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Computer-Aided Design AND APPLICATIONS

CNN-driven Art Design Decision Support System Based on Big Data

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Abstract. The aim of this article is to introduce an innovative approach to the visual interpretation of artistic scenes, leveraging the capabilities of Convolutional Neural Networks (CNN) to address the limitations of conventional rendering methods. Towards this objective, we employed advanced deep learning strategies to autonomously analyze and categorize artistic scene imagery by designing and refining CNN architectures. In our experimentation, we deliberately chose illustrative animal and plant images as test subjects to assess the algorithm's proficiency holistically. The findings reveal that our approach offers notable benefits in terms of both rendering swiftness and visual fidelity. In contrast to established practices, our optimized model has achieved a substantial decrease in rendering duration alongside a marked enhancement in visual quality, yielding sharper visuals and more intricate details. In conclusion, CNN-driven visual analysis techniques for artistic scenes have demonstrated considerable worth in elevating rendering efficiency and excellence, presenting fresh insights and utilities for scholars and practitioners alike in related domains.

Keywords: Big Data; Machine Vision; Art Design; Decision Support System; Image Rendering
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1 INTRODUCTION

With the swift advancement of information technology, big data has emerged as a pivotal force driving innovation across multiple domains. Art design, traditionally rooted in individual creativity and aesthetics, is now experiencing profound shifts induced by data-driven technologies. Notably, the convergence of mature machine vision and widespread Computer-Aided Design (CAD) usage is narrowing the gap between art and technology, paving the way for a new breed of Art Design Decision Support Systems (ADDSS). With the continuous development of deep learning technology, its applications in image processing and computer vision are becoming increasingly widespread.

Among them, deep learning models based on image transformation have played an important role in the field of art and design, bringing new ideas and methods for image rendering. Agarwal et al. [1] explored the application of deep learning models based on image transformation in art and design image rendering. Firstly, a deep learning model based on image transformation is a method of learning the mapping relationships between images by training deep neural networks. This model can convert one type of image into another, such as converting hand-drawn sketches into realistic rendered images. By training deep neural networks, models can learn the features and structures in images, thereby achieving high-quality image conversion. Deep learning models based on image transformation can be used to enhance and repair defects and deficiencies in images. For example, deep neural networks can be trained to remove noise, enhance colours, or improve clarity in photos. Historically, art design processes relied heavily on designers' personal experiences, instincts, and creative flair. However, as design tasks grow in complexity and market competition intensifies, sole reliance on individual designers for swift and precise design outcomes becomes challenging. With the development of computer vision and graphic rendering technology, artistic image rendering has become a key technology in fields such as digital art, game design, and film production. However, the automatic detection of components during the rendering process remains a challenging issue. Ben et al. [2] explored a method for automatically detecting art image rendering components by matching 3D CAD models with real 2D images. Firstly, we need to understand the characteristics and requirements of art image rendering components. Rendering components typically refer to objects, characters, props, and other elements in a scene that have complex shapes, textures, and lighting effects. The purpose of automatically detecting these components is to improve rendering efficiency and accuracy and reduce manual intervention and errors. Extract features that match the 3D CAD model, such as edges, corners, textures, etc., from the preprocessed image. These features should reflect the basic properties and structural information of rendering components. It matches the extracted features with the models in the 3D CAD model library to find the most similar model. This step can use some classic matching algorithms, such as feature point matching, shape context, etc. Based on the matching results, determine the position and pose of the rendering component in the 2D image, and recognize it. Some machine learning or deep learning algorithms can be used for classification and recognition. Hence, the integration of cutting-edge technologies like big data, machine vision, and CAD into art design workflows has become a pivotal development trend in the current art design landscape. With the development of technology, the combination of art and technology has become a new trend. Among them, the art image rendering technology based on aligning 3D interferometric synthetic aperture radar (ISAR) images with CAD models provides us with a new way of creation. Cai et al. [3] explored the basic principles, applications, and future development trends of this technology. ISAR is an imaging technique that utilizes radar signals to obtain target distance and angle information, capable of obtaining high-resolution 3D images. CAD model alignment is the process of aligning the 3D CAD model of the target with the ISAR image, achieving a match between the model and the actual target. Through this technology, detailed three-dimensional structural information of the target can be obtained, providing rich materials for artistic creation. This method can integrate real target structural information into artistic creation, making the work more realistic and expressive. Secondly, through CAD model alignment, precise control of target pose and position can be achieved, providing artists with more creative freedom. In addition, this method can also be applied to various complex environments and conditions, providing artists with more creative inspiration and possibilities. With the rapid development of digital art, cartoon images have been widely welcomed as a unique form of art. Among them, MOE-style cartoon pictures are popular on the Internet with their unique visual effects and cute images. However, effective classification and rendering of images with this style remains a challenge. Cao et al. [4] explored a bipolar rendering classification method for MOE-style cartoon images based on deep learning. Firstly, significant achievements have been made in the application of deep learning in the field of image processing. By training deep neural networks, features and structures in images can be learned, enabling efficient image classification and recognition. For MOE-style cartoon images, we can learn their features and classify them by training deep neural networks. Apply this method to practical MOE-style cartoon image classification tasks. In addition, further exploration of the extended application of this method can be conducted, such as generating cartoon images with specific styles and conducting style transfer. At the same time, fibre art, as a traditional art form, is deeply loved by people for its unique texture and expressive power. When these two are combined, we can see the birth of a new form of art - digital fibre art. This art form not only possesses the charm of traditional fibre art but also incorporates modern technological elements, providing artists with a broader creative space. Information literacy is a fundamental ability that people in the digital age must possess, which includes skills in acquiring, evaluating, processing, and applying information. In digital fibre art, information literacy plays a crucial role. Artists need to use digital image processing software to design, modify, and optimize patterns, which requires them to have a certain level of information technology knowledge. At the same time, they also need to understand the characteristics of different materials in order to choose the most suitable fibre material to express the design intent. In digital fibre art, pattern design is a crucial aspect. Artists need to use creativity and skills to transform digital images into fibre artworks that are aesthetically pleasing and practical. This requires them to have a solid foundation in pattern design, including colour matching, composition skills, and expression techniques. At the same time, they also need to understand market demand and consumer preferences in order to design fibre artworks that better meet people's needs [5].

With the advent of the digital age, the number and complexity of artistic images continue to increase, and how to quickly and accurately identify and classify these images has become an important issue. Deep learning-based image recognition methods have achieved significant results in many fields, but there are still challenges in processing complex sorted art images. Chen and Dong [6] discussed a fast recognition method for complex sorted art images based on deep learning. Firstly, deep learning techniques have played an important role in the field of image recognition. By training deep neural networks, features and structures in images can be learned, enabling efficient image classification and recognition. However, for complex sorted art images, traditional deep learning methods may not achieve ideal results due to their diversity and abstraction. To address this issue, this paper proposes a fast recognition method for complex sorted art images based on deep learning. This method adopts a Convolutional Neural Network (CNN) as the basic architecture and improves it to adapt to the characteristics of artistic images. The influx of big data technology has ushered in unprecedented possibilities for art design. By harvesting and analyzing vast troves of design data, underlying design principles, user preferences, and market trends can be uncovered, providing designers with scientific data backing. Nevertheless, harnessing big data's full potential demands proficiency in data processing, analysis, and visualization techniques. The evolution of machine vision technology has breathed new life into art design, enabling automatic recognition and analysis of visual information such as sketches, artworks, and live photographs. This, in turn, aids designers in swiftly drawing inspiration, evaluating concepts, and refining details. Furthermore, CAD technology's integration facilitates automated design data processing, intelligent design optimization, and efficient design presentation, elevating the art design profession to new heights. Realizing the effective operation of an ADDSS powered by machine vision and CAD hinges critically on accurate visual information interpretation within artistic contexts. Traditional image processing techniques often fall short when confronted with the diverse and abstract visual elements present in artistic scenes. To address this, our article introduces a visual understanding algorithm tailored for artistic scenes, leveraging the robust feature extraction and classification capabilities of CNN. This approach aims to facilitate deep learning-based automatic interpretation of artistic scene imagery, providing ADDSS with accurate and dependable visual information support.

Building on these foundations, our article delves deeper into the seamless integration of big data, machine vision, and CAD technologies to forge a comprehensive and efficient ADDSS. This system amalgamates advanced data processing techniques, machine vision algorithms, and CAD tools to streamline the entire workflow from data acquisition to design decision-making. Our article further elaborates on the system's architecture, functional modules, data flows, and real-world applications, offering a pragmatic roadmap for intelligent transformation in the art design sphere. In essence, this research carries profound theoretical significance and holds practical value. By forging an ADDSS anchored in machine vision and CAD, driven by big data insights, we aim to equip art designers with a refreshed toolbox and methodologies. This, in turn, paves the way for a more intelligent, efficient, and innovative art design industry. Moreover, the insights from this research serve as valuable references for researchers and practitioners alike in adjacent fields. The study's innovations encompass:

(1) This article comprehensively incorporates big data technology into the decision-making workflow of artistic design, efficiently gathering, manipulating, and interpreting vast amounts of design data. This integration offers unparalleled data support for artistic endeavours.

(2) Utilizing this approach, designers can tap into hidden patterns and trends buried within the data, bolstering the scientific rigour and precision of their design choices.

(3) Our research seamlessly blends CAD technology with machine vision, facilitating automated data processing, intelligent design optimization, and swift visualization of design outcomes within the artistic realm.

(4) Furthermore, we introduce an innovative visual comprehension algorithm tailored for artistic scenarios, leveraging the power of CNN to accurately decipher and categorize the intricate visual cues present in these settings.

This article delves into the advancements of ADDSS, driven by the symbiosis of machine vision, CAD, and big data. It begins by outlining the research's significance and background, before detailing the intersection of big data, machine vision, and CAD in artistic design, along with their seamless integration. Subsequently, it unveils a novel visual understanding algorithm tailored for artistic scenes, leveraging CNN. Culminating in the formulation of a comprehensive ADDSS, the article concludes with an assessment of its performance and future prospects.

2 RELATED WORK

Art and design play an important role in image processing, as they can enhance the beauty and visual effects of images, making them more in line with human aesthetic needs. Applying wavelet transform filters to art and design image processing can further leverage their advantages in image processing, improving image quality and visual effects. In terms of art and design, Danso et al. [7] utilized terahertz image features extracted by wavelet transform filters for image enhancement, style transformation, and other operations. By adjusting wavelet coefficients or using different wavelet basis functions, contrast enhancement, edge detection, texture analysis, and other effects of terahertz images can be achieved. These processes can further improve the quality and visual effects of terahertz images, making them more suitable for subsequent analysis and processing. Wavelet transform filters can also be combined with other image processing techniques to achieve more complex and efficient image processing. For example, wavelet transform can be combined with technologies such as neural networks and machine learning to build more intelligent and adaptive image processing systems. With the rapid development of technology, machine vision technology is playing an increasingly important role in various fields. Especially in the fields of industry and art, the application of machine vision has brought many innovations and breakthroughs. Kim et al. [8] explored the application of machine vision in industrial and artistic fields, as well as how to select prominent views through image rendering to achieve accuracy and efficiency in visual recognition. Firstly, machine vision has been widely applied in the industrial field. From product testing and quality control to automated production lines, machine vision plays an irreplaceable role. Through high-precision image acquisition and recognition, machine vision technology can quickly and accurately detect product appearance, size, and other parameters, improving production efficiency and product quality. Meanwhile, machine vision technology can also be applied in fields such as robot navigation and intelligent monitoring, promoting further development of industrial automation. With the rapid development of technology, 3D image rendering and recognition have become important research directions in the field of computer vision. Especially in the fields of art and design, there is an increasing demand for understanding and recognizing 3D models. Lee et al. [9] explored a 3D convolutional neural network for image rendering recognition and introduced its gradient-based artistic visual interpretation based on 3D CAD models. Firstly, 3D Convolutional Neural Network (3D CNN) is a rapidly developing deep learning model in recent years, which has strong feature extraction capabilities when processing 3D data. Compared to traditional 2D image processing methods, 3D CNN can better understand the structure and details of 3D models, thus achieving better results in image rendering and recognition. Secondly, gradient-based artistic visual interpretation based on 3D CAD models is a new method for understanding the artistic attributes and styles of 3D models. By calculating the surface gradient of the model, the shape, texture and other features of the model can be extracted, thereby quantitatively analyzing and explaining the artistic style of the model. With the rapid development of technology, graphic recognition technology has become an important branch in the field of computer vision. Among them, the Computational Visual Pattern Recognition (CbVBI) method has received widespread attention due to its efficiency and accuracy. Manavis et al. [10] introduced a novel computational-based visual pattern recognition (CbVBI) rendering design method aimed at improving the accuracy and efficiency of pattern recognition. Firstly, this method adopts an improved convolutional neural network (CNN) architecture for extracting features from images. Compared with traditional methods, this method not only improves the accuracy of feature extraction but also reduces the computational workload and number of parameters, thereby improving computational efficiency. Secondly, this method introduces an attention-based decoder to convert the extracted features into high-resolution images. Through the attention mechanism, the decoder can automatically focus on important areas in the image and generate more detailed and accurate images. In the fields of industrial automation and quality control, visual recognition technology is playing an increasingly important role. In order to accurately identify industrial parts, it is necessary to select an effective feature descriptor. Histogram descriptors are widely used in image recognition due to their simplicity and robustness. However, full histogram descriptors may result in high computational complexity and dimensionality, affecting recognition speed and accuracy. Therefore, selecting a suitable subset is particularly important. Merino et al. [11] explored the application of histogram-based descriptor subset selection in industrial part visual recognition. Machine learning methods learn a model by training data, which is used to predict the contribution of each histogram to recognition, and then select the histogram with a higher contribution. At present, there are still some challenges and limitations in the selection method of descriptor subsets based on histograms. For example, how to determine the appropriate subset size, how to process images under different lighting and perspectives, etc. Future research can delve deeper into these issues and propose more effective algorithms and methods. Interactive self-assessment art graphic rendering tool is an innovative tool that combines CAD technology and graphic rendering technology, allowing users to self-evaluate and adjust during the design process. The core of this tool lies in its interactivity and self-assessment function, which can help users better understand the visual effects of the design and provide real-time feedback and adjustment suggestions. There are many advantages to using interactive self-assessment art graphics rendering tools. Firstly, it can help users identify and solve potential problems in the early stages of design, avoiding discovering design defects only in the later stages. Secondly, this tool can improve the overall quality and aesthetics of the design, making it more in line with user expectations and needs. In addition, through real-time feedback and adjustment suggestions, users can improve their design and work efficiency more quickly. In practical applications, interactive self-assessment art graphic rendering tools can be applied in various fields, such as architectural design, product design, clothing design, etc [12]. With the rapid development of technology, data has become an indispensable basis in our decision-making process. In the field of visual arts, data-driven design methods are gradually receiving attention. Petrova et al. [13] explored how knowledge discovery techniques from different visual arts can be utilized to provide decision support for sustainable design. Firstly, we need to understand the core concepts of data-driven design. Data-driven design emphasizes data as the foundation, providing a basis for design decisions by analyzing and mining information in the data. This design method can help us better understand user needs, market trends, and product performance, thereby optimizing the design solution. In visual art, knowledge discovery is the process of extracting useful information from a large amount of data. By utilizing various technological means such as data mining, machine learning, and artificial intelligence, we can extract valuable information from images, videos, and artworks. These pieces of information can provide important decision support for sustainable design. With the rapid development of new media technology, visual communication technology and computer-aided interaction of art have been widely applied in various fields. This interactive approach not only provides designers with more efficient and flexible design tools but also brings a richer and more immersive visual experience to the audience. Wang [14] discussed the application and future development trends of computer-aided interaction between visual communication technology and art in new media scenarios. Firstly, the continuous development of new media technology has provided a broader stage for visual communication. Through computer-aided design software and digital technology, designers can create richer and more three-dimensional visual effects, conveying information to the audience in a more intuitive and vivid way. At the same time, the interactivity of new media technology also provides designers with more possibilities, allowing audiences to actively participate in visual communication and enhance the effectiveness of information transmission. With the continuous development of technology, computer graphics and image software have become indispensable tools in the field of design. In the field of ocean graphic design, the application of these tools provides infinite possibilities for designers. Zhang [15] explored the application of computer graphics and image software in ocean graphic design. Firstly, computer graphics provides strong technical support for ocean graphic design. Through computer graphics, designers can create realistic ocean scenes, simulating the dynamic effects of seawater, changes in light and shadow, and texture of waves. This technology allows designers to simulate real ocean environments on computers, providing richer visual elements and creative inspiration for graphic design. Secondly, image software provides efficient tools for ocean graphic design. Designers can use this software to edit, synthesize, and layout materials for ocean graphic design. Through this software, designers can quickly complete design tasks and improve work efficiency.

3 MACHINE VISION: INJECTING INTELLIGENT SOUL INTO ART DESIGN

In this age of overwhelming information, big data has permeated virtually every facet of existence, with the domain of artistic design being no different. Big data, like a treasure house, provides designers with inexhaustible inspiration and materials. By analyzing the subtle relationship between user behaviour, market trends, and design elements, big data enables designers to make more forward-looking and innovative decisions from a higher perspective. In real-world utilization, big data has showcased its allure across numerous artistic and design disciplines. Be it fashion designers harnessing big data insights to stay ahead of trends or architects leveraging it to refine their designs, and both scenarios underscore the unparalleled worth of big data in aesthetics and creativity.

Nevertheless, integrating big data comes with its own set of obstacles. Managing the intricate process of data gathering, refinement, and interpretation demands specialized technical expertise, posing fresh dilemmas for design professionals. Moreover, sifting through vast datasets to unearth precious nuggets of information requires not only a sharp analytical mind but also a wealth of experience. Additionally, concerns around data confidentiality and user privacy loom large, necessitating a delicate balance between data utilization and user rights protection. Despite these challenges, the outlook for big data in the arts and design remains promising. As technology marches onward and applications mature, there's optimism that big data will emerge as a pivotal driver of innovation and growth in the entire creative spectrum. Machine vision, a prominent ambassador of artificial intelligence, has secured notable accomplishments in areas including image identification and object localization. Its deployment in the realm of art and design is akin to a refreshing influx, offering designers a revitalized creative journey and enhanced decision-making support.

Scholarly investigations have firmly established the groundwork for the integration of machine vision within artistic and design pursuits. These studies not only expand the application fields of machine vision but also inject new vitality into art and design. In practical applications, machine vision technology has become a powerful assistant in multiple fields of art and design. Whether graphic designers use machine vision technology to screen materials or industrial designers quickly use machine vision to assess product appearance accurately, both demonstrate the broad application prospects of machine vision in art and design. However, the use of machine vision technology also faces some challenges. The diversity and complexity of artistic works pose higher requirements for image processing and recognition technology. Meanwhile, how to make reasonable use of machine vision technology while ensuring image copyright and privacy is also a question that requires careful consideration. In addition, the application of machine vision technology also needs to be closely integrated with the creativity and aesthetics of designers in order to truly realize its value.

4 CAD: RESHAPING THE CREATION AND EXPRESSION OF ART DESIGN

Computer-aided design (CAD), a groundbreaking design instrument, has made its mark in engineering design. As the art and design landscape continues to evolve, CAD technology has seamlessly blended into it, unlocking fresh avenues of creativity and expression for designers.

Moreover, CAD has emerged as a pivotal player in art and design education. The introduction of virtual simulation methods has empowered students to hone their skills in a risk-free virtual setting, fostering a deeper comprehension of design fundamentals and techniques. This innovation not only bolsters students' practical and creative abilities but also breathes new life into the educational realm of art and design.

Nevertheless, the integration of CAD in art and design presents its own set of hurdles. Primarily, there's a need to address the usability of CAD tools and make them more accessible to designers. Furthermore, striking a balance between the precision offered by CAD and the inventive spirit of artistic designs is crucial for harmonious technological and artistic growth. Lastly, in the dissemination and adoption of CAD, safeguarding intellectual property and copyright remains paramount to ensure that designers' original works are duly protected.

5 CNN-BASED ALGORITHM FOR VISUAL UNDERSTANDING OF ART SCENES

As deep learning technology keeps evolving, CNN has attained remarkable achievements in the domains of image processing and computer vision. This article proposes a CNN-based visual understanding algorithm for art scenes, aiming to achieve automatic understanding and classification through deep learning of images in art scenes and provide accurate and reliable visual information support for ADDSS.

5.1 Algorithm Design Ideas

Art scenes often contain rich visual elements and complex spatial relationships, and traditional image processing methods are often difficult to accurately understand and classify. Therefore, this article adopts CNN as the core algorithm, utilizing its powerful feature extraction and classification capabilities to perform deep learning and automatic understanding of images in art scenes.

Specifically, the design concept of the algorithm is as follows:

(1) Data preprocessing: This step involves preparing images of art scenes for CNN models by performing operations like cropping, scaling, and normalization. These adjustments ensure that the images align with the models' input specifications.

(2) Feature extraction: CNN models are employed to extract relevant features from the preprocessed images. The combination of convolutional layers, pooling layers, and nonlinear activation functions facilitates the extraction of image features, ranging from basic to complex, which are then organized into a feature map.

(3) Classification and recognition: Based on feature extraction, feature maps are classified and recognized through fully connected layers and classifiers. This article uses a Softmax classifier to output the probability distribution of each category, thereby achieving automatic understanding and classification of artistic scenes.

5.2 Algorithm Implementation Process

In the implementation process, this article adopts the classic CNN model structure and optimizes and improves it according to the characteristics of artistic scenes. The following are the key steps for algorithm implementation:

(1) Model design: Choose a suitable CNN architecture and tailor it to fit specific requirements. During the design phase, it's crucial to strike a balance between the model's intricacy and efficiency by carefully selecting parameters like depth, width, kernel dimensions, and stride length.

(2) Dataset curation: Gather a diverse collection of artistic scene imagery encompassing various styles, settings, and lighting scenarios. Ensure that the data is labelled and categorized appropriately to facilitate the creation of comprehensive training and testing sets.

(3) Model training: Employ the curated training set to refine the CNN model. Utilizing techniques such as backpropagation and gradient descent, iteratively refine the model's parameters to enhance its classification proficiency on the training dataset.

(4) Model application: Apply the trained CNN model to actual art scene image understanding and classification tasks. By inputting new art scene images, the model can automatically output classification results and probability distributions, providing accurate and reliable visual information support for ADDSS.

5.3 The Principles of Artistic Scene Rendering

The principle of artistic scene rendering is mainly based on the lighting, material, and geometric information in the scene, and the process of converting a 3D model or scene into a 2D image by calculating pixel-level colours and brightness. This process involves multiple core algorithms and technologies, among which the CNN-based visual understanding algorithm for art scenes plays an important role. In art scene rendering, lighting calculation simulates the interaction between light and objects, including ambient light, diffuse reflection, specular reflection, etc., to produce a realistic image. The material determines the reflection and refraction characteristics of light on the surface of an object, and different materials will present different visual effects. Geometric information describes the shape, position, and size of objects in the scene. The principle of artistic scene rendering is shown in Figure 1.

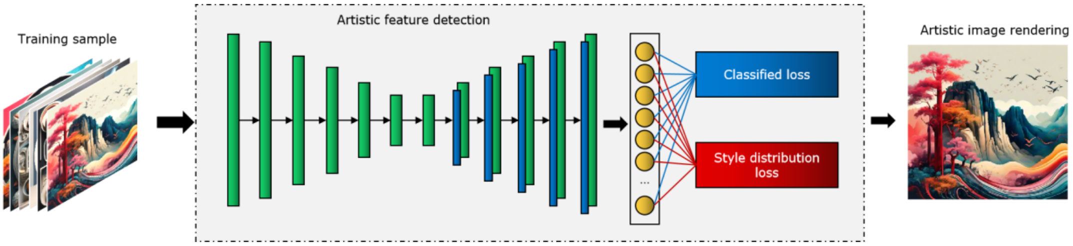

Figure 1: The principle of artistic scene rendering.

The proposed algorithm attains autonomous comprehension and categorization by deeply analyzing images depicting artistic scenes. It leverages the robust feature extraction and classification prowess of CNN to progressively extract features from basic to advanced levels, constructing a comprehensive feature map. Subsequently, a classifier is employed to categorize and recognize the derived feature map. In this way, the algorithm can accurately identify different objects, materials, and lighting effects in the scene, providing accurate visual information support for rendering. Set the connected region as C_i $i=1,2,\ldots,n$, where i represents the i-th connected region and n is the quantity of connected regions. The width, height and area of the connected region are expressed as L_i, W_i and S_i respectively. If the three meet the following conditions:

$$S_i \geq S_{\min} \cap S_i \leq S_{\max} \tag{1}$$

$$\frac{L_i}{W_i} \geq \left(\frac{L}{W}\right)_{\min} \cap \frac{L_i}{W_i} \leq \left(\frac{L}{W}\right)_{\max} \tag{2}$$

$$\frac{S_i}{L_i \times W_i} \geq \left(\frac{S}{L \times W}\right)_{\min} \tag{3}$$

Then the connected region is a candidate region. Where $S_{\min}$ and $S_{\max}$ represent the minimum and maximum values of the connected area; $\left(\frac{L}{W}\right)_{\max}$ and $\left(\frac{L}{W}\right)_{\min}$ represent the maximum length-width ratio of the connected region; $\left(\frac{S}{L \times W}\right)_{\min}$ represents the minimum duty cycle. The candidate regions are obtained by rough segmentation of known scene images, and the images are classified by extracting shape features.

To describe the target features within candidate regions in scene images, the computer vision technique known as SIFT (Scale-Invariant Feature Transform) is utilized. This method offers several advantages, including the preservation of positional and scale information, as well as rotation invariance for local image features. It identifies and characterizes key features within the candidate areas, efficiently reducing the amount of data the computer needs to process while maintaining crucial visual details.

To capture the internal target features of the scene, the process typically centers on SIFT feature points within the candidate region. Specifically, it involves calculating the gradient and direction of each pixel within a 16x16 window around these points. To enhance the adequacy of sampling and the clarity of the resulting image, this article opts for a dense sampling approach, which yields a higher density of SIFT feature points. Figure 2 illustrates this dense sampling technique.

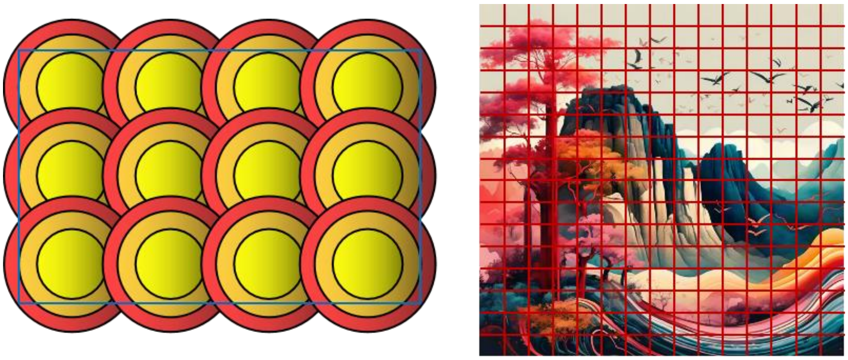

Figure 2: Schematic diagram of sifting feature point extraction.

In Figure 2, concentric circles composed of different colours represent the search range of SIFT features at different scales, and the search radii corresponding to the circles of three colours are r = 4, 8 and 12 pixels respectively. Calculate the SIFT descriptor at the center of the SIFT feature point, that is, the center of the concentric circle. Each SIFT descriptor is represented by a 128-dimensional feature vector, so each extraction point can be described by a 128×3=384-dimensional feature vector. By extracting SIFT features, a large quantity of extracted points should be clustered. The similar extraction points are quantized by K-Means clustering and merged into visual keywords. According to the order of extraction points, the keywords are sorted to form a visual dictionary, which improves the computational efficiency of the algorithm. According to the frequency of keywords, the corresponding keyword histogram is established to complete the target feature extraction of candidate areas.

After denoising the multi-frame plane image, its fidelity value u is as follows:

$$u = \arg\min_{c} \frac{1}{2\xi^2}\left\|\tilde{c} - c\right\|^2 + \mu\phi(c) \tag{4}$$

Where ξ stands for Gaussian fuzzy noise, $\tilde{c}$ stands for multi-frame plane image with noise, c stands for denoised image, $\phi(c)$ stands for regularization parameter, and μ stands for the relationship between regularization parameter and data fidelity term. When μ is too large, the denoising effect of the image is not obvious; When μ is small, the image detail denoising link is easy to lose and the image is easy to be unclear. Combined with the deep learning algorithm, the multi-frame plane image is denoised as follows:

$$u = G(\overline{c}, \zeta, \rho) \tag{5}$$

Where ρ represents the image network parameter. Then increase the noise dimension to the noise level diagram Q, as shown below:

$$u = G(\overline{c}, Q, \rho) \tag{6}$$

At this time, the multi-frame plane image with noise and the noise level map have the same Q dimension. The residual learning method is used to complete image denoising, and the process is as follows:

$$G_F(\tilde{c}, q) = \tilde{M} \tag{7}$$

Where $\hat{M}$ represents the estimated noise residual image and G_F represents the denoising process, and the input noise image $\tilde{c}$ is subtracted from the noise residual image $\hat{M}$ to calculate the denoised image u:

$$u = \tilde{c} - G_F(\tilde{c}, q) \tag{8}$$

Use O_z to represent the source low-resolution multi-frame plane image, O_j to represent the high-resolution multi-frame plane image, and O_o to represent the original interpolation image, and use the maximum posterior probability method to calculate the high-frequency information J of the high-resolution image with maximum probability, as follows:

$$P(J|O_z) = P(J|O_{zJ}, O_{zz}) \approx P(J|O_{zJ}) \tag{9}$$

However, due to the lack of prior knowledge, the texture information of the high-resolution multi-frame plane image can not be well preserved, so it is further processed to improve the texture detail information of the high-frequency part. Extracting the low-frequency information O_{zz} of the source low-resolution multi-frame plane image O_z includes the following steps:

$$O_{zz} = O_z * H_\zeta \tag{10}$$

Where H_ζ stands for Gaussian kernel function, $*$ stands for convolution operation, and then high-frequency information is obtained:

$$O_{zj} = O_z - O_{zz} \tag{11}$$

6 RESULT ANALYSIS AND DISCUSSION

To guarantee the precision of our experiment, we deliberately chose four diverse and representative images as our test subjects. These comprised two animal and two plant images, as depicted in Figure 3. The selected images are not only content-rich but also exhibit unique characteristics, enabling a thorough evaluation of the algorithm's performance. The visual characteristics of these two animal images are in sharp contrast, which is not only beneficial to the algorithm in learning the common characteristics of animal categories but also can challenge the algorithm's ability to identify different animal personality characteristics. There are also significant differences in visual characteristics between the two plant images, which not only helps the algorithm to learn the common characteristics of plant categories but also can test the ability of the algorithm to identify the growth environment and morphological characteristics of different plants. These images not only provide rich visual information but also cover the diversity of animals and plants.

Figure 3: Experimental image set.

In Figure 4, Figure 5 and Figure 6, the contrast results of image sharpness processed by reference [7], reference [8] and this algorithm are shown respectively. Through comparative analysis, it can be clearly seen that this algorithm has achieved remarkable advantages in image clarity, which exceeds the performance of the algorithms in literature [7] and literature [8].

Figure 4: Image clarity after processing by the algorithm in reference [7].

Observe Figure 4, that is, the image processed by the algorithm in reference [7]. The whole image presents a certain sense of blur, and the details are not clear enough. This is because the algorithm failed to effectively retain the high-frequency information of the image during processing, resulting in the loss of image details.

Figure 5: Image clarity after processing by the algorithm in reference [8].

Observe Figure 5, that is, the image processed by the algorithm in reference [8]. Although the clarity of Figure 5 is improved compared with Figure 4, there are still some blurred areas and the overall contrast is not high. This shows that the algorithm still has some limitations in image enhancement and fails to achieve the ideal clarity effect.

Figure 6: Image clarity of processing completed by this algorithm.

Examining Figure 6 reveals the image that has undergone processing by this algorithm. Notably, the image's overall clarity has undergone a marked enhancement, with finer and more defined details. Both contour lines and intricate textures exhibit remarkable sharpness. This underscores the algorithm's proficiency in preserving and amplifying the high-frequency components of the image during the processing stage, ensuring that the enriched image data remains intact.

Upon scrutinizing Figure 7, a comparison of average gradient values reveals that this algorithm surpasses the previous two algorithms mentioned in references [7] and [8]. This elevated average gradient is indicative of superior image clarity achieved by our algorithm. Through rigorous testing, it becomes evident that this algorithm not only enhances the colour profiles of multi-frame planar images via colour correction but also incorporates a contour interpolation supplementary algorithm. This holistic approach elevates the images to super-resolution quality, showcasing a more pronounced improvement in texture details compared to the methodologies outlined in references [7] and [8]. Consequently, the resulting images boast superior quality and definition.

In Figure 8 and Figure 9, the experimental results of comparing the visual understanding method of artistic scenes proposed in this article with the traditional rendering method in rendering efficiency and quality are shown. These comparative results fully reflect the advantages and innovation of this method.

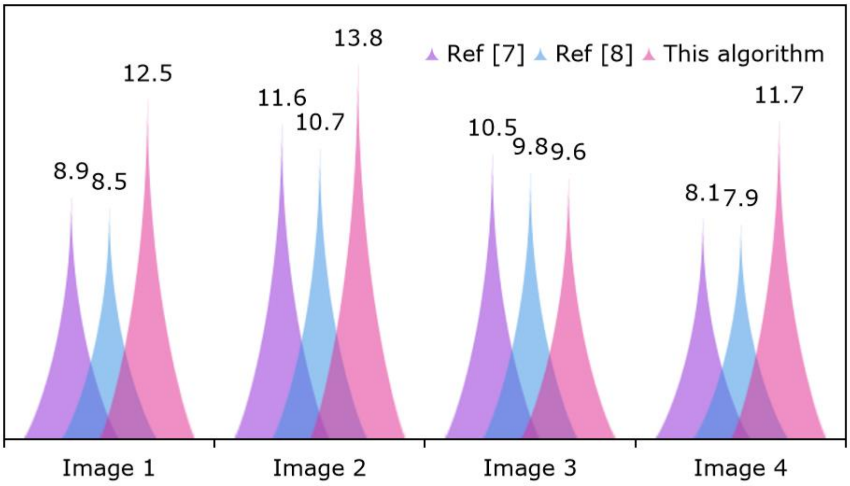

Figure 7: Average gradient values of different algorithms.

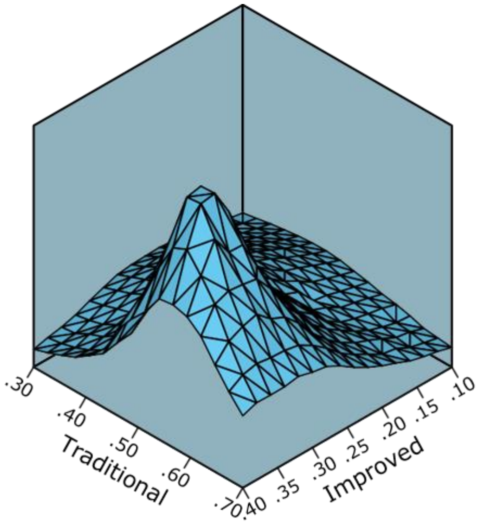

Figure 8: Rendering efficiency of different methods.

First, consider the comparison of rendering efficiency depicted in Figure 8. In contrast to conventional techniques, the model refined in this article demonstrates significant gains in terms of rendering speed. While traditional methods frequently demand extensive rendering durations, thus somewhat constraining their practical use, the approach outlined in this article effectively reduces rendering time and enhances efficiency through the utilization of advanced algorithms and optimization tactics.

Next, observe the rendering quality comparison shown in Figure 9. When compared to traditional practices, the optimized model described in this article has markedly enhanced the quality of rendering. Traditional methods may encounter issues during the rendering process, such as loss of fine details and colour distortions, ultimately resulting in unsatisfactory outputs. The methodology introduced in this article successfully elevates the rendering quality by refining the rendering algorithm and fine-tuning the rendering parameters.

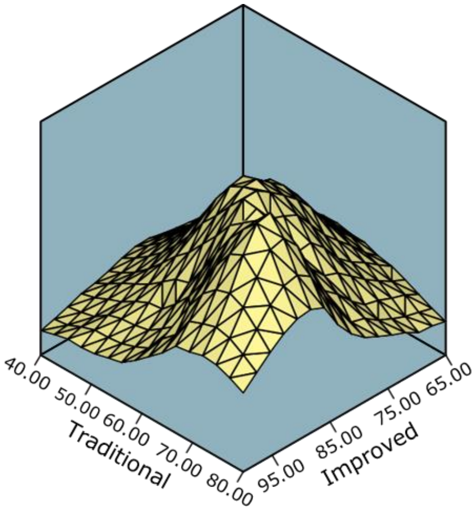

Figure 9: Rendering quality of different methods.

The artistic scene visual comprehension technique introduced in this article outperforms conventional methods in terms of both rendering efficiency and quality. This superiority primarily stems from the method's advancements in algorithm design, optimization strategy, and technological implementation. These innovations facilitate a better alignment with practical requirements and offer a more effective, high-calibre solution for artistic design and rendering endeavours.

7 CONCLUSION

The utilization of big data technology has ushered in remarkable prospects for artistic design. By amalgamating it with CAD technology, the automation of design data processing, intelligent refinement of design concepts, and streamlined presentation of design outputs become feasible, elevating the standards of artistic design significantly. This discussion delves into the development and deployment of an innovative ADDSS that integrates big data, machine vision, and CAD technology.

Through meticulous analysis of artistic vignettes, this integration of machine vision's efficient processing capabilities and CAD's precise modelling proficiency successfully facilitate intelligent decision support for artistic endeavors. The system outlined in this article leverages the strengths of big data, extracting valuable insights from a vast array of artistic and design-related datasets. These datasets encompass traditional artistic elements and principles alongside user behaviour patterns, market trends, and other diverse data streams, fostering a rich creative milieu for artistic innovation.

The introduction of machine vision technology enables the system to autonomously identify and dissect pivotal elements within artistic compositions, facilitating swift comprehension and assessment of designs. Meanwhile, the incorporation of CAD technology empowers designers to swiftly translate conceptual ideas into three-dimensional models, affording them an intuitive preview and refinement interface. This synergy not only expedites the design iteration cycle but also enhances designers' grasp of the design's holistic impact and finer nuances.

Furthermore, the visual comprehension algorithm rooted in CNN holds significant practical value within the ADDSS framework. Its proficiency in automatically comprehending and categorizing artistic scene imagery through deep learning methodologies offers designers precise and dependable visual cues, thereby propelling the innovative advancement of the artistic design industry. As technology continues to evolve and applications become more profound, the CNN-based visual comprehension algorithm is poised to play an increasingly pivotal role in shaping the landscape of artistic design.

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