Supplementary Material for: Toward Universal Texture Synthesis by Combining Texton Broadcasting with Noise Injection in StyleGAN-2

Jue Lin[a], Gaurav Sharma[b], Thrasyvoulos N. Pappas[a]

[a] *ECE Dept., Northwestern University, Evanston, IL, USA*
[b] *ECE Dept., University of Rochester, Rochester, NY, USA*

This document provides Supplementary Material for the paper [1] comprising additional image examples of textures generated by the proposed approach to illustrate its capability to: (a) generate textures of arbitrary spatial sizes (Section S.1), (b) interpolate in the learned latent space (Section S.2), and (c) both represent the textures in the training dataset and generalize beyond these (Section S.3). These additional image examples augment those presented in the main paper, where these points were also covered.

S.1. Additional textures synthesized by the proposed approach

From Figures S.1 to S.12, we provide additional synthesized textures at different spatial sizes. Results show that expanding the spatial size of the multi-scale Texton Broadcasting modules produces consistent textures.

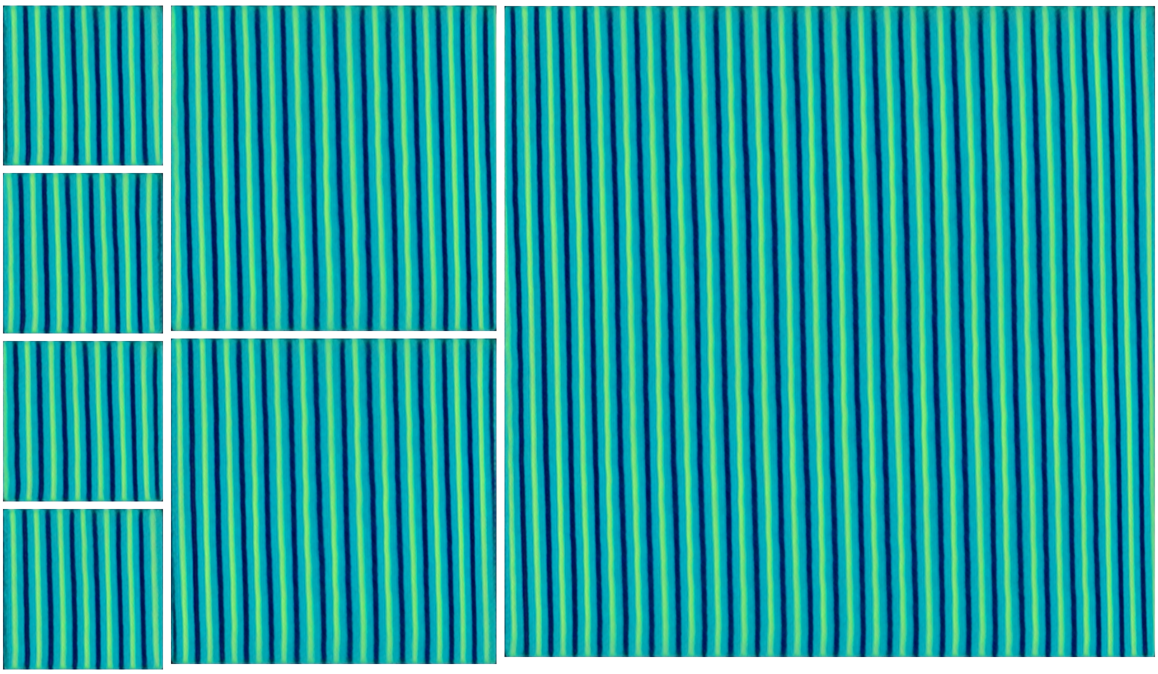


Fig. S.1: Textures synthesized at spatial sizes of 256×256,512×512 and 1024×1024 by the proposed model

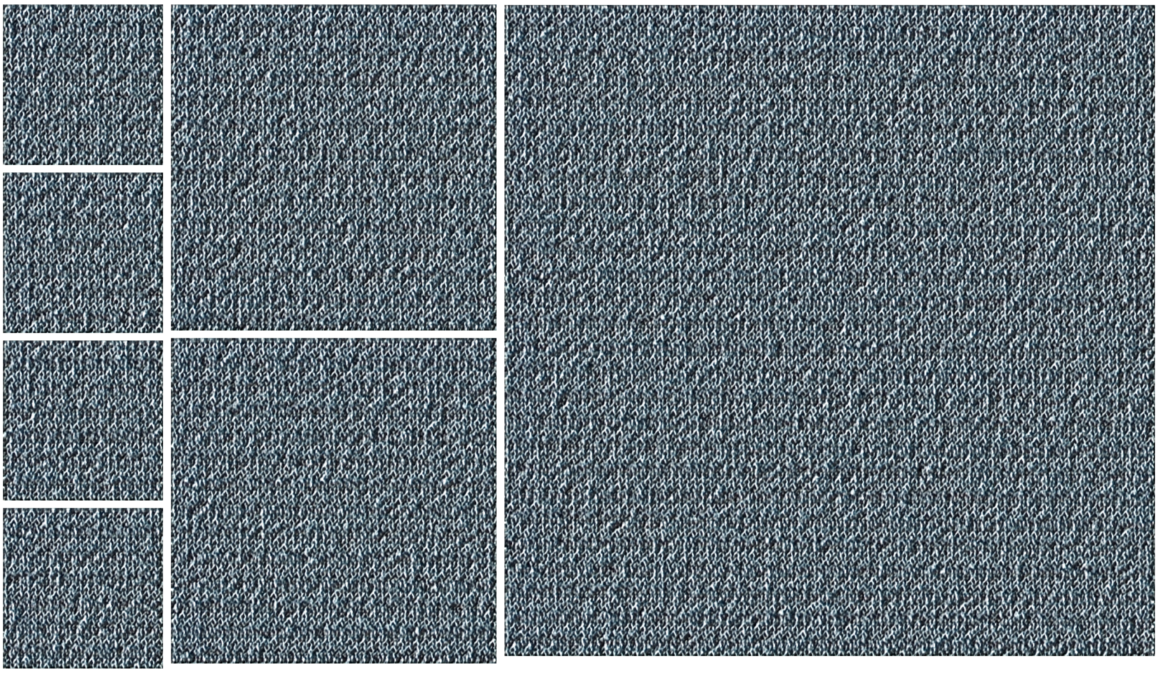


Fig. S.2: Textures synthesized at spatial sizes of 256×256,512×512 and 1024×1024 by the proposed model

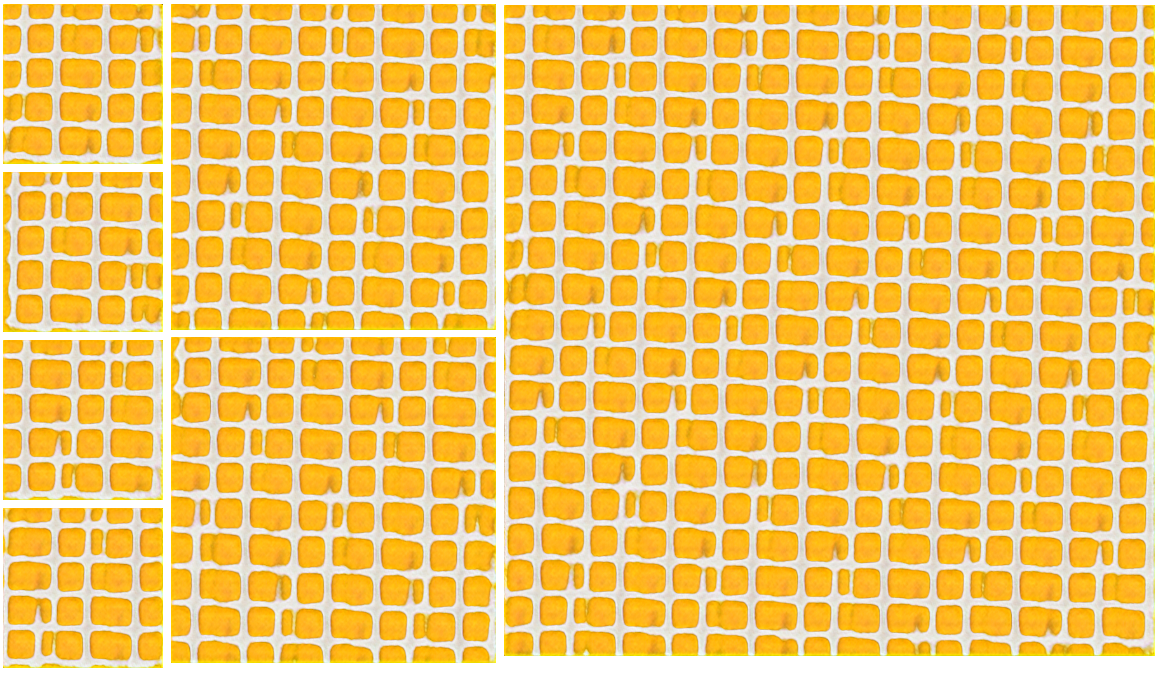


Fig. S.3: Textures synthesized at spatial sizes of 256×256,512×512 and 1024×1024 by the proposed model

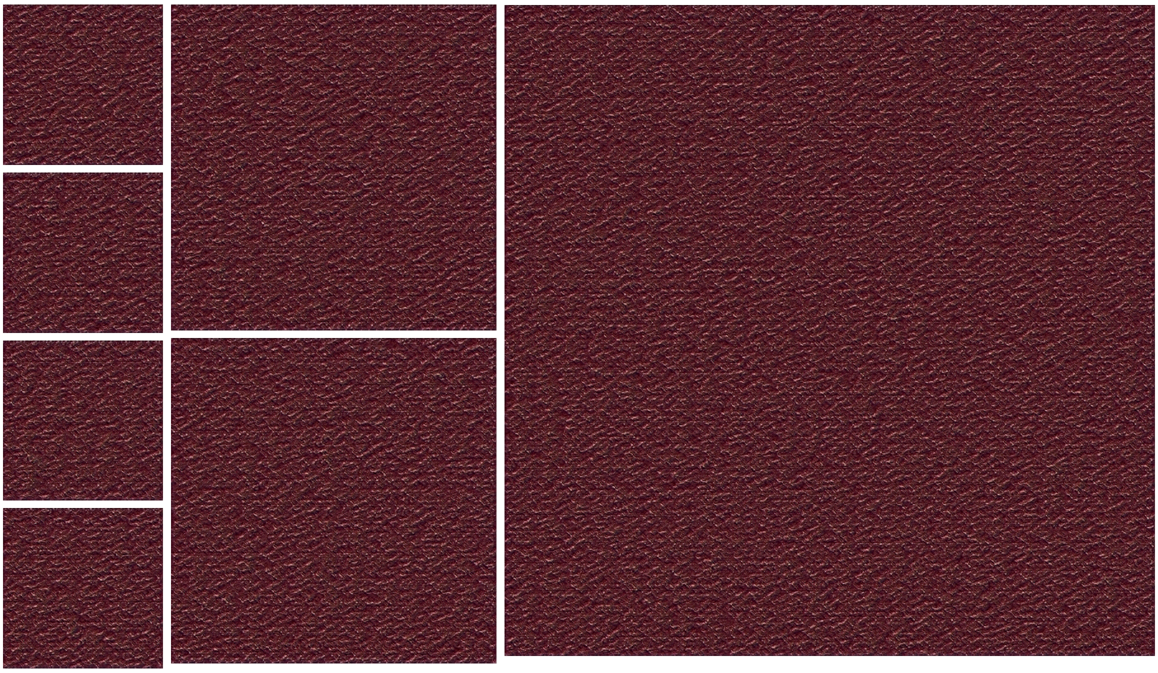


Fig. S.4: Textures synthesized at spatial sizes of 256×256,512×512 and 1024×1024 by the proposed model

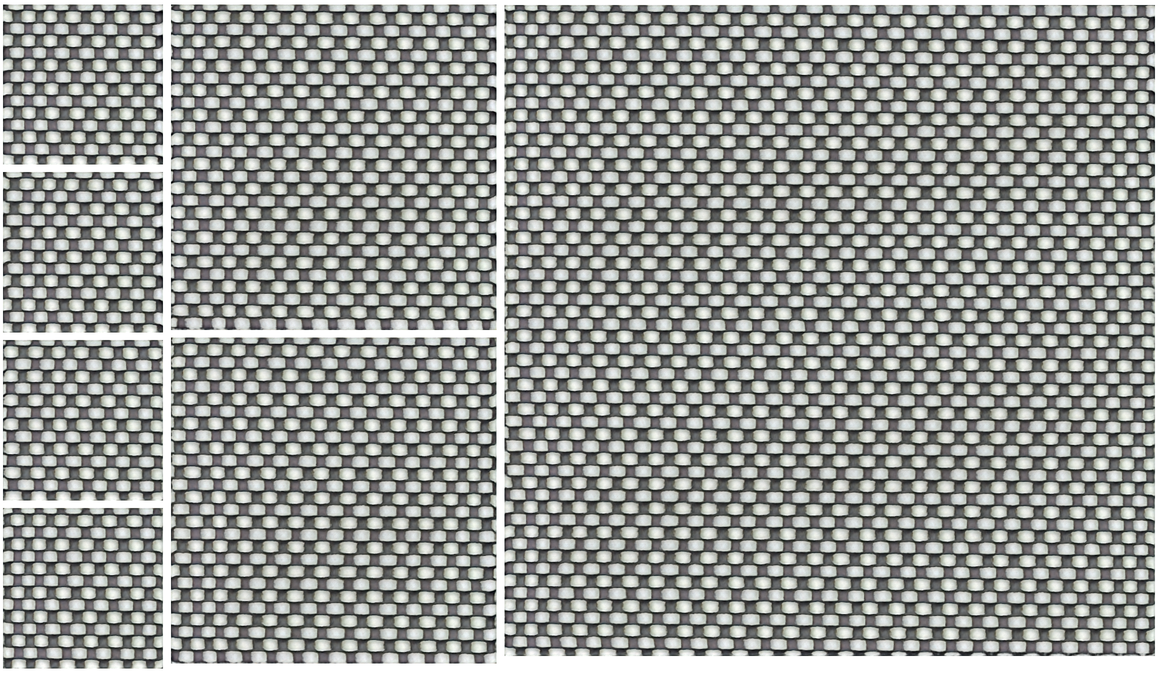


Fig. S.5: Textures synthesized at spatial sizes of 256×256,512×512 and 1024×1024 by the proposed model

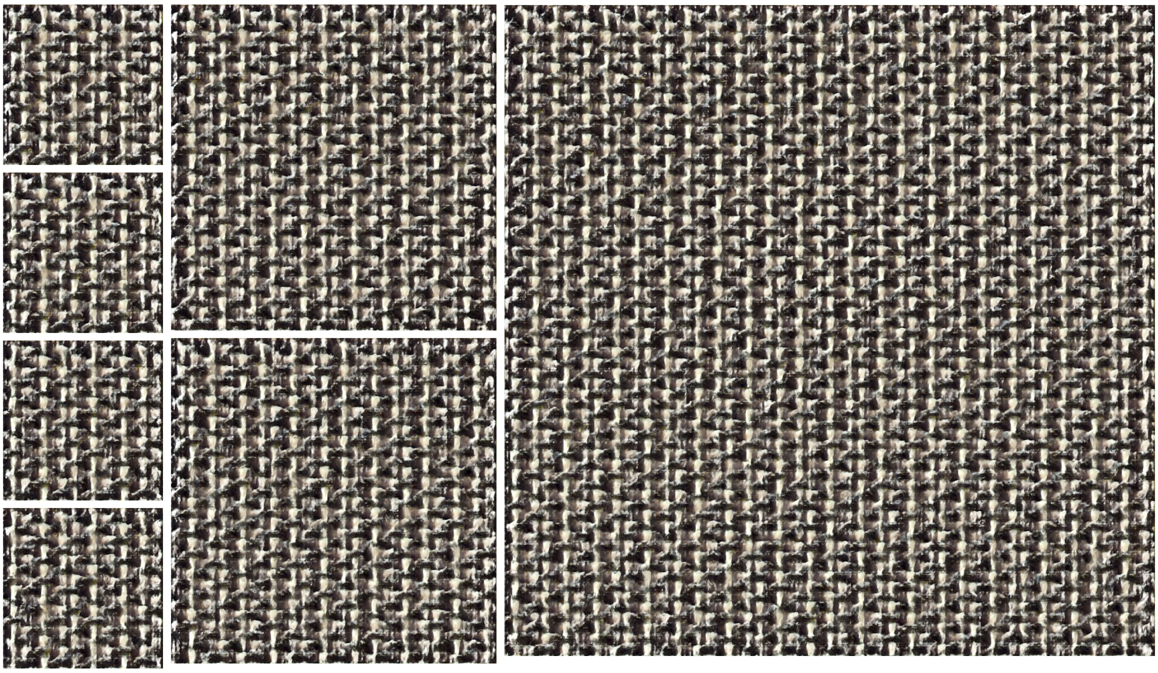


Fig. S.6: Textures synthesized at spatial sizes of $256 \times 256, 512 \times 512$ and 1024×1024 by the proposed model

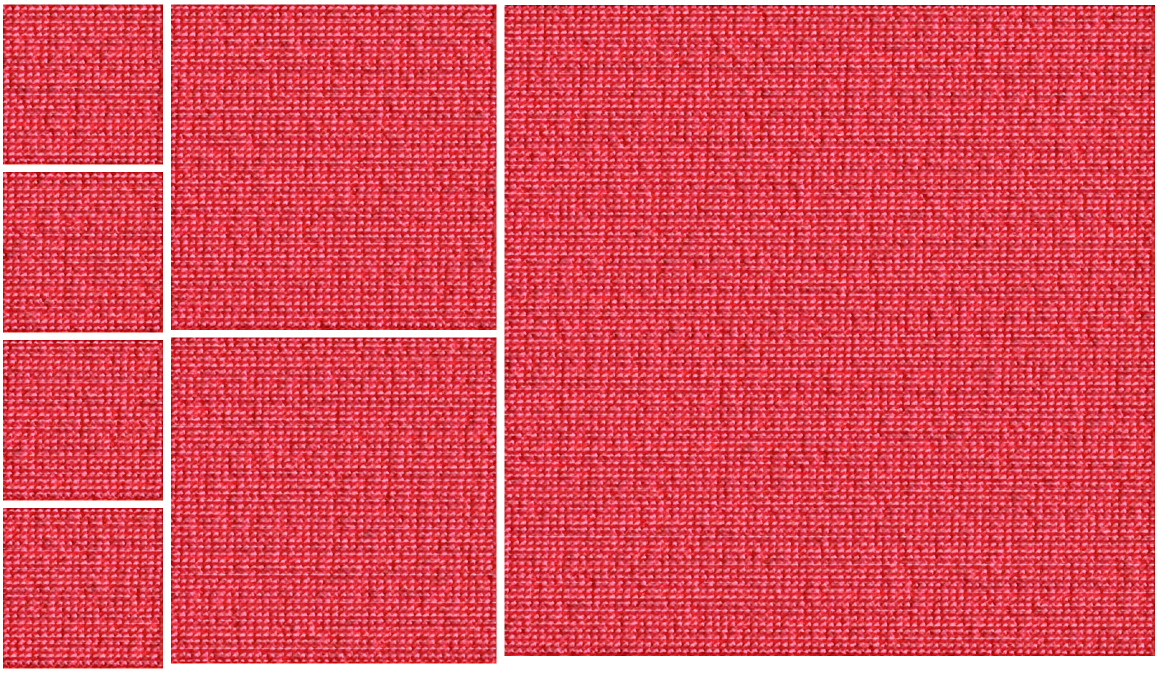


Fig. S.7: Textures synthesized at spatial sizes of $256 \times 256, 512 \times 512$ and 1024×1024 by the proposed model

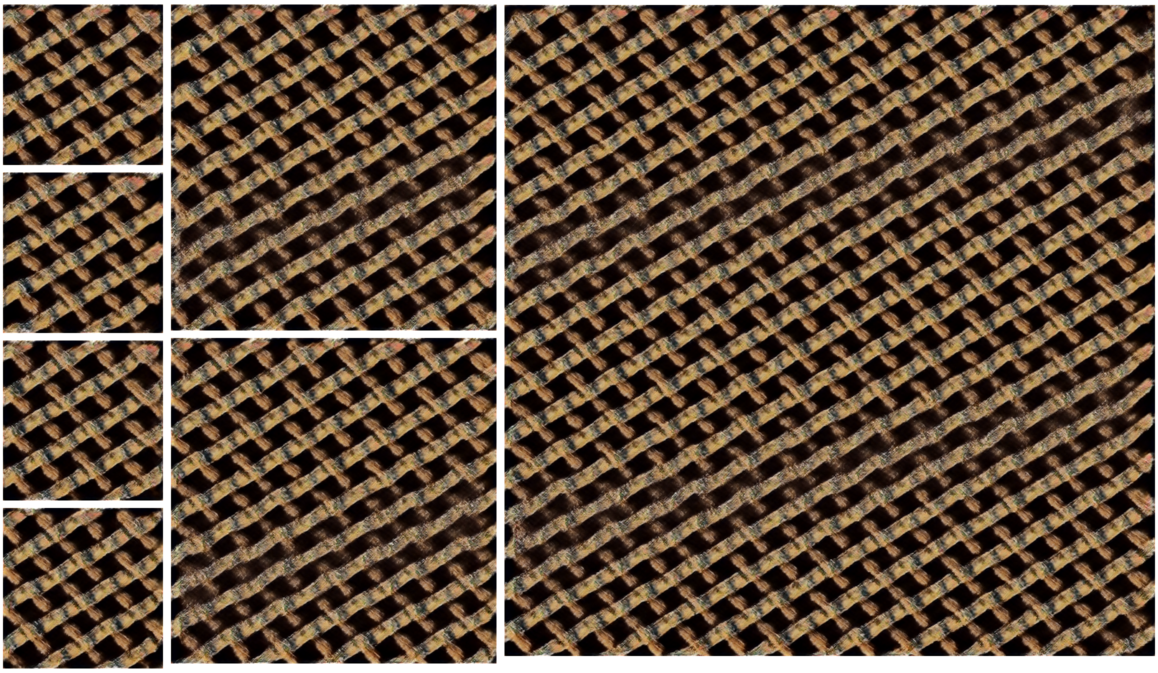


Fig. S.8: Textures synthesized at spatial sizes of 256×256,512×512 and 1024×1024 by the proposed model

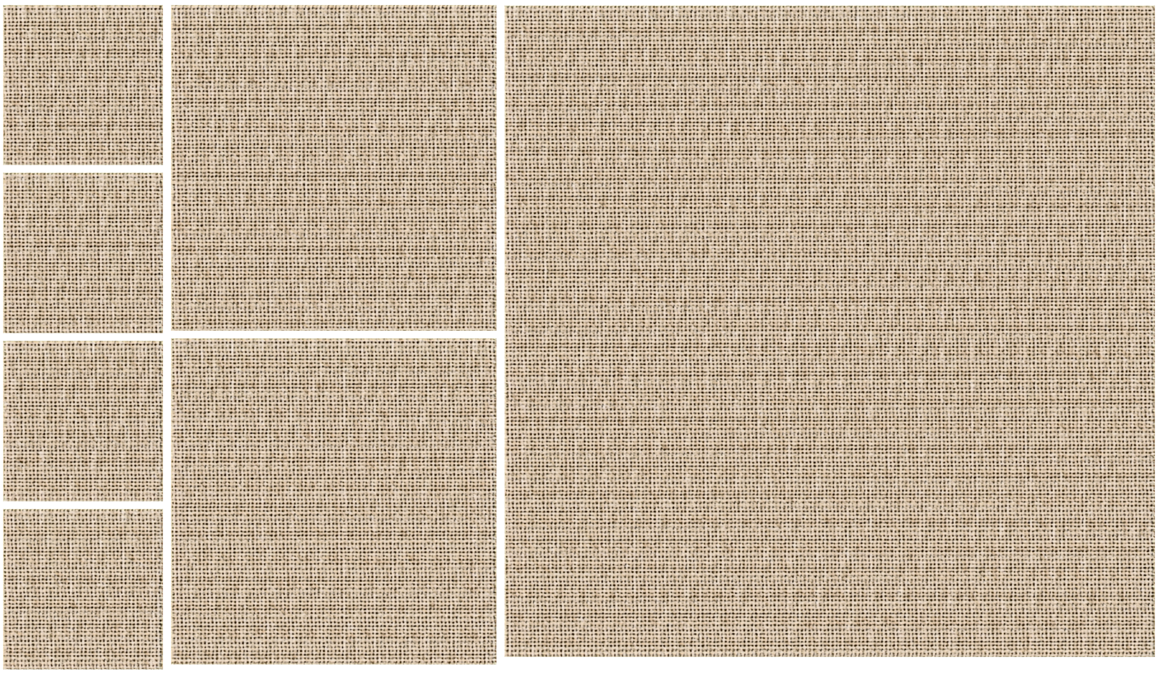


Fig. S.9: Textures synthesized at spatial sizes of 256×256,512×512 and 1024×1024 by the proposed model

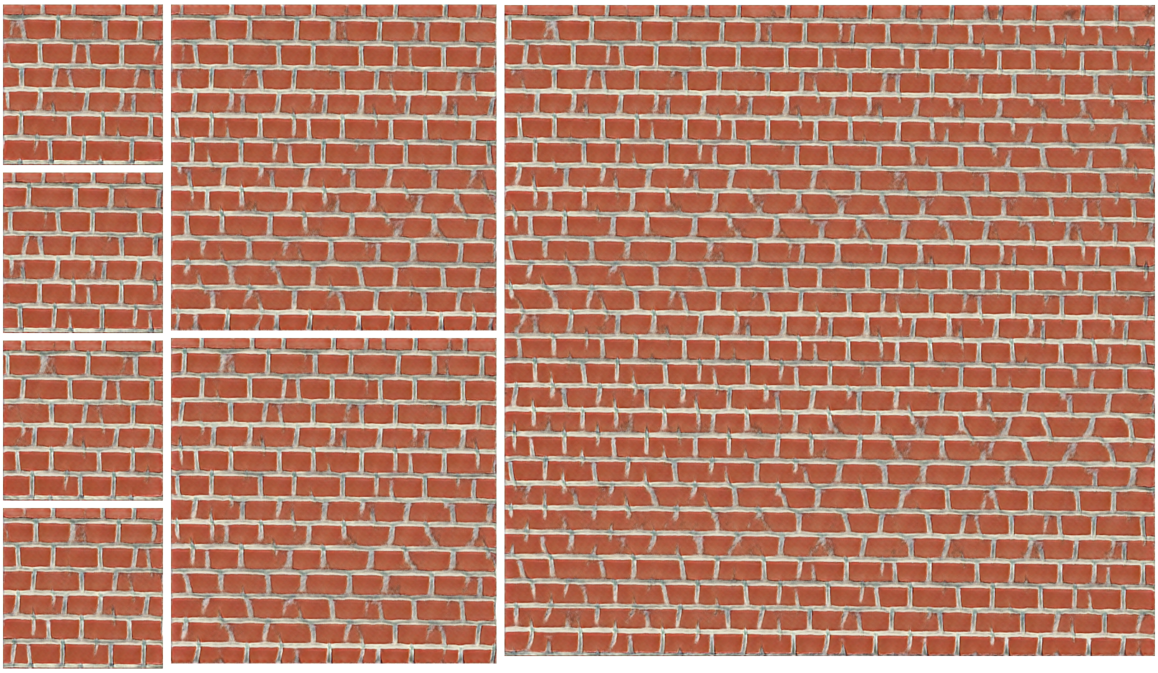


Fig. S.10: Textures synthesized at spatial sizes of $256 \times 256, 512 \times 512$ and 1024×1024 by the proposed model

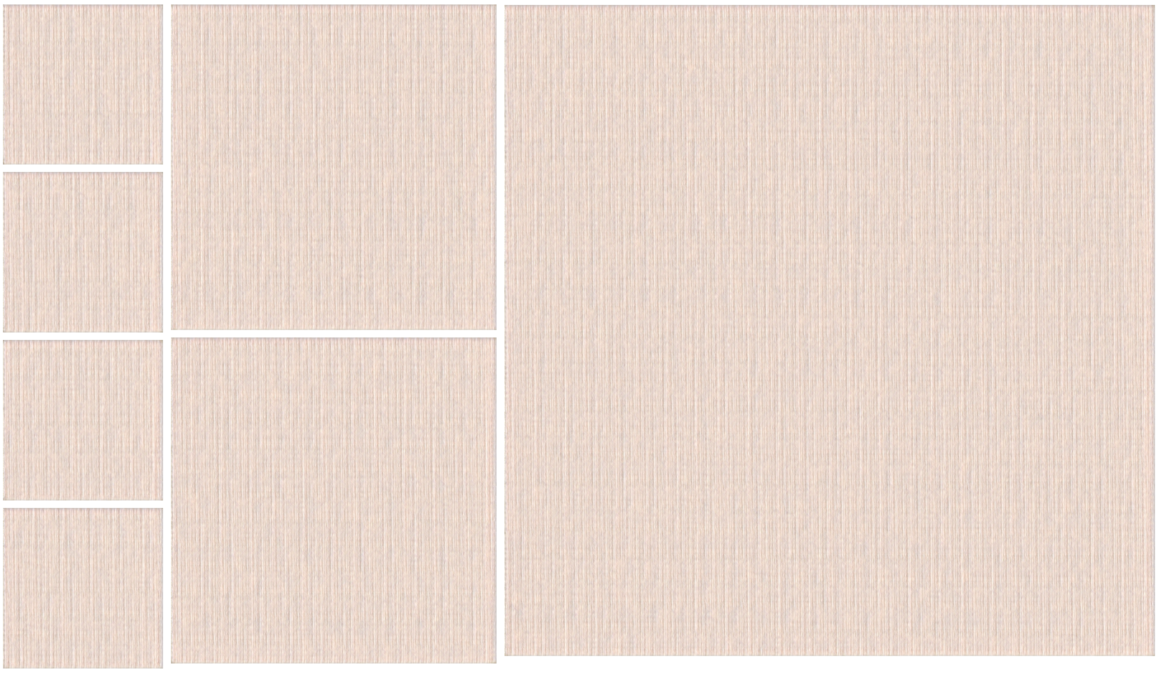


Fig. S.11: Textures synthesized at spatial sizes of $256 \times 256, 512 \times 512$ and 1024×1024 by the proposed model

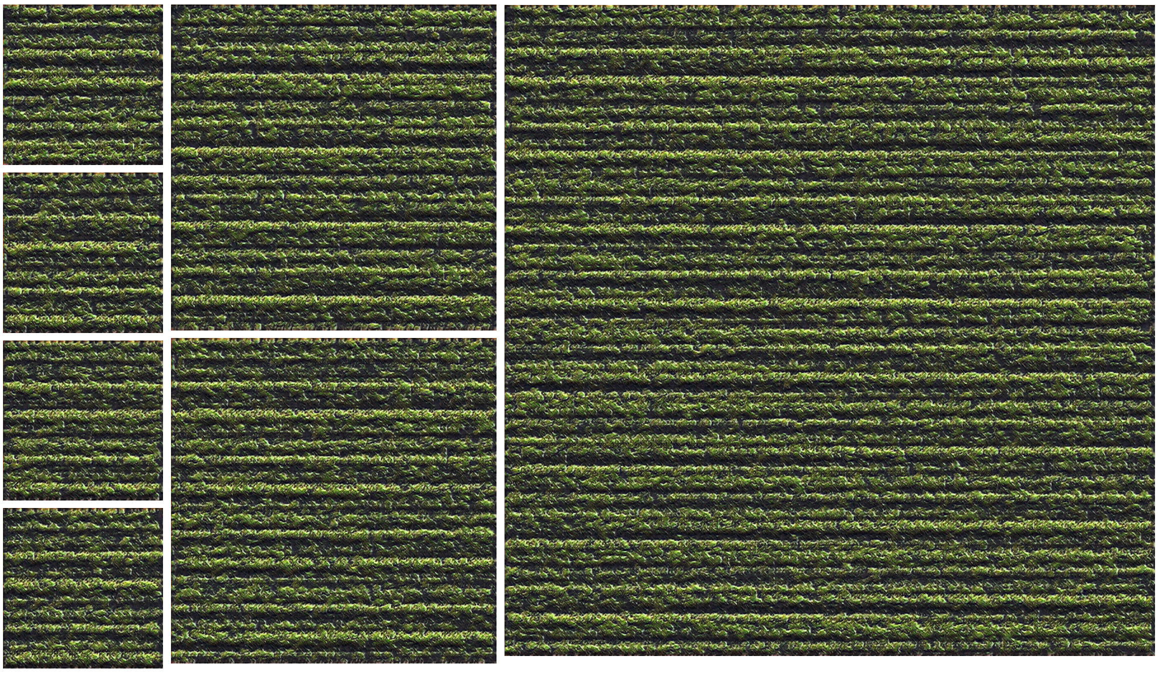
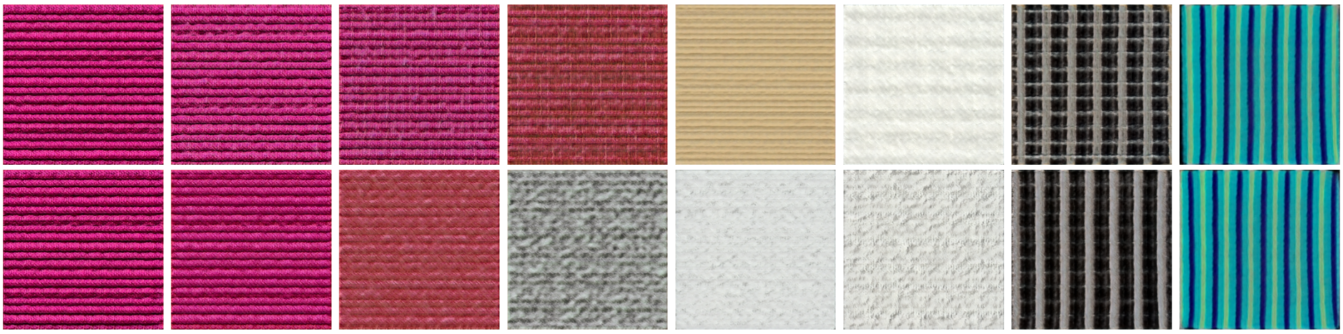


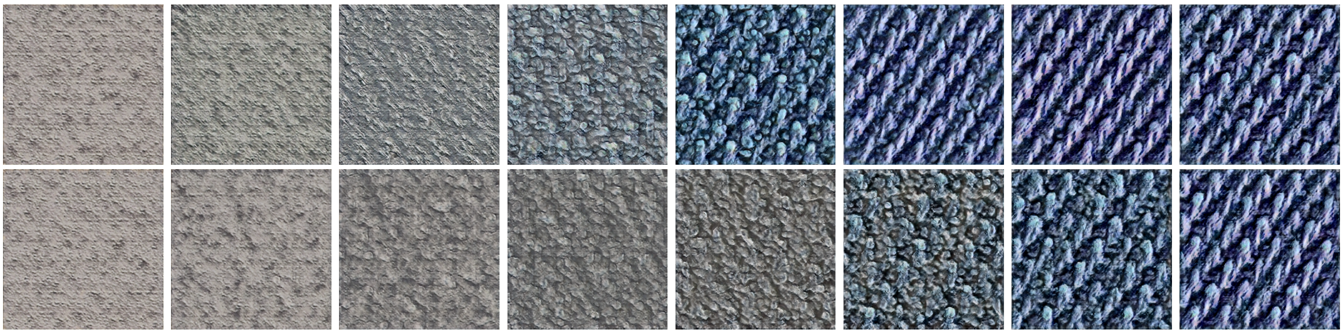
Fig. S.12: Textures synthesized at spatial sizes of 256×256,512×512 and 1024×1024 by the proposed model

S.2. Interpolations from the trained latent space

We randomly sample two textures via the trained StyleGAN-2 with the Texton Broadcasting module, and perform interpolation in the Z and W space, which are presented as the first and second row, respectively, for each subfigure of Fig. S.13. Each interpolated texture in the induced latent space is perceptually uniform.

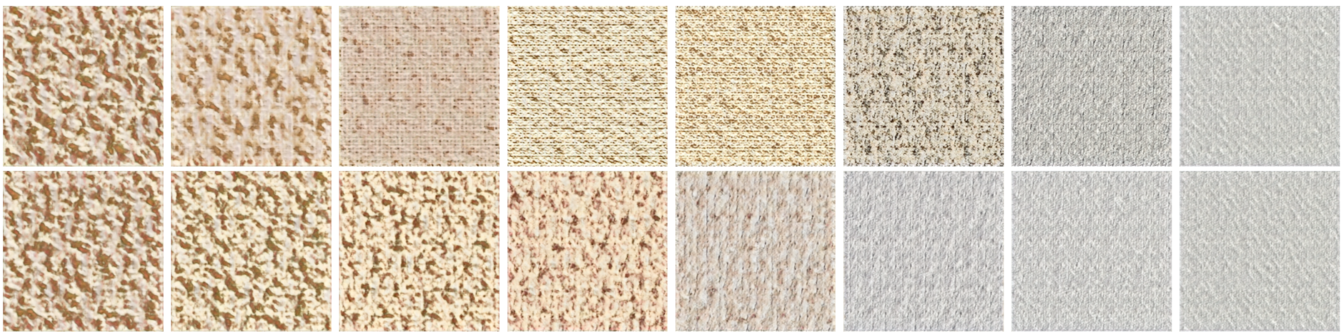


(a) Example of interpolation in Z/W space in first/second row, respectively



(b) Example of interpolation in Z/W space in first/second row, respectively

(c) Example of interpolation in Z/W space in first/second row, respectively



(d) Example of interpolation in Z/W space in first/second row, respectively

Fig. S.13: Additional examples of latent space interpolation

S.3. Can the proposed model generalize?

In this section, we generate multiple textures by sampling the latent space from the trained model, and then attempt to find the perceptually most similar texture in the training set, which are shown in corresponding columns in the top and bottom row, respectively, of Fig. S.14. This experiment is conducted to determine whether the proposed model is capable of generalizing to textures beyond the training set rather than simply overfitting the training dataset: if the model generalizes, we expect to see cases where the most similar texture from the training dataset does not provide a good approximation to the generated texture. Varying degrees of similarity between generated and training images can be observed, indicating that the network can learn the distribution of training data as well as generalize to novel textures.

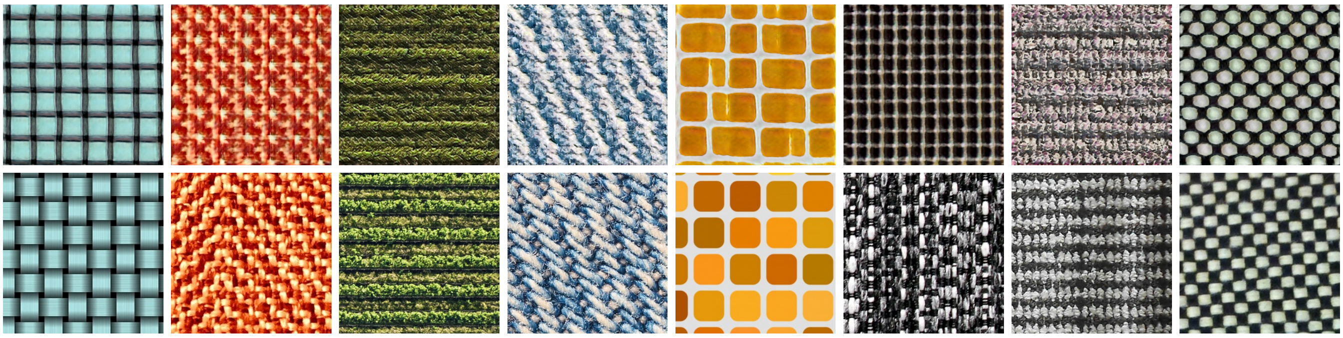


Fig. S.14: Examples of synthesized textures (top) and perceptually closest matches in the training set (bottom)

---

[1] J. Lin, G. Sharma, and T. N. Pappas, "Toward universal texture synthesis by combining texton broadcasting with noise injection in StyleGAN-2," *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, vol. 2, 2022, accepted, to appear.