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Computer-Aided Design AND APPLICATIONS

Digital Media Content Analysis and Visualization Expression based on Computer Vision Technology

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Abstract. The analysis of digital content is one of the core tasks in the field of computer vision. Deep learning (DL) and computer vision technology can automatically extract effective features by learning a large amount of data, improving the performance of digital content analysis. In the context of research in the field of digital media art (DMA), this article proposes an art image style reconstruction algorithm based on the atmosphere convolutional neural network (ACNN) and studies image processing and reconstruction techniques and their related assessment methods. During the training process, a strategy of multi-scale input and multi-task learning is adopted. By comparing the effects of different algorithms in image reconstruction, it was found that some algorithms may lead to image blurring and high smoothness, while our algorithm and other advanced algorithms perform better in edge details and restoration quality. This algorithm reduces the complexity of the model and improves computational and inference efficiency by optimizing the network structure and introducing effective training strategies. By classifying and identifying digital artworks of different styles, we can gain a deeper understanding of the characteristics of each style. This provides an opportunity for artists to explore new art styles.

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1 INTRODUCTION

With the rapid growth of digital media, people are exposed to more and more digital content, including digital games, movies, animations, and so on. These digital contents not only enrich people's entertainment lives but also become an important form of expression for digital art. With the rapid development of digital media, computer graphics processing technology is playing an increasingly important role in visual communication design. With its precise and efficient characteristics, computer graphics processing technology provides rich creative space and forms of expression for visual communication design. Fan and Li [1] discussed the application and importance of computer graphics processing in visual communication, digital media content analysis and design. Computer graphics processing technology refers to the process of generating, manipulating, and modifying graphics using computer software and hardware technology. These graphics can be simulations of the real world or completely fictional. Computer graphics processing technology is widely used in fields such as film and television production, game design, industrial design, and architectural design. Computer graphics processing technology can create realistic 3D models through 3D modeling software such as 3ds Max, Maya, etc. Designers can adjust materials, lighting, and rendering parameters as needed to achieve ideal visual effects. This 3D modeling and rendering technology provides richer forms of expression for visual communication design, making design works more three-dimensional and spatial. How to effectively analyze and express these digital contents is one of the research hotspots in the field of computer vision. Media information activities are playing an increasingly important role in social development. From social media to news websites, from forums to blogs, media platforms have become important channels for people to obtain information and exchange opinions. Predicting the development trend of media information activities is of great value for understanding social dynamics and formulating response strategies. Jaouedi et al. [2] explored how to predict media information activities based on feature new structures and deep learning models. In media information activities, feature extraction and representation are key to prediction. We propose a new feature structure to capture important information in media content, user behavior, and social network structure. By extracting features from multimedia data and utilizing deep learning models for processing and analysis, more accurate and efficient prediction of media information activities can be achieved. This method can not only be applied to social media analysis, but also to data analysis on other media platforms such as news websites, forums, and blogs. With the continuous development of big data and artificial intelligence technology, we have reason to believe that this method will play an increasingly important role in the field of information science in the future.

Traditional digital content analysis methods are often based on hand-designed feature extractors. Because the design of its feature extractor often depends on the experience and prior knowledge of domain experts, its universality has certain limitations. The integration of digital media content information models and AEC (Architectural, Engineering & Construction) immersive technology has become a new development trend. This fusion technology has brought revolutionary changes to various industries, especially in the fields of architecture, engineering, and construction. It has changed traditional ways of information transmission and decision-making. Khan et al. [3] explored this integration's advantages, disadvantages, opportunities, and threats through scientific SWOT analysis and provided an overview of key content. Through AEC immersive technology, digital media content can be presented to users more realistically, enabling users to understand and experience design solutions more intuitively. The digital media content information model can quickly generate and update design schemes, enabling decision-makers to make more accurate judgments based on real-time data. In the stages of architectural design, engineering planning, and construction, this integrated technology can reduce the investment of manpower and material resources and lower costs. The processing and transmission of digital media content involves a large amount of data, and ensuring the security and privacy of data is a major challenge. The digital media content information model needs to be further optimized to meet the requirements of AEC immersive technology and improve the accuracy and real-time performance of the model. DL technology can automatically extract effective features by learning a large quantity of data and improving the performance of digital content analysis. The style of artistic images is one of its important visual characteristics. Traditional artistic image style reconstruction methods are often based on image processing technology, and it isn't easy to deal with digital artistic images with complex artistic styles. With the continuous development of digital media and computer-aided design (CAD) technology, visual communication teaching systems also need to be updated and optimized accordingly. Liu and Yao [4] discussed how to use digital media content analysis technology and CAD technology to design an efficient and innovative visual communication teaching system. By utilizing digital media content analysis technology, a large amount of media content can be automatically classified and annotated. For example, based on the content of the image, it can be classified into categories such as "people", "scenery", "animals", and labeled with keywords to facilitate students' search and learning. Digital media content analysis technology can also perform emotional analysis on media content, thereby evaluating and providing feedback on design works. Through emotional analysis, we can understand the audience's emotional reactions to the work, guiding students to improve and optimize the design from the audience's perspective. Based on digital media content analysis technology, personalized recommendations can be made based on students' learning history and preferences, achieving precise teaching. For example, based on the browsing history and interests of students, relevant learning resources such as books, articles, videos, etc. can be recommended. The design of a visual communication teaching system based on digital media content analysis and CAD technology can effectively improve teaching quality and student learning outcomes. Therefore, how to design an effective artistic image style reconstruction algorithm based on DL technology is an urgent problem in the field of digital content analysis.

The early computer vision task mainly focused on the problem of what an image is, which is a completely coarse-grained image processing task. With the rapid development of technology, computer vision technology has become an important pillar in the field of digital media. It is changing our perception of digital media management with its unique advantages. This article will delve into the necessity and application of computer vision technology in managing digital media transformation. Computer vision technology is a technique that utilizes computer software and hardware to simulate, perceive, and understand visual information such as images, videos, and 3D models. It involves multiple fields, such as image processing, pattern recognition, and machine learning, providing people with more accurate and efficient data processing methods by analyzing visual information. In the digital media transformation, massive media content has become a management challenge. Computer vision technology can review and classify media content through techniques such as image recognition and text recognition. Prebanić and Vukomanović [5] use image recognition technology to identify sensitive information in videos and filter it out automatically. It utilizes text recognition technology to automatically analyze a large amount of text content and classify it based on the topic. Computer vision technology can achieve automated generation and editing. For example, using facial recognition technology, people can be automatically tracked and labeled. By using object recognition technology, objects in the scene can be automatically recognized and edited. These technologies can not only improve editing efficiency but also enhance the quality of editing. With the deepening of research, people's requirements for image processing are constantly improving. Visual content interactivity refers to the ability of users to interact with visual content. In the era of digital media, this interactivity has become an important component of user experience. In landscape design, this interactivity can interact with design representations in various ways. In the information age, digital media technology provides new ways of expression and tools for landscape design. Raaphorst et al. {6} explored how landscape design representation can be interpreted as digital media content analysis, and how this process interacts with visual content interactivity. In landscape design, digital media content analysis can help us understand and interpret the representation of landscape design. For example, through GIS (Geographic Information System) technology, we can collect, analyze, and visualize terrain data to understand terrain changes and the intentions of designers. Through image processing and analysis techniques, we can quantify and analyze elements such as plant configuration, water morphology, and their spatial relationships. In addition, computer vision and deep learning technologies can also be used to recognize and interpret symbols and landmarks in landscape design. By programming and controlling lighting, audio, and other equipment, the appearance and atmosphere of the landscape can be changed according to changes in time, climate, and other factors. In addition, interactivity can also be used to achieve sustainable development in landscape design. For example, by collecting and analyzing user data on landscape usage, the efficiency and sustainability of landscape usage can be evaluated, thereby guiding future design and renovation.

This article proposes an art image style reconstruction algorithm based on ACNN. This algorithm increases the receptive field and improves the feature extraction ability of the neural network by introducing the atrous convolution operation. At the same time, this article also conducts optimization and simulation tests on three types of digital art images: digital games, digital movies, and digital animations, verifying the performance of the algorithm. Finally, computer vision based digital content analysis and CAD visualization expression were achieved, providing new ideas for digital content analysis and digital art expression. In theory, this article studies digital content analysis methods and artistic image style reconstruction algorithms based on computer vision, expanding the research content in the field of computer vision. In practice, the algorithm proposed in this article can be applied to the analysis and expression of digital art images such as digital games, digital movies, and digital animations, promoting innovation in digital art. This study has the following innovations:

(1) An ACNN-based artistic image style reconstruction algorithm is proposed, which improves the feature extraction ability of the model and reconstructs the artistic image style more effectively.

(2) Previous studies have often only focused on one or two types of digital art images, while this article conducts comprehensive optimization and simulation tests on three types of digital art images.

(3) Through the algorithm proposed in this article, digital content analysis and CAD visualization based on computer vision can be achieved, making the analysis results easier to understand.

(4) The research work not only provides a new algorithm for reconstructing artistic image styles, but more importantly, it provides new research ideas and methods for digital content analysis and digital art expression.

This article first discusses the relevant theories and significance of digital content analysis and artistic image style reconstruction; Then, an art image style reconstruction algorithm based on ACNN was proposed; Then, based on this algorithm, conduct digital content analysis and CAD visualization expression; By analyzing the experimental results, some beneficial improvement ideas have been provided for DMA creation.

2 OVERVIEW OF RELATED WORK

In digital media content analysis, geometric pattern digital visualization is a method of presenting data in geometric form, which has the characteristics of being intuitive and easy to understand. The methodology of formal grammar provides a systematic theoretical framework for this process. Refalian et al. [7] explored how to use formal grammar methodology to guide the process of geometric pattern digital visualization and its value for digital media content analysis. The methodology of formal grammar has important application value in the visualization of geometric patterns in digital media content analysis. It not only guides the preprocessing of data, selection of geometric forms, parameter settings, and interaction design, but also ensures consistency and standardization in the presentation of data. By using formal grammar methodology to guide the process of geometric pattern digital visualization, we can better understand and analyze data or information in digital media content, providing strong support for data-driven decision-making. With the continuous development and progress of technology, the application scope and effectiveness of formal grammar methodology will also be further expanded and improved. Augmented reality (AR) has found widespread applications in many fields, including education, entertainment, healthcare, and business. However, most existing AR technologies are focused on small devices, such as smartphones and head mounted displays. The application on large interactive displays is still relatively limited. Reipschlager et al. [8] explored how to apply personal augmented reality (AR) technology to large interactive displays to achieve more effective information visualization. Augmented reality is a technology that integrates virtual information into the real environment. Through AR technology, users can see and interact with virtual objects in a real environment. Applying AR technology to large interactive displays can achieve the display of a large amount of information and data in a real environment, providing users with a more intuitive and rich visual experience. Applying personal augmented reality technology to large interactive displays can provide more effective methods for information visualization. By using AR technology, users can view and interact with virtual objects in a real environment, thereby obtaining a more intuitive and rich visual experience. This technology can be widely applied in fields such as information display, data analysis, interactive charts, and simulation visualization.

Digital media content analysis technology can extract valuable information from a large amount of digital media content, such as product defects, production process bottlenecks, etc. Through this information, enterprises can effectively monitor production processes, optimize production processes, and improve product quality. Digital media content analysis technology can also be applied to fault prediction and maintenance of industrial equipment. By analyzing the operational data of the equipment, it is possible to predict the possible faults that may occur, so as to carry out maintenance in advance and avoid production interruptions. Pattern recognition technology can help enterprises achieve real-time monitoring of key indicators such as product quality and equipment operation status. Serey et al. [9] can automatically perform quality inspections on products on the production line through image recognition technology to ensure product quality. In addition, pattern recognition technology can also be applied to monitor the operating status of equipment. By analyzing the operating data of the equipment, abnormal states of the equipment can be identified, and timely maintenance can be carried out to avoid the impact of equipment failures on production. Deep learning can also be applied to product design and improvement. By analyzing a large amount of product data, the advantages and disadvantages of the product can be identified, and targeted improvements can be made to enhance the product's market competitiveness. With the rapid development of digital media, cultural and artistic innovation has gradually become the focus of people's attention. The popularization and application of digital media technology have brought about significant changes in the way art is created and disseminated. However, the significance of cultural and artistic innovation in digital media lies not only in technological progress, but also in its challenge and subversion of traditional artistic hegemony. Sugita et al. [10] analyzed the role of digital media in cultural and artistic innovation. Traditional art creation and dissemination methods are often limited by time, space, and technology, and digital media technology breaks these limitations, making art creation and dissemination more convenient and efficient. Digital media technology can simulate the real world and create highly imaginative and expressive works of art, thereby expanding the boundaries and possibilities of art. Digital media technology makes the creation and dissemination of artistic works no longer dependent on traditional art institutions and authorities, but more focused on individual creativity and free expression. This decentralized creative approach makes art more diverse and democratic, challenging the monopolistic position of traditional art authorities. Digital media technology has also brought about changes in the evaluation criteria for artistic works. Traditional art evaluation standards are often influenced by authoritative institutions, experts, and the market, while art evaluation in the digital media era places more emphasis on public participation and interaction. This new evaluation method weakens the control of traditional art authority, making art works more diverse and democratic.

With the rapid development of digital media, people's demand for ways to interact with digital media content is also constantly changing. Traditional input devices such as mice and keyboards can no longer meet people's needs for efficient, natural, and intuitive interaction methods. Therefore, the design of gesture controlled digital media content analysis based on computer vision has become an important research direction. Tan et al. [11] explored how to apply computer vision and gesture control technology to digital media content analysis, and designed an efficient, natural, and intuitive interaction method. Computer vision is a technique that utilizes computer algorithms and models to simulate the human visual system. It can recognize and understand objects, scenes, and behaviors through data such as images and videos. Gesture control technology utilizes computer vision and image processing techniques to recognize and track gesture movements, and converts them into digital signals to achieve control over electronic devices. Combining computer vision and gesture control technology can achieve an efficient, natural, and intuitive way of interaction. By recognizing and tracking gesture actions, users can control the playback, pause, fast forward, fast rewind, and other operations of digital media content through simple gesture actions. With the rapid development of digital media technology, the analysis of digital media content from 3D asset synthesis pose sequences has become an important research field. This analysis method is of great significance for vision based activity analysis and can provide strong support for research in fields such as computer vision and human-computer interaction. Torres et al. [12] explored how to use digital media content analysis techniques for synthesizing pose sequences from 3D assets for visual based activity analysis. 3D asset synthesis pose sequence is a digital asset created using 3D modeling technology, which can be used to describe the poses and actions of characters or objects. Digital media content analysis technology can effectively process and analyze these 3D assets, extracting pose sequences contained within them. By analyzing the digital media content of 3D asset synthesized pose sequences, we can obtain various pose information of characters or objects. The analysis of digital media content from 3D asset synthesized pose sequences for visual based activity analysis is an important research direction in the field of digital media technology. This analysis method can help us better understand and analyze human behavior, thereby providing strong support for research in fields such as computer vision and human-computer interaction.

The era of new media has arrived, which has brought profound changes to the field of visual communication design. Visual communication design, as an important means of information dissemination, faces new challenges and opportunities in the era of new media. Wang [14] explores the computer-aided interaction between visual communication technology and art in new media scenarios, analyzes its characteristics and development trends. In the era of new media, audience participation and feedback have become particularly important for visual communication design. Computer assisted technology enables designers to obtain real-time feedback from the audience, thereby making real-time adjustments to the design and making interaction between the design and the audience possible. New media technology enables visual communication design works to be presented in a dynamic form, and computer-aided technology can help designers achieve dynamic effects in design, enhancing visual impact and expressiveness. In the era of new media, visual communication design is no longer a single graphic art, but is combined with interdisciplinary technologies such as multimedia technology and virtual reality technology. Computer assisted technology makes this cross-border cooperation more convenient.

With the rapid development of digital media, how to effectively manage and analyze massive media content has become an important issue. To address this issue, Zhang et al. [15] designed a queue interaction exploration visualization analysis system based on historical data of digital media content analysis. This system can help users better understand and analyze digital media content by storing historical data in a queue and using visualization techniques to present the data. The system uses queues to store and manage historical data for digital media content analysis. A queue is a first in, first out (FIFO) data structure that can be stored and retrieved in the order in which data enters the queue. By storing historical data in queues, we can easily sort, retrieve, and update the data. The system uses interactive visualization techniques to display historical data of digital media content analysis. By presenting data in charts, images, and other visual forms, users can better understand and analyze the data. For example, the system can display a chart arranged in chronological order, displaying indicators such as the number, type, and theme of media content per day. The system provides interactive exploration function, allowing users to interact with historical data of digital media content analysis. For example, users can view detailed information about a data point on a chart by clicking on it. In addition, users can also use the search function provided by the system to search for media content with specific themes or keywords. With the development of technology, digital CAD (computer-aided design) technology provides new solutions for heritage protection. Zhang et al. [16] found that knowledge visualization can better understand and utilize this data, thereby achieving more effective heritage protection and utilization. Knowledge visualization is a method of conveying and interpreting complex information through graphics, images, and other visual elements. In the digital protection of heritage, knowledge visualization can be used to create high-precision 3D models that capture detailed features and structures of heritage. In addition, knowledge visualization can also transform these models into easily understandable and usable information for researchers, scholars, and the public to use. By using digital CAD technology, we can create high-precision 3D models of heritage. These models can be used as digital archives for long-term preservation to prevent loss over time. Meanwhile, these digital archives can also be used for future academic research, exhibitions, and virtual restoration work. With the help of knowledge visualization, we can perform virtual restoration of heritage. By identifying and analyzing the structure and characteristics of heritage, we can predict and repair potential damage or destruction. This method can be carried out without touching the heritage, thereby reducing further damage.

3 ART IMAGE STYLE RECONSTRUCTION ALGORITHM BASED ON ACNN

3.1 ACNN Principle and Advantages

The analysis of digital content is one of the core tasks in the field of computer vision. Early digital content analysis methods mainly relied on manually designed feature extractors. These feature extractors are designed based on the experience and prior knowledge of domain experts to capture key information from images or videos. This method has obvious limitations, as manually designed feature extractors may not be able to adapt to a variety of digital content. With the rise of DL technology, neural network-based feature learning methods have gradually replaced traditional manually designed feature extractors. DL techniques can automatically learn effective feature representations from large amounts of data, improving the performance of digital content analysis.

Art image style reconstruction is an important branch of digital content analysis aimed at transforming an image into a specific artistic style expression. Early art image-style reconstruction algorithms were mainly based on image-processing techniques. Although these methods can achieve some simple artistic style transformations, they are difficult to handle images with complex artistic styles. In recent years, DL-based art image style reconstruction algorithms have made significant breakthroughs. Among them, CNN-based methods learn the transformation mapping of artistic styles by training a large number of pairs of artistic and non-artistic images. Generative Adversarial Networks (GAN) are also widely used in artistic image style reconstruction. Through adversarial training of generators and discriminators, high-quality and diverse artistic images can be generated. These methods provide effective solutions for the task of artistic image style reconstruction. In traditional CNN, convolution operations are performed on continuous regions of the input feature map, so each convolution kernel can only capture local information. However, in digital content analysis, especially when dealing with tasks such as artistic image style reconstruction, it is necessary to capture broader contextual information to understand and reconstruct complex artistic styles. ACNN is a special type of CNN that effectively expands the receptive field of neural networks by introducing hole operations without increasing model parameters and computational complexity. In atrous convolution, the convolutional kernel slides at a certain interval on the input feature map, which is called the void ratio. By adjusting the void ratio, the receptive field can be expanded without increasing parameters, allowing the neural network to capture a wider range of contextual information.

3.2 Design of Art Image Style Reconstruction Algorithm

The goal of the art image style reconstruction algorithm is to convert the input art image into an output image with a specified style while maintaining the content structure of the input image. Firstly, preprocess the input art image, including scaling, cropping, and other operations, to meet the input requirements of the model. Then, ACNN is used to extract features from the preprocessed art images. Next, the extracted features will be fused with the specified artistic style to generate an output image with the target style (Figure 1).

In the feature extraction stage, this article designs a multi-scale ACNN to extract multi-scale feature information from the input image. This network consists of multiple atrous convolution layers, each with a different void ratio, to capture contextual information at different scales. In the style transition phase, a style transition network based on adaptive instance normalization was designed. This network converts the input feature map into a feature map with the target style by adjusting its mean and standard deviation. The route convolution operation is shown in Figure 2. Figure 2 shows a 6 * 6 feature map (a) obtained after convolution with a 3 * 3 atrous convolution kernel, which has the same original image size as the 6 * 6 feature map (b) (assuming a bias term of 0). The example in the figure is a convolution operation with no padding (pad=2) and a step size of 1 (stream=1).

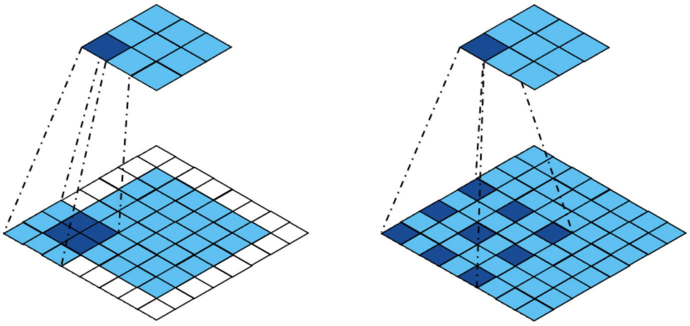

Figure 1: Schematic diagram of atrous evolution core.

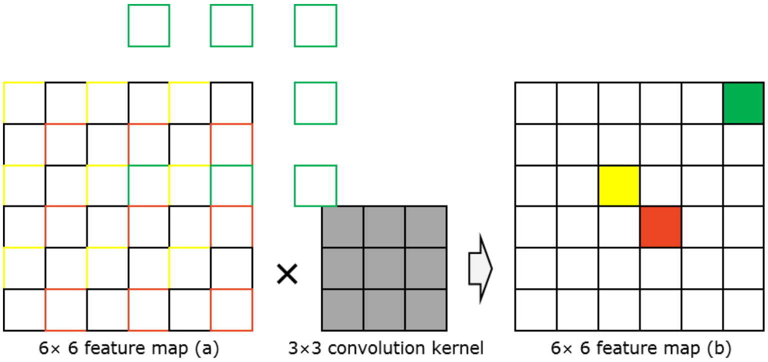

Figure 2: Atrous convolution operation.

The backward propagation of the hole convolution layer is similar to the fully connected backward propagation. In the fully connected backward propagation, we know that the relationship between δ^l and δ^{l-1} is:

$$\delta^l = \frac{\partial J(W,b,x,y)}{\partial z^l} = \frac{\partial J(W,b,x,y)}{\partial z^{l+1}}\frac{\partial z^{l+1}}{\partial z^l} = \delta^{l+1}\frac{\partial z^{l+1}}{\partial z^l} \tag{1}$$

Where W is a hole convolution parameter, which is expressed as an expanded parameter in the formula, and the expanded part is filled with 0. If you want to know the connection between δ^l and δ^{l-1}, you need to calculate $\frac{\partial z^{l+1}}{\partial z^l}$, and notice that there are:

$$z^l = a^{l-1} * W^l + b^l = \sigma(z^{l-1}) * W^l + b^l \tag{2}$$

So, there is:

$$\delta^{l-1} = \delta_l \frac{\partial z^l}{\partial z^{l-1}} = \delta^l * rot180(W^l) \bullet \sigma'(z^{l-1}) \tag{3}$$

Therefore, knowing the convolution layer δ^l, δ^{l-1} can be obtained by back propagation for subsequent back propagation. For the convolution layer itself, it is needed to find the gradient of parameters W and b, because the convolution layer z has the following relationship with W and b:

$$z^l = a^{l-1} * W^l + b^l \tag{4}$$

Therefore, there are:

$$\delta^l = \frac{\partial J\ W,b,x,y}{\partial z^l} = \frac{\partial J\ W,b,x,y}{\partial z^{l+1}} \frac{\partial z^{l+1}}{\partial z^l} = \delta^{l+1} \frac{\partial z^{l+1}}{\partial z^l} \tag{5}$$

It should be noted that b is only a vector, while δ^l is a three-dimensional tensor, so the sub-matrix items of δ^l are usually summed separately to get an error vector as the gradient of b :

$$\frac{\partial J\ W,b}{\partial b^l} = \sum_{u,v} \delta^l\ _{u,v} \tag{6}$$

During the training process, a strategy of multi-scale input and multi task learning is adopted. Multi scale input can enhance the sensitivity of the network to features at different scales, thereby enhancing the diversity and robustness of styles. Multi task learning can optimize both content loss and style loss simultaneously, improving the network's ability to balance content structure and style transformation.

3.3 Optimize Simulation Testing

This section conducted experimental verification on a publicly available dataset and compared it with existing advanced methods. The results show that the algorithm proposed in this article outperforms existing methods in terms of recognition error and operational efficiency. Figure 3 clearly shows the comparison between the algorithm proposed in this article and the traditional algorithm in terms of error in DMA style recognition. The art image style reconstruction algorithm based on ACNN has significantly lower recognition errors than traditional methods. Figure 4 shows a comparison of response times for different algorithms. The algorithm in this article reduces the complexity of the model and improves computational and inference efficiency by optimizing the network structure and introducing effective training strategies.

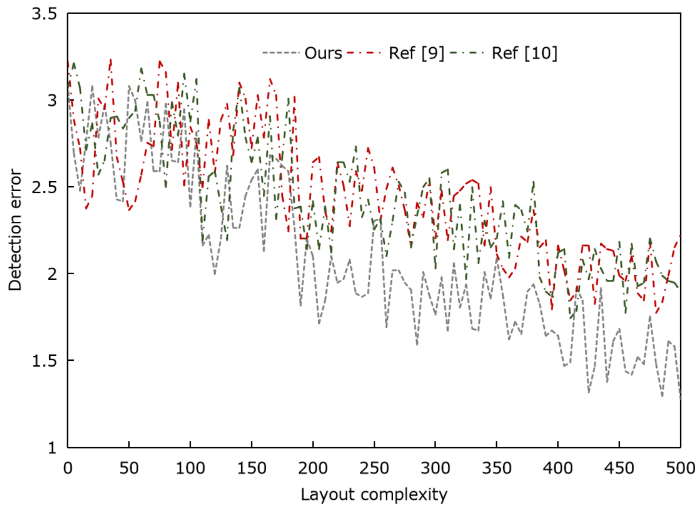

Figure 3: Identification errors of different algorithms.

By introducing atrous convolution, our algorithm can more effectively expand the receptive field and capture a wider range of contextual information. The algorithm in this article adopts multi-scale ACNN, which can extract features from different scales and more comprehensively capture the style features of artistic images. Atrous convolution expands the receptive field without increasing model parameters, avoiding additional computational overhead.

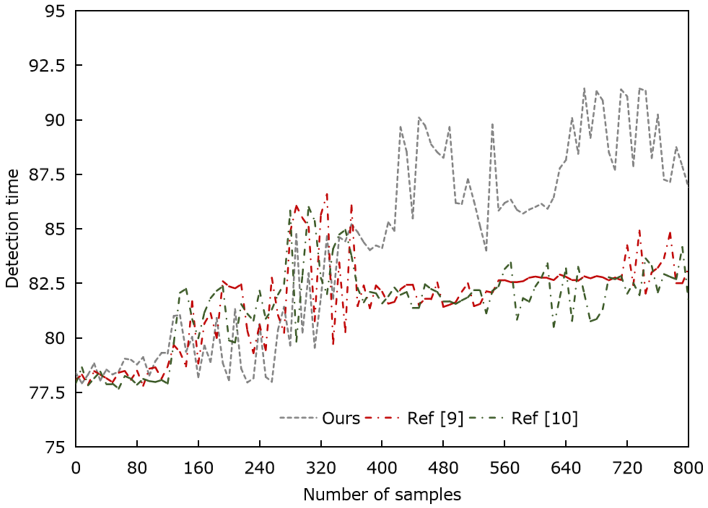

Figure 4: Response time of different algorithms.

In terms of operational efficiency, the algorithm presented in this article demonstrates significant advantages and can meet the requirements for fast response in practical applications. These advantages demonstrate the practicality of the algorithm proposed in this article in digital content analysis and artistic image style reconstruction tasks.

4 ANALYSIS OF DIGITAL CONTENT AND VISUALIZATION OF CAD

DMA, as a new form of expression that combines modern technology and artistic creation, has experienced rapid development in recent years. This art form not only enriches people's visual experience, but also provides artists with a broader creative space. How to effectively process and reconstruct images, as well as accurately assess the quality of DMA works, has always been a challenge for artists and researchers. For the quality assessment of DMA works, traditional methods are often too subjective and lack objective quantitative standards. This section aims to delve into CAD visualization techniques and corresponding quality assessment methods in DMA.

4.1 Visual Expression Methods

Figure 5 shows the simplest method of generating point drawings from 3D entities, which consists of two main steps: rendering and point drawing generation. During the rendering process, it is needed to set appropriate camera angles, lighting conditions, texture maps, and other parameters to ensure that the generated 2D image accurately reflects the appearance and details of the 3D solid scene. The rendering result is a two-dimensional image, which can be a color image in the RGB color space or a grayscale image. After obtaining the rendered 2D image, it is needed to use existing image dot drawing algorithms to generate the final rendered image. The dot drawing algorithm calculates the appropriate point distribution and density based on the color, brightness, and detail information of the image, in order to reconstruct the visual effect of the original image on the basis of discrete points.

The process of digital media image quality assessment based on SSIM is defined as:

$$SSIM(x,y)=\left[L(x,y)\right]^{\alpha}\cdot\left[C(x,y)\right]^{\beta}\cdot\left[S(x,y)\right]^{\gamma} \tag{7}$$

(a) 3D geometric model

(b) Traditional method rendering

(c) Stippling generated by image

Figure 5: Generating dots from 3D solid rendered images.

The definitions of $L(x,y)$, $C(x,y)$ and $S(x,y)$ in the above formula are as follows:

$$L(x,y)=\frac{\mu_x\mu_y+C_1}{\mu_x^2+\mu_y^2+C_1} \tag{8}$$

$$C(x,y)=\frac{2\sigma_x\sigma_y+C_2}{\sigma_x^2+\sigma_y^2+C_2} \tag{9}$$

$$S(x,y)=\frac{\sigma_{xy}+C_3}{\sigma_x\sigma_y+C_3} \tag{10}$$

Where $\mu_x,\mu_y,\sigma_x,\sigma_y,\sigma_{xy}$ stands for local mean, local variance and local cross-covariance. In general, take $\alpha=\beta=\gamma=1$ and $C_3=\frac{C_2}{2}$. Then, the definition of structural similarity measure can be simplified as follows:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{11}$$

SSIM can not only be used to assess the performance of image compression and transmission algorithms, but also to guide the optimization of image processing algorithms.

4.2 Assessment of CAD Visual Expression

The experimental image set consists of one content image and five style images. In style transfer tasks, by using one content image and multiple style images, it is possible to better observe the model's transfer ability between different styles. This experiment used a model construction and algorithm implementation based on Google's open-source DL framework TensorFlow. In style transfer tasks, TensorFlow can easily implement and optimize style transfer algorithms based on ACNN. The image generated after style reconstruction successfully transferred the artistic style of the style image to the content image, while preserving the scene contours of the content image. This indicates that the model has good performance in style transfer and can successfully balance style and content retention when handling such tasks. Figure 6 shows some of the experimental results.

Figure 6: Partial experimental results.

Figure 7 shows the kurtosis distribution of coefficients obtained from the basis function responses of different styles of test images and digital game images. The kurtosis value of the digital game test image is the highest, indicating that the coefficients obtained from the response of works of the same style to the basis functions of the same style are the sparsest. The response between digital game images and their design basis functions is very concentrated, with only a few coefficients showing significant responses. The lower kurtosis values of test images in other styles indicate that they do not belong to the same style as digital game design. Therefore, kurtosis can be used as an effective indicator to distinguish works of different styles. The kurtosis values of the three styles of works are distributed at different levels, with Impressionism in digital games at the top, digital film and television at the center, and digital animation images at the bottom. This hierarchical structure further validates the sparsity differences between different styles of works and the response of digital game basis functions. The image of digital film and television is closer to the style of digital games compared to digital animation images, so its kurtosis value is at the upper level of digital animation images. The regularity exhibited by digital animation images is vastly different from the Impressionist style of digital games, therefore the coefficients obtained when responding to the basis functions of digital games are the least sparse and the kurtosis value is the smallest.

The results in Figure 7 reveal the sparsity relationship and kurtosis distribution characteristics between different styles of works and the basis function response of digital game images. By analyzing the size and distribution hierarchy of kurtosis values, not only can non digital game images be distinguished from digital game images, but also digital art works that are similar to digital games and other digital art works that differ from digital game styles can be further distinguished.

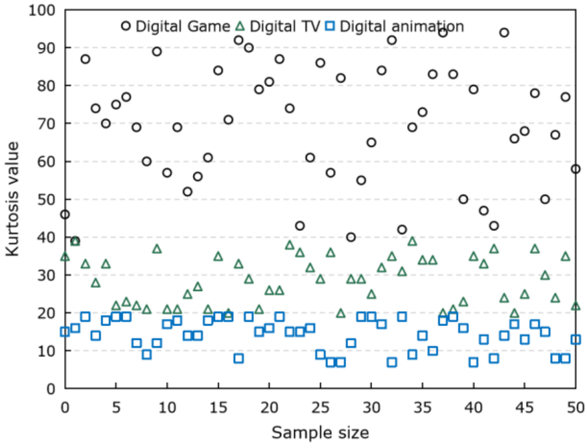

Figure 7: Whistle distribution map.

Figure 8 shows the SSIM assessment results of image reconstruction using several different methods. The reconstructed images of the ref [9] algorithm exhibit characteristics of multi degree smoothness and blurriness. In contrast, the reconstruction effects of the algorithm proposed in this article and the ref [14] algorithm are significantly better than those of the ref [9] algorithm in terms of edge details and overall restoration quality.

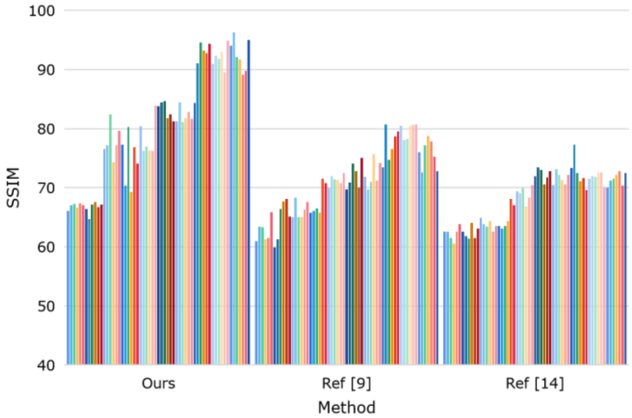

Figure 8: SSIM value of detail reconstruction results.

The ref [9] algorithm may overemphasize smoothness when reconstructing images, resulting in the loss of image details. Smooth operations are commonly used to remove noise, but excessive smoothing can lead to the loss of important information and textures in the image. Due to excessive smoothing, the edges and details of the image become less sharp, and the overall visual effect appears blurry. Edge details are one of the most important visual features in images. Compared with the ref [9] algorithm, the algorithm proposed in this article and the ref [14] algorithm can better preserve and restore the edge details of the original image when reconstructing images.

4.3 Result Discussion

Different image reconstruction algorithms can lead to completely different visual effects. The image blur and multi smoothness problems caused by the ref [9] algorithm significantly reduce the appearance of the work, while the algorithm in this article and the ref [14] algorithm do better in preserving edge details and improving restoration quality. This indicates that selecting suitable image processing and reconstruction algorithms is crucial in DMA creation. Identifying digital art works of different styles through kurtosis distribution can more accurately determine the stylistic attributes of the works. This classification method not only helps to distinguish digital game images from other styles of images, but also further subdivides digital art works of different styles. By classifying and identifying digital art works of different styles, we can gain a deeper understanding of the characteristics of each style. This provides an opportunity for artists to explore new art styles.

DMA, as a combination of art and technology, has ever-changing possibilities in its creative process. The ultimate goal of DMA is to communicate and interact with the audience. Therefore, it is very important to focus on user experience and feedback. By discussing and summarizing the above results, some beneficial improvement ideas have been provided for DMA creation. These ideas cover image processing algorithms, exploring new art styles, combining subjective and objective assessments, integrating art and technology, and providing user experience feedback. I hope these ideas can provide some useful references and guidance for the further growth of DMA.

5 CONCLUSION

In the context of the rapid growth of digital media, people are increasingly exposed to a variety of digital content, including digital games, digital movies, digital animations, and so on. Traditional digital content analysis methods often rely on manually designed feature extractors, which have certain limitations. Image processing and reconstruction algorithms play a crucial role in DMA creation. They directly affect the quality, visual effects, and aesthetics of the work, thus requiring continuous research and innovation. By accurately classifying and identifying digital art works of different styles, more sources of inspiration can be provided for artists, promoting the diversity and innovative growth of DMA. This article proposes an art image style reconstruction algorithm based on ACNN. This algorithm increases the receptive field and improves the feature extraction ability of the neural network by introducing the atrous convolution operation. This algorithm reduces the complexity of the model and improves computational and inference efficiency by optimizing the network structure and introducing effective training strategies.

By conducting in-depth research and applying new technological means, strengthening the combination of subjective and objective assessments, and focusing on user experience, DMA can be promoted to a higher level, bringing audiences a richer artistic experience. In practice, the algorithm proposed in this article can be applied to the analysis and expression of digital art images such as digital games, digital movies, and digital animations, promoting innovation in digital art.

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