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.

1. Introduction

Texture classification has generally been accomplished via a supervised method. This entails defining a set of predetermined classes into which a texture may be classified [1]. 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 [2]. 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 fail at this task.

We present a new approach to this extreme multi-class problem. Using our nonparametric multiscale MRF model [7], 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 a large portion of the unique characteristics of a texture. The proposed classification algorithm uses this identity to classify a texture on the basis that it has the same unique characteristics as a training class texture. Two textures are deemed to be from the same class, if they can be shown to have similar unique characteristics as defined by the nonparametric multiscale MRF model.

This new type of classification method we have termed "open-ended classification." The classification inference is made on the basis that similar unique statistical characteristics defines whether an unknown texture is of the same class as a predefined texture. 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 being of a certain class when it is not. To determine the effectiveness of this new approach, we employed the use of the MeasTex Test Suite [9].

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 [7]. 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 [8].

In [6] 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. 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 [3], which allows us to use the theorems from the ANOVA construction to estimate the LCPDF for the strong MRF model.

The ability to use a strong MRF model allowed us to not only to vary the neighbourhood size, but also the statistical order of the model. In the classification analysis, we were able to test the what order of statistics gave the best classification. Since we used a nonparametric model, this made the test independent of functional form.

3. Multiscale texture synthesis

To synthesise a texture we used our multiscale relaxation (MR) algorithm as formalised in [7]. The basis of the algorithm was 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 [4]. We implemented constrained SR through the use of our own novel pixel temperature function [7] which can be regarded as an implementation of *local annealing* in the relaxation process.

We used training textured images of size 128×128 pixels to estimate the LCPDF from which images of size 256×256 were synthesised. 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. This confirms 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 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 [5] 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 [6].

4.1 Comparative assessment of performance

In Table 1, a list of summary scores for a suite of nonparametric MRF models are presented. The key to the MRF model names is: n1 refers to a nearest neighbour neighbourhood, n3 refers to a 3×3 neighbourhood, n5 refers to a 5×5 neighbourhood. The number after the letter 'c' refers to the maximum statistical order used in the strong MRF model. The height of the multigrid used by the model is indicated by the number after the letter 't'. From first perusal of Table 1, it is evident (by looking at the relative ranks) that the nonparametric MRF model, based on a 3×3 neighbourhood using just 3rd order statistics and a four tier multigrid, gives the best performance with about 75% accuracy.

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.

If we look at the relative rankings of the different models presented in Table 1, we can get an overall impression of the effect of varying any one of the nonparametric MRF model's specifications. Table 3 demonstrates the general effect of increasing the neighbourhood size. As the average rank increases with neighbourhood size, we can surmise that a small neighbourhood is better for classification. In Table 4 it is the statistical order that is varied. From this table we can see that although it is advisable to keep the statistical order small, if the the statistical order gets too small the model will start to be undertrained. Lastly, in Table 5 we see that increasing the multigrid height improves the classification accuracy. Just from these three tables we can conclude that the optimal nonparametric MRF model would be MRF-n3c3t3. Now since the expected optimal nonparametric MRF model is the same one as identified in Table 1, we can also conclude that there is not too much interplay between these three model construction variables. These variables can be used almost independently to optimise the nonparametric MRF model. In fact since we have not imposed a functional framework to this analysis, any similar texture model could be similarly optimised.

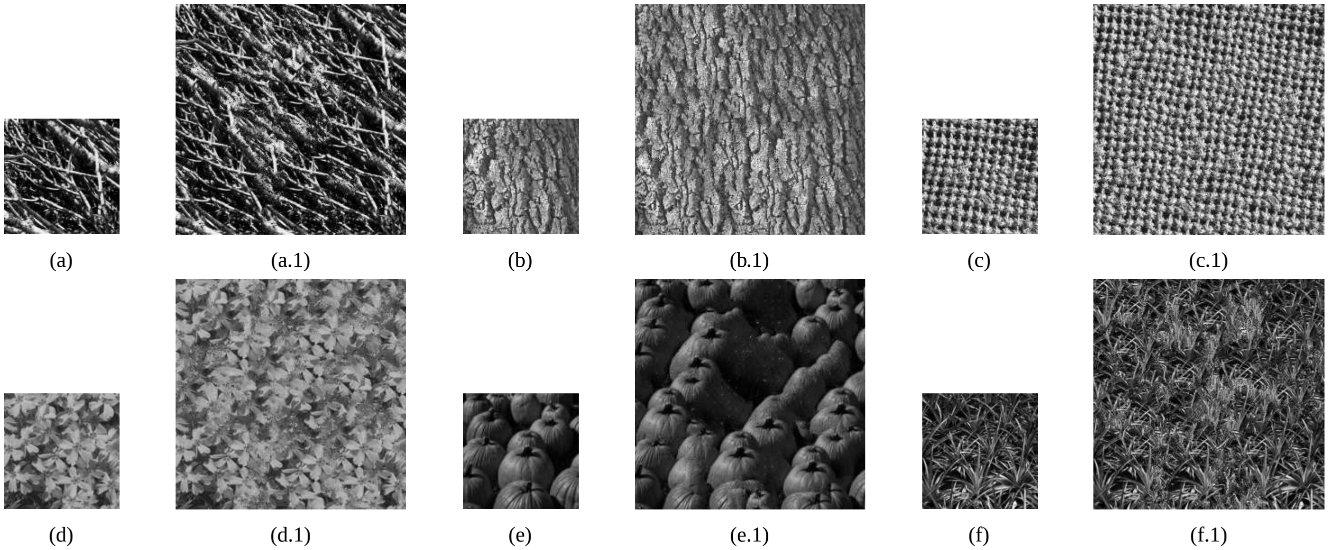

Figure 1. VisTex textures: (a) Bark.0003; (b) Bark.0009; (c) Fabric.0010; (d) Flowers.0003; (e) Food.0010; (f) Leaves.0016; (.1) Textures were synthesised from a nonparametric MRF model with a 7×7 neighbourhood.

Table 1. MeasTex test suite summary scores

Model	*Test Suites*					*Rank*
	Grass	*Material*	*OhanDube*	*VisTex*	*All*	
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

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

Table 3. Average rank for various neighbourhoods from Table 1

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 from Table 1

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

5. 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 was considered potentially valuable in the practical application of terrain mapping of SAR images.

Table 5. Average rank for various multigrid heights from Table 1

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

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