Texture Synthesis and Unsupervised Recognition with a Nonparametric Multiscale Markov Random Field Model

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Abstract

In this paper we present noncausal, nonparametric, multiscale, Markov Random Field (MRF) model for synthesising and recognising texture. The model has the ability to capture the characteristics of a wide variety of textures, varying from the structured to the stochastic. For texture synthesis, we use our own novel multiscale approach, incorporating local annealing, allowing us to use large neighbourhood systems to model some complex textures. We show how we are able to manipulate the statistical order of our high dimensional model without over compromising the integrity of the representation. Also by varying the statistical order of our model we are able to optimise it for the unsupervised recognition of textures with respect to textures that have not been modelled.

1. Introduction

MRF models have mainly been used for the *supervised* classification of texture, for which a library of pre-modelled textures must exist in order for discriminant analysis to be used [1]. However, this approach is cumbersome for SAR images of the Earth's terrain as they contain a myriad of different texture types, too many to be able build a library of pre-modelled textures.

We present a new approach to this problem by using our multiscale nonparametric MRF model to model just one source texture from which we produce a probability map of the source texture over a test image. We show that our MRF model, assessed by human vision, is able to synthesise highly representative textures [8]. On this basis, we determine that the model captures enough unique textural characteristics to be able to define a probability to an image segment without the use of discriminant analysis. This allows segmentation and texture recognition of images with undefined texture types, *i.e.,* it permits unsupervised texture recognition [7].

Although the synthesis test may indicate if a model has captured the specific characteristics of a texture, it does not determine whether the model is suitable for segmentation and classification. Using the philosophy from [10], a texture model should maximise its entropy while retaining the unique characteristics of the texture. In terms of the nonparametric MRF this is equivalent to reducing the statistical order of the model while retaining the integrity of the synthesised textures.

In this paper, we also present a method for reducing the statistical order of the nonparametric MRF model to a set of lower order statistical properties based on the *cliques* of the MRF [6]. We have shown in [5] that this reduced model still contains the unique characteristics required for synthesising representative texture, but due to the lower order statistics is able to perform better segmentation and classification [7]. By adjusting the extent of statistical reduction, the model can be optimised to capture the most unique characteristics while retaining the integrity of the synthesised textures, thereby producing a model suitable for unsupervised texture recognition.

2. Nonparametric MRF model

The nonparametric 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 [8]. 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 [9].

In [7] we showed that we may 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. This is a much stronger assumption than made for a normal MRF which defines a site as being conditionally independent upon its non-neighbouring sites given all of the neighbouring sites. This strong MRF model is equivalent to the Analysis-of-variance (ANOVA) construction [2, 7], which allows us to use the theorems from the ANOVA construction to estimate the LCPDF for the strong MRF model.

3. Multiscale texture synthesis

To synthesis a texture we used our multiscale relaxation (MR) algorithm as formalised in [8]. The basis of the algorithm is to perform stochastic relaxation (SR) at the coarsest resolution, and then successively at each finer resolution perform constrained SR with respect to the result from the previous resolution [3]. We implement constrained SR through the use of our own novel pixel temperature function [8] which may be regarded as an implementation of *local annealing* in the relaxation process.

We used source images of size 128×128 pixels to estimate the LCPDF from which images of size 256×256 were synthesised. A subjective comparison of the source and resulting synthetic textures, Fig. 1, show that the nonparametric multiscale Markov random field texture model is a highly representative model of natural textures. This confirms that the characteristics of the source texture have indeed been captured by the model.

4. Multiscale unsupervised texture recognition

To perform unsupervised texture recognition for a segment of our test image, we used the set of probabilities defined by the LCPDF over the segment, and compared them directly to the set of probabilities from the source texture [7]. We used the nonparametric Kruskal-Wallis test [4] to test the null hypothesis that the two sets of probabilities come from the same population. We then used the *confidence* associated with accepting the null hypothesis to form a probability map over the test image.

To prove the performance of our recognition algorithm, we tested it on images containing a mosaic of sub-images with similar grey levels (see Fig. 2(a) (b)). A conventional application of a (first order) histogram technique would not able to segment these. Also a mix of structured and stochastic sub images were chosen to illustrate how our nonparametric technique is able to recognise all types of textures. The results are probability maps with respect to one source texture. The model used was the strong MRF model with a 3×3 neighbourhood and pairwise cliques, as this was identified as our optimal model for unsupervised texture recognition [7].

5. Summary and conclusion

With the multiscale texture synthesis incorporating our novel pixel temperature function, we were able to use the nonparametric MRF model to synthesise realistic realisations of a source texture with minimal phase discontinuities. It was with this evidence that we concluded that the nonparametric MRF model captures all the unique characteristics specific to a particular texture. With such a model it became feasible to recognise other similar texture from an image containing multiple unknown textures. The model was used to determine the probability that an image segment was similar to a source texture with respect to its textural characteristics, thereby performing unsupervised texture recognition that did not require prior knowledge of the textures types present in the image. This technique was considered valuable to the practical application of terrain mapping of SAR images.

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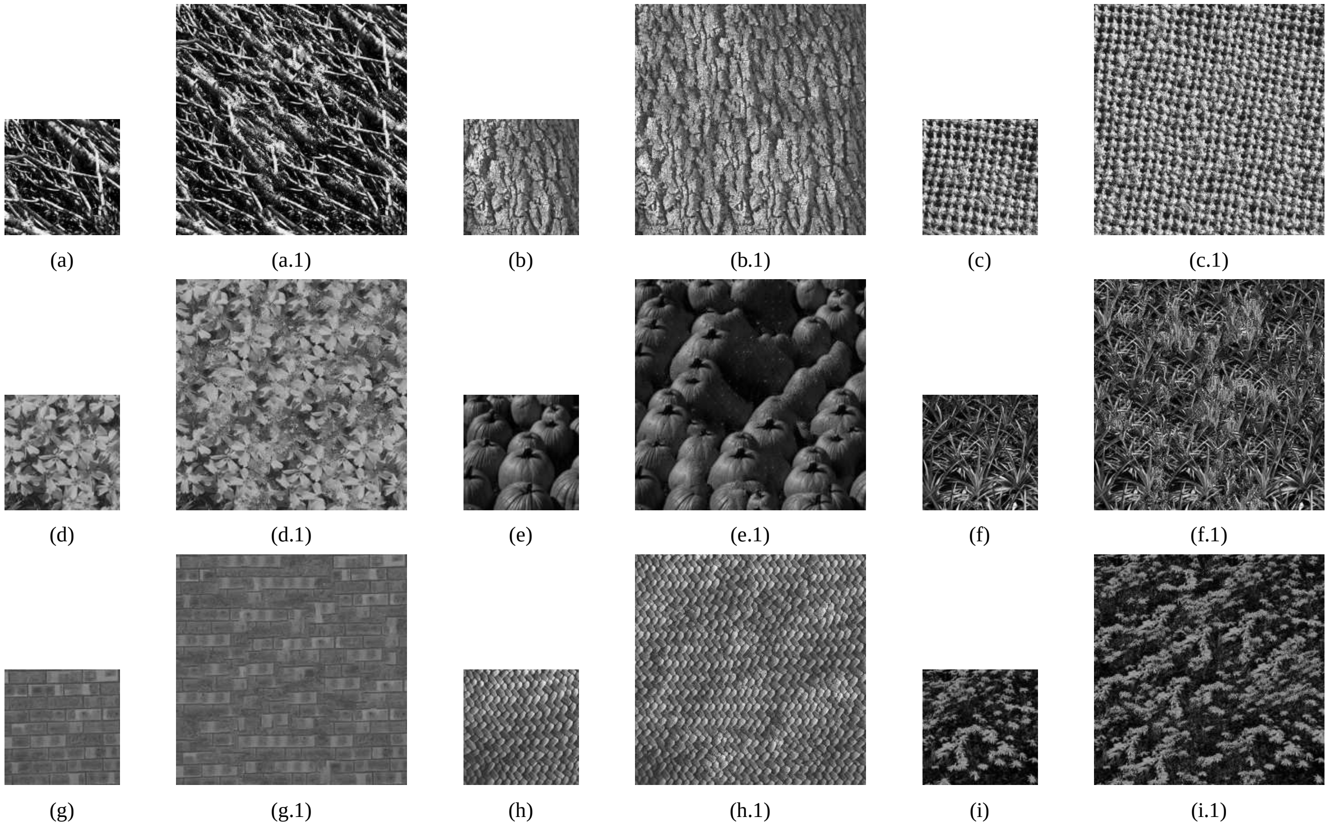

Figure 1. VisTex textures: (a) Bark.0003; (b) Bark.0009; (c) Fabric.0010; (d) Flowers.0003; (e) Food.0010; (f) Leaves.0016; (g) Brick.0000; (h) Fabric.0002; (i) Flowers.0000; (?.1) Textures were synthesised from a nonparametric MRF model with a 7×7 neighbourhood.

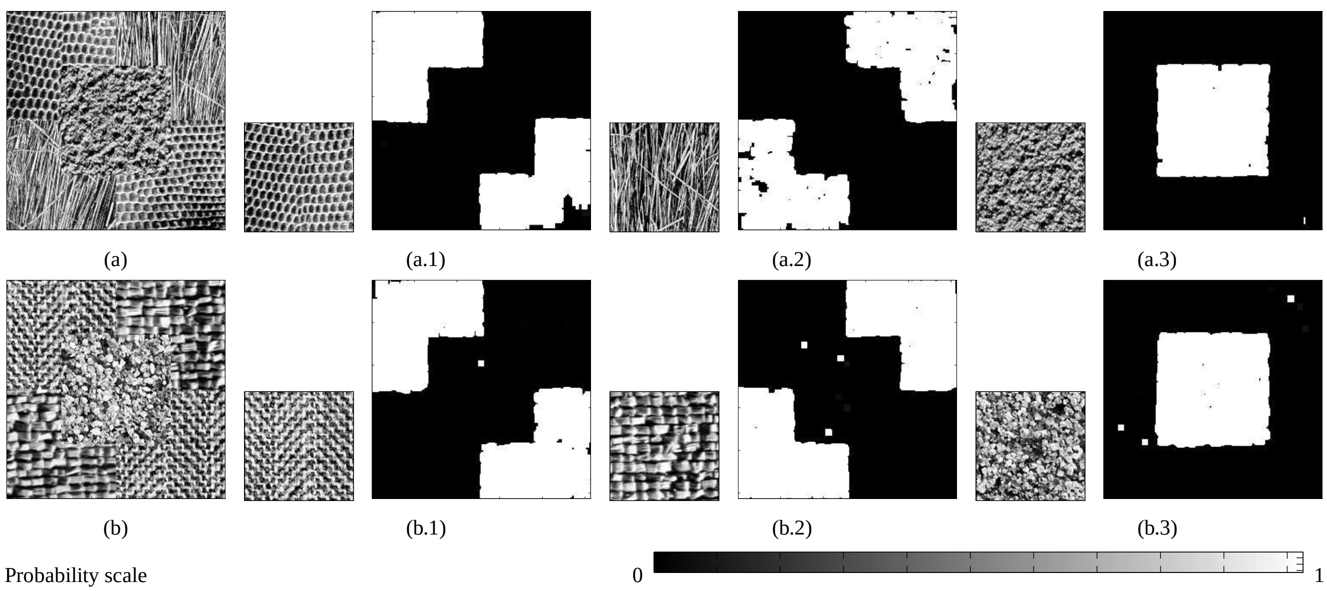

Figure 2. Probability maps of Brodatz texture mosaics (a) and (b) with respect to: (a.1) D3 - Reptile skin; (a.2) D15 - Straw; (a.3) D57 - Handmade paper; (b.1) D17 - Herringbone weave; (b.2) D84 - Raffia; (b.3) D29 - Beach sand.