

How Much Deep Learning does Neural Style Transfer Really Need?

An Ablation Study

(Supplementary Material)

Len Du
Australian National University
`Len.Du@anu.edu.au`

This supplementary file is to convince the readers that the results in the main paper is general to different combinations of content/style images. So we simply reproduce the original diagrams in the paper with different content and style images. Images are taken from [2].

References

- [1] K. He, Y. Wang, and J. Hopcroft. A powerful generative model using random weights for the deep image representation. In *Advances in Neural Information Processing Systems*, pages 631–639, 2016.
- [2] Y. Jing, Y. Yang, Z. Feng, J. Ye, Y. Yu, and M. Song. Neural style transfer: A review. *IEEE Transactions on Visualization and Computer Graphics*, 2019.

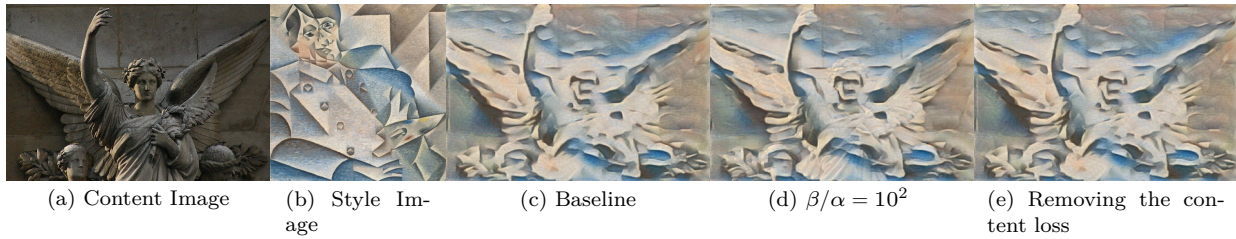


Figure 1: Removing the content loss

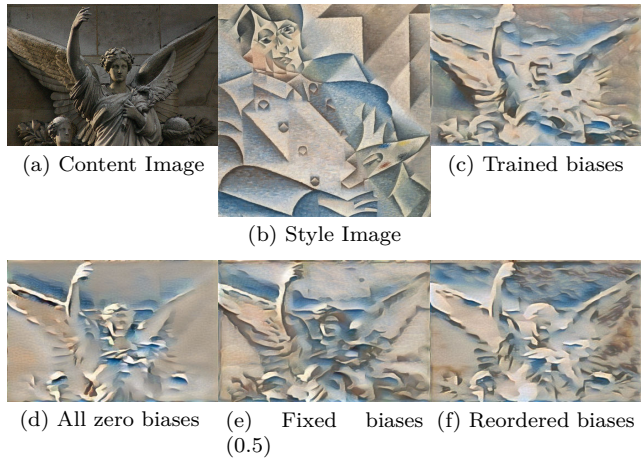


Figure 2: Varying the biases while keeping trained weights

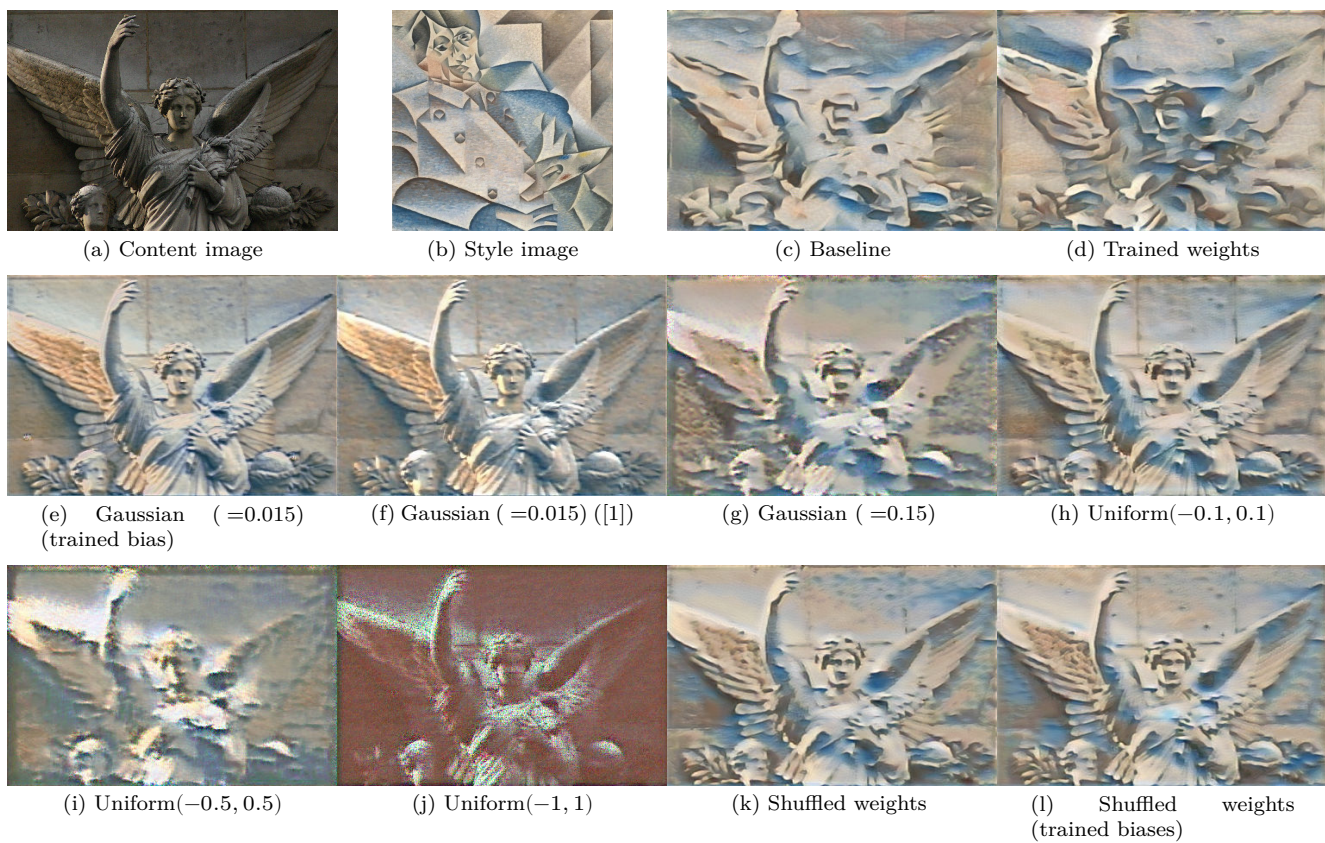


Figure 3: Continuously or densely distributed weights

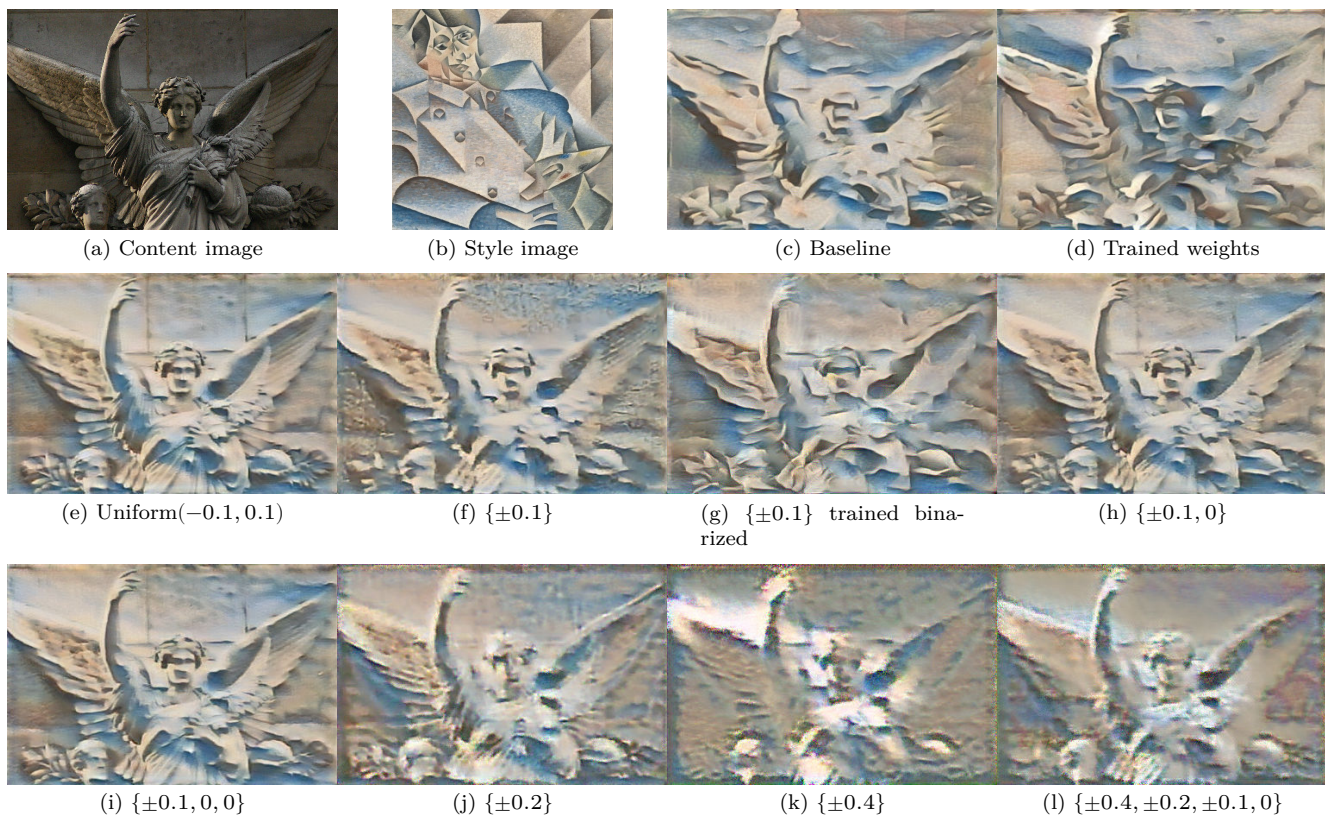


Figure 4: Symmetric discrete weights with fixed biases (0.5)

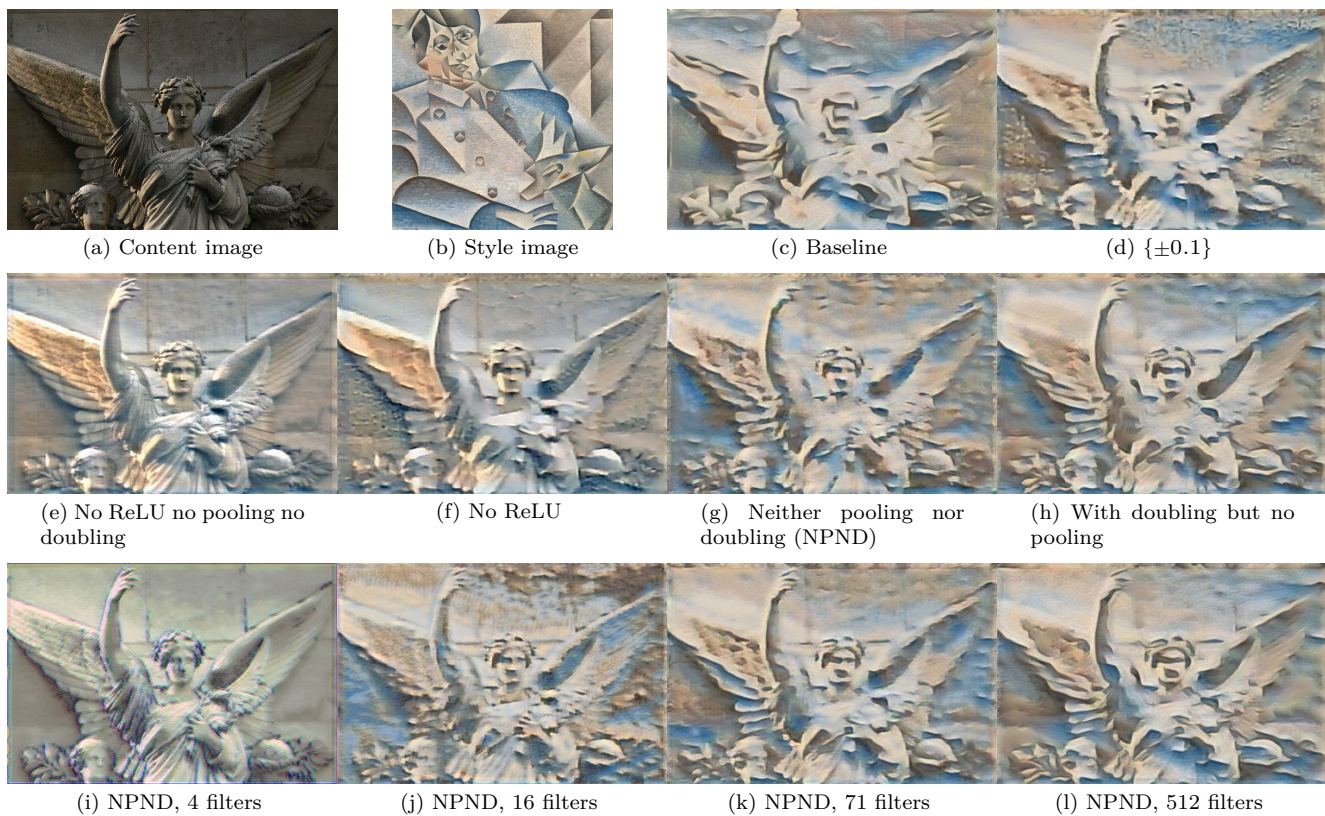


Figure 5: Removal of structure

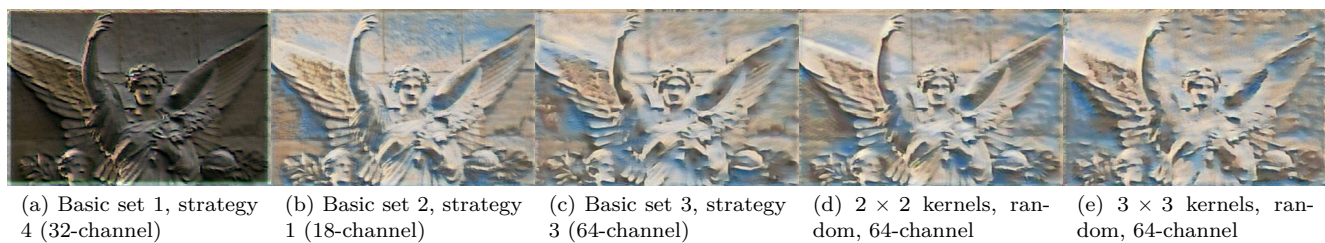
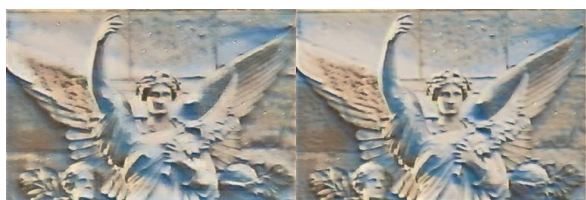
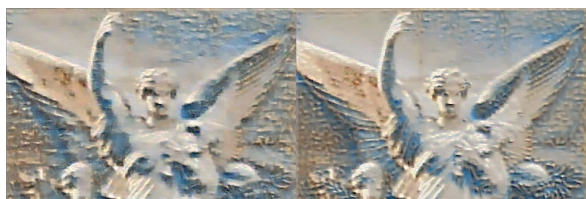


Figure 6: Alternative first-layer convolution kernels



(a) Gaussian pyramid without pooling

(b) Laplacian pyramid without pooling



(c) Gaussian pyramid with pooling

(d) Laplacian pyramid with pooling

Figure 7: Using image pyramids instead of multi-layer nonlinearities

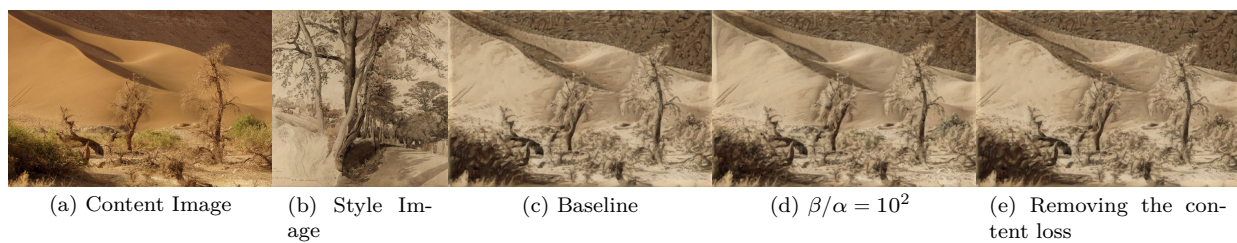


Figure 8: Removing the content loss

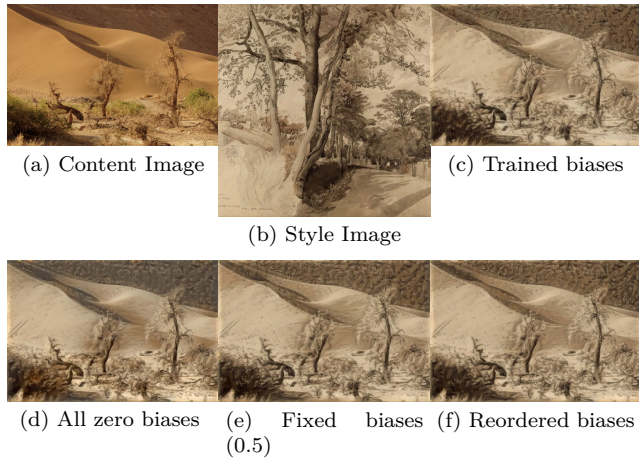


Figure 9: Varing the biases while keeping trained weights

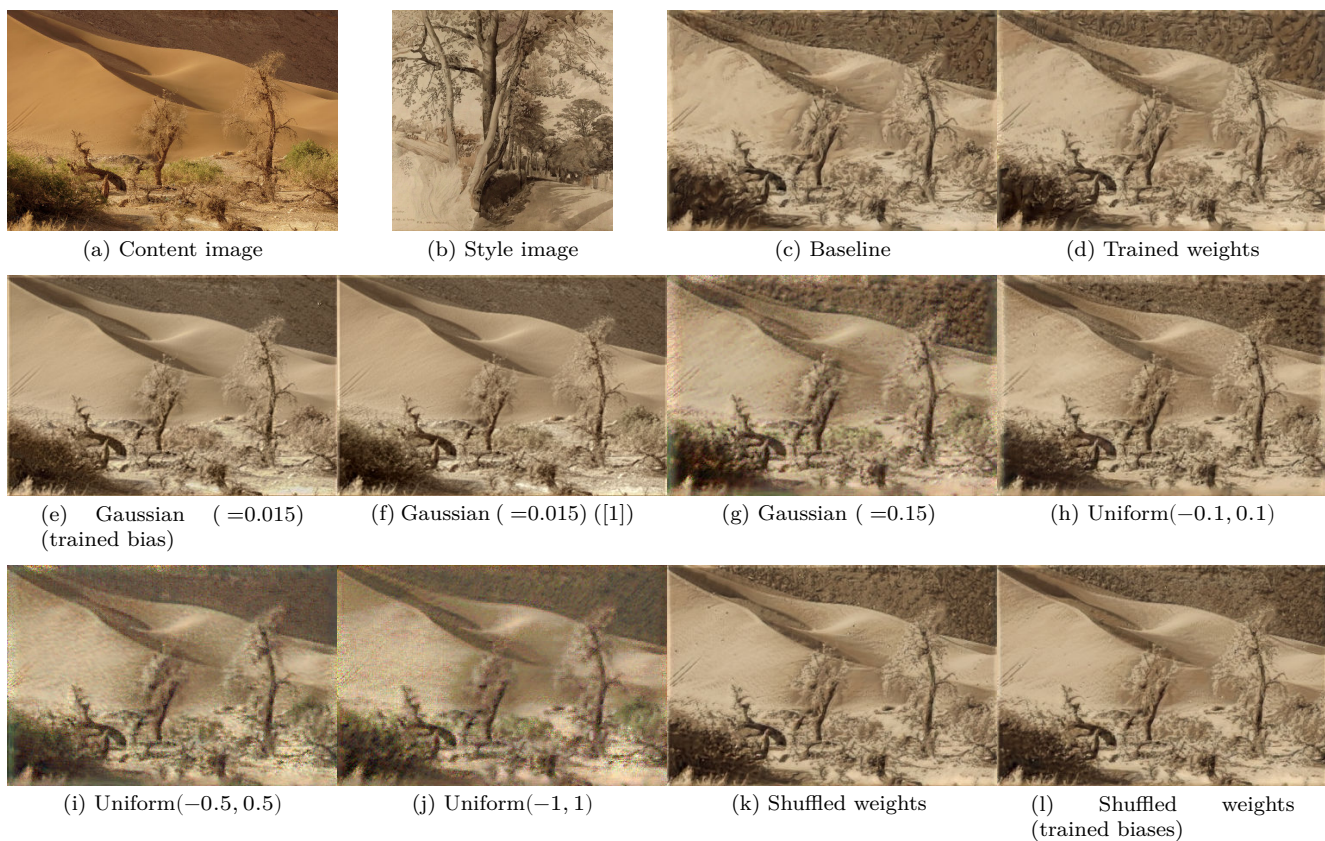


Figure 10: Continuously or densely distributed weights

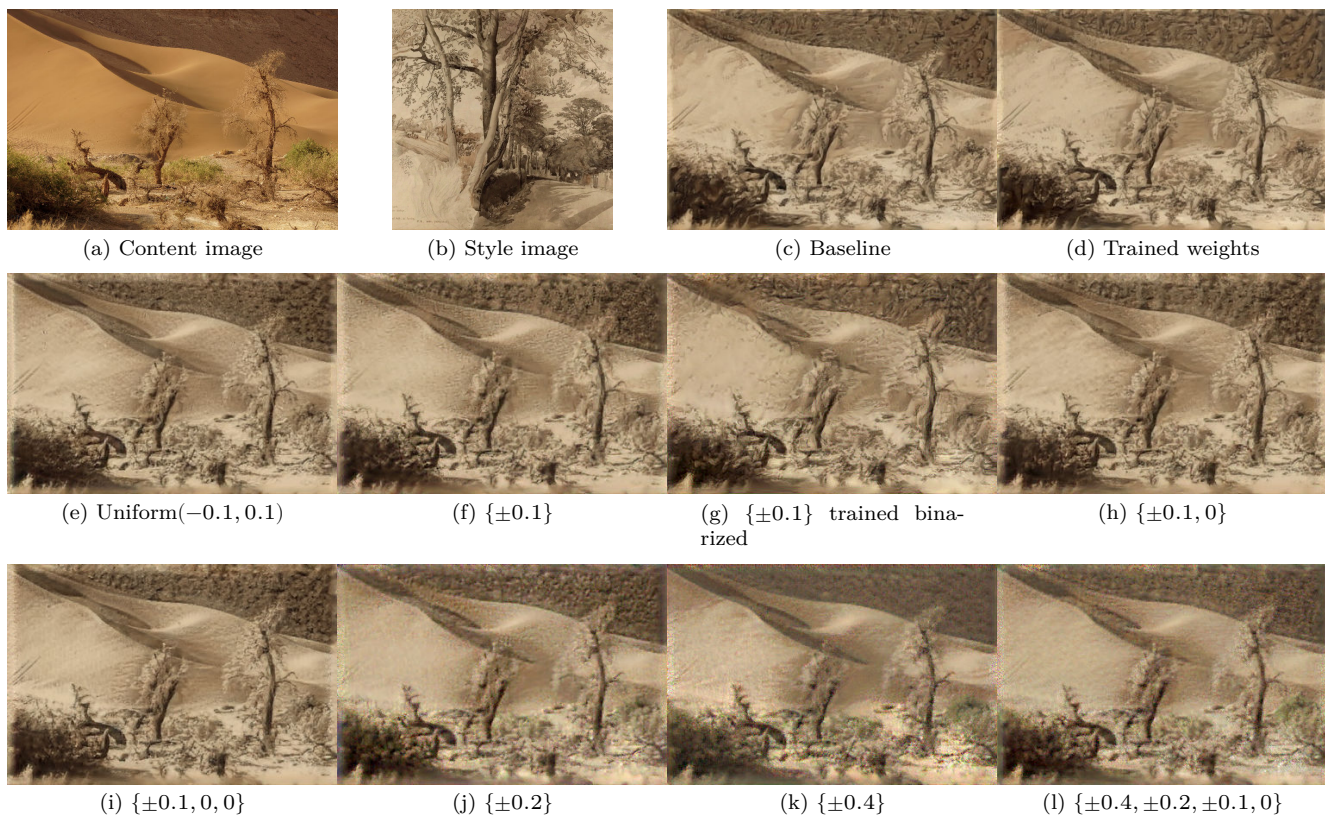


Figure 11: Symmetric discrete weights with fixed biases (0.5)

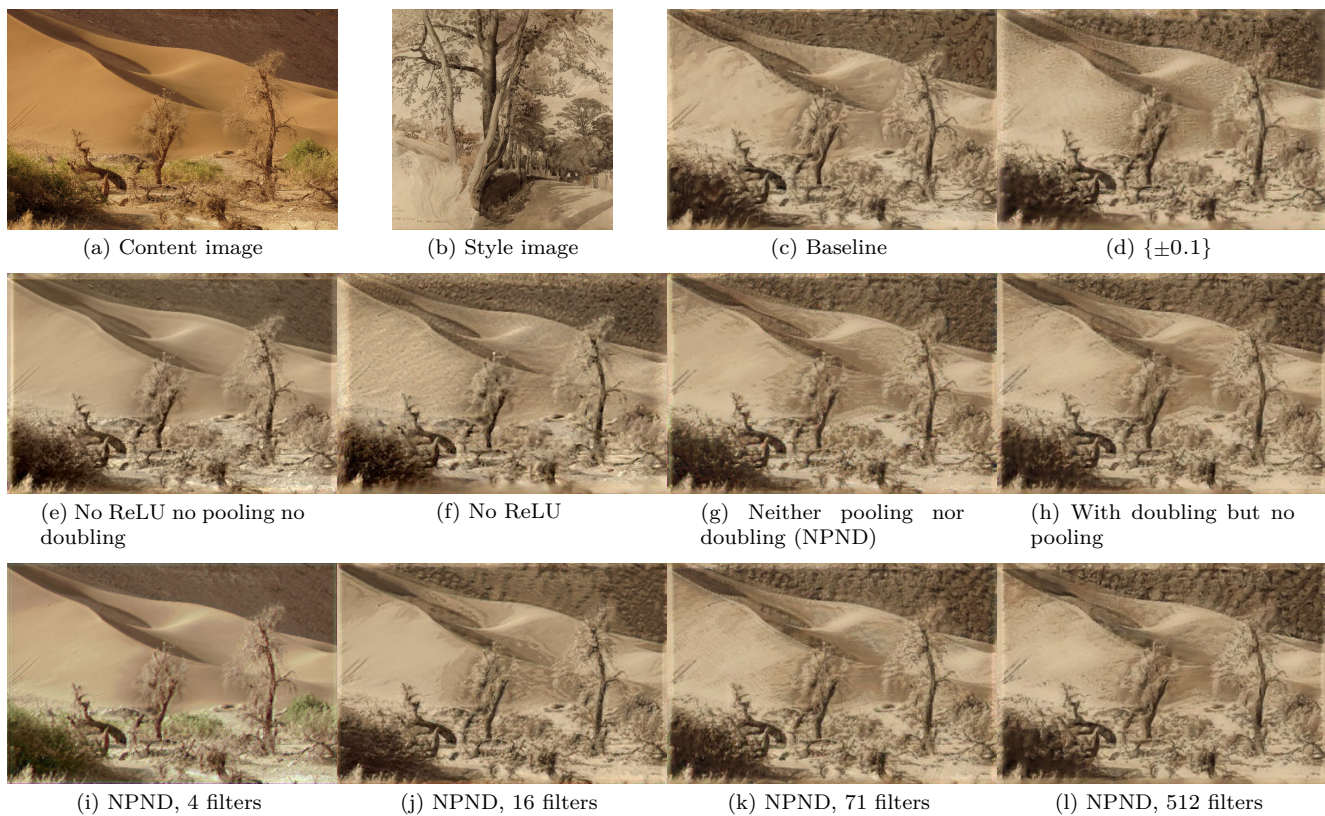


Figure 12: Removal of structure

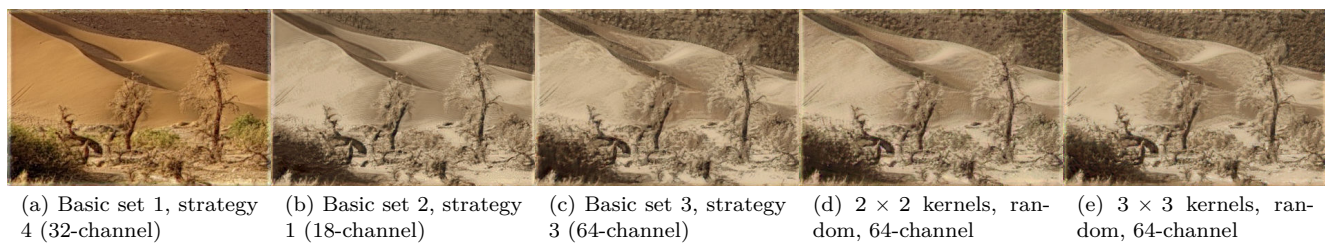
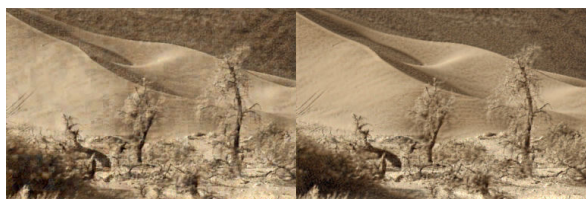


Figure 13: Alternative first-layer convolution kernels



(a) Gaussian pyramid without pooling

(b) Laplacian pyramid without pooling



(c) Gaussian pyramid with pooling

(d) Laplacian pyramid with pooling

Figure 14: Using image pyramids instead of multi-layer nonlinearities

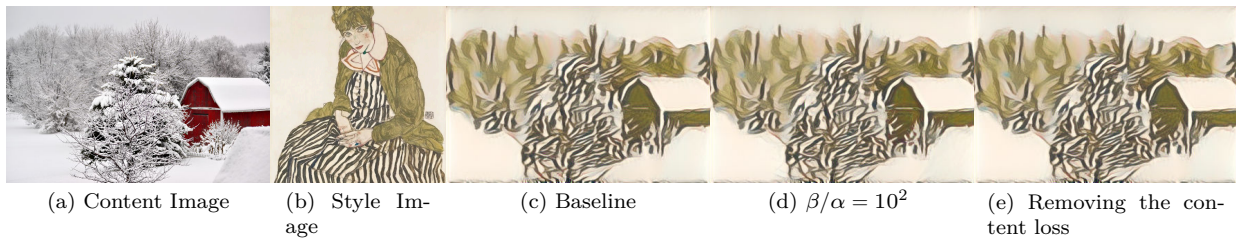


Figure 15: Removing the content loss

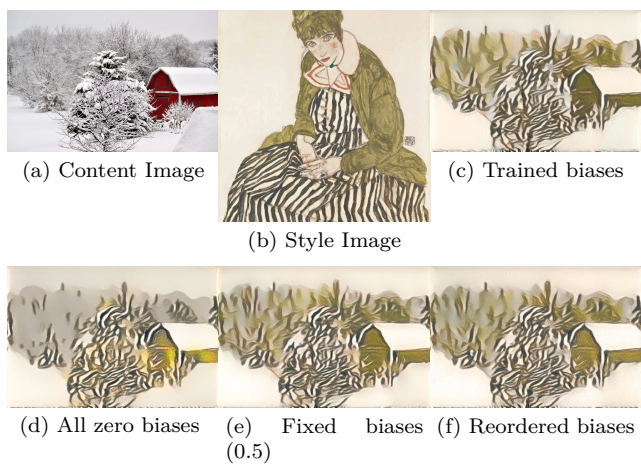


Figure 16: Varying the biases while keeping trained weights

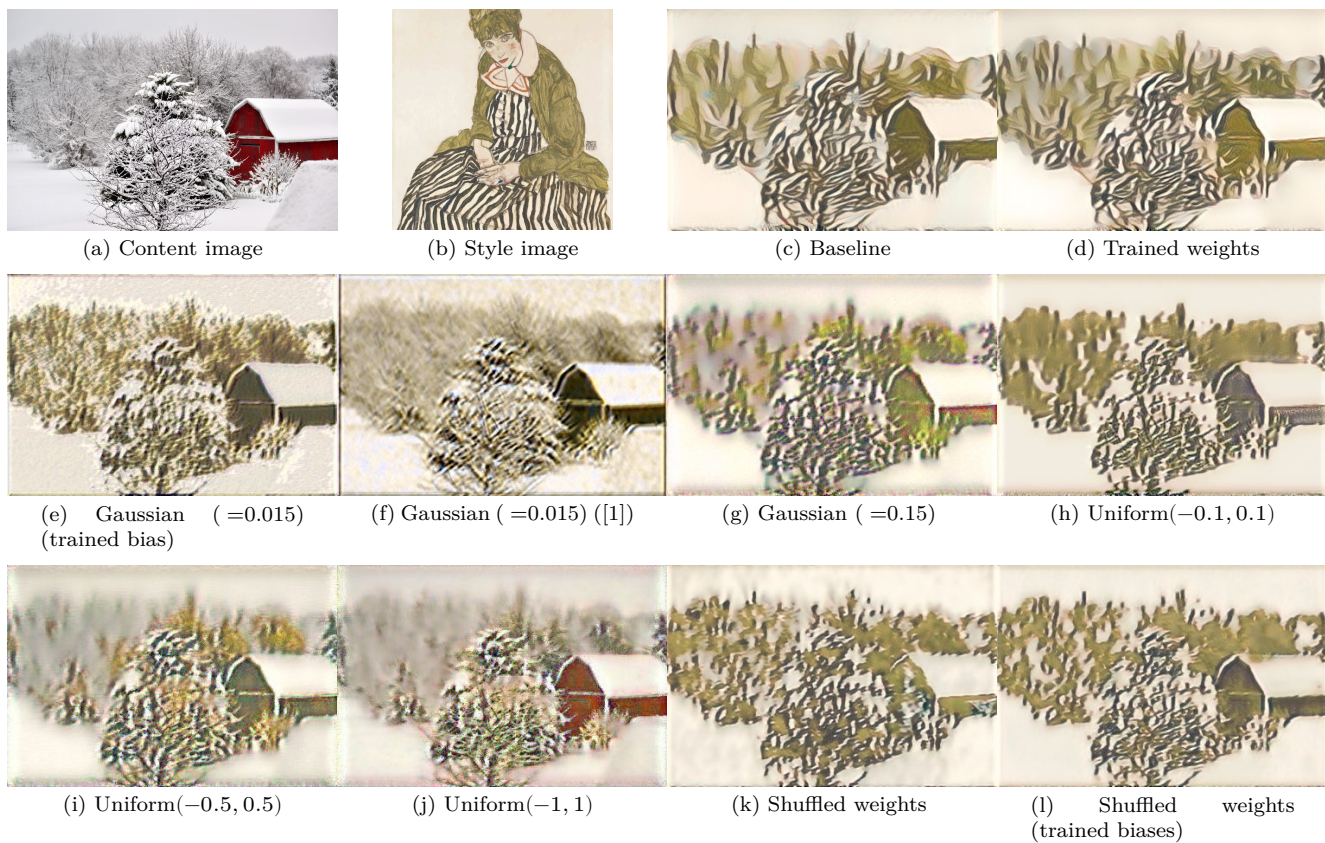


Figure 17: Continuously or densely distributed weights

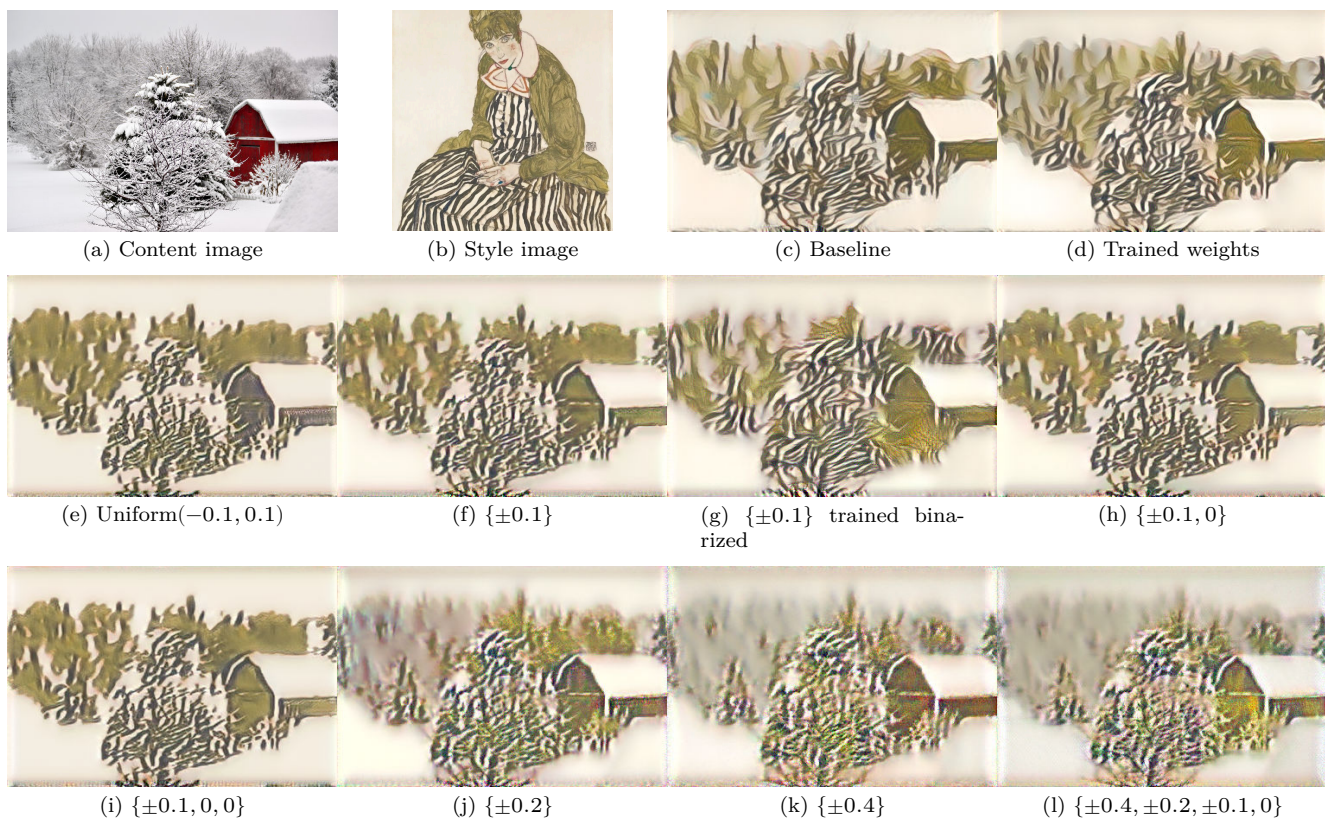


Figure 18: Symmetric discrete weights with fixed biases (0.5)

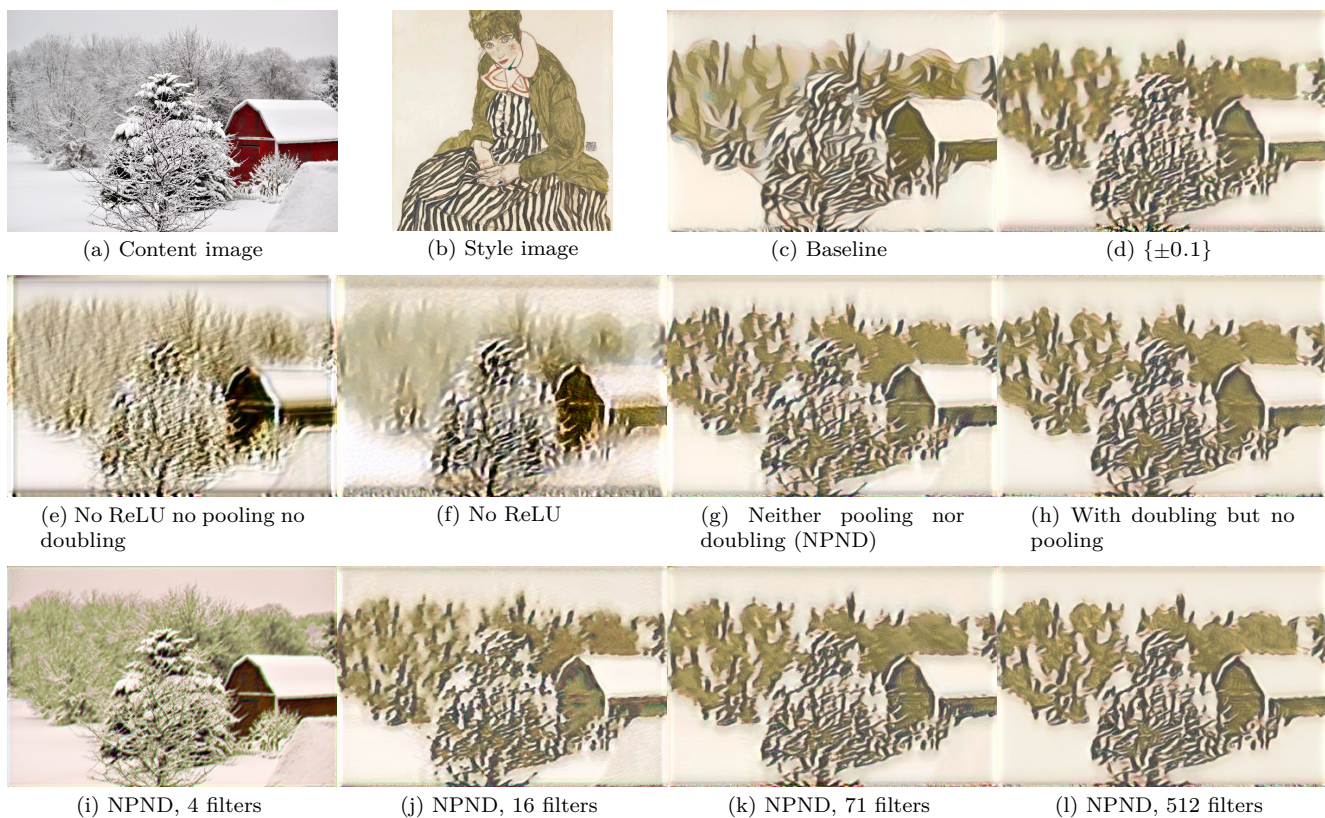


Figure 19: Removal of structure

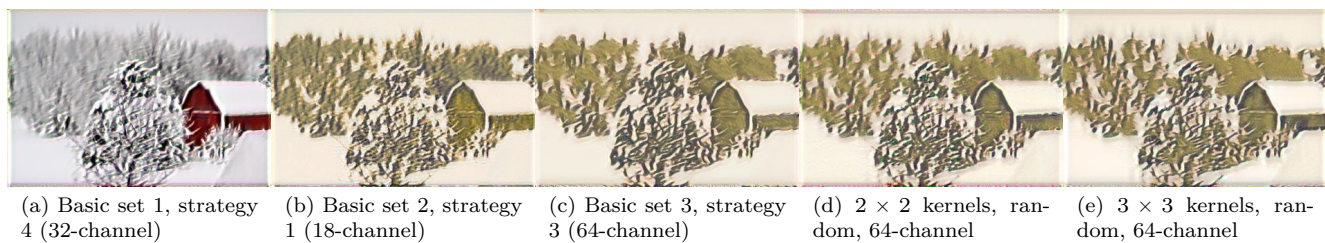


Figure 20: Alternative first-layer convolution kernels

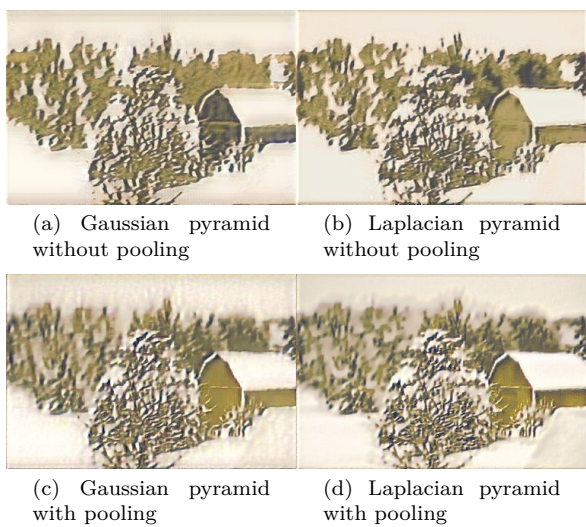


Figure 21: Using image pyramids instead of multi-layer nonlinearities



Figure 22: Removing the content loss

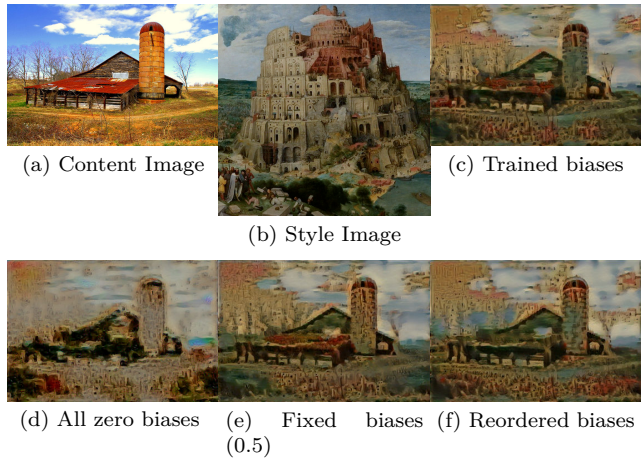


Figure 23: Varying the biases while keeping trained weights

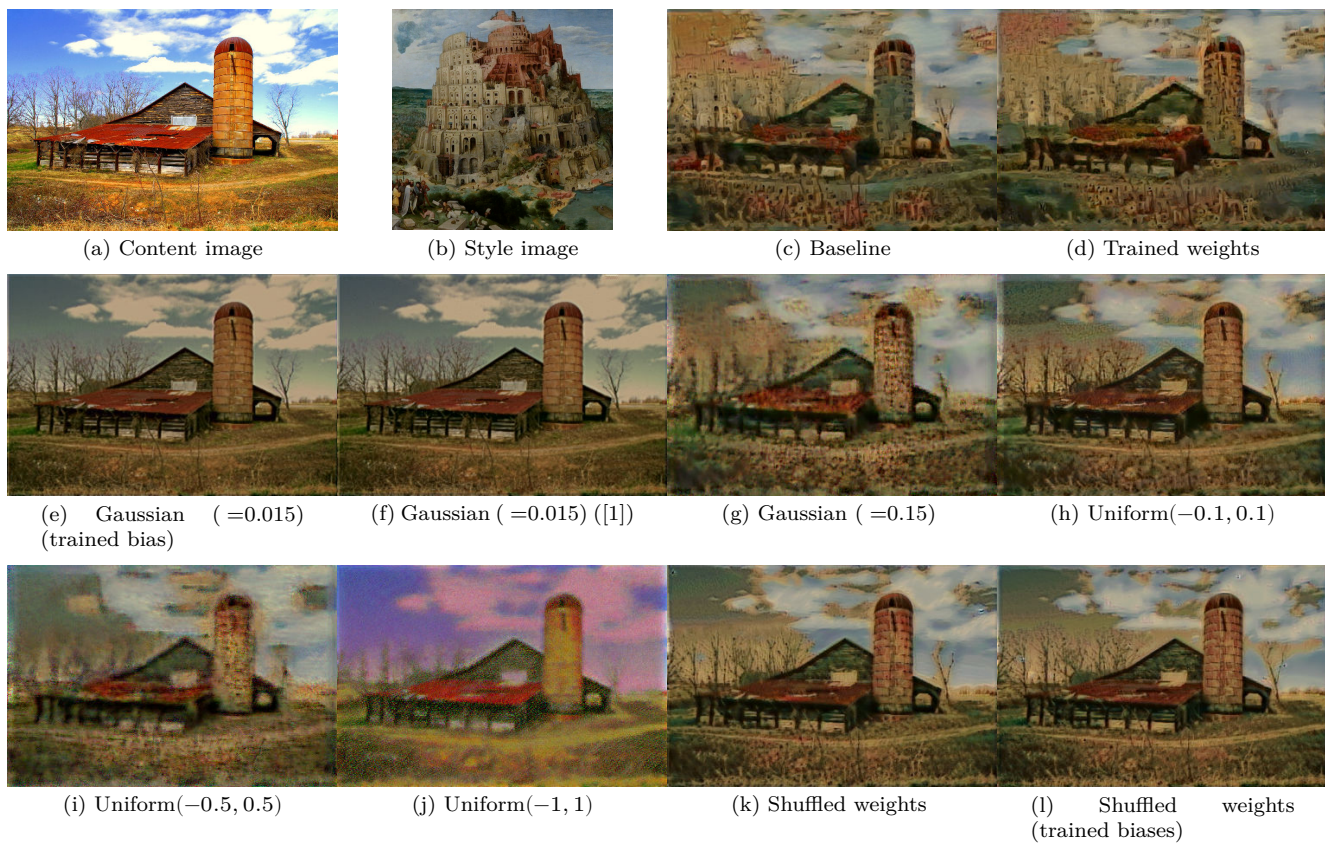


Figure 24: Continuously or densely distributed weights

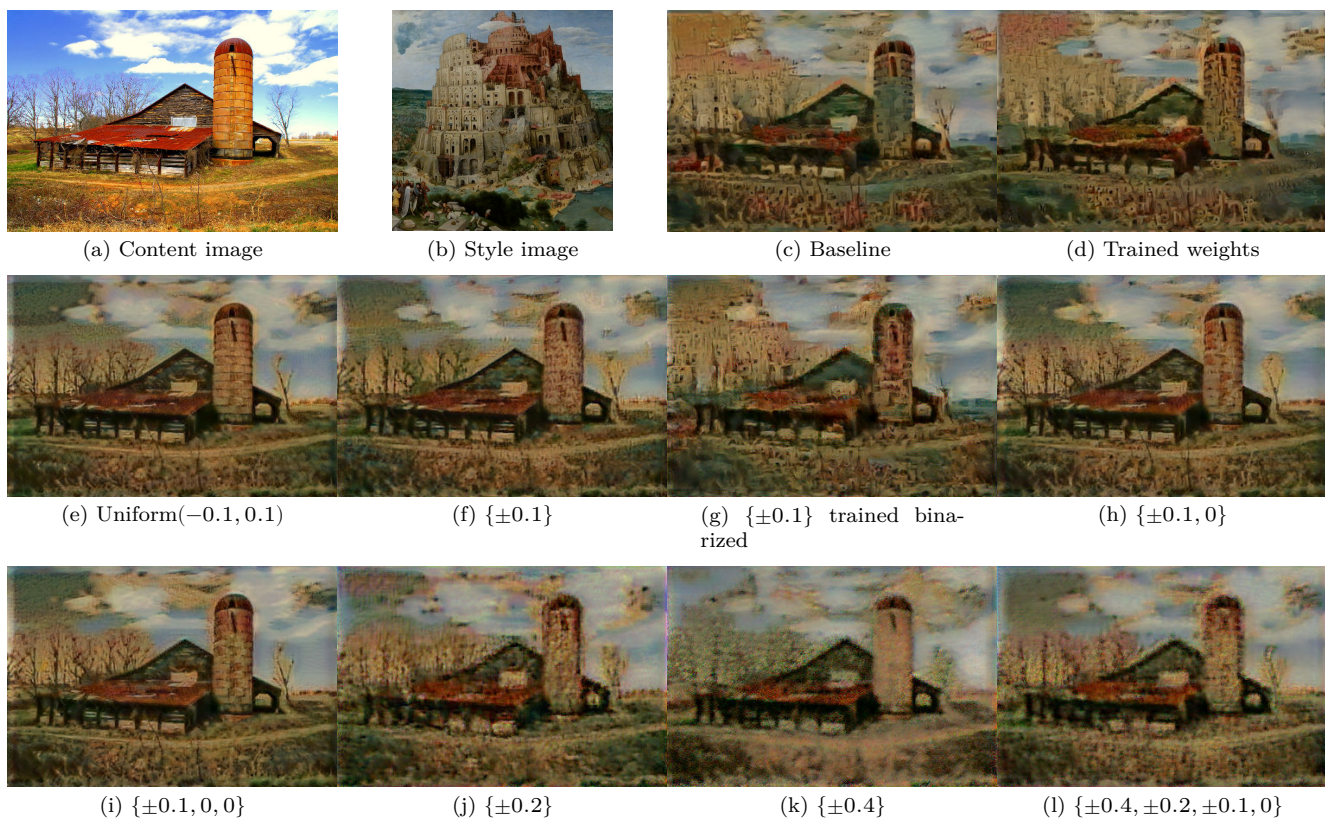


Figure 25: Symmetric discrete weights with fixed biases (0.5)



Figure 26: Removal of structure

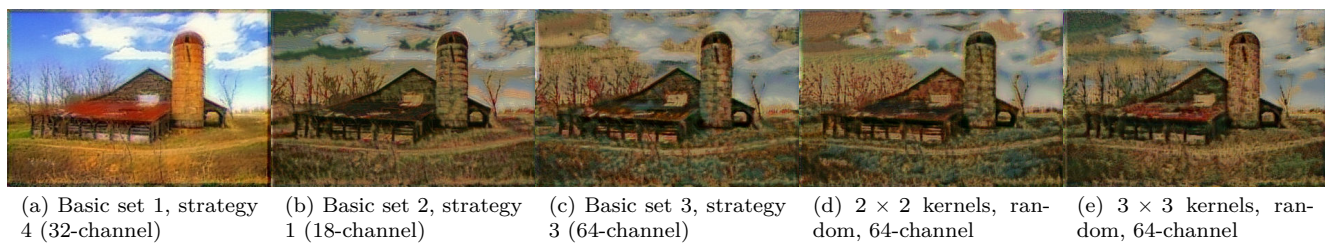


Figure 27: Alternative first-layer convolution kernels



(a) Gaussian pyramid without pooling

(b) Laplacian pyramid without pooling



(c) Gaussian pyramid with pooling

(d) Laplacian pyramid with pooling

Figure 28: Using image pyramids instead of multi-layer nonlinearities

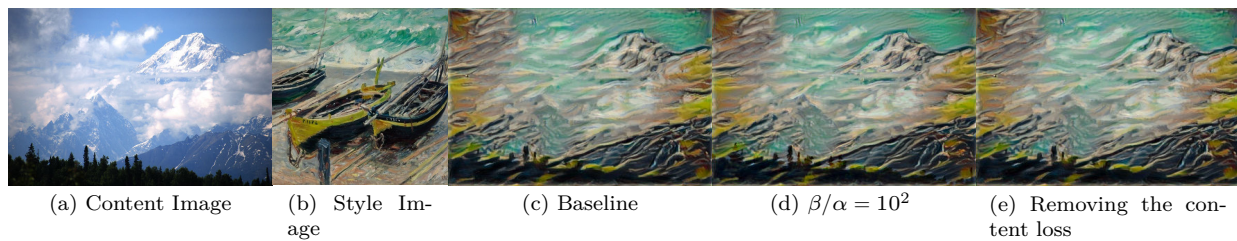


Figure 29: Removing the content loss

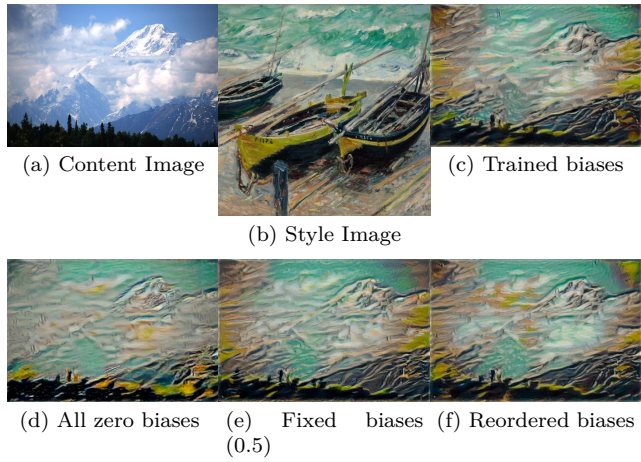


Figure 30: Varing the biases while keeping trained weights

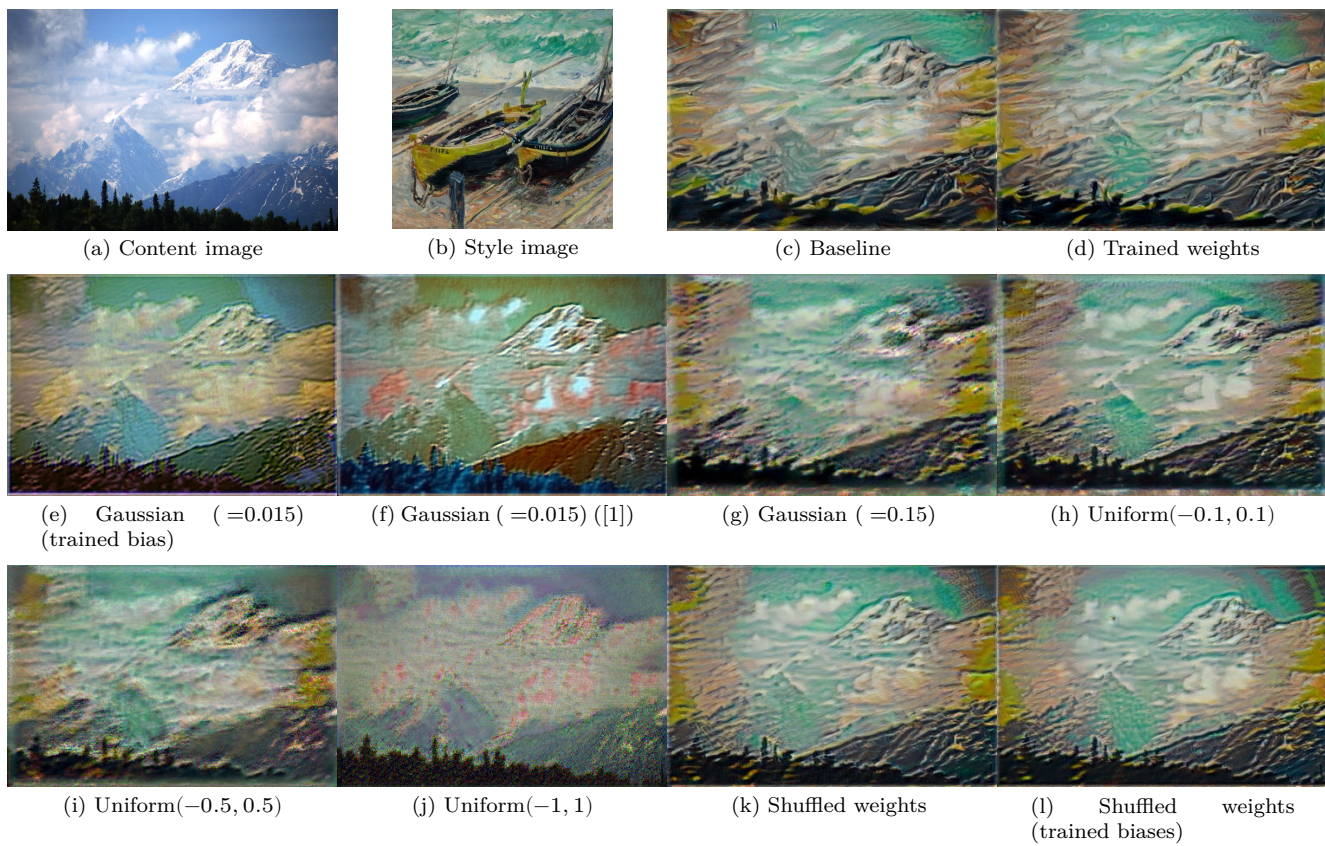


Figure 31: Continuously or densely distributed weights

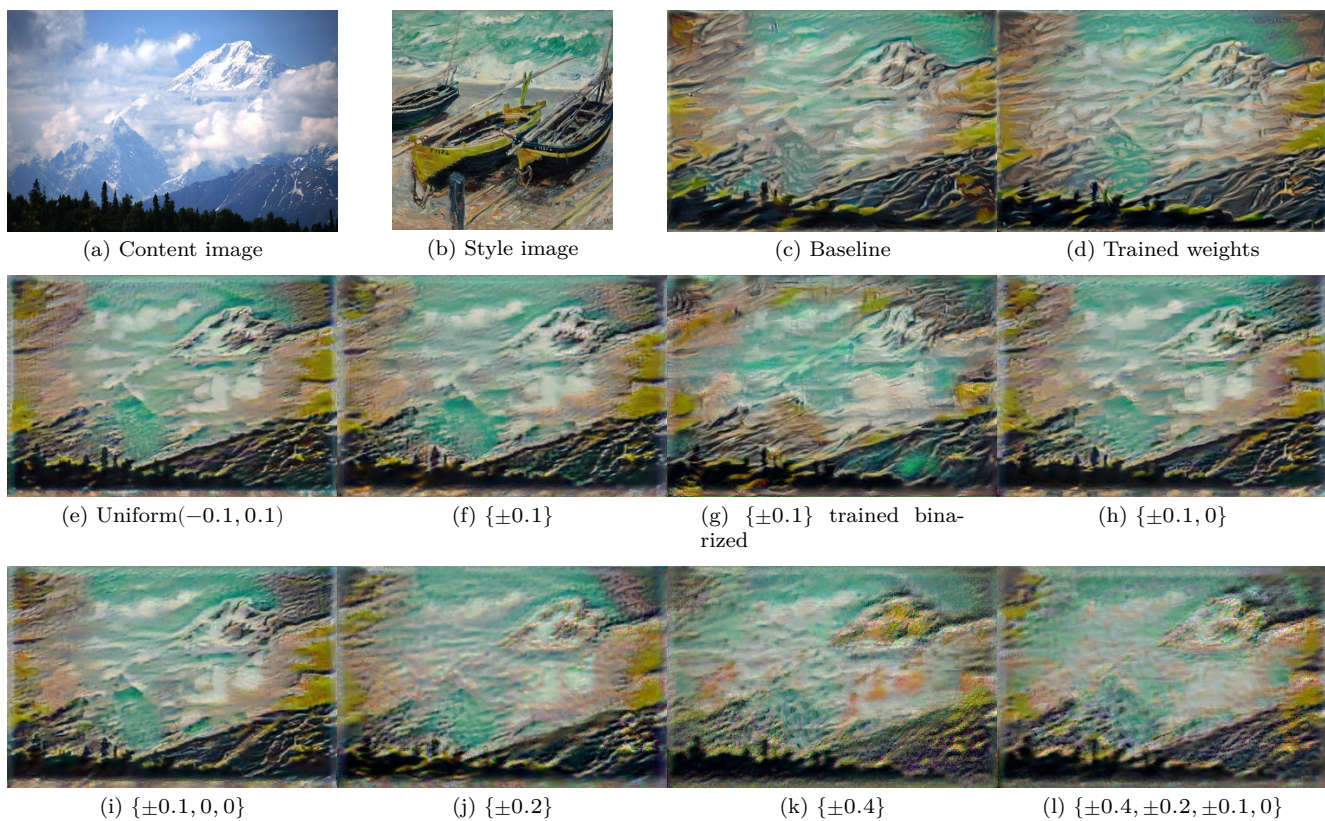


Figure 32: Symmetric discrete weights with fixed biases (0.5)

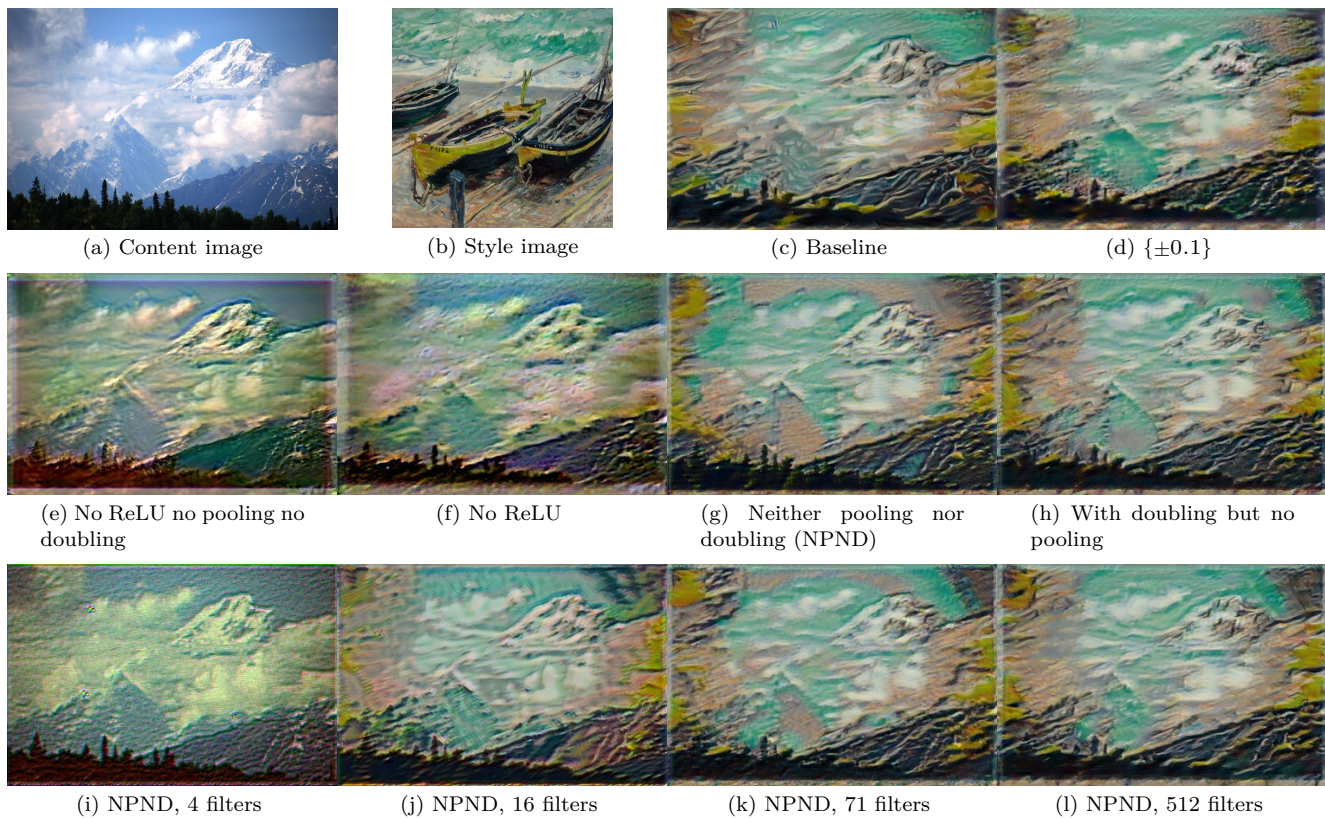


Figure 33: Removal of structure

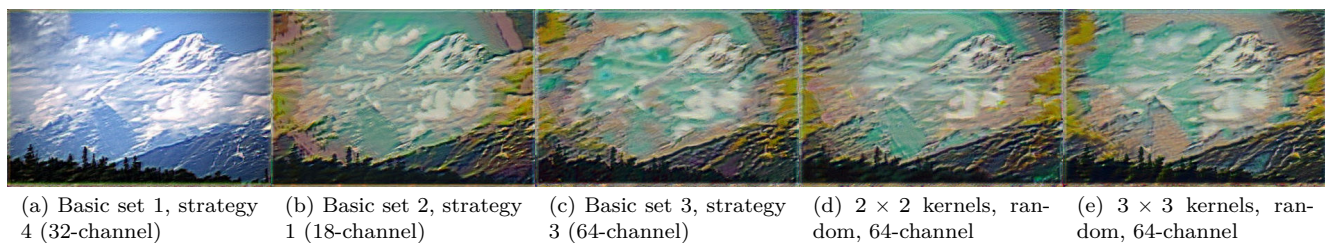
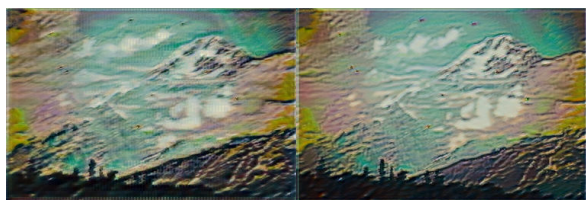
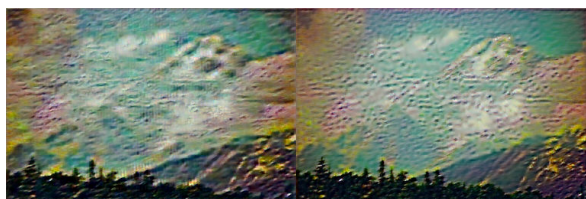


Figure 34: Alternative first-layer convolution kernels



(a) Gaussian pyramid
without pooling

(b) Laplacian pyramid
without pooling



(c) Gaussian pyramid
with pooling

(d) Laplacian pyramid
with pooling

Figure 35: Using image pyramids instead of multi-layer nonlinearities

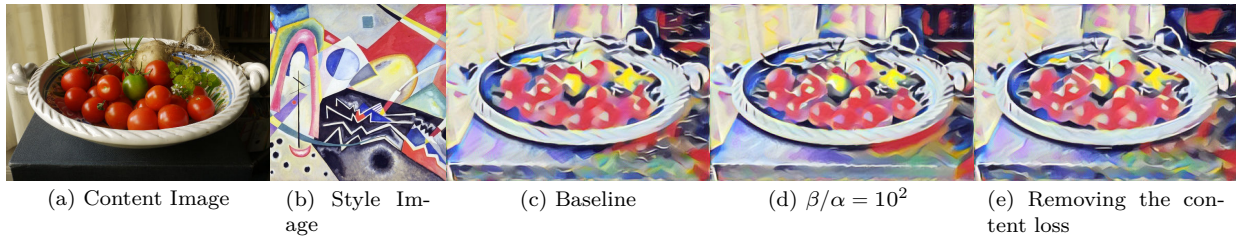


Figure 36: Removing the content loss

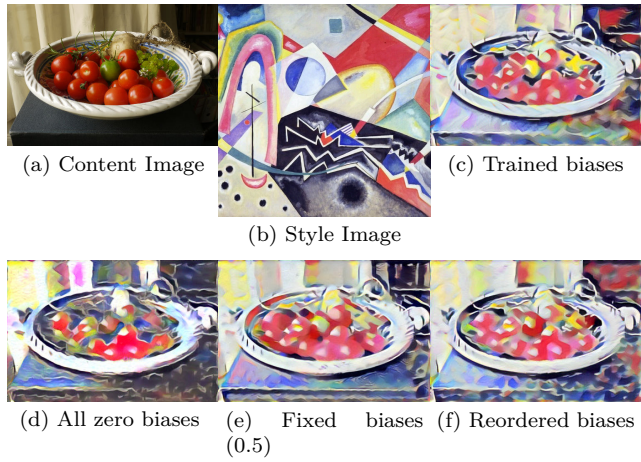


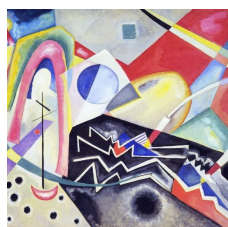
Figure 37: Varying the biases while keeping trained weights



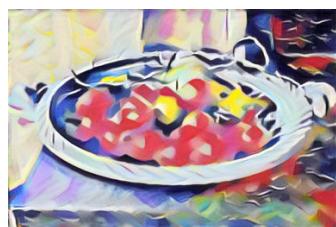
Figure 38: Continuously or densely distributed weights



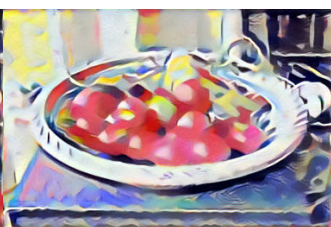
(a) Content image



(b) Style image



(c) Baseline



(d) Trained weights



(e) Uniform(-0.1, 0.1)



(f) $\{\pm 0.1\}$



(g) $\{\pm 0.1\}$ trained binarized



(h) $\{\pm 0.1, 0\}$



(i) $\{\pm 0.1, 0, 0\}$



(j) $\{\pm 0.2\}$



(k) $\{\pm 0.4\}$



(l) $\{\pm 0.4, \pm 0.2, \pm 0.1, 0\}$

Figure 39: Symmetric discrete weights with fixed biases (0.5)

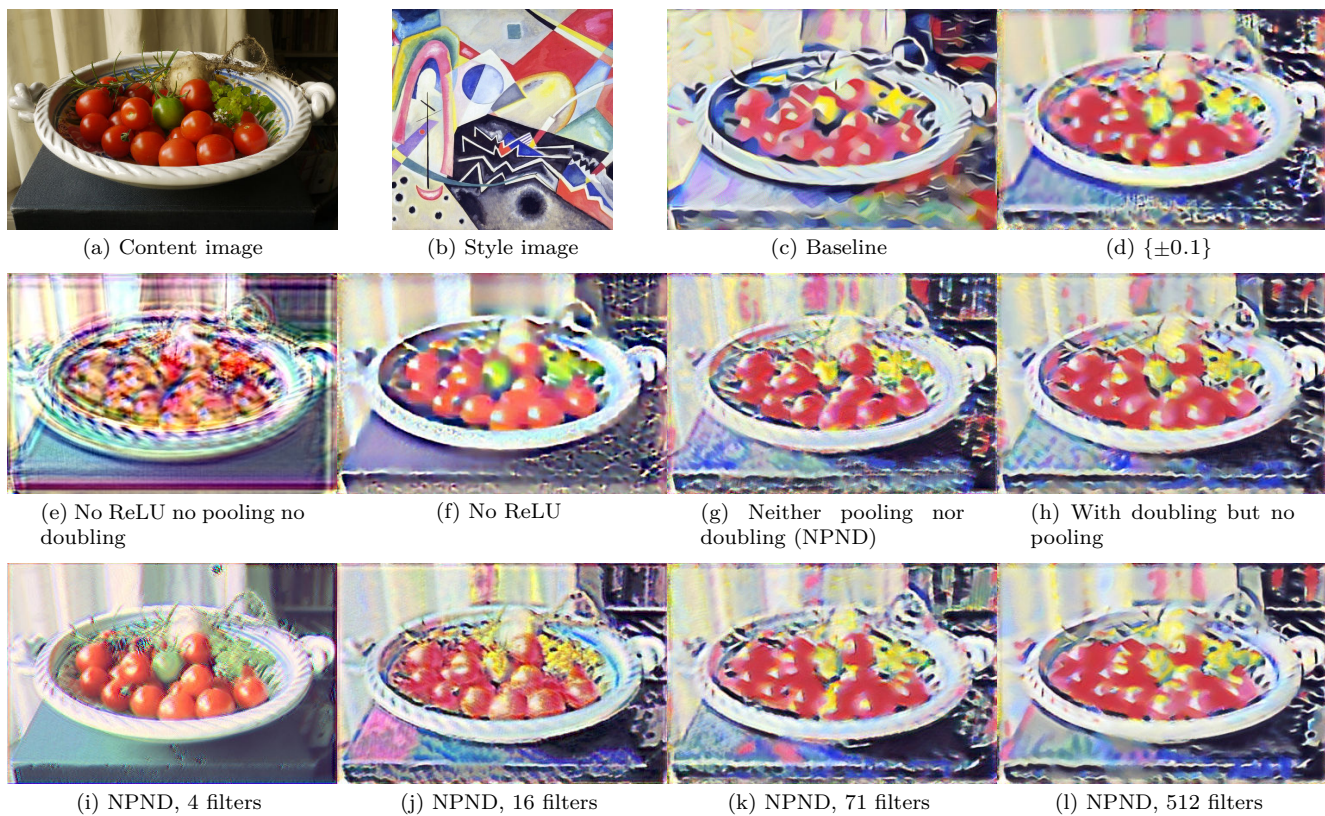


Figure 40: Removal of structure

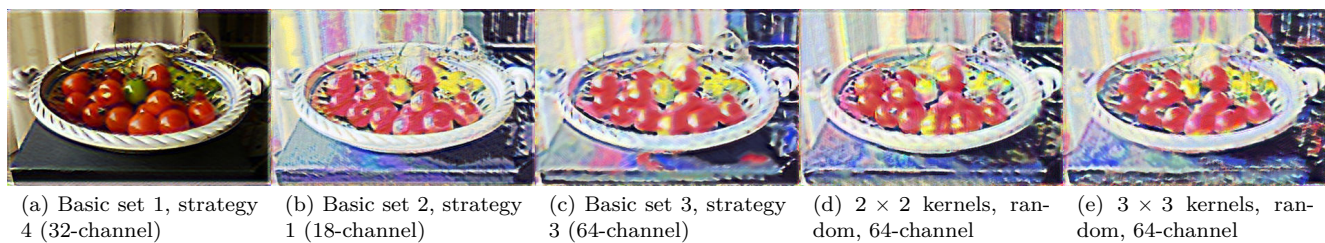


Figure 41: Alternative first-layer convolution kernels



(a) Gaussian pyramid without pooling

(b) Laplacian pyramid without pooling



(c) Gaussian pyramid with pooling

(d) Laplacian pyramid with pooling

Figure 42: Using image pyramids instead of multi-layer nonlinearities



Figure 43: Removing the content loss



Figure 44: Varying the biases while keeping trained weights



Figure 45: Continuously or densely distributed weights

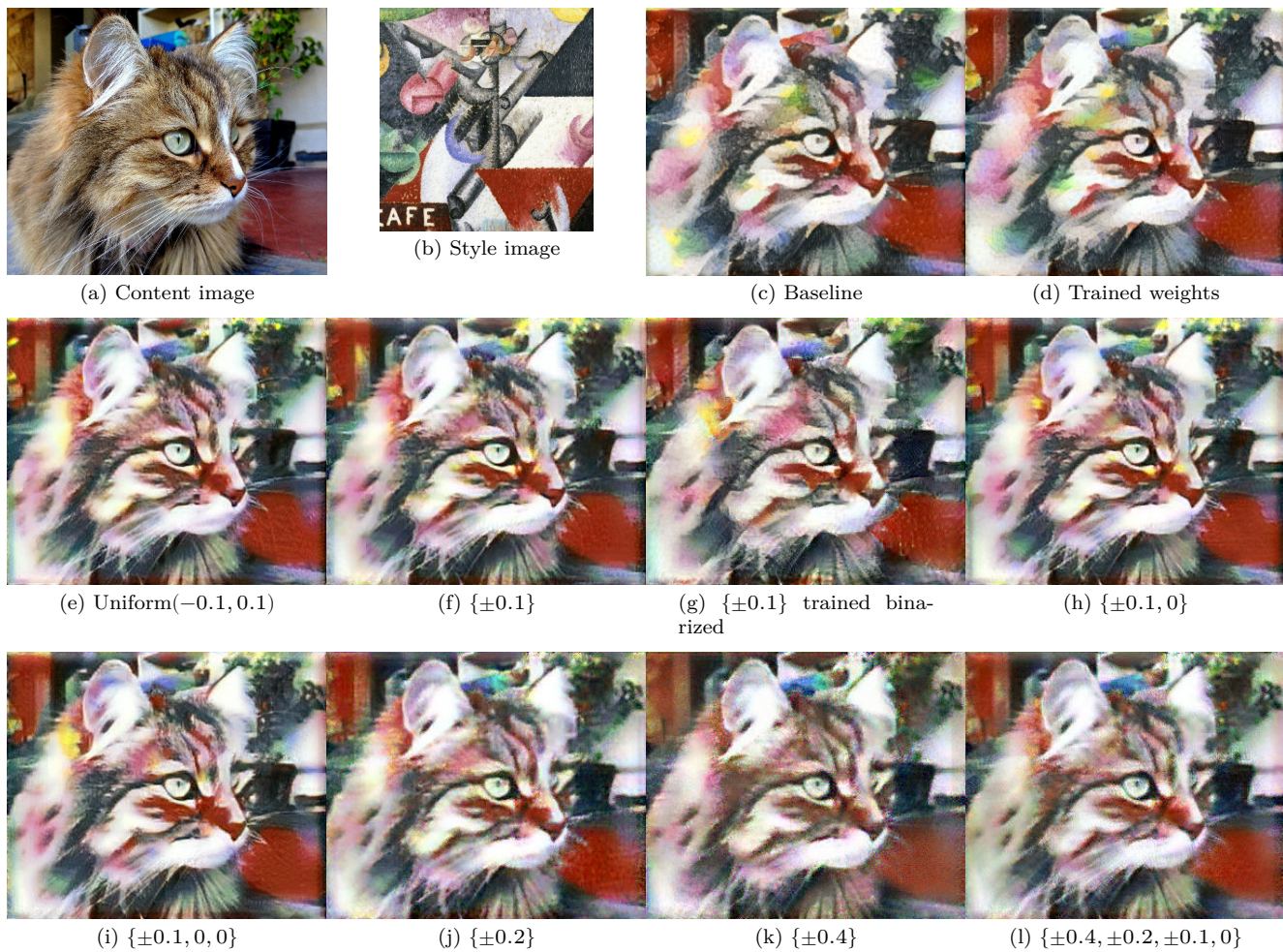


Figure 46: Symmetric discrete weights with fixed biases (0.5)



Figure 47: Removal of structure

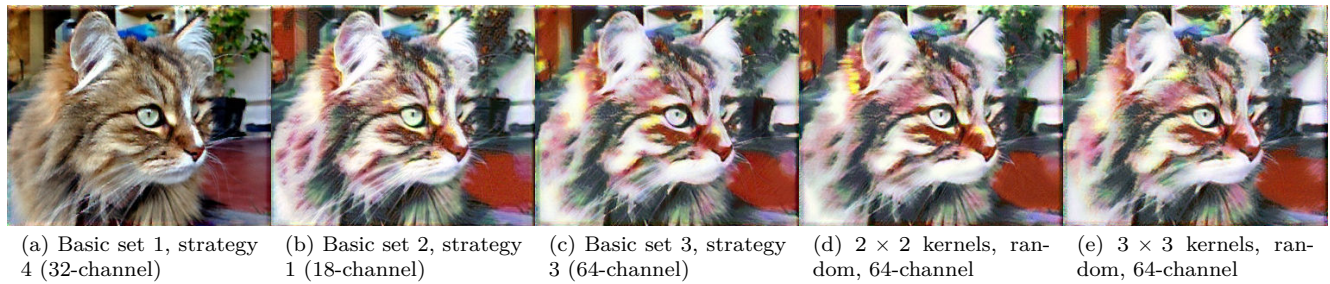


Figure 48: Alternative first-layer convolution kernels



(a) Gaussian pyramid without pooling

(b) Laplacian pyramid without pooling



(c) Gaussian pyramid with pooling

(d) Laplacian pyramid with pooling

Figure 49: Using image pyramids instead of multi-layer nonlinearities

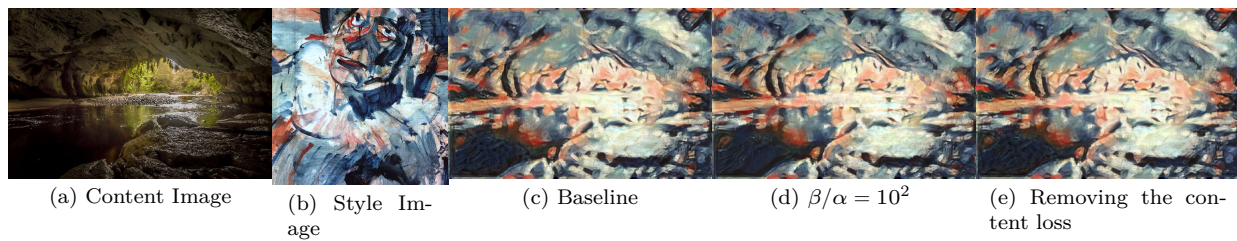


Figure 50: Removing the content loss

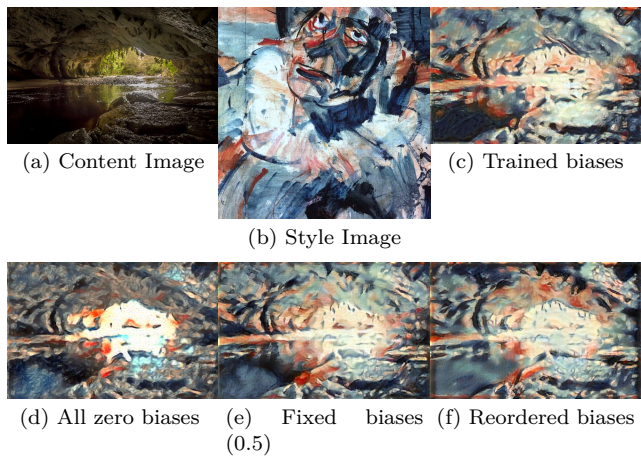


Figure 51: Varing the biases while keeping trained weights

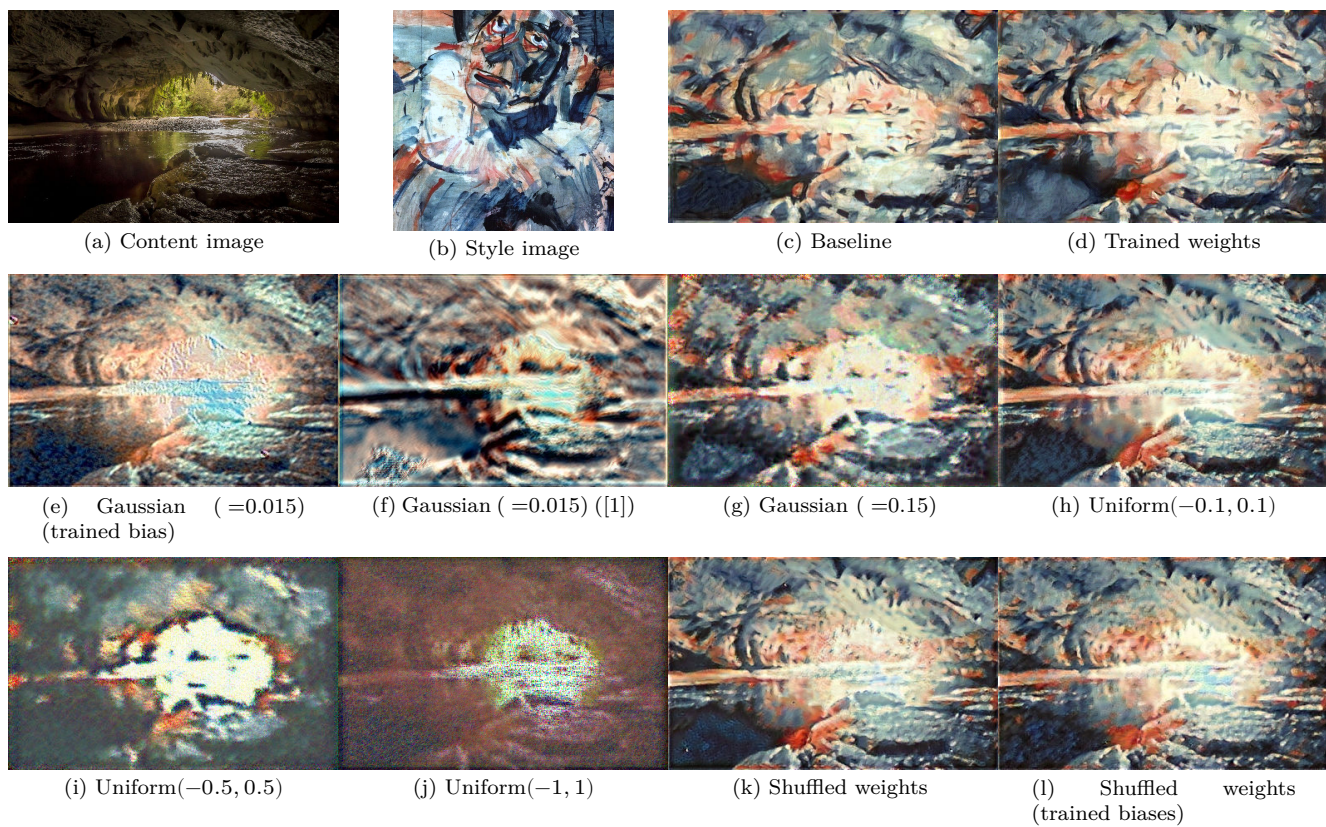


Figure 52: Continuously or densely distributed weights

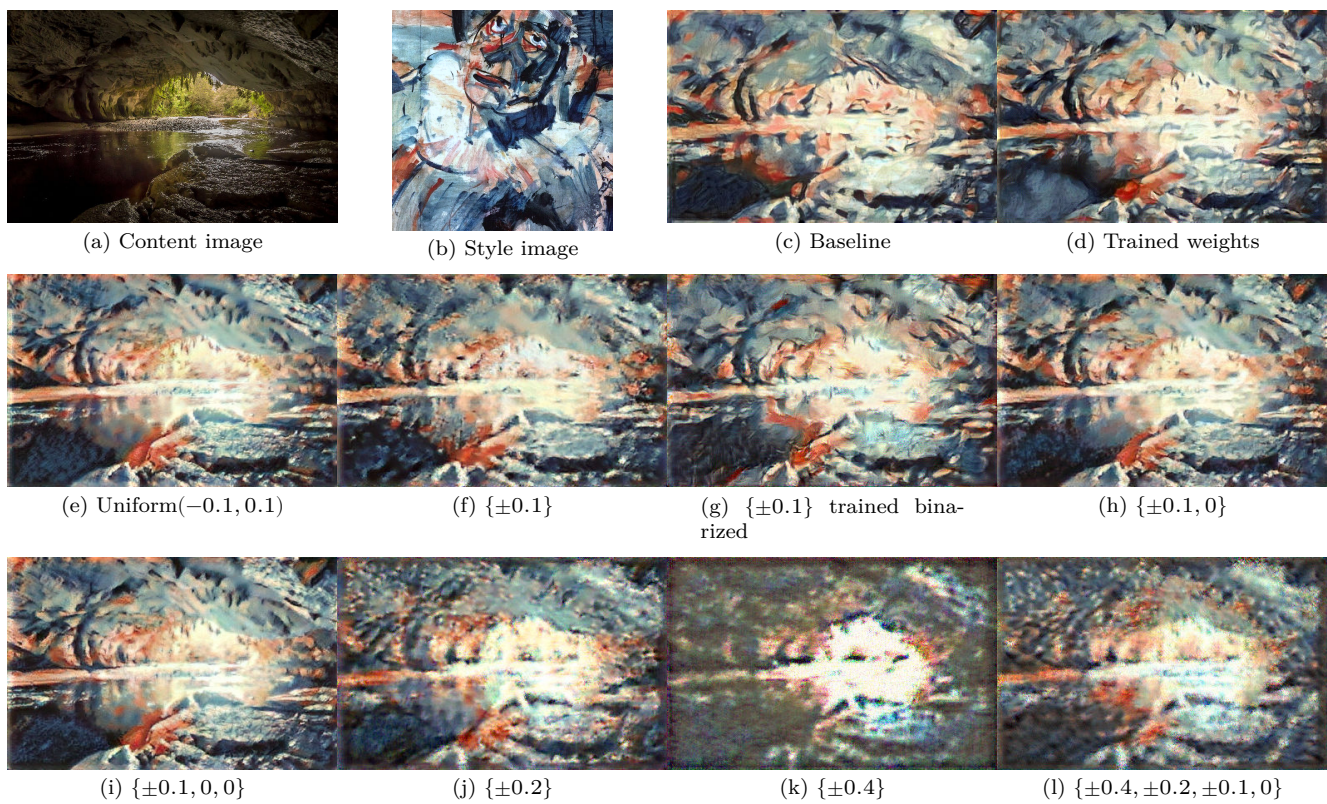


Figure 53: Symmetric discrete weights with fixed biases (0.5)

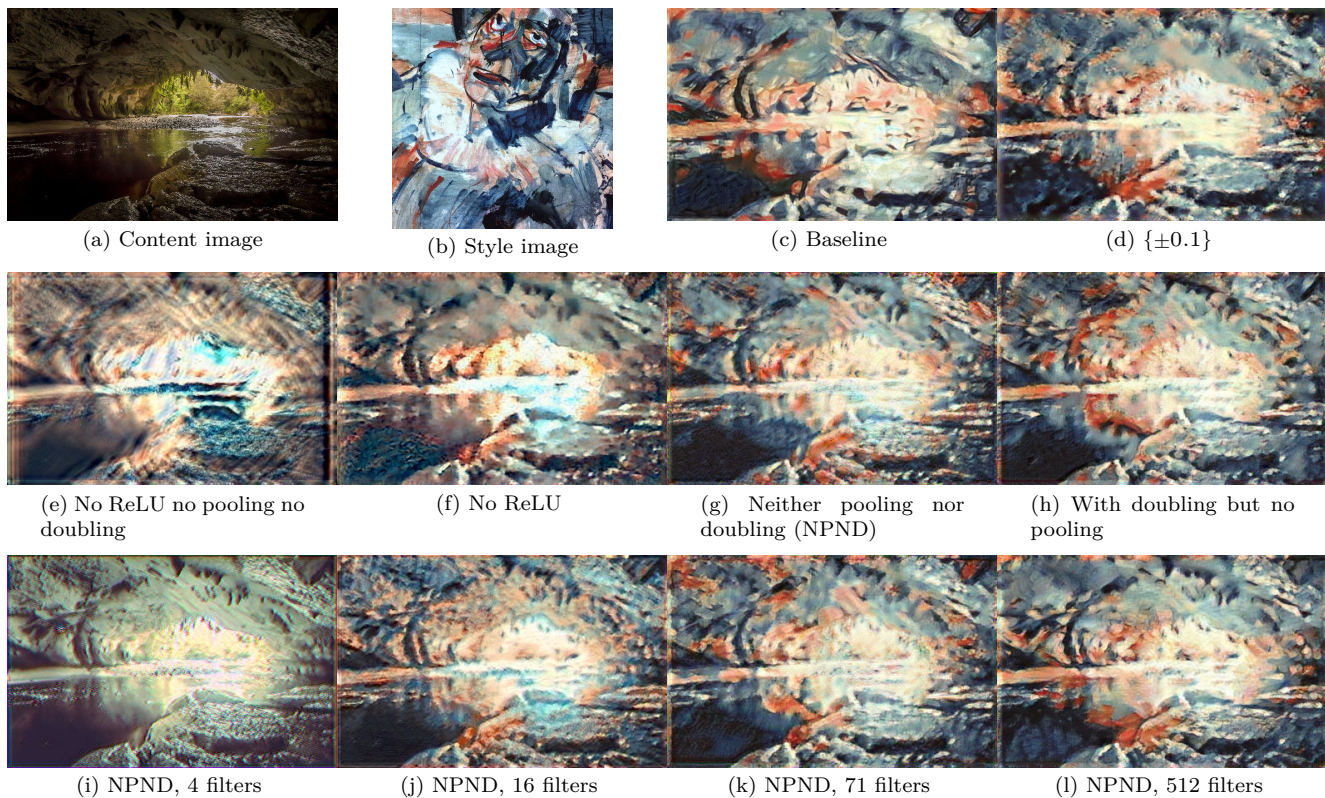


Figure 54: Removal of structure

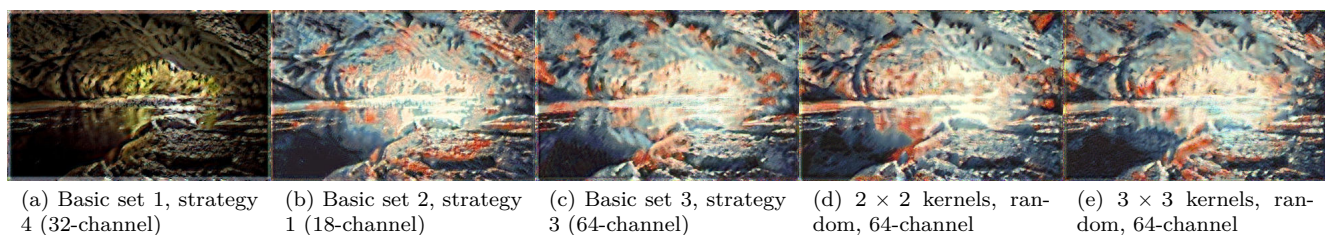
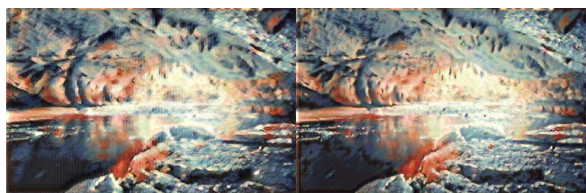
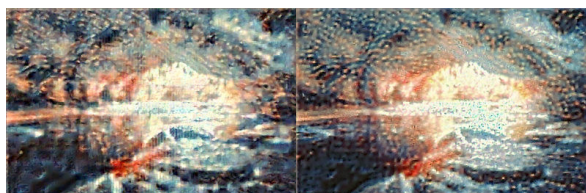


Figure 55: Alternative first-layer convolution kernels



(a) Gaussian pyramid
without pooling

(b) Laplacian pyramid
without pooling



(c) Gaussian pyramid
with pooling

(d) Laplacian pyramid
with pooling

Figure 56: Using image pyramids instead of multi-layer nonlinearities

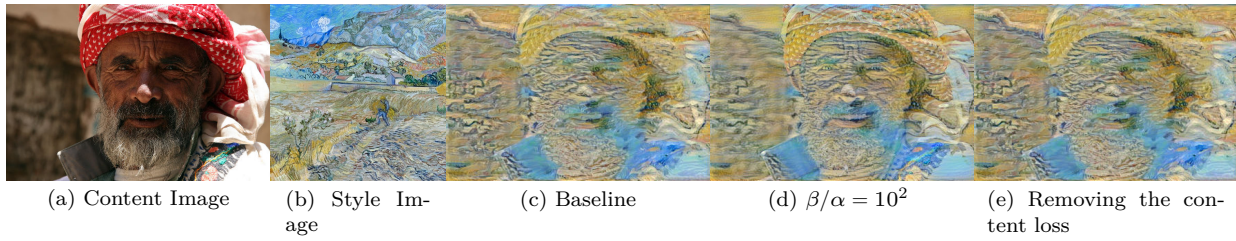


Figure 57: Removing the content loss

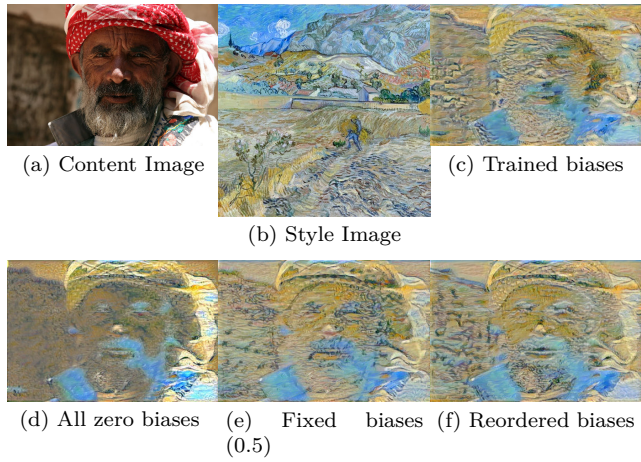


Figure 58: Varing the biases while keeping trained weights

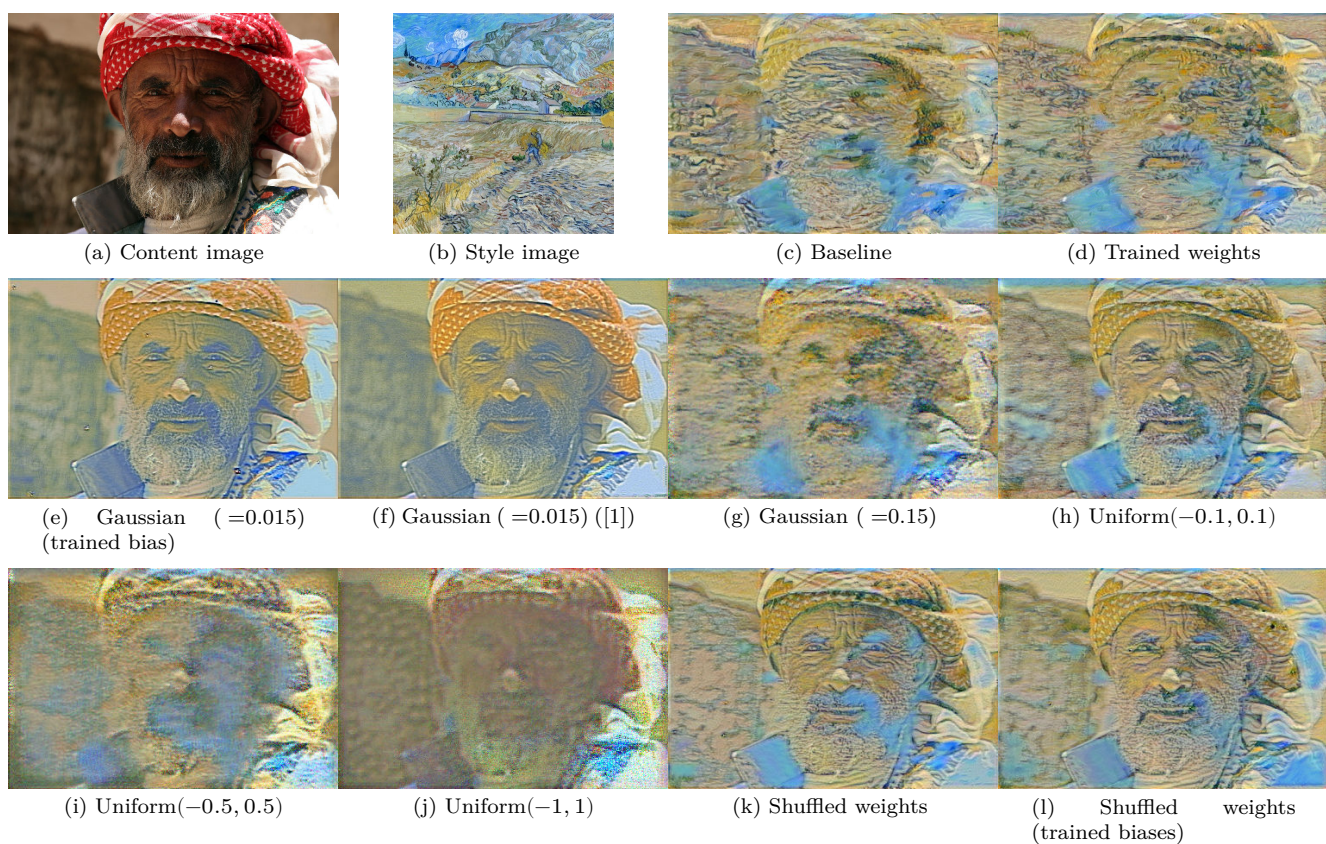


Figure 59: Continuously or densely distributed weights

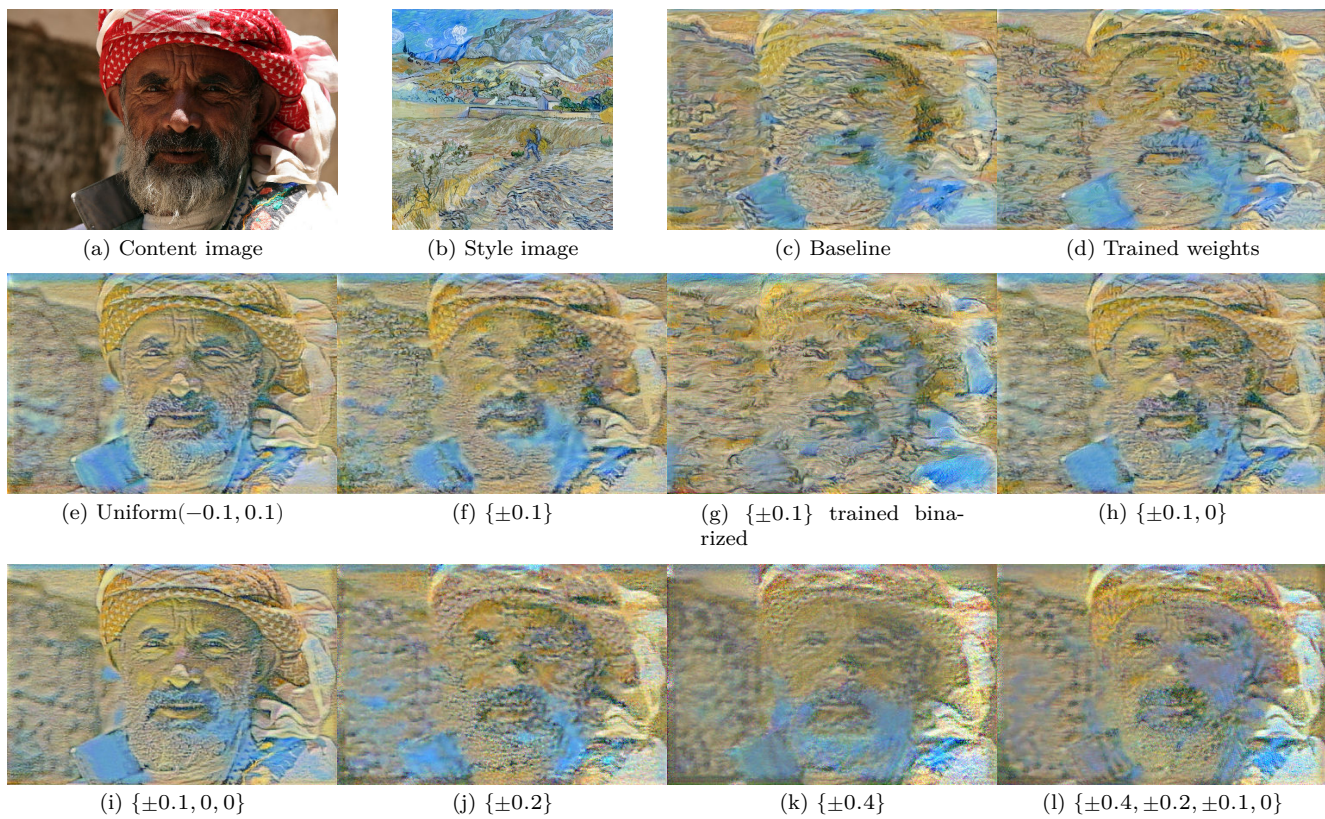


Figure 60: Symmetric discrete weights with fixed biases (0.5)



Figure 61: Removal of structure

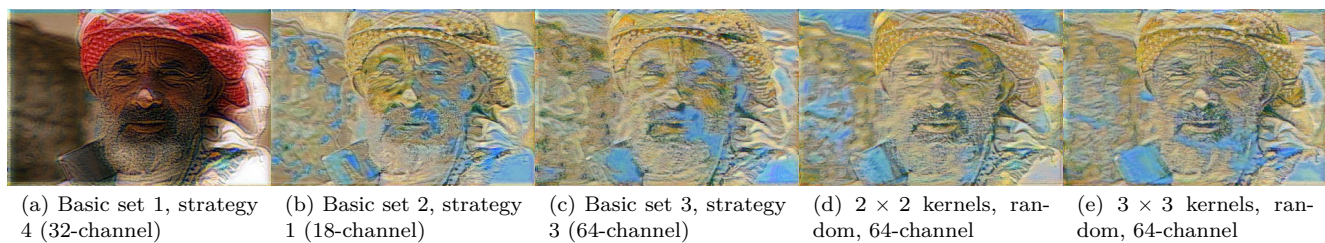
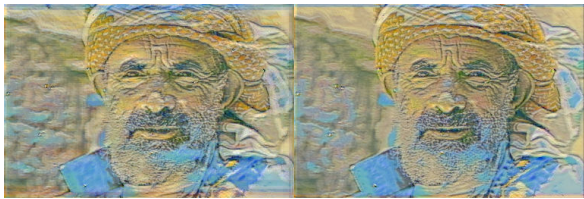


Figure 62: Alternative first-layer convolution kernels



(a) Gaussian pyramid without pooling

(b) Laplacian pyramid without pooling



(c) Gaussian pyramid with pooling

(d) Laplacian pyramid with pooling

Figure 63: Using image pyramids instead of multi-layer nonlinearities

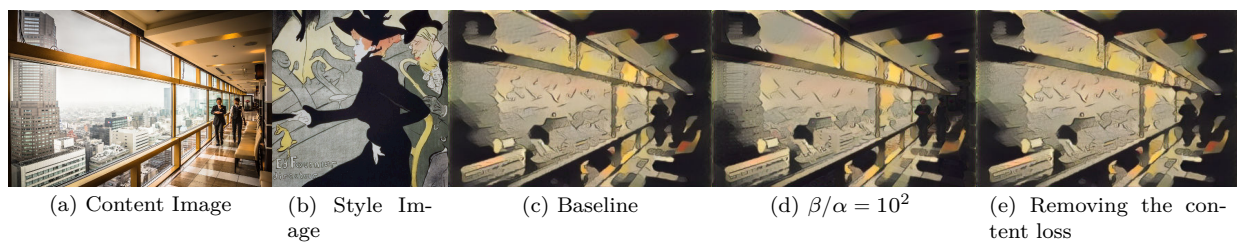


Figure 64: Removing the content loss

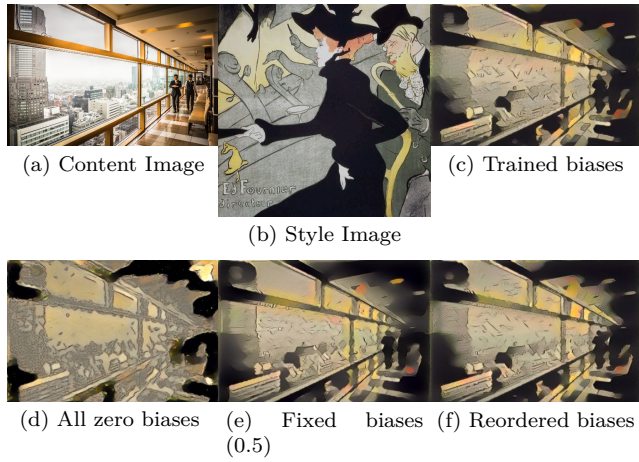


Figure 65: Varying the biases while keeping trained weights

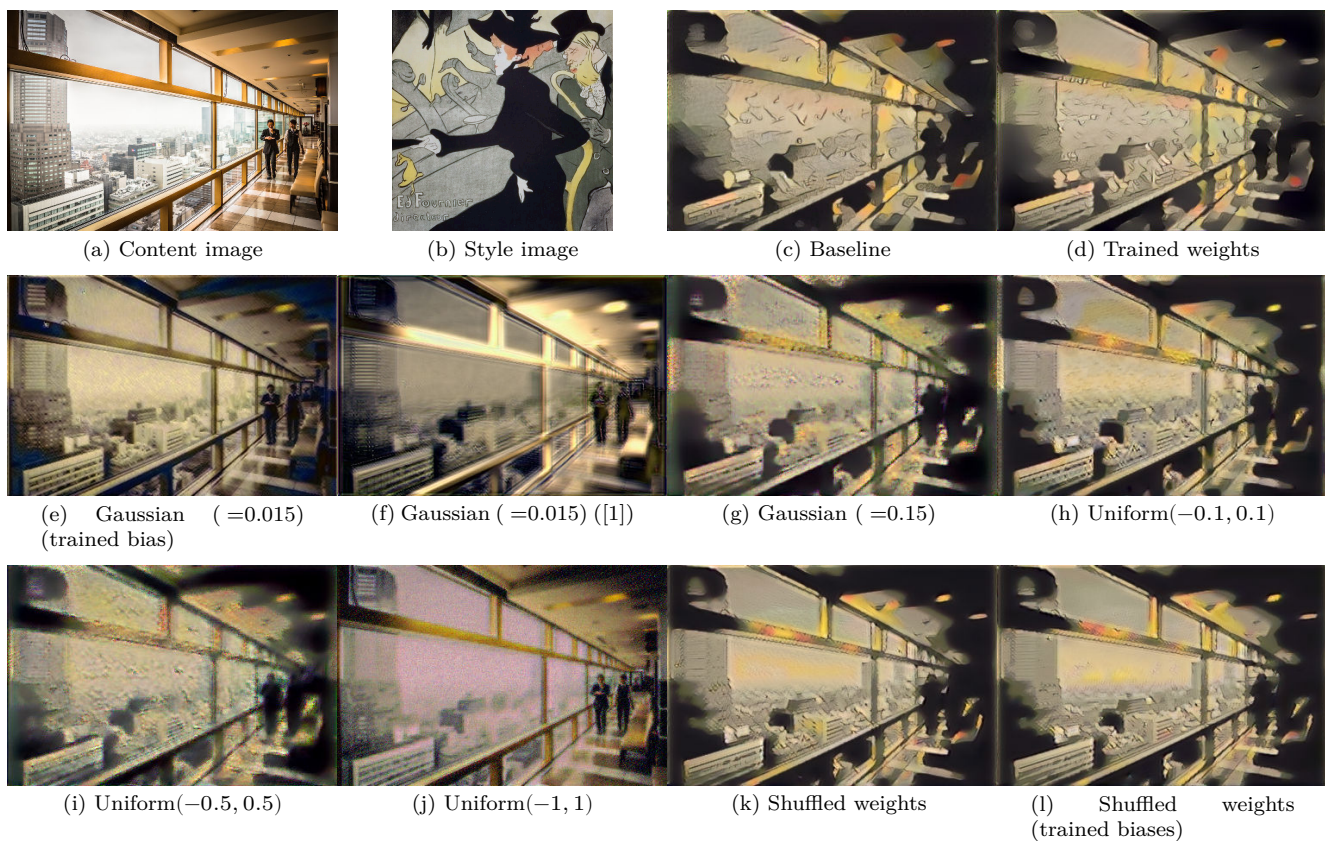


Figure 66: Continuously or densely distributed weights

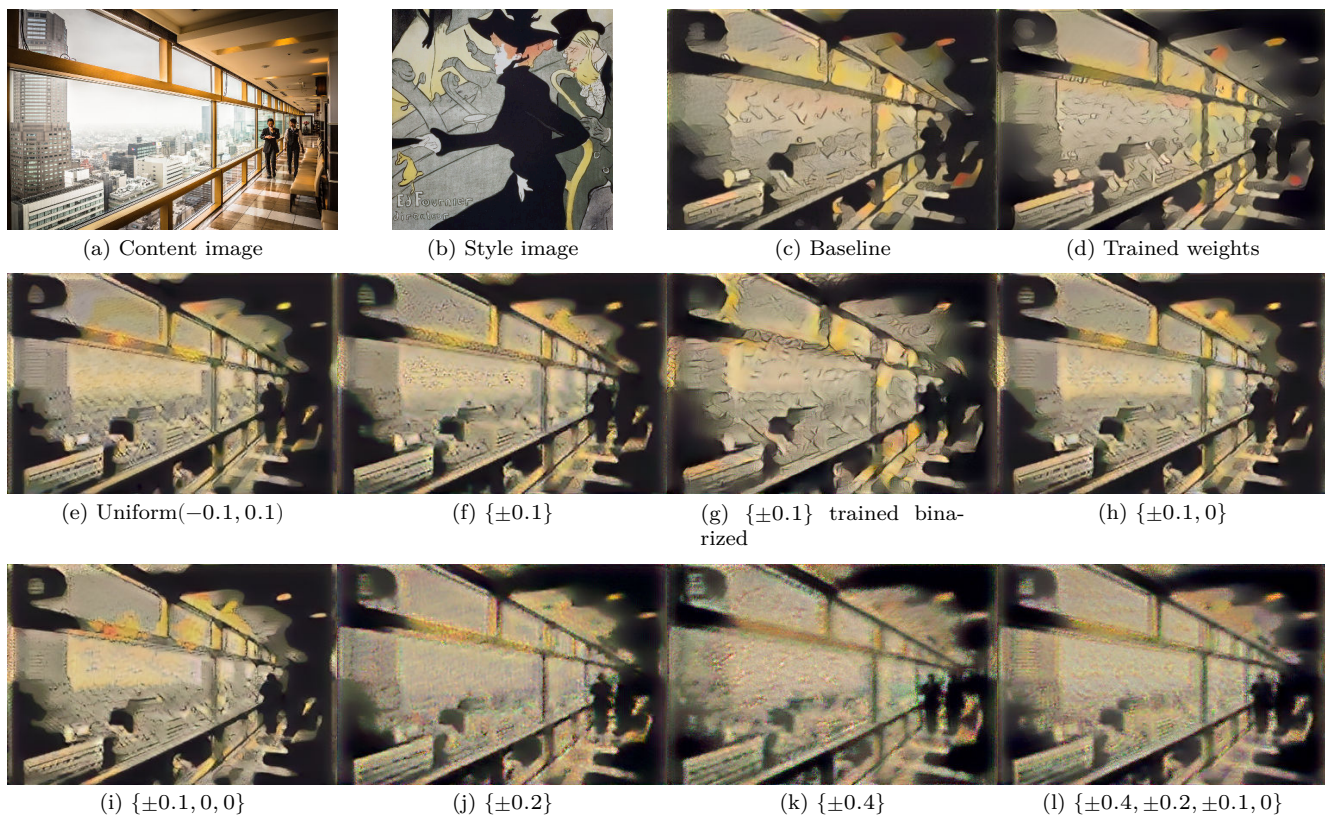


Figure 67: Symmetric discrete weights with fixed biases (0.5)



Figure 68: Removal of structure

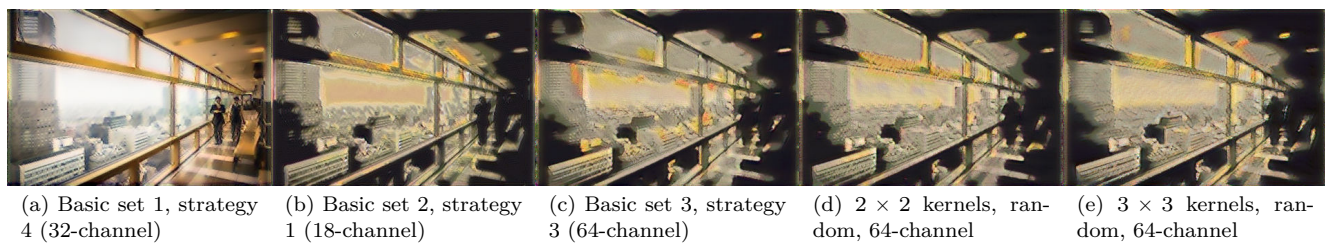
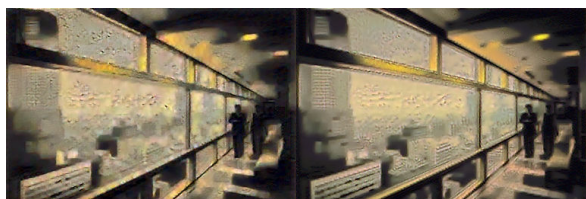


Figure 69: Alternative first-layer convolution kernels



(a) Gaussian pyramid without pooling

(b) Laplacian pyramid without pooling



(c) Gaussian pyramid with pooling

(d) Laplacian pyramid with pooling

Figure 70: Using image pyramids instead of multi-layer nonlinearities