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Research on Intelligent Optimization Algorithms for Product Form in Industrial Design Education

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Abstract The rapid development of computer technology has brought new opportunities for industrial design teaching. In order to improve the efficiency and quality of product form optimization in computer-aided industrial design teaching, this study constructs a product form optimization model based on ant colony algorithm. Methodologically, firstly, the perceptual engineering theory was used to determine the vocabulary of product target imagery, 21 gastrointestinal machine samples were classified into 6 categories through cluster analysis, an ant colony algorithm mathematical model containing pheromone updating and path selection probability was established, and the fitness function was designed to evaluate the value of perceptual imagery of the product morphology combinations. The results show that the total contribution of the gastrointestinal machine samples after clustering analysis reaches 98.32%, and the optimal product form design example combination adaptation degree obtained after the ant colony algorithm optimization search is 0.826, and the performance of the algorithm is significantly better than that of the genetic algorithm. In the satisfaction survey, 190 valid questionnaires show that 95.00% of users maintain a satisfactory attitude towards the product form optimization design scheme based on ACO algorithm. The conclusion shows that the ant colony algorithm can effectively solve the product morphology optimization problem, provide scientific method guidance for computer-aided industrial design teaching, and significantly improve the design efficiency and user satisfaction.

Index Terms Ant colony algorithm, product form optimization, computer-aided design, perceptual engineering, fitness function, cluster analysis

I. Introduction

Computer-aided industrial design is a required course for product form design majors [1]. Through the study, students have the design performance skills of product design assistant engineers, students comprehensively use three-dimensional software and rendering software to complete the design ideas expressed [2], [3]. With the development of computer technology, computer-aided engineering design has become an important part of modern industrial production, but also brings a more efficient, accurate and valuable design methods, and in order to get the best design solutions, shape optimization algorithms are widely used in computer-aided design (CAD) systems [4]-[7]. Shape optimization algorithms improve the efficiency and performance of design by optimizing the shape of the design object.

Shape optimization algorithms can be divided into two main categories, based on parametric shape description and based on free shape description [8]. The former represents the shape of the design object as a set of parameters, such as control point coordinates, curve parameters, etc., while the latter directly optimizes the geometric shape of the design object, and achieves the optimization goal by changing the control points of the shape, topology, etc. [9], [10]. Shape optimization algorithms for parametric shape description include the fitting method, parameter adjustment method and shape evolution method [11]. The fitting method fits the shape of the design object to a given target curve or surface by optimizing the parameters [12]. The parameter tuning method optimizes the shape of the design object by adjusting the constraints and objective function according to the changes in the desired properties of the design object [13]. Shape evolution method finds the optimal shape by transforming and evolving the shape of the design object [14]. Shape optimization algorithms for free shape description, including topology optimization method and shape evolution method [15]. The topology optimization method achieves shape optimization by changing the topology of the design object [16], [17]. The shape evolution method uses optimization methods such as evolutionary algorithms to improve the shape of the design object through iterative optimization [18].

In this paper, an intelligent optimization model based on ant colony algorithm is constructed with product form optimization as the core. Firstly, the theory of perceptual engineering is applied to establish the mapping relationship between user needs and product form features, and through systematic sample collection and imagery vocabulary extraction work, the key design elements affecting user perception are identified. Then the global search capability and parallel computing advantage of the ant colony algorithm are utilized to establish a mathematical model containing the pheromone updating mechanism and the path selection probability, and a suitable fitness function is designed to evaluate the advantages and disadvantages of different morphological combinations. Finally, the effectiveness of the algorithm is verified through empirical research, and the user's acceptance of the optimization results is analyzed through a satisfaction survey, which provides a scientific theoretical basis and practical guidance for computer-aided industrial design teaching.

II. Computer-aided industrial design teaching

II. A. Computer-aided industrial design content

The development of computer hardware has facilitated the development of computer-aided industrial design, making it possible to use advanced design means and design methods for industrial design. Computer-aided industrial design mainly includes three aspects, namely:

II. A. 1) Initial design phase

The use of the Internet and computers to investigate the market, obtain information, and analyze and summarize the information is a prerequisite for the formation of product design concepts. The completeness of the information determines whether the product design can be successfully modeled. In addition, network survey not only can obtain advanced and accurate information, but also a low-cost research method.

II. A. 2) Expression phase of the design program

This stage is the process of converting concepts into solid digital models through actual software, i.e., converting the conceptual model of the product design into a flat or solid three-dimensional digital model. This process requires designers to synthesize product conceptual design, environmental factors, product modeling, assembly, design modification and other techniques to make the established model more realistic and improve the accuracy of evaluation. Modifications to shape, color, etc. can be easily made after the model is created through the software.

II. A. 3) Computer-aided design to express design solutions

This stage is mainly to publicize, evaluate and display the product design, using the medium of computer media, such as product demonstration animation, network evaluation, multimedia product interaction and so on.

II. B. Importance of computer-aided industrial design

According to relevant surveys in the United States, computer-aided industrial design is of great importance in education. Computer aided industrial design is widely used in industrial design because of its high accuracy and ease of modification, storage and presentation and communication. The drawing design method uses prototyping technology which provides rapid modeling instead of clay models. Computer-aided industrial design is also a method of simulation and demonstration of products using virtual reality. Computer-aided industrial design has a shorter development cycle and can integrate design, analysis and manufacturing for parallel design and timely feedback of information.

II. C. Feasibility of computer-assisted teaching of industrial design

II. C. 1) Increased awareness of the integrated use of software

In the teaching process, teachers should teach the skills of software use appropriately and pay attention to cultivating students' awareness of using software to solve problems in order to improve students' design effect. The use of various design software in the computer to solve the problems in the design can save the time of design and improve the efficiency of design, for example, industrial designers can use the drafting software in the computer to draw graphics to improve the efficiency of mapping, and can also use the three-view drawing to show graphics to understand the design effect, in plane design, the use of three-dimensional software in the computer to adjust the perspective and rendering effect, can reduce the Plane class software in the realization of three-dimensional effects on the difficulties, improve the quality of graphic design.

II. C. 2) Emphasize software teaching in engineering classes

The main service object of industrial design is the manufacturing industry, and its product design and modeling work is to prepare for the future engineering design, so the engineering software will be involved in the stage of opening the model of the product. As an industrial designer, you need to consider whether the graphics of your own design can be finally processed and molded, and the continuous improvement of the functions of engineering software can enhance the energy of surface modeling, realize the drawing of many complex models, and provide industrial designers with more convenient modification functions and model analysis functions, so in the specific teaching process, teachers should pay attention to the teaching of engineering software, so that the students can be proficient in mastering and use engineering software to improve students' design ability.

II. C. 3) Rationalization of practical activities

In teaching, the textbook is an important basis for teachers to carry out teaching activities, according to the content of the textbook, guiding students to learn software operation, although it can let students master a wealth of professional theoretical knowledge, but is not conducive to the cultivation of students' practical ability, so in the actual teaching process, teachers need to be in accordance with the nature of the profession, combined with the content of the textbook, and reasonably arranged teaching activities, so that students can do theory and practice so that students can realize the combination of theory and practice, thus improving the quality of teaching. Teachers should actively improve the teaching methods, so that students can master the theoretical knowledge and at the same time have a strong practical ability to improve the professional level of students. For example, off-campus practical training activities can be carried out, so that students in the enterprise internship, familiar with and use of various software, in order to improve the comprehensive ability of students; or you can invite enterprise designers to the school to explain the process of the specific project, so that students can understand the requirements of the enterprise on the professional talent, so as to promote the students to grasp the professional knowledge and professional skills, so as to improve the effect of teaching.

II. C. 4) Examples of rational self-paced tutorials

With the continuous improvement of computer technology, the examples in the textbooks can no longer adapt to the teaching needs of the new period, and the old and outdated modeling methods are not suitable for students to learn, so the teachers need to make up their own tutorial cases according to the characteristics of the development of computers and the teaching needs to ensure that the teaching of the times and the scientific nature. Teachers can take the national standard teaching materials as the basis, combined with the needs of the times, reasonably write product modeling tutorials, write actual product cases, explain the skills of modeling, so that students can learn and master the design methods and design skills through specific pictures and videos. In addition, teachers can use the method of physical display to show the actual products, so that students can master the proportional relationship between the virtual model and the physical model by analyzing and thinking about the actual model, so as to improve students' design ability.

III. Design of Product Shape Optimization Algorithm

In this chapter, based on the theoretical analysis of computer-aided industrial design teaching in the previous section, the research samples and product target imagery vocabulary are first determined by using perceptual engineering methods, and the product morphology optimization algorithm design task is accomplished with the help of Ant Colony Algorithm (ACO). The detailed description is shown below:

III. A. Cognition of modeling imagery based on design cognition

In order to enable the research related to the optimal design of product form, this subsection identifies the research sample and the vocabulary of product target imagery using a perceptual engineering approach guided by design cognition theory.

III. A. 1) Design cognizance

As a field with distinctive practical characteristics, the research focus of design is more inclined to the study of design factors. Among the many factors affecting product design, “human factors” has become an important direction in the current design research field. However, the comprehensiveness and complexity of “human factors” make it far from enough to carry out research only from the perspective of the design profession, which is a multidisciplinary cross-field led by design, combined with psychology, computer science, mathematics and other disciplines. In addition, design itself is the transformation of user needs into usable and tangible substances through rational methods and means, such as materials, multimedia, and information technology. With the development of society, it is gradually realized that design should be human-centered in order to design products that satisfy users' needs. Therefore, the study of users has naturally become the focus of design, which is also linked to human cognition. This study will start from the process of imagery cognition in design cognition, analyze the psychological state and mental activity of the cognitive subject, and further excavate the influencing factors behind the generation of cognitive differences between each cognitive subject.

III. A. 2) Sample image selection

Before carrying out the product form optimization design driven by cognitive differences, the first step is to determine the research samples based on the process of design cognition from the perspective of the perception of the cognitive subject.

(1) Collection of sample pictures

The collection of sample pictures should be based on the theory of design cognition, through the cognitive analysis of product modeling, simulate the psychological activity process of “human” in perceiving the product, and eliminate unnecessary objective influencing factors to ensure the quality of sample pictures. We collect sample pictures of products through the Internet, books, magazines, journals, posters, physical photography and other means, and control the clarity of the pictures, so as to eliminate the sample pictures with poor clarity. In addition, the size and shooting angle of the pictures are standardized, and the pictures are processed in grayscale to eliminate the influence of color on the cognition of the product's morphological imagery, and the morphological contour lines of the product can be extracted when necessary to ensure the uniqueness of the influence of the product's morphology on the imagery. This completes the initial establishment of the sample image library

(2) Screening of sample images

Apply the interview method and KJ method to further screen the preliminary establishment of the sample image library, from the intuitive point of view of the morphological similarity of the sample images to be eliminated, to reduce the subsequent workload, the remaining sample images as a representative sample for research.

III. A. 3) Perception of modeling imagery

The formation of product modeling imagery comes from human cognition of product form, which refers to the use of imagery vocabulary to express the potential sensual needs of the cognitive subject. By exploring and studying the cognitive subject's perceptual needs about product modeling, it helps to convey the emotional language in product form design. This study analyzes the principle of imagery cognition to determine the target imagery vocabulary that meets the needs of the cognitive subject.

(1) Collection of Imagery Vocabulary

The relevant perceptual imagery vocabulary of the sample product is collected and studied through the Internet, journals, books, etc. In particular, the official introduction of the sample product's official website about the product usually contains the company's direct positioning of the imagery of the product. In addition, in order to intuitively understand the real feelings of people, the collected imagery vocabulary base is expanded by using the spoken language analysis method.

(2) Screening of product target imagery vocabulary

The imagery vocabulary database is screened using the clustering algorithm, and the target imagery vocabulary of the sample products is determined by judging the relevance of the imagery vocabulary to the research samples.

III. B. Product form optimization design model based on ant colony algorithm

III. B. 1) Ant Colony Algorithm

Ant colony algorithm mathematical modeling mainly contains pheromone updating and path selection probability, pheromone updating is a core part of the ant colony algorithm, which describes how the ants update the pheromone concentration on the paths in the process of finding solutions [19]. The process of pheromone release and volatilization on the path plays a key role in the performance of the ACO algorithm [20]. The pheromone updating process mainly consists of three parts: pheromone release, pheromone volatilization, pheromone updating, and pheromone concentration, and the pheromone updating formula is usually used as shown in equation (1):

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \rho\Delta\tau_{ij}(t) \tag{1}$$

where $\tau_{ij}(t)$ is denoted as the pheromone concentration on the path from i to j, ρ denotes the volatilization rate of the pheromone, and $\Delta\tau_{ij}(t)$ denotes the pheromone released by the kth ant on the path from i to j. The $\Delta\tau_{ij}(t)$ can be calculated based on the behavior of the ants and the characteristics of the problem, and its expression is shown in (2):

$$\Delta\tau_{ij}(t) = \begin{cases} \dfrac{Q}{L_k} & \text{Ant } k \text{ passes through path } [i,j] \\ 0 & \text{Other} \end{cases} \tag{2}$$

where Q is the total amount of pheromone released by the ants in finding the solution, and L_k is the length of the path $i-j$ traveled by the kth ant. The pheromone concentration $\tau_{ij}(t)$ is updated according to pheromone release and volatilization. After each iteration, $\tau_{ij}(t)$ is calculated according to the above pheromone update formula to reflect the new pheromone concentration of the path.

Path selection probability is a probability calculation used in the ant colony algorithm to guide the ants to select the next moving path. At each decision point, the ants calculate the selection probability of each path based on the pheromone concentration and the heuristic information. The ant colony heuristic information $\eta_{ij}(t)$ is calculated based on the characteristics of the problem and the ants' location i and the possible path j of the next move, and the heuristic information is used to guide the ants to make a decision based on the a priori knowledge of the problem [21]. Usually, the larger the heuristic information should be, the more attractive the path is and the more likely the ants are to choose it. The ant colony calculates the selection probability P_{ij} for each path $i-j$ at the decision point, the expression of which is shown in (3):

$$P_{ij}=\begin{cases}\dfrac{\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)}{\sum_{s\in C}\tau_{is}^{\alpha}(t)\eta_{is}^{\beta}(t)} & j\in C\\ 0 & j\notin C\end{cases} \tag{3}$$

In the ACO algorithm, the process of selecting the next node depends on a set of parameters and variables. Where C is the set of next selectable nodes, $\tau_{ij}(t)$ is the pheromone concentration, and $\beta_{ij}(t)$ is the heuristic information for paths $i-j$. The parameters α and β regulate the influence of pheromone concentration and heuristic information in path selection, respectively, and are used to achieve a balance between them. Specifically, increasing the value of α causes the ants to tend to choose paths with higher pheromone concentration, while increasing the value of β increases the likelihood that the ants will choose nodes with higher heuristic information as their next moving targets. $\eta_{ij}(t)$ indicates the degree of expectation from the current node to the next node, which affects the ants' path selection. $\eta_{ij}(t)$ is the degree of expectation from the current node to the next node, which can generally be expressed by equation (4):

$$\eta_{ij}(t)=\frac{1}{d_{jg}} \tag{4}$$

where d_{jg} is the Euclidean distance between the next node j and the target node g. The initial ant colony has more moving directions, and the pheromone concentration and heuristic information are usually fine-tuned in order to calculate the selection probability. Assuming that the sum of selection probabilities of all moving directions is 1, each selection probability is divided by the sum of selection probabilities of all possible directions, and then a random number generator is used to make a random selection so that the next moving direction can be computed with probability, and although the pheromone provides the direction with higher probability, the other directions still have a lower probability of being selected, and the above steps are repeated until the ants arrive at the target node or satisfy the termination condition Until. After each step, the updated pheromone concentration affects the selection of the next ant. When all ants complete the task, the final path of the colony is formed. The following mathematical model is expressed to calculate the selection probability of nodes:

$$P_{ij}=\frac{\left[\tau_{ik}^{\alpha}\cdot\eta_{ik}^{\beta}\right]}{\sum_{k}\left[\tau_{ik}^{\alpha}\cdot\eta_{ik}^{\beta}\right]} \tag{5}$$

where, P_{ij} is the probability of ants selecting node j from node i; τ_{ij} represents the pheromone concentration from node i to node j; η_{ij} represents the heuristic information from node i to node j; and α and β are the parameters controlling the weights of pheromone and heuristic information. Equation (5) well expresses the relationship between selection probability and the product of pheromone concentration and heuristic information, and the denominator is the sum of probabilities of all selectable nodes, which sums up to 1. The pheromone and heuristic information determine the calculation of selection probability of each node in order to support the ant's path selection. After repeated calculations, the ants will gradually find the best path through continuous trial and error.

The ant colony balances the search between global and local by the roulette rule, which helps to find the optimal solution of the problem.

III. B. 2) Modeling

The model consists of n design elements and m representative perceptual imagery. Design elements refer to the product appearance, parts related relationships, color matching 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 specific morphological features, such as color matching design elements may contain orange, blue and other morphological features; appearance design elements may contain streamlined, angular and other morphological features. Representative perceptual imagery refers to the adjectives that best represent the user's intuitive feeling of a product form, such as high-end, reliable, etc. Let $x_1, x_2, \cdots, x_n$ be a product form combination, F be the overall perceptual imagery value of the form combination, and F_k be the total contribution value of the form combination to the kth perceptual imagery. Based on this, the product form optimization design model Y can be described as:

$$\left.\begin{array}{c} Y = \max F(x_1, x_2, \cdots, x_n) = \max(F_1(x_1, x_2, \cdots, x_n) \\ F_2(x_1, x_2, \cdots, x_n), \cdots, F_m(x_1, x_2, \cdots, x_n)) \\ s.t.\ a_j \le x_j \le b_j, j = 1, 2, \cdots, n \\ x_j \in Z, k = 1, 2, \cdots, m \end{array}\right\} \tag{6}$$

where, x_j is the jth level design element, the maximum possible value is l_j, l_j is the number of morphological features of x_j, $l_j = b_j - a_j + 1$; Z is the space of the design elements; a_j, b_j are the values of the variables; and $j = 1, 2, \cdots, n$, is the level of the design elements.

III. B. 3) Probability formulas and contribution value update equations

In the product morphology optimization design model, each design element, x_j, has l_j optional morphological features. By selecting any one of the morphological features from each design element, a complete product morphology optimization solution is formed when all n design elements have completed their selection $(x_1, x_2, \cdots, x_n)$. The model adopts N-level design element decision model $(N = n)$, the first j-level design element x, including 4 nodes, the initial state of all the ants are located in the nodes in x_j, and the probability of selecting the first i-level node for the morphological feature in x_j is in equation (7) . For:

$$p_{ij} = \frac{\tau_{ij}}{\sum_{i=1}^{l_j} \tau_{ij}} \tag{7}$$

where τ_{ij} is the contribution value of the ith morphological feature in x_j to the total imagery, and the contribution value update equation is shown in equation (8). For:

$$\tau_{ij}^{new} = \rho \tau_{ij}^{old} + \frac{F}{Q} \tag{8}$$

where, ρ is the pheromone evaporation rate; F is the degree of adaptation; and Q is the intensity of pheromone increase.

III. B. 4) Adaptation function

In the product morphology optimization design model, the fitness function as the core evaluation mechanism directly guides the search direction of the ant colony algorithm, and its construction needs to synthesize the results of the analysis of the user perceptual imagery factor and the contribution value of the product morphology features in the semantics of perceptual imagery. Using quantitative theory I-like methods, the contribution value of each morphological feature to perceptual imagery is analyzed. Let the contribution value of the ith morphological feature element of the j th design element to the k th perceptual imagery be A_{ij}, then the total contribution value of the product morphological combination to the k th perceptual imagery F_k can be expressed as:

$$F_k = \sum_{j=1}^{n}\left(\sum_{i=1}^{l_j} A_{ij} x_{ij}\right) \tag{9}$$

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

The core idea of factor analysis, as a statistical method to study the relationship of variables, is to summarize a large number of observable variables into a few potential variables (i.e., factors) that are not directly observable. In the factor analysis of user perceptual imagery, a representative set of perceptual imagery that meets the user's needs is first screened, and then the weight coefficients of each perceptual imagery factor are determined through the perceptual imagery cognitive experiment of the target group. As a result, the adaptation function (F) is calculated as:

$$F = \sum_{k=1}^{m} w_k F_k \tag{10}$$

where w_k is the weight coefficient of the k th imagery.

III. B. 5) Model realization

The parameter settings used in the ACO algorithm depend on the problem characteristics and size, depending on the specific problem analysis. In order to determine the optimal range of parameter values, the algorithm needs to be run several times before setting the parameters. The implementation process of product form optimization design model based on ACO algorithm is as follows:

(1) Data organization. Obtain the vocabulary of product perceptual imagery through research and determine the weight of each perceptual imagery, and after deconstructing the representative picture samples of the target product to extract the morphological feature elements, calculate their contribution value, so as to obtain the basic data required for morphology optimization.

(2) Initialization parameters and data import. Set the number of iterations, the number of ants, the pheromone increase strength Q and the pheromone evaporation rate ρ according to the design object and import the algorithmic formula and morphology optimization data.

(3) Select morphological design element nodes. At each iteration of ants, the combination of Eq. and Randsample function is used to select nodes by roulette selection method, and one node is selected for each item each until all items are selected to obtain a product morphology combination.

(4) Calculate the degree of adaptation. After selecting one morphology feature node walk-through from each of all design elements, a morphology optimization combination scheme is obtained, after which the adaptation degree of each combination is calculated according to Eq.

IV. Analysis of empirical studies

IV. A. Vocabulary Extraction of Product Form Imagery

IV. A. 1) Collection and Screening of Imagery Semantics

(1) Selection of samples. This section takes the medical device product gastrointestinal machine as the research object, and consults the newspaper, browses the webpage, and participates in the medical device exhibition to collect the morphological pictures of the gastrointestinal machine, covering as far as possible the gastrointestinal machines produced and marketed by various domestic and foreign medical device enterprises in recent years. In order to avoid the subjects' preference for color affecting the objectivity of the study, the color pictures of the samples were processed in grayscale. Then the sample pictures of gastrointestinal machines were subjectively screened to exclude unclear and similarly shaped sample pictures. Finally, 21 images of different gastrointestinal machines with different overall morphology were collated as the initial sample and randomly numbered from 1 to 21.

(2) Selection of subjects. In order to select representative typical samples and adjective pairs of gastrointestinal machines, three researchers from the Northwest Mechanical Design Department, two doctors who operated gastrointestinal machines in hospitals for medical examinations, and one patient who had used a gastrointestinal machine for a medical examination were selected.

(3) Establishment of an imagery vocabulary database. Referring to product introductions, popular magazines, Internet forums, news reports, etc. related to medical devices, from which evaluation terms and users' psychological

feelings were compiled, and then subjectively eliminating adjectives that are not commonly used or have similar meanings, and pairing adjectives that have opposite meanings, a total of 40 pairs of product morphology imagery vocabulary were collected, thereby forming the Imagery Vocabulary Database.

(4) Product form imagery vocabulary screening. In order to make the intentional semantic adjectives more vivid, the researcher from the design department of Northwest Machinery selected 10 pairs of adjectives (Y1~Y10) screened for corrective embellishment.

IV. A. 2) Extraction of representative gastrointestinal machine samples

In order to simplify the number of samples, the 21 gastrointestinal machine samples were categorized using cluster analysis, and then representative morphological samples were selected.

(1) Sample selection. 21 grayscale images of gastrointestinal machines and 10 adjective pairs.

(2) Selection of subjects. 2 physicians who operated gastrointestinal machines in hospitals for medical examinations and 1 patient who had used a gastrointestinal machine for medical examinations.

(3) Sample extraction. The 3 subjects were made to score the similarity of 21 gastrointestinal machine samples based on 10 adjectives in a two-by-two comparison. The scores were taken from 0 to 5, with higher scores representing stronger similarity between the two samples. A 25*25 similarity matrix is listed. It is shown below:

$$x=\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{n1} & x_{n2} & \cdots & x_{nn} \end{bmatrix} \tag{11}$$

Calculate the average value of 5 groups of similarity matrices to obtain the average similarity matrix, and use SPSS software to perform cluster analysis on the results of the average similarity matrix to classify the product styling or color by analyzing the user's categorization and preference, so as to uncover the preference with similarity. The clustering tree diagram is shown in Figure 1. Then the 21 gastrointestinal machine sample graphs are able to be divided into 6 categories, the first category is 1, 2, the second category is 3, 4, 5, 6, 7, 10, 11, 12, 13, the third category is 8, 9, 14, 15, 16, the fourth category is 17, 18, the fifth category is 19, and the sixth category is 20, 21. analyze the sample graphs of each sample of the 6 categories, and filter out the sample graphs that are similar to the other samples of each category with the The sample with the highest similarity to the other samples in each class that best encompasses the characteristics of the samples in that class is used as the representative sample for that class. The results of the cluster analysis were summarized as shown in Table 1. The selected representative gastrointestinal machine samples were numbered again.

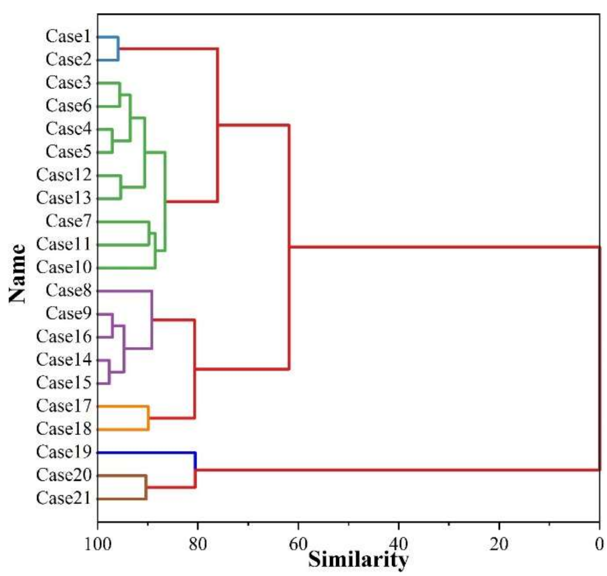

Figure 1: Clustering tree diagram

Table 1: Summary table of Cluster Analysis Results

Category number	Sample number	Quantity
1	1, 2	2
2	3, 4, 5, 6, 7, 10, 11, 12, 13	9
3	8, 9, 14, 15, 16	5
4	17, 18	2
5	19	1
6	20, 21	2

In order to facilitate data statistics and analysis. Firstly, a Likert 7-point scale was made, and 20 subjects were allowed to use 10 adjective pairs to rate the imagery of 6 representative gastrointestinal machine samples respectively, and then the mean of the ratings was calculated, and the imagery semantic mean is shown in Table 2. In order to simplify the 10 pairs of gastrointestinal machine style imagery semantic genes, we used a statistical analysis algorithm to import the product form imagery semantic averages from Table 2 into the SPSS software for analysis.The results of the SPSS analysis are shown in Table 3.When analyzing the data in the table, there are three factor eigenvalues greater than 1 for the product form imagery semantic factors, and the sum of their contributions is 98.32%.

Table 2: Average value of image semantics

N	1	2	3	4	5	6
Y1	1.023	-0.146	-1.785	0.02	0.346	-0.937
Y2	0.216	-0.141	-1.5	-1.299	0.628	0.372
Y3	-1.047	1.612	-0.081	-0.49	-0.712	-0.886
Y4	-1.195	-1.268	-1.393	-1.919	-1.41	-1.848
Y5	-1.83	-1.472	0.874	1.786	1.835	-0.296
Y6	-0.842	0.793	-0.367	1.138	-1.106	1.747
Y7	-1.634	-1.624	-0.38	-1.947	1.211	-0.985
Y8	-0.07	0.268	-1.79	1.929	0.448	1.379
Y9	1.7	-1.097	-0.516	1.197	-1.001	0.932
Y10	-1.927	1.09	1.192	-1.94	-0.655	-1.804

Table 3: Explanation of total variance

Component	Initial eigenvalue			Extract the sum of the load squares			The sum of squared rotating loads
	Total	Ratio	Accumulation	Total	Ratio	Accumulation	Total
1	4.975	49.75%	49.75%	4.975	49.75%	49.75%	4.534
2	3.611	36.11%	85.86%	3.611	36.11%	85.86%	3.927
3	1.246	12.46%	98.32%	1.246	12.46%	98.32%	1.371
4	0.065	0.65%	98.97%				
5	0.052	0.52%	99.49%				
6	0.023	0.23%	99.72%				
7	0.013	0.13%	99.85%				
8	0.009	0.09%	99.94%				
9	0.005	0.05%	99.99%				
10	0.001	0.01%	100.00%				

IV. B. Algorithm Validation Analysis

IV. B. 1) Optimal design solution

According to the product morphology imagery vocabulary extraction, 21 product morphology imagery images are obtained, and with the support of ant colony algorithm, the product morphology design instances that meet the user's needs can be screened out.As can be seen from the above, it is not difficult to get the class of the most similar design instances and the set of outlier design instances that are not difficult to get after the clustering analysis. Restricted by the length of the article, there are six modules of product form, as shown in Table 2, Module 1 contains three instances, respectively Case1, Case2. module 2 contains nine instances, respectively Case3, Case4, Case5, Case6, Case7, Case10, Case11, Case12, Case13. Module 3 contains 5 instances, Case8, Case9, Case14, Case15, Case16.Module 4 contains 2 instances, Case17, Case18. Module 5 contains 1 instance, Case19. Module 5 contains

2 instances, Case20, Case21. The affinity between each design instance is calculated by applying the formula and finally the distance matrix is obtained by applying the formula as shown in Table 4.

Table 4: Distance matrix of similar instances in each module

Case	1	2	3	4	5	6	7	8	…	21
1	0.826	0.788	0.768	0.391	0.737	0.269	0.448	0.495	…	0.723
2	0.441	0.234	0.751	0.824	0.774	0.43	0.51	0.89	…	0.342
3	0.461	0.363	0.547	0.737	0.501	0.575	0.416	0.217	…	0.612
4	0.29	0.837	0.393	0.255	0.505	0.474	0.786	0.334	…	0.236
5	0.454	0.5	0.787	0.785	0.454	0.834	0.87	0.254	…	0.807
6	0.489	0.433	0.772	0.543	0.711	0.47	0.464	0.306	…	0.339
7	0.364	0.817	0.202	0.532	0.47	0.24	0.31	0.595	…	0.746
8	0.353	0.89	0.288	0.789	0.838	0.776	0.797	0.875	…	0.557
…	…	…	…	…	…	…	…	…	…	…
21	0.335	0.598	0.327	0.614	0.333	0.661	0.795	0.205	…	0.228

The above ant colony algorithm is programmed with MATLAB, imported into the experimental data, set the number of iterations, the number of ants and so on. After repeated calculations of the experimental method, the pheromone weighted value is set to 0.5, and the concentration weighted value is set to 0.5 After calculations, the optimal product form design scheme is obtained, and the results of the ant colony algorithm's optimization search are shown in Figure 2. The optimal product form design example combination obtained is:

$$Case_{best} = \{Case_1, Case_8, Case_{12}, Case_{16}, Case_{19}\} \quad (12)$$

The shortest distance can be seen from Figure 2:

$$d_{best} = 1.119 \quad (13)$$

The degree of adaptation in the optimal combination of product form design instances is:

$$F_{best} = 0.922 \quad (14)$$

In summary, the use of ant colony algorithm to realize the product form design can maximally satisfy the user needs, and at the same time can also solve the problem of product form configuration, indicating that the ant colony algorithm has a certain degree of superiority in the product form design.

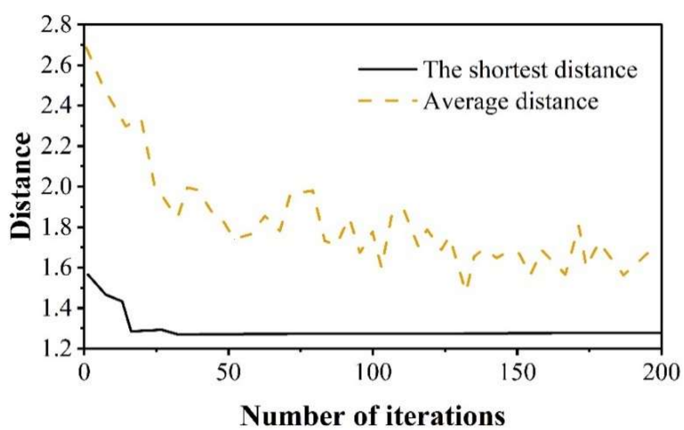

Figure 2: The optimization result of ant colony algorithm

IV. B. 2) Algorithm Performance Verification Analysis

A benchmark library, NDR, is used to validate the ACO-based product form design method proposed in this paper.NDR classifies the product forms into categories, which contains more than 700 representative product forms. During the experiment, the parameters of the algorithm were set to $\alpha = 0.5$, $\rho = 0.45$, $\omega = 4$, $\tau_0 = 0.04$, and $\tau_0' = 0.02$, with the maximum number of iterations being 200 and the number of ants in the colony being 50. In order to fully compare the performance of the two algorithms, this paper conducts statistical tests on the product morphology in the benchmark library, and obtains an average check all rate-check accuracy curve, as shown in Fig. 3, which shows that the algorithm in this paper can search the optimal morphology design of the product, and the performance is significantly higher than that of the genetic algorithm. The algorithm in this paper can search out more forms that meet the design intent for users to choose, and can provide guiding reference value for product form optimization in computer-aided industrial design teaching.

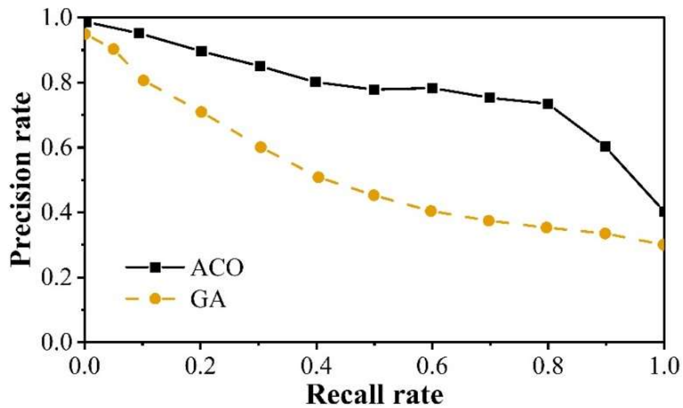

Figure 3: The recall - precision curves of the two algorithms

IV. C. Product Satisfaction Analysis

In order to further validate the effectiveness of the product form optimization design solution based on ACO algorithm, this subsection will analyze the data with the help of a questionnaire to analyze the satisfaction of the product form optimization design solution based on ACO algorithm. The details are as follows:

IV. C. 1) Questionnaire design

Referring to the relevant literature and information, the product satisfaction questionnaire is designed from the five aspects of product structure (A1), product material (A2), product texture (A3), product color (A4), and product structure (A5), which contains a total of 25 items, and each item has five options, which are very dissatisfied, dissatisfied, basically satisfied, satisfied, and very satisfied, respectively. Through the reliability test analysis, it can be seen that the questionnaire has excellent reliability and meets the standard requirements of this research. The questionnaire was distributed in a combination of online and offline mode, 100 questionnaires were distributed online and 100 questionnaires were distributed offline, a total of 200 questionnaires were distributed, 190 questionnaires were valid, and the effective recovery rate was 95.00%.

IV. C. 2) Statistics on basic user information

Through the collection and organization of the questionnaire, the statistical results of the questionnaire need to be analyzed, the first step is to summarize the basic information of the subjects in a general way, and the statistical results are shown in Table 5. Based on the analysis of the above table, it can be seen that in terms of gender, the proportion of men and women is basically the same, and the proportion of girls among the subjects is relatively more.

Table 5: Statistics of basic user information

Project	Information	Number	Proportion %
Gender	Male	110	57.89%
	female	80	42.11%
Age group	Under 18	25	13.16%
	18-25	33	17.37%
	26-30	92	48.42%
	31-40	11	5.79%
	Over 40	29	15.26%
Degree of understanding	Don't understand	13	6.84%
	Know a little	26	13.68%
	Understand	105	55.26%
	Understand very well	46	24.21%

IV. C. 3) Analysis of satisfaction results

With the help of questionnaire data, the satisfaction of product form optimization design scheme based on ant colony algorithm is explored, and the analysis of satisfaction results is shown in Fig. 4, where B5~B1 indicates very dissatisfied, dissatisfied, basically satisfied, satisfied, and very satisfied, respectively. It can be seen from the data in the figure that most of the users are satisfied and very satisfied with the product form optimization design scheme based on ACO algorithm, which fully confirms the effectiveness of the application of the product form optimization design scheme based on ACO algorithm.

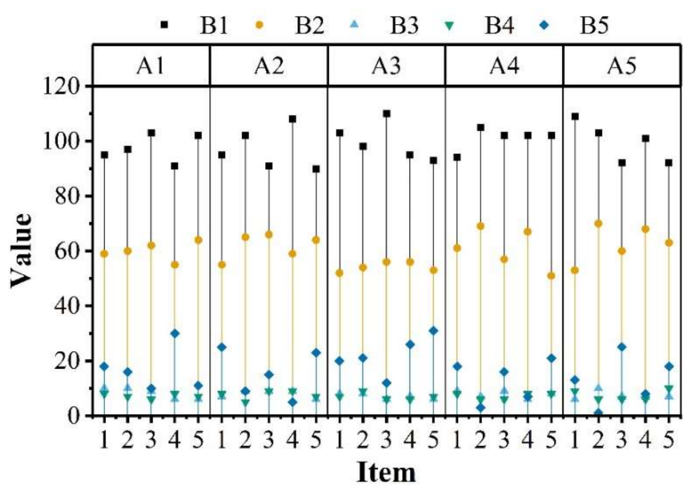

Figure 4: Analysis of Satisfaction Results

V. Conclusion

This study effectively solves the morphology optimization problem in computer-aided industrial design teaching by constructing a product morphology optimization model based on ant colony algorithm. The clustering analysis results show that the 21 gastrointestinal machine samples can be scientifically classified into 6 representative categories, and the sum of the contributions of the 3 main factors reaches 98.32%, which fully covers the core features of the product morphology. The ant colony algorithm shows significant advantages in product form design, and through 200 iterations and the search process of 50 ants, the optimal product form design scheme with an adaptation degree of 0.826 is obtained, which is significantly better than the performance of the traditional genetic algorithm. The user satisfaction survey further verifies the practical value of the algorithm, and among 190 valid questionnaires, the user satisfaction rate of the optimized design scheme reaches 95.00%, reflecting good user acceptance. The model successfully realizes the effective conversion from users' perceptual needs to product form characteristics, providing designers with a scientific decision support tool. The algorithmic model is not only able to deal with complex multi-objective optimization problems, but also has good convergence and stability, which provides a new theoretical framework and practical method for computer-aided industrial design teaching. This research result has important theoretical significance and application value for promoting the intelligent development of design education and improving the quality of product design, and lays a solid foundation for subsequent related research.

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