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Innovative Design of Product Modeling Based on Computational Geometry and Multimedia Technology

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Abstract. With the continuous breakthroughs in technology and the deepening of globalization, product design has evolved from a simple combination of art and handicrafts to a comprehensive innovation process that integrates interdisciplinary knowledge such as computer science, mathematics, and physics. Under the theoretical framework of computational geometry, product design can break free from the constraints of traditional manual drawing and model making and stride towards a new era of digitization, parameterization, and automation. This article aims to explore a revolutionary product styling innovation design method that deeply integrates the accuracy of computational geometry, the expressive power of multimedia technology, and the powerful optimization ability of interactive genetic algorithms (IGA). We compared the performance of traditional methods and IGA methods in multiple key dimensions such as design innovation, user satisfaction, modelling accuracy, and computational efficiency. The results show that the IGA method significantly surpasses traditional methods in terms of design innovation and user satisfaction, demonstrating higher modelling accuracy. Although slightly inferior in computational efficiency, considering its significant improvement in design quality and user experience, this method undoubtedly has broad application prospects.

Keywords: Computational Geometry; Multimedia Technology; Product Styling Design; Interactive Genetic Algorithm
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1 INTRODUCTION

With the advancement of science and technology and the acceleration of globalization, product design has gradually evolved from a simple combination of arts and crafts to a comprehensive innovation process that integrates interdisciplinary knowledge such as computer science, mathematics, and physics. Abdolrasol et al. [1] explored the application and advantages of artificial neural network technology in computer-aided innovative product design process planning. An artificial neural network is a computational model that simulates the structure and function of human brain neural networks with powerful learning, recognition, and optimization capabilities. In the field of innovative product design, artificial neural networks can learn a large number of design samples, grasp the inherent laws and characteristics of design, and generate new innovative design solutions. Specifically, artificial neural networks can be applied to the automatic generation, optimization, and evaluation of product styling. By constructing appropriate network structures and training algorithms, neural networks can learn and extract features of design elements, generating new shapes that meet design requirements. At the same time, neural networks can also automatically optimize the generated design scheme, improving the practicality and aesthetics of the design. In addition, multimedia technology, with its powerful audio-visual expression, injects richer and more vivid elements into product design, greatly enhancing the interactivity and user experience of design [2]. With the rapid development of information technology, the manufacturing industry is facing unprecedented changes. In this context, digital twin technology, as an emerging technological means, has brought revolutionary changes to the modelling and operation of the manufacturing industry. Bao et al. [3] will explore the modelling and operation of digital twins in the context of manufacturing, as well as related issues of manufacturing enterprise information systems, and analyze their significance and value in practical applications. Through digital twin modelling, manufacturing enterprises can more accurately grasp the structural and performance characteristics of products, predict their performance in different working environments, and provide the scientific basis for product design and improvement. In addition, digital twin modelling can also help enterprises identify potential problems and defects in the product design stage, thereby avoiding unnecessary losses and risks in the actual production process. Digital twin technology can help enterprises achieve real-time monitoring and scheduling of production processes. By constructing a digital twin model of the production process, enterprises can understand the operation status of the production line, the working status of equipment, and the quality status of products, thereby adjusting production plans on time, optimizing resource allocation, and improving production efficiency. Chaturvedi and Dwivedi [4] explored computer-aided design and analysis methods for brake products based on computational geometry and multimedia technology. Computational geometry techniques can be used for the precise modelling of brakes. By parameterization and geometric transformation, a three-dimensional model of the brake can be established, and the model can be quickly modified and optimized. This helps designers accurately design and modify brakes in virtual environments, improving design efficiency.

Gehrmann and Gunnarsson [5] analyzed the security architecture of industrial product automation and control systems based on digital twins, providing new solutions for security development in the industrial field. A digital twin is a method of creating virtual replicas of physical systems using digital technology, which can reflect the state and behaviour of physical systems in real-time. In industrial product automation and control systems, digital twins can simulate the operation process of the system, predict potential safety risks, and provide corresponding optimization suggestions. Through digital twin technology, engineers can design and test industrial products in a virtual environment, avoiding safety issues in actual production processes. At the same time, digital twins can also monitor the operation status of control systems in real-time, timely detect and handle potential security risks, and improve the stability and reliability of the system. The core objective of this article is to explore an innovative product modelling and design method based on computational geometry and multimedia technology. This method deeply integrates the accuracy of computational geometry, the expressive power of multimedia technology, and the optimization ability of IGA. We look forward to improving the efficiency of product design through this design process, bringing designers more creative inspiration and implementation possibilities.

Intelligent manufacturing has become an important development direction in modern industry. In this context, informed reverse design of product usage information data based on computational geometry and multimedia technology provides new ideas and methods for intelligent manufacturing. Hou and Jiao [6] discussed the current research status, technological applications, and future development in this field. Computational geometry and multimedia technology, as two independent disciplinary fields, have shown strong potential in cross-fusion in recent years. Computational geometry provides efficient algorithmic support for product design with its precise geometric analysis and processing capabilities; Multimedia technology, with its rich means of information display and interaction, provides diverse ways for the transmission of product usage information. Based on these two data, informed reverse design can achieve in-depth exploration and effective utilization of product usage information, providing strong support for intelligent manufacturing. Fault detection and isolation are crucial steps to ensure the normal operation of industrial processes, and are of great significance in avoiding safety hazards and improving production efficiency. Iqbal et al. [7] constructed a deep neural network inverse model for computing geometry. In industrial processes, sensors and other equipment can collect a large amount of production data in real time, which contains rich process information and potential fault signals. Reverse design based on computational geometry can not only be used for rapid prototyping and customized production of products but also for product optimization design and performance analysis. Under the framework of computational geometry, product design can evolve from traditional manual drawing and modelling to digitization, parameterization, and automation.

In order to achieve this goal, this article will first comprehensively sort out the application status of computational geometry and multimedia technology in product modeling design, and identify its main problems and development bottlenecks. Then, the basic principle of IGA and its unique advantages in product modelling design are discussed. On this basis, we will build an innovative design method framework and elaborate on its design process, key technologies and specific implementation steps. Any method proposed needs to be tested by practice. Therefore, in the follow-up part of the paper, we will verify the superiority of the proposed method through a series of experimental tests and comparative analysis. Through these empirical studies, we can not only prove the value of this method in practical application but also provide useful references for future product modelling design. The innovation and contribution of this article are summarized as follows:

(1) This article puts forward an innovative design method of product modelling, which combines the accuracy of computational geometry with the rich expressive force of multimedia technology. This method not only ensures the geometric accuracy of the design but also enhances the sensory experience and user interaction of the design through multimedia technology.

(2) This article innovatively introduces IGA into product modelling design. By simulating natural genetic mechanisms and combining them with human-computer interaction technology, it realizes the organic combination of computer intelligent optimization and user subjective assessment in the design process and improves the innovation of design results and user satisfaction.

(3) This article constructs an innovative design method framework of product modelling based on computational geometry, multimedia technology and IGA. This framework systematically integrates knowledge and technology in different fields and provides a brand-new and systematic design tool for designers.

Firstly, this article introduces the application background and present situation of computational geometry and multimedia technology in product modeling design; Then the principle of IGA and its applicability in design are expounded in detail. Then, the innovative design method based on these technologies is put forward and its effectiveness is verified by experiments. Finally, the full text is summarized and the future research direction is prospected.

2 RELATED WORK

The basic concepts involved in computational geometry include geometric elements such as points, lines, and surfaces, as well as their spatial relationships, attribute descriptions, and transformation operations. With the rapid development of technology, machine learning technology has gradually penetrated various fields, bringing revolutionary changes to product design innovation. Kumar et al. [8] explored the application of machine learning technology in innovative product design, as well as the latest developments in design, process, and production control. Product design is a creative and challenging process, and the introduction of machine learning technology provides designers with more possibilities and innovative ideas. Meanwhile, machine learning technology can also automatically evaluate and optimize design solutions, improving design efficiency and quality. Real-time monitoring and analysis of manufacturing process data through machine learning algorithms can achieve automatic adjustment and optimization of process parameters, improving production efficiency and product quality. With the rapid development of technology, intelligent product service systems are gradually becoming an important direction for industry innovation. The intelligent product service system integrates advanced hardware, software, and data technology to provide users with personalized, efficient, and convenient service experiences. Lee et al. [9] explored innovative structural service methods for designing intelligent product service systems and conducted in-depth analyses based on practical cases. In product design, the application of multimedia technology can greatly enrich the means of design expression and improve design efficiency. The intelligent manufacturing system based on digital twins has become an important direction for the transformation and upgrading of the manufacturing industry with its unique advantages. Leng et al. [10] explored the design and manufacturing of intelligent manufacturing systems based on digital twins in Industry 4.0 and analyzed their significance and value in practical applications. Digital twin technology refers to the creation of virtual copies of physical systems through digital means, achieving precise mapping and simulation of the physical world. In intelligent manufacturing systems, by constructing digital twin models of products, enterprises can design, analyze, and optimize products in a virtual environment, thereby shortening the product development cycle and improving design quality. Secondly, digital twin technology can be used for simulating and optimizing production plans. By simulating and analyzing the digital twin model of production lines, enterprises can predict the performance of production lines and evaluate the effectiveness of different production plans. Leung et al. [11] extracted valuable information from a large amount of data by using data mining and knowledge discovery techniques. The modelling of innovative features in product design is a crucial part of the design process, which directly affects the final appearance, functionality, and user experience of the product. With the advancement of technology, especially the rapid development of robotics and computer manufacturing technology, innovative feature modelling methods for product design are also constantly evolving and evolving. Li et al. [12] reviewed its historical evolution, explored newly developed feature modelling methods, and analyzed their applications in robotics and computer manufacturing. Early product design innovation feature modelling mainly relied on the designer's manual drawing and physical model production. This method is inefficient and difficult to accurately express complex shapes. With the introduction of computer technology, CAD (computer-aided design) systems are gradually becoming popular, and designers can use computers for 3D modelling and rendering. The emergence of CAD technology has greatly improved the efficiency and accuracy of modelling, providing a broader space for product modelling innovation.

As a cutting-edge technological innovation tool, digital twin technology is gradually changing the way product design innovation, design management, and business innovation are carried out. Based on the latest survey data, Lim et al. [13] delved into the application of digital twin technology and the changes it brings from the perspectives of product design innovation management and business innovation. Innovative product design is an important means to enhance the competitiveness of enterprises, and the application of digital twin technology injects new vitality into design management. By constructing a digital twin model of the product, designers can quickly iterate and optimize the shape of the product in a virtual environment, greatly shortening the design cycle and improving design efficiency. In addition, digital twin technology can also achieve comprehensive monitoring and management of the design process. Designers can use digital twin models to adjust various parameters in the design process in real-time, ensuring that the design results meet the expected requirements. The three-dimensional CAD (computer-aided design) system has become an important tool for the rapid design of industrial products due to its powerful modelling, analysis, and optimization functions. Liu [14] discussed the rapid design method and application of industrial products based on 3D CAD systems. The 3D CAD system can accurately construct the 3D model of a product through digital means, and conduct detailed analysis and optimization on it. Utilize the modelling function of the 3D CAD system to create a 3D model of the product based on conceptual design. During the modelling process, attention should be paid to the accuracy and completeness of the model. Based on the basic model, carry out detailed design, such as adding textures, adjusting colours, etc., to make the product more in line with design requirements. Taking automotive design as an example, the application of 3D CAD systems in automotive design is becoming increasingly widespread. Designers can use 3D CAD systems to create an overall model of a car, including various parts such as the body, engine, and chassis. By conducting detailed analysis and optimization of the model, designers can predict the performance of the car, identify potential problems in advance, and make improvements. In order to improve the reliability and efficiency of the machining process, a bionic-based digital twin modelling method for aerospace component machining has emerged. Liu et al. [15] introduced the basic principle, application advantages, and future development trends of this method. The digital twin modelling method for aerospace component processing based on bionics combines the advantages of bionics and digital twin technology. By simulating the growth, adaptation, and evolution process of organisms in nature, it achieves precise simulation and optimization of the aerospace component processing process. By accurately simulating and optimizing the machining process, errors and deviations can be effectively reduced, and the machining accuracy of components can be improved. The digital twin model can achieve real-time monitoring and prediction of the processing process, helping engineers discover and solve problems on time, and avoiding delays and waste in the production process. By optimizing and improving the processing process, unnecessary material and energy consumption can be reduced, and production costs can be lowered.

Traditional product development often relies on paper documents, manual drawings, and face-to-face meetings for discussion. However, with the widespread application of digital tools, these traditional methods are gradually being replaced by digital and automated processes. Digital tools make product design more intuitive and efficient. Designers can use 3D modelling software to create virtual models of products for real-time rendering and modification, greatly improving design efficiency and quality. In addition, digital tools also support simulation analysis, helping designers identify and solve potential problems in the early stages of product development. Marion and Fixson [16] explored how digital tools drive the transformation of the innovation process and analyzed their important role in new product development. Through technologies such as cloud computing and collaborative editing, team members can share documents, data, and design results, achieving real-time synchronization and collaboration. In addition, digital tools also support functions such as online meetings and instant messaging, allowing team members to communicate and discuss more conveniently. Multimedia technology, with its unique advantages, provides a new solution for the design and operation simulation of manufacturing systems. Mourtzis [17] explores the latest technologies and trends in multimedia-based manufacturing system design and operation simulation. Virtual reality technology has brought revolutionary changes to the design and operation simulation of manufacturing systems. By constructing a virtual manufacturing environment, designers can lay out manufacturing systems, configure equipment, and plan processes in the virtual space, achieving a highly realistic simulation experience. Meanwhile, VR technology can also simulate the operational status of manufacturing systems, helping engineers predict and solve potential problems. Augmented reality technology provides a more intuitive and convenient way for the design and operation simulation of manufacturing systems by overlaying virtual information onto the real world. Designers can perform virtual annotation, device positioning, and operation simulation in real environments to improve the accuracy and efficiency of design. In addition, AR technology can also be used for real-time monitoring and guidance of manufacturing processes, improving production efficiency and quality. Digital twin technology simulates, analyzes, and optimizes the entire product lifecycle by constructing virtual models that correspond to actual products. Computational geometry and multimedia technology, as the two core supports of digital twin technology, provide strong technical support and rich expressive means for product design. Tao et al. [18] explore a digital twin-driven product design framework based on computational geometry and multimedia technology, to promote innovation and development in the field of product design. Product design is a complex and multifaceted process that involves the intersection and integration of numerous disciplines and technologies. Traditional design methods often rely on the experience and trial and error of designers, making it difficult to cope with complex and ever-changing design needs. The emergence of digital twin technology has brought new ideas and means to product design. By constructing virtual models that correspond to actual products, digital twin technology can achieve precise simulation and prediction of products, providing designers with real-time feedback and optimization suggestions. Computational geometry and multimedia technology, as the two cornerstones of digital twin technology, play irreplaceable roles. Traditional assembly process design often relies on experience and trial and error, which is inefficient and prone to errors. In order to solve this problem, intelligent assembly process design based on digital twins has emerged. Yi et al. [19] introduced the intelligent assembly process design and application framework for complex products based on digital twins and demonstrated its practical application effects through case studies. Use digital twin models to simulate and analyze the assembly process. By simulating the physical behaviour, assembly sequence, and assembly path during the assembly process, potential problems and bottlenecks in the assembly process can be predicted. Taking complex mechanical equipment as an example, the application of intelligent assembly process design and application framework based on digital twins was put into practice. Firstly, a digital twin model of the mechanical equipment was constructed, including information on the geometric shape, assembly constraints, and assembly relationships of each component. Then, simulation software was used to analyze the assembly process and identify potential issues and bottlenecks during the assembly process. Subsequently, intelligent optimization algorithms were applied to optimize the assembly process, adjusting the assembly sequence and path.

3 IGA PRINCIPLE AND ITS APPLICATION IN PRODUCT DESIGN

A genetic algorithm (GA) is an optimization algorithm that simulates the genetic mechanism in nature. It represents the solution space of the problem as a chromosome by coding and iteratively optimizes the chromosome by using genetic operations such as selection, crossover and mutation to search for the optimal solution of the problem. GA has the advantages of strong global search ability, strong adaptability and high robustness, and is suitable for solving complex optimization problems.

In GA, firstly, we need to define the coding mode of the chromosome and map the solution space of the problem to the coding space of the chromosome. Commonly used coding methods include binary coding, real coding, symbol coding and so on. Then, a certain number of initial chromosomes are generated by initialization operation to form an initial population. Then, the fitness function is used to assess the chromosomes in the population, and excellent chromosomes are selected for genetic operation according to the assessment results to generate a new population. Through iterative optimization, the optimal solution to the problem is finally obtained.

IGA introduces man-machine interaction technology based on GA, which has the following characteristics:

⊖ High user participation: IGA regards users' subjective assessment as a part of the optimization goal, and requires users to provide real-time feedback information during the operation of the algorithm.

⊜ Clear optimization goal: As the subjective assessment of users is introduced, the optimization goal of IGA is more clear and specific. Users can assess the quality of product design according to their own needs and aesthetic standards, thus guiding the algorithm to search in the direction of meeting users' needs.

⊛ Personalization of search results: IGA fully considers the individual differences and subjective feelings of users, so the product design scheme searched is more personalized and differentiated.

The implementation process of IGA covers several key steps. First of all, it is necessary to define the chromosome coding method and generate the initial population. This step requires selecting the appropriate coding method according to the characteristics of product design problems and then generating a group of initial chromosomes to form the initial population. Secondly, the design of the fitness function and assessment method is very important. They will assess the product design scheme corresponding to each chromosome according to the user's needs and the specific characteristics of the problem. In this process, it is also necessary to establish a user assessment method to guide users to provide immediate feedback information. Subsequently, based on the fitness assessment results, excellent chromosomes will be selected and undergo a series of genetic operations (such as selection, crossover, mutation, etc.), thus generating new populations. The design of genetic operation needs to be customized and optimized in close combination with the characteristics of specific problems. Finally, through iterative optimization and user interaction, the algorithm will repeatedly perform a fitness assessment and genetic operation and constantly solicit users' assessment and feedback on the design scheme of new products. After each iteration, the algorithm will adjust the optimization objective and genetic strategy according to user feedback, so as to gradually approach the optimal design scheme that best meets the needs of users. The task decomposition process of IGA is shown in Figure 1.

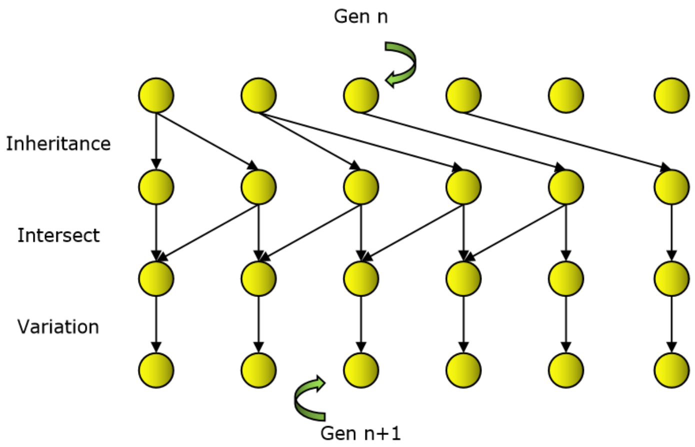

Figure 1: The task decomposition process of IGA.

In this study, we introduce a novel approach that combines product modelling design optimization with an enhanced AGA to address the given model effectively. The crossover probability within this enhanced AGA framework is adaptively determined:

$$p_c^q = \begin{cases} p_{c,\max} \times e^{-q/Q} & p_{c,\max} \times e^{-q/Q} < p_{c,\min} \\ p_{c,\min} & \text{other} \end{cases} \tag{1}$$

q represents the q iteration process, while Q denoting the total number of iterations performed. $p_{c,\max}, p_{c,\min}$, on the other hand, refers to the pre-set maximum and minimum crossover probabilities respectively.

In the context of the AGA, crossover refers to the process where two paired chromosomes swap a portion of their genes to create two distinct individuals. This serves as the primary mechanism for generating novel individuals within the population. In this study, we employ the arithmetic crossover method, which involves a linear blend of two-parent individuals to yield two offspring. Considering x_a^t, x_b^t the two parent individuals, the crossover operation results in the following two new individuals:

$$x_a^{t+1} = \alpha x_b^t + 1-\alpha \ x_b^t \tag{2}$$

$$x_b^{t+1} = \alpha x_a^t + 1-\alpha \ x_b^t \tag{3}$$

a is a randomly generated number within the interval of (0,1). When dealing with integer variables, the crossover operation may yield non-integer values; thus, we employ the rounding method to ensure integrity.

Traditional BPNN only adopts forward connection. In order to establish the mapping relationship between previous states more directly, this article proposes a new connection method: introducing two groups of weight connections between two layers of neurons. This means that there will be two connections in opposite directions between any two neurons in adjacent layers. The specific structure is shown in Figure 2. This improved design aims to improve the performance of the neural network model.

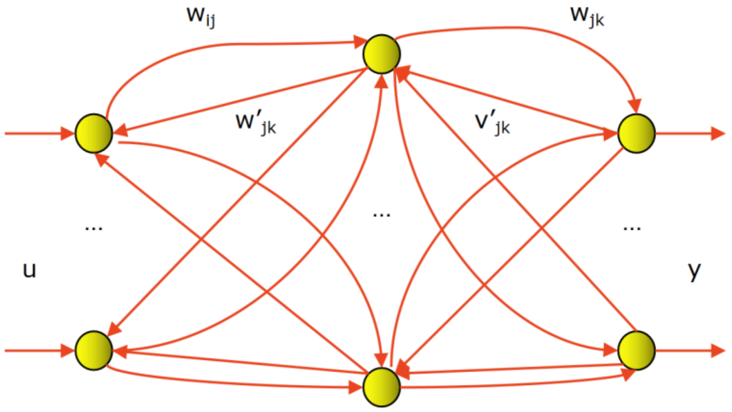

Figure 2: Three-layer bidirectional neural network structure.

This neural network architecture not only retains all the characteristics of the conventional forward network but also significantly enhances its robustness, fault tolerance and approximation ability by introducing reverse connection and previous state information when the number of nodes remains unchanged.

The aim of utilizing GA is to determine the optimal parameter AA for the fuzzy membership function, thereby achieving:

$$\min E=\frac{1}{2}\sum_{i=1}^{n} u-u_i^{\;\;2} \tag{4}$$

Here, u represents the desired output, while u_i denotes the actual output from the Fuzzy Neural Network Controller (FNNC). The objective of the learning process is to minimize the discrepancy, represented by E.

The global parameters of the FNNC undergo offline optimization through GA. Subsequently, real-time adjustments are made to achieve suboptimal or optimal performance of the FNNC. The training performance of the FNNC is assessed using a performance index function, which calculates the sum of squared errors between the expected and actual outputs:

$$E_{BTP}=\frac{1}{2}\sum BTP_{set}-BTP\ t^{\;\;2} \tag{5}$$

In this context, BTP_{set} represents the anticipated output, while $BTP\ t$ signifies the actual output generated by the FNNC. The aim of the learning procedure is to reduce E_{BTP} by modifying the FNNC weight, denoted as w_{ij}.

Fitness function can consider many factors, such as aesthetics, comfort and functionality. Furthermore, the user assessment method is formulated, and users are required to score or rank each design scheme so that the algorithm can obtain real-time feedback information from users.

According to the fitness assessment results, excellent chromosomes are selected for genetic operations (such as selection, crossover, mutation, etc.) to generate new populations. In this process, we can learn from the genetic laws in biology to design a reasonable genetic operation strategy to improve the search efficiency of the algorithm. Figure 3 shows the operation flow of IGA.

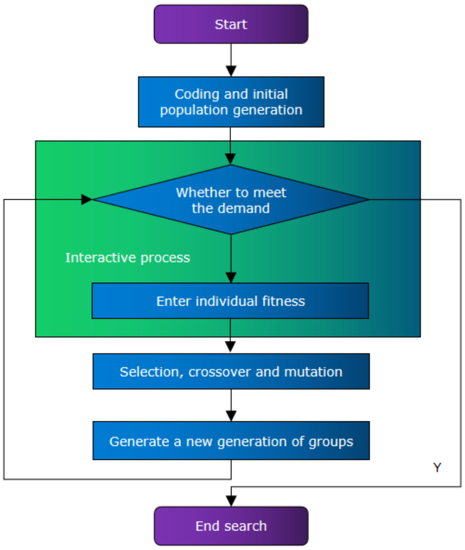

Figure 3: IGA operation process.

In every generation of the GA, let $s_{\max}$ represent the fitness score of the most optimal sequence, $\bar{s}$ indicate the average fitness score among all sequences, and s denote the fitness score of a particular sequence. Subsequently, the crossover probability P_c and mutation probability P_m for this specific sequence are determined as follows:

$$P_c = \begin{cases} \dfrac{k_1 \; s_{\max} - s}{s_{\max} - \bar{s}}, & s \geq \bar{s} \\ k_3, \quad s < \bar{s} & \end{cases} \tag{6}$$

$$P_m = \begin{cases} \dfrac{k_2 \; s_{\max} - s}{s_{\max} - \bar{s}}, & s \geq \bar{s} \\ k_4, \quad s < \bar{s} & \end{cases} \tag{7}$$

Where $k_1, k_2, k_3, k_4 \leq 1$.

Coding plays a fundamental role in GA. In this study, we introduce a more effective approach known as matrix coding. The matrix comprises elements represented by x_{ij}. When addressing the product modelling design challenge involving n vertices, we arrive at the coding matrix denoted as $n * n$.

$$A = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nn} \end{bmatrix} \tag{8}$$

While matrix coding shares a similar purpose with edge coding in representing elements, it surpasses the latter's limitations by effectively expressing and validating the legitimacy of individuals, exhibiting significant advantages.

In numerous enhanced GA, the initial population is typically generated randomly. However, in this study, we randomly generate a specific number of individuals and subsequently select the fittest ones to form the initial population. The assessment of each solution's merits is facilitated by the fitness function, which is defined as follows:

$$f=\frac{\sqrt[a]{n}}{\sum_{i\neq j} d_{ij}x_{ij}} \tag{9}$$

Where a is a preset constant, n is the number of product features, and $\sum_{i\neq j} d_{ij}x_{ij}$ is the sum of the selected edge distances.

The initial population P_0 is generated by combining design constraints, objective functions and aesthetic standards, where each individual x_i represents a potential product modelling design:

$$P_0=\{x_1,x_2,\ldots,x_N\} \tag{10}$$

The fitness function $f(x)$ is used to assess the advantages and disadvantages of an individual x and usually combines objective functions (such as modelling quality, cost, user satisfaction, etc.) and constraints (such as physical constraints, manufacturing process constraints, etc.):

$$f(x)=g(x)+h(x) \tag{11}$$

Where $g(x)$ is the objective function value and $h(x)$ is the sum of constraint violations? Genetic operations include selection, crossover and mutation. In an interactive genetic algorithm, these operations need to consider the feedback of users. Users assess the designs in the current population and rank the designs according to their preferences or put forward suggestions for improvement to guide the search process of the genetic algorithm. Updating the fitness function according to user feedback, and replacing the old population P_0 with the new population P_{new}:

$$P_{new}=\{x_1^{'},x_2^{'},\ldots,x_N^{'}\} \tag{12}$$

The algorithm terminates when it reaches the preset iteration times, fitness threshold or user satisfaction:

$$Ter\min ationCondition\left(\{x_1^{'},x_2^{'},\ldots,x_N^{'}\}\right)\leq 0 \tag{13}$$

Where θ represents a preset threshold. The optimal individual x^* output by the algorithm can be used as the final scheme of product modelling design.

According to user feedback, the optimization objective and genetic operation strategy are adjusted, and the optimal design scheme that meets users' needs is gradually approached. In this process, designers can communicate with users in real-time to understand their real needs and expectations, so as to better meet their needs.

4 RESULT ANALYSIS AND DISCUSSION

This study focuses on the differences between the traditional design method and the method combined with IGA in design innovation, user satisfaction, modelling accuracy and calculation efficiency. The experiment aims to comprehensively assess the practicability and superiority of the proposed method. As far as design innovation is concerned, the experiment adopts a variety of assessment indicators. As shown in Figure 4, the method based on IGA shows obvious advantages in design innovation. This advantage is mainly attributed to the fact that this method can introduce user feedback, and constantly iterate and improve the design scheme in the process of algorithm optimization, so as to better meet the needs of users and present higher innovation.

Figure 4: Design innovation assessment.

This study collected user satisfaction assessments of two different design methods through a questionnaire survey. As shown in Figure 5, user satisfaction with IGA-based design solutions is significantly higher than traditional methods, further confirming user preferences for participatory design and personalized customization.

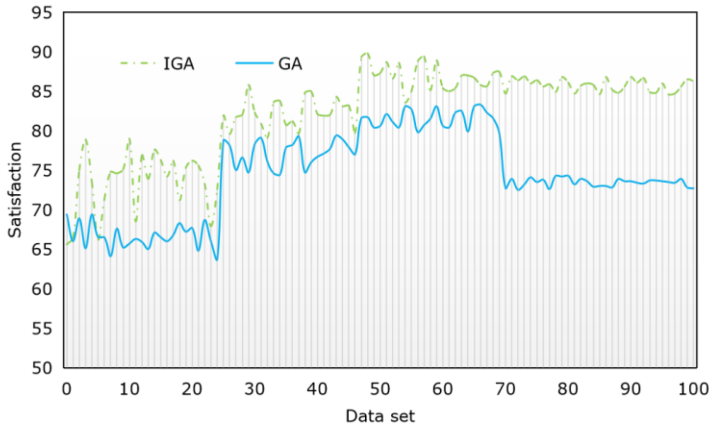

Figure 5: User satisfaction survey.

In the comparison of modelling accuracy, the prediction results of the traditional GA model and IGA model are compared with the actual observation values. As shown in Figure 6 and Figure 7, the prediction accuracy of the IGA model has been significantly improved compared with the traditional GA model, which is due to the introduction of user feedback and the optimization strategy of the algorithm.

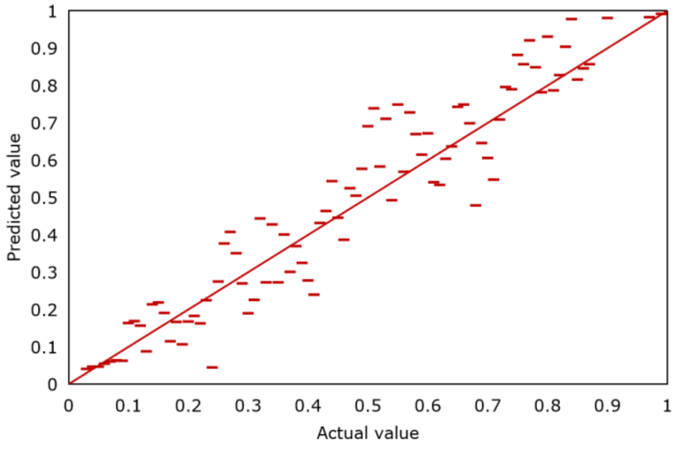

Figure 6: Scatter distribution of actual value and predicted value of traditional GA model.

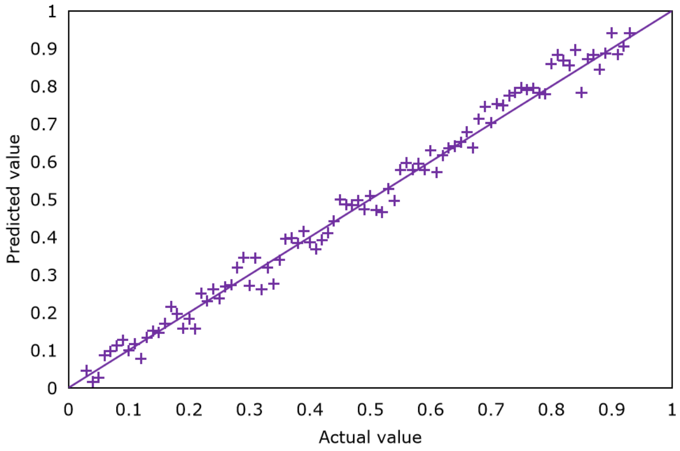

Figure 7: Scatter distribution of actual value and predicted value of IGA model.

The efficiency test of the algorithm is shown in Figure 8. Although the calculation efficiency of the method based on IGA is slightly lower than that of the traditional method (because the algorithm iteration and user interaction need extra time), considering the significant improvement of design quality and user satisfaction, this time cost is worthwhile.

As far as design innovation is concerned, the experimental results show that the method based on IGA is significantly superior to the traditional method in design innovation. This discovery is of great significance to today's innovative and personalized market. Traditional design methods often rely on the designer's personal experience and subjective judgment, and it is difficult to fully meet the individual needs of users. By introducing user feedback and algorithm optimization, the IGA method makes the design scheme better meet the needs of users, and presents higher innovation in design elements and principles. This user-centred design idea not only helps to enhance the market competitiveness of products but also enhances the emotional connection between users and brands.

The survey results of user satisfaction further confirm the advantages of the IGA method in improving user experience.

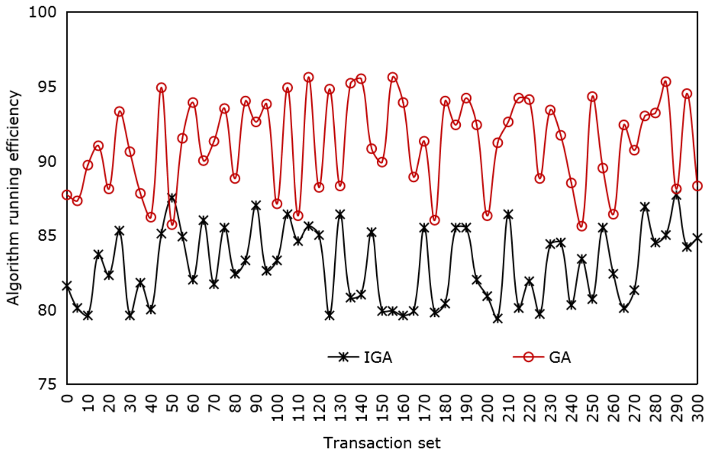

Figure 8: Algorithm running efficiency test.

The user's satisfaction with the design scheme based on IGA is obviously higher than that of the traditional method. This shows that users are more inclined to accept those design schemes that have been optimized by algorithms and participated by users. In today's user-centred era, user satisfaction and loyalty are very important for the long-term development of enterprises. Therefore, the IGA method provides an effective means to improve user satisfaction and enhance user loyalty.

In the comparison of modelling accuracy, the IGA model shows higher prediction accuracy than the traditional GA model. This is mainly due to the introduction of user feedback in the IGA method and the optimization strategy of the algorithm. The traditional GA model can only predict and optimize based on the existing data, but it is difficult to fully consider the actual needs and feedback of users. The IGA model can constantly improve and optimize the model through interaction and feedback with users, thus improving the accuracy and reliability of prediction.

Although the method based on IGA is excellent in design innovation, user satisfaction and modelling accuracy, its computational efficiency is slightly lower than that of traditional methods. This is mainly because the algorithm iteration and user interaction process need extra time investment. With the continuous development and optimization of computing technology, it is expected to further improve the computing efficiency of the IGA method in the future.

5 CONCLUSIONS

This study compares the traditional design method with the innovative design method of product modelling combined with IGA through experiments. The results show that the method based on IGA is significantly better than the traditional method in terms of design innovation, user satisfaction and modelling accuracy, although its computational efficiency is slightly lower. This discovery confirms the effectiveness of the IGA method in improving product design quality and user experience. By introducing user feedback and algorithm optimization, the IGA method can generate a more innovative design scheme that meets the needs of users. In addition, the improvement of prediction accuracy of the IGA model also shows the importance of user feedback and algorithm optimization to improve modelling accuracy.

To sum up, the innovative design method of product modelling based on IGA shows advantages in design innovation, user satisfaction and modelling accuracy. Although there is a slight deficiency in calculation efficiency, considering its remarkable benefits and potential, this method still has a wide application prospect and value. Future research can further explore how to combine advanced computing technology and optimization strategy to improve the computational efficiency of the IGA method so as to better meet the needs of practical applications.

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