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Research on the Aesthetic Evaluation Method of Seeding Machinery Based on RBF Neural Network

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Abstract

Aesthetic factors are an essential part of farm machinery development and design. In this paper, we take seeding machinery, typical farm machinery, as an instance and establish an aesthetic evaluation model for seeding machinery based on RBF neural network to predict design effects, which will provide important evidence to intelligent design of seeding machinery. Furthermore, aesthetic characteristic elements of seeding machinery are analyzed to establish an evaluation index system that is classified into three levels, of which the first-level index include technical and formal beauty, the second-level index contains beauty of function, material, shape and color and the third-level index comprises 17 factors. RBF neural network is employed to establish a mathematical model, where input layer is composed of 17 low-level evaluation index values and output layer is the comprehensive evaluation values of aesthetics by experts. Training and verification of 22 samples found that predictive effects of RBF neural network-based model on the evaluation model of seeding machinery modeling are superior to BP network-based prediction model, for it can better deal with uncertainties.

Keywords: *Radial Basis Function (RBF) neural network; seeding machinery; aesthetic evaluation*

1. Introduction

With the ever-growing market demands for products, people are increasingly demanding for products. This is also true of farm machinery design. Considering that aesthetic design of farm machinery has a direct bearing on its sales, aesthetic factors are essential to design farm machinery products to the needs of market and to users' satisfaction. Farm machinery products are of great importance to modernize the farm sectors, for they are geared to the needs of agriculture, rural areas and farmers. It is farmers who are the purchasers and users of farm machinery products. Social development and technology progress have contributed to continuous improvement of people's cultural living standard and to increasing pursuit of beauty. In the same vein, farmers have an ever-increasing demand for beauty. In this context, farm machinery should not only be used as means of production to meet the needs of production, but deliver beauty and artistic enjoyment through product form design. W. Chen analyzed the main content and features of formal and technical beauty in design of farm machinery products, but failed to explore how to guide the design and evaluation of farm machinery products using such aesthetical features [1-4]. For industrial products, there is much more literature concerning research on aesthetic features and evaluation methods of product design. C. W. Zhou and J. Qiu based on the analysis of aesthetic features of furniture products, established an evaluation model featuring 'beauty' and 'non-beauty' for characteristic factors of furniture product design from fuzzy theory [5]. Then, they calculated weight of each factor in aesthetic evaluation of product modeling through

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investigation, providing a way of furniture product design. L. Zeng and D. P. Liu analyzed factors for modeling beauty of furniture products, and on this basis, they established first and second-level indexes of furniture design beauty [6]. Then, index weights were calculated using AHP and an aesthetic evaluation was made on various pieces of furniture with fuzzy comprehensive evaluation method, hence fulfilling quantitative aesthetic evaluation of furniture products.

F.M. Kou and J. B. Cui analyzed both aesthetic feature concept and content of commodities, and expounded the influences of various product design factors on overall aesthetic effects using simple functions [7-9]. Y. Wang et al. researched landscape along highway by analyzing design factors influencing landscape beauty to serve as evaluation standards, making a quantitative analysis of various indexes and building a model with stepwise regression method to verify which indexes can effectively affect aesthetic quality of highway landscape [10].

As can be seen from related literature, research on aesthetic evaluation of products still depends on fuzzy or simple mathematical methods, and there has been a lack of practical mathematical evaluation model based on quantitative research. Even, research on aesthetic evaluation methods of farm machinery turns out to be much less, which is merely in relation to aesthetic factor analysis and without establishing evaluation models. Aesthetic evaluation faces great uncertainties, because it is concerned with fuzzy mental feelings of consumer group. Intelligence algorithms are conducive to deal with uncertainties. With the emergence and development of computer technology, intelligent algorithms have been widely applied in many industries. At present, BP neural network is much more popular, yet carrying significant limitations in global optimization capability and slow convergence rate. Therefore, there are certain gaps in comparison with objective evaluation results. RBF neural network, or Radical Basis Function neural network, is an efficient feed-forward neural network featuring simple structure and fast training speed, which is unique in optimal approximation performance and global optimum. Meanwhile, it can be widely used in such aspects as pattern recognition and approximation of non-linear function. Consequently, this paper presents an aesthetic evaluation model for seeding machinery using RBF neural network, in order to provide effective evidence to fulfilling automated design of seeding machinery.

2. Research Frameworks

This paper analyzes the aesthetic characteristics of products including formal and technical beauty as first-level aesthetic evaluation indexs, obtain 4 second-level aesthetic evaluation indexs containing the function of aesthetics, material aesthetics, aesthetic form and color aesthetics, and 17 third-level aesthetic evaluation indexs. The text selects seeding machinery as the research object which is widely used in agricultural machinery, screens shape design cases of seeding machinery through various channels, and analyzes shape design features of seeding machinery. On the network platform the samples selected are evaluated with aesthetic indexs. Then, with BP neural network, a correlated model was established between each third-level aesthetic values and comprehensive aesthetic evaluation values. Figure 1 is the flow chart of aesthetic evaluation.

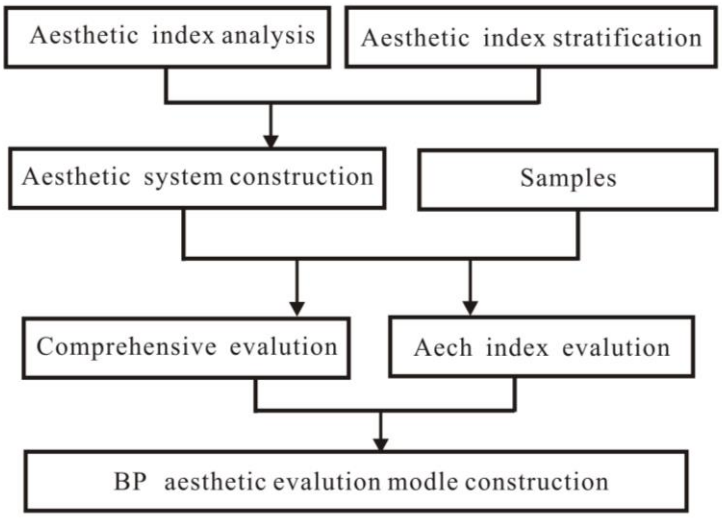

Figure 1. The Flow Chart of Research Frameworks

3. Establishment of Aesthetic Evaluation Standard

3.1. Aesthetic Characteristic Analysis of Seeding Machinery

Currently, farm machinery has less aesthetic demands in product design and development, going against market development and demands. As typical farm machinery, agricultural seeding machinery can be divided into multiple types based on different seeds. Generally, in the line of seeding methods, it can be classified into broadcast spawning, sowing in drill, hill (hole) and precision sowing [11]. This paper takes hole sowing as an example to research the aesthetic features of product design.

In general, product modeling beauty has at least two remarkable traits. One is formal beauty of product form exhibited in external perceptual form, while the other is technical beauty of product form resulting from harmony and orderly internal structure [12]. Design beauty is a process of psychological experience brought by artistic creation on the basis of technology development and form innovation. The establishment of design aesthetics is to seek a perfect combination of technical and form beauty and to guide design practice. All this aims at pursuing emotional and situational appeals in design, making it possible for consumers to experience emotional influences enjoyments. For this reason, aesthetic evaluation standards comprise technical and formal beauty [13]. The former is concerned with product functions, materials, technologies and interactions, while the latter relates to the natural attributes of materials, namely aesthetical features represented by color, shape, line and their combination laws.

3.2. Evaluation Indexes of Seeding Machinery

In this paper, aesthetic evaluation indexes of seeding machinery are divided into two first-level indexes, including technical and formal aesthetic evaluation; four second-level indexes, namely aesthetics of function, material, form and color; and 17 third-level indexes.

Table 1. Aesthetic Evaluation Index System for Seeding Machinery

Evaluation	First-level index	Second-level index	Third-level index

Aesthetic evaluation	Technical aesthetic evaluation	Function aesthetics	Conforming to cultivation practices
			Conforming to cultivation environment
			Definite functional area
			Consistent transition of functional area
			Meeting function requirements
		Material aesthetics	Reasonable selection of materials
			Surface treatment
			Detail treatment
	Formal aesthetic evaluation	Form aesthetics	Meeting function requirements
			Uniform style
			Appropriate proportion
			Equilibrium and stability
			Uniform changes
			Coordinated comparisons
		Color aesthetics	Meeting function requirements
			Overall color coordination
			Adjusting to service environment

4. Aesthetic Model based on RBF Neural Network

4.1. Principles of BP

BP (Back Propagation) neural network is a model which is now the most deeply studied in artificial neural network, and the most widely used. Figure 2 is its structure show.

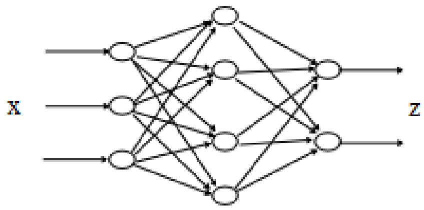

Figure 2. BP Network Structure

Figure 2 shows that x, z is the input and output vector of BP neural network, each neuron is as a node, and the network consists of input layer, hidden layer which can be both a single layer (Figure 2) and a multi-layer, and the weight coefficient is connected previous layer and nodes. While the BP neural network learning, the input signal changes from the input layer through the hidden layer to output layer. If the output layer gets the desired output, the learning algorithm ends, otherwise, turns to the back propagation. Back propagation is that error signal(the difference between the output and the network output) is back calculated according to the original connection, and adjusts the weights of each neuron by the gradient descent method to make error signal reduce. The specific process of weights of each layer is:

Defining the network output error is $E=1/2(d-O)^2=1/2\sum_{k=1}^{l}(d_k-o_k)^2$, which is in turn expanded to the hidden layer and input layer. On the principles of continuously reducing error, the adjustment quantity of weights should be proportional to the negative gradient of the error. The formula is:

$$\Delta w_{jk} \propto -\frac{\partial E}{\partial w_{jk}},\ j=0,1,2,\cdots m;\ k=1,2,\cdots l \tag{1}$$

$$\Delta v_{ij} \propto -\frac{\partial E}{\partial v_{ij}},\ i=1,2,\cdots n;\ j=1,2,\cdots m \tag{2}$$

Calculation formulas can be obtained form the derivation for the weights adjustment of each layer, vector form is:

$$\Delta W = \eta(\delta^o Y^T)^T \tag{3}$$

$$\Delta V = \eta(\delta^y X^T)^T \tag{4}$$

Where $X=(x_1,x_2,\cdots,x_n)^T$ denotes the input vector, and $Y=(y_1,y_2,\cdots,y_m)^T$ represents the output vector of hidden layer, $O=(o_1,o_2,\cdots,o_l)^T$ expresses the output vector, and $d=(d_1,d_2,\cdots,d_l)^T$ is the predicted output. Then, $W=[w_{jk}]_{m\times l}$ and $V=[v_{ij}]_{n\times m}$ respectively show the weight matrix of hidden layer to output layer and input layer to hidden layer.

The training process of BP network is as follows:

(1) Initialize the network, get values of network parameters and coefficients of weights, in which weights should take random number.

(2) Input training samples, calculate predicted values of each layer, compare with real values, conclude the output error of the network.

(3) According to rules of the back propagation error, adjust the weight coefficient between hidden layer and input layer and the hidden layer inside.

(4) Repeat (2)-(3) until the prediction error satisfying solution or training times reaching regulation occurs.

4.2. Working Principles of RBF

Radial basis function is a real-valued function, in which values depend only on the distance from the origin or from an arbitrary point C that is a central point, which can be expressed as $\Phi(X)=\Phi(\|X\|)$ or $\Phi(X,C)=\Phi(\|X-C\|)$ respectively [14]. Any Φ functions satisfying $\Phi(X)=\Phi(\|X\|)$ can be called radial basis function, and Euclidean distance is often used as a standard. Some radial basis functions are similar to the preciously given functions, which can be construed as a simple neural network. In support vector machine, the radial basis function is also regarded as kernel function. RBF network can approach any non-linear functions and deal with somewhat unexplained laws within the system, with sound generalization, and fast convergence rate. Therefore, it has been widely used in such aspects as approximation of non-linear function, time series analysis, data classification, pattern recognition, information processing, image processing, system modeling and fault diagnosis.

RBF (Radial Basis Function) can be regarded as a matter of surface fitting (approximation) in a high-dimensional space, and its essence is a recursive technique using backpropagation algorithm, which is called stochastic approximation in statistics. Basis function in RBF is to provide a function set in hidden units of neural network [15-18]. To be specific, when input pattern (vector) is extended to hidden space, the function set builds an arbitrary base. As a result, functions in the set are called radial basis function. RBF neural network structure consists of input, hidden and output layers shown in Figure 3. Input layer is linked to external environment; hidden layer makes non-linear transformations between input and hidden spaces; and output layer is linear, responding to input patterns in input layer.

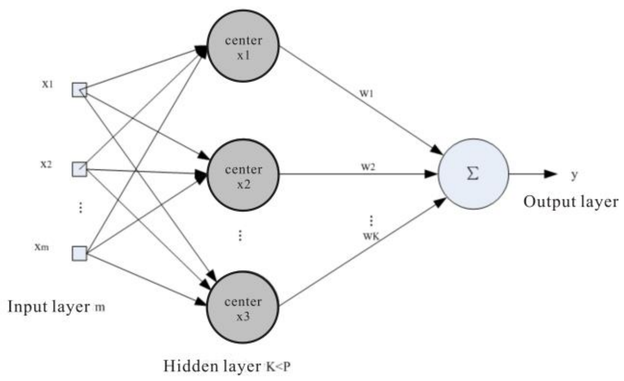

Figure 3. RBF Network Structure

Commonly used three radial basis functions nowadays
Multiquadric:

c $\phi(r) = \sqrt{1 + (\varepsilon r)^2}$

Inverse quadratic:

$$\phi(r) = \frac{1}{1 + (\varepsilon r)^2}$$

Inverse multiquadric:

$$\phi(r) = \frac{1}{\sqrt{1 + (\varepsilon r)^2}}$$

4.3. Aesthetic Evaluation Model based on RBF Neural Network

To establish an aesthetic evaluation model based on RBF neural network is mainly to determine factors of input and output layers and the number of hidden layers. In the aesthetic evaluation of seeding machinery, input layer consists of 17 low-level evaluation index values with 17 nodes correspondingly, while output layer is the comprehensive evaluation values by relevant experts with only 1 node.

5. Simulation Experiment

5.1. Sample Data Acquisition

This paper collects seeding machinery drawings of various brands from websites, books and periodicals. There are 22 typical tractor samples reserved upon two rounds of screening based on second-level evaluation indexes. Meanwhile, 120 subjects with design experience in industrial, mechanical and farm machinery products are selected to grade electronic drawings using Likert scale, a five-grade marking system. Score ranges from 1-5; 1 means non-beauty, 5 is beauty and 3 represents secondary. Table 2 shows the survey results of the samples. Besides, a comprehensive aesthetic evaluation is made on 22 samples by 22 relevant experts employing image scale method, as shown in Table 3.

Table 2. Aesthetic Evaluation Index Values of the Sample

Samples	X1	X2	X3	X4	X5	X6	X7	X8	X9	…	X14	X15	X16	X17
1	4.7	4.3	3.8	3.5	2.8	3.5	3.8	4.7	3.7	…	4.3	4.0	3.5	4.1

2	4.0	4.2	2.6	3.1	2.5	2.7	4.1	4.2	3.5	…	2.1	4.2	2.4	3.8
3	3.2	2.2	4.3	3.8	2.4	3.8	2.1	3.7	2.8	…	2.5	2.2	2.1	2.5
4	2.6	2.1	3.8	2.6	2.4	3.4	2.3	2.7	3.5	…	2.5	3.5	2.0	2.5
5	4.2	3.8	3.9	3.6	3.6	3.7	3.0	3.5	2.8	…	3.1	3.4	3.0	3.8
6	4.5	4.2	2.3	3.3	2.3	2.8	4.0	4.6	3.8	…	2.8	3.8	2.7	3.7
7	3.0	3.5	3.7	2.8	3.0	2.9	3.1	2.9	3.3	…	3.1	2.1	3.5	2.3
8	2.9	2.9	2.9	3.9	2.8	4.2	2.9	2.8	3.2	…	3.8	2.8	2.7	3.0
9	4.3	4.2	3.3	4.0	3.3	3.5	3.9	4.0	4.1	…	4.2	4.6	3.7	4.3
10	2.2	3.0	2.3	2.9	2.8	3.1	4.0	3.6	2.6	…	2.8	2.6	3.3	3.3
11	3.2	3.0	3.8	2.4	2.4	3.3	2.5	3.2	3.1	…	2.5	3.3	2.8	3.1
12	4.8	4.4	4.6	4.5	4.3	4.7	4.5	4.8	4.4	…	4.4	4.2	4.5	4.7
13	4.2	2.2	2.1	3.8	4.2	3.5	2.9	4.2	3.0	…	2.9	3.7	2.9	3.3
14	4.8	3.8	3.9	4.2	46	2.3	3.9	4.3	3.4	…	2.9	3.7	4.2	3.5
15	3.9	3.2	31	3.3	2.7	3.6	3.2	3.1	2.6	…	2.6	2.5	2.8	3.1
16	3.2	3.8	3.7	3.1	4.0	3.2	3.3	3.0	3.1	…	3.8	3.1	3.2	3.5
17	3.0	3.3	3.1	2.9	3.9	3.5	2.5	3.3	2.9	…	3.1	3.4	2.8	3.4
18	1.3	1.2	1.0	1.3	1.2	1.5	1.2	1.2	1.2	…	1.3	1.2	1.6	1.1
19	3.3	3.9	3.3	1.4	2.4	3.2	2.3	3.2	2.3	…	2.0	3.1	2.9	2.8
20	2.9	2.4	3.0	3.8	2.6	2.2	2.8	3.9	2.6	…	3.3	2.6	3.3	2.3
21	2.4	3.2	2.3	3.2	2.3	2.1	2.9	2.5	2.6	…	3.1	2.3	1.4	2.1
22	1.9	1.7	2.0	2.1	1.3	1.8	1.4	1.6	1.5	…	1.9	1.8	2.1	2.0

Table 3. Comprehensive Evaluation Results by Experts

Comprehensive evaluation results by experts														
1	2	3	4	5	6	7	8	9	…	18	19	20	21	22
67.0	54.4	52.5	48.0	59.5	55.8	51.5	53.5	66.6	…	21.3	47.0	48.3	41.4	30.1

5.2. Result Analysis of Simulation Test

There are 22 samples, 16 of which belong to training sample set and 6 of which to verification sample set. Then, an evaluation model is established based on RBF neural network where input layer is 17, namely 17 low-level evaluation index values and output layer is 1, namely evaluation results via expert scoring. Training via RBF and BP networks found that arithmetic speed of RBF is faster than that of BP, and the same goes for training results. As can be seen from Figure 4 and 5, the forecasting and actual values exhibit better fitting effects with less errors in RBF network training model.

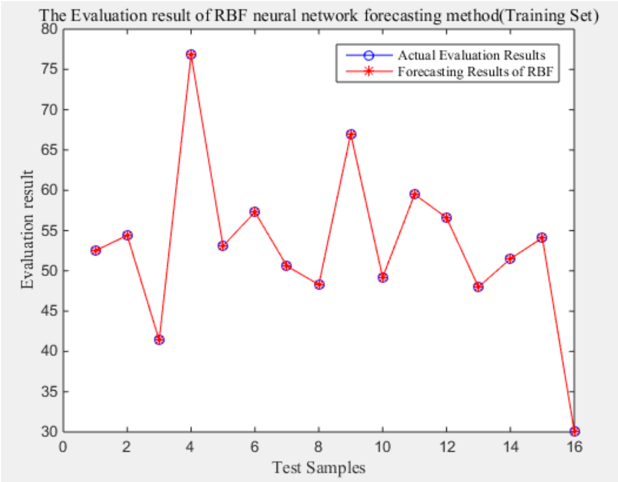

Figure 4. Comparison of Actual with Forecasting Values of RBF Training Samples

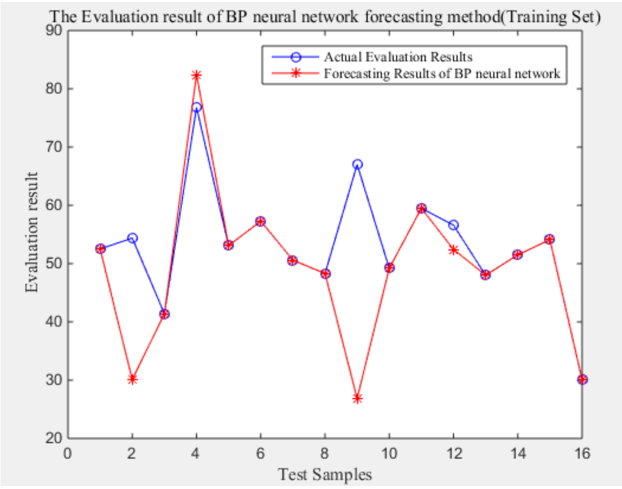

Figure 5. Comparison of Actual with Forecasting Values of BP Training Samples

Table 4. Error Rate Comparison of RBF with BP Test Samples

Actual output value	RBF network output value	BP network output value	RBF network error	BP network error
66.2	72.3712	48.3894	9.3221	26.9042
53.5	54.5226	50.0123	1.9115	6.5191
47.0	47.7731	48.4043	1.6449	2.9879
21.3	27.6684	30.7082	29.8987	44.1700
55.8	54.3909	51.3471	2.5252	7.9801
66.6	67.9784	54.4095	2.0697	18.3040

As shown in Table 4, test results of RBF are superior to BP.

6. Conclusions

This paper analyzes aesthetic features of agricultural seeding machinery. On this basis, the aesthetic evaluation model system is established with 2 first-level indexes, 4 second-level indexes and 7 third-level indexes. Furthermore, we establish an RBF neural network-based aesthetic evaluation model for agricultural seeding machinery, where input layer is composed of 17 low-level evaluation index values and output layer consist of comprehensive evaluation results by experts. A simultaneous training of RBF and BP networks demonstrates that forecasting and actual values exhibit better fitting effects in RBF training set. A comparison of forecasting with actual values also indicates that RBF network is better that BP network.

Acknowledgements

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