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Research Article

Optimization of Skipping Rope Training Method Based on Chaotic Logistics

Han Li and Yuxia Wang

Department of Physical Education, Ordos Institute of Technology, Ordos 017000, Inner Mongolia, China

Correspondence should be addressed to Yuxia Wang; wangyuxia@oit.edu.cn

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Skipping training belongs to a competitive event, which can not only lose weight but also improve the physical quality of trainers. At present, there are some problems in skipping training, such as unreasonable plan and unsatisfactory actual training effect. The original rough set method cannot solve the analysis of multivariate data in skipping training, and the ability to evaluate the training effect of skipping is poor. Aiming at the problems existing in the training of skipping rope, this paper puts forward a skipping rope training method based on a chaotic logistics algorithm, aiming at improving the training effect of skipping rope. First, the chaos theory is used to classify the training data. Different data classifications correspond to different training results, which eliminates irrelevant information in the training scheme and reduces the amount of single data analysis. Finally, the data after classification are optimized in a single stage, and the optimal results of different training items are obtained and summarized. After the MATLAB test, the chaotic logistics algorithm is superior to the rough set method in accuracy and convergence speed and meets the actual training needs. Therefore, the chaotic logic analysis method proposed in this paper is suitable for the evaluation of skipping training.

1. Introduction

At present, the state has increased its support for sports training. Skipping rope training is a national competitive activity, which has the dual effects of competition and leisure. As a national sport, skipping rope can not only improve the physical fitness of the masses but also belong to a leisure and entertainment project. At present, the training method of skipping rope is unreasonable, which cannot play the role of skipping rope. Therefore, looking for an effective exercise method is an urgent problem to be solved at present, which has very important practical significance. Ant colony algorithm and regression analysis methods cannot carry out continuous analysis and cannot achieve massive data analysis. Chaotic regression analysis method, which can reduce the amount of data analysis, more accurate data analysis, for skipping training method analysis, has a very obvious analysis advantage. Chaos theory is used to classify and analyze the data of skipping rope training, and logistic regression analysis is used to determine the main factors affecting skipping rope training. The integration of chaos theory and logistic regression can give full play to the advantages of massive data analysis in the early stage and accurate identification of later results. According to the survey data of skipping competition in 2021, skipping training accounts for 12.6% of sports competition, while the evaluation accuracy of skipping competition effect is only 45.3%, and some skipping competition training schemes are contrary to science. Domestic scholars have applied artificial normal, artificial speech, artificial portrait, and other algorithms to skipping training, aiming at providing data support for skipping training analysis [1]. On the basis of previous studies, this paper constructs a chaotic logistics algorithm to evaluate the training effect of skipping rope and find out its existing problems and shortcomings.

Because the data of the skipping training effect mainly exist in semistructured form and present nonlinear relationship, rough set cannot accurately evaluate skipping training. Chaotic logistics algorithm has better semi-structured data analysis ability, analyzes the mapping characteristics of various factors in skipping training, and carries out repeated iteration and self-training [2] to improve the accuracy of skipping training. Some scholars combine Apriori with chaos theory to build a prediction model of skipping rope training [3] and carry out actual case analysis. The results show that the combined analysis of chaos theory and the Apriori algorithm is better, and all indexes are significantly better than the Apriori algorithm [4]. The reason is that the chaotic logistics algorithm belongs to a comprehensive analysis method, which integrates training mechanism, classifies a series of problems in skipping training, and realizes comprehensive chaos analysis. Therefore, based on the chaotic logistics algorithm, this paper evaluates the training effect of skipping rope [5]. Chaos logistics algorithm research is mainly from the following aspects to improve (1) training parameters adjustment and training strategy change. There are also scholars to skipping training evaluation strategy research and compare three skipping training strategies, and the results show that the selection of appropriate strategy can achieve higher training results in a short time [6]. (2) Some scholars put forward an adaptive logical logistics algorithm, which integrates K-mean classification into logistic logistics, but this algorithm cannot classify the data of skipping rope training [7], and the evaluation speed of training results is slow [8]. From the point of view of time delay, some scholars use a logical logistics algorithm to analyze the training results of skipping rope and get the results in a dynamic and random way [9], but the accuracy of the results of this algorithm is cross. (3) Compared with classical theories, such as Bayesian theory and rough set, chaotic logistics algorithm has strong data sensitivity [10], which is suitable for massive data points. The specific survey results are shown in Table 1.

Table 1: Research situation of skipping rope training.

Time	Number of studies	Time	Number of studies
2006	45.92	2014	55.10
2007	15.31	2015	68.37
2008	61.22	2016	85.71
2009	61.22	2017	32.65
2010	27.55	2018	82.65
2011	81.63	2019	56.12
2012	67.35	2020	80.61
2013	52.04	2021	20.41

From Table 1, we can see that the research trend of skipping training is increasingly obvious, and it is increasing year by year. The data for 2007 were the smallest, followed by 2021 and finally 2010. However, the number of studies gradually increased in 2011, 2016, and 2020. On the whole, the research on skipping training methods is above year by year and presents ups and downs of the development trend. Therefore, the research demand on skipping training methods is increasing year by year, and it has become a research hotspot. All this research has very important theoretical and practical significance. All the above studies show that the single algorithm is not ideal in terms of calculation accuracy, search time, and overall convergence. In this paper, chaos theory and logics algorithm are integrated, and the chaos logics algorithm is proposed to analyze the results of skipping training and verify them.

2. Concepts Related to Research

2.1. Chaos Theory. Chaos theory was first put forward in the early 19th century [11], which belongs to a statistical analysis method, mainly solves the problems of data description, data analysis, and result prediction, and is widely used in ships, aviation, and other fields. Chaos theory is embodied in the persistent description of data. Different points are randomly selected for analysis. Its principle and structure are as follows: let g_{it} be a data set in i multidimensional space and t time, and any x belongs to g_{ij}, and then, the data can be analyzed by chaos theory.

Suppose 1: $(P_j(x) = \sum_{i,t=1}^{n}\{x_{it}^{j} \cdot k \cdot \varphi(k)\})$, $(\varphi(k) = C(x,\varepsilon))$, and then, $(P_j(x))$ is the best data set. Among them, $(C(x,\varepsilon))$ is the adjustment coefficient of x and ε, ε is the eigenvalue in logistic logistics at this time $(x_{it} = \sin(\tan \pi t/\rho))$, and ρ is the least common multiple set, and then, at this time $(\sin(\tan \pi t/\rho)^{j} < \sum_{i,j,t=1}^{n} x_{it}^{j} \cdot k)$, the data link in chaos theory is the shortest. The related theories of logistic logistics are as follows:

Theorem 1. *If the characteristic function of any data value is $(P_n(x))$, then the calculation formula of $(\varphi(x \cdot k))$, $(f(\cdot) \in B_t)$, and the evaluation result function is shown in the following formula:*

$$\int_{x \in G_{ij}} f(x)dx < Q(\widehat{f(x))} \cdot \varphi(k). \quad (1)$$

Among them, $(Q(f(x)))$ is the overall evaluation results of $f(\cdot)$.

Theorem 2. *If the following conditions $f(x)$ and $(f(x) < \varepsilon)$ are satisfied, any function value in logistic logistics is within the integral of the function $f(x)$, and the error is less than $(lin(1/x))$.*

Theorem 3. *Assume that the eigenvalues x_{it} of any data are normally distributed on X and Y axes, then the formula for calculating the deviation of any point is shown in the following formula:*

$$D(x, f(x)) = \text{lin}\sqrt{\log\left(P_j(x)\right)}. \quad (2)$$

Among them, $D(x, f(x))$ is in the set [0, 1].

From the above analysis, it can be seen that using the approximate integral of chaos theory, the relationship between the amplitude of evaluation results and data results can be obtained, and the massive training data in space can be reduced. Therefore, the functions processed by chaos theory can be used for logistics analysis, which does not provide a good theoretical basis for the calculation of evaluation results and reduces the influence of unstructured data. From Theorem 3, we can see that the error of data in chaos theory is $lin(1/x)$, and the average error is

$lin(1/\sqrt{x} \cdot \sqrt[t]{\log(P_j(x))})$, which shows that the single-phase error has nothing to do with the average error and needs to be controlled separately. Chaos theory and logistics algorithm are combined to control the amplitude of the evaluation results, which verifies the ability of chaos theory to control the training data and the superiority of this method. In this paper, this method is used for reference to optimize the training data of skipping rope and analyze it continuously.

2.2. Logistic Model. In this paper, chaos theory is chosen to optimize logistics model. This method belongs to a classification method, which is chaotic and adaptive, and can realize self-training [12]. Logistics analysis constantly revises the membership relationship between classification set and complete set. Logistics model is defined by the "IF" judgment mode, and its classification process is as follows.

If $x_i \in g_{ij}$ and $M(x) = C(x_i, x_{i-1})$, then $y = \sum_{i=1}^{n} y_i = \sum_{i=1}^{n} M(x_i) \cdot \lambda(x_i)$.

Among them, $\lambda(x_i)$ is a classification function, g_{ij} is classification set, $M(x)$ is constraint function, $C(x_i, x_{i-1})$ is relationship between any adjacent data, and x and y are classification results. The training part of chaos theory is clear, the training data is chaotic, and the evaluation result data is clear, so we can use chaos theory to reason the evaluation results and get the result evaluation combination. Assuming that any training variable is x_i, the membership relationship between each training variable x_i and the result evaluation variable y_i can be obtained by constraint rule M as shown in the following formula:

$$C \cdot g_{ij} = \sum_{i,j=1}^{n} \exp\left\{\frac{(x_i - c_{ij})}{b_{ij}}\right\}. \quad (3)$$

Among them, c_{ij} and b_{ij} are the eigenvalues of membership functions, C is a relational function, and g_{ij} is a chaotic set. According to the membership relationship, the classification calculation formula can be obtained, as shown in the following formula:

$$C \cdot g_{ij} = \delta \cdot \sum_{i,j,k=1}^{n} g_{ij}^{k}(x), \quad (4)$$

where δ is the classification adjustment coefficient, and k is the derivative coefficient. According to formulas (3) and (4), the evaluation value of the classification result can be obtained, as shown in the following formula:

$$y = \frac{\left[\delta \cdot \sum_{i,j,k=1}^{n} g_{ij}^{k}(x) \cdot f\left(P_j(x)\right]\right.}{\max \sum_{i,j=1}^{n} g_{ij}^{k}(x)}, \quad (5)$$

where $\max \sum_{i,j=1}^{n} g_{ij}^{k}(x)$ is the maximum value of $g_{ik}^{k}(x)$, which represents the maximum value of the sum of all $g_{ij}^{k}(x)$, and $f(P_j(x)$ represents the total scheme of skipping training, which is an arbitrary skipping scheme. Chaos theory not only shortens the processing time of skipping training data but also increases the amount of single data processing. Therefore, the model constructed in this paper can classify a large number of training data [13] and analyze them continuously to form a continuous data link. In formula (5), the value is y, the relation function is C, and the classification coefficient is δ.

3. Construction of Skipping Training Model

3.1. Initial Skipping Training Data. The chaotic logistics model constructed in this paper can be used for multidimensional and holistic analysis, reduce single-phase convergence, improve the search ability of feature data, and shorten the analysis time of training results. In the evolution strategy of data link in initial skipping training and multidimensional skipping training, convergence threshold and weighting factor are used to promote the association evolution of different data values and get the best result.

The preprocessing of data by chaos theory: according to the classical logistics algorithm, if the data link is randomly distributed in the initial skipping training and the uncertainty is very strong, the data link calculation in skipping training will fall into single-phase optimum, which will reduce the evaluation time of the overall training effect and increase the error rate of the evaluation results, in order to expand the scale of data link and increase the types of data in skipping training. In this paper, using the classical logistics principle for reference, the number of data links in skipping training of initial data is expanded, and the diversity of data links in skipping training is improved. The results are shown in Figures 1 and 2.

Among them, the data in Figure 1 are the skipping training data processed by chaos theory, which is scattered in the whole space and does not change greatly with the increase of data volume. At the same time, the position of data is relatively stable, showing a planar situation, which shows that chaos theory maps data and highlights the numerical attributes of data.

As can be seen from Figure 2, the distribution of data in space is relatively discrete, and it changes up and down, indicating that data not only have numerical attributes but also have other attributes. In the process of skipping rope training, only numerical attributes are analyzed. Therefore, the chaotic regression analysis method not only extracts the data numerically but also integrates other attributes into the mapping, resulting in better data analysis results. Figures 1 and 2 show the multidimensional initial chaos theory treated by random method and chaos theory method, respectively, and the number of segments of chaos theory is 60. By comparison, it is found that the data link generated by the random method is messy and nondirectional in skipping training. The data link in skipping training processed by chaos theory is more concentrated and directional. According to Theorems 1 and 2 of the logistics algorithm, the data set constructed by this algorithm has nothing to do with spatial dimension and is suitable for multidimensional data processing. Moreover, every time the skipping training data are obtained, the distribution effect of the initial data link is the same, and the stability of the data set is high. To sum up, chaos theory is selected to process the initial data link.

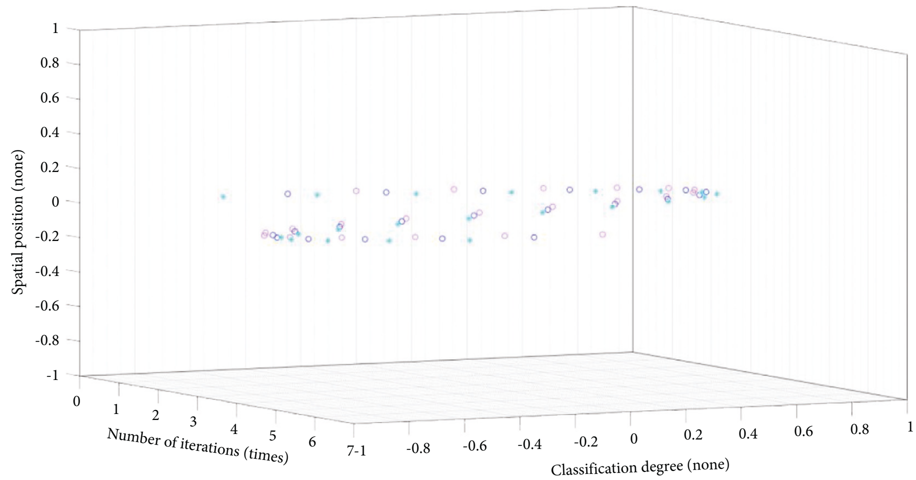

Figure 1: Random data constructed by chaos theory.

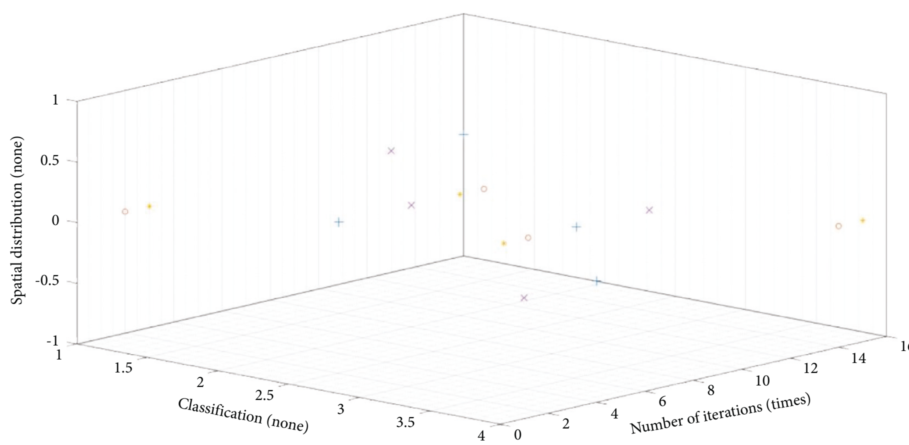

Figure 2: Data distribution constructed by chaotic logistics.

The synergy action between multiple strategies: the ability to evaluate the overall training effect is an important measure of the algorithm. In the initial stage of evaluation, the algorithm pays attention to the overall search and then progresses to the single-phase search [14]. In order to improve the evaluation efficiency of the algorithm, this paper introduces a multistrategy association method, which makes the stacks search according to different data links in skipping training and realizes overall and single-phase search. At present, the standard logistics algorithm is adopted, and there are other improved algorithms.

(1) Self-data model is shown in the following formula:

$$y_{ij}(T) = \omega \cdot y_{ij}(t)c_1 \cdot r_1 \cdot \frac{\left[\delta \cdot \sum_{i,j,k=1}^{n} g_{ij}^{k}\left\{x(t) \cdot f\left(P_j[x(t)]\right\}\right.}{\max \sum_{i,j=1}^{n} g_{ij}^{k}[x(t)]}. \tag{6}$$

(2) Population data schema is shown in the following formula:

$$y_{ij}(T) = c_2 \cdot r_2 \frac{\left[\delta \cdot \sum_{i,j,k=1}^{n} g_{ij}^{k}\left\{x(t) \cdot f\left(P_j[x(t)]\right\}\right.}{\max \sum_{i,j=1}^{n} g_{ij}^{k}[x(t)]}. \tag{7}$$

(3) Data judgment mode is shown in the following formula:

$$y_{ij}(T) = n \cdot \Delta \left| \frac{\left[\delta \cdot \sum_{i,j,k=1}^{n} g_{ij}^{k}\left\{x(t) \cdot f\left[P_j[x(t)]\right\}\right.}{\max \sum_{i,j=1}^{n} g_{ij}^{k}[x(t)]} \right|. \tag{8}$$

(4) A broad data schema is shown in the following formula:

$$y_{ij}(T) = \omega \cdot y_{ij}(t) \frac{\left[\delta \cdot \sum_{i,j,k=1}^{n} g_{ij}^{k}\left\{x(t) \cdot f\left(P_j[x(t)]\right\}\right.}{\max \sum_{i,j=1}^{n} g_{ij}^{k}[x(t)]}. \tag{9}$$

Among them, c_1 and c_2 are the correlation coefficient of different strategies, r_1 and r_2 are the correlation coefficient of different strategies, ω is the average weight of different strategies, and n is the number of different strategies. In this paper, the standard logistics function is improved in two aspects. On the one hand, the search scope is expanded. For every iterative evaluation, one chaos theory form will be randomly selected from the above five forms for self-evaluation of chaos theory. Chaos theory evaluation can avoid single-phase optimal evaluation results and expand the search range. Random selection of evaluation forms can keep the diversity of analysis data and increase the possibility of obtaining single-phase optimal results. On the other hand, the convergence is improved. In order to balance the whole search ability and single-phase search ability of chaos theory, nonlinear adjustment coefficient α and linear weight ω are added to improve the evaluation speed, as shown in the following formula:

$$\alpha = \frac{\mathrm{Line}_t^d - 1}{\mathrm{Line}_T^D}, \tag{10}$$

where e is the evaluation parameter, t is the evaluation time, T is the maximum time, d is the iteration number, and D is the maximum iteration number. In the initial stage, α shows a decreasing trend, so the overall optimal result can be evaluated. In the middle and late stages of evaluation, the number gradually increases, and the single-phase optimal result evaluation can be carried out. The linear weight is evaluated as shown in the following formula:

$$w = \sum_{d=1}^{D} \left[\left(w_{\max} - \sum_{t=1}^{T} \Delta w_i \right) \right]^d, \tag{11}$$

where $w_{\max}$ and $w_{\min}$ are the maximum and minimum weights, and the results of d, t, D, and T are the same as above.

The strategy selection in the process of data analysis: the chaotic logistics algorithm adopts different operations and strategies for different massive training data and adjusts corresponding training parameters to realize distributed association of multiple massive training data, so as to complete the association evolution process. In the model, chaos theory data are divided into five dimensions, and each massive training data represent subspace [15]. In each iteration, different massive training data evolve simultaneously. After an iterative evaluation is completed, the adaptation results of different massive training data are compared, and the position of the overall optimal results of each massive training data is recorded. Then, each submassive training data is progressively trained to the overall optimal result, and the optimal position of submassive training data is obtained in the simplest way, so as to improve the speed and efficiency of search and evaluation.

3.2. Rope Skipping Training Judgment Method Based on Chaotic Logistics Algorithm. The basic idea based on chaos theory is the association evolution of multitime massive training data, and the initial results and threshold results are adjusted and optimized [16] to obtain the optimal solution and reduce the evaluation result rate in skipping training. The specific steps are shown in Figure 3.

Step 1. Determine the massive training data of chaos theory and the data link structure in skipping training, and determine the data structure of chaos theory according to the data characteristic demand. The initial weight results and threshold results of the whole data as a whole are mapped to chaos theory. The massive training data of each chaos theory are weight results and threshold results, which determine the massive training data of chaos theory in this paper.

Step 2. Data initialization randomly initializes the related training parameters of chaos theory. Set the number of chaos theory and the correlation constant between different massive training data and the maximum iteration times.

Step 3. Generate the moderation function. The chaotic theory is used to generate the data link in the initial skipping training of the chaotic theory, and it is mapped to the chaotic theory as the initial weight result and threshold result. Through the self-training and training of formulas (1) ~ (7), the correlation coefficient of chaos theory is continuously obtained. Evaluate the accuracy of each chaos theory, and take the absolute result of its square sum as a moderate function.

Step 4. Search the optimal position of chaos theory and the optimal position of each subgenetic stack as a whole. The initial chaos theory is randomly divided into five subdata links in skipping training, the fitness ratio results are obtained, and the optimal overall position and the optimal position of each subdata link in skipping training are recorded.

Step 5. Iteration of optimal position and speed. In the evolution of data links in 5 seed skipping training, randomly select one for evolution, such as formula (7) ~ (10), and add nonlinear adjustment coefficients and linear weights, such as formula (11) and formula (12).

Step 6. Data links are associated and evolved simultaneously in each subskipping training. After an iterative evaluation is completed, the best overall evaluation position is selected, and the best position is shared with other data links in skipping training. In other subskipping training, the data link gradually iterates to this position to get the best position result.

Step 7. Determine whether to stop the iteration.

4. Case Analysis of Skipping Rope Training

4.1. Judgment of Chaotic Logistics Model. Using Sphere, Rastring, Ackley, and other functions, the classical chaotic logistics method is tested to verify the performance of the model proposed in this paper.

Sphere is the sole minimum result function [17] for the test model as a whole, as shown in the following equation:

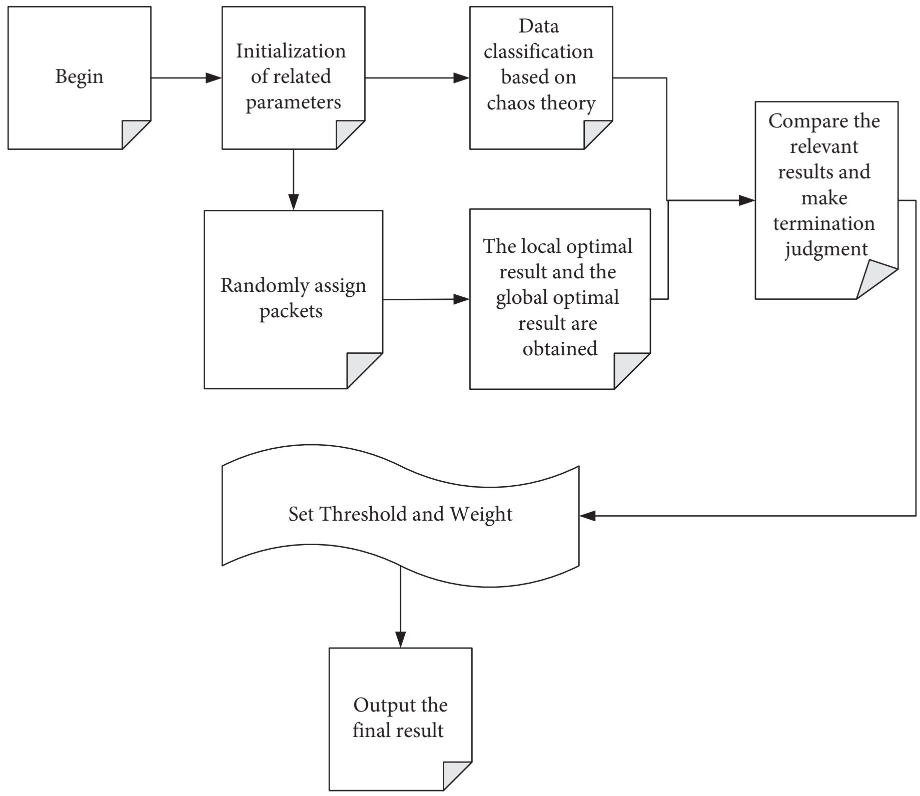

Figure 3: Evaluation process based on chaotic logistics algorithm.

$$F_1(x) = \sum_{i=1}^{n} \left[x_i^2\right]. \tag{12}$$

Rastring is based on the De Jong function and produces single-phase minimum results frequently through the cosine modulation transfer function to verify the practicability of the model solution [18], as shown in the following formula:

$$F_2(x) = \sum_{i=1}^{n} \left[x_i^2 - 10\cos\left(2\pi x_i\right) + 10\right]. \tag{13}$$

Ackley is a gradient optimization function for multidimensional points, testing the evaluation speed of multidimensional data to detect the overall convergence rate [19], as shown in the following equation:

$$\begin{aligned} F_3(x) = -20\exp\left\{-0.2\sum_{i=1}^{n}\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2}\right\} \\ - \exp\left\{\frac{1}{n}\sum_{i=1}^{n}\cos\left(2\pi x_i\right)\right\} + 20 + e, \end{aligned} \tag{14}$$

where n is the total number of indicators of evaluation data and x_i is any number of indicators. The result range of x_i is $\{-20, 20\}$ in Sphere, $\{-20, 20\}$ in Rastring, and $\{-20, 20\}$ in Ackley. For the convenience of evaluation, the number of chaos theory in this paper is $n = 50$, the maximum iteration number is $D = 20$, and the longest time is $T = 12$ min. The above three functions are tested, respectively. In order to improve the accuracy of data calculation, this paper uses the average value as the initial data, and the specific contents are shown in Table 2.

In order to further verify the results, different indexes of skipping training are compared, and the results are shown in Figures 4–6.

As can be seen from Table 1, compared with the logistics algorithm and chaos theory, the chaotic logistics algorithm proposed in this paper is closer to the overall optimal result. The chaotic logistics algorithm is superior to the other two algorithms in the aspects of standard deviation, average result, and range of taking result. Through the curve changes in Figures 4–6, we can see that the chaotic logistics algorithm has better stability and faster convergence speed. Therefore, the convergence speed, evaluation accuracy, and summation stability of chaotic logistics algorithm are better.

4.2. Preprocessing of Rope Skipping Training Data. The data set of skipping training includes physical fitness index, blood pressure, speed, endurance, and sensitivity [20]. After preliminary pretreatment, 982 rows of structured data and 12 rows of semistructured data were obtained, and other data were eliminated if they did not meet the requirements. In order to facilitate data analysis, the skipping training results are divided into five grades, which are accurate, normal, good, poor, and relatively poor. The processing results of data amount are shown in Table 3.

As can be seen from Table 2, the accuracy of all data results is better, all of which are more than 90%.

Table 2: Test results of different test functions.

Detection function	Algorithm	Physical strength	Endurance	Vital capacity	Overall training effect
Sphere	Chaotic logistics algorithm	91.84	94.90	93.88	98.2
	Logistics algorithm	98.98	99.90	99.88	
	Chaotic algorithm	94.90	98.98	96.94	
Rastring	Chaotic logistics algorithm	99.96	99.90	99.92	99.6
	Logistics algorithm	93.88	91.84	98.98	
	Chaotic algorithm	96.94	96.94	97.96	
Ackley	Chaotic logistics algorithm	99.90	99.88	99.86	95.3
	Logistics algorithm	91.84	94.90	94.90	
	Chaotic algorithm	98.98	98.98	96.94	

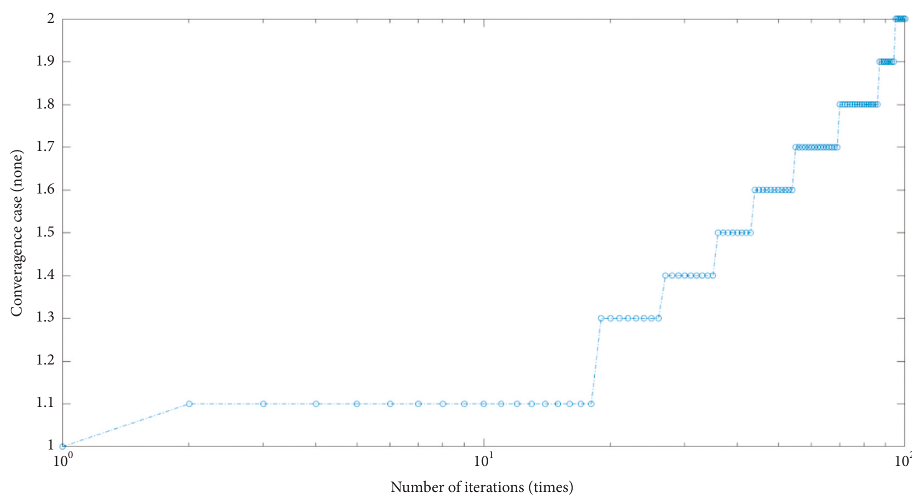

Figure 4: Strength test results.

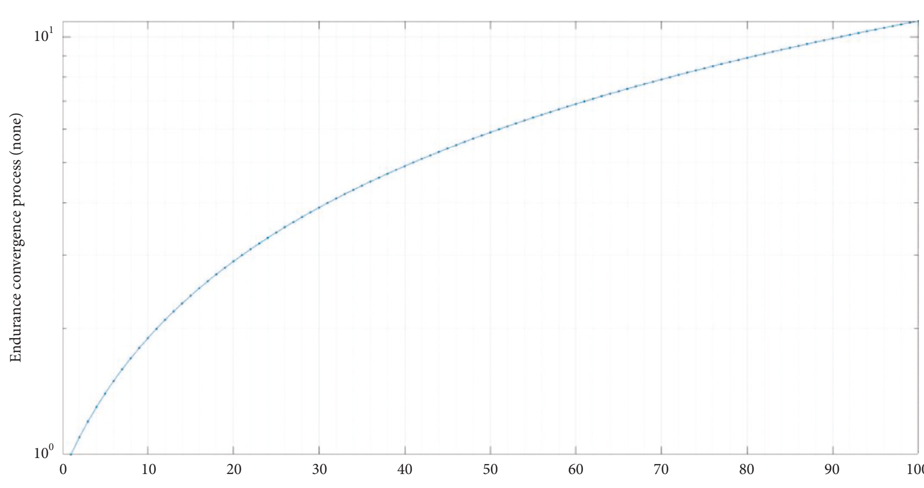

Figure 5: Endurance test results.

4.3. Test Results. In order to verify the chaotic logistics algorithm proposed in this paper, the results are compared with chaos theory and logistics algorithm, and the results are shown in Figure 7.

It can be seen from Figure 7 that the accuracy of the chaotic logistics algorithm is higher than that of the chaotic theory and logistics algorithm, but the error rate is lower, which shows that the evaluation of the chaotic theory and logistics algorithm is relatively stable, while the evaluation of chaotic theory and logistics algorithm is uneven. The average results of the above three algorithms are shown in Table 4.

It can be seen from Table 4 that the single chaos theory and chaos logistics method have the problems of insufficient accuracy and large variation of evaluation results in different

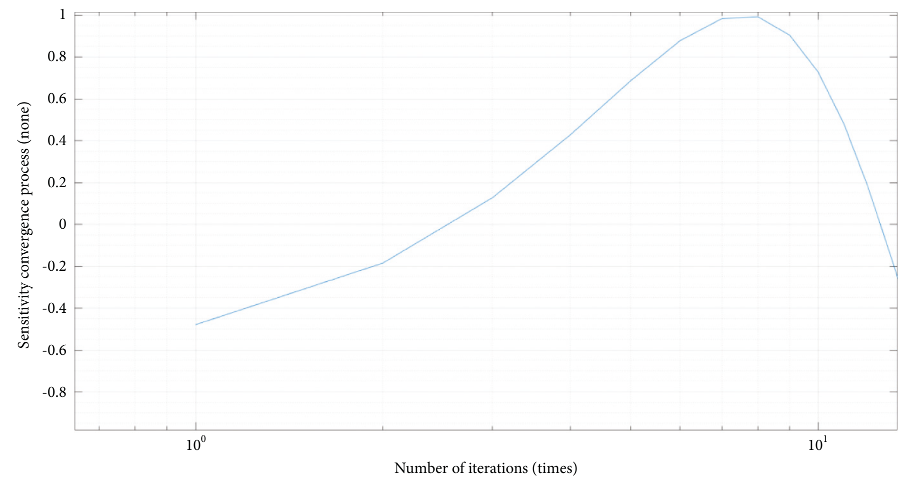

FIGURE 6: Sensitivity test results.

TABLE 3: Classification and quantity of skipping training.

Normal level	Amount of data	Accuracy
Accurate	123	93.91
Normal	543	91.21
Good	332	86.43
Poor	17	94.80
Comparatively poor	26	83.17

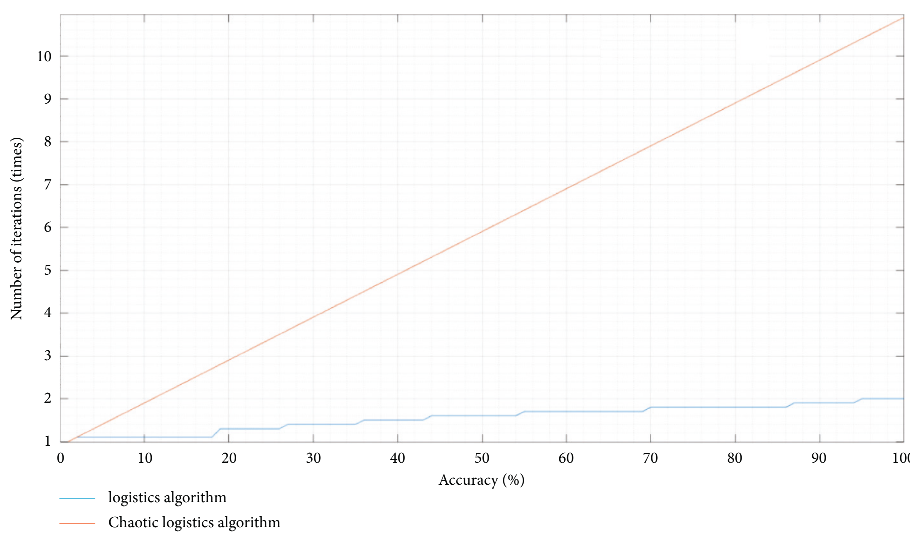

FIGURE 7: Test results of different algorithms.

TABLE 4: Comparison of prediction accuracy of different grades.

Algorithm	Accurate	Normal	Good	Poor	Comparatively poor
Logistics algorithm	77.23	69.22	77.28	78.34	75.94
Chaotic logistics algorithm	92.32	90.13	91.33	92.47	91.91
Chaotic algorithm	76.41	76.27	82.17	85.19	87.71

levels of skipping training prediction. Compared with chaos theory, the accuracy of the algorithm constructed in this paper is significantly improved. At the same time, the accuracy of the algorithm constructed in this paper is close to that of chaos theory, both of which are more than 80%, which is superior to chaos theory. In order to further verify

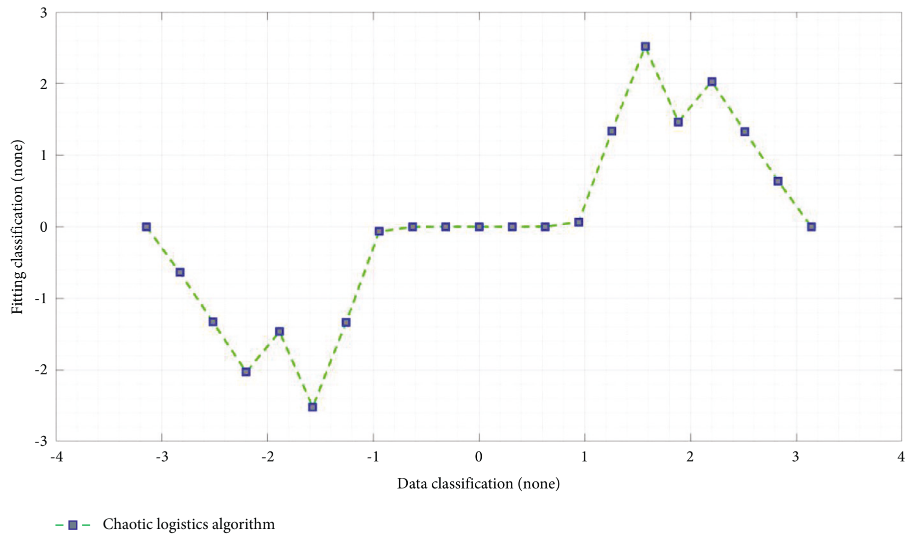

Figure 8: Fitting degree of chaotic logistics algorithm.

the superiority of the chaotic logistics algorithm, the optimal fitness results of different algorithms are compared, and the results are shown in Figure 8.

As can be seen from Figure 8, the optimization of fitness function results of chaotic logistics algorithm is more significant. The reason is that chaotic algorithm increases the adjustment, weight, and convergence factor of different massive training data. Consistent with relevant research results [21].

5. Conclusion

In this paper, chaos theory is proposed, and combined with the logistic evolution method, chaos theory is improved. At the same time, the threshold and weight of chaos theory are set, and the analysis model of skipping rope training is constructed. The results show that, compared with the classical chaos theory and chaos theory, the prediction accuracy and convergence of skipping rope training based on chaos theory and chaos theory are better, and it can be used to judge skipping rope training. However, in this model, the logistics strategy pays too much attention to training the overall effect evaluation ability, which leads to the relative decline of single-phase search ability and reduces the evaluation speed of the optimal solution. Therefore, in the future research, the logistic adjustment function will be added to improve the regression ability of the model.

Data Availability

The data supporting the conclusion of the article are shown in the relevant figures and tables in the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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