



# Diffusion-Enhanced PatchMatch:

## A Framework for Arbitrary Style Transfer with Diffusion Models

Mark Hamazaspyan, Shant Navasardyan



### Abstract

In this work, we present a novel method, **Diffusion-Enhanced PatchMatch (DEPM)**, that leverages Stable Diffusion for style transfer without any finetuning or pretraining. DEPM captures high-level style features while preserving the fine-grained texture details of the original image. By enabling the transfer of arbitrary styles during inference, our approach makes the process more flexible and efficient. Moreover, its optimization-free nature makes it accessible to a wide range of users.

### Main Contributions

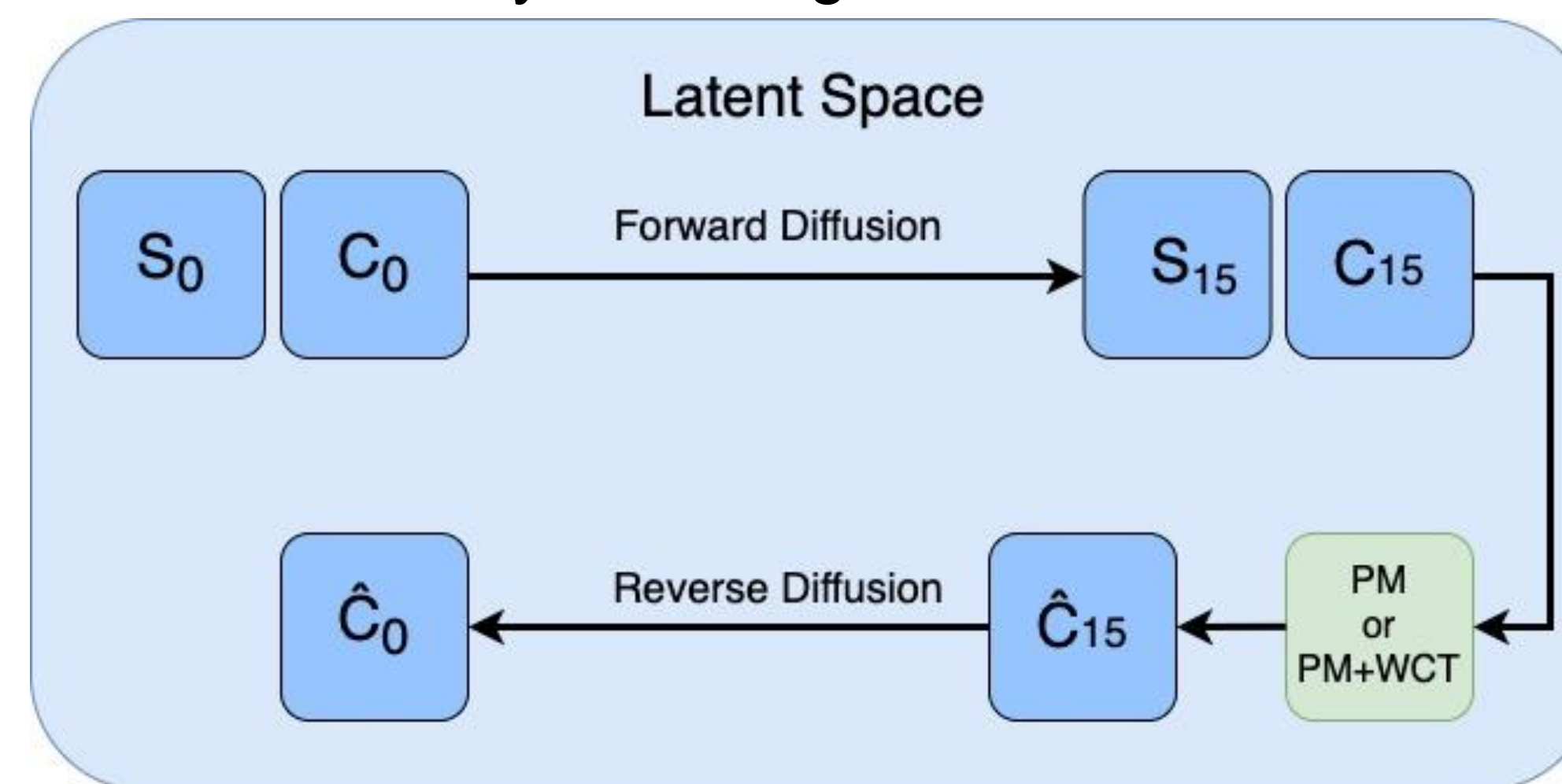
- We utilize patch-based techniques with whitening and coloring transformations in the latent space of Stable Diffusion for high-quality arbitrary style transfer.
- Our approach demonstrates superior performance in terms of color transformation while preserving the content details of the input image.
- Our method enables arbitrary style transfer without the need for any training, making it a highly flexible and efficient solution for a wide range of applications.

### Main Components

- Stable Diffusion: Stability AI
- Patch Match (PM): Chen et al., Fast patch-based style transfer of arbitrary style, 2016
- Whitening and Coloring Transform (WCT): Li et al., Universal style transfer via feature transforms, 2017

### Method

- $C_0$  and  $S_0$  are the latent representations of content and style images at timestamp  $t = 0$ .
- We perform  $t = 15$  steps of deterministic forward pass with LMSScheduler to get  $C_{15}$  and  $S_{15}$  (total number of steps is  $T = 100$ ), then we start the reverse diffusion process.
- At  $t = 15$  we perform PM or PM followed by WCT to get the latent representation  $\hat{C}_{15}$ . We finish the process by performing  $t = 15$  reverse diffusion steps on  $\hat{C}_{15}$  resulting in  $\hat{C}_0$ , the latent representation of the stylized image.



### Quantitative comparison

- Perceptual Similarity (LPIPS) Loss across 100 images with 3 different style transfer methods.

	DEPM (ours)	CMD	EFDM	DSTN
LPIPS	0.596	0.719	0.606	0.615

### Experiments and Comparison



### Summary

- We have presented a novel approach to style transfer that synergistically combines diffusion models with style transfer techniques, enabling the transfer of arbitrary styles during the inference step without any finetuning or pretraining.

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