Collaborative Application and Algorithm Optimization of CAD Modeling and Generative Adversarial Networks in Garment Design

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Abstract. Computer Aided Garment Design (GCAD) technology is built on the basis of interactive computer graphics, utilizing the powerful computing capabilities and efficient graphic processing capabilities of computers to assist in completing calculations, analysis, simulation, drawing, compilation, and other work in design. It is a specialized technology that computers help designers achieve product design and engineering design. Conditional Generative Adversarial Network (CGAN), as an extended form of Generative Adversarial Network (GAN), can guide the generation process by introducing conditional information, thereby generating more compliant data. This article proposes a CGAN-based GCAD modelling optimization method, which introduces deep learning (DL) technology into the field of garment design. By introducing conditional information to guide the generation process, more suitable garment models are generated. The results indicate that compared to the current neural network (RNN), CGAN-based methods can not only recognize more positive samples but also accurately determine the category of samples. The research results not only help promote the growth of GCAD technology and improve the level of garment design but also contribute to the transformation and upgrading of China's textile and garment industry and the enhancement of global competitiveness.

Keywords: Garment Design; CAD Modeling; Generating Adversarial Networks; Collaborative Applications
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1 INTRODUCTION

In today's society, garments are no longer just about meeting people's basic material needs but more about carrying individual self-expression, cultural identity, and spiritual pursuit. This transformation undoubtedly increases the complexity of garment design. Designers should not only focus on the practicality and comfort of the garment but also pursue its beauty, innovation, and personalization. For the garment industry, this is both a challenge and an opportunity. Especially after China's accession to the World Trade Organization, the textile and garment industry is facing unprecedented competitive pressure. Only through continuous innovation, improving its technological content and added value can it occupy a place in the global market. Agnese et al. [1] provided a detailed introduction to this technology and its application in clothing design surveys and classifications. A technique that converts text descriptions into images. This technique first takes the text description as input and then converts it into an image through a generator. Designers can express their design ideas through text descriptions and then use this technique to transform these ideas into realistic clothing images. This can help designers present their design concepts more intuitively and improve the accuracy of the design. This technology can also be used for clothing classification. For example, designers can express different types of clothing (such as casual wear, formal wear, etc.) through text descriptions and then use this technique to generate corresponding clothing images. This can help designers better understand the characteristics and market demands of different types of clothing, thereby formulating more precise design strategies.

In order to achieve this goal, more and more researchers are turning their attention to GCAD technology. GCAD technology to assist in garment design, manufacturing, and management. After decades of development, it has been widely used in sample making, grading, and layout, greatly improving the efficiency of garment production. How to further improve its design ability and innovation while maintaining its efficiency and accuracy has become the focus of current research. The performance of diving clothing is also constantly improving. In order to meet the needs of different fields, such as deep-sea exploration, marine scientific research, and military diving, the design and manufacturing of diving clothing need to be more refined and efficient. Boon et al. [2] will introduce the latest progress diving clothing. Fibre-reinforced polymer composite material is a composite material composed of fibre-reinforced material and polymer matrix. Reasonable structural design can improve the comfort, warmth, and protection of diving clothing. By optimizing material distribution, thickness, and structural form, the performance of diving clothing can be further improved. While reducing production costs. Through automation equipment such as robots and CNC machines, rapid manufacturing and precise processing of diving clothing components can be achieved. 3D printing technology is an additive manufacturing technology based on digital models. Through 3D printing technology, complex fibre-reinforced polymer composite components can be rapidly manufactured, with advantages such as high manufacturing accuracy, short production cycles, and low cost. Through automated cutting and assembly technology, rapid manufacturing and precise assembly of diving clothing components can be achieved. While reducing production costs. With the advancement of technology and the constant changes in consumer demand, the clothing design industry is facing more and more challenges. In order to address these challenges, many enterprises have begun to attempt to apply advanced technology to the clothing design process. Chen and Cheng [3] explore the development trends and application prospects of this system from several aspects. Train and optimize the Kansei engineering model using the BP neural network to improve prediction accuracy and efficiency. Based on the trained BP neural network model, generate clothing design product patterns that meet consumer needs, including design elements such as style, colour, and fabric. Evaluate and provide feedback on the generated clothing design product patterns to optimize and improve system performance continuously. Future clothing design will increasingly rely on data-driven design methods.

Doungtap et al. [4] explored the application of digital twins from the perspective of applied science. 3D reconstruction technology is a technique that uses computer vision and deep learning techniques to reconstruct a 3D model from images captured from multiple angles. In fashion design, 3D reconstruction technology can help designers quickly create and modify clothing styles, fabric textures, etc. Through 3D reconstruction technology, designers can more intuitively display design concepts to improve design efficiency and accuracy. Meanwhile, 3D reconstruction technology can also provide a data foundation for the subsequent generation of adversarial networks from the perspective of applied science, which generates highly realistic data such as images and audio through competitive learning. However, the data generated by GAN is often random, lacking controllability and directionality, which limits its application in certain fields. CGAN introduces a conditional variable based on GAN, which can be any type of data, such as labels, text, images, etc. By introducing conditional variables, CGAN can add more constraints and guidance in the process of generating data, thereby generating more compliant data in the field of garment design. CGAN can guide the generation of garment images that meet requirements by introducing conditional variables such as style, colour, material, etc., providing designers with more inspiration. In addition, CGAN can automatically extract garment features and styles by learning from existing garment image datasets, thereby generating more personalized garment images.

Generative Adversarial Networks (GANs), as a deep learning technique, have shown tremendous potential in clothing style design. Hu [5] discussed how to design and implement an intelligent clothing style CAD system based on generative adversarial networks intelligence of clothing design. Firstly, we need to collect a large number of images of clothing styles, including clothing of different styles, seasons, and populations. Then, preprocess these images, such as cropping, annotation, classification, etc., to facilitate subsequent training and generation. Meanwhile, the discriminator judges the authenticity of the images generated by the generator. Through continuous optimization and adjustment, the generator is able to generate more realistic and market-oriented new clothing images. On the basis of the GAN model, we will develop an intelligent CAD system to achieve automated clothing style design. The system includes functional modules such as user interface, image processing, model training, and style generation. Users can input design requirements through simple operations, and the system will automatically generate corresponding images of clothing styles. As an extension form of GAN, CGAN can guide the generation process by introducing conditional information, thereby generating data that better meets the requirements. This article proposes a CGAN-based GCAD modelling optimization method, which introduces DL technology into the field of garment design. By introducing conditional information to guide the generation process, more suitable garment models are generated. This study includes the following innovations:

(a) This article introduces DL technology into the field of garment design and optimizes GCAD modelling using CGAN.

(b) This article proposes a novel CGAN-based GCAD modelling optimization method, which guides the generation process by introducing conditional information to generate garment models that better meet the requirements.

(c) In the method proposed in this article, key information in GCAD modelling was extracted through effective data preprocessing, and an input data format suitable for the CGAN model was constructed. At the same time, a reasonable network structure was designed to enable the CGAN model to learn the inherent laws of garment design better.

(d) The research results contribute to promoting innovation in the Chinese textile and garment industry, improving product technology and added value, and enhancing the competitiveness of Chinese textile and garment enterprises.

The article first introduces the development process and application status of GCAD technology and analyzes its existing problems and challenges. Then, the basic principles, structure, and application advantages of CGAN in garment design will be introduced in detail. Next, a detailed description will be provided of how to optimize GCAD modelling using CGAN models, including data preprocessing, model construction, training stage, and other aspects. Finally, the practicality of the method proposed in this article was verified through experiments.

2 RELATED WORK

Tight-fitting clothing made of highly elastic materials is used in sports, fitness, and other fields. However, due to the tight fit between tight-fitting clothing and the human body, clothing pressure becomes an important factor, directly affecting the comfort and health of the wearer. Therefore, accurately estimating the pressure of tight-fitting clothing is of great significance for improving wearer comfort and protecting physical health. Horiba et al. [6] proposed a clothing pressure estimation method for tight-fitting clothing made of high-elastic materials using a hybrid approach of clothing CAD and finite element analysis software. This method achieves an accurate estimation of clothing pressure by simulating the interaction between tight-fitting clothing and the human body. Clothing design and manufacturing. When estimating the clothing pressure of tight-fitting clothing, the tight-fitting clothing. By discretizing and digitizing physical systems, simulation and analysis of physical systems can be achieved. When estimating the clothing pressure of tight-fitting clothing, we can use finite element analysis software to analyze the stress, strain, and other properties of the established tight-fitting clothing model. The application of CAD modelling and Generative Adversarial Networks (GANs) in three-dimensional clothing design is becoming increasingly widespread. Jankoska [7] explored how to synergistically apply CAD modelling and GAN in 3D clothing design to optimize the design process and improve design efficiency. CAD modelling is an important tool in clothing 3D design, which can help designers quickly create and edit 3D models, achieving a complete process from design sketches to the final product. Through CAD modelling, designers can accurately control the shape, size, and details of clothing, thereby better meeting market and consumer demands. In three-dimensional clothing design, GAN can improve existing design schemes. Through the GAN generation model, designers can select the best design scheme from a large number of design schemes, thereby improving design efficiency and quality. Collaborative application of CAD modelling and GAN in clothing 3D design can fully leverage their advantages and achieve optimization of the design process. Then, use GAN to generate new design solutions or improve existing design solutions. At the same time, designers can also use the GAN-generated solutions as input and use CAD modelling tools for fine-tuning and optimization. This collaborative application approach can improve design efficiency and quality while reducing designers' workloads.

Vision and deep learning have played important roles in many fields, especially in the clothing industry. Jeyaraj and Nadar [8] explored how to use deep learning algorithms to achieve automatic detection and classification of clothing and fabric defects through computer vision technology. The detection of fabric defects is an important and time-consuming task in the clothing production process. Traditional detection methods are usually manually completed, but this method is affected by eye fatigue and subjective factors, making it difficult to ensure the accuracy and efficiency of detection. Therefore, using computer vision and deep learning techniques for automatic detection and classification is an effective solution. Deep learning is a machine learning method that can automatically learn complex feature representations from a large amount of data. Computer vision is a technology that enables computers to "see" and interpret images and videos. By combining deep learning and computer vision, we can construct a system that can automatically detect and classify fabric defects. More and more consumers are starting to shop online. As an important category of goods, the retrieval and recommendation of clothing and fashion products are particularly important. Deep learning-based models can help us better process a large amount of clothing and fashion product data, thereby more accurately retrieving and recommending products. Jo et al. [9] introduced the development of clothing. We need to prepare a large amount of clothing fashion product data. For clothing and fashion products, we can use feature extraction technology to extract key information about the product. For example, the texture and shape of products. These features the attributes and characteristics of products, thereby more accurately retrieving and recommending products. In practical applications, we can take the user's query keywords as input, sort the search results according to relevance, and return the most relevant product list.

Neural networks have shown strong potential in multiple fields. Especially in the field of design, utilizing neural networks for complex pattern recognition and innovative design has become possible. Li et al. [10] explored normal filtering neural networks for feature-preserving mesh denoising in clothing design and how to collaborate with traditional design methods to improve design efficiency and quality. In the process of fashion design, designers often face the challenge of how to effectively extract truly valuable features from a large amount of noisy data. Traditional denoising methods may lead to the loss of important details, while normal filtering neural networks can better recognize and preserve these details through learning and training. We found that the collaborative application method using normal filtering neural networks can effectively extract the main features in clothing design in a short period of time while retaining these details and removing noise. More accurately understand and improve their designs. Moreover, compared to traditional design methods, this approach is more innovative and flexible. By applying normal filtering neural networks to grid denoising tasks in clothing design and collaborating with traditional design methods, we provide designers with a new tool and method to improve design efficiency and quality. Lee et al. [11] explored the implementation of an intelligent clothing automation manufacturing process using intelligent sports bras as a case study. By analyzing the automated manufacturing process of intelligent sports bras, summarize the key technologies and challenges in the implementation process, and propose corresponding solutions. Intelligent clothing utilizes advanced electronic technology, sensor technology, etc., to achieve real-time monitoring and feedback of various physiological parameters of the human body, improving the comfort and safety of the wearer. However, the manufacturing process of smart clothing is more complex than traditional clothing and requires the use of automated manufacturing technology to improve production efficiency and reduce costs. The development and debugging of smartphone applications need to be combined with hardware to ensure the accuracy and stability of real-time monitoring and feedback functions. In addition, factors such as the ease of use and user experience of the application also need to be considered. The construction of automated production lines requires consideration of factors such as equipment selection and configuration, as well as the design and optimization of production processes. At the same time, it is necessary to debug and optimize the production line to ensure its stability and production efficiency.

The application of CAD (Computer Aided Design) modelling and Generative Adversarial Networks (GANs). These advanced technologies provide designers with more creative tools and possibilities, driving innovation and development in fashion design. Särmäkari et al. [12] explored CAD modelling and GAN in fashion 4.0 designers, as well as how to use generative algorithms for experimentation and fashion design. CAD modelling is an important tool in fashion design, which can help designers quickly create and modify clothing styles, fabric textures, etc. Through CAD modelling, designers can present design concepts more intuitively, improving design efficiency and accuracy. Meanwhile, CAD modelling can also provide a data foundation for the subsequent generation of adversarial networks. The generative algorithm is a machine learning-based technique that can learn the inherent rules and features of data from a large amount of data and generate new data. In fashion design, generation algorithms can be used to generate new clothing styles, fabric textures, etc. By training the generation algorithm, we can enable the model to learn the inherent laws and characteristics of clothing styles, thereby generating new clothing that meets market demand. The design and manufacturing of wearable smart clothing need to be more refined and efficient. Wen et al. [13] introduced the application of CAD modelling and generative adversarial networks for wearable all-fibre smart clothing based on silk fibroin. Wearable all-fibre smart clothing is a type of smart clothing that integrates sensors, actuators, and other electronic devices. This type of clothing can achieve intelligent control and adjustment by sensing human physiological signals, environmental parameters, and other information. For example, wearing all fibre smart clothing can automatically adjust the breathability and warmth of the clothing according to changes in human temperature and humidity, improving wearing comfort. Generative Adversarial Network is a deep learning technique that learns the inherent laws and features of generating real data from random noise by training an adversarial network between the generator and discriminator. In the design of wearable all-fibre smart clothing, generative adversarial networks can be used to generate new clothing styles, fabric textures, etc. By training a generative adversarial network model, we can enable the model to learn the inherent laws and characteristics of clothing styles, thereby generating new clothing that meets market demand.

The digital transformation of the clothing industry has become a trend. Among them, using computer-aided design (CAD) technology and generative adversarial networks (GAN) to create virtual clothing models has become an emerging method. However, evaluating the similarity between these virtual clothing models and actual clothing remains a challenge. Won and Lee [14] aim to evaluate the fit similarity between actual pants contours and CAD modelling and GAN virtual clothing models by comparing their contours. There are certain differences in shape, lines, and details between the contours of the virtual pants generated by CAD modelling and GAN and the contours of the actual pants. This indicates that although the virtual pants model is already very close to the actual pants in appearance, there are still some subtle differences. This may be due to the limitations of data preprocessing, image processing techniques, and GAN models. In terms of fit evaluation, we found that the virtual pants model showed a good overall fit effect, but there are still some differences in some details, such as pockets, pants legs, and waist, compared to actual pants. This may be due to imprecise handling of these details or insufficient data when creating virtual pants models. Among them, Generative Adversarial Networks (GANs), as a deep learning technique, have shown great potential in clothing design. Yan et al. [15] explored how to collaboratively apply non-entangled generative adversarial networks for texture and shape to achieve intelligent fashion design. Fashion design is a field full of creativity and personalization, and designers need to have sharp insight and unique aesthetic views. However, the traditional clothing design process and the design results are often influenced by the designer's personal experience and subjective factors. Therefore, how to use advanced technological means is an important issue facing the fashion design field. GAN is a deep learning technique that learns the inherent laws and features of generating real data from random noise through adversarial training between the generator and discriminator. In clothing design, GAN can be used to generate new clothing styles, fabric textures, etc. By training the GAN model, we can enable the model to learn the inherent laws and characteristics of clothing styles, thereby generating new clothing that meets market demand.

This article applies CGAN to GCAD modelling, fully utilizing its generative adversarial properties to improve the innovation of garment design. During the model construction phase, the training stage of the model was optimized, including selecting appropriate loss functions and adjusting training parameters, etc., to achieve better performance of the model within a limited training time. Through data preprocessing and model structure optimization, it is enabled to achieve good performance in different garment design tasks.

3 PRESENT SITUATION AND PROBLEMS OF GCAD TECHNOLOGY

3.1 Main Application Fields of CAD Technology

(1) Sample production

Sample production is one of the key links in the garment production process, and it is also one of the earliest fields in which GCAD technology was applied. By using CAD software, designers can more accurately and quickly complete the design and production of templates, greatly improving production efficiency and the quality of templates. In addition, CAD software also has functions such as automatic calculation and material layout, which can reduce omissions in the template-making process.

(2) Grading

Grading refers to creating garment samples of different sizes based on the samples. The traditional grading method requires designers to perform manually, which is labour-intensive and prone to errors. By utilizing CAD technology, designers can automatically complete the grading process through software, improving work efficiency and accuracy.

(3) Material discharge

Layout refers to the reasonable arrangement of garment samples on the fabric to utilize the fabric and reduce waste fully. Using CAD technology, designers can automatically arrange materials based on factors such as fabric width and pattern. In addition, CAD software also has functions such as automatic calculation of materials and automatic generation of cutting diagrams, which can further simplify the production process.

(4) 3D effect display

With the increasing demand from consumers for the appearance and wearing effect of garments, 3D effect display has become an important part of garment design. Using CAD technology, designers can convert 2D garment samples into 3D renderings, more intuitively displaying the appearance and wearing effect of the garment. CAD software also has functions such as simulating human wearing and dynamic display, which can further enhance the purchasing experience of consumers.

3.2 Challenges and Issues Faced by GCAD Technology

(1) High learning costs

With the rapid growth of computer technology, GCAD technology is also constantly being updated and replaced. New software and features are constantly emerging, requiring designers to learn new knowledge and skills constantly. The high cost of learning and the high time cost are problems faced by many designers, which, to some extent, limits the widespread use of CAD in garment design.

(2) Poor data compatibility

Due to the different data formats and interface standards of different CAD software, the compatibility of data between different software is poor. This means that designers need to perform data conversion or redesign when using different software for design, which increases workload and design costs.

(3) Insufficient innovation ability

Although CAD technology provides more possibilities and convenience for garment design, many designers are still accustomed to traditional design patterns and methods. This leads to many CAD works lacking innovation and personalization, which cannot meet the needs of consumers for fashion and individuality.

(4) Security issues and privacy protection

With the growth of technologies such as cloud computing and big data, GCAD technology has also begun to migrate to the cloud. Therefore, the security and privacy protection issues brought about by cloud storage and cloud computing cannot be ignored. Ensuring the security of designer works and data and preventing data leakage and theft are important issues that CAD technology needs to solve.

4 PRINCIPLES AND APPLICATIONS OF CGAN

4.1 The Basic Principles of CGAN

CGAN is an extended form of GAN that guides the generation process by introducing conditional information, thereby generating data that better meets the requirements. In garment design, CGAN can be applied in multiple aspects, such as template generation, pattern design, colour matching, etc. Through continuous adversarial training, the generator gradually learns the distribution of real data and is able to generate new data similar to real data. CGAN introduces conditional information on the basis of GAN, which can be labels, images, text, etc. During the training stage, both the generator and discriminator receive conditional information as input to guide the generation process. The generator is responsible for producing data that satisfies certain criteria by referring to the conditional information, whereas the discriminator assesses whether the inputted data meets these criteria based on the same conditional information. Through continuous adversarial training, CGAN can learn how to generate data that meets the requirements under given conditions.

4.2 Application of CGAN in Garment Design

Traditional template-making requires designers to perform manually, which is labour-intensive and prone to errors. Using CGAN technology, designers can input the basic properties and style requirements of the template, and the model can automatically generate templates that meet the requirements. Using CGAN technology, designers can input the basic attributes and style requirements of the pattern, and the model can automatically generate patterns that meet the requirements. This method can quickly generate a large quantity of pattern design schemes, providing designers with more choices and inspiration. Colour matching is one of the key steps in garment design, and different colour combinations can create different atmospheres and styles.

Using CGAN technology, designers can input the basic properties and matching requirements of colours, and the model can automatically generate colour-matching schemes that meet the requirements. By utilizing CGAN technology, designers can customize designs based on consumer preferences and physical characteristics. This method can provide consumers with a more personalized service experience and improve brand loyalty and market competitiveness.

The process of dynamic fusion of garment features requires collecting a large amount of garment image data, preprocessing it, and annotating it for training GAN models. The task of the generator is to generate garment images based on input noise and conditional information, while the task of the discriminator is to determine whether the generated images are real. Using CNN and other techniques to extract features from garment images, including colour, texture, shape, etc. Dynamically integrate multiple garment features based on design requirements and condition information. For example, the combination and proportion of colour, texture, and shape can be adjusted according to different seasons, occasions, and styles to generate garment design schemes with different characteristics. The dynamic fusion method of garment features based on GAN is shown in Figure 1.

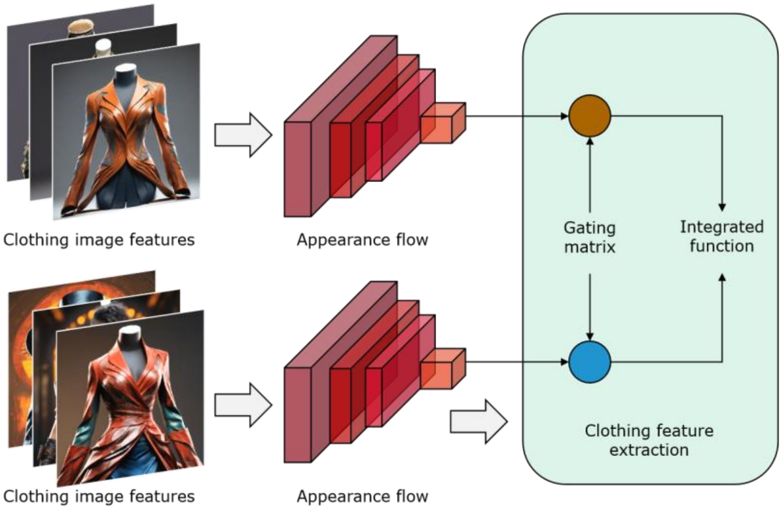

Figure 1: Dynamic fusion of garment features.

The dynamic game process between generator G and discriminator D can be transformed into the process of solving the following minimax objective function:

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

$$\max_D V(G,D) = E_{x\sim p_r}[\log D(x)] + E_{x\sim p_g}[\log(1-D(x))] \tag{2}$$

Then solve the following equation for the generator G :

$$\max_D V(G,D) = E_{x\sim p_g}[\log(1-D(x))] \tag{3}$$

5 OPTIMIZATION OF GCAD MODELING BASED ON CGAN

The basic principle of the CGAN-based GCAD modelling optimization method is to apply CGAN technology to the GCAD modelling process. Firstly, use CGAN to generate garment templates, patterns, and colour-matching schemes that meet the requirements, and then input these schemes into the CAD system for modelling and rendering. Through this method, a large quantity of design schemes can be quickly generated, and iterative optimization can be carried out based on feedback from designers. Firstly, it is necessary to prepare a training set that includes real data and corresponding conditional information. These data can come from the designer's hand-drawn drawings, scanned drawings, or existing CAD drawings. In order to improve the performance of the model, it is also necessary to preprocess and standardize these data. The network structure of the algorithm in this article is shown in Figure 2.

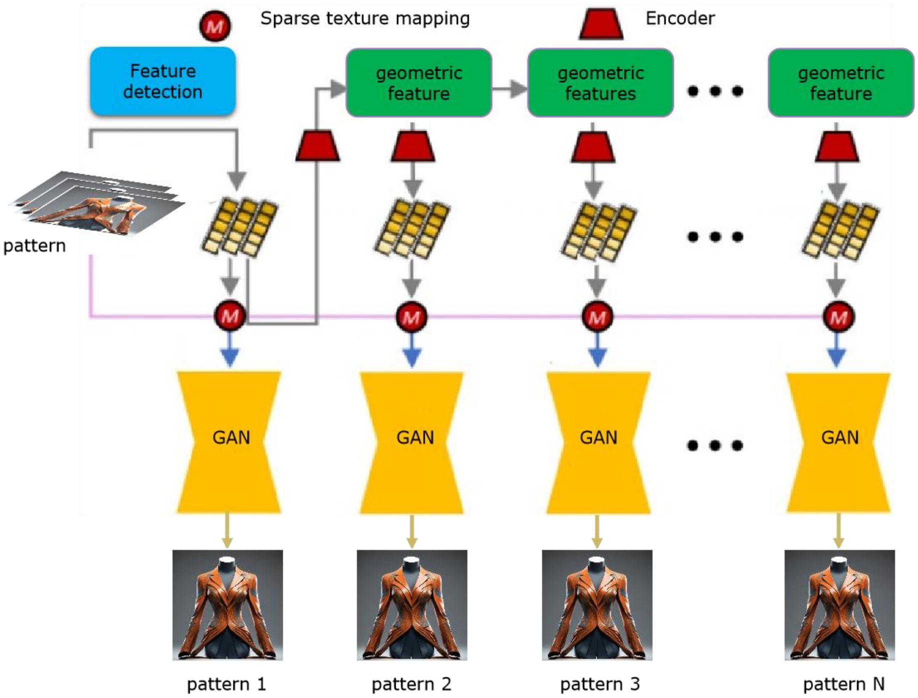

Figure 2: Network structure of the algorithm.

After the model construction is completed, adversarial training methods are needed to optimize the performance of the model continuously. In each training iteration, the parameters of the discriminator are first fixed, a batch of data is generated using the generator, and the parameters of the generator are adjusted based on the feedback of the discriminator. Then, fix the parameters of the generator, use a discriminator to discriminate the generated data, and adjust the discriminator parameters based on the discrimination results. Through continuous iterative training, the performance of the model can be gradually improved, and more suitable data can be generated. The discriminator network structure based on CNN is shown in Figure 3.

The risk function of the garment material texture recognition model is as follows:

$$\theta^{*} = \arg\min_{\theta} \frac{1}{N}\sum_{i=1}^{N} L(y_i, f(x_i;\theta)) + \lambda\phi(\theta) \tag{4}$$

$$L(Y, P(Y|X)) = -\log P(Y|X) = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M} y_{ij}\log(p_{ij}) \tag{5}$$

$$I_{truth} = \begin{cases} 1 & if \quad I_D \geq s \\ 0 & otherwise \end{cases} \tag{6}$$

$$L_{mask} = -\frac{1}{c}\sum_{i=0}^{C-1}(a \cdot y_i \ln(y_i^{'}) + \beta \cdot (1-y_i)\ln(1-y_i^{'})) \tag{7}$$

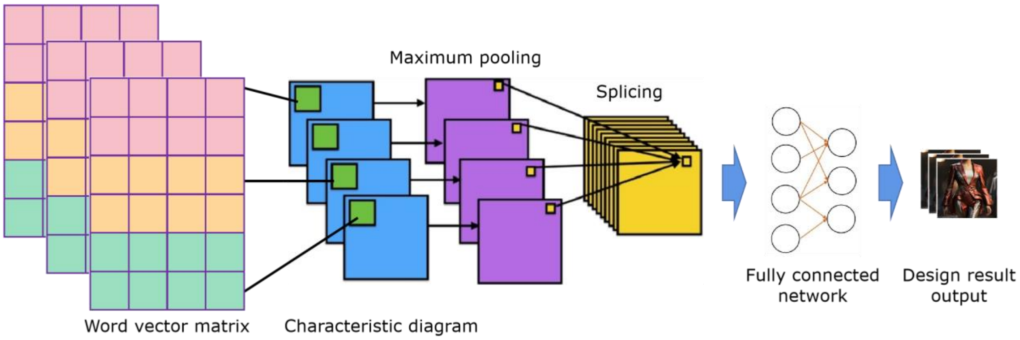

Figure 3: Discriminator network based on CNN.

Within this context, y_i it $y_i^{'}$ corresponds to the actual value and the model's predicted value for each target point within the image region, respectively.

Let's assume that the discriminator network employs a structural design consisting of a word embedding layer, a convolution layer, and, subsequently, a fully connected layer. The final output layer utilizes the sigmoid function to ascertain the probability value associated with authentic samples:

$$sigmoid(z) = \frac{1}{1+e^{-z}} \tag{8}$$

The discriminator network structure can be represented as:

$$D_{\varphi}(s) = sigmoid(\varphi_l^T F_{\varphi f}(s)) = sigmoid(\varphi_l^T f) \tag{9}$$

The output of this feature detection network can be denoted as f :

$$f = F_{\varphi f}(s) \tag{10}$$

In order to verify the effectiveness of the CGAN-based GCAD modelling optimization method, a series of experiments and tests were conducted in the following text. In this example, CGAN is first used to generate garment template patterns and colour-matching schemes that meet the requirements, and then these schemes are input into the CAD system for modelling and rendering. Through continuous iteration and optimization, a high-quality garment sample design scheme was ultimately obtained and received recognition and praise from the designer.

6 EXPERIMENT AND RESULT ANALYSIS

6.1 Experimental Environment and Settings

In terms of hardware. In terms of software, the operating system uses Ubuntu 18.04 LTS, and the DL framework uses TensorFlow 2.3.0. The dataset includes DeepFashion, Fashion MINIST, and OpenPose. Both CGAN and RNN use Adam optimizers. The quantity of training rounds is set to 200.

6.2 Experimental Process and Steps

Scale, crop, and normalize the DeepFashion and OpenPose datasets to unify the size of all images to 256 × 256. Normalize the Fashion-MNIST dataset and expand its size to 28 × twenty-eight × 1.

Adapt to the model input. CGAN: Built a generator and a discriminator. The generator uses transposed convolutional layers to generate images, while the discriminator uses convolutional layers to determine the authenticity of the images. RNN: A model structure with three layers of LSTM units and 256 hidden states was selected for processing and predicting sequence data.

In each training iteration, the parameters of the discriminator are first fixed, a batch of data is generated using the generator, and the parameters of the generator are adjusted based on the feedback of the discriminator. Then, fix the parameters of the generator, use a discriminator to discriminate the generated data, and adjust the discriminator parameters based on the discrimination results. Gradually improve the performance of the model and generate data that better meets the requirements through continuous iterative training. After completing CGAN training, save its model weights for subsequent testing.

The RNN undergoes training utilizing the stochastic gradient descent algorithm, aiming to refine the weights and biases of the model. Subsequent updates to the model parameters are made based on this gradient. Once the training of the RNN is concluded, the weights of the model are preserved for future testing purposes.

6.3 Experimental Results and Comparative Analysis

Figure 4 shows the garment design effect based on 3D solid rendering. Through 3D rendering technology, the drape and dynamic effects of garments in virtual space have also been well demonstrated. Through fine colour adjustments and light and shadow rendering, the transition between garment colours is natural and layered.

(a) Contour feature (b) Traditional method (c) This method

Figure 4: Garment design rendered from 3D solids.

In the experiments conducted on the DeepFashion, Fashion MINIST, and OpenPose datasets, in order to overcome overfitting or underfitting problems caused by insufficient sample quality and dataset richness, this article adopted data preprocessing methods such as flipping, rotation, translation, and scaling, as shown in Figure 5.

By flipping, the direction of the object can be changed, making the model more adaptable to objects in different directions. By performing rotation operations, it is possible to simulate various angles at which objects may appear in actual scenes, enhancing the model's robustness to angle changes. By performing translation operations, the movement of the camera or observer can be simulated, making the model more adaptable to changes in the position of objects. By zooming in and out, the model can simulate changes in the distance of an object, allowing it to learn the scale invariance of the object. By applying these methods comprehensively, the dataset can be effectively expanded, and the generalization ability of the model can be improved.

The experiment compared the CGAN-based method and the RNN-based method and obtained simulation results of recall and accuracy through the experiment, as shown in Figure 6 and Figure 7, respectively. Through repeated iterations, it was found that CGAN-based methods significantly improved recall and accuracy.

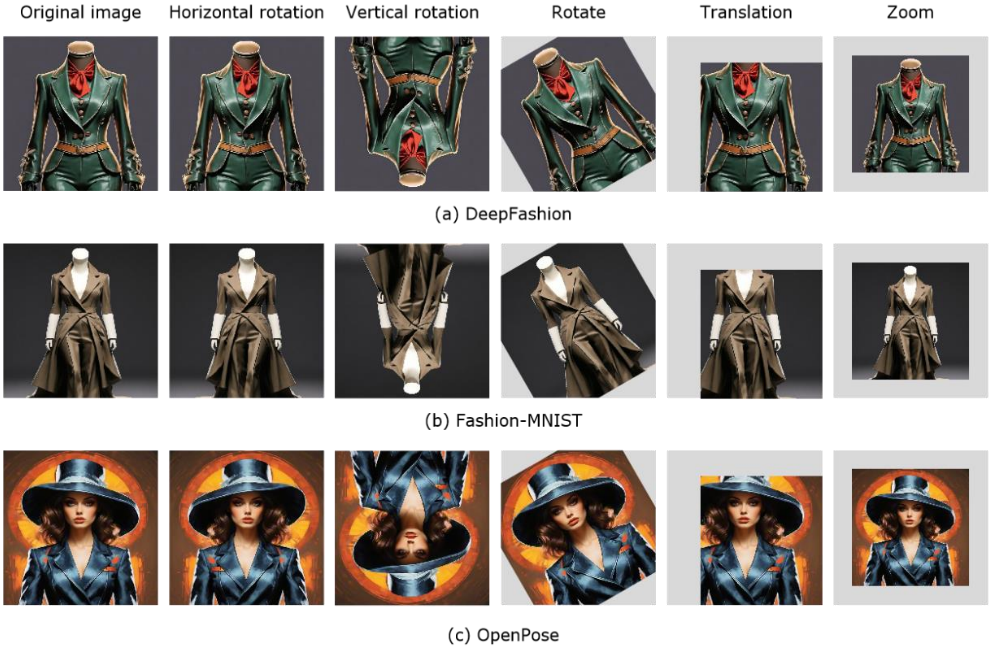

Figure 5: Data enhancement example of the training set in three data sets.

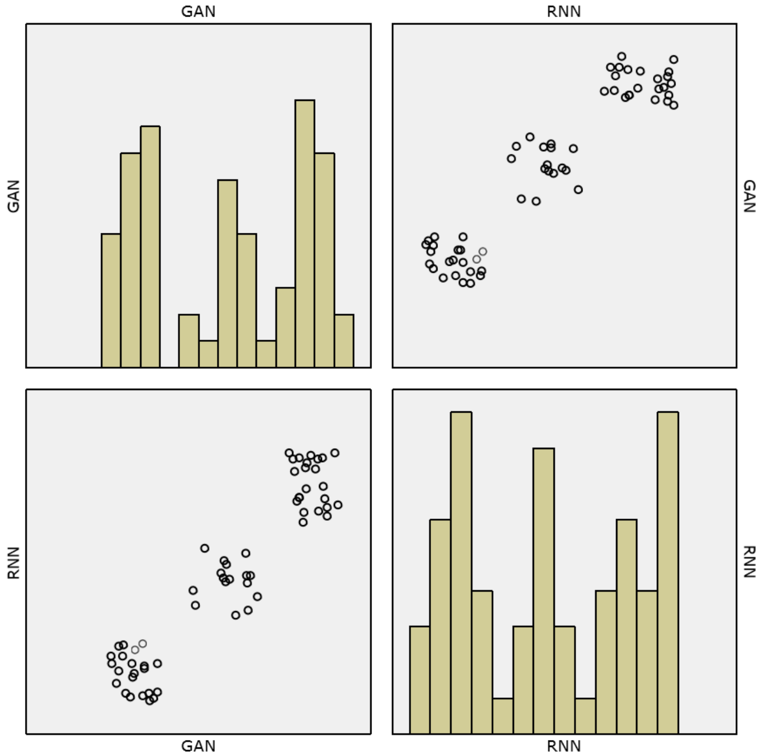

Figure 6: Comparison of recall.

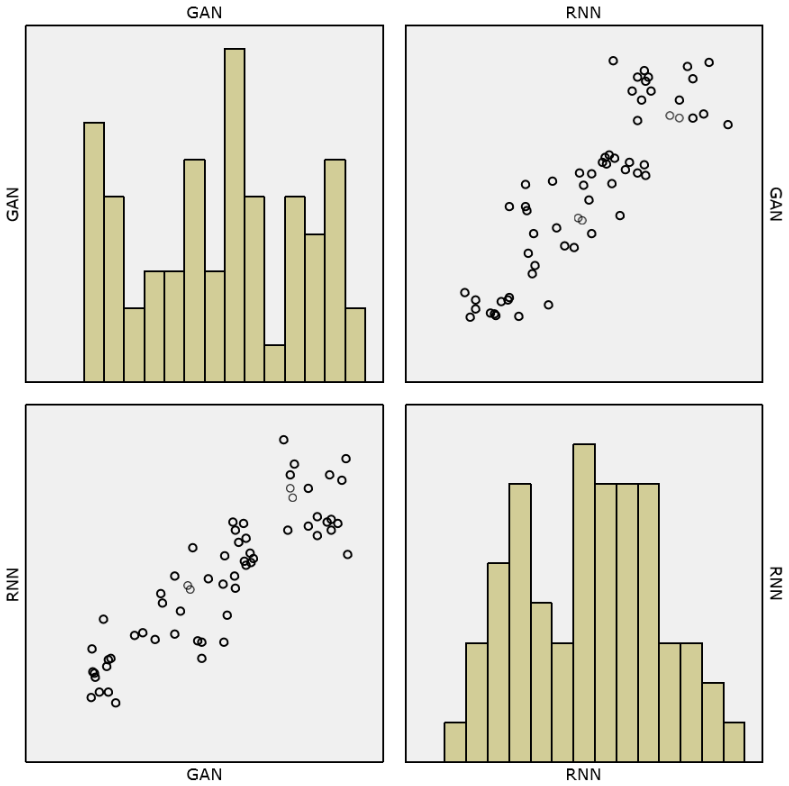

Figure 7: Comparison of accuracy.

The recall refers to the proportion of correctly identified positive samples by the model to all true positive samples. In Figure 6, the recall of the CGAN-based method gradually increases with the number of iterations. This indicates that CGAN-based methods can effectively identify more positive samples, i.e. better capture the true distribution in the data. In contrast, the recall of RNN-based methods is relatively low, and there is no significant improvement during the iteration process. In Figure 7, the accuracy of the CGAN-based method gradually improves with the increase in iteration times. This indicates that CGAN-based methods can not only recognize more positive samples but also accurately determine the category of samples. In contrast, the accuracy of RNN-based methods is relatively low, and there is no significant improvement during the iteration process. This further validates the effectiveness of CGAN-based methods in processing complex data. The research results not only help promote the growth of GCAD technology and improve the level of garment design but also contribute to the transformation and upgrading of China's textile and garment industry and the enhancement of global competitiveness. By introducing DL technology, garment designers can be given more inspiration.

7 CONCLUSION AND OUTLOOK

Nowadays, garments are no longer just meeting people's basic material needs but more carrying the pursuit of individual self-expression, cultural identity, and spiritual level. GCAD technology to assist in garment design, manufacturing, and management. CGAN can guide the generation of garment images that meet requirements by introducing conditional variables such as style, colour, material, etc., providing designers with more inspiration. This article proposes a CGAN-based GCAD modelling optimization method, which introduces DL technology into the field of garment design and guides the generation process by introducing conditional information. This article explores the application of CGAN and RNN-based methods on DeepFashion, Fashion MINIST, and OpenPose datasets and conducts a series of experimental verifications. Comparative experiments have proven that CGAN has superior performance compared to RNN in certain tasks.

The research results not only help promote the growth of GCAD technology and improve the level of garment design but also contribute to the transformation and upgrading of China's textile and garment industry and the enhancement of global competitiveness. By introducing DL technology, garment designers can be given more inspiration. In the future, experiments can be considered on larger and more complex datasets to verify the scalability and practicality of CGAN.

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REFERENCES

[1] Agnese, J.; Herrera, J.; Tao, H.; Zhu, X.: A survey and taxonomy of adversarial neural networks for text-to-image synthesis, Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 10(4), 2020, e1345. https://doi.org/10.1002/widm.1345

[2] Boon, Y.-D.; Joshi, S.-C.; Bhudolia, S.-K.; Gohel, G.: Recent advances on the design automation for performance-optimized fiber reinforced polymer composite components, Journal of Composites Science, 4(2), 2020, 61. https://doi.org/10.3390/jcs4020061

[3] Chen, D.; Cheng, P.: growth of design system for product pattern design based on Kansei engineering and BP neural network, International Journal of Garment Science and Technology, 2022(3), 2022, 34. https://doi.org/10.1108/IJCST-04-2021-0044

[4] Doungtap, S.; Petchhan, J.; Phanichraksaphong, V.; Wang, J.-H.: Towards digital twins of 3D reconstructed apparel models with an end-to-end mobile visualization, Applied Sciences, 13(15), 2023, 8571. https://doi.org/10.3390/app13158571

[5] Hu, L.: Design and implementation of a component-based intelligent garment style CAD system, Computer-Aided Design and Applications, 18(S1), 2020, 22-32. https://doi.org/10.14733/cadaps.2021.S1.22-32

[6] Horiba, Y.; Amano, T.; Inui, S.; Yamada, T.: Proposal of a method for estimating clothing pressure of tight-fitting garment made from highly elastic materials: hybrid method using apparel CAD and finite element analysis software, Journal of Fiber Science and Technology, 77(2), 2021, 76-87. https://doi.org/10.2115/fiberst.2021-0006

[7] Jankoska, M.: Application CAD methods in 3D garment design, Tekstilna Industrija, 68(4), 2020, 31-37. https://doi.org/10.5937/tekstind2004031J

[8] Jeyaraj, P.-R.; Nadar, E.-R.-S.: Computer vision for automatic detection and classification of fabric defect employing deep learning algorithm, International Journal of Garment Science & Technology, 31(4), 2019, 510-521. https://doi.org/10.1108/IJCST-11-2018-0135

[9] Jo, J.; Lee, S.; Lee, C.; Lee, D.; Lim, H.: Development of fashion product retrieval and recommendations model based on deep learning, Electronics, 9(3), 2020, 508. https://doi.org/10.3390/electronics9030508

[10] Li, Z.; Zhang, Y; Feng, Y.: Normalf-net: normal filtering neural network for feature-preserving mesh denoising, Computer-Aided Design, 127(5), 2020, 102861. https://doi.org/10.1016/j.cad.2020.102861

[11] Lee, S.; Rho, S.-H.; Lee, S.; Lee, J.; Lee, S.-W.; Lim, D.; Jeong, W.: Implementation of an automated manufacturing process for smart clothing: The case study of a smart sports bra, Processes, 9(2), 2021, 289. https://doi.org/10.3390/pr9020289
[12] Särmäkari, N.; Vänskä, A.: 'Just hit a button!'–fashion 4.0 designers as cyborgs, experimenting and designing with generative algorithms, International Journal of Fashion Design, Technology and Education, 15(2), 2022, 211-220. https://doi.org/10.1080/17543266.2021.1991005
[13] Wen, D.-L.; Pang, Y.-X.; Huang, P.; Wang, Y.-L.; Zhang, X.-R.; Deng, H.-T.; Zhang, X.-S.: Silk fibroin-based wearable all-fiber multifunctional sensor for smart clothing, Advanced Fiber Materials, 4(4), 2022, 873-884. https://doi.org/10.1007/s42765-022-00150-x
[14] Won, Y.; Lee, J.-R.: A Study on the comparison of fit similarity between the actual and virtual clothing according to the pants silhouette, Fashion & Textile Research Journal, 23(6), 2021, 826-835. https://doi.org/10.5805/SFTI.2021.23.6.826
[15] Yan, H.; Zhang, H.; Shi, J.; Ma, J.; Xu, X.: Toward intelligent fashion design: A texture and shape disentangled generative adversarial network, ACM Transactions on Multimedia Computing, Communications and Applications, 19(3), 2023, 1-23. https://doi.org/10.1145/3567596