Texture Synthesis and Style Transfer

Aman Kansal
170050027

Ansh Khurana
170050035

Kushagra Juneja
170050041

1. Introduction

refer abstract-intro from paper. Here we solve the problem of synthesizing a large image following the given input texture. Also, transferring the texture to another image.

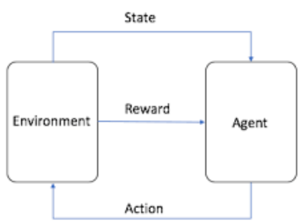


Figure 1: Reinforcement Learning Paradigm

2. Method

2.1. Quilting

Explain algo. Maybe add pseudocode in an algorithm block. Add figure with minimum boundary cut to explain the algo.

Figure 2: Boundary Cuts in Synthesis of Apple image

2.2. Texture Transfer

In the Approximate Q-Learning approach, the model the agent learns weights for features of states, where many states might share the same features. Function approximation learns the weights of different features during training. Using function approximation for parameterizing the problem of Q-Learning significantly reducing training time. It is important to recognize significant features on which the expected gain for the state will depend. For example, for approximating the Q-function for the Pac-Man game would depend upon features like Distance to closest ghost or dot, number of ghosts nearby, proximity to walls etc. Considering a linear model in the features, the update equations for the weights is given by:

2.3. Neural Network Style Transfer

Deep Learning does away with the need to handcraft features for the states. In the Deep Q-Learning based approach, the state is captured by an image of the current situation of the game. Deep Q-Learning is an extension of function approximation for Q-Learning. Deep Q-Learning uses a deep neural network to approximate the Q values for every action, given the current state. Thus, the output layer of the Deep Q-Network has dimensions = $|A|$ (The number of actions). The best action after learning the network can be taken by calculating an argmax over the output layer.

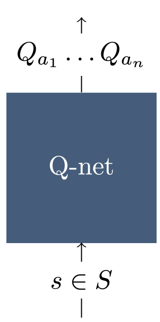


Figure 3: A generic Deep Q-Network

3. Experiments

3.1. Quilting

The effect of block size can be seen in figures x, y and z. These are our observations and here is why.

3.2. Transfer

Here are the observed effects of increasing block size. Trade-off between content preservation and similarity of

(a) B=20 (b) B=30 (c) B=40 (d) B=50

Figure 4: Effect of block size on Apples

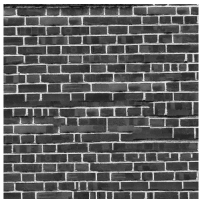
(a) B=20 (b) B=30 (c) B=40 (d) B=50

Figure 5: Effect of block size on Cans

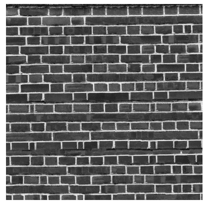
texture.

4. Results & Conclusion

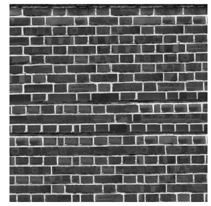
We have some amazing synthesis results below followed by transfer results.



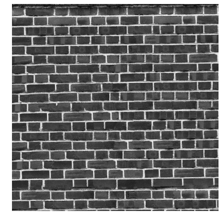
(a) B=20



(b) B=30



(c) B=40



(d) B=50

Figure 6: Effect of block size on Bricks

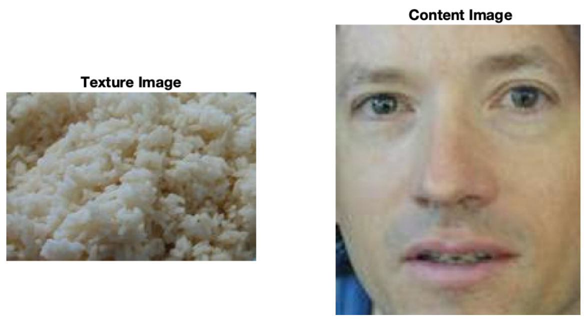


Figure 7: Rice-Bill

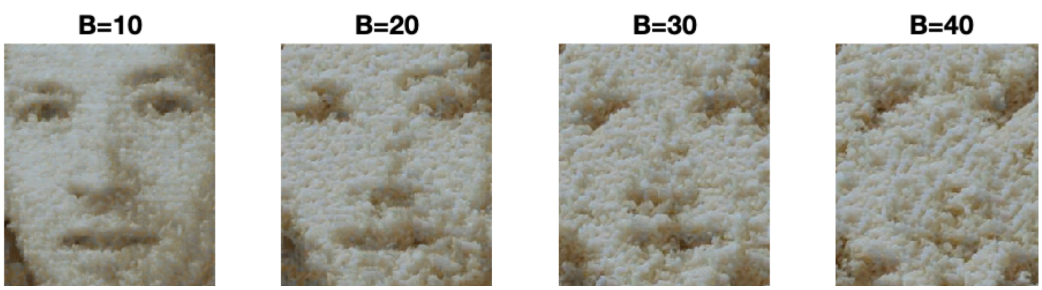


Figure 8: Rice-Bill, Block Size, B decay rate = 0.8

Figure 9: Rice-Bill, iterations, Block size=20, B decay rate = 0.8

Figure 10: Rice-Girl

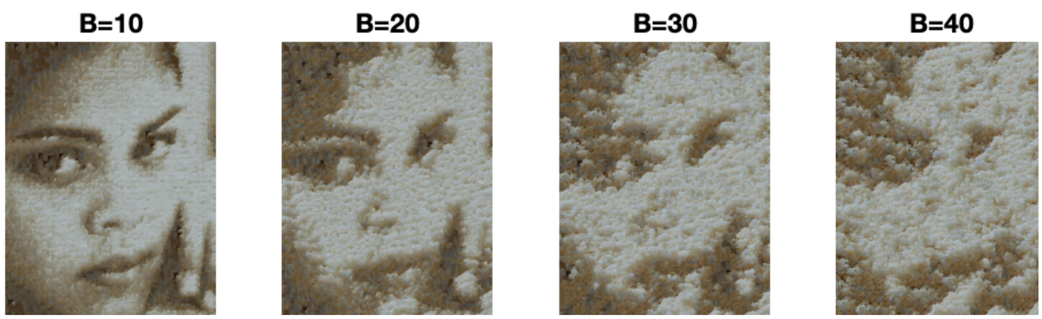


Figure 11: Rice-Bill, B decay rate = 0.7

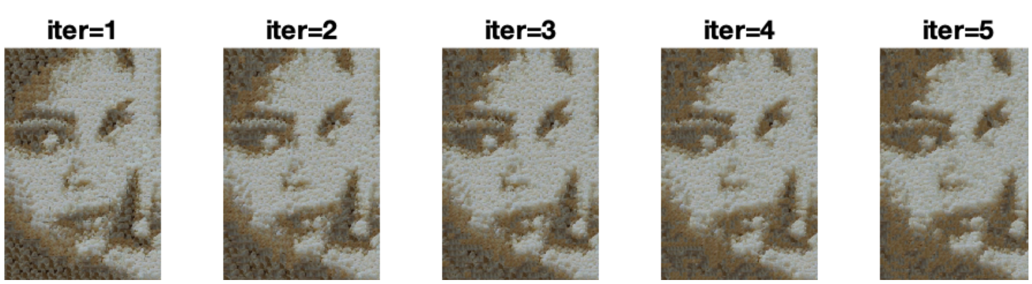


Figure 12: Rice-Girl, iterations, Block size=20, B decay rate = 0.8

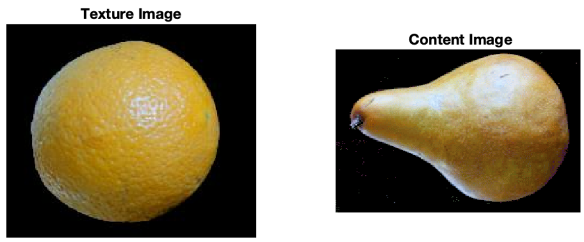


Figure 13: Orange-Pear

Figure 14: Orange-Pear, B decay rate = 0.9

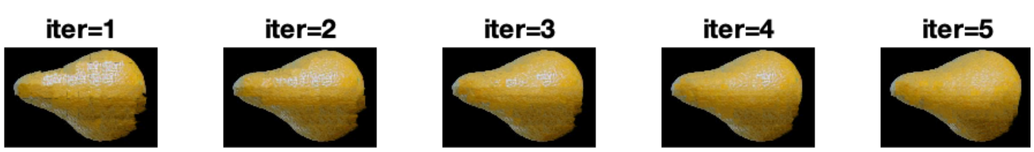
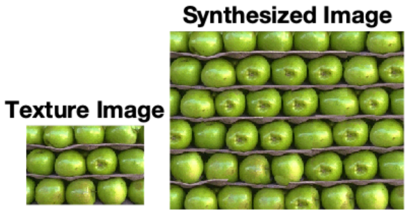
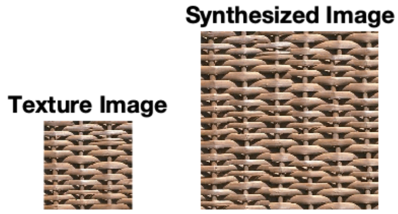


Figure 15: Orange-Pear, iterations, Block size=20, B decay rate = 0.8

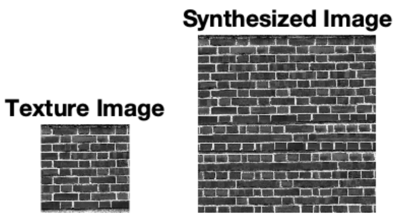


(a) Apples

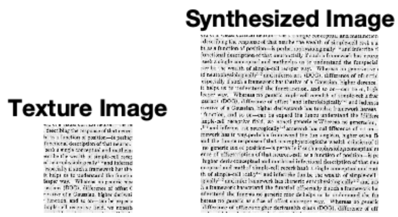


(b) Jute

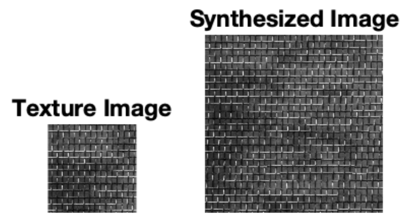
(c) Cans



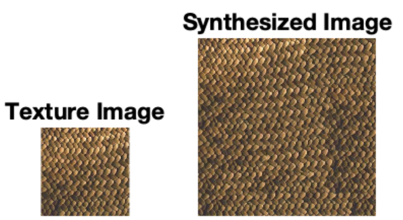
(d) D1



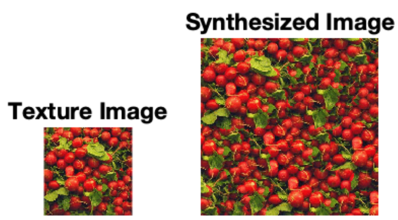
(e) text



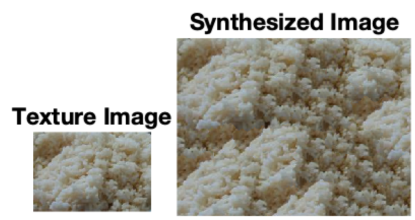
(f) Bricks B/W



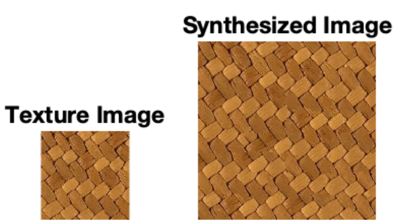
(g) Fabric



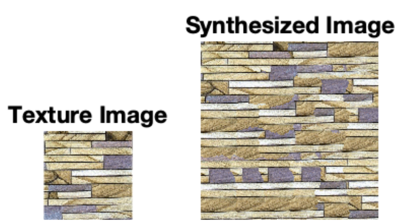
(h) Radishes



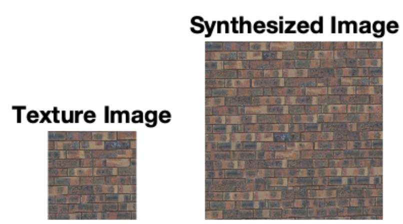
(i) Rice



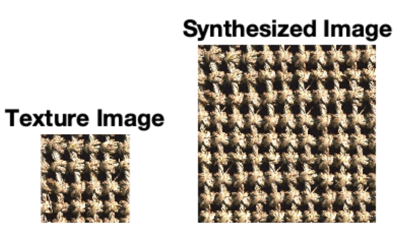
(j) Wood



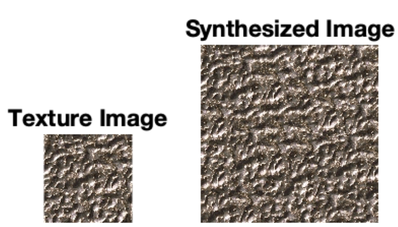
(k) Tiles



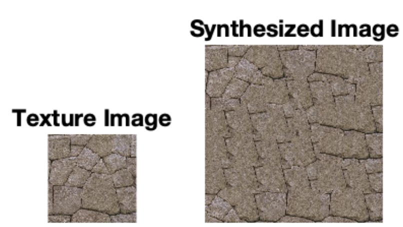
(l) Bricks



(m) Rope



(n) Pattern



(o) Stone

Figure 16: Quilting Results