College students jump performance prediction based on NGA-BP neural network and the computer simulation

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Abstract

In recent years, with the aggravation of the schoolwork burden, the physical quality of the student is declining. In order to encourage the college students to exercise, the State Council promulgated the "National Physical Training Standards". In this standard, the long jump is a very important physical test project. Using the computer technology to predict the long jump performance can make the targeted training effectively for the long jump performance. In the traditional prediction methods, BP neural network is a very common method. However, in the traditional BP neural network, there exist some questions about the weight and parameter setting. In order to overcome the questions, in this paper, we propose NGA-BP neural network based on k-mean clustering. Then, we use this algorithm to predict the long jump performance for the college students with the computer simulation. The finial computer simulation shows that the method has good results.

Keywords: Jump performance prediction; BP neural network; K-mean clustering; Computer simulation

1 Introduction

21 century is the century of the computer. The rapid development of the computer technology introduces the technology into every corners of our daily life. In the modern university physical education, using the computer technology not only provides the convenience for the daily life, but also gets the better physical exercise.

As the most ancient sports project, the long jump is a jump event which relies on the combination of the speed, power and other things. The long jump can develop the basic physical qualities of speed, power, coordination, flexibility and balance etc. for people. And it can also have great significance to promote the health of human beings. The long jump is a very important campaign in the "National Physical Training Standards". It is also a campaign that many college students love. Many scholars did relative studies about the long jump performance. Sun Junsheng studied a convenient, practical, accurate and scientific comprehensive evaluation method which can be used to evaluate the special quality for China's outstanding man three jumpers [1]. Yu Jun adopted the parameter mean difference analysis and the significant test to study the relative technology parameters for the Chinese and foreign excellent athletes [2]. And he found the main factors which influenced the long jump performance for the Chinese and foreign excellent athletes. At the same time, he applied the multiple regression analysis to establish a regression model. Zhao Bingjun[3] applied the cluster analysis and the multiple regression method to study the training indexes systematically which influenced the long jump performance for our long jump athletes. He also established the multiple regression models and verified the accuracy and the reliability of the model. Wang Ying analysed and studied the multi-questions which affected the long jump performance [4]. According to the method of investigation and the factor analysis etc., Cheng Hui discussed the composition of the specific quality index system and the performance prediction model for our excellent long jump athletes [5]. Fan Genus and Qi Ziyun applied the partial least squares regression to analyse the influencing factors for the performance of our athletes [6]. They used the partial least squares regression to study the relationship between the athletes and the technology parameters. According to the variable importance in projection index, we selected the technical parameters which influenced the long jump performance. By the cross validation test, we established the relationship model between the long jump performance and the technical parameters. Wang Feng analysed the impact of run-up speed and the take-off technique on long jump results of competitive athletes [7]. This literature combined the morphological index of Chinese male long jump athletes and the foreign excellent athletes. The results showed that the performance gap between our male athletes and the foreign athletes is widening gradually.

The neural network is one of the most mature and widely used artificial neural network modes [8-11]. The neural network has many advantages. At the same time, it also has a lot of disadvantages, such as the slow convergence speed, the unsure network structure, the poor prediction extrapolation effect etc. These disadvantages limit the application of the neural network. Therefore, in recent years, many scholars studied the neural network

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deeply and proposed many improved methods. These methods are mainly to improve the learning algorithm [12] and the network structure [13]. The niche genetic algorithm used the habitat concept of the biological. Compared with other common optimization methods, its search efficiency is higher. And it can obtain a plurality of the objective function extremum in one research. However, its local search capacity needs to improve. And the parameters determination has no certain standards. At present, the improvement of the niche genetic algorithm mainly focused on the parameters determination, such as the isolation niche technique and the adjustment of the distance parameters dynamically [14-16].

According to analysing the algorithm principle of the neural network, this paper introduces the niche genetic algorithm aiming to the question that the network is sensitive to the weight and threshold parameters. The defect of the algorithm is that this algorithm needs to estimate the pear radius of the solution space and the number of the peaks. However, the solution space of the most practical problems is complex and it is difficult to estimate the parameters of the algorithm. Aiming to solve the above defects, we proposed an algorithm that combines the k-means niche genetic algorithm and BP neural network. This algorithm combined the cluster analysis, niche genetic algorithm and BP neural network. This algorithm did not need to ensure the specific number of niche and the size of the niche radius. And it had small calculation and high search efficiency. The simulation result shows that the algorithm has better multi-peak search ability and improves the applicability of the algorithm. The structure of this paper is as follows. The first part is the introduction. The second part is neural network and niche genetic algorithm. In this part, we introduce the neural network and niche genetic algorithm. The third part is NGA-BP neural network based on k-mean clustering. In this part, we proposed a new BP neural network algorithm. The fourth part is the numerical analysis and the last part is the conclusion.

2. Neural network and niche genetic algorithm

2.1 NEURAL NETWORK

The neural network is a kind of mathematical model which simulates the brain structure. The main function is to process the information. It can change the external structure which is based on the external information. Neural network is an adaptive system. The modern neural network is a nonlinear statistical data model. Neural network models for the complicated relationship between input and output. Or it is a mode to use to explore the data.

2.1.2 The model structure of the BP network

The BP network is a three layer feed-forward neural network. It is composed by the input layer, hidden layer and the output layer. Each layer contains one or more neurons. Each layer neuron uses the whole connection mode. And the inner layer neuron is no connection. In the first layer of the BP network, the feed-forward process can be expressed as follows.

$$y' = f'(n') = f'(x'z') \tag{1}$$

Among them, the output vector of the first layer is as follows.

$$y' = [y'_1, y'_2, \cdots, y'_{s^l}], \tag{2}$$

f' Is the transfer function of the first layer. $n = [n_1, n_2, \cdots, n_{s^l}]$ Is the sum of the weighted vector of the first layer .we make the one-dimensional vector of the threshold b added to the weight matrix w.

$$x' = [w^l_{s^l * s^{l1}} \quad b^l_{s^l * 1}] = \begin{bmatrix} w'_{1,1} & \cdots & w'_{1,s^{l-1}} & b'_1 \\ \vdots & \vdots & \vdots & \\ w'_{s^l,1} & \cdots & w'_{s^l,s^{l-1}} & b'_{s^l} \end{bmatrix} s^l * (s^{l-1}+1)$$

In order to calculate conveniently, we make the threshold b as the special input.

$$z^l = \begin{bmatrix} y^{l-1} \\ 1 \end{bmatrix} (s^{l-1}+1) * 1$$

The core of the BP algorithm is the updated process of the weights. That is, we add an increment for the gradient direction to achieve the updated operations for the weights by using the error.

2.1.3 The weight update of the BP neural network

When the actual output is not compatible with the expected output, there exists error. We use e to express the error.

$$e = \sum_{s^L=1}^{L} (t_{s^L} - y^L_{s^L})^2 \tag{3}$$

Among them, t_{s^L} is the actual output. $y^L_{s^L}$ Is the expected output. The weight update of BP neural network is to add an increment along the negative gradients in order to achieve the weight update. The general expression of the weight update is as follows.

$$w^l_{s^l,s^{l-1}}(k+1) = w^l_{s^l,s^{l-1}}(k) - \alpha * g^l_{s^l,s^{l-1}}(k) \tag{4}$$

We assume the gradient

$$g^l_{s^l,s^{l-1}} = \frac{\partial e}{\partial w^l_{s^l,s^{l-1}}} = \frac{\partial e}{\partial n^l_{s^l}} * \frac{\partial n^l_{s^l}}{\partial w^l_{s^l,s^{l-1}}} \tag{5}$$

Then

$$\frac{\partial n^l_{s^l}}{\partial w^l_{s^l,s^{l-1}}} = \frac{\partial\{\sum_{s^{l-1}=1}^{s^{l-1}} (w^l_{s^l,s^{l-1}} * y^l_{s^l,s^{l-1}}) + b^l_{s^l}\}}{\partial w^l_{s^l,s^{l-1}}} = y^{l-1}_{s^{l-1}} \tag{6}$$

Make

$$\delta^l_{s^l} = \frac{\partial e}{\partial n^l_{s^l}} \tag{7}$$

We make the formula (5) and (6) into the formula (4), then we get

$$g^{l}_{s^l,s^{l-1}} = \delta^{l}_{s^l} * y^{l-1}_{s^{l-1}} \quad (8)$$

For $\delta^{l}_{s^l,s^{l-1}}$, the derivation process is divided into two steps. They are respectively $l < L$ and $l = L$. L The total number of the layer network.

(1) $l < L$

$$\delta^{l}_{s^l} = \frac{\partial e}{\partial n^{l}_{s^l}} = \frac{\partial e}{\partial y^{l}_{s^l}} * \frac{\partial y^{l}_{s^l}}{\partial n^{l}_{s^l}} \quad (9)$$

$\delta^{l}_{s^l}$ is a recursive derivation process which from back to front. Therefore, in the layer $l+1$, the total weight of each neuron involves the l layer.

$$n^{s^L}_{s^{l+1}} = \sum_{s^{l-1}=1}^{s^{l-1}} (w^{l}_{s^l,s^{l-1}} * y^{l}_{s^l,s^{l-1}}) + b^{l}_{s^l} \quad (10)$$

Then

$$\begin{aligned} \frac{\partial e}{\partial y^{l}_{s^l}} &= \frac{\partial e}{\partial n^{l+1}_{l}} * \frac{\partial n^{l+1}_{l}}{\partial y^{l}_{s^l}} + \cdots + \frac{\partial e}{\partial n^{l+1}_{s^{l+1}}} * \frac{\partial n^{l+1}_{s^{l+1}}}{\partial y^{l}_{s^l}} \\ &= \sum_{s^{j+l}=1}^{s^{j+l}} \left(\frac{\partial e}{\partial n^{l+1}_{s^{l+1}}} * \frac{\partial n^{l+1}_{s^{l+1}}}{\partial y^{l}_{s^l}}\right) \\ &= \sum_{s^{j+l}=1}^{s^{j+l}} \left(\frac{\partial e}{\partial n^{l+1}_{s^{l+1}}} * w^{l+1}_{s^{l+1},s^l}\right) \end{aligned} \quad (11)$$

Due to

$$\delta^{l}_{s^l} = \frac{\partial e}{\partial n^{l}_{s^l}} \quad (12)$$

Then we make the formula (12) as follows.

$$\frac{\partial e}{\partial y^{l}_{s^l}} = \sum_{s^{j+l}=1}^{s^{j+l}} (\delta^{l+1}_{s^{l+1}} * w^{l+1}_{s^{l+1},s^l}) \quad (13)$$

The formula (8) can be expressed as

$$\frac{\partial y^{l}_{s^l}}{\partial n^{l}_{s^l}} = \frac{\partial f^{l}(n^{l}_{s^l})}{\partial n^{l}_{s^l}} = f^{l}(n^{l}_{s^l}) \quad (14)$$

We make the formula (13) and (14) into the formula (9), then we get

$$\delta^{l}_{s^l} = \sum_{s^{j+l}=1}^{s^{j+l}} (\delta^{l+1}_{s^{l+1}} * w^{l+1}_{s^{l+1},s^l}) * f'^{l}(n^{l}_{s^l}) \quad (15)$$

(2) $l = L$

$$\delta^{L}_{s^L} = \frac{\partial e}{\partial n^{L}_{s^L}} = \frac{\partial e}{\partial y^{L}_{s^L}} * \frac{\partial y^{L}_{s^L}}{\partial n^{L}_{s^L}} \quad (16)$$

$$\frac{\partial e}{\partial y^{L}_{s^L}} = \frac{\partial \sum_{S^L=1}^{L} (t_{s^L} - y^{L}_{s^L})^2}{\partial y^{L}_{s^L}} = -2(t_{s^L} - y^{L}_{s^L}) = -2e_{s^L} \quad (17)$$

$$\frac{\partial y^{L}_{s^L}}{\partial n^{L}_{s^L}} = \frac{\partial f^{L}(n^{L}_{s^L})}{\partial n^{L}_{s^L}} = f^{L}(n^{L}_{s^L}) \quad (18)$$

We make the formula (17) and (18) into the formula (16), then we get

$$\delta^{L}_{s^L} = -2e_{s^L} * f'^{L}(n^{L}_{s^L}) \quad (19)$$

From the above equation, we can summarize the weight update process of BP neural network

$$w^{l}_{s^l,s^{s-1}}(k+1) = w^{l}_{s^l,s^{s-1}}(k) - \alpha * \delta^{l}_{s^l,s^{s-1}} * y^{l-1}_{s^{l-1}} \quad (20)$$

Among them

$$\delta^{l}_{s^l,s^{s-1}} = \begin{cases} \sum_{s^{j+l}=1}^{s^{j+l}} (\delta^{l+1}_{s^{l+1}} * w^{l+1}_{s^{l+1},s^l}) * f'^{l}(n^{l}_{s^l}) & l < L \\ -2e_{s^L} * f'^{L}(n^{L}_{s^L}) & l = L \end{cases} \quad (21)$$

2.2 THE NICHE GENETIC ALGORITHM (NGA)

In the niche technique, the most famous and the most used technique is the niche realization method based on the sharing mechanism. This method was proposed by Goldberg and Richardson in 1987. This genetic algorithm based on this method is short for the fitness sharing genetic algorithm (FSGA). The basic idea of the method is that the peak of the solution space can be regarded as the resource peak. The individuals around the peak share the resources. The sharing method is to use the individual fitness value divides the number of the individuals of this individual. That is, we reduce the selected probability of individual by reducing the fitness value of the individual. If one individual is far from other individuals, its fitness value is low. If one individual is close to other individuals, then its fitness value reduces. This method can enable the sparse individual to reproduce. Then it can maintain the diversity of the population. The fitness value sharing method generally performs before the selection operator of the genetic algorithm in order to use the adaptive value after sharing in selection operator.

2.2.1The standard fitness sharing algorithm

The algorithm belongs to the category of the fitness sharing algorithm. Firstly, it needs to give the radius of the niche about the solution space. And we assume the peak radius of the solution space is the same. The main steps of the algorithm are as follows.

(1)The sharing function $sh(d_{ij})$ of individual in the computation population is as follows. The calculation formula is as follows.

$$sh(d_{ij}) = \begin{cases} 1-\left(\dfrac{d_{ij}}{\sigma}\right)^{\alpha} & d_{ij} < \sigma \\ 0 & otherwise \end{cases}$$

Among them, d_{ij} is the distance between the individual i and the time j . σ Is the given peak radius. α is the parameters to control the sharing function shape. And $\alpha = 1$. The sharing value function of the two individuals is greater, the two individuals are closer.

(2)We calculate the niche count of the individual in the population m

$$m_i = \sum_{j=1}^{m} sh(d_{ij}), i = 1, 2, \cdots, n$$

Among them, n is the population scale. The bigger the number of the niche individual is, the more other individuals surround the individual.

(3) We calculate the shared fitness value of the individual in the population f_i

$$f_i' = f_i / m_i$$

Among them, f_i the fitness of the individual i before shares.

(4)We use the shared fitness value to select. The crossover and mutation can produce a new individual. And then it generates new populations.

The standard fitness value sharing algorithm needs to know the peak radius. And we assume the distribution of the peaks is homogeneous and has the same radius. The actual problems cannot meet these requirements. As the forerunner of the fitness value sharing algorithm, the search capability and the optimization speed of the standard fitness sharing are higher than the general level. However, the test of other standard multimodal optimazation problems shows that the optimization stability for the simple and the complex of the standard fitness sharing are better. If the solution space structure of the optimization object is not clear, and the easy degree is unknown, we firstly consider using the standard fitness sharing to optimize and obtain information.

2.2.2 The adaptive niche genetic algorithm

This algorithm consists two groups. They are called as the customer group and merchant individual group. We use the coevolution of these two individuals to achieve the multi peak optimization. The customer group is similar to the population of other fitness value sharing algorithm. The merchant group represents the set of the peaks in the search space. The individual number k of the merchant groups is larger slightly than the number of the niche in other fitness value sharing algorithm. The fitness value of the individual in the customer group is the same to the fitness value of the individual in other fitness value sharing algorithm. The individual fitness value in the merchant group belongs to the sum of the fitness values about all customers. The algorithm needs to search the individual which randomly places the merchant groups. The process is as follows.

The first step is to arrange the individual of each merchant group into the nearest merchant.

The second step is to calculate the number of the niche for all customers.

The third step is to calculate the individual shared fitness value of the customer group.

The fourth step is to select the shared fitness value in the customer group. And the individual crossovers and mutates new individual. Lastly, it generates new customer group.

The fifth step is to select the individual sequentially of each merchant group. And we make it mutate to generate new merchant. If the fitness value of the new merchant is higher than the old merchant and the distance is smaller than other merchants, we use the new merchant to replace the old merchant. Otherwise, we do another mutation operation until it generates a new merchant which can be replaced the old merchant or the number of mutation operation is more than the biggest mutation.

3 NGA-BP neural network based on k-mean clustering

3.1 CLUSTERING NGA

In the clustering analysis method, the most commonly used method is the k-clustering method. The basic steps are as follows.

The first step is to generate randomly q centres.

The second is to distribute each point to the nearest centre according to some distance measure.

The third step is to calculate the centre of gravity of the point which belongs to the centre. And it is as the new centre coordinate for each centre.

The fourth step is to return to the second step if one centre changes and return q clustering centres.

This k-means algorithm only can generate q centres. In the NGA algorithm, we only get a conservative value. If the position of centre in the first step is not good, we cannot get the result. For solving this problem, we introduce the shortest clustering distance. If the distance between two clustering centre is less than the shortest clustering distance after the third step, we combine two centres.

3.2 NGA BASED ON K-MEAN CLUSTERING

We call the improved method as NGA based on k-mean clustering. The steps of NGA based on k-mean clustering are as follows.

The first step is to generate the individuals to combine the groups and calculate the fitness $F_i (i = 1, 2, \cdots, M)$

The second step is to calculate the fitness after individuals sharing each other.

The third step is to cluster the groups with improved k-means method

The fourth step is to choose $N (N < M)$ individuals though proportion select method;

The fifth step is to select the individual to do crossover and mutation randomly in each cluster. Then it generates the new individual and enter into the next generation population until the population size reaching to N . The crossover and mutation adopt the single point crossover and the basic mutation of the basic genetic algorithm. If the peak radius genes of one individual become zero because of the crossover operator exchanging chromosome segments or the mutation operator changing the position, we need to select randomly one gene and make the value 1.

The sixth step is to determine whether the algorithm meets the condition to stop the criterion. If not satisfied, it returns to the first step. If it meets the stopping criterion, we use the clustering method to find the cluster centres from the current populations. And we make the cluster centre as the peak set.

3.3 NGA-BP NEURAL NETWORK BASED ON K-MEANS CLUSTERING

The parameters setting of BP neural network exists the great influence for the network performance. It includes the topology of the network and the initialization of the hidden foot node etc. From the domestic and foreign literatures, we use the experience to construct the network topology, set the hidden layer node, initialize randomly the weight threshold and use the network to solve the practical problems. Now, there is not a set of complete theory guiding the above problems. This can lead to a series of questions. For example, the decline of the network performance, the poor network generalization ability and the unstable network and so on. Therefore, this paper establishes the model by using the NGA-BP neural network based on k-mean clustering. We use the niche genetic algorithm which has the global search ability to optimize the weight threshold. Then we establish the prediction model and use BP to solve the actual prediction problems. The flow chart of the algorithm is as follows (Figure1).

This figure shows the flow chart of the algorithm of the NGA-BP neural network based on k-mean clustering. The flow chart combines the niche genetic algorithm with the neural network to establish a kind of new prediction model.

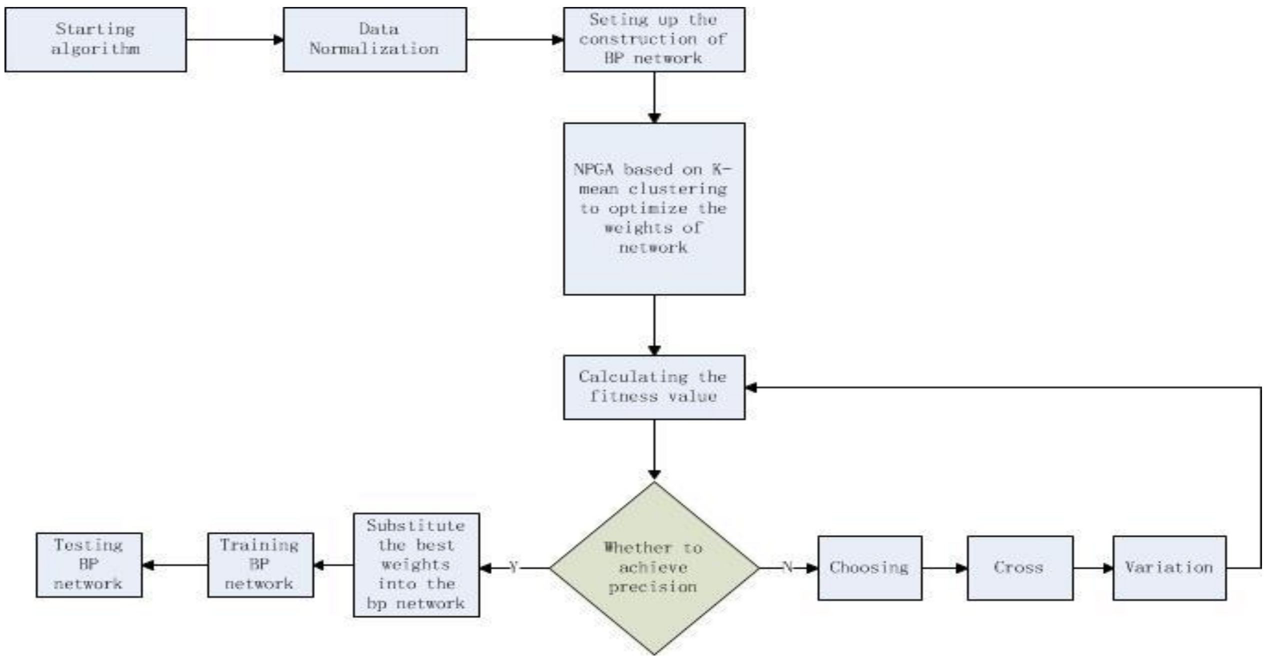

FIGURE 1 Tthe flow of NGA-BP neural network based on k-mean clustering

4 Numerical analysis

We selected three college students to predict their long jump performances. In one month, we tested the three college students ten times and got the experimental data. All data was divided into the training samples and the testing samples. The first seven data sets are as the training samples and the last three data sets are as the testing samples.

TABEL 1 The data of the training samples

No	X1	X2	X3
1	4.62	4.78	3.74
2	4.68	4.78	3.76
3	4.67	4.85	3.79
4	4.73	4.86	3.82
5	4.76	4.88	3.83
6	4.72	4.86	3.87
7	4.74	4.93	3.84

4.1 DATA FITTING

Firstly, we fit the data and obtain the fitted values. Then we calculated the error. The results are as follows

TABLE 2 The actual values and the fitted values

NO	X1			X2			X3		
	AX1 Actual values	FX1 Fitted values	Error	AX2 Actual values	FX2 Fitted values	Error	AX3 Actual values	FX3 Fitted values	Error
1	4.62	4.63	0.0021	4.78	4.80	0.0041	3.74	3.76	0.0053
2	4.68	4.66	-0.0042	4.79	4.79	0.0000	3.76	3.79	0.0008
3	4.67	4.68	-0.0043	4.85	4.86	0.0020	3.79	3.83	0.0106
4	4.73	4.71	-0.0042	4.86	4.87	0.0021	3.82	3.85	0.0079
5	4.76	4.78	0.0043	4.88	4.90	0.0040	3.83	3.84	0.0026
6	4.72	4.73	0.0008	4.86	4.84	-0.0041	3.87	3.86	-0.0027
7	4.74	4.74	0.0000	4.93	4.95	0.0041	3.84	3.85	-0.0026

4.2 PERFORMANCE PREDICTION

We can see that the results are good. Therefore, we forecast the data. Firstly, we forecast the last three data and got the predicted values. Then we compared the values with the training values and got the forecasting error. AX is the actual values and the PX is the predicted values. The results are shown as the table.3.

TABLE 3 The predicted values and the error

NO	X1			X2			X3		
	AX1 Actual values	PX1 Predicted values	Error	AX2 Actual values	PX2 Predicted values	Error	AX3 Actual values	PX3 Predicted values	Error
8	4.73	4.74	0.0021	4.95	4.93	-0.0040	3.85	3.86	0.0025
9	4.75	4.75	0.0000	4.92	4.94	0.0041	3.87	3.86	-0.0026
10	4.76	4.77	0.0021	4.89	4.91	0.0041	3.84	3.84	0.000

From the results and the forecasting error, we can see that the prediction result is very close to the training set. The error is very small. Our forecast method achieved good prediction effect.

5 Conclusion

The continuous improvement of the prediction technology accuracy and the development of the computer technology provide an opportunity for the sports. Through the prediction and the computer simulation, the college students and the sports practitioners can get more scientific and effective training. We did the following works. (1)Firstly, we introduced the BP neural network and the niche algorithm. (2) Secondly, aiming to the defects of the BP neural network and the niche genetic algorithm, we proposed NGA-BP neural network based on k-mean clustering algorithm. (3) Thirdly, we did the computer simulation and applied NGA-BP neural network based on k-mean clustering algorithm to predict the long jump performance of the college students. The simulation results showed that this method had achieved good effect on forecasting.

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