Transforming images into paintings and vice-versa using generative adversarial networks (SinGANs)

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Outline

1. Photo to paintings
2. Paintings to photo
   - Clipart to photo (direct application of the paper)
   - Training on the target distribution of patches
   - Generalization

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Task 1 : Transform a photo into a painting

Advantage of SinGAN

- Only 1 photo is needed to capture the style
- The style of a painter is expressed at different scale

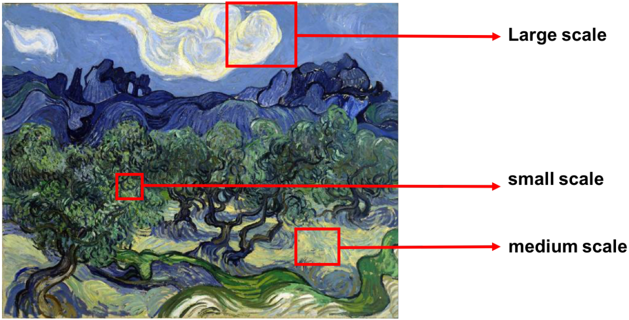


Figure: Style of Van Gogh expressed at different scales

Task 1 : methodology

- **Implementation of an extension of sinGAN**
- **Selection of the most relevant image**: trade-off between the characteristic scale of the painting and the target image

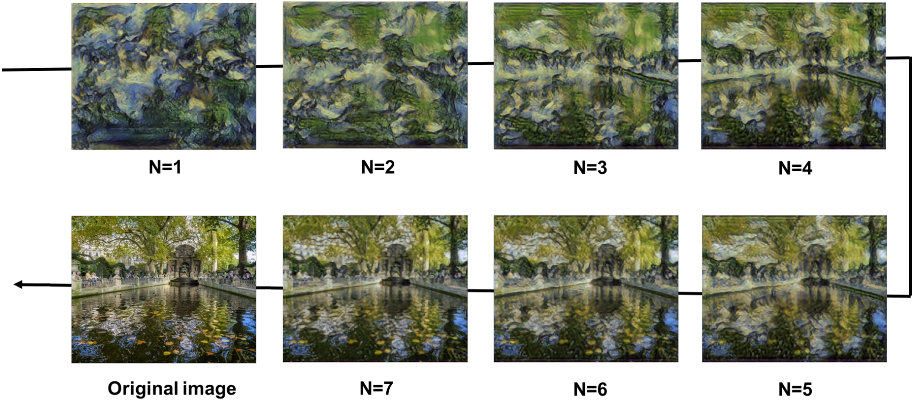


Figure: Scale selection

Task 1 : Results for different styles

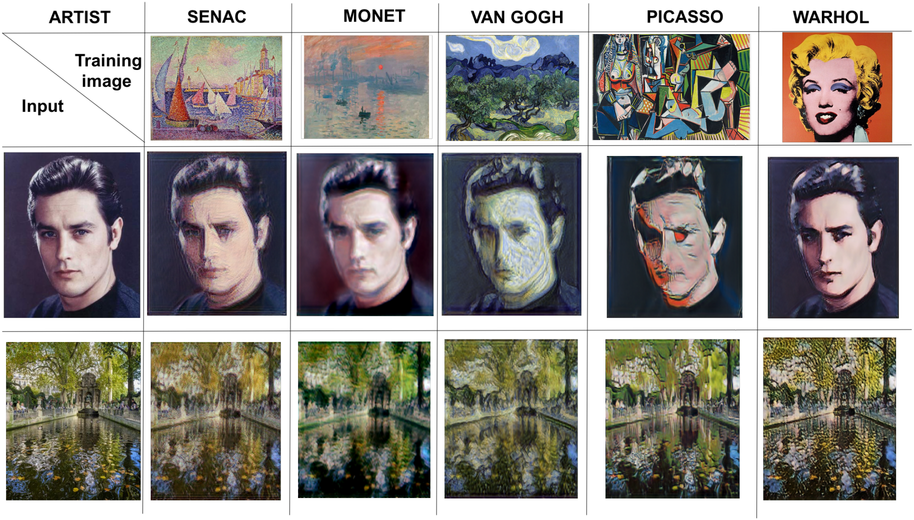


Figure: Results on two examples for different styles

Outline

Task: From clipart to picture

Figure: Performances of SinGAN, NST and Contextual Loss on the paint to image task

	SinGAN	**Neural Style Transfer**	**Contextual Loss**
SIFID	0.634	0.638	0.635

Table: Single Image Fréchet Inception Distance from the style image

[1], [2], [3]

SinGANs' robustness

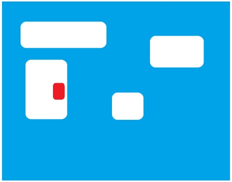
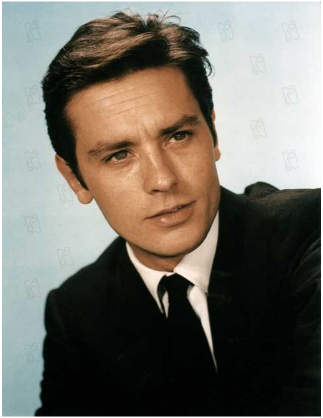


Figure: Perturbed entry

Figure: Results obtained with SinGAN, NST and Contextual Loss

A more complex task: from painting to picture



Two main challenges

- Different color histograms
- Learning objects at different scales

Transferring a different color histogram

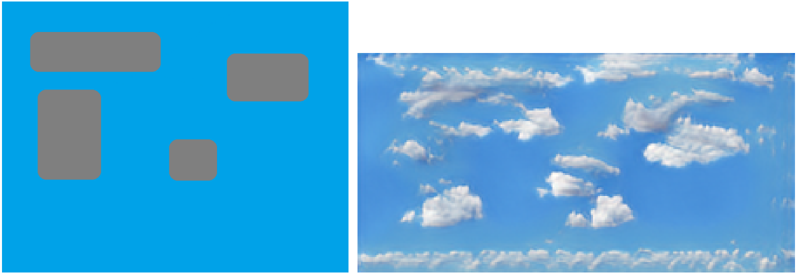


Figure: Left: Input with wrong color histogram, Right: Output of the SinGAN trained on a sky picture

Learning objects of different scales

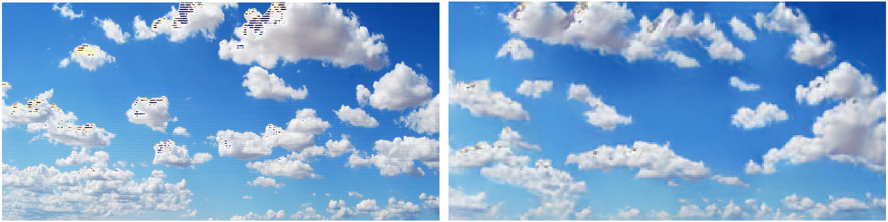


Figure: Left: Training image of a sky with high frequence noise, Right: Random sample generated with the SinGAN

Training on the target distribution of patches

- Is our implementation of photo2painting working ?

Figure: Step by step result of painting2photo

Improvement of the results with preprocessing

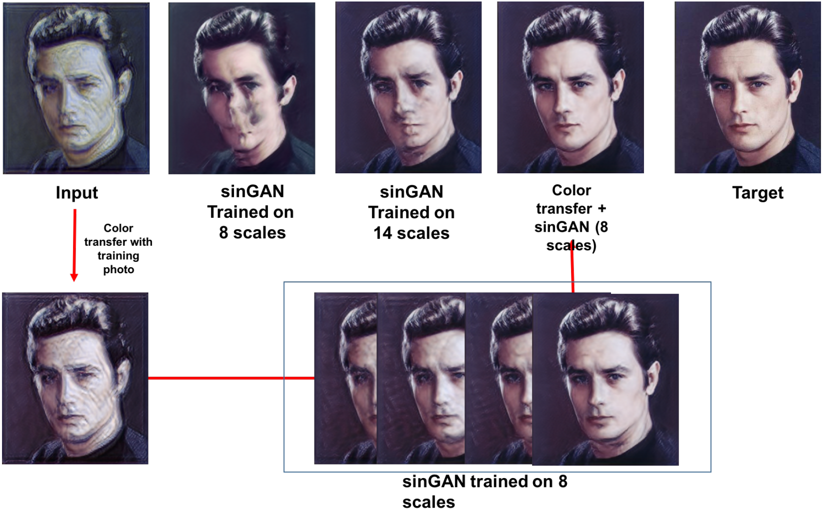


Figure: Comparison of our 3 methods

Extension to a different distribution of patches

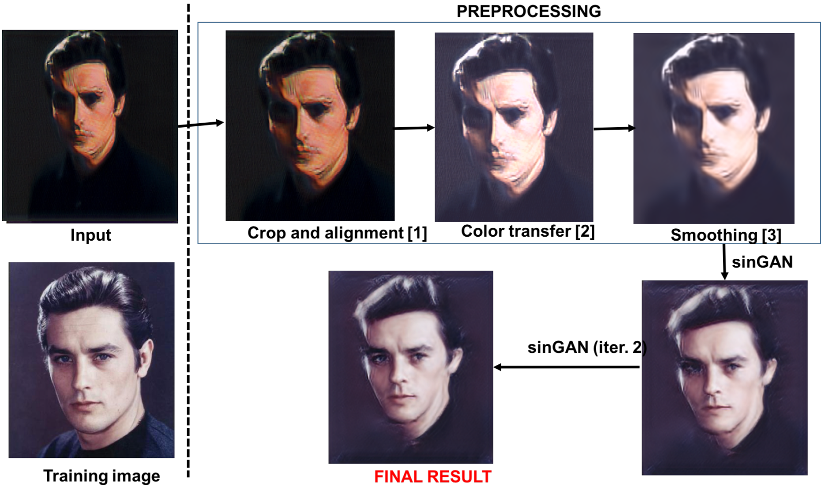


Figure: Results on a similar (but different) painting

Can we generalize to very different training photo/painting pair ?

- NO ! The source distribution of patches is not large enough

Input painting

Training image

Result (preprocessing + sinGAN X2)

Figure: Results for more similar pairs

Conclusion

- **Photo2Painting**: SinGAN can well capture well the style of a painter
- **Painting2Photo**: SinGAN is good for similar painting/photo pairs
- **Painting2Photo**: SinGAN fails for non similar painting/photo pairs

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