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Style Transfer by Relaxed Optimal Transport and Self-Similarity

Group 5:
Houda GHALLAB
Renzo MORALES
Carlos ARGUILAR
Mohamed Salim ARIFA
Ghaith MAKHLOUF

SUMMARY

1. Introduction
2. Fundamentals : Optimal Transport & Self Similarity
3. Methodology
4. Implementation and region control
5. Experiments and comparison to the related work
6. Conclusion

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INTRODUCTION

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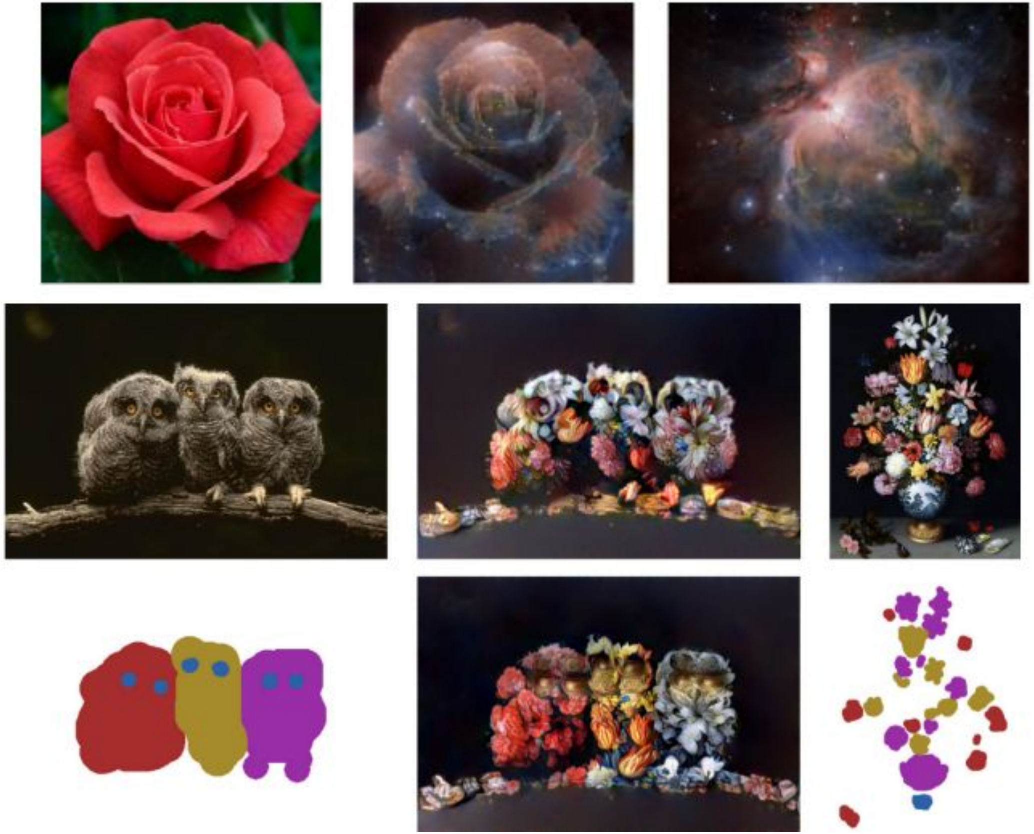
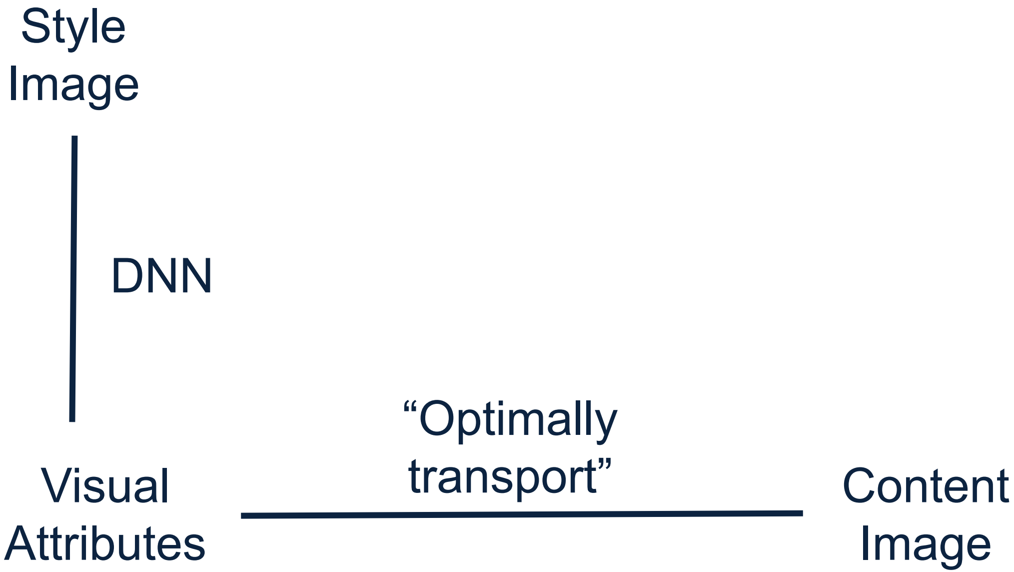
Content

Style

Combination



Style: a distribution over features extracted by a deep neural network



Style: a distribution over features extracted by a deep neural network

Style Image

DNN

Visual Attributes

"Optimally transport"

Content Image

with minimum distortion to the content

Content:

Self similarity: objects often have repeating patterns or elements within themselves

Content:

Human visual system: Relative appearance and surroundings

Content:

Self similarity: objects often have repeating patterns or elements within themselves

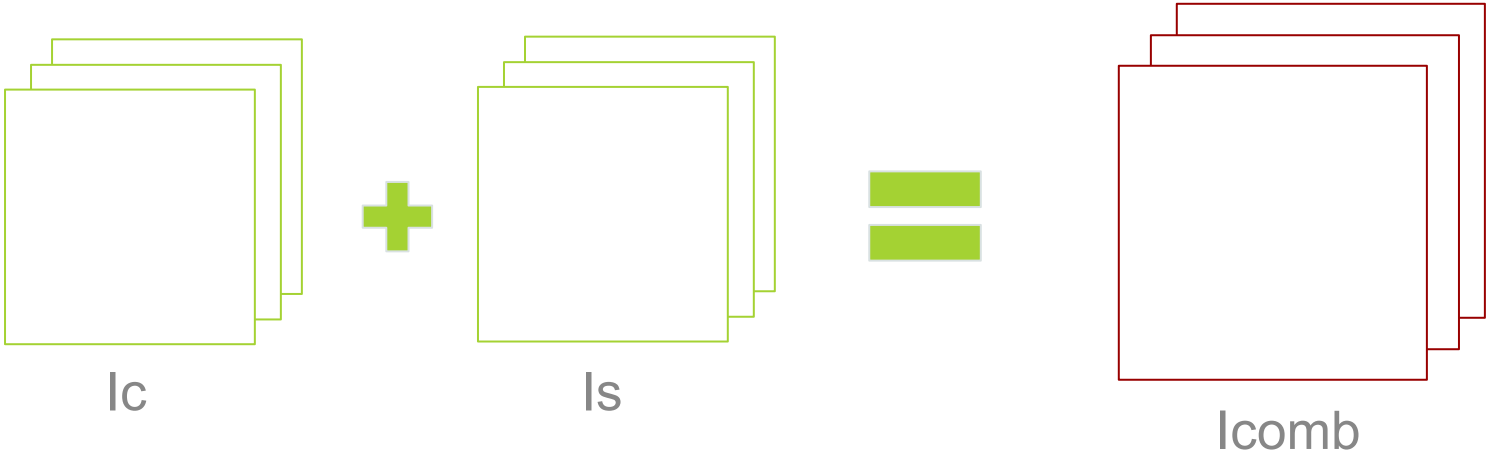
Human visual system: Relative appearance and surroundings

→

Preserve **semantics** and **spatial** layout of the content image

Content is not focused on the exact pixel values of the image, but rather on the relationships between those pixels.

1.3 Algorithm overview



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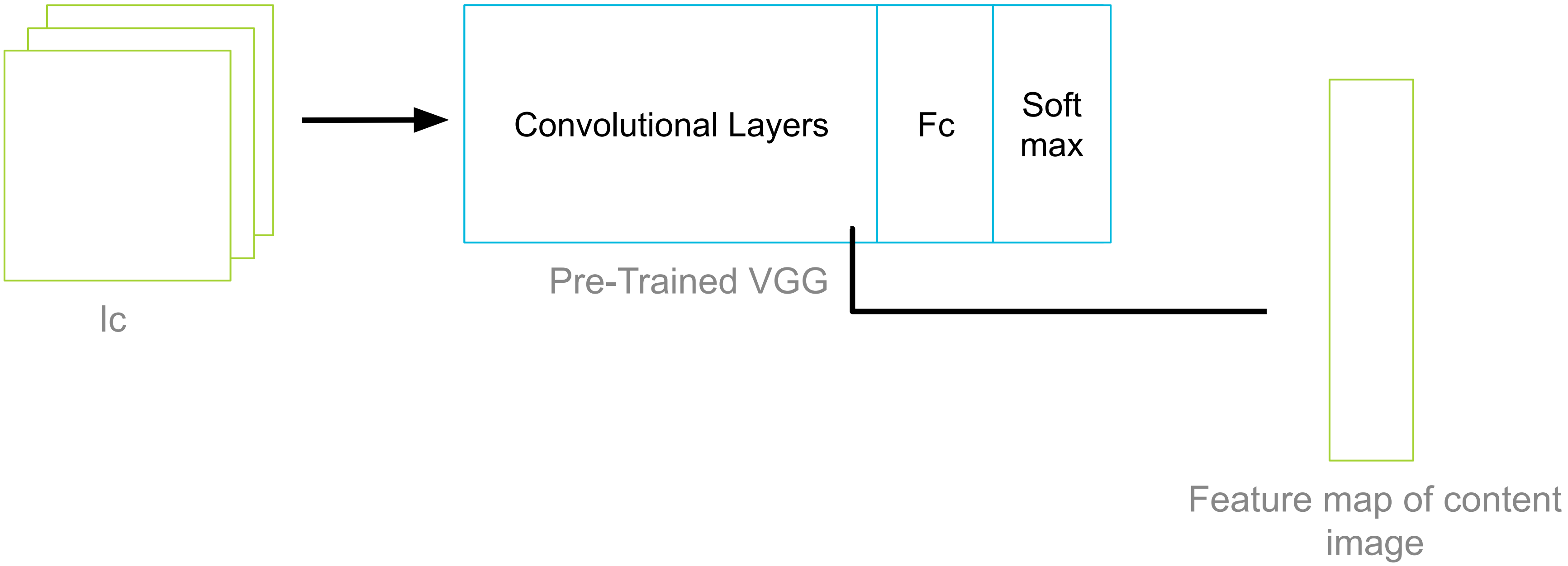
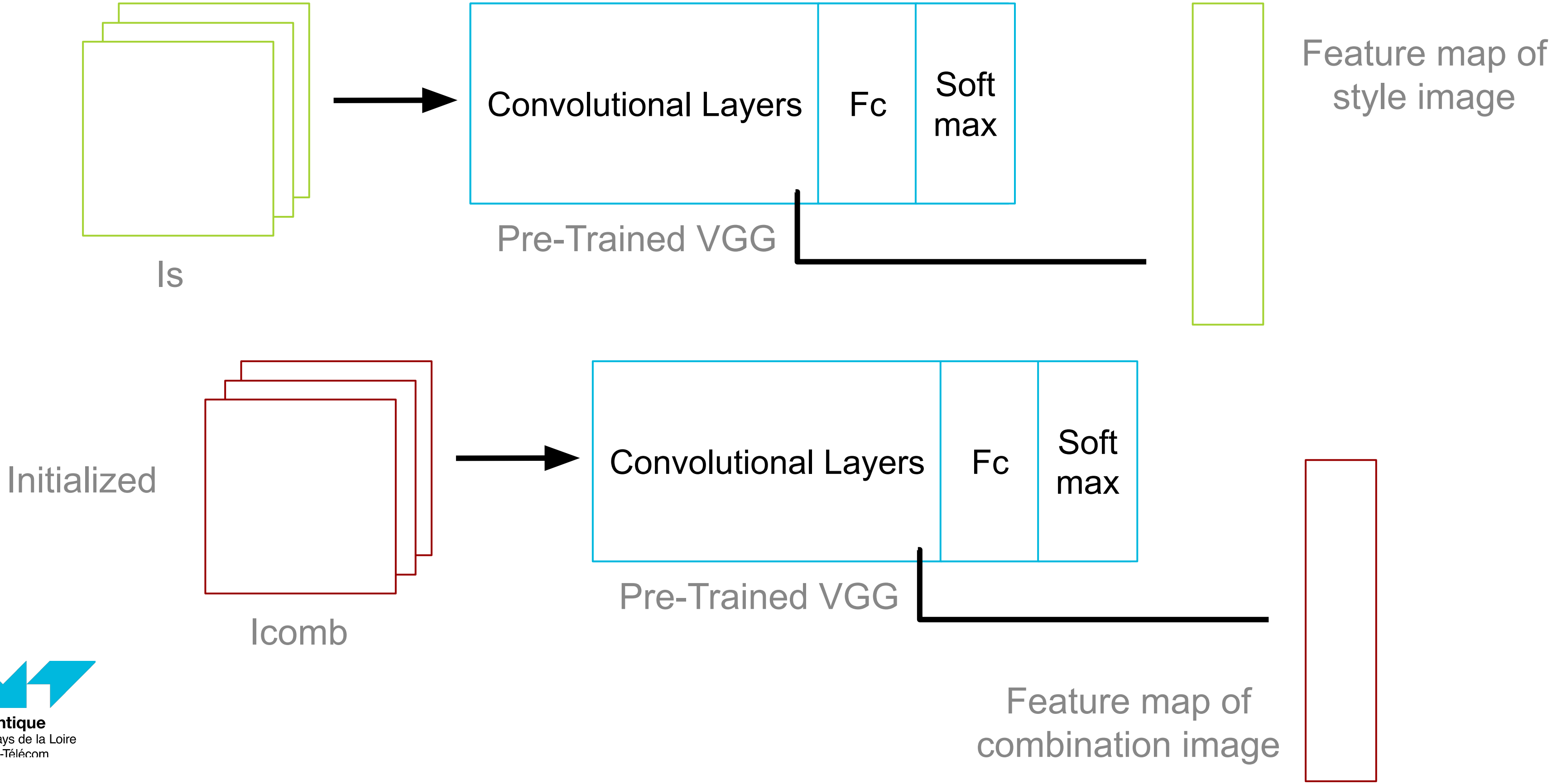

Convolutional Layers
Fc
Soft
max
Pre-Trained VGG
Ic
Feature map of content
image


Convolutional Layers
Fc
Soft
max
Feature map of
style image
Pre-Trained VGG
Is
Initialized
Convolutional Layers
Fc
Soft
max
Pre-Trained VGG
Icomb
Feature map of
combination image

Features extraction: **feature maps** of **content**, **style**, and **combination** images

Optimization: We want to measure how far our combination image is from a “Good combination”

Minimization of a loss function
Icomb_Loss = Loss(Ic) + Loss(Is)

Features extraction: **feature maps** of **content**, **style**, and **combination** images

Gradient descent

```
init Icomb
for e in range(epochs):
    calculate Icomb_loss
    derivative of loss
    update Icomb accordingly
```

FUNDAMENTALS

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- Let's break down the title of the paper:

Style Transfer by Relaxed Optimal Transport and Self-Similarity

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Style Transfer by Relaxed Optimal Transport and Self-Similarity

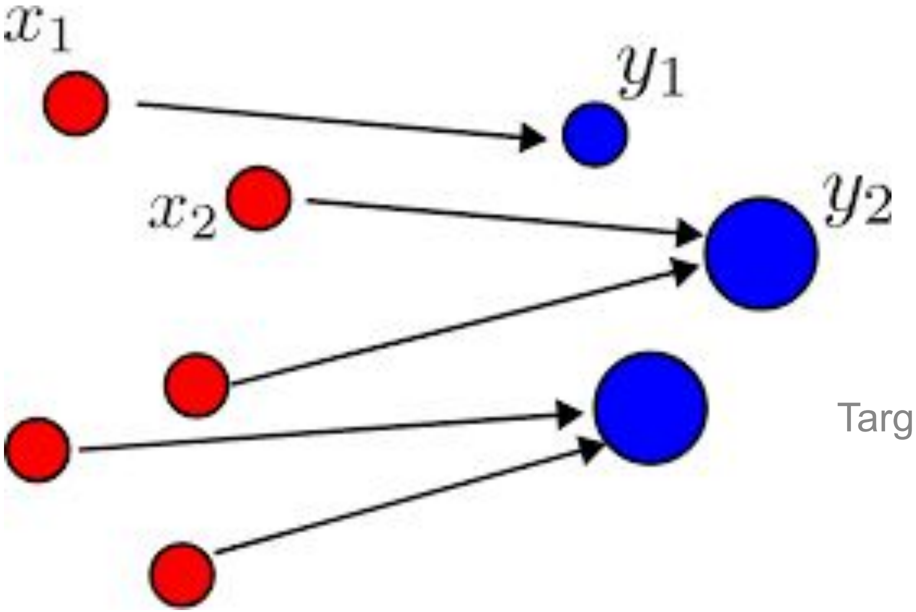
Optimal transport:

Measures: initial distribution of "mass" in a space and where we want to move it to

Cost function: cost of moving mass between points in the source and target spaces

Transport map: how to move the mass from the source distribution to the target distribution while minimizing the total cost

Source Space



Target Space

Optimal transport:

Given two probability measures u (source) and v (target) on a Polish space (a complete, separable metric space) X, and a cost function c: X x X → ℝ, the optimal transport problem seeks a transport map T: X → X that minimizes the total cost of transporting the mass:

don't know if
is slide is
ecessary

∫_X c(x, T(x)) dμ(x)
subject to the constraints that T pushes forward μ to v (i.e., for any measura
set A in X, v(A) = μ(T^(-1)(A)))

Solution: Earth mover's distance EMD

$$C_{ij} = D_{\cos}(A_i, B_j) = 1 - \frac{A_i \cdot B_j}{\|A_i\| \|B_j\|}$$

$$\mathrm{EMD}(A, B) = \min_{T \geq 0} \sum_{ij} T_{ij} C_{ij} \qquad (2)$$

$$s.t. \sum_j T_{ij} = 1/m \qquad (3)$$

$$\sum_i T_{ij} = 1/n \qquad (4)$$

A and B: Sets of vectors
T: Transport matrix
C: Cost matrix
n: len(A)
m: len(B)

$$\boxed{O(\max(m, n)^3)}$$

Exact match between features

Approximation: Relaxed earth mover's distance REMD

$$R_A(A,B) = \min_{T \geq 0} \sum_{ij} T_{ij} C_{ij} \quad s.t. \quad \sum_j T_{ij} = 1/m \quad (5)$$

$$R_B(A,B) = \min_{T \geq 0} \sum_{ij} T_{ij} C_{ij} \quad s.t. \quad \sum_i T_{ij} = 1/n \quad (6)$$

A and B: Sets of vectors
T: Transport matrix
C: Cost matrix
n: len(A)
m: len(B)

Approximation: Relaxed earth mover's distance REMD

$$\ell_r = REMD(A, B) = \max(R_A(A, B), R_B(A, B)) \quad (7)$$

This is equivalent to:

$$\ell_r = \max\left(\frac{1}{n}\sum_i \min_j C_{ij}, \frac{1}{m}\sum_j \min_i C_{ij}\right) \quad (8)$$

A and B: Sets of vectors
T: Transport matrix
C: Cost matrix
n: len(A)
m: len(B)

→ More imperfections in feature matching, more natural looking style transfer

Ideas to explain

- what is self similarity
- the mathematical basis and proofs used
- Link between theory and
- In id tortor sit amet augue.

#here the need for a self similarity descriptor to preserve the original content is described

Trying to define Self-Similarity

Content Image

Style image

Undesirable output and total loss of content

Trying to define Self-Similarity

= Same "content"
Same internal self similarity

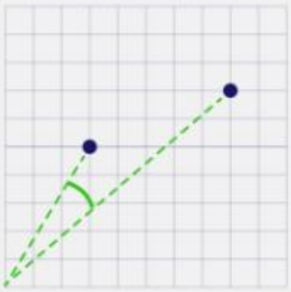
≠ different colours
different edges
different texture

another example of content preservation: Pareidolia

#trying to define what "content" is, impiortantly to say that the structure cannot be perceived logically but should be analysed within the context of an image

Solution:

Self similarity descriptor=

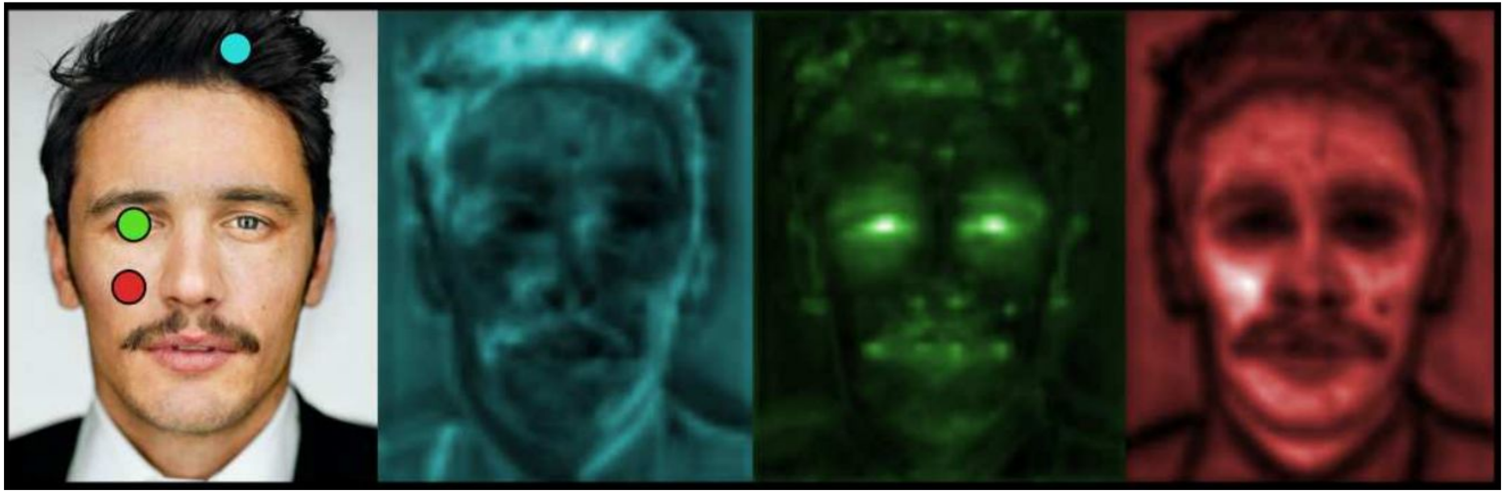


Cosine Distance

$$1 - \frac{A \cdot B}{||A|| \ \ ||B||}$$

doesn’t care about:

- -luminance
- -texture
- -scale
- -Colour



Self similarity Map (1- cosine_distance)

$$D_{ij} = \begin{array}{cc} & \begin{array}{cccc} a & & b & c \end{array} \\ \begin{array}{c} a \\ \\ b \\ c \end{array} & \begin{bmatrix} 0 & \cdots & 0.3 & 0.84 \\ \vdots & 0 & \vdots & \vdots \\ 0.3 & \cdots & 0 & \vdots \\ 0.84 & \cdots & \cdots & 0 \end{bmatrix} \end{array}$$

Self similarity Matrix (of cosine distances)

METHODOLOGY

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Loss Function

How are optimal transport and style similarity concepts used in our work ?

Loss Function :

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

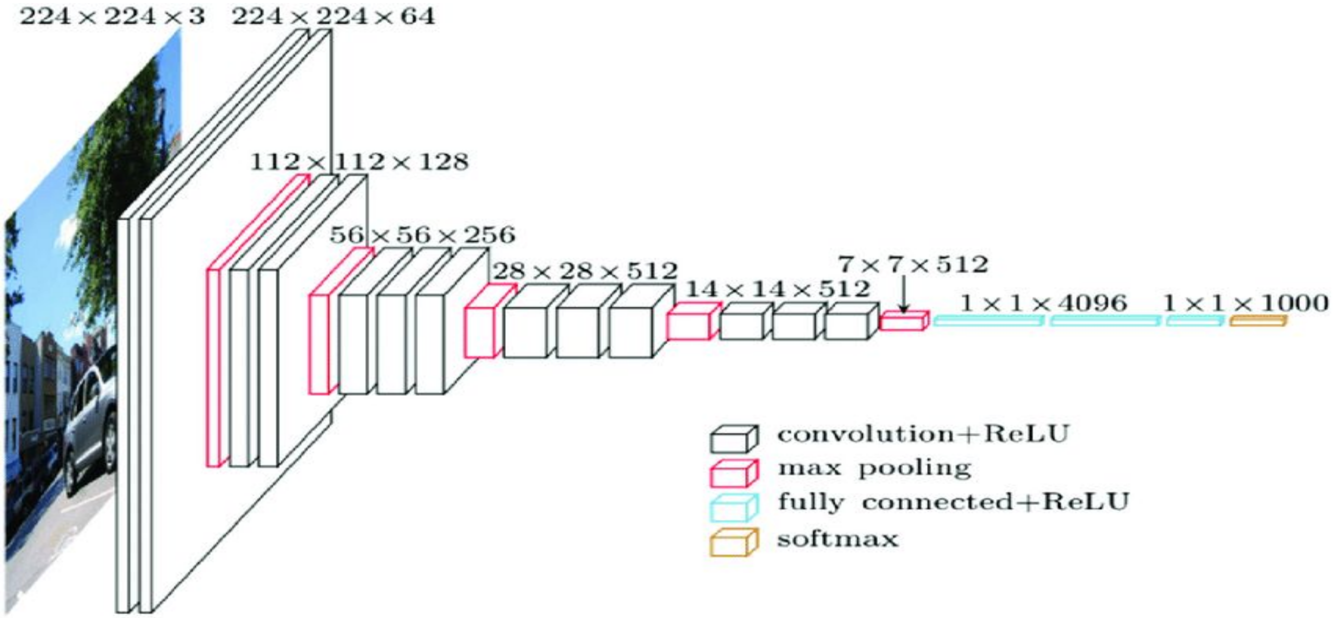
Loss Function

$$L(X, I_C, I_S) = \frac{\underbrace{\alpha \ell_C}_{\text{Content Loss}} + \underbrace{\ell_m + \ell_r + \frac{1}{\alpha}\ell_p}_{\text{Style Loss}}}{2 + \alpha + \frac{1}{\alpha}}$$

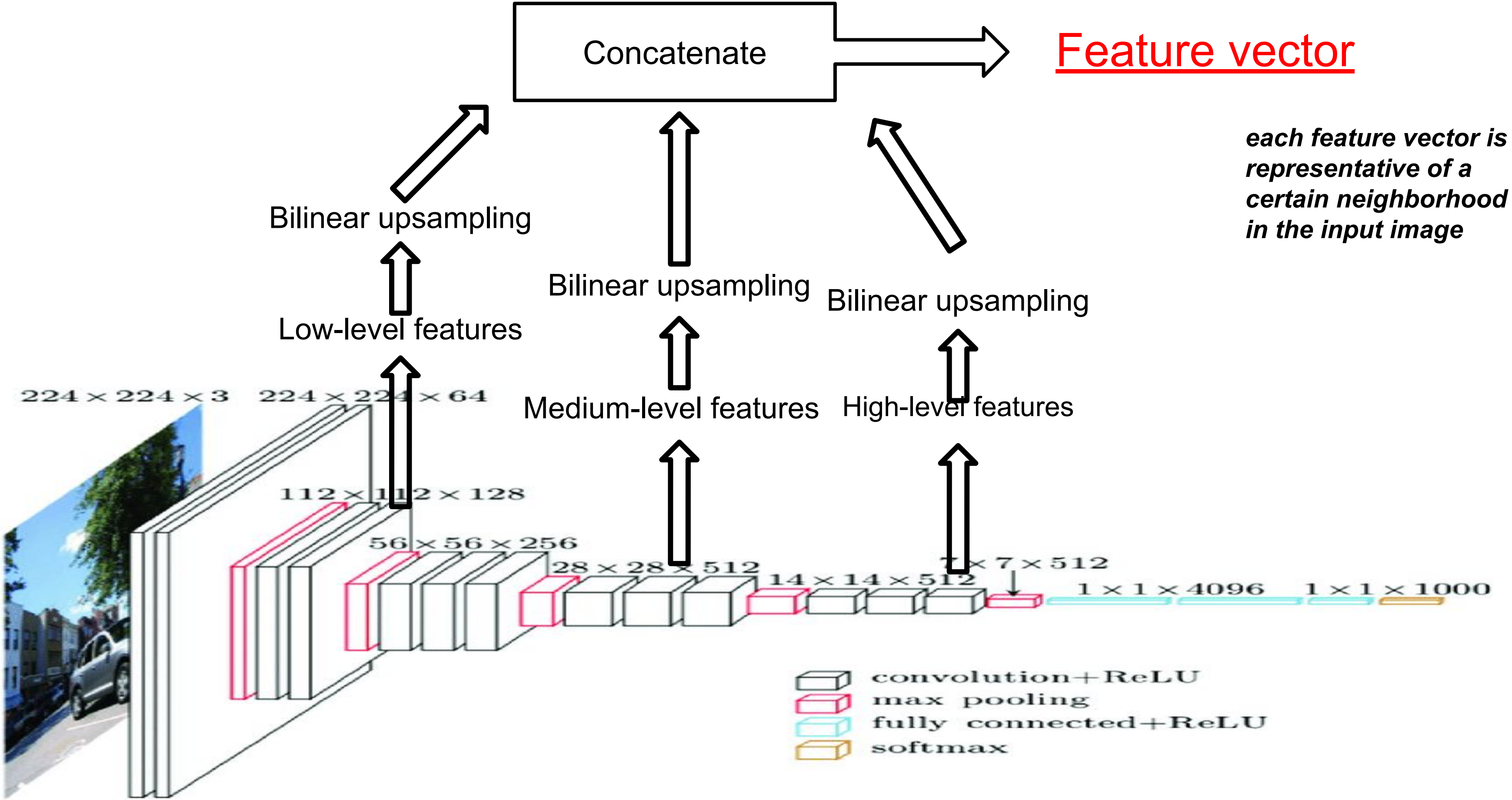
α: Hyperparameter: relative importance of content preservation to stylization

Both our style and content loss terms rely upon extracting a rich feature representation from an arbitrary spatial location.

VGG16 trained on ImageNet



VGG-16 for feature extraction



each feature vector is representative of a certain neighborhood in the input image

Content Loss

$$\mathcal{L}_{content}(X, C) = \frac{1}{n^2}\sum_{i,j}\left|\frac{D^X_{ij}}{\sum_i D^X_{ij}} - \frac{D^{I_C}_{ij}}{\sum_i D^{I_C}_{ij}}\right|$$

- D^X : The pairwise cosine distance matrix of all feature vectors extracted from X(t).
- D^{Ic} : The pairwise cosine distance matrix of all feature vectors extracted from Ic

Normalized cosine distance

Self-Similarity

$$\ell_m + \ell_r + \frac{1}{\alpha}\ell_p$$

Magnitude

Optimal Transport

Palette (colors)

Optimal Transport Problem

EMD ? $\Longrightarrow$ Costly: O(max(m,n)^3) $\Longrightarrow$ R-EMD

$$\ell_r = \max\left(\frac{1}{n}\sum_i \min_j C_{ij}, \frac{1}{m}\sum_j \min_i C_{ij}\right)$$

C: Cost Matrix: How far an element of A (set of feature vectors extracted from X) is from an element of B (set of feature vectors extracted from Is)

ℓ_r : Good transfer of the structural forms of the source image to the target. BUT..

ℓ_p : Color matching loss (palette) $\Longrightarrow$ R-EMD between X and Is

Magnitude of the feature vectors ignored by cosine distance $\Longrightarrow$ Visual Artifacts (under/over saturation)

Palette shifting is at odds with content preservation

$\Downarrow$

$$\frac{1}{\alpha}\ell_p$$

$$\ell_m = \frac{1}{d}\|\mu_A - \mu_B\|_1 + \frac{1}{d^2}\|\Sigma_A - \Sigma_B\|_1$$

- μ_A (μ_B) and **Σ**_A (**Σ**_B) are the mean and covariance of the feature vectors in set A (in set B).

IMPLEMENTATION AND REGION CONTROL

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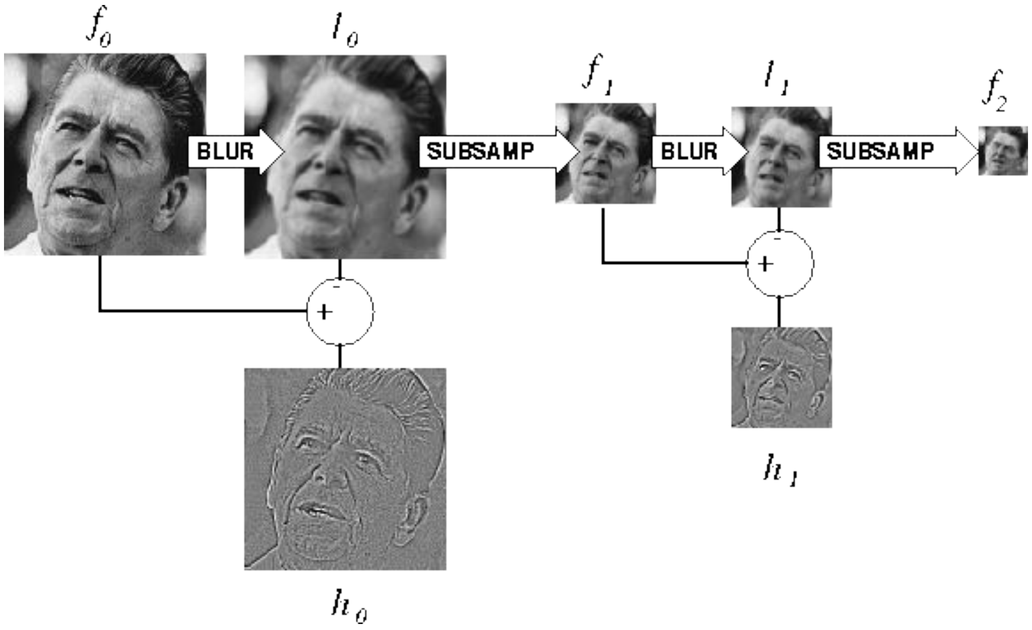
Laplacian Pyramid: Image representation consisting of band-pass images and low-frequency residual image:



Goal:

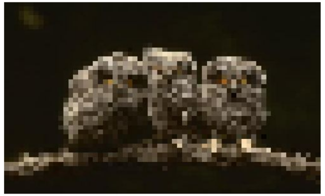
Content Image

Style Image

Stylized Image

STEP 0: INITIALIZATION

Δ (



Content Image (downscaled)

) + MC (

Style Image

) =

Stylized Image

Δ = **Laplacian**

MC = **Mean Color**

IMPLEMENTATION AND USER CONTROL

Step by Step

STEP 1: LAPLACIAN PYRAMID DE COMPOSITION

STEP 2: LOSS CALCULATION

L (


Content Image (downscaled)

,


Style Image (downscaled)

,

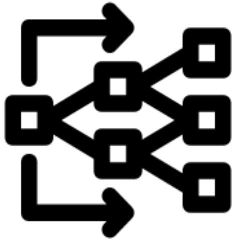

Stylized Image

)

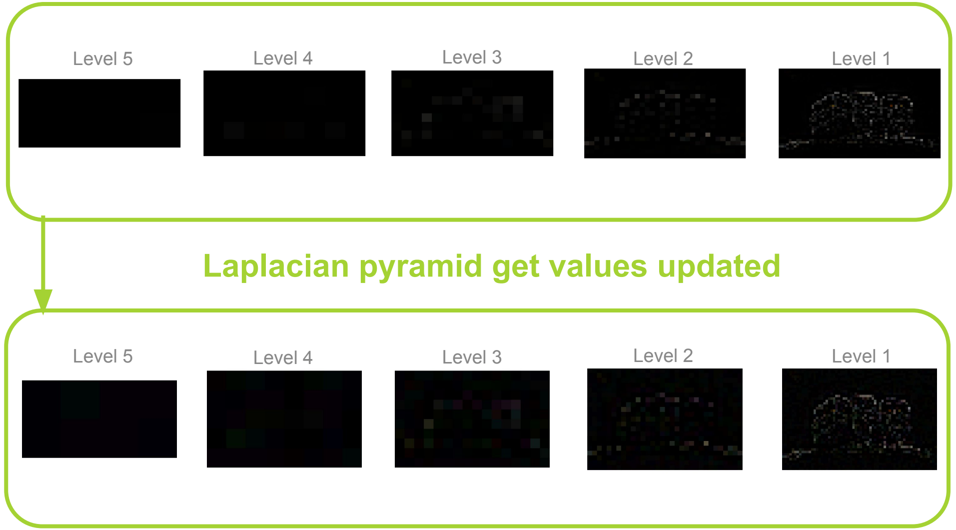
L = **Loss function**

STEP 2: BACKPROPAGATE AND UPDATE PYRAMID VALUES

$$L\left(\ \ldots\ \right)$$



Backpropagation



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L **= Loss function**

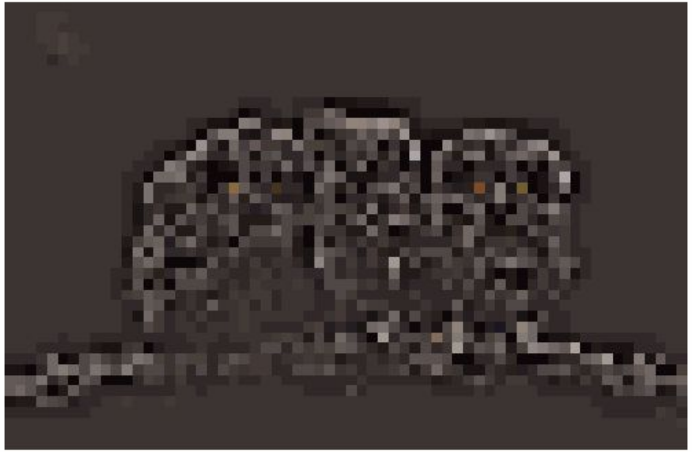
STEP 3: RECONSTRUCT IMAGE FROM UPDATED PYRAMID

Laplacian pyramid with updated values

(new) Stylized Image

Repeat step 1 to 3 (250 iterations) using the updated stylized image

Scale: 64 px, Iteration: 0



IMPLEMENTATION AND USER CONTROL

Multiple scale calculation

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 (α) for the next scale:

long side 64px

α

long side 128px

$\alpha/2$

long side 256px

$\alpha/4$

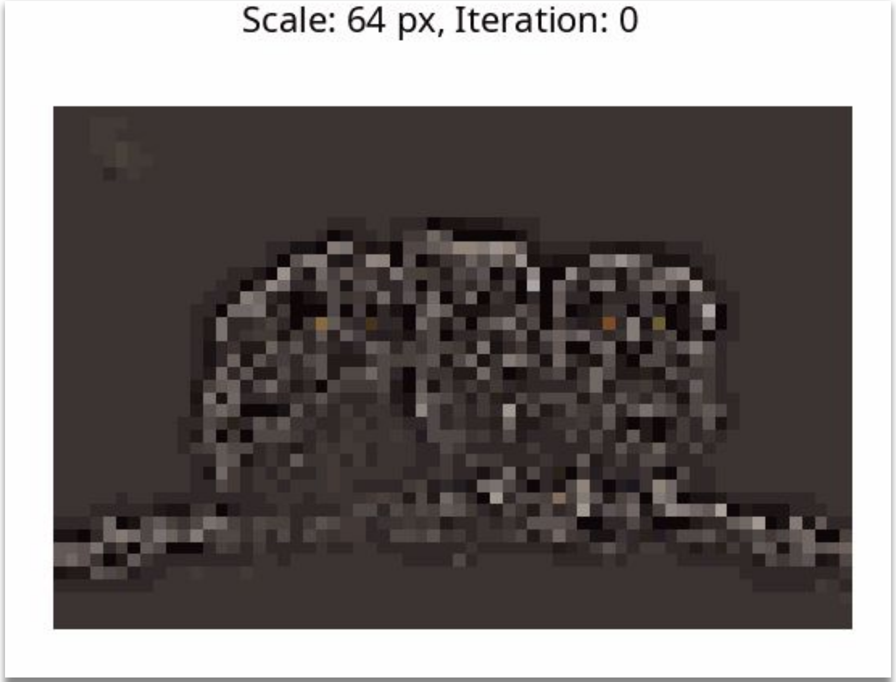
long side 512px

$\alpha/16$

Optimization followed by upscaling

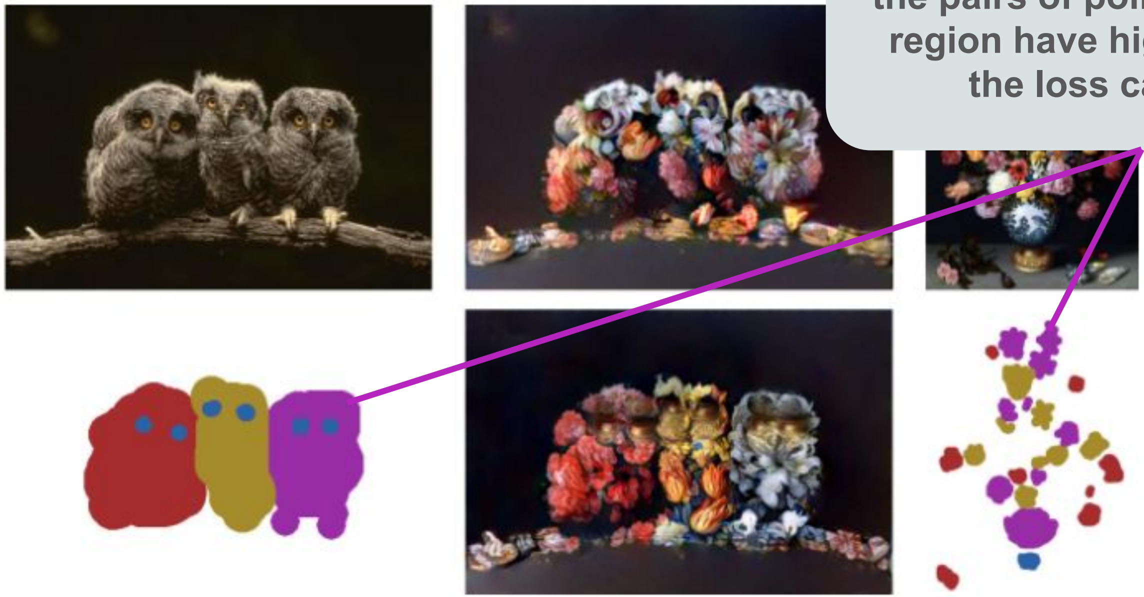
α: Content weight

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 (a) for the next scale



Mask specific areas to have the same style:

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

EXPERIMENTS AND RELATED WORK

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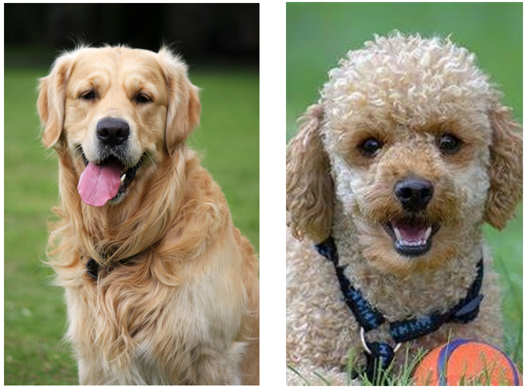
Regimes :

Paired

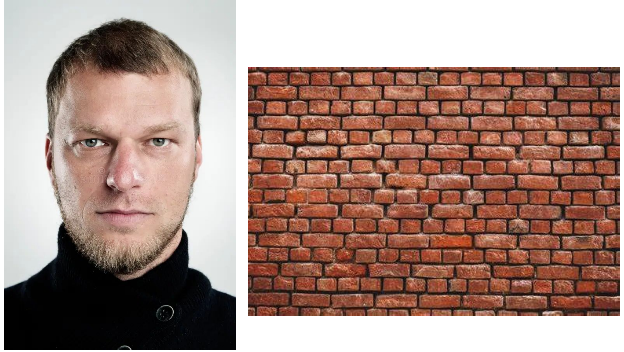


Content image = style image

Unpaired

Content image ≠ style image

Texture

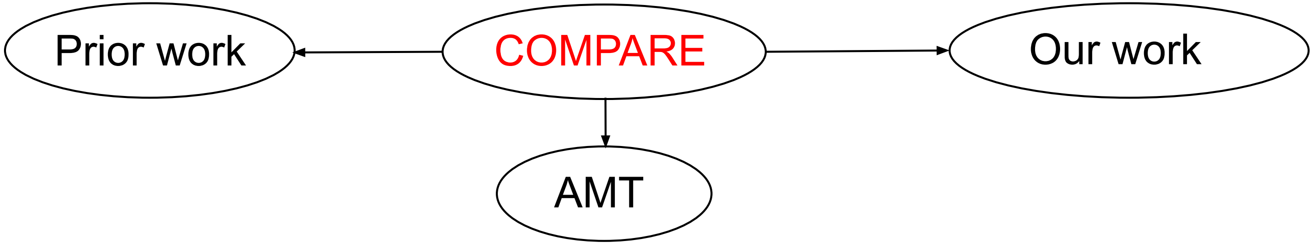


Content: Face photography
Style: Homogeneous texture

*30 style/content pairings (total of 90)

CHAPITRE 4 : EXPERIMENTS

4.1 Large-Scale human evaluation



An example of worker’s interfaces:

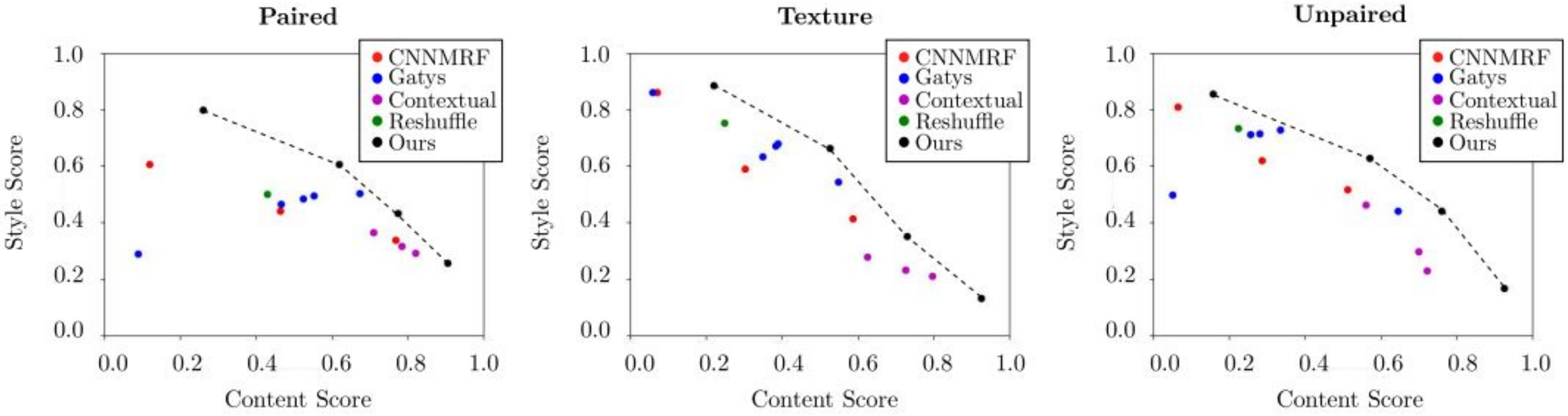
Evaluate whether Image A or Image B has more similar **style** to Image C

The style of Image C is most similar to…

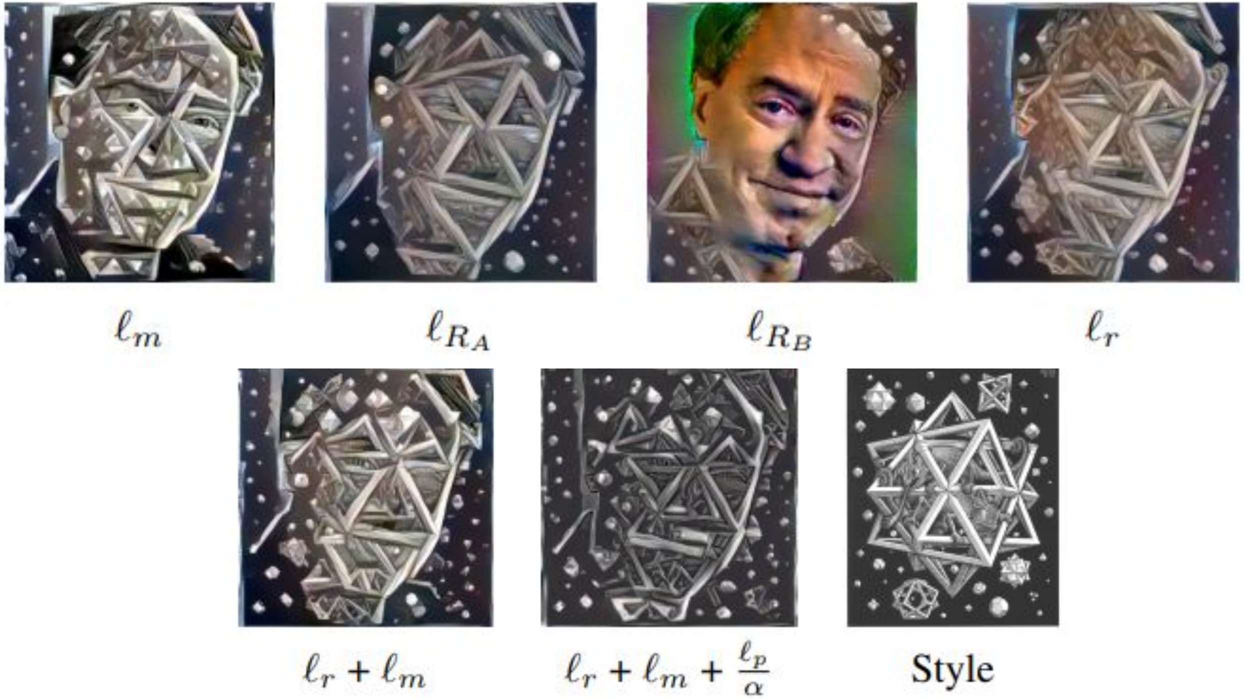
a) Image A
b) Image B
c) **Equally** A and B
d) **Neither** A or B

We test 3 sets of hyper-parameters: Content weight (high and low stylization)

The style score is defined analogously :



Effect of different terms of our style loss



4.3. Relaxed EMD Approximation Quality

$$\frac{REMD(A,B)}{EMD(A,B} \leq 1$$

4.4. Timing results

Image size	64	128	256	512	1024
Ours	20	38	60	95	154
Gatys	8	10	14	33	116
CNNMRF	3	8	27	117	X
Contextual	13	40	189	277	X
Reshuffle	-	-	-	*69**	-

CONCLUSIONS AND FUTURE WORK

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Conclusions

- Our algorithm demonstrates superior performance in style transfer compared to prior methods.
- We emphasize the importance of style-similarity losses for enhancing stylization quality.
- The simplicity and effectiveness of our earth movers distance approximation highlight its potential in style transfer applications.

Future work

- Further exploration of more accurate approximations for the earth movers distance.
- Improvement of algorithm speed through the incorporation of feed-forward style transfer methods using our proposed objective function.

QUESTIONS?

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Alex SZAPIRO

How does this method differ from Multimodal Style Transfer via Graph Cuts (Zhang et al., 2019) ?

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Pierre Monot

If the user control is also using a REMD loss, why not incorporate it in the content loss?

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Yosr DRIRA

The paper has mentioned cosine distance as a self similarity descriptor. Are there other descriptors that you could have used ?

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