Non-Stationary Texture Synthesis by Adversarial Expansion

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Classical Example-Based Texture Synthesis Tasks





► Stationary



► Regular



► Near-regular



Stochastic

Classical Example-Based Texture Synthesis Methods

Pixel-based synthesis



Patch-based synthesis





Classical Example-Based Texture Synthesis Methods

► Image Analogy



Layered Shape Synthesis



Classical Example-Based Texture Synthesis Methods

► With Guidance







(a) Input image I

(b) Matched features



(c) Structure lines

What Is Non-Stationary Textures?



Textures with large scale structures



Spatially variant



 Inhomogeneous textures

And This Paper Is...

► The first Method than can handle these challenging textures



Output

Contents

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► Authorship

- ► Methods
- ► Experiments

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► Train a GAN for each input exemplar.



Typically k = 128, exemplars are of size 600×400 .



- ► The receptive field should approach the size of the source block.
- ► Fully convolutional architecture \rightarrow arbitrary-sized inputs at test time
- PatchGAN discriminator



Generator

- > Loss: $\mathcal{L}_{total} = \mathcal{L}_{adv} + \lambda_1 \mathcal{L}_{L_1} + \lambda_2 \mathcal{L}_{style}$,
- ► adv: standard adversarial loss
- ► L1: L1 loss
- style: perceptual style loss
- ► Training: NVIDIA Titan Xp GPU (12GB)
- ► 5 hours for 100,000 iterations (usually <2hour for 36,000 iterations)

► Testing: 4–5 ms for a 600×400 input

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both non-stationary and stationary textures



both non-stationary and stationary textures

both non-stationary and stationary textures

► Diversification

► Taking two random crops as input.

► Diversification

reshuffling or perturbing the source texture

Output2

Output3

Output4

Output5

► Diversification

► Perlin noise.

- ► Ablation studies
- ► loss function

- ► Ablation studies
- ► loss function

- ► Ablation studies
- Discriminator patch size

Synthesis stability

Randomly crop the result and feed it as input again, repeated 4 times, without any re-training or fine-tuning the generator.

The final result (rightmost column) is still very sharp and natural looking.

► Extreme expansion, 32x (expanding 5 times)

► Not suited for artistic style transfer

► How to transfer: feeding the guiding image as input to a trained generator

► Limitation

Fig. 16. Artifacts in the border and corner regions.

► Limitation

Fig. 17. Failure cases of our method. For the stone tiles texture, our method failed to learn its large scale structure (left). While for the sunflower, our method failed to reproduce the singularity at the center (right).