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

Rushan Wang
Supervisors: Prof. Dr. Lorenz Hurni, Sidi Wu, Prashanth Chandran, Dr. Magnus Heitzler

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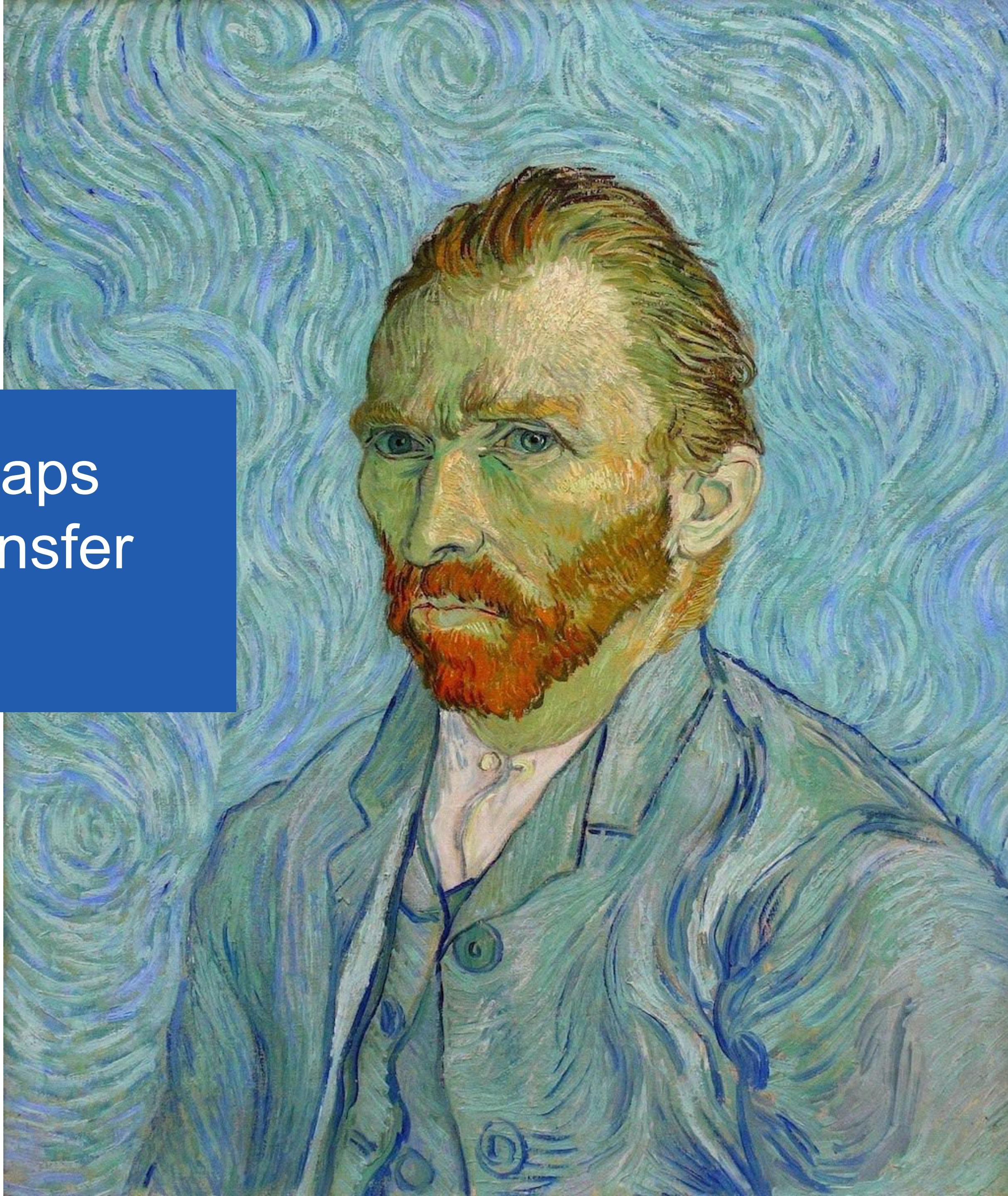
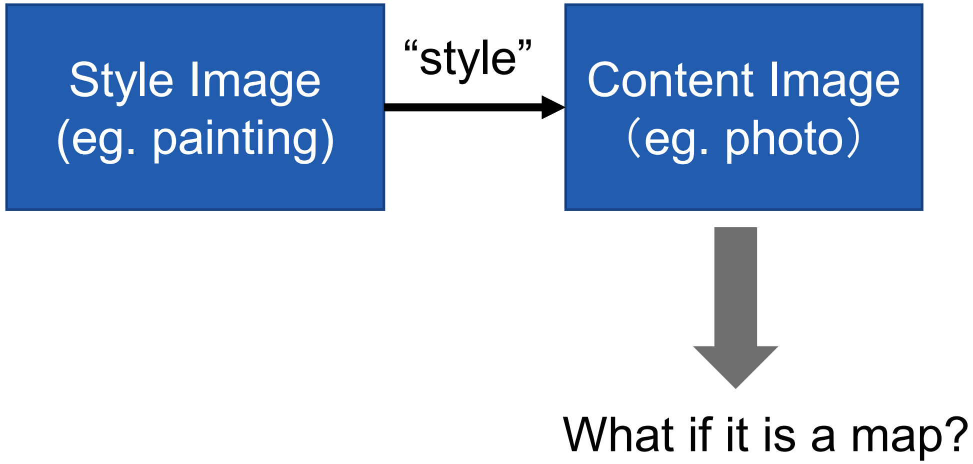


Agenda

1. **Introduction**
2. Method
3. Training
4. User study
5. Conclusion

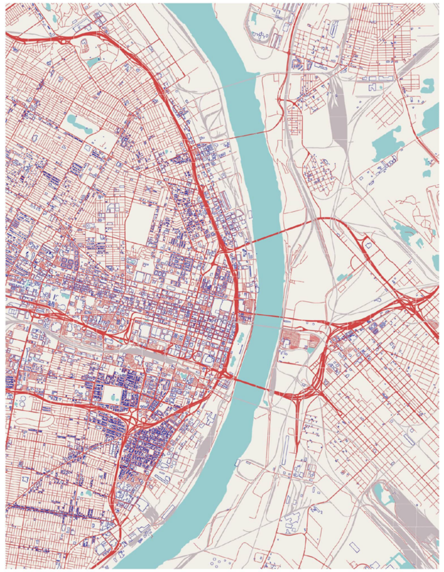
Introduction

- Neural style transfer[1] refers to the use of CNNs to transfer the underlying features to render the content image in the style of another image



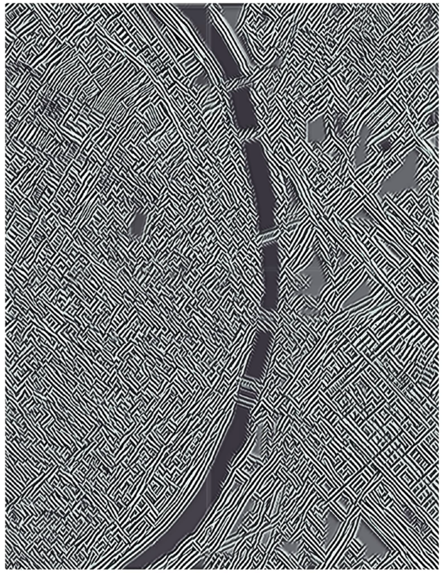
[1] A. Gatys, A. S. Ecker and M. Bethge, "Image Style Transfer Using Convolutional Neural Networks," 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016, pp. 2414-2423, doi: 10.1109/CVPR.2016.265.

Introduction



Content

Style



Result

- Not readable
- Lose map information

Figure1 : Failure case of style transform
Source: https://cdv.dei.uc.pt/stylised-maps/.

- Goal: Preserve the **spatial structure** and the **semantic contrast** of the map

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Method

- Transfer feature statistics from style image to content image
- AdaIN[1]: Adaptive instance normalization layer transfers the mean and variance of the style features to the content features
- AdaConv[2]: Improves AdaIN by considering the spatial structure of the feature values and using depthwise separable convolution

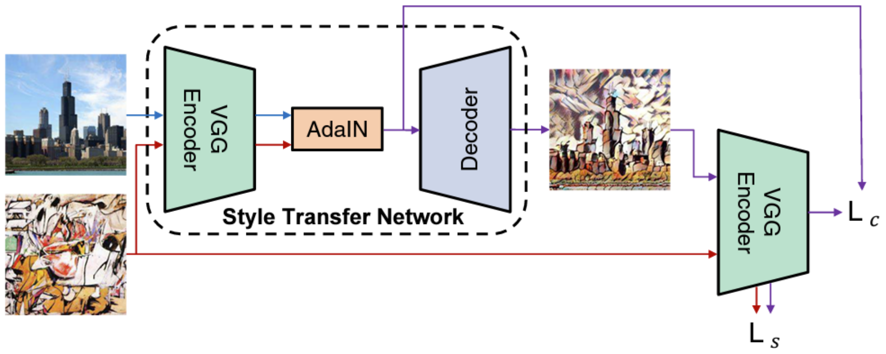

Figure 2. AdaIN Network architecture

[1] Huang, X., & Belongie, S. (2017). Arbitrary Style Transfer in Real-time with Adaptive Instance Normalization. doi:10.48550/ARXIV.1703.06868
[2] P. Chandran, G. Zoss, P. Gotardo, M. Gross and D. Bradley, "Adaptive Convolutions for Structure-Aware Style Transfer," *2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2021, pp. 7968-7977, doi: 10.1109/CVPR46437.2021.00788.

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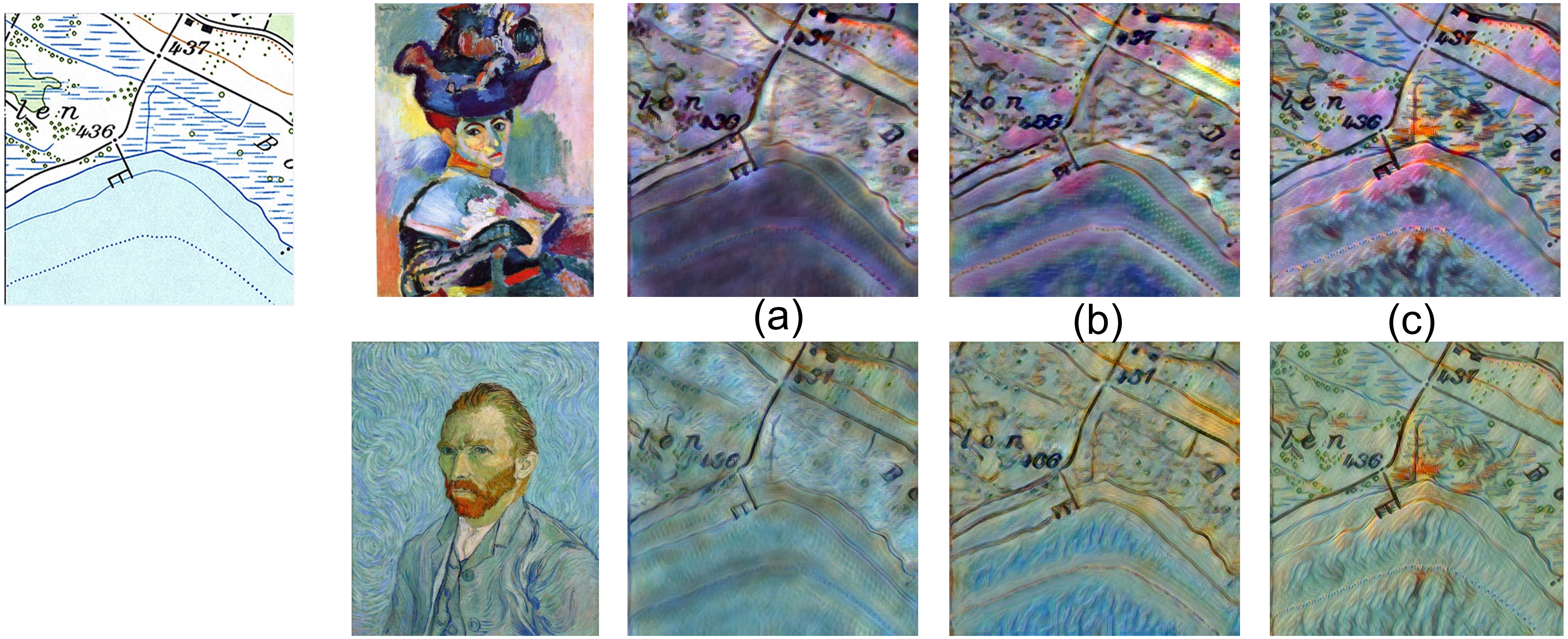
Training

- Network based on AdaIN vs. AdaConv
- Training set with single vs. multiple style inputs

Content | Style | AdaIN Single style | AdaConv Single style | AdaConv Multiple style



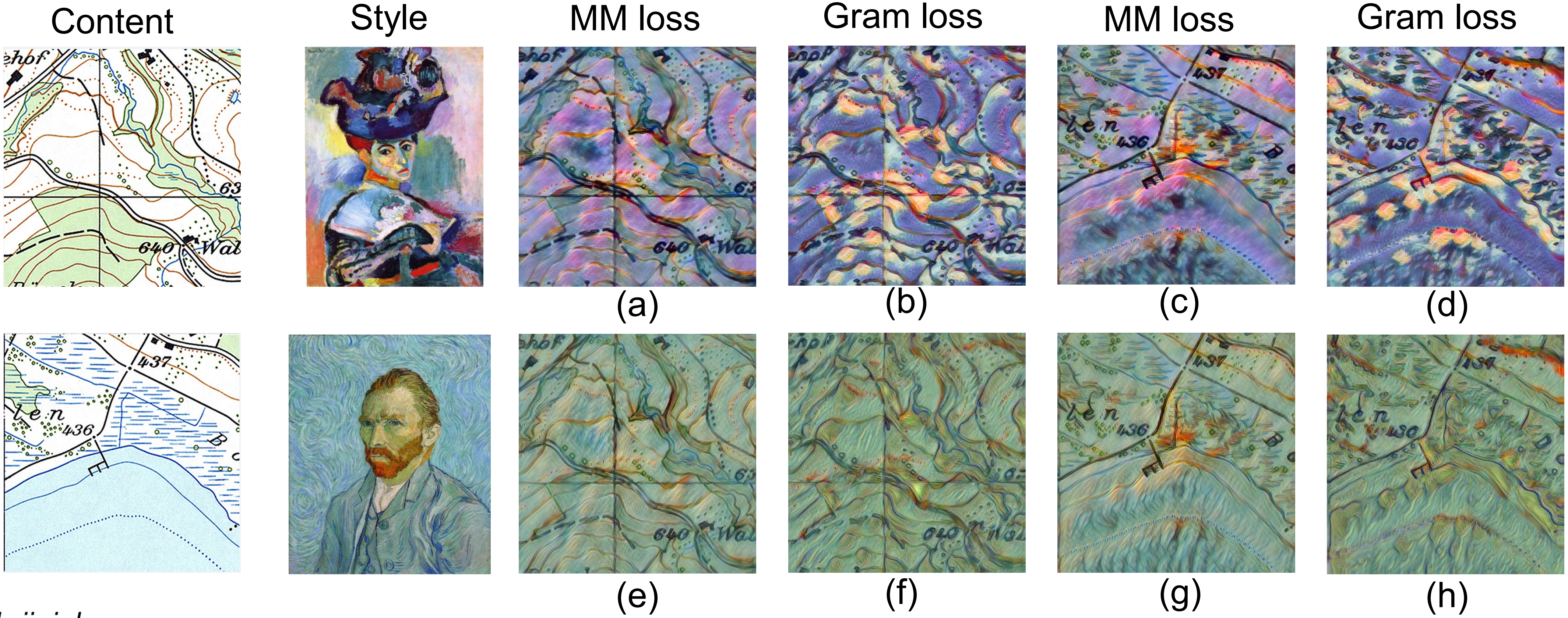
(a) (b) (c)

(d) (e) (f)

Training

Enhance contrast?

- Style Loss Comparision
  - Moment matching loss: features distribution
  - Gram loss: features co-occurrence



Training

- Contrast loss
  - Modulate standard deviation among different classes
  - Modulate cosine distance among different classes

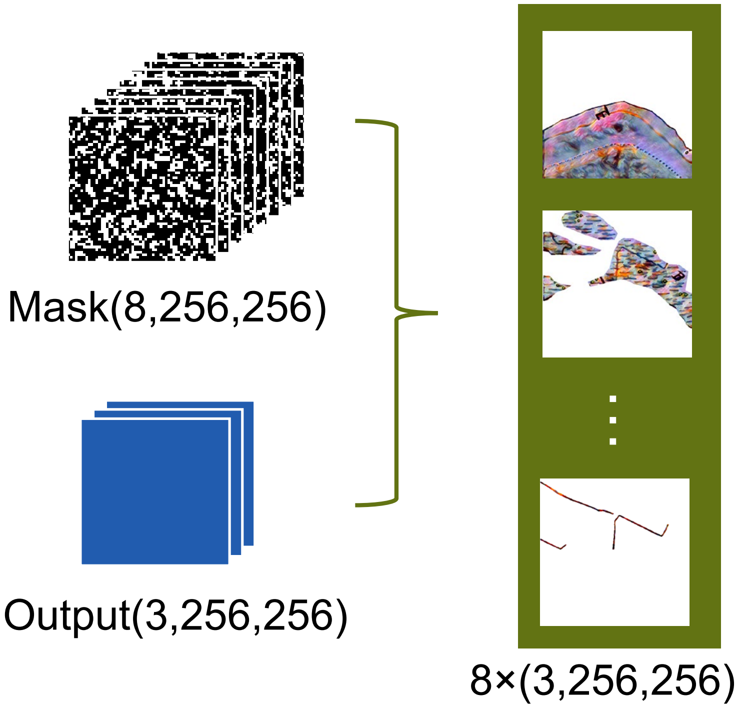


Figure 4. Enhance contrast

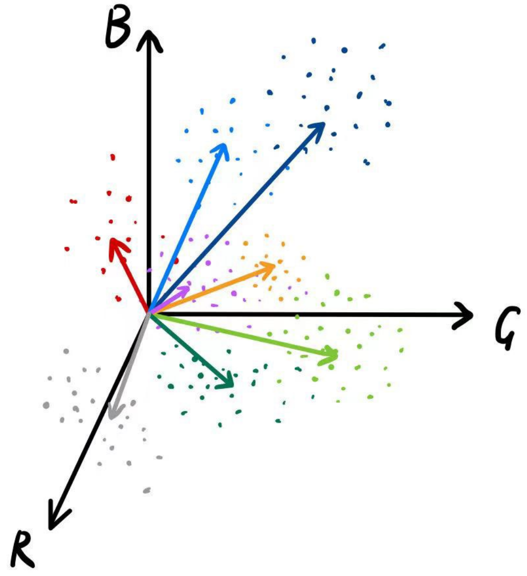
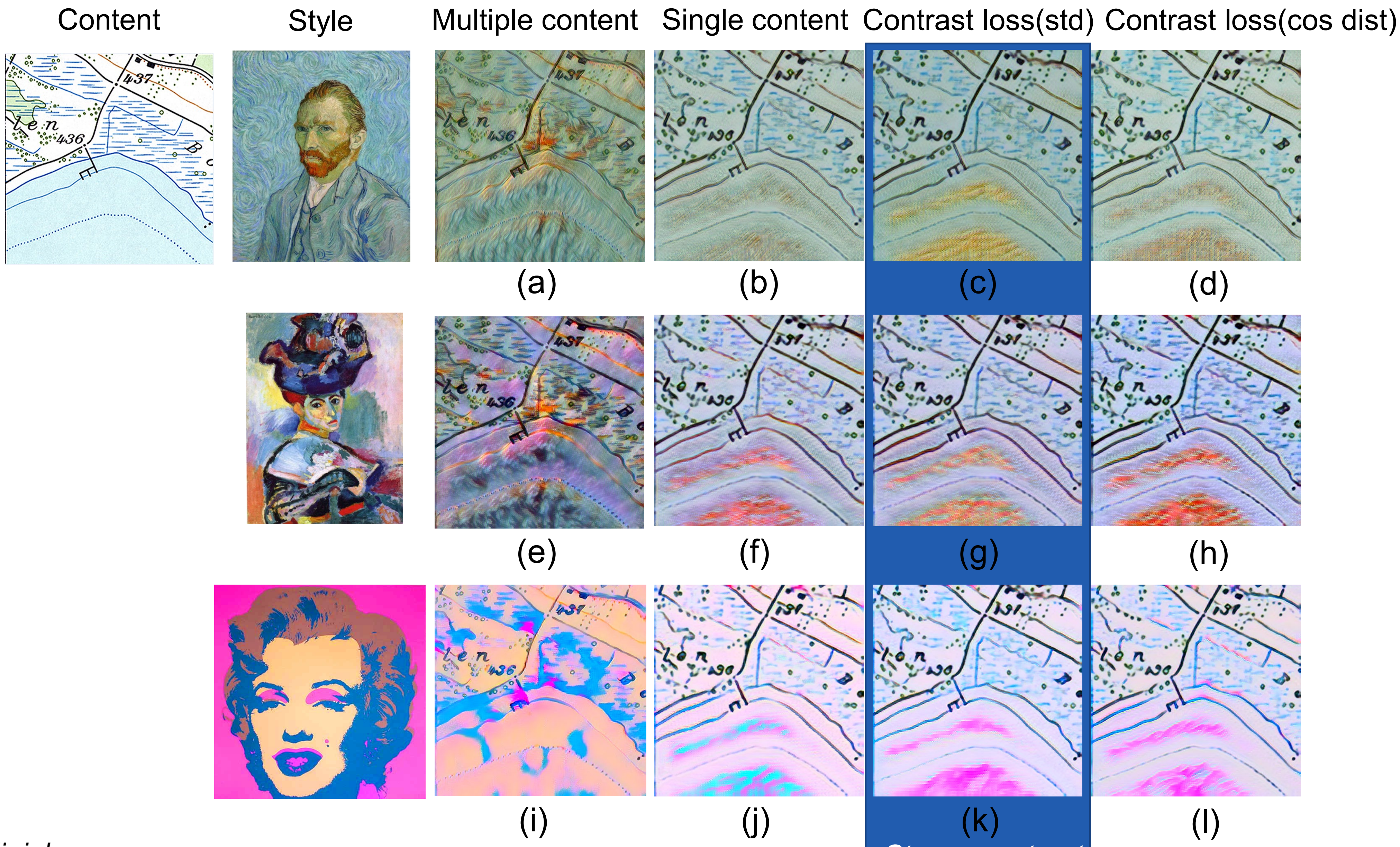


Figure 5. Distribution of different feature classes

Training



Strong contrast

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User Study

- Which style transfer result preserves the map information better?
  - Model trained with single content and single style
- Which style transfer result preserves the style information better?
  - Model trained with multiple content and with gram loss as style loss
- Which style transfer result is overall doing a better job in style transfer?
  - Model trained with multiple content and with gram loss as style loss

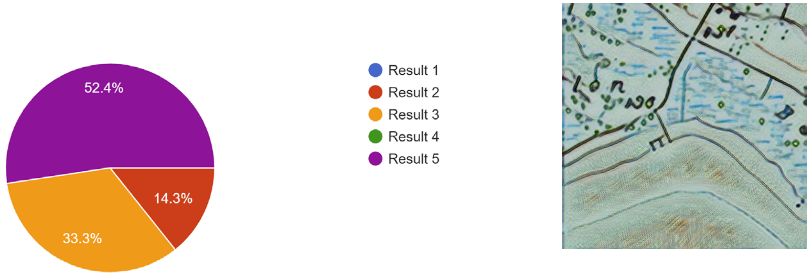

Figure 6. Statistic result for preserves the map information

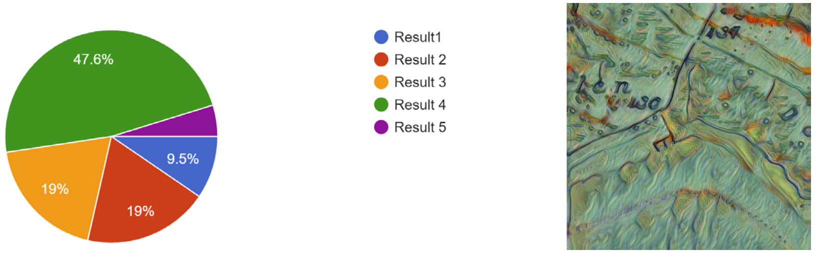

Figure 7. Statistic result for preserves the style information

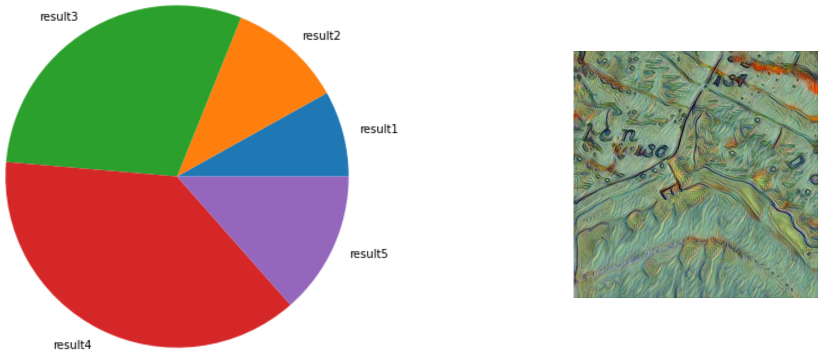

Figure 8. Statistic result for overall preformance

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Conclusion

- Readability is the most important for style transfer for map
  - Empirical understanding of colors (eg. blue is water, green is vegetation)
  - Clear text and symbols
- Our work has better performance in preserving line features from the map than area features
- In the future work
  - Extract various style features with regard to different colors
  - Specific brushstroke features can be applied to text and symbols

Thank you for listening!

Rushan Wang
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