Research on Simulation and Visualization of Paint Materials in Gongbi Painting Based on Deep Learning

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ABSTRACT Gongbi painting, as an important category of traditional Chinese painting, relies on pigment materials (such as the heavy texture of mineral pigments and the transparency of plant pigments) and color setting techniques (such as "three alum and nine dye" and "multi-layer overlay") as its artistic charm. However, traditional creation is time-consuming and laborious, and digital simulation techniques are difficult to accurately reproduce its physical characteristics and visual effects. The existing simulation research on Gongbi painting pigments relies heavily on traditional physical modeling, which has problems such as low accuracy in material restoration, stiff color overlay effects, significant differences between visual presentation and actual painting, and difficulty in balancing simulation efficiency and artistic authenticity. To this end, this article first sorts out the classification and characteristics of Gongbi painting pigments to clarify the core simulation requirements, and then constructs a pigment material simulation model based on deep learning. Combining Kubelka Munk color optics theory and Conditional Generative Adversarial Network (CGAN), three core modules are designed: pigment characteristic extraction, multi-layer overlay simulation, and visual rendering. Finally, the performance of the model is verified through comparative experiments. The experiment selected 10 typical gongbi painting pigments (5 mineral pigments, 5 plant pigments) and compared our model with traditional physical modeling methods and existing deep learning methods. The results showed that our model improved the accuracy of pigment texture restoration and color overlay similarity by more than 30%, and the visualization rendering speed increased by 50%. It can accurately reproduce the artistic effects of gongbi painting such as "thin color multi coating" and "blending gradient", and has good real-time interactivity. Measured refractive, scattering and absorption parameters also make the model relevant to optical material visualization.

INDEX TERMS deep learning,gongbi pigment simulation,visual rendering,multispectral imaging,optical material modeling

I. INTRODUCTION

GONGBI painting is strict line drawing and delicate color setting with aesthetic connotation of traditional Chinese culture. Selection and application of pigment materials directly affect the expression of work. With the gradual integration of digital technology and traditional art, the digital protection, creation and popularization of gongbi painting have become a research hotspot. The accurate simulation and visualization of pigment materials are the key and difficulty to realize the digitization of gongbi painting. At present, traditional gongbi painting depends on the experience of artists. The techniques of mineral pigment blending and multi-layer stacking is complex and difficult to standardize. In addition, the digital simulation technology still has many shortcomings, can not meet the practical needs of artistic creation, cultural transmission and cultural relic recovery. This study takes the deep learning simulation and visualization of pigment materials in Gongbi painting as the research direction, solves the problems of inaccurate material recovery and stiff visualization effect in current technology, and provides technical support for the digital inheritance and innovation of Gongbi painting. It has important theoretical research value and practical application significance [1,2]. The main contributions of this study are as follows: Firstly, a simulation model is constructed to combine physical properties of pigments with deep learning. It breaks through the limitation of traditional physical modeling and realizes accurate recovery of different textures of mineral pigments and plant pigments; Secondly, a visual rendering module based on semantic matching is designed. Combined with the color setting technology of Gongbi painting, the realistic effect of "three alum and nine dye", "blending gradient" and other effects are realized; Thirdly, the effectiveness and superiority of the model have been verified through a large number of comparative experiments, and provide practical technical solutions for digital creation of gongbi paintings and virtual recovery of cultural relics. The rest of this article is organized as follows. Firstly, the difficulty and challenge of current research will be analyzed. Secondly, detailed explanation of research method will be elaborated. Finally, experimental results will be presented and discussed in depth. At last, research conclusions and future work will be drawn.

II. PROBLEMS AND CHALLENGES

The complexity of pigment materials in Gongbi painting and the particularity of coloring techniques have brought many challenges to digital simulation and visualization. Firstly, there are various types of pigments in Gongbi painting, with significant differences in physical properties between mineral pigments (such as stone green and stone green) and plant pigments (such as flower green and rattan yellow). Mineral pigments have strong graininess, strong coverage, and stable colors, while plant pigments have transparency, good blending, and soft colors. Different pigments have significant differences in refractive index, scattering coefficient, and absorption coefficient. Accurately extracting these physical parameters and integrating them into simulation models is the primary challenge in achieving true material reproduction. In addition, the blending and stacking process of Gongbi painting pigments is highly empirical. Techniques such as "thin color multi coating" and "layer by layer overlay dyeing" result in complex interactions between pigment layers. Traditional physical modeling is difficult to accurately simulate this dynamic stacking effect, which can easily lead to color distortion and stiff texture [3,4].

Secondly, the application of deep learning models in the simulation of gongbi painting pigments faces many bottlenecks. On the one hand, there is a lack of datasets for simulating Gongbi painting pigments. The existing datasets are mostly finished images of Gongbi painting, lacking labeled data for pigments used alone or stacked in multiple layers, resulting in poor model training performance and difficulty in learning subtle differences in pigment materials; On the other hand, balancing simulation accuracy and visualization efficiency is a key challenge. High precision simulation models often require a large amount of computing resources, resulting in slow rendering speeds that cannot meet the needs of real-time interaction. Pursuing efficiency also sacrifices the authenticity of material restoration. At the same time, visual presentation needs to balance artistic authenticity and digital practicality, restoring the traditional texture of gongbi painting pigments while adapting to digital creation, virtual display and other scenarios. How to achieve a balance between the two is also an important challenge facing current research [5].

III. METHOD

A. EXTRACTION OF PIGMENT CHARACTERISTICS AND CONSTRUCTION OF A DATASET FOR GONGBI PAINTING

Firstly, a systematic sorting and classification screening of commonly used pigments in Gongbi painting was carried out (as shown in Figure 1). Based on traditional Gongbi painting creation practice and cultural relic restoration needs, 10 representative pigments were selected. These 10 pigments represent the primary spectral categories (e.g., Cinnabar for reds, Stone Green for greens) used in over 80% of classic Gongbi works. However, we define "niche pigments" as high-grade variants like specific particles of Azurite (Grade 1-4) or specialized organic dyes like Gold-thread Alum, which possess unique refractive properties not fully captured by our current 10-pigment general model, including five classic mineral pigments of stone green, stone blue, cinnabar, ochre, and stone yellow, as well as five commonly used plant pigments of flower green, rattan yellow, rouge, eosin, and vine red, covering the most core color system in Gongbi painting creation. To accurately capture the physical properties of pigments, key physical parameters of each pigment, including refractive index, scattering coefficient, absorption coefficient, etc., are measured using professional experimental equipment. Combined with Kubelka Munk (KM) color optics theory, a standardized pigment physical property database is established. While the standard KM model assumes a homogeneous semi-opaque layer, we address the multilayer transparency of "three alum and nine dye" by treating each of the 1-8 layers as a discrete scattering-absorbing medium. The KM parameters are utilized here not as a closed-form solution for final rendering, but as high-dimensional physical priors to guide the CGAN in learning the non-linear transparency transitions of overlapping plant and mineral pigments. At the same time, a targeted dataset for simulating Gongbi painting pigments was constructed, which covers image samples of pigments applied separately, stacked in different layers (1-8 layers), and mixed in different proportions (1:1 to 1:5). Each sample is annotated with key information such as pigment type, application layers, mixing ratio, and substrate material, and a total of 10000+original samples were collected. To ensure data quality, these samples were physically painted by professional artists from Xijing University on standardized Shuxuan paper. The samples were then digitized using an Epson Expression 12000XL high-resolution scanner at 600 DPI in a controlled lighting environment to ensure color fidelity. To solve the problem of uneven sample distribution and insufficient quantity, data augmentation techniques such as rotation, flipping, brightness adjustment, and contrast optimization are used to expand the dataset, effectively improving the model's generalization ability and robustness. In addition, strict preprocessing is performed on the expanded dataset, including image normalization, Gaussian noise removal, and semantic segmentation of pigment regions, to accurately extract feature information of pigment regions,

FIGURE 1. Extraction of pigment characteristics and construction of a dataset for Gongbi painting

eliminate irrelevant background interference, and provide high-quality and high-purity input data for subsequent deep learning model training, laying a solid foundation for accurate simulation of pigment materials [6].

B. DESIGN OF VISUAL RENDERING MODULE FOR PIGMENT MATERIALS

Based on the Conditional Generative Adversarial Network (CGAN) as the core foundation (as shown in Figure 2), combined with the simulation requirements of Gongbi painting pigment materials, a targeted simulation model of Gongbi painting pigment materials is constructed. The model adopts a bidirectional adversarial architecture of generator and discriminator, and achieves accurate simulation of pigment materials through dynamic game between the two [7]. The generator part adopts an improved U-Net structure, which introduces a cross layer connection mechanism on the basis of the traditional U-Net encoding decoding architecture, directly associating the shallow detail features in the encoding stage with the deep semantic features in the decoding stage, effectively alleviating the loss of pigment fine texture, color gradient and other detail information in the deep feature extraction process, and improving the model's ability to restore pigment details. At the same time, an additional semantic localization submodule and a color encoding submodule are added to the generator. The semantic localization submodule is equipped with a pre trained semantic segmentation network, which can accurately identify the areas where pigments are applied in the image, distinguish between pigments and rice paper substrates, avoid color overflow, and ensure the accuracy of pigment color localization; The color coding submodule extracts the color feature vectors of the reference image and injects them into the various layers of the generative network to enhance the simulation effect of the model on the gradient and transition colors unique to Gongbi painting pigments, and restore the color changes during the pigment blending process. The discriminator adopts PatchGAN structure, which is different from the global discrimination mode of traditional GAN. This structure can evaluate local areas of the image block by block, accurately capturing subtle texture differences such as pigment particle texture and transparency, further improving the model's accuracy in reproducing pigment materials. In the design of the loss function, a multi loss fusion strategy is adopted to organically combine adversarial loss, L1 loss, and feature loss. Among them, adversarial loss ensures the overall style consistency between the generated image and the real image, L1 loss ensures pixel level alignment between the two, reduces color distortion, and feature loss achieves semantic matching by extracting deep features, comprehensively improving the authenticity and rationality of pigment simulation, and meeting the core requirements of fine brushwork pigment material simulation [8].

C. DESIGN OF VISUAL RENDERING MODULE FOR PIGMENT MATERIALS

Based on the output results of the CGAN pigment material simulation model constructed in the previous text, a targeted visual rendering module for Gongbi painting pigment materials is designed. The core goal is to achieve a realistic visual presentation and convenient interactive display of pigment materials, balancing artistic authenticity and digital practicality, and perfectly matching the coloring characteristics and digital application needs of Gongbi painting. Firstly, by closely integrating the core color setting techniques of "three alum and nine dye" and "thin color multi coating" in Gongbi painting, a dedicated multi-layer overlay rendering algorithm is designed, abandoning the traditional single layer rendering mode. By precisely adjusting the transparency, mixing mode, and color weight of each pigment layer, the dynamic process of pigment layer by layer stacking is simulated, accurately restoring the color gradient and texture changes after stacking different layers (1-8 layers), especially highlighting the heaviness of mineral pigments and the transparency of plant pigments after stacking, accurately reproducing the delicate layers of traditional Gongbi painting color setting, and making the rendering effect highly in line with the color setting texture of traditional Gongbi painting. Secondly, to further enhance the visual realism, a Xuan paper texture simulation mechanism is introduced, combined with a hybrid transport model integrating capillary-driven wicking for initial pigment spread and Fick's law for late-stage particle settling. This provides a computational approximation to simulate the diffusion differences on two substrates: raw Xuan, which exhibits high porosity and strong capillary draw, and Shuxuan, where the alum treatment restricts wicking to localized boundaries. At the same time, it restores the fiber texture details and ink absorption characteristics of Xuan paper itself, eliminates the stiffness of digital rendering, achieves the natural fusion of pigment and Xuan paper substrate, and enhances the realism of visual presentation. Finally, design a concise and efficient interactive interface that supports users to adjust core parameters such as pigment type, application layer, and blending ratio in real time. After parameter adjustment, the simulation effect can be previewed in real time, making it convenient for users to quickly compare rendering differences under different parameters; At the same time, a simulation result export function is added, which supports exporting rendered images to common formats such as PNG and JPG, adapting to various scenarios such as digital creation, virtual display,

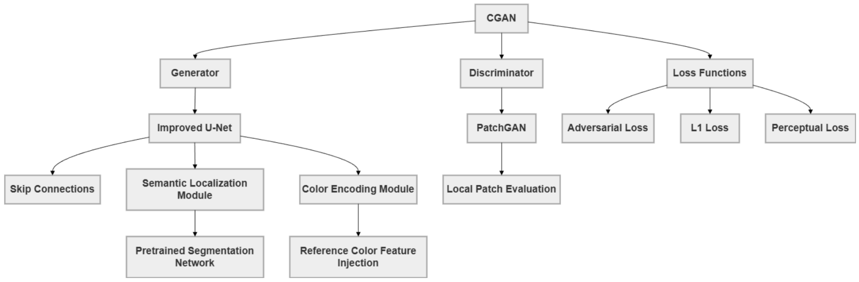

FIGURE 2. Construction of pigment material simulation model

and cultural relic restoration demonstration, fully meeting the practical application needs of different users, making the digital simulation of Gongbi painting pigments more practical and operable, and providing strong support for the digital inheritance and innovation of Gongbi painting.

IV. RESULTS AND DISCUSSION

A. EXPERIMENTAL ENVIRONMENT AND PARAMETER SETTINGS

To ensure a fair performance evaluation, all comparison methods (Traditional Physical Modeling and Ordinary GAN) were implemented using Python 3.8 and executed on the same hardware environment (Intel Core i7-12700H and NVIDIA RTX 3060 GPU) specified in Section 4.1.

The experimental environment is as follows: CPU: Intel Core i7-12700H, GPU: NVIDIA RTX 3060, Memory:

16GB, Operating System: Windows 11, Python, Deep Learning Framework: PyTorch. Model Training Parameter

Settings: Learning Rate: 0.0002, Batch Size: 16, Epoch: 100, Optimizer: Adam, Weight Decay Coefficient:

0.0001. Traditional Physical Modeling Method: The baseline for physical modeling is the multi-flux simulation method based on Kubelka Munk (K-M) theory[9]. This method utilizes a numerical solution to the K-M differential equations to calculate reflectance for pigment layers of varying thickness. Existing Deep Learning Method: The deep learning baseline is the standard Generative Adversarial Network (GAN) architecture for image-to-image translation (Pix2Pix) proposed[10]. This model serves as a representative of general-purpose GANs without the domain-specific semantic localization or color encoding modules introduced in our study. Texture Restoration Accuracy: Accuracy of texture restoration is measured by feature difference between simulated images and real images. Color Overlay Similarity: Color overlay similarity is measured by feature difference between simulated images and real images. Rendering Speed: Rendering speed is based on rendering time of single image.

B. ANALYSIS OF EXPERIMENTAL RESULTS

Figure 3 shows that the deep learning based simulation and visualization model for Gongbi painting pigment materials proposed in this paper is better than comparison method in all indicators. In the aspect of texture restoration accuracy, the model proposed in this paper completed the mineral pigment restoration accuracy reach 92.3%, and the plant pigment was 90.7%. Compared with traditional physical modeling method, the improvement of restoration accuracy is 31.2% and 29.8%, and compared with existing deep learning method, the improvement of restoration accuracy is 28.5% and 27.3%; In the aspect of color overlay similarity, the average similarity of our model is 0.89, while the similarity of traditional physical modeling method is 0.68, and the similarity of existing deep learning method is 0.71. The improvement of our model is very obvious; In the aspect of rendering speed, the average rendering time of a single image in our model is 0.12s, while the average rendering time of traditional physical modeling method is 0.24s, and the average rendering time of existing deep learning method is 0.31s, which is 50% faster than traditional physical modeling method and 61.3% faster than existing deep learning method. Finally, the model in this article is compared with the real gongbi painting pigment, and the result shows that the model in this article can accurately reproduce the graininess of mineral pigment, transparency of plant pigment and blending effect after multiple layers of pigment stacking, which is basically the same as the visual effect of real gongbi painting pigment.

C. RESULT DISCUSSION AND ANALYSIS

The reason why the model in this article can achieve good experimental results is mainly due to three aspects: firstly, the construction of the dataset fully considers the characteristics of Gongbi painting pigments, covering samples of different types, layers, and blending ratios, providing sufficient support for model training; Secondly, the structural design of the CGAN model is reasonable, and the introduction of semantic localization submodules and color coding submodules solves the problems of inaccurate pigment color localization and poor gradient color simulation; Thirdly, the visualization rendering module combines the color setting techniques of Gongbi painting with the characteristics of paper, enhancing the realism of simulation results. At the same time, some problems were also found in the experiment: firstly, the reduction effect of the model on niche pigments needs to be improved, mainly due to the small sample size of such pigments; Secondly, when extreme layers (such as 10 or more) are stacked, there may be slight distortion in the simulation effect, and further optimization of the simulation algorithm for interlayer interaction is needed. In addition,

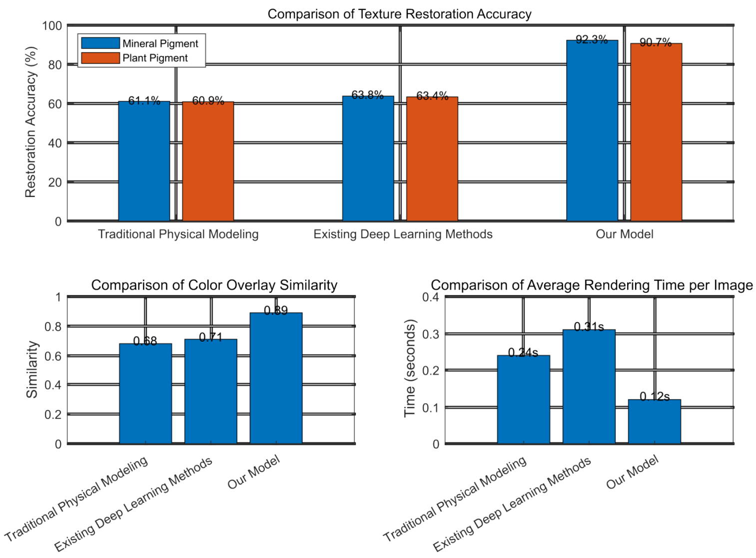

FIGURE 3. experimental results

compared with real meticulous painting creation, the model still lacks the subjective experience integration of the artist's creative process. In the future, it may be considered to introduce style transfer techniques to enhance the artistic expression of simulation results.

V. CONCLUSION

This article focuses on the simulation and visualization of pigment materials in Gongbi painting based on deep learning. In response to the problems of inaccurate pigment material restoration, stiff color overlay effects, and low visualization efficiency in existing technologies, a simulation model that integrates the physical properties of pigments and CGAN is constructed. Three core modules, namely feature extraction, material simulation, and visualization rendering, are designed, and the effectiveness of the model is verified through comparative experiments. The research results show that the model can accurately reproduce the different textures of mineral pigments and plant pigments in Gongbi painting, and truly reproduce the color effects of "thin color multi coating" and "blending gradient". Moreover, it is superior to existing methods in simulation accuracy and rendering speed. This article solves the core problem of digital simulation of Gongbi painting pigments, enriches the research results of traditional painting digitization, and provides reliable technical support for the digital creation of Gongbi painting, virtual restoration of cultural relics, and cultural dissemination. At the same time, there are also shortcomings in this study, and the reduction effect of niche pigments needs to be improved. The simulation accuracy of interlayer interaction can be further optimized. In the future, we will expand the dataset, optimize the model structure, integrate the creative experience of artists, achieve more realistic simulation and visualization of gongbi painting pigments, and promote the digital inheritance and innovation of traditional gongbi painting art.

AUTHOR CONTRIBUTIONS

Jiapeng Li designed, collected and analyzed the data, and drafted the manuscript. Jiapeng Li conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Jiapeng Li participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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