CONTENT -BASED RETINAL IMAGE RETRIEVAL BASED ON WAVELET TRANSFORM

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Abstract

The paper presents the content based retinal image retrieval (CBRIR) based on dual tree complex wavelet transform (DT-CWT) and multi wavelet. The multi wavelet transform is more retrieval accuracy compare to DT-CWT. It is less complexity and less retrieval time. In this work, the proposed method follows two steps. The firstly, apply the wavelet transform (either DT-CWT or multi wavelet) and energy is used for feature extraction. Energy function is the most suitable for texture characterization of the image. Secondly, calculate the similarity measures between query and database image feature vectors using Euclidian distance. The experimental data base diabetic retinopathy database (DRD) contains 1261 images. The experimental results shows that the retrieval efficiency and retrieval time of multi wavelet is less compare to DT-CWT.

Index Terms- *Diabetic retinopathy, CBIR, dual-tree complex wavelet and multi wavelet.*

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1. INTRODUCTION

Nowadays computer imaging and database techniques play an important role in medical field, which leads to the huge amount of digital images with a wide variety of image modalities, such as Computed Tomography(CT), Magnetic Resonance (MR), X-ray and ultrasound, generated in hospitals every day[1]. Developing efficient medical image indexing system is an urgent work. Recently Picture Archiving and Communication System (PACS) system is widely used in hospitals, but PACS provides only simple text-based retrieval capabilities using patient names or patient ID numbers. Content-Based Image Retrieval (CBIR) systems can greatly help to retrieve useful information within enormous amount of medical images. Presently the demand of multimedia information such as digital images and video rapidly increase [2]. Image Retrieval plays a vital role in many application areas, such as education, entertainment, art history, digital library, diagnostic medical image databases, journalism data management and general consumer use.

In [3], 1261 images are indexed in a generic fashion and adapted the wavelet basis within a lifting scheme framework. Wavelets like LeGall 5/3, Daubechies 9/7, Haar, cubic B-spline, Daubechies 4-tap, Daubechies 6-tap and adapted wavelets were evaluated. The wavelet coefficient distribution was mode lied using histogram and generalized Gaussian functions, out of which generalized Gaussian functions gave better results. In [4], the performance of the adapted non-separable wavelet filter bank and the separable wavelet filter bank was analyzed for Diabetic Retinopathy Database (DRD) consisting of 1045 photographs. Adapted wavelet using weighted distance between signatures is used for retrieving 1045 photographs from DRD in [5]. It has been proved that wavelet-based image features enable fast retrieval and increased retrieval performance [3]. The enhancement to the discrete wavelet transform (DWT) is the dual-tree complex wavelet transform (DT -CWT) due to its nearly shift invariant and directionally selective properties [6]. From the literatures related to existing methods, it is found that different wavelets along with probability distribution model Euclidian distance measure have been used for content-based retinal image retrieval. In [7], the DT -CWT has been successfully used for general texture retrieval purpose yielding better retrieval results and the same is adopted in this work.

In this paper is organized as follows. The DT-CWT is explained in II. Proposed method in section III. Retrieval measure in section IV. The simulation results are presented in Section V. Concluding remarks are made in Section VI.

II. DT-COMPLEX WAVELET TRANSFORM

The images in its original form may lead to computational complexity and burden as reported in the literature . Therefore, the first step in preprocessing is to separate the green component which has comparatively better contrast and energy than other components [2]. Hence, the green component of the retinal images is used in the subsequent stages of the retrieval process.

Next, the region of interest (ROI), i.e., the retina portion is cropped based on the locations of the extreme edge pixels obtained by applying the Sobel edge operator. Finally, the contrast of the ROI is enhanced further through contrast-limited adaptive histogram equalization (CLAHE) method.

It is a simply a non-decimated wavelet transform .The drawback in DT-CWT is more expansive wavelet transform in place of a critically-sampled one. The DT-CWT is separating the positive and negative frequencies thus differentiating and splitting the sub bands of a dyadic decomposition into sub bands orientated at ±15°, ±45°, ±75° as shown in figure 1.

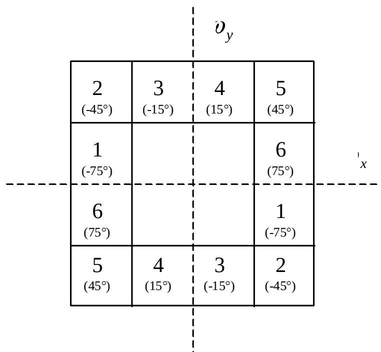

Fig 1: Frequency plane showing 6 orientated sub bands of the complex wavelet transform

The block diagram of decomposition of DT-CWT in two level is shown in fig.2.

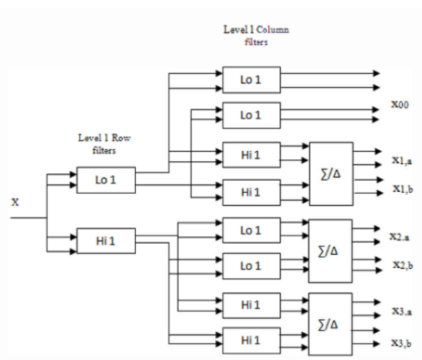

Fig 2 : block diagram of 2- dimensional DT -CWT

At each level contain two stages. The first one is generating the six sub bands of branch a and b in which satisfy the Hilbert pairs requirement. The Hilbert pairs are HLa, HLb, LHa, LHb, HHa and HHb. The two stages involved in gerting the sub-band coefficients are: (i) generation of the initial six sub-bands of branch a and b through filters satisfying the Hilbert pair requirement resulting in HLa, HLb, LHa, LHb, HHa and HHb and (ii) linear combination, either by averaging or differencing the real and imaginary part of the sub-band outputs as (HLa + HLb)/2, (HLa-HLb)I/2, (LHa+ LHb)/2, (LHa-LHb)/2, (HHa + HHb)/2, (HHa - HHb)/2 [16] The second one is find the average and difference the real and imaginary of Hilbert pairs. It is called linear combination. After that calculate the feature extraction of each sub band of DT-CWT GGD function will implemented.. The main advantages are Better directionality, Anti- aliasing effect, Good shift-invariant, Geometry of the image features retained from phase, Better robustness for smooth varying and Low computation compared with discrete wavelet transform. It is less retrieval accuracy, high computation and storage. So, to solve such a problem using multiwavelet transform as explain in next section.

III. PROPOSED METHOD

The block diagram of content-based retinal image retrieval technique is given in Fig.3 , which consists of three important stages namely wavelet transform, feature selection and similarity measurement as explain in sub section *A*,*B*, and *C*.

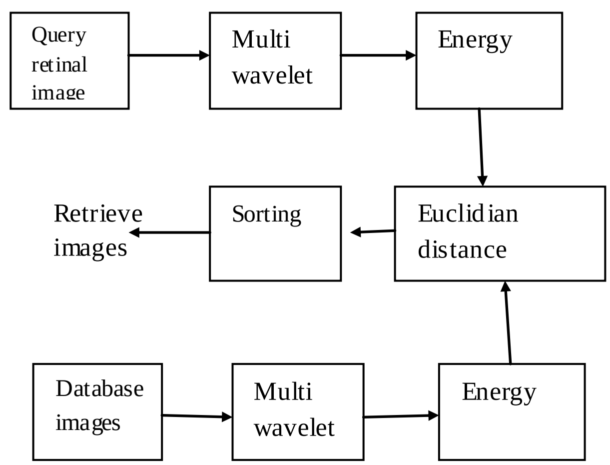

Fig 3 : block diagram of proposed method

A. Multi wavelet

It is also called two level transform. Multi wavelet is high retrieval accuracy, less complexity and storage. The discrete wavelet framework for image decomposition.The prefilter is first applied to all the rows of the image, before the first level decomposition is applied to each of the resultant rows. The first half of each row of the decomposition results contains coefficients corresponding to the first scaling function and the second half contains coefficients corresponding to the second scaling function. Then the prefilter and decomposition operations are repeated to the columns, such that the first half of each column contains coefficients corresponding to the first scaling function and the second half of each column corresponding to the second scaling function. At the end of the first of 2-D discrete wavelet decomposition, we have a 16-subband intermediate image as follows

L_1L_1	L_2L_1	H_1L_1	H_2L_1
L_1L_2	L_2L_2	H_1L_2	H_2L_2
L_1H_1	L_2H_1	H_1H_1	H_2H_1
L_1H_2	L_2H_2	H_1H_2	H_2H_2

,

Here a typical block 1 2L H contains low pass coefficients corresponding to the first scaling function in the horizontal direction and high pass coefficients corresponding to the second scaling function in the vertical direction. The next step of the cascade will decompose the "low-low pass" sub matrix. The L_1L_1 sub band resolution is high compare to other sub bands. In this fashion, an L-level decomposition of a 2-D image will produce 4(3L+1) sub bands. After this calculate energy of each sub band i.e to get the 12 feature values in a single image.

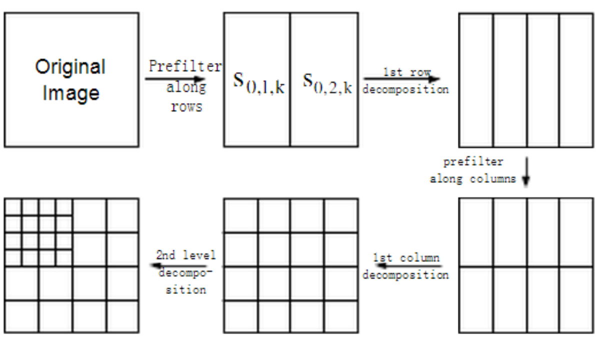

Fig 4: One level of 2-D multiwavelet decomposition of a 2-D image

B. Feature extraction

In order to have features that requires less computation and storage using energy. The energy calculation of each sub-image and defined as

$$E = \frac{1}{N}\sum_{i,j} x_{i,j}^{2}$$

Where X is the sub-band and N is the total number pixel in X sub-band. The wavelet energy features reflect the distribution of energy along the frequency axis over scale and orientation and have proven to be very powerful for texture characterization. Since most relevant texture information has eliminated the low pass filtering, we didn't consider the energy of the low resolution sub-images. The results shows showed that the performance of the energy feature was statistically better than the existing feature extraction methods.

C. Similarity measure

To compute the similarity measurement between the query feature vector and the ones in the feature dataset using Euclidian distance in which is based on square-root of feature vectors of query image and dataset images.

$$d = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

Where x is the query feature vector and y is the dataset feature vector. N is the total number of feature vectors.

IV. RETRIEVAL MEASURE

Precision and recall are the two widely used metrics for evaluating the performance of a content-based retinal retrieval method. Precision describes the amount of relevancy achieved by the system,

$$Precision = \frac{No.of\ relevant\ images\ retrieved}{Total\ No.of\ images\ retrieved}$$

Whereas, recall defines how fast the relevant images are retrieved.

$$Recall = \frac{No.of\ relevant\ images\ retrieved}{No.of\ relevant\ images\ in\ the\ database}$$

V. THE EXPERIMENTAL RESULTS

The experimental dataset of this work consists of the retinal images available in the MESSIDOR database. In this work implemented using MATLAB tool. The results of different retinal test images are shown below.

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Fig 5 : original image

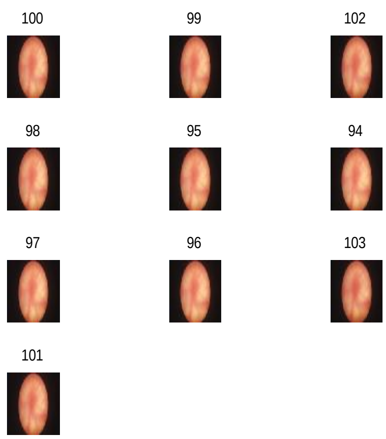

Fig 6 :. image retrieval using multi wavelet

Fig 7 : original image

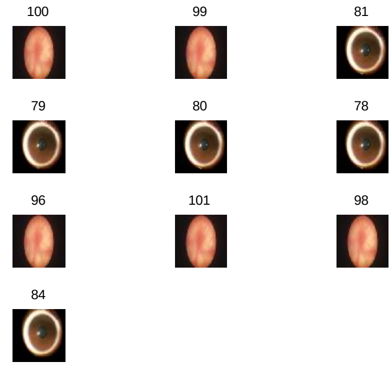

Fig 8 : image retrieval using dual tree wavelet

The graph between precision and recall for the multi wavelets and DT-CWT as shown in figure9. Where as precision taken on Y-axis and recall on X-axis. By comparing this we can say that multi wavelets can give better results.

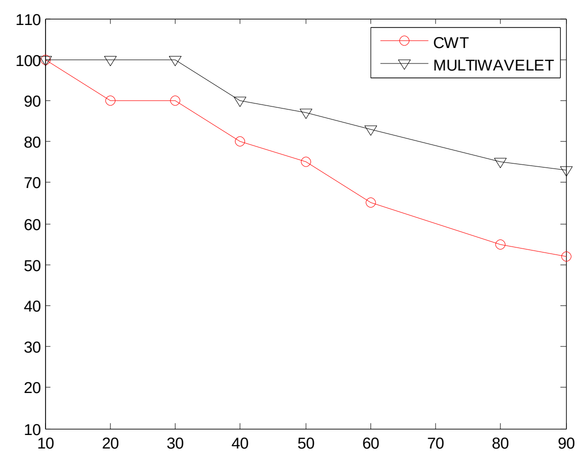

Fig 9 :graph between precision and recall

VI. CONCLUSION

The paper presents the retinal image retrieval based on multi wavelet and DT-CWT. The performance of retrieval efficiency in multi wavelet is better compare to DT-CWT as shown in experimental results. The multi wavelet system gives good results on the tests conducted. It is more powerful and efficient retrieval system for image and multimedia databases, content based queries must be combined with text, keyword predicate and it has shown that best in the sense of time and accuracy.

REFERENCES

[1] Wei Xiong, Bo Qiu, Qi Tian, Changsheng Xu, Sim Heng Ong, Kelvin Foong (2005), "Content Based Medical Image Retrieval using Dynamically optimised Regional Features,. ICIP (3) 2005: 1232- 1235

[2] Dong-Gi Lee and Sujit Dey ," Adaptive and Energy Efficient Wavelet Image Compression For Mobile Multimedia Data Services" ICC 2002. Volume: 4, On page(s): 2484- 2490 vol.4

[3] G. Quellec, M. Lamard, G. Cazuguel, B. Cochener, C. Roux, "Wavelet optimization for content-based image retrieval in medical databases," Proc. of Science Direct (Elsevier), Medicallmage Analysis, Vol. 14, No. 2, pp. 227-241, 2010.

[4] G. Quellec, M. Lamard, G. Cazuguel, B. Cochener, C. Roux, "Adaptive Non-Separable Wavelet Transfrm via Lifing ad its Application to Content-Based Image Retrieval", IEEE Trans Image Process, Vol.19,No.l,pp.25-35,2010.

[5] M. Lamad, G. Cazuguel, G. Quellec, L. Bekri, C. Roux, B. Cochener, "Content Based Image Retrieval based on Wavelet Transform coefcients distribution" in Proceedings of the 29th Annual International Conference of the IEEE EMBS, Lyon, France August 23-26, 2007.

[6] Ivan W. Selesnick, Richard G. Baraniuk, Nick G. Kingsbury, The Dual-Tree Complex Wavelet Transform", IEEE Trans Signal Processing, November 2005.

[7] Hua-Zhang Wang ,Sichuan Univ., Chengdu ,Xiao-Hai He ; Wen Jiao Zai ,"Texture image retrieval using dual-tree complex wavelet trans form", International Conference on Wavelet Analysis and Pattern Recognition, 2007, ICWAPR '07.

[8] L. O. Harvey and M. J. Gervais," Visual texture perception and Fourier analysis," Perception Psychophysics , Vol. 24, pp. 534-542, 1978.

[9] W. Richard and A. Polit, "Texture matching," Kybernetik, Vol. 16, pp. 155-162, 1974.

[10] S. A. Klein and C. W. Tyler, "Phase discrimination of compound gratings: generalized autocorrelations analysis," Journal of Optical Society of America A, Vol. 3, pp. 868-879, 1986.

[11] J. Beck, A. Sutter, and R. Ivry, "Spatial frequency channels and perceptual grouping in texture segregation," Computer Vision, Graphics and Image Processing, Vol. 37, pp. 299-325, 1987.

[12] H. C. Nothdurft, "Sensitivity for structure gradient in texture discrimination," Vision Research, Vol. 25, pp. 1957-1968, 1985.

[13] B. Julesz, "Experiments in the visual perception of texture," Scientific America, Vol. 232, pp. 34-43, April 1975.

[14] B. Julesz, "Textons, the elements of texture perception, and their interactions," Nature, Vol. 290, pp. 91-97, March 1981.

[15] B. Julesz, "Texton gradients, the texton theory revisited," Biological Cybernetics, Vol. 54, pp. 245-251, 1986.

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