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Color Image Retrieval Based on Full Range Gaussian Markov Random Field Model

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Abstract— ***This paper proposes a novel method, based on Full Range Autoregressive (FRAR) model with Bayesian approach for color image retrieval. The color image is segmented into various regions according to its structure and nature. The segmented image is modeled to RGB color space. On each region, the model parameters are computed. The model parameters are formed as a feature vector of the image. The Hotlling T^2 Statistic distance is applied to measure the distance between the query and target images. Moreover, the obtained results are compared to that of the existing methods, which reveals that the proposed method outperforms the existing methods.***

Keywords— FRAR model, query image, target image, feature vector, spatial features.

I. INTRODUCTION

Content-based image retrieval method, though many image mining techniques are available, evolving and plays a significant role in image mining and retrieval for the past two decades especially from the last decade. In this method, various features of the image are utilized to retrieve the appropriate images. In computer vision, feature representation schemes are classified as low-level, intermediate, and high-level. The low-level features are represented at pixel level while the high-level features are represented with abstract concepts, and the intermediate-level features represent something in between them. The low-level features are well studied and good understanding, whereas the middle-level and high level concepts are very difficult to grasp, and extremely difficult to represent by the computer bits [1, 2]. The difficulties can be explained in different perspectives: first, relevance is a high-level concept and is therefore difficult to describe numerically using computer bits; secondly, traditional indexing approaches mostly extract low-level features in a low-level fashion and it is therefore difficult to represent relevance using low-level features. Because low-level features can bear no correlation to high level concepts, the burden of relevant retrieval has to be on high-level retrieval strategies, which is again hard. The middle-level features contain rich structural information of images that facilitates the high-level visual perception and image analysis [2]. Similarly, middle-level features take local measurements of orientation, contrast, disparity, color, spatial frequency into account for inferring image structure [3]. In this paper, it is believed that the low-level features make clear physical meanings and also related to high-level perceptual concepts. Because, the low-level features such as color, texture and spatial orientation of the pixels play vital role in color image formation. The spatial orientation of the pixels forms a shape or structure in an image. Next, the color features refine and enhance the shapes, and perceptually distinguish the regions from each other. Thus, most of the works use low-level features such as color, shape, texture and spatial orientation, and that are used for mine and retrieve the images. One of the most important issues in an image retrieval system is the feature extraction process, where the visual content of the images is mapped into a new space called as feature space. Mainly, the key issue to develop a successful retrieval system relies on identifying and choosing the right features that represent the images as strong as possible. Feature representation of the images may include color [1,4,6,8,13,15], texture ([5,19,24,25] and shape [1,9,11,12,13] information.

Zujovic et al. [5] performed a similarity metric test and suggested that the texture features: mean, variance, covariance, autocorrelation are sufficient to represent the structural texture similarity of the images, and can be used for image retrieval. The spatial orientation of the pixels plays a noteworthy role in pattern recognition. But, in the case of image retrieval, a limited number of literatures are available that use the structure and spatial orientation features [1,2,10,16]. It is observed from the literature that the low-level features such as texture attributes -- fine texture, coarse texture, texture description, and spatial orientation of the texture play a significant role in image processing, viz. image classification, segmentation, edge and boundary detection, etc. Wu et al. [14] proposed a texture descriptor for browsing and similarity retrieval, and they have reported that the descriptor yields good results. The spatial orientation of the textures is not still used effectively in the image retrieval domain. These texture features are more effective than other low-level features. This motivated us to develop the proposed method.

In this paper, a novel technique based on Full Range Autoregressive (FRAR) model is proposed, which characterizes the texture properties such as spatial orientation of the texture and untexture or structure (edge, boundaries) properties. It also gives unique representation to the characterized textures. To experiment the proposed FRAR model, the given input untexture or structure query image is segmented into various regions according to its structure and nature, because most untexture or structure images both color and gray-scale are not distributed to Gaussian random variable. The pixel values in the segmented homogeneous regions are attributed to a Gaussian distribution, since most of the pixels in the segmented regions are homogeneous. The segmented image regions are modeled as RGB color space. On each region of R, G and B spaces, individually, the model parameters are estimated based on Bayesian approach. The model coefficients are computed using the parameters. The model parameters form the feature vectors (FVs) region-wise. Because of the proposed model attributed to the stochastic properties, it is most appropriate for the stochastic type of texture images, and it also yields better results to the periodic type of textured images, since the circular functions *sine* and *cosine* are encompassed in estimating the parameters of the model. The FRAR model coefficients K, α, θ and ϕ are considered as features, because α represents the strength of the linear dependency of the pixels on its neighboring pixels; the other parameters θ and ϕ are associated with the circular functions *sine* and *cosine* and their values ranging from 0 to 1; K is a real valued function and it follows t-distribution. Since the parameter, α, represents the strength of the dependency of the pixels, it extracts the textures attributes, i.e. fine, coarse etc. The FVs play a significant role in determining the storage space, retrieval accuracy, and the retrieval time [4]. The FVs are compared region wise to that of the feature vectors of the target images in the image database. The distance measure *Hotlling* T^2 *Square* [27] distance is employed to measure the distance between the query and target images. Noteworthy features of the model are discussed in the next section.

II. Proposed Model for Image Retrieval

Let $X(k, l)$ be a two-dimensional random variable that represents the intensity value of a pixel at location (k, l) in an image. It is assumed that the pixel, X, may include noise and is considered independent and identical to a distributed Gaussian random variable with discrete time space and continuous state space with mean zero and variance σ^2 and is denoted as $\varepsilon(k, l)$, i.e. $\varepsilon(k,l) \sim N(0,\sigma^2)$. Thus, the images are assumed to be affected by a Gaussian random process.

Since $\{X(s); s \in S\}$ is a stochastic process, where $S=\{s: (k,l); 1 \le k, l \le M\}$, $\{X(s)\}$ can be considered as a Markov process as it has the conditional probability,

$$\begin{aligned} &P\{X(s_n) = i_n \,|\, X(s_k) = i_k : k = 0,1,2,\ldots,n-1\} \\ &\qquad = P\{X(s_n) = i_k \,|\, X(s_{n-1}) = i_{n-1}\} \end{aligned}$$

for all $i_k, k = 0,1,2,\ldots,n-1$ and s_k belonging to the state space S and $s_0 < s_1 < \ldots < s_n$.

Thus, we propose an FRAR model as in equation (1),

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

$$\text{where, } \Gamma_r = \frac{K\sin(r\theta)\cos(r\phi)}{\alpha^r} \tag{2}$$

and K, α, θ and ϕ are real parameters. The Γ_rs are the model coefficients, which are computed by substituting the model parameters K, α, θ and ϕ in equation (2). The model parameters are interrelated.

The proposed model is employed to analyse a two dimensional discrete color image. With the Markovian assumption, in the image processing context, the conditional probability of $X(k, l)$ given all other values only depends upon the nearest neighbourhood pixels.

The initial assumptions on the parameters are $K \in R$, $\alpha > 1$, and $\theta, \phi \in [0, 2\pi]$. Further restriction on the range of the parameters is placed by examining the identifiability of the model. It is interesting to note that some of the models used in the previous works such as white noise, Markov random field models and autoregressive models with finite and infinite orders can be regarded as a special case of the proposed FRAR model.

Thus,

i) if we set $\theta = 0$, then the FRAR model reduces to the white noise process.

ii) when α is large, the coefficients $\Gamma_r s$ become negligible as r increases. Hence, the FRAR model reduces to a AR(r) model approximately, for a suitable value of r, where r is the order of the model.

iii) when α is chosen to be less than one, the FRAR model becomes an explosive infinite order model.

The fact that $X(k, l)$ has regression on its neighborhood pixels gives rise to the terminology of Markov process. However, in this case, the dependence of $X(k, l)$ on neighborhood values may be true to some extent. In fact, the process is Gaussian under the assumption that the $\varepsilon(k, l)$s are Gaussian, and in this case, its probabilistic structure is completely determined by its second order properties. Second order properties meant for the proposed FRAR model is asymptotically stationary up to order two, provided $1-\alpha < K < \alpha - 1$. Finally, the range of the parameters of the model is set with the constraints $K \in R$, $\alpha > 1$, $0 < \theta < \pi$, $0 < \phi < \pi/2$.

III. Parameter Estimation

In order to implement the proposed FRAR model, we have to estimate the parameters. The parameters, K, α, θ and ϕ are estimated by taking the suitable prior information for the hyper parameters β, γ, and δ, based on Bayesian methodology. The hyper parameters meant the parameters of the prior distribution of the actual parameters K, α, θ and ϕ of the model proposed in equation (1). The hyper parameters are approximately estimated by using the mean and standard deviation of the pixel values in the region. Only for the computational purpose, the pixel values of each subimage are arranged as one-dimensional vectors $X(t)$, t =1, 2, 3, . . ., N. Since, the error term $\varepsilon(k, l)$ in equation (1) is independent and identical to distributed Gaussian random variable, the joint probability density function of the stochastic process $\{X(t)\}$ is

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

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

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

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

By expanding the square in the exponent, we get

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

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

The above joint probability density function can be written as

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

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

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

The prior distribution of the parameters is assigned as follows:

1. α is distributed as the displaced exponential distribution with parameter β, i.e.

$$P(\alpha) = \beta \exp(-\beta(\alpha - 1)) \; ; \; \alpha > 1; \; \beta > 0 \tag{7}$$

2. σ^2 has the inverted gamma distribution with parameter ν and δ, i.e.

$$P(\sigma^2) \propto \exp(-\nu/\sigma^2)\,(\sigma^2)^{-(\delta+1)}; \; \sigma^2 > 0; \; \nu, \delta > 0 \tag{8}$$

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

$$P(\Theta) \propto \beta \exp(-\beta(\alpha-1) - \nu/\sigma^2)(\sigma^2)^{-(\delta+1)}; \quad \sigma^2 > 0,\ \alpha > 1,\ 0 < \theta < \pi,\ 0 < \phi < \pi/2. \tag{9}$$

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

Using (6), (9) and Bayes theorem, the joint posterior density of K, α, θ, ϕ and σ^2 is obtained as

$$P\left(\Theta/X\right) \propto \exp(-\beta(\alpha-1)) \exp(-1/2\sigma^2)(Q+2\nu)\left(\sigma^2\right)^{-\left(\frac{N}{2}+\delta+1\right)}; \quad K \in R,\ \alpha > 1,\ 0 < \theta < \pi,\ 0 < \phi < \pi/2 \text{ and } \sigma^2 > 0. \tag{10}$$

Integrating (10) with respect to σ^2, the posterior density of K, α, θ and ϕ is obtained as

$$P(K, \alpha, \theta, \phi / X) \propto \exp(-\beta(\alpha-1)) (Q+2\nu)^{-\left(\frac{N}{2}+\delta\right)}; \quad K \in R,\ \alpha > 1,\ 0 < \theta < \pi,\ 0 < \phi < \pi/2 \tag{11}$$

where,

$$[Q+2\nu] = \left[\left(K^2 \sum_{r=1}^{N} S_r^2 T_{rr} + 2K^2 \sum_{\substack{r,s=1 \\ r<s}}^{N} S_r S_s T_{rs} - 2K \sum_{r=1}^{N} S_r T_{0r}\right) + T_{00} + 2\nu\right] \tag{12}$$

That is,

$$\begin{aligned}(Q+2\nu) &= aK^2 - 2Kb + T_{00} + 2\nu, \\ &= C\left[1 + a_1 (K - b_1)^2\right]\end{aligned} \tag{13}$$

where,

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

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

$$b = \sum_{r=1}^{N} S_r T_{0r}; \quad a_1 = \frac{a}{C}; \quad b_1 = \frac{b}{a}$$

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

$$P(K, \alpha, \theta, \varphi / X) \propto \exp(-\beta(\alpha-1)) \left[C\left\{1 + a_1 (K - b_1)^2\right\}\right]^{-d} \quad K \in R,\ \alpha > 1, 0 < \theta < \pi,\ 0 < \varphi < \pi/2 \tag{14}$$

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

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(α, θ, ϕ / *X*), can be obtained by integrating (14) with respect to K. Thus, the joint posterior density of α, θ and ϕ is obtained as

$$P(\alpha, \theta, \varphi / X) \propto \exp(-\beta(\alpha-1)) C^{-d} a_1^{-1/2} \quad \alpha > 1,\ 0 < \theta < \pi,\ 0 < \phi < \pi/2 \tag{15}$$

The marginal posterior density of α, θ and ϕ in (15) is a complicated function and is analytically not solvable. Therefore, we can find the original posterior density of α, θ and ϕ numerically from the joint density (15).

That is,

$$P(\alpha) \propto \iint P(\alpha, \theta, \phi \;/\; X)\, d\theta\, d\phi$$

Similarly,

$$P(\theta) \propto \iint P(\alpha, \theta, \phi \;/\; X)\, d\alpha\, d\phi \text{, and} \qquad (16)$$

$$P(\phi) \propto \iint P(\alpha, \theta, \phi \;/\; X)\, d\alpha\, d\theta$$

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, we first obtain the posterior mean of α numerically. Then fix α at its posterior mean and evaluate the conditional means of θ and ϕ fixing α at its mean. We fix α, θ and ϕ at their posterior means respectively and then evaluate the conditional mean of K.

Thus, the estimates are

$$\begin{aligned} \hat{\alpha} &= E(\alpha) \\ (\hat{\theta}, \hat{\phi}) &= E(\theta, \phi \;/\; \alpha = \hat{\alpha}) \quad \textit{and} \\ \hat{K} &= E(K \;/ \hat{\alpha}, \theta = \hat{\theta}, \phi = \hat{\phi}). \end{aligned} \qquad (17)$$

The estimated parameters K, α, θ and ϕ are adopted to compute the coefficients Γ_rs of the model in equation (1). The model parameters are utilised to compute the autocorrelation coefficient, which is used to identify the texture primitives and micro textures present in the image.

The parameters of the model are combined together and formed as FVs. The same kind of features is also extracted from the target image to be retrieved from the image database. These features are treated as two different FVs $\vec{x}$ and $\vec{y}$

IV. Similarity Measure

In order find the similarity of the query and target images, the *Hotlling T^2 statistic* (T^2) [27] expressed in equation (15) is applied on the feature vectors $\vec{x}$ and $\vec{y}$ of the query and target images.

$$T_d^2(X,Y) = \frac{n_x \cdot n_y}{n_x + n_y} (\overline{X} - \overline{Y})' A^{-1} (\overline{X} - \overline{Y}) \qquad (15)$$

Where,

$$\overline{X} = \frac{1}{n_x} \sum_{i=1}^{n_x} X_i \,, \qquad \overline{Y} = \frac{1}{n_y} \sum_{i=1}^{n_y} Y_i$$

are the sample means, and

$$A_x = \frac{\sum_{i=1}^{n_x} (X_i - \overline{X})(X_i - \overline{X})^T}{n_x - 1}, \qquad A_y = \frac{\sum_{i=1}^{n_y} (Y_i - \overline{Y})(Y_i - \overline{Y})^T}{n_y - 1}$$

$$A = \frac{A_x + A_y}{n_x + n_y - 2}$$

is the unbiased pooled covariance matrix of the query and target images.

If $T_d^2 \le \frac{(N_x + N_y - 2)p}{N_x + N_y - p - 1} F_{\alpha; N_x + N_y - p - 1}$, then it is inferred that the query and target images are same or similar (i.e., belongs to the same class); otherwise, the two images are different (i.e. belongs to different classes). $F_{\alpha; N_x + N_y - p - 1}$ represents values in statistical F-table at the level of significance $\boldsymbol{\alpha}$ with degrees of freedom $N_x + N_y - p - 1$; p represents the size of the feature vectors. Based on the distance values, the images are marked and indexed in ascending order, and the indexed images are retrieved.

V. Measure of Performance

In order to validate the performance of the proposed method, the precision and recall measures [6] are used, which are given in equations (17) and (18).

$$\text{Precision}\,(P) = \frac{\left|\{\text{retrieved images}\} \cap \{\text{relevent images}\}\right|}{\left|\text{retrieved images}\right|} \tag{17}$$

$$\text{Recall}(R) = \frac{\left|\{\text{retrieved images}\} \cap \{\text{relevant images}\}\right|}{\left|\text{relevant Images}\right|} \tag{18}$$

Where $|\cdot|$ returns the size of the set. The precision (P) represents the ratio of the number of images relevant to the query image among retrieved images to the number of retrieved images. The recall (R) represents the ratio of the number of images relevant to the query image among retrieved images to the number of images relevant to the query image.

VI. Experimental Settings and Design of Image Databases

In order to implement the proposed method, 1277 color images of size 512×512 pixels have been collected from various sources such as 293 texture images from Brodatz Album; 488 images from Corel image database; 496 images from VisTex image database; and 268 images with size 128×128 are photographed by a digital camera; 257 images with size 128×128 have been downloaded from various websites. The texture images collected from Brodatz, Coral and VisTex image databases are divided into 16 non-overlapping sub-images of size 128×128. To examine the proposed system is invariant for rotation and scaling, the images are rotated through 90^o, 180^o and 270^o degrees, and scaled. Thus, totally there are ((16 × (293+488+496)) + (268 + 257)) × 3 (rotated through 90^o, 180^o and 270^o) + 20,957 (scaled) = 83,828 images. Based on these image collections, an image database and their FV database are constructed.

The input query image is segmented into various regions according to its shapes and structure, and it is modelled to RGB colour space. The proposed method is employed on R, G and B components individually for extracting the image features as discussed in sections 2 and 3. On each region, the parameters and autocorrelation coefficients are computed, and they are combined together and formed as FVs database. The extracted features are classified into various groups according to their nature using fuzzy c-means algorithm [21]. For each group, the median value is calculated, and based on it the FVs are indexed. Based on the classes of the FVs, images in the database are classified into different groups, and it establishes a link between the images and the corresponding FVs of each class. Now, the extracted FVs of the query image are compared to that of the index of the FVs in the image feature database and is identified using the expression given in the equation (15). Then the FVs of the query image are matched with the FV database, and retrieves the same or similar images from that class. If the FVs of the query image do not match with any classes of the FV database, then it is formed as a new FV class.

If the given input image is structured, it is segregated into various regions according to its shapes and structure; if it is texture image, then it considered as it is for retrieving the same or similar images from the image database. The input query image is identified whether it is texture or structure by computing the coefficient of variation (CV), and the CV value is compared to a threshold value $\boldsymbol{t}$. If CV > $\boldsymbol{t}$ then it is assumed that the input image is structured image, and if CV < $\boldsymbol{t}$ then the input image is assumed to be texture image. The threshold $\boldsymbol{t}$ is fixed as 25%.

VII. Experiments and Results

In order to validate the proposed system, the image in Figure 1(a) is given as input query image to the system, and it retrieves the images in columns 1, 2 and 3 of Figure 1(b) while the level of significance is fixed at 0.001; the images in column 1, 2, 3 and 4 are retrieved at 0.02 level of significance; at 0.01significance level, the system retrieves the images in column 1, 2, 3, 4 and 7; at the level of significance 0.1, the system retrieves all the images presented in Figure 1(b).

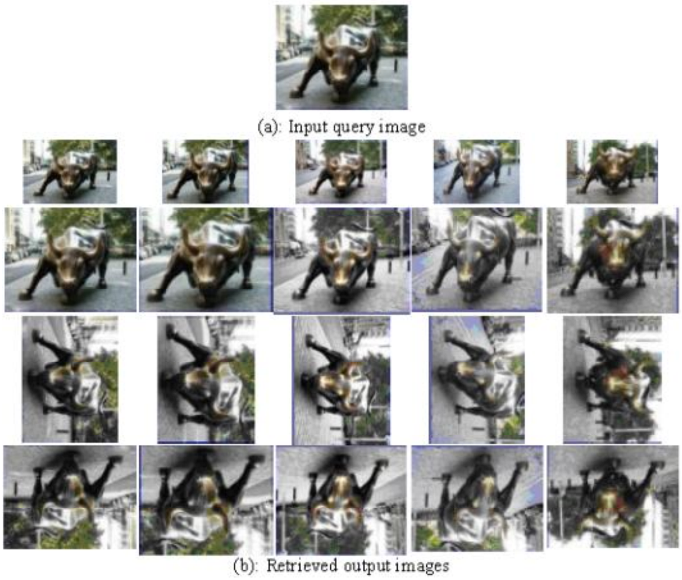

Figure 1. Wall Street Bull – downloaded from the internet. (a): Input query image; (b): Retrieved output images: row 1 – scaled down image of size 75 × 100; row 2 – actual image with size 96 × 128; row 3 - images in row 2 are rotated clockwise by 90 degrees; row 4 – images in row 2 are rotated clockwise by 180 degrees.

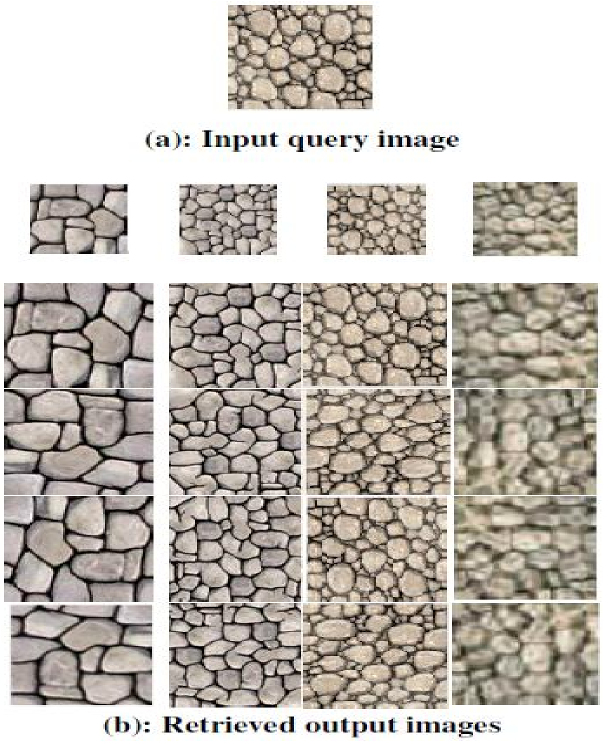

Figure 2: VisTex image database – Structural Texture Images: 1(a) - Input query image; 1(b) - row 1: scaled down image; row 2: actual images; row 3: actual images rotated clockwise by 90 degrees; row 4: actual images rotated clockwise by 180 degrees; row 5: actual images rotated clockwise by 270 degrees

To emphasis the effectiveness and efficiency of the proposed system, another type of structural texture image with stochastic pattern is given as input, which is presented in Figure 2(a). The proposed system retrieves the images in columns 3 of the Figure 2(b) when the level of significance is fixed at 0.001; the images in column 2, 3 and 4 are retrieved at 0.04 level of significance; at 0.08 level of significance, the system retrieves all the images in Figure 2(b).

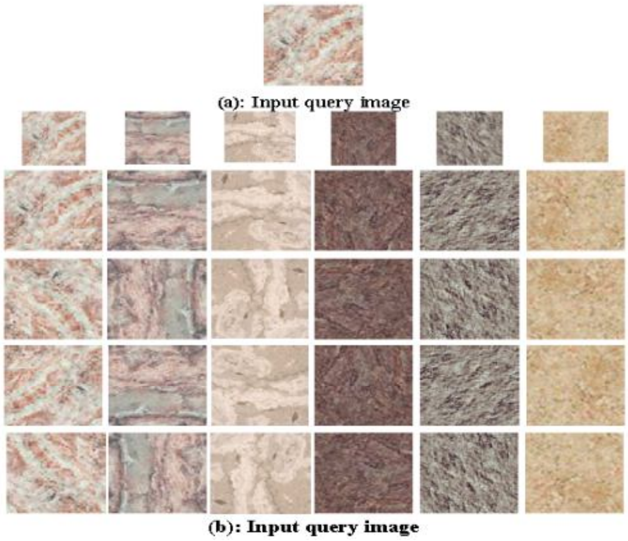

Figure 3: Bordatz image database - Texture Images: 1(a) - Input query image; 1(b) - row 1: scaled down image; row 2: actual images; row 3: actual images rotated clockwise by 90 degree; row 4: actual images rotated clockwise by 180 degrees; row 5: actual images rotated clockwise by 270 degrees.

Furthermore, to emphasis the effectiveness of the proposed system, another type of texture image with stochastic patterns given in Figure 3(a) is given to the system. The system retrieves the images in column 1 of Figure 3(b) while the level of significance is fixed at 0.001; the images in column 1, 2 and 3 are retrieved for the level of significance is at 0.03; while fixing the level of significance at 0.08, the system retrieves the images in column 1, 2, 3 and 4; while the level of significance is at 0.12, the system retrieves all the images in Figure 3(b).

Table 1: Performance measure of the proposed method with other existing methods

Image Database	Proposed method (α is above 0.12)		Orthogonal polynomial		Gabor wavelet		Contourlet Transform	
	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision
Brodatz	0.7981	0.8012	0.8435	0.7001	0.8651	0.7001	0.8481	0.6908
VisTex	0.8692	0.7835	0.8016	0.7901	0.8102	0.6901	0.8251	0.6191
Structure Images	0.9011	0.8446	--	--	--	--	0.8812	0.7009

A comparative study is performed with the existing methods such as orthogonal polynomial [24], Gabor wavelet transform [25] and Contourlet transform [26] techniques by computing the precision and recall values for the retrieval results obtained. Averages of the precision and recall values are computed for various methods, and are presented in Table 1. The average of the precision and recall values are obtained at the level of significance (α) is above 0.1 (i.e. 10%). It is observed from the results that the proposed method outperforms the existing methods.

VII. Discussion and Conclusion

In this paper, a novel scheme is proposed for both structure and texture, color image retrieval based on the FRAR model with Bayesian approach. The model coefficients are computed using the circular functions *sine* and *cosine* as discussed in section 2, the proposed scheme characterizes the structure and texture primitives in the periodic texture patterns also. Since the FRAR model characterizes the texture primitives and provides a unique decimal number, it matches exact images in the image database and retrieves. Because, the proposed system facilitates the user to fix the level of significance for the test statistic T_d^2, the user can fix the significance level α at a desired level by which the user can retrieves only the required same or similar images, and not all the relevant images in the database as in the other existing systems. For example, at or below the significance level 0.001 (1%), the system retrieves only the same image, and the rotated and scaled images of the same query image. But there is one disadvantage that if the same image is in the database, it retrieves the image; otherwise, it results that no image is matched with the query image. This problem can be overcome by fixing the significance level $\boldsymbol{\alpha}$ at more than 0.001, by which the system retrieves the similar images. The user can fix the significance level himself at his own convenience. Because the proposed system is a distributional approach, it is also invariant for rotation and scaling.

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