

Computational Imaging Project

Combining Markov Random Fields and Convolutional Neural Networks for Image Synthesis

Team 5-a

Content



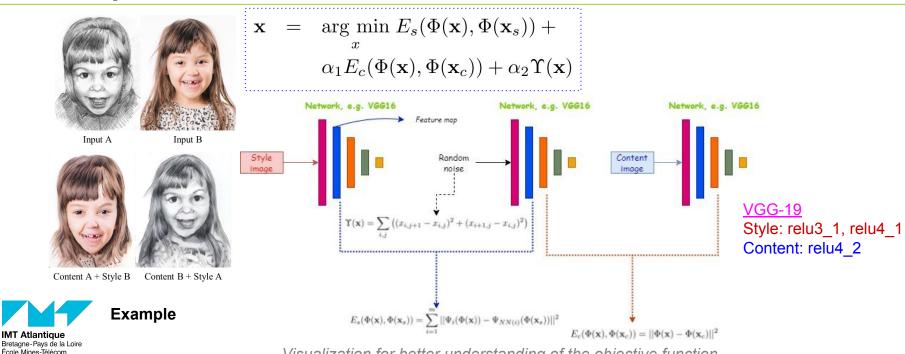
1. Summary of methodology

2. Choice of network + Metrics

3. Results and Discussion

Objective:

Synthesize an image x with its template guided by a content image x_c and having the textures from a style image $x_c \to A$ minimization problem:



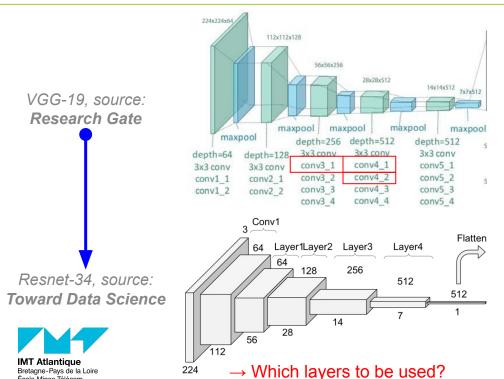
Visualization for better understanding of the objective function.

CHAPTER 2: Network choice and Metrics

2.1 Network

Idea:

Change pretrained VGG-19 to another pretrained network.



Layer name	Resnet-34 7x7, 64, stride 2 3x3, max pool, stride 2	
conv1		
pool1		
conv2_x	$\begin{bmatrix} 3 \times 3, 64 \\ 3 \times 3, 64 \end{bmatrix}$	× 3
conv3_x	$3 \times 3, 128 \\ 3 \times 3, 128$	× 4
conv4_x	$3 \times 3,256 \\ 3 \times 3,256$	× 6
conv5_x	$3 \times 3,512 \\ 3 \times 3,512$	× 3
fc1	4x1, 512, stride 1	
pool time	1x10, avg pool, stride 1	
fc2	1x1, 50	

CHAPTER 2: Network choice and Metrics

2.2 Quantitative measurement

Idea:

Choose some relevant metrics for **quantitative** evaluation of synthesized images (*This is a bonus* section beside the qualitatively perceptual metric).

→ Wang, Zhizhong & Zhao, Lei & Chen, Haibo & Zuo, Zhiwen & Li, Ailin & Xing, Wei & Lu, Dongming. (2021). **Evaluate and improve the quality of neural style transfer.** Computer Vision and Image Understanding. 207. 103203. 10.1016/j.cviu.2021.103203.

<u>3 metrics:</u> Content fidelity (CF), Global effect (GE) and Local pattern (LP) → *Use simplified version*

Content fidelity

$CF(\vec{x}, \vec{c}) = \frac{1}{N} \sum_{l=1}^{N} \frac{f_l(\vec{x}) \cdot f_l(\vec{c})}{\|f_l(\vec{x})\| \cdot \|f_l(\vec{c})\|}$

Global effect

$$GC(\vec{x}, \vec{s}) = \frac{1}{3} \sum_{c=1}^{3} \frac{hist_c(\vec{x}) \cdot hist_c(\vec{s})}{\|hist_c(\vec{x})\| \cdot \|hist_c(\vec{s})\|}$$

$$HT(\vec{x}, \vec{s}) = \frac{1}{N} \sum_{l=1}^{N} \frac{\mathcal{G}(f_l(\vec{x})) \cdot \mathcal{G}(f_l(\vec{s}))}{\|\mathcal{G}(f_l(\vec{x}))\| \cdot \|\mathcal{G}(f_l(\vec{s}))\|}$$

$$GE(\vec{x}, \vec{s}) = \frac{1}{2}(GC(\vec{x}, \vec{s}) + HT(\vec{x}, \vec{s}))$$

Local pattern

$$LP_{1}(\vec{x}, \vec{s}) = \frac{1}{Z} \sum_{l=1}^{N} \sum_{i=1}^{n_{x}} \frac{\boldsymbol{\Phi}_{i}^{l}(\vec{x}) \cdot \boldsymbol{\Phi}_{CM(i)}^{l}(\vec{s})}{\|\boldsymbol{\Phi}_{i}^{l}(\vec{x})\| \cdot \|\boldsymbol{\Phi}_{CM(i)}^{l}(\vec{s})\|}$$

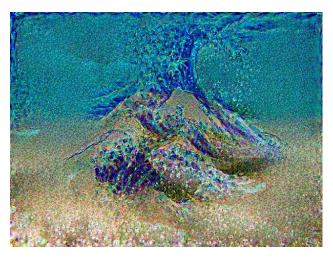
$$LP_2(\vec{x}, \vec{s}) = \frac{1}{N} \sum_{l=1}^{N} \frac{t_{cm}^l}{t_s^l}$$

$$LP(\vec{x}, \vec{s}) = \frac{1}{2}(LP_1(\vec{x}, \vec{s}) + LP_2(\vec{x}, \vec{s}))$$





Content + Style 1 CF = 0.78 GE = 0.76 LP = 0.0147



```
Content + Style 2

CF = 0.82

GE = 0.55

LP = 0.0149
```



<u>Credit:</u> Code implementation was adapted and modified from the one of git user jonzhaocn https://github.com/jonzhaocn/cnnmrf-pytorch (and he/she used a different initialization)



Content + Style 1 CF = 0.78 GE = 0.76 LP = 0.0148



```
Content + Style 2

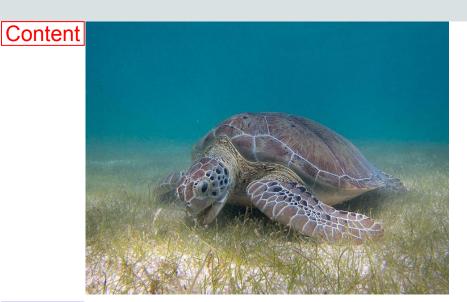
CF = 0.53

GE = 0.55

LP = 0.0143
```

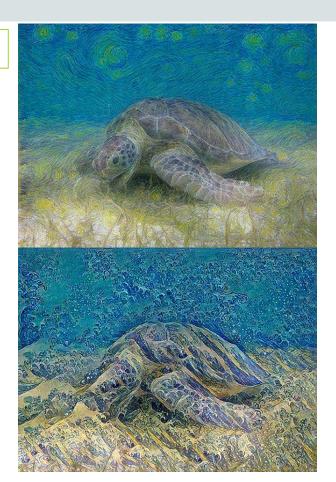


<u>Credit:</u> Code implementation was adapted and modified from the one of git user jonzhaocn https://github.com/jonzhaocn/cnnmrf-pytorch (and he/she used a different initialization)



VGG-19 results

Content + Style 1 CF = 0.781866 GE = 0.7619 LP = 0.014755



Style

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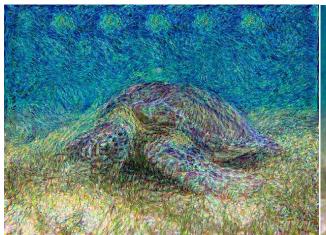


Content + Style 2 CF = 0.531313 GE = 0.55236 LP = 0.014287

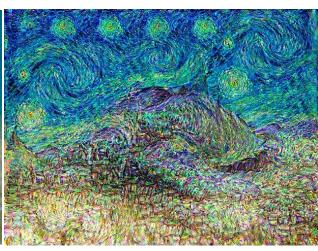
Style 1

Style 2

Results on different layers, style_weight = 0.5, number of iterations = 60, number of resolutions = 3, style patch size = 3, stride = 1







```
Content = conv4_5
content_weight = 0.3
Style = conv3_1
CF = 0.83
GE = 0.77
LP = 0.0151

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Bretagne-Pays de la Loire
```

```
Content = conv4_5

content_weight = 0.3

Style = conv4_1

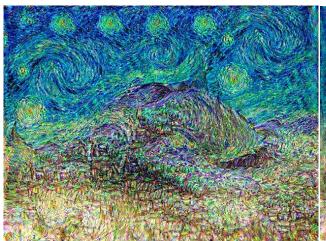
CF = 0.88

GE = 0.60

LP = 0.0084
```

Results on different layers, style_weight = 0.5, number of iterations = 60, number of resolutions = 3, style patch size = 3, stride = 1

Style weight variation







```
Content = conv4_5
content_weight = 0.3
Style = conv3_1, conv4_1

CF = 0.68
GE = 0.80
LP = 0.0161
```



Results on different layers, style_weight = 0.5, number of iterations = 60, number of resolutions = 3, style patch size = 3, stride = 1

Style patch size + Stride variation





Content = conv5_3 Style = conv4_2, conv4_5





Content = conv5_3

Style = conv4_1, conv4_2

stride = 3

CHAPTER 3: Results and Discussion

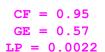
Content + Style 1

Results on different layers, style_weight = 0.1, number of iterations = 60, number of resolutions = 3, style patch size = 3, stride = 2

Style patch size + Stride variation



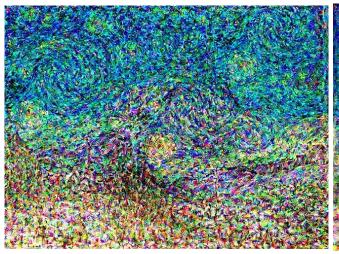






Content = conv5_3
Style = conv4_1, conv4_2
style patch size = 5
stride = 1

Some other extreme cases (some parameters are abnormal)





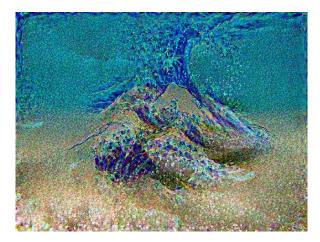


CHAPTER 3: Results and Discussion

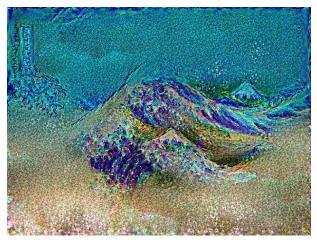
Content + Style 2

Bretagne-Pays de la Loire

Results on different layers, α_1 = 0.5 number of iterations = 150, number of resolutions = 3, style patch size = 3, stride = 1

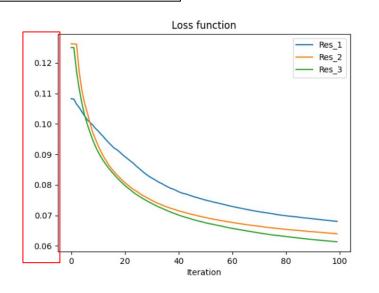


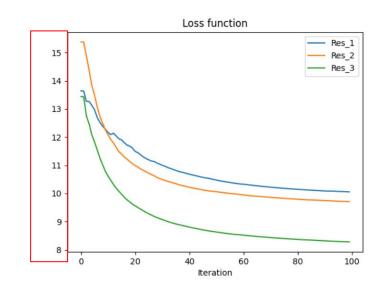




CHAPTER 3: Results and Discussion

LOSS FUNCTION EVOLUTION





Resnet34



 $\underset{x}{\operatorname{arg min}} E_s(\Phi(\mathbf{x}), \Phi(\mathbf{x}_s)) + \alpha_1 E_c(\Phi(\mathbf{x}), \Phi(\mathbf{x}_c)) + \alpha_2 \Upsilon(\mathbf{x})$

VGG19



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Thank you for your attention

Team 5-a