A Comprehensive Study of Art Image Style Transfer Methods Based on Generative Adversarial Networks

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Abstract: Image style transfer is a cutting-edge technique that seamlessly merges one image's content with another's distinct style. The rapid progress of deep learning has led to significant advancements in image style transfer technology. Nevertheless, this technology still encounters several issues, such as the inability to attain the optimal expression effect of artistic attributes, and the mismatch between semantic and style characteristics. Based on the generative adversarial network (GAN), this paper examines the improved algorithmic applications of image style transfer technology in ink painting, animation, and oil painting. Additionally, using quantification and comparative analysis of the outcomes of the improved style transfer algorithm applied in diverse art forms, Foreseen are the obstacles to be tackled and the expected development path of image style transfer technology in the future. The application of image style transfer technology in the domain of art still demands more efficient algorithms and more artistic outputs. This study focuses on summarizing popular algorithms in image style transfer technology and driving forward innovation in style transfer techniques.

1 INTRODUCTION

Image style transfer constitutes a deep learning technique, it can transfer the style of one image to another, thereby generating a new image. In recent years, image style transfer has been extensively applied across various fields. In the transportation sector, Lin has proposed day-night style transmission for detection purposes of vehicles during the night, to reduce the incidence of car accidents (Lin, Huang, and Wu, et al, 2021). In medicine, Yin improves medical image accuracy through a context-aware framework (Xu and Li, 2020). Lv adds to the authenticity of blood vessel image generation through the application of deepnet (Tmenova, Martin, and Duong, 2019). In art, migrating imagery is used more frequently. By incorporating the Cantonese dialect into the creation of porcelain patterns, the Cantonese porcelain culture can be preserved and passed on (Chen, Cui, Tan, et al., 2020).

Painting is an ancient form of artistic expression. The most common way to create paintings with different styles is Generative Adversarial Network (GAN). Chinese Ink Painting with rice paper and ink. They integrate and intermingle, creating a sense of depth. Anime uses simple strokes to create images. Oil paintings have rich colors and strong three-dimensional texture. Most experiments on style transfer employ GAN to generate new images. Nevertheless, as time goes by, the majority of basic GANs to doing things fail to satisfy people's requirements for generating images. There are many problems arising: differences in skills and styles between ink painting and Western painting contribute to style transfer in ink painting's suboptimal performance. When transferring animation styles, there exist problems regarding anime image feature texture is missing and the generated image quality is not good. When transferring oil painting styles, there

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are often issues with image local minutiae are missing and style area and content do not match.

To address these issues, several new models have emerged. The purpose of this article is to discuss some new GAN-based model for use in various types of paintings and introduce their advantages and disadvantages. The aim is to provide some basis for the subsequent research on style transfer in paintings.

2 METHOD

In this section, the application of image style transfer technology in the field of art will be elaborated, focusing on three main categories: ink painting, animation, and oil painting.

2.1 The Overview of GAN

GAN, which stands for Generative Adversarial Network, is a type of deep learning model comprised of two primary components: the generator and the discriminator. As illustrated in Figure 1, the generator G takes random noise Z as input and produces an image G(z), while x represents the input image. The discriminator D assesses whether x is a real image and outputs D(x) as the probability of its authenticity. A probability closer to 1 indicates higher authenticity of the image; conversely, a probability closer to 0 suggests lower authenticity. The objective of G is to generate images that are highly realistic to deceive D, while D strives to differentiate real photos accurately. They engage in a mutual game to enhance their respective discriminative capabilities.

2.2 Ink Painting

Due to the significant differences between Chinese ink painting and Western painting techniques, the direct application of existing image style conversion methods is ineffective. Hu improved on the existing ChipGAN model to promote the standard and white space effect related to the generated image, replacing the ResNet residual network in the generator with a residual dense network (RDN), which enables the network to reuse shallow features of the image and to extract more feature information by combining shallow and deep features (Hu, 2023). The PatchGAN discriminator is substituted with a multi-scale discriminator to enhance the discriminative ability of images at different scales. The white space loss is added based on the original loss function, the image background is processed by threshold segmentation, and the background white space is constrained using the L1 loss and the SSIM loss to generate an image that is more in line with the ink style.

2.3 Animation

To solve the previous problem of imperfect style migration of anime images, derived from edge improvement and coordinated attention Hong et al. proposed an animation translation method, called FAEC-GAN, to help complete the task of migrating from real photos to anime faces (Lin, Xu, Liu, 2023). Firstly, they introduced an edge discriminative network consisting of an edge detection module and an edge discriminator. The edge detection module obtains edge information from the image and sends it

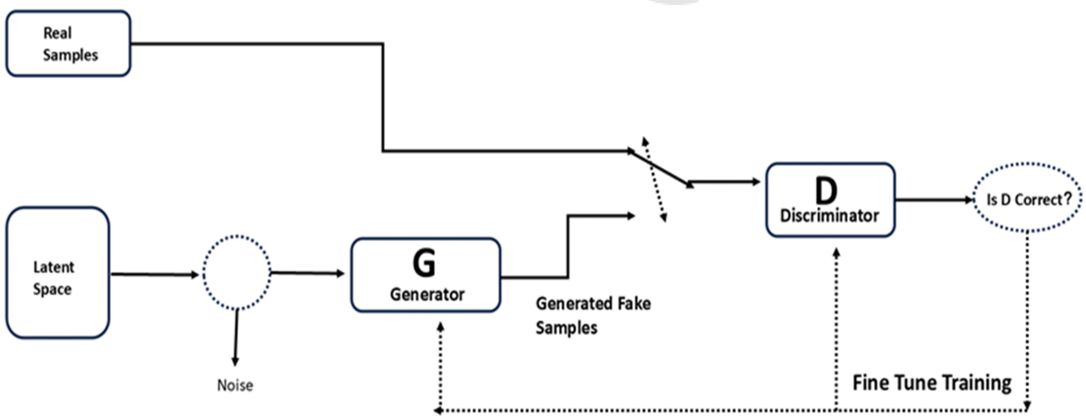

Figure 1: The structure of GAN (Photo/Picture credit: Original).

to the edge discriminator for evaluation. Next, they designed a novel loss function that measures the image discrepancy between the focusing frequency loss and the spatial loss (Lin, Xu, Liu, 2023).
Zhao proposed a new image canonisation architecture that extracts anime image features independently, making it controllable and scalable in practical applications (Zhao, Zhu, Huang, et al., 2024). The architecture is a GAN model based on multiple decompositions. The image features generated by the generator network training are decomposed and extracted, and the texture module takes the extracted texture and trains the image using a discriminator to create textures with more cartoon image features. Such a structural module uses the pre-trained network to efficiently extract image structural features and preserve image content information (Zhao, Zhu, Huang, et al., 2024).

Li proposed an improved GAN-based style migration algorithm for anime images (Li, Zhu, Liu, et al., 2023). Firstly, the improved inverted residual block and the efficient attention mechanism are used to form a feature transformation module, which enriches the local feature attributes of the migrated image and improves the expression ability of style features; secondly, the style loss function is improved to suppress the interference of colour and luminance on texture learning. Experiments reveal that the introduced algorithm excels in producing images with superior quality and enhanced visual realism (Li, Zhu, Liu, et al., 2023).

2.4 Oil Painting

To solve the detail loss and blurring that appears locally in the generated oil painting images problem, Han proposed a multi-feature extractor to perform style transfer of shape, texture, color, and space in oil painting (Han X, Wu Y, and Wan R, 2023). The extractor contains U-net, MiDas, texture extraction network, and chromatic histogram. Meanwhile, the autoencoder structure is employed as the main framework for feature extraction. After identifying the input and style images, DE-GAN is trained using the model architecture, generating a network that shares style parameters with the feature extraction module. Finally, implement the generation of realistic photos in the oil painting style (Han, Wu, and Wan, 2023).

To address the challenges of generating and reconstructing image details in oil painting, Liu proposed a method that combines the LBP algorithm with an improved loss function (Liu, 2021). Liu initially applied the Wasserstein metric to the GAN's objective function to enhance training stability(Liu, 2021). Then add gradient penalty to loss function (WGAN-GP), it can deal with gradient vanishing during training. By incorporating noise control in the CycleGAN loss function, boundary details and surface patterns are enhanced after oil painting style transfer, along with the addition of LBP structural features and total variation.

3 RESEARCH

3.1 Quantitative Results of Ink Painting Experiments

Hu's experiments found that the ChipGAN model, which incorporates a residual dense network and introduces a multi-scale discriminator, can largely improve the quality of the generated images (Hu, 2023). The quality of an image is assessed by quantitatively analyzing the image using Peak Signal Noise Ratio (PSNR), Structural Similarity (SSIM), Frechette's Distance (FID), and Cosine Similarity (CosSim) as metrics (Hu, 2023). PSNR is used to measure the generation quality of an image, and the higher its value, the closer the style-migrated image is to the original content, maximizing the retention of content information. FID is used to compute the similarity between two images in terms of feature vectors, the smaller its value, the more similar it represents the distribution of the generated image and the real image in space. CosSim is used to measure the pixel-wise similarity of two images, with higher values indicating a smaller angle between the two vectors represented by the image features and a higher degree of similarity. SSIM is a measure of the structural similarity of the two images, where higher values indicate that the reconstructed image is more similar to the original image in terms of brightness, contrast, and structural inverse.

Hu uses four methods, method 1 is ChipGAN, method 2 is ChipGAN based on RDN, method 3 is ChipGAN using a multi-scale discriminator, and method 4 is ChipGAN based on RDN and multi-scale discriminator. Among them, method 1 is for the ChipGAN model without any improvement, which is a variant of GAN. The basic principles include: generative network generates IC layout according to the input design parameters; discriminative network accepts the generated layout and the real layout and outputs the true-false discriminative results; optimizing the generative network and discriminative network through adversarial training, so that the quality of the generated layout is continuously improved, and at the same time, the discriminative ability of the discriminative network is improved. Finally, the quality of the generated plates is gradually improved by optimizing the loss function. For method 2, ChipGAN based on RDN is combined with the basic principle that the generative network utilizes a deep convolutional neural network, which, integrated with the architecture of RDN, can enhance the multilevel feature extraction capability to generate accurate and high-quality plat maps. For method 3, which introduces a multi-scale discriminator, the basic principle is that the generated IC layout is evaluated for multi-level and multi-scale fidelity, and combined with the adversarial training of the GAN, the generative network is continuously optimized to generate a layout that is realistic at different scales, to achieve automatic generation of IC layouts with higher accuracy and quality. For method 4, both combines RDN and multiscale discriminators. For the performance comparison of these four methods (Hu, 2023), as shown in Table 1, it can be concluded that the SSIM, PSNR, and CosSim are greater than the base ChipGAN model when RDN or multiscale discriminator is introduced alone. The reconstructed image is closer to the original image in terms of brightness, contrast, and structure, and the generated image is of higher quality, with less difference from the original one and higher similarity of image or text features. At the same time, the FID is all lower than the base ChipGAN model, representing a closer distribution of the generated image to the real image in the feature space. The performance data is further improved by combining both residual dense networks and multi-scale discriminators (Hu 2023). Hu's experimental results demonstrate that the ink-style images generated by the improved model have significant improvement in both visual quality and white space effect (Hu, 2023). As in Figure 2, it can be seen from the examples of apples, flowers, and fish that the ink-style images generated by the improved model have significant improvement in visual quality and white space effect, and have good generalization ability on different datasets.

Table 1: Comparison of different model performance

Evaluation metrics	Method 1	Method 2	Method 3	Method 4
SSIM	0.8064	0.8127	0.8092	0.8191
PSNR	13.9860	14.5329	14.2367	14.7879
FID	172.44	167.04	166.95	165.62
CosSim	0.9733	0.9825	0.9785	0.9841

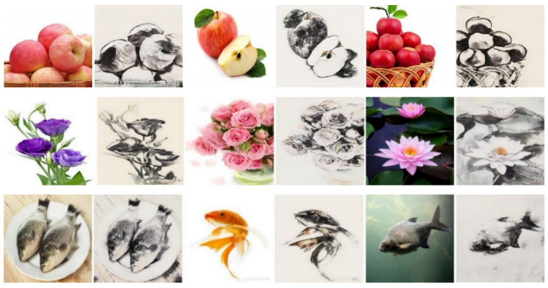

Figure 2: Examples of apples, flowers, and fish in the improved model of image generation representation (Hu, 2023)

3.2 The Result of Animation

3.2.1 FAEC-GAN

LIN used two datasets, self2anime, and ce2anime, to propose the FAEC-GAN method, a style migration method based on edge enhancement and coordinated attention mechanisms (Lin, Xu, Liu, 2023).

To validate the FAEC-GAN model's effectiveness, LIN used FID and KID measures in the experiments. On self2anime, FAEC-GAN reduced FID by 1.95 and KID by 0.37 compared to the best-performing ACL-GAN in the baseline (Lin, Xu, Liu, 2023). On the ce2anime dataset, FAEC-GAN reduces FID by 3.03 and KID by 0.61 compared to SpatchGAN. By delivering top results on several datasets, FAEC-GAN proves its capacity to learn from different data distributions and generate highly realistic anime faces. In addition, the method achieved the lowest scores on both evaluation metrics, which further demonstrates that FAEC-GAN performs very well regardless of which metric is used.

Table 2: Comparison of six methods for FID and KID under two datasets (Lin, Xu, Liu, 2023)

Model \ Dataset	Self2anime		Ce2anime	
	FID	KID*100	FID	KID*100
FAEC-GAN	92.92	2.91	60.28	2.71
Cycle-GAN	114.54	3.80	70.90	3.67
U-GAT-IT	105.78	3.93	68.28	3.21
NICE-GAN	112.62	5.41	68.04	3.61
ACL-GAN	94.87	3.28	63.69	2.81
SpatchGAN	98.78	3.71	63.31	3.32

3.2.2 GAN Expansion of Animation 1

Zhao proposed a GAN-based method to combine the features used in the generator for extracting deep networks with the attention mechanism, and in terms of content, real-world photographs were used as test data. Stylistically, cartoon images from the films of

Table 3: Uses FID to assess the similarity between real and synthetic anime images and the stability of different styles of results relative to baseline results (Zhao, Zhu, Huang, et al., 2024).

Methods	Photo	CycleGAN	CartoonGAN	GDWCT	(Zhao, 2024)
FID to cartoon	165. 70	140. 37	145. 21	136. 21	110. 39
FID to photo	N/A	121. 11	86. 48	100. 29	35. 79
Methods	Photo	Hayao Style	Paprika style	ShinkaiStyle	(Zhao, 2024)
FID to cartoon	165. 70	127. 35	127. 05	129. 52	110. 39
FID to photo	N/A	86. 48	118. 56	37. 96	35. 79

two directors, Hayao Miyazaki and Makoto Shinkai, are used respectively, and the proposed method is compared with Cycle GAN, CartoonGAN, and GDWCT (Zhao, Zhu, Huang, et al., 2024).

To find the differences between the methods more precisely, Zhao employed FID to assess the similarity between authentic and generated anime images, as well as the consistency of results across various styles compared to the baseline. As in Table 3, Zhao's methods all have minimum errors (Zhao, Zhu, Huang, et al., 2024).

To compare the visual quality of the images generated by each method more objectively, TABLE 4 shows the percentage of each method selected as the best method, with higher percentages indicating more popularity, which is used to assess the visual quality of the images.

Table 4: Percentage of the four methods selected as the best method under different styles (Zhao, Zhu, Huang, et al., 2024).

Methods	Hayaostyle	Paprika style	Shinkai style
CycleGAN	16.20%	7.37%	15.24%
CartoonGAN	32.40%	39.69%	40.36%
GDWCT	10.88%	3.1%	2.3%
(Zhao, 2024)	40.50%	49.84%	49.84%

3.2.3 GAN Expansion of Animation 2

The content image set selected for Li's experiments is from real images on the Flickr website, and the style image set is from four sets of anime film frames produced by Hayao Miyazaki and Makoto Shinkai (Li, Zhu, Li, et al., 2023). The improved method uses a channel blending operation combined with a modified inverted residual block to form a feature transformation module to enhance the local feature attributes of the images, and in the meanwhile, invokes an efficient attention mechanism to further improve the stylistic feature expression capability.

Li combined the proposed algorithm with three algorithms, Cycle GAN, CartoonGAN, and AnimeGAN, to perform anime style migration on two content images in the test set (Li, Zhu, Li, et al., 2023). According to the experimental results, the CycleGAN algorithm generates over-stylized images loses the semantic content of the input images, and cannot accurately determine the object information. CartoonGAN algorithm generates anime images with green artifacts and more distortions in the level of detail; at the same time, it loses the color information of the original images due to the lack of constraints of the color loss function. AnimeGAN algorithm still has image details on local areas, but it is not possible to determine the object information accurately. local area still exists image content detail loss and point artifacts, and there is a problem of structural adhesion for the portrayal of the distant region. Li's proposed algorithm incorporates an enhanced inverted residual block within the feature transformation module, which focuses on emphasizing local image details while effectively maintaining global information through feature reuse and fusion techniques (Li, Zhu, Li, et al., 2023). At the same time, an efficient attention mechanism is introduced to help the model better focus on the stylistic feature information in anime images. In the style loss function part, the color and luminance information of the image is erased, so that the generated image presents obvious anime texture and avoids color shifting.

Table 5: Stylistic and Semantic FIDs of Images Generated by Different Algorithms (Li, Zhu, Li, et al., 2023)

algorithm	Hayao style		Shinkai style	
	Style FID	Semantic FID	Style FID	Semantic FID
original	179. 16	—	135. 81	—
CycleGAN	123. 03	163. 55	106. 61	107. 32
CartoonGAN	157. 72	90. 64	114. 38	79. 58
AnimeGAN	160. 90	89. 12	116. 72	87. 73
(Li, 2023)	154. 61	71. 97	115. 64	63. 48

Li also computes the FID scores for images produced by various algorithms on the test set. This helps assess how closely the generated images match the content of the content image and the style of the style image. Separate FID scores are calculated for content and style (Li, Zhu, Li, et al., 2023).

As shown in Table 5, the initial values of the style FID of the original image are 179. 16 and 135. 81, and the style FID values of their proposed algorithm are second only to the CycleGAN algorithm and CartoonGAN algorithm in Miyazaki and Makoto Shinkai styles, whereas there is a significant decrease in the semantic FID values, which reaches 71. 97 and 63. 48. The CycleGAN algorithm, compared with the others, has the style FID score the lowest, this is because the CycleGAN algorithm only matches the stylistic information of the target image and ignores the semantic information of the original image, so the generated image produces semantic distortion (Li, Zhu, Li, et al., 2023).

3.3 Oil Paintiong

3.3.1 DE-GAN

Han and three others proposed DE-GAN, 1. a style transfer scheme based on GAN, capable of deeply extracting the artistic style from artistic works to target image (Han, Wu, and Wan, 2023). For verifying the efficacy of this approach, four indicators are used for a single picture as an evaluation criterion. There are feature similarity index (FSIM), mean SSIM index (MSSIM), image average gradient, and average reasoning time. SSIM ranges from 0 to 1, where larger scores signify greater image similarity (Han, Wu, and Wan, 2023). FSIM is an extension of SSIM, its evaluation system is similar to SSIM. MSSIM is the greater the average gradient of the image, the sharper the image, and the better the texture details. According to this indicator, DE-GAN was compared with StyleGAN and CycleGAN. StyleGAN is a GAN-based model that uses style to influence the face and body shape in the generated images. CycleGAN is a model based on GAN that can transform photos into oil painting styles. The comparison results of these three methods are shown in Table 6.

Table 6: Evaluation and comparison of different models (Han, Wu, and Wan, 2023)

Methods	StyleGAN	CycleGAN	DE-GAN
FSIM1	0. 72	0. 68	0. 74
FSIM2	0. 62	0. 60	0. 64
FSIM3	0. 64	0. 62	0. 66
MSSIM1	0. 52	0. 52	0. 54
MSSIM2	0. 48	0. 51	0. 53
MSSIM3	0. 50	0. 52	0. 53
averagegradient1	0. 31	0. 23	0. 41
average gradient2	0. 45	0. 41	0. 52
average gradient3	0. 52	0. 58	0. 63
Average Reasoning Time for a Single Picture (ms)	15. 64	26. 78	42. 63

These three methods can all effectively transfer the painting style. However, it is clear from Table 6 that the migration images obtained by DE-GAN all show small improvements in FSIM, MSSIM, and average gradient. From this, it may draw such conclusion, that the artistic images generated by this method have better performance in structural features, image distortion, image clarity, and texture detail compared to others. This method is inferior to StyleGAN and CycleGAN in speed.

3.3.2 Expansion of WGAN-GP

Liu proposed an Improved GAN for gradient punishment to solve the difficulty of algorithm training high, and the loss gradient of the generator and discriminator disappears in the transfer of oil painting style (Liu, 2021). WGAN-GP is a model that uses Deep Convolutional Neural Network architecture. It can solve the problem of loss gradient disappearance of the generator and the discriminator is difficult to train. This method is to transform a model based on WGAN. To further assess the efficacy of this approach., Contrast, SSIM, Entropy, PSNR, MSE, and speed were used for evaluation. Contrast and Entropy are two important indicators for measuring image information in style transfer. MSE is employed to evaluate the disparity between the generated output and the target picture. Speed can be seen as the algorithm efficiency. Liu uses CycleGAN + L1 regularization and CycleGAN to evaluate these six indicators using this method (Liu, 2021). WGAN-GP was only compared with this speed method. The image quality of CycleGAN can be further improved by CycleGAN + L1 regularization. A comparison of these four methods is shown in Table 7.

Table 7: Performance comparison of different methods

Methods	CycleGAN	CycleGAN+L1	(Liu Y, 2021)	WGAN-GP
Contrast	28374.4	28736.2	29, 215. 9	
SSIM	0.223	0.129	0. 251	
Entropy	5.839	6.411	7. 216	
PSNR	11.553	12.187	12. 638	
MSE	3826.8	3769.6	3544. 7	
Speed (Landscape 1)	2837.38s	2736.46 s	2637. 33 s	1384. 32 s
Speed (Landscape 2)	2365.32s	2645.56 s	2736. 73 s	1463. 23 s
Speed (Landscape 3)	3026.83s	2937.73 s	3173. 78 s	1183. 28 s
Speed (Landscape 4)	2653.43s	2736.82 s	2557. 38 s	1583. 41 s

In Table 7, most of the indicators of this approach are better than CycleGAN + L1 regularization and CycleGAN. This suggests that the visual quality of this approach surpasses other methods and offers higher practicality. In terms of efficiency, Original WGAN-GP is more efficient than CycleGAN. The results of time complexity for all are similar. Therefore, to improve the speed of operation of the law becomes a new problem.

4 CONCLUSIONS

Image style migration, as an emerging image processing technique, has been widely used in several fields This paper provides an overview of GAN-based art image style translation techniques in three art types: ink painting, animation, and oil painting, and focuses on highlighting the significance of the application, research implications and results of these improved new models, as well as the advantages over existing techniques.

In terms of ink painting, due to the special characteristics of the style, such as white space and other features that need to be fragmented to learn the drawing, optimized based on ChipGAN is more efficient in solving this problem, because it can flexibly control the effect of the generated ink paintings by inputting different conditional information, such as brush strokes, ink color, composition, etc., and perfecting the details of the ink intensity, penetration patterns, etc. can also make the generated ink paintings more realistic. Additionally, the model can learn and master the characteristics of ink drawings from ink drawing datasets, enabling it to generate new works with strong generalization abilities. Moreover, training ChipGAN models requires significant computational power.

There are not many papers on anime as an image style, and three methods are mentioned in this paper which are applied to migrate two image styles, landscape and people respectively. FAEC-GAN addresses the issue of image edge distortion caused by the migration process. In contrast, Zhao employs a new architecture that efficiently extracts structural features using a pre-trained network while preserving image content. Additionally, Li's proposed algorithm offers significant advantages in terms of quality and visual realism in the generated images. Quality and visual realism, Li's proposed algorithm has significant advantages in terms of the quality and visual realism of the generated images. Each of the three approaches solves different problems faced by the application, and it is a challenge to implement a more comprehensive approach to get better results for anime images.

AUTHORS CONTRIBUTION

All the authors contributed equally and their names were listed in alphabetical order.

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