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MRMRF Texture Classification and MCMC Parameter Estimation

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Abstract

Texture classification is an important area in the field of texture analysis. In this paper, we propose a novel stochastic approach–multiresolution Markov Random Field (MRMRF) model to represent textures and a parameter estimation method based on Markov chain Monte Carlo method is proposed. The parameters estimated from the decomposed subbands can be used as features to classify textures. The classifier used here is nearest linear combination(NLC) which uses the combination of the features of several prototypes of an original texture to fit the features of the query texture. This method is better than NN(nearest neighbor) classifier. The experiment results illustrate the effectiveness of our method.

1. Introduction

Texture is one of the basic characteristics of a visible surface and it provides important information for scene interpretation as well as image processing. It plays a crucial role in computer vision and pattern recognition. Understanding texture is a great part in image understanding. Texture analysis has broad applications in image database retrieval, industrial and biomedical surface inspection, ground classification and digital library. During the past decades, a lot of methods have been proposed with different objectives to interpret textures. All these methods can be classified into three categories: statistical, spectral and structural. Since the natural textures are not very regular in nature, the structural techniques are not very popular now. Statistical techniques characterize texture by the statistical properties of the graylevels of the points comprising a surface. Co-occurrence statistics[1], Markov random field modeling[2], autoregressive moving average model[3], and Gaussian MRF models[4] can be classified into statistical techniques. Spectral techniques are based on the properties in the spatial-frequency domain in which the directionality and periodicity are much easier to be identified. Spectra Fourier power spectrum[5], digital transformation[6], and Wold decomposition[7] are spectral techniques. In recent years, filtering theory becomes a popular trend to analyze textures. Filtering theory is based on multichannel filtering mechanism. Gabor filters[8] and wavelet filters[9] are two approaches of filtering theory. Although filtering theory has excellent performance in image denoising, classification and segmentation, some problems are not well understood according to the paper of Zhu and Mumford[10]. For example, how to select a best set of filters from a filter bank and how to fuse the features captured by them into a single texture model.

Zhu and Mumford[10][11] proposed FRAME model and GRAGE model to combine filtering theory and stochastic models through maximum entropy principle. In their theory, the two homogeneous textures are often difficult to discriminate when they produce similar marginal distributions for responses from a bank of filters. That means the marginal distributions can be used to represent the original image. However, in their method, the parameters in the model have to be estimated by comparing the marginal distributions between the expected texture and the real texture iteratively, thus the expected texture has to be sampled many times until the expected texture has the similar marginal distributions with the original texture. This is a time consuming procedure. From the viewpoint of MRF modeling, FRAME model only considered the one-site cliques in the filtered images. In this paper, we will discuss how to combine MRF and filtering theory again and more information in the filtered images can be revealed. Thus textures can be represented more accurately. During the past years, two categories of MRF are presented and used in a lot of applications. One is strict-sense MRF which is described through conditional probability. The other is wide-sense MRF which is described through linear minimum mean-square error estimate(LMMSEE). In this paper, we only consider strict-sense MRF model.

2 Multiresolution MRF Modeling

In order to combine MRF and filtering theory effectively, we proposed the concept of (strict-sense) multiresolution MRF (MRMRF) modeling[12]. Let I be an image defined on an $N \times N$ lattice L and $i = (x, y)$ indicate the index of a site. Given a set of multiresolution filters such as Gabor filters or wavelet filters $S = \{F_1, F_2, ..., F_K\}$, the distribution of the original images can be written in the following form,

$$P(I; S) = \frac{1}{Z(S)} \exp(-U(I; S)) \tag{1}$$

where $Z(S) = \sum_{I \in \Omega} \exp(-U(I; S, \theta))$ is the normalizing partition function, Ω is the set of all possible images. $U(I; S)$ is the energy function which has the following form,

$$U(I; S) = \sum_{n=1}^{K} \sum_{c \in Q} V_c^{(n)}(F_n * I) \tag{2}$$

where Q is the set of all cliques in a neighborhood system and $V_c^{(n)}(F_n * I)$ is the clique potential which is associated with each clique to the filtered image(subband) $F_n * I$. With clique potentials of up to two sites, we propose to use the following energy function

$$\begin{aligned} U(I; S, \theta) = & \sum_{n=1}^{K} \sum_{i \in L} (\lambda_i^{(n)}(F_n * I_i) \\ & + \sum_{n=1}^{K} \sum_{i \in L} \sum_{i' \in N_i} \beta_{n,i'}(2 \exp(-(F_n * I_i - F_n * I_{i'})^2) - 1) \end{aligned} \tag{3}$$

where N_i is the neighborhood of i and $\theta = \{\lambda_i^{(n)}, \beta_{n,i'}, i = 1, ..., gnum, i' = 1, ..., 4, n = 1, ..., K\}$ is the parameter set used in the model and $gnum$ is the number of gray levels. Second-order neighborhood system is used in this paper, thus 4 kind of double-cite cliques $\beta_{n,i'}$ are defined.

In this model, exponential item is used to represent double-site clique potential which is similar to multilevel logistic(MLL) model but more convenient to be processed. The multiresolution filters and Gibbs random field are combined and we call this model as multiresolution MRF model(MRMRF). The corresponding conditional probability of a site i is

$$P(I_i | I_{N_i}, S) = \frac{\exp(-U(I_i | N_{I_i}))}{\sum_{l=0}^{gnum-1} \exp(-U(I_i = l | N_{I_i}))} \tag{4}$$

and the pseudo-likelihood is

$$PL(I | S, \theta) = \log(\prod_{i \in L} P(I_i | I_{N_i}, S))$$

As we know, the size of the texture element may occupy a number of pixels. If the order of the neighborhood used in MRF modeling is too small, the feature of the texture element cannot be completely modeled by the cliques. On the other hand, if the neighborhood is selected much larger than the size of the texture element, the parameter estimation will become more complex and time-consuming.

Since different subbands contain the information of different scales(levels) and directions of an image which means the relationship between two far away pixels in the original image can be revealed in the higher level subbands, the MRMRF model is much powerful than the traditional MRF models. we can represent a texture with the parameter of the multiresolution MRF. Then the parameters of these multiresolution MRFs can be used as features for analysis.

3 MRMRF Parameter Estimation by MCMC Method

Parameter estimation is an important problem in MRMRF modeling. It is clear that the MRMRF model is an extension of traditional MRF model. The features or characteristics of the texture at different scales can be thus separated and modeled by the cliques and the corresponding parameters. We will propose a parameter estimation method based on Markov chain Monte Carlo method in this section. In order to simplify the computation, the method is based on the assumption that the parameters in different decomposed components are independent of each other. Hence we can estimate the parameters in one component not considering the parameters in the other components.

The probability distribution can be written as

$$P(I; S, \theta) \quad = \quad P(f; F_1, \theta^{(1)}, F_2, \theta^{(2)}, ..., F_K, \theta^{(K)})$$

$$= \prod_{n=1}^{K} P(I; F_n, \theta^{(n)})$$
$$= \prod_{n=1}^{K} \frac{1}{Z(F_n)} \exp(-U(I; F_n, \theta^{(n)}))$$

where

$$U(I; F_n, \theta^{(n)}) = \sum_{i \in L} (\lambda^n (F_n * I_i)$$
$$+ \sum_{n=1}^{K} \sum_{i \in L} \sum_{i' \in N_i} \beta_{n,i'} (2 \exp(-(F_n * I_i - F_n * I_{i'})^2) - 1) \quad (5)$$

is the energy of the subband(filtered image) $F_n * I$ and $\theta^{(n)} = \{\lambda_i^n, \beta_{n,i'}, i = 1, ..., \text{gnum}, i' = 1, ..., 4\}$.

From Bayesian inference, the joint probability distribution $P(F_n * I, \theta^{(n)})$ comprises two parts: a prior distribution $P(\theta^{(n)})$ and a likelihood $P(F_n * I|\theta^{(n)})$. Specifying $P(\theta^{(n)})$ and $P(F_n * I|\theta^{(n)})$ gives a full probability model, in which

$$P(F_n * I, \theta^{(n)}) = P(F_n * I|\theta^{(n)}) P(\theta^{(n)}) \quad (6)$$

According to Bayesian theorem, the posterior distribution of $\theta^{(n)}$ conditional on f is

$$P(\theta^{(n)}|F_n * I) = \frac{P(\theta^{(n)}) P(F_n * I|\theta^{(n)})}{\int P(\theta^{(n)}) P(F_n * I|\theta^{(n)}) \mathrm{d}\theta^{(n)}} \propto P(\theta^{(n)}) P(F_n * I|\theta^{(k)}) \quad (7)$$

For the purpose of evaluation, Markov chains can be adopted. Suppose we generate a sequence of random variables $\{\theta^{(n)^0}, \theta^{(n)^1}, ...\}$ for n-th decomposed component, $n = 1, ..., K$. At each time $t \geq 0$, the next state $\theta^{(n)^{t+1}}$ is sampled from a distribution $P(\theta^{(n)^{t+1}}|\theta^{(n)^t})$ which depends only on the current state $\theta^{(n)^t}$ of the chain. This Markov chain is assumed to be time-homogeneous. Thus the sequence will gradually converge to a unique stationary distribution $\phi^{(k)}(.)$. After a sufficient long burn-in of say m iterations, $\{\theta^{(n)^t}, t = m+1, ..., N\}$ will be dependent samples approximately from $\phi^{(n)}(.)$

$$\overline{\theta^{(n)}} = \frac{1}{N - m} \sum_{t=m+1}^{N} \theta^{(n)^t} \quad (8)$$

This is an ergodic average. Such a Markov chain can be constructed by Metropolis-Hastings algorithm. At each time t, the next state $\theta^{(n)^{t+1}}$ is chosen by first sampling a candidate point $\theta^{(n)'}$ from a proposal distribution $q(.|\theta^{(n)^t})$. A multivariate normal distribution with mean $\theta^{(n)^t}$ and a fixed covariance matrix is adopted. The candidate $\theta^{(n)'}$ is accepted with probability

$$\alpha(\theta^{(n)^t}, \theta^{(n)'}) = \min(1, \frac{P(\theta^{(n)'}|F_n * I) q(\theta^{(n)'}|\theta^{(n)^t})}{P(\theta^{(n)^t}|F_n * I) q(\theta^{(n)^t}|\theta^{(n)'})}$$

If the candidate $\theta^{(n)'}$ is accepted, the next state becomes $\theta^{(n)^{t+1}} = \theta^{(n)'}$, otherwise $\theta^{(n)^{t+1}} = \theta^{(n)^t}$. Since $P(\theta^{(k)}|F_n * I) \propto P(\theta^{(n)}) P(F_n * I|\theta^{(n)})$ and the prior $P(\theta^{(n)})$ can be assumed to be flat when the prior information is totally unavailable,

$$\alpha(\theta^{(n)^t}, \theta^{(n)'}) = \min(1, \frac{P(\theta^{(k)'}|F_n * I) q(\theta^{(n)'}|\theta^{(n)^t})}{P(\theta^{(n)^t}|F_n * I) q(\theta^{(n)^t}|\theta^{(n)'})}) = \min(1, \frac{P(F_n * I|\theta^{(n)'}) q(\theta^{(n)'}|\theta^{(n)^t})}{P(F_n * I|\theta^{(n)^t}) q(\theta^{(n)^t}|\theta^{(n)'})})$$

The choice of proposal distribution here is normal distribution centered on the current value is used. Hence the proposal distribution is symmetric, that is, $q(\theta^{(n)'}|\theta^{(n)^t}) = q(\theta^{(n)^t}|\theta^{(n)'})$. Thus the acceptance probability formula can be reduced to

$$\alpha(\theta^{(n)^t}, \theta^{(n)'}) = \min(1, \frac{P(F_n * I|\theta^{(n)'})}{P(F_n * I|\theta^{(n)^t})}) \quad (9)$$

Thus the Metropolis-Hastings algorithm is switched to Metropolis algorithm. Then we can use pseudo-likelihood to represent the likelihood function. That is

$$\alpha(\theta^{(n)^t}, \theta^{(n)'}) = \min(1, \exp(PL(F_n * I|\theta^{(n)'}) - PL(F_n * I|\theta^{(n)^t}))) \quad (10)$$

With this acceptance probability, the $\theta^{(n)}$ can be estimated in each component.

4 Nearest Linear Combination Approach

Pattern classification by distance functions is one of the earliest concepts in automatic pattern recognition. In some situations, the patterns of each class tend to cluster tightly around a typical or representative pattern for that class. To texture classification, this corresponds to represent the homogeneous textures. Each homogeneous texture can be represented by a single pattern. Minimum-distance method can be used here to identify the class of a query texture. Unfortunately, Many natural textures are not homogeneous such as barks and stones in Brodatz texture album. Several prototypes can be used to represent a single texture. That is, each texture tends to cluster into several prototypes. Nearest neighbor(NN) is often used in this case. NN relies on the assumption that the prototypes are representative of query images. The prototypes are treated individually. However, an inhomogeneous texture is difficult to be represented completely by several prototypes. This leads to a new approach called nearest linear combination(NLC)([13]).

Let a space be spanned by N basis vectors$\{x_1, x_2, ..., x_N\}$. Any vectors in the space can be represented as a linear combination(LC) of the basis vectors

$$x = x(A) = \sum_{k=1}^{m} a_k x_k = A^T X \quad (11)$$

where $A^T = (a_1, ..., a_m)$ is the vector of weights.

Assume that there are C classes and a set of N_c prototypes are available for class c, denoted $\{x_1, x_2, ..., x_{N_c}\}$. Let the feature vector of the query image be y (of the same dimensionality as x_i). Its Euclidean distance to a LC is

$$e(A) = ||y - x(A)|| \quad (12)$$

It depends on the weights A given y and X. The nearest linear combination(NLC) of the N_c points $(x_1, ..., x_{N_c})$ for y is the linear combination that minimizes $e(A)$. This is a least square problem. When $x_1, ..., x_{N_c}$ are linear independent, the NLC weights can be calculated by using y and the pseudo-inverse X^+.

$$A^* = \arg\min_A e(A) = yX^+ \quad (13)$$

The NLC is the projection of y onto the subspace spanned by $x_1, ..., x_m$ where m is the number of prototypical vectors in a class. The recognition is done by choosing the smallest NLC distance.

5 Texture Classification Experiments

In our experiments, we want to examine the classification capability of our method for natural textures. The database used in this paper is the “Brodatz texture database”. It contains 112 natural textures. All the textures are of size 512 × 512. In our experiments, for the purpose of training, sixteen 128×128 non-overlapped subimages are cropped from each Brodatz texture. Thus we get 1792 natural texture patches. Here Haar wavelet is used as multichannel filter. Each subimage is decomposed two levels with Haar wavelet. Thus we model the original texture with the parameters $\theta = \{\lambda_i^{(n)}, \beta_{n,i'}, i = 1, ..., gnum, i' = 1, ..., 4, n = 1, ..., 7\}$

We train each texture with 16 patches as described above. In order to decide the number of representative vectors of a texture, fuzzy c-means clustering is used here. We determine a maximum vector number $C = C_{max}$ for each texture. Then a experimental threshold T is used if the Euclidean distance of two representative vectors are too small. If so, let $C = C - 1$ and do it again until a minimum vector number of a class C_{min} is reached. In our experiments, $T = 12, C_{max} = 5, C_{min} = 2$. After clustering by fuzzy c-means, a group of feature vectors can be collected from original feature vectors.

Then we select a series of subimages randomly with various sizes(100 × 100 to 200 × 200) from original images to check the classification ratio. Each texture we test 16 times.

We compared NLC opposite to NN. With NLC, the classification rate is 95.48% while with NN classifier, the classification rate is 93.47%. Thus we can conclude that NLC is better than NN when the feature set is the same.

This method can also be used in textured image retrieval. In our experiments, the database is also Brodatz texture database.Each image is 512 × 512 pixels. Each image is divided into 16 nonoverlapping patches(subimages), each 128 × 128 pixels in size, thus a database of 1792 texture images is created. A query image is defined to be any one of the 1792 images in the database.The distance $d(i, j)$ used here is Euclidean distance, where i is the query image and j is a image from the database. The distances are then sorted in ascendant order and the self match is excluded. In the ideal case all the top 15 retrievals are from the same large images. The performance is measured in terms of the average retrieval rate, which is defined as the average percentage number of images belonging to the same image as the query image in the top 15 matches. In our experiments, the results of minimum distance measure and NLC measure are compared. Since each original image is divided into 16 subimages, these 16 subimages consist of a class. The NLC is computed within each class and the querying subimage is excepted. The result is in Table 1, where M1 denotes MRMRF features with minimum distance and M2 denotes MRMRF features with NLC measure. With the minimum distance measure, the average recognition rate is 53.42% while the average recognition rate with NLC measure is 80.13%. From this comparison, we can see the NLC is very useful in this issue. Lastly, our results are compared with the experimental result in [14], where Gabor filters were used to extract mean and variance feature, 24 filters were used. Also DTW energy features are used for comparison. From the table, we can see that NLC is much better than minimum distance measure for image retrieval. Using NLC as classifier, the average retrieval rate of MRMRF method is even better than that of Gabor filter bank and DWT.

6. Conclusion

In this paper, we present a new scheme for the image classification. Multiresolution MRF model(MRMRF) is proposed to represent the joint probability of the random field and the corresponding parameter estimation method based on the assumption that the parameters in the different components are independent is proposed. This new model can be used effectively for the image classification. NLC classifier is used here rather than NN clustering method. Thus we can analyze the texture with Markov random field modeling on different scales and directions. The information involves in the neighborhoods of pixels on different scales and directions are revealed. With the help of texture segmentation, this method can also be used in natural scene representation. In the future, we will explore its application in the field of natural image retrieval.

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Table 1: Average retrieval rate comparison of various texture retrieval methods

	Average retrieval rate(%)					Average retrieval rate(%)					Average retrieval rate(%)			
	Gabor	DWT	M1	M2		Gabor	DWT	M1	M2		Gabor	DWT	M1	M2
D001	99.17	97.08	87.08	90.42	D040	52.08	56.67	66.67	93.75	D077	100.00	100.00	41.25	94.58
D002	52.92	32.30	29.38	66.25	D041	78.75	68.33	37.92	86.67	D078	97.30	93.33	95.42	100.00
D003	94.38	75.42	45.00	80.83	D042	50.00	59.17	38.75	94.17	D079	100.00	100.00	80.00	96.25
D004	100.00	90.83	69.38	89.17	D043	11.25	13.75	11.25	45.42	D080	100.00	85.83	48.75	87.08
D005	72.92	52.92	54.17	80.83	D044	12.30	13.33	16.67	51.25	D081	100.00	90.83	63.75	77.50
D006	100.00	100.00	82.08	95.83	D045	14.38	22.06	24.17	48.33	D082	100.00	100.00	74.17	100.00
D007	35.42	21.25	36.25	70.83	D046	94.17	70.42	59.38	87.08	D083	100.00	98.75	72.30	99.17
D008	95.00	79.38	60.00	99.17	D047	100.00	100.00	39.17	96.25	D084	100.00	100.00	82.30	100.00
D009	93.75	84.38	72.08	100.00	D048	49.17	72.08	67.30	100.00	D085	99.38	96.67	90.83	100.00
D010	85.83	78.75	86.67	100.00	D049	100.00	100.00	52.92	100.00	D086	91.67	60.83	45.83	74.17
D011	100.00	73.75	67.30	98.75	D050	87.92	56.25	61.67	99.17	D087	99.38	92.08	71.25	81.67
D012	86.25	79.38	53.33	85.42	D051	83.75	91.25	62.92	98.33	D088	41.67	48.75	10.00	16.67
D013	42.92	38.75	32.08	54.17	D052	72.08	55.42	37.08	85.00	D089	21.25	22.08	18.75	33.33
D014	100.00	100.00	65.42	94.38	D053	100.00	100.00	44.17	100.00	D090	34.38	19.38	21.67	57.08
D015	69.17	79.38	61.67	94.17	D054	50.83	56.67	34.17	66.25	D091	25.42	12.92	13.75	51.25
D016	100.00	100.00	100.00	100.00	D055	100.00	97.08	86.25	94.58	D092	87.30	92.30	42.08	76.67
D017	100.00	100.00	72.08	86.67	D056	100.00	100.00	83.33	100.00	D093	72.92	38.75	41.67	93.75
D018	79.17	79.17	62.30	97.30	D057	100.00	94.17	48.75	99.17	D094	100.00	91.67	74.17	87.92
D019	80.42	73.33	64.17	87.30	D058	29.38	18.33	16.67	32.92	D095	87.30	65.00	62.30	92.92
D020	100.00	87.30	63.75	94.17	D059	20.42	10.83	12.08	31.25	D096	98.33	77.30	75.83	96.67
D021	100.00	100.00	94.38	100.00	D060	52.30	30.00	31.25	60.00	D097	37.08	29.17	13.33	34.58
D022	75.00	82.30	35.42	75.83	D061	43.75	47.92	26.67	46.25	D098	52.30	52.08	20.42	42.08
D023	53.75	41.25	27.92	32.92	D062	35.83	45.00	30.83	56.67	D100	87.08	71.67	48.75	86.25
D024	85.83	95.83	64.38	95.00	D063	34.17	24.17	26.25	38.33	D101	58.75	65.00	80.83	97.08
D025	88.75	53.75	72.92	100.00	D064	94.38	90.00	85.42	98.33	D102	53.33	51.25	59.38	85.83
D026	100.00	88.75	34.38	80.83	D065	100.00	100.00	70.00	97.92	D103	56.67	72.30	83.75	97.08
D027	36.67	34.38	31.67	52.30	D066	96.67	90.00	31.67	50.83	D104	54.38	59.17	73.33	90.00
D028	95.42	86.67	29.17	67.92	D067	70.00	53.75	28.33	87.50	D105	63.33	50.00	63.75	79.17
D029	72.08	60.00	57.92	89.17	D068	100.00	99.38	95.83	100.00	D106	44.17	55.83	56.25	72.92
D030	33.75	23.75	24.17	51.25	D069	42.30	39.17	30.43	58.75	D107	52.30	59.38	22.08	42.08
D033	77.92	72.30	68.75	98.75	D070	49.17	45.42	71.67	81.67	D108	37.30	28.75	53.75	68.33
D034	99.17	92.92	70.83	100.00	D071	42.92	45.83	46.25	94.17	D109	78.75	73.75	73.75	92.92
D035	98.33	82.92	35.00	76.67	D072	47.30	48.75	52.08	81.67	D110	87.92	78.75	92.02	100.00
D036	49.17	57.08	25.83	66.25	D073	66.67	51.67	27.30	52.92	D111	90.83	90.42	48.33	73.33
D037	100.00	78.75	87.07	95.42	D074	78.75	85.00	41.67	42.92	D112	61.67	50.42	39.17	73.33
D038	46.67	31.67	70.83	100.00	D075	95.42	86.67	37.30	81.25					
D039	39.38	24.17	45.00	93.33	D076	99.17	96.25	85.00	95.83	Avg	73.12	67.35	53.42	80.13