Grey Relational Analysis based Artificial Neural Networks for Product Design: A Comparative Study

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Abstract: Artificial neural networks (ANNs) have been applied successfully in a wide range of fields due to its effective learning ability. In this paper, we propose a grey relational analysis (GRA) based ANN model that can be used to build a design decision support database for facilitating the product design process and matching specific consumers' preferences. The result of an empirical application and a comparative study on fragrance bottle form design shows that the ANN models outperform the grey prediction models, indicating that the ANN technique is promising to help product designers design a new product that best meets consumers' needs.

1 INTRODUCTION

An artificial intelligent system is defined as an emerging approach to learning and reasoning with the human mind in an uncertainty and imprecision environment (Jang et al., 1997; Lin et al., 2012). The techniques applied in the artificial intelligent system are supposed to possess humanlike expertise within a specific domain, adapt themselves and learn to do better in changing environments, and explain how they makes decisions (Jang et al., 1997). As an artificial intelligent technique, artificial neural networks (ANNs) have been applied successfully in a wide range of fields (Lai et al., 2005; Lin et al., 2012; Negnevitsky, 2002) due to its effective learning ability.

Shiizuka (2011) has revealed that the 21st century is a human-centered century, while the 20th century is called a machine-centered century. The key factor that influences the success of a new product is capturing the "voice of consumers" (Wang, 2011). However, how to grasp consumers' preferences accurately and to design products that match their needs is indeed a major challenge for product designers (Wang, 2011). To address this challenge, we adopt the ANN technique in this paper to formulate a consumer-oriented product design process (Lai et al., 2005; Lin et al., 2014). Moreover, the grey relational analysis (GRA) and grey prediction (GP) technques used in a grey system (Deng, 1982) are also used in this paper, as they can be used to explore the relationship between product design elements and consumers' preferences, where the information available is grey, meaning uncertain and incomplete (Lai et al., 2005). GRA and GP have been successfully used in a wide range of fields, including some research application results highlighting their effective handling of incomplete known information for exploring unknown information (Lai et al., 2005; Lin et al., 2012; Yang, 2011).

In this paper, we conduct an empirical application and a comparative study on fragrance bottle form design by using GRA, ANNs and GP, to find out what specific technique can be used to help product designers determine the optimal form combination of product design that best meets consumers' needs for a desirable product image.

2 METHODOLOGY

In this section, we briefly present the GRA, ANNs, and GP methods used.

2.1 Grey Relational Analysis (GRA)

A grey system (Deng, 1982) can be built to answer specific research questions in product design with respect to product form and product image, which are grey in essence. This is because there is no way

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to identify all the product form elements that affect a particular product image perceived by consumers (Lai et al., 2005; Yang, 2011). The GRA is used to determine the relationship (similarity) between two series of stochastic data in a grey system. One is the reference series, and the other is the comparison series. If the GRA value of the element *i* is higher than the element *j*, then the element *i* is closer to the reference than the element *j*. In the application of product design, the GRA is used to identify the most influential elements of product form for a given product image (Lai et al., 2005).

2.2 Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) are non-linear models and are widely used to examine the complex relationship between input variables and output variables. The ANNs have been applied successfully in a wide range of fields, using various learning algorithms (Negnevitsky, 2002). The ANNs are well suited to formulate the product design process for matching product design elements (the input variables) to consumers' preferences (the output variables), which is often a black box and cannot be precisely described (Lai et al., 2005; Lin et al., 2014). In this paper, we use the multilayered feedforward ANNs trained with the backpropagation learning algorithm, as it is an effective and the most popular supervised learning algorithm (Negnevitsky, 2002).

2.3 Grey Prediction (GP)

The GP model uses a grey differential model (GM) to generate data series from the original data series of a dynamic system (Deng, 1982). The data series generated by the GM are converted back to the original data series by a reverse procedure to predict the performance of the system (Lai et al., 2005). Since the generated data series are more coherent than the original, the accuracy of the modelling is enhanced. The GM has three basic operations (Deng, 1982): (1) accumulated generation, (2) inverse accumulated generation, and (3) grey modelling. The accumulated generation operation (AGO) is used to build differential equations. The GM is usually represented as *GM(M,N)* for dealing with *Mth*-order differential equations with *N* variables (Lai et al., 2005). Since any higher-order differential equation can be transferred into a first-order differential equation, we use the first-order differential equation in this paper.

3 AN EMPIRICAL APPLICATION

This section addresses how the GRA based ANNs can be used to model the consumer-oriented product design process. As an illustration, we have conducted a consumer-oriented experiment on fragrance bottle form design, due to its wide variety of appearances (Wei et al., 2011; Lin and Wei, 2014).

3.1 The Consumer-oriented Experiment on Fragrance Bottle Form Design

In previous studies (Wei et al., 2011; Lin and Wei, 2014), we have investigated and categorized various world-famous fragrances. As a result of a morphological analysis, seven product form elements and 21 associated product form types have been identified, as shown in Table 1 (Wei et al., 2011). The seven product form elements are "Transparency of bottle top (x_1)", "Shape of bottle top (x_2)", "Shape of bottle body (x_3)", "Texture of bottle body (x_4)", "Transparency of bottle body (x_5)", "Width ratio of bottle body (x_6)", and "Bottleneck (x_7)".

Table 1: The result of morphological analysis.

	Type 1	Type 2	Type 3	Type 4	Type 5
Transparency of bottle top (x_1)	Transparent (x_{11})	Opaque (x_{12})			
Shape of bottle top (x_2)	Sphere (x_{21})	Pie (x_{22})	Cylinder (x_{23})	Cuboid (x_{24})	Irregular (x_{25})
Shape of bottle body (x_3)	Sphere (x_{31})	Cylinder (x_{32})	Cuboid (x_{33})	Trapezoid (x_{34})	
Texture of bottle body (x_4)	Smooth (x_{41})	Textured (x_{42})			
Transparency of bottle body (x_5)	Transparent (x_{51})	Matte (x_{52})	Opaque (x_{53})		
Width ratio of bottle body (x_6)	Narrow (x_{61})	Wide (x_{62})			
Bottleneck (x_7)	Connected the bottle (x_{71})	Independent bottleneck (x_{72})	No bottleneck (x_{73})		

According to the morphological analysis, the fragrance bottle sample can be coded by the value of 1, 2, 3, 4 or 5, if it has a particular design element type for each of its seven product form elements, as shown in Table 2. For each selected fragrance bottle sample in Table 2, the first column shows the fragrance bottle sample number and Columns 2-8 show the corresponding type number for each of its seven product form elements, as given in Table 1. Additionally, in this paper, we use two image words, "Quiet-Energetic (Q-E)" and "Rational-Emotional (R-E)", to represent consumers' preferences as shown in the last two columns of Table 2. Table 2 provides a numerical data source for the quantitative analyses (GRA, ANNs, and GP), which can be used to develop a hybrid consumer-oriented model.

Table 2: Product form elements and consumers' preferences.

No.	X_1	X_2	X_3	X_4	X_5	X_6	X_7	*Q-E*	*R-E*
1	2	2	2	1	2	2	2	3.08	3.19
2	2	2	2	1	2	2	2	4.12	4.15
3	2	1	2	1	2	2	2	3.23	5.35
4	2	2	2	1	2	2	2	3.96	2.77
5	2	2	2	1	1	2	1	3.62	3.65
6	1	2	2	1	3	2	2	4.27	3.19
7	1	1	1	1	1	1	2	4.38	5.77
8	1	2	3	2	1	1	2	4.35	5.04
9	2	2	3	1	1	1	2	3.73	3.27
10	2	3	3	1	3	1	2	3.81	1.77
11	2	2	3	1	3	2	2	3.19	2.00
12	2	3	2	1	1	2	1	3.85	3.50
13	2	3	2	1	1	2	1	4.31	3.15
14	2	3	3	1	2	2	1	3.42	3.50
15	2	3	2	1	1	2	3	4.00	5.04
16	2	3	2	1	2	2	3	4.04	4.27
17	2	3	2	1	2	2	3	3.50	2.54
18	2	3	2	2	3	2	3	3.73	5.65
19	2	3	2	1	2	2	3	3.50	4.08
20	2	3	2	2	2	2	3	4.19	3.85
21	2	4	3	1	2	1	3	4.19	4.38
Test 1	2	5	3	1	2	2	3	3.77	3.12
Test 2	2	4	4	1	2	2	3	4.73	5.12
Test 3	2	5	4	1	1	2	2	3.69	4.42
Test 4	2	3	4	1	2	2	2	3.42	4.46
Test 5	2	3	4	2	1	2	2	4.38	5.12
Test 6	1	5	4	2	2	1	2	3.77	3.12

3.2 GRA to Identify the Influential Product Form Elements

We perform the GRA to determine the most influential form elements of fragrance bottles for the Q-E and R-E image words, using the 21 training samples shown in Table 2. The GRA calculates the grey relational degree between each comparison series and the reference series. In this paper, the comparison series are the seven form elements, whose values are given in Columns 2-8 of Table 2. The reference series are the average Q-E and R-E image values respectively, as given in the last two columns of Table 2.

Table 3 shows the GRA value between the image words and the form elements, with the values ranging from 0 to 1. Each of the seven form elements is obtained by the GRA. The higher the GRA value, the more influential the form element. Table 3 shows that "Shape of bottle top (x_2)" form element affects the Q-E and R-E images the most (the highest GRA value of 0.674 and 0.687, respectively), followed by "Shape of bottle body (x_3)" (the GRA value of 0.643 and 0.658). This implies that the product designers should focus their attention more on these most influential form elements, when the design objective is to achieve the desirable Q-E and R-E images.

Table 3: The result of GRA.

GRA	*Q-E*	Ranking	*R-E*	Ranking
x_1	0.521	7	0.513	7
x_2	0.674	1	0.687	1
x_3	0.643	2	0.658	2
x_4	0.561	4	0.584	5
x_5	0.553	5	0.624	3
x_6	0.522	6	0.536	6
x_7	0.601	3	0.620	4

On the contrary, the product designers can pay less attention to the less influential form elements, such as "Transparency of bottle top (x_1)" (the lowest GRA value of 0.521 and 0.513, respectively), and "Width ratio of bottle body (x_6)" (the GRA value of 0.522 and 0.536), as these form elements contribute relatively little to the consumers' preferences of the Q-E and R-E images on the fragrance bottle form design.

In this paper, the result of GRA is not only used to determine the most influential form elements, but is also used as a basis to construct the ANN and GP models, as presented in the following section.

3.3 Analysis of ANNs

In order to determine the relationship between the product form elements and the consumers' preferences, we develop nine ANN models (3*3=9), called ANN, GRA-1-ANN, and GRA-2-ANN, respectively. Each model is associated with the following three most widely used rules (labelled as -HN1, -HN2, and -HN3, respectively) (Lai et al., 2005):

(The number of input neurons + the number of output neurons) / 2 (1)
(The number of input neurons * the number of output neurons) ^ 0.5 (2)
(The number of input neurons + the number of output neurons) * 2 (3)

Each rule is used to determine the number of hidden neurons in the single hidden layer. In the ANN models, the 21 form types of the seven form elements in Table 1 are used as the 21 input variables (neurons). If the fragrance bottle has a particular form type, the value of the corresponding input neuron is 1; otherwise, the value is 0. The ANN models combine the two consumers' preferences as two output neurons, using the average Q-E and R-E image values respectively. Based on the GRA result, the GRA-1-ANN models use the six most influential form elements (i.e. excluding the least influential form element, the lowest GRA value), while GRA-2-ANN models use the five most influential form elements (i.e. excluding the two least influential form elements). Consequently, the GRA-1-ANN models have 19 input neurons (21-2=19, two form types of x_1), and the GRA-2-ANN models have 17 input neurons (21-2-2=17, two form types of x_1 and two form types of x_6). Table 4 shows the neurons of the total nine ANN models, including the input layer, hidden layer, and output layer.

Table 4: Neurons of the nine ANN models.

ANN models: Input layer: 21 neurons for 21 types of 7 form elements. Output layer: 2 neurons for the Q-E and R-E images. HN1: Hidden layer: 12 neurons, (21+2)/2=11.5=12. HN2: Hidden layer: 6 neurons, (21*2)^0.5=6.48=6. HN3: Hidden layer: 46 neurons, (21+2)*2=46.
GRA-1-ANN models: Input layer: 19 neurons for 19 types of 6 most influential form elements. Output layer: 2 neurons for the Q-E and R-E images. HN1: Hidden layer: 11 neurons, (19+2)/2=10.5=11. HN2: Hidden layer: 6 neurons, (19*2)^0.5=6.16=6. HN3: Hidden layer: 42 neurons, (19+2)*2=42.
GRA-2-ANN models: Input layer: 17 neurons for 17 types of 5 most influential form elements. Output layer: 2 neurons for the Q-E and R-E images. HN1: Hidden layer: 10 neurons, (17+2)/2=9.5=10. HN2: Hidden layer: 6 neurons, (17*2)^0.5=5.83=6. HN3: Hidden layer: 38 neurons, (17+2)*2=38.

The 21 fragrance samples in the training set, given in Table 2, are used to train the ANN models. The learning rule used is Delta-Rule and the transfer function is Sigmoid for all layers. Additionally, the learning rate and momentum are both 0.5. When the cumulative training epochs are over 10,000, the training process is completed.

3.4 Analysis of GP

In this paper, we develop six GP models. Each of two image words has three GP models, called GP, GRA-1-GP, and GRA-2-GP, respectively. The GP model includes all the seven form elements identified from the experimental study, while the GRA-1-GP model uses the six most influential form elements (i.e. excluding the least influential form element) resulting from GRA. In addition, GRA-2-GP model uses the five most influential form elements. The 21 training samples given in Table 2 are used as the data set for building these six GP models. The result of GP shows that Equations (4), (5), and (6) can be used to predict the value of the Q-E image, while Equations (7), (8), and (9) can be used for predicting the R-E image.

$$GP(Q\text{-}E)= [3.08-0.337x_1^{(1)}(k+1)+1.103x_2^{(1)}(k+1)-0.767x_3^{(1)}(k+1)-1.397x_4^{(1)}(k+1)+0.298x_5^{(1)}(k+1)-1.646x_6^{(1)}(k+1)-0.209x_7^{(1)}(k+1)]\ e^{-0.584k}+0.337x_1^{(1)}(k+1)-1.103x_2^{(1)}(k+1)+0.767x_3^{(1)}(k+1)+1.397x_4^{(1)}(k+1)-0.298x_5^{(1)}(k+1)+1.646x_6^{(1)}(k+1)+0.209x_7^{(1)}(k+1) \quad (4)$$

$$GRA\text{-}1\text{-}GP(Q\text{-}E)= [3.08+1.008x_2^{(1)}(k+1)-0.890x_3^{(1)}(k+1)-1.268x_4^{(1)}(k+1)+0.293x_5^{(1)}(k+1)-1.740x_6^{(1)}(k+1)-0.242x_7^{(1)}(k+1)]\ e^{-0.628k}-1.008x_2^{(1)}(k+1)+0.890x_3^{(1)}(k+1)+1.268x_4^{(1)}(k+1)-0.293x_5^{(1)}(k+1)+1.740x_6^{(1)}(k+1)+0.242x_7^{(1)}(k+1) \quad (5)$$

$$GRA\text{-}2\text{-}GP(Q\text{-}E)= [3.08+2.239x_2^{(1)}(k+1)+0.050x_3^{(1)}(k+1)-1.005x_4^{(1)}(k+1)-4.995x_5^{(1)}(k+1)+0.025x_7^{(1)}(k+1)]\ e^{-0.201k}-2.239x_2^{(1)}(k+1)-0.050x_3^{(1)}(k+1)+1.005x_4^{(1)}(k+1)+4.995x_5^{(1)}(k+1)-0.025x_7^{(1)}(k+1) \quad (6)$$

$$GP(R\text{-}E)= [3.19-0.024x_1^{(1)}(k+1)+1.133x_2^{(1)}(k+1)-0.085x_3^{(1)}(k+1)-2.305x_4^{(1)}(k+1)+1.113x_5^{(1)}(k+1)-2.533x_6^{(1)}(k+1)-0.684x_7^{(1)}(k+1)]\ e^{-0.709k}+0.024x_1^{(1)}(k+1)-1.133x_2^{(1)}(k+1)+0.085x_3^{(1)}(k+1)+2.305x_4^{(1)}(k+1)-1.113x_5^{(1)}(k+1)+2.533x_6^{(1)}(k+1)+0.684x_7^{(1)}(k+1) \quad (7)$$

$$GRA\text{-}1\text{-}GP(R\text{-}E)= [3.19+1.128x_2^{(1)}(k+1)-0.097x_3^{(1)}(k+1)-2.289x_4^{(1)}(k+1)+1.111x_5^{(1)}(k+1)-2.537x_6^{(1)}(k+1)-0.689x_7^{(1)}(k+1)]\ e^{-0.713k}-1.128x_2^{(1)}(k+1)+0.097x_3^{(1)}(k+1)+2.289x_4^{(1)}(k+1)-1.111x_5^{(1)}(k+1)+2.537x_6^{(1)}(k+1)+0.689x_7^{(1)}(k+1) \quad (8)$$

$$GRA\text{-}2\text{-}GP(R\text{-}E)= [3.19-0.003x_2^{(1)}(k+1)-2.379x_3^{(1)}(k+1)-0.806x_4^{(1)}(k+1)+3.772x_5^{(1)}(k+1)-1.836x_7^{(1)}(k+1)]\ e^{0.372k}+0.003x_2^{(1)}(k+1)+2.379x_3^{(1)}(k+1)+0.806x_4^{(1)}(k+1)-3.772x_5^{(1)}(k+1)+1.836x_7^{(1)}(k+1) \quad (9)$$

4 PERFORMANCE EVALUATION AND DESIGN DECISION SUPPORT

To evaluate the performance of the nine ANN and six GP models developed in this paper in terms of their prediction ability in determining the combination of form elements for matching a given set of image words, the six test samples identified in Table 2 are used. Rows 3 and 4 of Table 5 show the average image values (i.e. Q-E and R-E) of the six test samples assessed by 26 participants, which are used as a comparison base for the performance evaluation. With the six test samples as the input, Table 5 shows the corresponding image values predicted by using the ANN, GRA-1-ANN, GRA-2-ANN, GP, GRA-1-GP, and GRA-2-GP models, respectively. The last column of Table 5 shows the root mean squared error (RMSE) of these models in comparison with the assessed image values. To evaluate the performance of a model, the RMSE is commonly used, given as:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}\left(x_i - x_{0(i)}\right)^2}{n}} \tag{10}$$

where x_i is the *i-th* output value predicted by the model and $x_{0(i)}$ is the expected values assessed by the participants in this paper. If there is no difference or error between the predicted value and the assessed value, the RMSE is 0.

The RMSE given in the last column of Table 5 is normalized, with the values (the assessed values and the predicted values) being transformed into a value between 0 and 1. As indicated in Table 5, the RMSE value of ANN-HN1 model for Q-E image is 0.12. This result indicates that this model has an accuracy rate of 88% (100%-12%) for predicting the value of Q-E image about fragrance bottles. Table 5 shows that the average RMSE value of GRA-1-ANN-HN1 model (0.14) is the smallest, followed by the ANN-HN1, ANN-HN2, and GRA-1-ANN-HN3 models (0.16). It indicates the GRA-1-ANN-HN1 model is the best or most suitable for modeling the consumers' preferences about fragrance bottles. Moreover, it is noteworthy that the RMSE of the ANN models is smaller than the GP models. This implies that the prediction performance of the ANN models is better than the GP models. In other words, the ANN models are a more effective technique to formulate the product design process for determining the optimal combination of product form elements to best match to desirable product images (Lai et al., 2005).

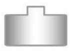
Table 5: RMSE of the ANN and GP models developed.

	Image	Test sample T1	T2	T3	T4	T5	T6	RMSE	
Consumers	Q-E	3.77	4.73	3.69	3.42	4.38	3.77		
	R-E	3.12	5.12	4.42	4.46	5.12	3.12		
ANN-HN1	Q-E	2.79	4.01	3.57	3.81	4.88	4.92	0.12	0.16
	R-E	5.32	4.34	4.25	3.35	4.30	4.03	0.19	
ANN-HN2	Q-E	3.69	3.72	4.25	4.12	4.71	4.93	0.12	0.16
	R-E	3.82	4.23	3.44	3.29	5.22	5.38	0.20	
ANN-HN3	Q-E	2.93	4.02	4.22	4.57	5.81	5.57	0.19	0.21
	R-E	4.85	4.18	3.48	3.00	3.80	4.71	0.23	
GRA-1-ANN-HN1	Q-E	3.38	3.99	3.92	4.00	4.77	4.68	0.10	0.14*
	R-E	3.67	4.26	3.19	3.03	4.76	4.84	0.19	
GRA-1-ANN-HN2	Q-E	2.50	4.12	3.76	4.07	4.98	5.10	0.14	0.17
	R-E	3.60	5.09	3.60	3.14	5.23	5.38	0.19	
GRA-1-ANN-HN3	Q-E	2.80	3.89	4.06	4.13	4.99	5.19	0.15	0.16
	R-E	4.69	4.28	3.68	3.09	4.90	4.14	0.18	
GRA-2-ANN-HN1	Q-E	3.47	4.76	4.54	4.33	6.00	5.35	0.18	0.17
	R-E	4.06	5.03	3.53	3.12	4.84	4.49	0.16	
GRA-2-ANN-HN2	Q-E	2.95	4.86	4.13	3.73	5.43	5.06	0.13	0.17
	R-E	3.98	4.67	3.26	2.54	4.37	4.99	0.22	
GRA-2-ANN-HN3	Q-E	3.43	4.83	5.03	4.29	5.68	5.94	0.21	0.20
	R-E	4.44	3.76	3.26	2.75	4.23	3.34	0.20	
GP	Q-E	1.60	2.43	1.98	2.82	3.57	1.59	0.25	0.28
	R-E	1.58	2.20	1.84	2.43	4.16	1.15	0.30	
GRA-1-GP	Q-E	1.79	2.68	2.23	3.04	3.76	1.88	0.22	0.26
	R-E	1.60	2.22	1.86	2.44	4.18	1.17	0.30	
GRA-2-GP	Q-E	0.52	0.92	0.39	1.33	0.61	0.70	0.47	0.34
	R-E	2.00	3.07	3.94	2.24	4.30	2.60	0.20	

Consequently, product designers can use the GRA-1-ANN-HN1 model to build a fragrance bottle design decision support database that can be generated by inputting each of all possible combinations (1,440, 2×5×4×2×3×2×3) of product form elements for generating the associated image values. In other words, 1,440 design alternatives generated by the GRA-1-ANN-HN1 model can be chosen to best match specific consumers' preferences. Product designers can also specify a desirable image value for a new fragrance bottle form design, and the design decision support database can then work out the optimal combination of form elements. For example, the product designer can use a computer-aided design (CAD) or a computer-aided manufacture (CAM) system to facilitate the product design in the new fragrance development process. As an illustration, Figure 1 shows the new fragrance bottle form design by CAD/CAM system with "rational" image, and Table 6 shows its corresponding combination of form elements (out of 1,440 design alternatives).

Figure 1: The new fragrance bottle design with the "rational" image.

Table 6: The optimal combination of form elements for the new fragrance bottle design with "rational" image.

	Form element	Form type
x_2	Shape of bottle top	 Irregular (x_{25})
x_3	Shape of bottle	 Spheres (x_{31})
x_4	Texture of bottle	 Smooth (x_{41})
x_5	Transparency of bottle	 Opaque (x_{53})
x_6	Width ratio of bottle	 Wide (x_{62})
x_7	Bottleneck	 Independent bottleneck (x_{72})

5 CONCLUSIONS

In this paper, we have built a GRA-based ANN model for best matching specific consumers' preferences in the fragrance bottle form design. The result of the comparative study has shown the ANN models have a higher prediction performance than the GP models, indicating that the ANN is a promising technique to model the consumer-oriented product design process. In addition, the design decision support database generated by the GRA-based ANN model can help product designers comprehend consumers' preferences for a specific form design of fragrance bottle. Although the fragrance bottle is chosen as the experimental sample product, the GRA-based ANN model presented can be applied to other consumer products with various design elements.

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