

Orthogonal Polynomial Model Based Image Retrieval using Multiresolution Spatial-Temporal Features

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ABSTRACT: In this paper, we propose orthogonal polynomial based image retrieval using multiresolution wavelet features. Orthogonal polynomial high-order coefficient and low-order coefficient are enables the low-frequency and high-frequency subbands in multiresolution structure. For effective content based image retrieval we used combined these two features. Here polynomial model used to posses the localization frequency information in spatial-temporal domain. Wavelet Packet (WP) transforms is used to construct various subbands in order to extract the feature such as color and texture. For color features we used color autocorrelogram and for texture features we consider the second order statistics in each subbands. Based on these features, feature vector is formed and the experimental result is implemented in two databases. City-block distance method is incorporated to find the distance between query image and target image. The experimental results reveal that the proposed method performs better retrieval accuracy when compared to those existing methods.

KEYWORDS: multiresolution, texture, CBIR, orthogonal polynomial, wavelet packet.

I. INTRODUCTION

With fast growth of image and video content, Content based image retrieval become a challenging one for researches to retrieve relevant image from the huge amount image content which is rapidly accumulated day-today[1]. First, Kato developed a method in 1992 for automatic image retrieval which containing more than 205 pictures and termed as CBIR. In CBIR, images are indexed based on color descriptor, texture, shape and combination of them which alternate to traditional text-based image retrieval method [2]. Color plays an important role to determine low visual features it is invariant to image size and orientation [3]. Recent literatures reveals that color histogram [2], color coherence vector [3], color correlogram [4], color autocorrelogram [5], MPEG-7 color descriptor [8] describing visual features. The color histogram representing global color distribution and most researchers used in this method in image retrieval it is invariant to image translations but it ignores the spatial color information. Recently, J Huang [4] introduces a method which describes the probability of finding color pairs at a fixed pixel distance and provides effective spatial information. Subsequently, Huang improved color correlogram method and coined as color autocorrelogram which captures the spatial correlation between identical colors at a fixed distance and shows computational benefits over color histogram, color coherent vector (CCV) and color correlogram methods. Color space plays an important role in CBIR with appropriate color with quantization is key issue for color features extraction in CBIR. So far different color spaces have been used and the simplest one is RGB (Red-Green-Blue) color space which shows remarkable results in image retrieval but it is inaccurate to human visual system and statistical analysis. HSV color space provides better performance retrieval accuracy over RGB color space [13] improvements over the RGB based autocorrelogram and HSV based histogram. Recently literature reveals that, HMMD (Hue, Min, Max, Diff) color space provides better results which incorporated with MPEG_& multimedia content description [9]. Another important feature of CBIR is texture; color features describe the visual content of image whereas texture features characterize the

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structure and pattern which contains the image. There are a numerous sophisticated methods reported texture characteristics in CBIR. The approach can be categories into structural, statistical and stochastic measures. The first category of approach is Structural texture which measures the texture pattern, based on a set of primitives likes textons, texels, etc. Second approach represents a texture pattern by their underlying statistical properties. The two commonly used properties in this approach are the co-occurrence matrices (GLCM) and Autocorrelogram features. Gabor filters and Wavelet Transform features used in signal processing approach and it more adopted in world approaches. Finely, model based approach plays an important role in CBIR, in this row, stochastic texture model attempts to capture the texture pattern by parameters another methods such as Gaussian Markov random field and Wold-based represent the texture pattern of the selected image. Haralick[6], Tamura [7], Wavelet transform method[11], local binary pattern (LBP) and, Gabor filter are most popular statistical texture methods used in CBIR systems. Haralick [6] and Tamura [7] texture representations plays a vital role in texture characterization in CBIR. They defined six textural features such as coarseness, contrast, directionality, line-likeness, regularity, and roughness, and related them to psychological measurements of human subjects.

In this paper, we have proposes orthogonal polynomial model based image retrieval in multiresolution domain. Low-order polynomial represents the low-frequency and high-order polynomial denoted high-frequency which effectively deals with image

The following key points proposed in this method, they are

- (i) Orthogonal polynomial based low-order and high-order coefficients are represent low-frequency and high frequency subbands in multiresolution.
- (ii) Orthogonal polynomial low-frequency coefficients represent scaling coefficients which contains color information and Orthogonal polynomial high-frequency coefficients represent the detailed wavelet coefficients contains details coefficients
- (iii) Wavelet packet (WT) transform is used construct multiresolution subbands.
- (iv) Two features, such as color autocorrelogram, second order statistical extracted from low-frequency subbands and high-frequency subbands respectively.

The forthcoming section the multiresolution based orthogonal polynomial model presented which represent the low-order and high-order coefficients in multiresolution environment. In section III, describe the proposed image retrieval method consist of color and texture extraction method and subband characterization. Section IV explains similarity and performance measures method, Section V provides experimental results and discussion, finally the conclusion section concludes in section VI.

II. MULTIREOLUTION BASED ORTHOGONAL POLYNOMIAL MODEL

In this section we presented multiresolution based orthogonal polynomials [9] model coefficients are used to construct scaling and details wavelets in multiresolution domain. Generally subbands in multiresolution simulate low-order and high-order polynomial coefficients and it influences the captures characteristics of various subbands. The function of wavelet $f(t) \in V_j$ [24] is given in equation 1.

$$f(t) = \sum_{kk} c_{j_0}(k) \phi_{j_0,k}(t) + \sum_{kk} \sum_{j=j_0}^{J-1} d_j(k) \psi_{j,k}(t) \quad (1)$$

Where $c_{j_0} = \langle f(t), \phi_{j_0,k}(t) \rangle$ represent scaling function and $d_j(k) = \langle f(t), \psi_{j,k}(t) \rangle$ denotes wavelet coefficients. The coefficients c 's and d 's represent linear combination of different order moments [16]. The order up to $k-1$ denotes the low order coefficients, for any polynomial with order lower than k , all its wavelet coefficients will be zero. Therefore entire signal coefficients represent scaling function space and have power to represents polynomial of degree up to $k-1$. The proposed system used orthogonal polynomial $P_n(x)$ to form the scaling and wavelets functions by re-ordering of low-order and high-order polynomials coefficients through the given equation 2

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$$\begin{aligned} \phi_{ij}(x) &= \sum_{k=0}^{2^j} a_{jik} P_k(x) \\ \psi_{ji}(x) &= \sum_{k=2^{j+1}}^{2^{j+1}} b_{ijk} P_k(x) \end{aligned} \tag{2}$$

where $\phi_{ij}(x)$ and $\psi_{ji}(x)$ denotes scaling and wavelets functions.

III. PROPOSED IMAGE RETRIEVAL METHOD

The past decade wavelet has witnessed an emerging new tools from mathematics and was quickly adopted by diverse fields of signal processing. The traditional wavelet transforms consider approximation subbands of image for further decomposition whereas Wavelet packet transform [8] [10] has accounted both approximation and detailed subbands into next level decomposition. Wavelet packet transform has three parameters and well localized in time-frequency, can be defined as

$$W_{j,p,k}(x) = 2^{-j/2} W_p(2^{-j}x - k) \tag{3}$$

Where j represents scaling resolution level, k denotes position-localization and p represent the oscillation parameter

$$\begin{aligned} W_n(x), n = 0, 1, 2, \dots \text{ by} \\ W_{2n}(x) &= \sqrt{2} \sum_{k=0}^{2N-1} h(k) W_n(2x - k) \\ W_{2n+1}(x) &= \sqrt{2} \sum_{k=0}^{2N-1} h(k) W_n(2x - k) \end{aligned} \tag{4}$$

Where $W_0(x) = \phi(x)$ the scaling is function and $W_1(x) = \psi(x)$ is the wavelet function. Wavelet packet decomposition produces tree with a total of $N \log N$ coefficients as shown in figure 2.

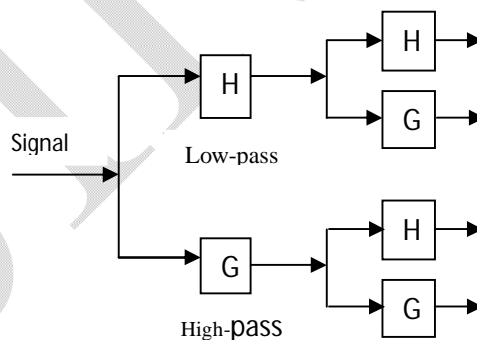


Fig.1 Two-level wavelet packet decomposition

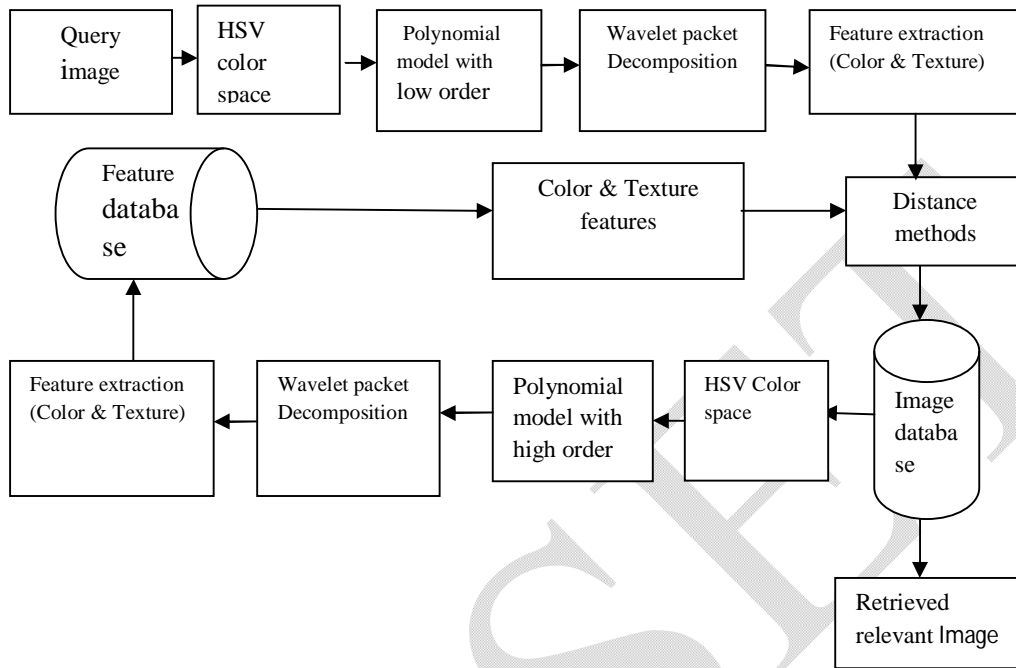


Fig.2 Block diagram of proposed system

Color feature extraction

The proposed system incorporated color autocorrelogram [12] to extract color features and it overcomes global features of Histogram method and it find probability of identical color at fixed distance and also it provides significant computational benefits over the color correlogram and Color Scale descriptor. The autocorrelogram method defined as

$$\alpha^k(l) = Pr[p' \in I \mid |p' - p| = k \text{ and } p' \in I(l) \text{ for } p \in I(l) \subset I] \quad (5)$$

$$l \in \{0, 1, \dots, L - 1\}$$

where Pr[.] represents the probability satisfying the condition, I denotes size of pixel in image, and $I(l)$ the set of pixels of color l which is requantized with L levels, $\alpha^k(l)$ represents the probability of a pixel of distance k from the given pixel color l .

The figure 3 shows color feature extraction procedure from decomposed various sub-bands



Fig.3. Process of color feature extraction.

Texture feature extraction

The proposed system used Gray level concurrence matrix (GLCM) [12] captures properties of structural and statistical from subband coefficients to characterize the texture features. The process of the texture features extraction is given in fig. 4.

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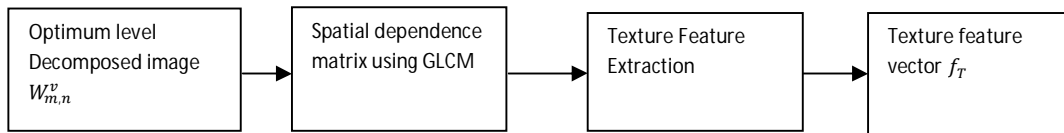


Fig.4. process of texture features extraction

The following set of statistical texture features are computed on GLCM of $W_{m,n}^V$ and they are defined as *Contrast*

$$f_1 = \sum_{i,j} |i - j|^2 p(i, j) \tag{6}$$

Correlation

$$f_2 = \sum_{i,j} \frac{(i-\mu_i)(j-\mu_j)p(i,j)}{\sigma_i\sigma_j} \tag{7}$$

Variance

$$f_3 = \sum_i \sum_j (x - i)^2 p(i, j) \tag{8}$$

Where feature f_1 - intensity of contrast between a pixel and its neighborhood; f_2 - correlates a pixel to its neighborhood and f_3 -the sum of squared elements measured as non-uniformity of energy, uniformity, and angular to moment. Based on these features, texture feature vector is formed in the following

$$f_t = [f_1, f_2, f_3] \tag{9}$$

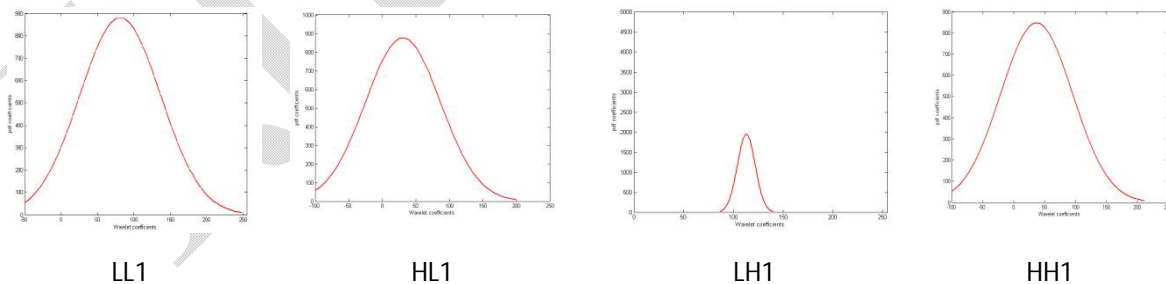
Gaussian distribution function for subband characterization

The proposed system used both color and texture features from each subbands in order to find the relevant images. The proposed system to determine whether statistical behavior for each subbands to fulfill the condition of normal distribution or Gaussian distribution[15] to extract the second order statistical. The Gaussian distribution function [14] is presented in equation 10 and result of each subband is presented figure 5

$$f_{\alpha,\beta}(x) = \frac{\beta}{2\alpha\Gamma\left(\frac{1}{\beta}\right)} e^{-\left(\frac{|x|}{\alpha}\right)^\beta} \tag{10}$$

Where α is scale factor, related to standard deviation of Gaussian function, β is a shape parameter.

The figure 5 shows resultant of the generalized Gaussian distribution of various subband images. The proposed system determines to extract statistical features from each subband.



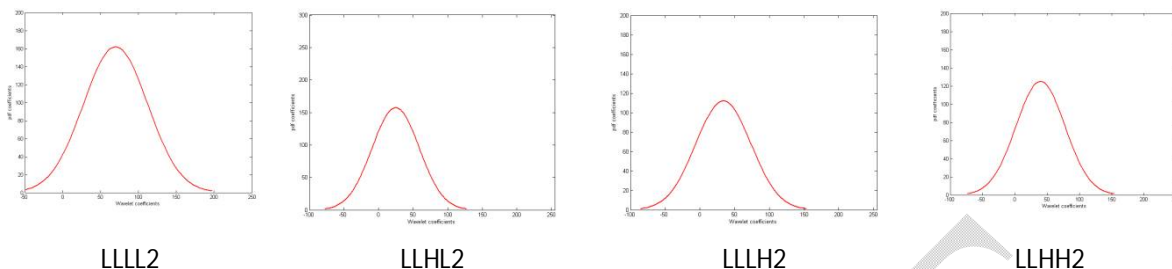


Fig.5 Various subbands with generalized Gaussian model of sample image.

IV. SIMILARITY AND PERFORMANCE MEASURES

In the image processing analysis, the distance methods measures the distance for each point in object from nearest boundary. City-block distance method [17] is basic metric measure the path between pixels based on 4-neighbourhood pixel diagonally touch two unit apart and whose edge touch 1 unit apart which is defined

$$d_{ij} = \sum_{k=1}^N |x_{ik} - x_{jk}| \tag{11}$$

Where x denotes feature vector and k-represent number of features consist of both color and texture, the city block distance result reveals that always greater than or equal to zero. If query image target image are same the result will be zero otherwise target image differ from query image.

Further we evaluate the performance proposed work in terms of Precision (P) and Recall (R) measurement,

$$R(q) = \frac{\text{Number of relevant images}}{\text{Total number of relevant images}}$$

$$P(q) = \frac{\text{Number of relevant images}}{\text{Number of retrieved images}} \tag{12}$$

V. EXPERIMENTAL RESULTS AND DISCUSSION

In order to evaluate the proposed method we undertaken two benchmark databases: Corel [16] and Brodatz [15] databases. These images consider about 12000 and various sizes 512x512, 256x256 with pixel ranges 0-255.

During the experimentation, the proposed method decomposes the images into various multiresolution subbands subbands using wavelet packet transform which is discussed in section II. The features such as color autocorrelogram and texture features are extracted from each subbands, based on these features, the feature vector is constructed which is discussed in section III. The Canberra distance method is incorporated to find distance between query image and target image in constructed databases which is discussed in section IV. The obtained results presented in fig. 6.

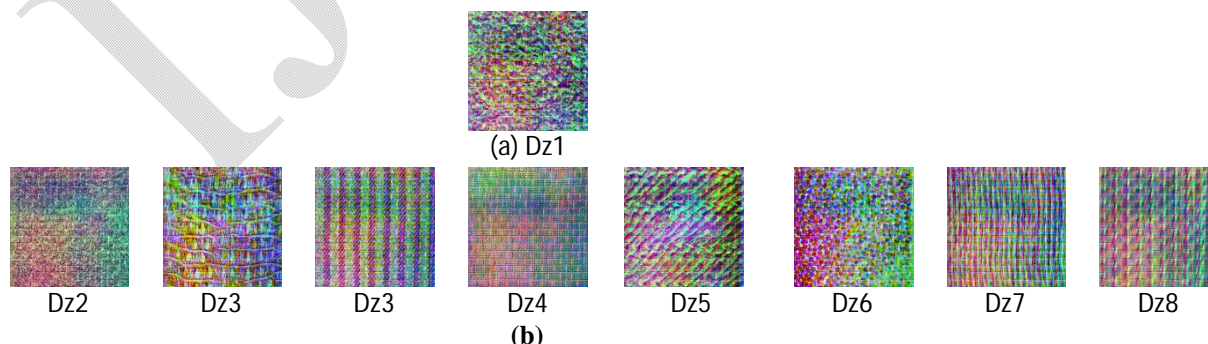


Fig.6 (a) query image (b) relevant images retrieved by proposed method from brodatz database

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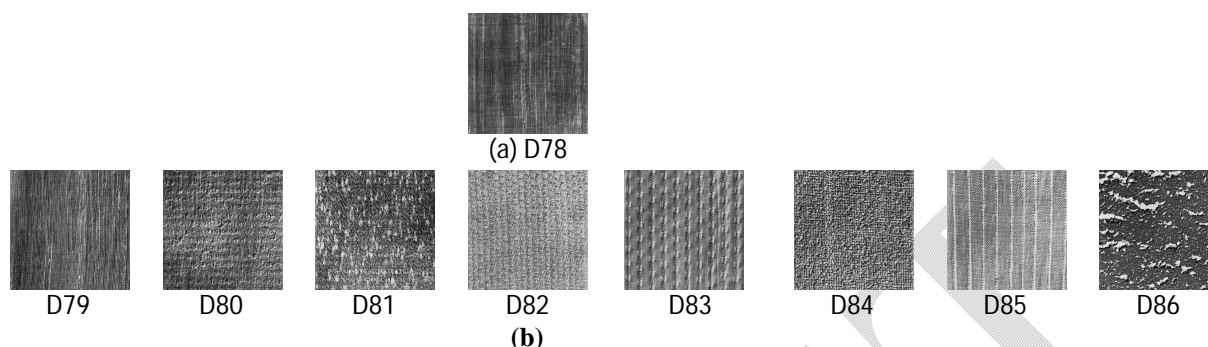


Fig.6 (b) query image (b) relevant images retrieved by proposed method from Corel database

The proposed method evaluated for the efficient and effectiveness, fair comparisons are made with orthogonal polynomial model, DCT based retrieval method and Gabor wavelet based retrieval method [18]. In terms of top recognition, the precision and recall methods and average recognition rate are considered. For accuracy of retrieval with existing system the top 8 matches are consider, same query images are presented in fig.6(a) from the Brodatz database and fig.6(b) from Corel database. The precision and recall methods values of existing techniques and proposed method are presented in table-1. The proposed method obtains the average precision and recall as 91% and 78% on Brodatz database and 80% and 71% on Corel database and results are presented with existing method. Therefore the proposed method obtains better retrieval are when compared to that of existing methods

Table-1 Performance measure of the proposed system with other existing methods

Database	Proposed system		DCT based method		Gabor based retrieval method	
	precision	recall	precision	recall	precision	recall
Brodatz	0.912	0.780	0.881	0.730	0.729	0.661
Corel	0.803	0.712	0.791	0.752	0.751	0.711

VI. CONCLUSION

In this paper, the wavelet based orthogonal polynomial model used to extract color and texture features in multiresolution environment. The combination of orthogonal polynomial model and multiresolution technique influences localizes frequency information in the image. Orthogonal polynomial high-order coefficient and low-order coefficient are enables the low-frequency and high-frequency subbands in multiresolution structure. Here polynomial model used to posses the localization frequency information in spatial-temporal domain. Wavelet Packet (WP) transforms is used to construct various subbands in order to extract the feature such as color and texture. For color features we used color autocorrelogram and texture features, second order statistics is incorporated. Based on these features, feature vector is formed and the experimental result is implemented in two databases. City-block distance method is incorporated to find the distance between query image and target image. The experimental results reveal that the proposed method performs better retrieval accuracy when compared to those existing methods

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