Artistic Style Discovery with Independent Components

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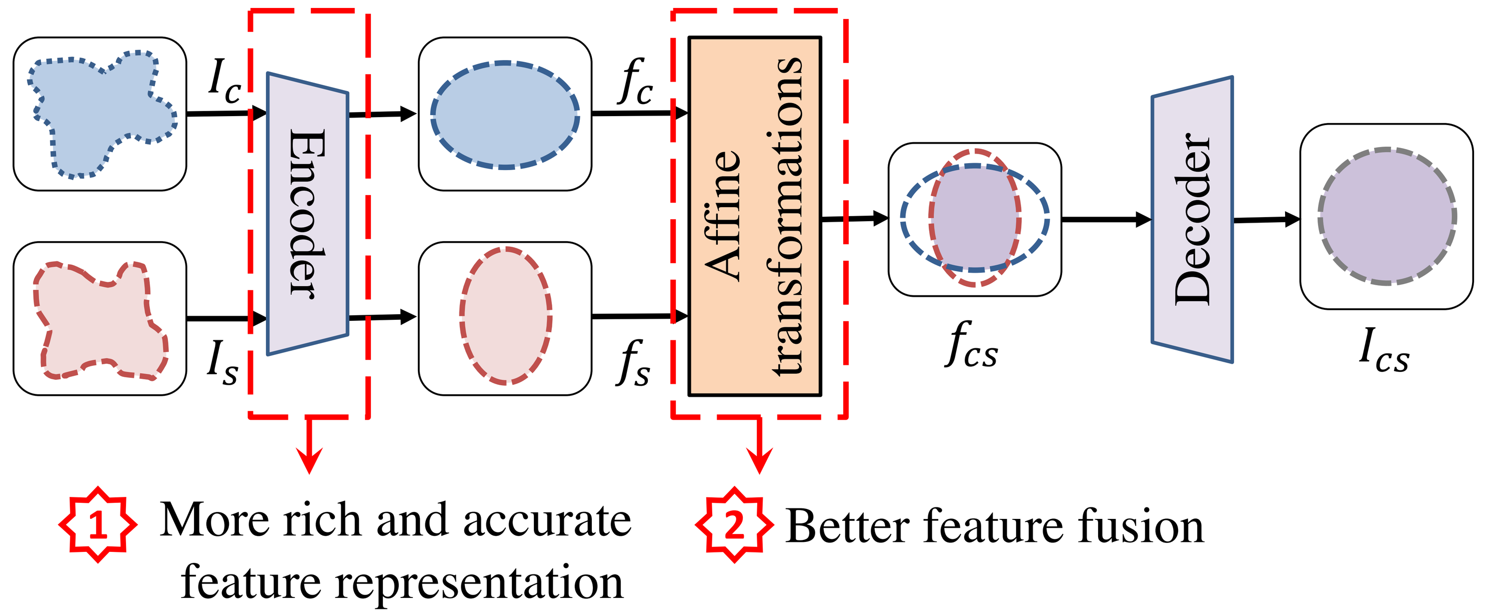
Problem Definition

Goal: unsupervised style discovery and personalized style manipulation.

Motivation:



In style transfer, feature extraction and feature fusion are optimization targets to achieve more high-quality stylization. But there are several drawbacks:

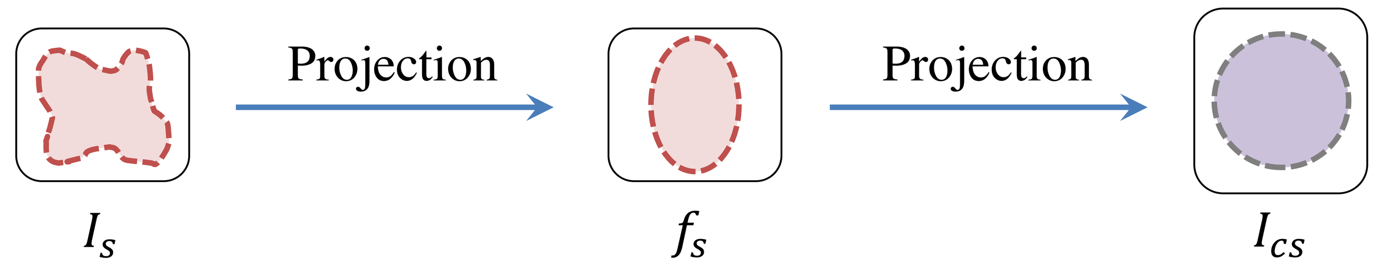
- Large device memory.
- Limited style controllability and diversity.
- Style dataset requirement.

Key Contributions

- We introduce a novel unsupervised algorithm that can discover various styles from the latent space, advancing the ability of controllable stylization.
- We obtain the independent style components from the mixed latent style dimensions in style transfer, resulting in multiple artistic stylizations and lowering computational costs.
- Our method is generally applicable without training and we demonstrate the effectiveness and flexibility of our approach via abundant experiments on several state-of-the-art style transfer models.

Methodology

Rethink style transfer mechanism:



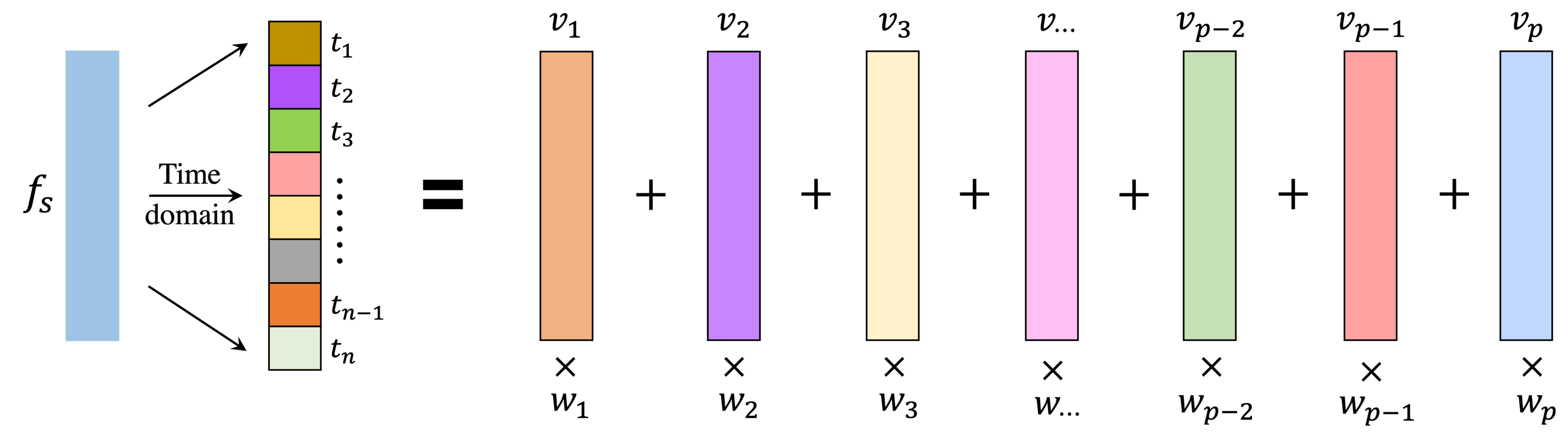
The essence of style transfer is projecting the image from one space to another space. Let us take AdaIN model as an example to make analysis:

$$f_{cs} = AdaIN(f_c, f_s) = \sigma(f_s)\left(\frac{f_c - \mu(f_c)}{\sigma(f_c)}\right) + \mu(f_s)$$

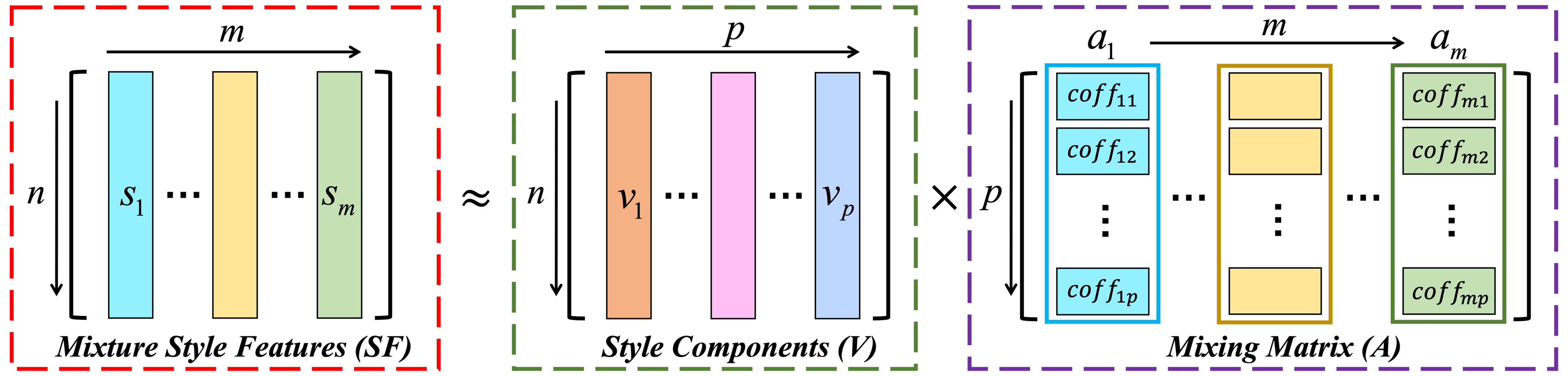
We can always extract the style feature f_s which is the root factor that controls the whole style.

Artistic Ingredients Separation:

Inspired by the Fourier transform, time-domain and frequency-domain analysis of signals, we argue that the style features is mixed discrete series which can be separate into independent components as follow, and different artistic components control different style effect.

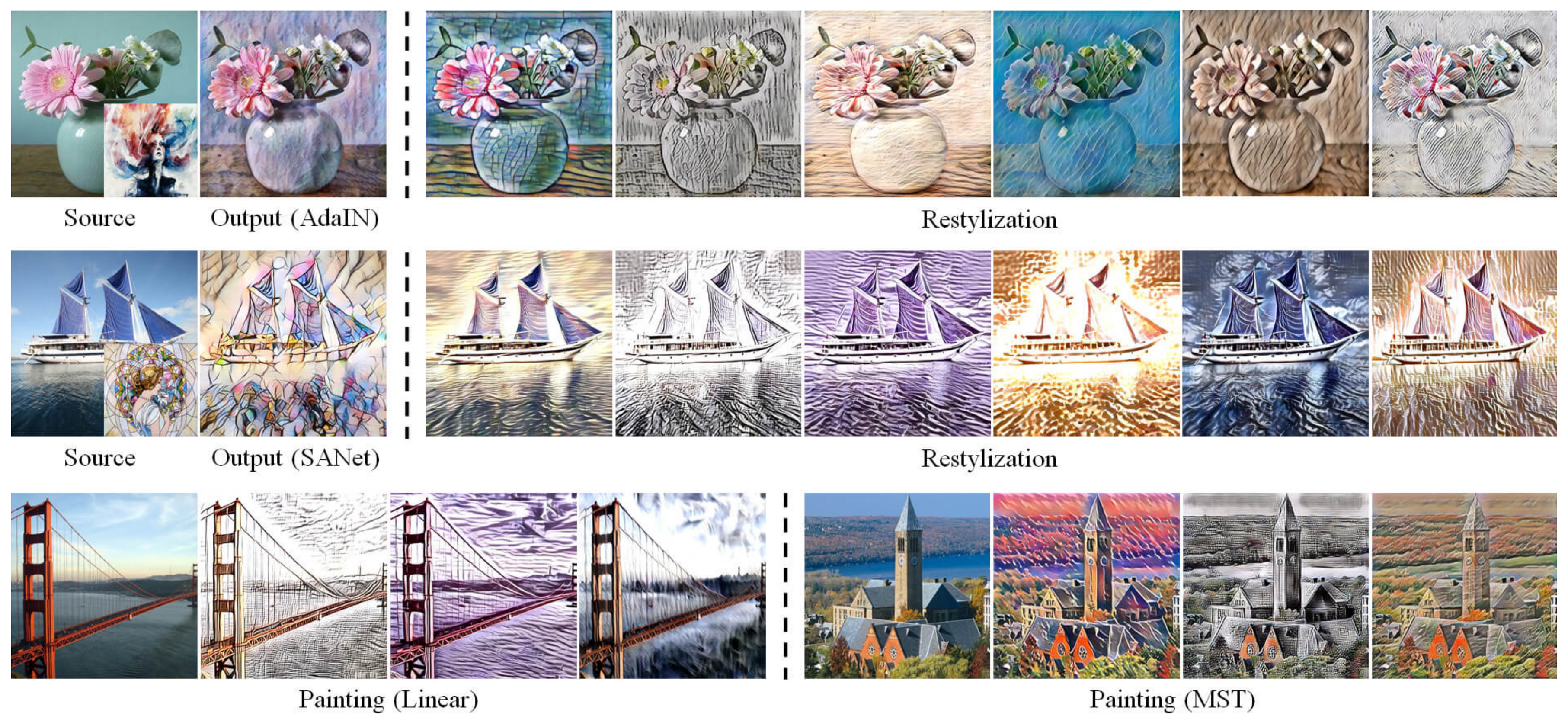


In a word, the style features are linear sum of style components. Without loss of generality, we sample m style features to build the mixed matrix SF, which are used to obtain p artistic components by FastICA algorithm like the cocktail party problem.

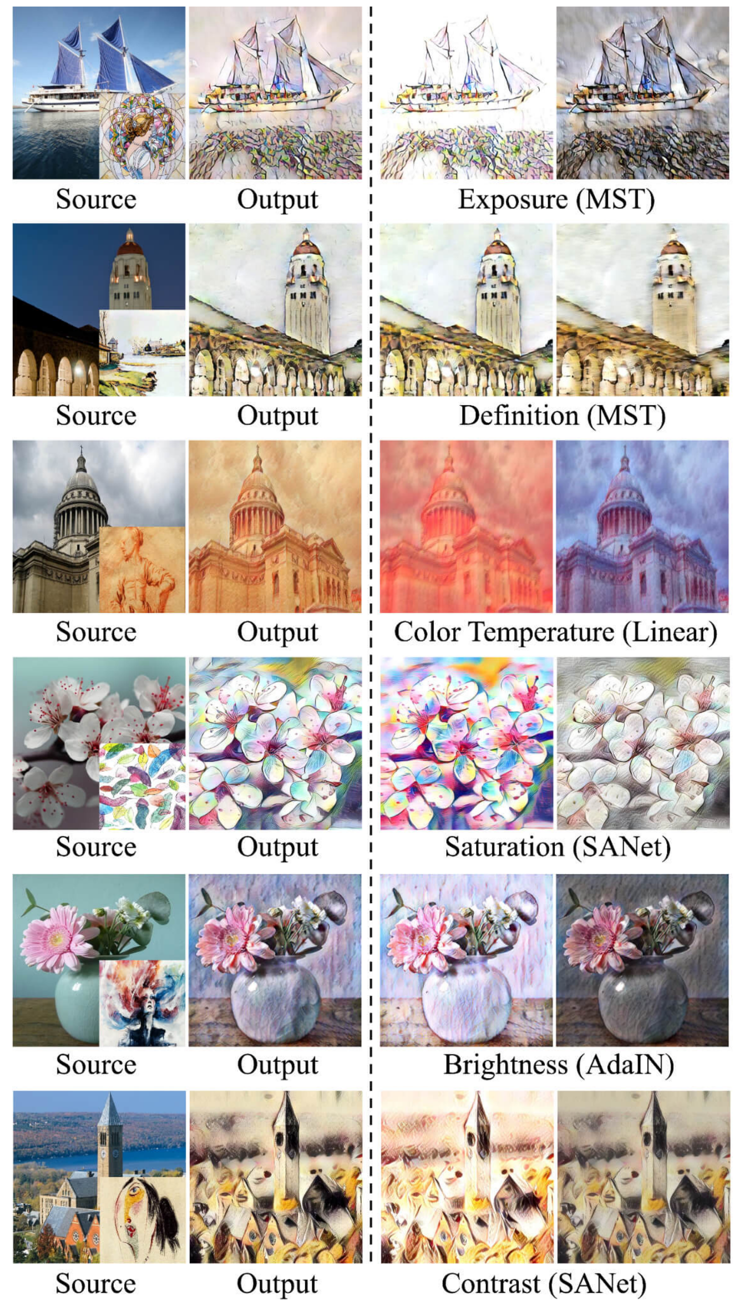


Experiments

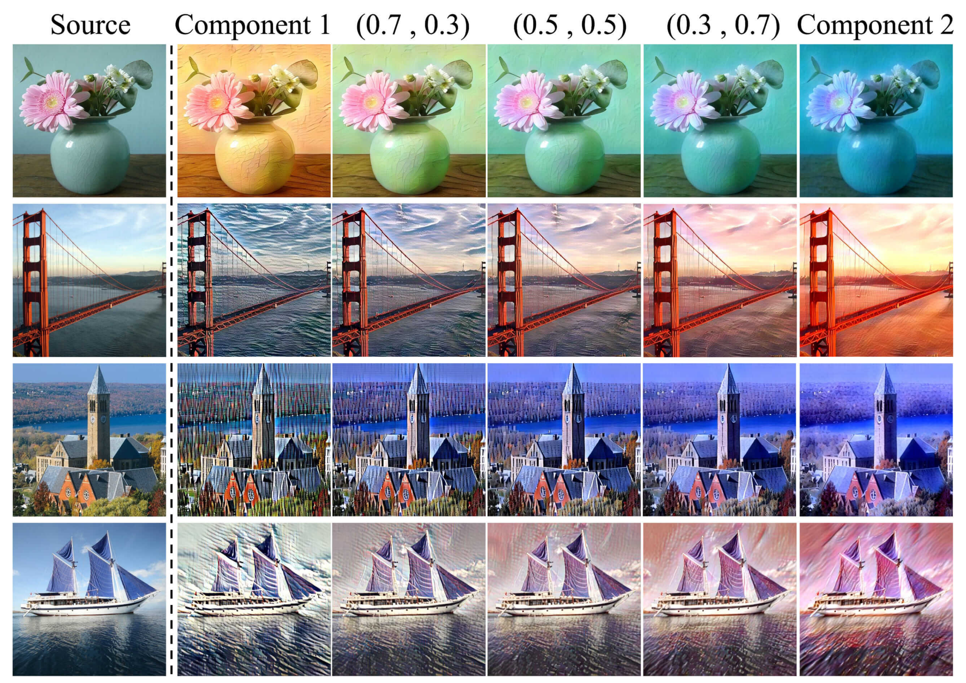
We utilize independent artistic components to make diverse restylized artworks from different backbones including AdaIN, Linear, SANet and MST.



➢ Color Tone for Artwork



➢ Interpolation of Style Components



➢ Artwork adjustment