Chinese Painting Synthesis Based on Deep Learning: A Review

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Abstract— **With the development of deep learning, various deep learning techniques have achieved impressive results in various image synthesis tasks. They have become a hot spot in computer vision research due to their impressive performance in various applications. Deep learning of the Chinese painting generation is one of them. This paper introduces the research progress of deep learning in the generation of Chinese paintings in recent years, mainly including the generation of Chinese paintings based on style transfer and the generation of Chinese paintings based on sketches. We analyze and summarize the datasets, methods, and pros and cons used in these applications and give an outlook on the work after the generation of Chinese paintings.**

Index Terms—**Deep learning Chinese painting style transfer sketch to generate Chinese Painting**

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I. INTRODUCTION

Deep learning :Deep Learning is a new research direction in machine learning (ML, Machine Learning) and is a subset of machine learning. Traditional machine learning algorithms rely on artificially designed features and feature extraction, while deep learning methods do not require manual labor but rely on algorithms to extract features automatically. Deep learning imitates how the human brain operates and learns from experience to acquire knowledge. As far as the specific research content is concerned, it mainly involves three types of methods :(1) Neural network system based on convolution operation, namely convolutional neural network (CNN).(2) Auto-encoding neural networks based on multi-layer neurons, including Auto-encoder and Sparse Coding, which have received extensive attention in recent years. (3) Pre-training is performed in a multi-layer self-encoding neural network, and then combined with the discriminant information to further optimize the neural network weights' deep belief network (DBN). With the rapid development of computer software and hardware, at this stage, deep learning is used to simulate the human brain to interpret data, including images, text, audio, and other content. The main application fields of deep learning are smartphones, speech recognition, machine translation, automatic Driving, etc. Of course, deep learning can also be seen in other fields, such as risk control, security, smart retail, medical, recommendation system, etc.

Style transfer: Mainly through the neural network, a style image and an ordinary photo (content image) are subtly merged to form a very interesting picture. The pioneering work is the article published by Gatys et al. in 2015 [1]. This article is the first to use deep learning for art-style learning. A new image is obtained by incorporating the painting style of the style image into the content image. The new image: that is, to keep the original image content of the content image (the content painting is a car, it should still be a car after fusion and cannot become a motorcycle), but also to maintain the unique style of the style image (such as texture, tint, brushstrokes, etc.).

Generative Adversarial Networks [2](GAN) is a deep learning model and one of the most promising methods for unsupervised learning on complex distributions in recent years. The model produces quite good output through (at least) two modules in the framework: the mutual game learning of the Generative Model and the Discriminative Model. The basic principle of GAN is very simple. During the training process, the generation network G Aims to try to generate real pictures to deceive the discriminant network D. The goal of D is to try to separate the pictures generated by G from the real pictures. In this way, G and D constitute a dynamic "game process." The final game's result is: in the most ideal state, G can generate " real " pictures.

II. GENERATING CHINESE PAINTINGS BASED ON STYLE TRANSFER

Wang et al. [3] proposed a novel photo-Chinese painting transfer task that can simultaneously capture high-level information and local foreground. To better delineate the local foreground, this paper introduces a multi-scale self-attention mechanism to select the details scattered in the features of each layer. It also proposes a new large dataset, P2ADataset, which contains unpaired photos and traditional Chinese paintings, for the photo-Chinese painting transfer task.

He et al.[4] proposes ChipGAN and the first weakly supervised deep network architecture to perform photo-to-Chinese ink style transfer, with special consideration given to three fundamental techniques of Chinese ink painting: white space, brushstroke, ink tone, and diffusion. The article introduces the stylized perception research of professional artists, evaluates the stylistic consistency between generated and real paintings, and analyzes the techniques of Chinese ink painters with the help of deep neural networks. The first dataset based on real scenes and images of Chinese ink painting, named ChipPhi, is also established to facilitate training and testing of the

proposed method and follow-up research on Chinese ink painting style transfer.

Sheng et al.[5] proposed a new CPST algorithm, which The algorithm sets four key constraints, that is, special consideration is given to the characteristics of Chinese Painting such as brush strokes, diffuse ink color, space retention, and yellowing, paving the way for the automatic conversion of Chinese Painting. In addition, different strategies are proposed to make the generated Chinese paintings transfer not only ink tones but also painting techniques. The CPST algorithm performs better in various Chinese paintings than other algorithms.

Zhang et al.[6] proposed a framework CycleGAN-AdaIN for image translation from real photos to ink paintings using CycleGAN One loop (X2Y2X) instead of two loops (X2Y2X + Y2X2Y). Compared with the baseline model, the method not only preserves the content of the generated images better but also saves a lot of training time. The method also designs an additional AdaIN module for learning the style information of ink painting. Adding this element before the generator's decoding process not only preserves the spatial structure of the generated image while preserving its content but also produces a more realistic ink spread. To correct the details of the generated images, the cycle consistency loss and MS-SSIM loss are combined with strengthening the constraints on the generative network, resulting in more realistic and natural ink paintings.

Li et al.[7] proposed an MXDoG Filter to abstract the image's content and used it to convey the style of traditional Chinese Painting. We propose three MXDoG-based loss terms to guide the neural network on how to "abstract" and demonstrate its effect on test images under different conditions. In this way, we also verify that the representations of "abstract content," "content," and "style" of an image can be separated by a neural network. A new database of traditional Chinese paintings is collected to facilitate research on the transformation of traditional Chinese painting styles.

Luo et al.[8] proposed a multimodal fusion framework and system to generate traditional Chinese paintings. The article selects appropriate existing networks for the different elements generated in this oldest art tradition and finally fuses these networks and elements to create a whole new painting. Meanwhile, a divide-and-conquer strategy is also proposed to generate large images with limited GPU resources. Our end-to-end system automatically turns a large image into a traditional Chinese painting within minutes. The results show that the multimodal fusion framework works well, and the artificial intelligence method performs well in creating Chinese paintings.

III. CHINESE PAINTING GENERATION BASED ON THE SKETCH

Zhou et al.[9] proposed an interactive generation system based on the GAN idea, which uses the user's simple sketch input to generate Chinese landscape painting documents. A dataset of Chinese landscape documents, including the sketch and painting domains, is collected and organized. Experiments show that the generated Chinese landscape painting files are of high quality.

Wang et al.[10] implemented different generative adversarial networks (GAN) such as cGAN, DCGAN, and WGAN and modified WGAN on its Chinese painting dataset to recover original paintings from edge maps and generate realistic paintings. The article also compares the generation results of different GANs. By comparison, it is found that WGAN and the modified WGAN are more stable and can produce higher-quality images. In particular, the improved WGAN performs well in solving the mode collapse problem.

Yang et al.[11] propose a new photo-guided painting tool that can easily generate the most popular Chinese Painting by stylizing rough sketch lines on photo images. Artistic strokes in a representative flower painting style. While existing style transfer methods aim to process whole images, this method describes a stroke-based stylization framework to perform detailed style features better and capture user intent. The steps in the technique are first to correct the user's inaccurate strokes, to mark the candidates for the style patterns on the Painting and skeletal paths on the photo, then to select the best pattern for each skeletal stroke, and finally to combine the patterns through shape calculation and texture synthesis. They are mapped to bone strokes. This tool is tolerant of errors from user input and works on touch devices. Experiments have shown that the technique helps the general user generate paintings close to the specified style and aesthetic satisfaction.

Xue et al.[12] propose Sketch-Paint GAN, the first end-to-end framework capable of producing high-quality Chinese paintings with understandable, edge-defined landscapes. The article also launched a new database of 2,192 high-quality traditional Chinese landscape paintings specially curated by art museums. In the experimental evaluation phase, the article presents an experiment of a 242-person visual Turing test study. The results showed that the artwork generated by the model was considered human-created with more than half the probability.

Fu et al.[13] proposed a Flowers-GAN framework to generate Chinese art paintings of flowers in multiple styles. This model provides an effective solution for developing floral styles in traditional Chinese art paintings. A new loss function, MSSSIM loss, is introduced in the Flower-GAN system. A multi-scale comparison of the distance between the source image and the reconstructed image is performed from three metrics: brightness, contrast, and structure. Combining style and content consistency with cycle consistency loss can accurately generate style consistency and content consistency, which solves the problem of poor results in previous methods. The paper also builds the first unpaired flower dataset that includes three classic traditional painting styles: line drawing, fine brushwork, and ink wash.

Lin et al.[14] proposed a deep generative adversarial network to create surprising Chinese paintings by inputting simple sketches. It can train both generative and discriminative models using multi-scale images, setting both models as fully convolutional networks. By adding an edge detector, the generative model can also be viewed as a neural style transfer method. The proposed method is also effective for other image-to-image translation problems, such as image colorization and super-resolution.

IV. CONCLUSION

In recent years, deep learning has proven to be one of the most powerful tools in artificial intelligence and is starting to change our lives. In computer vision, deep learning has been widely used in face recognition, street view image recognition, image retrieval and other fields. Another interesting discussion in deep learning today is how it might affect and shape our future cultural and artistic production. However, the generation of artworks is challenging, especially for Chinese paintings. As a special art category, Chinese Painting has unique painting characteristics and requires a high threshold for drawing. Therefore, using deep learning to realize the generation of Chinese Painting can allow more and more people to feel the charm of Chinese Painting, which is more powerful than Chinese Painting—the promotion of digital protection.

V. REFERENCES

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