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CMPT 461: Computational Photography

Dr. Aksoy

Assignment 1

Texture Synthesis and Transfer

March 16, 2024

Part 1 – Texture Synthesis

This report presents the implementation and findings of Texture Synthesis and Transfer methods based on Efros and Freeman's work "Image Quilting for Texture Synthesis and Transfer". The assignment aimed to explore techniques for generating realistic textures and re-rendering images in different styles.

1.1 – Results

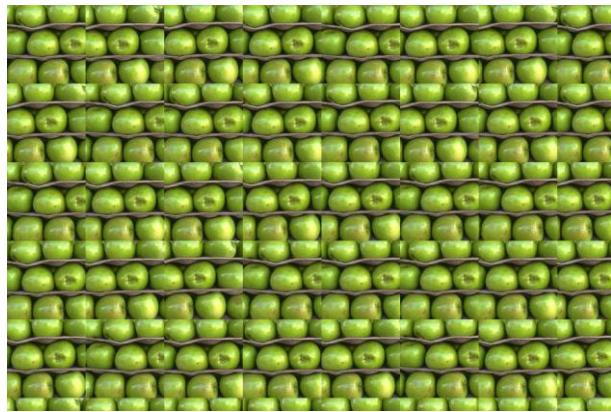
In Method 1, patches are randomly selected from the input texture for synthesis. This approach is straightforward but lacks coherence in the synthesised texture, often resulting in noticeable edge artifacts. Determining an optimal patch size for Method 1 poses challenges, particularly for textures that are less complex and light. However, in cases where the texture is highly intricate and dark, such as "random.png", the synthesised texture may appear acceptable as the edges are less noticeable due to the texture's complexity.

In Method 2, patches are selected based on their similarity to the pixels in the overlapping region, as determined by the SSD error. Meanwhile, Method 3 involves computing a minimum error cut for the overlapping region, effectively reducing edge artifacts in the synthesised texture. During experimentation with both methods, I observed that setting the overlap region size to approximately 1/6 of the patch size yielded satisfactory results across different textures. Consequently, this rule was consistently applied during the exploration of various patch sizes, ensuring a uniform approach to determining overlap region size.

apples.png



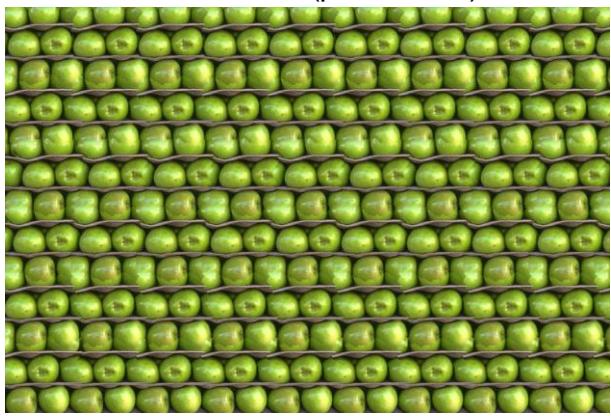
Original texture



Method 1 (patch: 120)



Method 2 (patch: 80, overlap: 15)

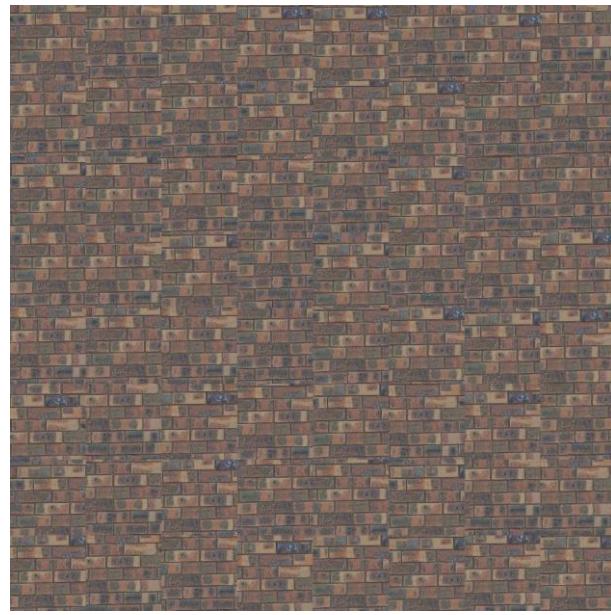


Method 3 (patch: 120, overlap: 20)

brick.jpg



Original texture



Method 1 (patch: 120)



Method 2 (patch: 80, overlap: 15)



Method 3 (patch: 120, overlap: 20)

grass.png



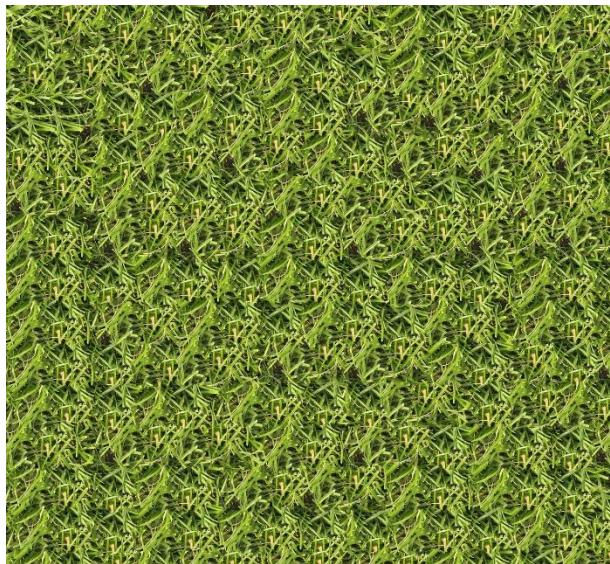
Original texture



Method 1 (patch: 120)



Method 2 (patch: 120, overlap: 20)

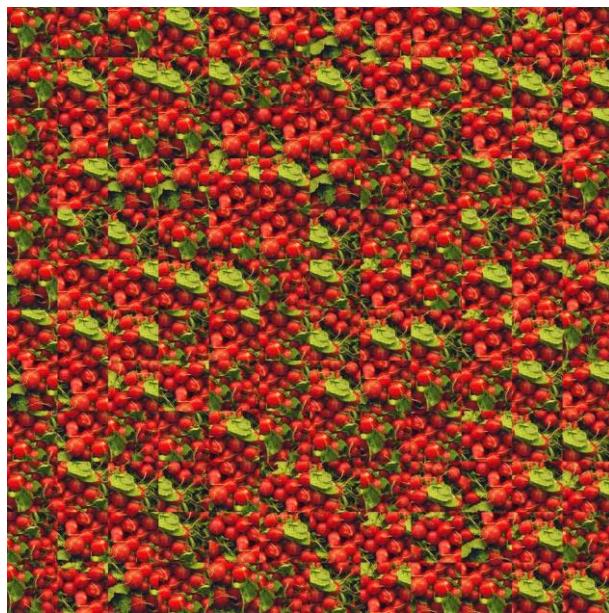


Method 3 (patch: 120, overlap: 20)

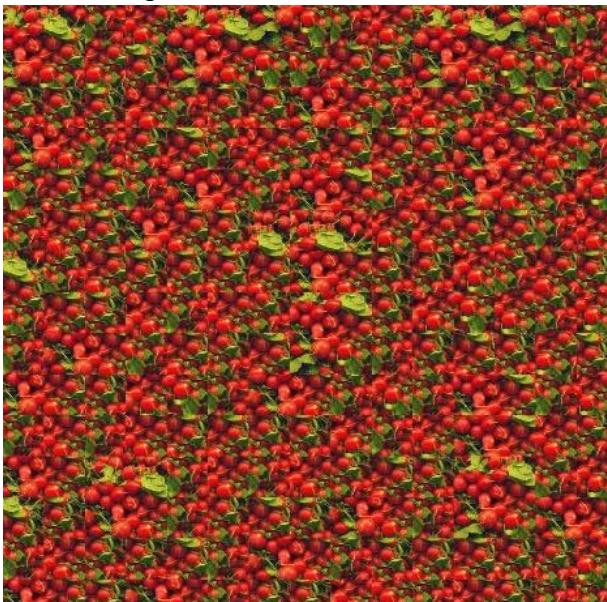
radishes.jpg



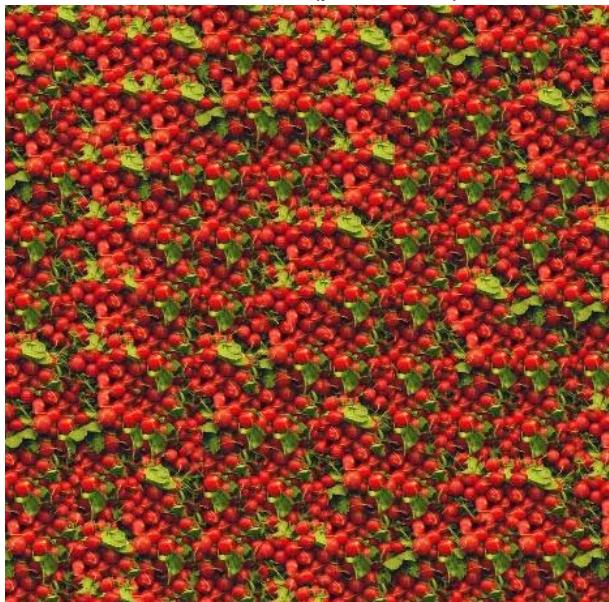
Original texture



Method 1 (patch: 80)

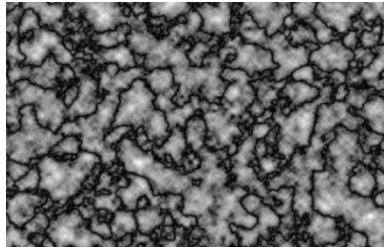


Method 2 (patch: 80, overlap: 15)

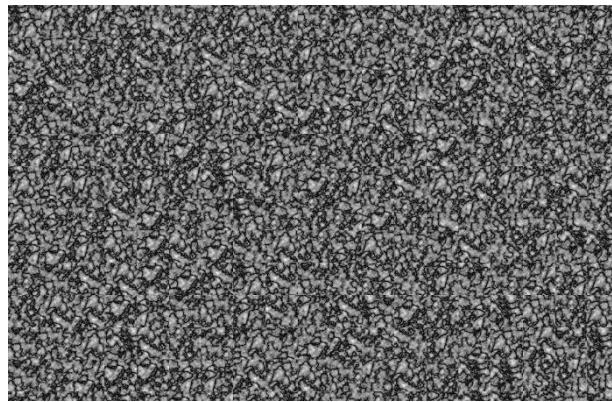


Method 3 (patch: 120, overlap: 20)

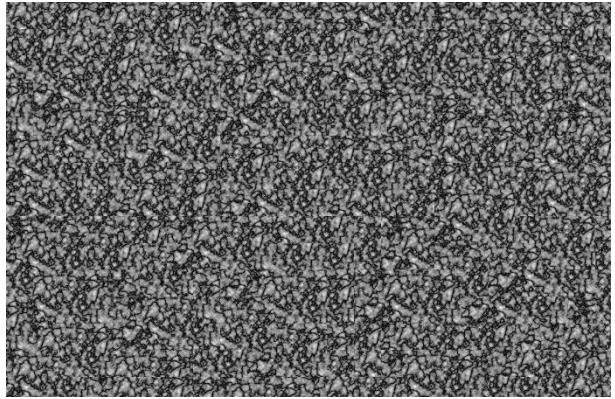
random.png



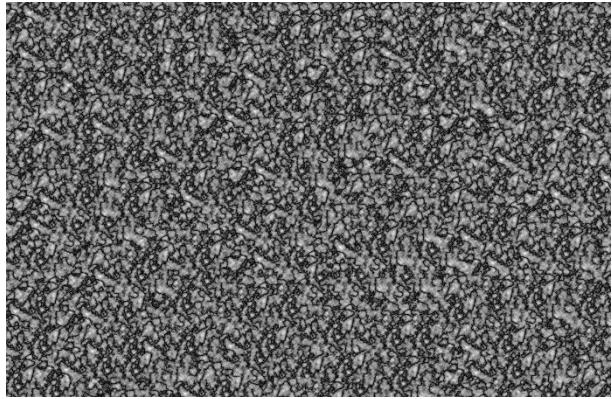
Original texture



Method 1 (patch: 120)

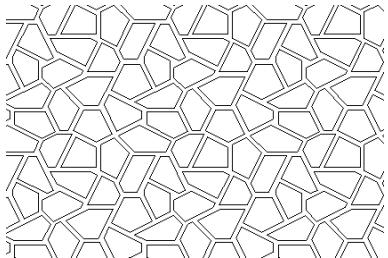


Method 2 (patch: 120, overlap: 20)

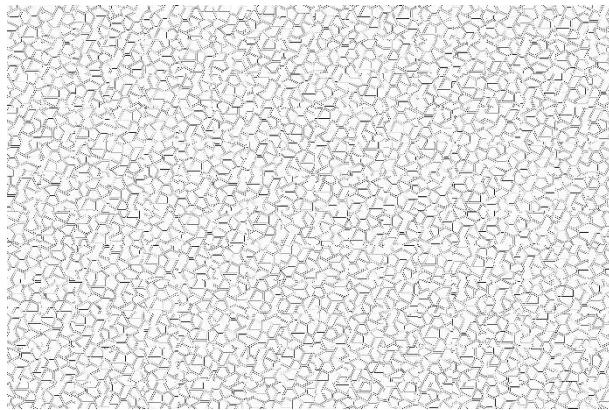


Method 3 (patch: 120, overlap: 20)

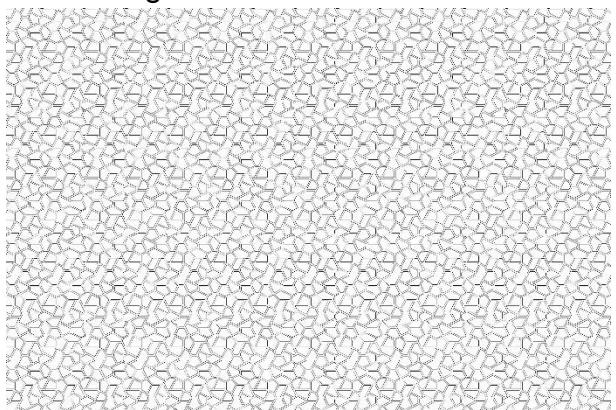
random3.png



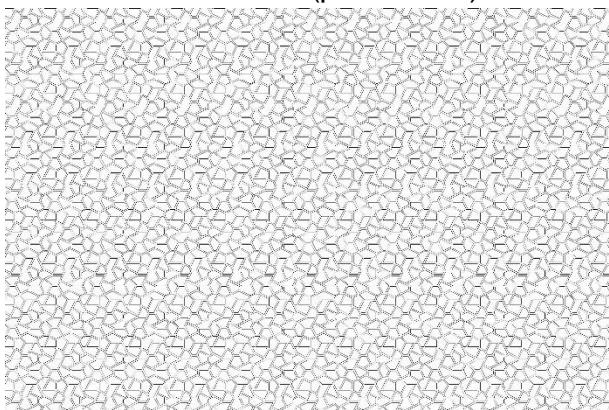
Original texture



Method 1 (patch: 120)



Method 2 (patch: 120, overlap: 20)

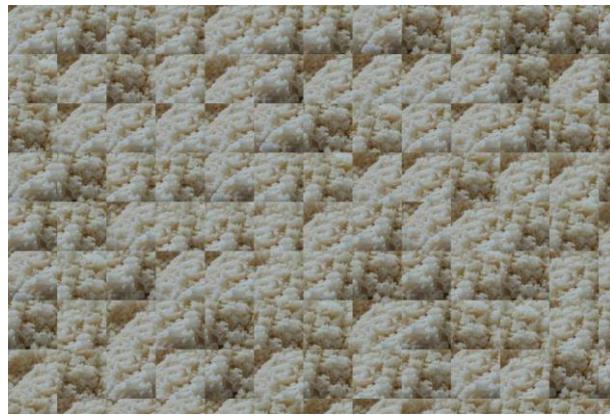


Method 3 (patch: 120, overlap: 20)

rice.bmp



Original texture



Method 1 (patch: 80)



Method 2 (patch: 40, overlap: 7)



Method 3 (patch: 40, overlap: 7)

text.jpg

describing the response of that neuron as a function of position—is perhaps the most functional description of that neuron. We seek a single conceptual and mathematical framework that can describe the wealth of simple-cell receptive fields neurophysiologically¹⁻³ and inferred especially if such a framework has the added benefit of helping us to understand the function in a deeper way. Whereas no generic model exists, the difference of Gaussians (DOG), difference of offset Gaussians (DOG), derivative of a Gaussian, higher derivatives, function, and so on—can be expected to provide a good approximation to the simple-cell receptive field, we nonetheless

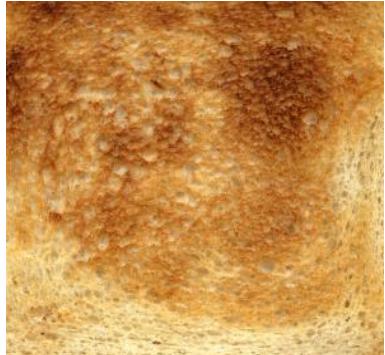
Original texture

Method 2 (patch. 180, overlap. 25)

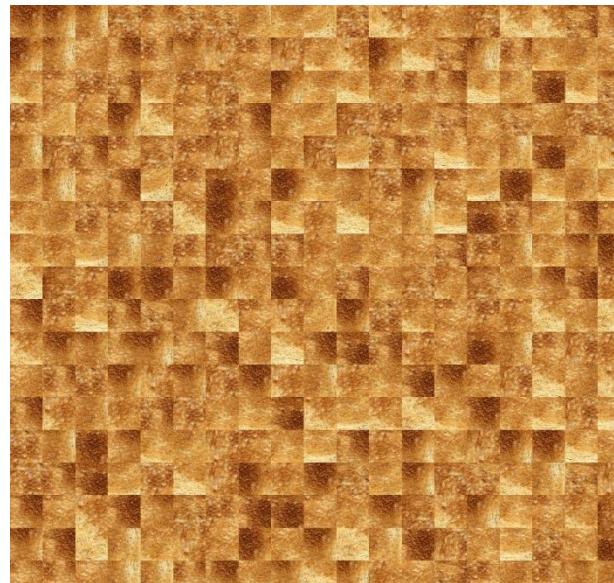
Method 1 (patch: 80)

Method 3 (patch. 120, overlap. 20)

toast.png



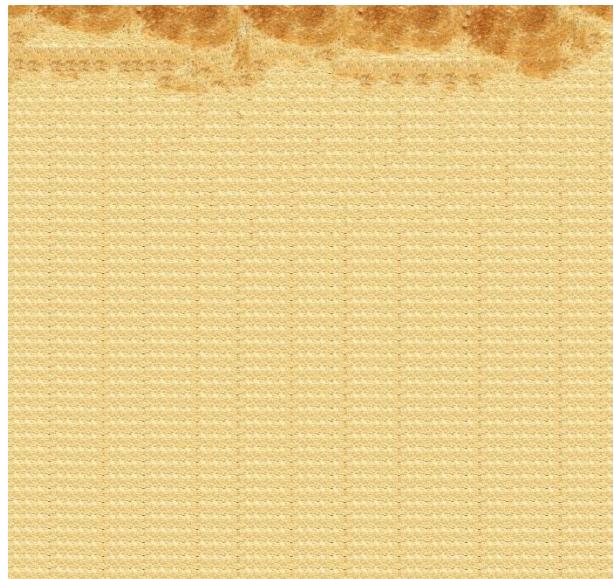
Original texture



Method 1 (patch: 80)



Method 2 (patch: 40, overlap: 7)



Method 3 (patch: 40, overlap: 7)

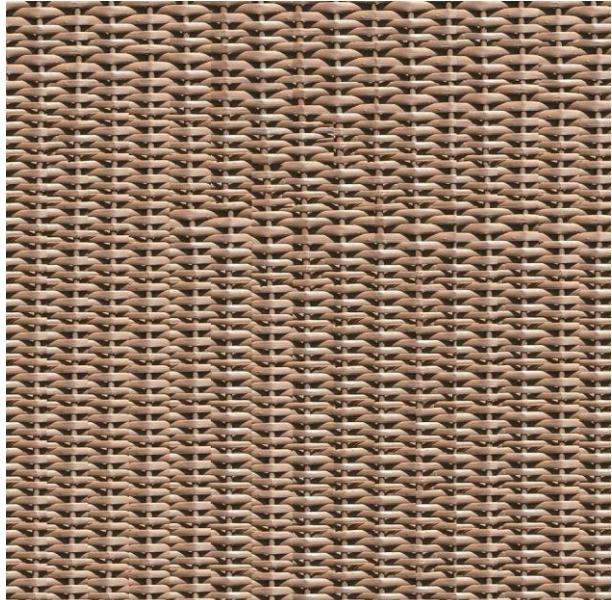
weave.jpg



Original texture



Method 1 (patch: 120)



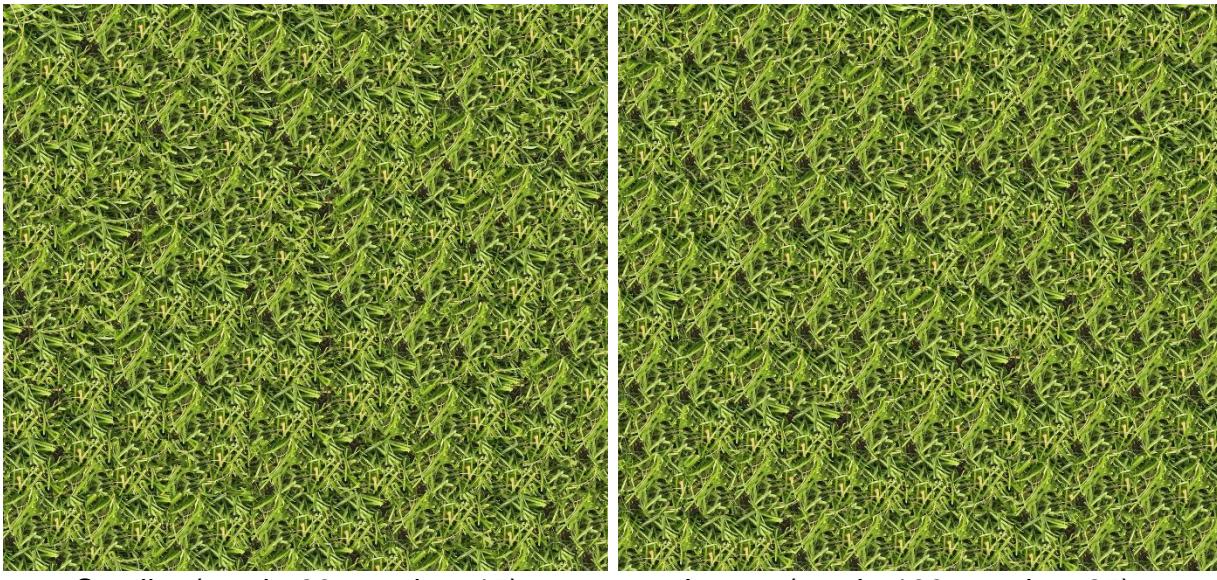
Method 2 (patch: 80, overlap: 15)



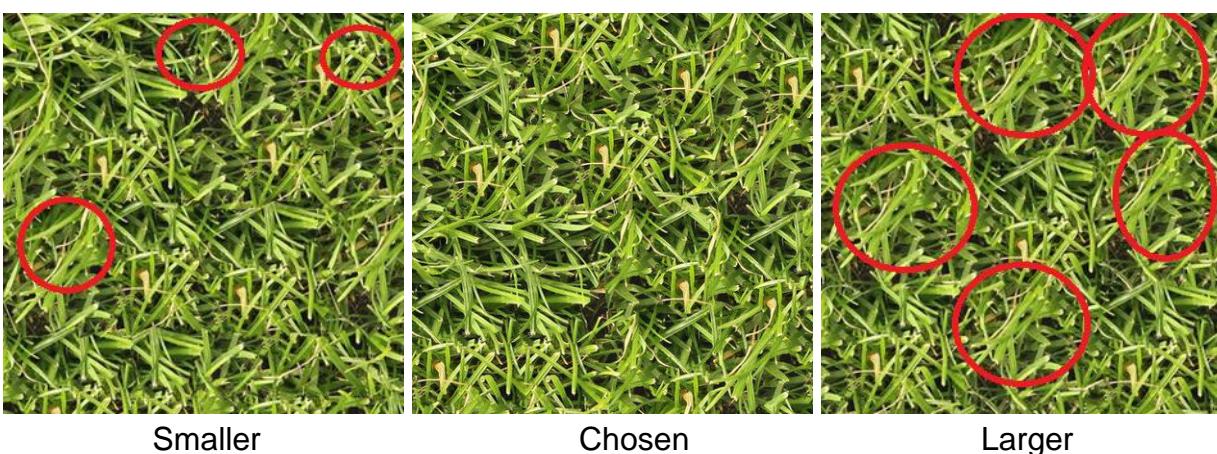
Method 3 (patch: 120, overlap: 20)

1.2 – Additional Results

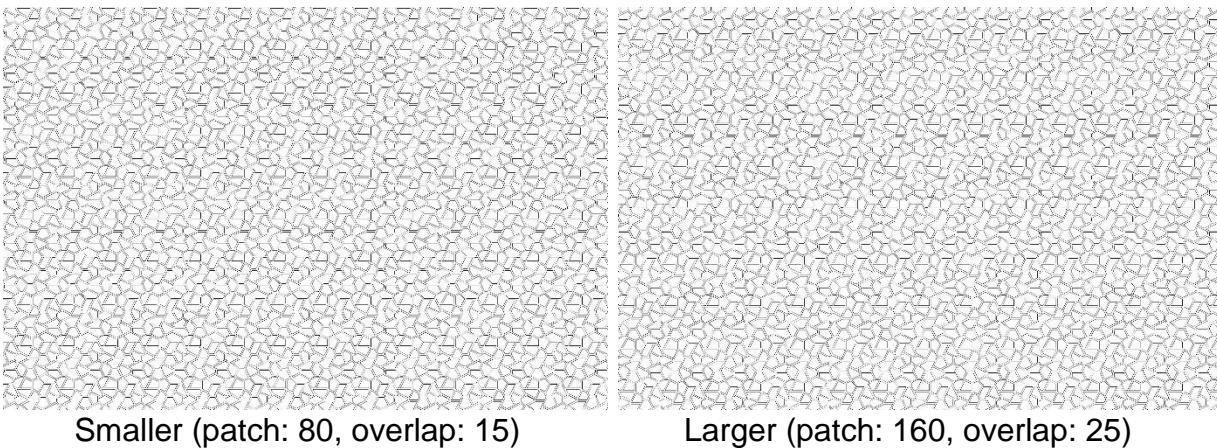
grass.png



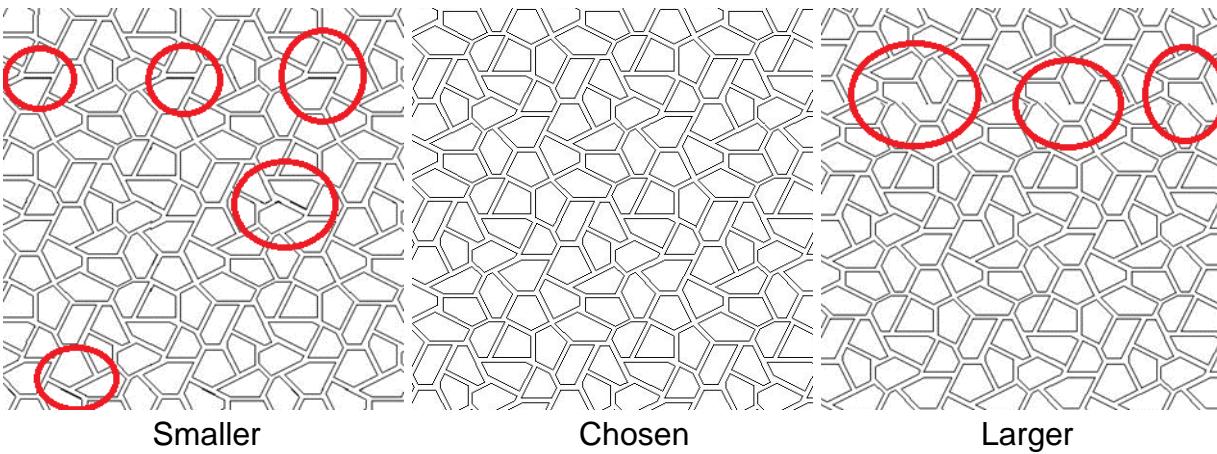
In comparison to the results obtained with the optimal patch size in Method 3, using a smaller patch size resulted in the presence of tiny pieces of yellow grass covering many places of the synthesised texture, giving it an unnatural appearance akin to white noise. Conversely, employing a larger patch size led to a noticeable repetition of the same large piece of grass throughout the texture. The chosen patch size effectively avoids both issues, resulting in a more realistic and visually pleasing grass texture synthesis.



random3.png



In comparison to the results obtained with the optimal patch size in Method 3, using a smaller patch size resulted in thicker lines in certain areas, possibly due to patches overlapping in unusual ways. On the other hand, employing a larger patch size introduced artifacts where some lines were disconnected from others, leading to noticeable errors in the texture construction.



text.jpg

Smaller (patch: 80, overlap: 15)

Larger (patch: 160, overlap: 25)

In comparison to the results obtained with the optimal patch size in Method 3, using a smaller patch size led to the text being placed on slightly different levels, with one part of the sentence appearing slightly higher than the other. Conversely, employing a larger patch size resulted in the majority of the text having a darker background, which appeared slightly odd. The chosen patch size effectively avoids both phenomena, resulting in a more visually appealing texture synthesis.

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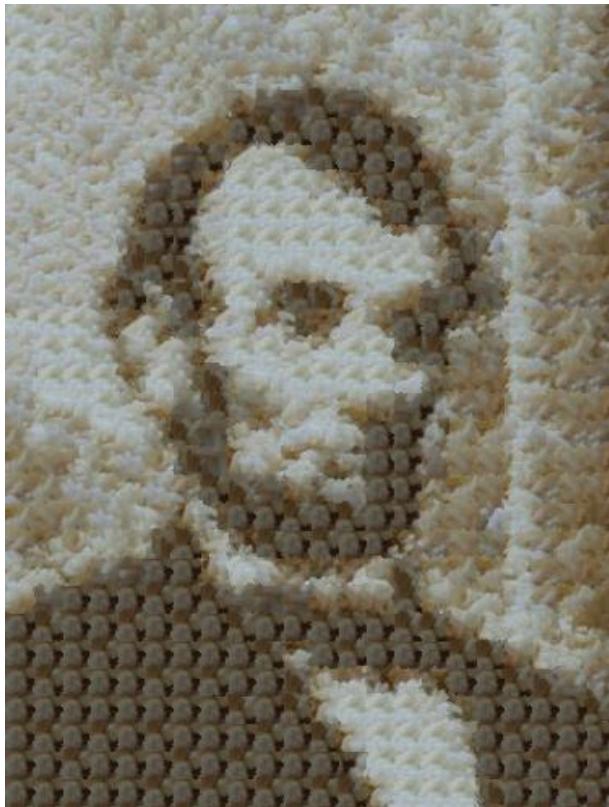
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Part 2 – Texture Transfer

2.1 – Results



$\alpha = 0.4$



$\alpha = 0.5$



$\alpha 0.3$



$\alpha 0.5$

2.2 – Additional Results



α 0.2



α 0.7

Observing the results generated using varying α values, a notable distinction emerges. Larger α values prioritise texture fidelity over image likeness, orienting the synthesis process towards replicating the texture rather than faithfully rendering the image content. Conversely, smaller α values strike a balance, ensuring a harmonious integration of both texture and image characteristics in the synthesised output.