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Application and Research Analysis of Image Style Transfer Based on Neural Networks

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Abstract. Style transfer, as a key branch in the field of computer vision, is rapidly developing in various fields such as art creation and film and television. This article summarizes the image style transfer methods based on neural networks in recent years, and divides them into two types: GAN and diffusion models based on network structure. The variations of these methods with different structures are compared and analyzed, and the main characteristics of each category method and the suitable image categories for processing are summarized. Then, based on the application of style transfer in several commonly used fields, case studies were presented to demonstrate its value. Finally, challenges were identified from the perspectives of fidelity, cost, and ethical and legal aspects of style transfer, and corresponding solutions and research directions for the future were proposed. This article provides a comprehensive analysis of the development and application of image style transfer, hoping to provide research directions for researchers in related fields.

1 Introduction

Nowadays, with the rapid development of deep learning in the field of computer vision, image style transfer technology has become a hot topic. The concept of image style transfer technology is to collect the style of one image and apply it to another image, so that the other image has different style effects based on the original image content. Early image style transfer began with research on texture synthesis, mainly through the use of filter operations or statistical feature matching methods to achieve style replacement. However, the style transfer effect of these methods is relatively limited; After the proposal of neural style transfer in 2015, this innovative achievement quickly promoted the development of image style transfer based on neural networks.

In recent years, many researchers have done different types of work; Zhang et al. considered the role of adaptive instance normalization in style control. They first considered giving each input image a specific optimization objective, then setting dynamic cross channel correlations, and finally combining them with activation functions as feature selectors. This study used the three different optimization methods mentioned above to improve more accurate control of global style. The experimental results show that adaptive style modulation can effectively solve the problem of style mixing, and has a good effect on artistic style

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transfer [1]. Yang et al. proposed a residual adversarial network model to address the issue of partial loss of content and style information, which is mainly caused by pixel level convolution in current style transfer. After combining the structure of multi-layer residual links, the front-end information of the network can be effectively combined with the deep level structure. The innovation of this model lies in introducing a new loss function and updating the optimized decoder parameters; Overcoming the difficulty of losing some information in traditional methods [2]. At the same time, style transfer has a wide range of applications in real life. In the context of ink wash animation creation, He et al. analyzed different main features such as color, structure, and ink halo, and used a combination of two neural networks, image generation network and loss function network, to study the preservation of original features and semantic information by passing the content map through the conv2-2 layer of the VGG19 model. In this way, the edge contours of the processed image objects are richer and more suitable for the line features of ink wash painting [3]. Huang proposed an improved CycleGAN model, which introduces self attention mechanism and adds an auxiliary classifier module on the basis of the original model to help the model improve the capture of facial features, thereby making the generated anime face images more realistic and delicate, greatly improving the style transfer effect in facial morphology images [4].

This article focuses on the development and application of neural networks in image style transfer. Firstly, it summarizes the current mainstream method variants and analyzes their characteristics. Then, it summarizes the main applications of image style transfer in different fields. Finally, it proposes the current limitations and future development directions, hoping to provide some future research directions for researchers in the field of image style transfer.

2 Overview of Style Transfer Methods Based on Different Network Structures

2.1 Style transfer based on GAN

At present, many researchers have made different improvements and optimizations to models based on GAN style transfer, which can be roughly divided into CycleGAN model, StyleGAN model, Pix2Pix and other main methods

CycleGAN, as an unsupervised learning method, can achieve transformation without paired data. However, CycleGAN also has some shortcomings, such as unnatural texture transfer or background distortion in some complex images. Currently, the main research on this issue tends to use the Convolutional Block Attention Module module to integrate it, because this module can assign different weights to different regions of the image according to the needs of attention, which greatly improves the global perception ability of the model. At present, the convenient and fast advantages of CycleGAN are also widely used by researchers [5].

The StyleGAN method has the characteristic of not relying on a large amount of data, but it also requires more balanced training; For example, transfer learning and other methods can be used to train StyleGAN models based on attention mechanisms. Figure 1 shows one of the improved structures. When the model no longer uses transform encoding blocks and instead uses residual modules, it can generate high-quality stylized images while training with minimal data. Compared to the CycleGAN model, this model has extremely high controllability and can accurately control the details and attributes of images, making it more suitable for generating faces or game characters [6].

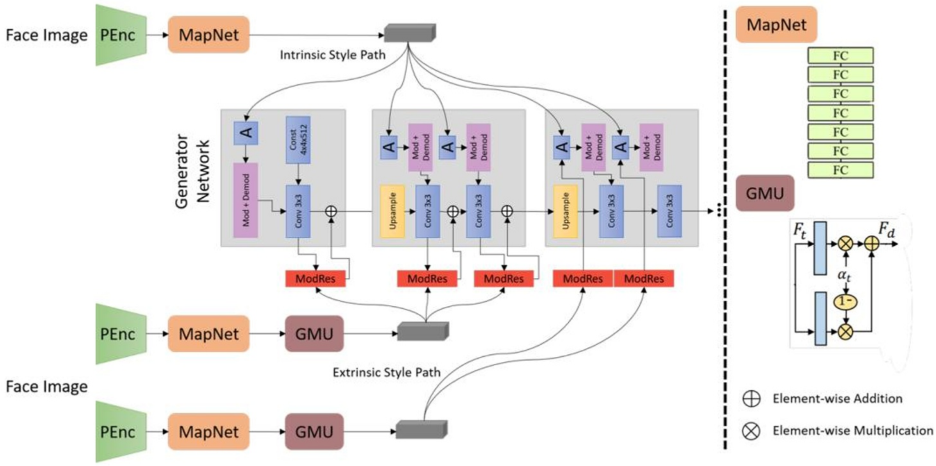

Fig. 1. StyleGAN model network structure based on attention mechanism [6]

2.2 Style transfer based on Diffusion

Compared to traditional GAN models, diffusion models can better balance style transfer and semantic consistency, meaning that there will be no excessive transfer that leads to images being too artistic or insufficient transfer, and only simple changes in color and approximate shape. Researchers have used diffusion models to combine pre trained LDM with LoRA models, controlling initial noise and redrawing details to achieve stable and high-quality style conversion. This has enabled cartoon style conversion in a real-world 3D scene, providing researchers with a new perspective. Figure 2 shows a method design based on diffusion models [7].

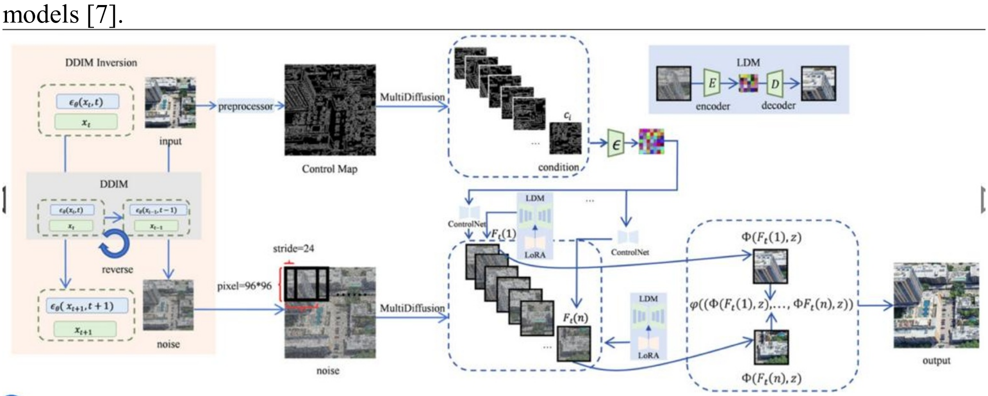

Fig. 2. Design of diffusion model method combining LDM and LoRA model [7]

Although diffusion models can generate more stable and high-quality style images compared to GAN models, they also sacrifice some training speed. Due to the multi-step denoising process of diffusion models, the training time is longer, and the computational resources of diffusion models have higher requirements compared to GAN models. The complex process requires a large amount of GPU computing, so when facing different needs, the choice can be made according to the characteristics of the two main models.

3 The application of image style transfer in different fields

3.1 The field of film and television

Image style is widely used in fields such as film and animation production. Nowadays, many animation studios have begun to use style transfer techniques to achieve the fusion of traditional animation and different styles, such as anime, cyberpunk, retro, etc; And apply different styles according to different levels. For example, if you want to create a style full of futuristic design, you can apply realistic style to the characters in the animation, then apply neon style to the background in the animation, and finally apply some fault art style to the special effects layer. Such rendering time usually only needs a few hours to complete [8].

3.2 Personalized design for e-commerce

With the rapid development of the internet, e-commerce platforms have also begun to use style transfer models in their designs, such as placing style elements that different consumer groups like on corresponding product images for style conversion, and then designing and mass producing the converted images to achieve the expected results. In addition to style transfer for basic products, there are also customization tasks such as avatar customization. For example, the SD Art system achieved a user satisfaction rate of 94.7% in the avatar customization task, with an average monthly user monetization of 1200 yuan during the platform's trial operation stage, verifying the feasibility of style transfer in e-commerce monetization.

3.3 Medical impact field

Style transfer also has different applications in the medical field. For example, in processing virtual staining of pathological images, Zhang et al. used generative adversarial networks to accurately locate the structure of cells and tissues by capturing long-distance pixel dependencies, solving the problem of deviation from position or loss of speech information in staining. At the same time, they integrated multi-scale structures to process both fine cell textures and overall cell structures. This collaborative processing method makes the generated stained images more realistic than traditional chemical staining and even some medical image synthesis methods [9].

4 Challenge and Limitations Analysis

4.1 Challenge

The main challenges faced by image style transfer can be divided into the following points. Firstly, disrupting the inherent consistency of the content source will reduce the fidelity of the content and make it different from stylization. Some details of the image, such as facial expressions or partial hair, are prone to disappear during the conversion process [10]. Secondly, although the effect of style transfer has been improved by combining transformer and diffusion models, the computational cost is usually relatively high, requiring more memory and time, which limits the use of scenarios and makes it difficult to ensure high efficiency. Finally, as there is currently no clear legal guarantee, there may be issues of infringement and data abuse when some artworks are created or converted by AI.

4.2 Prospect

In the face of the different challenges mentioned above, there may be further research directions or solutions in the future. For the problem of low fidelity, priority can be given to combining attention mechanisms to enhance the ability to process details, allowing content and style to be independently distinguished and transformed. In response to the current issues of high costs and slow processing times, a unified universal model can be explored in the future, using architectures such as state space models to attempt to reduce computational complexity. In response to issues of data abuse and art infringement, more comprehensive laws can be formulated in the future, while developing more secure image protection technologies to ensure that copyrighted works are not easily stylized.

5 Conclusion

This article summarizes the recent development and technical applications of neural networks in image style transfer. Firstly, based on different network structures, it is mainly divided into two mainstream methods: GAN and diffusion model. After analyzing some different variant methods, it is found that diffusion model can generate higher quality images, but it also occupies more computing resources. Subsequently, in Chapter 3, the application of current style transfer in different fields was organized and relevant cases were listed for analysis, mainly focusing on film and television creation, e-commerce product design, and medical imaging. Finally, the main existing problems and future research directions are proposed. This article aims to provide relevant researchers with different research directions for more in-depth study.

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