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Kansei Evaluation Model of Tractor Shape Design Based on GA-BP Neural Network

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Abstract

To mine users' perceptual demand for product shape, it is very important to build the relational model between design elements of product shape and users' Kansei evaluation. We apply Kansei engineering to the shape design of wheeled tractor. The design elements obtained by morphological analysis constitute the input layer, and perceptual semantic evaluation obtained by semantic differential method constitutes the output layer. Genetic algorithm-back propagation (GA-BP) neural network is used to construct the relational model between design elements of product shape and users' Kansei evaluation. Experiment shows that the predicted values using the training samples are consistent with Kansei evaluation values based on GA-BP neural network. Meanwhile, the relative error between the predicted and measured values of users' Kansei evaluation using the testing samples is less than 3%. However, There is a larger deviation between the predicted values using the training samples and Kansei evaluation values based on BP model. Furthermore, the relative error between the predicted and measured values of users' Kansei evaluation using the testing samples is more than 10%. Comparison GA-BP with BP neural network modeling shows the perceptual evaluation model based on GA-BP is superior to BP network model. Therefore, the model is capable of accurate prediction of users' Kansei evaluation about product shape utilizing GA-BP neural network modeling and can be used to guide product shape design. This will not only improve the efficiency of product research and development, but also enhance enterprises' competitiveness.

Key words: Kansei evaluation, The tractor shape, GA-BP neural network, Design element

1. Introduction

With the progress of economy and technology, the product market has been transformed from the mode of designer and manufacturer domination to the mode of consumer demand domination. Therefore, mining for deep psychological and perceptual demand of the consumers is the route that must be taken towards innovative product design. Product shape is an important part of product design, and users' perception and perceptual evaluation of the product shape determines the value of the products and the style of the brand.

Kansei engineering (KE) is the process of converting users' vague and perceptual demand and sensory perception into design elements of the product. The core issue is quantification of Kansei and to turn the quantification results into guidelines for automatic innovative design of product shape. This also represents a major aspect of KE [1].

To visualize the unobservable emotions and perceptions of the consumers, some psychological methods are needed. Conventional evaluation methods in KE include semantic differential, verbal protocol analysis, factor analysis, clustering analysis and multi-scale analysis [2-5]. These methods only quantify the perceptions, without building the relational model between Kansei semantics and design elements. Thus they cannot be used to provide guidance for the practice of product shape design. To find out quantified connections between users' Kansei information and design elements, regression analysis, quantification theory I and neural network algorithm have been adopted. Mathematical statistics and regression analysis are the most commonly used methods for building linear relations. For example, Chitoshi Tanoue et al.[6] and Yongfeng Li applied quantification theory I to the design of automotive interiors and door lock and built the relations between design elements and Kansei semantics [7]. The dominant variables were used to predict quantitative baseline variables, and the perceptual descriptions were related to the design elements of product shape. Ying Wang and Yan Chen used KE principles and techniques to quantify the design elements of women's overcoat and built the linear regression model based on users' Kansei evaluation, by combining with quantification theory I [8]. Junsheng Kuang and Pingyu Jiang performed questionnaire survey and regression analysis to explore for consumers' sensory perception about mobile phone and then established the quantitative relationship with respect to the design parameters [9]. Zhenghong Liu et al. proposed the use of multiple regression analysis to build the mapping relationship between multi-dimensional modeling features and Kansei experience about numerically controlled machine tool [10]. Thus the Kansei evaluation model was obtained.

But when it comes to highly delicate objects, linear models may fail to meet the precision requirement for correlation analysis. Addressing this problem, intelligent algorithms are now used, especially neural network algorithm. Meiyu Zhou and Qian Li [11]built the relationship between Kansei experience and design elements of product shape for computer-controlled microwave oven by using neural network algorithm. An optimal combination of shape features with the highest value of Kansei evaluation was determined by the training of neural network and then used for redesign of product shape. Yan Zhou et al. decomposed the shape of mobile phone into elements and built the relational model between design elements and Kansei evaluation using BP neural network [12]. On this basis, the product shape design was improved by KE and the perceptual design was finished. Mengdar Shie and Yuen Yeh combined partial least squares method and neural network algorithm in designing a shape design support system for running shoes based on the mining for users' perception [13]. Thus the appearance elements were quantitatively correlated to consumers' Kansei. Lijing Wang et al. decomposed the interiors of airplane cabin into elements and applied KE to obtain users' Kansei evaluation[14]. Finally the relational model between interior design elements and Kansei evaluation was constructed by neural network algorithm.

2. GA-BP neural network

Some achievements have been made in the applications of BP neural network to the correlation between perceptual evaluation and design elements. But BP neural network alone lacks global optimization ability and has slow convergence. It is still inferior to some objective evaluation techniques. We propose GA-BP neural network algorithm for building the relationship between design elements and users' perception for tractors. This provides an effective and objective method of shape design evaluation and serves as the basis for redesign.

2.1 BP neural network

2.1.1 Fundamental principle of the BP neural network

The concept of Back Propagation Neural Network (BPNN, the same below) was initiated by a group of scientists led by Rinehart and McClelland in 1986. This multi-layer feedforward network that is trained by backward propagation of errors has become one of the most popularized neural network models [15]. BP neural network can learn and store a large amount of mapping relations of input-output model without the need for revealing the mathematical functions that describe the mapping relations. Method of gradient descent is used as the learning rule, by which the weights and thresholds are constantly based on the propagation direction so that the error sum of squares is the smallest. The typology of the BP neural network consists of input layer, hidden layer and output layer, as shown in Fig. 1.

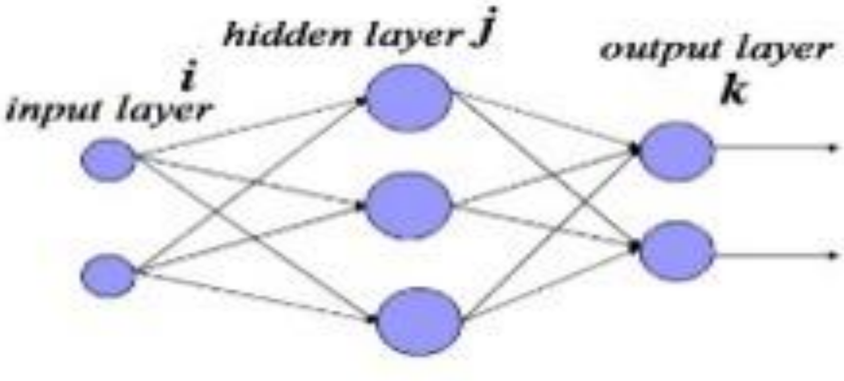

Fig.1. Typology of BP neural network

The BP algorithm consists of two processes: forward propagation of data flow input, and backward propagation of error signals [16]. The direction of forward propagation is "input layer-→hidden layer-→output layer", and the status of one layer of neurons can and only can act on the neurons of the next layer. If any actual output in the output layer is not the target one, the backward propagation of error signals begins [17]. Through the two alternative processes, the gradient descent strategy is performed in the weight vector space where a group of weight vector is searched in a dynamic and iterative manner to minimize network error function, so that the process of information extraction and memory is completed.

2.1.2 characteristics of BP neural network modeling

The main characteristics of BP neural network contain:

(1) Nonlinear mapping capability. The BP neural network can approach any nonlinear continuous function at arbitrary precision;

(2) Parallel processing and distributed processing. Data in BP neural network undergo distributive storage and parallel processing.

(3) The ability of self-study and self-adaptability. The neural network that receives training can extract regular knowledge from input data and output data, remembering and generalizing it in the form of neural weight. Online learning is also allowed.

(4) Data integrity. BP is capable of simultaneous processing with regard to quantitative data and qualitative data.

(5) Multi-variable system. The number of input variables and output variables is arbitrary.

2.2 BP neural network trained by GA

The genetic algorithm, initiated mainly by Prof. John Holland at the University of Michigan during 1960s -1970s, is essentially a parallel and global search heuristic that generates useful solutions to optimization and search problems in a highly-efficient manner [18]. Information of search space (possible solutions) can be automatically acquired and accumulated when genetic algorithm traverses the solution space. What is more, the search process undergoes self-adapting control in search for optimal solutions. Currently, there are three methods for the genetic algorithm to solve problems in limited neural networks: the evolution of network weight and threshold, the evolution of network structure, and the evolution of learning principles.

The evolution of network weight and threshold is adopted in the paper to offset the low rate of global optimization and convergence [19]. It starts from an initialized population. By conducting genetic operations on this group, such as stochastic selection, crossover, and mutation, this method endows the fittest chromosome with the maximum chance to survive. In this way, after evolution from generation to generation, the population members enter better and better localities in the search space.

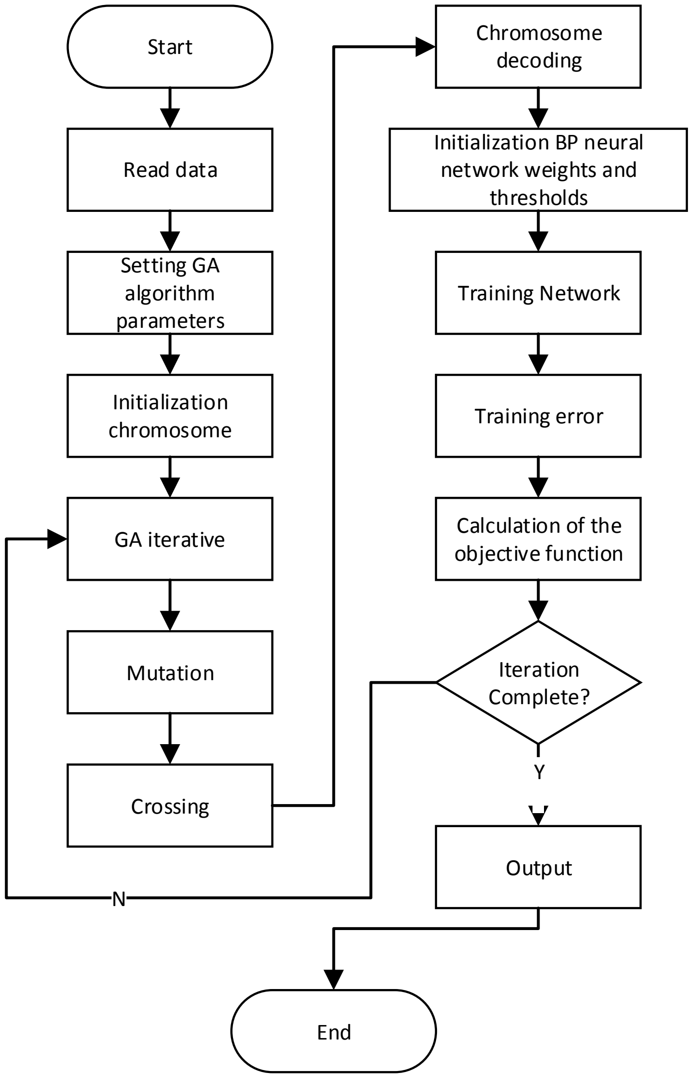

Fig.2. Flow chart of GA-BP neural network

The connection weights of all neurons in BP neural network are encoded into individuals represented by binary strings, and the initial population of the strings is generated randomly. Then, the conventional optimization computation can be done with the help of the genetic algorithm. The strings are decoded into weights to constitute a new BP neural network every generation of computation. By calculating the training samples, the mean square error of neural network output is obtained for determination of individual fitness. After several generations of calculation, the BP neural network will evolve to the extent that producing the minimum global error. BP neural network can be trained by GA, which optimizes weights and thresholds, while the number of hidden layer, node number and connection mode between the nodes remain constant. The work flow is shown in Fig. 2.

3. KE analysis of tractor shape

The shape design schemes of tractors are screened, analyzed and decomposed to obtain the design elements. Users' Kansei is measured and analyzed using adjective describing perception about product shape. KE is applied to build the relationship between shape design elements and users' Kansei evaluation. To do this, we need to first collect the shape design samples and perform optimization of users' perception information.

3.1 Collection of tractor shape design samples

Tractors have more complicated shape than other industrial products because its model, power, working environment and purposes all have an impact on shape [20]. By structure tractors are divided into walking tractors, wheeled tractors and caterpillar tractors, which have very different shape design [21]. In this study, we focus on wheeled tractors. The design schemes are collected from the Internet, books, magazines, periodicals, and photos of outlets and exhibitions. The brands of tractors collected include John Deere, Dongfanghong, Kubota, Shifeng, Foton, JCB, Fendt, Valtra, Masseyferguson, Claas, Caterpillar, Caseih and Newholland. The samples of tractor shape design total 120 and a sample library is built.

First the graphics are processed to eliminate the influence of color and logo. All shape design schemes display tractors from the same angle. By multi-group analysis, discussion and 3 rounds of sample screening, 18 shape design samples are finally included and numbered. Fig.3 is the front view of the tractors.

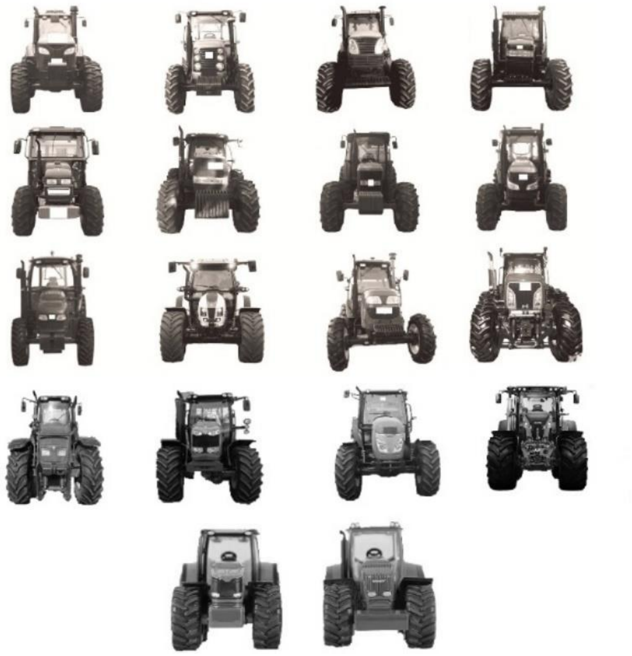

Fig.3. Front views of tractors

3.2 Collection of adjectives

The selected design samples are made into electronic album. The subjects tested include experts, users and people who are interested in the product, and more 200 adjectives describing tractor shape are collected by on-line interview. Fifty-five pairs of high-frequency words are selected with the removal of words having the same or similar meanings. By factor analysis and clustering analysis, four pairs of adjectives are obtained for subsequent mining for users' perceptual evaluation [22]. They are light-heavy, compact-complex, smooth-stiff, and linear-streamlined.

3.3 Decomposition of design elements

Morphological analysis is applied to shape decomposition, first into several independent items and then into many independent design elements. These variable design elements are the provenance of product shape redesign and design evaluation [23]. Through several rounds of discussion with the designers and ordering by significance of design features perceived by the users, the tractors are divided into three parts: front face, cabin and side face of the trunk. The front face is further divided into 5 design elements and 22 design categories; cabin is divided into 4 design elements and 17 design categories; side face of the trunk is divided into 5 design elements and 23 design categories. Thus there are a total of 14 design elements, as shown in Table 1.

Table.1. List of shape design elements

Design area	Design element	Design category
Front engine hood		Arc type
	Air-inlet screen X1	Right angle type
		Curve type
		other type
	Lamp X2	
	Front engine hood X3	
	Functional area transition X4	
	Suspension member X5	
Cabin	Windshield X6	
	Roof X7	……
	Side frame X8	
	Rear frame X9	
Side bodywork	Side contour of the trunk X10	
	Lateral engine hood X11	
	Heat exchange area X12	
	Fender X13	
	Side shield X14	

3.4 Kansei evaluation and design elements

The light-heavy semantic pair is selected for Kansei evaluation. A questionnaire is prepared based on the electronic album of 18 design samples using Likert scale and semantic differential [24]. The users are instructed to score the design samples on the 1-5 point scale with an interval of 1. Point 1 indicates very light, and point 5 indicates very heavy, with point 3 neutral. Thirty subjects with some professional background, including Industrial Design, Mechanical Design, Agricultural Mechanical Design and so on, are chosen so as to eliminate potential interference. The results of Kansei evaluation are shown in Table 2.

Table.2. Kansei evaluation values of the samples (light-heavy)

The sample	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14	Kansei evaluation value
1	1	2	2	1	1	1	2	1	1	1	1	1	2	2	2.31
2	3	2	1	2	1	1	2	1	1	1	1	1	1	2	2.08
3	4	3	3	2	1	2	2	4	2	3	2	3	2	1	3.38
4	3	3	2	1	2	1	3	2	3	1	3	3	1	1	4.47
5	1	2	2	2	3	1	1	1	2	2	2	1	1	1	2.75
6	1	3	3	2	1	1	2	2	2	3	1	1	1	1	3.53
7	2	3	2	1	2	1	2	2	1	3	2	1	3	1	2.96
8	3	2	3	1	2	3	1	3	1	2	2	1	2	1	3.60
9	2	4	4	3	4	4	3	4	3	5	4	3	4	4	3.78
10	4	1	3	1	1	1	2	2	1	3	2	2	1	3	3.22
11	1	1	1	2	4	1	2	1	2	2	2	1	1	1	3.17
12	2	2	2	1	2	2	1	2	1	2	1	2	1	2	3.01
13	2	4	5	5	4	3	4	5	4	5	4	5	3	5	2.55
14	3	2	1	2	1	1	1	1	3	1	2	1	2	3	3.48
15	2	2	3	3	1	3	1	2	1	1	3	2	1	1	1.97
16	4	3	4	2	3	4	1	2	3	4	3	2	3	1	2.11
17	3	1	3	1	1	3	1	2	1	2	2	2	2	1	3.21
18	4	4	4	5	4	4	4	5	4	3	5	4	4	3	2.84

4. Kansei evaluation model based on GA-BP neural network

It is necessary to build the relationships between users' Kansei and design elements if the design is consumer-oriented. But the problem is made difficult by individual variation in users' perceptual demand. To fit the non-linear relationship between the two, we use GA-BP neural network.

4.1 Structuring of Kansei evaluation model based on BP neural network

Before the BP-based model is built up, it is a necessity to determine the types of parameters in the input layer and the output layer, and the number of modes in all the layers as well. For this research, the design factors of tractor shape are used as the input vector, being represented by $x=(x1, \cdots xm)^T$. The emotional evaluation result for tractor shape design is the output vector that is denoted by y. Wi is the weight coefficient. The relationship between input vector and output vector is:

$$y = f\left(\sum_{i=1}^{m} w_i x_i - \theta\right) \quad (1)$$

Where θ is a threshold, and f(X) is an excitation function which can be either linear or nonlinear.

Assuming that there are P training samples, which are equal to P input-output pairs. (I_p, T_p) = 1, ..., P, Where the input vector is:

$$I_p = (i_{p1},\ldots, i_{pm})^T \tag{2}$$

The targeted output vector is:

$$T_p = (t_{p1},\ldots, t_{pn})^T \tag{3}$$

The actual output vector is:

$$O_p = (o_{p1},\ldots, o_{pn})^T \tag{4}$$

Wij represents the weight from the jth input vector component (j=1,⋯,m) to the ith output vector component (i=1,⋯,n). In general, there is an error between the ideal output value and actual output value. The meaning of neural network learning is to minimize error sum of squares through a constant comparison between the pair of output values as well as wij modification according to the minimum principle.

$$\min \sum_{i=1}^{n} (t_{pi} - o_{pi})^2 \tag{5}$$

4.2 Structuring of Kansei evaluation model based on GA-BP neural network

The steps to establish a GA-BP neural network compound model that is correlated with the said BP-based model are:

(1) Preprocess the design form data and emotional evaluation data of tractor shape design, and normalize the initial data in a way that the data interval is within [0, 1]. The normalization formula is:

$$\bar{x}_i = (x_i - x_{\min})/(x_{\max} - x_{\min}), i = 1,2,\ldots,m \tag{6}$$

Where x_i denotes either input data or output data, x_{min} represents the minimum value in the data interval, and x_{max} is the maximum value in the data interval.

(2) Initial weight optimization

Below is the steps to optimize learning process by the genetic algorithm:

①Initialize parameters of population P, including the crossover scale, the crossover probability P_c, and the mutation probability P_m.

②Compute the error function of the neural network, and determine the function value of its fitness. The larger the error is, the smaller the fitness value is.

③Some individuals with large fitness values are directly passed to the next generation, and the rest are passed according to the corresponding probability determined according to fitness values.

④Process the present population with genetic operations such as mutation and crossover, and the next generation of population is produced accordingly.

⑤Repeat ②-③ until the satisfying solution occurs.

(3) Establishment of a modified GA-BP neural network compound model

After n times of iterative GA optimization, the globally optimized network weight and threshold are obtained to replace the initial counterparts in all BP neural network layers. Then, the sample data undergo normalized processing, with the shape design factors as the input layer and the emotional user evaluation as the output layer. Finally, the modified GA-BP neural network compound model is established, mapping sensual user data to shape design factors.

(4) Data processing in the model

The normalized sample data are inputted to the modified BP-based model, and the predicted result data are outputted. Then, with anti-normalization, the predicted value is compared with the actual value for error computation.

(5) Evaluation on the network model

After the sample data undergo learning, training and prediction with the use of BP and GA-BP neural network, the relative error rate, namely the ratio of the actual value to the prediction value, is analyzed. Finally, the performance of the system model is summarized and evaluated.

5 Training of BP neural network by GA

The light-heavy semantic pair is chosen. In the optimized BP neural network, 14 design elements constitute the input layer (input node number 14) and Kansei evaluation values constitute the output layer (output node number 1); the hidden layer has 8 nodes. From 18 samples, 13 samples are selected as the training samples, and the remaining as the testing samples. The learning rate is set as 0.05, network learning precision 0.00001, and 1000 times trainings. The number of populations and number of generations are constantly varied in GA, with mutation probability of 0.05 and probability of crossover 0.7. The final number of populations is 50 and the number of generations is 300. Fig. 4 shows the convergence curve.

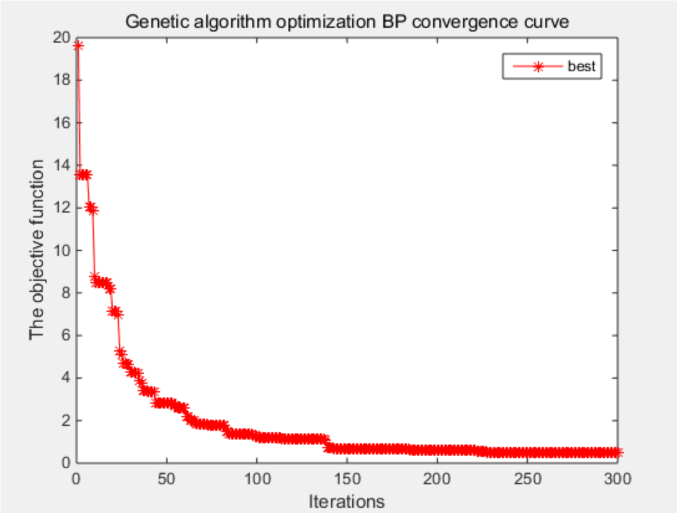

Fig.4. Convergence curve

As shown in Fig.5, the randomly simulated values of Kansei evaluation using 13 out of 18 training samples are basically consistent with the measured values of Kansei evaluation. This indicates high prediction precision using the training samples. According to Figure 6, the prediction trend of the test sample resembles the actual trend.

By contrast, for both the training sample and the test sample in the BP-based model, the prediction values fit the actual values poorly, as shown in Fig. 7-8.

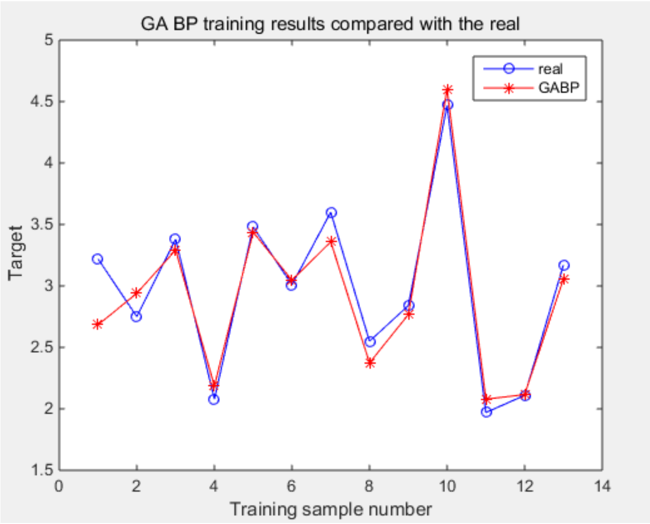

Fig.5. Comparison of predicted and measured values of Kansei evaluation based on GA-BP neural network from the training samples

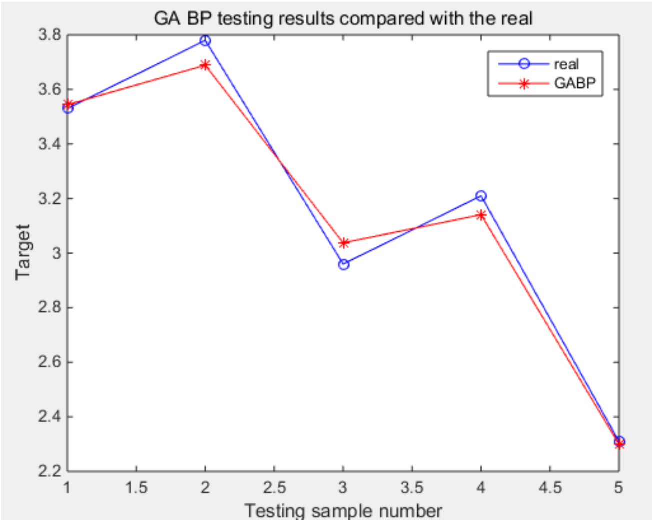

Fig.6. Comparison of predicted and measured values of Kansei evaluation based on GA-BP neural network from the testing samples

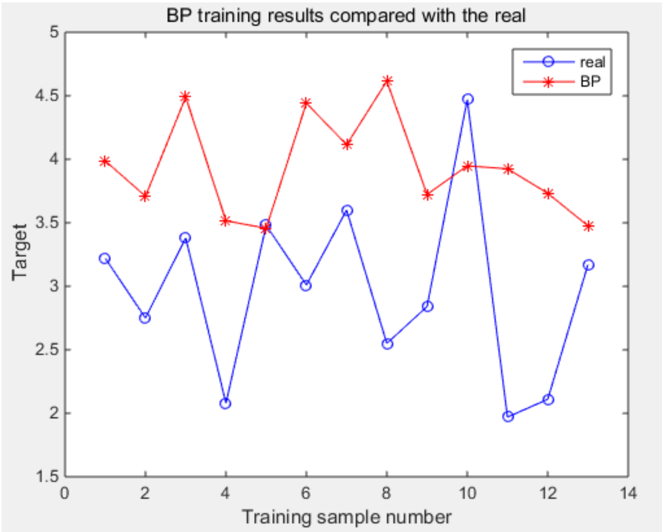

Fig.7. Comparison of predicted and measured values of Kansei evaluation based on BP neural network from the training samples

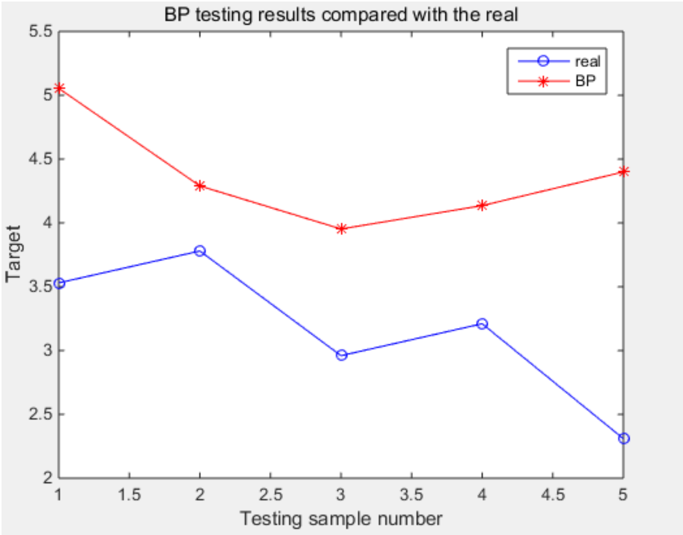

Fig.8. Comparison of predicted and measured values of Kansei evaluation based on BP neural network from the testing samples

To test for generality, the prediction performance is evaluated using 5 testing samples. The comparison between the predicted and measured values of Kansei evaluation is shown in Table 3. Relative errors of sample 1-5 are 0.3966%, 2.4101%, 2.6284%, 2.1464% and 0.4372%, respectively, all of which are below 3%. Moreover, a good agreement is achieved with the subjective evaluation surveyed.

However, in the BP-based model, the relative error rates for the same test samples are 43.1785%、13.4841%、33.5304%、28.8287%、90.4459%, respectively, all of which exceed 10%. This phenomenon shows that the relative error rate of the BP-based model is high.

Table.3. Verification of GA-BP and BP neural network

Testing sample	Measured value	Predicted value of GA-BP	Predicted value of BP	Relative error of GA-BP(Re/100)	Relative error of BP(Re/100)
1	3.5300	3.5440	5.0542	0.3966	43.1785
2	3.7800	3.6889	4.2897	2.4101	13.4841
3	2.9600	3.0378	3.9525	2.6284	33.5304
4	3.2100	3.1411	4.1354	2.1464	28.8287
5	2.3100	2.2999	4.3993	0.4372	90.4459

6 Discussion

In order to study on the sensual evaluation characteristics of product form, quantitative research is conducted during the collection of fuzzy sensual evaluation data. With a transition from the simple quantitative methods, linear methods, and numerical statistical methods to nonlinear approaches, the relationship between emotional factors and shape elements has been modelled, albeit at an exploratory stage. The intelligent algorithm is the main solution to nonlinear problems. Single algorithm has already been used for quantitative research into sensual evaluation. For the research herein, the relative error rate of the BP-based model is high, while the relative error rate of the GM-modified BP-based model is low, and as such the test result and the simulation result for the latter model is favorable. This achievement shows that the classical GA-BP neural network compound algorithm can mitigate the shortages of single algorithm. Despite some achievements, the research in the paper still has several deficiencies of sensual evaluation quantification for follow-up in-depth research, such as:

(1) How we deal with the fitness of sensual evaluation model for a new product type?

(2) For various kinds of compound algorithms, what is the difference among their requirements on research objective data?

(3) For a fixed research objective, what is the impact of different compound algorithms on data processing and model establishment during the construction of a sensual evaluation model?

7 Conclusion

We apply KE to capture the non-linear relationship between shape design elements of tractors and users' Kansei evaluation with the building of GA-BP neural network. Tractor shape is decomposed into design elements by morphological analysis, and users' Kansei evaluation is extracted by semantic differential. The GA-BP neural network takes the design elements as the input layer and the Kansei evaluation as the output layer, and the network is trained using 13 out of 18 samples. The remaining 5 samples are used for testing. The results show that the relative errors between the predicted and measured values of Kansei evaluation are 0.3966%, 2.4101%, 2.6284%, 2.1464% and 0.4372%, respectively, all of which are below 3%. However, for both the training sample and the test sample in the BP-based model, the prediction values fit the actual values poorly, and all the relative error rates for the test samples exceed 10%. Therefore, the usage of Modified GA-BP neural network model to establish a sensual evaluation model complies with reality better. Moreover, the prediction results agree well with the subjective evaluation surveyed. The model can be applied to acquire users' Kansei about tractor shape design and achieve efficient Kansei evaluation. This provides valuable reference for product redesign.

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