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NONPARAMETRIC MULTISCALE MARKOV RANDOM FIELD MODELS FOR SYNTHESISING NATURAL TEXTURES

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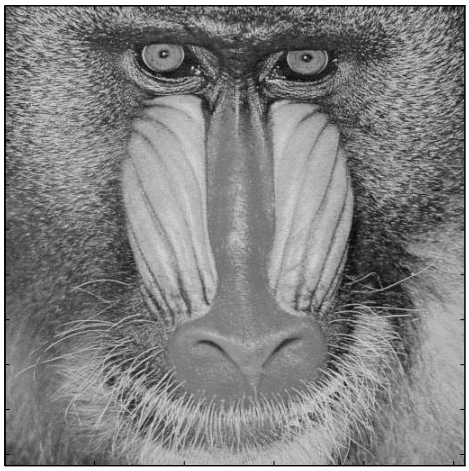
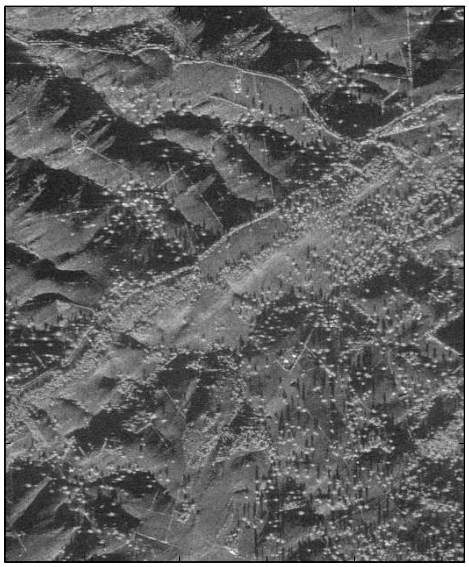
Texture in Images



Baboon face



Airborne SAR

Figure 1: Texture in Images

Texture is the visual characteristics within an area of an image which identify that area as belonging to a certain class.

Class may be associated with a particular physical interpretation such as: grass, hair, water, or sand.

Analysis is the modelling of texture by analytically capturing its characteristics.

Aim to find a model that is capable of capturing the unique characteristics of a texture for segmentation and classification.

Markov Random Field Model

For a texture to be modeled as a MRF, the value of each pixel in the texture must be dependent on a local set of neighbouring pixels. This dependence is then modeled by a local conditional probability density function (LCPDF) which defines the probability of a pixel being a certain value given the values of its neighbouring pixels.

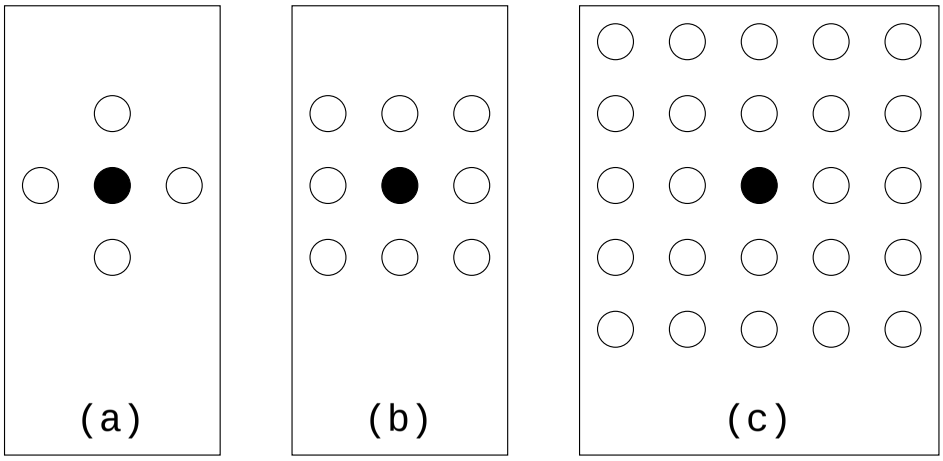


Figure 2: Neighbourhoods. (a) The first order or "nearest-neighbour" neighbourhood; (b) second order neighbourhood; (c) eighth order neighbourhood.

Problem 1 Determining the correct neighbourhood size.

Problem 2 Estimation of the LCPDF.

Model 1: Nonparametric MRF

Estimation of nonparametric LCPDF.

Step 1 Choose a neighbourhood size.

Step 2 Build a multi-dimensional histogram with the neighbourhood from the texture. Example:

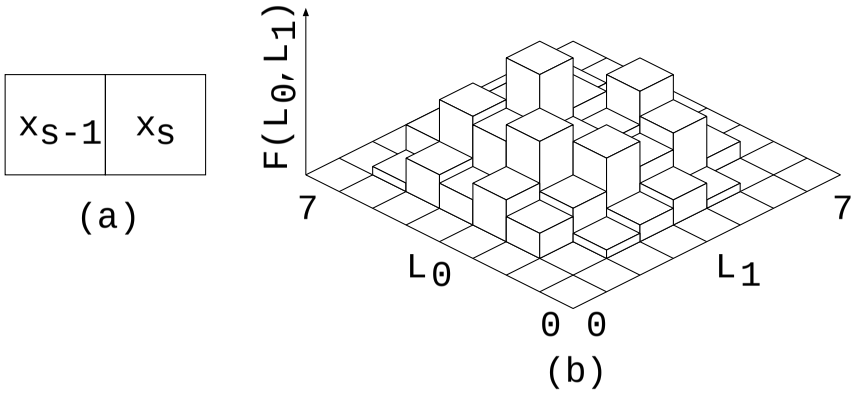


Figure 3: Neighbourhood and its 2-D histogram.

Step 3 Smooth multi-dimensional histogram via nonparametric Parzen density estimation.

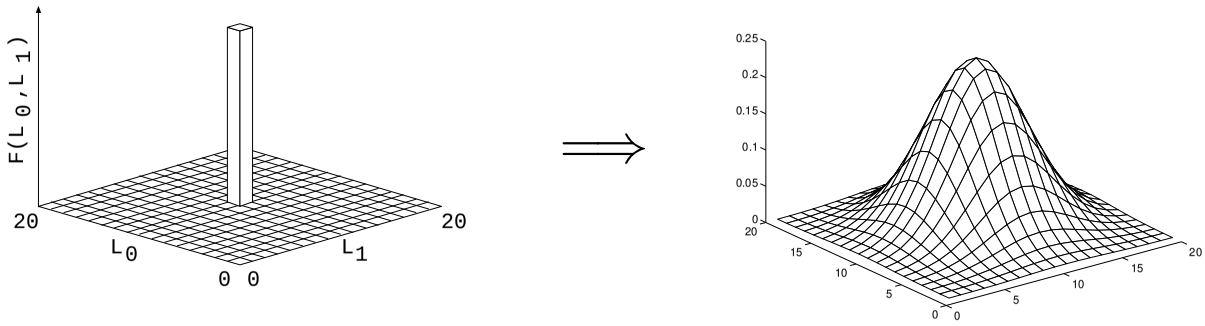


Figure 4: Histogram point is convolved with Gaussian kernel.

Model 2: Strong MRF

Estimation of strong nonparametric LCPDF.

Step 1 Choose a neighbourhood $\mathcal{N}_s$.

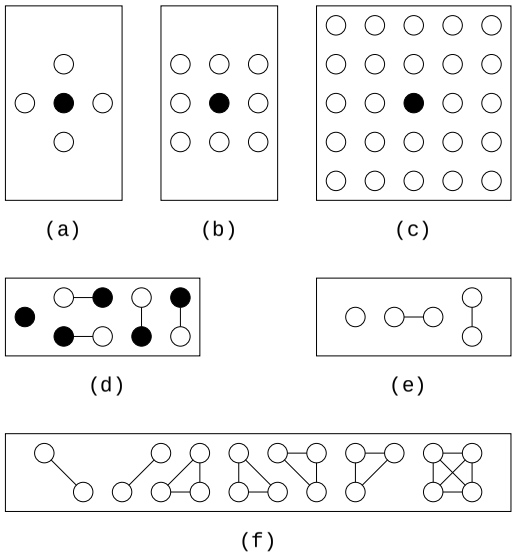


Figure 5: Neighbourhoods and their cliques.

Step 2 Choose a set of major cliques $\{C \subset \mathcal{N}_s\}$, cliques that are not subsets of other cliques.

Step 3 For each major clique, estimate the marginal distribution LCPDF_C.

Step 4 The simple estimate of the strong LCPDF is,

$$\text{LCPDF} = \prod_{\substack{C \subset \mathcal{N}_s, \\ C \not\subset C' \subset \mathcal{N}_s}} \text{LCPDF}_C.$$

Multiscale Texture Synthesis

To test whether a texture model has captured all the relevant characteristics: use the model to synthesise textures and compare the similarity between the synthetic textures and the original.

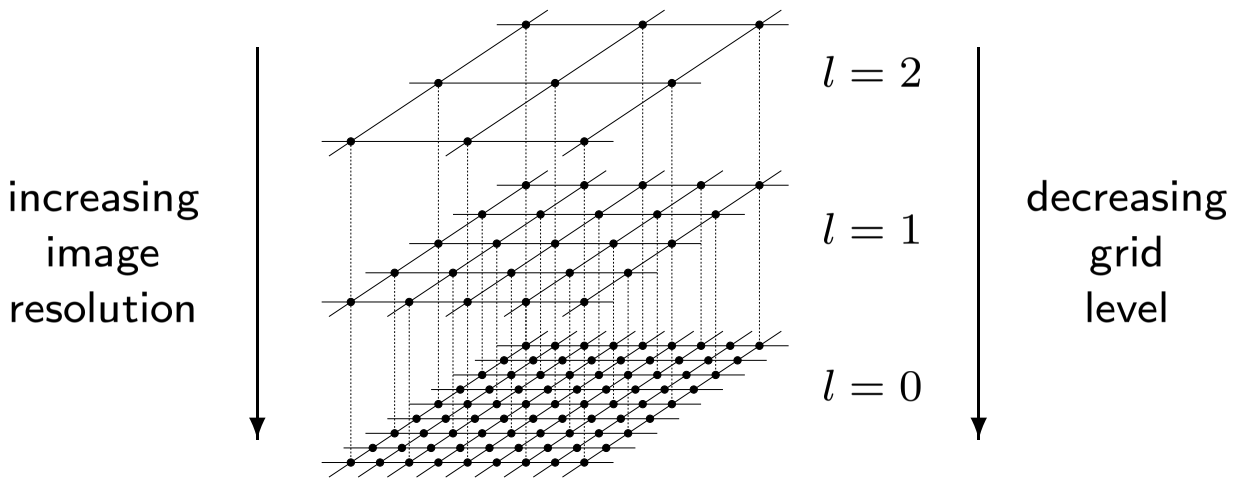


Figure 6: Grid organisation for multiscale modelling of a MRF.

The multiscale synthesis algorithm starts from the top and works its way down performing the following at each resolution:

- Estimation of LCPDF from original texture at same resolution.
- Applying stochastic relaxation (SR) (*i.e.*, ICM or Gibbs sampler).
- Constraining SR with respect to the above image.

Pixel Temperature

The pixel temperature helps constrain the SR process while implementing local annealing.

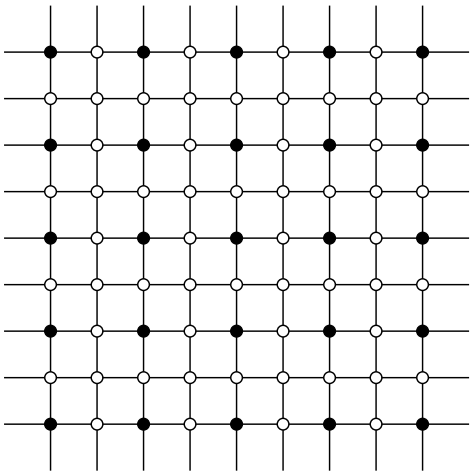


Figure 7: The sites "•" are from the above level.

Step 1 Initialize pixel temperature t_s,

$$t_s = \begin{cases} 1 & \text{if site} s = \circ \quad \Rightarrow \quad \text{low confidence} \\ 0 & \text{if site} s = \bullet \quad \Rightarrow \quad \text{high confidence} \end{cases}$$

Step 2 Modify the estimate of the LCPDF to be more dependent on pixels with low temperature (*i.e.*, high confidence).

Step 3 After a pixel has been relaxed $\Rightarrow$ decrease pixel temperature (*i.e.*, increase confidence).

Model 1: Synthetic Textures

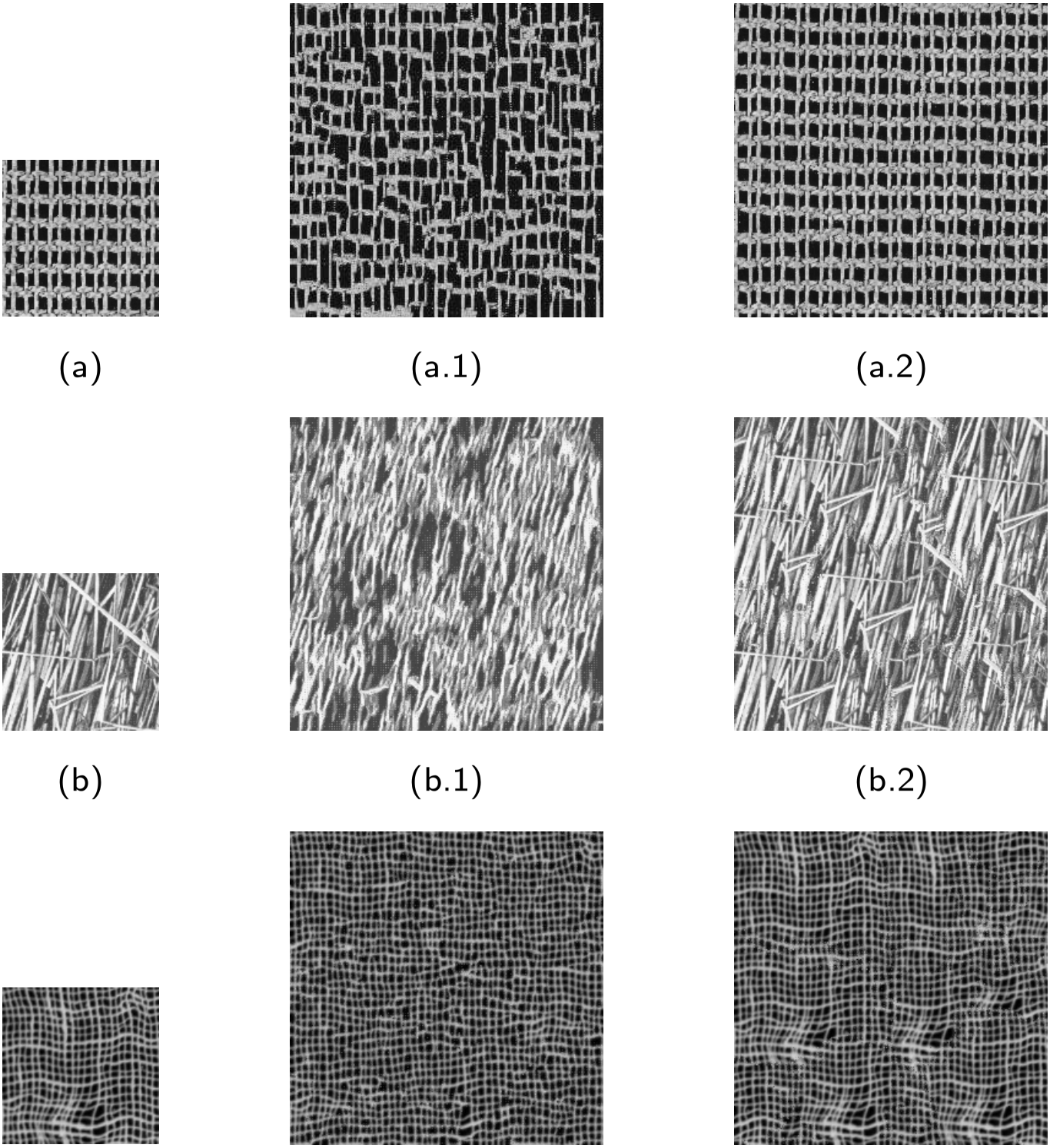


Figure 8: Brodatz textures: (a) D20 - magnified French canvas; (b) D15 - straw; (c) D103 - loose burlap; (?.1) textures synthesised with small neighbourhood; (?.2) textures synthesised with large neighbourhood.

Model 2: Synthetic Textures

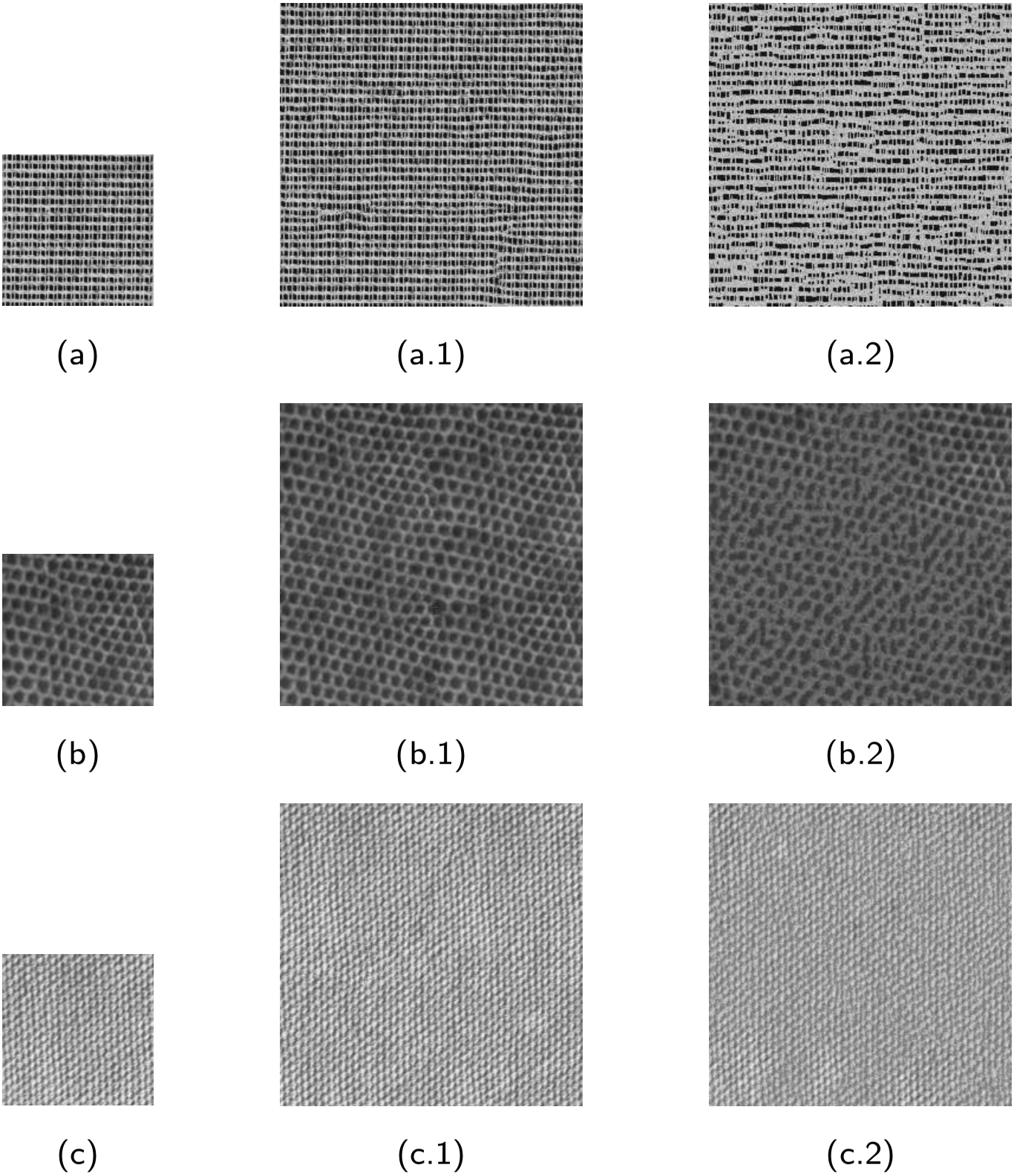


Figure 9: Brodatz textures: (a) D21 - French canvas; (b) D22 - Reptile skin; (c) D77 - Cotton canvas; (?.1) textures synthesised with Model 1; (?.2) textures synthesised with Model 2.