectiveness of the multiclass interactive martial arts teaching optimization method based on the Euclidean distance, the MCITLBO algorithm is simulated and tested by the test function.

4.1. Experimental Environment and Dataset. The algorithm operating platform conditions are as follows: the operating system is Windows 7 (x32), the CPU is Intel Celeron CPU B815 (1.60 GHz), and the programming language operating environment is MATLAB (2016a). The algorithm parameter is set to the number of students in class (i.e., the number of populations) $NP = 10$, the number of subjects for each student (that is, the dimensionality of the search space) is 30, the maximum value of the teaching factor is $TF_{\max} = 2$, and the minimum value is $TF_{\min} = 1$. Since students face a teacher, their self-confidence will be relatively low, and when they face classmates, they are more likely to believe in their own knowledge, so the self-confidence takes the experience constant $w_1 = 0.1, w_2 = 0.5$ and the maximum number of iterations $\max \text{Gen} = 100$.

4.2. Comparison Results of Optimization Effects. In order to verify the optimization effect of the proposed method, the algorithm runs 20 times independently, selects the average value of 20 iterations as the comparison standard, compares

the proposed method with the method in reference [8] and the method in reference [9], and obtains the optimization effect comparison results of different methods as shown in Figure 4.

As can be seen from Figure 4, as the number of iterations increases, the function fitness values of different methods decrease. Among them, the convergence of the proposed method is obviously better than the methods in reference [8] and reference [9]. At 50, it has achieved convergence, and its optimization effect is good, which can effectively improve the convergence of the algorithm.

4.3. Comparison Results of Optimization Accuracy. On this basis, the optimization accuracy of the proposed method is further verified, and the algorithm including the standard deviation of the optimal solution is used as the evaluation index. The smaller the standard deviation, the higher the optimization accuracy of the method. By comparing the method in reference [8], the method in reference [9], and the proposed method, the optimization accuracy of different methods is obtained, and the comparison results are shown in Figure 5.

It can be seen from Figure 5 that the standard deviation of the optimal solution of different methods gradually increases with the increase of the number of iterations. When the number of iterations is 100, the standard deviation of the optimal solution of the method in reference [8] is 9.1, the standard deviation of the optimal solution of the method in reference [9] is 14.2, and the standard deviation of the optimal solution of the proposed method is 6.5. It can be seen that compared with the method in reference [8] and the method in reference [9], the standard deviation of the optimal solution of the proposed method is smaller, indicating that the optimization accuracy of the proposed method is higher. This is because in the "learning" stage, the cluster partition method of euclidean distance is adopted to cover different types of individual members into different learning groups, which improves the utilization rate of resource information and effectively improves the technical accuracy of the optimal solution.

4.4. Comparison Results of Running Time. As can be seen from Figure 6, with the increase of the number of iterations, the running time of different methods increases. When the number of iterations is 100, the running time of the method in reference [8] is 39 s, the running time of the method in reference [9] is 55 s, and the running time of the proposed method is only 21 s. It can be seen that the running time of the proposed method is shorter than that of the method in reference [8] and the method in reference [9]. Because the proposed method selects K-means algorithm, the teaching

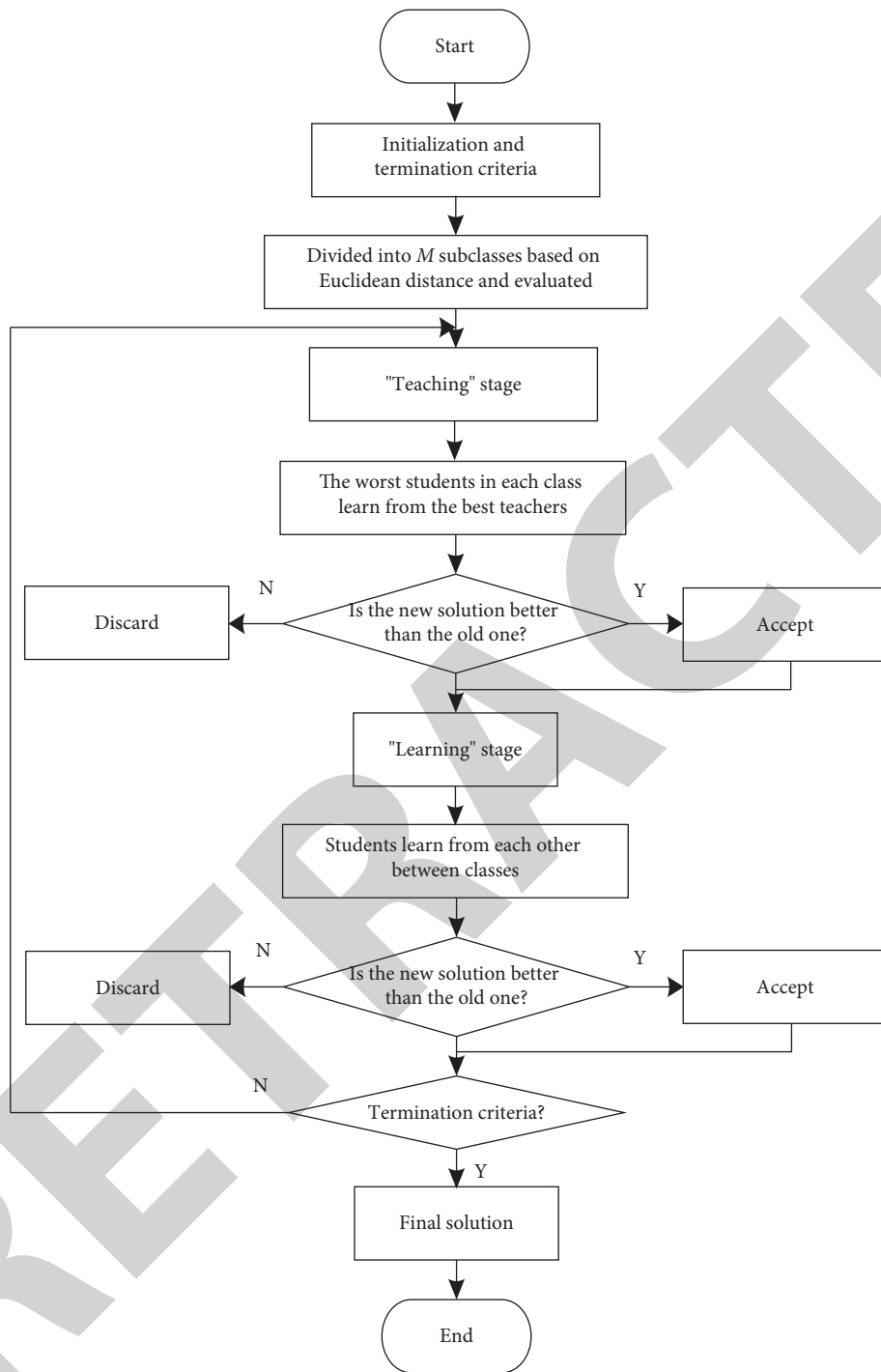


FIGURE 3: MCITLBO algorithm flowchart.

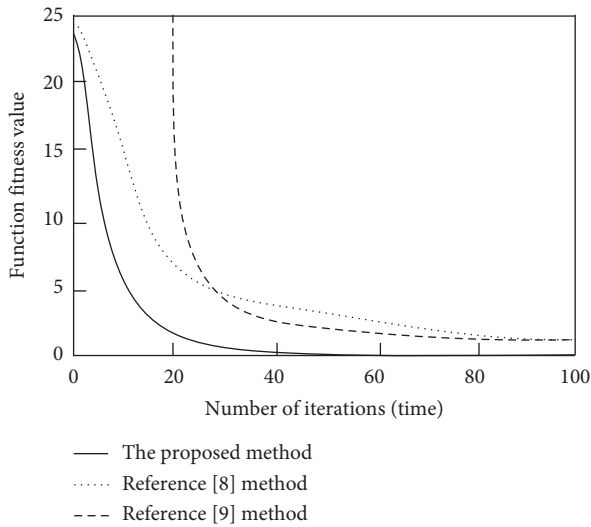


FIGURE 4: Comparison results of optimization effects of different methods.

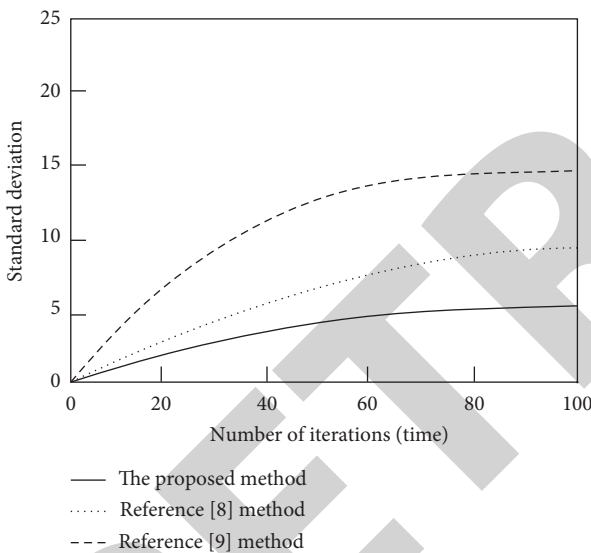


FIGURE 5: Comparison results of optimization accuracy of different methods.

optimization algorithm has good global search ability, effectively shortening the running time of the method.

5. Conclusion

In order to further optimize the effect of Wushu teaching, this paper gives full play to the advantages of the basic teaching and learning optimization algorithm and designs a multiclass interactive Wushu teaching optimization method combined with the clustering division method based on Euclidean distance. The algorithm has good optimization effect, high convergence and optimization accuracy, and short running time. However, the tacit understanding between teachers and students only depends on the function of the number of iterations. Therefore, in the next research, we

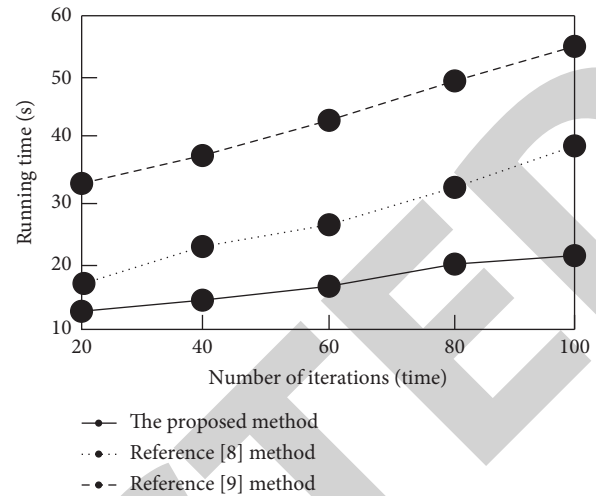


FIGURE 6: Comparison results of running time of different methods.

need to find a function not only dependent on the number of iterations but also related to the difference between teachers and students, so as to further intelligentize the tacit understanding value.

Data Availability

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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