OPEN-ENDED TEXTURE CLASSIFICATION FOR TERRAIN MAPPING

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ABSTRACT

This paper introduces a new classification scheme called "open-ended texture classification." The standard approach for texture classification is to use a closed n-class classifier based on the Bayesian paradigm. These perform supervised classification, whereby all the texture classes have to be predefined. We propose 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 are deemed to be from the same population of statistics as those that define a specific texture class. This new "open-ended texture classification" is considered potentially valuable in the practical application of terrain mapping of Synthetic Aperture Radar (SAR) images.

1. INTRODUCTION

Texture classification has generally been accomplished via a supervised method based on the Bayesian paradigm [1]. This entails defining a set of predetermined classes into which a texture can be classified [2]. Under such an arrangement, each unknown texture to be classified must fall within 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, images of Earth's terrain. Texture classification of Earth's terrain from Synthetic Aperture Radar images has many logistical advantages [3]. However from a implementation point of view, it is hard to predefine the types of textured terrains that a Synthetic Aperture Radar images is liable to visualise. Therefore the standard texture classification algorithm predominantly fails at this task.

We present a new approach to this extreme multi-class problem. The proposed classification scheme is based on the assumption that their exists a texture model which can capture the unique statistical characteristics of the desired texture class. Given such a model, a classification can be made on the basis of whether or not an unknown texture exhibits significantly similar unique statistical characteristics as compared to the desired texture class. Either the unknown texture belongs to this class or it does not. In this way, when a texture is being classified, not all the texture classes need to be predefined. In fact the classification algorithm is open to textures that do not fit any predefined class. These textures are just left as "unknown". This is a much better scenario than labelling an unknown texture as a predefined class when it is not.

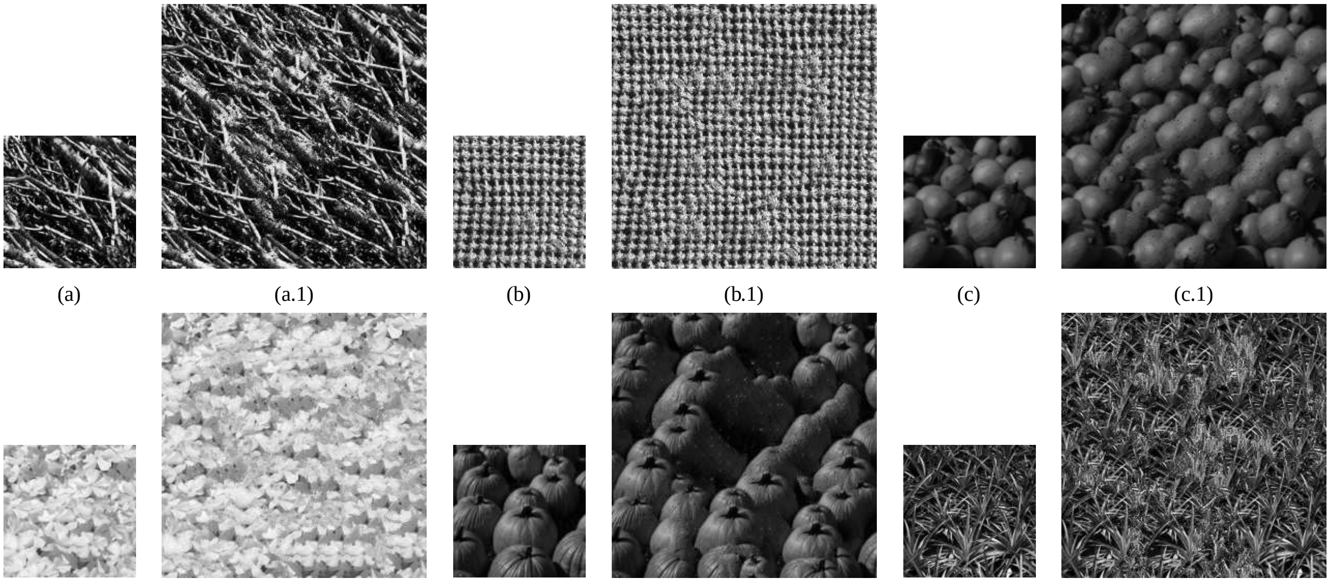
In [4], we presented a nonparametric multiscale MRF texture model. From this model we were able to synthesise multiple natural textures with high fidelity. Examples of the reproduction qualities are given in Fig. 1. From this experiment, and many more, we ascertained that the nonparametric multiscale MRF model captured the unique characteristics of the textures. Therefore we have a model that can be used for our new type of classification method we have termed "open-ended texture classification."

2. NONPARAMETRIC MULTISCALE MRF MODEL

The nonparametric multiscale MRF model is based on estimating the local conditional probability density function (LCPDF) from a multi-dimensional histogram of a neighbourhood over a homogeneous textured image [4]. When the sample data is sparsely dispersed over the multi-dimensional histogram domain (as in our case), nonparametric estimates of the LCPDF tend to be more reliable than their parametric counterparts if the underlying true distribution is unknown [5].

3. MULTISCALE TEXTURE SYNTHESIS

To synthesis a texture we used our multiscale relaxation (MR) algorithm as formalised in [4]. The basis of the algorithm is to perform stochastic relaxation (SR) at the coarsest resolution, and then successively at each finer resolution to perform constrained SR with respect to the result from



(a) (a.1) (b) (b.1) (c) (c.1)

(d) (d.1) (e) (e.1) (f) (f.1)

Fig. 1. 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.

the previous resolution [6]. In our implementation, we performed constrained SR via our own novel pixel temperature function [4], which can be regarded as an implementation of *local annealing* in the relaxation process.

From training textured images of size 128×128 pixels we estimated the LCPDF and then synthesised images of size 256×256. A subjective comparison of the training and resulting synthetic textures, Fig. 1, shows that the nonparametric multiscale MRF model is a highly representative model for natural textures. The larger synthesised images confirm that the unique characteristics of the training textures have indeed been captured by our model.

4. OPEN-ENDED TEXTURE CLASSIFICATION

To perform open-ended texture classification we first built an LCPDF from the training texture. This LCPDF was then used to collect probabilities from an unknown texture and a training texture. The classification was made by performing a significance test on whether the two sets of probabilities were from the same population. We used the nonparametric Kruskal-Wallis test [7] to test this null hypothesis. A significance test for the classification process was deemed possible when 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. In Table 1, we show the percentage error for open-ended texture classification of 100 VisTex texture mosaics [8].

Although it is possible to make a yes/no classification directly from the Kruskal-Wallis hypothesis test [7], it is also possible to attain a goodness-of-fit measure. As the Kruskal-Wallis hypothesis test returns a value that is chi-squared-distributed with one degree of freedom, the goodness-of-fit is given by the probability of recording a larger chi-squared-distributed value [9]. Fig. 2 shows various probability maps for a texture mosaic and a training texture.

5. PRACTICAL APPLICATION

The practical application of terrain mapping a SAR image of Cultana, Fig. 3, shows the two results if: 1) the training class was a patch of trees from the bottom left corner, Fig. 3(b); or 2) the training class was a patch of grass from the bottom right corner, Fig. 3(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.

6. 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 all the unique characteristics specific to a particular texture. With such a model it became

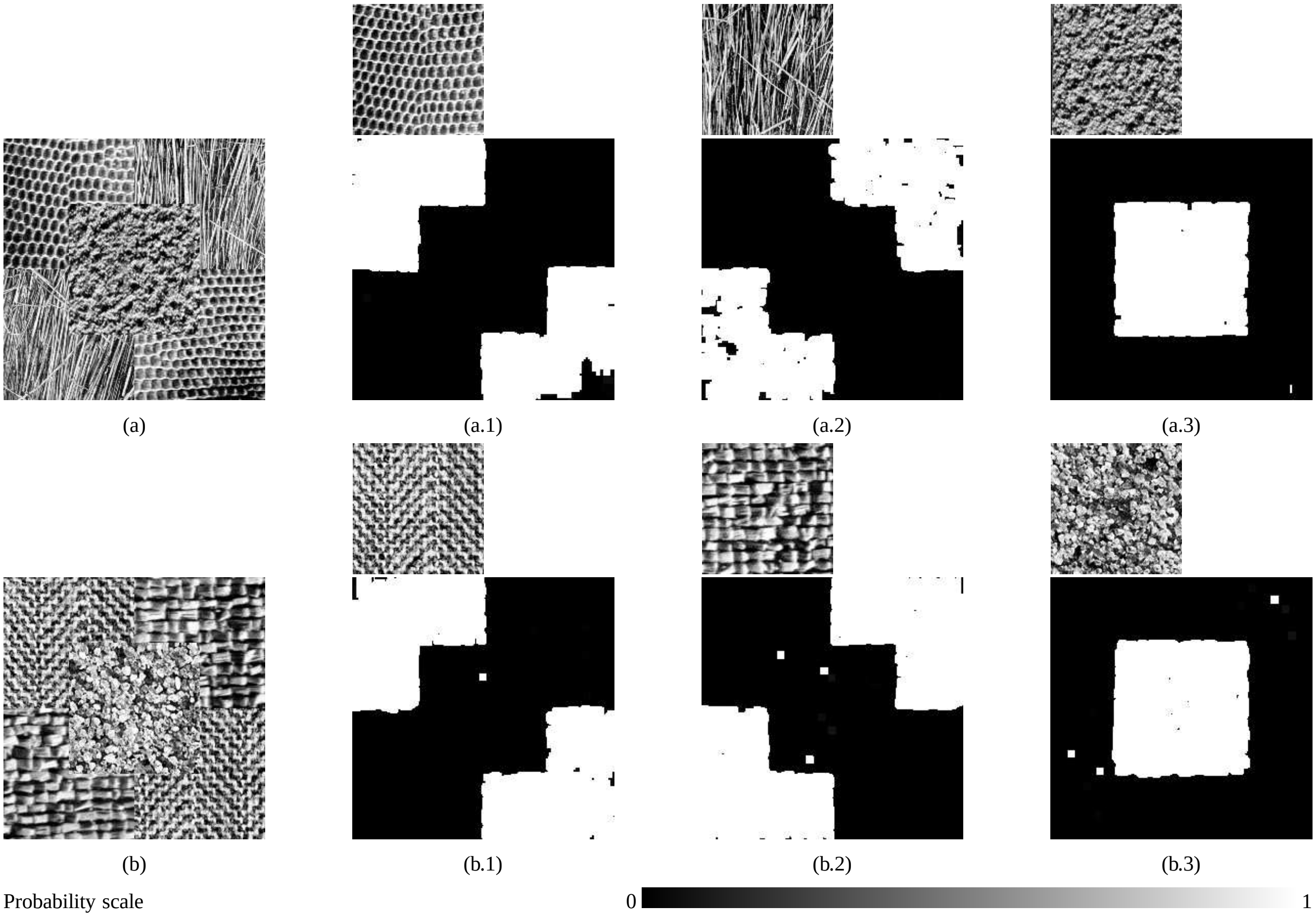


Fig. 2. Probability maps of Brodatz texture mosaics (a) and (b) with respect to: (a.1) D3 - Reptile skin; (a.2) D15 - Straw; (a.3) D57 - Handmade paper; (b.1) D17 - Herringbone weave; (b.2) D84 - Raffia; and (b.3) D29 - Beach sand.

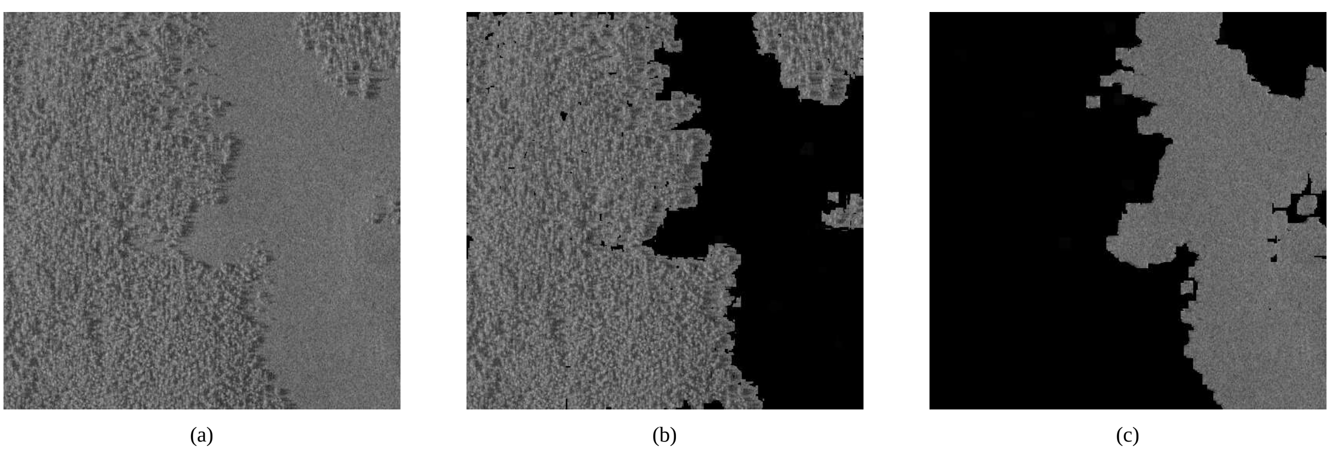


Fig. 3. Airborne SAR image of Cultana [11] with the probability maps of the trees and grass superimposed.

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 statis-

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 [8], and Vision Texture Archive of the MIT Media Lab [10]

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

tical characteristics, thereby performing open-ended texture classification. This technique is considered potentially valuable in the practical application of terrain mapping of SAR images.

7. REFERENCES

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