Painting as your like: Colorization and Neural Style Transfer

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## Introduction

Image colorization and Neural Style Transfer are awesome!

### Examples

Colorization and Neural Style Transfer



# Convolutional Neural Network

1x1	1x0	1x1	0	0
0x0	1x1	1x0	1	0
0x1	0x0	1x1	1	1
0	0	1	1	0
0	1	1	0	0



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Figure: The moving window(kernal): Green, original matrix: Blue, output: Orange

# Introduction

LAB[Papadakis et al., 2000, Segnini et al., 1999,

Yam and Papadakis, 2004]

L\* represents Lightness, a\* represents the color from green to red, and b\* represents the color from blue to yellow.

LAB knows the texture.

► RGB

Red, Green and Blue for human perception.

► LAB<->RGB[Leon et al., 2006]



Figure: https://commons.wikimedia.org/wiki/File:RGBchannelsseparation.png http://shutha.org/node/851

### Related Work

Colorization

Colorful Image Colorization[Zhang et al., 2016] User-guided Colorization[Zhang et al., 2017] ChromaGAN [Vitoria et al., 2020] Instance-aware[Su et al., 2020]

 Neural Style Transfer Domain-Aware [Hong et al., 2021] Adaptive attention mechanism[Liu et al., 2021]

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# Colorization Network[Su et al., 2020]



Figure: Model architecture for Instance-aware colorization network[Su et al., 2020]

## Visual Comparison



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# Quantitative Comparison

	ChromaGAN		Inst		CIC2		CIC	
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
NCD	19.90	0.926	22.45	0.924	21.49	0.908	19.52	0.905
COCO	25.04	0.951	23.52	0.875	23.36	0.870	21.97	0.857
Imagenet1k	25.30	0.950	22.88	0.876	23.48	0.870	21.95	0.857
VOC	25.77	0.955	24.16	0.893	24.49	0.887	22.96	0.876

Table: Quantitative Comparison on the image evaluation index of PSNR<sup>↑</sup> and SSIM<sup>↑</sup>. We do this comparison on four datasets, containing over 10k image.[Anwar et al., 2020, Lin et al., 2014, Everingham et al., 2010, Deng et al., 2009],[Vitoria et al., 2020, Su et al., 2020, Zhang et al., 2017, Zhang et al., 2016]

**PSNR** and **SSIM** 

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2$$
(1)  

$$PSNR = 10 \cdot \log_{10} \left( \frac{MAX_l^2}{MSE} \right)$$
  

$$= 20 \cdot \log_{10} \left( \frac{MAX_l}{\sqrt{MSE}} \right)$$
(2)  

$$= 20 \cdot \log_{10} (MAX_l) - 10 \cdot \log_{10} (MSE)$$

where m,n is the weight and weight of the image.

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$
(3)

where x,y are two moving window.  $c_1 = (k_1L)^2$ ,  $c_2 = (k_2L)^2 c_2 = (k_2L)^2$  two variables to stabilize the division with weak denominator; L is the dynamic range of the pixel-values; $k_1 = 0.01$  and  $k_2 = 0.03 k_2 = 0.03$  by default.

### Strength and Weakness

#### Strength

Cleverly introduces the Mask-RCNN to detect objects in pictures, which solves the poor color performance of instances in the past. Proposes the fusion module in the fusion of object and background.

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#### Weakness

Simple design of the loss function(only smooth 11 loss) The low efficiency of the fusion module

# Neural Style Transfer Network[Liu et al., 2021]



Figure: Model architecture for attention neural style transfer network[Liu et al., 2021]

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# Visual Comparison



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Figure: Visual results of Neural Style Transfer. The images at the left column are style including color pencil, oil painting, cubism, impressionism, sketch and expressionism. The image at the first row are content. The other image are style transfer image.

### Strength and Weakness

#### Strength

This paper introduces an adaptive attention mechanism network using multi-scale feature outputs.

Weakness

In terms of the network not having panoramic perception, the network is deficient in learning spatial information of images, especially those with a particular color gradient in the background.

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# Conclusion

- Study the algorithm of image coloring and style transfer.
- Autoencoder and decoder construction
- The choice of latent space
- Adaptive attention mechanisms
- Semantic segmentation can solve the weakness of both paper.

# References I



# References II



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