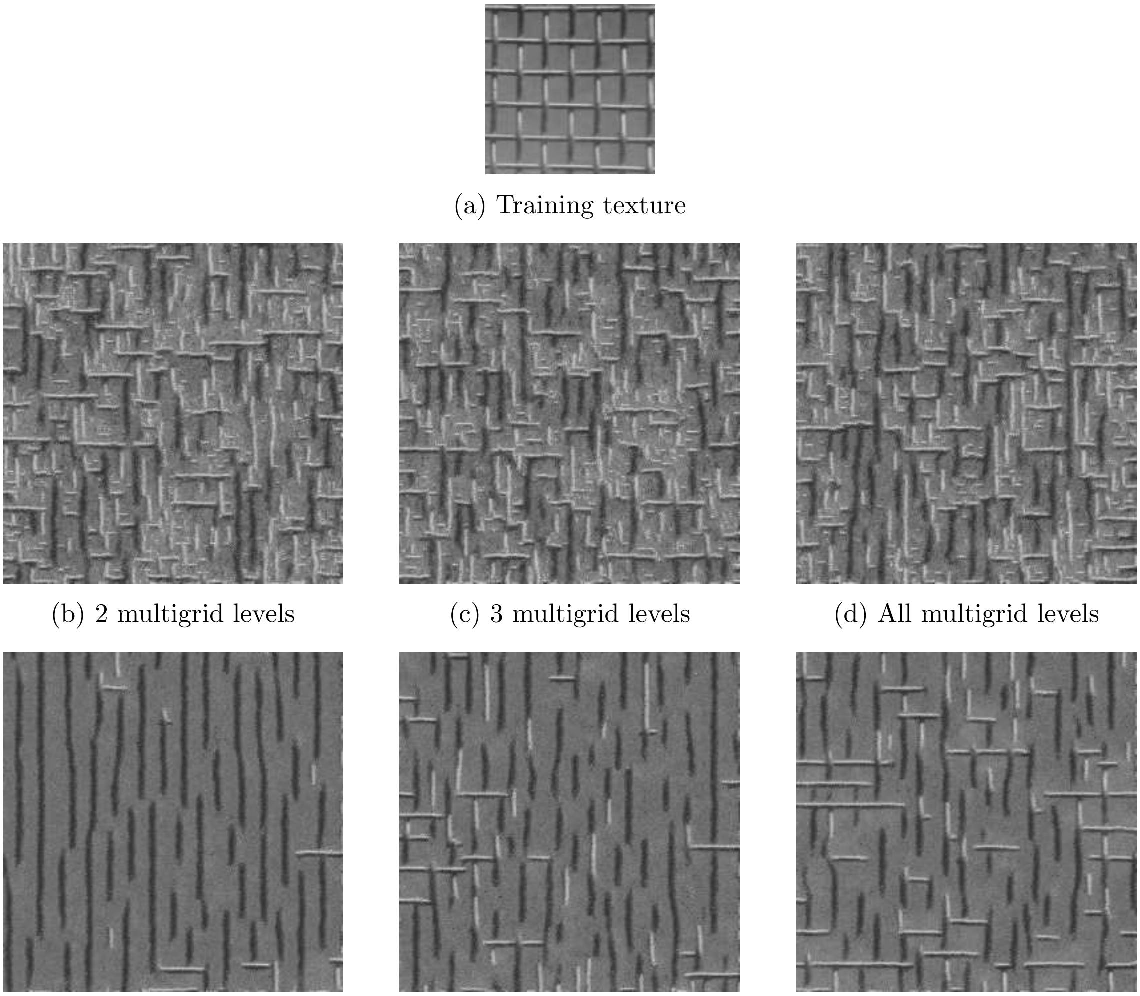
B.2 Textures synthesised with various multiscales

In our multiscale texture synthesis algorithm, as outlined in Fig. 7.4, one of the variables is the multigrid height. In the presented algorithm we have set the variable to the maximum height possible. This however, is a default setting and is not a requirement. In the following Figs. B.167–B.175 we explore the possibility of synthesising various Brodatz textures [28] with different settings of the multigrid height. For each training texture a synthetic texture was produced, one using 2 multigrid levels, another 3, and also all multigrid levels. In each case, we used a 5×5 neighbourhood and also a 7×7 neighbourhood. Again the training textures were 128×128 pixel images, and the synthetic counterparts were 256×256 pixel images.

The synthesis results, Figs. B.167–B.175, indicate that it is possible to limit the multigrid to just a couple of levels. As discussed in Section 7.7, the lower the multigrid height can be set the better. In fact, with some of these textures, we can successfully model them with just two grid levels. In combination with neighbourhood size this gives an indication of the spatial extent of the direct interactions between pixels, *i.e.,* the required spatial extent of the neighbourhood. From the observational results, the required spatial extent of a neighbourhood is related to the macro-texture and how spatially diverse it is. That is, fine texture like Fig. B.174 can be modelled with a small neighbourhood at a low multigrid height, while coarse texture like Fig. B.170 needs to be modelled with a larger neighbourhood at a higher multigrid height.

The neighbourhood size and maximum multigrid height are two parameters that can be used to optimise the "ideal" model for open-ended texture classification. Basically an ideal model is optimised when it captures all of the characteristic features of a texture class, but no more. The ideal model does not want to be overtrained by capturing features that are only specific to the training texture and not to the class it belongs. Therefore the choice of neighbourhood size and maximum multigrid height should be made on the basis that they are the minimum required to reproduce representative synthetic texture of the texture class.



(a) Training texture

(b) 2 multigrid levels

(c) 3 multigrid levels

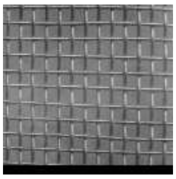
(d) All multigrid levels

(e) 2 multigrid levels

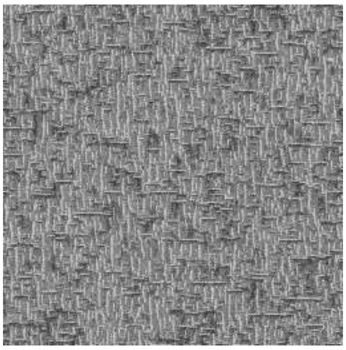
(f) 3 multigrid levels

(g) All multigrid levels

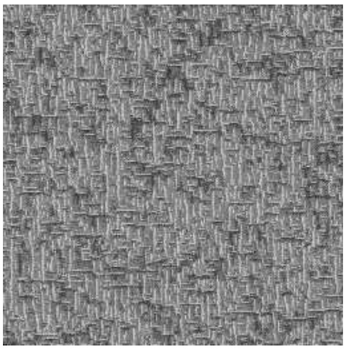
Figure B.167: Brodatz texture D001a: (a) original 128×128 image; (b–g) synthesised 256×256 images using Gibbs sampling; (b) using 5×5 neighbourhood and 2 multigrid levels; (c) using 5×5 neighbourhood and 3 multigrid levels; (d) using 5×5 neighbourhood and all multigrid levels; (e) using 7×7 neighbourhood and 2 multigrid levels; (f) using 7×7 neighbourhood and 3 multigrid levels; (g) using 7×7 neighbourhood and all multigrid levels.



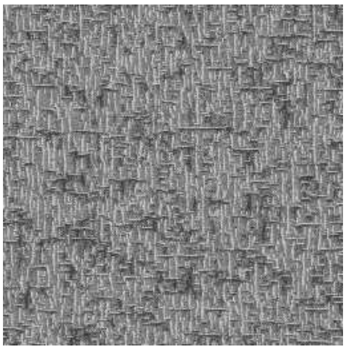
(a) Training texture



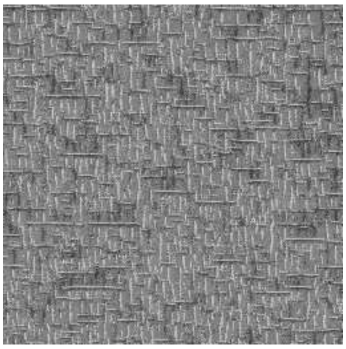
(b) 2 multigrid levels



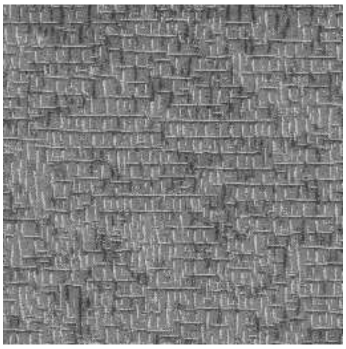
(c) 3 multigrid levels



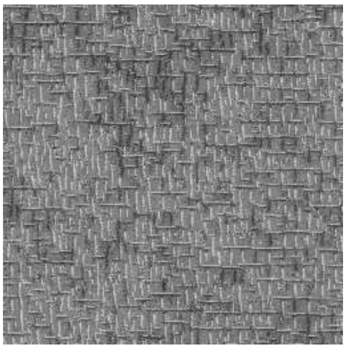
(d) All multigrid levels



(e) 2 multigrid levels

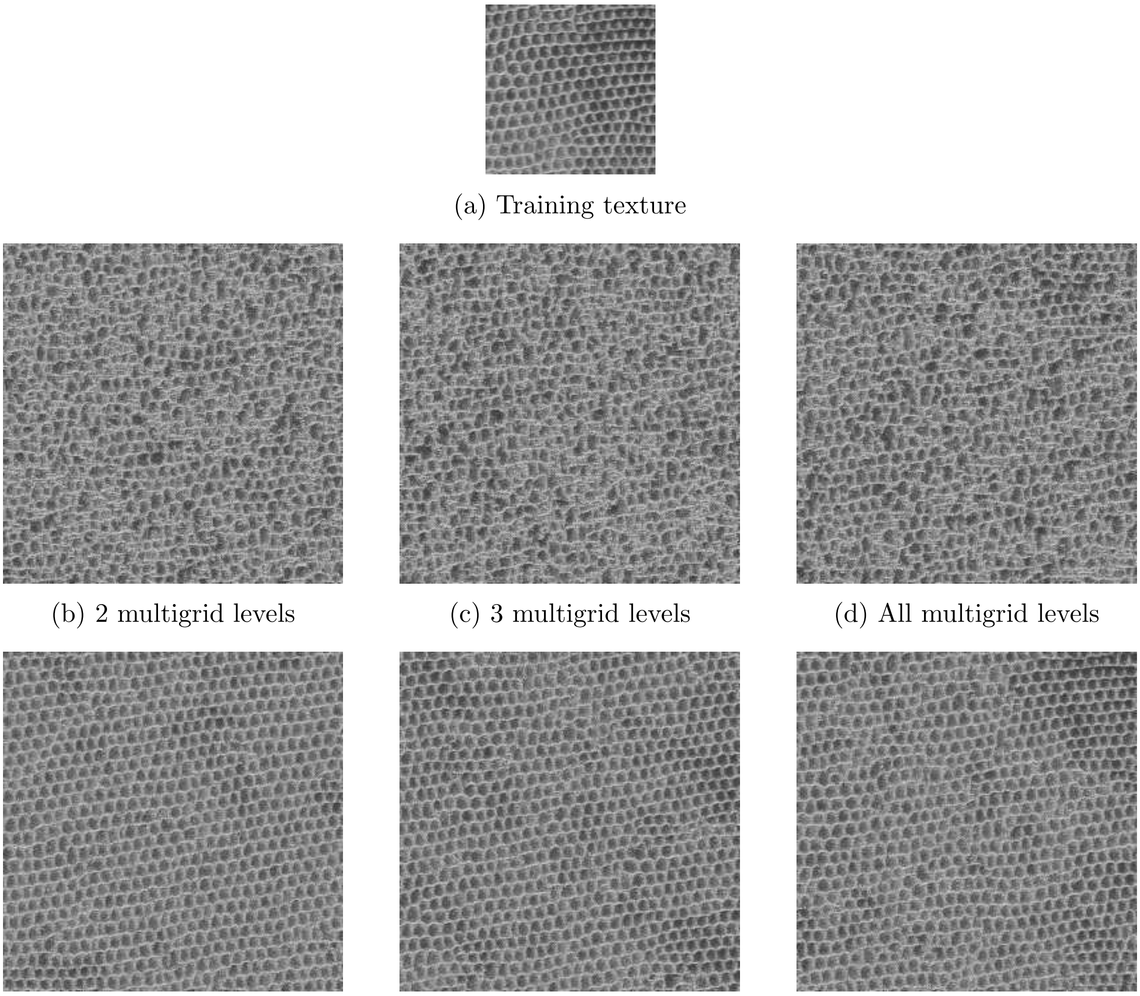


(f) 3 multigrid levels



(g) All multigrid levels

Figure B.168: Brodatz texture D001c: (a) original 128×128 image; (b–g) synthesised 256×256 images using Gibbs sampling; (b) using 5×5 neighbourhood and 2 multigrid levels; (c) using 5×5 neighbourhood and 3 multigrid levels; (d) using 5×5 neighbourhood and all multigrid levels; (e) using 7×7 neighbourhood and 2 multigrid levels; (f) using 7×7 neighbourhood and 3 multigrid levels; (g) using 7×7 neighbourhood and all multigrid levels.



(a) Training texture

(b) 2 multigrid levels

(c) 3 multigrid levels

(d) All multigrid levels

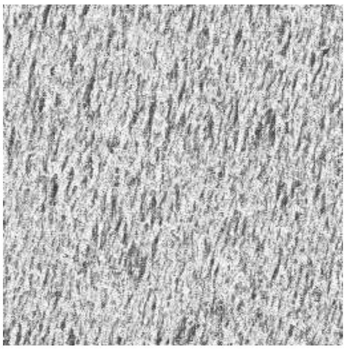
(e) 2 multigrid levels

(f) 3 multigrid levels

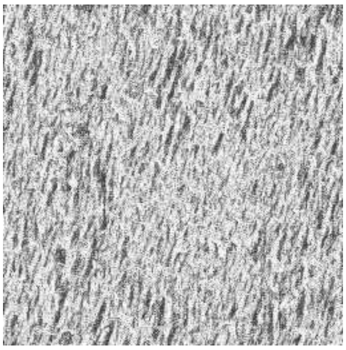
(g) All multigrid levels

Figure B.169: Brodatz texture D003a: (a) original 128×128 image; (b–g) synthesised 256×256 images using Gibbs sampling; (b) using 5×5 neighbourhood and 2 multigrid levels; (c) using 5×5 neighbourhood and 3 multigrid levels; (d) using 5×5 neighbourhood and all multigrid levels; (e) using 7×7 neighbourhood and 2 multigrid levels; (f) using 7×7 neighbourhood and 3 multigrid levels; (g) using 7×7 neighbourhood and all multigrid levels.

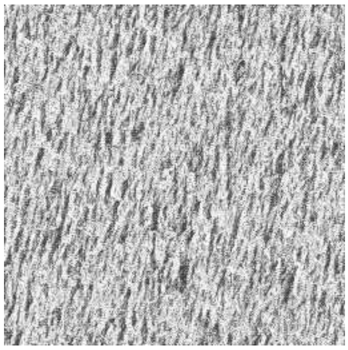
(a) Training texture



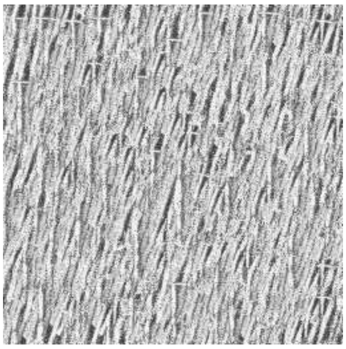
(b) 2 multigrid levels



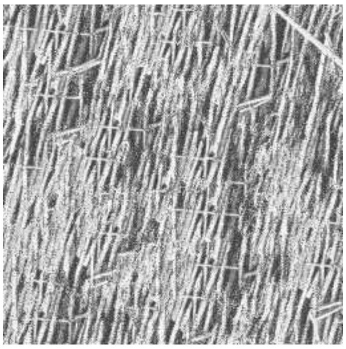
(c) 3 multigrid levels



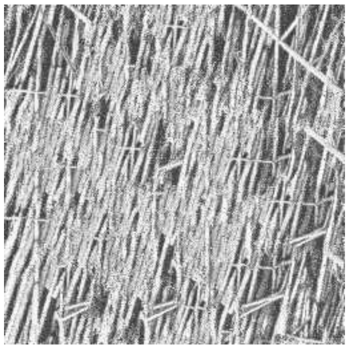
(d) All multigrid levels



(e) 2 multigrid levels

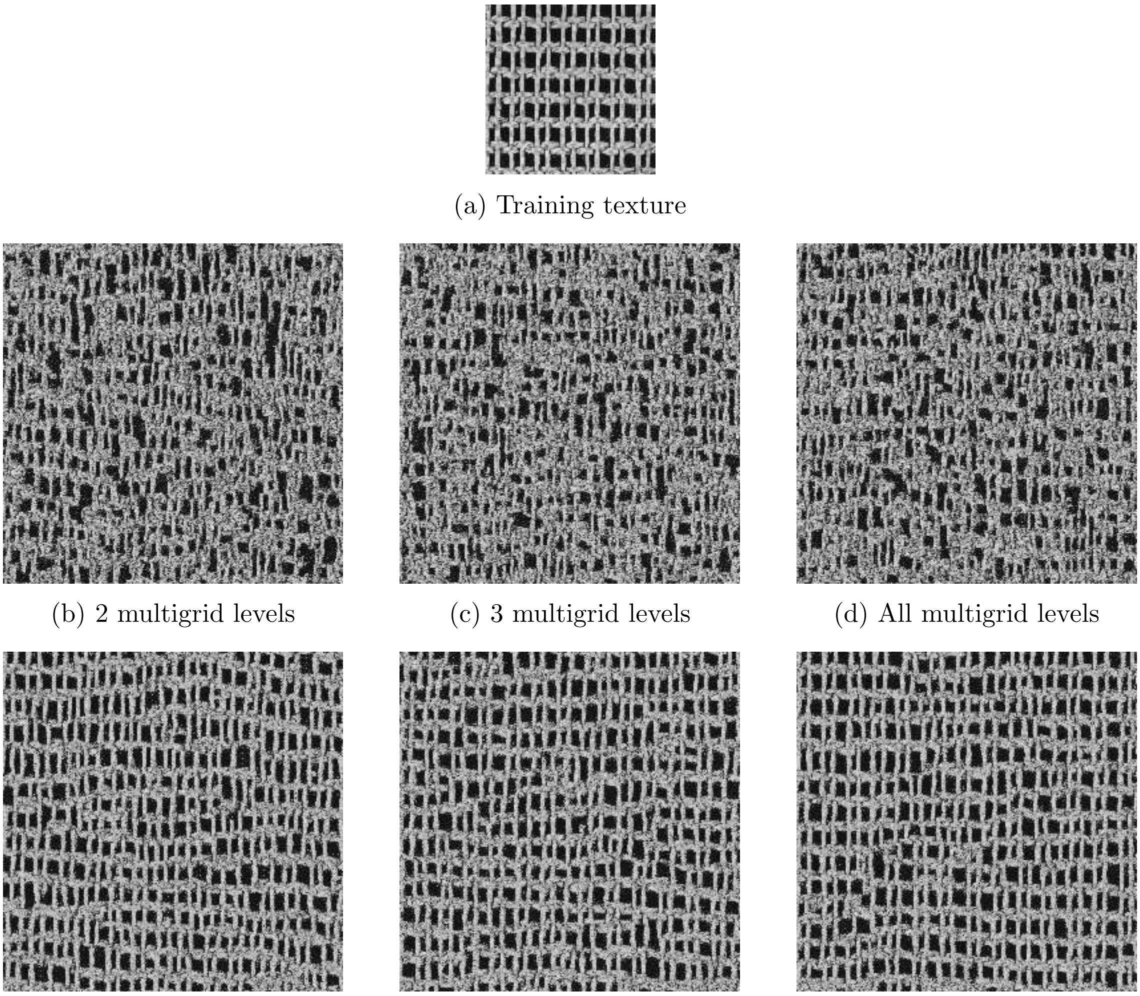


(f) 3 multigrid levels



(g) All multigrid levels

Figure B.170: Brodatz texture D015a: (a) original 128×128 image; (b–g) synthesised 256×256 images using Gibbs sampling; (b) using 5×5 neighbourhood and 2 multigrid levels; (c) using 5×5 neighbourhood and 3 multigrid levels; (d) using 5×5 neighbourhood and all multigrid levels; (e) using 7×7 neighbourhood and 2 multigrid levels; (f) using 7×7 neighbourhood and 3 multigrid levels; (g) using 7×7 neighbourhood and all multigrid levels.

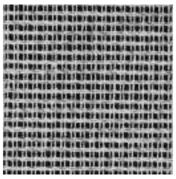


(a) Training texture

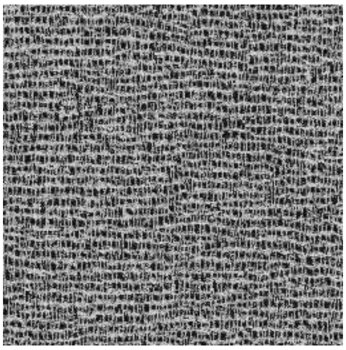
(b) 2 multigrid levels (c) 3 multigrid levels (d) All multigrid levels

(e) 2 multigrid levels (f) 3 multigrid levels (g) All multigrid levels

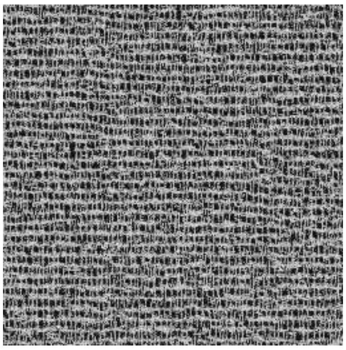
Figure B.171: Brodatz texture D020a: (a) original 128×128 image; (b–g) synthesised 256×256 images using Gibbs sampling; (b) using 5×5 neighbourhood and 2 multigrid levels; (c) using 5×5 neighbourhood and 3 multigrid levels; (d) using 5×5 neighbourhood and all multigrid levels; (e) using 7×7 neighbourhood and 2 multigrid levels; (f) using 7×7 neighbourhood and 3 multigrid levels; (g) using 7×7 neighbourhood and all multigrid levels.



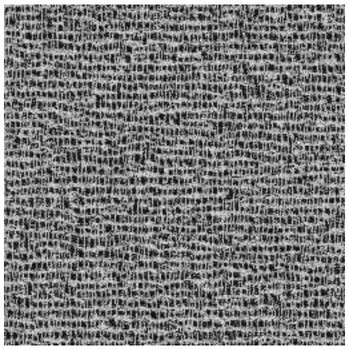
(a) Training texture



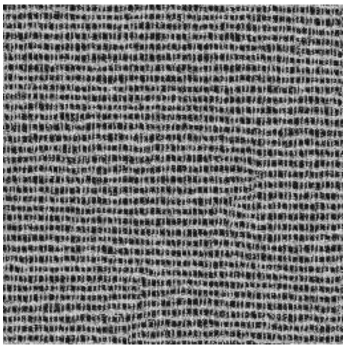
(b) 2 multigrid levels



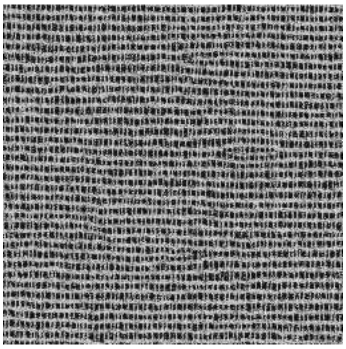
(c) 3 multigrid levels



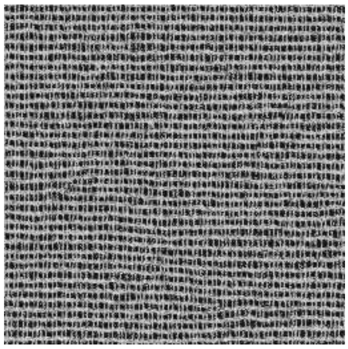
(d) All multigrid levels



(e) 2 multigrid levels

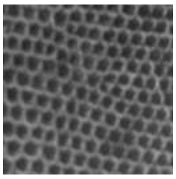


(f) 3 multigrid levels

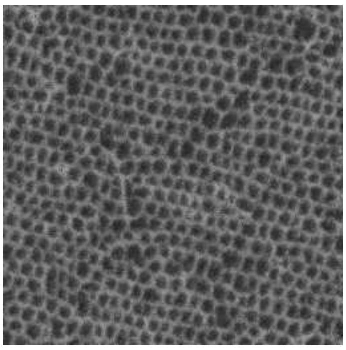


(g) All multigrid levels

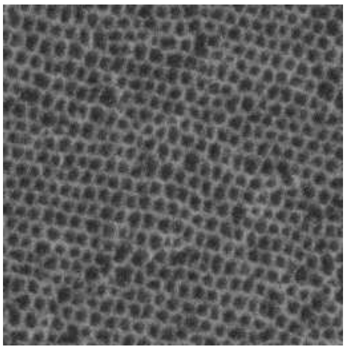
Figure B.172: Brodatz texture D021a: (a) original 128×128 image; (b–g) synthesised 256×256 images using Gibbs sampling; (b) using 5×5 neighbourhood and 2 multigrid levels; (c) using 5×5 neighbourhood and 3 multigrid levels; (d) using 5×5 neighbourhood and all multigrid levels; (e) using 7×7 neighbourhood and 2 multigrid levels; (f) using 7×7 neighbourhood and 3 multigrid levels; (g) using 7×7 neighbourhood and all multigrid levels.



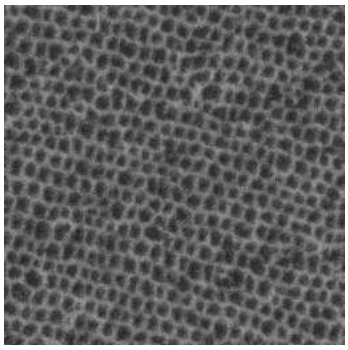
(a) Training texture



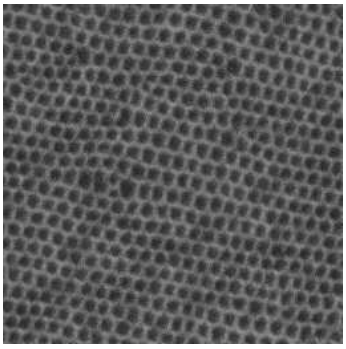
(b) 2 multigrid levels



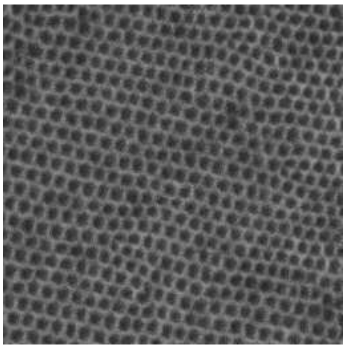
(c) 3 multigrid levels



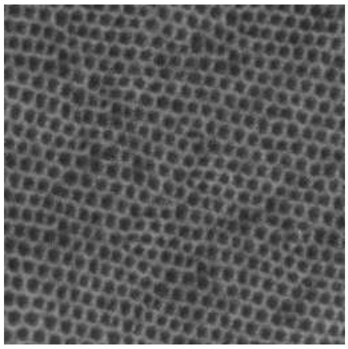
(d) All multigrid levels



(e) 2 multigrid levels

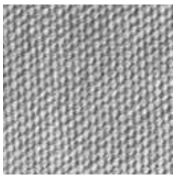


(f) 3 multigrid levels

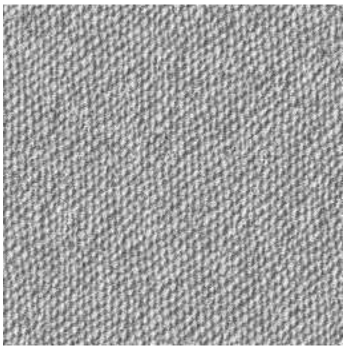


(g) All multigrid levels

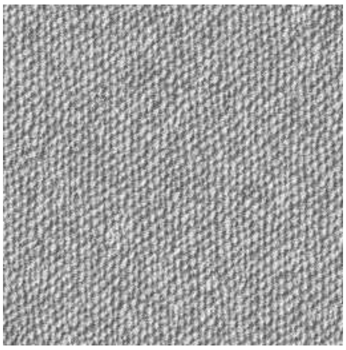
Figure B.173: Brodatz texture D022a: (a) original 128×128 image; (b–g) synthesised 256×256 images using Gibbs sampling; (b) using 5×5 neighbourhood and 2 multigrid levels; (c) using 5×5 neighbourhood and 3 multigrid levels; (d) using 5×5 neighbourhood and all multigrid levels; (e) using 7×7 neighbourhood and 2 multigrid levels; (f) using 7×7 neighbourhood and 3 multigrid levels; (g) using 7×7 neighbourhood and all multigrid levels.



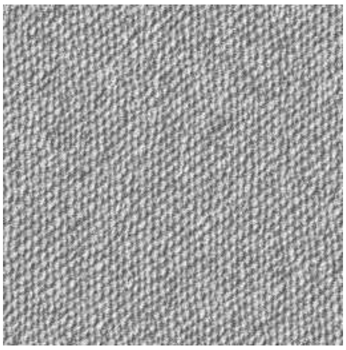
(a) Training texture



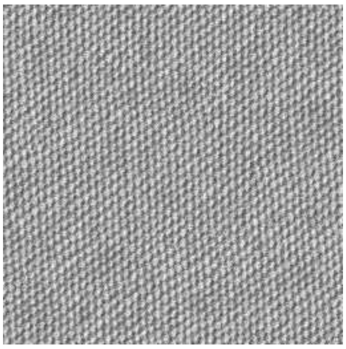
(b) 2 multigrid levels



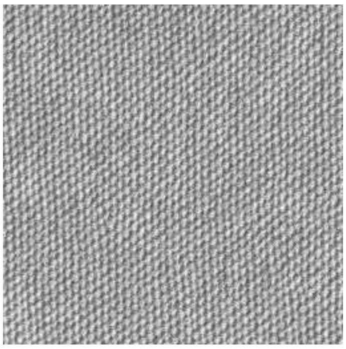
(c) 3 multigrid levels



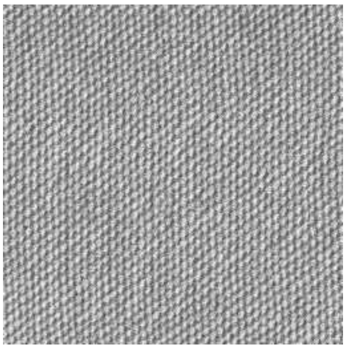
(d) All multigrid levels



(e) 2 multigrid levels

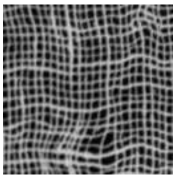


(f) 3 multigrid levels

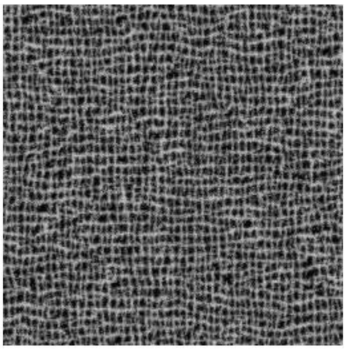


(g) All multigrid levels

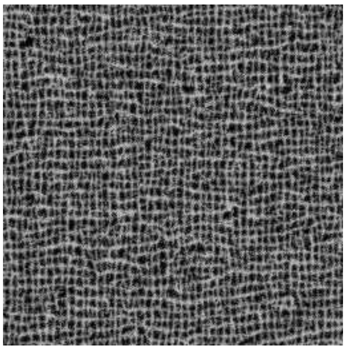
Figure B.174: Brodatz texture D077a: (a) original 128×128 image; (b–g) synthesised 256×256 images using Gibbs sampling; (b) using 5×5 neighbourhood and 2 multigrid levels; (c) using 5×5 neighbourhood and 3 multigrid levels; (d) using 5×5 neighbourhood and all multigrid levels; (e) using 7×7 neighbourhood and 2 multigrid levels; (f) using 7×7 neighbourhood and 3 multigrid levels; (g) using 7×7 neighbourhood and all multigrid levels.



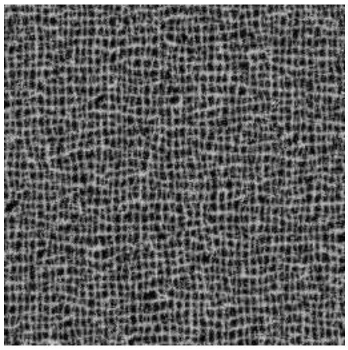
(a) Training texture



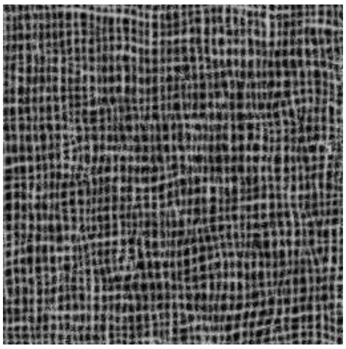
(b) 2 multigrid levels



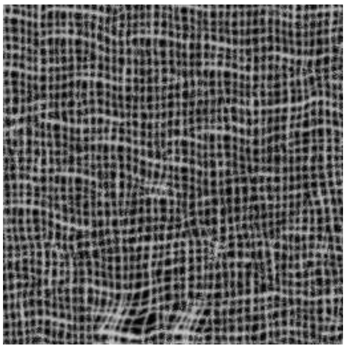
(c) 3 multigrid levels



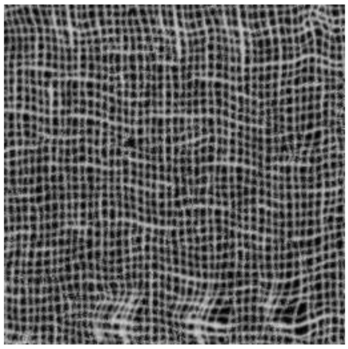
(d) All multigrid levels



(e) 2 multigrid levels



(f) 3 multigrid levels



(g) All multigrid levels

Figure B.175: Brodatz texture D103a: (a) original 128×128 image; (b–g) synthesised 256×256 images using Gibbs sampling; (b) using 5×5 neighbourhood and 2 multigrid levels; (c) using 5×5 neighbourhood and 3 multigrid levels; (d) using 5×5 neighbourhood and all multigrid levels; (e) using 7×7 neighbourhood and 2 multigrid levels; (f) using 7×7 neighbourhood and 3 multigrid levels; (g) using 7×7 neighbourhood and all multigrid levels.

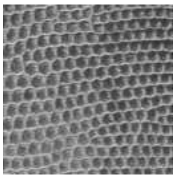
B.3 Textures synthesised with various clique sets

An important aspect of the texture synthesis algorithm is its ability to test the statistical order required to model various textures. By choosing the maximum clique size that is used in the strong MRF model, we can test to see if the defined model can be used to synthesise a representative version of the training texture. If indeed the synthetic texture is visually similar to that of the training texture, we may say that the texture contains no significant statistical information greater than the order representative of the maximum clique size.

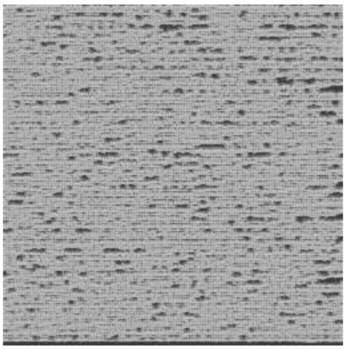
In Figs. B.176–B.179 we use various forms of the strong MRF model to synthesise the texture. We look at the difference between using the direct estimate, Eq. (6.10), and the simple estimate, Eq. (6.49), of the LPDF. As discussed in Section 6.6, the direct estimate is really only applicable for the strong MRF model when no greater than second order cliques are used. This accounts for the fact that using fourth and third order cliques in the strong MRF model did not produce representative versions of the training texture. Better results were obtained with using the simple estimate. However Fig. B.179(b) does show the surprising capability of the direct estimation technique.

Choosing small clique sizes is one method for reducing the statistical content in the model. Another method is to reduce the number of cliques by discriminating on the basis of their associated entropy. In the following Figs. B.176–B.179, we test to see how many third order cliques are required to achieve an adequate reproduction of a training texture. in each case we choose a subset of the third order cliques that had the lowest entropy. Unfortunately this was almost a random process, as all clique entropies were virtually the same.

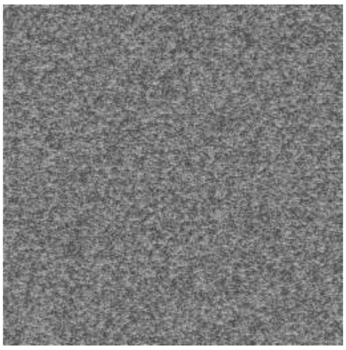
A further set of synthesised textures is presented in Figs. B.180–B.221. Again the strong MRF model was used, but this time only pairwise cliques were incorporated. The training texture were from VisTex [203].



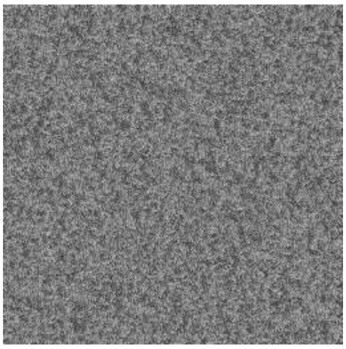
(a) Training texture



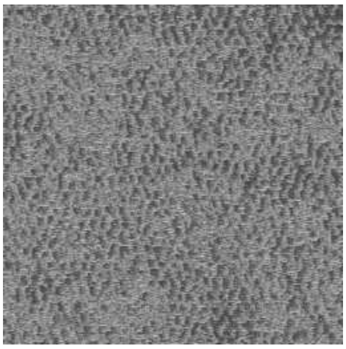
(b) 2nd and lower order cliques



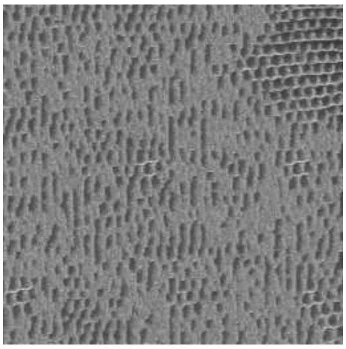
(c) 2nd order cliques



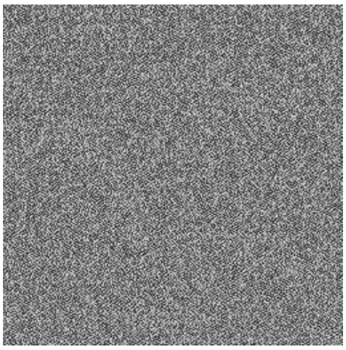
(d) 3rd order cliques



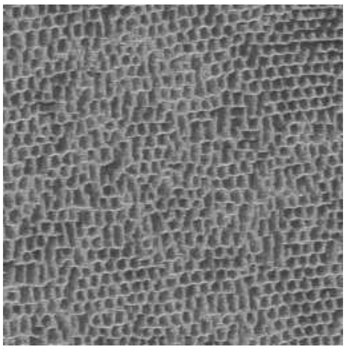
(e) 3rd order cliques



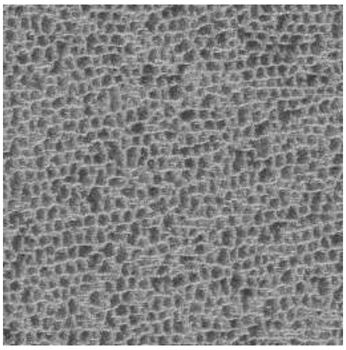
(f) 3rd order cliques



(g) 4th and lower order cliques

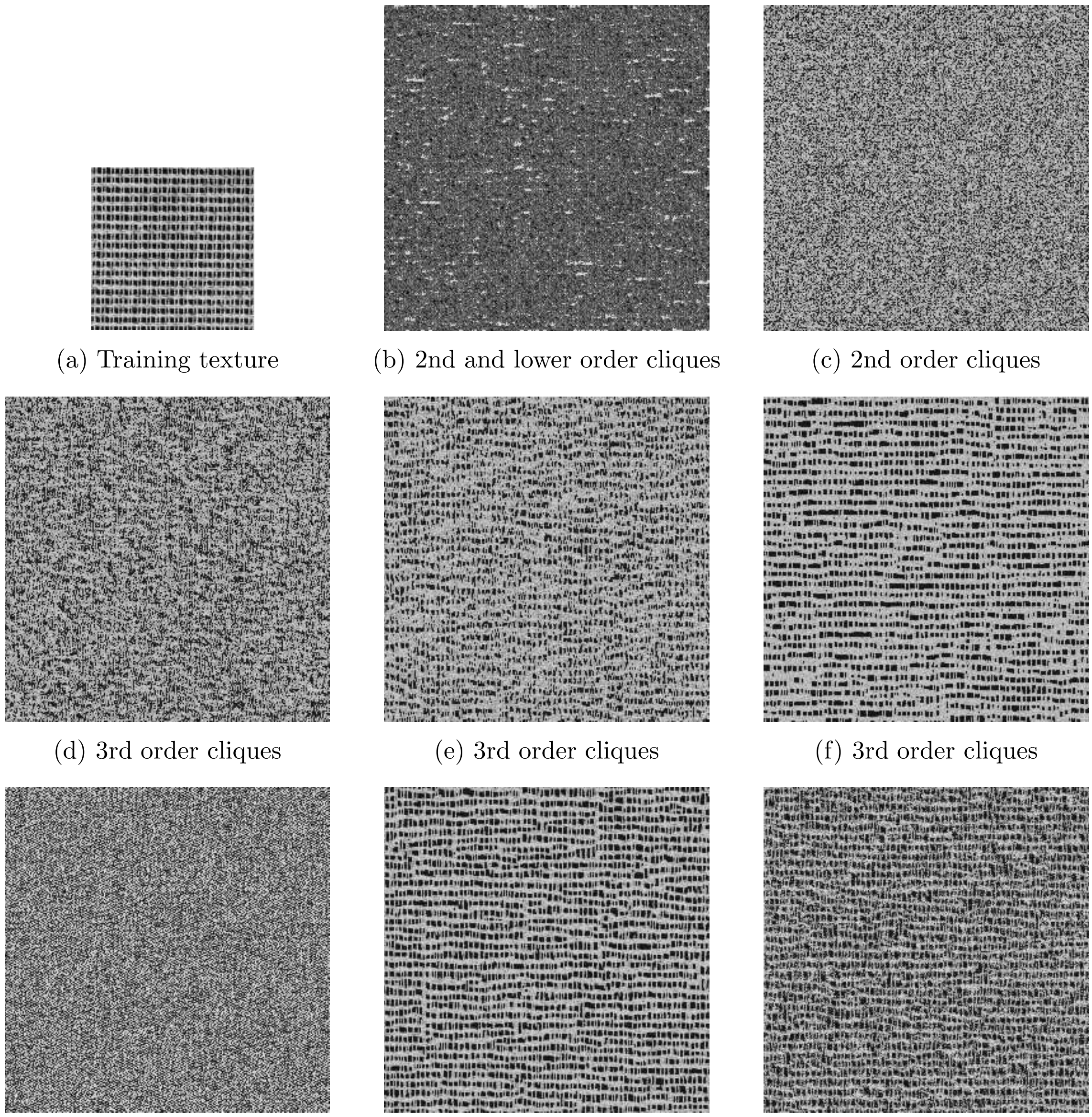


(h) 4th order cliques



(i) No cliques

Figure B.176: Brodatz texture D003a: (a) original 128×128 image; (b–i) synthesised 256×256 images using Gibbs sampling and 5×5 neighbourhood; (b) using pairwise and single site cliques; (c) using just pairwise cliques; (d) using just 10 of the 3rd order cliques with the lowest entropy; (e) using just 20 of the 3rd order cliques with the lowest entropy; (f) using just 3rd order cliques; (g) using 4th and all lower order cliques; (h) using just 4th order cliques; (i) using plain nonparametric MRF.



(a) Training texture

(b) 2nd and lower order cliques

(c) 2nd order cliques

(d) 3rd order cliques

(e) 3rd order cliques

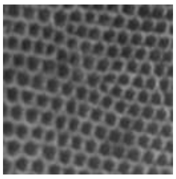
(f) 3rd order cliques

(g) 4th and lower order cliques

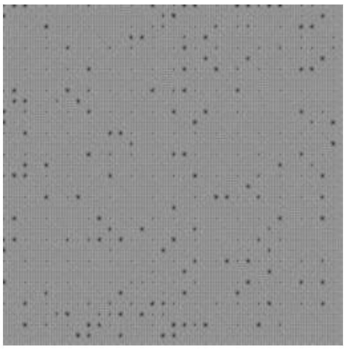
(h) 4th order cliques

(i) No cliques

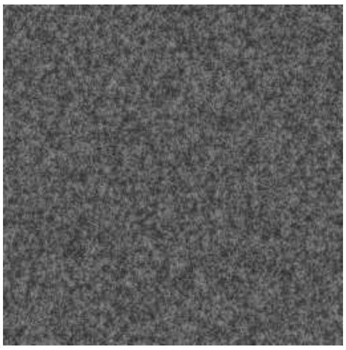
Figure B.177: Brodatz texture D021a: (a) original 128×128 image; (b–i) synthesised 256×256 images using Gibbs sampling and 5×5 neighbourhood; (b) using pairwise and single site cliques; (c) using just pairwise cliques; (d) using just 10 of the 3rd order cliques with the lowest entropy; (e) using just 20 of the 3rd order cliques with the lowest entropy; (f) using just 3rd order cliques; (g) using 4th and all lower order cliques; (h) using just 4th order cliques; (i) using plain nonparametric MRF.



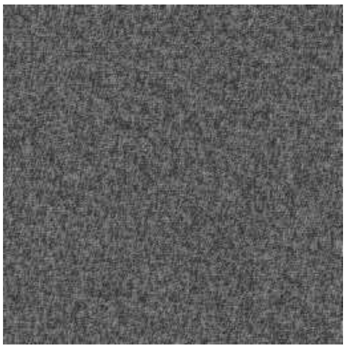
(a) Training texture



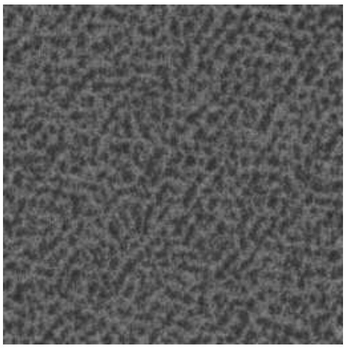
(b) 2nd and lower order cliques



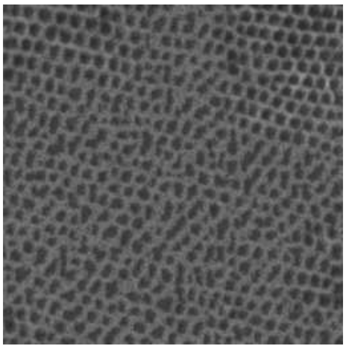
(c) 2nd order cliques



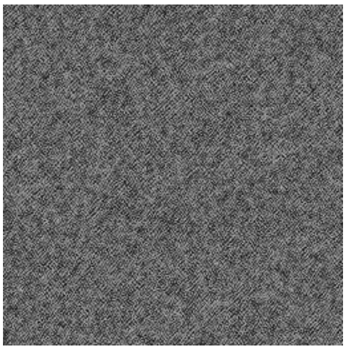
(d) 3rd order cliques



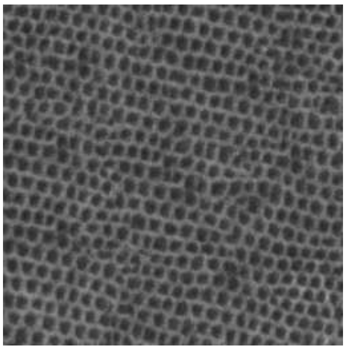
(e) 3rd order cliques



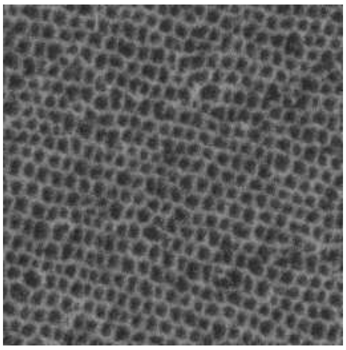
(f) 3rd order cliques



(g) 4th and lower order cliques

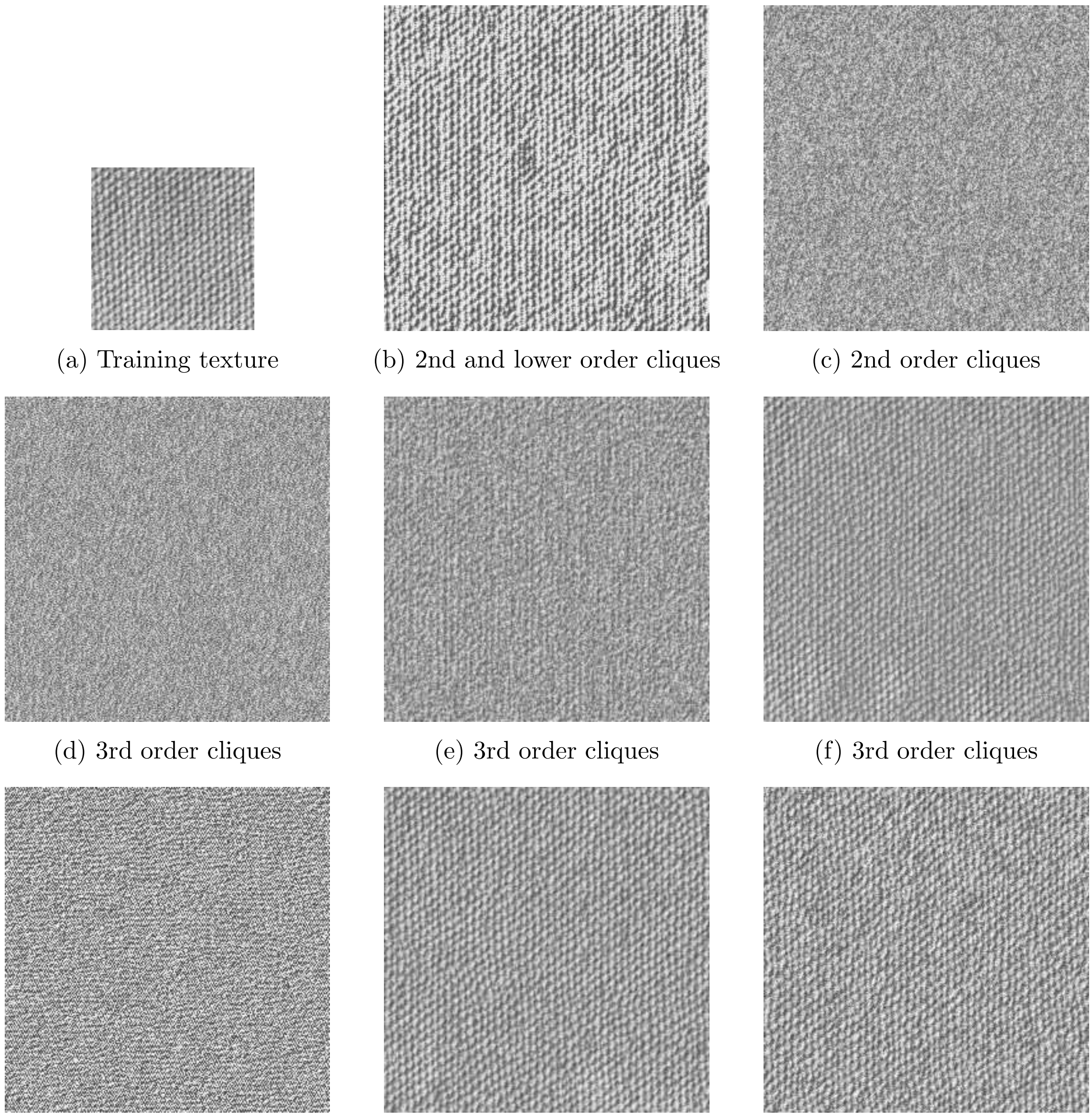


(h) 4th order cliques



(i) No cliques

Figure B.178: Brodatz texture D022a: (a) original 128×128 image; (b–i) synthesised 256×256 images using Gibbs sampling and 5×5 neighbourhood; (b) using pairwise and single site cliques; (c) using just pairwise cliques; (d) using just 10 of the 3rd order cliques with the lowest entropy; (e) using just 20 of the 3rd order cliques with the lowest entropy; (f) using just 3rd order cliques; (g) using 4th and all lower order cliques; (h) using just 4th order cliques; (i) using plain nonparametric MRF.

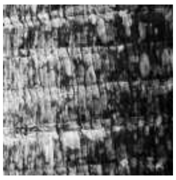


(a) Training texture (b) 2nd and lower order cliques (c) 2nd order cliques

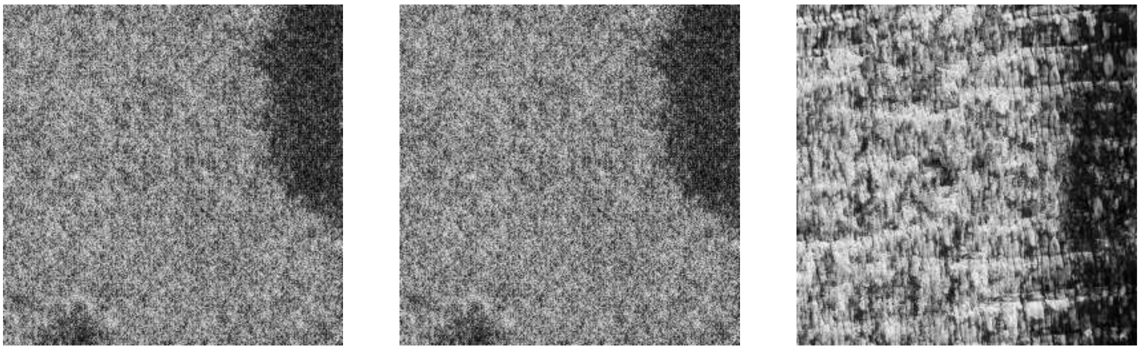
(d) 3rd order cliques (e) 3rd order cliques (f) 3rd order cliques

(g) 4th and lower order cliques (h) 4th order cliques (i) No cliques

Figure B.179: Brodatz texture D077a: (a) original 128×128 image; (b–i) synthesised 256×256 images using Gibbs sampling and 5×5 neighbourhood; (b) using pairwise and single site cliques; (c) using just pairwise cliques; (d) using just 10 of the 3rd order cliques with the lowest entropy; (e) using just 20 of the 3rd order cliques with the lowest entropy; (f) using just 3rd order cliques; (g) using 4th and all lower order cliques; (h) using just 4th order cliques; (i) using plain nonparametric MRF.

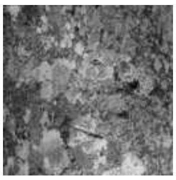


(a) Training texture

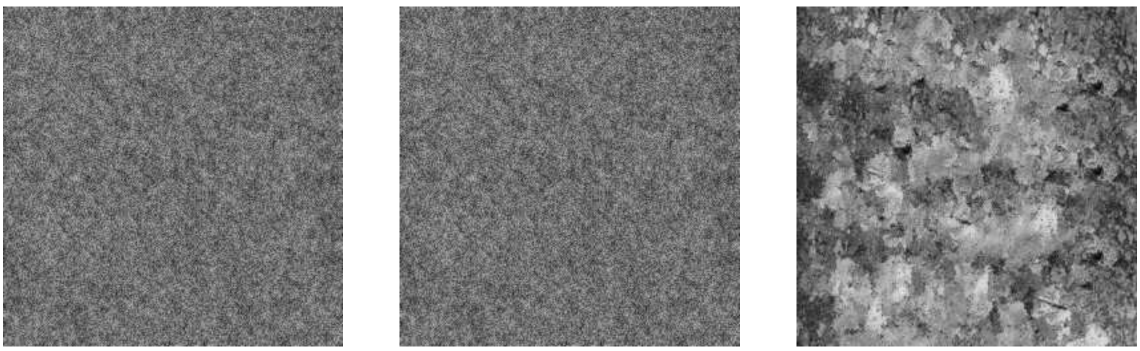


(b) 2nd order cliques (c) 2nd order cliques (d) No cliques

Figure B.180: VisTex texture Bark.0000: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.

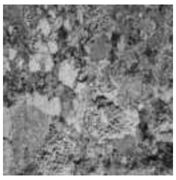


(a) Training texture

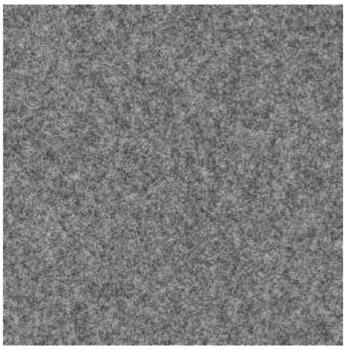


(b) 2nd order cliques (c) 2nd order cliques (d) No cliques

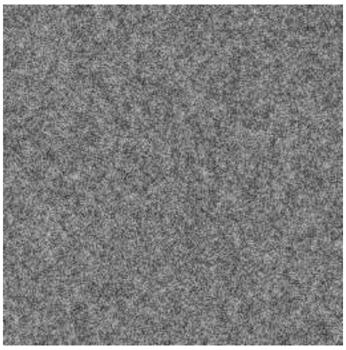
Figure B.181: VisTex texture Bark.0001: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.



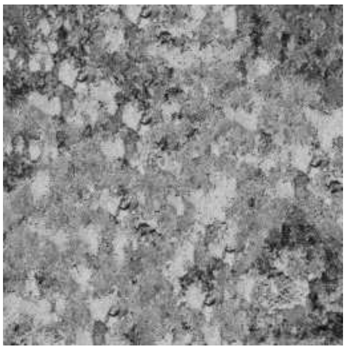
(a) Training texture



(b) 2nd order cliques



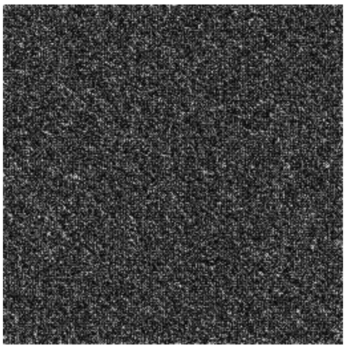
(c) 2nd order cliques



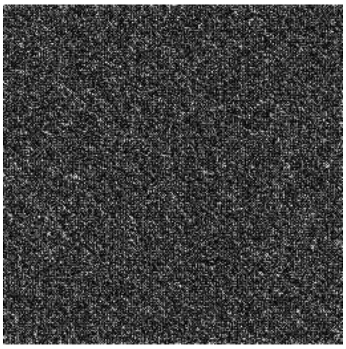
(d) No cliques

Figure B.182: VisTex texture Bark.0002: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.

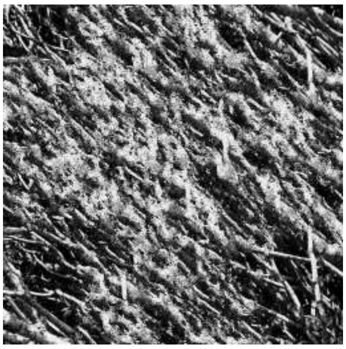
(a) Training texture



(b) 2nd order cliques



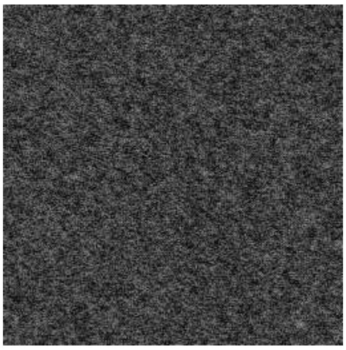
(c) 2nd order cliques



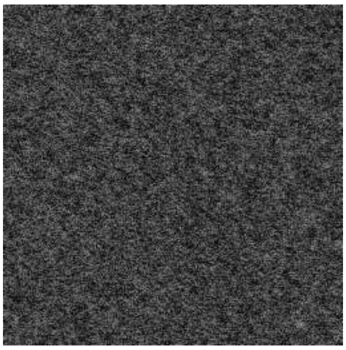
(d) No cliques

Figure B.183: VisTex texture Bark.0003: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.

(a) Training texture



(b) 2nd order cliques

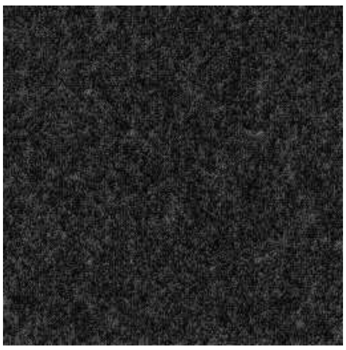


(c) 2nd order cliques

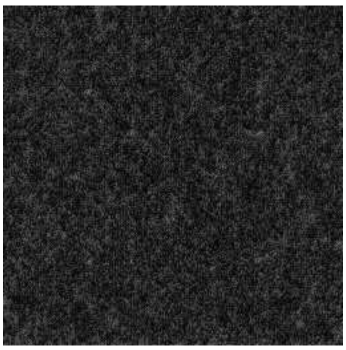
(d) No cliques

Figure B.184: VisTex texture Bark.0004: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.

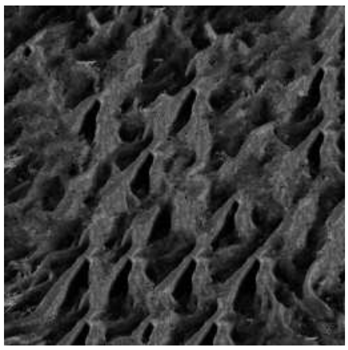
(a) Training texture



(b) 2nd order cliques

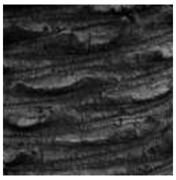


(c) 2nd order cliques

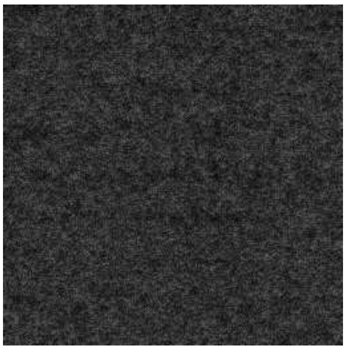


(d) No cliques

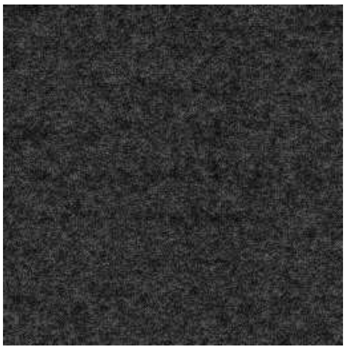
Figure B.185: VisTex texture Bark.0005: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.



(a) Training texture



(b) 2nd order cliques

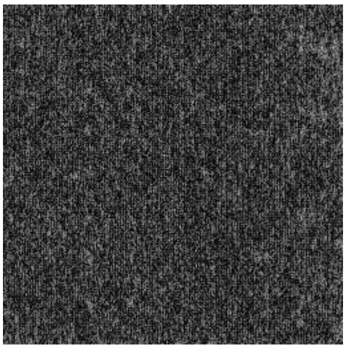


(c) 2nd order cliques

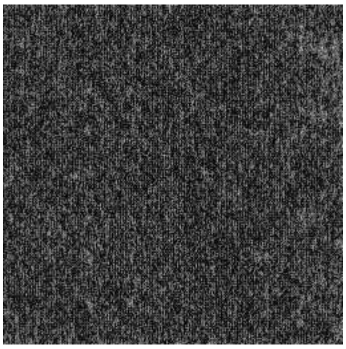
(d) No cliques

Figure B.186: VisTex texture Bark.0006: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.

(a) Training texture



(b) 2nd order cliques

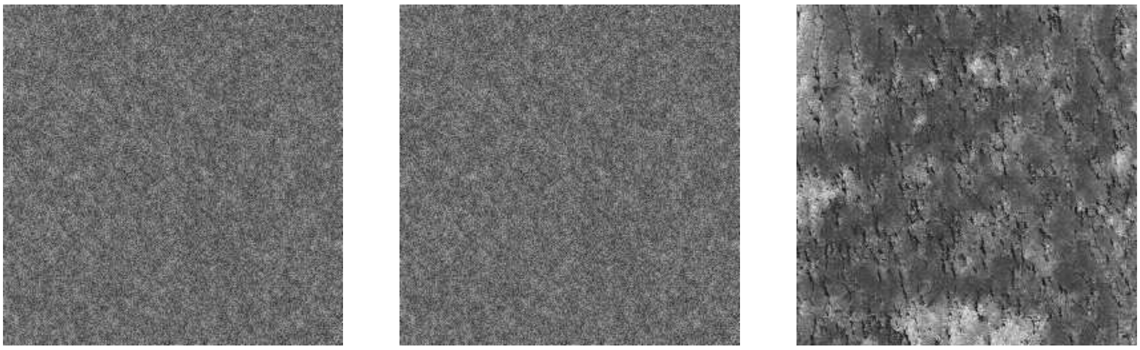


(c) 2nd order cliques

(d) No cliques

Figure B.187: VisTex texture Bark.0007: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.

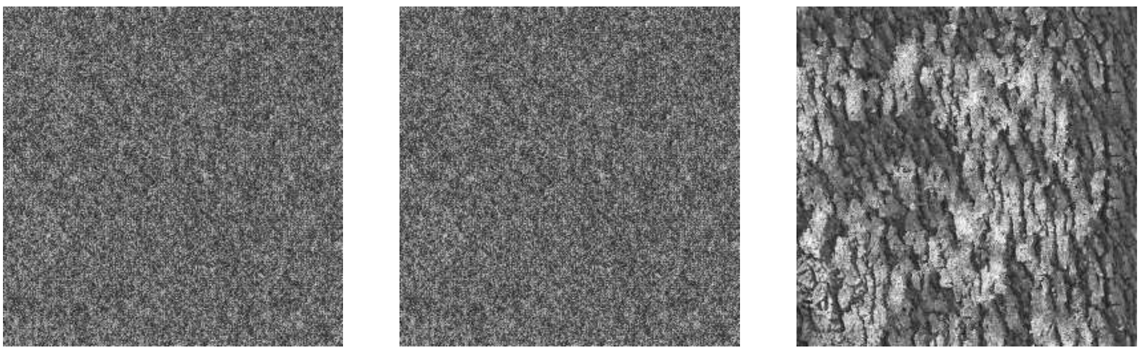
(a) Training texture



(b) 2nd order cliques (c) 2nd order cliques (d) No cliques

Figure B.188: VisTex texture Bark.0008: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.

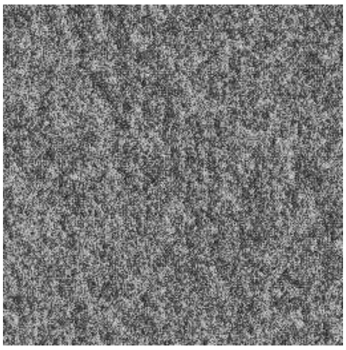
(a) Training texture



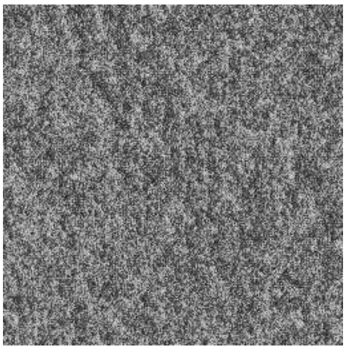
(b) 2nd order cliques (c) 2nd order cliques (d) No cliques

Figure B.189: VisTex texture Bark.0009: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.

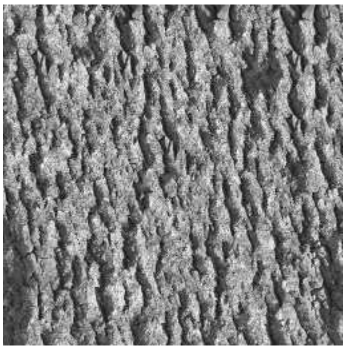
(a) Training texture



(b) 2nd order cliques



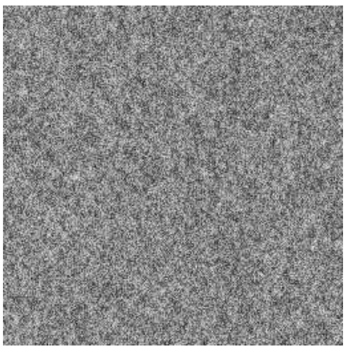
(c) 2nd order cliques



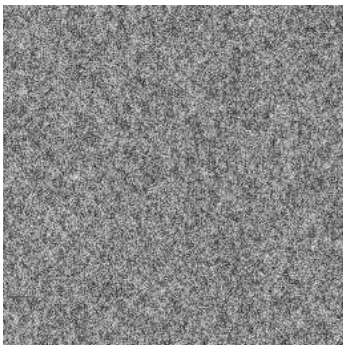
(d) No cliques

Figure B.190: VisTex texture Bark.0010: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.

(a) Training texture



(b) 2nd order cliques

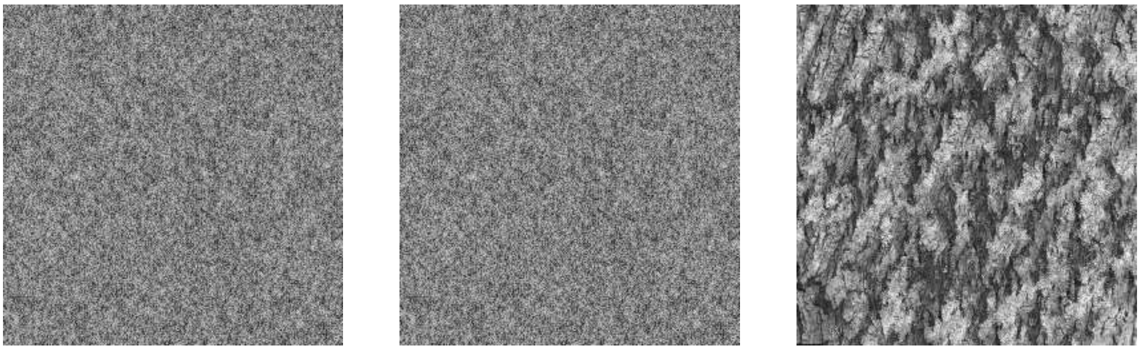


(c) 2nd order cliques

(d) No cliques

Figure B.191: VisTex texture Bark.0011: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.

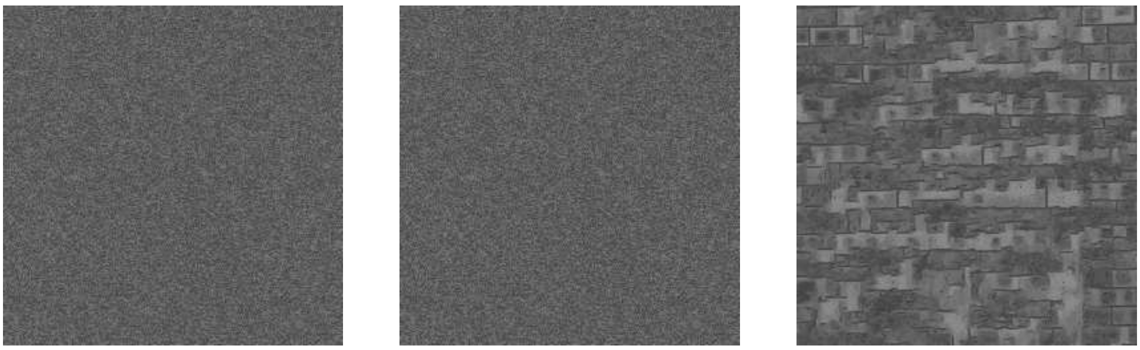
(a) Training texture



(b) 2nd order cliques (c) 2nd order cliques (d) No cliques

Figure B.192: VisTex texture Bark.0012: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.

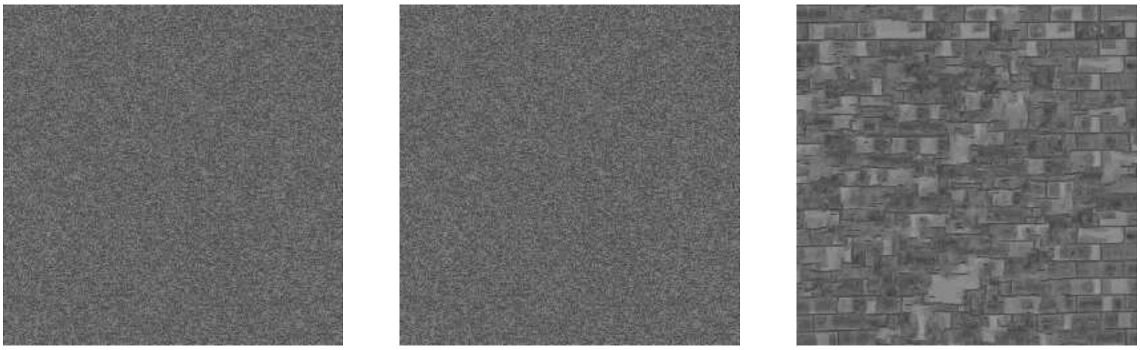
(a) Training texture



(b) 2nd order cliques (c) 2nd order cliques (d) No cliques

Figure B.193: VisTex texture Brick.0000: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.

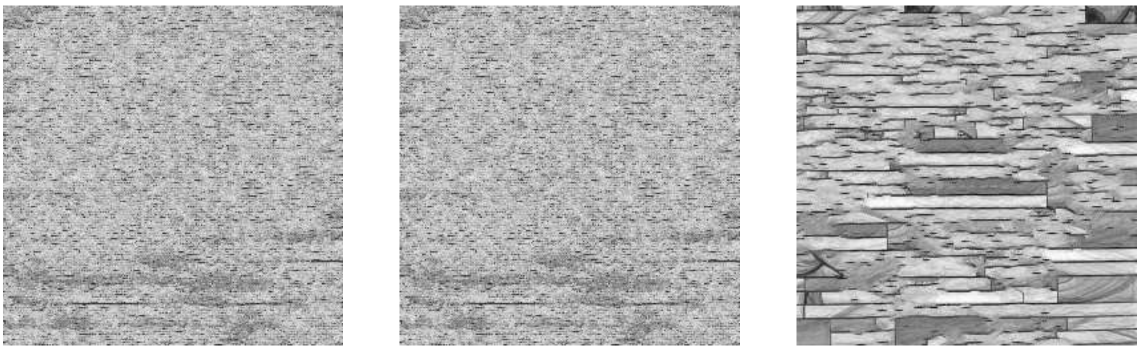
(a) Training texture



(b) 2nd order cliques (c) 2nd order cliques (d) No cliques

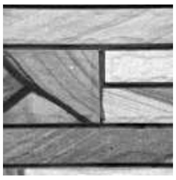
Figure B.194: VisTex texture Brick.0001: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.

(a) Training texture

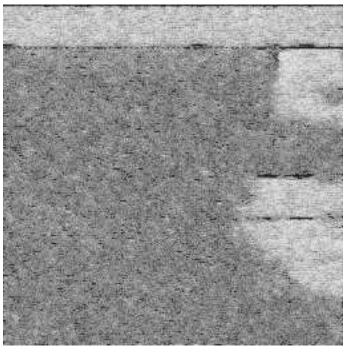


(b) 2nd order cliques (c) 2nd order cliques (d) No cliques

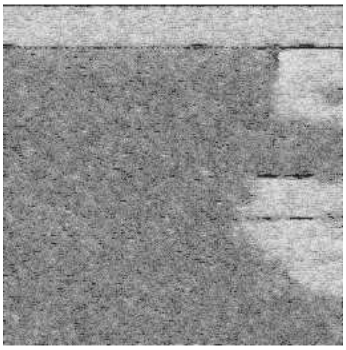
Figure B.195: VisTex texture Brick.0002: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.



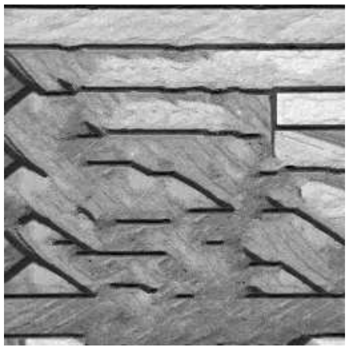
(a) Training texture



(b) 2nd order cliques



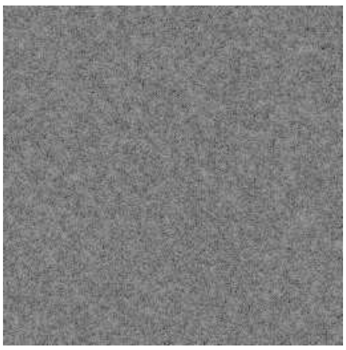
(c) 2nd order cliques



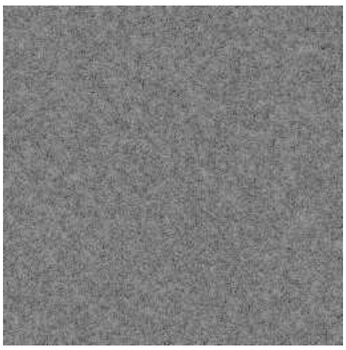
(d) No cliques

Figure B.196: VisTex texture Brick.0003: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.

(a) Training texture



(b) 2nd order cliques

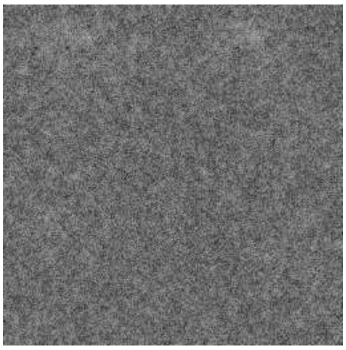


(c) 2nd order cliques

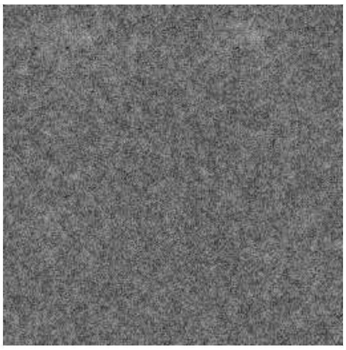
(d) No cliques

Figure B.197: VisTex texture Brick.0004: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.

(a) Training texture



(b) 2nd order cliques

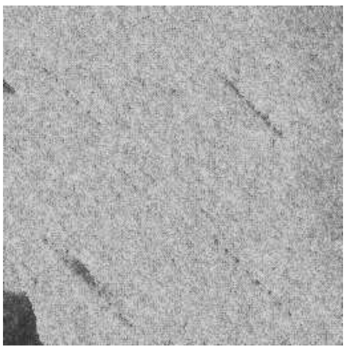


(c) 2nd order cliques

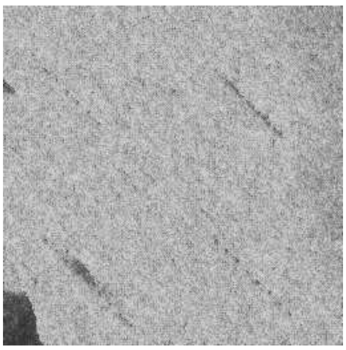
(d) No cliques

Figure B.198: VisTex texture Brick.0005: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.

(a) Training texture



(b) 2nd order cliques

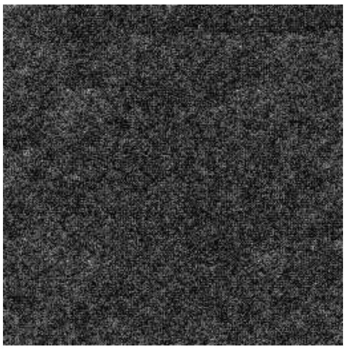


(c) 2nd order cliques

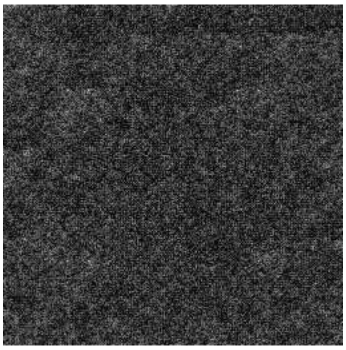
(d) No cliques

Figure B.199: VisTex texture Brick.0006: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.

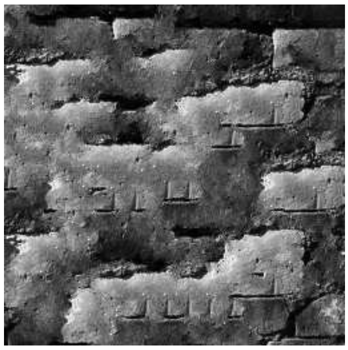
(a) Training texture



(b) 2nd order cliques



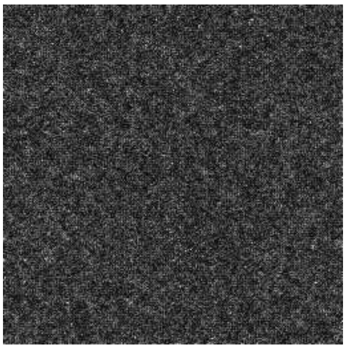
(c) 2nd order cliques



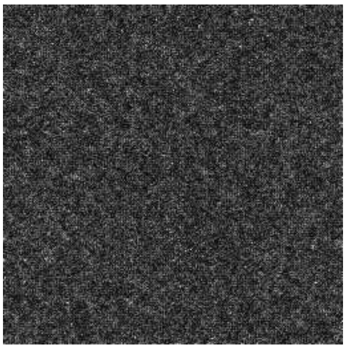
(d) No cliques

Figure B.200: VisTex texture Brick.0007: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.

(a) Training texture



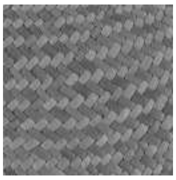
(b) 2nd order cliques



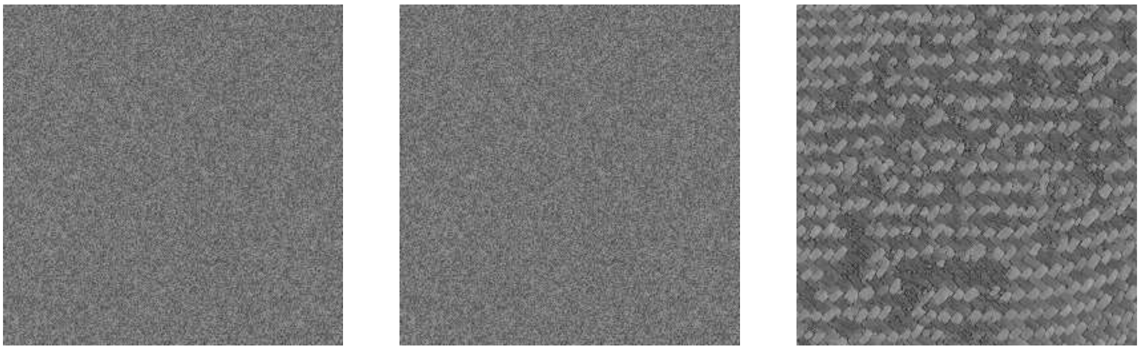
(c) 2nd order cliques

(d) No cliques

Figure B.201: VisTex texture Brick.0008: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.

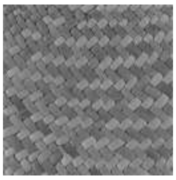


(a) Training texture

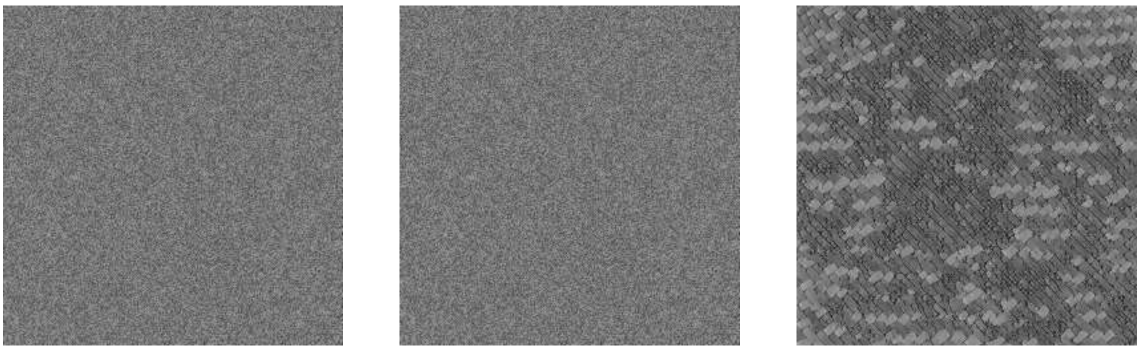


(b) 2nd order cliques (c) 2nd order cliques (d) No cliques

Figure B.202: VisTex texture Fabric.0000: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.

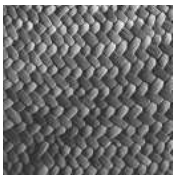


(a) Training texture

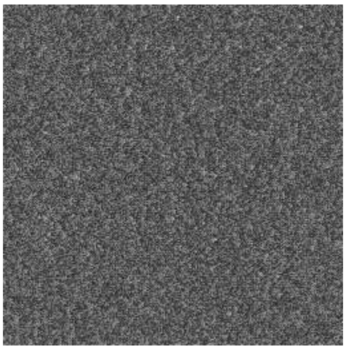


(b) 2nd order cliques (c) 2nd order cliques (d) No cliques

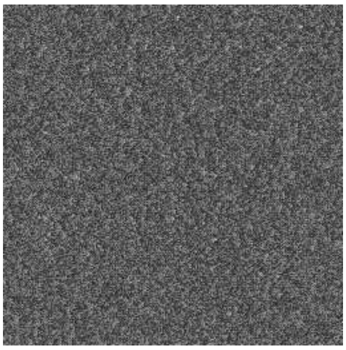
Figure B.203: VisTex texture Fabric.0001: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.



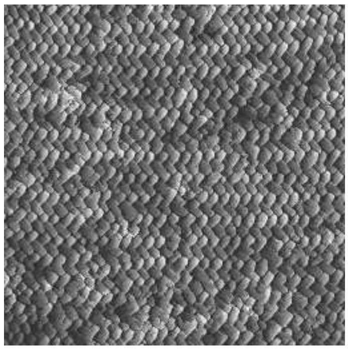
(a) Training texture



(b) 2nd order cliques

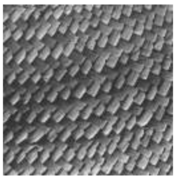


(c) 2nd order cliques

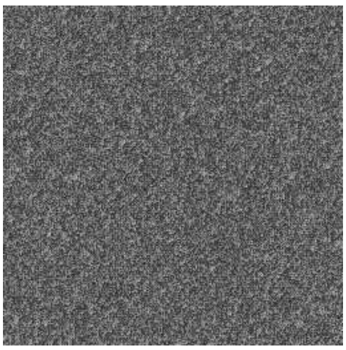


(d) No cliques

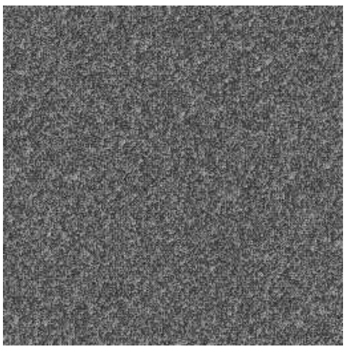
Figure B.204: VisTex texture Fabric.0002: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.



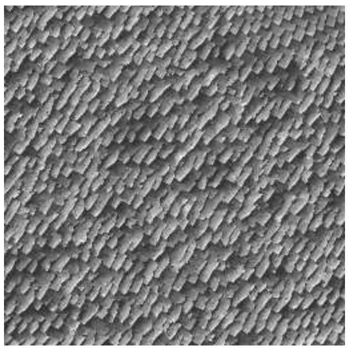
(a) Training texture



(b) 2nd order cliques



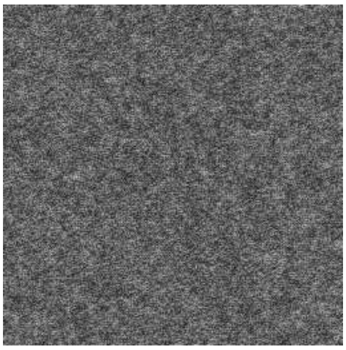
(c) 2nd order cliques



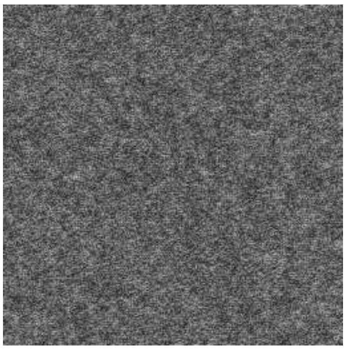
(d) No cliques

Figure B.205: VisTex texture Fabric.0003: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.

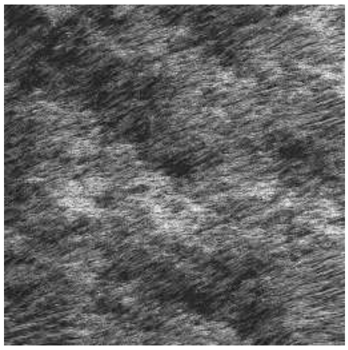
(a) Training texture



(b) 2nd order cliques



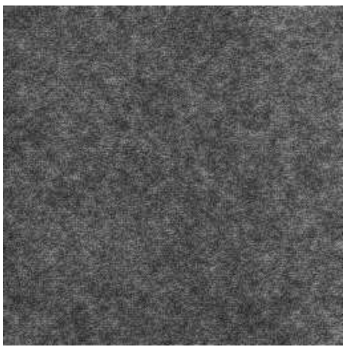
(c) 2nd order cliques



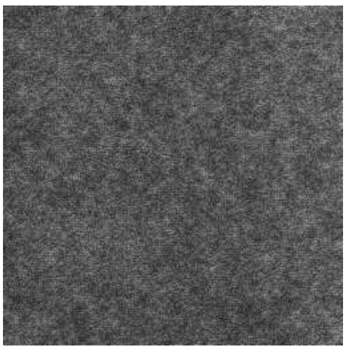
(d) No cliques

Figure B.206: VisTex texture Fabric.0004: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.

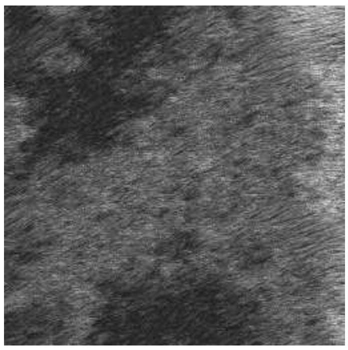
(a) Training texture



(b) 2nd order cliques



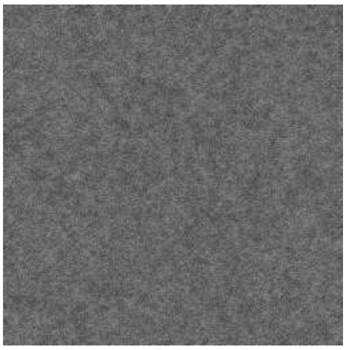
(c) 2nd order cliques

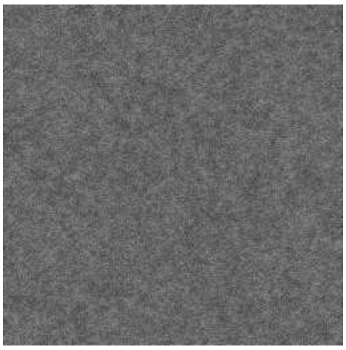


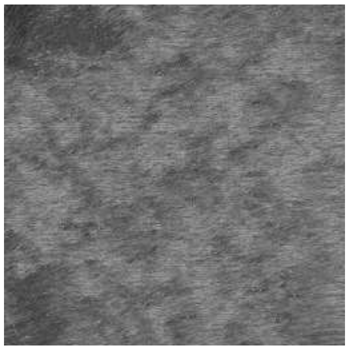
(d) No cliques

Figure B.207: VisTex texture Fabric.0005: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.

(a) Training texture



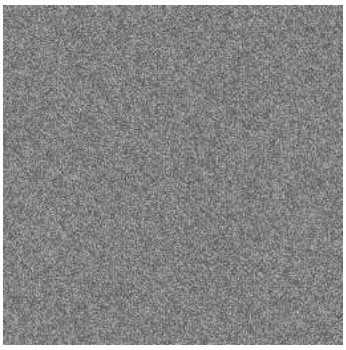


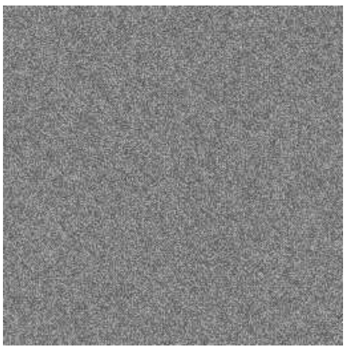


(b) 2nd order cliques (c) 2nd order cliques (d) No cliques

Figure B.208: VisTex texture Fabric.0006: (a) original 128 × 128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.

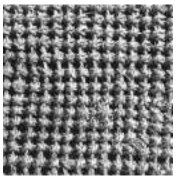
(a) Training texture



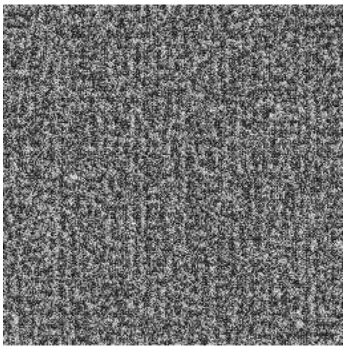


(b) 2nd order cliques (c) 2nd order cliques (d) No cliques

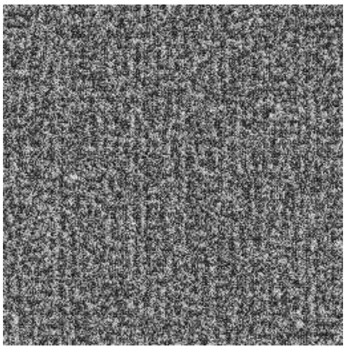
Figure B.209: VisTex texture Fabric.0007: (a) original 128 × 128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.



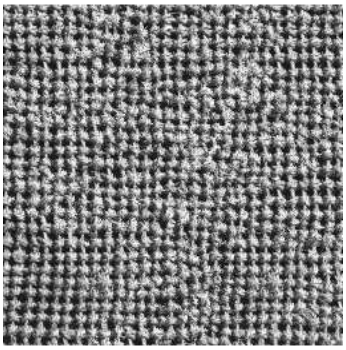
(a) Training texture



(b) 2nd order cliques

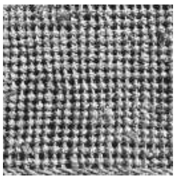


(c) 2nd order cliques

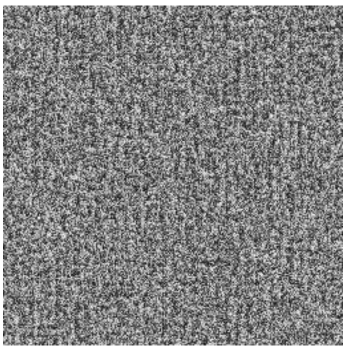


(d) No cliques

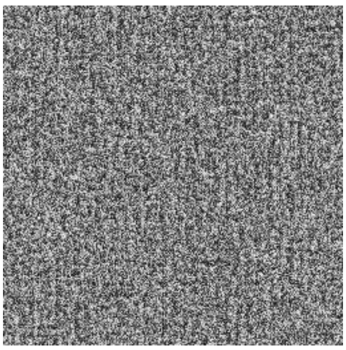
Figure B.210: VisTex texture Fabric.0008: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.



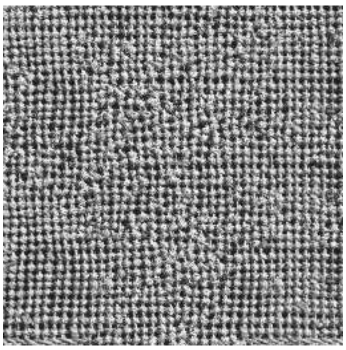
(a) Training texture



(b) 2nd order cliques

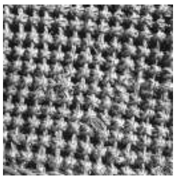


(c) 2nd order cliques

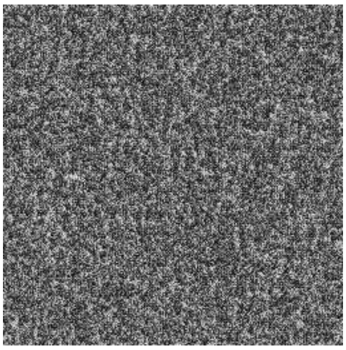


(d) No cliques

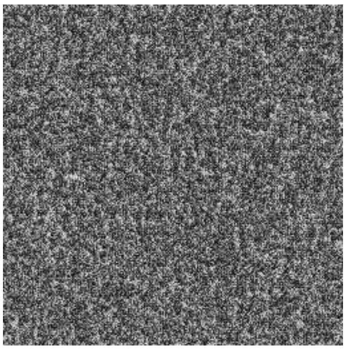
Figure B.211: VisTex texture Fabric.0009: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.



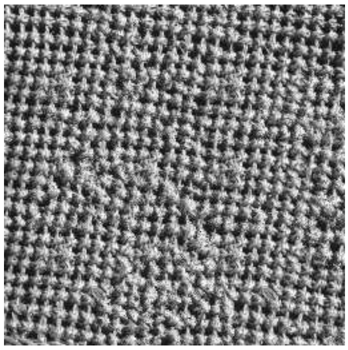
(a) Training texture



(b) 2nd order cliques



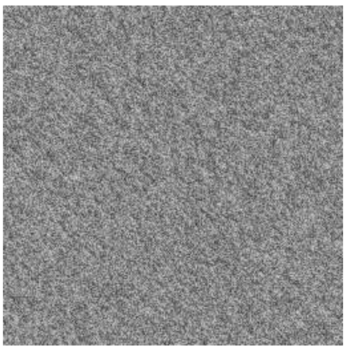
(c) 2nd order cliques



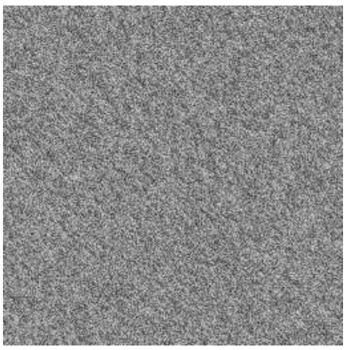
(d) No cliques

Figure B.212: VisTex texture Fabric.0010: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.

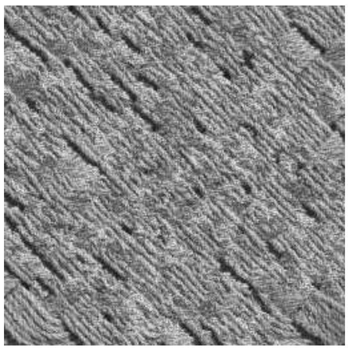
(a) Training texture



(b) 2nd order cliques

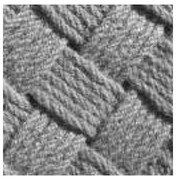


(c) 2nd order cliques

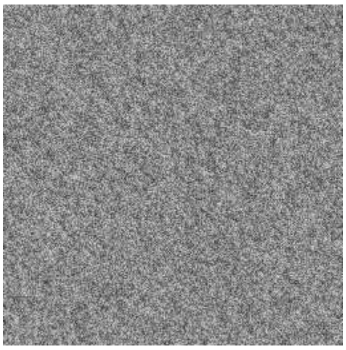


(d) No cliques

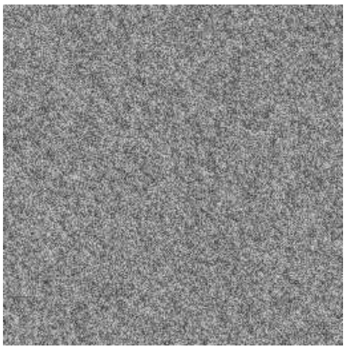
Figure B.213: VisTex texture Fabric.0011: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.



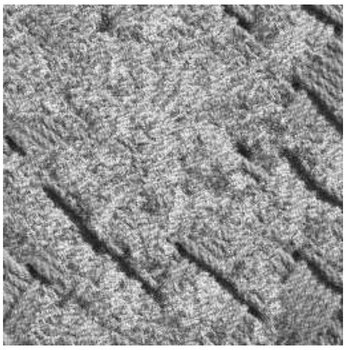
(a) Training texture



(b) 2nd order cliques

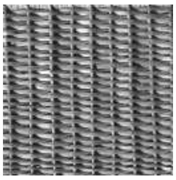


(c) 2nd order cliques

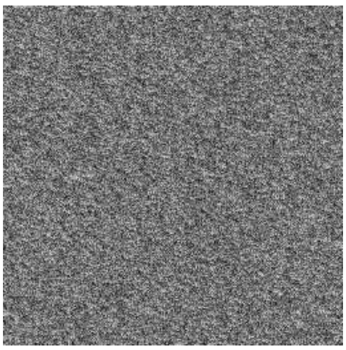


(d) No cliques

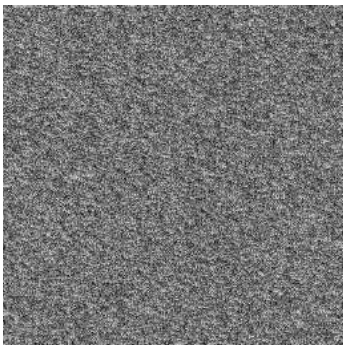
Figure B.214: VisTex texture Fabric.0012: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.



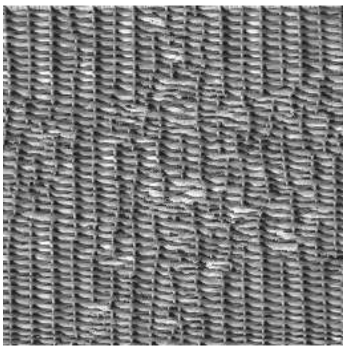
(a) Training texture



(b) 2nd order cliques

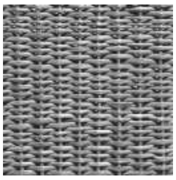


(c) 2nd order cliques

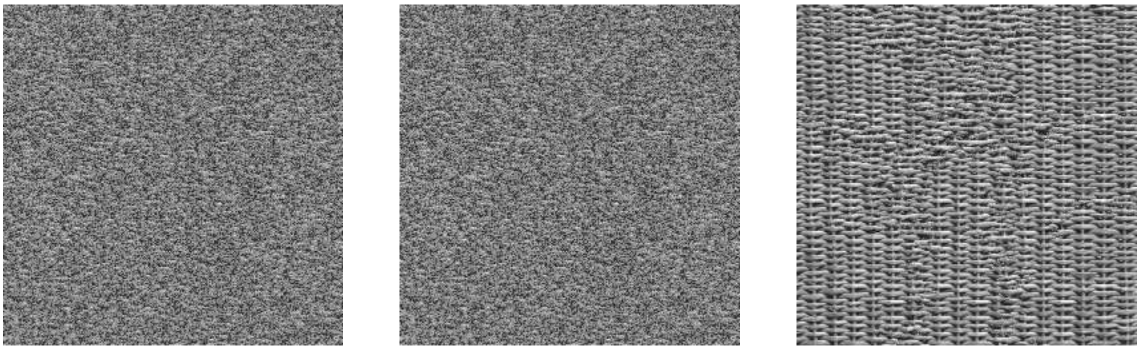


(d) No cliques

Figure B.215: VisTex texture Fabric.0013: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.

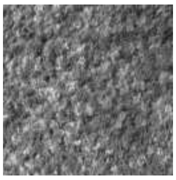


(a) Training texture

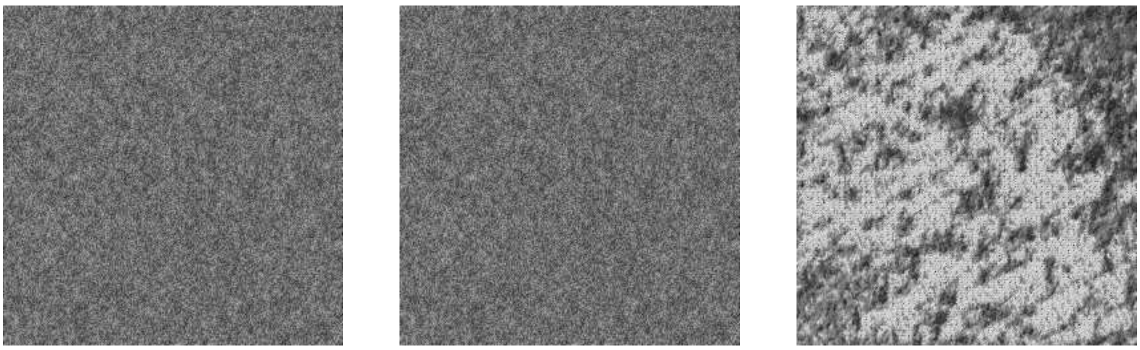


(b) 2nd order cliques (c) 2nd order cliques (d) No cliques

Figure B.216: VisTex texture Fabric.0014: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.

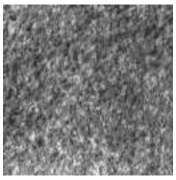


(a) Training texture

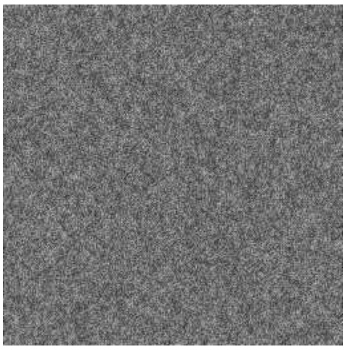


(b) 2nd order cliques (c) 2nd order cliques (d) No cliques

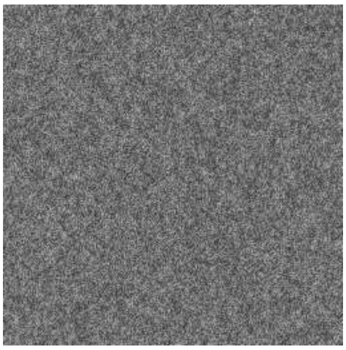
Figure B.217: VisTex texture Fabric.0015: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.



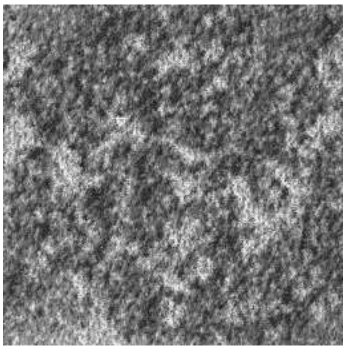
(a) Training texture



(b) 2nd order cliques

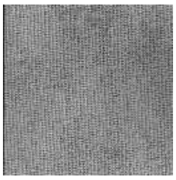


(c) 2nd order cliques

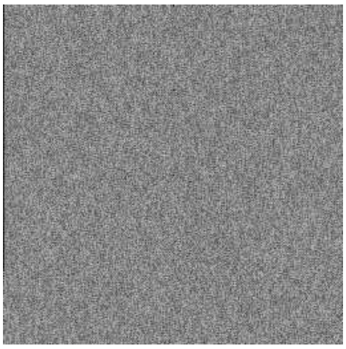


(d) No cliques

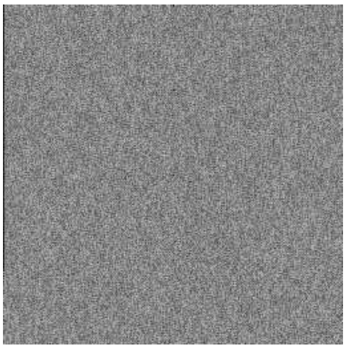
Figure B.218: VisTex texture Fabric.0016: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.



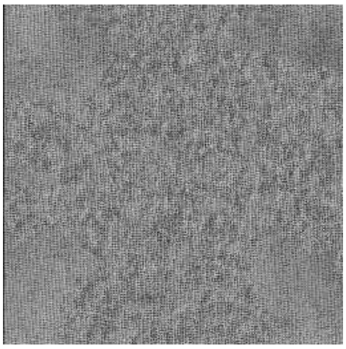
(a) Training texture



(b) 2nd order cliques



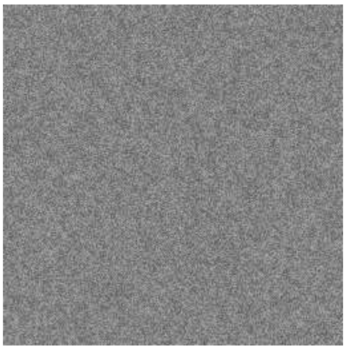
(c) 2nd order cliques



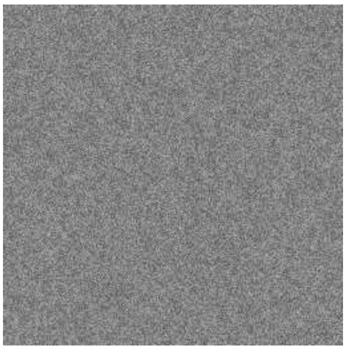
(d) No cliques

Figure B.219: VisTex texture Fabric.0017: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.

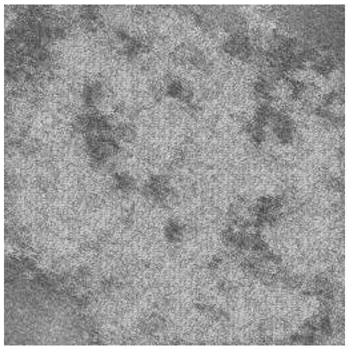
(a) Training texture



(b) 2nd order cliques



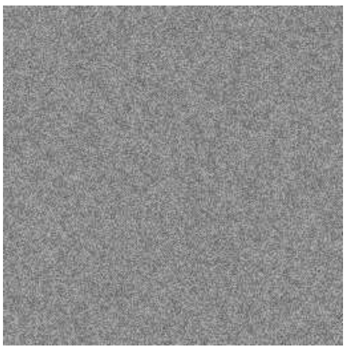
(c) 2nd order cliques



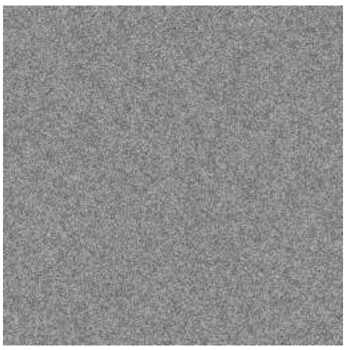
(d) No cliques

Figure B.220: VisTex texture Fabric.0018: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.

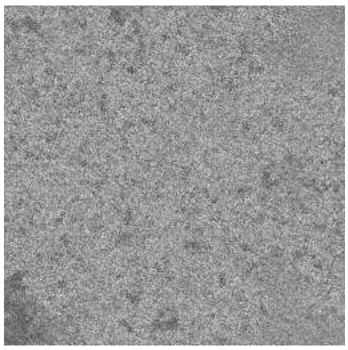
(a) Training texture



(b) 2nd order cliques



(c) 2nd order cliques



(d) No cliques

Figure B.221: VisTex texture Fabric.0019: (a) original 128×128 image; (b–d) synthesised 256×256 images using a 5×5 neighbourhood; (b) using Gibbs sampling and just pairwise cliques; (c) using ICM sampling and just pairwise cliques; (d) using plain nonparametric MRF.

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