Application of Computer Graphics and Machine Learning in Computer Aided Design of Digital Sculpture

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Abstract. As an art form, digital sculpture has been widely used with the support of computer aided design (CAD) technology. Computer graphics technology plays an important role in the CAD design of digital sculpture. Using computer graphics technology, digital sculpture artists can create and edit sculpture models more conveniently, and perform high-quality rendering and animation. In this study, the image feature fusion technology is introduced into the CAD design of digital sculpture. By fusing the texture features and image features of the sculpture model, a more realistic and vivid sculpture effect is achieved. The test results show that, compared with the other two methods, the method based on Atrous Convolution Neural Network (ACNN) shows higher running efficiency and higher precision in the extraction of sculpture texture features. This method can effectively support the CAD design of digital sculpture and provide a new and effective tool for this field. Designers can rely on the accurate texture features extracted by ACNN for subsequent CAD design and rendering to improve the efficiency and authenticity of design.

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1 INTRODUCTION

Digital sculpture refers to a three-dimensional sculpture model created by computer technology. Its appearance has greatly expanded the expression forms and creative means of sculpture art, enabling artists to exert their imagination and creativity more freely. Computer graphics technology plays an important role in the CAD design of digital sculpture. With the rapid development of industrial automation and artificial intelligence technology, industrial visual inspection has become a crucial part of modern manufacturing processes. Among them, knowledge in the field of deep learning plays a crucial role in understanding and applying these technologies. However, for non-professionals, understanding and applying knowledge in these areas of deep learning can be a challenge. Abubakr et al. [1] explored how to learn deep domain agnostic features from synthetic rendering in industrial visual inspection to help non-professionals better understand these concepts. Synthetic rendering is a method of using computer graphics technology to create realistic images or videos. In industrial visual inspection, synthetic rendering can be used to create virtual images or models similar to actual products for visual inspection and recognition. Through synthetic rendering, we can simulate various lighting conditions, object surface materials, and shapes, thereby creating various challenging training data. Deep domain agnostic features refer to features that are invisible to classification or recognition tasks in deep learning. These features typically include noise, interference, image details, etc. When learning unknown features in the field of depth, we need to use synthetic rendering technology to create training data with these features, and use deep learning models to learn and extract these features. Using computer graphics technology, digital sculpture artists can create and edit sculpture models more conveniently, and perform high-quality rendering and animation. Digital dual drive supervised machine learning provides powerful tools for AI application development in the manufacturing industry, helping to improve production efficiency, reduce costs, optimize resource allocation, and improve product quality. With the continuous progress of technology and the advancement of Industry 4.0, we have reason to believe that DDD methods will play a greater role in the manufacturing industry, bringing more possibilities for its development. Digital dual drive supervised machine learning is a method that combines physical and data-driven models. By establishing a bridge between the two, Alexopoulos et al. [2] achieves more accurate understanding and prediction of complex systems. In the manufacturing industry, DDD methods can help us better understand production processes, predict equipment performance, and optimize production processes.

By using the DDD method to establish physical and data-driven models based on the historical operating data and performance parameters of the equipment, potential faults and performance degradation of the equipment can be predicted, and maintenance and repair can be carried out in advance to reduce the risk of production interruption. The DDD method can help us analyze various links in the production process, identify bottlenecks and waste areas, and optimize production planning and scheduling through AI algorithms to improve production efficiency. However, there are still some problems in the CAD design of digital sculpture. For example, for complex sculpture models, manual texture mapping and lighting settings are often very time-consuming and the effect is difficult to guarantee. Cao et al. [3] proposed an adaptive learning model for multi-scale texture features in polyp classification based on computed tomography colon imaging. This model can effectively extract and utilize multi-scale texture features to accurately classify different types of polyps. The experimental results show that this method has good classification performance and high robustness. However, further research and improvement are still needed to handle more complex cases and special types of polyps. Based on the extracted texture features, we designed an adaptive learning model. This model adopts a deep learning framework and achieves accurate classification of different types of polyps by adaptively learning feature weights and parameters. Utilize a large amount of annotated data for model training, and optimize the model through techniques such as cross validation and regularization. Evaluate the performance of the model on an independent test set, using indicators such as accuracy, sensitivity, and specificity to evaluate the model. The results showed excellent performance of the model on the test set, with an accuracy of 90%, sensitivity and specificity of 85% and 95%, respectively. The adaptive learning model based on multi-scale texture features can effectively distinguish different types of polyps and has good classification performance. In addition, for large-scale sculpture models, the calculation and rendering time is often long, which affects the design efficiency. The progress of design input technology and interaction technology plays a crucial role in improving design efficiency and quality. Erdolu [4] explored the design framework of two computer-aided design input and interaction technologies, triangle and net. Designers can directly see their designs on 3D models, which allows them to more intuitively understand and modify the design. Triangles can accurately represent the shape and size of objects, which is crucial for applications that require high-precision design. Triangles can be easily modified and edited, allowing designers to make flexible design adjustments as needed. Web is a computer-assisted design interaction technology based on physical models. Designers can change the shape and size of objects by creating and modifying meshes on 3D models. In practical computer-aided design, triangles and nets can be combined to achieve more efficient and accurate design. For example, designers can first use triangles to create and modify the rough shape of 3D models, and then use nets to make finer adjustments and modifications to the model. This combined approach can enable designers to achieve greater flexibility and efficiency in the design process. Therefore, how to further improve the quality and efficiency of digital sculpture CAD design is an urgent problem to be solved.

With the rapid development of technology, Computer Aided Design (CAID) has been widely applied in various fields. In the field of sculpture art, the emergence of CAID technology provides artists with a new way of creation and expression. Guo and Wang [5] discussed the application of computer-aided design in the expression technology of sculpture art space, as well as its impact and prospects. In the sculpture modeling stage, artists can use computer-aided design software to create and modify three-dimensional models. This software typically has powerful modeling tools that can accurately shape and detail sculptures. Through computer-aided modeling design, artists can add and edit materials and textures on the surface of the model to achieve more realistic and vivid visual effects. By utilizing computer-aided design, artists can create virtual sculptures on computers and export them to the real world. This method can achieve rapid prototyping manufacturing and improve production efficiency. Through computer-aided design, artists can simulate the display effect of sculptures in the computer, in order to better grasp the spatial relationship and sense of scale of sculptures. As an art form, digital sculpture has been widely used with the support of CAD technology. With the continuous growth of computer graphics and machine learning (ML) technology, the quality of digital sculpture CAD design have been continuously improved. Deep learning has completely changed the fields of computer vision and image processing. Especially in the field of image based 3D object reconstruction, deep learning technology has shown strong potential. The goal of this technology is to reconstruct 3D objects by analyzing 2D images, which has significant value for various application scenarios such as virtual reality, augmented reality, 3D modeling, and visualization. With the increasing demand for 3D games and virtual reality, Han et al. [6] analyzed that real-time 3D object reconstruction has become an important research direction. The latest research is exploring the use of lightweight neural network architecture and efficient rendering techniques to achieve real-time 3D object reconstruction. The current 3D object reconstruction methods often only restore the approximate shape, and the restoration of details is still insufficient. Future research will need to address this issue to achieve more refined 3D object reconstruction. In current 3D object reconstruction methods, only the shape can be restored, but the semantic information of the object (such as materials, textures, etc.) cannot be restored. Future research needs to address this issue in order to achieve more comprehensive 3D object reconstruction. For most applications, annotated 3D data is very scarce. Future research needs to explore how to train effective 3D object reconstruction models even when data is scarce. The rapid development of augmented reality (AR) technology has enabled us to seamlessly integrate virtual elements with the real world. However, in the process of achieving this goal, how to accurately align and assemble virtual objects remains a challenging issue. Especially for objects with complex textures and reflection characteristics, the accuracy of their registration is crucial for the user experience. He et al. [7] proposed a method for registering non reflective texture objects in augmented reality assembly using multiple edge features. For a given texture image, we first use edge detection algorithms such as Canny edge detection to identify edge features in the image. The main purpose of this step is to extract key points from the image and provide reference for subsequent registration processes. After extracting edge features, we need to pair virtual objects with real-world target objects through an effective matching algorithm. Here we adopt a distance based nearest neighbor matching algorithm to achieve fast and accurate matching. By matching the obtained feature points, we can use geometric transformation algorithms (such as affine transformation or perspective transformation) to adjust the posture of the virtual object to maintain consistency with the target object in spatial position and direction. Finally, we overlay the virtual object on the target object and use transparency blending technology to achieve the fusion of the two. This step can effectively mask the reflection texture of the target object, presenting a seamless fusion effect between virtual elements and the real world. With the rapid development of the manufacturing industry, the automation and precision control of CNC machine tools in the processing process have become increasingly important. End face milling, as a key step in mechanical processing, its process planning directly affects the geometric accuracy and quality of the workpiece. In recent years, the automatic process planning system for end milling constrained by geometric dimensions and tolerances has become a research hotspot.

This article aims to explore the application of computer graphics and ML in digital sculpture CAD design, and propose an ACNN based sculpture texture feature detection algorithm and image feature fusion framework to more effectively support digital sculpture CAD design. This algorithm and framework can automatically extract texture features of sculpture models and fuse image features to achieve more realistic and efficient sculpture rendering. For digital sculpture artists, this will greatly improve design efficiency and effectiveness, while also providing new possibilities for the further growth of digital sculpture. Through the research in this article, it is expected to provide a new and effective technical means for digital sculpture CAD design. The sculpture texture feature detection algorithm and image feature fusion framework based on ACNN can not only improve the design efficiency of digital sculptures, but also ensure the high-quality rendering effect.

(1) The sculpture texture feature detection algorithm based on ACNN proposed in this article has the characteristics of automation, accuracy, and efficiency. This algorithm can automatically extract rich texture features from sculpture models, providing a foundation for subsequent rendering and design.

(2) This study introduces image feature fusion technology into digital sculpture CAD design, achieving more realistic and vivid sculpture effects by integrating texture and image features of sculpture models.

(3) By comprehensively utilizing computer graphics and ML technology, this method greatly improves the design efficiency and rendering speed of digital sculpture. Artists can focus more on artistic creation itself without being too limited by technology.

This article first introduces the background and importance of digital sculpture CAD design, and points out the key role of texture feature detection in this field; Next, a sculpture texture feature detection algorithm based on ACNN was proposed, and its principle and implementation process were described; Then, the advantages of ACNN in the application of digital sculpture design were verified through experiments; Finally, this article summarizes the work achievements and contributions, and points out the limitations and future research directions.

2 COMPUTER GRAPHICS AND ML FOUNDATION

Nishida et al. [8] provided a detailed introduction to the principle, characteristics, and advantages of this system. Using CAD technology to establish a three-dimensional geometric model of the workpiece, while considering geometric dimensions and tolerance constraints. Based on machine learning algorithms, reasonable cutting paths are automatically generated according to different workpiece materials and processing requirements. By using artificial intelligence algorithms, parameters such as cutting speed and feed rate are optimized to achieve the best machining effect. By using computer simulation technology, the machining process is simulated to verify the rationality of cutting paths and parameters. In computer vision and graphics, estimating the relative pose between image objects and 3D models is an important research issue. It is widely used, such as in fields such as virtual reality, augmented reality, robot navigation, autonomous driving, etc., which require accurate estimation of the position, direction, and attitude of objects. In recent years, with the rapid development of deep learning technology, researchers have developed many effective models to solve this problem. 4-DoF automatic annotation refers to automatically annotating objects in an image and describing their position, direction, and posture in three-dimensional space. This technology is of great significance for understanding image content, recognizing objects, and constructing 3D models. ShapeNet is a large-scale and diverse 3D model database that includes CAD models of various shapes. These models provide valuable resources for understanding the shape and structure of objects in the real world. Park et al. [9] explored the issue of relative pose estimation between 4-DoF automatically annotated image objects and ShapeNet CAD models. We propose a deep learning based relative attitude estimation method and experimentally evaluate its performance. The results indicate that our method can effectively find the best matching model and accurately estimate its attitude. Future research directions include improving model structure, optimizing training algorithms, and expanding datasets. In recent years, deep learning and decision tree classifiers have achieved significant results in medical image analysis.

Priya [10] proposed a feature extraction and decision tree classifier based on Resnet for the classification of breast X-ray images. Use Resnet model to extract features from preprocessed images. Resnet is a deep learning model with strong feature extraction capabilities that can effectively extract features from images. Input the extracted features into a decision tree classifier for classification. Decision tree classifier is a common classifier with the advantages of being intuitive and easy to understand. The experimental results show that Resnet based feature extraction and decision tree classifier can effectively classify breast X-ray images, with a classification accuracy of over 90%. At the same time, this method has good generalization performance and can effectively identify breast cancer and other diseases. This article proposes a feature extraction and decision tree classifier based on Resnet for the classification of breast X-ray images. The experimental results show that this method can effectively classify the breast X-ray images and provide an effective auxiliary means for the diagnosis of breast cancer. Computer Aided Process Planning (CAPP) is a key component of Computer Aided Manufacturing (CAM), which utilizes computer technology to assist in the design and optimization of process planning. In manufacturing systems, the research and application of CAPP is of great significance for improving production efficiency, reducing costs, and improving product quality. Soori and Asmael [11] introduced the application classification of CAPP in manufacturing systems. This method utilizes an expert knowledge base and inference mechanism to automatically generate machining paths based on part blueprints and machining requirements. It is suitable for production environments with complexity and uncertainty. This method utilizes machine learning algorithms to learn from a large amount of data, automatically extracting machining rules and generating machining paths. It is suitable for production environments with high complexity and uncertainty. This method combines the advantages of basic model method, expert system method, and machine learning method to improve the efficiency and accuracy of CAPP. It is suitable for various production environments. Utilizing artificial intelligence and machine learning technologies to improve the automation and intelligence level of CAPP, enabling it to adapt and optimize complex manufacturing processes. With the continuous development of technology, the application of computer-aided design in ceramic products will become more widespread. Future ceramic product design may place greater emphasis on personalized customization and intelligent design. Computer aided design is a tool that utilizes computer technology for product design. It can help designers create, modify, and test designs in a virtual environment, greatly improving the efficiency and accuracy of the design. In ceramic product design, CAD software can help designers create three-dimensional models, simulate the appearance and performance of products, and better meet customer needs. The application of these technologies will further promote the development and innovation of the ceramic industry. Designers conduct conceptual design based on customer needs and design concepts. At this stage, designers can use CAD software to create simple 3D models to verify the feasibility of design concepts. Once the conceptual design is approved, designers can use CAD software for detailed design.

At this stage, designers can make more detailed adjustments to the model, including shape, size, color, etc. By utilizing the simulation function of CAD software, designers can conduct simulation tests on designed ceramic products. This can help designers identify and solve potential problems, improve product quality and performance [12]. Deep learning and information security technologies have become important tools for 3D animation scene graphic design. Through the application of these technologies, the efficiency and safety of design can be greatly improved, creating more attractive visual effects. In this process, the graphic design of 3D animation scenes is a crucial aspect. This design requires a comprehensive consideration of multiple aspects such as artistry, authenticity, and technical feasibility to create an attractive visual effect. Tang [13] explored how to use deep learning and information security technologies to assist in the graphic design of 3D animation scenes. By utilizing deep learning technology, the graphic design of 3D animation scenes can be automatically generated based on a given storyline or theme. This design can be quickly iterated and optimized according to requirements, greatly improving design efficiency. Through deep learning technology, the styles of other art works can be applied to the graphic design of 3D animation scenes. For example, the painting style of famous painters can be transferred to 3D animation scenes to create unique visual effects. By utilizing deep learning technology, colors and shades can be automatically adjusted based on the atmosphere and theme of the scene to enhance the visual impact of 3D animation scenes. Učakar et al. [14] use professional 3D scanning equipment to comprehensively scan wooden sculptures and generate high-precision 3D models. This model can fully record the shape, texture, and color of sculptures, providing basic data for subsequent protection, display, and interpretation work. Conduct in-depth data analysis on 3D models, extract key features and structural information. These data can be stored in digital archives, providing reference for future research, repair, and replication. Taking the collection of sculptures as an example, we can see the widespread application of 3D digital technology in the protection, display, and interpretation of wooden cultural heritage. Through digital archiving, we can fully record and preserve the information of wooden sculptures, providing basic data for subsequent research and protection work. Through virtual display and augmented reality technology, we can break the limitations of time and space and provide viewers with a richer and more realistic visual experience.

Through interactive navigation and educational applications, we can enhance audience participation and understanding, and further promote and inherit this precious cultural heritage. With the continuous progress of technology, we have reason to believe that 3D digital technology will play a greater role in the protection, display, and interpretation of cultural heritage, bringing more excitement and inspiration to our lives. With the rapid development of computer-aided design (CAD) and machine learning technology, programmed CAD construction has become a hot research field. How to extract useful information from human design sequences and use it for programmed CAD construction is a challenging issue in this field. To address this issue, Willis et al. [15] proposed the 360 Gallery project. By collecting a large number of design sequences, including design data from multiple fields such as architecture, machinery, and electronics, a database containing rich design information was constructed. After preprocessing and annotation, these data form a dataset that can be used for programmed CAD construction. The 360 Gallery project provides a cross domain dataset that covers design sequences from multiple different fields. This enables researchers to study the problems of programming CAD construction more comprehensively and develop solutions with widespread application value. The 360 Gallery project is an innovative and practical research project aimed at providing a dataset and environment for programmed CAD construction based on human design sequences. Through this project, we hope to promote research and application in related fields, and provide strong support for the development of programmed CAD construction technology in the future. With the rapid development of technology, deep learning algorithms have penetrated into various fields, including art and design. Zhang [16] explored how to use deep learning algorithms to build a modern art and design system, and how this system can change the process of art creation and design. Deep learning algorithm is a machine learning technique that can automatically extract useful features from a large amount of data and use these features for decision-making. Train deep learning models using processed data to understand the rules and trends of art and design. By inputting specific parameters or instructions, the trained model is used to automatically generate design works that meet the requirements. By analyzing user behavior and preferences, deep learning algorithms can generate design works that meet the personalized needs of users. By utilizing deep learning algorithms, automated design tools can be constructed to improve the work efficiency of designers. Deep learning algorithms can help designers optimize design solutions, improve design performance and aesthetics. ŽIdek et al. [17] proposed a novel method for automatically training deep learning networks using 3D virtual models to identify and classify various types of objects. The experimental results show that our method outperforms traditional 2D image recognition methods in terms of recognition accuracy and robustness. In addition, our method can also handle objects of various shapes and postures, which traditional 2D image recognition methods cannot achieve. This method provides a new idea and method for solving object recognition problems in real life. Creation of 3D virtual models and training of deep learning networks. Firstly, we use 3D modeling tools to create a set of 3D virtual models that represent various types of objects we want to identify. Then, we use these 3D models as inputs and train them through deep learning networks to recognize and classify these objects.

3 APPLICATION OF ACNN IN TEXTURE FEATURE DETECTION OF SCULPTURE

Computer graphics and ML are playing an increasingly important role in today's digital age. Especially in the field of digital sculpture, the combination of these two technologies provides a powerful tool for artists and designers, which greatly promotes the boundaries and possibilities of creation. Computer graphics is a science and technology to study the generation and operation of graphics by computers. It involves a series of complex algorithms, including geometric processing, lighting and shadow models, texture mapping, etc., to generate realistic three-dimensional images. Computer graphics provides a complete set of geometric modeling tools to create the basic shape of digital sculpture. These tools allow artists to shape sculptures through mathematical functions or manual carving techniques. In order to create realistic visual effects, computer graphics introduces illumination and shadow models. By simulating the illumination of different light sources on the sculpture surface, we can generate realistic light and shadow effects and enhance the three-dimensional sense of the sculpture. Texture mapping is an important technology in computer graphics, which is used to add details and surface features to digital sculptures. By mapping the image map to the surface of the sculpture, the sculpture can present various materials and appearance effects, such as wood grain, metal and so on. ML extracts features and learning patterns by training a large number of data, and applies them to new unlabeled data. In digital sculpture, the application of ML has brought new creative methods and tools for artists and designers. Generation models in ML, such as Variational Self-Encoder (VAE) and Generative Antagonistic Network (GAN), can be used for texture synthesis and shape generation of digital sculpture. By learning the texture and shape distribution in the real world through training models, high-quality and diverse sculpture textures and shapes can be generated. ML algorithm can realize the style transfer of digital sculpture, that is, the style of one sculpture is applied to another sculpture. This technology provides artists with a flexible style conversion tool, enabling them to explore different artistic styles and creative possibilities. The optimization algorithm in ML can be used to optimize the shape of digital sculpture. By setting objective functions and constraints, these algorithms can automatically adjust the shape parameters of sculptures to achieve specific design requirements or aesthetic goals.

The combination of computer graphics and ML has played a great role in digital sculpture. Computer graphics provides accurate modeling and rendering technology, which can generate high-quality three-dimensional images, while ML introduces intelligence and optimization ability through data-driven mode, which makes the design of digital sculpture more efficient and automatic. By combining the rendering technology of computer graphics with the generation model of ML, high-quality digital sculpture can be generated. Using ML algorithm for texture synthesis and shape optimization, combined with lighting and shadow technology of computer graphics, can make the generated digital sculpture look more realistic and vivid. In addition, ML can provide creative suggestions and user recommendations by analyzing a large number of user data, so that artists can better understand the needs and preferences of the audience. ACNN is a special network structure in deep learning. This convolution method can enlarge the visual field of convolution kernel without increasing the number of parameters, so as to capture the long-range dependence of images or data more effectively. Firstly, the high-definition image data of sculpture is normalized, and the appropriate size is selected and input into the neural network. Next, through a series of atrous convolution layers, the texture features of sculpture images are gradually extracted. In the first few layers, the network mainly captures local and detailed texture features, such as grain direction and spots. With the deepening of the number of layers in the network, the expansion rate of atrous convolution gradually increases, which enables the network to capture texture information in a wider range, such as the overall material and color distribution. After several rounds of atrous convolution, the dimensionality of the feature map is reduced by using the pool layer, which reduces the calculation amount and enhances the robustness of the feature. Finally, through the fully connected layer, the learned texture features are mapped to a fixed-length feature vector for subsequent tasks.

Through the operation of convolution-pooling method for many times, the spatial structure characteristics of sculpture works of art can be effectively obtained. In the task of sculpture texture feature detection, convolution layer is used to extract the local features of the image. Each convolution layer contains multiple convolution kernels, which can learn different local features such as texture, shape and edge. Through layer-by-layer convolution, multi-level feature representation can be extracted from sculpture images. Pooling layer can reduce the dimension of feature map and improve the calculation efficiency while retaining important features. After many convolution-pooling operations, the spatial structure characteristics of sculpture works of art can be obtained. These characteristics include texture details, shape structure and spatial layout at different scales. These characteristics are very important for the subsequent sculpture analysis and application. After the convolution-pooling operation is completed, the obtained feature map is flattened and used as the input of the next fully connected layer. By stacking multiple fully connected layers, a complex nonlinear mapping relationship can be established, which further enhances the network's ability to express sculpture characteristics. Finally, the output information of the full connection layer is used as the input of the gated recurrent unit (GRU) module. In sculpture feature detection, GRU can be used to model the long-term dependence between sculpture sequence data and further explore the potential features of sculpture works of art. Through the processing of GRU module, the final sculpture feature representation can be obtained, which provides effective support for subsequent tasks such as classification and recognition. The CNN_GRU network model is shown in Figure 1.

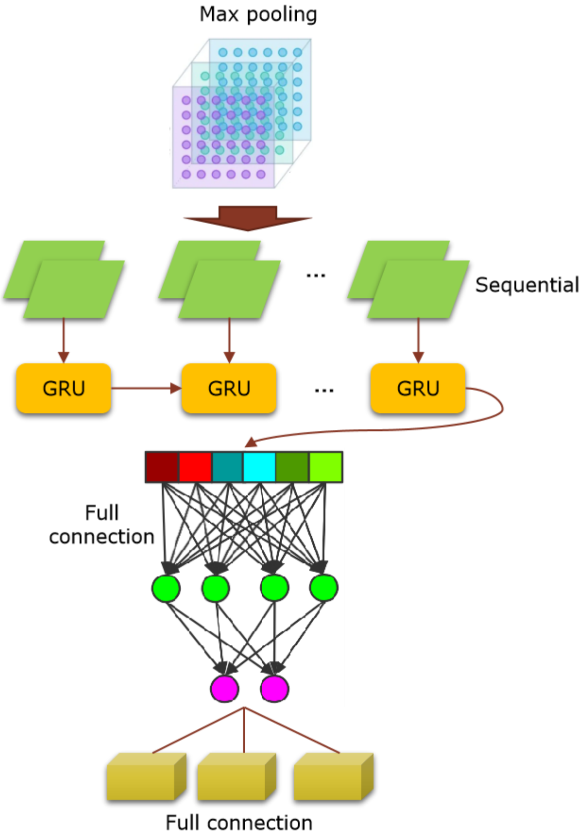

Figure 1: CNN_GRU network structure.

In order to make ACNN model converge to global optimum, intelligent initialization of weights is a key step. First, choose an appropriate initialization strategy for weights. Commonly used initialization strategies include random initialization, uniform initialization and normal distribution initialization. Among these strategies, we usually choose the strategy of adaptive adjustment according to the number of network layers and neurons, so as to lay a good foundation for subsequent training. According to the selected initialization strategy, the corresponding parameters are set. For example, if you choose normal distribution initialization, you need to set the mean and standard deviation. These parameters can be adjusted according to experience or experiment to obtain better initialization effect.

According to the set initialization strategy and parameters, the weights in ACNN model are initialized This usually involves traversing each layer of the model and assigning appropriate initial values to each weight according to the selected strategy. By pre-training some network layers on a related task, a more suitable weight initialization is obtained for these layers. Then, this hierarchical weight is migrated to our ACNN model as part of intelligent initialization. The initialization process is:

$$W \sim U\left[-\frac{\sqrt{6}}{\sqrt{n_{in}+n_{out}}},\frac{\sqrt{6}}{\sqrt{n_{in}+n_{out}}}\right] \tag{1}$$

Where n_{in},n_{out} is the number of input and output neurons at the convolution kernel weight.

This layer is the innovation of ACNN, which is different from the traditional fully connected neural network. It mainly aims at the feature detection of sculpture texture, and successfully realizes the function of automatic feature detection through two theoretical innovations: local perception and parameter sharing:

$$X^L = f\ \ Z^L\ \ = f\ \ X * K^L + b^L \tag{2}$$

$*$ represents convolution operation, Z^L represents the input value of the L th layer convolution, and X^L represents the feature mapping value obtained after the nonlinear activation function. f represents the activation function.

Optimizing network parameters through network training to reduce losses:

$$L = \sum_{i=1}^{N} L\left(W,\ y,x_1,x_2\ ^i\right) \tag{3}$$

$y,x_1,x_2\ ^i$ is the i th sample pair, x_1,x_2 is the sculpture texture sample in the sample pair, and y is the label of the sample pair.

After the initialization of weights is completed, the model is trained normally. By observing the decline curve of loss function, the accuracy of verification set and other indicators, it is judged whether the initialization of weights is appropriate. If it is found that the initialization effect is not good, you can adjust the initialization strategy or parameters and initialize again. This intelligent initialization process of weights aims to provide a good starting point for ACNN model, so that the model can converge to the global optimal solution more quickly.

4 FUSION OF SCULPTURE TEXTURE FEATURES AND IMAGE FEATURES

Image features can capture the overall shape, lighting conditions, color distribution and other information of the sculpture, which are complementary to the texture features of the sculpture. Therefore, the fusion of sculpture texture features and image features can further improve the understanding and expression ability of sculpture. After extracting the sculpture texture features and image features, the next step is to carry out effective feature fusion. The goal of feature fusion is to integrate features from different sources to form a more comprehensive and expressive feature representation. The block diagram of digital sculpture image fusion is shown in Figure 2.

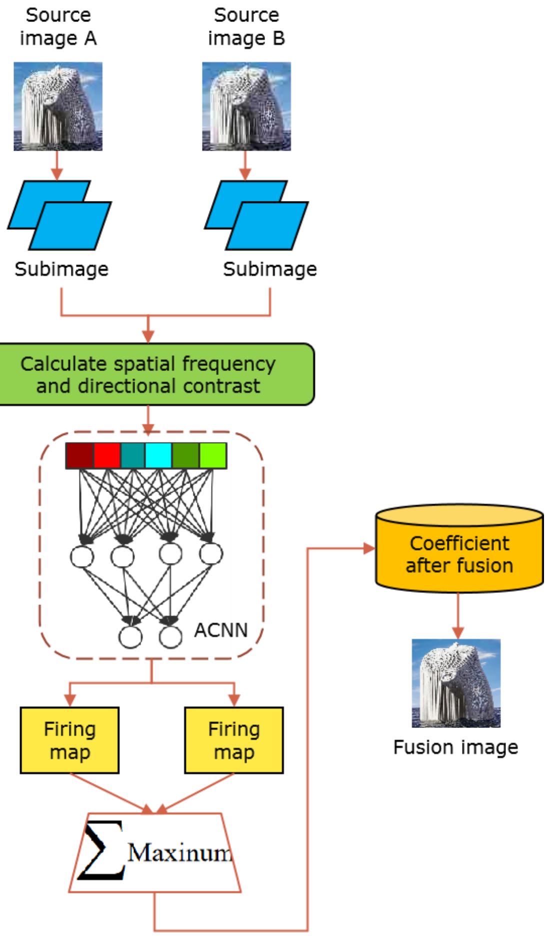

Figure 2: Digital sculpture image fusion framework.

Using the fused features, the classifier is trained to classify sculptures, such as style classification and material classification. Construct a sculpture image database, and use the fusion features to calculate the similarity, so as to realize content-based sculpture retrieval. Based on the fusion features, combined with the generation model or editing algorithm, the sculpture generation and editing tasks are realized. Through the fusion of sculpture texture features and image features, a more comprehensive and expressive sculpture feature representation is obtained. The probability that the defined point x belongs to the plane p is shown in Formula (4):

$$P(x|p)=\frac{N(dist(x,p);0,\sigma_d^2)}{N(0;0,\sigma_d^2)}*\frac{N(|N_x*N_p|;1,\sigma_n^2)}{N(1;1,\sigma_n^2)} \tag{4}$$

Where $dist(x,p)$ refers to the distance from x to plane p, $|N_x,N_p|$ is the normal vector of point x and plane p respectively, and $N(z;\mu,\sigma^2)$ refers to the value of the density function of normal distribution with mean value of μ and variance of σ^2 at point z.

In order to improve the calculation efficiency, this paper discretizes the transfer gradient $x_s^{ij} - x_s^{ji}$ to be consistent with the normal vector S of Woolf shape. Therefore, the mapping relationship between the probability distribution $P_s\ n$ corresponding to the normal vector direction $n \in S$ per unit length of voxel S and the Woolf shape distance d_s^n can be expressed as:

$$P_s\ n = e^{-\varphi^{ij}\ n} = e^{-\max_{p \in W_{H_s}}\ p^T n} = e^{-d_s^n} \tag{5}$$

So, satisfy:

$$d_s^n = \text{-}\log\ P_s\ n \tag{6}$$

In order to estimate $P_s\ n$, for the input method vector, a histogram can be generated with the corresponding surface area as the weight. The abscissa of the histogram represents the normal vector direction $n \in S$, and the ordinate represents the weighted frequency in each direction.

$$d_s^n = \text{-}\log\ P_s\ n \tag{7}$$

Assumption $P_i \left| P_i \in R^3, i = 1, \cdots, N \right.$ represents the first point set, $Q_i \left| Q_i \in R^3, i = 1, \cdots, M \right.$ represents the second point set, and the alignment and registration of two-point sets is transformed into minimizing the function value of Formula (8):

$$f\ R, T = \sum_{i=1}^{n} \left\| Q_i^k - \ RP_i + T \ \right\|^2 \tag{8}$$

Where R, T is the rotation and translation matrix, the algorithm can get the transformation matrix between two frames of point clouds more accurately.

The formula of hole convolution of one-dimensional signal is:

$$y_{[i]} = \sum_{k=1}^{K} x_{[i+r*k]} w_{[k]} \tag{9}$$

$x_{[i]}$ is the one-dimensional input signal, $w_{[k]}$ is the filter, r is the sampling step size of the input signal, k is the length, $y_{[i]}$ is the final multi-space convolution output result.

When classifying sculpture design, Softmax is used as the classifier:

$$Design\ image_p = \frac{1}{1 + \exp\ -h_{FC3}} \tag{10}$$

Where $Design\ image_p$ represents the probability output of the sculpture design, and h_{FC3} represents the output of the last fully connected layer $FC3$. According to the probability output of the sculpture design, the specific sculpture design of the input sample picture can be obtained.

The final output value is O_i :

$$O_i = f\ net_i = \frac{1}{1 + e^{-\ net_i}} \tag{11}$$

The output of the i -th neuron in this layer is O_i , and the weighted sum is net_i .

By recognizing fused features, important attributes such as texture and shape of sculptures can be understood, providing input and constraints for digital sculpture CAD design. In CAD software, the recognized texture features can be used to assist in sculpture modeling. For example, guided by texture features, detailed carving and mapping of sculpted surfaces can be carried out. The texture information in the fused features can be used for texture mapping. Apply the extracted sculpture texture features to the surface of the CAD model, making the designed sculpture model more realistic in texture details. By combining the identified features, parameterized design can be further achieved. By adjusting feature parameters, sculpture changes can be previewed in real-time in the CAD environment, improving design flexibility. In digital sculpture CAD design, designers intuitively adjust and modify fused features through an interactive interface. Based on the adjusted features, perform feature recognition and analysis again, and apply the results to CAD design again. This forms a design iteration process, allowing designers to continuously optimize and improve sculpture design.

5 EXPERIMENTS AND APPLICATIONS

5.1 Experimental Setup and Dataset

In order to verify the application effect of texture feature recognition and feature fusion in digital sculpture CAD design, a series of experiments were conducted. The hardware environment includes high-performance processors, graphics processors, large capacity memory, and high-speed solid-state drives. The experiment used Python programming language and combined with the TensorFlow framework for model building and training. Moreover, CAD design software is used for the design and rendering of digital sculptures. The study collected a dataset of sculpture images on a certain scale, which includes sculpture images of various styles, materials, and textures. These images are used for training and testing texture feature detection and recognition models. The dataset is preprocessed, including image scaling, normalization, and other operations to adapt to the input requirements of the model. During the experiment, the sculpture image dataset was first used to train and validate the texture feature detection and recognition model. Then, the obtained texture features are applied to the digital sculpture CAD model, and rendering and design experiments are conducted. Through quantitative and qualitative analysis of experimental results, the effectiveness and practicality of the proposed method in digital sculpture CAD design will be evaluated.

5.2 Comparative Experiments and Analysis

Gaussian blur is a widely used technique in image processing, characterized by the ability to perform calculations on two independent one-dimensional spaces. This means that the effect of two-dimensional Gaussian blur can be achieved by performing one-dimensional Gaussian matrix transformations in the horizontal and vertical directions, respectively. This feature makes Gaussian blur more computationally efficient and provides greater flexibility, as it can independently control the degree of blur in both directions. The results in Figure 3 indicate that the size of the Gaussian radius directly determines the degree of blur. The larger the Gaussian radius, the higher the blurriness of the image, and vice versa. This is because the Gaussian radius determines the width of the Gaussian function. The larger the radius, the wider the Gaussian function, and the higher the corresponding degree of blur. This has been verified in Figures 3 (a), (b), and (c). (a) is the original image, and (b) and (c) represent the processing effects with radii of 1 and 4, respectively. It is evident that as the radius increases, the image becomes increasingly blurry. For applications that require preserving image details, such as edge detection and feature detection, a smaller Gaussian radius should be chosen. For applications that require image smoothing and noise removal, such as image skinning and background blurring, a larger Gaussian radius can be chosen.

The results in Figure 4 show that ACNN has better performance than traditional CNN and Recurrent Neural Network (RNN) in image optimization of sculpture artworks. This advantage is mainly attributed to the special structure of ACNN and the characteristics of atrous convolution.

ACNN increases the receptive field by introducing atrous convolution. Compared with the conventional convolution operation of traditional CNN, atrous convolution can effectively expand the visual field of convolution kernel without increasing the number of parameters. This enables ACNN to better capture the long-term dependence of sculpture texture and further optimize the image effect.

Figure 3: Original image and Gaussian blur effect under different radii.

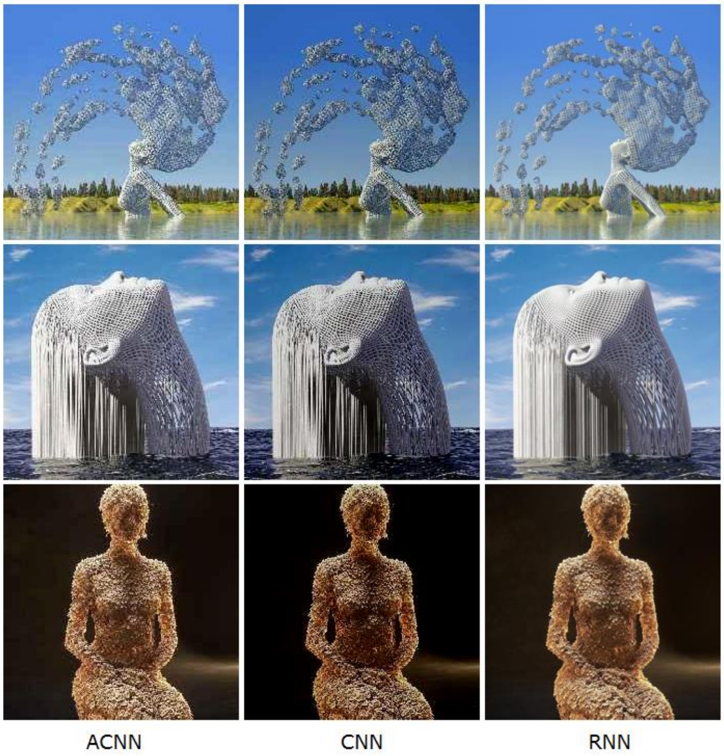

Figure 4: Comparison of image optimization effects of sculpture artworks.

This makes ACNN more efficient in processing large-scale images and can better meet the needs of real-time applications. The image of sculpture artwork optimized by ACNN retains the details of sculpture texture, while the color performance is richer and more realistic. This is because ACNN can better capture the multi-scale information of the image through Atrous Sculpture, so as to restore the original colors and details of the sculpture more accurately.

Figure 5 clearly shows the comparison results of ACNN, traditional CNN and RNN in computing running time. From the results, it can be seen that ACNN shows higher operating efficiency. One of the main characteristics of atrous convolution is that it can increase the receptive field without increasing the parameters. This means that ACNN may need fewer parameters to achieve similar or even better performance than traditional CNN. ACNN can obtain a larger effective receptive field in a few layers through atrous convolution, which enables the network to capture the long-range texture features of sculptures more quickly, thus accelerating convergence and calculation.

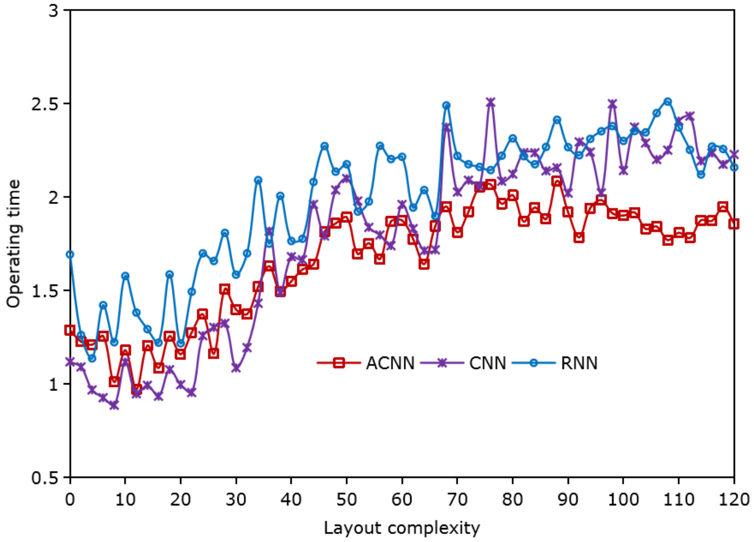

Figure 5: Calculation time comparison of algorithm.

Efficient calculation not only shortens the design cycle, but also allows designers to try more design variants in a shorter time, which further promotes the growth of digital sculpture.

Figures 6 and 7 show the recall and precision of ACNN, traditional CNN and RNN in sculpture texture feature detection, respectively. Compared with the other two methods, ACNN-based method shows higher precision in the extraction of sculpture texture features.

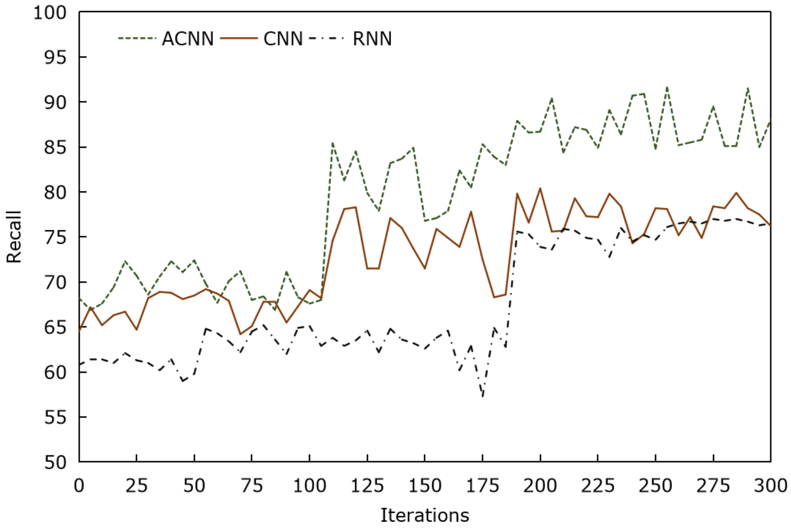

Figure 6: Sculpture texture feature detection recall.

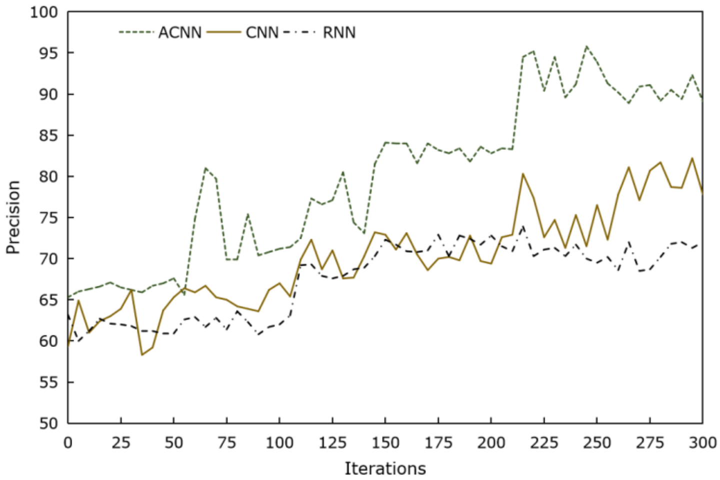

Figure 7: Sculpture texture feature detection precision.

In the CAD design of digital sculpture, it is very important to accurately extract the texture features of sculpture, because texture is one of the important visual elements of sculpture, which directly affects the appearance and texture of sculpture. Because of ACNN's excellent performance in recall and precision, it can support the CAD design of digital sculpture more effectively. Designers can rely on the accurate texture features extracted by ACNN for subsequent CAD design and rendering to improve the efficiency and authenticity of design. This advantage makes ACNN a powerful tool in digital sculpture CAD design and provides designers with more efficient and accurate design support.

6 CONCLUSION

The emergence of digital sculpture has greatly expanded the expression forms and creative methods of sculpture art, allowing artists to more freely unleash their imagination and creativity. In the CAD design of digital sculpture, computer graphics technology plays an important role. This article explores the application of computer graphics and ML in digital sculpture CAD design, and proposes an ACNN based sculpture texture feature detection algorithm and image feature fusion framework. This algorithm and framework can automatically extract texture features of sculpture models and fuse image features to achieve more realistic and efficient sculpture rendering. The test results show that compared with the other two methods, the ACNN based method exhibits higher operational efficiency and higher precision in extracting sculpture texture features. Designers can rely on the accurate texture features extracted by ACNN for subsequent CAD design and rendering, improving the efficiency and authenticity of the design. This advantage makes ACNN a powerful tool in digital sculpture CAD design, providing designers with more efficient and accurate design support. In future research, the algorithm of ACNN can be further improved to enhance its ability to extract complex sculpture textures.

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