Nonlinear Solution for Digital Instrument Interface Based on Kansei Engineering

Huiliang Zhao

School of Mechanical Engineering, Guizhou University, Guiyang 550025, Guizhou, China

Lin He

Guizhou Normal College, Guiyang 550018, Guizhou, China

Li Lin

School of Mechanical Engineering, Guizhou University, Guiyang 550025, Guizhou, China

Abstract
The digital instrument interface designers in industrial circle must face the typical nonlinear and uncertainty of the relationship between Kansei images (KIs) and product attributes (PAs), and the shortage of the statistical sample. It is conducted thorough research to the problem of nonlinear processing method, pointed out a new way that using combinatorial methods to solve the complex problem of small samples and poor information, and then put forward the grey-neural network (GNN) to deal with the relationship between KIs and PAs for digital instrument interface, to determine the best design combination of interface design elements for matching a given Kansei image represented by a word pair. A case study involving the design of digital tachometer interface is presented to demonstrate the proposed method. It was shown a strong feasibility through the test comparison with the grey and BP neural network prediction.
Key words: DIGITAL INSTRUMENT INTERFACE, KANSEI IMAGE, GREY-NEURAL NETWORK, PRODUCT ATTRIBUTES.

1. Introduction

With the increasing various electronic devices in industry control system, the traditional mechanical or simulated instrument interface cannot satisfy the need of massive electronic information. Digital instruments integrated with instrument panel information, which increasing the human-machine communication and improving the human-machine experience effectively and reducing the produce cost for enterprises, have been widely used in aerospace, nuclear power monitoring, intelligent transportation, the special vehicle information remote monitoring, and some other complex human-machine interface interaction system areas. It is obvious that digital instrument interface design plays an important role in the process of system development. On the premise of guarantee reliable function of it, the comprehensive consider of user perceptual cognitive need and Kansei images are reasonably important that affecting product efficient and easy to use. Smith explored the relationships between automobile head-up display presentation image designs and drivers' Kansei images using quantification theory type I [1]. Guo pointed that the drivers' attitude towards and preference for head-up display system are crucial to design the functional framework, and explored the relationships between drivers' attitude and head-up display presentation designs using stated preference data from questionnaire survey[2]. Therefore, how to deal with the challenge of science and technology for human nature, match user's higher levels of psychological need, is worthy of great attention in digital instrument interface design.

Kansei Engineering (KE) is one important theory to process the relationship between affective responses and product attributes for industrial [3]，as its procedure presented in Figure 1. In the KE, customers' affective responses about a set of design alternatives of a product are represented in the form of Kansei image words (affective responses) such as "fashionable", "contracted", "sporty", "technological", etc., and quantified by the degree of semantic scale ratings. Meanwhile, the design alternatives of the product can be decomposed into a set of design elements (product attributes). With the assistance of appropriate mathematical tools and advanced computer technologies, the relations treated as Kansei knowledge between the quantified Kansei words and design elements can be established. At present, the correlation technology between on Kansei images and product design elements in KE can be roughly divided into linear and nonlinear processing mode. The linear mode mostly adopts quantification theory type I, multiple regression and grey theory, etc., the nonlinear model is focused on the rough set, neural network, genetic algorithm and support vector machine, etc.

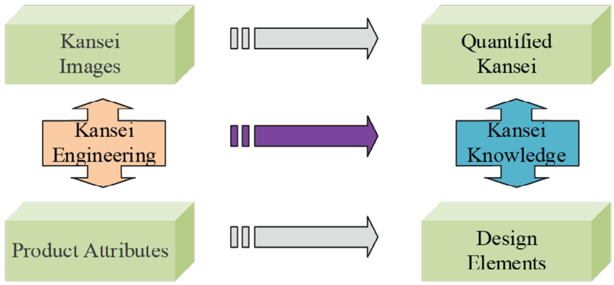

Figure 1. Kansei Engineering process

Due to the user's particular subjective feeling and cognitive factors on digital instrument interface, which causing complicated nonlinear and uncertain relation between Kansei images and design elements, and the shortage of the statistical sample, that is not capable of providing accurate and reliable outcomes by using the existing technology like quantification theory type I and neural network which involving a large volume representative training samples. A case study involving the design of digital tachometer interface is presented to demonstrate the proposed method.

2. Nonlinear relationship between KIs and PAs analysis

One of the frequently encountered problems when modeling in KE is how to deal with the relationship between the Kansei images (KIs) and product attributes (PAs). Among the existing studies, the modelling process used multiple linear regression analysis technique for look-and-feel of the mobile phone was investigated[4], and used to model the relationship between the usability and the design human interface elements[5]. Jindo describes a design support system using quantification theory type I in designing office chairs[6], Su applied quantification theory type I to decompose mobile phone form elements and establish the corresponding mathematical analysis model, and quantify the relationship between KIs and mobile phone form design elements[7]. And the partial least squares regression was used to select important design variables for modeling product usability[8]. Generally, Their work are all treating the relationship as single linearity, and the linear regression model of quantification theory type I is a most popular one tool to derive the relationships between KIs and PAs [9].

In fact, with the development of artificial intelligence such statistical tools assume linear relations among the various variables may not be true in most cases, these nonlinear techniques are proved to be more suitable for building the prediction model of KIs. Hsiao and Huang demonstrated the ability of neural network (NN) to deal with non-linear relationships between the KIs and PAs [10]. The rough set theory was applied in Kansei Engineering as a knowledge discovery tool to analyze the KIs and PAs [11, 12]. Su Jian-ning studied the interrelation of it combined with genetic algorithm[13]. And Multiclass support vector machine (SVM) was used to construct model for is constructed for relating KIs and PAs [14, 15].

Kansei Engineering involves much human evaluation data which usually contain considerable rough and ambiguous information with uncertainty and non-linear characteristics. Therefore it is very difficult to derive precise decision knowledge from such data [12, 16]. The nonlinearity and uncertainty inherent in the Kansei data have encouraged much research efforts to be put on the development of new tools for Kansei Engineering analysis.

3. The proposed method

Relative to the single prediction algorithm, combined forecasting method has advantages of high accuracy, good stability and reliability, which has been widely applied in the prediction field. Combining grey prediction and neural network to realize hydraulic pump's life prediction, machine tool thermal error and other industrial applications[17, 18], is proved one strong effective means. However, fewer is used to deal with the relationship between KIs and PAs for digital instrument interface. Therefore, the method in this study, which combines the grey prediction and neural network, is adopted to manage the relationship between KIs and PAs for digital instrument interface, and used to build model for the shortage of the statistical sample and poor information with uncertainty.

3.1 Grey prediction

According to the grey GM prediction model [19], it transforms the original sequence into differential equation and quantify the abstract model, and then implement the modeling and prediction in the absence of system feature indicator. The time data sequence was defined as follow $x^{(0)}$:

$$x^{(0)} = \left(x_t^{(0)} \middle| t = 1,2,...,n\right) = \left(x_1^{(0)}, x_2^{(0)}, ..., x_n^{(0)}\right) \tag{1}$$

Generate a new data sequence $x^{(1)}$ by accumulating the original sequence $x^{(0)}$, the $x^{(1)}$ at time t the sum of the original data sequence $x^{(0)}$ at time t before, where

$$x^{(1)} = (x_t^{(1)} | t = 1,2,...,n) = \left(x_1^{(0)}, \sum_{t=1}^{1} x_t^{(0)}, \sum_{t=1}^{2} x_t^{(0)}, ..., \sum_{t=1}^{n} x_t^{(0)}\right) \tag{2}$$

According to new data sequence $x^{(1)}$, build the albino equation calculated by

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = u \tag{3}$$

It can be solved by

$$x_t^{*(1)} = (x_1^{(0)} - u/a)e^{-a(t-1)} + u/a \tag{4}$$

$x_t^{*(1)}$ is the predicted value of $x_t^{(1)}$, and $x_t^{*(0)}$ is the predicted value of $x^{(0)}$, which can be accumulated by the accumulative subtraction of $x_t^{*(1)}$, where

$$x_t^{*(0)} = x_t^{*(1)} - x_{t-1}^{*(1)} \quad t = 2,3,...n \tag{5}$$

It is presented a law of exponential growth when sequence $x_t^{(1)}$ be accumulated by the accumulative addition of $x_t^{(0)}$. So it can be used with a continuous function or differential equation for data fitting and prediction.

3.1 BP neural network

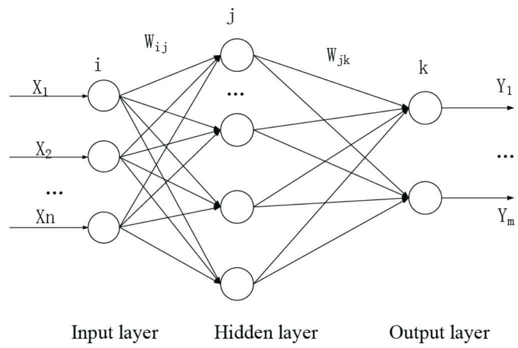

Figure 2. The BP neural network structure

BP neural network by the gradient descent method to cumulative value and threshold value to realize the minimum mean square error (MSE) of the actual output values and the desired output value for the network, and its structure is shown in Figure 2.

Its procedure involves the following six steps:

Step 1: Network initialization

$t = 2,3,...n$

where n is the number of network input layer node, l is the number of network hidden layer node, m is the number of network output layer node, w_{ij} is the weight between input layer and hidden layer, w_{jk} is the weight between hidden layer and output layer, o_k is the output value of the output layer, y_k is the expected output value, threshold of hidden layers $a = [\mathrm{a}_1, \mathrm{a}_2, \dots \mathrm{a}_l]$, Threshold of output layers $b = [\mathrm{b}_1, \mathrm{b}_2, \dots \mathrm{b}_m]$.

Step 2: Forward calculation

Output of hidden layer

$$h_j = f\left(\sum_{i=1}^{n} \mathrm{W}_{ij} x_i + \mathrm{a}_j\right), \; \mathrm{j} = 1,2,\ldots,l \tag{6}$$

Where f is the hidden layer incentive function, usually taking sigmoid function, x_i is the input node variables at i.

Output of output layer

$$o_k = f(\sum_{i=1}^{n} h_j w_{jk} + \mathrm{b}_k), \mathrm{k} = 1,2,\ldots,m \tag{7}$$

Step 3: Calculate the error between the output layer value o_k and the expected output value y_k

$$\delta_k = o_k(1-o_k)(y_k-o_k) \quad (8)$$

Step 4: Reverse distribution error value to the input layer nodes

$$\delta_j = h_j(1-h_j)\left(\sum_{i=1}^{n} W_{jk}\delta_k\right) \quad (9)$$

Step 5:Updating weights and threshold values , η is the learning efficiency

$$w_{ij}(t+1) = w_{ij}(t) + \eta h_j \delta_k \quad (10)$$

$$b(t+1) = b(t) + \eta\delta_k \quad (11)$$

$$w_{jk}(t+1) = w_{jk}(t) + \eta x_i \delta_j \quad (12)$$

$$a(t+1) = b(t) + \eta\delta_j \quad (13)$$

Step 6: Determine target error function J whether meet the requirements, return to step 2 if not satisfied

$$J = \frac{1}{2n}\sum_{p=1}^{n}\sum_{k=1}^{m}(y_k - o_k)^2 \quad (14)$$

In addition, the standard BP algorithm convergence speed is slow and easy to fall into local minimum value, many scholars have put forward various improved algorithms, such as the conjugate gradient method, gauss-newton method, Levenberg-Marquardt method, adaptive adjustment of learning rate and improved momentum method, etc.

3.2 Grey neural network model

In order to express conveniently, the original sequence $x_t^{(0)}$ is set as $x(t)$, the data sequence $x_t^{(1)}$ generated by accumulating the original sequence $x_t^{(0)}$ is set as $y(t)$, and predicting Outcome is set as $z(t)$.The differential equation of grey neural network model having n parameter is defined as pressed as

$$\frac{dy_1}{dt} + ay_1 = b_1y_2 + b_2y_3 + ... + b_{n-1}y_n \quad (15)$$

Where $y_2, y_3, ..., y_n$ are the system input parameters, y_1 is the output parameters, $a, b_1, b_2, ..., b_{n-1}$ are the coefficient of differential equation, time response of Formula (15) is calculated by

$$z(t) = \left(y_1(0) - \frac{b_1}{a}y_2(t) - \frac{b_2}{a}y_3(t) - ... - \frac{b_{n-1}}{a}y_n(t)\right)e^{-at} + \frac{b_1}{a}y_2(t) + \frac{b_2}{a}y_3(t) + ... + \frac{b_{n-1}}{a}y_n(t) \quad (16)$$

If

$$d = \frac{b_1}{a}y_2(t) + \frac{b_2}{a}y_3(t) + ... + \frac{b_{n-1}}{a}y_n(t)$$

Then the Formula (16) can be transformed to

$$z(t) = \left((y_1(0) - d) - y_1(0) \bullet \frac{1}{1+e^{-at}} + 2d\frac{1}{1+e^{-at}}\right) \bullet (1+e^{-at}) \quad (17)$$

Make the transformed Formula (17) map to an extended BP neural network can get the grey neural network which having n input parameters and one output parameter, the topology is shown in Figure 3.

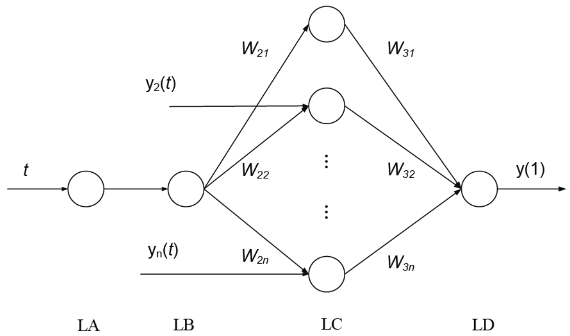

Figure 3. The grey neural network topology

Where the t is serial number for the input parameters, $y_2(t), y_3(t), ..., y_n(t)$ are the network input parameters, $y(1)$ is the network predicting value, w_{11}, w_{21}, w_{22}, w_{2n}, w_{31}, w_{32}, w_{3n} are the network weights, LA, LB, LC, LD represent the four layers of grey neural network structure respectively.

4. The application of grey neural network forecasting

Tachometer is widely used in the engine, motor, supercharger, reducer, motor, etc., especially in the intelligent cars, electric vehicles, aircraft and other special vehicles remote operation interface which occupying the position of the visual center, directly reflecting the operation state of the equipment. With the rapid development of computer communication and sensing technology, the wide use of digital tachometer become a trend. Therefore, this study selects the digital tachometer interface design as an example for digital instrument, using grey-neural network method to the Kansei engineering based nonlinear design by the following research.

4.1 The determination of design elements

First, extract the 31 frontier industrial digital tachometer samples that are widely from Internet and magazine under the premise that considering illumination, observation distance, as shown in Figure 4. Meanwhile, select the Kansei words through business investigation, operators and designers interview, and the literature analysis, and it is filtrated 4 groups of Kansei words from the 75 adjectives pair picked out from the behalf of the speed meter design with clear meanings using factor analysis, including “innovative-conservative”, “readable-difficult”, “technological-realistic”, “tough-soft”.

Second, it is found 8 representative interface design elements by cross compared the product attributes of digital tachometer, including “outline style”, “integral style”, “overall style”, “display pattern”, “main color”, “display style”, “font style” and “dial style”. In view of the “outline style” is limited by a digital tachometer application scenarios, it is not re-

Figure 4. Industrial digital tachometer samples

searched as influencing factors of interface Kansei image, and each design element is decomposed into several different interface design categories, as shown in table 1.

Table 1. Digital tachometer interface design elements

Design element	Category				
	1	**2**	**3**	**4**	**5**
Outline style $\mathbf{X_0}$	Round	Oval	Semicircular	Fan-shaped	
Integral style $\mathbf{X_1}$	Vertical	Flat			
Overall style $\mathbf{X_2}$	Loose	Compact			
Display pattern $\mathbf{X_3}$	Static	Dynamic			
Main color $\mathbf{X_4}$	White	Orange	Blue	Green	Secondary colors
Display style $\mathbf{X_5}$	Pointer	Text type	Hybrid		
Font style $\mathbf{X_6}$	Sharp	Vigorous	Smooth		
Dial style $\mathbf{X_7}$	Lattice	Line array	Area array	Hybrid	

Finally, use the 7-point scale (1-7) of semantic differences method and select 50 expert to investigate, to score the above 4 groups Kansei words; "technological-realistic" is selected as an example to discuss in this study, that the option 1 indicates that tend to be "realistic", select 4 is said for the evaluation of the sample in a neutral attitude, choose 7 is said tend to "technological". The Kansei image evaluation space composed of results of the survey is shown in table 2.

Table 2. The Kansei image evaluation space for "technological-realistic"

Samples	$\mathbf{X_1}$	$\mathbf{X_2}$	$\mathbf{X_3}$	$\mathbf{X_4}$	$\mathbf{X_5}$	$\mathbf{X_6}$	$\mathbf{X_7}$	Evaluating value
1	2	1	1	1	3	3	1	2.81
2	2	1	2	1	2	2	4	4.36
3	2	1	1	4	2	1	4	3.82
4	2	2	1	1	3	2	2	2.24
5	2	1	1	2	1	3	2	3.79
6	1	1	2	5	2	2	3	5.38
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
26	2	1	1	1	2	3	2	3.78
27	2	1	1	3	1	3	2	4.16
28	2	1	2	3	2	3	2	5.07
29	2	2	1	4	3	1	3	3.29
30	1	2	2	3	1	3	4	4.43
31	2	2	2	5	3	1	4	4.09

4.2 Establish grey neural network prediction model

The Kansei image prediction algorithm process for digital tachometer based on grey neural network (GNN) is shown in Figure 5. Combining with the research in 4.1, the interface design elements which is 7 dimension data is the input, and the Kansei image which is 1 dimension data is the output layer, of which constitute the grey neural network model with 1-1-8-1 structure. Namely, there is 1 node in LA layer, whose input is time series t, 1 node LB in layer, 8 nodes in LC layer, the unitary data of 2-6 are “integral style”, “overall style”, “display pattern”, “main color”, “display style”, “font style” and “dial style” respectively.

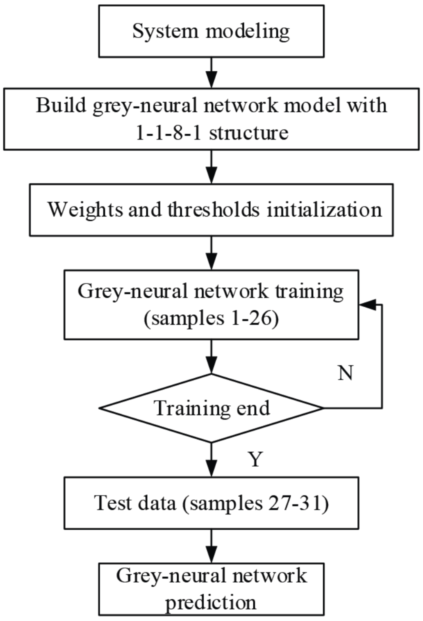

Figure 5. Kansei image prediction algorithm process for digital tachometer based on GNN

The former 26 samples is trained based on the proposed above method with MATLAB, Figure 6 is shown the fitting results, which the network learning evolution is set 100 times. The trained grey neural network model is established in the nonlinear mapping relationship between the input layer (design elements) and the output (Kansei word value), providing ability to predict the any other similar sample.

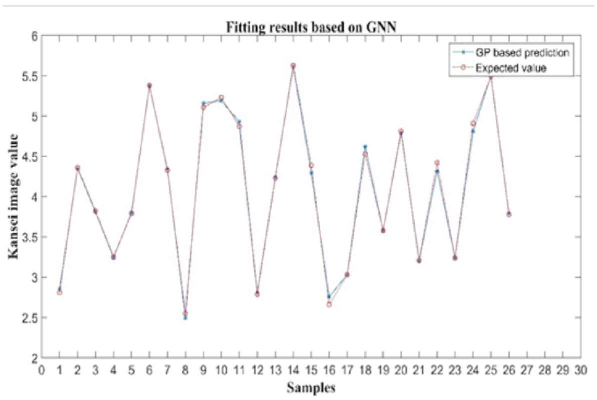

Figure 6. Fitting results based on GNN

4.3 Analysis of experimental results

Use the last 5 samples in table 2 to test the performance of network, it can be seen coincidence basically through the comparison between predicted output values and the expected value. The results of single grey prediction, BP neural network and grey neural network are shown in Figure 7, Figure 8 and Figure 9 respectively, indicating that the established grey neural network implemented the correct mapping between the design elements (product attributes) and the Kansei image. Furthermore, grey neural network was shown better prediction accuracy reaching 98.56%, while the grey prediction and the BP neural network prediction was 95.97% and 96.75%, verifying the validity of proposed method.

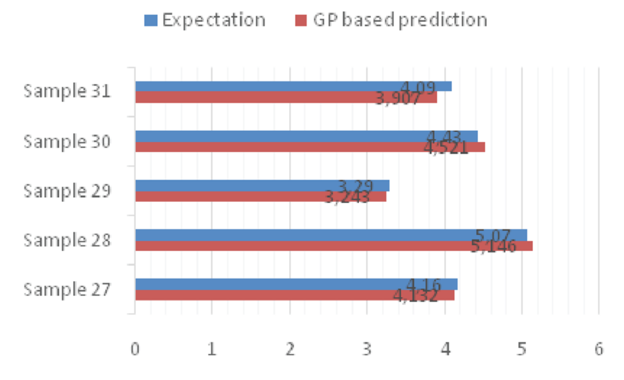

Figure 7. Results comparison between GP based prediction and expected value

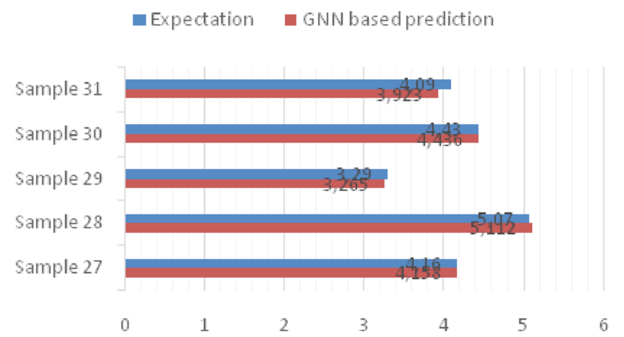

Figure 8. Results comparison between BP based prediction and expected value

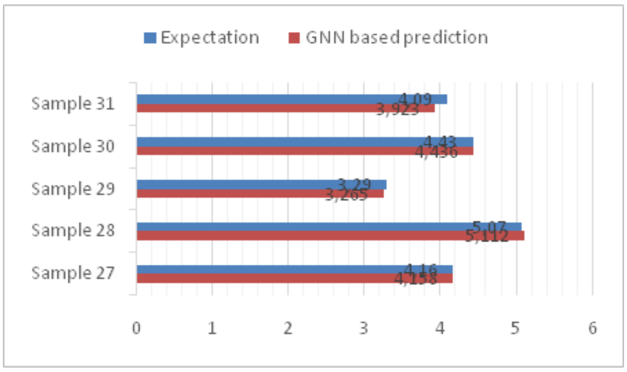

Figure 9. Results comparison between GNN based prediction and expected value

At the same time, there were existing 1440 (2*2*2*5*3*3*4) kinds of designing scheme for the digital tachometer interface design in the Kansei word pair "technological-realistic". The maximum value of evaluation based on GNN is 5.631, minimum value is 2.251. The corresponding combination of design elements numbers can be found "1 1 2 3 2 3 3"and "2 2 1 1 3 2 2" respectively associated with the table 1, which represented the optimized "technological" and "realistic", as shown in table 4.

Table 3. Corresponding combination of design elements numbers for optimized Kansei words

Design element	Optimized "technological"	Optimized "realistic"
Integral style $\mathbf{X}_1$	Vertical	Flat
Overall style $\mathbf{X}_2$	Loose	Compact
Display pattern $\mathbf{X}_3$	Dynamic	Static
Main color $\mathbf{X}_4$	Blue	White
Display style $\mathbf{X}_5$	Text type	Hybrid
Font style $\mathbf{X}_6$	Smooth	Vigorous
Dial style $\mathbf{X}_7$	Area array	Line array

5. Conclusion

The interface design of digital instrument has become an important part of the human-machine interface design and development in the field of industry control. It is a pressing task for digital meter designers and companies on how to get and understand users' Kansei demand and match the design scheme effectively. In practice, the digital instrument interface designers in industrial circle must face the typical nonlinear and uncertainty of the relationship between Kansei images and product attributes, and the shortage of the statistical sample, which can't been done well by the traditional quantification theory type I and neural network which involving a large volume representative training samples.

It is conducted thorough research in this study to the problem of nonlinear processing method, pointed out a new way that using combinatorial methods to solve the complex problem of small samples and poor information, and then put forward the GNN to deal with the relationship between ARs and PAs for digital instrument interface.

Combined with digital tachometer interface design as an example, this study uses the gray neural network fitting the nonlinear mapping relationship between user Kansei image "technological-realistic" and 7 design elements (product attributes), establishing the dependable mathematical forecasting model.

It is confirmed that the grey-neural network has good prediction ability by comparing the gray prediction and BP neural network, fully embodying its feasibility in solving the nonlinear relationship between user Kansei images and design elements of digital instrument interface design, providing scientific basis for designers and decision makers to select digital instrument design schemes and shorten the interface design and development cycle.

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Optimization and Experiment on the Main Direction of Incremental Forming

Guangcheng Zha[1,2], Xiaofan Shi[1,2], Wei Zhao[1,2], Fanxin Kong[1,2], Chuankai Lu[1], Menglin Wu[1,2]

[1] School of Materials Science and Engineering, Nanjing Institute of Technology, Nanjing 211167, Jiangsu, China
[2] Jiangsu Key Laboratory of Advanced Structural Materials and Application Technology, Nanjing 211167, Jiangsu, China