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Identification And Characterization of DPLD Patterns Using CT Images

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Abstract*—In the computer aided schemes in computed tomography (CT) lung analysis identification and characterization of diffuse parenchyma lung disease (DPLD) patterns is a challenge. Due to low contrast and noisy images it is hard to perceive these patterns . In this paper, we propose adaptive enhancement techniques at different wavelet scales using dual tree complex wavelet processing. Moreover, dual tree complex wavelet transform also provides an special feature extraction method for identification and characterization of DPLD patterns. The algorithm projected in this paper has been experimented on number of clinical images, the results are compared with those obtained from other algorithms proposed in the literature through both analytical indexes and the opinions of radiologists. From the results obtained it can be concluded that the proposed algorithm improved the diagnosis in the early detection schemes with respect to other approaches.

Index Terms—*Dual tree Complex wavelet transform, feature extraction, image analysis, image enhancement*

I. INTRODUCTION

The various lung diseases can be appropriately detected through Computed tomography (CT) images because of its high-resolution CT (HRCT) scan protocols that allows to visualize limited portion of lung parenchyma (LP) and Multidetector CT (MDCT) permits to acquire volumetric datasets with isotropic voxels, also allows the visualization, characterization, and quantification of the entire extent of lung anatomy. Thus helps to characterize the diffused parenchyma lung diseases (DPLDs) specially with non uniform distribution in the lung. The actual functioning parts of a human or animal lung is medically described by the term Lung parenchyma. It has the alveolar walls as well as the blood vessels within it. Pneumonia is an inflammation of the lungs generally caused due to infection with viruses or bacteria and less commonly on microorganisms and certain drugs. The cough, chest pain, fever, and difficulty in breathing are the common symptoms of pneumonia. There can be thirty different factors causing pneumonia and detecting this factor resulting in pneumonia is very important as the overall treatment of pneumonia depends on its cause [7].

It is difficult to review based on image data as no standardized criteria is available for assessing its complex and variable morphological appearance. In order to improve management decisions, Computer-aided diagnosis (CAD) schemes have been proposed which automatically identify and characterize radiologic patterns of DPLDs. This paper presents a computer identification and characterization of interstitial pneumonia (IP) in MDCT. The proposed method is differed from previously reported schemes by employing a feature extraction technique by means of dual tree complex wavelet transform. The features are extracted and subsequently normal and infected images are identified and characterized by employing DTCWT[1]. CAD scheme. have been proposed by Korfiatis et al for detection and characterization of Interstitial Pneumonia patterns in MDCT in which firstly the CT scan segmentation has been done in two levels - lung field segmentation and vessel tree segmentation. The segmentation process is followed by the extraction of eleven GLCM feature vectors in five distances across four different directions using co-occurrence matrix for all regions . This results in high dimensionality, which has been reduced through stepwise discriminant analysis (SDA). Finally, k-NN classifier is used for classification of image into three different classes. KNN classification method is also been discussed by Francisco Moreno-Seco in which he focuses on the advantages and disadvantages of KNN classification and proposed a modified classifier called K-NSN classifier which is more efficient than KNN classifier. M. Gomathi proposed the lung segmentation by applying fuzzy technique along with four other different techniques. The modified fuzzy segmentation technique is used in which the average weight used for redefining cluster centers gives better performance than the ordinary fuzzy segmentation[2][3]. Chaux et. al. have developed the *M*band dual-tree CWT, generalizing the delay condition for the Hilbert pair property in [4]. Gopinath introduced the phaselet transform [5], where more than two critically sampled DWTs are used together. In this transform, each of *M* low pass filters are offset from each other by increments of 1/*M* samples, a generalization of the half sample delay condition. Another generalization is the double-density dual-tree CWT [7] where two over-sampled (double-density) DWTs are used together. This is further generalized in [6] Another type of generalization in higher dimensions is the hyper-CWT.

II. IMAGE ACQUISITION

Image acquisition process includes collection of MDCT scans of various patients for analysis purpose. The complete dataset including 10 MDCT scans imges is used which has five samples of normal patients and five samples of patients diagnosed with IP secondary to connective tissue diseases. These MDCT scans of five patients diagnosed with IP and MDCT scans of three normal patients were used to extract the features for pneumonia detection and characterization. Remaining MDCT scan of a normal patient (one out of five) was used to control of the proposed system performance on LP identification and characterization. Image acquisition is followed by preprocessing step for enhancing the input image so that it is suitable for further processing. Preprocessing includes transforming the images from RGB to gray and from eight-bit to double precision thus facilitating the manipulation of the images in subsequent steps. Finally histogram equalization technique is used to remove illumination effects in normalized image.

III. FEATURE EXTRACTION

The next step is the feature extraction through which the most discriminating information present in an input pattern is extracted for accurate detection of individuals. Only the important features among the extracted features of the lungs are encoded so that different templates can be carried out. This is done using wavelets transform, and more specifically the 2-D Dual-tree Complex Wavelet Transform. The 2-D complex dual-tree discrete wavelet transform (C-DT-DWT) has twice as many wavelets as that of R-DTDWT (two wavelets in each direction). The wavelets are oriented in the same six directions as those of the R-DTDWT. In each direction, one of the two wavelets can be recognized as the real part of a complex-valued 2D wavelet, while the other wavelet can be recognized as the imaginary part of a complex-valued 2D wavelet. For the dual trees, linear-phase perfect reconstruction biorthogonal filter sets are to be selected & they should have good smoothness and rational coefficients. In this work, we have selected the most appropriate filter sets. It can be concluded that the implementation of the dual-tree complex wavelet transform requires that the first stage of the dual–tree filter bank be different from the succeeding stages. All the filters used are of same length based on Selesnick's approach unlike Kingsbury's approach. To get uniform interval between the samples of both trees after level-1, filters in one tree must provide delays that are half a sample different from those in opposite tree. The half-sample delay condition is equivalent to uniformly oversampling the low-pass signal at each scale by 2:1, thus largely avoiding the aliasing due to the lowpass down samplers. Hence, half sample delay condition leads to a nearly shift-invariant wavelet transform. To extract the significant details of the lung image, a 4-level DTCWT is applied to the normalized image. Selesnick's Dual- Tree Complex Wavelet Transform is shown in fig.1. DT-CWT is formulated by Kingbury and Selesnick [8], [9] using two trees (real and imaginary tree) of DWTs with different filter real coefficients for imaginary tree filters designed from the coefficients of real tree filters to overcome the limitations of DWTs. The details of DT-CWT and feature extraction are stated in following subsections.

IV. DUAL TREE COMPLEX WAVELET TRANSFORM

The Dual-Tree Complex Wavelet Transform (DT CWT) is an effective Complex Wavelet Transform (CWT) method newly introduced by Nick Kingsbury in the year 1998 . It is a CWT based on complex-valued wavelet and complex valued scaling function:

$$\Psi_c(t) = \Psi_r(t) + j\Psi_i(t) \qquad (1)$$

where, $\Psi_r(t)$ - real and even part, $j\Psi_i(t)$ -imaginary and odd part, $\Psi_c(t)$ - analytic signal;

Nick Kingsbury tried to build up a transform which generates analytic signal resembling Fourier transform with following properties:

1. Smooth non-oscillating magnitude;
2. Nearly shift-invariant magnitude;
3. Significantly reduced aliasing effect;
4. Directional wavelets in higher dimensions

In dual-tree, two real wavelet trees are used as shown in Figure 1, each capable of perfect reconstruction (PR). One tree generates the real part of the transform and the other is used in generating complex part [10]. It has been shown [11] that if filters in both trees be made to be offset by half-sample, two wavelets satisfy Hilbert transform pair condition and an approximately analytic wavelet is given by Eq(1).

$$\psi(x) = \psi_h(x) + j\psi_g(x) \qquad (1)$$

Thus, if

$$G_0(\omega) = H_0(\omega) \times e^{-i\Theta\omega} \text{ and } \Theta(\omega) = \omega/$$

then, $\psi_g(\omega) = -j\psi_h(\omega), \omega > 0$ and

$$= j\psi_h(\omega), \omega < 0 \qquad (2)$$

From Eq(1) and (2), low pass filters after the first stage and at first stage respectively are given by Eq(3):

$$g_0(n) = h_0(n-0.5) \qquad \text{and}$$

$$g_0(n) = h_0(n-1) \qquad (3)$$

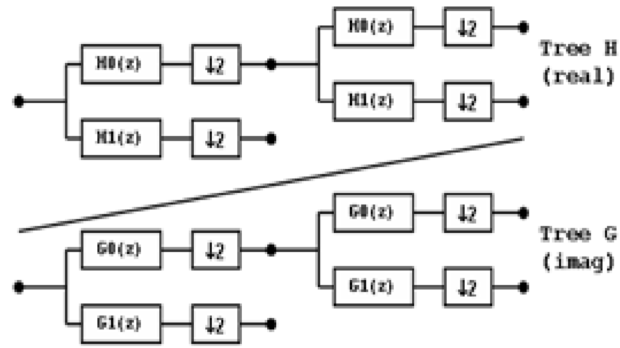

Figure1. Selesnick's Dual Tree DWT

Similar relations also hold true for high pass filters of both the trees. In this algorithm, (10,10)-Tap near orthogonal wavelet filters are used in first stage and 'db7' filters are used for higher stages in the real tree (i.e. h0 and h1) [10] The imaginary low pass filter is derived from the above half sample delayed condition. The high pass filter is the quadrature-mirror filter of the low pass filter. The reconstruction filters are obtained by time reversal of decomposition filters. All the filters used are of same length based on Selesnick's approach [10],[11],[12],[13] unlike Kingsbury's approach. The 2D separable DWT can be written in terms of 1D scaling functions (φ) and wavelet functions(ψ) as:

$$\begin{aligned} \psi^{0}(x,y) &= \phi(x)\psi(y) \\ \psi^{90}(x,y) &= \psi(x)\phi(y) \\ \psi^{\pm 45}(x,y) &= \psi(x)\psi(y) \end{aligned} \qquad (4)$$

Oriented non-separable 2D wavelet transform is derived by combining the sub-bands of two separable 2D DWTs. The pair of conjugate filters are applied to two dimensions (x and y), which can be expressed by Eq(5) as given below:

(hx+jgx)(hy+jgy) = (hxhy - gxgy)+ j(hx gy+ hygx) (5)

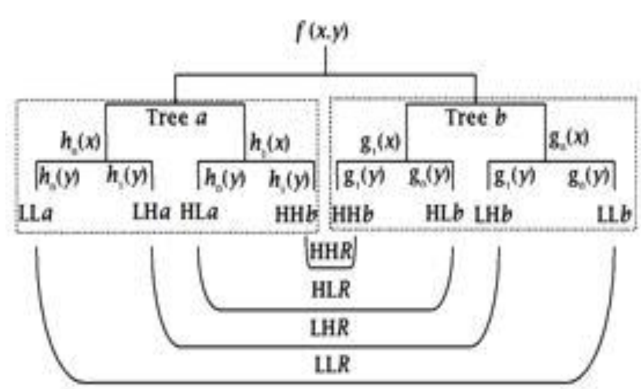

Figure2. Formation of Real Tree DT CWT

Thus, the decomposition for each mode is performed in a standalone mode, in one after another stage i.e. total of 6 detailed coefficients are derived at each stage; three for the real tree and three for the imaginary tree. 3-stage decomposition is performed. At each stage, coefficients are oriented towards their respective directions as stated in Eq(4). Following six wavelets, as given by Eq(6), are used to obtain oriented 2-D separable wavelets [20]:

$$\psi_{1,1}(x,y) = \phi_h(x)\psi_h(y), \quad \psi_{2,1}(x,y) = \phi_g(x)\psi_g(y),$$
$$\psi_{1,2}(x,y) = \phi_h(x)\psi_h(y), \quad \psi_{2,2}(x,y) = \phi_g(x)\psi_g(y),$$
$$\psi_{1,3}(x,y) = \phi_h(x)\psi_h(y), \quad \psi_{2,3}(x,y) = \phi_g(x)\psi_g(y), \qquad (6)$$

where, $\psi_{1,i}$ correspond to the coefficients derived from the real tree and $\psi_{2,i}$ correspond to the coefficients derived from the imaginary tree. They can be combined by Eq(7) to form complex wavelet coefficients.

$$\psi_i(x,y) = \frac{1}{\sqrt{2}}(\psi_{1,i}(x,y) - \psi_{2,i}(x,y)), \qquad (7)$$
$$\psi_{i+3}(x,y) = \frac{1}{\sqrt{2}}(\psi_{1,i}(x,y) + \psi_{2,i}(x,y))$$

Normalization by $1\sqrt{2}$ is used so that the sum difference operation constitutes an ortho-normality. Thus, in particular, 2D dual-tree wavelets are not only approximately analytic but also oriented and are shift invariant because of its analytic structure[20].

VI. PROPOSED ALGORITHM

In the following section, we propose an algorithm for image features extraction using DTCWT. The source image is first resized to the size of MxN for M=N=512 where, *M* -number of rows, *N* – number of columns. The resized image is converted from a RGB color space image to grayscale image. Histogram equalization is then performed on the gray scale image followed by feature extraction by applying DTCWT on these images. This transform decomposes into lowpass and bandpass components. Each image has imaginary and real parts. The extracted wavelet features form the image feature vectors which are stored in the database. Finally the transform provides the reconstructed as well as post processed image.

VII. EXPERIMENTAL RESULTS

The proposed algorithm, is designed for a Computer Aided Diagnosis system approach for detecting pneumonia patterns in lung images using dual-tree complex wavelet transform. The goal of the implemented experiments is to choose a decomposition level where the accuracy of the extracted information is highest and the feature extraction time is optimum. To estimate the results produced by each of the DTCWT levels *l=1, 2, 3, 4,* the feature vector length, feature extraction time and the number of the generated wavelet coefficients has been computed and compared. The time required for image feature extraction increases at each level as it is dependent on the time required for image energy computation by the highpass and lowpass filters at each level separately. Thus, with the subsequent level the feature extraction time increases. Also, as the number of levels of the wavelet decomposition increments, the number of the generated wavelet coefficients reduces. The dual-tree CWT is a valuable enhancement of the traditional real wavelet transform that is nearly shift invariant and, in higher dimensions, directionally selective. Since the real and imaginary parts of the dual-tree CWT are, in fact, conventional real wavelet transforms, the CWT benefits from the vast theoretical, practical, and computational resources that have been developed for the standard DWT.

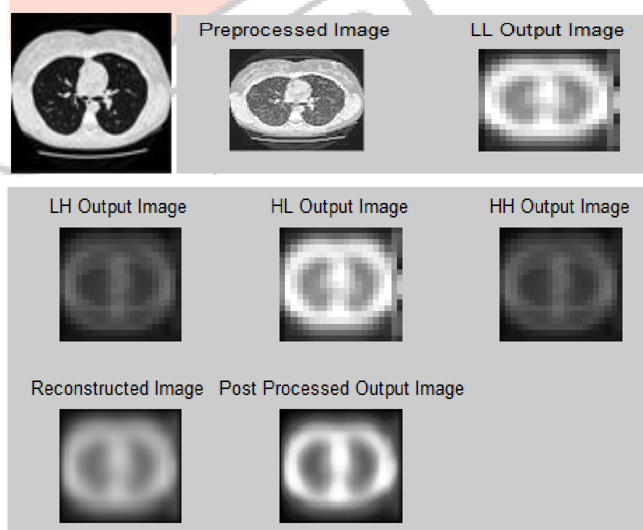

Fig.3 Input as Normal Lung Image and the corresponding outputs for DTCWT

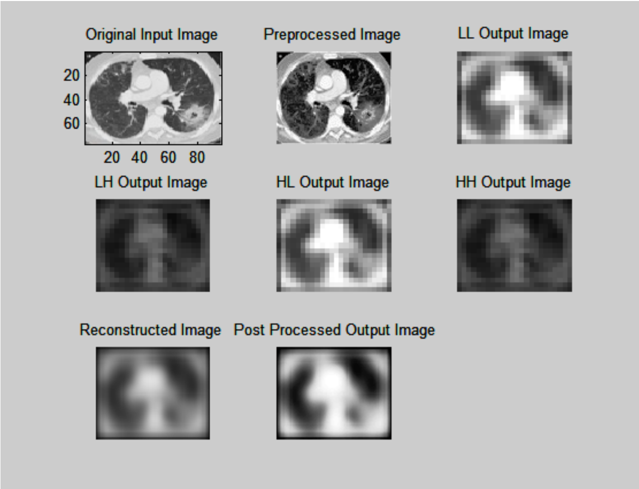

Fig.4 Input as Infected Lung Image witrh Pnemonia patterns and the corresponding outputs for DTCWT

CONCLUSION

In this paper, an image processing approach for detecting pneumonia patterns in lung images using dual-tree complex wavelet transform has been implemented. Experimental results showed that the above algorithm based on DTCWT have demonstrated the effectiveness of the proposed method in terms of improving the recognition rate as compared to previous methods. Inherent shift invariance is the added advantageous feature of this proposed method. This shows that our approach is promising to improve DPLD pattern identification.

REFERENCES

[[1] Panayiotis D. Korfiatis, Anna N. Karahaliou, "Texture Base Identification and Characterization of Interstitial Pneumonia Patterns in Lung Multidetector CT", *Transactions on Information Technology In Biomedicine*, Vol.14, No.3, May 2010

[2] S.R.Avinash Kautham , Kavitha Ravi Analysis of Multi CT cans for diagnosis of Interstitial Pneumonia Patterns.

[3] M.H. fazelzarandi, m. Moeen, sh. Norouzzadeh and sh. Teimourian, "fuzzy Image processing for diagnosing inflammation in pulmonary biopsies", *Transaction e: industrial engineering,* vol. 16, no. 2, sharif university of Technology, december 2009, pp 3

[4] C. Chaux, L. Duval, "2D dual-tree m-band wavelet decomposition," in *Proc. IEEE Int. Conf. Acoust., Speech, Signal Processing),* Philadelphia, Mar. 2005, vol. 4, pp. 537–540.

[5] R. Gopinath, "The phaselet transform—An integral redundancy nearly shiftinvariant wavelet transform," *IEEE Trans. Signal Processing*, vol. 51, no. 7, pp. 1792–1805, July 2003.

[6] R. Gopinath, "Phaselets of framelets," *IEEE Trans. Signal Processing*, vol. 53, no. 5, pp. 1794–1806, May 2005.

[7].W. Selesnick, "The double-density dual-tree discrete wavelet transform," *IEEE Trans. Signal Processing*, vol. 52, no. 5, pp. 1304–1314, May 2004.

[8] J.O. Chapa and R.M. Rao, "Algorithms for designing wavelets to match a specified signal," *IEEE Trans. Signal Processing*, vol. 48, no. 12, pp. 3395–3406, Dec. 2000.

[9] C. Chaux, L. Duval, and J.C. Pesquet, "2D dual-tree m-band wavelet decomposition," in *Proc. IEEE Int. Conf. Acoust., Speech, Signal Processing* , Philadelphia, Mar. 2005, vol. 4, pp. 537–540.

[10] Ivan W. Selesnick, Richard G. Baraniuk, and Nick G. Kingsbury,"The Dual Tree Complex Wavelet Transform: A Coherent Framework for Multiscale Signal and Image Processing", *IEEE Signal Processing Magazine*, Nov 2005, pp. 123-151.

[11] N.G. Kingsbury, "The dual-tree complex wavelet transform: A new technique for shift invariance and directional filters," in Proc. *8th IEEE DSP Workshop*, Utah, Aug. 9–12, 1998,r no. 86.20.

[12] M. Kokare, P.K. Biswas, and B.N. Chatterji, "Rotation invariant texture features using rotated complex wavelet for content based image retrieval," *in Proc. IEEE Int. Conf. Image Processing, Singapore,* Oct. 2004, vol. 1, pp. 393–396.

[13] Rajesh Bodade and Sanjay Talbar, "Iris Recognition Using Multi-Directional Wavelets: A Novel Approach" Journal of *Advances in Engineering Sciences Sect. C (3),* July-September 2008, (special issue on Image Processing) ISSN: 0973-9041

[14] E. Lo, M. Pickering, M. Frater, and J. Arnold, "Scale and rotation invariant texture features from the dual-tree complex wavelet transform," *in Proc. IEEE Int. Conf. Image Processing, Singapore,* Oct. 2004, vol. 1, pp. 227–230.