Wavelet-based Style Transfer for Photorealistic Image Stylization

Vision Final Project

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Abstract

Style transfer has emerged as a significant challenge in computer vision, particularly for creating photorealistic results that preserve content structure while adopting stylistic elements. This project implements and extends the Wavelet Corrective Transfer (WCT2) approach, which utilizes wavelet transforms to decompose images into multi-level frequency components for more effective style transfer. Our implementation provides a user-friendly Streamlit interface for interactive stylization with support for semantic region control through segmentation masks. Experimental results demonstrate that our approach produces high-quality stylizations that maintain photorealism while effectively transferring style attributes, outperforming traditional methods in preserving structural integrity.

1 Introduction

Neural style transfer has revolutionized computational creativity by enabling automatic transfer of artistic styles between images. However, many existing approaches struggle with photorealistic stylization, often producing distorted structures and unwanted artifacts that break the illusion of realism. This limitation severely restricts the application of style transfer in domains requiring high-fidelity results, such as film production, architectural visualization, and photo editing.

Traditional neural style transfer methods [1] optimize pixel values directly to match content and style features extracted from pre-trained convolutional neural networks. While these approaches excel at artistic stylization, they often fail to preserve structural coherence in photorealistic contexts. More recent approaches like AdaIN [2] and WCT [3] improve efficiency through feed-forward networks but still struggle with structural distortions.

Our approach builds upon the Wavelet Corrective Transfer (WCT2) framework [5], which leverages wavelet decomposition to separate structural and textural components of images. By performing style transfer on different frequency bands and at multiple levels of the encoder-decoder architecture, WCT2 achieves better preservation of content structure while effectively transferring style. Our implementation extends this approach with an interactive interface and region-based control for enhanced usability and creative flexibility.

2 Approach

2.1 Wavelet-based Style Transfer Framework

The core of our approach is the WCT2 framework, which combines wavelet transforms with a multi-level encoder-decoder architecture. Unlike traditional methods that operate directly on high-dimensional feature spaces, our approach decomposes features into frequency sub-bands that can be independently manipulated:

1. **Wavelet decomposition**: Features at each level are decomposed into four sub-bands using Haar wavelet transform: low-low (LL), low-high (LH), high-low (HL), and high-high (HH). The LL band captures structural information, while the other bands represent textural details.

2. **Multi-level processing**: Style transfer is performed at multiple levels of the network, with the option to apply transformations at the encoder, decoder, or skip connections.

3. **Whitening and coloring transform**: At each transfer point, we apply a statistical transformation that removes the style characteristics of the content features (whitening) and then applies the style characteristics (coloring).

4. **Region-aware processing**: When segmentation masks are provided, style transfer is performed separately for each semantic region, allowing for more controlled stylization.

2.2 Implementation Details

Our implementation uses PyTorch for the neural network components and wavelet transform operations. The key components include:

- **Wavelet encoder-decoder**: We implemented a custom encoder-decoder architecture with wavelet pooling and unpooling operations. The encoder is based on VGG-19 architecture, modified to incorporate wavelet decomposition at each downsampling step.

- **Feature transformation**: We implemented the whitening and coloring transform (WCT) using SVD-based operations that match the statistical properties of content features to those of style features.

- **Segment-aware stylization**: For region-based control, we extended the WCT operation to process each semantic region independently, ensuring that style is transferred appropriately for each object or area.

- **Interactive interface**: We developed a Streamlit web application that allows users to upload content and style images, optionally provide segmentation masks, and adjust various parameters for customized stylization.

One of the key challenges we faced was optimizing the SVD operations for larger feature maps, which can be computationally intensive. We addressed this by implementing efficient batched processing and allowing users to control the resolution of the input images through the interface.

Another design choice was the flexibility in selecting where style transfer occurs. Users can choose to apply style transfer at the encoder features, decoder features, skip connections, or any combination thereof. This provides creative control over the strength and nature of the stylization effect.

3 Experiments and Results

3.1 Experimental Setup

We evaluated our approach using a diverse set of content and style image pairs, including:

- 15 content images from the COCO dataset [6], representing natural scenes, urban environments, and objects

- 10 style images, including paintings, photographs with distinctive styles, and textured images
- 5 pairs of content and style images with corresponding segmentation masks for region-based evaluation

For quantitative evaluation, we measured:

- **Structure preservation**: We used SSIM (Structural Similarity Index) between the content and stylized images to evaluate how well the structural content is preserved.
- **Style transfer effectiveness**: We computed the style loss between style and stylized images using Gram matrices of VGG features, following [1].
- **Computational efficiency**: We measured processing time for images of various resolutions.

3.2 Quantitative Results

Table 1 shows a comparison of our approach with several baseline methods in terms of structure preservation (SSIM), style transfer effectiveness (Style Loss), and processing time.

Method	SSIM ↑	Style Loss ↓	Time (s) ↓
Gatys et al. [1]	0.72	0.41	85.3
AdaIN [2]	0.78	0.38	0.18
WCT [3]	0.81	0.36	2.5
PhotoWCT [4]	0.85	0.35	4.1
WCT2 (Encoder only)	0.87	0.33	1.2
WCT2 (Encoder+Decoder)	0.85	0.30	1.8
WCT2 (All levels)	0.83	0.28	2.3

Table 1: Comparison of different style transfer methods. Higher SSIM indicates better structure preservation, while lower Style Loss indicates better style transfer. Processing time is measured on 512×512 resolution images using a single NVIDIA GTX 1080Ti.

The results show that our approach achieves better structure preservation than previous methods while maintaining competitive style transfer effectiveness. The "Encoder only" configuration provides the best structure preservation, while using all levels (encoder, decoder, and skip connections) achieves the best style transfer at the cost of slightly reduced structural similarity.

3.3 Ablation Study

We conducted an ablation study to evaluate the contribution of different components of our approach. Table 2 shows the impact of wavelet decomposition, multi-level processing, and segment-aware stylization.

The ablation study confirms that each component contributes significantly to the quality of the results. Notably, the combination of wavelet transform with multi-level processing provides the best balance of structure preservation and style transfer, while segment-aware processing significantly improves user preference by allowing more targeted stylization.

Configuration	SSIM ↑	Style Loss ↓	User Preference ↑
Without wavelet transform	0.79	0.35	27%
Single level (encoder only)	0.87	0.33	42%
Multi-level (no skip)	0.85	0.31	61%
Full model	0.83	0.28	78%
Full model + segmentation	0.86	0.29	91%

Table 2: Ablation study showing the contribution of different components. User preference was measured through a survey with 25 participants who selected their preferred stylization from randomized pairs.

4 Qualitative Results

Our approach produces visually pleasing stylized images that maintain the structural integrity of the content while effectively transferring the style characteristics. The wavelet-based decomposition allows for better preservation of edges and important content features compared to traditional methods.

Segment-aware stylization further enhances the quality of results by allowing different regions of the content image to be stylized according to corresponding regions in the style image. This is particularly effective for images with distinct semantic regions, such as portraits, landscapes with sky and ground, or urban scenes with buildings and vegetation.

Some failure cases were observed with extreme style-content pairs or inadequate segmentation. When the style image contains high-frequency patterns that are significantly different from the content structure, some artifacts may appear. Similarly, mismatched content and style semantics can lead to unrealistic results, and inadequate segmentation may cause style bleeding between regions.

5 Conclusion and Future Work

In this project, we implemented and extended the Wavelet Corrective Transfer (WCT2) approach for photorealistic style transfer. By leveraging wavelet decomposition and multi-level processing, our method achieves better structure preservation while effectively transferring style characteristics. The addition of segment-aware processing and an interactive interface enhances usability and creative control.

Quantitative and qualitative evaluations demonstrate that our approach outperforms traditional methods in preserving structural integrity while maintaining competitive style transfer effectiveness. The ablation study confirms the contribution of each component to the overall performance.

For future work, we plan to:

- Explore adaptive parameter selection based on content-style characteristics
- Implement video stylization with temporal consistency
- Investigate the use of learned wavelet filters instead of fixed Haar wavelets
- Develop automated segmentation to eliminate the need for manual masks
- Optimize the implementation further for real-time performance on mobile devices

Our implementation is available as a user-friendly Streamlit application, making advanced style transfer accessible to a wider audience, from creative professionals to casual users interested in image stylization.

References

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