A Simple Computational Model for Texture Based Image Retrieval with Orthogonal Polynomials

R. Krishnamoorthi and S. Sathiya Devi

***Abstract*—The exponential growth of digital image data has created a great demand for effective and efficient scheme and tools for browsing, indexing and retrieving images from a collection of large image databases. To address such a demand, this paper *proposes* a new content based image retrieval technique with orthogonal polynomials model. The proposed model extracts texture features that represent the dominant directions, gray level variations and frequency spectrum of the image under analysis and the resultant texture feature vector becomes rotation and scale invariant. A new distance measure called Deansat is proposed as a similarity measure that uses the proposed feature vector for efficient image retrieval. The efficiency of the proposed retrieval technique is experimented with the standard Brodatz, USC-SIPI databases and is compared with Discrete Cosine Transform (DCT), Tree Structured Wavelet Transform (TWT) and Gabor filter based retrieval schemes. The experimental results reveal that the proposed method outperforms well.**

***Index Terms*—Content based image retrieval, orthogonal polynomials, texture analysis, similarity measure, rotation and scale invariant.**

I. Introduction

With the rapid growth of digital and information technologies, more and more multimedia data are generated and made available in digital form. Searching and retrieving relevant images in this huge volume of data is a difficult task and has created an urgent need to develop new tools and techniques. One such solution is the Content Based Image Retrieval (CBIR). As the image databases grow larger, the traditional keyword-based approach for retrieving a particular image becomes inefficient and suffers from the following limitations (i) Vast amount of labor is required for manual image annotation and (ii) Limited capacity for retrieving the visual content of the image and subjectivity of human perception. Hence, to overcome these difficulties of manual annotation approach, content based image retrieval has emerged. CBIR is a collection of techniques and algorithms which enable querying the image databases with low level image content such as color, texture, objects and their geometries rather than textual attributes such as image name or other keywords [1]. Many image retrieval systems have been developed using all or some of these features. The extensive literature and the state of art methods about content based image retrieval can be found in [2]-[7]. Among different visual characteristics for the analysis of different types of images, texture is reported to be prominent and vital low level feature [8]. Even though no standard definition exists for texture, it is defined as a set of local properties in the image region with a constant, slowly varying or approximately periodic pattern and 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 [9] and [10]. There are many categories of methods that exist for identifying and manipulating the texture: (i) Statistical methods (Gray level Co occurrence matrix (GLCM) [11]), (ii) Model Based methods such as Markov Random Fields (MRF) [12], Simultaneous Auto Regression (SAR) [13], World decomposition [14] and (iii) Signal Processing methods (Gabor filters [15]-[17], Wavelet Transforms [18] and [19] and DCT [20]). Some of these techniques depend on the comparison values of second order statistics obtained from query and stored images [21] for measuring the texture similarity.

Currently, most of the techniques have an explicit and implicit assumption that all the images are captured under the same orientation. In many applications such an assumption is unrealistic. Also, the approaches discussed above are sensitive to the changes of orientation and scale of the texture image to be searched in the database. Hence, we propose a new and simple content based image retrieval technique that identifies the coarseness, regularity and directionality of both regular and inhomogeneous textures with orthogonal polynomials model. The proposed technique captures the statistical and spectral properties of the texture such as gray level variation, dominant directions and energy.

The rest of this paper is organized as follows. In Section II, the proposed image retrieval technique with orthogonal polynomials model is presented. A detailed description for obtaining the orthogonal a polynomials model coefficient is also presented. Effective rotation and scale invariant texture feature vector extraction process is presented in Section III. For retrieval purposes, a new similarity measure called *Deansat* is described in Section IV. The experiments and results are presented in Section V. Finally conclusion is presented in Section VI.

II. Proposed Image Retrieval System

In this section we present a new texture based image retrieval technique with orthogonal polynomials model. The block diagram of the proposed image retrieval system is shown in Fig. 1. In the proposed system, the images and the query image all of size $(M \times N)$ are given, it is partitioned into $(n \times n)$ blocks where $n < M, N$ and n be a power of 2 and then each block is subjected to the orthogonal polynomials based

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transformation. From the transformed coefficients, texture feature extraction process is proposed and obtain a feature vector that represents the spatial characteristics (such as direction) and frequency band information (Energy). We propose a new similarity distance measure called *Deansat* and is utilized for efficient retrieval from a large image database. The retrieved relevant images are sorted in ascending order and the top ten images are displayed to the user.

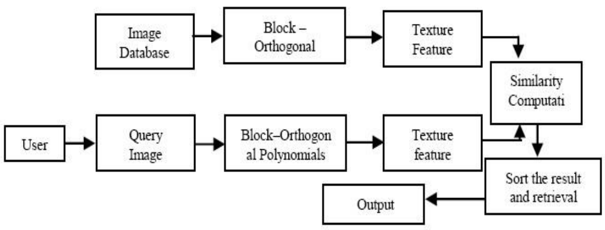


Fig. 1. Proposed image retrieval system.

A. Block Orthogonal Polynomials Model

In this sub 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 [22] and [23] have been extended for this proposed CBIR system.

In order to analyze the content of an image for proposing efficient 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 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 $(n \times n)$ 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.

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

The linear two dimensional transformation can be defined by the point spread operator $M(x, y)$ ($M(i, t) = u_i(t)$) as shown in (2).

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

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

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

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

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

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 (4) for $n \geq 2$ and $t_i = i$. The generating formula for the polynomials is as follows.

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

$u_1(t) = t - \mu$, 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

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

B. The Orthogonal Polynomials Basis

Having devised the forward transformation in the previous subsection, in this subsection we present the inverse transformation in terms of basis functions due to the proposed orthogonal polynomials. For the sake of computational simplicity, the finite Cartesian coordinate set X, Y is labeled as $\{1, 2, 3\}$. The point spread operator in (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 (4) as follows.

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

The set of polynomial basis 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 $|M|$.

For example, polynomial basis operators of size (3×3) are $\left[O_{00}^3\right] = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$, $\left[O_{01}^3\right] = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$, $\left[O_{10}^3\right] = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix}$,

$\left[O_{11}^3\right] = \begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$, $\left[O_{12}^3\right] = \begin{bmatrix} -1 & 2 & -1 \\ 0 & 0 & 0 \\ 1 & -2 & 1 \end{bmatrix}$, $\left[O_{20}^3\right] = \begin{bmatrix} 1 & 1 & 1 \\ -2 & -2 & -2 \\ 1 & 1 & 1 \end{bmatrix}$

$\left[O_{21}^3\right] = \begin{bmatrix} -1 & 0 & 1 \\ 2 & 0 & -2 \\ -1 & 0 & 1 \end{bmatrix}$, $\left[O_{22}^3\right] = \begin{bmatrix} 1 & -2 & 1 \\ -2 & 4 & -2 \\ 1 & -2 & 1 \end{bmatrix}$ $\left[O_{02}^3\right] = \begin{bmatrix} 1 & -2 & 1 \\ 1 & -2 & 1 \\ 1 & -2 & 1 \end{bmatrix}$, With the transformed coefficients β' by the orthogonal polynomials model, we present the texture feature vector extraction process in the next section.

III. Proposed Feature Vector Extraction

Since the low level image features are best examined in micro level, we propose to extract the texture features based on certain statistical and spectral properties applied on the uncorrelated transformed coefficients β' by dividing the image into blocks of size ($n \times n$) where n is the power of 2. Since the texture features can be defined as spectrum energies in different localizations of a local block, the statistical and spectral properties are captured using the low frequency coefficients due to the orthogonal polynomials model. In the orthogonal polynomials model, it is observed that when the block in an image is rotated the magnitudes of the orthogonal polynomials model coefficients remain unaltered but their position and the sign change. At the same time the absolute Euclidean distance between the corresponding matrices of the initial and the rotated block in the zig – zag sequence is zero. Hence the proposed method takes the absolute value of the transform coefficients for extracting the rotation invariant texture feature.

Since the transformation is unitary and complete [19], the spectral energy is concentrated on the low frequency coefficient β'_{00}. Hence in this work we model the coefficient β'_{00}, the averaging factor due to proposed transformation as spectral component and is denoted as a.

$$a = \beta'_{00} \tag{6}$$

The directionality property of the texture in the proposed technique is extracted from the set of low frequency transformed coefficients β'_{ij} in horizontal (h), vertical (v) and diagonal (d) directions excluding β'_{00} as

$$h = \sum_{j=1}^{n-1} |\beta'_{0j}| \tag{7}$$

$$v = \sum_{i=1}^{n-1} |\beta'_{i0}| \tag{8}$$

$$d = \sum_{i=j=1}^{n-1} |\beta'_{ij}| \tag{9}$$

We then extract the frequency information Fe as the sum of frequency components f_1, f_2 and f_3 based on the set of transformed coefficients β'_{ij} as follows.

$$Fe = f_1 + f_2 + f_3 \tag{10}$$

where $f_1 = \sum_{i=0}^{(\frac{n}{2})-1} \sum_{j=0}^{(\frac{n}{2})-1} |\beta'_{ij}|$ excluding β'_{00} & $f_2 = |\beta'_{ij}|$, where $i = 0$ and $j = (\frac{n}{2}+1)$ and $f_3 = |\beta'_{ij}|$, where $i = (\frac{n}{2}+1)$ and $j = 0$.

For each ($n \times n$) block, the above mentioned process is repeated and the features energy, horizontal, vertical and diagonal directionality and frequency information are computed. The mean and variance are calculated with the corresponding elements of all the ($n \times n$) block of an image and acts as a texture feature. Thus the global texture feature vector of dimension 10 is obtained and is denoted as FV_G.

$$FV_G = (M_a, V_a, H_h, V_h, M_v, V_v, M_d, V_d, M_{Fe}, V_{Fe}) \tag{11}$$

where M_a, V_a, H_h, V_h, M_v, V_v, M_d, V_d, M_{Fe}, V_{Fe} are mean and variance of the texture features viz spectral energy, horizontal, vertical and diagonal directionality and frequency information corresponding to all the ($n \times n$) blocks respectively. The elements of the global feature vector are divided by the size of the image for accomplishing scale invariance.

IV. Similarity Measure and Measure of Retrieval Performance

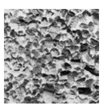
In this section a new similarity measure is proposed for retrieving the relevant images from the database against the query image utilizing the texture features described in the previous section since it is a key component of any content based image retrieval system. The proposed transformation domain similarity measure $D(Q, I)$ is termed *Deansat* and is defined as

$$D(Q,I) = \sum_{i=1}^{n} \left| \frac{f_i^{\,2} - f_i'^{\,2}}{f_i^{\,2} + f_i'^{\,2}} \right| \tag{12}$$

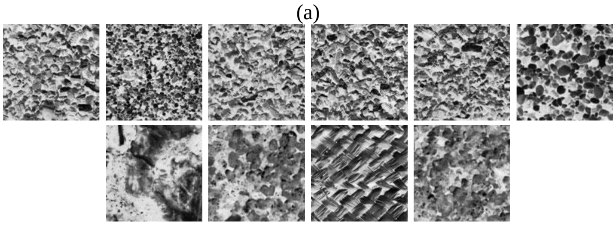
where f_i is a feature vector of Query image Q(x, y) and f_i' is the feature vector of image I (x, y) in the database. The proposed measure avoids the scaling effect since the numerator signifies the difference and the denominator normalizes the difference. The efficiency of the proposed technique is measured with average retrieval rate, retrieval accuracy as a function of number of top images considered and the retrieval result obtained for top 10 matches. The average retrieval rate is defined as the percentage of retrieved images in top matches which belongs to the same class as a query image.

V. Experiments and Results

The retrieval efficiency and effectiveness of the proposed orthogonal polynomials based texture feature vector and the similarity measure *Deansat* are experimented with Brodatz [24] texture album and the experimental results are presented in this section. The Brodatz texture image database consists of 111 images, each of size (256 × 256) with pixel values in the range 0 – 255. Each (256 × 256) image is divided into four (128 × 128) non-overlapping sub images, thus creating a new database of 444 texture images. During experimentation, the image under analysis is divided into (4 × 4) blocks and each block is subjected to the orthogonal polynomials transformation as described in Section 2.1. Then the local texture feature vector viz spectral energy (*a*), directionality and frequency information (*Fe*) are extracted from the transformed coefficients β'_{ij} . The directionality of the texture in horizontal (*h*), vertical (*v*) and diagonal (*d*) directions are extracted based on the (7), (8) and (9) respectively. The other feature vector elements viz frequency information (*Fe*) and energy (*a*) are obtained with (10) and (3) respectively. Then the global texture features mean and variance are obtained as described in Section III. Now, in the query phase, for a given query image the above steps are repeated and the texture features are extracted. Then the similarity measure is computed using the proposed *Deansat* distance metric as presented in equation (12) utilizing the global feature vector FV_G of each pair of query and database images. The distances are then sorted in ascending order and the top 10 images are retrieved. For example, when the query image D5 is considered from [24] and is shown in Fig. 2(a). The orthogonal polynomials based texture image retrieval technique retrieves all sub images out of 4 sub images (100%) of the same class among top 10 matches and also retrieves perceptually similar images. The top 10 retrieval results for the query image D5 obtained with the orthogonal polynomials model based texture feature retrieval are shown in Fig. 2(b).



(a)



(b)

Fig. 2. (a) Query image D5 from Brodatz (b) Top 10 retrieval result with the proposed model.

We also measure the performance of the proposed technique with average recognition rate as described in section 4. For this, every image in the Brodatz database is considered as query image and the texture feature vector is extracted as described in Section III. Then the average recognition rate is obtained. The proposed orthogonal polynomials based texture image retrieval yields a retrieval rate of 90% for Brodtaz database images. The obtained results are presented in the Table I.

The retrieval performance of the proposed technique is further measured as a function of number of top retrieved images by considering both database images with different query images and the top 10, 20, 30, … ,100 matches of retrieval are obtained along with the percentage of retrieval and is plotted as a graph with number of top matches in X axis and average recognition rate in Y axis and the same is presented in Fig. 3. From the experimental results, it is evident that the orthogonal polynomials based texture image retrieval model yields high retrieval rate and the high retrieval rate is achieved between 90 and 100 top matches.

TABLE I: AVERAGE RETRIEVAL ACCURACY OF THE PROPOSED, DCT, TWT AND GABOR METHODS FOR THE BRODATZ DATABASE IMAGES.

Database	Proposed method	DCT	TWT	Gabor
Brodatz	90%	74.8%	71 %	91%

To evaluate the effectiveness and efficiency of the proposed texture feature based image retrieval, performance comparisons are made with Discrete Cosine Transform (DCT) based features [20], Tree Structured Wavelet Transform (TWT) [19] and Gabor Wavelet features [16] in terms of performance measures as described in Section IV using Brodatz Database images. For the same query image D5 the top 10 retrieval results for these existing three methods are shown in the Fig. 4(a), 4(b) and 4(c). It can be observed from the Fig. 4(a), 4(b) and 4(c) that the DCT, TWT and Gabor were unable to discover the perceptually similar images.

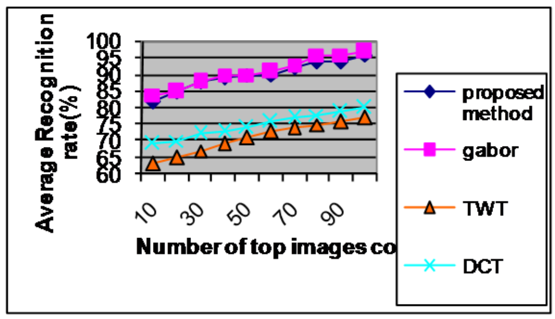
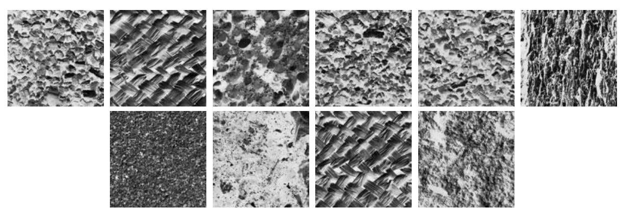
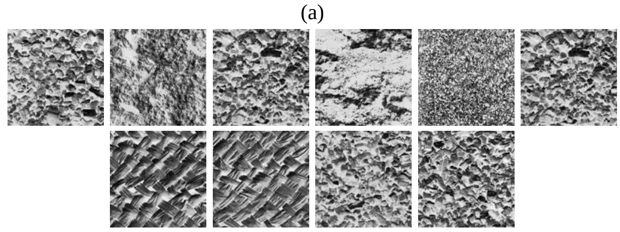


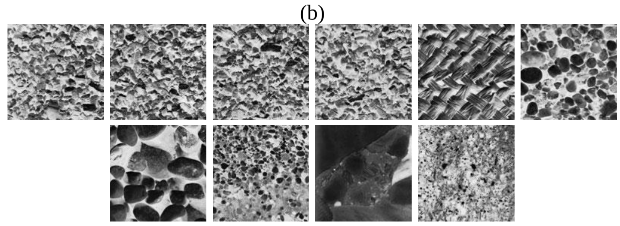
Fig. 3. Graph on retrieval performance with Brodatz database.



(a)



(b)



(c)

Fig. 4. The Retrieval result for the Query image D5 of Brodatz Database image (a) DCT method (b) TWT (c) Gabor Wavelet.

We also calculate the average retrieval rate for these existing three methods and the retrieval results obtained are incorporated into the same Table I. The average retrieval accuracy of DCT, TWT and Gabor methods are 74.8%, 71% and 91% respectively for the Brodatz database images. It is evident from these results that the proposed method is superior when compared to other three methods and the proposed feature vector is expressive in characterizing the texture.The retrieval performance of the existing three methods are further measured as a function of number of top retrieved images by considering the database images with different query images from the same database and the top 10, 20, 30, … ,100 matches of retrieval are obtained along with the percentage of retrieval and the results are incorporated into the same Fig. 3 as a graph. It can be observed from the graph that the proposed method performs well when compared to DCT, TWT and Gabor Wavelet especially when the top matches are between 25, 30, 40 and 50 and yields a high retrieval rate of 90%.

Rotation and Scale Invariant

The retrieval performance of the orthogonal polynomials based texture image retrieval technique for scaling and rotation invariance are experimented with the standard rotated USC-SIPI [25] database images and the results are presented in this sub section. During experimentation, the texture feature is extracted as described in section 3 for these rotated images. For the query image Bark30 as shown in Fig. 5(a), the top 10 retrieval results are shown in Fig. 5(b). From the Fig. 5(b), it is evident that the proposed texture image retrieval method with orthogonal polynomials model retrieves both scaled and rotated texture images in the top 10 retrieval result. The proposed technique is then compared with rotation invariant Gabor wavelet [17] utilizing the same database images. For the same query image Bark30 the top 10 retrieval result based on Gabor wavelet is shown in the Fig. 5(c). The Gabor method retrieves the rotated images but fails to retrieve the scaled images.

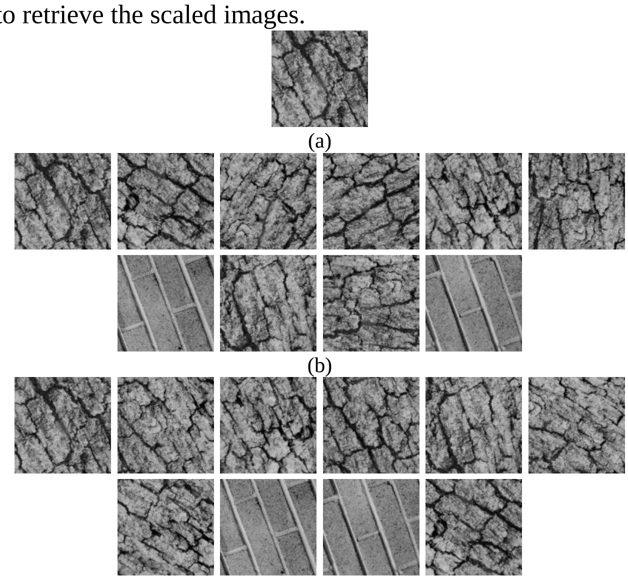


Fig. 5. The Retrieval result for the query image Bark30 for USC-SIPI Database (a) query image (b) proposed technique (c) rotated Gabor Wavelet.

The retrieval performance is further measured as a function of number of top retrieved images by considering the database images with different query images from the same database and the results are presented as graph in the Fig. 6. It can be apparent from the graph that the proposed technique performs well for the top matches between 70, …, 100 for the USC-SIPI database images. From the results obtained it is evident that the proposed method gives high retrieval rate for normal and geometrically distorted images.

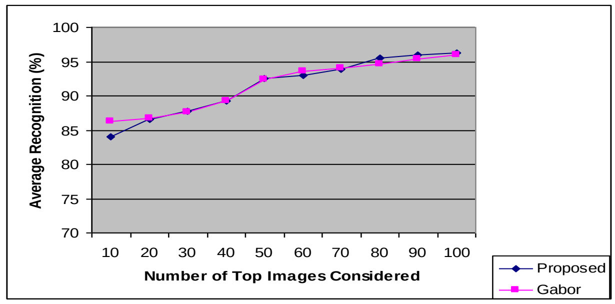


Fig. 6. Graph on retrieval performance with USC-SIPI database images.

VI. Conclusion

In this paper, we have proposed a new and simple content based image retrieval with textural features extracted with orthogonal polynomials model. The proposed texture feature vector describes the spatial variation in the dominant directions such as horizontal, vertical and diagonal and the frequency band information. The proposed feature vector is also rotation and scale invariant. We have also proposed a new distance metric called *Deansat* for retrieving the similar images. The performance results on the Brodatz and USC-SIPI databases demonstrate that the proposed feature vector and the distance metric *Deansat* outperforms well in retrieving similar images when compared existing DCT and Gabor based methods.

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