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Nonparametric Markov Random Field Model Analysis of the MeasTex Test Suite

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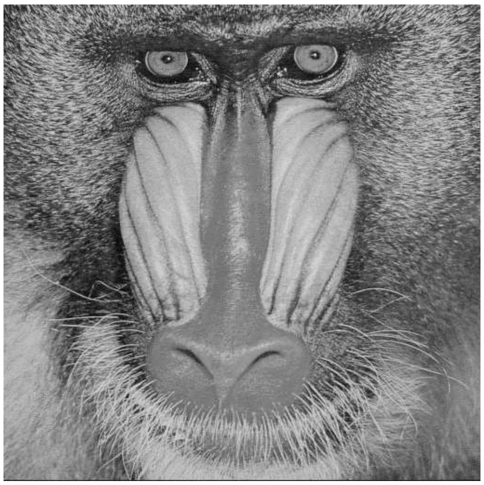
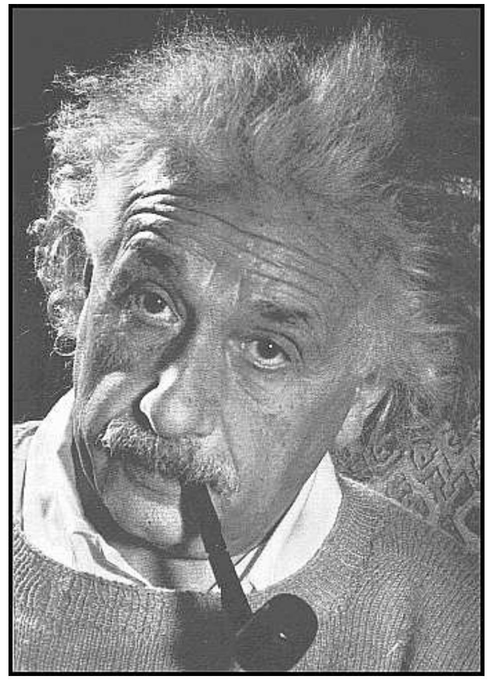
Abstract

This paper looks at the nonparametric, multiscale, Markov Random Field (MRF) model and its application in classifying the MeasTex Test Suite. The MeasTex Test Suite is a standard by which various texture classification algorithms can be compared. Typically, todays texture classification algorithms have been based on supervised classification, whereby all the classification classes have been predefined. We look at a new texture classification scheme, one that does not require a complete set of predefined classes. Instead our texture classification scheme is based on a significance test. A texture is classified on the basis of whether or not its statistical properties can be deemed to be from the same population of statistics as that define a training set texture. If not, texture is deemed unknown. The advantages and disadvantages of such a scheme are discussed in this paper.

Texture in Images



(a) Baboon



(b) Einstein

Figure 1: Texture in images can represent different types of hair, skin, or the jumper someone is wearing.

Aim To find a model that is capable of capturing a large portion of the unique characteristics of a texture for "open-ended" classification.

Method Use a nonparametric multiscale Markov random field texture model.

Advantages

- Imposes few underlying constraints on the texture.
- Only requires a small amount of sample data.
- Can easily 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.

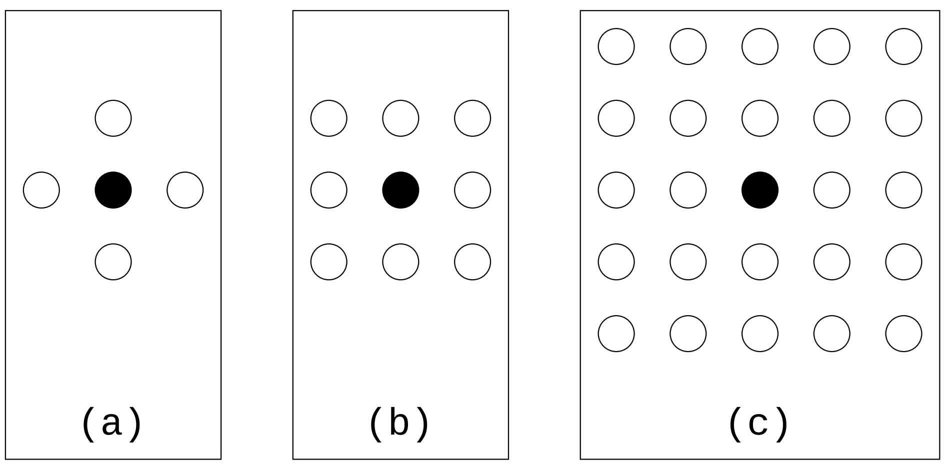


Figure 2: Neighbourhoods. (a) The first order or "nearest-neighbour" neighbourhood; (b) second order neighbourhood; (c) eighth order neighbourhood.

Problem 1 Determining the correct neighbourhood size.

Problem 2 Estimation of the LCPDF [3, 7].

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:

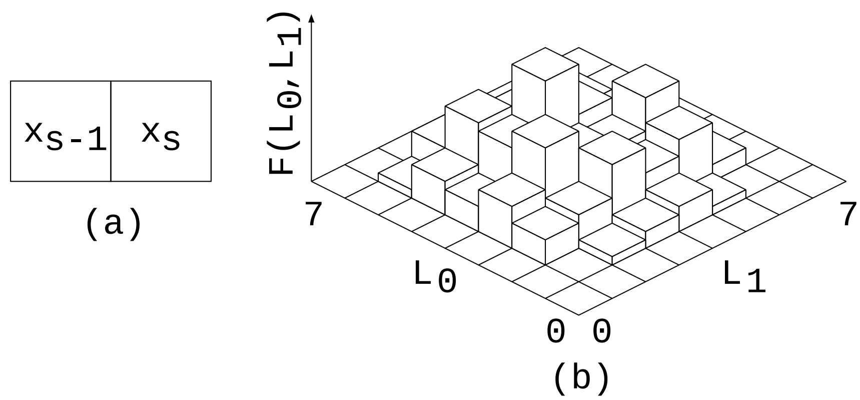


Figure 3: Neighbourhood and its 2-D histogram.

Step 3 Smooth multi-dimensional histogram via nonparametric Parzen density estimation [8].

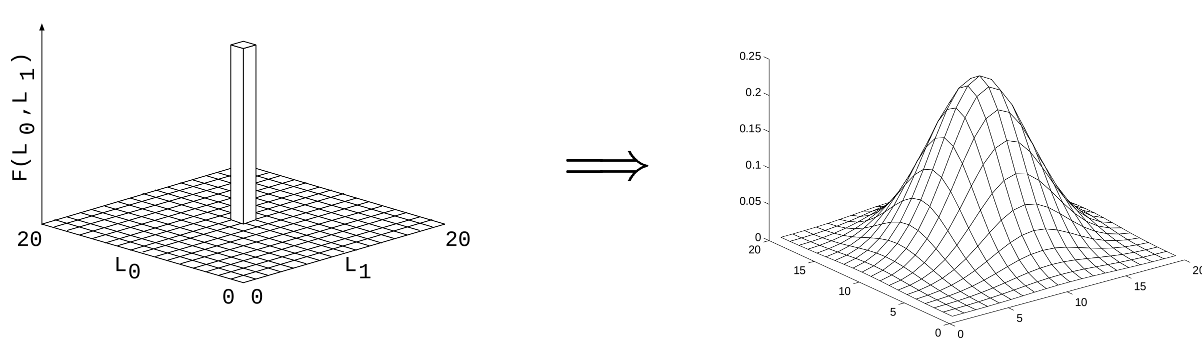


Figure 4: Histogram point is convolved with Gaussian kernel.

Strong Nonparametric MRF

In [5] 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 $\mathcal{N}_s$.

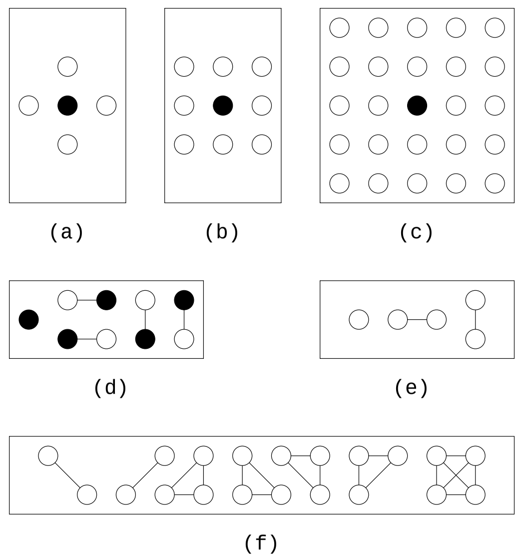


Figure 5: Neighbourhoods and their cliques.

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,

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

Multiscale Texture Model

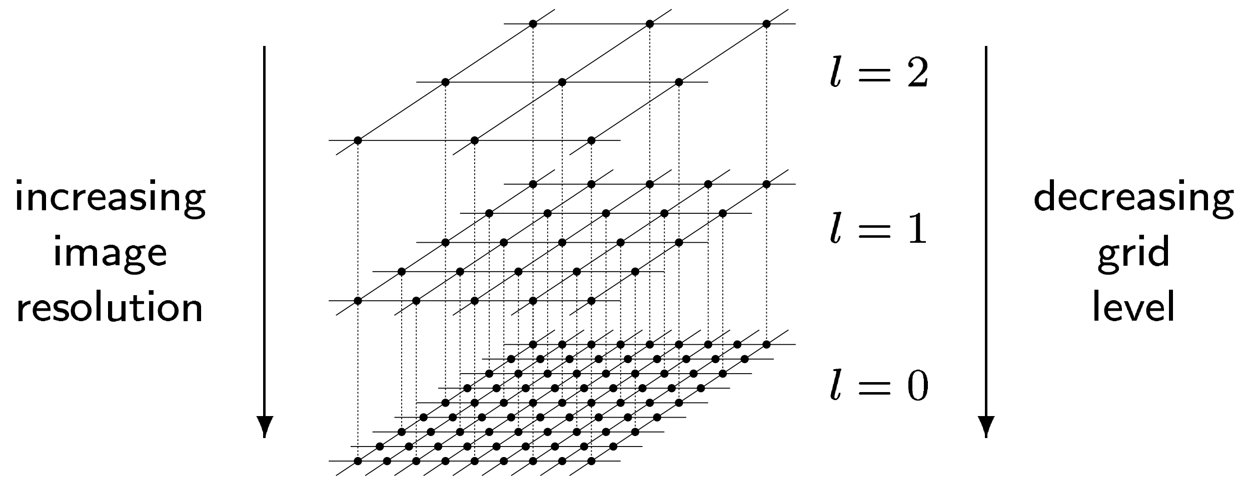


Figure 6: Grid organisation for multiscale modelling of a MRF.

The multiscale synthesis algorithm starts from the top and works its way down performing the following at each resolution [6]:

- Estimation of the LCPDF from original texture at same resolution.
- Applies stochastic relaxation (SR) (*i.e.*, ICM or Gibbs sampler) [1].
- While constraining the SR with respect to the above image [2]. We implemented constrained SR through the use of our own novel pixel temperature function [6] which can be regarded as an implementation of *local annealing* in the relaxation process.

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.

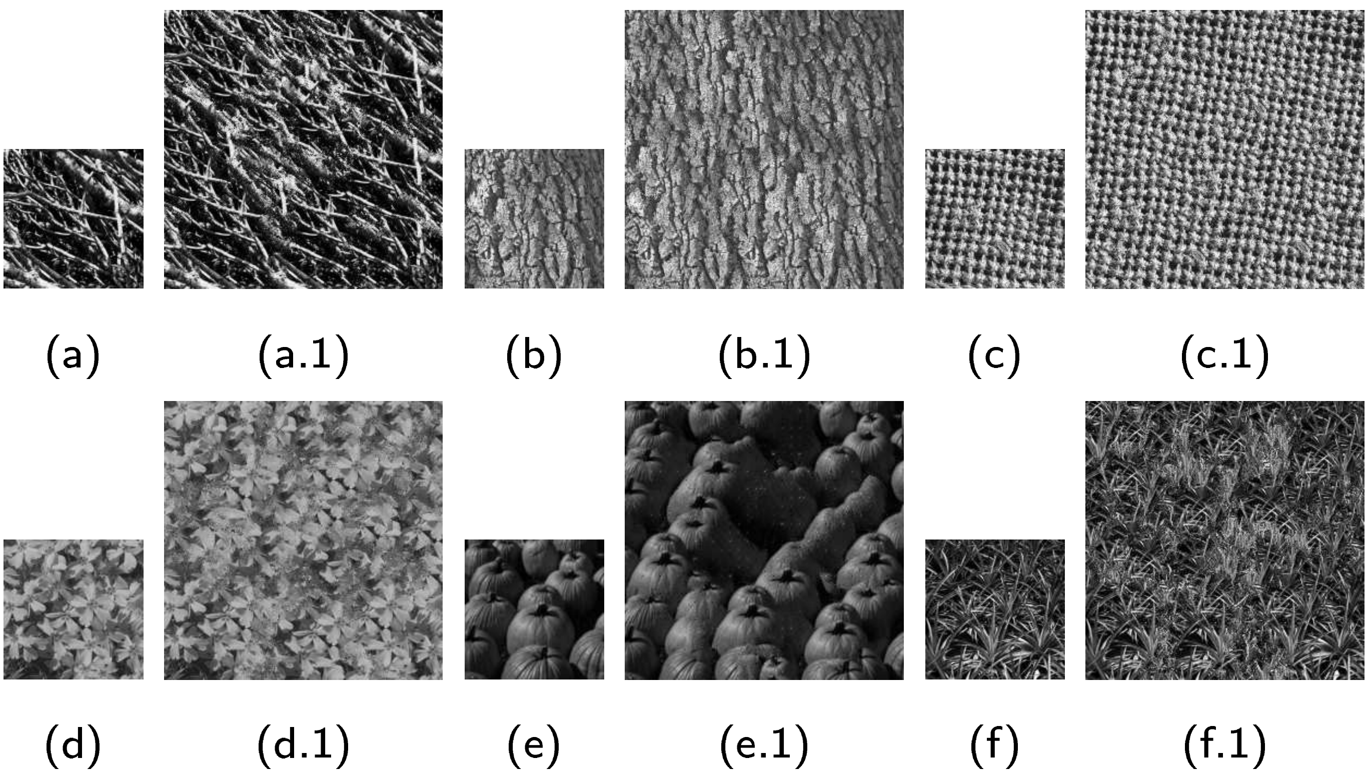


Figure 7: VisTex textures: (a) Bark.0003; (b) Bark.0009; (c) Fabric.0010; (d) Flowers.0003; (e) Food.0010; (f) Leaves.0016; (?.1) Textures were synthesised from a nonparametric MRF model with a 7×7 neighbourhood.

Open-ended Texture Classification

To perform open-ended texture classification for a texture from the MeasTex Test Suite [9], we first built an LCPDF from the training texture. This LCPDF was then used to collect probabilities from the unknown texture and the training texture. The classification was made by using a significance test on whether the two sets of probabilities were from the same population. We used the nonparametric Kruskal-Wallis test [4] to test this null hypothesis. This classification process was deemed possible when the LCPDF involved in collecting the probabilities was able to reproduce synthetic textures similar to the training texture. This ensured that the statistics, or features, involved in the classification were unique to the texture class. Any texture with similar unique statistical characteristics would be of the same class.

Although we were able to make a yes/no classification directly from the Kruskal-Wallis hypothesis test, the MeasTex Test Suite [9] required a probability associated with the classification. As the Kruskal-Wallis hypothesis test returned a value that was chi-squared-distributed with one degree of freedom, the probability we returned was the probability of recording a larger chi-squared-distributed value [5].

Open-ended Classified Textures

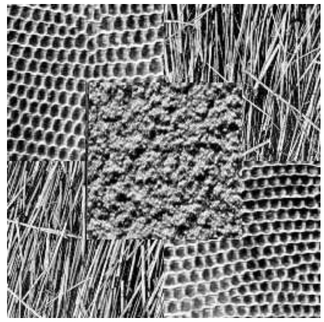
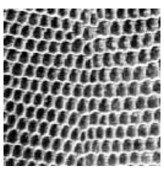


Fig. 1

Fig. 2



(a)

Fig. 1(a)

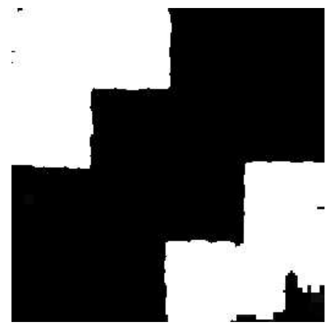
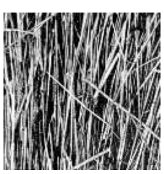


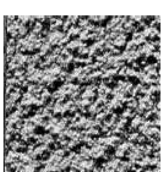
Fig. 2(a)



(b)

Fig. 1(b)

Fig. 2(b)



(c)

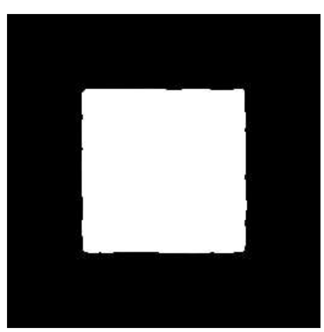


Fig. 1(c)

Fig. 2(c)

Probability scale 0  1

MeasTex Test Suite Summary Scores

Table 1: MeasTex test suite summary scores

Model	Test Suites: *Grass*	*Material*	*OhanDube*	*VisTex*	*All*	*Rank*
MRF-n1t0	.732157	.767600	.680725	.680725	.723510	11
MRF-n1t1	.743578	.785322	.674175	.731708	.733695	8
MRF-n1t2	.764700	.784077	.677600	.747062	.743359	3
MRF-n1t3	.766828	.788995	.653425	.748470	.739429	4
MRF-n3c2t0	.638350	.687390	.604525	.650675	.645235	21
MRF-n3c2t1	.629728	.680813	.600075	.674262	.646219	19
MRF-n3c2t2	.621550	.678654	.589850	.692154	.645552	20
MRF-n3c2t3	.598307	.673072	.589975	.696625	.639494	22
MRF-n3c3t0	.720214	.776863	.691475	.709325	.724469	10
MRF-n3c3t1	.729285	.781795	.694400	.730533	.734003	7
MRF-n3c3t2	.747414	.789036	.690425	.749175	.744012	2
MRF-n3c3t3	.754221	.792018	.697400	.748270	.747977	1
MRF-n3t0	.733535	.761781	.668525	.705537	.717344	12
MRF-n3t1	.746742	.782454	.665350	.722929	.729368	9
MRF-n3t2	.766721	.788022	.650625	.742450	.736954	5
MRF-n3t3	.763900	.795795	.640075	.745591	.736340	6
MRF-n5c2t0	.659707	.681550	.601325	.668487	.652767	17
MRF-n5c2t1	.653392	.678340	.597475	.687891	.654274	16
MRF-n5c2t2	.643614	.677272	.586175	.689083	.649036	18
MRF-n5t0	.686642	.726740	.670875	.677470	.690431	14
MRF-n5t1	.678828	.737050	.649075	.699741	.691173	13
MRF-n5t2	.689757	.748400	.621250	.700987	.690098	15

MRF model key: n: is the neighbourhood index, referring to the max distance from the centre pixel. c: indexes the maximum statistical order (clique size) used in the strong MRF model. t: is the multigrid height index.

Comparative Assessment

Table 2: MeasTex test suite summary scores

Model	*Test Suites*					*Rank*
	Grass	*Material*	*OhanDube*	*VisTex*	*All*	
Fractal	.906778	.908636	.904875	.813645	.883483	8
Gabor1	.889978	.967772	.978875	.906591	.935804	3
Gabor2	.880185	.955313	.985975	.898791	.930066	5
GLCM1	.891328	.944863	.883100	.820283	.884893	7
GLCM2	.916157	.964986	.866675	.852266	.900021	6
GMRF-std1s	.917492	.966918	.972000	.885616	.935506	4
GMRF-std2s	.917971	.977545	.991125	.932058	.954674	2
GMRF-std4s	.948892	.969340	.988175	.932437	.959711	1

The results in Table 1 for the nonparametric MRF models can be directly compared to the results in Table 2 for the fractal, Gabor, GLCM, and Gaussian MRF models. The structure of these models are given in [9]. Even the worst performing standard model (the Fractal model) does better than the best nonparametric MRF model (and is computationally more efficient). What this shows is that our method of open-ended texture classification is outperformed by the standard supervised classification techniques when the all the required texture classes are known.

Analysis of Performance

Table 3: Average rank for various neighbourhoods

Neighbourhood Size	*Except clique models*	*All models*
nearest 4	6.50	6.50
3×3	8.00	11.17
5×5	14.00	15.50

Table 4: Average rank for various clique sizes

Clique Size	*N3 models*	*All models*
2	20.50	19.00
3	5.00	5.00
-	8.00	9.09

Table 5: Average rank for various multigrid heights

Multigrid Height	*Except clique models*	*All models*
1	12.33	14.17
2	10.00	12.00
3	7.67	10.50
4	5.00	8.25

These tables (which show the general effect of varying one of the MRF model's specifications) give an expected optimal MRF model as the one identified in Table 1. We can therefore surmise that these variables are relatively independent. The optimisation result is also fairly general, as no functional framework was imposed on the model.

Practical Application

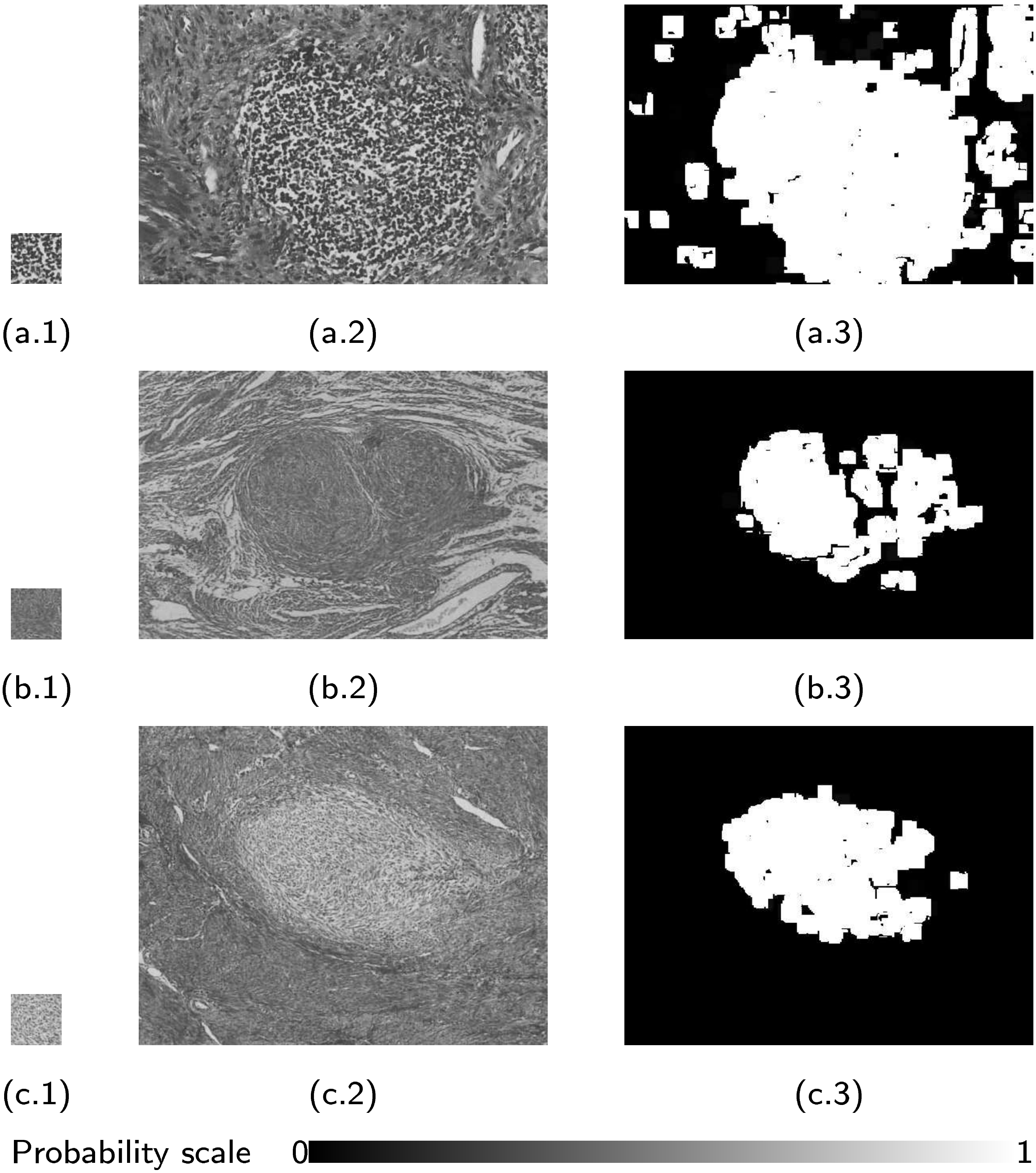


Figure 8: Probability maps of medical images: (a) lymphoid follicle in the cervix; (b) small myoma; (c) focus of stromal differentiation in the myometrium.

Practical Application

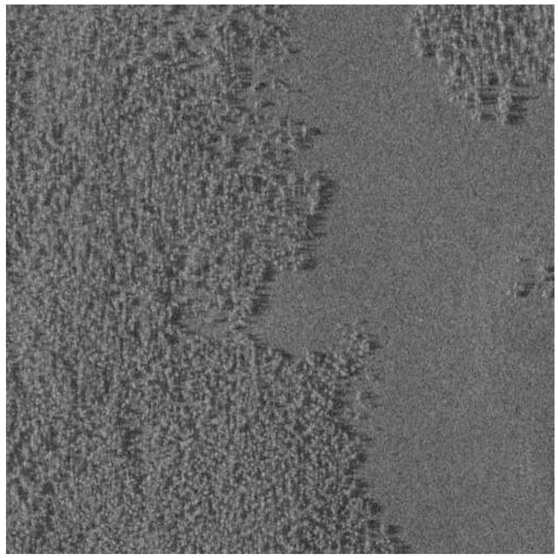


Figure 9: Airborne SAR image of Cultana.

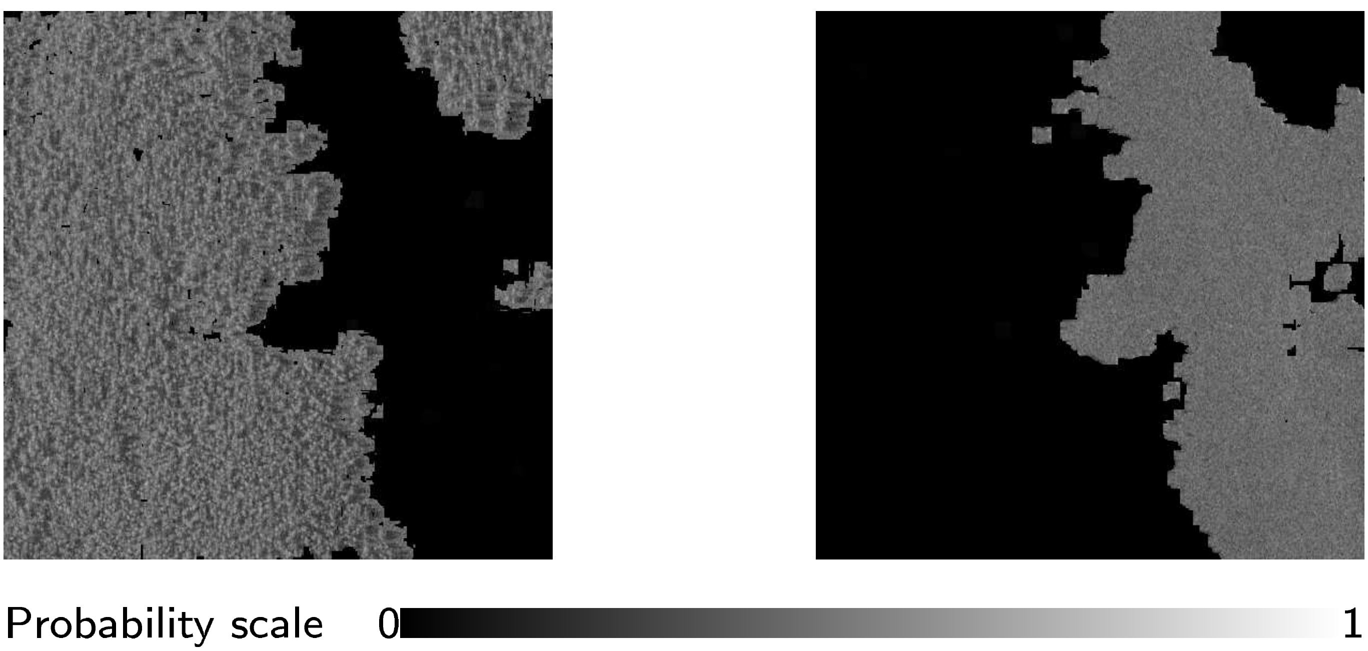


Figure 10: Probability maps of the trees and grass superimposed on to Cultana image.

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 MRF model captured all 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.

References

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