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Analysis on the Application of Advanced PSO Neural Network in Sports

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Abstract

Sports analysis has always been the main research direction and this paper builds human motion model based on the characteristics of Kinesiology and then introduces BP neural network to carry out analytical prediction of human motion. By introducing Particle Swarm Optimization in BP neural network, it overcomes the randomness of BP neural network's initial weight as well as the network oscillation brought in determining the network structure and the local solution problem, which can effectively improve the generalization ability of neural network. What's more, we can have the advanced BP neural network based on simulation experiment comparative analysis, which can improve the prediction accuracy in terms of human motion.

***Keywords**: BP Neural Network; Genetic Algorithm; Human Motion Injuries*

1. Introduction

Data mining technology has played a significant role in various industries, especially in human motion injuries[1]. Both domestic and foreign scholars have conducted a glittering array of researches on the data mining in terms of medical treatment and literature [2] comes up with the idea to analyze the previous data based on data mining technology so as to have guidance. In addition, literature [3] puts forward to take advantage of decision tree, which is popular in data mining technology and combine athletic records to have relevant data mining so as to have better education. Moreover, literature [4] suggests to organize research literature in terms of data mining of sports scientific field to analyze sports management, race application, physical education, and reviews based on sports statistics. Literature [5] suggests to carry out deep research on the current application status of data mining in terms of sports and *etc* based on literature reviews. Literature [6] believes that the informationization of sports field generates large data and we have to analyze and process these data. Furthermore, literature [7] puts forward to full play the potential value of data mining in terms of analysis of competitive techniques and tactics, national physical fitness surveillance, motion monitoring data *etc* and describe sports data platform establishment, mining tools and data vine-crossing technology *etc*.

This paper adopts advanced BP neural network to carry out analytical prediction for medical malpractice based on the above literature review. To begin with, it introduces genetic algorithm and overcomes the randomness of BP neural network's initial weight as well as the network oscillation brought in determining the network structure and the local solution problem. What's more, we can have the advanced BP neural network based on simulation experiment comparative analysis, which can improve the prediction accuracy in terms of human motion.

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2. Human Motion Model Description

The model simulates the connecting condition of various joints based on kinematic chain and all joints are organized in dendritic structure. In addition, almost all joints expect root node have a parent node and are rotating in the coordinate system. Moreover, the root node also carries out translational motion. Then, the human motion can be described as

$$V(t) = (T_{root}(t), R_{root}(t), R_1(t), R_2(t) \ldots R_n(t)) \qquad (1)$$

In the formula, $T_{root}(t)$ and $R_{root}(t)$ refer to translation and rotation of root node while $R_{root}(t)$ refers to node i rotating around parent node.

Define the potential energy of a certain node, and suppose the zero potential energy of local posture i is B_i^0 and its elasticity coefficient is k_i. In local coordinate system, if the node bone is guided by muscle and rotating around V_i^t, its potential energy expression is shown as follows:

$$PE = k_i(\alpha \cos(\frac{B_i^0 \cdot V_i^t}{|B_i^0||V_i^t|}))^2 \qquad (2)$$

Define the expression of kinetic energy of nodes, $N(i)$ refers to the collection of node i and all descendant nodes. Suppose V_i^t refers to the orientation of i in local coordinate system on t while M_i refers to the synthetic centroid of all nodes in $N(i)$ and the formula shows as follows:

$$M_i = \frac{\sum_{j \in N(i)} m_j c_j}{\sum_{j \in N(i)} m_j} \qquad (3)$$

Therefore the power KE namely the kinetic energy of node i changing posture shows in the following:

$$KE = \frac{1}{2} m_i v_i^{t2} + \frac{1}{2}(\sum_{j \in N(i)} I_i^t) w_i^{t2} \qquad (4)$$

3. PSO-RBF Neural Network Model

RBF neural network has simple structure with quick convergence speed which can realize strong robust ability. What's more, RBF neural network includes three layers: input layer, hidden layer and output layer. PSO algorithm is not only can have overall optimization but also local optimization. This paper adopts subtractive clustering algorithm to determine the number of RBF centers and initial solution of PSO based on $K-means$. Besides, it also takes advantage of the PSO algorithm to train the broadband, hidden layer and output layer of Gaussian function in RBF neural network.

3.1. Subtractive Clustering Algorithm

This approach takes every data sample as center to determine the cluster center based on its density index which can effectively feedback the data distribution condition. If M data samples are listed in N dimensional spaces, then we have the following density formula to represent each data point:

$$D_i = \sum_{j=1}^{M} \exp(-\frac{\| x_i - x_j \|^2}{(\lambda / 2)^2}) \qquad (5)$$

In formula (17), i and j respectively represent two data samples while λ represent density index. We choose the highest density point as the first cluster center, showing in D_{c1} then we can have the following formula to show the density index for each data point:

$$D_{c1} = D_i - \sum_{j=1}^{M} \exp(-\frac{\| x_i - x_{cs} \|^2}{(\lambda / 2)^2}) \qquad (6)$$

After updating the density index, we choose the next cluster center x_{c2} to have continuous iteration and if $D_{\max} < D_{c1}\lambda$, the clustering can be ended.

3.2. $K-means$ Algorithm

Randomly choose K data objects in M data objects and each object refers to a cluster center. Then, based on the distance from the cluster center of other data objects to K data object, we can make the extra data center close to its closest cluster center and at the same time, we should continually update the data objects and introduce the data into existed data cluster centers with iteration until the cluster center no longer changes.

3.3. PSO Algorithm

PSO algorithm is an intelligent algorithm, which is mainly used to simulate bird mass fly foraging behavior. In D-dimensional space, the location as well as the speed of i particle $(i = 1, 2, \cdots, m)$ is $Z_i = (z_{i1}, z_{i2}, \cdots, z_{iD})$ and $V_i = (v_{i1}, v_{i2}, \cdots, v_{iD})$. What's more, P_{id} refers to the optimal location of i particle flight and p_{gd} refers to the historical optimal location in population. In addition, the speed as well as location of particle is updated based on the following formula:

$$\begin{aligned} v_{id}(t+1) = \omega \times v_{id}(t) + c_1 \times rand() \times (p_{id}(t) - z_{id}(t)) \\ + c_2 \times rand() \times (p_{gd}(t) - z_{id}(t)) \end{aligned} \qquad (7)$$

$$z_{id}(t+1) = z_{id}(t) + v_{id}(t+1) \qquad (8)$$

Among which, t refers to the number of iterations; c1 and c2 refer to learning factors; rand refers to the random number between [0,1]; ω is the inertia weight. This paper adopts the linear transformation to update the inertia weight and the concrete manifestation is shown as follows:

$$\omega = t + \frac{\omega_{\max} - \omega_{\min}}{t_{\max}} \qquad (9)$$

Among which, $\omega_{\max}$ refers to initial weight; $\omega_{\max}$ is final weight; $t_{\max}$ is maximum iteration; t is current iteration number.

3.4. PSO-RBF Algorithmic Model

（1）Choose M sample size, x is the sample point. The sample is normalized based on formula (10) and the dimension of sample data is between [0,1].

$$x_i = 1 - \frac{x_i}{x_{\max} - x_{\min}} \qquad (10)$$

（2）Based on formula (10), we can calculate the density of data point and at the same time, we look for the data point of $\max\{D_1, D_2, \cdots D_M\}$ as the first cluster center. Meanwhile, based on the formula (18), we are able to have the density index to find $D_{\max}$ and if we cannot find it we have to keep searching so as to determine the number of cluster centers.

（3） We keep the number of cluster center as $K-means$ and then implement $K-means$ algorithm to generate a group of cluster groups. In k clustering, we can have the result $C_{k1}, C_{k2}, \cdots C_{kn}$ with iteration until K. After the clustering analysis, we can initialize the number of particle swarm optimization based on $K-means$ and set its initial population size as K. Then we have to carry out K cluster so as to generate K initial particles.

（4）Integrate the primary function of K, K RBF neural network weight w_i and Gaussian function radius r into $C_{k1}, C_{k2}, \cdots C_{kn}, w_{p1}, w_{p2}, \cdots w_{pk}, r_p$ so as to have K particles, which can be beckoned as the initial solution of particle swarm optimization. By continuously updating the speed and quality of particles and the ending situation is satisfied the iteration can be ended. Finally all parameters of RBF function can be determined.

4. Analysis of Data Mining In Human Motion

Carry out classification for different human motions, and adopt relevant $x_1, x_2, \cdots x_k$ as training samples to establish neural network model and then we have $x_{k+1}, x_{k+2}, \cdots x_{k+s}$ as test samples which can be adopted to verify the accuracy of neural network model, showing in Table 1. This paper adopts human motion samples of 10 people and the result is shown in Table 2.

Table 1. Training Samples and Test Samples

Sample types	Sample serial number	Input			Output
		x_i	x_{i+1}	x_{i+2}	x_{i+3}
	0	0.7104	0.8750	0.7132	0.7630
	1	0.8750	0.8132	0.8630	0.7232
	2	0.7134	0.8730	0.9232	0.8121
	3	0.7730	0.9232	0.9120	0.8828
	4	0.9231	0.9120	0.9828	0.9162
Training samples	5	0.8120	0.8828	0.7162	0.8217
	6	0.8829	0.9162	0.9271	0.9276
	7	0.8162	0.9182	0.9276	0.7803
	8	0.9218	0.9276	0.7803	0.7942
	9	0.8277	0.7803	0.7747	0.8124
	10	0.7803	0.7747	0.8124	0.8600
	11	0.8742	0.8124	0.8181	0.8882
	12	0.8124	0.8600	0.8882	0.8531
Test samples	13	0.9602	0.9182	0.8395	0.7797
	14	0.9182	0.8395	0.8997	0.7951
	15	0.8395	0.7697	0.7558	0.7248

Table 2. Comparison Table between Standard BP Neural Network and Forecast Value Result in this Paper

Project Serial number	Motion number	Standard BP neural network forecast value	Relative error	Advanced PSO-BP neural network forecast value	D-value	Relative error
1	660	389	-0.25435	417	-46	-0.09765
2	640	600	-0.05692	615	-35	-0.05785
3	500	340	-0.31021	451	-49	-0.01298
4	764	887	0.78333	512	-88	-0.14962
5	739	612	-0.17185	629	-109	-0.16752
6	821	915	0.14375	724	-82	-0.21211
7	720	661	-0.08194	695	-19	-0.02178
8	621	610	-0.42782	612	-24	-0.03482
9	730	623	-0.26713	648	-47	-0.06346
10	780	689	-0.21538	629	-79	-0.10256

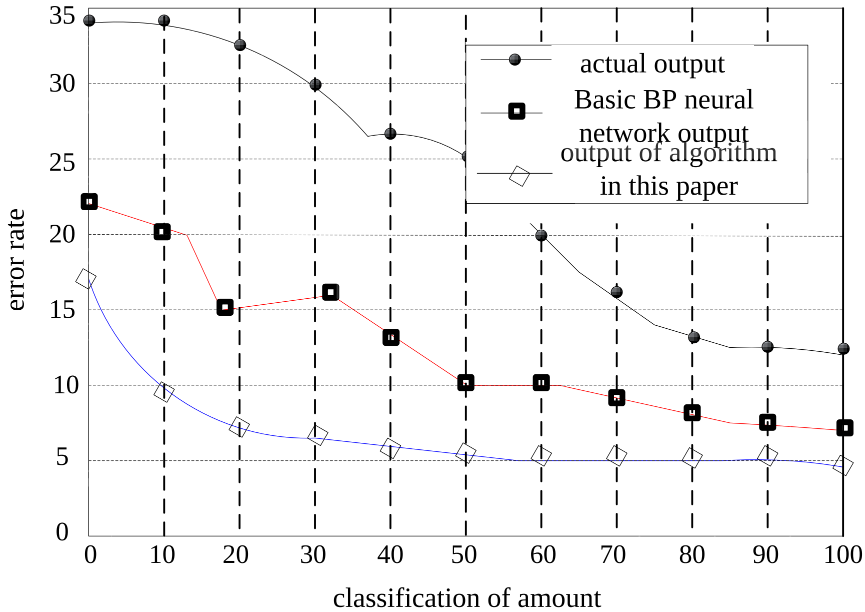

Figure 2. Comparison of Simulation Results

From the simulation result of Table 1-2 we can find out that the maximum relative error of standard BP neural network is 52.17% and the maximum relative error of algorithm in this paper is 17.212%. It elaborates that the output result calculated based on the algorithm in this paper can effectively forecast the human motion. Figure 2 is simulation result comparison and in forecast result, when the maximum relative error is 10, the standard BP neural network output relative error is 20% and the relative error of the algorithm in this paper is 9.8%. So, it indicates that the forecast result calculated based on this algorithm is more accurate with higher precision.

5. Conclusion

This paper adopts advanced BP neural network to carry out analytical prediction for human motion data. By introducing Particle Swarm Optimization in BP neural network, it overcomes the randomness of BP neural network's initial weight as well as the network oscillation brought in determining the network structure and the local solution problem, which can effectively improve the generalization ability of neural network. Furthermore, the data and simulation experiment can verify that the algorithm put forward in this paper can have higher accuracy of human motion.

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