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BIOMEDICAL IMAGE RETRIEVAL USING LBWP

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Abstract - *A new design of feature descriptor is proposed in this paper, which could be used in retrieval, analysis or recognition purposes. This paper mainly focus on retrieval of biomedical images, i.e. CT and MRI images. The new feature descriptor is LBWP (Local Bit-Plane Wavelet Pattern). In this a wavelet function is applied onto different bit planes of an image, thus capturing fine and coarse details present in an image. The wavelet function would help in encoding the inter and intra pixel relationship in an image. Thus guaranteeing effective retrieval rate and efficient performance. The training and testing data where taken randomly from TCIA database. The experimental results shows a promising efficiency.*

***Key Words*: LBWP, Bit-plane, Wavelet, Pixel, TCIA**

I. INTRODUCTION

Content based image retrieval has always been a vast research topic for many years. In the field of medical analysis, there is no chance for any kind of failure or error, as it may cost lives of patients. The factor of accuracy stands so important in life and death decisions. Content based image retrieval (CBIR) may play a major role in disease diagnosis, tutorial and research purposes. But due to increase of population, the number of disease subject also increases. As a result there is always a need of efficient and accurate image retrieval measure. Hence, it would help in searching, indexing and retrieving methods.

Moreover, when the similarity measure comes to medical images, the values may be varying so less, for they all seem similar. The values may show a slight variation, due to presence of tumor, or due to a small lesion or cut. But it is extremely important to find the specific problem for whatever the reason is. Because as the time delays, the chance of patient's survival decrease. This paper mainly focus on CT and MRI images.

The basic instinct of CBIR is based on color, texture, shape, structure etc. The detailed description of literature survey is mentioned in [13-18]. CBIR usually, is based on pattern recognition, thus captures image's detailed information. Using the retrieval system, doctors could recognise the disorder or could retrieve the most similar report from the medical histories.

The principle behind any skeleton system for retrieval is the measurement of similarity amoung the image. The similarity between the index image and images from the databases are measured. This similarity measurement is done with the help of feature vectors. The feature vector generates a value for a particular image. This value is checked over the entire database to find the similarity. The performance and effectiveness of the system is heavily depended on this feature vectors.

In this paper, we present a method that uses wavelet function in each layer of images. This layering is based on depth of the bit planes. Each bit planes captures different information based on the depth of images. The new proposed system, is expected to have the efficiency along with information by capturing all fine and coarse details. Thus the encoded information, and improvised wavelet function is confined together to provide hike in accuracy, compared to other existing system.

II. RELATED WORK

Many researches and studies are conducted on feature vectors and retrieval systems. In image processing, the information of images are encoded in many possible manners. This information encoding can be done using feature vectors. Feature vectors are the basic unit of any systems used for classification, analysis, recognition and retrieval. Without these feature vectors, the system built, would be a body without soul.

An extensive literature survey on content based image retrieval is done in [13-18]. The revolution in usage of feature vector started with introduction of LBP (local binary pattern) by Ojala et al [8] due to reduced complexity. Depending on this concept a lot of variants of LBP evolved. Other generalised concept that gained a lot of attention include LTP [9], LTrP [19], Local Diagonal Extrema Pattern [18], LMeP [10] etc.

An example of generalization of the LBP, is local ternary pattern (LTP) [9] for face recognition under changing lighting conditions. Local mesh patterns

(LMeP) [10], peak valley edge patterns (PVEP) [11], and local mesh PVEP [12] are other state-of-art descriptors proposed for the biomedical image retrieval. Dubey et al. introduced LTrP (Local Tetra Patterns)[19] and Local Diagonal Extrema Pattern [18] for the retrieval of CT images.

Depending on the existence of local structure, in MR images of brain, a retrieval method was proposed by Unay et al [5]. In creation of LWP (Local Wavelet Pattern) by Dubey et al. [1] a wavelet function is used to encode relationship between centre pixel and neighboring pixel. Similarly in LBDP (Local Bit-Plane Decoded Pattern) various bit planes are evaluated to include more image information [2].

After the detailed study, an idea of system along with more information in an encoded manner with all intra- and inter-pixel relationship was idealised. Thus a wavelet function is applied locally on a central pixel and neighboring pixels, on different bit planes, to store more information. The paper illustrates the system design, and includes the performance evaluation and concluding remarks as follows.

III. PROPOSED SYSTEM FRAMEWORK

In the area of biomedical images and their retrieval, it is found that encoding the relationship of pixel's intensity is very important. The retrieval can be effectively done, if more information about a particular pixel or it's neighbors are included. In most of the methods the intensity value of pixel is taken directly without much transformations.

After analysing a few works, these pixel intensity values were undergone some mathematical transformation. The proposed system is a design of new feature descriptor, LBWP (Local Bit-Plane Wavelet Pattern) for the retrieval of biomedical images. It aims at defining a powerful feature vector for efficient retrieval of biomedical images and also to encode the maximum relationship information of central and neighboring pixels. The proposed system also focus on, transformed intensity values of each pixel in separate bit planes. The architecture of system is as shown in Fig 1. Along with this, an SVM classifier is introduced to distinguish if the query image is CT or MRI from the database.

The principle idea is to include more information about the relationship between the intensity of central pixel and neighboring pixel. For this, each pixel of image is decomposed to several bit planes depending upon it's depth. The LBWP (Local Bit-plane Wavelet Pattern) encodes the relationship among neighbors in each bit-plane separately, using local bit-plane transformation which generates the local bit-plane transformed values and then encodes the relationship of centre pixel with each transformed values. It then applies the wavelet function to them thus generating a new feature descriptor.

Local Neighborhood extraction: In order to compute feature vector, it is assumed that a centre pixel have equally spaced neighboring pixels. The nearest ones amoung them are taken into consideration. They are assumed to be in a circular manner,

Hence the coordinates of these pixels are converted from polar system to cartesian ones[1].

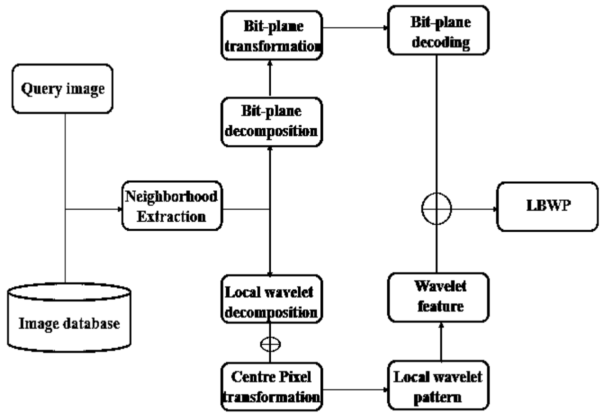

Fig 1. Proposed system framework of LBWP for biomedical image retrieval.

Fig 2 shows the skeleton of a basic unit of local neighborhood, along with the variables used to refer them. Let M be an image of dimension m1 x m2. Then P be the pixel at (i,j) coordinate. N will be the total number of neighbors surrounding the central pixel and t is used to denote a particular pixel. R be the radius distance between central and neighbouring pixel. A particular pixel in (i,j) coordinate surrounded by N neighbours, at distance R from central pixel is represented as $P^{i,j}_{R,N.t}$. The intensity of this Pixel is represented as $I^{i,j}_{R,N,t}$

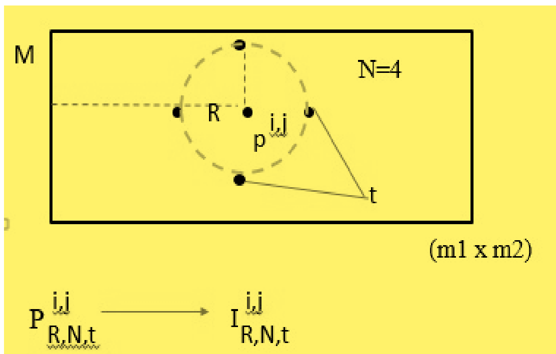

Fig 2: Skeleton of basic unit of local neighborhood

Bit-plane Decomposition: The local bit-plane decomposition step is performed to separate each bit-plane of the local neighboring structure of pixel, where k is the positive integer having values between 1 and N. the local bit plane decomposition step yields the binary values in each bit plane and is applied over only neighbors $P_{R,N}^{i,j}$. Note that this step is not applied over the centre pixel $P^{i,j}$. Certain functional changes are applied to the intensity of centre pixel, in order to obtain, intensity values of neighbors[2].

Bit-plane Transformation: The concept of local bit-plane transformation, which captures the local information in each bit-plane separately, with lower and higher bit-plane to capture the fine and coarse details respectively. The idea is to generate a binary pattern called as local bit plane decoded pattern by exploring the relation between intensity value of a centre pixel with the local bit-plane transformed values for each bit-plane. The local bit plane transformed values for a particular bit plane is computed by summing up of each weight values using $2^{(t-1)}$ values in that plane.

$$v_{R,N,t}^{i,j,k} = \sum_{k=1}^{N} I_{R,N,t}^{i,j,k} \times 2^{(t-1)} \qquad 2.1$$

Bit-plane Decoding: Bit plane coding generate a binary pattern called as local bit-plane decoded pattern. This is generated by exploring the relation between of a centre pixel with the local bit-plane transformed values for each bit-plane. The intensity values of pixels are used to explore or to identify the relationship between the pixels of an image. The decomposed and transformed values are combined together to obtain a single value with which new feature descriptor is calculated. Here signed function is applied to the difference of intensity of centre pixel and local bit plane transformed values[2].

Local Wavelet Decomposition: For wavelet decomposition 1 D Haar wavelet function is used. It is function of intensity of neighboring pixels and recursive basis function[1].

Central Pixel Transformation: Here the encoding of relationship of central pixel and neighboring ones are done. After wavelet decomposition the range of wavelet has changed. To perform any mathematical operation on these functions, their ranges must be matched. Thus range matching is the role of centre pixel transformation [1].

Local Wavelet Pattern: Wavelet function and centre pixel transformed values are used to encode relation between centre and neighboring pixels. It is done by using signed function of the difference between wavelet function and centre pixel transformed values. Thus a binary value is originated which will be used for creation of local wavelet pattern map.

LBWP Feature Generation:

Local wavelet pattern map is generated for each pixel that surrounds the centre pixel. Similarly local bit plane decoded value for each pixel that surrounds the centre pixel is calculated. Both of them are combined together to form local bit-plane wavelet pattern.

IV. RESULTS AND DISCUSSIONS

The performance measures for the proposed system are evaluated relevant to the performance parameters ARP (Average Retrieval Precision), ARR (Average Retrieval Rate) and F-score. The term peak ARP (Average Retrieval Precision) is an expression for the ratio of the number of relevant images to the number of images retrieved. Similarly ARR (Average Retrieval Rate) is an expression for the ratio of the number of relevant images retrieved to the number of relevant images in database [7]. The database considered for performance evaluation is TCIA (The Cancer Image Archive). The images for training and testing were downloaded from TCIA.

$$ARP = \frac{Number\ of\ relevent\ images\ retrieved}{Number\ of\ images\ retrieved}$$

$$ARR = \frac{Number\ of\ relevent\ images\ retrieved}{Number\ of\ relevent\ images\ in\ database}$$

$$F - Score = \frac{2 \times ARP \times ARR}{ARP + ARR}$$

Performance evaluation was conducted on a number of CT and MRI images to verify the effectiveness of the proposed scheme. All experiments were implemented on a computer with an intel i5 core processor, 4.00 GB memory, Windows operating system and the programming environment was MATLAB 2013. Several set of images are chosen as test images. The parameters such as precision, recall and F-score are checked. . In simple words, high precision means that retrieved images consists of more relevant images, and high recall means most of the retrieved ones are relevant.

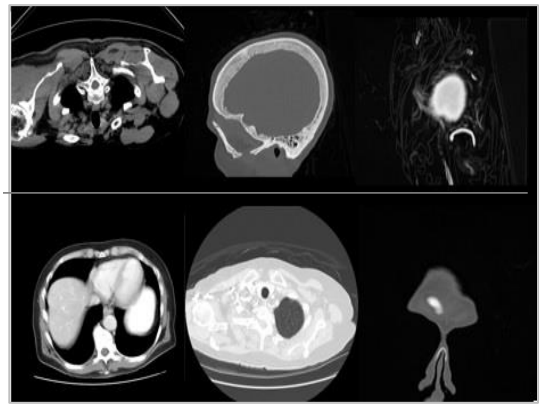

Fig 3: Examples of CT images from TCIA database

Each database image of database is considered as a query image and matched with all images. The top matching images are retrieved based on distance measure. The results of the performance analysis are shown in the table below. The input image where randomly chosen by the user from test cases. And the results from the system proved that the proposed system has a better result compared with the existing system.

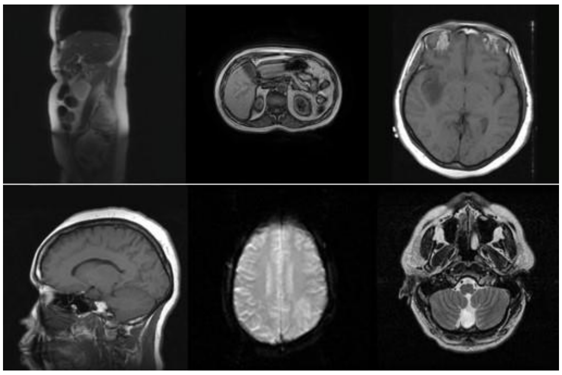

Fig 4: Examples of MRI images from TCIA database

The LWP feature vector has already proven to be better than existing methods [1] during testing. Hence we consider only comparison of LBWP with LWP. As we can see, all ARP, ARR and F-Score values are higher for LBWP, it is clear that it outperforms LWP. We can also notice that the recall rate is so close to 100%.

Table 1: Performance evaluation of LBWP and LWP feature vectors on selected dataset

METHOD	MODE	ARP	ARR	F-MEASURE
LBWP	CT	53.0	99.98	71.7
	MRI	49.1	99.92	67.11
LWP	CT	45.5	82.3	58.6
	MRI	45.8	88.01	59.5

V. CONCLUSIONS

We proposed a new local Bit-plane Wavelet Pattern based image feature descriptor in this paper for biomedical image retrieval. LBWP, which gave us an incredible performance on retrieval rate. It encoded all kinds of fine and coarse details in different bit planes along with an application of wavelet function between central and neighboring pixels. The wavelet function was applied locally over a central pixel and neighboring ones. In order to test this descriptor we downloaded some images from The Cancer Imaging Archive (TCIA) that formed the training and testing dataset. The performance was measured using ARP, ARR and F-Score. It is seen that, the LBWP outperformed the LWP, which was the best, compared to all existing methods on basis of retrieval rate.

VI. FUTURE WORKS

The feature descriptor can also be used in retrieval of non-medical images. In image processing, LBWP feature vector can also be used in all analysis, recognition and retrieval systems

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