

Deep Tiling: Texture Tile Synthesis Using a Constant Space Deep Learning Approach

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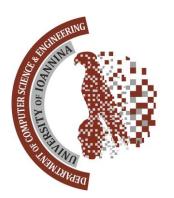








- Scope
- Introduction
- Related Work
- Deep Tiling
- Experiments
- Conclusions











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Scope

In this paper:

- a novel approach to example-based texture synthesis for creating tiles of arbitrary resolutions that resemble structurally an input texture is proposed
- less memory limited owing to the fact that a new texture tile of small size is synthesized and merged with the existing texture and secondly can easily produce missing parts of a large texture
- a method for removing seams between new synthesized tiles is proposed

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Introduction (1/2)

- Texture synthesis & expansion play a cardinal role in Geographic Information System (GIS) and games
- Structural similarity is the key factor on texture synthesis
- However, many methods that are based on similarity pattern extraction and resemblance are aiming to doubling the size of an input texture → no scalability because of memory limitations on GPUS
- Deep learning has made many steps forward on texture synthesis
 - Limited: no capability to create smaller or arbitrary resolution textures & memory restrictions
 - Solution: Tiling









Introduction (2/2)

Our method:

- is capable of generating new tiles that match structurally and have the same morphology with the original input texture
- utilizes a space invariant deep neural network to produce a new tile that can be used to expand the original texture
- builds a new texture of arbitrary shape and size (tile by tile) by artificially synthesizing tiles in any direction by using constant memory.











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Related Work

- Gatys, L.A., Ecker, A.S., Bethge, M.: Texture synthesis using convolutional neural networks. In: Proceedings of the 28th International Conference on Neural Information Processing Systems
 - example-based method employing 2 instances of a CNN trying to optimize mean square displacement of feature representation across their layer
- Zhou, Y., Zhu, Z., Bai, X., Lischinski, D., Cohen-Or, D., Huang, H.: Non-stationary texture synthesis by adversarial expansion. ACM Trans. Graph
 - GAN correlate image features to produce a new synthesized high resolution texture map through this
 process: generator produces 2s × 2s from s x s smaller input texture's pieces using a loss function
 consisted of adversarial loss, loss with original sub-texture and style loss
- Frühstück, A., Alhashim, I., Wonka, P.: Tilegan: synthesis of large-scale non-homogeneous textures. ACM Transactions on Graphics
 - homogenizing texture tiles outputs of GANs trained on lower resolution textures to produce a higher one with no seam artifacts by using Markov Random Fields (MRF)









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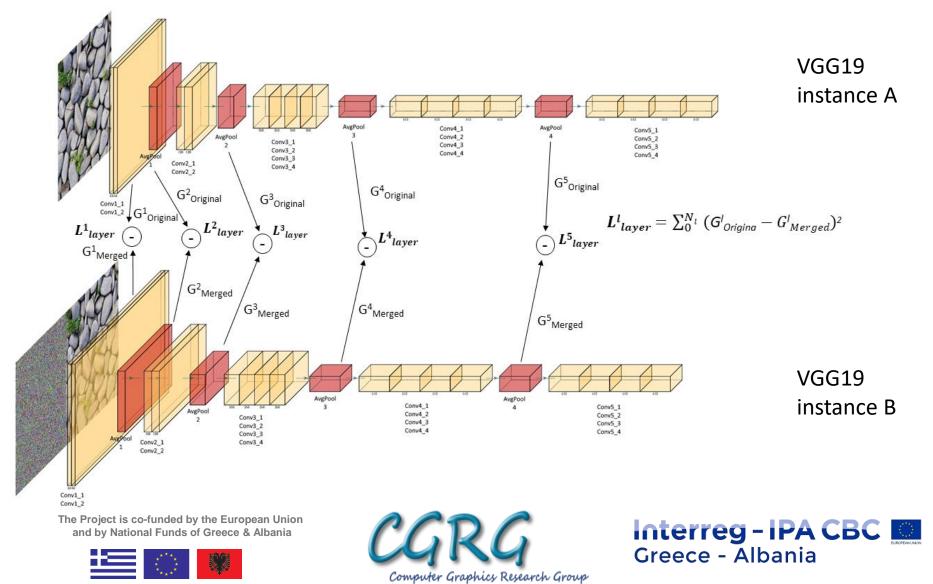






Deep Tiling (1/4)









Deep Tiling (2/4)



- We follow Gatys's idea and we base our new method to one observation: by the use of Gram Matrices inputs are not mandatory to have equal size (dot product of filters of pre-fixed size not inputs' one)
- To capture correlations among network layers we extract their feature space representation F_{li}^l of a general feature map $F^l \in R^{n_f imes vs_f}$, where l is a layer having n_f filters of size vs_f reshaped into one dimensional vectors

• Achieved by use of Gram: $G_{rc}^{l} = \sum_{i} F_{ki}^{l} F_{li}^{l}$

• Loss: $L_{total}(I_{original}, I_{merged}) = \sum_{l=1}^{N^L} \frac{w^l}{4n_f^{l^2} v s_f^{l^2}} \sum (G_{original}^l - G_{merged}^l)^2$, where

 $I_{original}$ is the original texture and I_{merged} is a white noise texture merged with the original one having been forwarded to our system



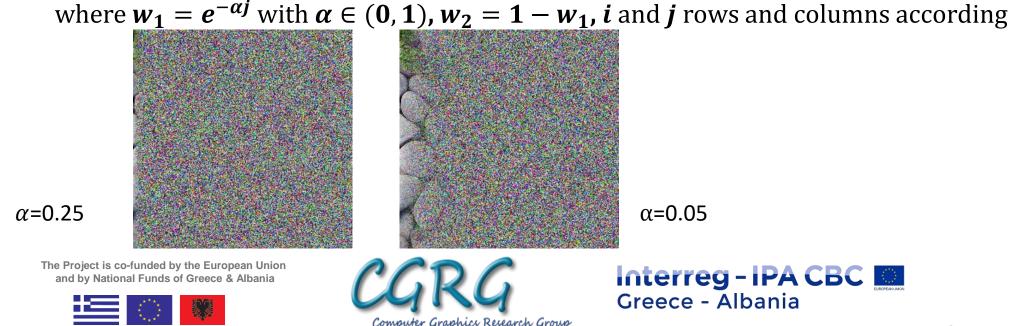




Deep Tiling (3/4)



- In some texture input cases the output of our method produces some noise in the boundaries of the original and deep generated tile
- Solution \rightarrow Mirroring with attenuation
- Seam Removal: every pixel for the *Merged* part of our model is computed as: $Noise(i, j) = w_1 Original(i, width - j - i) + w_2 Random Color,$



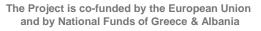
Deep Tiling (4/4)

Seam Removal optimal α:

$$\alpha = -\frac{50 \ln(0.5)}{c}$$

where $c \times r$ is the resolution of the input texture and optimal visual result is derived by setting as target an attenuation of 50% (i.e. $w_1 = 0.5$) of the original mirrored image when we reach the 2% of the total number of columns (i.e. j = c/50)

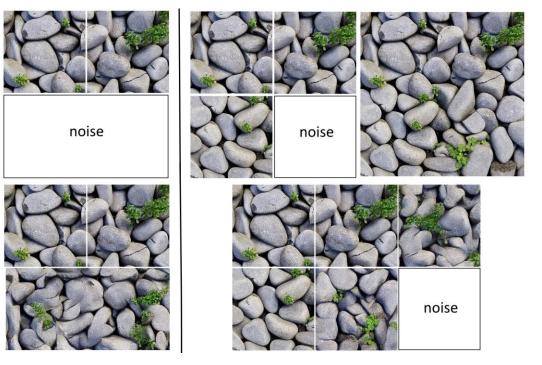
- Tiling process:
 - Left: Simple Right & then Down Tiling
 - Right: The second method is capable of keeping ٠ constant the amount of memory needed to expand
 - a texture to any direction















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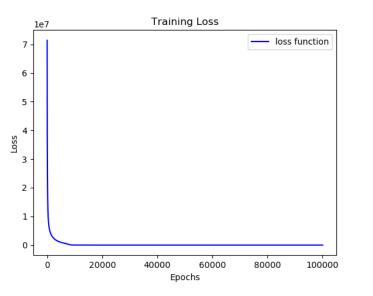








Experiments (1/2)



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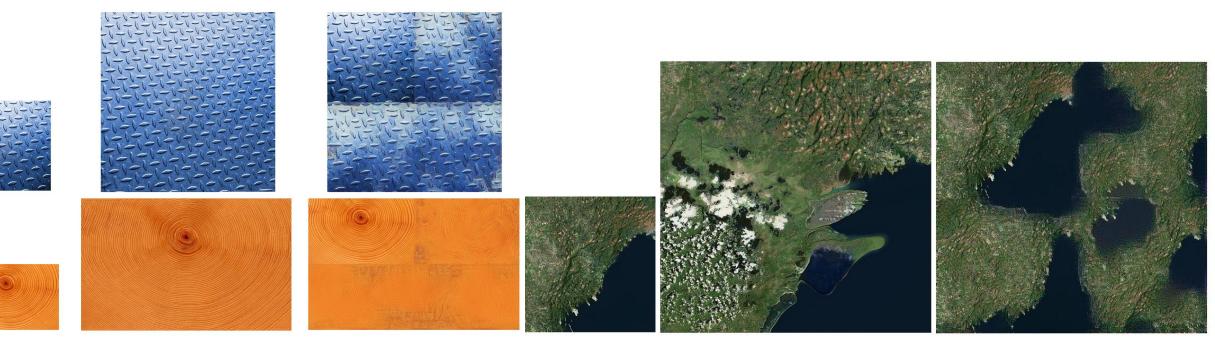


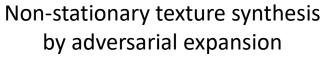
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Experiments (2/2)



Informal comparison with state-of-the-art methods •





Tilegan: synthesis of large-scale non-homogeneous textures











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Conclusions

- An innovative tiling synthesis method is proposed that is capable of producing new texture tiles in any direction and there are techniques to keep memory consumption constant
- Introduction of Seam Removal to texture synthesis
- A limitation of our approach is that noise is passed on from one tile to another
- Targeting on creating tiles with style transfer for a non homogenous style & pattern texture synthesis











Thank you for your attention







