Optimal Design of Product Culture Image Modeling Based on FNN Model and PSO Algorithms

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Abstract: In order to solve the problem of strong subjectivity of cultural image modeling design in today's market and single optimization result caused by product cultural image transformation design method, the evaluation method of product cultural image modeling based on FNN model and the optimization design method of product cultural image modeling based on PSO algorithm were both proposed. Firstly, the representative samples were determined, and the cultural images were sorted out and classified to quantify the shape parameters of the samples; then, the membership function of the product shape parameters was established to fuzzify them, and the mapping relationship between the "product shape parameters-cultural image fitness" was obtained by using three-layer BP neural network, and the evaluation method of the product cultural image modeling was established; By updating the speed and position of representative sample population, adjusting its modeling parameters based on PSO algorithm, the optimization design mechanism of product cultural image modeling was established. Finally, taking the design optimization design of Miao embroidery products in Songtao area of Guizhou Province as an example, the results showed that the optimization design method could well adapt to the optimization design of cultural image modelling and had injected new vitality into cultural creative design.

1. Introduction
Cultural products can not only meet the basic needs of users for functions, but also bring users cultural emotional enjoyment, making products more popular with consumers. Today's wave of cultural design makes the purpose of design not only to give products meaningful functions, but to convey a cultural spirit and concept to users. The purpose of this paper is to find an optimal design method that can make the product modeling elements and cultural images one by one correspond to each other, so as to improve the accuracy of cultural images in product expression.

Cultural image is a cultural symbol with relatively fixed meanings and profound associations[1]. Cultural products, with their unique modeling elements and rich cultural connotations, make people feel the profound connotation behind products and trigger corresponding images. Document [2] applied Chinese traditional architectural elements to furniture design. Document [3–4] respectively explored the design strategy oriented by cultural image recognition and the application of semiotic theory to cultural image design in Jiangnan region. However, the above-mentioned literature lacks effective integration with computer technology in the study of the relationship between cultural image and product form, which is not conducive to the development of computer-aided image design.

At present, many scholars at home and abroad have carried out relevant research on how to apply evolutionary algorithm to product image modeling design. For example, document [5] put forward the optimization design method of product image modelling based on genetic algorithm, used multi-
dimensional scale method and morphological analysis method to analyze product modelling features, and then obtained the quantitative relationship between modelling features and perceptual images by a quantitative method, and finally carried out genetic optimization to obtain the design scheme. In literature [6], the mapping relationship between high-speed train design module library and sensory image set was obtained by using text mining method and BP neural network, which provided effective assistance and support for high-speed train modeling design. Literature [7] established and improved the neural network model of product design evaluation. The feasibility and validity of the model were validated by taking the design of garden tool mower as an example. The mapping relationship between design parameters and product perceptual image was obtained by using support vector machine in document [8]. In document [9], the improved particle swarm optimization algorithm was used to optimize the radial basis function artificial neural network, and a prediction model was established. The color emotion of each user was predicted by the model. The above scholars have achieved good research results in seeking the mapping relationship between perceptual image and the elements of morphological design.

However, the above research focuses on the matching between the implicit perceptual needs of users and the elements of product shape, and lacks the design method of mapping cultural images into product shape. Therefore, with the deepening of research and the help of computer technology, effective improvement measures are provided to solve the problems of strong subjectivity in cultural image modelling design and single optimization result caused by image transformation design method. Based on this, this study uses the fuzzy neural network to objectively evaluate the perceptual part of the cultural image which is difficult to say clearly, and to establish the mapping relationship between the cultural image and the shape. In order to provide reference and support for the further programmability and intellectualization of creative product design, a computer-aided optimization design method for cultural image products is proposed, which combines the excellent searching ability of particle swarm optimization algorithm to optimize and innovate product multi-modeling schemes.

The full-text framework is shown below.

![Optimum design process of cultural image modelling](image-url)
2. Initialization of Product Culture Image Modeling Design

Initialization of cultural image modeling of cultural products includes collecting information of cultural image perceived by users and parameterization of product shape. Because the product color factor can interfere with the user’s perception of the product, the color factor is not taken into account in the analysis of product modeling parameters. The research process of this part can be divided into three stages (Fig. 2).

2.1. Collection of Product Samples and Analysis of Cultural Images
Collect product samples in cultural theme websites, newspapers, books, magazines, and related literature, then conduct preliminary screening. Through the analysis of three levels of consumer cognitive matching model of regional cultural image, it is concluded that the implicit value layer of cultural image contains the most cultural semantic information and has the most cultural identification. Therefore, exploring the spiritual connotations contained in cultural products and translating the semantics and vocabulary are the preconditions for the next step of cultural image semantics selection.

2.2. Selection of the Meaning of Cultural Images
For the semantic selection of cultural images in a certain region, through field research, expert interviews, reading literature and other methods to collect images and image vocabulary describing cultural products, combined with Semantic Differential Method (SD), Rough Semantic Set $A$ which is more in line with the local cultural image is selected from a large number of vocabulary.

\[ A = \{A_1, A_2, \ldots, A_n\} \]

In formula, $A_i = \{a_{i1}, a_{i2}\}$, $i = 1, 2, \ldots, n, a_{i1}$ is the image of things, $a_{i2}$ is the perceptual image. Therefore, Rough Semantic Set $A$ contains two subsets, namely, object image set $F$ and perceptual image set $I$.

\[ F = \{a_{11}, a_{21}, \ldots, a_{n1}\}, \quad I = \{a_{12}, a_{22}, \ldots, a_{n2}\} \]

2.3. Establishment of Product Form Parameter Set
The preliminary screened samples of cultural products in the first stage are classified as representative sample set $N$. $x$ is the number of representative samples, The sample set is:

\[ N = \{N_1, N_2, \ldots, N_x\} \]
According to the content of "Morphology" in the outline of art education in China, the formal genes of patterns can be divided into force image and perceptual force field[13], which can be used as the basis of product morphological deconstruction. Quantitative indicators of force image and field are proposed by design experts (Fig. 3, Fig. 4). They are summed up as force image coefficients $l$ and field density coefficients $\rho$. Thus, the dimension of shape parameters of each sample is 2. The sample dimension is expressed as:

$$X_i = \{X_{i1}, X_{i2}\}$$

![Figure 3. The force image coefficient $l$ of the structural line (unit: degree)](image1)

![Figure 4. The field density factor $\rho$ of the main contour (unit: 1)](image2)

The morphological parameter set $X$ of representative sample set $N$ is:

$$X = \begin{bmatrix}
X_{11} & X_{12} \\
X_{21} & X_{22} \\
\vdots & \vdots \\
X_{x1} & X_{x2}
\end{bmatrix}$$

In the matrix, $i = 1, 2, ..., x$.

3. Cultural Image Evaluation of Product Modeling Based on FNN Model

A cultural image evaluation system is constructed by using simple fuzzy reasoning theory and three-layer forward BP neural network, which provides criteria for judging the quality of product cultural image modeling and terminating operation. In view of the fact that the force image coefficient $l$ and field density coefficient $\rho$ involved in this study can not determine their magnitude and degree, the two coefficients are fuzzified. The evaluation architecture is as follows: the first layer is the data preprocessing layer, which takes the shape parameters of the product as input variables and imports them into the fuzzifying neurons; the second layer is the middle layer, which contains many hidden nodes and plays a role of connecting transition[14]; the third layer is the output layer, which outputs the actual evaluation value and cultural image fitness value of the sample rough linguistic meaning set $A$, respectively. This value indicates whether the sample fits the local cultural image. The structure of the network is shown in Fig. 5.
3.1. Data preprocessing
The input variables \((X_{i1} = l, X_{i2} = \rho)\) are fuzzified by membership function. Each fuzzy input variable is divided into three fuzzy subspaces, which are expressed by extreme (E), general (C) and weak (W) linguistic variables respectively, and the membership function is a triangular distribution function.

3.2. Intermediate and Output Layer Processing
By consulting literature [15], the empirical formulas for determining the number of nodes in the middle layer are as follows:

\[
n_l = \sqrt{n + m + a}
\]

In the formula, \(n_l\) is the number of nodes in the middle layer, \(n\) is the number of nodes in the input layer, \(m\) is the number of nodes in the output layer, and \(a\) is a constant between 1 and 10\(^{15}\). After the initial value of the number of nodes in the middle layer is determined by empirical formula, the optimal number of nodes in the middle layer is determined by numerical experiments, that is, increasing the number of nodes gradually, and training with the same sample, from which the number of nodes corresponding to the minimum error is determined\(^{16}\).

3.3. Derivation process and evaluation process between layers
The input product shape parameters are transformed into the cultural image evaluation value of the product through a certain form. In this study, \(i\) represents ordinal number of products, \(X_{i1} = l, X_{i2} = \rho\).

3.3.1. Derivation from Fuzzy Layer to Intermediate Layer. Input value of \(j\) node in middle layer \(I_j = w_{(\mu_1)}I_1 + w_{(\mu_2)}I_2 + w_{(\mu_3)}I_3 + w_{(\mu_4)}I_4 + w_{(\mu_5)}I_5 + w_{(\mu_6)}I_6 + \theta\), the output value of middle layer \(y_j = f_i(I_j), \ j = 1, 2, \ldots, n\). As shown in Fig. 6.

Figure 5. Cultural Image Evaluation Network Structure
3.3.2. Derivation from Intermediate Layer to Output Layer. \( f_z(A_z) = f_z(w_z(y_1) \mu_1 + w_z(y_2) \mu_2 + \ldots + w_z(y_{n'}) \mu_{n'}, \mu = 1, 2, \ldots, n' \). All the output results are regarded as the actual evaluation values of the rough semantic set \( A \) of cultural images. After error analysis with the expected output, the error is conversely transmitted. The weights and thresholds are updated to make the actual evaluation values close to the expected output, as shown in Fig. 7.

3.3.3. One-way Derivation in Output Layer. The first layer of the output layer participates in the reverse transmission of errors, while the second layer does not. There is only forward transmission of numerical values between the two independent layers. After updating the weights and thresholds of the network, the adjusted actual evaluation value \( z_1, z_2, \ldots, z_{n'} \) is input into the \( \alpha \) node. The weights \( w_{2n} \) of each evaluation value are obtained according to the statistical data of the questionnaire. The threshold \( \theta_\alpha \) makes the fitness value change within a certain range. The range of values is 0~1. The cultural image fitness \( \alpha_i = w_{1\alpha} z_1 + w_{2\alpha} z_2 + \ldots + w_{n'\alpha} z_{n'} + \theta_\alpha \), then normalize it.
3.3.4. Ending Conditions of Network Adjustment. If the error between the actual evaluation value and the expected output is within the set range, the update of the termination weights and thresholds will result in good network performance. After inputting the shape parameters of the product, the actual evaluation value and the cultural image fitness $\alpha$ are output, $\alpha \geq 0.5$ means it consists with local cultural images, the closer to 1, the higher the fit; $\alpha < 0.5$ means it deviates from local cultural images, the closer to 0, the higher the deviation.

4. Optimum Design of Product Culture Image Modeling Based on PSO Algorithms

Design activities are not only the process of integrating several elements to achieve a specific goal or satisfy a certain demand, but also the process of searching for the best solution through a certain design procedure or method. Because each designer has different understanding of cultural image, he often relies on personal experience and intuitive judgment to design the image of cultural products.

To solve this problem, an optimal design of product cultural image modeling based on PSO algorithm is proposed, The flow chart is shown in Fig. 9.

![Optimum Design Flow Based on PSO Algorithms](image)

**Figure 9. Optimum Design Flow Based on PSO Algorithms**

4.1. Particle population parameterization

Consider each cultural product sample as a particle unit in the algorithm $x_i$. The representative sample set $N$ is the initial population of particles. If the two morphological parameters $X_{i1}$ and $X_{i2}$ of the product are regarded as the two search dimensions of the algorithm, the particle searches for the individual optimal position $x_{ib}$ with a certain speed $v_i$ in the two-dimensional target search space.

$$x_i = (X_{i1}, X_{i2}), \quad v_i = (V_{i1}, V_{i2})$$

When the fitness value $F(x_i)$ of particle $x_i$ reaches its maximum, individual optimal solution:

$$F_{\text{max}}(x_i) = F(x_{ib})$$

4.2. Determination of fitness value

The fitness value of the algorithm is the basis for judging the position of particles. The goal of optimum design of cultural image modelling is to get a more suitable product form for local cultural image. Therefore, the fitness value of particles is cultural image fitness $\alpha$.

$$F(x_i) = \alpha_i$$
4.3. Particle position and velocity updating

This study focuses on the optimal design of product cases, not on the optimization of solution groups, so the "social part" of particles is zero. That is, the acceleration factor \( c_2 = 0 \). The updating formula of particle position and velocity is as follows:

\[
\begin{align*}
    v_i(t+1) &= \omega \times v_i(t) + c_1 \times \text{rand} \times (x_{ib} - x_i) \\
    x_i(t+1) &= x_i(t) + v_i(t+1)
\end{align*}
\]

4.4. Optimum Design Flow Based on PSO Algorithms

The initial position of particle \( x_i \) is recorded as \( x_i(0) \), and the initial velocity \( v_i(0) = 0 \). Input the shape parameters \( X_{i1}, X_{i2} \) to calculate the image predictive value \( \alpha \) in the product modeling culture image evaluation system based on FNN model. Taking \( \alpha \) as the historical optimal solution \( F(x_{ib}) \) of particle \( x_i \). Update the particle's velocity and position every time according to the above formula, import its morphological parameters into the cultural image evaluation system to calculate the fitness value \( F_t(x_i) \) of generation \( t \) new particle \( x_i(t) \), compare it with individual extreme value \( F_{xib} \). If \( F_t(x_i) \geq F_{xib} \), then it is regarded as a non-inferior solution and the individual extreme value is updated to \( F_t(x_i) \), all non-inferior solutions constitute a set of non-inferior solutions. If the particle has reached the limit velocity \( v_{max} \), the updating of the non-inferior solution is stopped.

5. Example analysis

5.1. Parameterization of product form and Semantic Analysis of Cultural Images

Based on the analysis of the correlation between the selected 30 images of seedling embroidery samples in Songtao area and the local culture, 12 representative samples were simplified (Fig. 10). The cultural image semantics is summed up as the sentence pattern of "object image - perceptual image". Rough semantics set \( A \) (Table 1) is selected through SD questionnaire. After quantitative description of the structure line and main contour line of the pattern sample, the sample morphological parameters (Table 2) are obtained.

![Representational Miao Embroidery Samples](image-url)
Table 1. Rough Semantic Set A (F-I)

| Imagery semantics 1 | Flying horse —— Animal worship |
|---------------------|--------------------------------|
| Imagery semantics 2 | Lofty ridges and towering mountains —— Fear of Nature |
| Imagery semantics 3 | Harmony between Luan and Phoenix —— Husband and wife and aesthetic feeling |
| Imagery semantics 4 | Ichthyosaurus diving —— Indomitable feeling |
| Imagery semantics 5 | Birds fall on Peony —— Need To Breed |
| Imagery semantics 6 | Butterfly Dance Blossoms —— A sense of happiness in life |

Table 2. Sample morphological parameters

| Sample serial number | Sample force image coefficients $l$ | Sample field density coefficients $\rho$ |
|----------------------|-------------------------------------|----------------------------------------|
| Sample number 1       | 62.1                                | 3.5                                    |
| Sample number 2       | 13.4                                | 5.8                                    |
| Sample number 3       | 90.0                                | 1.2                                    |
| Sample number 4       | 56.2                                | 6.7                                    |
| Sample number 5       | 34.8                                | 8.1                                    |
| Sample number 6       | 78.5                                | 4.3                                    |
| Sample number 7       | 22.6                                | 2.7                                    |
| Sample number 8       | 45.7                                | 7.9                                    |
| Sample number 9       | 86.3                                | 6.5                                    |
| Sample number 10      | 30.8                                | 3.2                                    |
| Sample number 11      | 52.9                                | 4.0                                    |
| Sample number 12      | 17.2                                | 6.1                                    |

There are six groups of vocabulary in Semantic Set A. The evaluation values of each sample are $T_1$, $T_2$, $T_3$, $T_4$, $T_5$, and $T_6$. Morphological parameters of each sample $X_{il}$, $X_{i2}$ (62.1, 3.5), (13.4, 5.8), (90.0, 1.2), (56.2, 6.7), (34.8, 8.1), (78.5, 4.3), (22.6, 2.7), (45.7, 7.9), (86.3, 6.5), (30.8, 3.2), (52.9, 4.0), (17.2, 6.1) constitute the morphological parameter set $X$, sample number $i = 1, 2, ..., 12$.

5.2. Establishment of FNN Evaluation System

The membership function of force image coefficient $l$ is:

$$
\mu_l = \begin{cases} 
1 & x \leq 0 \\
\frac{64.15 - x}{64.15} & 0 < x < 64.15 \\
0 & x \geq 64.15 
\end{cases}
$$

The membership function of field density coefficient $\rho$ is:

$$
\mu_\rho = \begin{cases} 
0 & x \leq 0 \\
\frac{x}{64.15} & 0 < x < 64.15 \\
\frac{128.3 - x}{64.15} & 64.15 \leq x < 128.3 \\
64.15 & x \geq 128.3 \\
0 & 
\end{cases}
$$
According to the membership function, the size of image coefficient $l$ can be judged to guide the follow-up optimization design. Similarly, the membership function of field density coefficient $\rho$ can be obtained. The number of nodes in the input layer $n = 6$, the number of nodes in the output layer $m = 6$, $a = 1$, and the number of nodes in the middle layer $n_l = 4$. Setting initial weight $w_{ij} = 0.2$, $w_{jc} = 0.5$, according to the percentage of the sample of each semantic vocabulary in the questionnaire, conclude $w_{1a} = 0.08$, $w_{2a} = 0.06$, $w_{3a} = 0.29$, $w_{4a} = 0.17$, $w_{5a} = 0.22$, $w_{6a} = 0.18$. Set initial threshold $\theta_1 = 0.6$, $\theta_2 = 0.3$, the activation function $f(x)$ of each node chooses S-type function and inputs the morphological parameters $X_i$ and $X_2$ of each sample into the network for training. After 4286 training sessions, the error between the adjusted actual evaluation values of $z_1$, $z_2$, $z_3$, $z_4$, $z_5$, $z_6$ and the expected output of $T_1$, $T_2$, $T_3$, $T_4$, $T_5$, and $T_6$ is close to 0.1. The training process is shown in Figure 11 and the output of the network is shown in Table 3.

![Figure 11. Convergence process of network](image)

### Table 3. Expected Output and FNN Output

| Number | Sample 1 | Sample 2 | Sample 3 | Sample 4 | Sample 5 | Sample 6 | Sample 7 | Sample 8 | Sample 9 | Sample 10 | Sample 11 | Sample 12 |
|--------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|-----------|-----------|
| $T_1$  | 0.78     | 0.86     | 0.68     | 0.45     | 0.37     | 0.30     | 0.90     | 0.29     | 0.35     | 0.88     | 0.85      | 0.46      |
| $z_1$  | 0.81     | 0.80     | 0.59     | 0.52     | 0.28     | 0.36     | 0.83     | 0.20     | 0.41     | 0.79     | 0.76      | 0.55      |
| $T_2$  | 0.22     | 0.35     | 0.10     | 0.60     | 0.58     | 0.54     | 0.21     | 0.51     | 0.50     | 0.54      | 0.57      | 0.48      |
| $z_2$  | 0.18     | 0.46     | 0.15     | 0.53     | 0.62     | 0.44     | 0.28     | 0.60     | 0.57     | 0.61      | 0.52      | 0.40      |
| $T_3$  | 0.66     | 0.27     | 0.20     | 0.75     | 0.81     | 0.43     | 0.26     | 0.52     | 0.90     | 0.56      | 0.73      | 0.44      |
| $z_3$  | 0.62     | 0.21     | 0.25     | 0.82     | 0.73     | 0.38     | 0.22     | 0.60     | 0.85     | 0.65      | 0.77      | 0.53      |
| $T_4$  | 0.80     | 0.66     | 0.90     | 0.34     | 0.61     | 0.59     | 0.42     | 0.20     | 0.49     | 0.72      | 0.82      | 0.42      |
| $z_4$  | 0.86     | 0.57     | 0.82     | 0.41     | 0.68     | 0.53     | 0.49     | 0.25     | 0.56     | 0.66      | 0.90      | 0.34      |
| $T_5$  | 0.33     | 0.84     | 0.87     | 0.90     | 0.10     | 0.12     | 0.89     | 0.51     | 0.79     | 0.38      | 0.23      | 0.45      |
| $z_5$  | 0.41     | 0.78     | 0.82     | 0.80     | 0.05     | 0.16     | 0.79     | 0.60     | 0.73     | 0.34      | 0.27      | 0.53      |
| $T_6$  | 0.11     | 0.15     | 0.10     | 0.19     | 0.43     | 0.46     | 0.90     | 0.78     | 0.12     | 0.17      | 0.28      | 0.13      |
| $z_6$  | 0.18     | 0.07     | 0.12     | 0.23     | 0.51     | 0.55     | 0.83     | 0.72     | 0.20     | 0.26      | 0.35      | 0.09      |
| $\alpha$ | 0.89   | 0.76     | 0.41     | 0.52     | 0.80     | 0.68     | 0.87     | 0.63     | 0.79     | 0.85      | 0.96      | 0.46      |

### 5.3. Optimum Design Results of PSO Algorithms

Let inertia weight $\omega = 0.8$, acceleration factor $c_1 = 0.5$ and $rand_i = 1$, then the velocity and position update formula of particles is as follows:

$$v_i(t+1) = 0.8v_i(t) + 0.5(x_{ib} - x_i)$$
\[ x_i(t + 1) = x_i(t) + v_i(t + 1) \]

Gradually update the speed and position of individuals and populations. If the limit speed \( |V_{\text{max}}| = 10 \) is reached, the operation is terminated and the final modeling scheme of each pattern sample is output. Because of the limited space, the final modeling scheme is shown in Figure 12, taking Sample 1 as an example.

Figure 12. Sample 1 Final Modeling Scheme

5.4. Verification of optimization design results

Using SD method, 23 Miaoxue experts and 56 design teachers were assessed with questionnaires. The results were normalized and compared with the original samples to verify whether the image of the optimized scheme retained the original cultural image. Take Sample 1 as an example, its evaluation value \( T_1 = 0.89, T_2 = 0.12, T_3 = 0.46, T_4 = 0.82, T_5 = 0.25, T_6 = 0.07 \), compared with the evaluation value of the original sample (see Table 3), the new pattern "Image Semantic 1" and "Image Semantic 4" have high evaluation value, which shows that the new pattern has the same cultural image as the original pattern.

6. Conclusion

(1) In the process of identifying and evaluating cultural images, many concepts that are difficult to explain Daoming are transformed into numerical values for quantitative analysis by using the powerful reasoning ability of fuzzy logic of fuzzy neural network and the unique parallel and distributed information processing ability of artificial neural network\(^{[17]}\), so as to determine the attributes of cultural images and establish a cultural image evaluation system with good accuracy.

(2) The particle swarm optimization is used to search for the best particle in the solution space\(^{[18]}\), which can make the initial sample achieve the local optimum without deviating from the specific cultural image, and turn the disadvantage of PSO into advantage, so as to simulate the divergent thinking for the innovation of cultural image modeling design.

Acknowledgements

Foundation Project: National Natural Science Foundation Project(51865003，51465007); Science and Technology Project of Guizhou Province(Qian Kehe Platform Talents[2018]5781).

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