Open-Ended Texture Classification for Terrain Mapping

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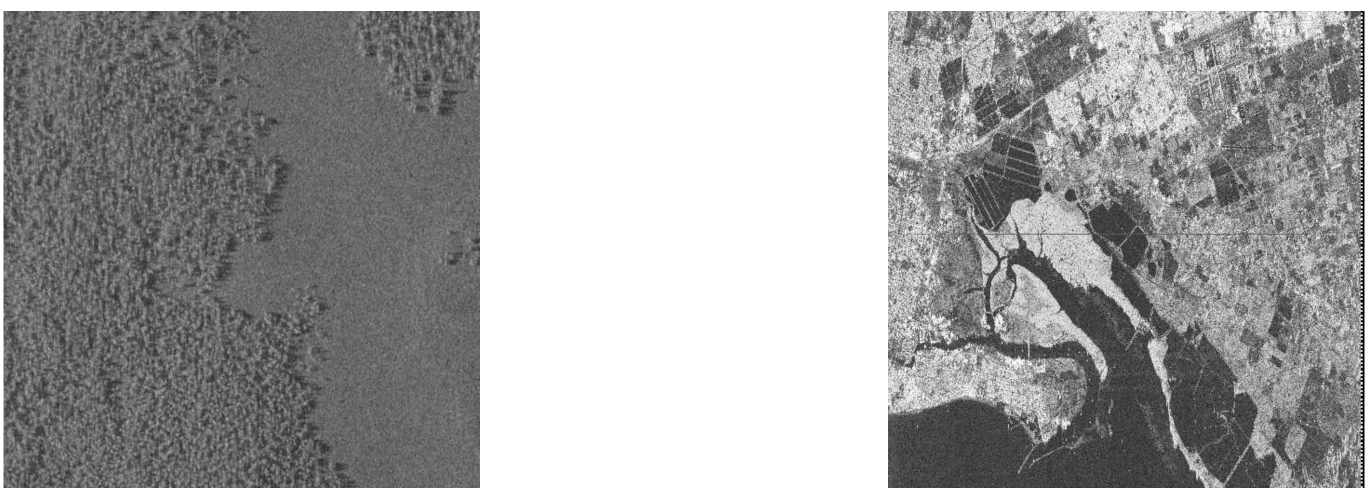
This work was supported by the Cooperative Research Centre for Sensor, Signal, and Information Processing.

Introduction

- The standard texture classifier uses a closed n-class classifier based on the Bayesian paradigm [1].
- These perform supervised classification, whereby all the texture classes have to be predefined [2].
- Under such an arrangement, each unknown texture is classified into one of these predetermined classes.
- The problem comes when there is no guarantee that all the required texture classes have been predefined. Consider for example, Synthetic Aperture Radar (SAR) images of Earth's terrain.



(a) Cultana, Australia (b) Adelaide, Australia

Figure 1: SAR images show the possibility of terrain identification.

SAR Terrain Recognition

Advantages of using SAR: Airborne or spaceborne SAR systems are particularly attractive because they are not affected by atmospheric conditions or the degree of light present (unlike LANDSAT or SPOT).

Terrain mapping of SAR: The terrain identification process, as used on the LANDSAT and SPOT images, is not as easily implemented on the SAR images.

- Limited number of frequency bands.
- Lower resolution.
- Presence of noise called "speckle".

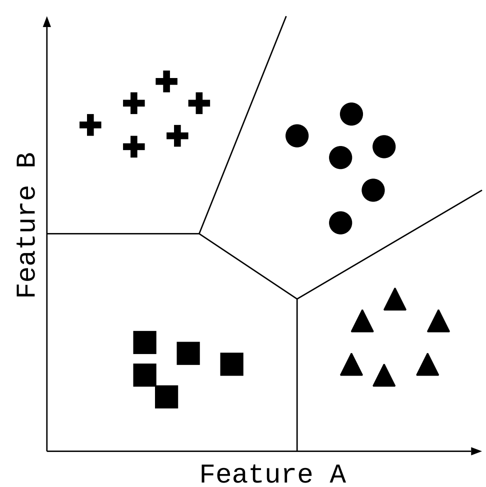
Best Option: It is evident from inspecting different SAR images, as in Fig. 1, that certain types of terrain have unique textural patterns associated with them.

Previous work: Supervised texture classification of SAR images have already achieved quite a degree of success [3].

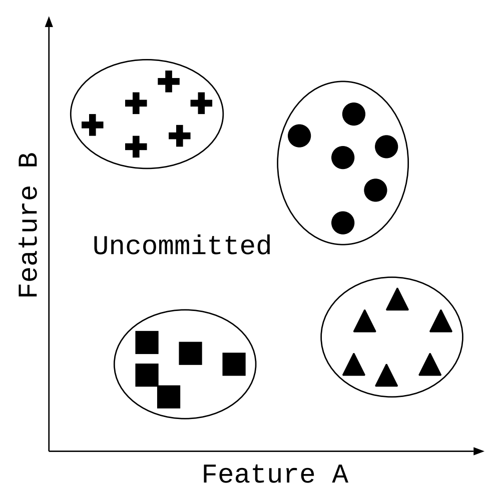
Problem: However there still remains the problem that supervised classification requires all of its classes to be predefined.

Proposed Scheme

- We present a new approach to this extreme multi-class problem.
- A new classification scheme called "open-ended" texture classification.
- This scheme is based on a significance test.
- Whereby the assumption is that the feature space is complete, and that every class can be individually modelled in its own unique space.



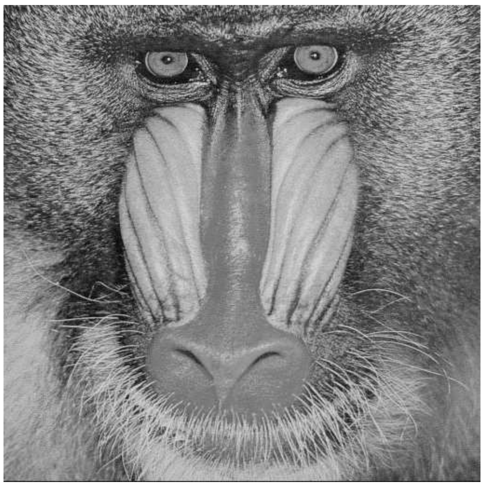
(a) Conventional N class classifier



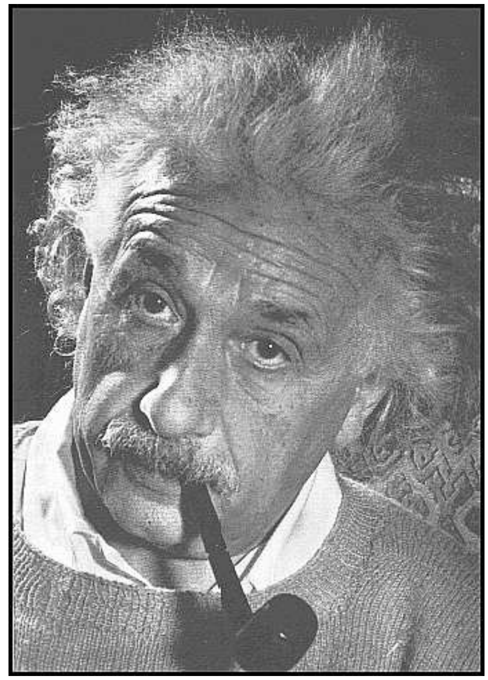
(b) open-ended classifier

Figure 2: Opened and closed classifiers

Texture Model Requirements



(a) Baboon



(b) Einstein

Figure 3: Texture in images can represent different types of hair, skin, or the jumper someone is wearing.

Requirements: The proposed classification scheme is based on the assumption that their exists a texture model which can capture MOST of the unique statistical characteristics of the desired texture class.

Classification: is based on whether or not an unknown texture exhibits significantly similar unique statistical characteristics to a particular texture class.

Chosen Texture Model

- Unfortunately, obtaining a model that captures *all* the unique characteristics specific to a particular texture is still an open problem [4].
- However, a reasonable way to test whether a model has captured all the unique characteristics is to use the model to see if it can synthesise subjectively similar texture.
- Some of the more successful models for synthesising texture have been based on the MRF model [5].
- For Classification, however, a model should maximise its entropy while retaining the unique characteristics of the texture [6].
- That is, it should lower its statistical order while retaining the integrity of its synthesised textures.
- We chose the nonparametric multiscale MRF model.
  - It imposes few constraints on the texture.
  - Can model varying orders of textural 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.

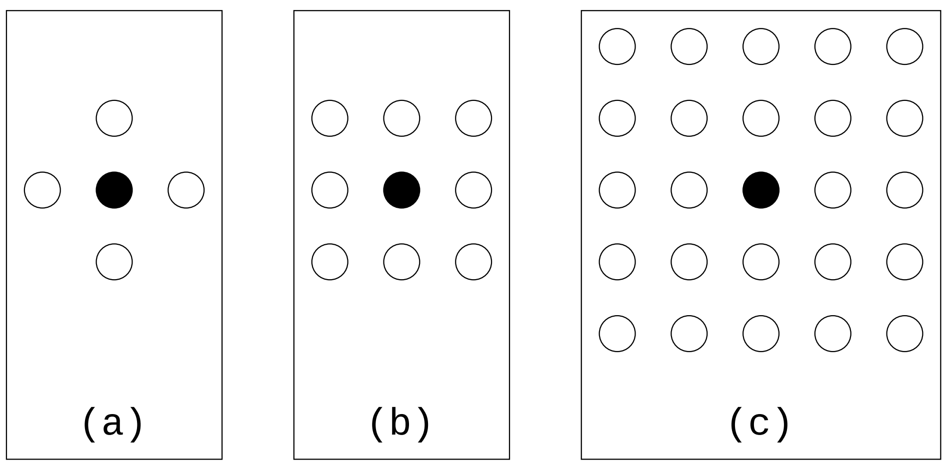


Figure 4: Neighbourhoods. (a) The first order or "nearest-neighbour" neighbourhood; (b) second order neighbourhood; (c) eighth order neighbourhood.

Problem 1 Determining the correct neighbourhood size.

Problem 2 Estimation of the LCPDF [7, 8].

Nonparametric MRF Estimation

Step 1 Choose a neighbourhood size.

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

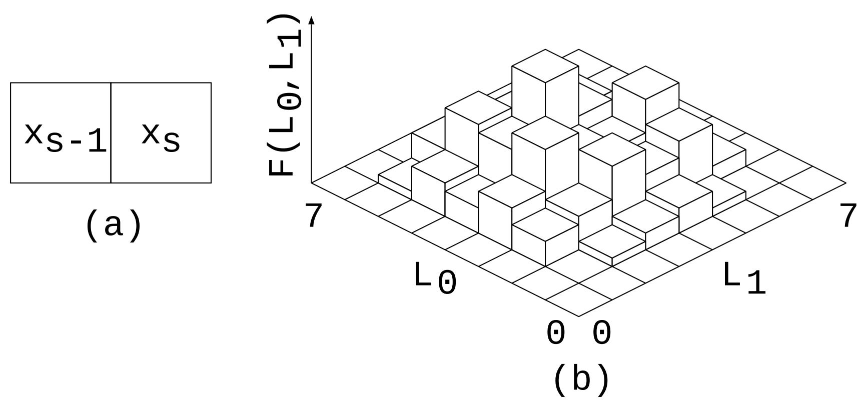


Figure 5: Neighbourhood and its 2-D histogram.

Step 3 Smooth multi-dimensional histogram via nonparametric Parzen density estimation [9].

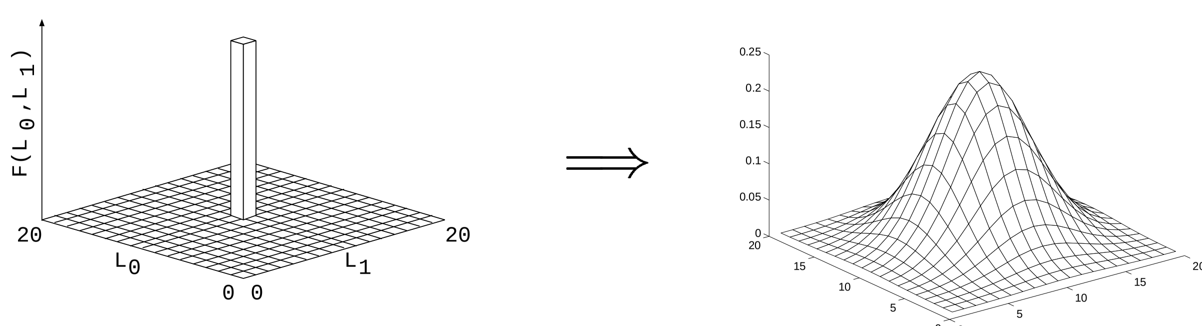


Figure 6: Histogram point is convolved with Gaussian kernel.

Strong Nonparametric MRF

In [10] we showed that we can estimate the LCPDF as a function of its marginal distributions by assuming that there is conditional independence between non-neighbouring sites for any subset of the image lattice.

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

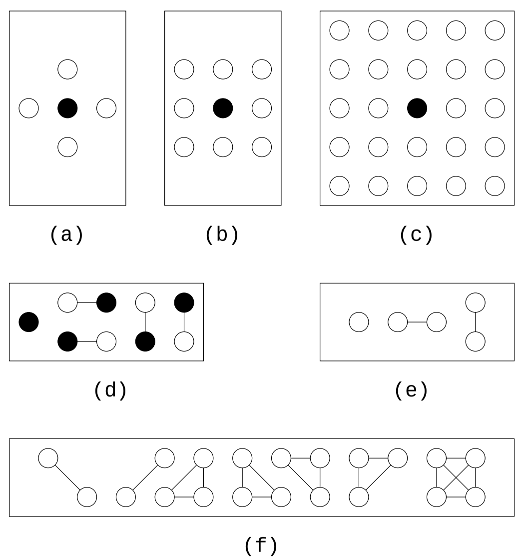


Figure 7: Neighbourhoods and their cliques.

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$_C$.

Multiscale Texture Model

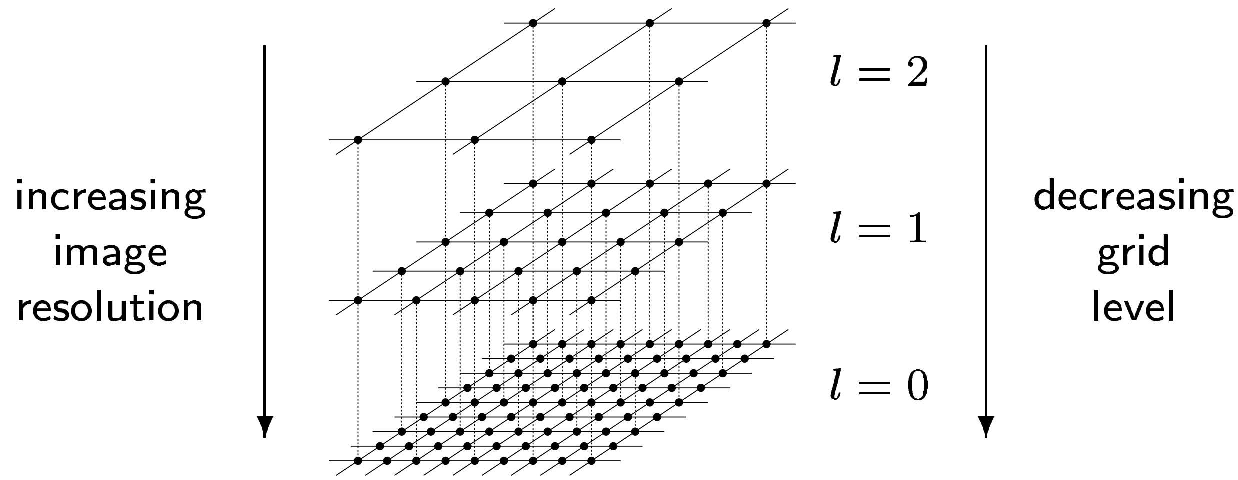


Figure 8: Grid organisation for multiscale modelling of a MRF.

The multiscale synthesis algorithm starts from the top and works its way down performing the following at each resolution [11]:

- Estimation of the LCPDF from original texture at same resolution.
- Applies stochastic relaxation (SR) (*i.e.*, ICM or Gibbs sampler) [12].
- While constraining the SR with respect to the above image [13]. We implemented constrained SR through the use of our own novel pixel temperature function [11] which can be regarded as an implementation of *local annealing* in the relaxation process.

Multiscale Synthetic Textures

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.

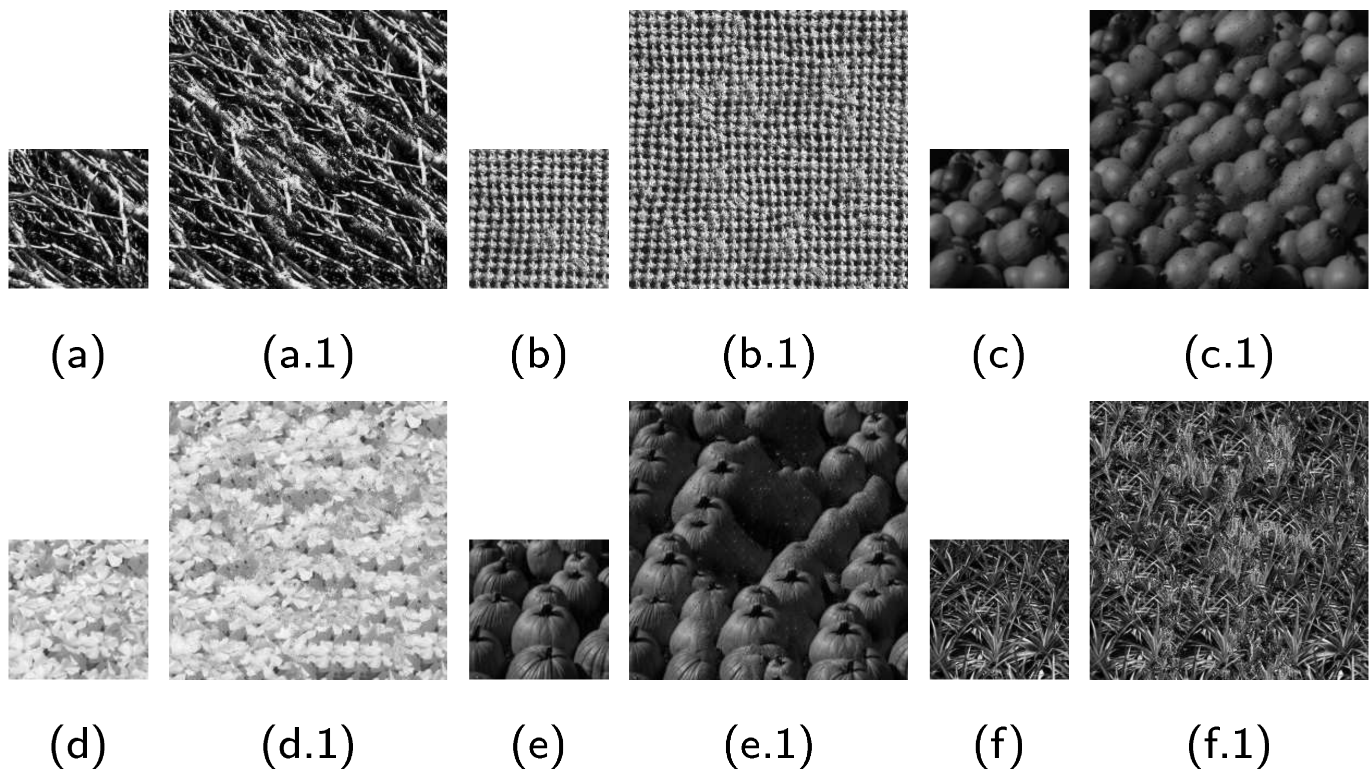


Figure 9: VisTex textures: (a) Bark.0003; (b) Fabric.0008; (c) Food.0011; (d) Flowers.0006; (e) Food.0010; (f) Leaves.0016; (.1) Textures were synthesised from a nonparametric multiscale MRF model with a 7×7 neighbourhood.

Strong MRF Synthetic Textures

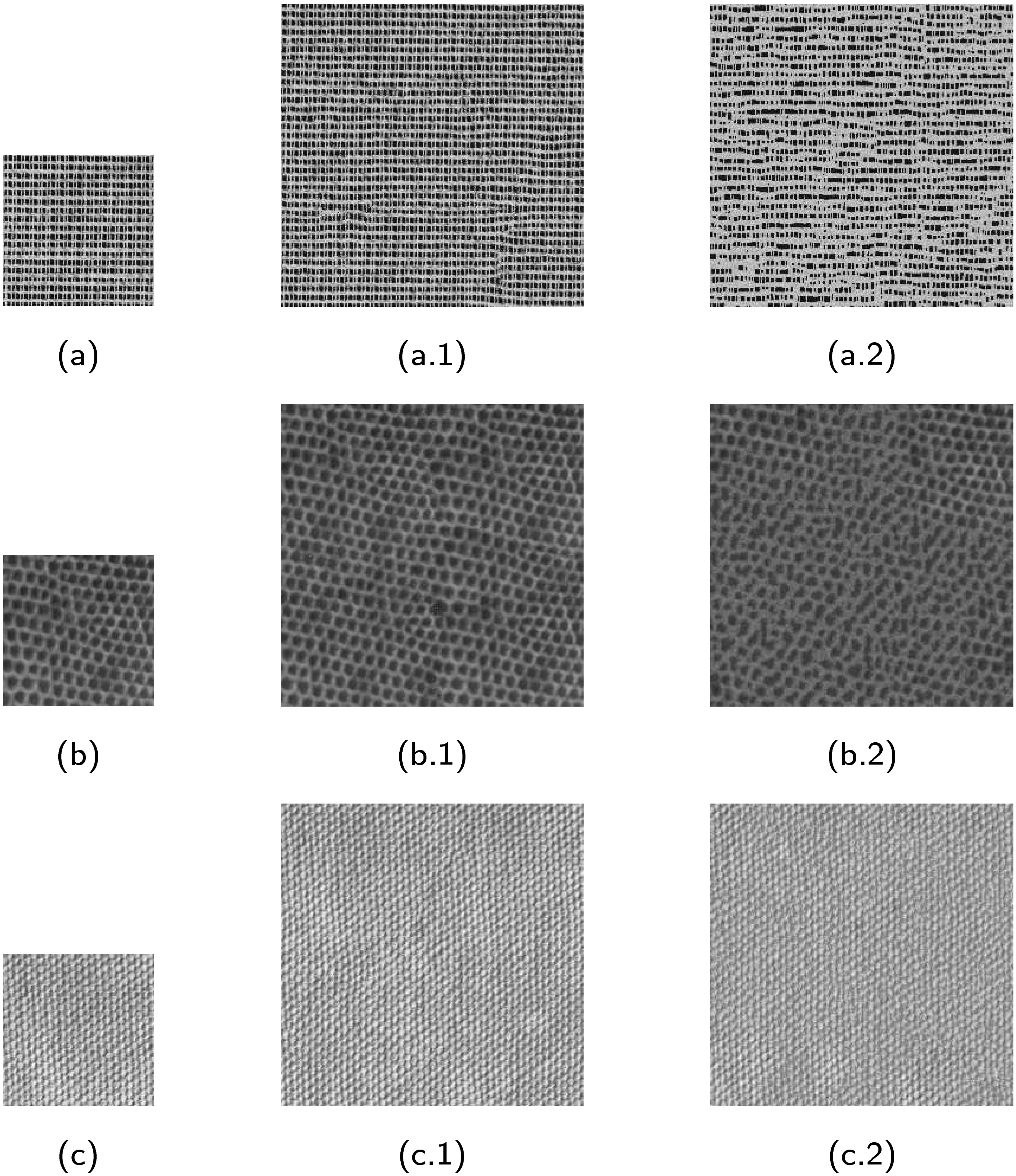


Figure 10: Brodatz textures: (a) D21 - French canvas; (b) D22 - Reptile skin; (c) D77 - Cotton canvas; (-.1) textures synthesised with MRF Model; (-.2) textures synthesised with Strong MRF Model.

Open-ended Texture Classification

- To perform open-ended texture classification we first build an LCPDF from the training texture.
- This LCPDF is then used to collect probabilities from an unknown texture and a training texture.
- The classification is then made by performing a significance test on whether the two sets of probabilities are from the same population.
- We used the nonparametric Kruskal-Wallis test [14] to test this null hypothesis.
- A significance test for the classification process was deemed possible if the LCPDF involved in collecting the probabilities was able to reproduce similar synthetic textures to the training texture.
- This ensured that the statistics, or features, involved in the classification were unique to the texture class.
- A texture with significantly similar unique statistical characteristics would then be deemed to be of the same class.

Open-ended Classified Textures

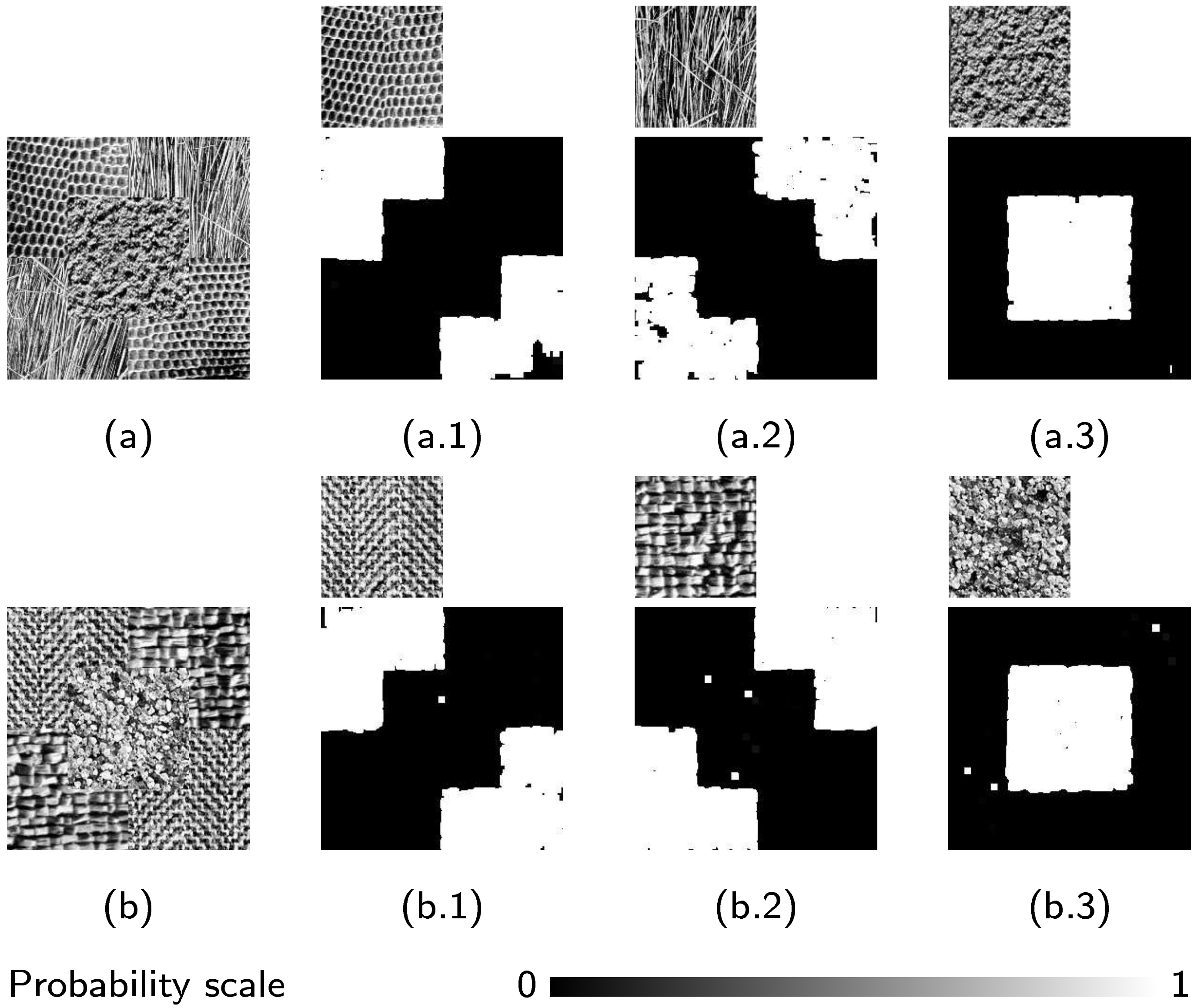


Figure 11: Probability maps of Brodatz texture mosaics (a) and (b) with respect to: (a.1) D3 - Reptile skin; (a.2) D15 - Straw; (a.3) D57 - Handmade paper; (b.1) D17 - Herringbone weave; (b.2) D84 - Raffia; and (b.3) D29 - Beach sand.

Analysis of Performance

Table 1: Percentage error for open-ended texture classification of 100 VisTex texture mosaics = percentage area of false negatives + percentage area of false positives. VisTex Texture mosaics courtesy of Computer Vision Group at the University Bonn [15], and Vision Texture Archive of the MIT Media Lab

Neighbourhood Size	*Clique Size*	*Multigrid Height*	*Percentage Error*	*Rank*
3×3	2	0	15.67	6
3×3	2	1	12.94	1
3×3	2	2	13.85	3
3×3	2	3	18.33	8
3×3	3	0	23.70	18
3×3	3	1	18.58	10
3×3	3	2	17.62	7
3×3	3	3	21.80	17
3×3	-	0	24.04	20
3×3	-	1	19.45	12
3×3	-	2	18.40	9
3×3	-	3	21.79	16
5×5	2	0	14.69	4
5×5	2	1	13.48	2
5×5	2	2	15.22	5
5×5	2	3	21.55	15
5×5	3	0	21.45	14
5×5	3	1	18.74	11
5×5	3	2	19.46	13
5×5	3	3	25.48	22
5×5	-	0	25.54	23
5×5	-	1	24.38	21
5×5	-	2	23.98	19
5×5	-	3	30.33	24

Practical Application

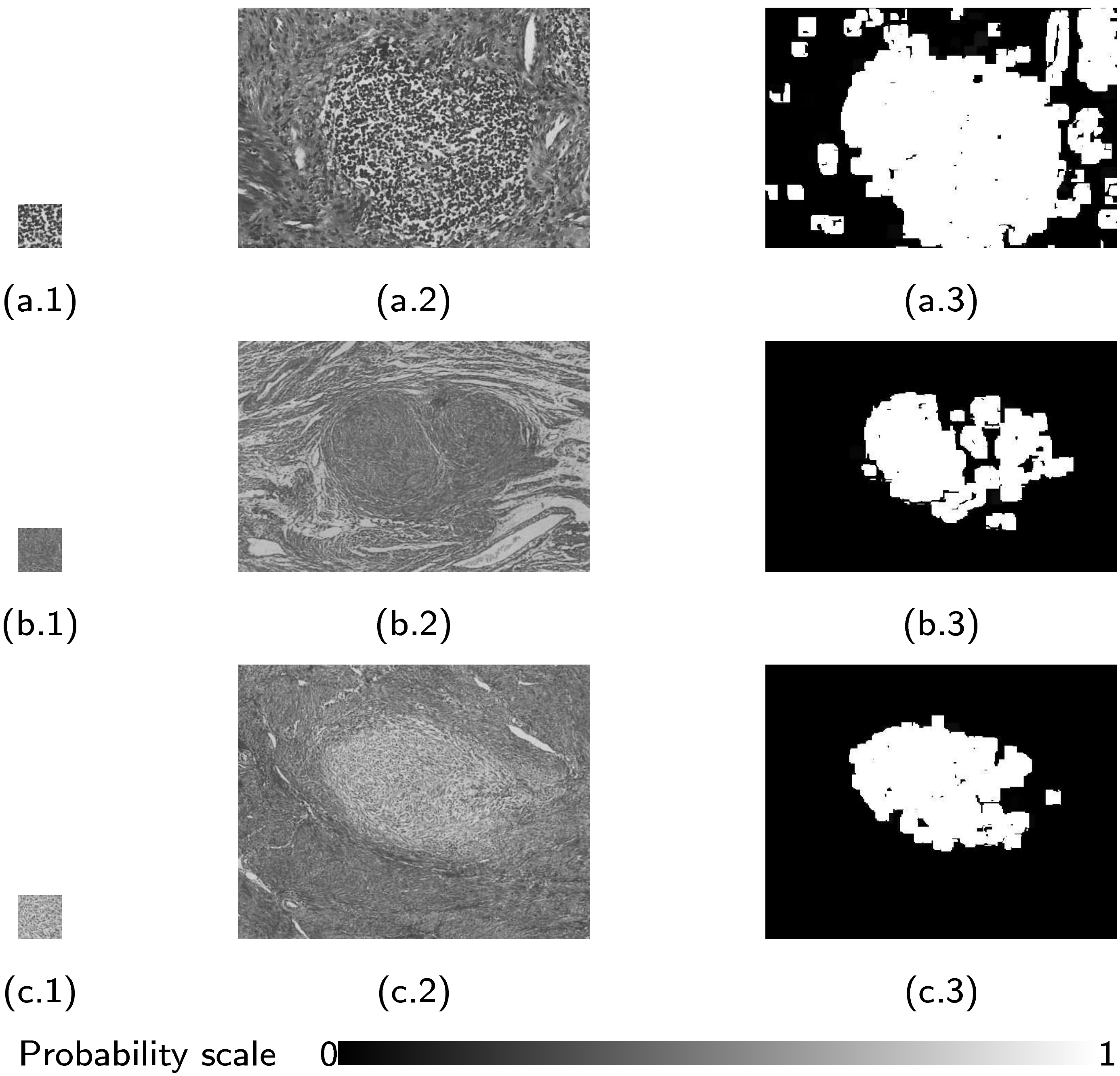
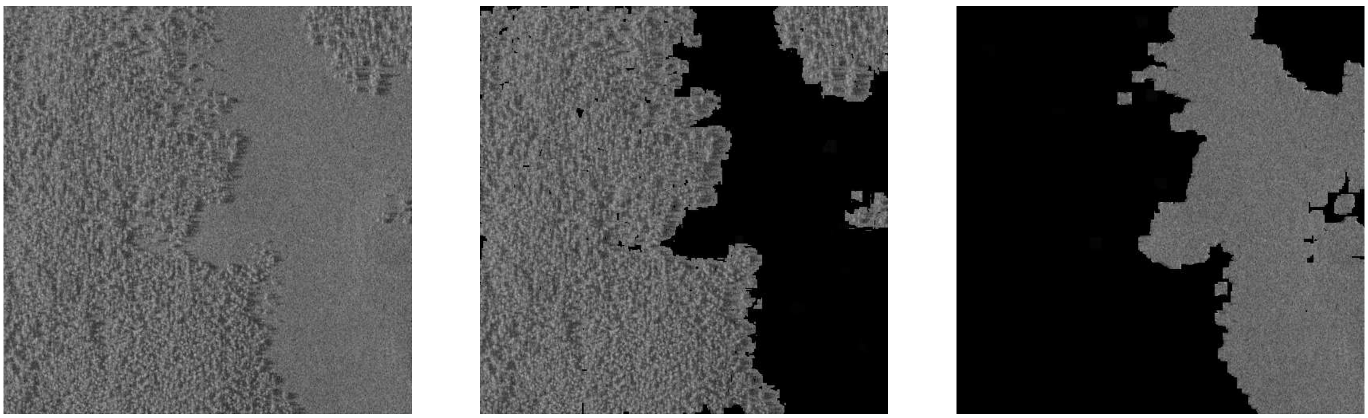


Figure 12: Probability maps of medical images: (a) lymphoid follicle in the cervix; (b) small myoma; (c) focus of stromal differentiation in the myometrium.

Practical Application



(a) (b) (c)

Figure 13: Airborne SAR image of Cultana [16] with the probability maps of the trees and grass superimposed.

The practical application of terrain mapping a SAR image of Cultana, Fig. 13, shows the two results if: 1) the training class was a patch of trees from the bottom left corner, Fig. 13(b); or 2) the training class was a patch of grass from the bottom right corner, Fig. 13(c). In both cases the resulting probability maps have been superimposed on to the original SAR image. This gives a clear indication of how the open-ended texture classification has performed.

Summary and Conclusion

- We were able to use our nonparametric MRF model to synthesise realistic realisations of a training texture.
- It was with this evidence that we concluded that the nonparametric multiscale MRF model captured most of the unique characteristics specific to a particular texture.
- With such a model it became feasible to recognise other similar textures from an image containing multiple unknown textures.
- The model was used to determine the probability that an unknown texture was similar to a training texture with respect to its unique statistical characteristics, thereby performing open-ended texture classification.
- This technique is considered potentially valuable in the practical application of terrain mapping of SAR images.

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