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Automatic Generation and Optimization of Product Shapes Based on Generative Artificial Intelligence (AIGC) and Computational Geometry Algorithms

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Abstract. As a pivotal subset of artificial intelligence (AI), generative AI (AIGC) has exhibited remarkable potential in diverse domains like imaging, voice, and text, owing to its distinctive generative capabilities. In this study, we introduce a novel approach that integrates AIGC with computational geometry techniques for the automated creation and refinement of product models. Through a comparative analysis of the representational and categorical performance of three deep learning frameworks—Deep Convolutional Generative Adversarial Network (DCGAN), Generative Adversarial Network (GAN), and Convolutional Neural Network (CNN)—in the context of product shape image processing, we unveil the strengths and weaknesses of each model across various use cases. Additionally, this article presents an enhanced feature detection algorithm aimed at mitigating the challenge of prolonged feature detection times that can hinder the design workflow. By minimizing computational redundancies and complexities, this algorithm significantly accelerates feature detection, offering designers more expedient feedback. Our findings indicate that, in contrast to conventional algorithms, our proposed method exhibits substantial improvements in feature detection speed, promising notable efficiency gains in product design practices. This research not only underscores the efficacy of deep learning in product design but also paves the way for innovative approaches to optimizing feature detection methodologies.

Keywords: Generative Artificial Intelligence; Computational Geometry Algorithm; Product Modeling; Automatic Generation
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1 INTRODUCTION

With the rapid development of science and technology, artificial intelligence has entered various aspects of social life and is playing an increasingly important role. As an important subset of artificial intelligence, AIGC has shown extraordinary potential in fields such as images, speech, and text due to its unique generation ability. Abbott et al. [1] trained a model to generate molecular potential energy surfaces automatically. The molecular potential energy surface describes the energy states of molecules with different configurations, which is crucial for understanding molecular properties, and reaction mechanisms, and optimizing chemical reactions. Traditional calculation methods are often time-consuming and complex, making it difficult to handle the potential energy surface calculations of large-scale and complex molecules. The introduction of machine learning models provides a new solution to this problem. In product design, AIGC technology excels at generating novel and unique product shapes by analyzing a large number of existing design examples, thereby significantly enhancing the creativity of designers. Angrish et al. [2] have become a search engine based on 3D CAD models, providing a new solution for product procurement and manufacturing services. Traditional search engines mainly rely on text keywords for searching, but for complex 3D CAD models, relying solely on text descriptions often makes it difficult to accurately express key information such as shape, structure, and function. The search engine based on 3D CAD models has introduced advanced computer vision and artificial intelligence technologies. It realizes the extraction and analysis of the three-dimensional shape, geometric features, and semantic information of the model, thereby achieving a more accurate and efficient search. The application prospects of search engines based on 3D CAD models in product procurement and manufacturing services are broad. For buyers, search engines can quickly find 3D CAD models that meet their needs, avoiding spending a lot of time and effort filtering and comparing in traditional markets. Meanwhile, search engines can intelligently match models based on their geometric features and performance parameters, providing buyers with more accurate product recommendations. Through an automated, integrated CAD platform, Dalpadulo et al. [3] designed components more efficiently and evaluated and optimized manufacturing solutions in real-time during the design process. In the automatic integration CAD platform method, a detailed performance requirement analysis of the components is required first. This includes requirements for the load-bearing capacity, wear resistance, corrosion resistance, and other aspects of the components. Based on these requirements, the platform can automatically select materials suitable for additive manufacturing and determine corresponding process parameters. At the same time, the platform can automatically generate support structures based on the geometric shape and manufacturing requirements of the components to ensure the stability and accuracy of the components during the manufacturing process.

Ferro et al. [4] explored optimization algorithms for automatic structural design of product shapes and introduced their computer methods in applied mechanics and engineering. By parameterizing the geometric shape of the product structure and using optimization algorithms to find the optimal shape that meets performance requirements. This helps to reduce material consumption and improve structural strength and stability. Based on the functional requirements and performance constraints of the product, optimization algorithms can calculate the optimal distribution of materials in the structure. This helps to achieve lightweight design and improve product economy and environmental friendliness. Optimization algorithms can analyze the impact of different connection methods on product performance and find the optimal connection solution. This helps to improve the overall performance and reliability of the product. Getuli et al. [5] proposed a computational design method based on TBM data for generating a complete infrastructure information model of mechanized tunnels on demand. Based on the processed TBM data, key features and patterns during tunnel construction are extracted using mathematical modelling and algorithm analysis techniques. These features and patterns can reflect the geological conditions, construction difficulty, and potential risks of tunnels. STEP is an international standard used for exchanging product model data, supporting complex product data exchange, including geometric shapes, material characteristics, assembly relationships, etc. On the other hand, STL is a relatively simple format mainly used for rapid prototyping and 3D printing. It only focuses on the surface geometric information of the model, while ignoring other non-geometric information. The STEP format has significant advantages in GD&T information and PMI. GD&T information is used to define the geometric dimensions and tolerances of a product and is a key element in product design. PMI includes various information required during the product manufacturing process, such as annotations, markings, process requirements, etc. The STEP format can fully store and express this information, providing comprehensive data support for product design, analysis, and manufacturing

[6]. In this era, the automatic generation of product shapes no longer relies solely on traditional engineer experience or manual design, but integrates the power of collective intelligence and artificial intelligence. As an important technical means, homology modelling is gradually playing an increasingly important role in the automatic generation of product shapes. Hameduh et al. [7] achieved precise descriptions and efficient generation of product shapes by capturing and expressing the inherent correlation and consistency between shapes. In the era of collective and artificial intelligence, the application of homology modelling has been greatly expanded and improved. Collective intelligence provides rich data sources for homology modelling. In the past design process, designers often relied on personal experience and intuition to design shapes. These collective intelligence data provide valuable materials for homology modelling, enabling the model to better capture the inherent patterns and consistency between shapes.

In this study, a method combining AIGC with a computational geometry algorithm will be proposed for the automatic generation and optimization of product modelling. The research has the following innovations:

(a) This article applies DCGAN to the generation of product modelling. By training the DCGAN model, it can learn and simulate the design cases in the real world, so as to generate innovative and artistic product modeling.

(b) Aiming at the problems of insufficient geometric precision and unreasonable structure in the preliminary product modelling, this article introduces a computational geometry algorithm to optimize it. By extracting and analyzing the geometric features of the preliminary generation results, the geometric attributes and spatial relationship of product modelling are accurately described, and the optimization strategy is used to adjust.

(c) This article not only discusses the application of AIGC and computational geometry algorithm in product modelling generation and optimization in theory but also verifies the feasibility of the proposed method through concrete implementation and experiments. This research method of combining theory with practice makes the research results of this article more practical and instructive.

Firstly, this article expounds the research background and significance through the introduction, and clarifies the research problems; Then, the theoretical basis of AIGC and DCGAN is introduced to provide support for the follow-up research. Then the application of computational geometry algorithm in product modeling is discussed, which lays the foundation for optimizing the generated results. Based on the aforementioned foundation, a detailed description of the automatic generation technique for product modelling, which combines AIGC and computational geometry algorithms, is presented. The efficacy of this approach is then substantiated through experimental design and a thorough analysis of the results. In conclusion, a comprehensive summary of the entire discussion is provided, along with a forward-looking perspective on potential future research directions.

2 RELATED WORK

In the manufacturing industry, the hierarchical structure of product assembly is an important data structure that describes the assembly and dependency relationships between various components of a product. As product complexity increases, manually building component hierarchies becomes increasingly difficult and error-prone. Therefore, achieving automatic generation of product assembly levels with complex connection relationships is of great significance for improving assembly efficiency and reducing manufacturing costs. Jiang and Wang [8] analyzed the automatic generation of product assembly hierarchical structures with complex connection relationships. Based on the extracted features and component information, construct a topological relationship diagram between the various components of the product. This is of great significance for product shape optimization and the automatic generation of geometric digital twins. Mirzaei et al. [9] explored how to use point cloud structures to optimize product shapes and automatically generate corresponding geometric digital twins, thereby promoting innovation and development in the manufacturing industry. This provides a reliable data foundation for subsequent shape optimization. Based on optimized point cloud data, geometric digital twins of products can be automatically generated. Geometric digital twins refer to virtual models created through digital means that correspond to the physical object, with geometric shapes and physical characteristics similar to the physical object. Özen et al. [10] explored methods for optimizing the manufacturing parameters of FDM 3D printed PETG products and the geometric structure of tensile specimens. The selection of manufacturing parameters has a crucial impact on the quality and performance of PETG products in the FDM 3D printing process. The main manufacturing parameters include printing temperature, printing speed, layer thickness, filling density, etc.

Mo et al. [11] discussed the importance, methods, and applications of product information modelling that captures design intent in computer-aided intelligent assembly modelling. Design intent refers to the ideas and intentions that designers need to express during the product design process, including requirements for product functionality, structure, appearance, and other aspects. Capturing design intent is crucial in ensuring the correctness and completeness of the product during the assembly modelling process. By capturing design intent, this model can better meet the requirements of designers, improve assembly accuracy and efficiency, and reduce errors and rework during the assembly process. Sommer et al. [12] explored the automatic generation of digital twins in product shapes and analyzed their value and significance in practical applications. Object detection technology can automatically recognize and locate objects through computer vision algorithms. In the production planning process, the combination of these two technologies can provide precise object data support for the production process. Object detection technology can perform real-time detection of materials, semi-finished products, and finished products during the production process, ensuring production quality and efficiency. The automatic generation of product shape digital twins has important value in production planning. Sun and Wang [13] provided mechanical engineers with a comprehensive and in-depth understanding of artificial neural network proxy modelling in aerodynamic design. Proxy modelling is a technique that utilizes mathematical or statistical methods to construct approximate models to simulate and predict the behaviour of complex systems. In aerodynamic design, alternative models can replace expensive experiments or complex numerical simulations to obtain key performance indicators of the system at a lower cost and in a shorter time. Mechanical engineers need to have a deep understanding of the basic principles and application skills of neural networks and choose appropriate network structures and parameter settings based on specific engineering problems. At the same time, attention should also be paid to the quality and quantity of data, as well as the validation and calibration process of the model, to ensure the accuracy and reliability of the proxy model.

In the field of product design, utilizing deep learning and graphic algorithms to achieve automatic generation of product layouts is becoming a trend. Wang et al. [14] explored how to utilize these advanced technologies to achieve automatic generation of product layout, and analyzed their advantages and potential applications. Deep learning is a machine learning technique that simulates the structure and function of human brain neural networks. It can extract features and learn patterns from a large amount of data. Graph algorithms are specifically designed to handle graphic structures and relationships, providing effective computational methods for solving complex problems. The combination of deep learning and graphic algorithms can play a huge role in product layout. Through deep learning techniques, we can train models to recognize and understand various features of products, such as size, shape, colour, etc. Meanwhile, using graphic algorithms, we can accurately calculate and optimize the layout of the product to ensure its aesthetics and practicality. The automatic generation service of intelligent products has become an important means to meet the rapidly changing and personalized needs of the market. Positive and innovative design thinking is the key driving force for building this service model. Wang et al. [15] explored a method of constructing an intelligent product automatic generation service model based on positive innovative design thinking, providing useful references for the development of related fields. Positive and innovative design thinking encourages knowledge and skills from different disciplines to form comprehensive solutions. Starting from user needs, by deeply understanding user behaviour and expectations, design intelligent products that better meet market demands. Through rapid prototyping and testing, continuous feedback and optimization are collected to achieve continuous improvement of the product. The intelligent product automatic generation service model based on positive innovative design thinking has broad prospects in practical applications.

Williams et al. [16] explored the effectiveness of 3D CNN design libraries and their applications in additive manufacturing. Compared with traditional 2D convolutional neural networks, 3D CNN can process 3D data with spatial dimensions. By performing 3D convolution operations on multiple consecutive layers, 3D CNN can capture spatial information and features of data, thereby achieving more accurate classification, recognition, and generation tasks. By using a 3D CNN design library to construct a deep learning model for additive manufacturing components, and through learning and training a large amount of sample data, automatic optimization of component design is achieved.

Wu and Ma [17] explored a BIM-based method for automatically generating construction schedule products, particularly by combining ontology constraint rules and genetic algorithms to achieve this goal. BIM technology integrates the full lifecycle information of construction projects through digital means, providing rich data support for formulating construction schedule plans. The use of BIM models can accurately extract geometric information, material information, process requirements, etc. of buildings, providing a reliable basis for formulating construction schedule plans. Extract relevant information on construction projects through BIM models, and construct constraint conditions for construction progress based on ontology constraint rules. Then, a genetic algorithm is used to encode and search the scheduling, and the optimal solution that meets the constraint conditions is found through continuous iterative optimization. Xiouras et al. [18] utilized these advanced algorithms to achieve automatic generation and optimization of crystal shapes, bringing a revolutionary breakthrough to the field of materials science. Artificial intelligence and machine learning technologies can learn and analyze a large amount of crystal shape data, discover patterns and trends, and thus achieve automatic design and optimization of crystal shapes. Construct a crystal shape generation model using deep learning and neural network algorithms, and train the model to learn the inherent laws and features of crystal shape. Xue et al. [19] focused on introducing semantic segmentation and registration methods based on non-derivative optimization and explored their application in the automatic generation of completed building information models. Semantic registration is the process of integrating semantic segmentation results into BIM, aiming to achieve accurate correspondence between three-dimensional spatial information and semantic information.

3 METHODOLOGY

AIGC involves the utilization of AI technology for generating fresh content, works, or designs. This technology possesses the capability to replicate and devise distinctive and imaginative content by analyzing vast quantities of data. In the realm of product design, AIGC can autonomously produce novel and ingenious product models, leveraging existing design databases. This not only significantly enhances design productivity but also spurs creativity among designers. Technically speaking, the essence of AIGC is rooted in deep learning and the deployment of GAN. Deep learning facilitates the automatic extraction and acquisition of high-level features from data through the establishment of intricate neural network architectures. Meanwhile, GAN achieves the creation and refinement of new content through the interactive training of two neural networks: the generator and discriminator. When these two technologies are combined, AIGC has a strong generation and innovation ability. AIGC also draws on other AI technologies such as reinforcement learning. Reinforcement learning enables the AI system to learn and optimize strategies through trial and error, so that AIGC can be constantly adjusted and improved during the generation process, thus generating a product shape that is more in line with users' needs. This self-learning and optimization ability makes AIGC have great application potential in the field of product design.

Computational geometry, a significant subset of computer science, focuses on the efficient representation, storage, and manipulation of geometric objects and their interrelationships within computers. In the realm of product modelling design, the computational geometry algorithm holds a pivotal position. This algorithm precisely captures crucial details of product modelling, including geometric attributes, spatial relationships, and movement variations, thereby offering designers precise and user-friendly design tools and platforms. The core of computational geometry algorithms lies in the establishment and operation of geometric data structure. By establishing appropriate data structures, such as the representation and storage of basic geometric elements such as points, lines and surfaces, computational geometry algorithms can efficiently deal with complex geometric objects and their relationships. Furthermore, through the operation and calculation of these basic geometric elements, such as intersection calculation, distance calculation, area calculation, etc., computational geometry algorithms can realize accurate descriptions and analyses of product modelling. In computational geometry algorithms, space division and search algorithms are two important technical means. The space partition algorithm divides the whole design space into several small subspaces, and processes geometric objects and their relationships independently in each subspace, thus improving the processing efficiency; The search algorithm can quickly find geometric objects or solutions that meet specific conditions in the design space through specific search strategies, such as depth-first search and breadth-first search.

AIGC and computational geometry algorithm have their own advantages in product design, but they also have some limitations. Although AIGC can generate innovative product modelling, it often lacks geometric accuracy and practicality. Although computational geometry algorithms can provide an accurate geometric description and analysis tools, it is difficult to directly generate innovative product modelling. Therefore, it is an important research direction in the field of product design to organically integrate AIGC with computational geometry algorithms to realize complementary advantages and collaborative innovation. This fusion can be realized in two ways: first, based on the product modelling generated by AIGC, the geometric accuracy is improved and the structure is optimized by the computational geometry algorithm; Secondly, under the framework of the computational geometry algorithm, the generation and innovation ability of AIGC is introduced to realize the automatic generation and optimization of new product modelling. Both of these methods need in-depth research and practical verification to explore the best integration strategy and implementation scheme.

The integration and examination of AIGC and computational geometry algorithms in product design carry immense importance. Through a thorough comprehension and proficiency in the theoretical underpinnings and practical applications of these technologies, we can furnish future product design endeavours with more streamlined, precise, and ingenious technical solutions and toolsets. This advancement not only enhances design efficiency and elevates the quality of outcomes but also catalyzes innovation and progress within the broader design industry. Looking ahead, it is imperative to investigate fresh avenues for technological amalgamation and application to align with evolving market trends and user aspirations. The GAN network comprises a generator, denoted as G, and a discriminator, labelled as D, as illustrated in Figure 1. The generator's primary objective is to learn the distribution of authentic sample data specified by the task requirements. This enables it to produce sample data, including texts, images, and similar content. On the other hand, the discriminator functions as a binary classifier. It receives both real and generated sample data as inputs and provides a confidence score, aiding in the assessment of the generated samples' quality. The generator strives to learn the distribution of genuine samples and produce authentic-looking generated samples. These samples should be so realistic that they deceive the discriminator, making it challenging to distinguish them from actual samples. Conversely, the discriminator aims to detect the falsified data produced by the generator and assign a low score to these generated samples.
The dynamic interplay between the generator referred to as G, and the discriminator, known as D, can be conceptualized as a process of optimizing the following minimax objective function:

$$\min_G \max_D E_{x\sim p_r}\left[\log D\ x\ \right]+E_{\tilde{x}\sim p_g}\left[\log\ 1-D\ \tilde{x}\ \ \right] \quad (1)$$

In this context, x represents the authentic sample data, p_r describes the distribution pattern of the real sample x, p_g corresponds to the distribution of the generated samples, and $z\sim \mathrm{P}_z$ is determined when $\tilde{x}=G\ z$. Additionally, z serves as the input, specifically a sample from a basic noise distribution. The approach to resolving the mentioned formula can be separated into two distinct phases. Initially, the equation below is employed to determine the discriminator, denoted as D:

$$\max_{D} V(G,D) = E_{x\sim P_r}\left[\log D(x)\right] + E_{x\sim P_g}\left[\log(1-D(x))\right] \tag{2}$$

Next, tackle the subsequent equation to determine the generator, designated as G:

$$\max_{D} V(G,D) = E_{x\sim P_g}\left[\log(1-D(x))\right] \tag{3}$$

The discriminator's role is to accurately discern whether a sample belongs to the real or false set, thereby fulfilling its discriminatory function. Meanwhile, the generator aims to enhance the quality of its generated samples to such a degree that the discriminator struggles to differentiate them from genuine data. Training involves optimizing both the generator, denoted as G, and the discriminator, labelled as D. The primary objective of optimizing the discriminator, referred to D, is to maximize the confidence value for real sample outputs while minimizing it for generated samples. Notably, these two models operate independently during the training process.

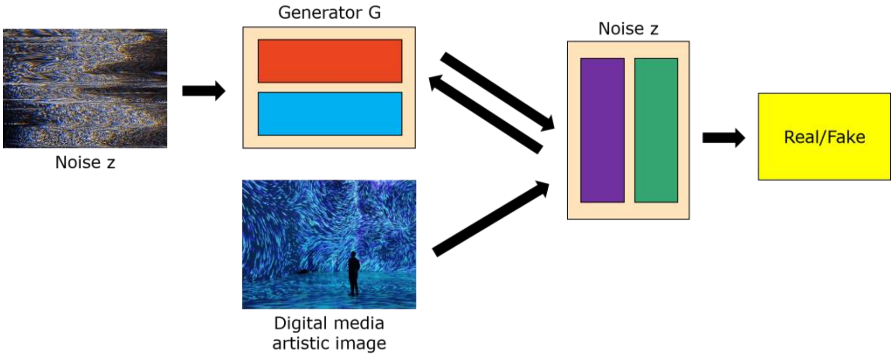

Figure 1: GAN model.

During the training of a GAN, there's continuous competition between the generating model, labelled as G, and the discriminating model, known as D. They engage in alternating iterative optimization until a balance is gradually achieved. The formula representing the objective function for GAN optimization is as follows:

$$\min_{G}\max_{D} V(D,G) = E_{x-P_{data}(x)}\left[\log D(x)\right] + E_{z-P_z(z)}\left[\log(1-D(G(z)))\right] \tag{4}$$

In the given context, $D(x)$ denotes the likelihood of the authentic sample x being recognized as genuine after undergoing assessment by the discriminant model. Meanwhile, $G(z)$ signifies the sample data produced by introducing random noise z into the generation model. $D(G(x))$, on the other hand, represents the probability that the generated sample data will be deemed authentic upon assessment by the discriminant model. Essentially, the objective function of a GAN can be likened to a "minimum-maximum optimization" challenge. This two-fold objective function is addressed consecutively: firstly, by refining the discriminant model D, and secondly, by enhancing the generation model G. Commencing with the optimization of the discriminant model D:
on of the discriminant model D:

$$\max_{D} V(D,G) = E_{x-P_{data}(x)}\left[\log D(x)\right] + E_{z-P_z(z)}\left[\log(1-D(G(z)))\right] \tag{5}$$

The subsequent step involves refining the generation model, designated as G.

$$\min_G V(D,G) = E_{z-P_z(z)}\left[\log(1-D(G(z)))\right] \tag{6}$$

In the modelling generation stage, the system automatically generates a series of preliminary product modelling design schemes by using computer-aided design (CAD) software or special modelling generation tools combined with design rules and constraints. These schemes may include different shapes, structures, materials and TINT, aiming at covering as wide a design space as possible and providing sufficient materials for subsequent assessment and optimization. In the assessment stage, the multi-criteria decision analysis method is used to comprehensively assess each generated design scheme. These assessment criteria may include functionality, aesthetics, manufacturability, cost-effectiveness and user preferences. The optimization link is to adjust and improve the design scheme by using the optimization algorithm based on the assessment results. These algorithms may include genetic algorithms, neural networks, particle swarm optimization, etc. They can automatically adjust the design parameters according to the assessment results to find the optimal solution under various constraints. Figure 2 shows the principle of automatic generation and optimization of product modelling in this article.

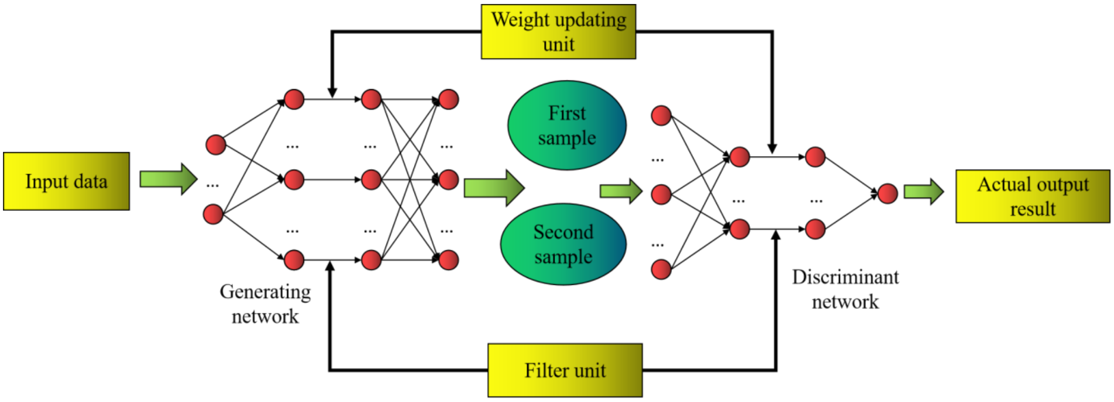

Figure 2: Automatic generation and optimization principle of product modelling.

In this study, the optimization of the discriminator, denoted as D, is addressed independently. The training process for the discriminator, labelled D aims to reduce the cross-entropy between the anticipated and actual outputs. The loss function for the discriminator can be formulated as follows:

$$L_D(\theta_D,\theta_G) = -\frac{1}{2}E_{x\sim P_{data}(x)}\left[\log D(x)\right] - \frac{1}{2}E_{Z\sim P_z(z)}\left[\log(1-D(g(x)))\right] \tag{7}$$

The given formula, x designates genuine data that follows the distribution of real data P_{data}, while z denoting random noise inputted into generator G, adhering to the prior distribution $P_z(z)$. $E(\cdot)$ represents the expected value. To attain the optimal solution, the aforementioned formula is minimized while keeping the generator G constant. Assuming the function's continuity, the formula can be reformulated as follows:

$$\begin{aligned} L_D(\theta_D,\theta_G) &= -\frac{1}{2}\int_x P_{data}(x)\log(D(x))dx - \frac{1}{2}\int_z P_z(z)\log(1-D(g(z)))dz \\ &= -\frac{1}{2}\int_x \left[P_{data}(x)\log(D(x)) + p_g(x)\log(1-D(x))\right]dz \end{aligned} \tag{8}$$

For arbitrary nonzero real numbers a and b, given that the real number y falls within the range of 0 to 1, the formula attains its minimum value at $\frac{a}{a+b}$.

$$-a\log y - b\log 1-y \tag{9}$$

When the generator G is predetermined, the loss function of the discriminator D attains its minimal value according to the subsequent formula, representing the most optimal solution under the circumstances. The explicit formula is presented below:

$$D_G^* x = \frac{P_{data} x}{P_{data} x + P_g x} \tag{10}$$

4 RESULT ANALYSIS AND DISCUSSION

4.1 Experimental Setup

The objective of the experimental phase is to conduct a thorough evaluation of the deep learning model's efficacy in the realm of product modelling design, with a particular emphasis on the proficiency of the feature detection algorithm. To guarantee the dependability and broad applicability of our findings, we have meticulously compiled a diverse dataset encompassing product modelling images of varied styles. This dataset has been further segmented into training, validation, and testing subsets to facilitate the model's training, refinement, and ultimate performance evaluation. In the experimental environment, we have configured a high-performance GPU server and a software environment suitable for deep learning tasks to ensure an efficient training and inference process.

Aiming at three representative deep learning models, DCGAN, GAN and CNN, this study adopts corresponding training strategies and optimization methods respectively and pays close attention to key performance indexes such as loss function and accuracy rate of the models during the whole training process. In order to compare the efficiency of different feature detection algorithms, we implemented the algorithm proposed in this article and the traditional algorithm as a benchmark and assessed the performance by recording the processing time. Finally, the experimental data are analyzed and visualized in detail, and the performance differences of different models in product modelling design and the time comparison results of feature detection algorithms are displayed through intuitive charts.

4.2 Result Display

Figure 3 shows that adjusting the weight ratio of content and style will have a significant impact on the generated results. When the weight of the style image is dominant, the generated image is highly similar to the style image in colour, but more details are lost, only the basic structural information is retained, accompanied by an obvious blurring effect. On the contrary, when the weight of the content image is increased, the details of the generated image are gradually enhanced. Furthermore, the color gradually becomes closer to the original color of the content image, and the color difference with the style image is increased. It can be seen that the content and style of the image are not completely separated but can be carefully adjusted according to the specific input image and application requirements.

After collecting various types of product modelling images covering geometry, organic, bionic and humanization, the three deep learning models, DCGAN, GAN and CNN, were tested. The purpose of the test is to explore the expression and classification ability of these models in processing product modelling images, and the relevant results have been shown in detail in Figure 4 to Figure 6.

From the results, DCGAN has achieved the highest classification accuracy in all types of clothing products tested. DCGAN is a variant of GAN, which is specially designed for processing image data. DCGAN effectively merges the convolutional properties of CNN with the generative adversarial nature of GAN, resulting in superior performance in image generation and classification tasks.

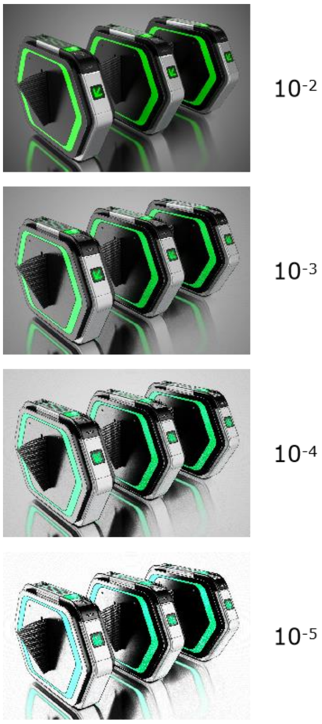

Figure 3: Weight generation diagram for different content and style.

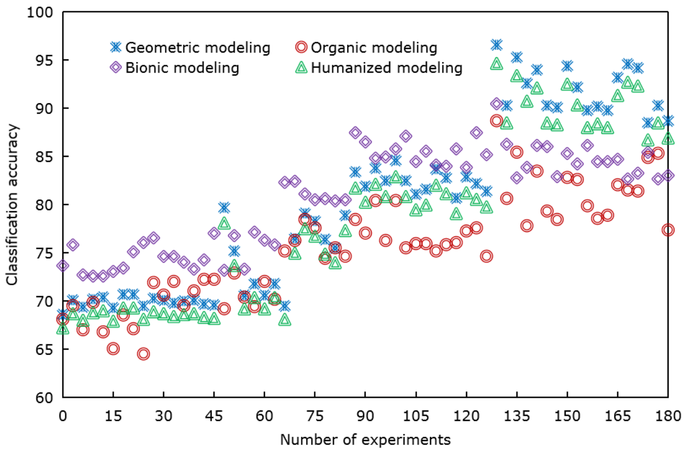

Figure 4: DCGAN classification performance.

You mentioned that DCGAN enhances the receptive field without altering the parameter count, thereby capturing more contextual image information. This contextual awareness contributes to improved classification accuracy. In contrast, the standard GAN exhibits lower classification accuracy due to its limited optimization for image data and shallower capture of image details and context. While CNN typically excels in image classification, its performance in this test lags behind DCGAN. This is because CNN is primarily designed for recognition rather than generation, whereas DCGAN integrates both generative and cognitive capabilities.

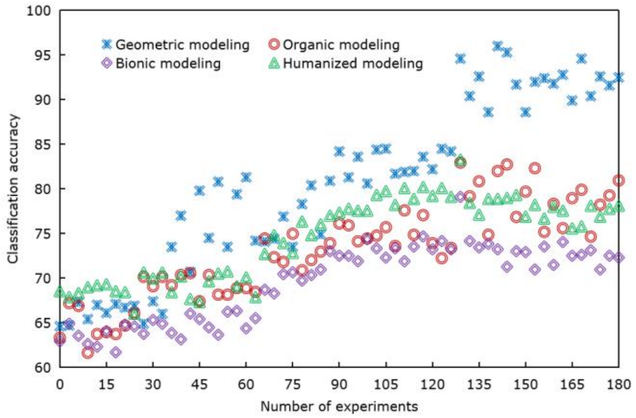

Figure 5: GAN classification performance.

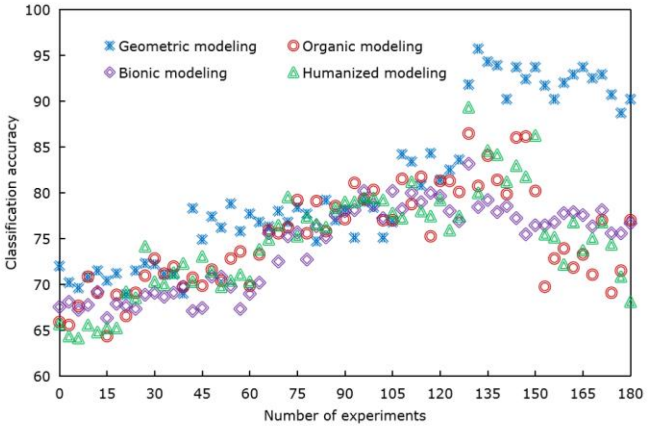

Figure 6: CNN classification performance.

When dealing with intricate and varied clothing product forms, DCGAN demonstrates higher accuracy, affirming its superiority in image classification, especially for detailed and contextual images. This advantage stems from DCGAN's integration of CNN's deep convolutional features and GAN's generative adversarial characteristics. This integration enables deeper comprehension of image structure and content, leading to enhanced classification accuracy.

In product modelling design, feature detection plays a crucial role, involving extensive data processing and analysis. Prolonged feature detection times can significantly hinder the overall design process. Figure 7 compares the feature detection times of various algorithms, revealing that the algorithm presented in this article significantly outperforms traditional methods in terms of response time.

During the process of product modelling design, it is imperative for designers to receive timely feedback and results to facilitate necessary adjustments and optimizations. Prolonged feature detection times can lead to significant delays in obtaining results, thereby impeding the efficiency of the design process. To address this issue, the algorithm presented in this article incorporates more advanced computational techniques that effectively minimize redundancy and simplify the calculation process.

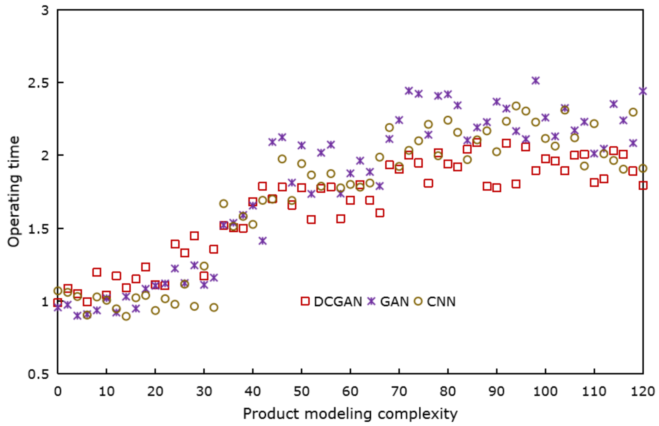

Figure 7: Feature detection time of different algorithms.

4.3 Analysis and Discussion

From the results of Figure 4 to Figure 6, three deep learning models, DCGAN, GAN and CNN, show their own characteristics in product modelling image processing. These models are different in expression ability and classification performance, which depends on their respective network structures and training methods. For example, by combining the advantages of CNN and GAN, DCGAN is outstanding in generating product modelling images with diversity and rich details. CNN, on the other hand, occupies a place in the task of image classification with its powerful feature extraction ability. These results provide a strong basis for us to choose the appropriate deep-learning model in different application scenarios.

The comparison results depicted in Figure 7 underscore the significance of algorithm efficiency in product design, revealing that the algorithm introduced in this article boasts a notably shorter feature detection time compared to traditional methods. This advantage holds immense importance in enhancing designers' work efficiency and ensuring a smoother design process. In real-world scenarios, designers can swiftly obtain feedback and results, enabling timely adjustments and optimizations to the design scheme, ultimately leading to improved design quality.

When it comes to product modelling design, selecting an appropriate deep learning model is paramount to enhancing the expressiveness and classification accuracy of image processing. Additionally, optimizing feature detection algorithms to minimize processing time is crucial for boosting design efficiency. The remarkable performance of the algorithm presented in this article in terms of feature detection time brings forth new advancements and opportunities in the realm of product design.

5 CONCLUSIONS

In the field of product design, AIGC technology can automatically generate novel and unique product shapes by learning a large number of existing design cases. As the basis of computer graphics, computational geometry algorithm has powerful geometric processing ability and optimization strategy, which can accurately describe and optimize product modelling while maintaining design creativity. The research results show that AIGC technology can efficiently generate diversified product design schemes and provide designers with rich creative inspiration. Furthermore, combined with a computational geometry algorithm, this article realizes accurate detection and rapid optimization of product modelling features, which significantly improves the quality of the design process. The performance of this algorithm in feature detection time is particularly prominent.

Compared with traditional methods, it greatly reduces the processing time and provides designers with immediate feedback and adjustment space. This not only improves the iterative speed of design but also helps to maintain the creative enthusiasm and work efficiency of designers. In conclusion, the approach outlined in this article represents a significant advancement in product modelling design, achieving an integrated workflow for automatic generation and optimization. Looking ahead, as technology continues to evolve and innovative applications expand, the product modelling design methodology that combines AIGC with computational geometry algorithms is poised to have a profound impact on industrial design, driving the intelligent transformation of the design industry.

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