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Research Article

Research on Evaluation Method of Product Style Semantics Based on Neural Network

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Abstract: This study sets up the corresponding relation between product modeling elements and style semantics based on neural network. First, establish matrices of office chair modeling elements and style semantics by questionnaire method respectively. Then, build standard Back Propagation Neural Network (BPNN), BPNN on Levenberg-Marquardt (L-M) algorithm, standard Radial Basis Function (RBF) neural network and RBFNN on K-means clustering algorithm by MATLAB software and compare the simulating results on two kinds of BPNN and RBFNN. Finally, choose the RBFNN on K-means clustering algorithm as the best model to guide product modeling design. The effectiveness and applicability of this method are demonstrated by experimental results on the office chair design. It is shown that this method not only improves the efficiency of existing products style semantics judgment but also can be used to evaluate the style semantics of each design candidate.

Keywords: BP neural network on L-M algorithm, product modeling design, RBF neural network on K-means clustering algorithm, standard BP neural network, standard RBF neural network, style semantics

INTRODUCTION

Determining the corresponding relation between product design elements and style semantics can improve the efficiency of existing products style semantics judgment and make the style semantics evaluation of each design candidate more conveniently. Many researchers have analyzed survey results by statistical method in the guidance of Kansei engineering and have summarized qualitatively characteristics of product modeling elements corresponding to style semantics.

For the purpose of making design job become more convenient, four kinds of mathematics models based on neural network are built in this study. By analyzing and comparing the simulating results of these neural network models, it shows that RBF neural network on K-means clustering algorithm is the best model. Designer can obtain the evaluation of product style semantics immediately by inputting product modeling elements with this model. Wu (2009) have a research on imagery of product design concept generation phase. Li (2011) have a research on improved BP neural network applications in water quality assessment. Fathi and Aghakouchak (2007) study the prediction of fatigue crack growth rate in welded tubular joints using neural network. Adel and Mohamed (2007) have a research of the sizing of stand-alone photovoltaic systems using neural network adaptive del. Zhu *et al*. (2010) study the improved k-means clustering algorithm.

This study sets up the corresponding relation between product modeling elements and style semantics based on neural network. First, establish matrices of office chair modeling elements and style semantics by questionnaire method respectively. Then, build standard Back Propagation Neural Network (BPNN), BPNN on Levenberg-Marquardt (L-M) algorithm, standard Radial Basis Function (RBF) neural network and RBFNN on K-means clustering algorithm by MATLAB software and compare the simulating results on two kinds of BPNN and RBFNN. Finally, choose the RBFNN on K-means clustering algorithm as the best model to guide product modeling design. The effectiveness and applicability of this method are demonstrated by experimental results on the office chair design. It is shown that this method not only improves the efficiency of existing products style semantics judgment but also can be used to evaluate the style semantics of each design candidate.

ANALYSIS ON PRODUCT MODELING ELEMENTS AND STYLE SEMANTICS

This study uses office chair design as a case study.

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Fig. 1: Representative office chair pictures

Table 1: The design elements on office chair

	Type no.					
Modeling elements	1	2	3	4	5	6
Material (X1)	Leather	Cloth	Artificial leather	Plastic	Wood	Others
Shape of chair's back (X2)	Geometrical	Streamlined	Others	-	-	-
Armrest shape (X3)	Anteverted	Horizontal	Retroverted	No armrest	Others	-
Shape of chair's legs (X4)	Universal wheel	Fixed support	Others	-	-	-
Adjustability (X5)	Adjustability of seat height	Non-adjustability of seat height	Adjustability of chair's back angle	Non-adjustability of chair's back angle	Adjustability of seat height and chair's back angle	Others
Specific ornament (X6)	Chair's back	Armrest	Chair's back and armrest	Non	Others	-

Table 2: The matrix of modeling design elements of office chair

No.	X1	X2	X3	X4	X5	X6
Chair no. 1	4	2	4	1	1	1
Chair no. 2	3	2	3	1	1	4
Chair no. 3	5	1	2	1	1	3
Chair no. 4	1	3	1	1	1	5
Chair no. 5	5	1	3	1	1	1
Chair no. 6	4	1	4	1	1	4
Chair no. 7	4	2	5	2	6	5
Chair no. 8	1	3	2	2	5	5
Chair no. 9	1	3	3	1	1	4
Chair no. 10	3	2	2	1	1	5
Chair no. 11	4	3	2	1	1	5
Chair no. 12	1	2	2	1	5	5
Chair no. 13	2	2	1	1	1	4
Chair no. 14	3	3	2	1	1	1
Chair no. 15	1	3	1	1	5	5
Chair no. 16	2	2	2	2	6	5

Table 3: The final determined semantics vocabularies

Modern-classical	Elegant-rude	Concise-decorated	Harmonious-contrastive
Luxurious-plain	Bardian-popular	Sprightly-deep	Frivolous-decorous
Commercial-casual	Virile-gentle	Streamlined-geometrical	Lovely-solemn
Eastern-western			

Elements of product form and material: Survey information and data are obtained by Kansei engineering method. First, All kinds of recent pictures about office chair which nearly cover overall style and form of office chairs are collected. Then determine 16 representative pictures after repeated screening and choose three pictures to test and verify neural network model. Sixteen pictures on office chair are shown in Fig. 1.

In the process of collecting and choosing pictures, office chair's morphology is decomposed into 6 design elements by morphological analysis (Xuemin, 2009), including material, the shape of chair's back, the shape of chair's legs, armrest shape, adjustability and detail ornament. Each design element is sorted into a number of types, such as classified the shape of chairs back into three types: geometrical, streamlined and others. The design elements of office chair are shown in Table 1. The matrix of design elements of sixteen samples about office chair is shown in Table 2.

Evaluation of product style semantics: In the same way, survey information and sample data can be obtained by Kansei engineering method. First, delete the adjectives with similar meaning in the chosen style semantics vocabularies, invite three designers to pick out the most representative semantics vocabularies after matching antonyms with reserved adjectives. Secondly, design questionnaire beforehand by Likert Scale method of five rank and test 30 peoples. Get average value of each semantics vocabularies on the questionnaires by statistical method, sort by value and achieve 13 pairs of the most important style semantics vocabularies, as shown in Table 3. Then design formal questionnaire by Semantic Difference Scale method of five ranks, send these questionnaires to 135 peoples and gain evaluation result of 13 pairs of style semantics vocabularies on 16 office chair samples. Finally, calculate average values on the evaluation result of each pair of semantics vocabularies and get the matrix of style semantics.

RESEARCH ON EVALUATION METHOD OF PRODUCT STYLE SEMANTICS BASED ON BP NEURAL NETWORK

BP neural network (Wenjuan, 2011) is a multilayer feed-forward network trained by the algorithm of the error back-propagation. BP neural network takes advantage of weights and thresholds of every net node, learns and stores plenty of mapping relations about input-output mode and realizes any nonlinear mapping from the input to the output but doesn't need to build mathematic equation describing the mapping relations beforehand (Fathi and Aghakouchak, 2007). In generally, BP neural network is a kind of three-layer network topology with one hidden layer (Adel and Mohamed, 2007). This study, respectively builds standard BP neural networks and BP neural network on L-M algorithm by MATLAB software. Training samples are the thirteen representative office chairs. Input parameter is the matrix of form and material elements and output parameter is the matrix of style semantics. Train two kinds of networks, simulate them with other three sample data and verify their availability. Finally analyze and compare the difference of two networks.

Characteristic of standard BP neural network and BP neural network on L-M algorithm: This study selects standard BP neural networks and BP neural network on L-M algorithm to set up correspondence relation between product form and material elements and style semantics:

- **Standard BP neural network:** Standard BP neural network makes a set of sample's input and output transform into a nonlinear optimization problem and it is a kind of learning method that solves weight values using an iterative calculations by the negative gradient descent algorithm, but the convergence is slow and it is easy to fall into local minimum.
- **L-M algorithm:** L-M algorithm is a more effective learning algorithm, but doesn't need to calculate Hessian Matrix. Weight adjustment of L-M algorithm is shown in the following formula (1):

$$w_{i+1} = w_i - \left[J^T J + \mu I\right]^{-1} J^T e \tag{1}$$

where,

J = Jacobian Matrix that the error is differential to the weight
e = Net error vector
I = Unit matrix
μ = The coefficient of self-adaptive adjustment

When v→∞, the formula becomes steepest descent method, when μ→0, the formula becomes Newton method and uses approximate Hessian Matrix.

Analyzing on training and simulating results of two kinds of BP neural networks: For standard BP neural network and BP neural network on L-M algorithm, node number of the hidden layer is 13 that are determined by trial and error method. Network architecture is the type of 6×13×13. Other training parameters, such as learning rate, maximum training times, training accuracy and momentum factor and so on, vary slightly with each kind of algorithm, as shown in Table 4. In the built BP neural network model, the transfer function of hidden layer is S type function and the transfer function of output layer is linear function. As shown in Table 5, from the training result parameters of BP neural network with two kinds of different learning algorithm, it's known:

- Standard BP neural network stops training when training times is 5000, fail times of variable validation is zero, training error accuracy is 0.0653, training goal is 0.0001 and training time is 49 sec.
- BP neural network on L-M algorithm is only trained to 5 times, error accuracy arrives 2.05×10^{-7}. And fail times of variable validation is only 4, training time is 0 sec. 0 sec means time is very little.

Seen from above training results, training times is more, time is long and accuracy is low for standard BP neural network. For BP neural network on L-M algorithm, training times is little, training accuracy is high and time is short, it shows that convergence speed is faster and efficiency is higher. From above analysis, it is known that BP neural network on L-M algorithm is the better network model.

Table 4: Training parameters of two BP neural networks

	Transfer function	Node numbers of hidden layer	Training times	Training goal	Learning rate
Standard	Tansig, purelin	13	5000	0.0001	0.01
L-M algorithm	Tansig, purelin	13	5000	0.0001	0.01

Table 5: Training result parameters of two BP neural networks

	Training times	Training time	Training accuracy	Momentum	Descending gradient	Variable validation
Standard BPNN	5000	49 sec	0.0653	-	0.03740	0
BPNN of L-M algorithm	5	0 sec	2.05 E-07	1E-08	0.00042	4

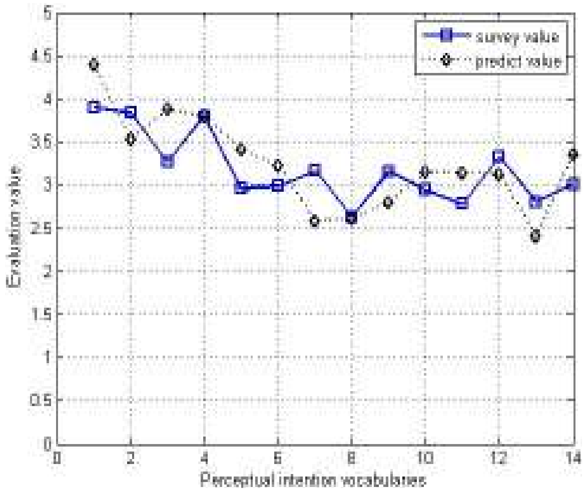

Fig. 2: Simulation results of sample 1 by standard BPNN

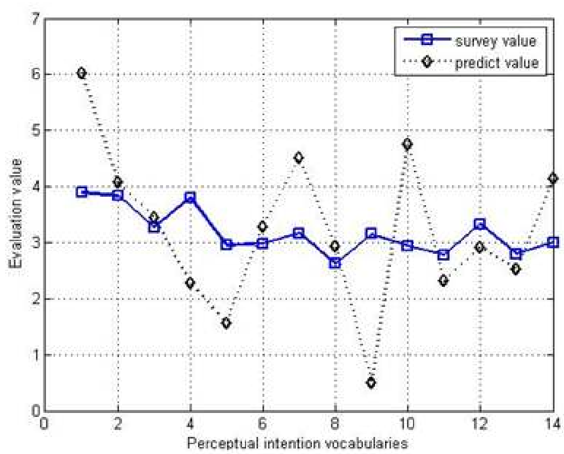

Fig. 3: Simulation results of sample 1 by BPNN on L-M algorithm

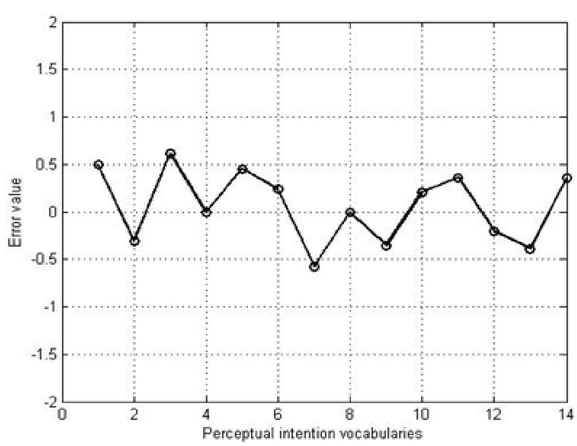

Fig. 4: Simulation errors of sample 1 by standard BPNN

After that, use the other three sample data to simulate and test the built BP neural network model.

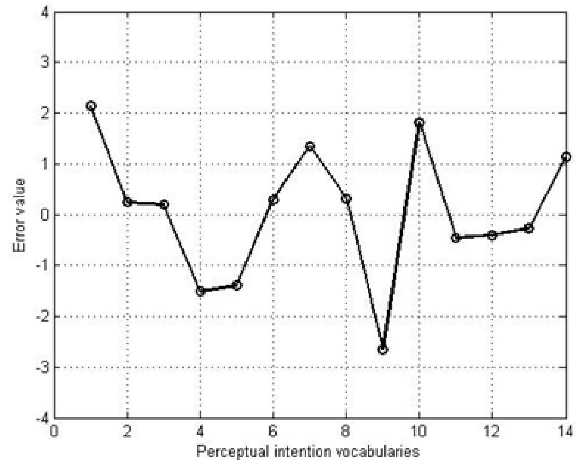

Fig. 5: Simulation errors of sample 1 by BPNN on L-M algorithm

For simulation results of two BP neural network models, sample one as an example, are as shown in Fig. 2 and 3. Their simulating errors are as shown in Fig. 4 and 5.

By comparing and analyzing on simulation result, prediction result can express the relation between form and material elements and style semantics and absolute error and relative error lie in the smaller range. But prediction accuracy still has some difference for different algorithm. Seen from Fig. 4 and 5, the prediction value has bigger fluctuation for BP neural network on L-M algorithm, most of error values exceed 1. But error values are basically less than 0.5 and closes to zero for standard BP neural network. So standard BP neural network is the better network model for the analysis on prediction accuracy.

RESEARCH ON EVALUATION METHOD OF PRODUCT STYLE SEMANTICS BASED ON RBF NEURAL NETWORK

Radial Basis Function (RBF) neural network is an efficient Feed forward neural network with single hidden layer. The transfer function of its hidden layer is symmetrical radial basis function and frequently uses Gaussian function as a radial basis function. This study, respectively builds standard RBF neural network and RBF neural network on K-means clustering algorithm to establish the correspondence relation between product modeling elements and style semantics. Input matrix, output matrix and the distribution of training sample and simulation sample are same with BP neural network.

Characteristic of standard RBF neural network and RBF neural network on K-means clustering algorithm:

Standard RBF neural network: There are three learning parameters for RBF neural network: the

Table 6: Training parameters of two RBF neural networks

	Transfer function	Node number	Spread constant	Terminal condition	Weight calculation of hidden layer and output layer
Standard RBF neural network	Gaussian function	13	1	MSE = 0	Least square method
RBF neural network on K-means clustering algorithm	Gaussian function	13	1	MSE = 0	Pseudo-inverse

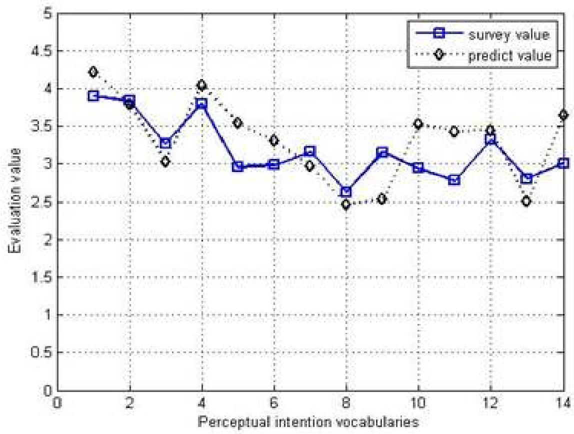

Fig. 6: Simulation results of sample 1 by standard RBFNN

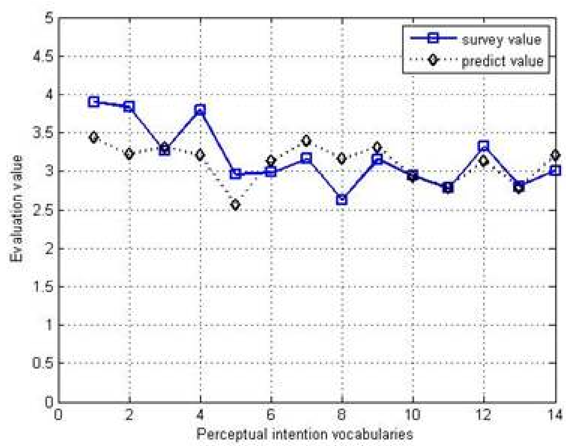

Fig. 7: Simulation results of sample 1 by RBFNN on K-means clustering algorithm

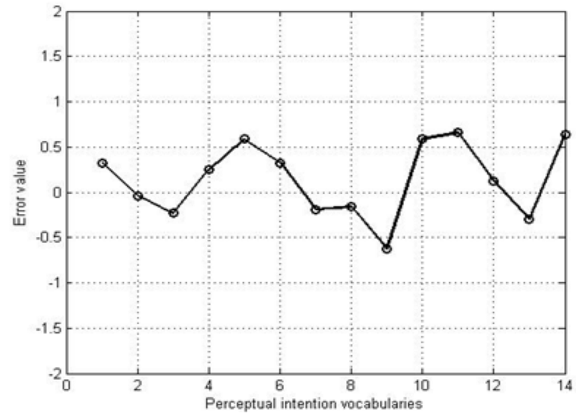

Fig. 8: Simulation errors of sample 1 by standard RBFNN

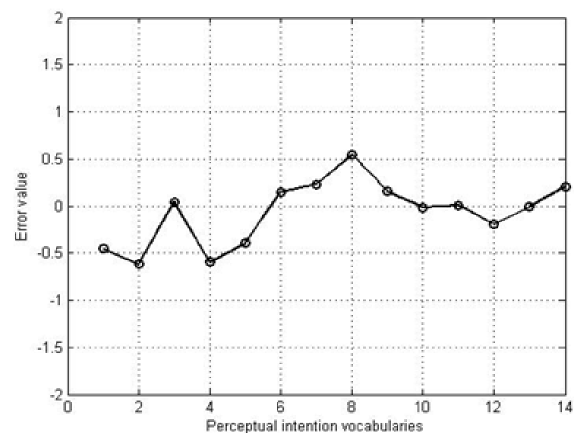

Fig. 9: Simulation errors of sample 1 by RBFNN on K-means clustering algorithm

number of hidden layer of radial basis function and its data center c, spread constant r and the connection weights value w of hidden layer and output layer. Standard RBF neural network determines c and r by the conventional method and determines w by the least square method.

RBF neural network on K-means clustering algorithm: The principle of K-means clustering algorithm is that quadratic sum is the smallest for the distance from the data point to the center of the category in each clustering. The basic idea is to move all kinds of clustering center by successive iteration until get the best clustering results.

K-means clustering algorithm beforehand sets the number of center M (hidden node number of hidden layer) before it determines the location of data center. M is generally determined by the test method.

K-means clustering algorithm is simple and efficient, but must set beforehand the number of cluster centers. It is sensitive to noise and isolated data points, a small amount of this data will have a huge impact on the clustering results and the algorithm cannot ensure convergence to the optimal solution, its performance is dependent on the initial position of the clustering centers (Jian and Wang, 2010).

ANALYZING ON TRAINING AND SIMULATING RESULTS OF TWO KINDS OF RBF NEURAL NETWORKS

Standard RBF neural network gets c and r by the trial and error method, determine the weights of the output layer, the threshold and termination conditions by minimum mean square error between hidden layer and output layer. RBF neural network on K-means clustering algorithm determine the weights of the output layer, the threshold and termination conditions by the pseudo-inverse method. In this study, termination conditions of two RBF neural networks are that MSE is equal to zero. Their training parameters are shown in Table 6.

Similarly, with sample one as an example, simulating results of two RBF neural networks are shown in Fig. 6 and 7. The simulating errors are shown in Fig. 8 and 9.

Seen from the simulating results of two RBF neural networks, the majority of prediction values are close to survey values. The individual values have bias for RBF neural network on K-means clustering algorithm and its reverse for standard RBF neural network. Seen from the simulating error, error values of two RBF neural networks are less than 1. Majority of the points basically approach zero line for the error line of RBF neural network on K-means clustering algorithm. So RBF neural network on K-means clustering algorithm is superior to the standard RBF neural network.

Comparing on BP neural network and RBF neural network: Seen from Fig. 2 to 9, absolute error values of RBF neural network are in the smaller rang. The prediction accuracy of RBF neural network is higher than the one of BP neural network. It's shown that generalization ability and stability of RBF neural network are better than the one of BP neural network. Seen from simulating error, error values of BP neural network on L-M algorithm are bigger, but error values of RBF neural network on K-means clustering algorithm are smaller. So RBF neural network on K-means clustering algorithm is the better model for applying for product modeling design.

CONCLUSION

In the guidance of Kansei engineering method, this study gains the matrices of product form and material elements and style semantics. By MATLAB software, two kinds of BP neural network models and two kinds of RBF neural network models, including standard BP neural network, BP neural network on L-M algorithm, standard RBF neural network and RBF neural network on K-means clustering algorithm, are built to research the corresponding relation between product modeling elements and style semantics. By comparing the training and simulating results, it shows that RBF neural network on K-means clustering algorithm is the better network model. This method can be used to not only predict the style semantics of each design candidate in the process of research and development of office chairs, but also evaluate the style semantics for existing office chairs. This method can be applied to predict and evaluate the style semantics of other products.

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