AUTOREGRESSIVE MODEL BASED ON BAYESIAN APPROACH FOR TEXTURE REPRESENTATION

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Abstract

In this study autoregressive model based on Bayesian approach is proposed for texture classification. Based on auto correlation coefficients, micro textures are identified and represented locally and then globally. The identified micro texture is represented as a local description, called texnum. The global descripter, texspectnum, is obtained by simply observing the numbers of occurrences of the texnums that cover the entire image. The proposed representation scheme has been employed in both supervised and unsupervised classifications of textured images. The supervised classification is based on simple tests of hypotheses and the unsupervised classification is based on the modified K-means algorithm with minimum distance classifiers. The proposed method is demonstrated for classification of different types natural textured images. The average correct classification is better than the existing methods.

Keywords:

Texnum, Texspectnum, Microtexture, K-Means Algorithm, Supervised & Unsupervised Classification

1. INTRODUCTION

Texture classification and analysis play a major role in computer vision and image understanding. Texture is a key feature to achieve these problems. So, it must be properly represented, before analysing it. The proper representation of structures of the textures will lead to right path of texture analysis. Texture can be defined as a structure composed of a large number of more or less similar primitives or patterns. Texture analysis is broadly classified as statistical, geometrical, structural, model-based and signal processing techniques [1]. He and Li Wang [2] proposed a scheme for texture characterization and discrimination based on local as well as global properties.

The textures in an image can be described by number of primitives and its types and the spatial organisation or layout of its primitives. The spatial organisation ma be stochastic or periodic, may have a pair wise dependence of one primitive on a neighbouring primitive, or may have a dependence of n primitives at a time. The dependence may be structural, probabilistic or functional like a linear dependence.

In recent years, model based methods, such as, Hidden Markov Random field [3], Markov random field [4], Autoregressive [5, 6], Multiresolution Guassian Autoregressive [7] and Gibbs field [8] models have attracted many researchers for texture classification, segmentation and textured image compression. They reported that these models gave better results for low-level texture analysis.

In this study autoregressive model based on Bayesian methodology for texture identification, representation and classification is discussed. The aforementioned texture analyses are performed using the autocorrelation function derived from the coefficients $\Gamma_r s$ of the proposed model. The coefficients $\Gamma_r s$ are computed by substituting the model parameters K, α, θ and ϕ in the equation. Based on this autocorrelation values, a number called texnum is proposed to represent the micro texture present in the small image region. By considering non-overlapping regions with raster scan fashion, the frequency of a number of occurrences of texnums is computed in the entire image and is called texspectrum. The texspectrum describes the global information of the texture present in the image. Based on the proposed representation scheme, the supervised and unsupervised classifications are performed with different textspectra as training set for different textures present in the target image. The supervised classification is performed is on the basis of autocorrelation coefficients, which are subjected to homogeneity tests, such as t-test and Bartlett's test [9,10] at the desired levels of significance. The k-means [11,12] algorithm is applied in unsupervised classification.

2. THE PROPOSED MODEL FOR TEXTURE

Representation: Let X be a random variable that represents the intensity value of a pixel at location (k, l) in an image. We also assume that X may have noise and is considered as independently and identically distributed Gaussian random variable with discrete time space and continuous state space with zero and variance σ^2 and is denoted as,

$$\varepsilon(k, l) \text{ i.e., } \varepsilon(k, l) \sim N(0, \sigma^2). \tag{1}$$

As $\{X(t); t \in S\}$ is a stochastic process, where $S = \{t: (k, l); 1 \le k, 1 \le M\}$ is a Markov process for all $t_0 < t_1 < \ldots < t_n$, we have $P_r\{X(t_n) = i_n \mid X(t_k) = i_k ; k = 0, 1, 2, \ldots, n - 1\} = P_r\{X(t_n) = i_k \mid X(t_{n-1}) = i_{n-1}\}$ for all i_k, $k = 0, 1, 2, \ldots, n - 1$ and t_k belong to the state space S. The pixel at location $X(k, l)$ in a 2-D monochrome image can be modeled through the Eq.(2).

$$X(k,l) = \sum_{\substack{p=-1 \\ p=q\neq 0}}^{M} \sum_{q=0}^{M} \Gamma_r [X(k + p, l + q)] + \varepsilon(k, l) \tag{2}$$

In the Eq.(2) $X(k + p, l + q)$ accounts for the spatial variation owing to texture and $\varepsilon(k, l)$ is the spatial variation owing to additive noise and $\Gamma_r = \dfrac{K \sin(r\theta)\cos(r\phi)}{\alpha^r}$, $\forall_q$ is the rth coefficient of variation among the texture primitives in the small

region. The coefficients are interrelated. The relationship is established through the parameters K, α, θ and ϕ which are real.

Parameter estimation: In order to implement the proposed FRAR model, we must estimate the parameters. The parameters K, α, θ and ϕ are estimated, by taking suitable prior information for the hyper parameters β, v and δ, based on numerical integration technique and Bayesian methodology. Only for the computation purpose the pixel values of each subimage are arranged as one-dimensional vectors $X(t)$, $s = 1, 2, 3, ..., N$ ($M \times M = M^2 = N$). Since the error term $\varepsilon(k, l)$ in the Eq.(2) are independent and identically distributed Gaussian random variable, the joint probability density function of the observations is given by,

$$P\!\left(X\!\big/\!\Theta\right) \propto \left(\sigma^2\right)^{-N/2} \exp\!\left[-\frac{1}{2\sigma^2}\sum_{t=1}^{N}\left\{X_t - K\sum_{r=1}^{\infty} S_r X_{t-r}\right\}^2\right] \quad (3)$$

where,

$$X = (X_1, X_2, ..., X_N)$$
$$\Theta = (K, \alpha, \theta, \phi, \sigma^2) \text{ and}$$
$$S_r = \frac{\sin(r\theta)\cos(r\phi)}{\alpha^r}.$$

When we analyze the real data with finite number of N observations, the range for the index r viz., 1 to ∞, reduces to 1 to N and so in the joint probability density function of the observations given by the Eq.(3) the summation $\sum_{r=1}^{\infty}$ can be replaced by $\sum_{r=1}^{N}$ which gives,

$$P\!\left(X\!\big/\!\Theta\right) \propto \left(\sigma^2\right)^{-N/2} \exp\!\left[-\frac{1}{2\sigma^2}\sum_{t=1}^{N}\left\{X_t - K\sum_{r=1}^{N} S_r X_{t-r}\right\}^2\right]. \quad (4)$$

By expanding the square in the exponent, we get,

$$P\!\left(X\!\big/\!\Theta\right) \propto \left(\sigma^2\right)^{-N/2} \exp\!\left[-\frac{1}{2\sigma^2}\left\{T_{00} + K^2\sum_{r=1}^{N} S_r^2 T_{rr}\right.\right.$$
$$\left.\left. + 2K^2 \sum_{\substack{r,s=1\\r<s}}^{N} S_r S_s T_{rs} - 2K\sum_{r=1}^{N} S_r T_{0r}\right\}\right] \quad (5)$$

where, $T_{rs} = \sum_{t=1}^{N} X_{t-r} X_{t-s}$, $r, s = 0, 1, 2, ...N$.

The above joint probability density function can be written as,

$$P\!\left(X\!\big/\!\Theta\right) \propto \left(\sigma^2\right)^{-N/2} \exp\!\left[-\frac{Q}{2\sigma^2}\right] \quad (6)$$

where,

$$Q = T_{00} + K^2\sum_{r=1}^{N} S_r^2 T_{rr} + 2K^2 \sum_{\substack{r,s=1\\r<s}}^{N} S_r S_s T_{rs} - 2K\sum_{r=1}^{N} S_r T_{0r}$$

$$K \in R, \alpha > 1, 0 < \theta < \pi, 0 < \phi < \pi/2 \text{ and } \sigma^2 > 0.$$

The prior distribution for the parameters is assigned as follows:

1. α is distributed as the displaced exponential distribution with parameter β, i.e. $P(\alpha) = \beta\exp(-\beta(a-1))$; $a > 1$; $\beta > 0$

2. σ^2 has the inverted gamma distribution with parameter v and i, i.e. $P(\sigma^2) \propto \exp(v/\sigma^2)(\sigma^2)^{-(\delta+1)}$; $\sigma^2 > 0$, v, $\delta > 0$

3. K, θ and ϕ are uniformly distributed over their domain, i.e. $P(K, \theta, \phi) = C$, a constant $K \in R$, $0 < \theta < \pi$, $0 < \phi < \pi/2$

So, the joint prior density function of Θ is given by,

$$P(\Theta) \propto \beta\exp\!\left(-\beta(\alpha-1) - v/\sigma^2\right)\!\left(\sigma^2\right)^{-(\delta+1)};$$
$$\sigma^2 > 0, \alpha > 1, 0 < \theta < \pi, 0 < \phi < \pi/2 \quad (7)$$

where, P is used as a general notation for the probability density function of the random variables given within the parentheses following P.

Using the Eq.(5), Eq.(6) and Bayes theorem, the joint posterior density of K, α, θ, ϕ and σ^2 is obtained as,

$$P\!\left(X\!\big/\!\Theta\right) \propto \left[\sigma^2\right]^{-N/2} \exp\!\left(-Q/2\sigma^2\right)\exp\!\left(-\beta(\alpha-1) - \gamma/\sigma^2\right)\!\left(\sigma^2\right)^{-(\delta+1)}$$
$$\propto \exp\!\left(-\beta(\alpha-1)\right)\exp\!\left(-1/2\sigma^2\right)\!\left(Q+2v\right)\!\left(\sigma^2\right)^{-\left(\frac{N}{2}+\delta+1\right)}$$
$$K \in R, \alpha > 0, 0 < \theta < \pi, 0 < \phi < \frac{\pi}{2} \text{ and } \sigma^2 > 0.$$

$$(8)$$

Integrating Eq.(7) with respect to σ^2, the posterior density of K, α, θ and ϕ is obtained as,

$$P(K, \alpha, \theta, \varphi / X) \propto \exp\!\left(-\beta(\alpha-1)\right)\!\left(Q+2v\right)^{-\left(\frac{N}{2}+\delta\right)}. \quad (9)$$
$$K \in R, \alpha > 1, 0 < \theta < \pi, 0 < \phi < \pi/2$$

where,

$$[Q + 2v] = \left[\left\{K^2\sum_{r=1}^{N} S_r^2 T_{rr} + 2K^2 \sum_{\substack{r,s=1\\r<s}}^{N} S_r S_s T_{rs}\right.\right.$$
$$\left.\left. - 2K\sum_{r=1}^{N} S_r T_{0r}\right\}\right] + T_{00} + 2v$$

That is,

$$(Q + 2v) = aK^2 - 2Kb + T_{00} + 2v$$
$$= C[1 + a_1(K - b_1)^2].$$

where,

$$C = T_{00} - \frac{b^2}{a} + 2v$$

$$a = \sum_{r=1}^{N} S_r^2 T_{rr} + 2 \sum_{\substack{r,s=1\\r<s}}^{N} S_r S_s T_{rs}$$

$$b = \sum_{r=1}^{N} S_r T_{0r}$$

$$a_1 = \frac{a}{C}$$

$$b_1 = \frac{b}{C}.$$

Thus, the above joint posterior density of K, α, θ and ϕ can be rewritten as,

$$P(K,\alpha,\theta,\varphi/X) \propto \exp(-\beta(\alpha-1))\left[C\left\{1+a_1(K-b_1)^2\right\}\right]^{-d}$$
$$K \in R, \alpha > 1, 0 < \theta < \pi, 0 < \varphi < \frac{\pi}{2} \quad (10)$$

where, $d = \dfrac{N}{2} + \delta$.

This shows that, given α, θ and ϕ the conditional distribution of K is t distribution located at b_1 with $(2d-1)$ degrees of freedom. The proper Bayesian inference on K, α, θ and ϕ can be obtained from their respective posterior densities. The joint posterior density of α, θ and ϕ, namely, $P(\alpha, \theta, \phi/X)$, can be obtained by integrating the Eq.(10) with respect to K. Thus, the joint posterior density of α, θ and ϕ is obtained as,

$$P(\alpha,\theta,\varphi/X) \propto \exp(-\beta(\alpha-1))C^{-d}a_1^{-\frac{1}{2}}$$
$$\alpha > 1, 0 < \theta < \pi, 0 < \varphi < \frac{\pi}{2} \quad (11)$$

The above posterior density of α, θ and ϕ in Eq.(11) is a complicated function and is analytically not solvable. Therefore, the original posterior density of α, θ and ϕ are found numerically from the joint density.

That is, $P(\alpha) \propto \iint P(\alpha, \theta, \varphi/X)\mathrm{d}\theta\mathrm{d}\varphi$.

Similarly, $P(\theta) \propto \iint P(\alpha, \theta, \varphi/X)\mathrm{d}\alpha\mathrm{d}\varphi$ and $P(\phi) \propto \iint P(\alpha, \theta, \varphi/X)\mathrm{d}\alpha\mathrm{d}\theta$.

The point estimates of the parameters α, θ and ϕ may be taken as the means of the respective marginal posterior distribution i.e. posterior means. With a view to minimize the computations, the posterior mean of α is obtained numerically. Then α is fixed at its posterior mean to evaluate the conditional means of θ and ϕ fixing α at its mean. By fixing α, θ and ϕ at their posterior means respectively the conditional mean of K is evaluated.

Thus, the estimates are,

$$\hat{\alpha} = E(\alpha)$$
$$(\hat{\theta}, \hat{\phi}) = E(\theta, \phi/\alpha = \hat{\alpha}) \quad \text{and}$$
$$\hat{K} = E(K/\hat{\alpha}, \theta = \hat{\theta}, \phi = \hat{\phi})$$

The estimated parameters $\hat{K}$, $\hat{\alpha}$, $\hat{\theta}$ and $\hat{\phi}$ are employed to compute the coefficients $\Gamma_r s$ of the model in 1.

The advantage of the present approach is that the number of parameters fixed are only four and the order does not increase the computational complexity, since the estimation of these parameters is the same irrespective of the order of the model and hence it increases the efficiency of the model.

Texture identification: To identify the textures in the image, the model parameters K, α, θ and ϕ are estimated, as discussed in the preceding paragraph for small region of image interested at centre pixel. The small image region is computed by dividing the whole image into various overlapping regions of size 3×3. The model coefficients $\Gamma_r s$, ($r = 1, 2$) are determined by applying the estimated parameters K, α, θ and ϕ. The autocorrelation function (ρ_k) is derived from the model coefficients $\Gamma_r s$ as follows,

$$\rho_1 = \frac{\Gamma_1}{1-\Gamma_2}$$

$$\rho_2 = \frac{\Gamma_1^2 + \Gamma_1 - \Gamma_2^2}{1-\Gamma_2} \quad \text{and}$$

$$\rho_3 = \frac{\Gamma_1(\Gamma_1^2 + 2\Gamma_1 - \Gamma_2^2)}{1-\Gamma_2}.$$

Similarly, the kth order autocorrelations can be obtained by solving the Eq.(12) using recurrence relation. The patterns are governed by the second order linear difference equation.

$$\rho_k = \Gamma_1\rho_{k-1} + \Gamma_2\rho_{k-2} \quad (12)$$

where, $1 \le k \le m$.

From Eq.(12), the autocorrelation coefficients (ρ_k) are computed. To identify the micro level textures present in the small image region, a test has to be conducted to find the significance of the autocorrelation. The test statistic as introduced in Pena [13] for autocorrelation is defined as follows,

$$D_m = n\left[1 - \left|\tilde{R}_m\right|^{1/m}\right] \quad (13)$$

where, $\tilde{R}_m$ is the correlation matrix built by using the standardized autocorrelation coefficients $\tilde{\rho}_k$. That is,

$$\tilde{R}_m = \begin{bmatrix} 1 & \tilde{\rho}_1 & \cdots & \tilde{\rho}_m \\ \tilde{\rho}_1 & 1 & \cdots & \tilde{\rho}_{m-1} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{\rho}_m & \tilde{\rho}_{m-1} & \cdots & 1 \end{bmatrix} \quad (14)$$

where, $\tilde{\rho}_k^2 = \dfrac{(n+2)}{(n-k)}\rho_k^2$, n is the number of samples and m is the lag variable.

The significance test on the statistic D_m can be based on the measure $\pm\alpha(\sigma/\sqrt{n})$, where α is level of significance and σ is standard deviation. To make a confidence test at a given significance level α for the null hypothesis of no autocorrelation at lag k, sample coefficient is to be compared with the aforementioned measure. If the sample coefficient falls outside the given bands then the hypothesis is rejected at level of significance α i.e., the autocorrelation does exist among the data. Otherwise the null hypothesis is accepted. If the autocorrelation is highly significant, then it is identified that there exist micro textures in the small image region. Otherwise, it is identified that these exist other properties. i.e., these are no micro textures in the region.

Texture representation: In order to represent the identified micro textured regions, the computed autocorrelation value is placed at the centre position of the small image region (3×3) in another matrix array with the same size corresponding to the actual image. The computed autocorrelation values fall in the range -1 to $+1$. A simple transformation ($\rho * 100$) + 100 is used on the autocorrelation values, to obtain decimal number, which ranges from 0 to 200. Now, the encrypted local description of micro texture is quantified as a texture number. This number can

be called texnum. The texnum is a local descriptor as it describes the local information of the textured image region. The calculation of texnum is repeated for the entire image by considering subsequent overlapping image regions taken in the raster scan fashion. The number of occurrences of those texnums is computed as a spectrum and is called texspectrum. The texspectrum of an image describes the textures present in the image globally. Since the texnum ranges from 0 to 200, there are in all 201 components in the texspectrum. Based on this texture number, the proposed scheme characterizes and represents the different types of textures. It also explores the spatial interrelationship between the pixels and tonal primitives of the micro textures in the small image region since autocorrelation represents the relationship among the pixels.

Texture classification: To validate the performance of the proposed texture representation scheme, classification analyses are conducted on the global descriptors obtained in the previously. The task of classification is the identification of groups of pixels or a region in the image that are cohesive to be clustered from other types of pixels or a region in the image and assign each possible cohesive group of pixel or regions to a known class of texture.

The clustered regions are mutually exclusive and each region corresponds to a particular class of homogeneous texture. Generally, the method of classification is broadly categorized into two types, namely, supervised and unsupervised. Prior information about the image to be recognized is available in the supervised classification whereas no prior information is available in the unsupervised classification. The use of the proposed texture representation scheme is highlighted in both the supervised and unsupervised classifications.

Supervised classification: In order to classify the different types of textures present in the input target image, the supervised classification is presented here. The global descriptor, that is, texspectrum computed from the known input images is used to classify the textures in the target image. Two simple test statistics, Bartlett's test statistic and t-statistic[9,10] are employed to classify the input target image into known L classes of texture images with the use of prior information about the reference images R_j where $j = 1, 2, …, L$.

Unsupervised classification: Here, the usage of the proposed global descriptor, texspectrum is highlighted in unsupervised classification of a target image with the help of modified k-means algorithm.

To find the typical distance between these k clusters, the distance $d[C_i, C_j]$ between the C_i^{th} and C_j^{th} centres over all pairs of centres is computed. The α-trimmed mean of these values is computed to obtain the typical distance. Next a smallest proportion of the typical distance is fixed for use as the threshold t for testing whether a distance is too close or not.

After classifying the target image by the proposed method in both supervised and unsupervised schemes, the misclassification error is evaluated as follows,

$$\text{Misclassification error} = \frac{\text{Number of misclassified pixels}}{\text{Total number of pixels in the region}}.$$

The mathematical procedures adopted in this study for texture analysis, that is, texture identification, texture

representation and classification of both supervised and unsupervised based on the representation, are given in the algorithimic form as follows,

Step 1: Input target image of size 256×256

Step 2: Compute autocorrelation coefficients (ρ_k) on target and reference images

Step 3: Compute texnum by applying the transformation ($\rho * 100) + 100$ on autocorrelation coefficients

Step 4: Compute texspectra, by calculating the numbers of occurrences of texnums

Step 5: Supervised classification is performed

Step 6: Unsupervised classification is performed

Step 7: Stop

3. RESULTS

In order to identify the presence of texture, the test of autocorrelation is applied on the autocorrelation coefficient computed for the small region with size 3x3. If the coefficient falls outside the confidence limit at 75% level of significance, then it is concluded that the region under analysis is textured region. Otherwise, it is identified as undetextured region with edges. The obtained results are shown in Fig.1.
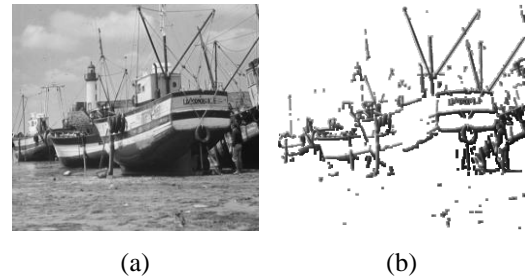

(a)   (b)

Fig.1(a). Original Image (b). Untextured region with edges

A large number of different types of hand-coded texture primitives are included in the experiment conducted for texture representation. For sample, some of them are given in Fig.1. The proposed method, discussed previously for testing the presence of texture has been employed to these primitives. The corresponding texnum, obtained for these primitives given in Fig.2 have been obtained as outcome of the experiment are summarised in Table.1. The obtained texnum are unique.
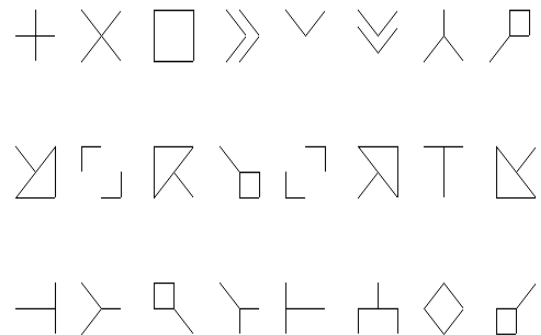

Fig.2. Texture primitives

Table.1. Texnum values

132	155	174	152	109	141	102	145
163	134	151	148	154	150	128	170
169	133	138	118	144	164	124	147

Satisfied with different hand-coded texture primitives and identified untexturedness, then an experiment is conducted extract the micro texture present in the image. For this purpose different 2-D monochrome images taken from standard Brodatz [14] Album and nature scenes are used in the experiment. Four such images viz. D16, D109, D38 and D93, taken from the standard Brodatz Album are given in Fig.3. All these images are of size 256×256 with pixel values in the range 0-255.
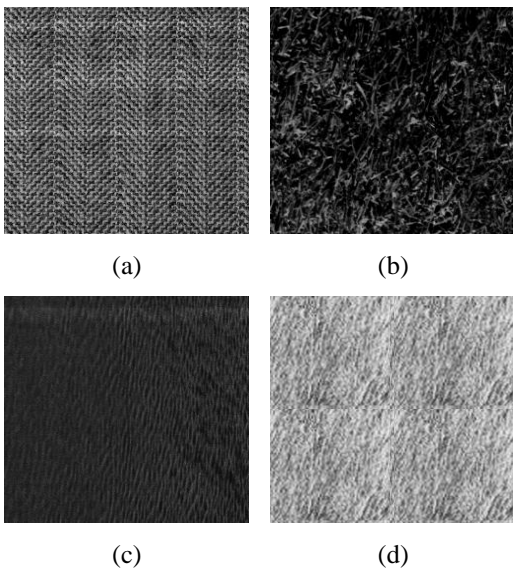
Fig.3. Original Images: (a) D16 (b) D109 (c) D38 (d) D93

As proposed earlier, autocorrelation coefficients are computed on these images by considering the small image regions of size (3×3), after computing the FRAR model coefficients $\Gamma_r s$ from the model parameters K, α, θ and ϕ. By testing the homogeneity of variances, textures are identified and are numerically represented as texnum. By considering sliding window, in the raster scan fashion, the entire image is then subjected to texture analysis and as a result texspectrum as global descriptor is obtained. Two such texspectra of the images shown in Fig.3(c) and Fig.3(d) at the 5% and 20% of significance levels are shown in Fig.4.
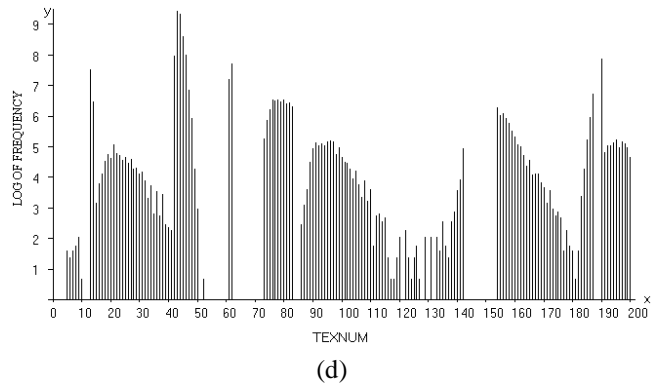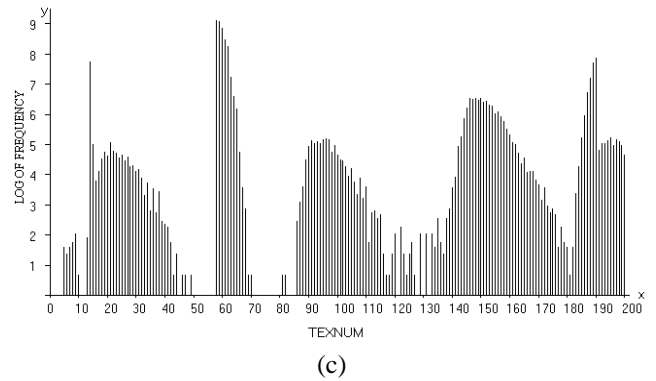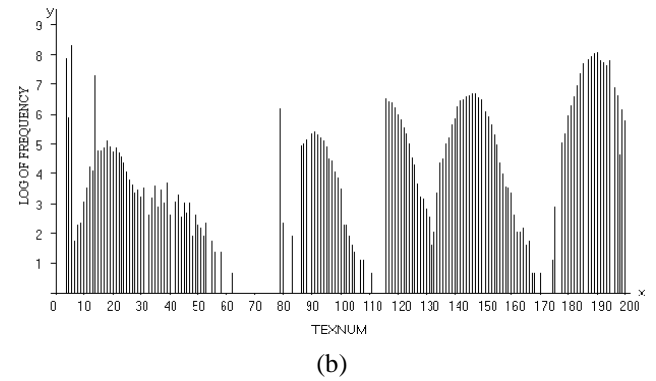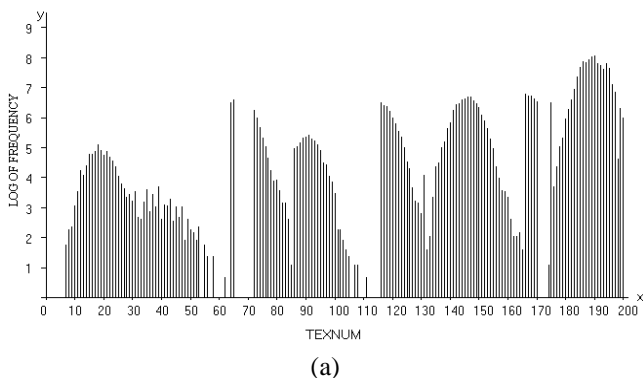

(a)

(b)

(c)

(d)

Fig.4. Texspectra: (a) Texspectrum of D38 at 5% of significance level, (b) Texspectrum of D38 at 20% of significance level, (c) Texspectrum of D93 at 5% of significance level, (d) Texspectrum of D93 at 20% of significance level

The performance of the proposed AR model based local and global descriptors are then highlighted in classification. A target image is formed by considering the four textured images mentioned above. This target image is shown in Fig.5.
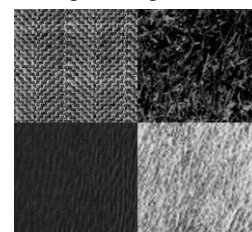

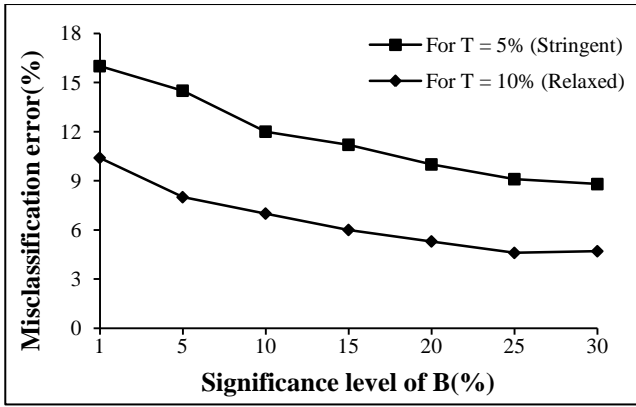Fig.5. Target image formed by four different images for classification
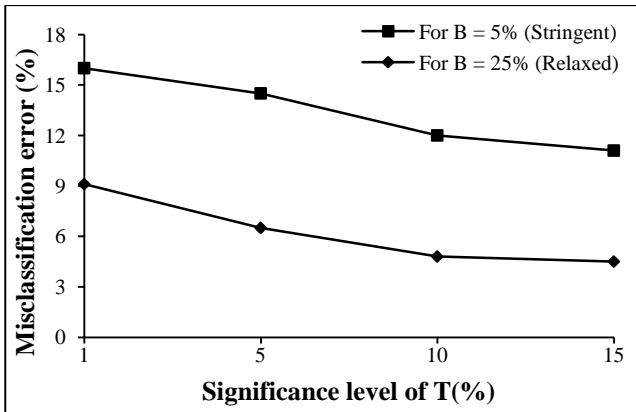
Fig.6(a) B versus misclassification error

Fig.6(b) T versus misclassification error

As explained in the previously the target image is subjected to both supervised and unsupervised classifications. Bartlett's test statistic (B) and t-statistic (T) are employed to test the homogeneity of variances and means of the target image and the reference images at various significance levels, with different combinations and the misclassification errors are computed. A window of size (28 × 28) is considered for this purpose. The obtained average misclassification values against different significant levels of Bartlett's test (B) and t-test (T) are plotted on the graph and are presented in Fig.6.

Fig.7. Classified image (Supervised)

Fig.8. Classified image (Unsupervised)

Misclassification results Fig.6(a) and Fig.6(b) with the significance level as 10% in t-test and 25% in the Bartlett's test, a correct classification of 99.62%, 98.27%, 96.81% and 87.34% are obtained in each of the image regions of D16, D109, D38 and D93 respectively. This leads to an average correct classification of 95.51%. Based on this classification, the target image is segmented and the segmented output of the target image shown in Fig.5 is presented in Fig.7.

The proposed FRAR model is also employed on the same target image for unsupervised classification. The modified k-means algorithm as explained earlier is used to classify the merged regions of the target image using the proposed global descriptor texspectrum. The minimum distance classification is used to classify the homogeneous image region from the target image by using their texspectra. A correct classification of 98.46, 97.38, 95.23 and 86.12% are obtained in each of the image regions of D16, D109, D38 and D93 respectively. This leads to an average correct classification up to 94.3%. The classified pixels corresponding to various texture classes are grouped to form various segments. The segmented homogeneous image regions are shown in Fig.8.

It is evident from the results that the proposed Full Range Autoregressive model based scheme could give most of the pixels of same class into homogeneous regions.

4. CONCLUSION

This paper has presented an autoregressive model using Bayesian approach for texture classification is presented. The autocorrelation coefficient is derived from the model coefficients. Two texture descriptors are proposed: (i) texnum, the local descriptor and (ii) texspectrum, the global descriptor. The decimal numbers are proposed to represent the textures that range from 0 to 200. These numbers uniquely represent the texture primitives. Totally it has 201 components. The textured image under analysis is represented globally by observing the frequency of occurrences of the texnums. The proposed texture representation scheme is successfully used in both supervised and unsupervised classifications of textured images into different textured regions. In the supervised classification, the texspectra of the known texture classes, as the training set of feature vectors and homogeneity tests are used. The average correct classification up to 95.51% is obtained. In the unsupervised classification, the modified k-means algorithm is used and an average correct classification of 94.3% is possible. The proposed scheme gives better results.

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