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A New Texture Image Retrieval Scheme with Full Range Auto Regressive (FRAR) Model

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Abstract: In any Content Based Image Retrieval (CBIR) system, texture plays a significant role in retrieval process. Hence, in this study, a new texture based image retrieval scheme based on Full Range Auto Regressive model is proposed. With the proposed model, auto correlation coefficients are computed with positional difference to capture the texture present in the small image region under analysis. Autocorrelation functional features and directionality features are also extracted and utilized to propose an efficient CBIR system. The proposed scheme is experimented with standard images and is tested with two existing schemes. The retrieval rate and speed performs more efficient than the existing systems in image retrieval.

Key words: Content Based Image Retrieval (CBIR), texture, feature extraction, autocorrelation coefficients, feature set, Image Database (IDB)

INTRODUCTION

The world is dominated with visual information and a tremendous amount of such information is being added day by day. It would be impossible to cope with this explosion of visual data, unless they are organized to retrieve them efficiently and effectively. Content Based Image Retrieval (CBIR) is a promising approach to search through an image database with image features such as texture, edge, shape, color or any combination of them. The CBIR technique automatically extracts the primitive visual features from the image and retrieves the images on the basis of these features. Among these low level features texture a plays significant role in any CBIR system.

Over the recent years, a number of approaches have been developed to solve the low-level texture analysis problems. These existing research works are broadly classified based on the first-order and second-order statistical properties, geometrical, structural, model based and signal processing techniques (Tuceyrane and Jain, 1993). Over a decade, Multi channel methods (Chen *et al*., 1995), Multi resolution analysis (Krishnamachari and Chellappa, 1997), Wavelet features (Chang and Kuo, 1993; Mojsilovic *et al*., 1997; Zhang *et al*., 1998) and Gabor features Grigorescu *et al*. (2002) are used extensively for low-level analysis of textures.

In this study, a new feature extraction scheme is introduced. Texture conveys essential information of an image and therefore applied to image retrieval. The proposed FRAR model extracts the features of the texture images using the low level features. The image retrieval takes place with the combination of the extracted features. The main focus of this study is to construct a global CBIR system using low level features. The texture features such as autocorrelation features, horizontal directionality and vertical directionality features are being extracted.

Related works: Early researches on image retrieval can be traced back to late by 1970's. Early CBIR systems such as QBIR (Flicker *et al*., 1995), NETRA (Manjunath and Ma, 1997), Photobook etc., employed texture as one of the dominant features for image retrieval. Manjunath and Ma (1997) and Pentland *et al*. (1994) represented a texture image with Gabor features obtained with Gabor Wavelet transform coefficients. Smith and Chang (1994) used Wavelet transform to characterize a texture and the statistics extracted from the Wavelet sub-bands were used as features. Strand and Taxt (1994) compared various methods of texture analysis. The co-occurrence matrix (Haralick *et al*., 1973) method is based on the joint probability distribution of pixels in an image. Galloway (1975) proposed the run length method, in which, the run of gray levels are used to characterize the textures for further analysis. The Fourier power spectrum method was proposed by Weszka *et al*. (1976) to characterize the micro level textures present in the textural images.

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Later, He and Wang (1990) proposed a scheme for texture characterization and discrimination based on local and global properties. The frequency of occurrences of texture numbers represents the global texture properties of the image. It is reported in Ganesan and Bhattacharyya (1995) that the scheme of He and Wang (1990) does not distinguish the textured regions. Hence, Ganesan and Bhattacharyya (1995) modeled another technique based on statistical approach that maps the small textured image region at centre pixel on to a set of binary numbers called pronum that range from 0-255.

Kulkarni and Verma (2003), proposed a fuzzy logic based approach for the interpretation of textured queries, where Tamura feature extraction technique was used to extract texture features of images in the database. Sanjay Kumar Sha *et al.* (2004) designed and implemented an experimental CBIR system that used a texture co-occurrence matrix. Jalaja *et al.* (2005), proposed a structural method of texture analysis for CBIR. Kourosh and Hamid (2005), presented another approach for rotation invariant texture classification with wavelet energy features and used them for image retrieval. Recently, Yue Jiang *et al.* (2008), presented a multi-resolution approach for texture classification based on the moment features that were extracted in the x-direction and y-direction, of a histogram in each image resolution.

Even though, considerable amount of work had already been done for texture images, lot of issues exists in extracting the orientation, directionality and regularity features for the image retrieval. The issues so far discussed constitute the main motivation for propose the Full Range Auto Regressive model for feature extraction on images. In the proposed model, the image retrieval is done by extracting the features using autocorrelation coefficients and directionality features.

MATERIALS AND METHODS

Texture based image retrieval with frar model

The FRAR model: In this study, a Full Range Auto Regressive model has been presented for texture identification and representation. The auto correlation function is derived with the auto correlation coefficients and is utilized for content based image retrieval.

Let X be a random variable that represents the intensity value of a pixel at location (k, l) in an image of size $(L \times L)$. It is also, assumed 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 mean zero and variance σ^2 and is denoted as $\varepsilon(k, l)$. That is, $\varepsilon(k, l) \sim N(0, \sigma^2)$.

Since, $\{X_t;\ t \in S\}$ is a stochastic process, where $S = \{t(k\text{-}l);\ 1 \le k,\ 1 \le N\}$, $\{X(t)\}$ can be considered as a Markov process if it has the conditional probability,

$$P\left\{X(t_n) = i_n \left| \begin{matrix} X(t_k) = i_k; \\ k = 0, 1, 2, L, n-1 \end{matrix} \right. \right\} \quad (1)$$

$$P\{X(t_n) = i_k \,|\, X(t_n - 1) = i_n - 1\} \quad (2)$$

$\forall i_k$, k = 0, 1, 2, ... , n-1 and t_k belonging to the state space S and $t_0 < t_1 < \ldots < t_n$.

The two dimensional monochrome images are modeled $\{X(K, l),\ 1 \le k,\ l \le N\}$ by means of discrete spatial interval of equal distance with Gaussian Markov Random Field (MRF).

Thus, the proposed Eq. 3, a family of models by a discrete-time stochastic process $\{X(t)\}$, $t = 0, \pm 1, \pm 2, \pm 3, \ldots$, is called the Full Range Auto Regressive (FRAR) model, by the difference Eq. 3:

$$\begin{aligned} X(k,l) &= \sum_{\substack{p=-1 \\ p=q\neq 0}}^{\infty} \sum_{q=-1}^{\infty} \frac{K\sin(r\theta)\cos(r\varphi)}{\alpha^r} X(k+p,\ 1+q) + \varepsilon(k,l) \\ &= \sum_{\substack{p=-1 \\ p=q\neq 0}}^{\infty} \sum_{q=-1}^{\infty} \Gamma_r X(k+p,\ 1+q) + \varepsilon(k,l) \end{aligned} \quad (3)$$

Where:

$$= \Gamma_r = \frac{K\sin(r\theta)\cos(r\varphi)}{\alpha^r} \text{ and } r = |p+q|$$

In the Eq. 3 X(k + p, 1 +q) accounts for the spatial variation owing to image properties and $\varepsilon(k,l)$ is the spatial variation owing to additive noise and the model coefficient,

$$\Gamma_r = \frac{K\sin(r\theta)\cos(r\varphi)}{\alpha^r}$$

is the rth coefficient of variation among the low-level primitives in the small image region. The coefficients are interrelated. The interrelationship is established through the model parameters K, α, θ and ϕ which are real. The model parameters are estimated on the intensity values of sub image with the concept of Bayesian approach. The model coefficients (Γ_rs) in the Eq. (3) are functions of K, α, θ and ϕ as well as n.

Such that:

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

where, K∈R: set of real numbers; $\alpha > 1$; $\theta, \phi \in (0, 2\pi)$ and $n \in \{1, 2, \ldots\}$. Finally, the range of the parameters of the model are set with the constraints $K \in R$, $\alpha > 1$, $0 < \theta < \pi$, $0 < \phi < \pi/2$ and $\epsilon(k, l)$ are independent and identically distributed Gaussian random variables with mean zero and variance σ^2.

Texture identification with FRAR model: To identify the textures in the image under analysis, the model parameters K, α, θ, φ are estimated. Small image regions are considered by dividing the whole image into various overlapping regions of size (3×3). The rationale behind the consideration of small regions is: Micro textures can easily be identified in small areas and The time complexity for computation will be less. The model coefficients Γr s (r = 1, 2) are determined by applying the estimated parameters K, α, θ and φ in Eq. 3. The auto correlation function (ρ_k) is derived from the model coefficients Γ_rs as follows:

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

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

and

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

Similarly, the auto correlations of kth order can be obtained by solving the Eq. 3 using recurrence relation. The patterns are governed by the second order linear difference equation:

$$\rho_k = \Gamma_1\rho_{k-1} + \Gamma_2\rho_{k-2} \tag{4}$$

where, $1 \le k \le m$. From the Eq. 4, the auto correlation coefficients (ρ_k) are first computed. To identify the micro level textures present in the small image region, a test is conducted, that finds the significance of the auto correlation.

Representation of textures using auto correlation coefficients: In this study, the proposed Full Range Auto Regressive model has been presented for the representation and retrieval of gray scale texture images. The autocorrelation function has been utilized to extract the texture features using auto correlation coefficients for content based image retrieval.

The micro textures in a small region are identified by employing the test for homogeneity of variances among the autocorrelation coefficients. The identified textures are then represented locally as a decimal number called autonum and globally for the entire image under analysis called auto-spectrum. The usage of this texture representation is highlighted for proposing CBIR.

Auto correlation function evaluates the linear spatial relationships between primitives. If the primitives are large, the function decreases slowly with increasing distance whereas it decreases rapidly if texture consists of small primitives.

However, if the primitives are periodic, then the auto correlation increases and decreases periodically with distance. The set of autocorrelation Coefficients [C_{ff}] is modeled to extract the texture features for image retrieval as shown:

$$C_{ff}(p,q) = \frac{MN\sum_{i=1}^{M-p}\sum_{j=1}^{N-q} f(i,j)f(i+p,j+q)}{(M-p)(N-q)\sum_{i=1}^{M}\sum_{j=1}^{N} f^2(i,j)} \tag{5}$$

where, (p, q) is the positional difference, in which the values range from (0, 0) to (r - 1, s - 1) such that $1<r<M/2$ and $1<s<N/2$, i, j are directions and M, N are image dimensions.

When, the positional difference (p, q) varies from (0, 0) to (r-1, s-1), the extracted texture feature is represented as a matrix as shown:

$$C_{ff}(p,q) = \begin{bmatrix} C_{ff}(0,0) & C_{ff}(0,1) & C_{ff}(0,2) & \cdots & C_{ff}(0,s-1) \\ C_{ff}(1,0) & C_{ff}(1,1) & C_{ff}(1,2) & \cdots & C_{ff}(1,s-1) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ C_{ff}(r-1,0) & C_{ff}(r-1,1) & C_{ff}(r-1,2) & \cdots & C_{ff}(r-1,s-1) \end{bmatrix} \tag{6}$$

In order to represent the identified micro textured regions, the auto correlation coefficients are calculated using the Eq. 5 and are stored in an array for various sub-images. The computed auto correlation values ranges from 0-1. A simple transformation (ρ * 100) is applied on the auto correlation values to obtain decimal number that range from 0-100, where, ρ is the auto correlation coefficient. The autonum ranges from 0-100, there are 101 components in the auto spectrum. Based on this texture number, the proposed scheme characterizes and represents different types of textures. It also explores the spatial interrelationship between the pixels and tonal primitives of micro textures in the small image region since auto correlation represents the relationship among the pixels. The usage of the autonum in establishing the feature vector is also discussed in the this study.

Texture based feature extraction with frar model: In order to retrieve images, we must be able to compare two images to determine the similar contents. An efficient matching scheme further depends upon the discriminatory information contained in the feature vectors of the images. Let $I = \{I_1, I_2, \ldots, I_N\}$ be the sequence of all gray-level images in an Image Database (IDB). Thus, each I_i denotes a gray-scale image of size (M×N) with pixel values in the range 0-255. A grayscale input image I_i of size (M×N) from the image database is considered for the extraction of feature vectors and is divided into k sub-images of size (n×n). viz. $S_1, S_2, \ldots S_k$ using the formula:

$$k = 2^{2(n-1)}$$

where, n <= M,N. The feature vectors are extracted with the proposed FRAR model for each of the k non-overlapped sub regions using auto-correlation coefficients. In the proposed FRAR model, the feature vectors of the images are extracted on the basis of the auto correlation coefficients with horizontal and vertical directionality features.

Feature extraction with auto correlation coefficient: The Feature vectors of each sub-images are computes using the Eq. 5 with the positional differences (p, q). Hence, the Feature Matrix (F_k) of the kth sub-region of the input image with the positional differences (r, s) is extracted and auto correlation co-efficient values of kth block are converted into autonums with the value ranges 0-100 and are represented into feature matrix as shown:

$$F_k = \begin{bmatrix} C_{ff}(0,0) & C_{ff}(0,1) & L & C_{ff}(0,q-1) \\ C_{ff}(1,0) & C_{ff}(1,2) & L & C_{ff}(1,q-1) \\ M & M & & M \\ C_{ff}(p-1,0) & C_{ff}(p-1,0) & L & C_{ff}(p-1,q-1) \end{bmatrix} \quad (7)$$

The values obtained with the feature matrix of each block are considered as the auto correlation features. In addition to these features, the horizontal and vertical directionality features are extracted to generate the feature set.

Feature extraction on using directionality features: The texture feature extraction process in terms of the proposed full range autocorrelation method has been presented in the aforementioned section. Since textures can be best examined with directionality, we present in this section, a new feature texture extraction with directionality on the proposed FRAR. The proposed feature vector is aimed to concentrate on the horizontal and vertical directions with the auto-correlation coefficients with the positional difference p and q in i, jth directions.

Horizontal directionality: In the proposed model, the horizontal directionality is computed by applying the positional difference q = 0 in the Eq. 5 with the size (M×N) of the input image I_i. The auto-correlation coefficients on Horizontal Directionality (C_{hff}) is represented in Eq. 8

$$C_{hff}(p,0) = \frac{mn\sum_{i=1}^{m-p}\sum_{j=1}^{n} f(i,j).f(i+p,j)}{[m-p][n]\sum_{i=1}^{m}\sum_{j=1}^{n} f^2(i,j)} \quad (8)$$

There are r feature vectors extracted as column matrix (F_h) by reflecting the horizontal directionality of texture present in the input image I_i with q = 0 in Eq. 8 and the same is presented as:

$$F_h = \begin{bmatrix} C_{hff}(0,0) \\ C_{hff}(1,0) \\ C_{hff}(2,0) \\ \vdots \\ \vdots \\ C_{hff}(r-1,0) \end{bmatrix} \quad (9)$$

where p ranges from 0 to r-1.

Vertical directionality: In the proposed model, the vertical directionality is computed by applying the positional difference p = 0 in the Eq. 5 with size (M×N) of the input image I_i. The Auto-correlation coefficient features on Vertical Directionality (C_{vff}) is represented in Eq. 10.

$$C_{vff}(0,q)=\frac{mn\sum_{i=1}^{m}\sum_{j=1}^{n-q}f(i,j).f(i,j+q)}{[m][n-q]\sum_{i=1}^{m}\sum_{j=1}^{n}f^{2}(i,j)} \quad (10)$$

where p, q is the positional difference in the i, j direction and m, n are image dimensions Hence, there are r feature vectors extracted as column matrix (F_v) by reflecting the horizontal directionality of the input image I_i with p = 0 in Eq. 10 and the same is presentedIn Eq. 11.

$$F_v=\begin{bmatrix} C_{vff}(0,0) \\ C_{vff}(0,1) \\ C_{vff}(0,2) \\ \vdots \\ \vdots \\ C_{vff}(0,s-1) \end{bmatrix} \quad (11)$$

where, q ranges from 0 to s.

Generation of feature sets: With the proposed FRAR model, the feature set (Fs_k) is generated with the extracted autocorrelation features, the horizontal and vertical directionality features of each k-block of the image as represented in Eq. 12.

$$Fs_k=\{F_k,H_k,V_k\} \quad (12)$$

Where:
F_k = Auto correlation feature vectors of kth block
H_k = The feature vector of the horizontal directionality
V_k = The feature vector of the vertical directionality

The feature set (Fs) is generated with the above mentioned auto correlation features, with horizontal and vertical directionality features of all the k-blocks of the input image. Hence, the feature set (Fs) of the input image (I_i) is generated and the graphical representation of the feature set (Fs) is shown in Fig. 1, where F_1, F_2, ..., F_k are auto correlation features of the respective blocks.

H_1, H_2, ..., H_k and V_1, V_2, ..., V_k are the horizontal and vertical features, respectively.

The generated feature sets (Fs) of all the textured images in the image database are stored as the feature data base.

Similarity and performance measures: In the proposed FRAR Model for CBIR system, Euclidean Distance is

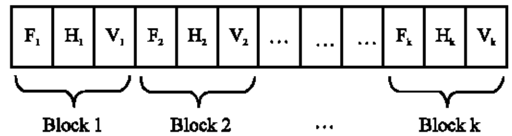

Fig. 1: Graphical representation of proposed texture feature set

considered to find the distance between the feature vectors of the target image and the query image. The difference between two images I_1 and I_2, can be expressed as the distance 'd' between the respective feature vectors f_1 and f_2.

In the proposed FRAR Model, the performance is measured in terms of Precision (P) and Recall (R) which are defined:

$$P=\frac{r}{n_1}=\frac{\text{Number of relevant images}}{\text{Number of retrieved images}}$$

$$R=\frac{r}{n_2}=\frac{\text{Number of relevant images}}{\text{Total number of relevant images in IDB}}$$

The retrieval performance of the proposed scheme is also measured in terms of average recognition rate by considering each image as a target image and the number of relevant images corresponding to the target image available in the database are listed.

RESULTS AND DISCUSSION

The proposed Full Range Auto Regressive (FRAR) model for texture based image retrieval is experimented with the images from different databases such as Vistex and Brodatz album. The texture images considered in this experiment are of size (256×256) with pixel values in the range 0-255. Some of the sample texture images considered for experimentation from the standard database (Brodatz album) is shown in the Fig. 2.

Each image of the considered Brodatz texture image database are subjected to the above mentioned texture extraction process with the proposed full range auto regressive model. First, the image under analysis is partitioned into k blocks, each block of size (n×n) and the feature set is generated. For illustration, when we consider the image D27 as target image shown in Fig. 3. Then, the feature set of the target image is compared with the feature sets in the feature database using the Euclidean distance measure. The distances are then stored in ascending order and the top 10 relevant images of the

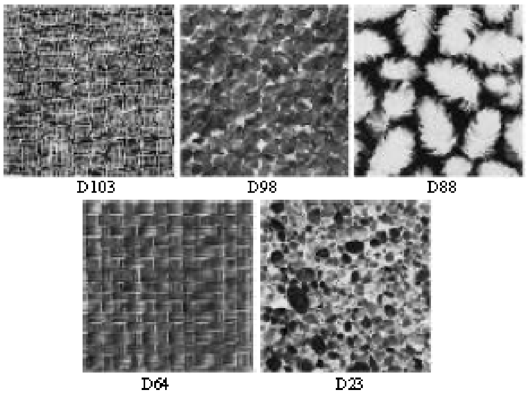

Fig. 2: Sample texture images taken from Brodatz texture database

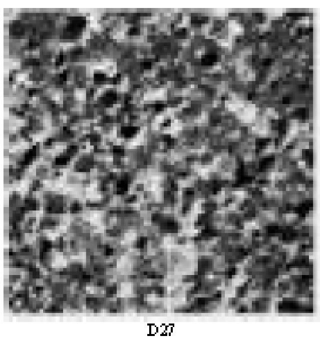

Fig. 3: Target image

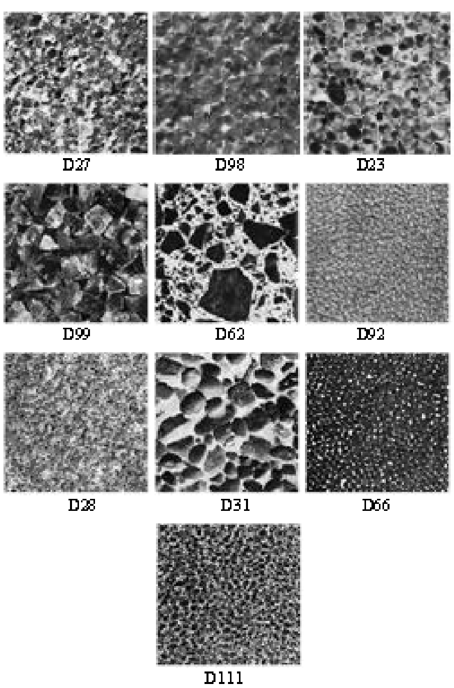

Fig. 4: The Retrieval results obtained with the proposed method

Table 1: Comparison result of proposed method with GLCM method and Law's method

Proposed method		GLCM method		Law's method	
Recall	Precision	Recall	Precision	Recall	Precision
0.92	0.78	0.72	0.54	0.81	0.68

target image are retrieved. The retrieval results for the target image D27 using the proposed method is shown in Fig. 4.

We measure the retrieval performance of our proposed method in terms of precision and recall by considering each image in the database as a query image and the above mentioned procedure is repeated for calculating them. The precision and recall for the proposed method are 0.92 and 0.78, respectively. These results are shown in Table 1.

It can be observed from the above table that the proposed FRAR model based texture feature for CBIR works well than the other two existing systems.

CONCLUSION

In this study, a new statistical approach based on a family of FRAR model for CBIR system with the auto correlation function for texture based images retrieval has been presented. The auto correlation coefficients are computed with the positional differences and the local descriptor autonum is proposed to represent the texture primitives that ranges from 0-100. The auto correlation functional features and directionality features are used to generate the feature set of the image and stored in the feature database. The proposed FRAR model based texture retrieval is experimented with standard images and is compared with the existing GLGM method and Law's method.

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