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If Van Gogh or Picasso Painted Maps – Explorations of Neural Style Transfer Applied to Maps

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1 Introduction

Neural style transfer[1] refers to the use of CNNs to transfer the style features to render the content image in the style of another image. This study aims to apply style transfer on maps, which have more focus on spatial structure and semantic contrast than realistic images.

2 Method Overview

- Given an input content feature channel with value $x \epsilon \mathbb{R}$, a and b are the mean and standard deviation of the style features:

$$AdaIN(x; a, b) = a\left(\frac{x - \mu(x)}{\sigma(x)}\right) + b$$

- AdaConv[3] improves AdaIN[2] by considering the spatial structure of the feature values and introducing depthwise seperable convolution.
- Given $N(x)$ as the neighborhood around x. $AdaConv_{dw}$ is depthwise AdaConv variant. For an input with C feature channels, p is a separable pointwise convolution tensor:

$$AdaConv_{dw}(x; f, b) = \sum\nolimits_{x_i \in N(x)} AdaIN(x; f_i, b)$$

$$AdaConv(x; p, f, b) = \sum_{c} p_c AdaConv_{dw}(x_c; f_c, b_c)$$

- The global style encoder aims to increase the receptive field. The kernel predictor Kn outputs depthwise seperable kernels.

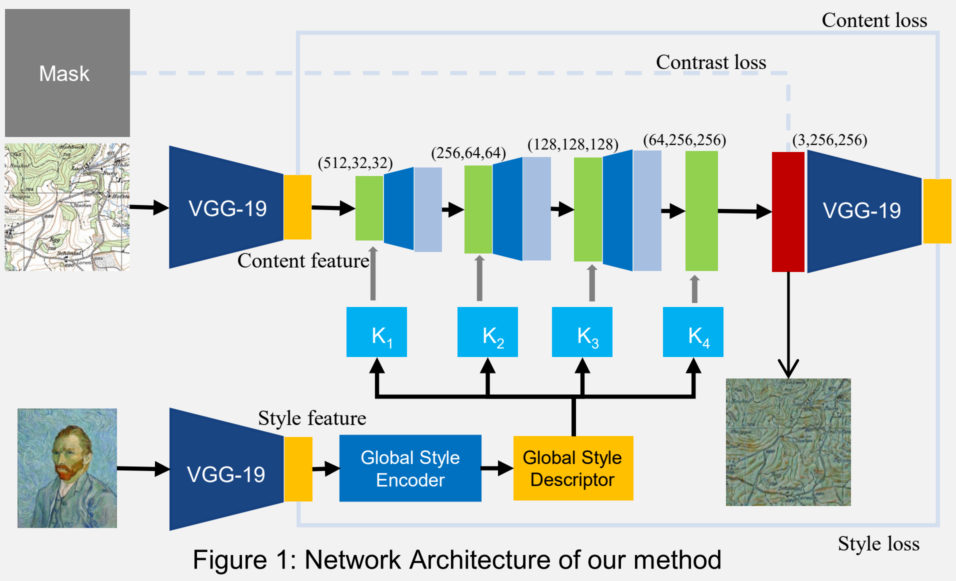

Figure 1: Network Architecture of our method

3 Training

- Learning rate: 0.0001; Iteration: 160 000
- Content loss: MSE loss
- Style loss: moment matching loss or gram loss
- Feature loss is added to enhance contrast among different feature classes
- Different setting of training style and content input (single or multiple image)

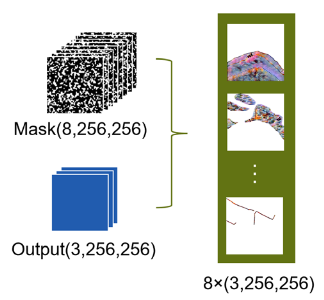

Figure 2: Enhance contrast

4 Results

A user study was conducted to evaluate the models trained with different input setting and loss function. According to the result, models with gram loss as style loss and trained with multiple style images and content images are better in preserving style information have overall better performance, as(d)(k).

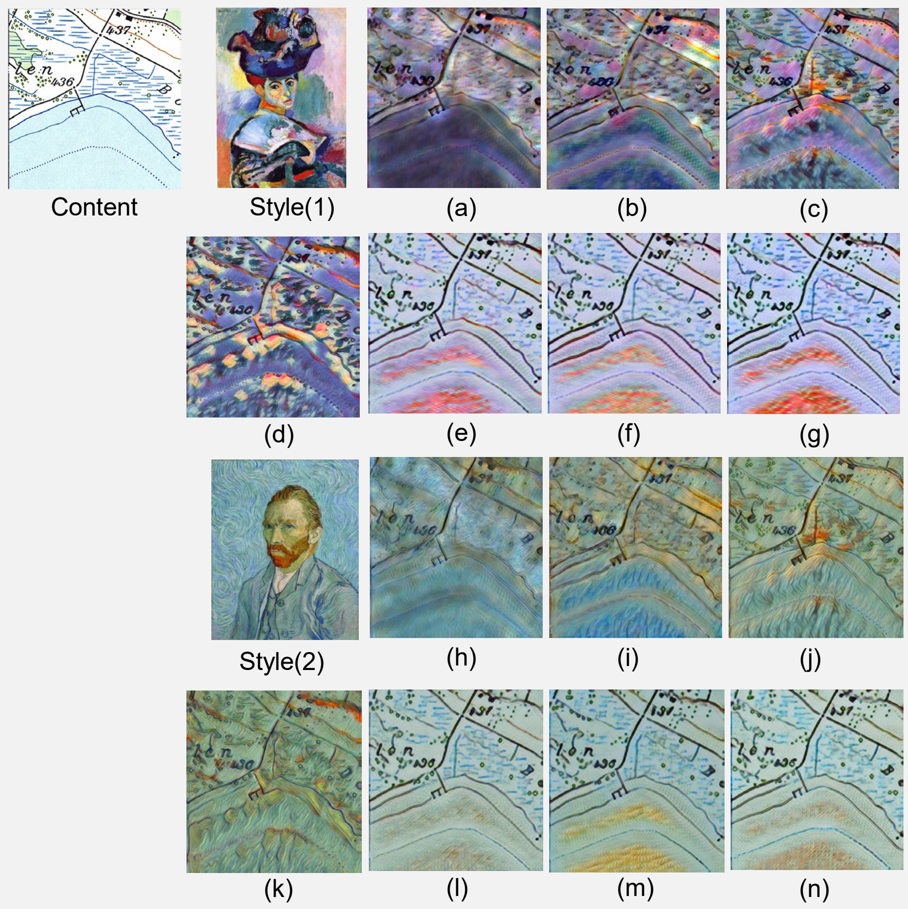

Figure 3: Style transfer results (a)(h) AdaIN,single style,multiple content; (b)(i) AdaConv,single style,multiple content; (c)(j) Change input setting to multiple style, multiple content; (d)(k) Change style loss function from moment matching loss to gram loss;(e)(l) Change input setting to single style, single content;(f)(m) Add contrast loss by modulating standard deviation; (g)(n) Add contrast loss by modulating cosine distance

5 Conclusion

- Readability is important for the stylized map which includes an empirical understanding of color and clear symbols.
- In this study line features from the map are better preserved than area information.
- In future work, we can focus on extracting various style features with regards to different colors.

References

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