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Neural Network Model Aerobics Athlete Athletic Ability and Athletic Performance Assessment

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Abstract: In order to improve the efficiency and scientific training athletes, while providing a more effective tool for coaches, athlete's athletic ability departure from this article, establish an evaluation system. Research on the use of cluster analysis and sports performance evaluation index greater contact and then use the BP neural network model was constructed to assess model predicted many times training and testing, found that some of the data to predict the impact the accuracy and convergence velocity model, then such data is removed. Studies have shown that, BP neural network model established in this study for Athletes prediction error range within 0.1 and confirmed its accuracy.

Key words: Performance evaluation, athletic ability, neural network model, aerobics athlete

INTRODUCTION

Aerobics world since the late 20 70s, early 80s the rise, with its strong vitality quickly became popular all over the world. Many people choose to operate their own fitness major way, the formation of a worldwide "aerobics hot." In 1983 the United States held the first Aerobics Competition, 1984 inaugural Far East aerobics competition held in Japan. International events organized each year include: Aerobics World Championships, World Cup, World Championships and World Tour. In 1987, Beijing hosted the first National Aerobics Invitational, followed by 1988, 1989, 1990, 1991 in Beijing, Guiyang, Kunming, Beijing hosted the fourth tournament. 1992 changed its name to the National Championship, becoming the traditional event held annually. September 1992 established the China Association of aerobics, headquartered in Beijing. In addition, the 1992, 1995 in Beijing organized two National Aerobics Championship (Cui and Yang, 1998). organized a National Championship and National Aerobics Games. Aerobics extensively in China, while the strength of aerobics ranks among the world's leading.

Most experts only are teaching aerobics, aerobics shallow study effects on the body and so on, but mostly qualitative research. Quantitative study of their impact on the nature of Aerobics, technology development and athletic performance factor is very small, especially the study of aerobics athlete athletic ability and athletic performance assessments few. This study therefore has important theoretical and practical significance (Zhang and Feng, 2013).

Back in 1998, Cui Yunxia on the factors affecting the composition and athletic ability Aerobics been studied. She pointed out that these factors are mainly specialized physical training, body posture and improve before the election and create natural motion performance capabilities. Meanwhile obtained aerobics athlete athletic endurance is the ability of the foundation. Qi Zihua studied the quality of men's body shape aerobics athletes. His body shape of the nine indicators and physical indicators of six subjects were tested and the test results were normal hypothesis testing. In the results on the basis of the correlation coefficient R cluster based on his stepwise regression analysis, select a significant impact on the achievement of aerobics body shape and physical indicators (Qi, 1999). He then established a multiple regression equation and significant test, draw ribs and abdomen leg raise, chin-up and straddle hop aerobics performance contribution is significant. Yan waves, Wu Yanxi studied the neural network model in Biomechanics, Sports Biomechanics information discussed issues generalized inverse transform (Yan and Wu, 1999). Shot by studying the movement, they established a transformation model features the original amount of information (Wu, 2013). Zhong Ping, Gongming Bo hammer thrower Gu Yuan achievements as training samples of artificial neural networks, the establishment of a hammer thrower Physical Fitness and Performance models and draw between the quality level of training and Specific Performance curve, so as to scientific training provides a theoretical basis (Hou, 2011). Shao Shu together BP neural network model of mass aerobics nonlinear correlation analysis results (Cui, 2013). She has

developed and nine evaluation criteria and on this basis to establish a model, the model established good results reflect the nonlinear relationship between indicators of achievement and a total score of between nine and relative error of about 5% .

Most athletic performance prediction models generally use multiple regression method and gray model, they pointed out that the relationship between indicators of achievement and training in some respects, but have done a number of assumptions, such as assuming that the mathematical expression in the form of a good prediction model. Obviously, this is not true. Therefore, these methods are simple to apply and will definitely have a great error.

On the basis of these studies, the study aspect aerobics athlete athletic ability and athletic performance have been studied to select the appropriate assessment indicators and establish an assessment system. The use of cluster analysis and artificial neural network model, the establishment embodied athlete athletic ability and athletic performance assessment models. This model overcomes the deficiencies and gray regression model; more objectively reflect the correlation between athletic ability and achievement among athletes and get a higher accuracy.

EVALUATION MODEL

Evaluation system: Difficult action is an important basis to measure the technology level of aerobics special action. Therefore, through the research on all the difficult action of competitive aerobics, this study screens out difficult actions that reflect aerobics technique levels (Table 1) and uses it as a basis to establish evaluation system of athlete's action technical level.

According to the above twelve action indicators, this study gives score standards of athletes' difficult actions. Through the scores of twelve difficult actions by six experienced referees, a particular action's scores of one athlete can be drawn; this study presents the score of the j-th action. Assuming the referee's scores were, respectively $s_1, s_2, s_3, s_4, s_5, s_6$, then the score:

$$g_j = \frac{s_1 + s_2 + s_3 + s_4 + s_5 + s_6}{6}$$

Then, an overall difficult action score of the athlete is:

$$G = \sum_{j=1}^{12} k_j g_j$$

Wherein:

$$k_j = \frac{c_j}{\sum_{j=1}^{12} c_j}$$

C_j is the weight coefficient for the j-th difficult action?

Factors indicators affecting sports performance: Athlete's physical fitness is an important foundation for their athletic ability and is the main factors that affect movement technology level. This study starts from the body shape and physical quality, identifies forty indicators and then uses SPSS software for association analysis and finds that the significance levels of thirty-two indicators are less than 0.1. This indicates that they and action technical level have a relatively high correlation. Suppose these thirty-two indicators, respectively are $a_i (i = 1, 2, \cdots, 32)$, then conduct cluster analysis and cluster these indicators into 7, 8, 9 class; the following results are obtained (Table 2).

These above results obtain that some indicators have a very high correlation degree. This shows that for athletes, if an indicator score is good then another related indicator's score is also excellent and vise verse. Therefore, in such class we only select one representative indicator. By parity of reasoning, this study has selected six representative indicators: one minute push-ups, 30 m

Table 1: Difficulty action

Action name	Difficulty coefficient	Weight coefficient
No support vertical splits	0.3	0.04
No support Yi liu Xin cheng vertical ground splits	0.7	0.10
Swivel 540 degrees tuck jump	0.5	0.07
Swivel 360 degrees pike straddle leg jump into front support	0.8	0.12
Shear mode turn swivel 360 degrees	0.7	0.10
Swivel 360 degrees Cossack jump to swivel 180 degrees	0.7	0.10
Pike straddle leg jump	0.3	0.04
Swivel 180 degrees pike jump and Swivel 180 degrees into front jump	0.7	0.10
Straddle leg support swivel 360 degrees	0.4	0.06
Right-angle straddle leg combination support swivel 720 degrees	0.8	0.12
Vincent pushups	0.3	0.04
Hip lift spring up swivel 180 degrees	0.7	0.10

Table 2: Clustering results

Index	α_1	α_2	α_3	α_4	α_5	α_6	α_7	α_8	α_9	α_{10}	α_{11}	α_{12}	α_{13}	α_{14}	α_{15}	α_{16}
	α_{17}	α_{18}	α_{19}	α_{20}	α_{21}	α_{22}	α_{23}	α_{24}	α_{25}	α_{26}	α_{27}	α_{28}	α_{29}	α_{30}	α_{31}	α_{32}
7	1	1	2	2	2	2	3	3	3	1	1	4	4	4	4	5
	6	7	7	4	8	8	8	10	4	7	10	2	5	5	9	10
8	1	1	1	2	2	2	3	3	4	5	2	3	4	4	2	4
	3	2	2	4	5	5	3	6	6	2	2	3	5	6	8	8
9	1	1	1	1	3	2	2	1	3	3	4	4	4	5	3	3
	1	3	4	4	3	3	6	3	3	4	5	7	5	7	3	5

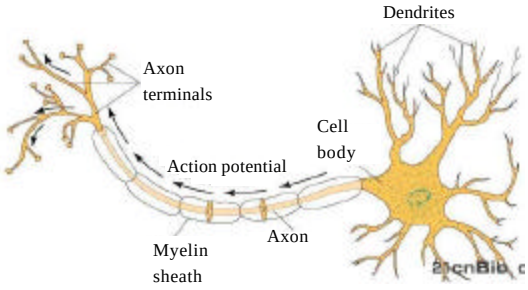

Fig. 1: Neuron structure

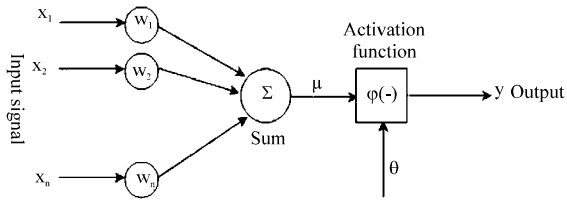

Fig. 2: Neuron model

run, horizontal splits index, 800 m run, cross jump tests and one minute rope skipping.

Feasibility analysis of neural networks: The human brain is a highly complex, non-linear and parallel processing information processing system made □□ of a large number of neurons connected to each other complicatedly (Fig. 1). Because the human brain has huge amount of neurons, each neuron can be connected to thousands of other neurons and the processing speed of many problems is much faster than the computer.

Therefore, people take advantage of the brain's structure and operating mechanism features, start from imitation of the human brain intelligence, explore new information representation, storage and processing methods, design a new computer processing structure model and construct a information processing system more close to human intelligent, i.e. the artificial neural network system.

As a basic unit of artificial neural networks (Fig. 2), a neuron model has three basic elements: a set of connections, the connection strength is denoted by the weights on each connection, the positive weight values activation and negative indicates inhibition; a summing unit, used to get the weighted sum (linear combination) of input signals; a nonlinear activation function, have non-linear mapping function effect and from and limit the output amplitude of the neuron to a certain range.

In addition to unit characteristics, the network topology is also an important feature of the artificial neural network. Looking at it from the connection type there are two main ways.

Forward feed networks: Each neuron receives input of the previous layer and output to the next level and there is no feedback. Nodes are divided into two categories, namely the input unit and the calculating unit; each calculating unit may have any number of inputs, but only one output. Usually the forward feed networks can be divided into different layers, the input of the i-th layer is connected to the output of the i-1-th layer; the input and output nodes connect to the outside, while the other intermediate layers are called hidden layers.

Feedback network: All nodes are computing unit, also can receive input and output to the outside, each of these connection arcs are bidirectional. If the total number of units is n, then each node has n-1 inputs and one output.

The work process of artificial neural networks is divided into two stages: The first stage is the learning phase, when the status of each computing unit is unchanged, the weights on each connection line can be modified through learning; The second stage is the work stage, at present the connection weights are fixed, the state of calculating unit changes in order to achieve a steady state.

From the perspective of effect, forward feed network is mainly function mapping, which can be used for pattern recognition and function approximation. Feedback network can be divided into two categories according to the use of the minimum point of the energy function: the first category is the mean role of all minimal points of the energy function, which in this class is primarily used for various memories; second category only uses global minimum point, which is mainly used to solve optimization problems.

By learning from the environment to acquire knowledge and to improve itself performance is an important feature of artificial neural network. In normal circumstances, the performance improvement is achieved gradually over time by adjusting their parameters (such as weight) according to some predetermined measurement. The common learning rule algorithm has the following three ways:

Error correction learning: Suppose $y_k(n)$ is the actual output of the input x(n) and neuron k at the moment n, $d_k(n)$ represents the appropriate deserved output, the error signal can be written as:

$$e_k(n) = d_k(n) - y_k(n)$$

The ultimate purpose of error correction learning is to make an objective function reach minimum based on $e_k(n)$, to make the actual output of each output unit in the network gain on the deserved output in a statistical sense. Once you have selected the objective function, the error correction learning becomes a typical optimization problem, commonly used objective function is the mean square error criterion, defined as:

$$J = E\left(\frac{1}{2}\sum\nolimits_k e_k^2(n)\right)$$

Parameter E is the expectation operator. Since when directly take j as the objective function, need to know the statistical properties of the whole process; To solve this problem we often use the instantaneous value ε(n) of j at time n in place of j, i.e.:

$$\varepsilon(n) = \frac{1}{2}\sum\nolimits_k e_k^2(n)$$

Using the steepest gradient descent algorithm the following can be obtained:

$$\Delta w_{kj}(n) = \eta(n) e_k(n) x_j(n)$$

where, η(n) is the learning step. The successful application neural network model of this learning rule is very extensive; the most classic application is the back-propagation learning algorithm, also known as BP algorithm.

Hebb learning: Neuropsychologist Hebb's learning rule can be summarized as "When the neuron activation of synapses (connections) ends is in synchronization (the same activation or the same inhibition), the connection strength should be increased, on the contrary should be weakened." It can be described as a mathematical model:

$$\Delta w_{kj}(n) = F\left(y_k(n), x_j(n)\right)$$

In the formula $y_k(n), x_j(n)$ respectively is the state of w_{kj} neurons of both ends and the most common kind of situation is as follows:

$$\Delta w_{kj}(n) = \eta y_k(n) x_j(n)$$

As Δw is in the proportional relevance with $y_k(n), x_j(n)$, sometimes it is referred to relevant learning rule. Specific application of this learning rule has discrete Hopfield network and continuous Hopfield network.

Assessment model establishment: BP neural network model is an artificial neural network, belongs to multilayered forward feed network and its structure is shown in Fig. 3. Its powerful features is using the output error to estimate the error of the direct precursor layer and anti-go down layer by layer, so get the error estimates of all the other layers. Then form the process that the error of the output layer transmits to the input layer of the network along a direction inverse to input transfer direction. The neurons of BP neural network model remains neuron; for a neuron, its input can be expressed as:

$$net = x_1 w_1 + x_2 w_2 + \cdots + x_n w_n$$

So, we use S-type function as activation function of the neuron and its expression is:

$$y = f(net) = \frac{1}{e^{-net} + 1}$$

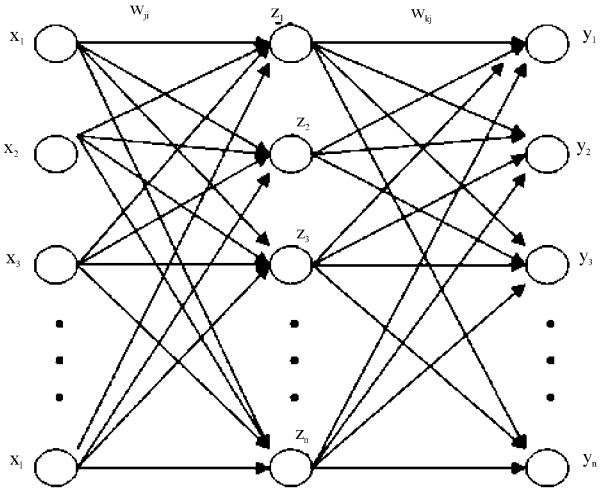

Fig. 3: BP neural network structure

Table 3: Data processing results

x_1	x_1	x_2	x_3	x_4	x_5	T
0.41	1	0.57	0.25	1	0.15	0.38
0.06	1	0.74	0	0.07	0	0.27
0	1	0.72	0.11	0.62	0.35	0.06
1	0.94	0.71	1	0	0.82	0.36
0.82	0.77	0.67	0.25	0.9	0.31	0.28
0.18	0.68	0.44	0.25	1	0.46	1
0.5	0.65	0.8	0	1	0.47	0.15
0.48	0.12	0.9	0.44	0.6	0.24	0.77
0.29	0	0.15	1	1	1	0
0.41	0.55	0.03	0.63	0	0.69	0.33
0.46	0	0.52	0.67	0	0.65	0.9
0.6	0.65	1	0.78	0	0.88	1
0.53	0.45	0.06	0.63	0.28	0.31	0.07
0.52	0.06	0	0.44	1	0	0.07

Table 4: Data results

Input sample						Output ample	Error
x_1	x_1	x_2	x_3	x_4	x_5	T	ΔT
0.41	1	0.57	0.25	1	0.15	0.44	-0.05
0.06	1	0.74	0	0.07	0	0.13	0.14
0	1	0.72	0.11	0.62	0.35	0.13	0.06
1	0.94	0.71	1	0	0.82	0.34	-0.01
0.82	0.77	0.67	0.25	0.9	0.31	0.31	-0.04
0.18	0.68	0.44	0.25	1	0.46	0.98	0.02
0.5	0.65	0.8	0	1	0.47	0.17	0.01
0.48	0.12	0.9	0.44	0.6	0.24	0.76	-0.01
0.29	0	0.15	1	1	1	0.03	-0.03
0.41	0.55	0.03	0.63	0	0.69	0.31	0.02
0.46	0	0.52	0.67	0	0.65	0.89	0.01
0.6	0.65	1	0.78	0	0.88	0.96	-0.04
0.53	0.45	0.06	0.63	0.28	0.31	0.09	-0.01
0.52	0.06	0	0.44	1	0	0.07	0.01

Therefore, this study uses BP neural network model to establish the evaluation model of aerobics athlete athletic ability and athletic performance. Steps are as follows:

- The first step, bring all inputs to the network and calculate the output of the network and use the error function to calculate error sum of squares of all target in the training set
- The second step, calculate the Jacobean matrix J of the error on the weight differential: Marquardt sensitivity is:

$$S_i^m = \frac{\partial E}{\partial n_i^m}$$

The recursive relationship is:

$$S_q^m = E(n_q^m)(w^{m+1})^T S_q^{m+1}$$

Can be seen by the above formula the sensitivity can reversely spread by the last layer through the network to the first layer. Calculate the Jacobean matrix elements:

$$[J]_{h,t} = \frac{\partial e_{k,q}}{\partial w_{i,j}^m} = S_{i,h}^m a_{j,q}^{m-1}$$

The third step, according to the weight adjustment formula to calculate:

$$\Delta w = (J^T J + \mu I)^{-1} J^T e$$

- The fourth step, according to the w+Δw double counting the error sum of squares, once the new sum is smaller than the sum in the first step; then use μ to divide θ and at the same time make w = w+Δw go to the first step, otherwise let μ = μθ go to the third step. If the sum of squared errors falls below a certain target error, the algorithm is convergent

The above resulting six represented indicators are denoted by and suppose that T represents their corresponding movement results. In order to ensure the scientific and fairness of the model, use the normalization for unified treatment of male and female students data and the ultimate results are shown in Table 3. Through repeated training and prediction test, find that some of the data affect the prediction accuracy and convergence speed of the model; then we will remove such data.

Take the above processed data and six representative indicators as training samples, use BP algorithm to learn the training samples based on the above four steps. The maximum training times is 70,000 and the target error is 0.1. After completion of training, data obtained are shown in Table 4.

By the above results, BP neural network model established in this study has the error range of 0.1 to predict athletic performance. This shows that the model has high prediction accuracy.

CONCLUSION

This study conducted research on athletic ability and athletic performance of aerobics athlete, selected the appropriate assessment indicators and established evaluation system. It used cluster analysis and artificial neural network model, established the evaluation model that embody competitive ability and athletic performance, more scientifically reflected the link between athlete's athletic ability and performance and used the BP algorithm training samples for learning. The maximum training times is 70,000, target error is 0.1 and it gets a higher accuracy.

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