Medical Artificial Intelligence Laboratory
At Yonsei University

Image Style Transfer

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ACM SIGGRAPH

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Domain Enhanced Arbitrary Image Style Transfer via Contrastive Learning

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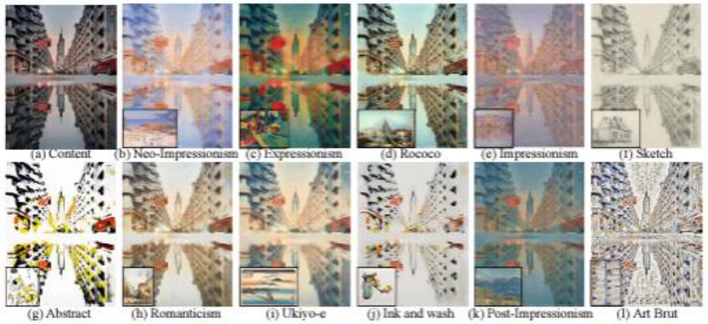

Figure 1: Style transfer results using our method, which can robustly and effectively handle various painting styles. The input content image is in the top-left corner and the style reference is shown as the inset for each result. Our method can faithfully capture the style of each painting and generate a result with a unique artistic visual appearance. Style image credits: [(b) Henri Edmond Cross, (c) Vasily Kandinsky, (d) Michele Marieschi, (e) Claude Monet, (h) Richard Parkes Bonington, (i) Utagawa Hiroshige, (k) Paul Cezanne]/The Art Institute of Chicago (CC0), (f) Vincent van Gogh/National Gallery of Art (CC0).

ABSTRACT

In this work, we tackle the challenging problem of arbitrary image style transfer using a novel style feature representation learning method. A suitable style representation, as a key component in image stylization tasks, is essential to achieve satisfactory results. Existing deep neural network based approaches achieve reasonable results with the guidance from second-order statistics such as

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Background & Goal

Previous research limitation

- Methods that utilize secondary statistics fail to utilize sufficient style information, resulting in artifacts such as l ocal distortions or style inconsistencies

Goal

- To learn style representation directly from image features, by analyzing the similarities and differences between m ultiple styles and considering the style distribution

(a) Content (b) Style (c) Ours (d) AdaAttN (e) IEST

Fig 1. Compared with models which rely on second-order statistic s

Zhang, Y., Tang, F., Dong, W., Huang, H., Ma, C., Lee, T. Y., & Xu, C. (2022, July). Domain enhanced arbitrary image style transfer via contrastive learning. In *ACM SIGGRAPH 2022 conference proceedings* (pp. 1-8).

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Network Architecture

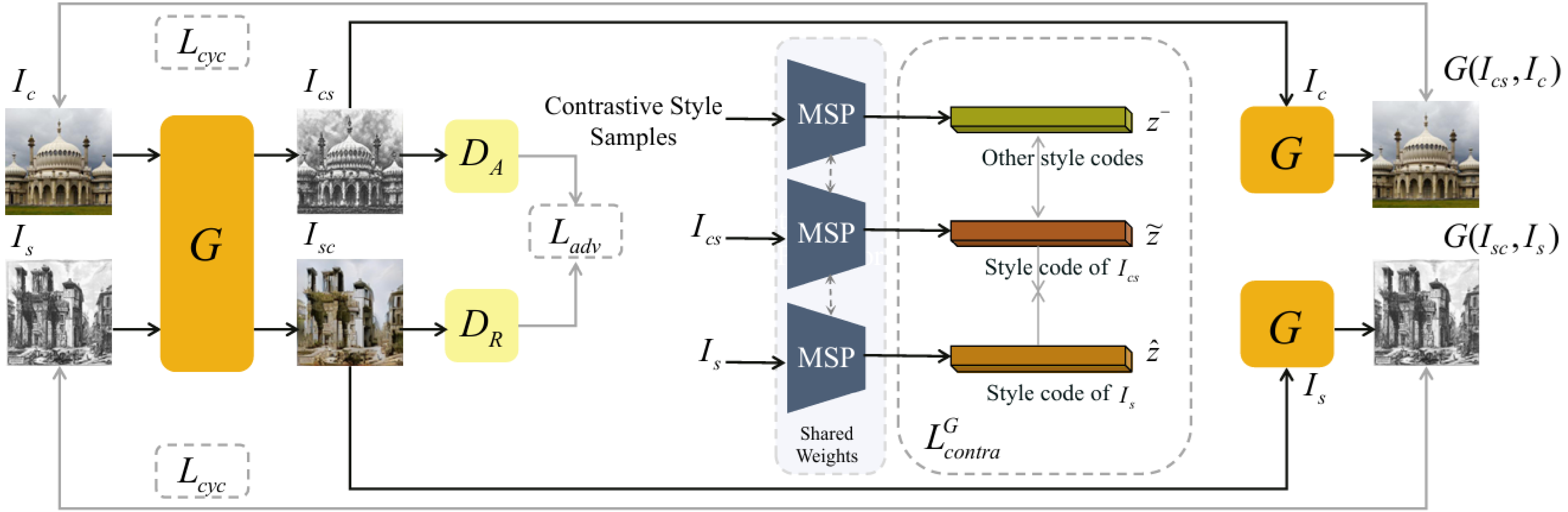

Fig 2. Overview of Network Architecture

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Loss functions

Multi-layer style projector

- MSP projects features of different layers into separate latent style spaces to encode local and global style cues

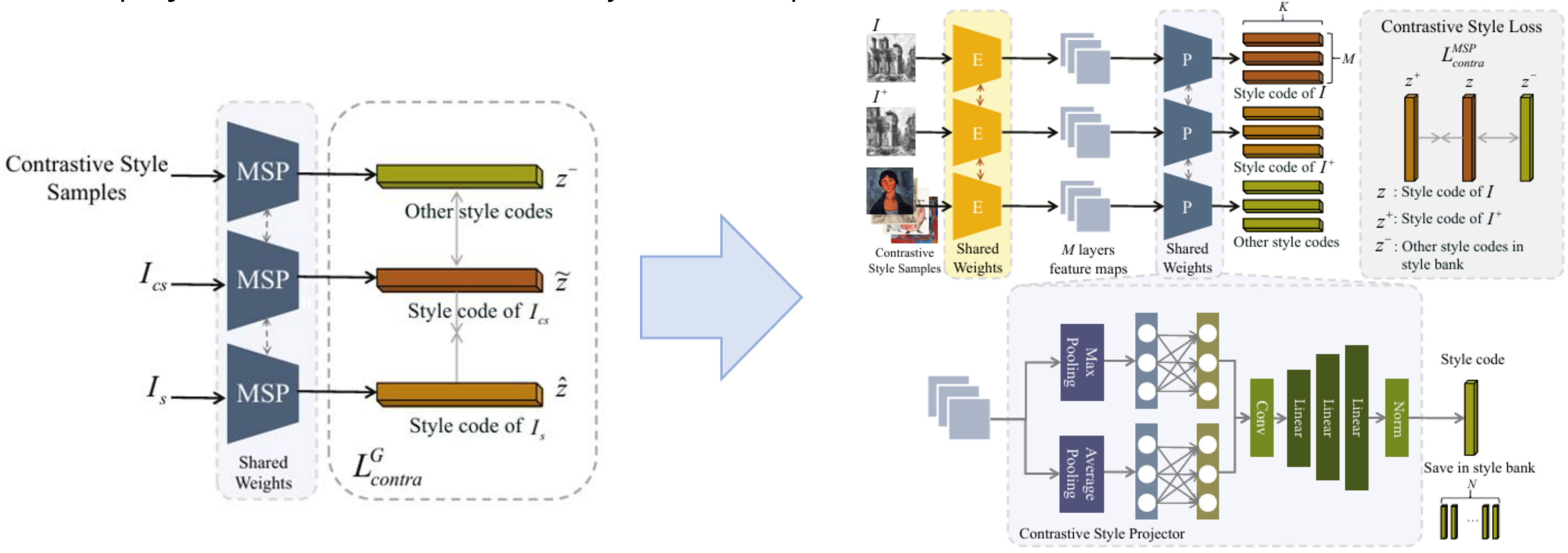

Fig 3. Overview of MSP Module

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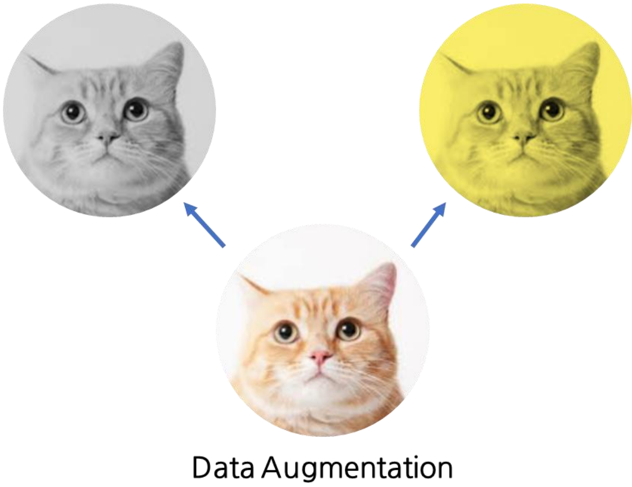
Loss functions

Contrastive Style Learning

- Contrastive learning learns to encode images in a low-dimensional space so that similar images are close toget her and dissimilar images are far apart



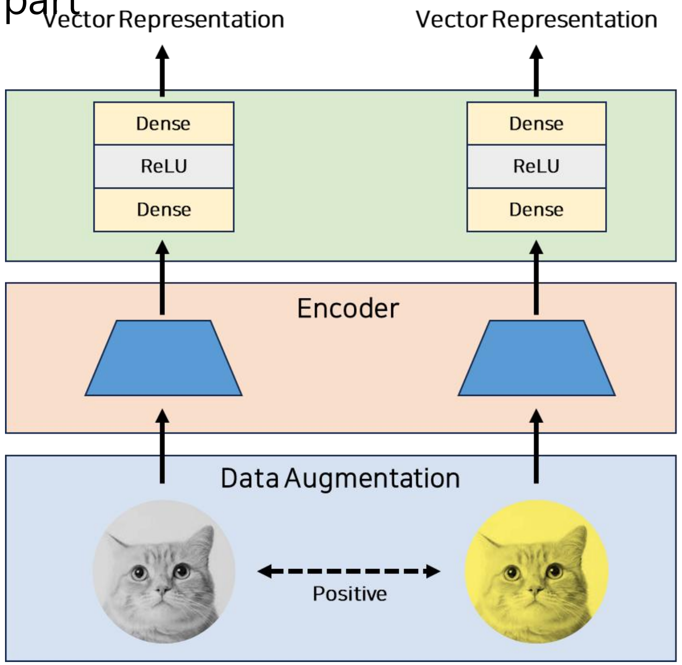


Fig 4. Contrastive learning

$$-\log \frac{\exp(z_0 \cdot z_1)}{\sum_{i=1}^{K} \exp(z_0 \cdot z_i)}$$

Eq 1. Contrastive loss function

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Loss functions

Contrastive Style Learning

- Because of the lack of ground truth style code, adopt contrastive learning & design a novel contrastive style lo ss
- Eq 2: Learn how to distinguish different styles well with style codes
- Eq 3: Learn to make the style of the converted image similar to the style of the original style image

$$\mathcal{L}_{contra}^{MSP} = -\sum_{i=1}^{M} \log \frac{\exp(\mathbf{z}_i \cdot \mathbf{z}_i^{+}/\tau)}{\exp(\mathbf{z}_i \cdot \mathbf{z}_i^{+}/\tau) + \sum_{j=1}^{N} \exp(\mathbf{z}_i \cdot \mathbf{z}_{i_j}^{-}/\tau)}$$

Eq 2. Contrastive loss function to train MSP module

$$\mathcal{L}_{contra}^{G} = -\sum_{i=1}^{M} \log \frac{\exp(\tilde{\mathbf{z}}_i \cdot \hat{\mathbf{z}}_i/\tau)}{\exp(\tilde{\mathbf{z}}_i \cdot \hat{\mathbf{z}}_i/\tau) + \sum_{j=1}^{N} \exp(\tilde{\mathbf{z}}_i \cdot \mathbf{z}_{i_j}^{-}/\tau)}$$

Eq 3. Contrast loss between z,̃ which maps the style-transf erred content image, and ẑ, which maps the style image

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Loss functions

Domain Enhancement

- Domain Enhancement with adversarial loss to enable the network to learn the style distribution
- To maintain the content information of the content image, Add a Cycle consistency loss

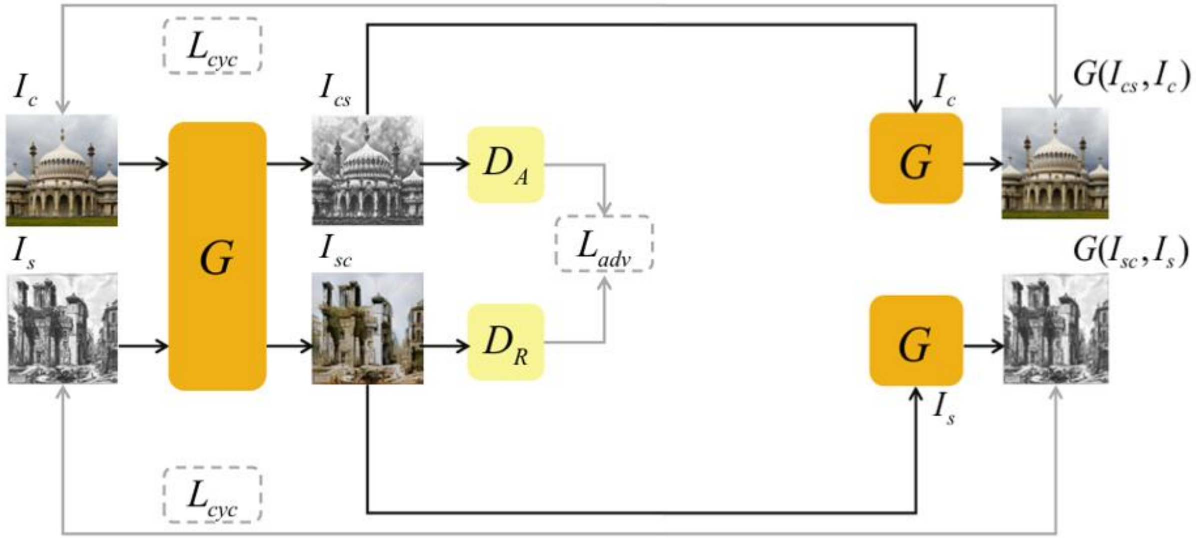

Fig 5. Overview of Domain Enhancement

$$\mathcal{L}_{adv} = \mathbb{E}[\log D_R(I_c)] + \mathbb{E}[\log(1 - D_R(I_{cs}))] + \mathbb{E}[\log D_A(I_s)] + \mathbb{E}[\log(1 - D_A(I_{sc}))]$$

Eq 4. Adversarial loss

$$\mathcal{L}_{cyc} = \mathbb{E}[\|I_c - G(I_{cs}, I_c)\|_1] + \mathbb{E}[\|I_s - G(I_{sc}, I_s)\|_1]$$

Eq 5. Cycle consistency loss

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Experiments

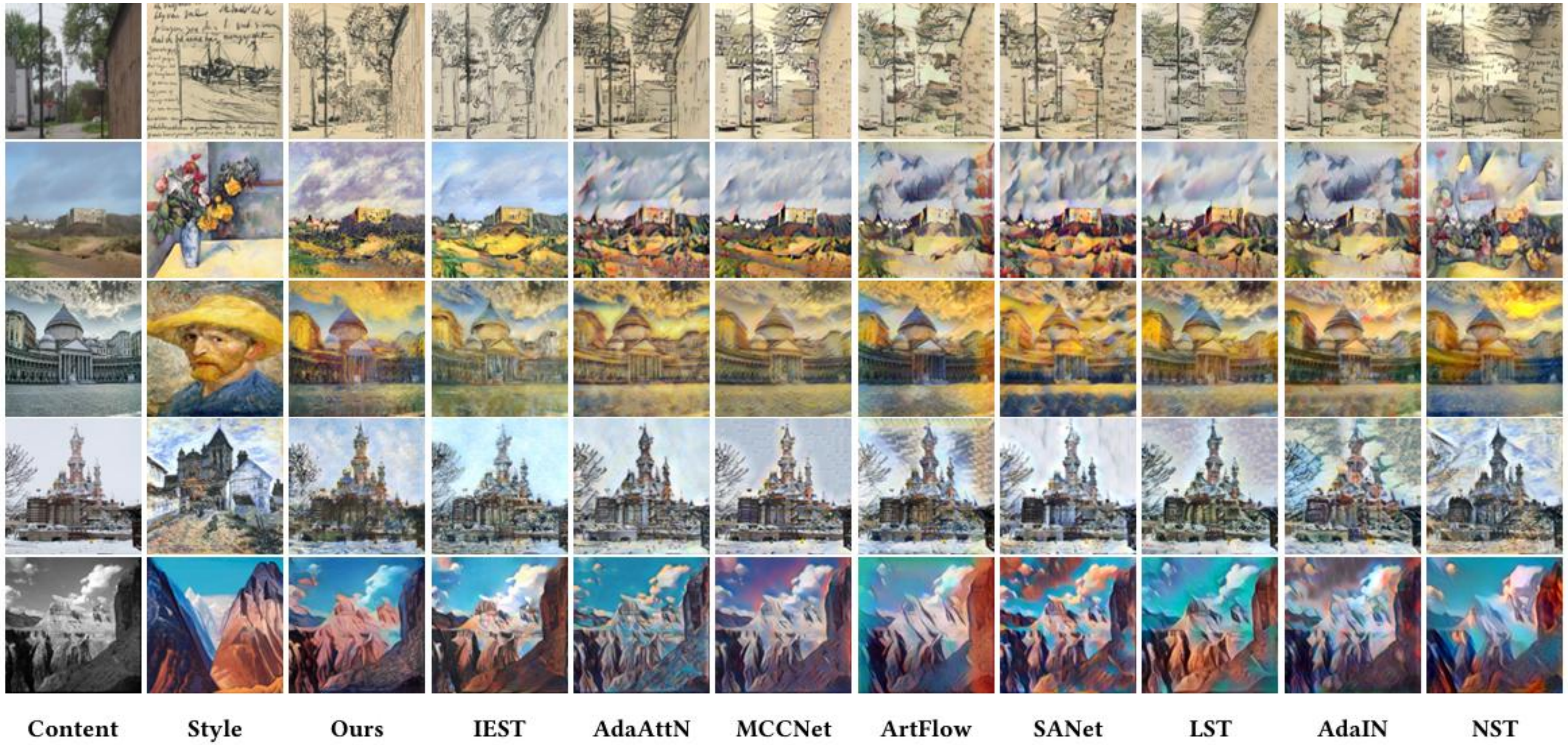

Fig 6. Qualitative comparisons with several SOTA style transfer methods

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Experiments

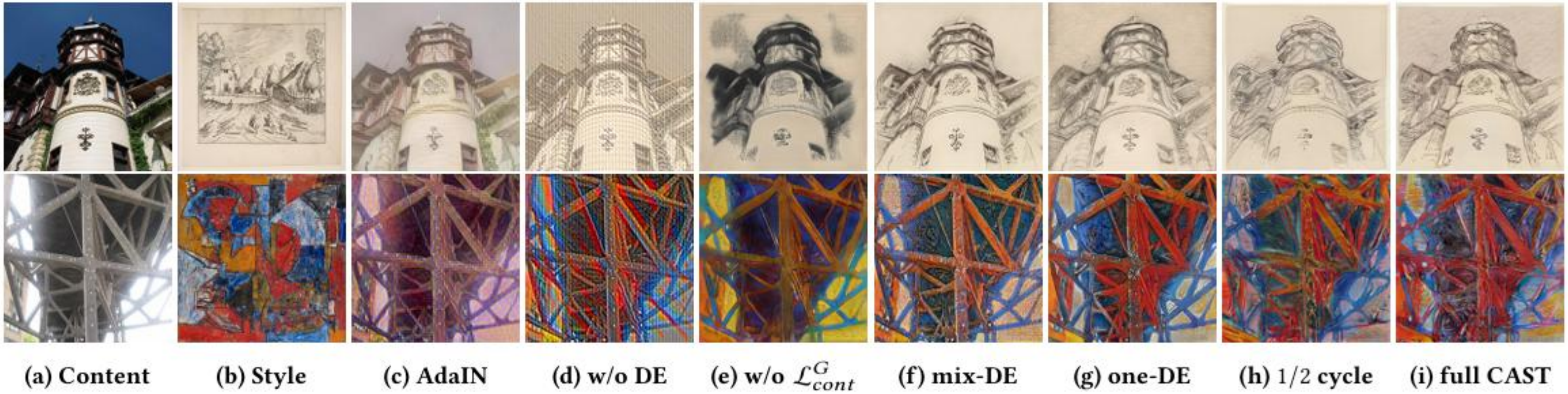

Fig 7. Ablation study results

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Implications & Limitations

Implications

- Use image features directly by introducing an MSP module for style encoding
- Propose a DE scheme to effectively model the distribution of realistic and artistic image domains

Limitations

- The patch-based discriminator has limitations, leading to inconsistencies in style uniformity.