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Progressive Artistic Aesthetic Enhancement For Chinese Ink Painting Style Transfer

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Introduction

The rapid advancement of deep learning has significantly impacted image style transfer, which has primarily focused on Western abstract paintings. In contrast, the style transfer of Chinese ink paintings—a traditional art form characterized by intricate brushwork and unique techniques—remains underexplored. The distinct features of ink paintings, such as negative space and ink diffusion, present unique challenges for style transfer. While pioneering methods like Gatys et al. utilized CNNs for artistic style transfer, their slow optimization processes hinder practical applications. GANs have emerged as a solution, providing more realistic outputs. However, existing methods still struggle with style integration, fine-grained feature capture, and balancing content and style, often resulting in distorted outputs and diminished aesthetic quality. This highlights the need for more effective approaches to achieve high-quality style transfer for Chinese ink paintings, which not only preserve the essence of the original artworks but also enhance their visual appeal.

Main contributions

- ★ We present the Progressive Artistic Aesthetic Enhancement Style Transfer (PAAEST) model for Chinese ink painting style transfer, which generates artistically enhanced ink paintings from real images.
- ★ Central to our approach is the Progressive Multi-scale Aesthetic Style Attention (PMASA) module, which extracts and integrates multi-scale stylistic information using channel attention to capture both abstract and specific aesthetics.
- ★ We introduce Covariance Transform Fusion (CTF) for aligning multi-scale style and content features, alongside the Adaptive Spatial Interpolation Module (AdaSIM) to refine details using shallow-level content features in the decoder.
- ★ Through extensive experiments and expert evaluations, PAAEST demonstrates superior aesthetic quality, achieving SOTA performance.

Methodology

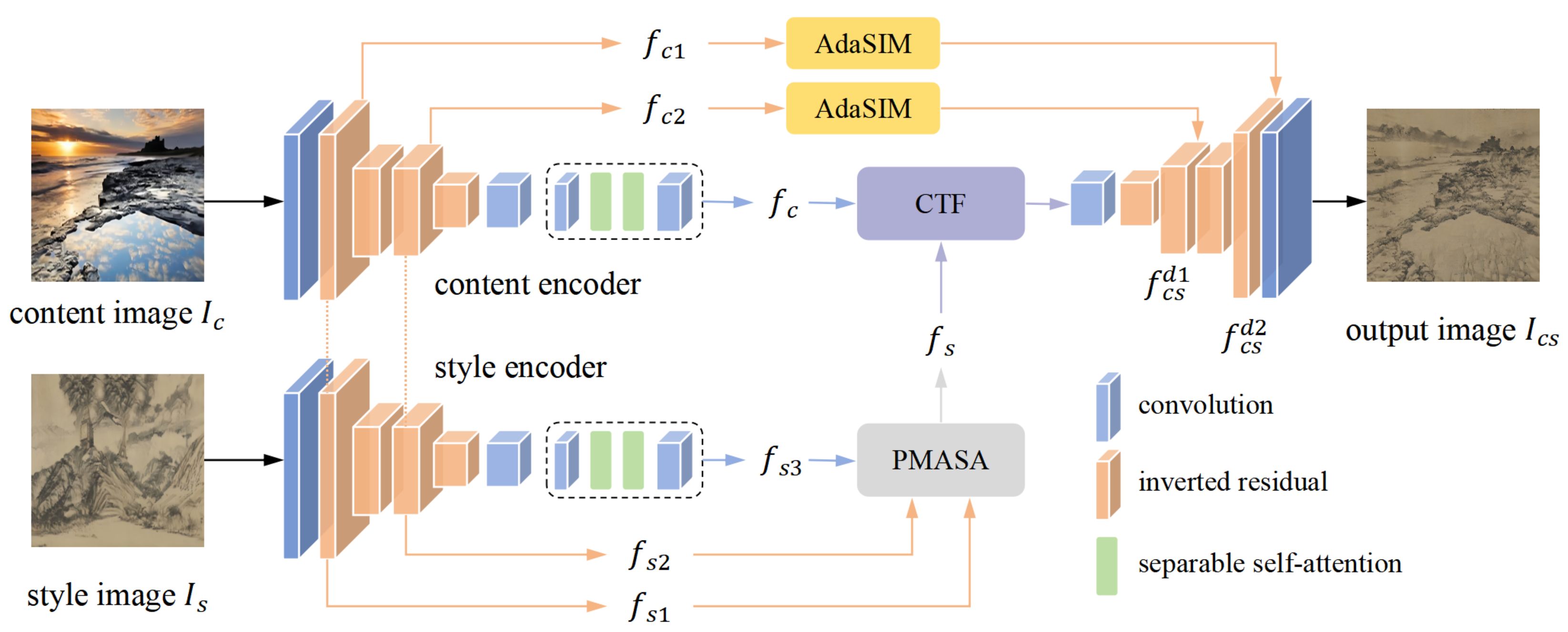

Figure 1: The PAAEST framework processes content and style images through encoders to extract multi-scale features. Style features are combined with content features in the Covariance Transform Fusion module, while the Adaptive Spatial Interpolation module in the decoder generates the final output image.

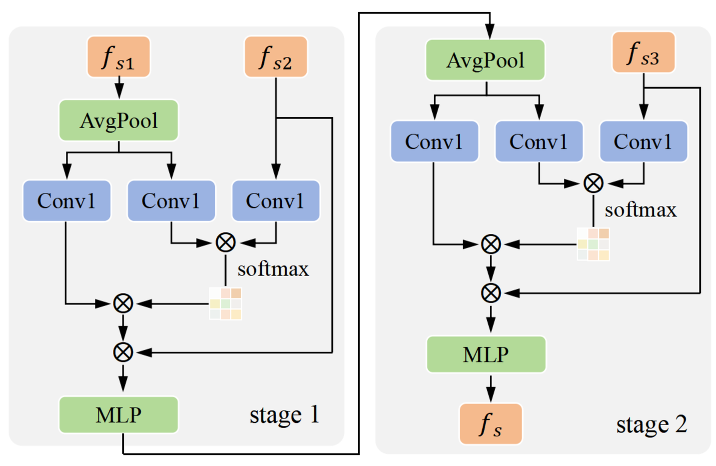

Figure 2: Structure of progressive multi scale aesthetic style attention module.

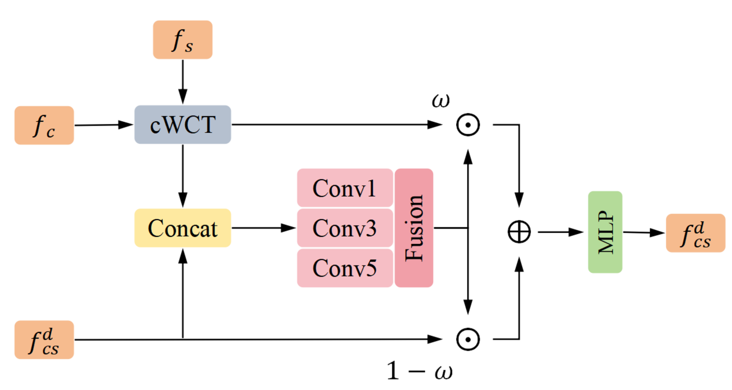

Figure 3: Structure of adaptive spatial interpolation module (AdaSIM).

Results

We employ both automatic evaluation and expert assessments to comprehensively evaluate the performance and aesthetics of PAAEST compared to advanced models.

Figure 4: The visual comparison between PAAEST and previous SOTA methods.

Table 1: Quantative comparison between our PAAEST and other advanced algorithms.

Model	FID ↓	KID ↓	PSNR ↑	SSIM ↑
ChipGAN	231.08	0.734	8.19	0.891
AnimeGAN	225.73	0.672	9.28	0.913
TwinGAN	210.91	0.446	11.89	0.916
QS-Attn	201.31	0.204	16.26	0.928
ACGAN	197.55	0.175	17.19	0.930
PAAEST(Ours)	**183.37**	**0.124**	**23.65**	**0.942**

The PAAEST model excels in Chinese ink painting style transfer, offering superior content representation and aesthetic appeal. Visual comparisons show that it effectively captures the nuances of ink painting, while other models struggle with artifacts and color preservation. Quantitative evaluations confirm its effectiveness, with significant improvements in FID, KID, PSNR, and SSIM compared to previous SOTA methods.

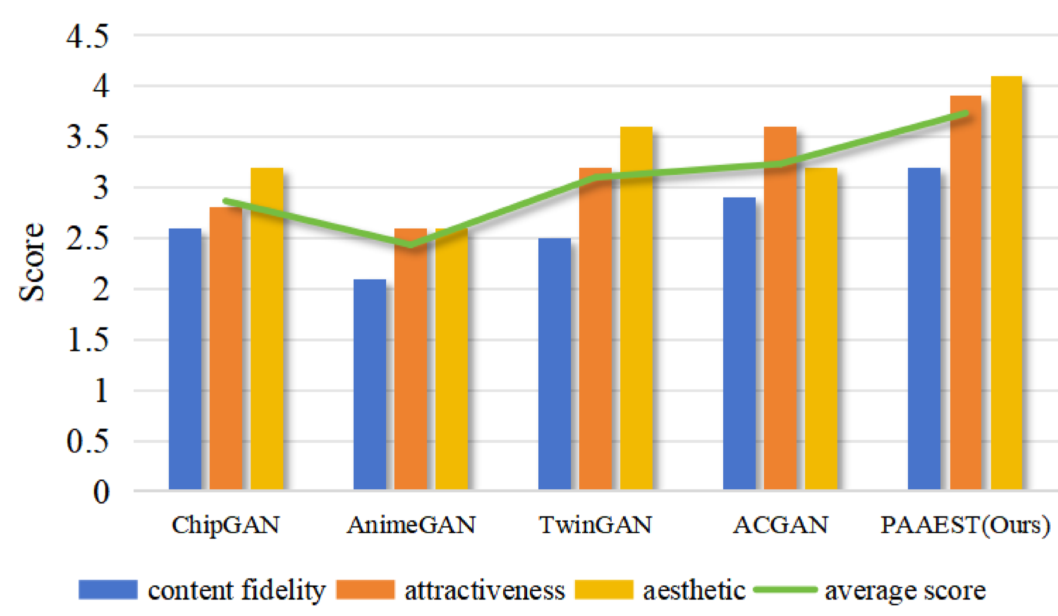

Figure 5: Human evaluation results of different style transfer method, where the average score line is the mean of three metrics.

PAAEST significantly outperforms other algorithms in content fidelity, attractiveness, and aesthetic appeal, scoring an average of 1.3 points higher than the lowest-performing model and 0.5 points higher than the best. Notably, it excels in aesthetic appeal, making the generated Chinese ink painting style images more visually pleasing to both professionals and the general audience.

Conclusion

This paper presents the PAAEST model for Chinese ink painting style transfer. The model employs the PMASA module to integrate multi-scale stylistic information, addressing dissonance in stylized patterns. The CTF module aligns multi-scale style and content features, enhancing transfer results. Additionally, the AdaSIM utilizes shallow-level content features to restore details, reducing artifacts and detail loss. Experimental results show that PAAEST achieves state-of-the-art performance in both automated metrics and human expert evaluations.

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Research Field: Deep learning, diffusion model, 3D reconstruction, adversarial attack

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