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A Framework for Histology Image Retrieval Based on Orthogonal Polynomial Model

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ABSTRACT: This paper presents an efficient method for histology image retrieval based on orthogonal polynomial model. Wavelet Packet (WP) transforms and Daubechies-4 (Db-4) transforms are jointly used to perform image decomposition. In multiresolution domain, the orthogonal polynomial model reordering the low order coefficient into low frequency and high order coefficients into high frequency components. In this paper, the image is represented using the features namely dominant color descriptor (DCD) and color autocorrelogram, BDIP and BVLC. The DCD extracts percentage of representative colors and its variances and color autocorrelogram extracts color and its global as well as local spatial information. BDIP (block difference of inverse probabilities) extracts edges and valleys and BVLC (block variation of local correlation coefficients) extracts textures smoothness. From the computed BDIP and BVLC its global as well as local spatial information is extracted and it is used to represent the image. The DCD and color autocorrelogram are computed from the low-frequency components and BDIP and BVLC are computed from the high-frequency components. The extracted features of the image are combined together and normalized using Z-Score normalization method. Radial Basis Function neural network (RBFNN) is employed for classification of feature vector. The Manhatten distance measure is used to find the similarity between the query and target images in the benchmark database. The efficiency of the proposed method is measured using the precision, recall and F-score. The experimental results show that the proposed method attains better results.

KEYWORDS: Dominant color descriptor, Color autocorrelogram, BDIP, BVLC, Orthogonal Polynomial model.

I. Introduction

Nowadays, medical imaging systems generates much more digitized images using different modalities such as X-ray tomography, Microscopy, MRI, nuclear imaging, Mammogram, etc. Since medical images consist of various pathological conditions of the patients, they are very useful for disease diagnostic, research and teaching. However, the amount of images we are generating nowadays is so vast. Thus, the medical image databases requires efficient image indexing and retrieval techniques for speedy and accurately access of images in databases. Generally medical images are retrieved either using text-based or content based methods. In text-based method, manually annotated images are retrieved and it has some limitations that a single medical image may have number of different pathological conditions and images of different anatomical regions or organs may have same pathological conditions. In such kind of cases, manual annotation is fully depends on the physicians perception. Moreover, developing a keyword database for various pathological conditions in the medical images is very difficult. Apart from that text based methods are tedious, less in accuracy and time consuming one. Thus, to address the aforesaid issues, content based medical image retrieval methods are developed. In content based approach, images are indexed and retrieved from databases based on their visual content such as color, shape, texture and spatial information, etc.

Over the decade, researchers focused their attention for developing various methodologies for effectively retrieving the medical images including the ASSERT (Automatic Search and Selection Engine with Retrieval Tools) [1-3], X-ray image retrieval for human cervical and lumbar spine [4], Cervigram Finder system to study the uterine cervix cancer [5], SPIRS (Spine Pathology and Image Retrieval System) [6], Shape based spine X-ray image retrieval [7, 8], image retrieval using fractal dimension [9], Breast density patterns for mammogram image retrieval [10], retrieval system for diabetic retinopathy and mammogram images using the image signatures computed from the wavelet transformed image [11], retrieval of mammogram images using BI-RADS (Breast Imaging Reporting and Data System) [12], liver diagnosis using CT images is proposed by Megha et al., [13], medical image retrieval using local ternary co-occurrence patterns which encodes the co-occurrence of similar ternary edges [14], image retrieving system [15] for heterogeneous

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medical image database using CLD, EHD, color moments, GLCM, edge frequency, primitive length, Gabor moments, Tamura moments, SIFT, LBP, LBP-I, CEDD, FCTH, autocorrelation coefficient as visual features and “Bag of words” as textual feature to represent the image, heterogeneous medical image retrieval approach is described in [16] using the SIFT and Spherical SOM (Self Organizing Map) built with a geodesic data structure. In [17], retrieval system for heterogeneous medical image database is presented using color autocorrelogram, micro-textures and modified EOAC (Edge Orienatation Autocorrelogram) and it is reported that it outperforms the existing techniques in terms of accuracy, time and storage cost. In this vein, a number of research efforts have been taken over the decades.

However, still there is a lack in effective representation of medical images. Moreover, medical images of modalities like X-ray, CT, PET, etc are in grey scale and images produced by Endoscopy, Microscopy are in color. It is strongly believed in this paper that it is more complicated to develop a high accuracy system for heterogeneous medical databases. Because, color and texture features play a central role in histology images whereas shape feature is also essential in the case of medical images of X-ray, CT, etc. With this underlying truth, in this paper, image retrieval system for histology images is reported based on orthogonal polynomial model in multiresolution domain [18]. The dominant color descriptor (DCD) [19], color autocorrelogram, modified representation of effective BDIP and BVLC [20] are used as features. The modified representation of BDIP and BVLC captures rich texture and its spatial information. The comprehensive experiments on benchmark database confirm that the proposed approach provides better results than the existing systems [17] in terms of accuracy, computational and storage cost.

This paper organized as follows. In Section 2, proposed system is explained. Section 3 deals with experiments and results. Section 4 gives conclusion.

II. PROPOSED SYSTEM

In the proposed system wavelet Packet and Daubechies-4 transforms [18] are jointly used to perform image decomposition. The level of decomposition is determined empirically and it is two in the proposed work. The wavelet transformation process at each level has both approximation and detailed components. By incorporating the orthogonal polynomial model in the multiresolution domain [18], the low order coefficients are reordered into low frequency and high order coefficients are reordered into high frequency components. From the low frequency components, *dominant* color descriptor (DCD) and color autocorrelogram is extracted. The BDIP and BVLC are extracted from the high frequency components. From the computed BDIP and BVLC its global as well as local spatial information [20] is extracted and it is used to represent the image.

The computed DCD, color autocorrelogram, global as well as local spatial correlation of BDIP and BVLC are combined together to form single a feature vector and is normalized by using the Z-score normalization method to attain the values of all features in the same range. Since variety of images in the databases contributes to the high complexity in the context of image retrieval and classification. Thus, classification of images is so important for a huge medical image databases. In the proposed system RBFNN [21] is adopted for performing classification task. The Manhattan similarity [22] measure is used to measure the similarity between the query image and target images in the benchmark database.

2.1. Wavelet based orthogonal polynomial model

In this paper, set of low-order and high-order polynomial coefficients is used to construct a multiresolution reordering subband structure [18]. To create scaling and wavelet functions in multiresolution domain by re-grouping low-order and high-order polynomials coefficients is done using the linear combination of orthogonal polynomial model [18]. The wavelet transform of a function $f(t) \in V_J$ vector subspace L^2 can be defined as in [18].

$$f(t) = \sum_{kk} c_{j0}(k)\varphi_{j0,k(t)} + \sum_{kk} \sum_{j=j0}^{j\ 1} d_j(k)\psi_{j,k}(t) \quad (1)$$

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Vol. 2, Issue 11, November 2014

where $c_{j0} = < f(t), \varphi_{0,k}(t) >$ and $d_j(k) = < f(t), \psi_{i,j}(t) >$ are scaling coefficients and wavelet coefficients respectively, $\varphi(t)$ and $\psi(t)$ are scaling and wavelet functions. If the signal $f(t)$ is in polynomial form, the coefficients c's and d's are linear combination of different order moments. If the moment of wavelet function is zero up to certain order n-1, for any polynomial with order lower than q, all its wavelet coefficients will be zero. Thus, the linear combination of orthogonal polynomial model is incorporated as in [18] to create the scaling function and wavelet by re-grouping of low and high order polynomials coefficients [18] through

$$\varphi_{ji}(x) = \sum_{k=0}^{2} a_{jik} p_k(x)$$

$$\psi_{ji}(x) = \sum_{k=2+1}^{2+1} b_{jik} p_k(x) \tag{2}$$

where $\varphi_{ji}(x)$ and $\psi_{ji}(x)$ are scaling and wavelet functions respectively and a_{ijk} and b_{ijk} are coefficients of scaling and wavelet functions. Wavelet and scaling functions spanning an orthogonal basis of a multiresolution analysis [1] and need to full fill the following orthogonal conditions:

$$\begin{aligned} &< \varphi_{ji}, \psi_{ji} > w = \partial_{ij} \\ &< \varphi_{ji}, \psi_{ml} > w = \partial_{ij}\, \partial_{jm} \\ &< \varphi_{ji}, \psi_{ml} > w = 0, (m \geq = j) \end{aligned} \tag{3}$$

where w represents the weight, and $< \varphi_{ji}, \psi_{ml} > w = 0$ represents orthogonal between scaling and wavelet function (1), we have obtain

$$\begin{aligned} &< \varphi_{ji}, \psi_{ji} > w = \sum_{k=0}^{2^j} \sum_{x=0}^{2} a_{jik}\, a_{mln} < p_k, p_x > w \\ &< \varphi_{ji}, \psi_{ml} > w = \sum_{k=2^j+1}^{2^{j=1}} \sum_{x=2^m+1}^{2^{m+1}} b_{jik}\, b_{mln} < p_k, p_x > w \\ &< \varphi_{ji}, \psi_{ml} > w = \sum_{k=0}^{2^j} \sum_{x=2^j+1}^{2^{m+1}} a_{jik}\, b_{mln} < p_k, p_x > w \end{aligned} \tag{4}$$

It is obvious that due to the orthogonality of the polynomial $(< P_k, P_n > w = \partial_{kn})$ choice of the coefficients a, b alone determines the orthogonality properties of the basis. Therefore, we get

$$\begin{aligned} &< \varphi_{ji}, \psi_{jl} > w = \sum_{k=0}^{2^j} a_{jik}\, a_{jik} \\ &< \varphi_{ji}, \psi_{jl} > w = \partial_{jm} \sum_{k=2^{j+1}}^{2^{j+1}} b_{jik}\, b_{jik} \\ &< \varphi_{ji}, \psi_{ml} > w = 0 (m \geq j) \end{aligned} \tag{5}$$

Here Legendre polynomials is used with associated weight w(x)=1 as basis function [18]. The orthogonal polynomial coefficients c_j and d_j obtained from the eq. (1) which represents scaling and wavelet coefficients. The coefficients are reordered into $(3\log_2 N + 1)$ multiresolution subbands where N is power of 2.

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Vol. 2, Issue 11, November 2014

2.2. Color feature extraction

2.2.1. Dominant Color Descriptor (DCD)

It is a MPEG-7's color descriptor and it provides compact report of the representative colors in the image. Color quantization is performed to extract number of representative color in the image. The DCD [19] is defined in equation (6) as follows

$$DCD = \{\{c_i, p_i, v_i\}, s\} \tag{6}$$

where i=1, 2, . . . , N and N is the total number of dominant colors in the image and it differs from image to image, c_i is dominant color value, p_i is the percentage of each dominant color, v_i is color variance of each color and s is the spatial coherency that represents the overall spatial homogeneity of the dominant colors in the image. In the literature [19], it is revealed that maximum 8 numbers of dominant colors is sufficient to represent the image in an efficient manner.

2.2.2. Color Autocorrelogram

The color autocorrelogram calculates the spatial information of color and shape respectively. It is also reported that color autocorrelogram is more robust to color, appearance, contrast and brightness changes and also invariant to translation and scaling [17, 23]. Hence, in this paper, the color autocorrelogram is selected as a color descriptor.

Let I is an image of size N X N. Assume that the colors in I is quantized into m colors say c1, c2, . , . , . , cm. Let us consider the pixels p1 and p2 where p1=(x1, y1) and p2=(x2, y2). Let a distance between p1 and p2 is *d* and $d \in N$. The correlogram for image I is defined in equation (7) as in [23].

$$\varphi^{d}_{c_i c_j}(I) \overset{\Delta}{=} \Pr_{p_1 \in i_{c_i}, p_2 \in i_{c_j}} [p_2 \in I_{c_i} \mid |p_1 - p_2| = k] \tag{7}$$

where $k \in d$ and $i, j \in m$. For any pixel of color c_i in the image, $\varphi^{d}_{c_i c_j}(I)$ gives the probability that a pixel at distance k away from the given pixel is of color. c_j. The autocorrelogram of I captures spatial correlation between identical colors only and is defined in equation (8) as in [23]

$$\Phi^{k}_{c}(I) \overset{\Delta}{=} \varphi^{d}_{c_i c_j}(I) \tag{8}$$

Since smallest correlation distance offers in depth local properties of an image, the color autocorrelogram extracts the spatial correlation between the identical colors at distance *d*= 1 [23].

2.2.3. Texture feature extraction

2.2.3.1. BDIP

BDIP is an entropy operator and is defined as the difference between the number of pixels in a block and the ratio of the sum of pixel intensities in the block to the maximum in the block, and it uses local probabilities in an image block to measure the local brightness variations. The BDIP captures the both the edges and valleys. In an image, edge pixels represent the local intensity maximum and pixels in the valley represent local intensity minima. Both the edges and valleys play a central role in human visual perception system to recognize an object. Based on the fact, BDIP is suggested in [23] and is computed as follows in equation (9).

$$BDIP^{d}(l) = \frac{\frac{1}{B_l^d} \sum (x,y) \in B_l^d \left(\max_{(x,y)\in B_l^d} f(x,y) - f(x,y)\right)}{\max_{(x,y)\in B_l^d} f(x,y)} \tag{9}$$

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where f(x,y) designates the pixel intensity at location (x,y) in the block B_l^k of size (k+l) x (k+l), l is the place index of the block in an image and k is the maximum distance of pairs of pixels in the block. Therefore, $B_l^k = (k+1)^2$. The maximum intensity variation in a block and the representative value in a block are expressed in the numerator and denominator of equation (9) respectively.

2.2.3.2. BVLC

BVLC [23] is the difference between the maximum and minimum of local correlation coefficients according to four orientations $(0^\circ, 90^\circ, 45^\circ, -45^\circ)$ in a block. This feature measures the texture smoothness using variations of local correlation coefficients in an image blocks as follows in equation (10).

$$\rho(k,l) = \frac{\frac{1}{M^2}\sum_{(x,y)\in B} f(x,y)f(x+k,y+l) - \mu_{0,0}\mu_{k,l}}{\sigma_{0,0}\sigma_{k,l}} \tag{10}$$

where B is a block of size M x M and $\mu_{0,0}\mu_{k,l}$ is the local mean, and $\sigma_{0,0}\sigma_{k,l}$ is the local standard deviation. The (k, l) represents a pair of horizontal shift and vertical shift associated with four orientations $(0^\circ, 90^\circ, 45^\circ, -45^\circ)$. After shifting the M x M windows in each of four directions, compute *p(0,1), p(1,0), p(1,1), p(1,-1)* then the BVLC is computed as shown in equation (11).

$$BVLC^d(l) = \max_{\Delta(k)\in O_4} [\rho^k(l, \Delta(k))] - \min_{\Delta(k)\in O_4} [\rho^k(l, \Delta(k))] \tag{11}$$

Where $\Delta(k) = (\Delta_x(k), \Delta_y(k))$ stands for shift in one four directions and $O_4 = \{(-k,0), (0,-k), (0,k), (k,0)\}$

2.3. Similarity Measure

Measuring the distance between the query and target images using the derived feature vectors is an indispensable module of any image retrieval system. Different distance measures from computational geometry, statistics and information theory are described for image retrieval systems. In the proposed work, Manhatten distance [22] measure is used because of it significance performance in image retrieval. The computational cost of Manhatten distance is also less. It is computed as follows in equation (12).

$$D(Q_i, T_i) = \sum_{i=1}^{N} \left| Q_i - T_i \right| \tag{12}$$

Where Q and T stand for the query and target image feature vectors respectively and n is the number of features in each feature vector. The features are placed in increasing order that the value in the top most gives high similarity.

2.4. Performance Assessment

The performance of the proposed system is measured using the most widely used precision (percentage of retrieved images that are also relevant) and recall (percentage of relevant images that are retrieved) methods [15, 17, 18, 19] and is defined as follows in equation (13) and (14)

$$\Pr ecision = \frac{R_i}{T_i} \tag{13}$$

$$\text{Re call} = \frac{R_i}{T} \tag{14}$$

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Vol. 2, Issue 11, November 2014

Where Ri is the total number of relevant images retrieved, T is the total number of relevant images in the image database, and Ti is the total number of all retrieved images. The effectiveness of the proposed system is also measured in terms of average recognition rate (ARR), which is defined as the percentage of retrieved images in top matches.

The precision and recall measures cannot be considered as accuracy for the whole image retrieval systems. Thus, F-Score is incorporated in the proposed approach. F-score combines the precision and recall into a single value that defines the overall accuracy of image retrieval system. *F*-Score is defined in equation (15) as follows

$$F_{Score} = 2 * \frac{Precision \times Recall}{Precision + Recall} \tag{15}$$

III. EXPERIMENTAL RESULTS

For the implementation of the proposed approach, the benchmark database used in [17] is incorporated. It is a collection of 6400 images of various modalities including CT, MRI, Microscopy, Mammogram, Ultrasound and Endoscopy with ground truth. The benchmark database consists of 1708 microscopy images. Since the discussion in this paper is limited with histology images, we only consider the 457 histology images from the microscopy category for the experiments. In addition to 457, few images are collected from various private laboratories. So, totally 634 images of four categories are available in the database. The categories are Hematoxylin and Eosin, Masson's trichrome, **t**hionine staining, periodic acid–schiff staining, toluidine blue staining. The benchmark databases contain images in different size and are in JPEG format. For instance, some of the sample images from the benchmark database are presented in Figure. 1. Query images are chosen randomly from the each category of benchmark database

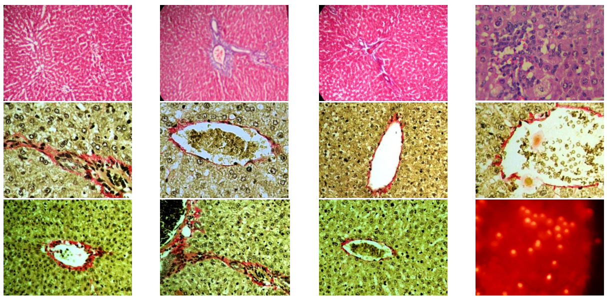
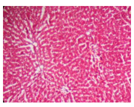
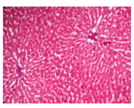
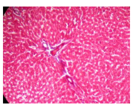


Fig.1. Sample images from the benchmark database

The proposed method is carried out in two stages. In the first stage, features are extracted for all the images in the image database. After categorizing the feature vectors, they are stored in a separate database called feature vector database. The feature vectors in the feature database are categorized into number of classes in order to reduce the search space considerably by filtering out the unrelated classes of images and it increases the speed of retrieval.



(a)

(b) (c)

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(An ISO 3297: 2007 Certified Organization)

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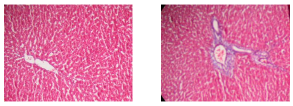

(d) (e)

Fig. 2. (a) Query image. (b)- (e). Top most 4 akin images with query image for the proposed image retrieval

In the second stage, query image is given to the proposed and existing approaches to retrieve relevant images from the image database. For the proposed system, the most relevant images are displayed to the user in the top as shown in Fig.2. The proposed CBMIR system is implemented using the MATLAB with the system configuration: Pentium® Dual core personal computer with 2.20 GHz processor and 2 GB RAM.

The feature extraction and representation and similarity measurement plays vital role in measuring the effectiveness of the image retrieval system. In the proposed approach, they have been chosen very carefully in order to retrieve relevant images more accurately with low computational and storage cost. The precision, recall and F-Score metrics are employed in the proposed approach to measure the performance of the system and these measures also ensure the stability of the results. Either precision or recall as a single cannot be a whole measure of the retrieval systems. That is the reason why we have incorporated F-score also for measuring the performance.

In the experiments comparative study has been conducted between the proposed and existing approach. The proposed approach extracts DCD, color autocorrelogram, BDIP and its spatial information and BVLC and its spatial information from the orthogonal polynomial based multiresolution domain of the image. Whereas the existing system uses color autocorrelogram, micro-textures and modified Edge orientation correlogram. Table 1 shows the average precision of image classes for the proposed and existing [17] image retrieval approaches. The overall average precision of proposed method is 84.21% which is higher than the existing method [17] and is 82.78%. The overall average recall of the proposed method is 86.72% which is higher than the existing method [17] and is 84.33%. The overall average F-score of proposed method is 85.44% which is higher than the existing method [17] and is 83.54%. In Fig.3, precision versus recall for the proposed approach is depicted. It is observed from the results that the proposed approach is considerably better than the existing one [17] based on the measures precision, recall and F-Score.

Table 1. Comparison of proposed with the existing method based on average precision, recall and F-score for the histology images in the benchmark database.

Measures	Proposed Method	Existing Method [17]
Precision %	84.21	82.78
Recall %	86.72	84.33
F-score%	85.44	83.54

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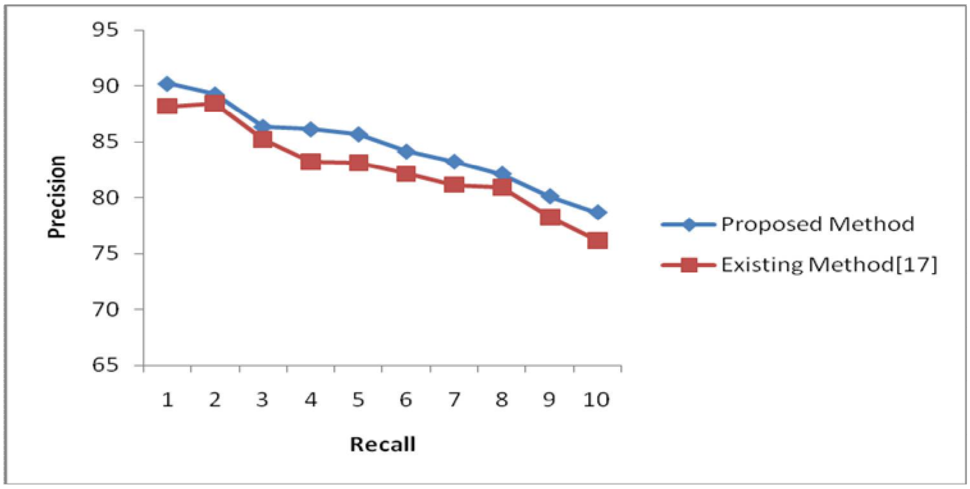

Fig.3. Precision Vs recall for the proposed and existing method [17]

IV. CONCLUSION

The proposed system extracts dominant color descriptor, color autocorrlogram, BDIP values and its spatial information, BVLC values and its spatial information from the orthogonal polynomial model based multiresolution domain for histology image retrieval. The Wavelet Packet transforms and Daubechies-4 (Db-4) transforms are jointly used to perform image decomposition. The results revealed that the proposed system is significantly superior in accuracy than the existing system.

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