TEXTURE SYNTHESIS AND UNSUPERVISED RECOGNITION WITH A NONPARAMETRIC MULTISCALE MRF MODEL

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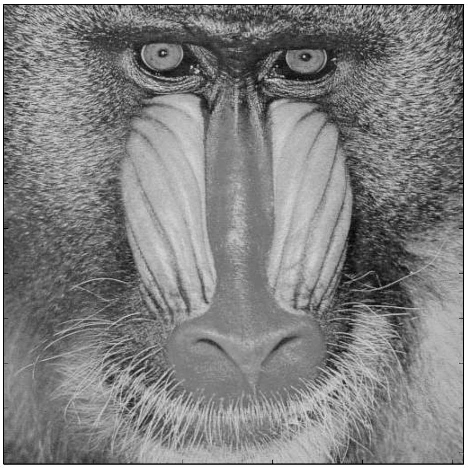
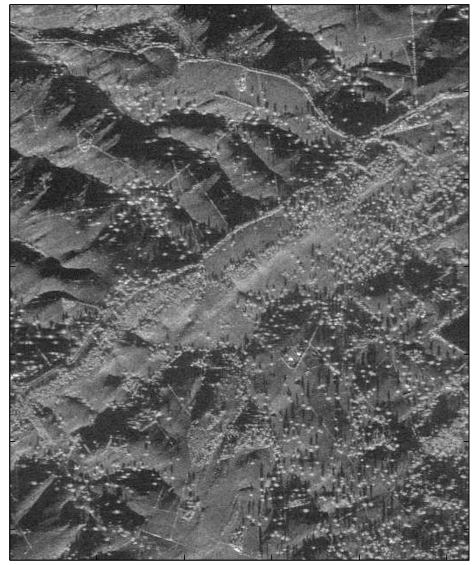
Texture in Images



Baboon face



Airborne SAR

Texture Is the visual characteristics within an area of an image which identifies that area as having a particular physical interpretation.

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

Method Use a nonparametric multiscale Markov random field texture model.

Advantages

- Does not require parameter estimation.
- Only requires a small amount of sample data.
- Can model high dimensional statistics.

Markov Random Field Model

For a texture to be modelled 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 modelled 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.

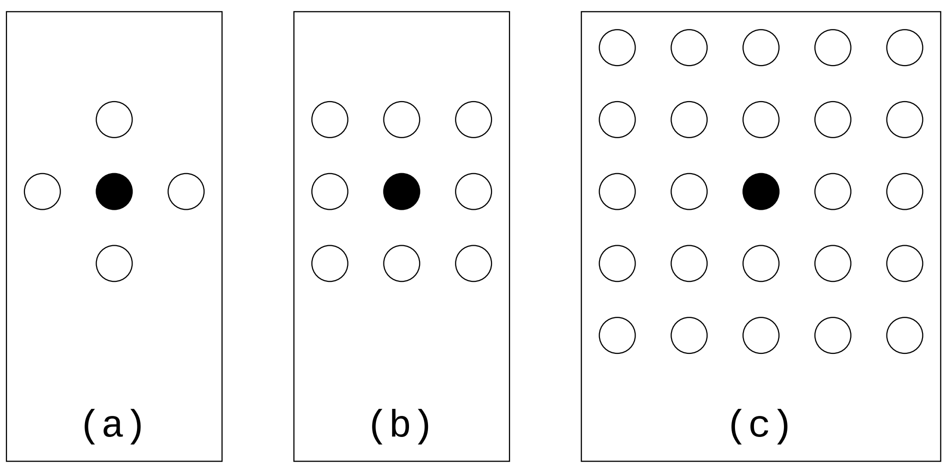


Figure 1: Neighbourhoods. (a) The first order or "nearest-neighbour" neighbourhood; (b) second order neighbourhood; (c) eighth order neighbourhood.

Problem 1 Determining the correct neighbourhood size.

Problem 2 Estimation of the LCPDF.

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:

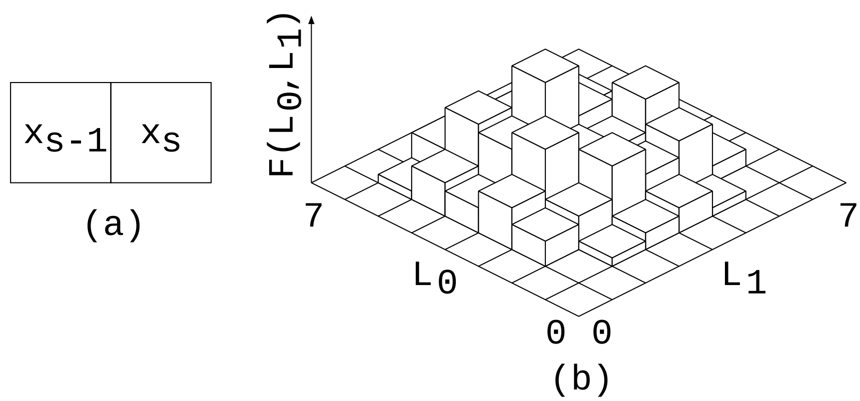


Figure 2: Neighbourhood and its 2-D histogram.

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

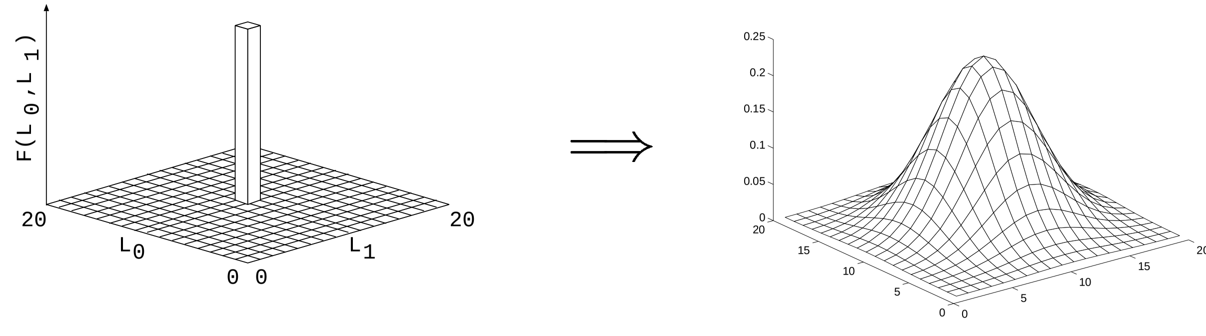


Figure 3: Histogram point is convolved with Gaussian kernel.

Multiscale Texture Synthesis

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

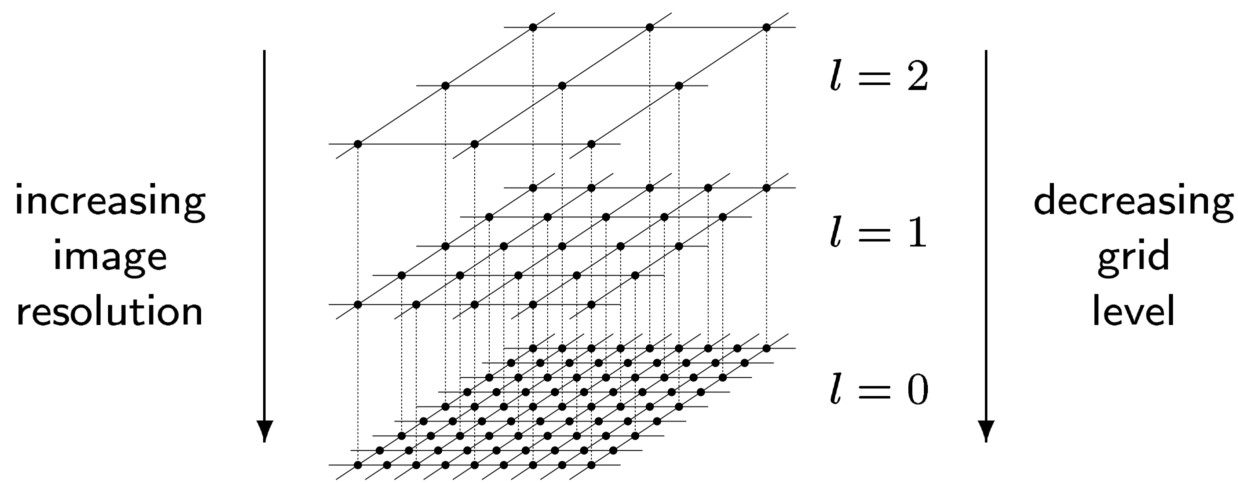


Figure 4: Grid organisation for multiscale modelling of a MRF.

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

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

Pixel Temperature

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

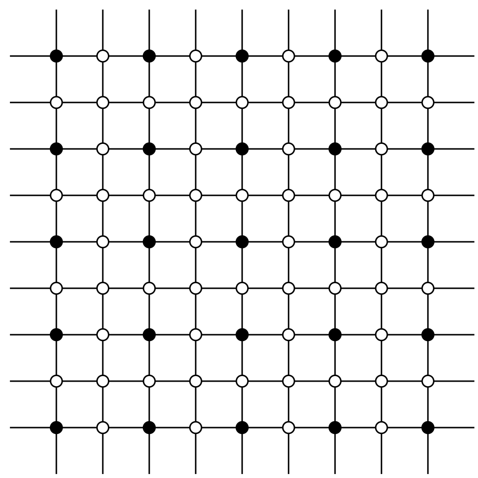


Figure 5: The sites "•" are from the above level.

Step 1 Initialise 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).

Synthetic Textures

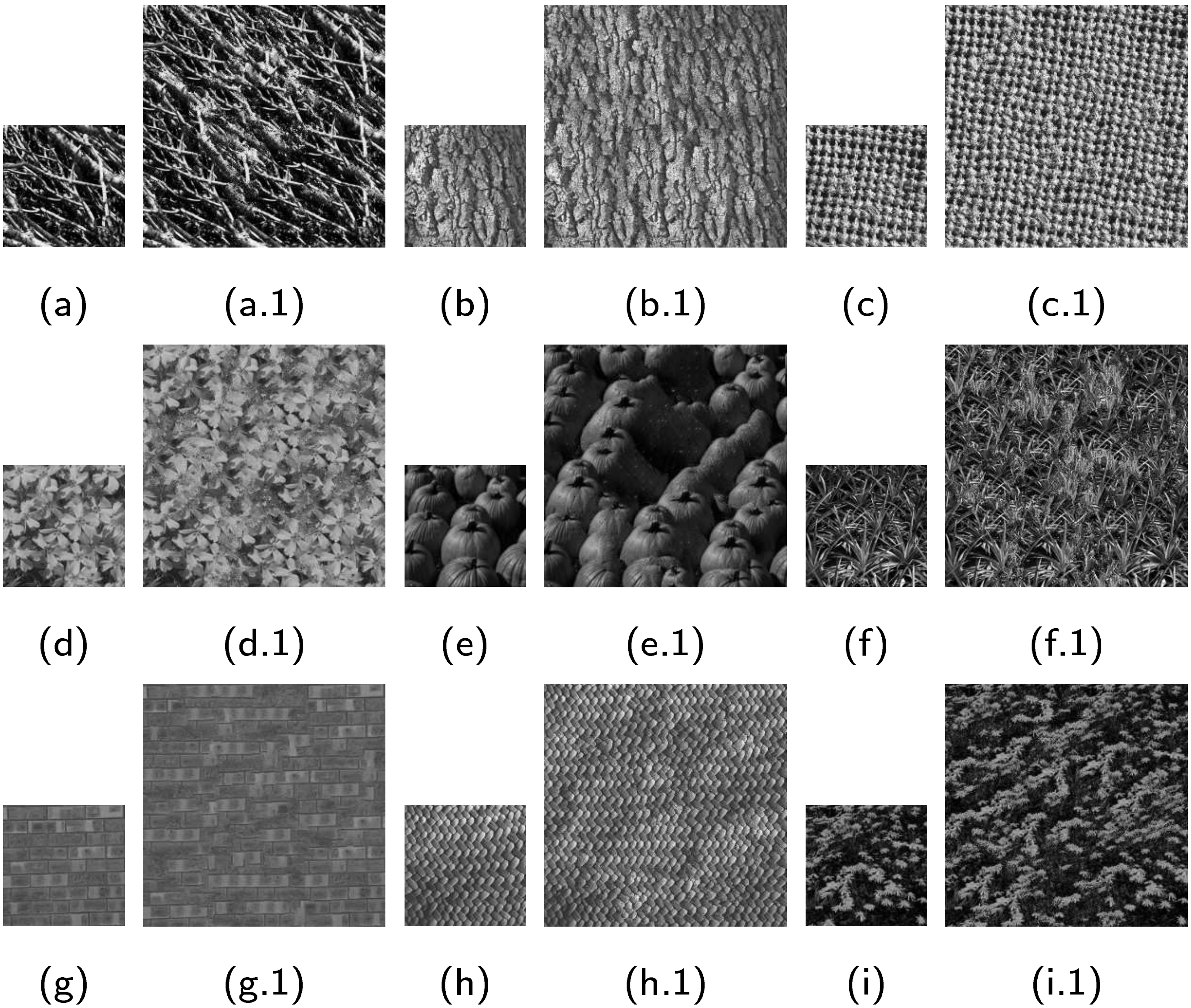


Figure 6: VisTex textures: (a) Bark.0003; (b) Bark.0009; (c) Fabric.0010; (d) Flowers.0003; (e) Food.0010; (f) Leaves.0016; (g) Brick.0000; (h) Fabric.0002; (i) Flowers.0000; (?.1) Textures were synthesised from a nonparametric MRF model with a 7×7 neighbourhood.

Strong Nonparametric MRF

Estimation of strong nonparametric LCPDF.

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

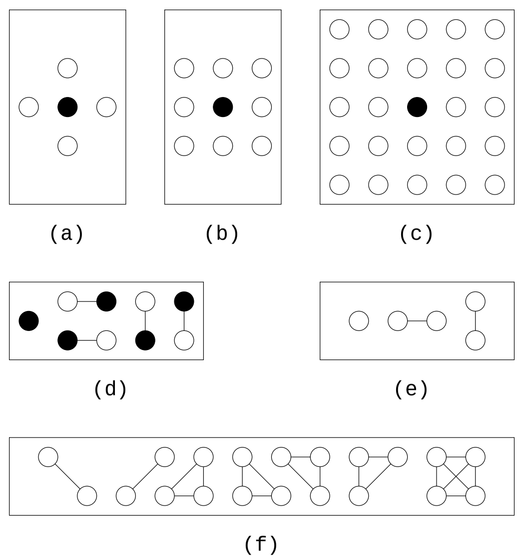


Figure 7: Neighbourhoods and their cliques.

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,

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

Synthetic Textures for Strong MRF

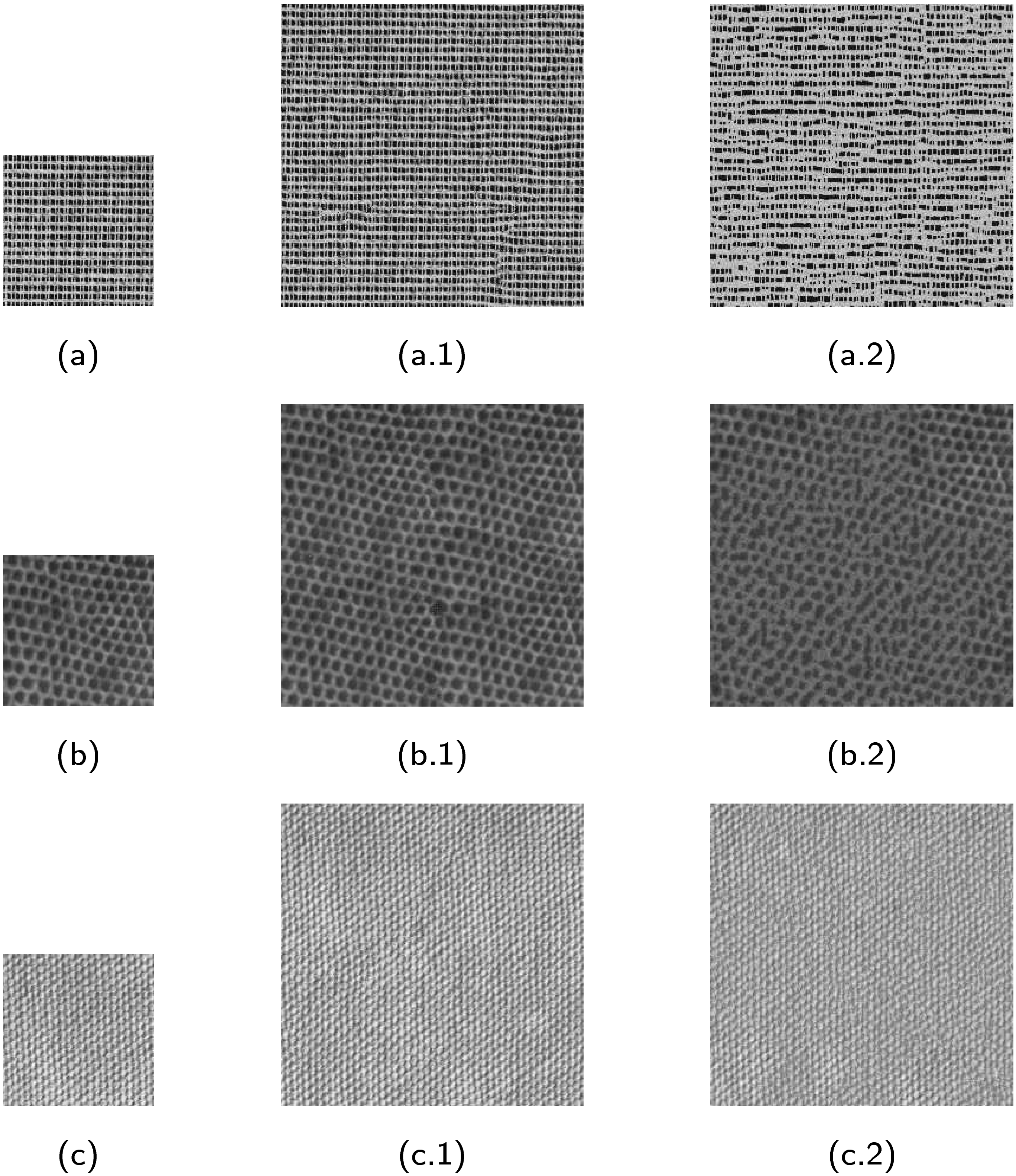


Figure 8: Brodatz textures: (a) D21 - French canvas; (b) D22 - Reptile skin; (c) D77 - Cotton canvas; (?.1) textures synthesised with MRF Model; (?.2) textures synthesised with Strong MRF Model.

Classification

Probability Measurement

1. Get an **unbiased** set of local probabilities from sample texture $\mathbf{y}$: $\{\mathrm{LPDF}_s\}$
2. Get a set of local probabilities from a segment window in image $\mathbf{x}$: $\{\mathrm{LPDF}_r\}$
3. Make comparison between the two sets via the Wilcoxon test.

Edges

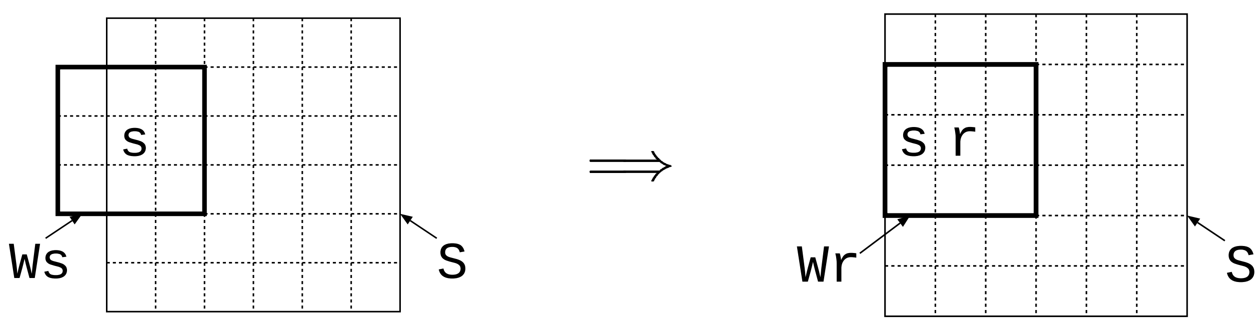


Figure 9: Move the window position for an edge pixel

Boundaries

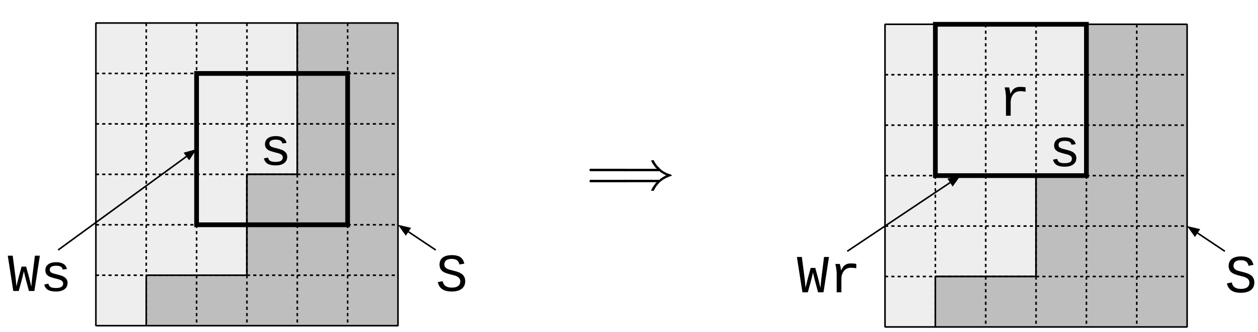


Figure 10: Move the window position for a boundary pixel

Segmented and Classified Textures

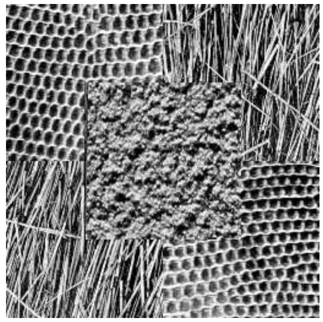
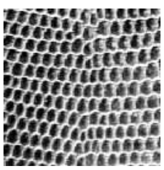


Fig. 1

Fig. 2



(a)

Fig. 1(a)

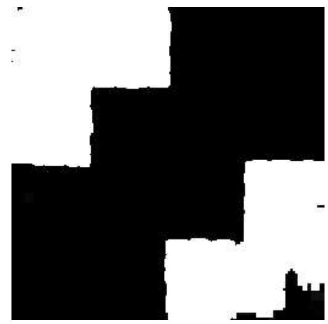
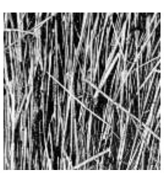


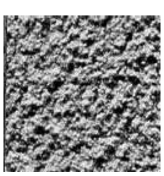
Fig. 2(a)



(b)

Fig. 1(b)

Fig. 2(b)



(c)

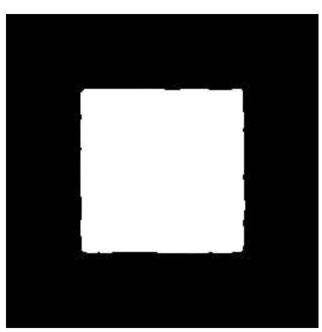


Fig. 1(c)

Fig. 2(c)

Probability scale 0  1

Practical Application

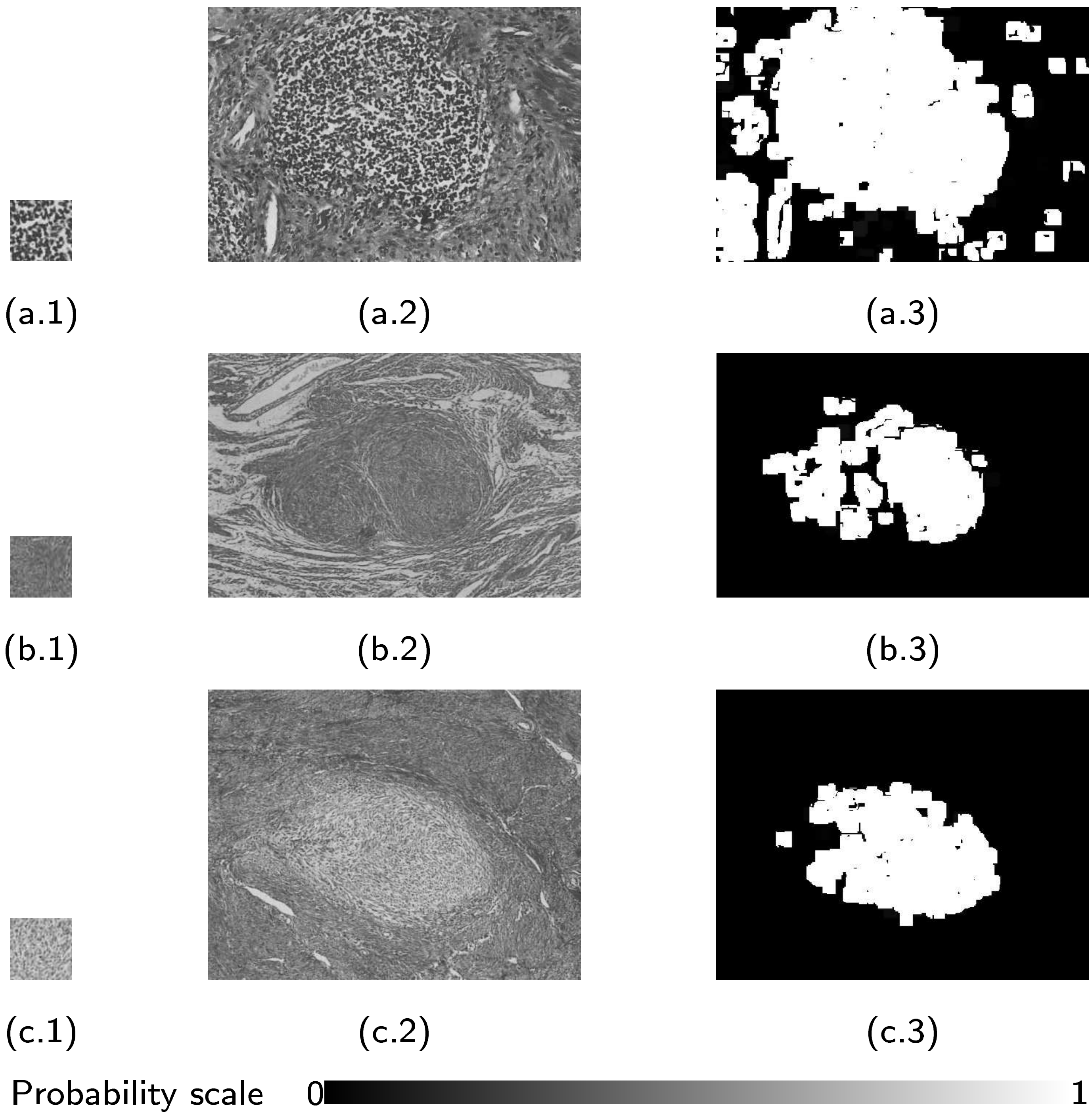


Figure 11: Probability maps of medical images: (a) lymphoid follicle in the cervix; (b) small myoma; (c) focus of stromal differentiation in the myometrium.

Practical Application

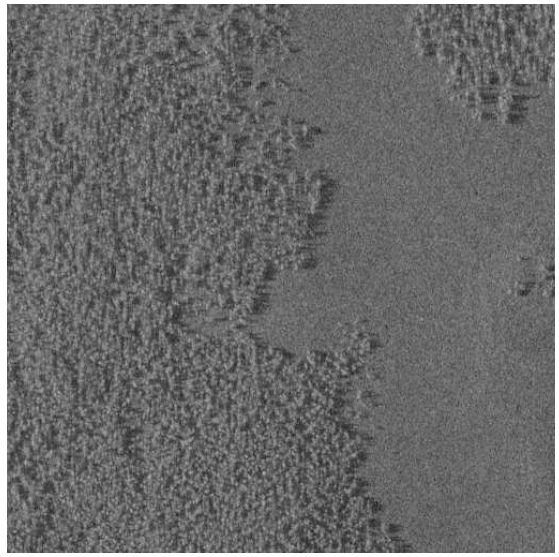


Figure 12: Airborne SAR image of Cultana.

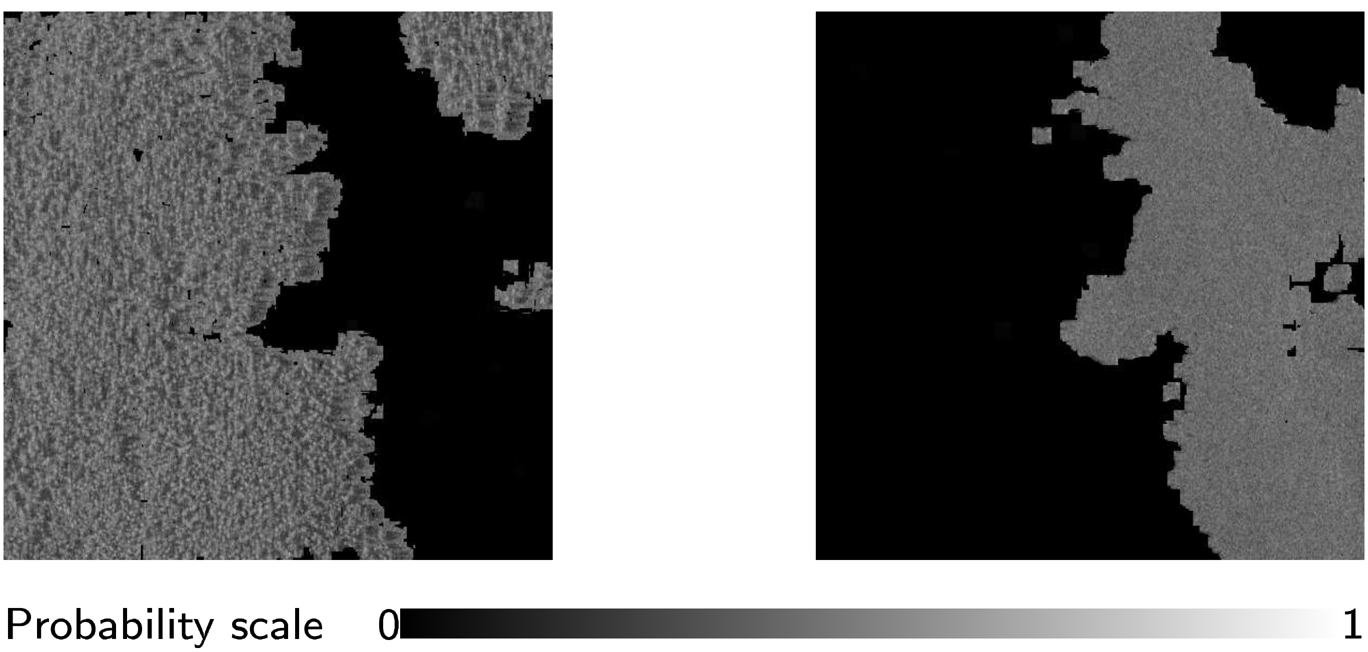


Figure 13: Probability maps of the trees and grass superimposed on to Cultana image.