

#### IMT Atlantique

Bretagne-Pays de la Loire École Mines-Télécom

# Style Transfer by Relaxed Optimal Transport and Self-Similarity

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#### **SUMMARY**



- 1. Method recap
- 2. Hyperparameters
- 3. User control
- 4. Examples and results
- 5. Conclusion

## **METHOD RECAP**









Style



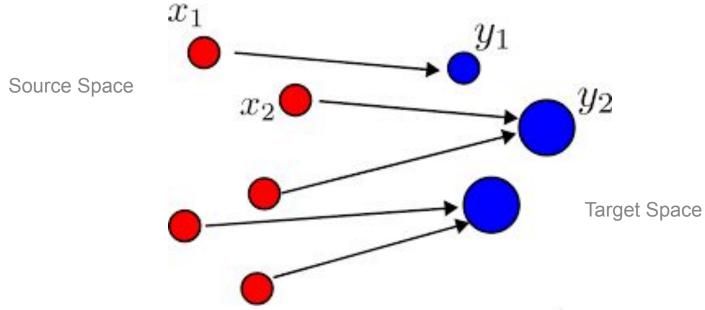
Combination



#### **CHAPITRE 1: METHOD RECAP**

**Optimal Transport** 

The optimal transport is the problem that tries to find the transport map





$$\ell_r = \max\left(\frac{1}{n}\sum_{i}\min_{j}C_{ij}, \frac{1}{m}\sum_{i}\min_{i}C_{ij}\right)$$

Feature map

Iterative process: Gradient descent

Icomb Ic Is Convolutional Layers Fc Soft max

Pre-Trained VGG

$$L(X, I_C, I_S) = \frac{\alpha \ell_C + \ell_m + \ell_r + \frac{1}{\alpha} \ell_p}{2 + \alpha + \frac{1}{\alpha}}$$

3 Backpropagate, reconstruct





Alpha pondered content

$$L(X, I_C, I_S) = \frac{\alpha \ell_C + \ell_m + \ell_r + \frac{1}{\alpha} \ell_p}{2 + \alpha + \frac{1}{\alpha}}$$

Palette loss

Content loss



Moment loss

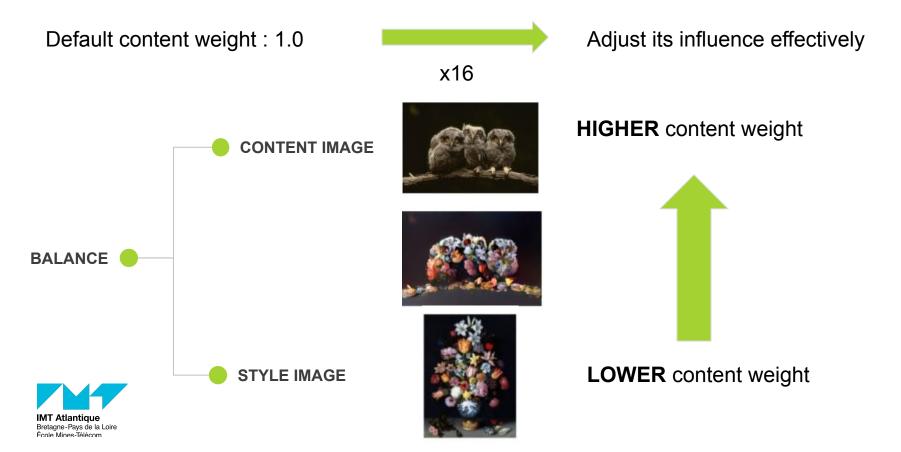
Style Loss

**REMD Loss** 

### **HYPERPARAMETERS**



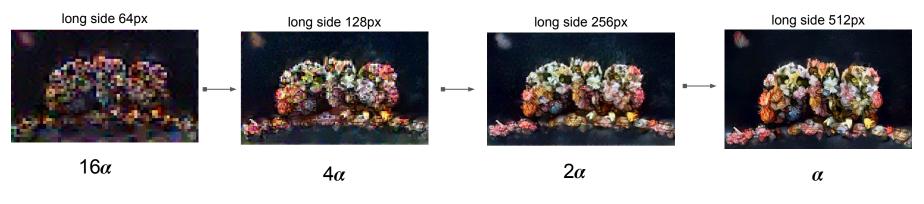
# **CHAPITRE 2 : HYPERPARAMETERS**CONTENT WEIGHT (α)



#### **CHAPITRE 2: HYPERPARAMETERS**

#### CONTENT WEIGHT ( $\alpha$ )

The iterative process described previously is made for 4 different scales using the (upscaled) output of the previous scale as input, halving the content weight  $(\alpha)$  for the next scale:



Optimization followed by upscaling



# CHAPITRE 2: HYPERPARAMETERS LEARNING RATE (Ir)

Learning rate influences the **CONVERGENCE SPEED** and **STABILITY OF THE OPTIMIZATION PROCESS** 

The algorithm strikes a balance between **rapid convergence** and **fine-tuning**. By a higher Ir, the algorithm can explore solution space more extensively.



### **USER CONTROL**

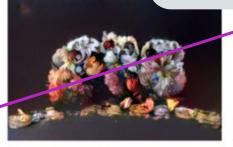


#### **CHAPITRE 3: USER CONTROL**

Mask specific areas to have the same style:

Control is enforced by making the pairs of points in the same region have higher weight in the loss calculation













Content mask

Style mask



## **EXAMPLES AND RESULTS**



#### **Unguided Style Transfer**

























#### Varying content weight













 $\alpha = 0.2$   $\alpha = 0.5$ 

 $\alpha = 1$ 

 $\alpha = 2$ 

 $\alpha = 4$ 

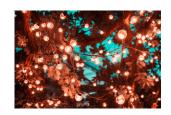




#### **Varying learning rate**

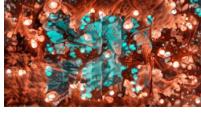
 $\alpha = 1$ 







Ir = 0.2 76.451s



 $Ir = 0.02 \quad 77.522s$ 



Ir = 2e-3 76.912s



Ir = 2e-4 76.556s



Ir = 2e-5 76.691s

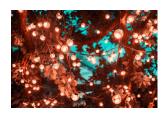


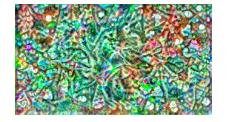
Ir = 2e-6 79.937s



#### Varying learning rate









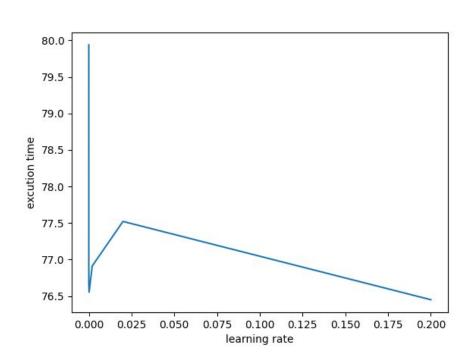
Ir = 0.2 76.451s

Ir = 2e-3 76.912s





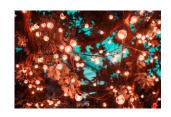
Ir = 2e-6 79.937s



#### Losses

 $\alpha = 1$ Ir = 2e-3











No REMD

No moment loss



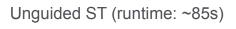
**Guided Style Transfer (masks)** 













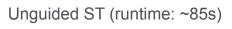


Guided ST (runtime: ~273s)















Guided ST (runtime: ~273s)



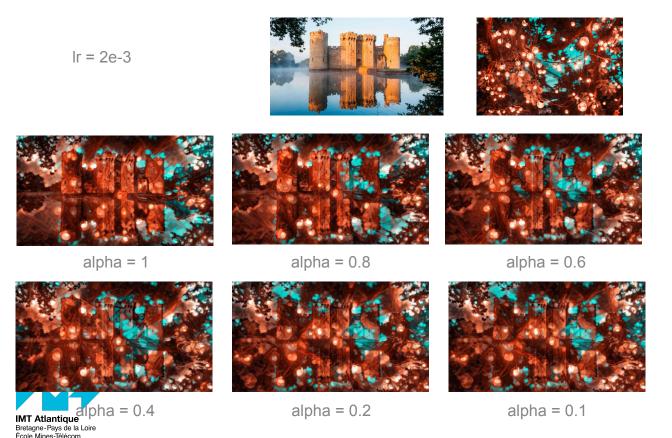


- Algorithm implementation give good aesthetic results but takes a fairly big amount of time to run.
- User control with guided style can increase the control of the output by the user, but may not always generate better results for all applications.
- Runtime running with masks increases too much, making a excessive long runtime even in fairly powerful GPU's.

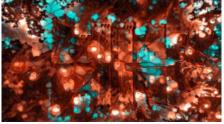


#### **CHAPITRE 5: RESULTS AND TIME TO RUN**

Impact of content weight alpha:



average running time on Colab's gpu: 74s



alpha = 0.01

# THANK YOU FOR YOUR ATTENTION. ANY QUESTIONS?

