Design of Fusion Texture Feature with Orthogonal Polynomials Model and Co-Occurrence Property for Content Based Image Retrieval

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Abstract **- In this paper, a new fusion texture feature with orthogonal polynomials based multiresolution subband and the Gray Level Co-occurrence Matrix (GLCM) is presented. The proposed orthogonal polynomials based multiresolution subband coefficients posses the localized frequency information and the GLCM matrices capture the structural and statistical properties from the subband coefficients for characterizing the texture features. A set of texture features is derived and is experimented with the popular texture database Broadtz for texture image retrieval. The experiment shows that the proposed fusion texture feature outperforms well for the regular, irregular and weak directionality texture images. The proposed method yields high retrieval rate when compared with Discrete Wavelet Transform (DWT) based retrieval scheme with less computational cost.**

Index Terms-**Orthogonal polynomials, Texture image retrieval, Gray level Co-occurrence matrix, Multiresolution, Subband.**

1 INTRODUCTION

With the wide spread use of digital and multimedia technology, storage, searching and retrieval of images from the large database become difficult. In order to facilitate efficient searching and retrieving of images from the digital library, new tools and techniques have emerged. The need to find a desired image from a large collection is shared by many professional groups including journalists, design engineers, art historians and researchers etc. One such approach is Content Based Image Retrieval (CBIR). Compared with text based approach for retrieving similar images from the database, CBIR does not require manual annotation for each image and is not limited by the availability of lexicons instead this framework utilizes the low level features that are inherent in the images, such as color, shape and texture. In CBIR, some types of similarity between images are computed using image features extracted from them. Thus, users can search for images similar to query images quickly and effectively.

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Among different visual characteristics such as color and shape for the analysis of different types of images, texture is reported to be prominent and vital low level feature [1-2]. Even though no standard definition exists for texture, Sklansky [3] defined the texture as a set of local properties in the image region with a constant, slowly varying or approximately periodic pattern. It is measured using its distinct properties such as periodicity, coarseness, directionality and pattern complexity for efficient image retrieval particularly on the aspects of orientation and scale [4 – 5]. Many techniques exit for extracting the texture feature: They are (i) Statistical methods (Gray level Co occurrence matrix (GLCM) [6]), (ii) Model Based methods such as Markov Random Fields (MRF) [7], Simultaneous Auto Regression model (SAR) [8], Wold decomposition model [9] and (iii) Signal Processing methods (Gabor filters [10], Wavelet Transforms [11 - 12]). Among these techniques, recently multiresolution based method such as Discrete Wavelet Transform (DWT) and Gabor transform along with co occurrence features are extensively used for texture image retrieval. G. V. D. Woumer et. al [13] have shown that concurrence features extracted in the wavelet domain can improve texture characterization. K.O. Cheng et. al [14] have proposed the use of co-occurrence matrix features computed from multi scale directional filter bank for texture image retrieval. They claimed that their method significantly improves the retrieval rate for the regular and the weak directionality and periodicity texture images. D. A. Clausi et. al [15] designed the fusion texture feature with Gabor filter and co occurrence probabilities for texture segmentation and demonstrated that it outperforms well for noisy images and the high dimensional feature vector. The DWT based color co-occurrence feature for texture classification is explained in [16].

Though these methods are widely used, appropriate tuning of filter parameter for different scale and orientation is difficult and the computational cost is high. Hence, we propose a new and simple fusion texture feature for texture image retrieval with multi resolution subband coefficients due to orthogonal polynomials and co-occurrence matrix with less computational cost. The statistical and energy properties are computed from the detailed and approximate region of the orthogonal polynomials based multiresolution subband decomposition image. The co-occurrence features are extracted from the approximate region of the decomposed image and proved that the retrieval rate is high for the combination of statistical, spectral subband and co occurrence features.

This paper is organized as follows. In Section 2, detailed description on the proposed computational model with orthogonal polynomials is described. The proposed reordering of the orthogonal polynomials coefficients into a multi resolution like structure and the effective fusion texture feature vector extraction process with subband statistics and co-occurrence features for texture image retrieval are presented in section 3. Section 4 discusses the performance evolution metric of the CBIR system. In section 5, we present the experiments and the results. Finally conclusion is presented in Section 6.

2 ORTHOGONAL POLYNOMIALS MODEL

In this section we describe the proposed orthogonal polynomials model for analyzing the content of the image. The orthogonal polynomials that have already been well established for image coding [17 - 18], have been extended in this proposed CBIR system.

In order to analyze the content of an image for efficient proposal of CBIR system, a linear 2-D image formation system is considered around a Cartesian coordinate separable, blurring, point spread operator in which the image I results in the superposition of the point source of impulse weighted by the value of the object function f. Expressing the object function f in terms of derivatives of the image function I relative to its Cartesian coordinates is very useful for analyzing the low level features of the image. The point spread function $M(x, y)$ can be considered to be real valued function defined for $(x, y) \in X \times Y$, where X and Y are ordered subsets of real values. In case of gray-level image of size (n X n) where X (rows) consists of a finite set, which for convenience can be labeled as $\{0, 1, \ldots, n\text{-}1\}$, the function $M(x, y)$ reduces to a sequence of functions.

$$M(i, t) = u_i(t), \quad i, t = 0, 1, \ldots, n-1 \tag{1}$$

The linear two dimensional transformation can be defined by the point spread operator $M(x, y)(M(i, t) = u_i(t))$, as:

$$\beta'(\zeta, \eta) = \int_{x \in X} \int_{y \in Y} M(\zeta, x)\, M(\eta, y)\, I(x, y)\, dx\, dy \tag{2}$$

Considering both X and Y to be a finite set of values $\{0, 1, 2, \ldots n-1\}$, equation (2) can be written in matrix notation as follows.

$$|\beta'_{ij}| = (|M| \otimes |M|)^t |I| \tag{3}$$

where $\otimes$ is the outer product, $|\beta'_{ij}|$ are n^2 matrices arranged in the dictionary sequence, $|I|$ is the image , $|\beta'_{ij}|$ are the coefficients of transformation and the point spread operator $|M|$ is

$$|M| = \begin{vmatrix} u_0(t_1) & u_1(t_1) & \cdots & u_{n-1}(t_1) \\ u_0(t_2) & u_1(t_2) & \cdots & u_{n-1}(t_2) \\ & \vdots & & \\ u_0(t_n) & u_1(t_n) & \cdots & u_{n-1}(t_n) \end{vmatrix} \tag{4}$$

We consider the set of orthogonal polynomials $u_0(t)$, $u_1(t)$, …, $u_{n-1}(t)$ of degrees 0, 1, 2, …, n-1, respectively to construct the polynomial operators of different sizes from equation (4) for $n \geq 2$ and $t_i = i$. The generating formula for the polynomials is as follows.

$$u_{i+1}(t) = (t - \mu)u_i(t) - b_i(n)u_{i-1}(t) \text{ for } i \geq 1, \tag{5}$$

$u_1(t) = t - \mu$, and $u_0(t) = 1$,

where $b_i(n) = \dfrac{\langle u_i, u_i \rangle}{\langle u_{i-1}, u_{i-1} \rangle} = \dfrac{\sum_{t=1}^{n} u_i^2(t)}{\sum_{t=1}^{n} u_{i-1}^2(t)}$

and $\mu = \dfrac{1}{n}\sum_{t=1}^{n} t$

Considering the range of values of t to be $t_i = i$, $i = 1, 2, 3, \ldots n$, we get

$$b_i(n) = \frac{i^2(n^2 - i^2)}{4(4i^2 - 1)}, \quad \mu = \frac{1}{n}\sum_{t=1}^{n} t = \frac{n+1}{2}$$

2.1 THE ORTHOGONAL POLYNOMIAL BASIS

For the sake of computational simplicity, the finite Cartesian coordinate set X, Y is labeled as $\{1,2,3\}$. The point spread operator in equation (3) that defines the linear orthogonal transformation for image analysis can be obtained as $|M| \otimes |M|$, where $|M|$ can be computed and scaled from equation (4) as follows.

$$|M| = \begin{vmatrix} u_0(x_0) & u_1(x_0) & u_2(x_0) \\ u_0(x_1) & u_1(x_1) & u_2(x_1) \\ u_0(x_2) & u_1(x_2) & u_2(x_2) \end{vmatrix} = \begin{vmatrix} 1 & -1 & 1 \\ 1 & 0 & -2 \\ 1 & 1 & 1 \end{vmatrix} \tag{6}$$

The set of polynomial operators $O_{ij}^n (0 \leq i, j \leq n\text{-}1)$ can be computed as

$$O_{ij}^n = \hat{u}_i \otimes \hat{u}_j^t$$

where $\hat{u}_i$ is the $(i + 1)^{st}$ column vector of $|M|$.

It can be shown that a set of $(n \times n)$ $(n \geq 2)$ polynomial operators forms a basis, i.e. it is complete and linearly independent.

3 PROPOSED FEATURE VECTOR EXTRACTION

3.1 MULTIRESOLUTION REORDERING

In this subsection, we present a multiresolution representation of the proposed orthogonal polynomials coefficients as an effective method to analyze the content of the image for texture feature retrieval. The orthogonal polynomials coefficients β'_{ij} obtained from the previous section are reordered to provide image sub bands in a multiresolution decomposition like structure. The transformed coefficients β'_{ij} are reordered into ($3\log_2 N$+1) multi resolution subbands for the (N x N) block where N is a power of 2. The following assumptions are made to reorder the coefficients β'_{ij} into the required multiresolution form. For a coefficient β'_{ij}, let $2^{a-1} \leq i < 2^a$ and $2^{b-1} \leq j < 2^b$ where a and b are integers and $i, j = 0 \ldots (N-1)$ then the coefficient β'_{ij} be stored into a particular subband S_y, with y computed as

$$y = \begin{cases} 0 & \text{for } m = 0 \\ 3(m-1) + 2(a/m) + (b/m) & \text{otherwise} \end{cases} \quad (7)$$

where $m = \max(a, b)$. The similar process is repeated for each (N x N) block of the whole image of size (R x C) where R is the height and C is the width. Thus the image has 10 multi resolution subbands namely S_0, S_1, S_2, …,S_9 and is similar to three level wavelet decomposition. Then the reordered location R of the coefficient β'_{ij} is then determined by the function presented in equation (8) for the block $B(z, w)$, where z and w represent the row and column values of the block B.

$$R = (2^{m-1}z + i-2^{a-1}, 2^{m-1}w + j - 2^{b-1}) \quad (8)$$

For example considering a (8 x 8) block, the transformed coefficients of the orthogonal polynomials model are rearranged into ten multiresolution subbands, similar to the structure of the wavelet subband and is shown in Fig 1. In this reordered multiresolution structure, the subband S_0 is modeled to contain frequency information and the other subbands are utilized to extract texture features.

3.2 FUSION TEXTURE FEATURE EXTRACTION

In this section the feature extraction process with the texture primitives that present in the image under analysis with the orthogonal polynomials model in the multiresolution reordered subband and the subband Co-occurrence features are presented.

3.2.1 STATISTICAL SUBBAND FEATURE EXTRACTION

The statistical and spectral properties such as mean, standard deviation and energy are computed from the S_0, S_1…S9 subband coefficients as described in the previous section. Let X and Y be the size of each subband and β'_{ij} be the subband's coefficients where i and j represent the row and column values of the subband images respectively. The mean (μ_k), standard deviation (σ_k) and the spectral energy (E_k) for each subband are modeled respectively as

$$\mu_k = \frac{1}{XY}\sum_{i=0}^{X}\sum_{j=0}^{Y}|\beta'_{ij}| \quad (9)$$

$$\sigma_k = \frac{1}{XY}(\sum_{i=0}^{X}\sum_{j=1}^{Y}|\beta'_{ij} - \mu_k|) \quad (10)$$

$$E_k = \sum_{i=0}^{X}\sum_{j=0}^{Y}|\beta'_{ij}| \quad (11)$$

where k denotes the specific subband.

3.2.2 SUBBAND CO OCCURRENCE FEATURE EXTRACTION

Gray Level Co-occurrence Matrix (GLCM) is a popular statistical technique for extracting texture features from different types of images. The elements of the co-occurrence matrix $C(i, j)$, represents how often pairs of transformed co efficient with values i and j separated by a distance d occurs. In our proposed fusion texture feature extraction process, the S_0 subband is considered for calculating the co-occurrence matrix $C(i, j)$ with horizontal, vertical and diagonal directions such as 0°, 45°, 90°and 135° respectively with the distance d as 1. The eight co-occurrence features such as inertia (P_1), total energy (P_2), entropy (P_3), local homogeneity (P_4), maximum probability (P_5), cluster shade (P_6), cluster prominence (P_7) and correlation (P_8) are computed similar to the method proposed in [13] from the normalized co occurrence matrix $P(i, j)$.

$$P(i,j) = \frac{C(i,j)}{\sum_{i=0}^{R-1}\sum_{j=0}^{C-1} C(i,j)} \quad (12)$$

where R and C are the row and column values of the co occurrence matrix $C(i, j)$. The eight co occurrence features are defined as follows:

$$P_1 = \sum_{i=0}^{Row-1}\sum_{j=0}^{Col-1}(i-j)P(i,j) \quad (13)$$

$$P_2 = \sum_{i=0}^{Row-1}\sum_{j=0}^{Col-1}P(i,j)^2 \quad (14)$$

$$P_3 = \sum_{i=0}^{Row-1}\sum_{j=0}^{Col-1}P(i-j)\log P(i,j) \quad (15)$$

$$P_4 = \sum_{i=0}^{Row-1}\sum_{j=0}^{Col-1}\frac{1}{1+(i-j)^2}P(i,j) \quad (16)$$

$$P_5 = \sum_{i=0}^{Row-1}\sum_{j=0}^{Col-1}\max P(i,j) \quad (17)$$

$$P_6 = \sum_{i=0}^{Row-1}\sum_{j=0}^{Col-1}((i-G_x)+(j-G_y))^3 P(i,j) \quad (18)$$

$$P_7 = \sum_{i=0}^{Row-1}\sum_{j=0}^{Col-1}((i-G_x)+(j-G_y))^4 P(i,j) \quad (19)$$

where $G_x = \sum_{i=0}^{Row-1}\sum_{j=0}^{Col-1} iP(i,j)$ and

$$G_y = \sum_{i=0}^{Row-1}\sum_{j=0}^{Col-1} jP(i,j)$$

$$P_8 = \frac{P_3 - H_{xy}}{\max(H_x, H_y)} \quad (20)$$

where $H_{xy} = \sum_{i=0}^{Row-1}\sum_{j=0}^{Col-1}P(i-j)\log Q_x(i)Q_y(i)$,

$Q_x(i) = \sum_{i=0}^{Row-1}P(i,j)$ and $Q_x(i) = \sum_{i=0}^{Col-1}P(i,j)$,

$H_x = \sum_{i=0}^{Row-1} S_x(i) \log S_x(i)$,

$H_y = \sum_{j=0}^{Col-1} S_y(j) \log S_x(j)$

The above mentioned features are calculated for the 4 directions with unit displacement d and all the corresponding feature elements are summed up to form 8 global statistical subband co-occurrence features. Based on the equations (9), (10) and (11), the subband statistical and spectral texture features mean, standard deviation and energy are calculated for the 10 subbands resulting the feature vector of dimension 10 * 3 = 30 and is represented as:

$$F_1 = (E_0, \mu_0, \sigma_{i0}, E_1, \mu_1, \sigma_1, \ldots\ldots\ldots E_{3\log_2 N+1}, \mu_{3\log_2 N+1}, \sigma_{3\log_2 N+1}) \quad (21)$$

Then the eight co occurrence features are computed from S_0 subband based on the equation from (13) to (20) resulting in the feature vector of dimension 8 and included in the global fusion texture feature vector F of dimension 38 and is represented as.

$$F = (F_1, P_1, P_2, P_3, P_4, P_5, P_6, P_7, P_8) \quad (22)$$

4 SIMILARITY AND PERFORMANCE MEASURE

Having extracted the fusion texture features in the previous section, in this section our aim is to retrieve the relevant images from the database against the query image using the similarity measure since it is a key component of the content based image retrieval system. In the proposed retrieval scheme, the similarity is calculated using the well known Canberra distance metric as shown in equation (23), as the same is reported to be the best among different distance metric [19].

$$d_C(x,y) = \sum_{i=1}^{d} \frac{|x_i - y_i|}{|x_i| + |y_i|} \quad (23)$$

where x_i is a feature vector of query image Q, y_i is the feature vector of image I in the database and d is the size of the feature vector. In the above equation, the numerator signifies the difference and the denominator normalizes the difference. Thus the distance value will never exceed one whenever either of the feature components is zero and also reduces the scaling effect. The performance of the proposed method is measured in terms average recognition rate, retrieval time and indexing time. The average retrieval rate is defined as the percentage of retrieved images belonging to the same class as a query images in top matches.

6 EXPERIMENTS AND RESULTS

The retrieval efficiency and effectiveness of proposed fusion texture feature is experimented with the popular texture image database Brodatz [20] and the experimental results are presented in this section. The Brodatz texture image database consists of 111 images and each image is of size (512 x 512) with pixel values in the range 0 – 255. Each (512 x 512) image is divided into sixteen (128 x 128) non-overlapping sub images, thus creating a database of 1776 texture images. Some of the sample texture images considered from Brodatz album are shown in the fig 2.

Each image in the database is divided into (8 x 8) blocks and is subjected to the proposed orthogonal polynomials based transformation as described in section 2. The transformed coefficients β'_{ij} are then reordered into subbands as described in section 3. The subband statistical and spectral property of the texture feature with energy are calculated from the ten subbands S_0, S_1,…S_9 resulting the feature vector of dimension 10 x 3 = 30 as explained in the section 3.2.1. The eight subband co-occurrence features are derived from the S_0 suband as described in section 3.2.2. Thus the feature vector of dimension 38 is obtained and stored in the feature database. Then the similarity measure is computed using the Canberra distance metric as presented in equation (23) for each pair of database and query images. The performance of the proposed feature vector is measured in terms of average recognition rate as described in section 4. The average recognition rate is computed by taking each image in the database as a query image. The obtained results are reported in the table I. The experimental results show that the use of co occurrence features along with the subband statistics yields the mean retrieval rate of 90.738%. The performance of the proposed fusion texture feature is compared with DWT based co-occurrence features and the results are incorporated in to the same table I. The mean success rate of DWT based co occurrence feature is 82.981% and the retrieval rate of irregular and poor directionality texture is low while the proposed method results high retrieval rate for the same. For some texture images (as shaded in table I) the proposed method gives high retrieval rate and results in superior performance than the DWT based technique.

The effectiveness of the proposed method is also measured with respect to CPU utilization time for extracting the feature vector and search time of database images for a given image. We conduct experiments with Pentium IV, Java (Jdk1.5) and MS Access. These results are reported in the table II. It can be observed from the table that the time required for computing the co occurrence matrix and its feature are high for both the methods. Since the feature vector extraction for database images is usually performed offline, the searching and retrieval time is considered. The proposed method retrieves the similar images in 0.04 seconds while DWT retrieves in 0.06 seconds and hence the proposed method is computationally attractive.

7 CONCLUSION

In this paper, a new and simple fusion texture feature extraction method directly from the orthogonal polynomials based transformed coefficients, incorporating the multiresolution approach with subband co occurrence features have been proposed. The proposed transformed coefficients are reordered into multiresolution like structure and the statistical and energy features are extracted from them along with the eight subband co occurrence features. The proposed method is experimented with the standard Brodatz texture database and proved to outperform well in retrieving similar images when a query image is given. The results of the proposed method are also compared with DWT based method on the same database and proved that retrieval accuracy of the proposed method is high with less computational complexity compared to DWT based method.

REFERENCES

[1]. K. Jalaja, C. Bhagvati, B. L. Deekshatulu and Arun K. Pujari, “Texture Element Feature Characterizations for CBIR”, IEEE proceedings of Geosciences and Remote Sensing Symposium, 2005, IGARSS '05, Vol. 2, pp. 733 - 736, 2005.

[2]. T. Sikora, “The MPEG-7 visual standard for content description – an overview”, IEEE Transaction on Circuits Systems and Video Technology, Vol. 11, no. 6, pp.696 – 702, 2001.

[3]. 17. J. Sklansky, “Image segmentation and feature extraction”, IEEE Transaction on Systems, Man and Cybernetic, Vol.8, no. 4, pp. 237 - 247, 1978.

[4]. 18. H. Tamura, S. Mori and T. Yamawaki, ”Texture features corresponding to visual perception”, IEEE transaction on Systems, Man and Cybernetics, Vol. 6, no. 4, pp. 460 - 473, 1976.

[5]. W. Niblack, R. Barber, W. Equitz, M. D. Flickner, E.H. Glasman, D. Petkovicr, C. Faloutsos and G. Taubin, “The QBIC Project: Querying images by content using Color, texture and Shape”, Proceedings of Conference on Storage and Retrieval for Image and Video Databases, SPIE, Vol. 19, no. 8, pp. 173 – 187, 1993.

[6]. R.M. Haralick, ”Statistical and structural approaches to Texture”, Proceedings of IEEE, Vol. 67, no. 5, pp. 786 - 804, 1979.

[7]. G. Cross and A. Jain, ”Markov random field texture models” ,IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 5, no.1, pp. 25 - 39, 1983.

[8]. J. Mao and A Jain, ”Texture classification and segmentation using multi resolution simultaneous autoregressive models”, Pattern Recognition, Vol. 25, no. 2, pp. 173 - 188, 1992.

[9]. F. Liu and R. Picard, “Periodicity, directionality and randomness: Wold features for image modeling and retrieval”, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 18, no. 7, pp. 722 - 733, 1996.

[10]. A. K. Jain, and F. Farroknia, “Unsupervised texture segmentation using Gabor filters”, Pattern Recognition, Vol. 24, no.12, pp.1169 -1186, 1991.

[11]. T. Chang and C.C.J. Kuo, “Texture analysis and classification with tree structured wavelet transform”, IEEE Transaction on Image Processing, Vol. 2, no. 4, pp. 173 - 188, 1992.

[12]. A. Laine and J.Fan, “Texture classification by wavelet packet signatures”, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.15, no. 11, pp. 1186 – 1191, 1993.

[13]. G.V. D. Woumer, P. Scheunders and D. V. Dyck, “Statistical texture characterization from discrete wavelet representations” , IEEE transaction on Image Processing, Vol.8, pp. 592 – 598, 1999.

[14]. K. O. Cheng, N.F. Law and W. C. Siu, ”Co-occurrence features of multi scale directional Filter Bank for Texture characterization”, Proceedings of IEEE, pp. 5499 – 5502, 2006.

[15]. D. A. Clausi and H. Deng, ”Design Based Texture Feature Fusion Using Gabor Filters and Co- Occurrence Probabilities”, IEEE Transactions on Image Processing, Vol.14, N0, 7, 2005.

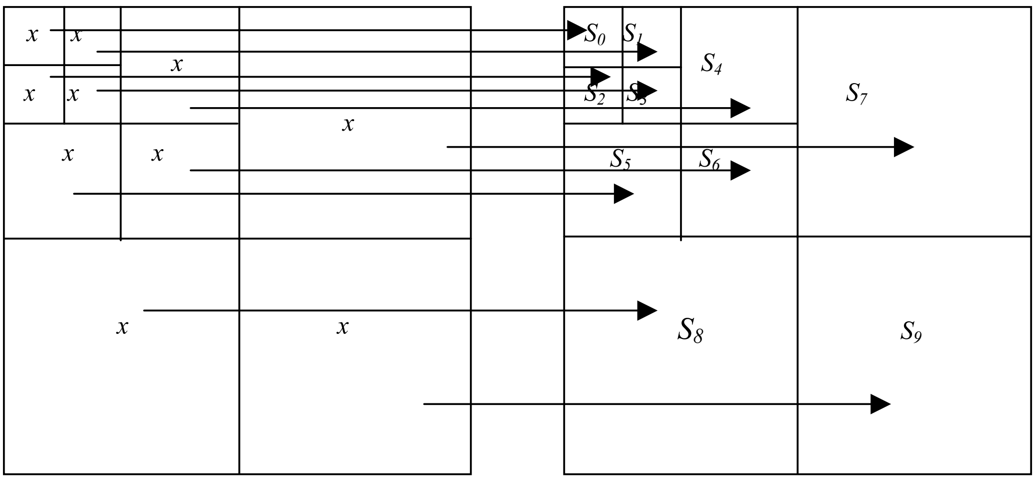
[16]. S. Arivazhagan, L. Ganesan and V. Angayakanni, “ Color Texture Classification using Wavelet transform”, Proceedings of the Sixth International conference on Computational Intelligence and Multimedia Applications (ICCIMA’05), 2005.

[17]. R. Krishnamoorthi and P. Bhattacharyya, ”A New Data Compression Scheme Using Orthogonal Polynomials”, International Conference on Information, Communications and Signal Processing ICICS '97, Vol. 1, pp. 490 - 494, 1997.

[18]. R. Krishnamoorthi, “Transform coding of Monochrome Image with Statistical Design of Experiments Approach to Separate Noise”, Pattern Recognition Letters, Vol. 28, No.7, pp. 771 - 777, 2007.

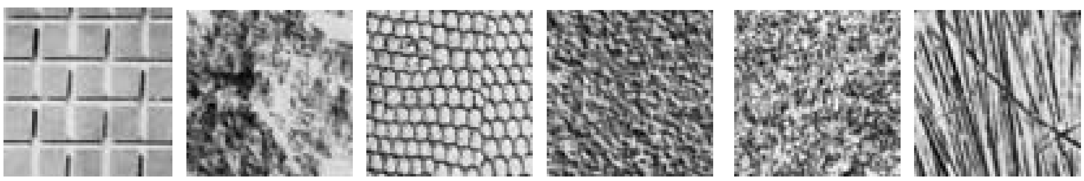
[19]. M. Kokare, B.N. Chatterji and P.K. Biswas, “Comparison of Similarity metrics for texture image retrieval”, IEEE proceedings on TENCON 2003, Conference on Convergent Technologies for Asia-Pacific Region, Vol. 2, pp. 571 - 575, 2003.

[20]. P. Brodatz, “Textures: A Photographic album for artists and designers”, New York: Dover, 1966.



(a) (b)

Fig 1. (a) Transformed coefficients of (8 X 8) block (b) reordered coefficient of (8 X 8) block



D1 D2 D3 D4 D9 D14

Fig 2. Sample texture images from Brodatz texture database

Table I. Average retrieval accuracy of the proposed and DWT methods

Image Name	Average Recognition rate		Image Name	Average Recognition Rate		Image Name	Average Recognition rate		Image Name	Average Recognition Rate	
	proposed method	DWT		proposed method	DWT		proposed method	DWT		proposed method	DWT
D1	97	95	D30	100	100	D58	75	59	D86	85	85
D2	95	95	D31	72	56	D59	70	52	D87	94	92
D3	90	78	D32	100	89	D60	80	50	D88	82	70
D4	100	100	D33	95	93	D61	85	62	D89	92	62
D5	100	100	D34	99	100	D62	92	58	D90	88	70
D6	97	100	D35	100	100	D63	87	67	D91	62	32
D7	75	65	D36	90	75	D64	99	100	D92	100	88
D8	96	97	D37	100	98	D65	100	100	D93	90	88
D9	96	94	D38	95	73	D66	100	100	D94	97	91
D10	92	88	D39	95	74	D67	85	72	D95	100	100
D11	100	100	D40	82	65	D68	100	95	D96	100	100
D12	96	85	D41	85	85	D69	96	97	D97	57	28
D13	51	42	D42	84	86	D70	92	86	D98	74	72
D15	92	74	D43	23	32	D71	91	84	D99	78	70
D16	100	100	D44	45	30	D72	90	45	D100	82	70
D17	100	100	D45	75	39	D73	95	68	D101	96	88
D18	99	100	D46	97	98	D74	100	92	D102	100	93
D19	97	97	D47	100	99	D75	100	98	D103	100	73
D20	100	100	D48	100	96	D76	100	100	D104	89	79
D21	100	100	D49	100	100	D77	100	100	D105	90	71
D22	87	82	D50	75	75	D78	100	100	D106	90	60
D23	61	59	D51	100	88	D79	100	100	D107	100	78
D24	92	89	D52	100	100	D80	100	100	D108	64	52
D25	90	90	D53	100	100	D81	100	96	D109	88	74
D26	96	93	D54	100	100	D82	100	100	D110	80	68
D27	91	85	D55	100	100	D83	100	100	D111	80	74
D28	95	88	D56	100	100	D84	100	100	D112	87	70
D29	100	100	D57	100	100	D85	93	85			
Average retrieval rate for proposed feature = 90.738%											
Average retrieval rate for DWT with co occurrence feature = 82.981%											

Table II. Performance of various texture feature retrieval time (On Pentium IV machine)

	Feature extraction time				Searching and retrieval time (Seconds)
	Statistical & Spectral Suband Feature computation (seconds)	Co occurrence Matrix computation (Seconds)	Co occurrence Feature Computation (Seconds)	Total (Seconds)	
Proposed method	0.06	0.32	0.03	0.41	0.04
DWT based method	0.07	0. 35	0.03	0.45	0.06