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Product form optimization algorithms for computer-aided industrial design instruction

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ABSTRACT

Based on the concept of "user-centered", this paper designs a product form optimization model based on ant colony algorithm. Through mining the online reviews of the products, we determine the perceptual imagery of users, and categorize the perceptual imagery and determine the weights from the perspective of user satisfaction. Combining the factor analysis of perceptual imagery and the contribution value of morphological features on perceptual imagery, the product morphology optimization fitness function is constructed. Solve the model according to the basic principle of ant colony algorithm, and study the decision-making method to assist product optimization. Take a brand A model forum word-of-mouth data as an example to analyze, obtain users' perceptual imagery through SO-PMI algorithm, and assign values to perceptual intention weights with the help of cluster analysis. Determine the contribution value of morphological features through the SD investigation of product morphological differences. Genetic algorithm is introduced to carry out comparative experiments to verify the superiority of ant colony algorithm in optimizing model solving. Finally, the application effect of the predictive model solving scheme is analyzed through user satisfaction survey. The results show that the output of the product optimization design model based on ACO algorithm Model A is 8. 23.11% of the users are very satisfied with the optimized Model A, 65.55% of the users are satisfied, and 85.72% of the survey respondents are very willing and ready to buy the optimized Model A.

Keywords: product optimization design, SO-PMI algorithm, cluster analysis, ant colony algorithm

1. Introduction

Computer as a tool to assist design, it also changes the traditional design method [1-4]. Computer-aided industrial design (CAID), that is, with the support of computers and their corresponding computer-aided industrial design systems, various creative activities in the field of industrial design. It is a product of the information age environment with computer technology as the backbone [5-8].

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Compared with the traditional industrial design, CAID has undergone qualitative changes in design methodology, design process, design quality and efficiency. The teaching of computer-aided industrial design related software directly affects the design performance ability of industrial design students [9-12].

Computer-aided industrial design mainly involves the use of computer software to assist in the completion of various stages of product design, from conceptual design to manufacturing process can be assisted by the computer in all aspects [13-15]. This process usually includes the establishment of product concepts, the construction of 3D models, material selection, product testing and verification, as well as the generation of the final design documents and other aspects of the design can improve the efficiency and quality of the design, reduce the cost of trial and error and time, and to facilitate the management of design documents and collaboration [16-19]. With the continuous development of computer technology, computer-aided industrial design will play an increasingly important role in the field of industrial design [20].

In this paper, by applying Apriori algorithm to mine user perceptual imagery, SO-PMI algorithm is used to calculate perceptual imagery evaluation value. A mathematical model is constructed using quantitative class I theory to obtain the total contribution value of product morphological features to perceptual imagery. Based on the ant colony algorithm, construct the product form optimization design model, and rely on the MATLAB system to complete the model implementation. The proposed model is used for example analysis to calculate the sound volume and emotion of users in the review data. Visualize the distribution of sound volume and emotion, and determine the weights of perceptual imagery through cluster analysis. Genetic algorithm and ant colony algorithm are introduced to carry out a controlled test of model solving to evaluate the performance of ant colony algorithm on the optimal module division problem. Combine VR technology and questionnaire survey to analyze user satisfaction and test the effectiveness of the solution scheme.

2. Product form optimization model based on ant colony algorithm under the perspective of user requirements

2.1. User Perceptual Intention Mining

The user's evaluation of product features contained in online reviews reflects to a certain extent the user's emotional attitude towards the product features. Data mining begins with the original review text and ends with clearly structured and readable review data, from which appropriate methods can be used to mine the user demand for the product. Demand mining is mainly done by understanding how users evaluate different features of the product as a whole, i.e., to understand which features, functionality, of the product are evaluated by the users and how they are evaluated. Therefore, the method of mining user demand is to mine users' emotional attitudes towards product features from the online reviews of the product, and to understand users' emotional preferences for each feature.

First, the online review data of the product is crawled and data preprocessing is performed, and the Apriori algorithm based on association rules is applied to mine the product attributes that users pay attention to with high frequency. Second, extract the corresponding emotion words based on the obtained product attributes, and apply the SO-PMI algorithm to calculate the product attribute evaluation value. The flow of product attribute mining and attribute evaluation value calculation is shown in Fig. 1, which specifies each step.

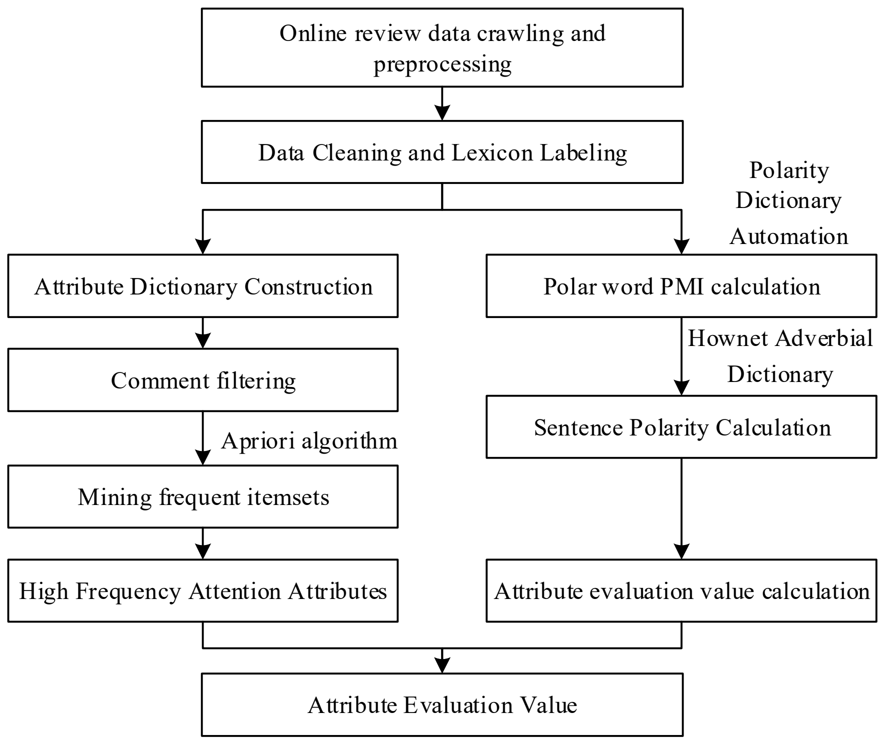

Fig. 1. Product attribute mining and attribute evaluation value calculation

2.1.1. Data Crawling and Preprocessing. First determine the data source, use the crawler tool to crawl the online comments, store the crawled data into the file library, and then carry out data preprocessing, the preprocessing content mainly includes data cleaning and lexical labeling.

2.1.2. Calculation of assessed value of attributes. After mining to get the product attributes that users pay attention to, extract the sentiment words in the comment sentences corresponding to the attributes, and apply the sentiment analysis method of product attributes to get the user's sentiment tendency for each attribute of the product, and this paper adopts the SO-PMI algorithm to calculate the evaluation value of each attribute of the product.

The calculation of product attribute evaluation value takes the sentence in which the attribute words appear as a unit for analysis, and comprehensively analyzes the polarity of the sentiment words appearing in the sentence.The core idea of SO-PMI algorithm is point mutual information, which is mainly used to represent the relationship between words and vocabulary in the text analysis, and is mainly used to calculate the value of mutual information between the attributes.The SO-PMI algorithm will comprehensively take into account the polarity words in calculating the intensity of the polarity of the sentence, adverbs, and negatives when calculating the polarity strength of a sentence, and gives a formula to quantify the polarity degree of the whole sentence. The degree of polarity is the direction and intensity of the commenter's emotion, and the polarity words (adjectives, verbs, and nouns), as the core of the sentence, contain most of the information of the entire comment sentence, while the adverbs and negatives are the components that further modify the polarity of the entire comment sentence on the basis of the polarity words. The process of this application of SO-PMI algorithm is divided into three steps: word polarity strength calculation, sentence polarity strength calculation, and attribute comment value calculation.

1) Word polarity strength calculation. Polarity words are categorized into positive, neutral and derogatory words. Among them, neutral words contain users' emotional attitudes; positive words express positive evaluations of product attributes; and derogatory words express pejorative meanings.

Because the review data is created by human beings, it will be easier to judge it manually, but due to the large amount of data, the manual method will be very time-consuming and cannot be calculated quantitatively, therefore, this paper adopts the method of polarity lexicon to calculate the polarity word strength by calculating the strength of association between an unknown word and the words in the HowNet Sentiment Dictionary and then calculating the polarity strength of the word, and the polarity strength of vocabulary W is calculated by the strength $SCORE(W)$ formula is as follows:

$$\begin{cases} score(W) = \dfrac{\sum_{w_+ \in W_+} PMI(W, w_+)}{N_+} - \dfrac{\sum_{w_- \in W_-} P(W, w_-)}{N_-} \\ P(W, w) = \log_2 \dfrac{P(W, w)}{P(W, w)} \end{cases} \tag{1}$$

In the above formula, $p(W)$ is the probability that the sentiment word W appears in the same comment, $p(w)$ is the same, and $p(W, w)$ indicates the probability that W and w appear at the same time in the same comment, the formula is used to calculate the mutual information between the unknown pending emotion word and the seed word, if the final value is large, it means that the mutual information of the two values is high, indicating that the meaning of the two words is similar, if the final value is small, it means that the mutual information of the two values is low, indicating that the meaning of the two words is far apart.

According to the above formula, firstly, the mutual information between the emotion words of known category and the emotion words of unknown category is calculated, and then, the difference between the mutual information calculated for the emotion word and the emotion words of different categories is calculated to determine the emotional tendency of the emotion word.

2) Sentence polarity strength calculation. To judge the polarity strength of a sentence, we need to analyze the specific components of the sentence. In the sentence that expresses the emotion of product attributes, the polarity word is the carrier of emotion, but the appearance of these polarity words is often accompanied by adverbs that play the role of modifiers to enhance or weaken the intensity of the emotion words, which are generally adverbs of degree, and can be roughly classified into four levels according to the classification of adverbs of degree in HowNet.

In addition to adverbs of degree, the role of negatives appearing in sentences on emotion polarity words should not be neglected, and negatives tend to express emotional tendencies opposite to those of the publisher. Negation words are calculated with the help of Hownet's dictionary, $I(deny) = -0.5$ if the negation word appears in the sentence and $I(deny) = 1$ if it does not.

The polarity effect of adverbs and negatives on the whole sentence is analyzed comprehensively and calculated as:

$$S = \frac{\sum_{i=1}^{m} score(W_i) \cdot d \cdot I(deny) + \sum_{j=1}^{n} score(W_j) \cdot d \cdot I(deny)}{m + n} \tag{2}$$

In the above equation, m and n represent the number of positive and negative polarity words respectively.

3) Calculation of attribute evaluation value. After calculating the polarity strength of all sentences corresponding to different attribute words, the weighted average method is applied to calculate the comprehensive evaluation value of the attribute. The formula is:

$$w_a = \frac{\sum_{i=1}^{n} s_i}{n} \tag{3}$$

where W_a is the composite comment value for attribute a and S_i is the polarity strength of the i th comment sentence for attribute a.

2.2. Product form key gene association analysis

In the process of studying the morphogenetic of the product, the user's perceptual intention factor and the morphogenetic gene of the product are determined firstly, and then the mathematical model is constructed by using the quantitative class I theory, and the mathematical model is solved to calculate the bias correlation coefficient of the morphogenetic gene to the perceptual intention factor and the contribution value of the elements of each morphogenetic gene, so as to analyze the relationship between perceptual imagery and morphogenetic features.

Quantitative theory is a branch of multivariate analysis, and all the methods of multivariate analysis are used to analyze and process data to study the laws contained in the data and the relationship between some random variables. Due to the different nature of each variable, they can be divided into 2 classes: one class is quantitative variables, such as semantic gene evaluation value; one class is qualitative variables, such as designing the morphological classification of genes, which can be divided into trapezoidal, trapezoidal-like, polygonal-like polygonal, and so on. Quantitative class I theory is to establish and solve mathematical models to study the relationship between a set of independent variables and dependent variables, i.e. qualitative variables and quantitative variables, through multiple regression analysis.

2.2.1. Modeling. Morphological trait genes were used as independent variable x (qualitative variable) and perceptual imagery genes were used as dependent variable y (quantitative variable). With N samples, the 1st morphological trait gene X_1 has p_1 number of morphological categories $x_{11}, x_{12}, \cdots\cdots x_{1p1}$, the 2nd morphological trait gene X_2 has p_2 number of morphological categories $x_{21}, x_{22}, \cdots\cdots x_{2p2}$, and the n th morphological trait gene X_n has p_n number of morphological categories $x_{n1}, x_{n2}, \cdots\cdots x_{npn}$, so there are a total of $\sum_{r=1}^{n} x_r = m$ morphological trait categories. If $\delta_i(j,k)$ is called the response of the k th morphological category of the j th morphological trait gene in the i th sample, then

$$\delta_{\mathrm{i}}(j,k) = \begin{cases} 1 & \begin{array}{l}\text{The qualitative data of the jth morphology}\\ \text{design gene in the ith sample is the kth}\\ \text{morphology category}\end{array} \\ 0 & \text{Other} \end{cases} \tag{4}$$

Definition:

$$x = \left\{\delta_i(j,k)\right\} \tag{5}$$

where $\left(i = 1,2,\ldots,N; j = 1,2,\ldots,n; k = 1,2,\ldots,x_r\right)$

Then, the matrix x of $N \times m$ formed by $\delta_{\mathrm{i}}(j,k)$ is called the reaction matrix as follows:

$$x = \begin{bmatrix} \delta_1(1,1) & \ldots & \delta_1(1,p_1) & \delta_1(2,1) & \ldots & \delta_1(2,p_2) & \ldots & \delta_1(n,1) & \ldots & \delta_1(n,p_n) \\ \delta_2(1,1) & \ldots & \delta_2(1,p_1) & \delta_2(2,1) & \ldots & \delta_2(2,p_2) & \ldots & \delta_2(n,1) & \ldots & \delta_2(n,p_n) \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\ \delta_N(1,1) & \ldots & \delta_N(1,p_1) & \delta_N(2,1) & \ldots & \delta_N(2,p_2) & \ldots & \delta_N(n,1) & \ldots & \delta_N(n,p_n) \end{bmatrix} \tag{6}$$

As the dependent variable of perceptual imagery y and each morphological trait gene, the response of morphological categories can be modeled mathematically as follows:

$$y_i = \sum_{j=1}^{n}\sum_{k=1}^{x_i}\delta_i(j,k)b_{jk} + \varepsilon_i \tag{7}$$

where b_{jk} is the coefficient to be determined for the k rd morphological class that depends only on the j nd morphological trait gene; and ε_i is the random error in the i th sampling.

2.2.2. Model solving. The least squares estimate $\overline{b_{jk}}$ of the coefficient b_{jk} is obtained by the principle of least squares so that Q is minimal.

$$Q = \sum_{i=1}^{N}\varepsilon_i^2 = \sum_{i=1}^{N}\left[y_i - \sum_{i=1}^{n}\sum_{k=1}^{x_i}\overline{b_{jk}}\delta_i(j,k)\right]^2 = \sum_{i=1}^{N}\left(y_i - \overline{y}\right)^2 \tag{8}$$

Then, solving for the partial derivative of Q with respect to the valuation $\overline{b_{jk}}$, making it 0, leads to equation (9):

$$\sum_{j=1}^{n}\sum_{k=1}^{x_n} f(uv, jk)\overline{b_{jk}} = \sum_{i=1}^{N} y_i\delta(u,v)$$
$$\left(u = 1,2,3,\ldots,n; v = 1,2,3,\ldots,x_u\right) \tag{9}$$

Among them:

$$f(uv, jk) = \sum_{i=1}^{N}\delta_i(u,v)\delta_j(j,k) \tag{10}$$

The least squares estimate of b_{jk}, $\overline{b_{jk}}$, is obtained from Eq. (9), Eq. (10):

$$\overline{y_i} = \sum_{j=1}^{n}\sum_{k=1}^{x_i}\overline{b_{jk}}\delta_i(j,k) \tag{11}$$

To more easily explain the correspondence between perceptual imagery and morphological feature genes, the model can be further assumed as follows:

$$\overline{y_i} = \overline{y} + \sum_{j=1}^{n}\sum_{k=1}^{x_n} b_{jk}^{*}\delta_i(j,k) \tag{12}$$

where $\overline{y}$ is the evaluative value of perceptual imagery, i.e., the value of:

$$\overline{y} = \frac{\sum_{i=1}^{N} y_i}{N} \tag{13}$$

b_{jk}^{*} is the standardized coefficient, and the relationship between and $\overline{b_{jk}}$ is given by:

$$b_{jk}^{*} = \overline{b_{jk}} - \frac{1}{N}\sum_{k=1}^{x} N_{jt}\overline{b_{jt}} \tag{14}$$

where N_{β} is the number of Type 1 responses for the j rd morphologic characterization gene in the N sets of samples, and

$$\sum_{i=1}^{x_r} N_{jt} = N\left(j = 1,2,3,\ldots,n\right) \tag{15}$$

The prediction accuracy was measured using the complex correlation coefficient R, solved by Eq:

$$R=\left[\sum_{i=1}^{x}\left(\overline{y_i}-\overline{y}\right)^2\bigg/\sum_{i=1}^{x}\left(y_i-\overline{y}\right)^2\right]^{\frac{1}{2}} \tag{16}$$

The coefficient of determination R^2 is commonly used to express the accuracy of the model.

The partial correlation coefficient is utilized to measure the contribution of each morphological feature gene to the perceptual imagery. The correlation matrix between perceptual imagery y and the elements of the morphological characterization genes is A, and its inverse matrix is A^{-1}. i.e.

$$A=\begin{bmatrix} 1 & a_{y1} & a_{y2} & \dots & a_{yn} \\ a_{1y} & 1 & a_{12} & \dots & a_{1n} \\ a_{2y} & a_{21} & 1 & \dots & a_{2n} \\ \dots & \dots & \dots & \dots & \dots \\ a_{ny} & a_{z1} & a_{22} & \dots & 1 \end{bmatrix} \tag{17}$$

Therefore, the bias correlation coefficient between the perceptual imagery rating value y and the j nd morphological trait gene is:

$$R_{ij}=\frac{-a_{jy}}{\sqrt{a_{ji}a_{yy}}} \tag{18}$$

That is, the contribution of the j st morphological characterization gene to the perceptual imagery rating value y is R_{yj}.

2.3. *Product form optimization design model construction*

The principle of ant colony algorithm is that ants release pheromone on the path, and later ants will choose the path with higher concentration of pheromone, thus forming a positive feedback, and finally the ant colony finds the optimal foraging path. According to the basic principle of ant colony algorithm, the product form optimization design model based on ant colony algorithm is constructed, and the model implementation is completed by using MATLAB system.

2.3.1. Modeling. The model consists of n design element and m representative perceptual images. Design elements refer to the product appearance, component correlation, color and shadow collocation and other significant impact on the product intuitive feeling of the form of the characteristics of the broad categories, each type of design elements contain a variety of corresponding form of characteristics to choose from, such as color collocation design elements include orange and yellow, blue and other form of characteristic elements; representative of the perceptual imagery for the most representative of the user's intuitive feeling of the form of a product of the adjectives, such as high-end, reliable, and so on. Setting $x_1,x_2,\ldots,x_n$ as a product form combination, F as the value of the perceptual imagery of this form combination, and F_k as the total contribution of the form combination to the k th perceptual imagery, the morphology optimization design model Y can be described as follows

$$\left.\begin{aligned} Y&=\max F\left(x_1,x_2,\cdots,x_n\right) \\ &=\max\left(F_1\left(x_1,x_2,\cdots,x_n\right),F_2\left(x_1,x_2,\cdots,x_n\right),\cdots,F_m\left(x_1,x_2,\cdots,x_n\right)\right) \\ s.t.a_j\le x_j\le b_j&,j=1,2,\cdots,n,x_j\in Z,k=1,2,\cdots,m \end{aligned}\right\} \tag{19}$$

where: x_j is the design element of level j, with the maximum possible value of l_j, l_j is the number of morphological features $l_j=b_j-a_j+1$ of x_j; Z is the space of the design element: a_j, b_j is the range of values of the variable, and $j = 1,2,\dots,n$, is the level of the design element.

2.3.2. Model solving. The solution process of product morphology optimization design model is shown in Fig. 2, in order to avoid mutual influence between product morphology design elements, a hierarchical design strategy is adopted, with multi-class morphology design elements constituting a multi-level decision-making model, each level controlling a specific aspect of the product morphology, and selecting a morphology feature at each design element level in order to form a combination of morphologies, so that each design variable can be varied independently without directly affecting other variables. This allows each design variable to change independently without directly affecting the other variables. For example, the color and shadow matching design element level contains multiple color choices, and the orange-yellow color is chosen as a choice that does not affect the product's appearance and shape, component correlation, or other level choices.

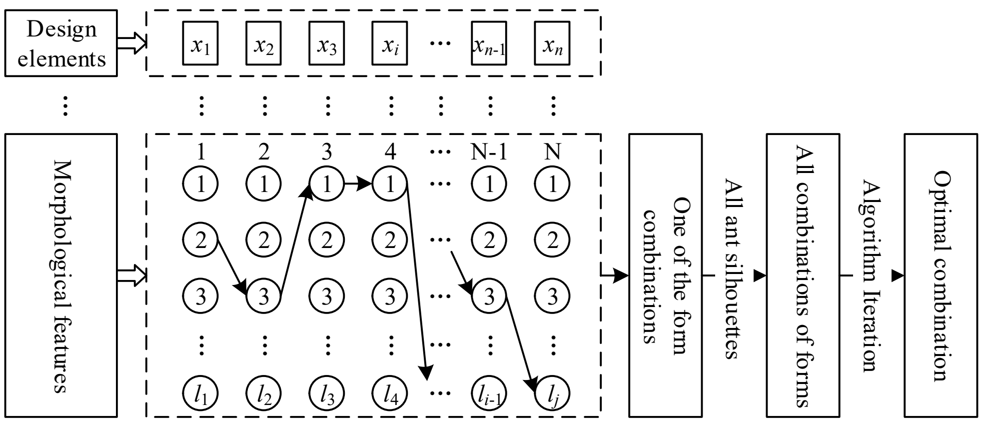

Fig. 2. Solution process of the product shape optimization design model

1) The probability formula and the contribution value update equation. x_j has l_j morphological characteristics. Select any one of these morphological features until all n design elements have been selected to form a 1 solution for product morphology optimization $(x_1, x_2, \dots, x_n)$. n design elements to construct a N-level design element decision model, where $N = n$. Level j design element x_j includes l_1 nodes, the initial state all ants are positioned in the nodes in x_1, the probability of selecting the i th morphological feature node in x_j, as in Equation (20), and i is the ranked value of the morphological feature nodes under the same level design element.

$$p_{ij} = \frac{r_{ij}}{\sum_{i=1}^{T} r_{ij}} \tag{20}$$

where τ_{ij} is the contribution value of the i rd morphological feature in x_j to the total imagery. The contribution value update equation is shown in equation (21).

$$\tau_{ij}^{new} = \rho \cdot \tau_{ij}^{ojd} + \frac{F}{Q} \tag{21}$$

where: ρ is the pheromone evaporation rate: F is the adaptation degree: Q is the pheromone increase intensity.

2) Establishment of fitness function. In the product form optimization design model, the fitness function is in the core position, guiding the execution of the ant colony algorithm. Constructing this function needs to synthesize the user perceptual imagery factor analysis and the contribution value of the product morphological features on the semantics of perceptual imagery. Using the quantitative theory of I categories, the contribution value of each morphological feature to perceptual imagery is analyzed. Assuming that the contribution value of the i th morphological feature element to the k th perceptual imagery in the j th design factor is A_{ij}, then the total contribution value F_k of the product morphological combination to the k th perceptual imagery can be expressed as

$$F_k = \sum_{j=1}^{n} \left(\sum_{i=1}^{l_i} A_{ij} x_{ij} \right) \tag{22}$$

where: x_{ij} is taken as 0 or 1 depending on whether the design feature is a design factor or not.

Factor analysis is a 1 statistical method for examining the relationship of variables and is used to identify the underlying structure behind the variables. In factor analysis, multiple observed variables are grouped into a few unobserved variables, and the unobserved variables are referred to as factors. In the factor analysis of user perceptual imagery, a large number of perceptual imagery that meets the user's needs are screened out, and then the semantic importance of each perceptual imagery, i.e., the weight of each imagery, is derived from the perceptual imagery cognitive experiments conducted on the target group. As a result, the calculation formula of the fitness function is

$$F = \sum_{k=1}^{m} w_k F_k \tag{23}$$

where: w_k is the weight coefficient of the k nd imagery, which is derived from factor analysis. According to Eq. (23) the morphological combination fitness obtained by a particular ant during the ACO algorithm's optimization process can be calculated.

3. Example analysis of the application of product form optimization algorithm based on ant colony algorithm

This chapter will take a brand A model as an example to verify the effectiveness of the user demand identification and product optimization decision-making method described in this study.

In this paper, the word-of-mouth review data of the brand A model is selected as the research object, and the Python tool is used to write a crawler program to crawl the data, and then carry out data preprocessing. The collection time of the document starts from March 21, 2020, and ends on September 19, 2023, and a total of 1,084 word-of-mouth review data of the A model of the Automotive Home Forum have been collected. In order to obtain as much relevant information as possible, this experiment selected user name and user gender related to user information, purchase model, time, location, price, etc. related to car purchasing information, and word-of-mouth title, publication time, and word-of-mouth content related to word-of-mouth information in the data field selection stage.

3.1. Product form optimization fitness function construction

3.1.1. User perceptual imagery acquisition. The SO-PMI algorithm calculates the absolute maximum standardized result of the absolute value of the relative intermediate sound volume distance $\overline{t}_N$, the maximum standardized result of the absolute value of the average sentiment $\overline{P}_N$, and the group negative sentiment tendency value I_N for all feature words in the processed comment data, and the results of the calculation of the sound volume and sentiment are shown in Table 1, in which the volume of the sound volume is recorded as t_N, the sentiment as Q_N, the relative intermediate sound volume is recorded as t_m, and the average sentiment is recorded as P_N.

Table 1. Results of emotional calculation of sound volume

Feature	t_N	Q_N	t_m	P_N	$\overline{t}_N$	$\overline{P}_N$	I_N
Appearance	2197	16863.98	2157.5	6.35	0.73	0.34	2.59
Oil consumption	1948	786.32	1934	1.98	0.63	0.17	2.86
Space	3982	1375.35	3967	3.23	1.53	0.23	3.02
Assembly gap	95	87.24	54.5	2.02	0.0045	0.094	2.18
Technology	297	1048.39	278	2.98	0.083	0.19	1.97

According to the results in Table 1, the results of sound volume sentiment distribution visualization are shown in Figure 3. From Figure 3, we can obtain the feature attributes with high relative intermediate sound volume values and low average sentiment, i.e., the features that users are both concerned and dissatisfied with, and there are a total of 71 features that fall in the fourth quadrant.

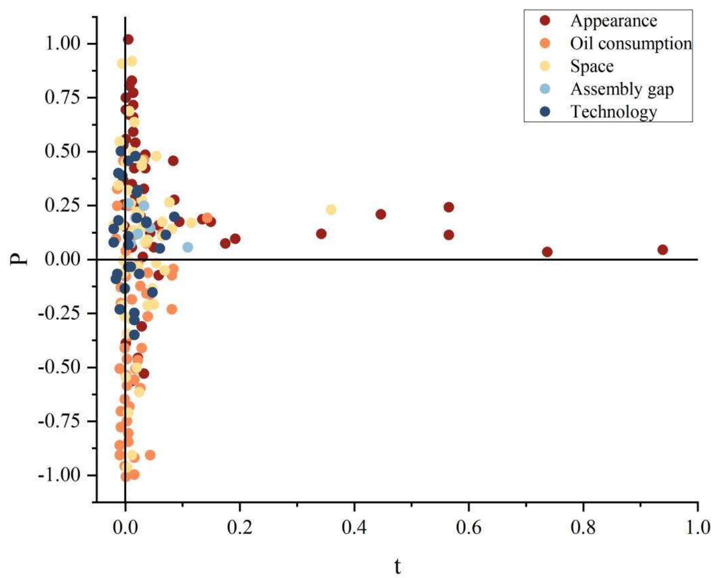

Fig. 3. Distribution of emotional and sound volume

3.1.2. Determination of perceptual imagery weights. The purpose of this section is to conduct further priority assessment of user requirements on the basis of identifying 71 key requirements, obtaining weights to provide reference for product optimization decisions. Before prioritization, it is necessary to perform sentiment clustering analysis on word-of-mouth (IWOM) review documents in order to establish evaluation criteria that match the actual situation of the current review collection. The sentiment score of the whole review can be obtained by summing up all the “feature-opinion pair” sentiment scores in a word-of-mouth document. The analysis shows that the sentiment values of word-of-mouth documents can be clustered into four categories, and the distribution results are shown in Figure 4. By analyzing the distribution of sentiment values in word-of-mouth documents, the emotional score range and boundaries of "liking", "taking it for granted", "reluctantly accepting" and "disliking very much" can be obtained. Based on this, the satisfaction rating standard is established, that is, the weight of the user's perceptual image is determined.

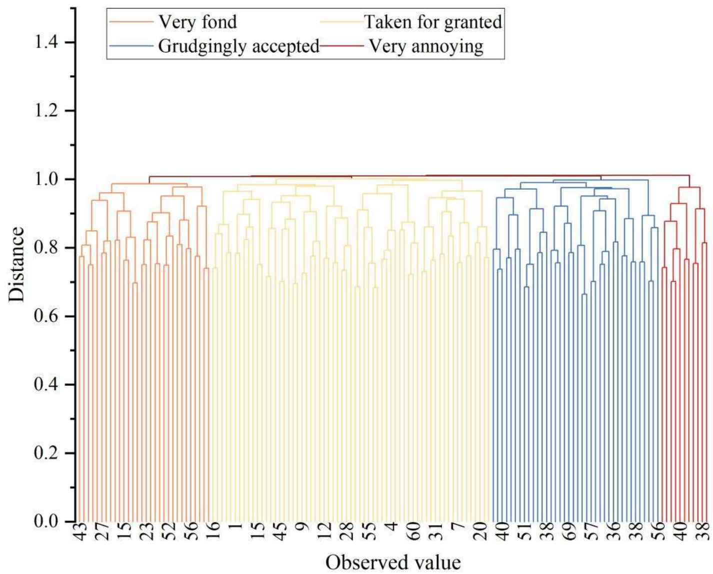

Fig. 4. Emotional value distribution of word-of-mouth documents

3.1.3. Determination of Contributing Values for Morphological Characteristics. Six versions of model A were selected as representative samples, and the semantic differential method was applied to construct the SD questionnaire on the degree of difference of the product form, 50 valid questionnaires were issued and recovered, and the mean value of the questionnaire data was calculated, and the obtained degree of difference matrix is shown in Table 2.

Table 2. Difference degree matrix

	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6
Sample 1	0	4	2	7	3	9
Sample 2	4	0	6	3	7	2
Sample 3	2	6	0	5	3	6
Sample 4	7	3	5	0	3	2
Sample 5	3	7	3	3	0	5
Sample 6	9	2	6	2	5	0

Using multidimensional scale analysis to process the difference degree matrix, the constructed product morphology perception space is shown in Figure 5. By introducing the results of the comprehensive evaluation of user perceptual imagery into the product morphology perception space in the form of the third dimension, the contribution value of morphological features to user perceptual imagery can be determined, and then the product morphology optimization adaptation function can be constructed.

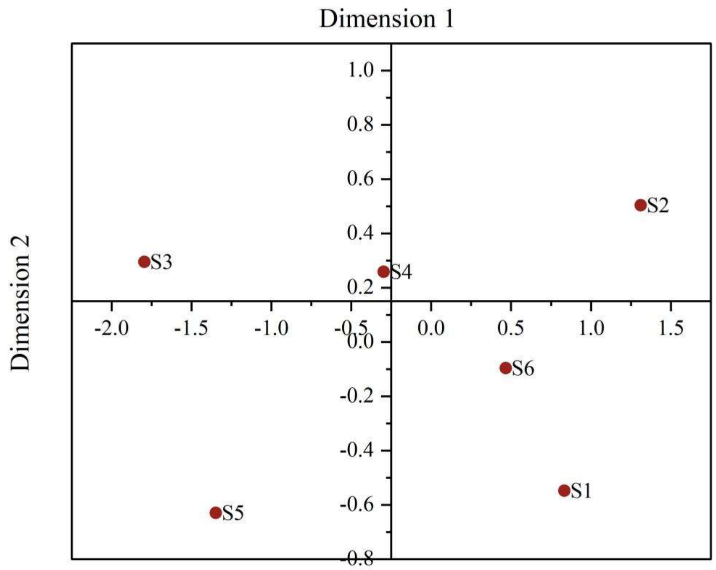

Fig. 5. Form perception space of series products

3.2. Product form optimization model solution

The product form optimization model based on traditional genetic algorithm and the product form optimization model based on ant colony algorithm proposed in this paper are used to solve the optimal solution for model A respectively. First of all, the initial morphology design element combination of the product optimization design model is divided into hierarchical clusters, set its similarity coefficient as a=1, and divide the initial morphology into 8 sub-morphologies, and the specific clustering results are shown in Table 3.

Table 3. Initial form clustering results

Subform number	Number of chromosomes/pheromones	The average hamming distance
a	32	48.25
b	16	48.19
c	25	47.38
d	19	47.92
e	38	47.05
f	41	47.56
g	36	48.03
h	32	47.29

In order to verify the effectiveness and advantages and disadvantages of the proposed ant colony algorithm for product optimization and design model optimization, this experiment tests the traditional genetic algorithm with initial chromosome rows of 6 and the ant colony algorithm from the convergence speed and solving ability of the algorithm respectively, and the convergence test results are shown in Fig. 6. Analyzing Fig. 6, it can be seen that the ant colony algorithm and the traditional genetic algorithm begin to converge when the number of iterations is less than 10. Among them, the fitness of ACO algorithm reaches its maximum at 55 iterations and maintains at 420 in the subsequent iterations, while the fitness of traditional genetic algorithm with initial chromosome rows of 6 reaches its maximum at 95 iterations and maintains at about 300. As a result, the ACO algorithm is superior to the traditional genetic algorithm with an initial chromosome row number of 6 in terms of convergence speed and solving ability, and is more suitable for solving the optimization problem of the product design model constructed in this study.

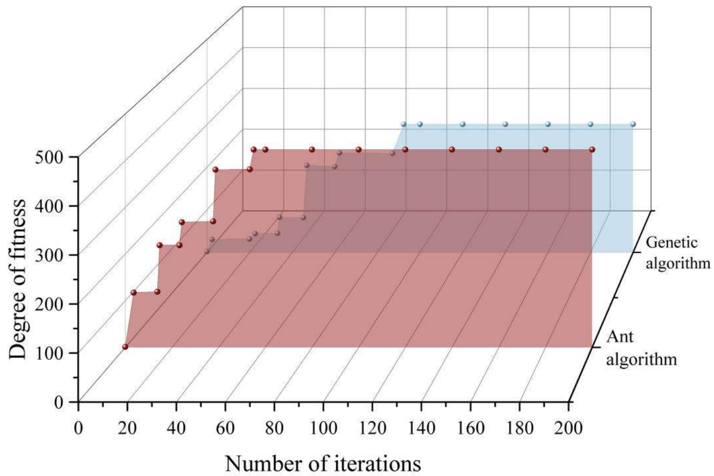

Fig. 6. Convergence test results

The pheromone and change of the optimization seeking pheromone of the product optimization design model based on ACO algorithm are shown in Fig. 7. Analysis of Fig. 7 shows that the output of the product optimization design model based on ACO algorithm for model A is 8. In this case, the traditional genetic algorithm with initial chromosome rows of 6 is unable to solve the optimization problem in which the number of modules exceeds its own initial chromosome rows, and it is unable to find the optimal solution of the product optimization design model.

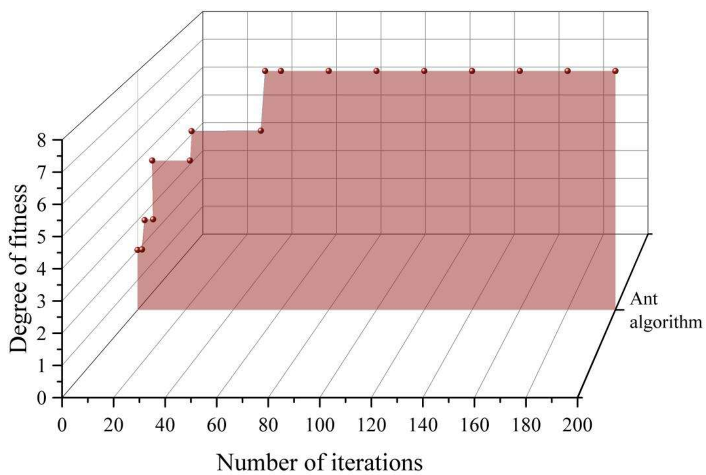

Fig. 7. Changes of pheromone sum in optimal module division

In summary, the ant colony algorithm is able to search the pheromone with the optimal fitness, and then obtain the optimal solution of the product optimization design model, which proves the effectiveness and robustness of the ant colony algorithm for solving the optimization problem of the product optimization design model.

3.3. Effectiveness of Product Form Optimization Model

VR technology can accurately simulate and display complex design solutions and environments in a three-dimensional form, making up for the lack of experience in spatial layout, dimensional proportions, lighting effects, etc., when users observe two-dimensional pictures. In addition, using VR technology for program evaluation can significantly reduce the production cost and time of physical prototypes, allowing multiple iterations and modifications of the design at a lower cost. Therefore, in order to further validate the effectiveness of the product form optimization design model based on the ant colony algorithm, this paper uses the VR virtual device to carry out VR simulation experiments to evaluate the selected optimization scheme with satisfaction.

This part is carried out for users who have purchased A model, and a total of 260 questionnaires were distributed through online and offline methods. After carefully identifying the recovered questionnaires, 22 questionnaires were found to be invalid, so they were deleted, and finally 238 valid questionnaires were obtained. The validity rate reached 91.54%, indicating good completion and allowing the questionnaire to be analyzed. The questionnaire includes users' overall satisfaction with the optimized A model and their willingness to purchase the optimized A model.

The statistics of users' overall satisfaction with the optimized Model A and their willingness to purchase the optimized Model A are shown in Table 4. Table 4 shows that 23.11% of the users are very satisfied with the optimized Model A, 65.55% are satisfied, and 11.34% are generally satisfied and dissatisfied with the optimized Model A, which indicates that the optimized Model A basically meets the psychological expectations of the users. 85.72% of the respondents are willing to buy the optimized Model A, while only 14.28% of the respondents are generally satisfied and dissatisfied. Only 14.28% of the respondents chose “average” and “unwilling”. This shows that most users are willing to buy the optimized Model A, and the optimized Model A has a better market prospect.

Table 4. Results of questionnaire survey

Satisfaction	Subtotal	Proportion	Willingness	Subtotal	Proportion
Very satisfied	55	23.11%	Very willing	56	23.53%
Satisfied	156	65.55%	Willing	148	62.19%
Normal	19	7.98%	Normal	23	9.66%
Unsatisfied	8	3.36%	Unwilling	11	4.62%
Total	238	100%	Total	238	100%

4. Conclusion

In this paper, we design a product form optimization algorithm based on ant colony algorithm under the perspective of user demand, and analyze its application effect through examples.

The results of the control experiments show that the fitness of ACO reaches its maximum at 55 iterations and is maintained at 420 in the subsequent iterations, while the fitness of the traditional genetic algorithm with an initial chromosome row number of 6 reaches its maximum at 95 iterations and is maintained at about 300. The final output of the product optimization design model based on ACO algorithm for model A is 8.

The result of user satisfaction shows that 23.11% of users are very satisfied with the optimized model A, 65.55% of users are satisfied, and 85.72% of survey respondents are very willing and ready to buy the optimized model A. The results show that the product form optimization algorithm designed in this paper is effective in practical applications, and the optimized Model A meets the users' needs.

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