Available online www.jocpr.com

Journal of Chemical and Pharmaceutical Research, 2013, 5(9):256-262

Research Article

ISSN : 0975-7384
CODEN(USA) : JCPRC5

Evaluation model research of 100 meters sprint exercise capacity based on fuzzy neural network

[1]Bing Zhang, [2]Sheng Zhang and [3]Guang Lu

[1]Institute of Physical Education, Huanggang Normal University, Huangzhou, China
[2]Physical Education Department, Hebei University, Baoding, China
[3]Wuhan Institute Of Physical Education, Wuhan, China

ABSTRACT

Based on the research on the exercise capacity influencing factors of 100m sprint, this paper proposes comprehensive evaluation and prediction model based on fuzzy neural network, which is the improvement of the existing athletic ability evaluation systems and overcomes the shortcomings of traditional methods' strong subjectivity. The obtained fuzzy neural network system cannot only ensure continuous learning and correction, but also can make the network converge quickly according to the practical significance of the specific parameters. Through examples test, the evaluation results are objective and have the ideal precision. The model can not only be used to simulate and predict the athletic performance, as a basis to develop targeted training programs, but also can provide quantitative criteria in the athletes selection process, which has a high application value and broad application prospects.

Key words: Fuzzy neural network, sprint, exercise capacity

INTRODUCTION

Many domestic and foreign experts and sports personalities are studying how to improve sprint performance, look for the factors that affect the results and hoping to have a complete and scientific evaluation system and performance prediction model from athletes selection to daily training plan development. After years of research, little consensus has been reached, that is, Sprint as a typical physical project, athletic ability is the biggest factor of scores [1]. Exercise capacity refers to ability that people demonstrate in sport. Physical fitness is the basis of athletic ability, which plays a decisive role. In addition, the athletic ability also receives the effect of individual physiology, body shape, psychological state athletics, sport technical level and external environment. Athletic ability directly manifests sports results, and the relationship between the influence indicators is nonlinear [2]. With the development of modern athletics and increasingly scientifically sound training level, in order to further improve the performance, the best way starts with athletic ability; without good athletic ability, even with better training methods, it is difficult to obtain excellent results [3]. And research on exercise capacity in the sprinter selection stage is also very important; due to the body's own characteristics, each person's potential in the sport is different; early detection of potential talent, scientific and accurate evaluation of his athletic ability can avoid the enormous waste in the human, material and financial aspects, what the entire sports industry has been working for.

Because the factors that affect exercise capacity are multifaceted, this gives the evaluation of athletic ability difficult [4]. The traditional method of exercise capacity evaluation is mainly expert scoring, one or more experts score on various indicators; conduct weighted average in accordance with index weights; the advantage of this method is simple to implement; disadvantages are also obvious, that is too subjective and strong arbitrary, and its results receive the effects of the expert's level and emotion [5]. The evaluation results of different experts on the same person will be very different. It also requires an objective and accurate exercise capacity evaluation method.

Therefore, the current evaluation of exercise capacity on the human body is mostly in qualitative level; research on systematic and quantitative evaluation method is still in its infancy. There are many domestic and foreign scholars using AHP, gray system and multiple regression method to establish evaluation model, these methods are not ideal in performance of adaptability, convergence and prediction accuracy, forecasting is ineffective [6].

Neural network is the representation theory of non-linear relationship research in recent years with rapid development, which has achieved widely application and significant results in many areas. It has strong function mapping capabilities, and different from other nonlinear methods, it does not suffer restrict of non-linear model [7]. According to different input and output data of neural network, obtain a non-linear mapping by learning to describe the relationship between input and output [8]. After learning the neural networks can be used to get an output for a given input; in this process it does not need to know the determined relationship between the input and output, which has a good dynamic performance and robustness [9]. There are many domestic scholars using neural network model to conduct any relevant studies on sprint exercise capacity; although its model also has some effect and you can get the relation between sports results and related indicators, the logical reasoning ability of the model is slightly inadequate [10].

This Paper combines fuzzy systems with neural networks, first through the learning of input and output data of the training sample to get rules roughly, re-use fuzzy system to adjust membership functions and rules, and then complete self-learning and adaptive process of the network. Neural networks have good learning ability but lack the logical reasoning ability, and fuzzy systems lack sufficient learning ability. The resulting fuzzy neural network system combining the two can ensure continuous learning and correction of the system, but also can make the network converge quickly according to the practical significance of the specific parameters, which is difficult to do for a simple neural network model. Throughout the system, neural networks and fuzzy systems give full play to their respective advantages, each is independent subsystem, but also an organic whole around the same target and this combination is the future development direction of intelligent control technology.

EVALUATION INDEX SYSTEM

After a review of the relevant literature and consultation over several experts' advice, combining with the exercise characteristics of 100m sprint and the evaluation research results in the sports relevant field at home and abroad, ultimately boils down to index system of 4 major items and 12 small items, shown in Table 1 below:

Table 1: Evaluation index system of sprint exercise ability

First level index A	Secondary index B	Third level index C
100m sprint sport exercise capacity evaluation system	Body shape B1	Height C1
		Quetlet index(weight/height × 1000)(g/cm)C2
		Lower limbs length/height × 100% C3
		Thigh length/calf length × 100% C4
		Ankle circumference/ten do calcareous length × 100% C5
	Physiological function B2	Heart rate(time/m) C6
		Vital capacity/weight (ml/kg)C7
	Psychological quality B3	Sound reaction time(ms)C8
	Sport quality B4	60m run(s) C9
		Standing triple jump(m) C10
		Stride frequency(step/s) C11
		Back throw shot(m)C12

The index system took into account the possible various factors that may affect sprint performance, in the selection process we try to avoid indexes that may be influenced by subjectivity.

EVALUATION PREDICTION MODEL OF FUZZY NEURAL NETWORK

Establish evaluation index system based on the movement characteristics of 100m sprint and the above part of the text, the network model designed is the five-layer forward neural network. Its network topology is shown in Figure 1:

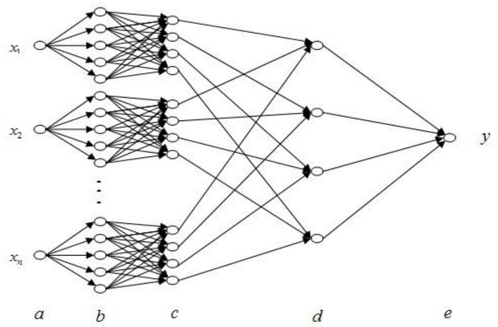

Fig.1: Five-layer forward neural network topology

Layer a is the input layer, composed by the12 input neurons of corresponding evaluation indexes. Evaluation index value of each sample corresponds to an input vector, passing to the next layer through this layer, namely:

$$f(x_i) = x_i \tag{1}$$

Layer b represents the hidden layer of each sub-network, and its structure and the number of neurons will affect network learning and convergence speed; we use the traditional BP algorithm sigmoid function to inspire:

$$\left.\begin{aligned} s_{ij}^{(1)} &= w_{ij}^{(1)} x_i \\ f\left(s_{ij}^{(1)}\right) &= \frac{1}{1+e^{-s_{ij}^{(1)}+q_{ij}^{(1)}}} \\ y_{ij}^{(1)} &= f\left(s_{ij}^{(1)}\right) \end{aligned}\right\} \tag{2}$$

Wherein, $s_{ij}^{(1)}$ is the weighted sum of the weights $w_{ij}^{(1)}$ for all input values of the j –th neurons of i -th sub-network hidden layer; $q_{ij}^{(1)}$ is the threshold of the j –th neurons for the i -th sub-network hidden layer, to control whether to continue the pass down of input value; if greater than the threshold, continue to pass down to the next layer by $y_{ij}^{(1)}$. The layer neurons number is calculated using the following formula:

$$n = \sqrt{n_0 + n_i} + a \tag{3}$$

Wherein n is the node number of the sub-network hidden layer, n_0 is the node number of the sub-network input layer; each sub-network in this article has only one input, so $n_0 = 1$; n_i is the node number of the sub-network output layer, a is any value between 1 and 10, by comparison, this paper chooses $a = 3$, namely the node number of sub-network hidden layer is 5.

Layer c is the output layer of sub-network; the input values passes through the hidden layer, the result less than the threshold will be passed to this layer, and transformed into the corresponding membership degree output. The excitation process of this neuron layer is:

$$\left.\begin{aligned} s_{ik}^{(2)} &= \sum_j w_{ijk}^{(2)} y_{ij}^{(1)} \\ f\left(s_{ik}^{(2)}\right) &= s_{ik}^{(2)} + q_{ik}^{(2)} \\ y_{ik}^{(2)} &= f\left(s_{ik}^{(2)}\right) \end{aligned}\right\} \tag{4}$$

Wherein, $s_{ik}^{(2)}$ is the weighted sum of the weights $w_{ijk}^{(2)}$ for all input values of the k –th neurons of i -th sub-network output layer; $q_{ik}^{(2)}$ is the threshold of the k –th neurons of i -th sub-network output layer, to control whether to continue pass the result of sub-network down to the fuzzy inference layer; if greater than the threshold, pass down to the next layer by $y_{ik}^{(2)}$.

The sub-network of first three layers of the entire model uses a three-layer forward BP neural network, whose role is to simulate the membership function of participating factor; the training process uses the traditional BP algorithm, which is used more often currently, is also more mature algorithm; these sub-networks can obtain a satisfactory degree of membership through learning and training.

Establish fuzzy inference layer with fuzzy system theory for Layer d , the neuron number and the neuron number of sub-network output layer is equal. The i –th node only connects with the i –th output neuron of each sub-network; the weighted sum of the output value for the i –th node of each sub-network is the input value of the layer, the calculation formula of this layer is:

$$\left.\begin{aligned} s_l^{(3)} &= \sum_i w_{ikl}^{(3)} y_{ik}^{(2)} \\ y_l^{(3)} &= f\left(s_l^{(3)}\right) = s_l^{(3)} \end{aligned}\right\} \tag{5}$$

In the formula, $w_{ikl}^{(3)}$ is the connection weights between the layer c and layer d neurons; $s_l^{(3)}$ is the membership obtained after re-weighted sum of output values for the l -th neuron of all sub-networks; This membership is denoted by $y_l^{(3)}$ and export to the next layer.

Layer e is the network output layer, via normalized inverse transform output results can be converted back to 100m results, that is, performance evaluation or prediction results under certain input indicators. Through the network learning of training samples, you can find a suitable set of weights; by the weighted summation of the quantized value of each evaluation index and the membership of each level for certain athlete, a continuous quantitative values of his 100m scores can be obtained. Still use the identical linear form as excitation function of the layer neuron, i.e. the output of layer e is expressed as:

$$z = s^{(4)} = \sum_l w_l^{(4)} y_l^{(3)} \tag{6}$$

In the formula, $w_l^{(4)}$ are connection weights of neurons between the layer d and layer e ; $s^{(4)}$ is the weighted sum of input values for the layer e neurons .

LEARNING ALGORITHMS DESIGN

Typically for BP neural network learning, it is easy to fall into local minimum. In order to avoid such a situation and accelerate network convergence, combined with the evaluation characteristics of 100m sprint exercise capacity, learning algorithm in this paper is divided into two phases. The first phase is the offline training phase, for the training samples using standard BP network learning algorithm to generate the initial membership functions. The membership function generated at this stage is not very accurate, which needs to make adjustments in the second stage of training. The role of the second stage is to generate rules, improve the front membership functions and perfect the rules. First fix the membership function, adjust the initial parameter and weight of the model. Take the network errors as the control condition, when the error is less than the setting threshold, network convergence, obtain the preliminary rules; then, based on the obtained rules and then adjust the membership function, taking network error as the objective function, so as to reach the minimum value. The second stage is the training of the fuzzy inference layer; the training process starts from the output of the network, taking the sum of the squared error of output as the objective function, and the sum of squared errors is defined as:

$$E = \sum_{n=1}^{N} \sum_{m=1}^{M} \frac{1}{2} \left(d_m^{(n)} - z_m^{(n)} \right)^2 \tag{7}$$

In the formula, N is the number of samples; M is the neuron numbers for the output layer; For the n –th sample data, $d_m^{(n)}$ means the expected output of the m –th output neuron, $z_m^{(n)}$ means the actual output of the m –th output neuron; through this stage of training we can obtain the minimum sum of squared errors and E. In the training process, the corrected value of weights and thresholds values will continuously decrease, the weights and thresholds will get learning in accordance with the following rules:

$$w(t+1) = w(t) + \Delta w = w(t) + \eta\left(-\frac{\partial E}{\partial f}\cdot\frac{\partial f}{\partial s}\cdot\frac{\partial s}{\partial w}\right) \tag{8}$$

In the formula, w is the connection weights between neurons; η is the learning rate; f is the excitation function, t is the learning number; s is the weighted sum of neurons input values. In the learning process weights and the correction value of error can be adaptively adjusted, thus improving the learning efficiency of each layer and accelerating the convergence speed of fuzzy neural network; the amount adjustment and adjustment process of each layer errors are as follows, threshold has a similar adjustment method:

1) Layer e

$$\left.\begin{aligned} & e^{(4)} = d - z \\ & \Delta w_l^{(4)} = e^{(4)} y_l^{(3)} \end{aligned}\right\} \tag{9}$$

In the formula, $e^{(4)}$ is the error of the output neurons; $\Delta w_l^{(4)}$ is the correction value of connection weights between the layer d and the layer e neuron.

2) Layer d

$$\left.\begin{aligned} & e_l^{(3)} = \frac{-\partial E}{\partial s_l^{(3)}} = \frac{-\partial E}{\partial s^{(4)}}\cdot\frac{\partial s^{(4)}}{\partial s_l^{(3)}} = e^{(4)} w_l^{(4)} \\ & \Delta w_{ikl}^{(3)} = e_l^{(3)} y_{ik}^{(2)} \end{aligned}\right\} \tag{10}$$

In the formula, $e_l^{(3)}$ is the error of the l –th neuron of layer d; $\Delta w_{ikl}^{(3)}$ is the correction value of connection weights between the layer c and the layer d neuron.

3) Layer c

$$\left.\begin{aligned} & e_{ik}^{(2)} = \frac{-\partial E}{\partial s_{ik}^{(2)}} = \sum_l e_l^{(3)} w_{ikl}^{(3)} \\ & \Delta w_{ijk}^{(2)} = e_{ik}^{(2)} y_{ij}^{(1)} \\ & \Delta q_{ik}^{(2)} = e_{ik}^{(2)} \end{aligned}\right\} \tag{11}$$

In the formula, $e_{ik}^{(2)}$ is the k –th neuron error of layer c for the i -th sub-network; $\Delta w_{ijk}^{(2)}$ is the correction value of connection weights between the layer b and the layer c neuron; the value of $\Delta q_{ik}^{(2)}$ is equal to $e_{ik}^{(2)}$, is the correction values of this neuron threshold.

4) Layer b, the excitation function is the sigmoid function:

$$\left.\begin{aligned} e^{(1)} &= y_{ij}^{(1)}\left(1-y_{ij}^{(1)}\right)\cdot\sum_k e_{ik}^{(2)} w_{ijk}^{(2)} \\ \Delta w_{ij}^{(1)} &= e_{ij}^{(1)} x_i \\ \Delta q_{ij}^{(1)} &= e_{ij}^{(1)} \end{aligned}\right\} \tag{12}$$

In the formula, $e_{ij}^{(1)}$ is the j –th neuron error of layer b for the i -th sub-network; $\Delta w_{ij}^{(1)}$ is the correction value of connection weights between the layer a and the layer b neuron; the value of $\Delta q_{ij}^{(1)}$ is equal to $e_{ij}^{(1)}$, is the correction values of this neuron threshold. The standard deviation of training sample is:

$$R_{MSE} = \frac{1}{N}\sum_{i=1}^{N}\left(z_0^{(i)} - z^{(i)}\right)^2 \tag{13}$$

In the formula, parameter N is the number of training samples. When R_{MSE} satisfies the constraint conditions, and is less than pre-specified error, network convergence, and the study end; otherwise re-learn, until the error is small enough.

APPLICATION EXAMPLES

In order to test the correctness of research methods and the validity of fuzzy neural network model, this paper selected 12 index data of 28 university sprint boys, as shown in Table 2, in which 20 people as training samples of network, eight people as test samples.

Table 2: Evaluation index data sheet

Serial number	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	Performance
1	180	376	53.1	70.6	104	74	80	100	7.40	9.12	4.4	14.5	12.33
2	172	402	52.3	68.9	99	72	81	95	7.37	8.75	4.8	13.5	12.00
3	170	405	51.4	71.2	94	75	78	101	7.13	8.88	4.9	12.9	11.98
4	175	385	50.9	72.3	98	78	77	103	7.10	9.00	4.4	13.4	11.85
5	177	375	52.4	69.0	102	70	84	98	7.09	8.65	4.5	13.2	11.90
6	170	379	51.2	68.0	100	80	87	110	7.22	8.71	4.7	12.8	12.02
7	171	382	51.6	67.2	103	82	80	108	7.23	8.72	4.7	12.4	11.85
8	176	370	51.5	66.9	95	81	82	106	7.25	8.66	4.5	13.5	11.80
9	169	368	51.9	70.1	91	78	81	113	7.14	9.02	4.8	13.0	12.21
10	168	392	52.3	71.0	99	76	79	94	7.16	8.55	5.0	12.9	12.13
11	171	390	52.2	69.2	105	75	76	98	7.20	9.00	4.9	12.8	11.75
12	170	385	52.4	68.3	102	80	83	103	7.23	8.96	4.9	13.2	11.72
...	...	...	...	...	...	...	...	...	...	...	...	...	...

In order to eliminate the influence of the different evaluation index dimensions, the original data needs normalized processing, all of which is converted into a value of $[-1,1]$, using the equation:

$$x' = 2\left(x - x_{\min}\right)/\left(x_{\max} - x_{\min}\right) - 1$$

Take the former 20 training samples as the input variables of 12 neurons for fuzzy neural network input layer; output variables are the normalized results of the 100m Sprint, there are five neurons in hidden layer of sub-network. Maximum number of training is set to 800, the minimum gradient is 0.0001, and the sum of squared errors is set to 0.0001.

After learning the 20 training data and 623 iterations the error sum of squares is less than 0.0001; study finishes, the change process of the number of iterative steps is shown in Figure 2:

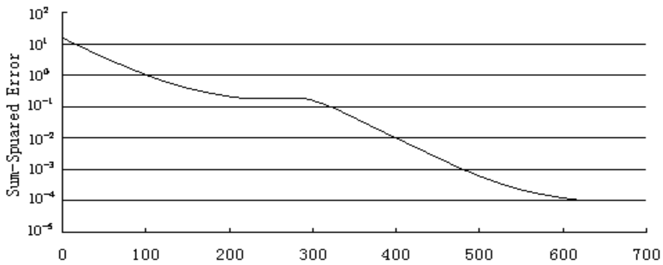

Fig.2: Sum of squared error of fuzzy neural network

Test the trained neural network on the test set, the results are shown in Table 3 below:

Table 3: The comparison table of test set measured value and fuzzy neural network predictive value

Serial number	1	2	3	4	5	6	7	8
Actual value	12.42	12.31	11.98	12.12	12.01	11.95	11.84	11.71
Network predicted value	12.33	12.15	11.90	12.11	12.10	12.08	11.80	11.78
Error	0.007	0.013	0.006	0.001	0.007	0.011	0.003	0.006

From the above table it can be seen, the error of the output results based on the evaluation index value of fuzzy neural network and the actual value is very small (<0.013), which can be considered as the random errors of samples is related to the stability of play. The predicted results illustrate that it is feasible and effective to use this model to predict the exercise capacity evaluation and performance prediction of 100m sprint.

CONCLUSION

In this paper, athletic ability comprehensive evaluation model of 100 meters sprint based on fuzzy neural network is the improvement on the existing exercise capacity evaluation systems, and effectively overcomes the shortcomings of strong subjectivity for traditional methods; evaluation result is objective and has a high accuracy. The resulting model can not only be used for simulation and prediction of athletic performance, as a basis to develop targeted training programs, but also can provide quantitative criteria in the athletes selection process. The research method can also be used for athletic ability evaluation system of other projects, and has a high application value and broad application prospect.

REFERENCES

[1] Bing Zhang, Yan Feng, **2013**. *International Journal of Applied Mathematics and Statistics*, 40(10), 136-143.
[2] Bing Zhang, **2013**. *International Journal of Applied Mathematics and Statistics*, 44(14), 422-430.
[3] Deng Yun-ling, Zhang Guang-lin, Xu Shi-yan, **2007**. *Journal of Northwest Normal University*(Natural Science), 43(2),98-101.
[4] Du He-ping, **2006**. *Journal of Guangzhou Sport University*, 26 (5),85-87.
[5] Haibin Wang, Shuye Yang, **2013**. *International Journal of Applied Mathematics and Statistics*, 39(9), 243-250.
[6] Wang Peng, **2009**. *Sports Science Research*, (1),65-67.
[7] Yang Min, **2002**. *Journal of Guangzhou Physical Education Institute*, 22(3),52-54.
[8] Ye Sheng-shun, **2005**. *Journal of Jilin Institute of Physical Education*, 21(4),62-63.
[9] Yuan Yun-ping, **2004**. *Journal of Shenyang Institute of Physical Education*, 23(2), 43-44.
[10] Zhang Cang-yan, **2002**. *Journal of Beijing University of Physical Education*, 25(3),80-83.