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Research Article

The Prediction Model of Dance Talent Training in Fuzzy Neural Network Algorithm

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In view of the existing problems in the training of dance talents, particularly in China, the focal and key goal of this investigation is to examine and train a predictive model using the fuzzy neural network algorithm. In order to enhance the training, improve the quality of dance talents, and further promote the development of dance professional education, this paper implements the fuzzy neural network procedure to train prediction models for dance talents. Moreover, we carry out research and, then, establish a prediction model, through the fuzzy neural network algorithm, to predict the quality and effect of dance talent training. The model can be, then, used to deliver a fundamental and a key reference for the training of dance talents in the social sectors across the world. The experimental setup and obtained outcomes show that the suggested algorithm has good usability for the training and prediction of dance talents in terms of accuracy. We observed that the fuzzy-based technique is approximately 17.6% more precise than the classical scheme. Moreover, the prediction correctness was observed more than 98.5%.

1. Introduction

Before it was deemed beautiful, dance already existed as a cultural form. As time goes on, productivity increases, class distinctions become more clear, and the transition from cultural to aesthetic dancing has become a historical necessity. Moreover, dance becomes an art in the strictest sense when it develops aesthetic importance. In fact, the dance also progressively develops a discipline for the dance art, which leads to the creation of a new discipline called dance aesthetics. The creative quest for dance beauty is embodied in dance art, which acerbically and dynamically seeks out goodness, truth, and beauty in the social life of humans, as well as, spreading these qualities. Moreover, it creates different dance pictures, connects with the hearers, uses different action forms to represent the aesthetic consciousness and aesthetic emotion of dance, and satisfies their aesthetic demands.

Many academics have started using the BF and fuzzy approximation model for engineering design for the reason that the fuzzy neural network model, as demonstrated in [1], is effective at approximating functions. The fuzzy neural network is a particular kind of the feedforward neural network with a single, or more than one, hidden layer(s) that is capable of realizing both the nonlinear and linear mappings for the hidden layers, as well as, and the output network layer. A local response to the input signal is produced by the action function of the hidden layer node of the fuzzy neural network. When the input signal of the network model is near the central assortment of the neural network model, then the buried layer node generates a significant and considerable output. This should be noted that the fuzzy neural network's training algorithm is examined in the light of the fuzzy neural network model.

Lin and Lee [2] suggested an RNN-FLCS, or reinforcement neural-network-based fuzzy logic control system, to address a variety of reinforcement learning issues. For the implementation of a fuzzy logic control system, a general connectionist model known as the neural fuzzy control network (NFCN) is suggested [3–6]. Similarly, a developing fuzzy neural network (termed as EFuNN) along with an artificial neural network (ANN) model which is trained by means of the scaled conjugate gradient procedure (CGA) and the well-known backpropagation (BP) procedure is presented, and these are the widespread soft computing techniques taken into consideration in the research conducted in [7]. The extrapolation of many benchmark chaotic structures and the time series is evaluated using a variety of neural and neuro-fuzzy models with various learning techniques in [1]. Lin et al. [8–10] proposed the SANFN-GSE technique, which stands for the self-adaptive neural fuzzy network with group-based symbiotic evolution. Moreover, Barbounis et al.[27] projected the LF-DFNN model (termed as locally feedback dynamic fuzzy neural network) for simulating the temporal processes. Yilmaz et al.[3] introduced the FWNN model (termed as fuzzy wavelet neural network) and other similar forecasting models for nonlinear dynamical systems, their identification along with prediction. Chang et al.[4] offered a novel technique that uses evolving partly connected neural networks (EPCNNs) as inputs to forecast stock price trend. In order to create models with greater accuracy and parsimony, Alexandridis et al.[5] introduced a unique technique for training the radial basis function (RBF) networks. Other noteworthy works is the work demonstrated by Micheli-Tzanakou et al.[1].

In order to enhance the training of dance talents, advance the quality of dance aptitudes, and further promote the development of dance professional education, this paper uses a fuzzy neural network algorithm to train dance talents. Carry out research and establish a prediction model, through the algorithm to predict the quality and effect of dance talent training [16–19]. This study builds the fuzzy function neural network model diagram. In fact, using the reiterated learning of the sample data, the fuzzy neural network (FNN) model depicts the nonlinear growth correlation of the complete structure in order to forecast the unknown data. As a result, the sample data used in the training are crucial for the neural network's capacity to generalize and fit accurately [20, 21].

The remaining five parts of this manuscript make up its general structure as follows. The background and importance of dance aesthetic traits are discussed in Section 1 before the primary topic of this article is introduced. Section 2 mostly introduces the state of dance aesthetic study both domestically and internationally. The fuzzy neural network model is introduced in Section 3. Section 4 introduces dance's artistic qualities and examines the experimental portion. The complete material is summarized in Section 5. Also, some prominent directions for future research are also listed in this section [22].

2. Fuzzy Neural Network (FNN)

2.1. The Basic Structure of Fuzzy Neural Network. The basic structure diagram of the classical fuzzy neural network is revealed in Figure 1.

Among them, every node that belongs to the input layer contains a synthesis function and an activation function, which are used to process information from linked nodes and to output the corresponding active value. The quantity of A_1 neurons is numerically equivalent to the amount of input variables or nodes, and the function is mathematically illustrated in the following equation:

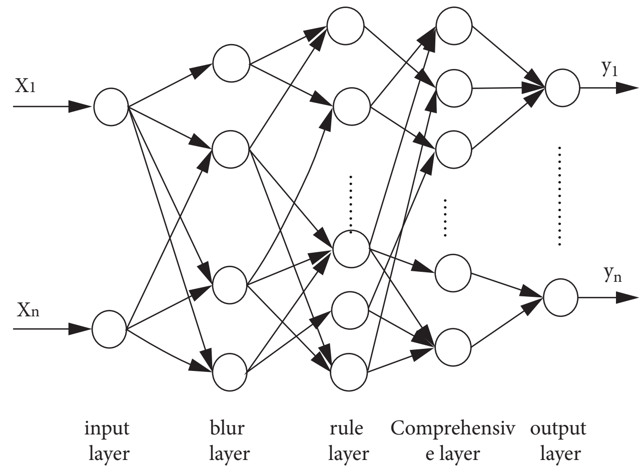

Figure 1: The basic organization of the fuzzy neural network.

$$f_k = u_k^{(1)}, \quad \alpha_k = f_k \left(1 \le k \le A_1\right). \tag{1}$$

The second obscure layer represents the number of neurons A_2, which depends on the number of obscure subsets A_1 and the corresponding obscure subset. If all input variables $A_2 = A_1 \times a_2$ have the same number of obscure subsets, then $(|T(X_i)| = a_2, \quad i = 1, 2, \ldots, A_1)$ is satisfied. Each neuron represents an ambiguous subset, the member function assumes a Gaussian function, and then, the relationship is given by the following equation:

$$f_k = \frac{\left(u_i^{(2)} - m_{ij}^{(2)}\right)^2}{\left(\sigma_{ij}^{(2)}\right)^2}, \quad \alpha_k = e^{f_k}\left(1 \le k \le A_2\right), \tag{2}$$

where $m_{ij}^{(2)}$ and $\sigma_{ij}^{(2)}$ are the center and width of the member function of the j^{th} obscure subset that corresponds to the i^{th} input variable, respectively.

The third layer is the rule layer, which implements the logical operation between fuzzy logic and fuzzy rules. In this layer, the value of A_3 is identical to the amount of fuzzy rules, and then, the relationship is given by the following equation:

$$f_k = \min_{1 \le j \le A_1}\left(u_{kj}^{(3)}\right), \quad \alpha_k = f_k\left(1 \le k \le A_3\right). \tag{3}$$

In formula (3), $u_{kj}^{(3)}$ is numerically equal to the j^{th} input value, in particular, corresponding to the k^{th} node.

The fourth layer is the synthesis layer, which primarily executes the logic or functionality between nodes to obtain ambiguous rules. Its expression is mathematically illustrated in the following equation:

$$f_k = \sum_{j=1}^{A_{4k}} u_{kj}^{(4)}, \alpha_k = \min\left(1, f_k\right)\left(1 \le k \le A_4\right). \tag{4}$$

In formula (4), A_{4k} represents the number of inputs connected to the kth node, and $u_{kj}^{(4)}$ is numerically equal to the j^{th} input value corresponding to the k^{th} node. Furthermore, all the connected loads in this layer are equal to 1.

The fifth layer is the output layer, which derives the result through the functionality of the function and expresses its value using the following equations:

$$f_k = \sum_{j=1}^{a_5} m_{kj}^{(5)} * \sigma_{kj}^{(5)} * u_{kj}^{(4)}, \tag{5}$$

$$\alpha_k = \frac{f_k}{\sum_{j=1}^{a_5} \sigma_{kj}^{(5)} * u_{kj}^{(5)}}, \quad (1 \le k \le A_5). \tag{6}$$

2.2. Learning Algorithm of the Fuzzy Neural Network. In this paper, it is necessary to determine the training prediction model of dance skills, network connection load $\omega_{ij}(i = 1, 2, \ldots, n; j = 1, 2, \ldots, n)$, mean value of membership function m_{ij}, and variance $h_{ij}(i = 1, 2, \ldots, n; j = 1, 2, \ldots, n)$. The erroneous active expression of the dance skills training prediction in this paper is given by the following equation:

$$\text{err} = \frac{1}{2} \sum (f_k - f_i)^2. \tag{7}$$

In formula (7), f_k is the expected output value of the network, and f_i is the actual output value of the network.

Once the connection load, mean, and variance of the network parameters have been trained by the suggested neural network algorithm, then their mathematical expressions are illustrated in the following equations:

$$\begin{aligned} \omega_{ij}(k+1) &= \omega_{ij}(k) - \beta \frac{\partial E}{\partial \omega_{ij}}, \\ m_{ij}(k+1) &= m_{ij}(k) - \beta \frac{\partial E}{\partial m_{ij}}, \\ h_{ij}(k+1) &= h_{ij}(k) - \beta \frac{\partial E}{\partial h_{ij}}. \end{aligned} \tag{8}$$

3. Establishment of Dance Talent Training Model

For dance skills training quality coefficient S_i, it is available through several years of continuous training quality, and its structure is built across the $S^0 = (S_{i1}^0, S_{i2}^0, \ldots, S_{im}^0)$ time grade. The steps to build the model are as follows:

Step (1): after accumulating the initial time series $S^0 = (S_{i1}^0, S_{i2}^0, \ldots, S_{im}^0)$, the value for $S^1 = (S_{i1}^1, S_{i2}^1, \ldots, S_{im}^1)$ can be obtained, where the specific expression of the accumulated time series is given by the following equation:

$$S_{ij}^1 \sum_{k=1}^{j} S_{ik}^0, \quad j = 1, 2, \ldots, m. \tag{9}$$

Step (2): then, the accumulated first-order differential equation is established, and its expression is given by the following equation:

$$\begin{bmatrix} a \\ b \end{bmatrix} = (B^T \ B)^{-1} B^T Y_M. \tag{10}$$

In formula (10), a and b represent coefficient terms and constant terms, respectively.

In addition, it is given that $z_k^1 = 1/2(S_{ik}^1 + S_{i,k-1}^1)$ $k = 1, 2, 3, \ldots m$, and thus, using the following formula (11), we obtain the value for B:

$$\begin{aligned} B &= \begin{bmatrix} -z_2^1 \\ \vdots \\ z_m^1 \end{bmatrix}, \\ Y_m &= \begin{bmatrix} S_{i2}^0 \\ \vdots \\ S_{im}^0 \end{bmatrix}. \end{aligned} \tag{11}$$

Step (3): the obtained fitting value $\widehat{S}_i^1$ is illustrated using the following equation:

$$S_{i,k-1}^1 = \left(S_{i1}^0 - \frac{b}{a} \right) e^{-k} + \frac{b}{a}, \quad k = 1, 2, \ldots m. \tag{12}$$

Step (4): restore the fitted value $\widehat{S}_i^1$, and then mathematically, it is expressed as given in the following equation:

$$\widehat{S}_{i,k+1}^0 = \widehat{S}_{i,k+1}^1 - \widehat{S}_{i,k}^0, \quad K = 1, 2, \ldots, m. \tag{13}$$

Subject to the availability of the following constraint given by the following equation:

$$S_{i,k+1}^0 = (1 - e^a) \left(S_{i1}^0 - \frac{b}{a} \right) e^{-ak}, \quad k = 1, 2, \ldots, m. \tag{14}$$

From this, it is possible to predict the training of dance talents in the coming years using the proposed fuzzy neural network algorithm.

4. Simulation Analysis and Results

This paper practices the MATLAB software tool to model and evaluate the fuzzy neural network. Furthermore, we make predictions through the network training from the aspects of dance performance, choreography, and dance teaching in the training process. In fact, the evaluation will help us so as to understand the professional qualities along with dance teaching abilities of the dance students.

After the fuzzy neural network model automatically learns and trains the data matrix of the input sample, it obtains the actual prediction data of the input sample data. As shown in Figure 2, five years of dance performance sample data are input, and the output results obtained after network training are compared with the actual results. It can be easily understood from the investigation in the figure that

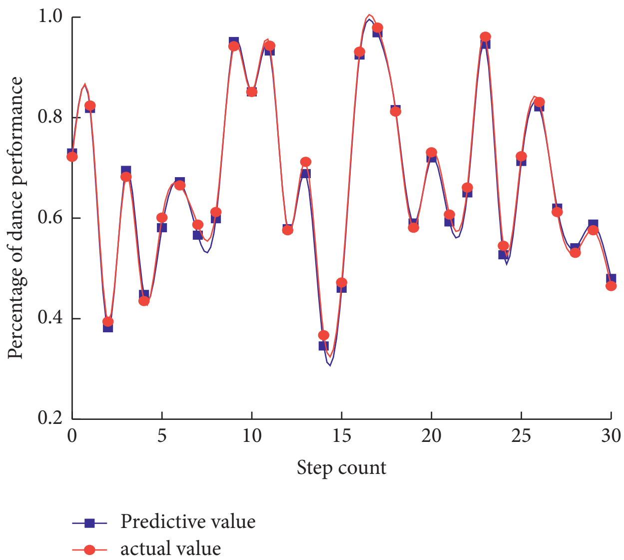

Figure 2: The effect of network training results and actual output.

Table 1: Fuzzy neural network error of dance performance.

Actual value	Predictive value	Relative error
0.722	0.73	0.011
0.824	0.82	−0.007
0.394	0.38	−0.031
0.682	0.69	0.019
0.435	0.45	0.030
0.601	0.58	−0.033
0.665	0.67	0.011
0.587	0.57	−0.036
0.612	0.60	−0.021
0.942	0.95	0.010
0.851	0.858	−0.008
0.943	0.93	−0.011
0.576	0.58	0.005
0.712	0.69	−0.033
0.367	0.35	−0.058
0.472	0.46	−0.024

the actual dance performance training effect is basically consistent with the training effect of the fuzzy neural network.

The errors between the proposed model prediction and the actual values are shown in Table 1. This could be understood from the reported values in Table 1 that the error range amongst the anticipated values and the actual values is significantly small, and the predicted trend of the dance performance effect is basically consistent with the actual situation.

In addition, this paper inputs the data samples of choreography to the network training, and the output effect after the network training is revealed in Figure 3. This is very clearly observed from the exploration of the above figure, and it can be comprehended that the output value of the choreographer after the network training is roughly consistent with the actual value. Except for a small part of the training value that has a certain error, the rest of the training data results are close to the actual ideal value.

The errors amongst the model anticipated values and the actual values of the choreographer are given away in Table 2. We can easily observe from the outcomes reported in Table 2 that the error range amongst the anticipated values and the real values is significantly small. Furthermore, the predicted trend of the choreography effect tends to be consistent with the actual value, and the results are relatively similar.

Finally, this paper inputs the sample data of the dance teaching into the suggested fuzzy neural network, and the training output outcomes and actual values are shown in Figure 4. The training outcomes show that the fuzzy neural network has a noble application impact in the prediction of dance teaching, with exact applicability.

The errors amongst the model forecasted values and the actual values of the dance teaching are given away in Table 3. From looking at the figure and reported values in Table 3, this could be comprehended from the table's outcomes that the error range amongst the expected values and the real values is significantly small. Furthermore, we observed that

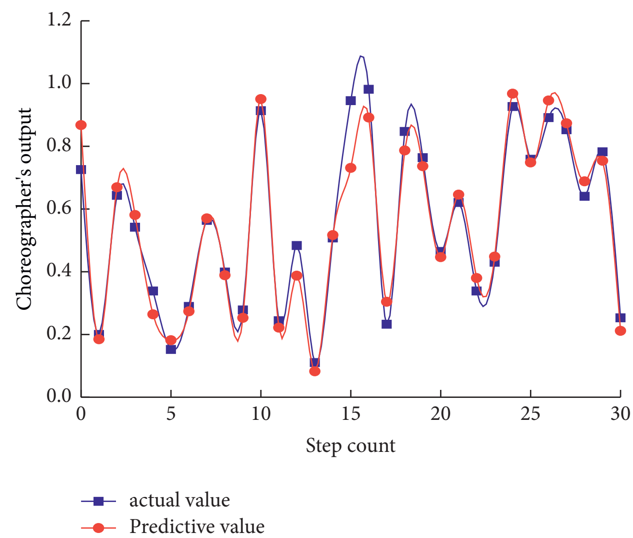

Figure 3: The network training results and actual output effects of the choreographer.

Table 2: Fuzzy neural network error of choreographer.

Actual value	Predictive value	Error
0.73	0.87	0.195
0.20	0.18	−0.077
0.64	0.67	0.040
0.54	0.58	0.072
0.34	0.26	−0.219
0.15	0.18	0.192
0.29	0.27	−0.054
0.56	0.57	0.012
0.40	0.39	−0.026
0.28	0.25	−0.091
0.91	0.95	0.044
0.24	0.22	−0.090
0.48	0.39	−0.199
0.11	0.08	−0.250
0.51	0.52	0.018
0.95	0.87	−0.079

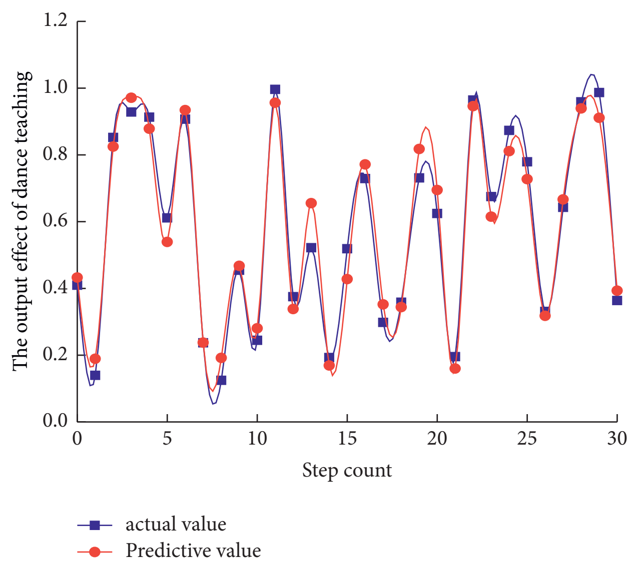

Figure 4: The network training results and actual output effects of the choreographer.

Table 3: Fuzzy neural network error in dance teaching.

Actual value	Predictive value	Error
0.409	0.433	−0.057
0.139	0.189	−0.356
0.852	0.825	0.032
0.928	0.971	−0.046
0.913	0.879	0.038
0.611	0.539	0.118
0.907	0.934	−0.030
0.237	0.238	−0.003
0.125	0.192	−0.542
0.454	0.468	−0.029
0.245	0.281	−0.147
0.996	0.956	0.040
0.375	0.338	0.098
0.522	0.655	−0.256
0.193	0.169	0.122
0.519	0.428	0.176

the predicted trend of the dance teaching effect is basically the same, that is, almost similar, as the actual values, and subsequently, the results are also similar.

5. Conclusions and Future Work

In this paper, depending on the characteristics of the dance skills training, we determined the functional characteristics of the model input layer along with the hidden layer(s) and the output layer neurons, including the configuration of the obscure neural network. Furthermore, we applied the obscure control theory to optimize the network training process. The network models improve neuronal connection load and the training performance. In the process of predicting dance skills training, network predictions can be obtained by comparing the error between the predictive result data and the actual operational data, in order to improve the precision and performance (real-time) of the prediction and bring the obtained predictive data closer to the reality. In fact, this bears a good resemblance to the actual values and confirms the high accuracy of the model data obtained.

In the future, we will account for larger data sets of the dance skill while taking additional parameters into account. Furthermore, we will investigate how deep learning models will perform against the proposed fuzzy neural network architecture. We will use big data technologies so that they can be integrated into the training process that usually is computationally intensive. We believe that using big data is essential to improve the runtime of the training and prediction phase. In future work, we will look into the computational complexities and how they can be significantly reduced using the edge and cloud computational schemes.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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