

Fissure Extraction using Dual Tree Complex Wavelet Transform and Lung Lobe segmentation from CT Lung images

¹M.Jannathl Firdouse, ²Dr. M. Balasubramanian

¹R& D Centre, Bharathiar University, Coimbatore, India

²Asst. Professor, Dept. of CSE, Annamalai University, India

Abstract: The lungs play a very vital role in human respiratory system. It has five separate lobes which are detached by fissures of three types such as left and right oblique fissure and a horizontal fissure. The way of identifying the fissure lobes in computed tomography scanned lung images are difficult for the medical practitioners because of the incorrect shapes alongside with less contrast and the extraordinary noise associated with it [1]. The last phase of the lung cancer treatment is the elimination of the unhealthy lung by the major surgery. So, it is required to identify the location of the cancer affected part of the lungs by extracting the fissure lobes before making the proposal for the surgery. This paper presents a mechanized process of extracting the left oblique fissures and right oblique fissures by applying the Dual Tree Complex Wavelet Transform from the Computed Tomography lung images. This will help the medical practitioner to identify the lobar fissures from the computed tomography lung images.

Keywords: Oblique fissure, Horizontal fissure, DTCWT, fissure lobes, Discrete wavelet Transform, Filter bank and fissure sweep.

1. INTRODUCTION AND LITERATURE SURVEY

Human lungs are having five lobes which are parted by visceral pleura which are known as pulmonary fissure. The right lung comprises of three lobes such as upper, middle and lower. The right minor fissure divides right upper and middle lobes, whereas the right major fissure bounds the lower lobe from the rest of the lung. Because of the incomplete fissures and anatomical variations, the segmentation of pulmonary lobes is tedious. The framework of a human lung is shown in Figure 1.

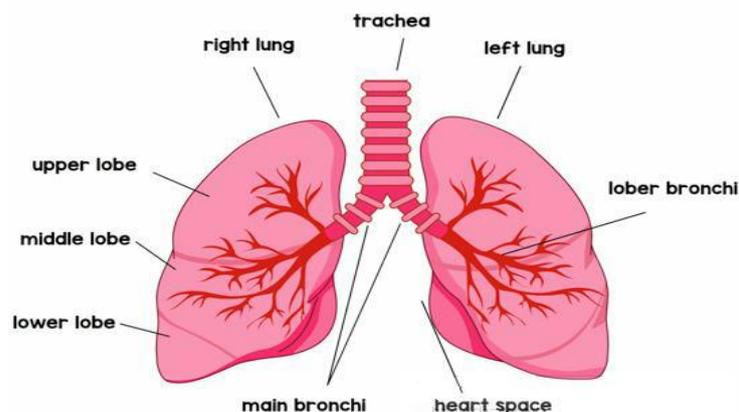


Figure1. Anatomy of Human Lung

For the experienced medical practitioner, the recognition of the fissures from the CT image is hard because of image's different shape beside with low dissimilarity and more noise along with it. In order to do the surgery of lung removal, it is essential to recognize the site by eliminating the lobar fissures before the start of surgical procedure. The lung cancer has beaten the breast cancer as it was taken as the important reason of demises in females due to cancer [2]. The cells form a tumor which is different from the surrounding tissues. The analysis process of lump is created on whether the respiratory nodule is usual or tumorous. It can be identified by inspecting the growing rate of nodule. The tumorous nodule become binary in size on a middling of every quarter year and the usual nodule do not grow much at all. Another way of differentiating the cancerous nodule from the normal nodule is by examining the size and the surrounding surface. Irregular shapes, lumpy surface and color variations are the identification marks of cancerous nodule. Whereas, the normal nodules are regular in shape, smoother and the color is evenly distributed. Mostly, CT scanned images are used for the effective diagnosis.

The CT slice of lung image has three fissures such as right horizontal fissure, right and left oblique fissure. The medical practitioners check the stack of two dimensional CT lung images to identify the diseased lung for the surgical planning. This will take long time to decide and start the surgical procedures. We propose the concept of extracting the boundaries of the lung lobe fissures by the DTCWT to reduce the surgical planning time. Three phases are in the proposed method and are implemented as explained below. The region of fissure is identified in the first phase. The lobar fissures are identified and found oblique fissures are extracted in the second phase. The horizontal fissure is identified and extracted in the third phase.

2. PROPOSED WORK AND METHODOLOGY

The isotropic CT images are preprocessed to remove the unwanted noises present in the input images. The noise removal is done by using the mean filter. The filter size of 3 x 3 matrix is preferred. Each input point is replaced by the mean of the neighbourhood points. The noise in CT input image uses the Gaussian distribution of the mean filter. This only balances the noise elimination and over hiding of the images. For finding the fissures in the isotropic CT image, the adaptive fissure sweep is employed. The lung section is divided from the context [3] by analyzing the histogram and the connected component labeling. The flow chart of fissure extraction is given in Figure 2.

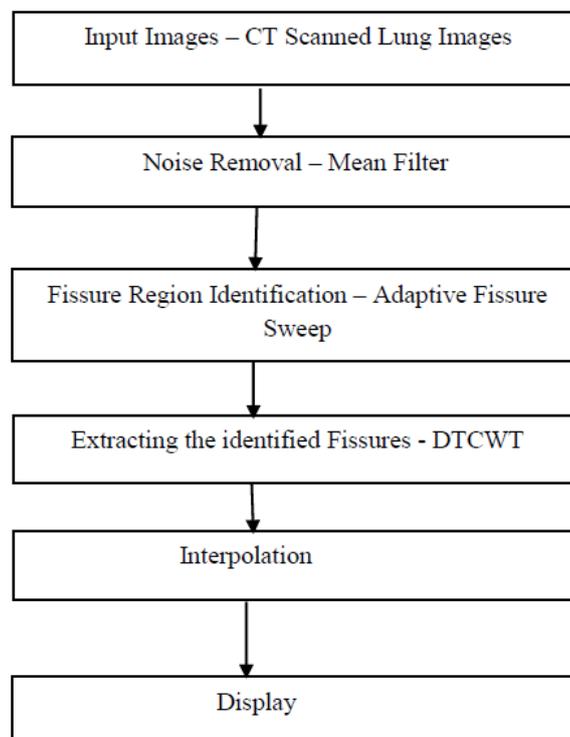


Figure2. Flow chart of Fissure extraction

2.1 Noise Removal – Mean Filter

The process before the adaptive fissure is preprocessing the input images in demand to remove the surplus noise present in the input image. The additional noise in the input image is removed by the mean filter. This will do the primary noise removal from the CT input image. The filter size of 3 x 3 is employed to remove the noise. The mean filter replaces each pixel of the input image by the weighted average of the neighbourhood pixels.

2.2 Fissure Region Identification using Adaptive Fissure Sweep

The adaptive fissure sweep is the main step of the lobe segmentation process. This is used to find the fissure sections from the isotropic CT scanned lung images after attainment of input images. The lung area is partitioned from the background by using the histogram inquiry and the connected component labeling. The lung segmentation also involves the region growing, morphological operations and watershed algorithms etc. [4]. The removal of the fat and muscles surrounding the lungs is implemented by choosing the threshold value T_r which is based on the histogram. The T_r is calculated by the equation $T_r = \frac{I_{FM} - I_{BL}}{2} + I_{BL} \dots \dots (1)$, where I_{FM} is the mean pixel strength values of top analogous to the fat or muscles and is the mean pixel strength value of heights matching to the background or lung parenchyma respectively. The histogram of a computed tomography lung image [8] is shown in Figure3.

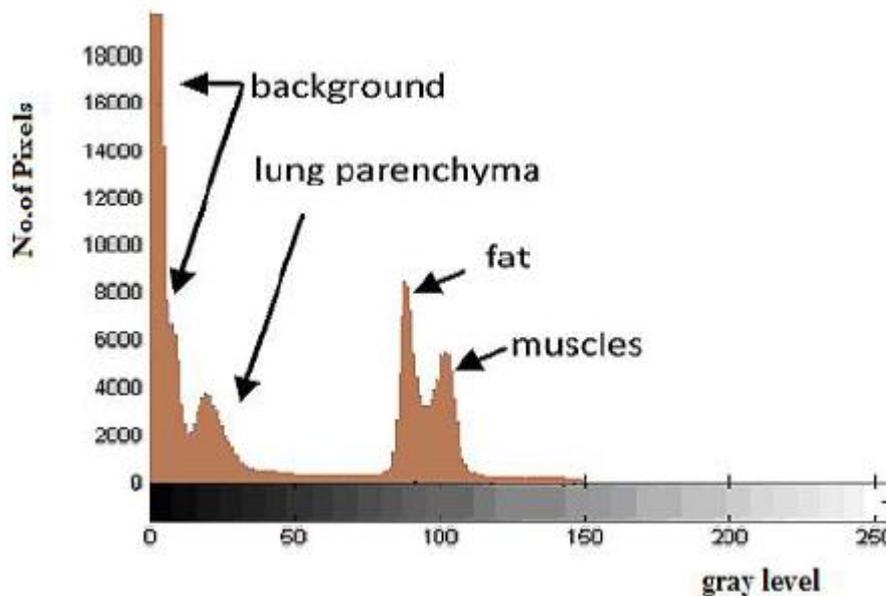


Figure3. CT lung image Histogram

The two lungs are extracted by performing the bounding box and connected component labelling by the specified algorithm. Due to the presence of the bronchial and vascular tree, the extracted lung boundaries are irregular. By smearing the circular morphological closing operator the above said problem is rectified [4]. To smooth the lung boundaries, the filter size of 10 x 10 pixel is applied to collect the original shape of the lung. On each segmented lungs, the adaptive fissure sweep is achieved. This locates the fissure section within the partitioned lungs. The borders of the lung lobes are also identified. The morphological dilation operator is performed to enhance the vascular and bronchial trees [5]. These steps permit an enhanced framework for discovering the fissure section in the isotropic CT images.

2.3 Extracting Identified Fissures – DTCWT

The DTCWT computed the compound transform [6] using two separate Discrete Wavelet Transform decompositions of tree a and tree b which is presented in Figure4. DTCWT is implemented to remove the identified fissures from the isotropic CT images. If the filters used are different from each other, it is possible to have one DWT to create the real coefficient and the other one is considered as imaginary.

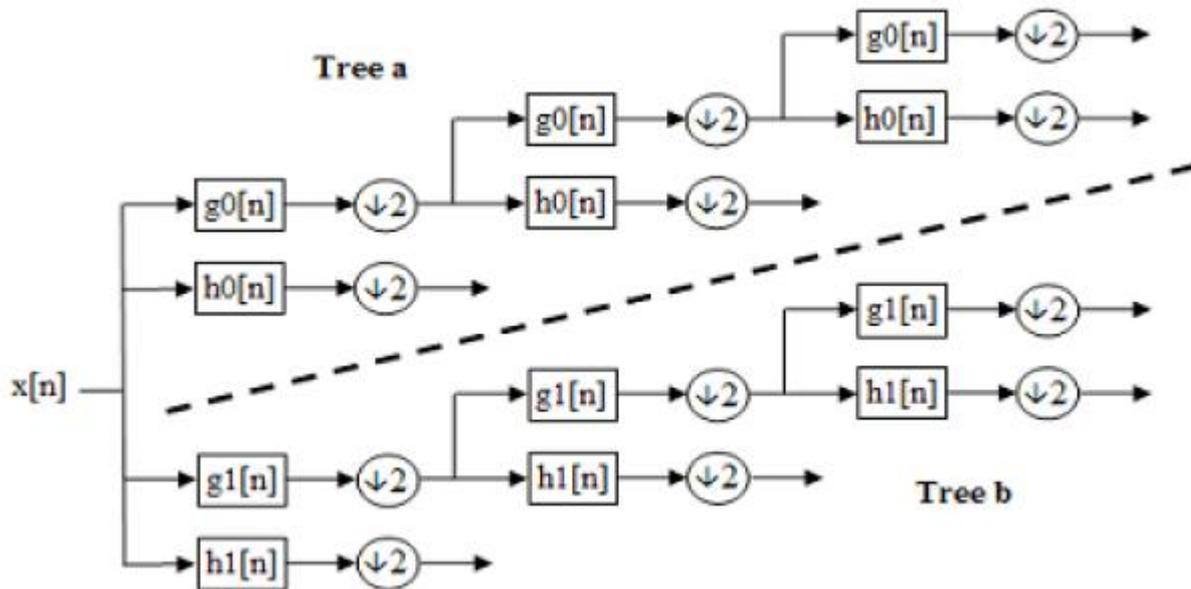


Figure4. Filter structure of DTCWT

The h_0 is the real valued high pass and h_1 is the real valued low pass filters respectively. Similarly, g_0 and g_1 is the imaginary tree. The important characteristics to be followed while designing the filters are:

- i. The two trees are differing by half of the sample period in the low pass filter.
- ii. Reconstructing the filters is the reverse process of analysis.
- iii. Tree „a“ filters are considered as the opposite of tree „b“ filters.
- iv. All filters are from the same orthonormal set.
- v. Both the trees must have the same frequency response.

The static DWT uses a low pass and high pass filter to split the input image simultaneously. This will lead the formation of detailed coefficients of an input image. To convert the rows and columns, a 2D-DTCWT involves one dimensional DTCWT. The 2D – DTCWT [9] gives four sub images entails of three high pass filtered images such as: horizontal, vertical and diagonal and the low pass version of the original image, unlike the stationary 2D conventional DWT. This space invariance property [7] allows the procedure to find the fissure position and the curve using the detailed coefficient of the image.

Most of the lobar fissures look as if horizontally across the fissure sections so that the horizontal aspect of the sub image is used for the advance analysis. This is due to find the adaptive fissure sweep that

familiarizes with the fissure sections which is along the fissure directions. The longest continuous lines crossing the fissure region is found by applying fissure search technique in the lobe segmentation algorithm. This algorithm bearings point by point analysis and employing the anchor points automatically at remoteness of 5 points apart for identifying the fissures. The current fissure anchor points are compared with their matching part on a previous adjacent fissure. In two adjacent isotropic CT images, the fissure changes are very small. To define a precise fissure, the following criteria is used

$\frac{1}{M} \sum_{j=1}^{M-1} Z_j, 1-Z_j, 2 \leq 3$ pixels and $Z_j, 2-Z_j, 1 \leq 9$ pixels) ---- (3), M represents the amount of anchor points used for a fissure and is the z -coordinate of the j th anchor point. The fissures lies between the adjacent CT images tend to change in the vertical direction. Hence z coordinate is used instead of Euclidian distance. The last three CT slices are reflected by applying the anchor points of this fissure to guide the fissure search in the next adjacent slice. This only finds the correct fissure. The identified fissures are discontinuous. So, the linear interpolation finds the continuous fissures. The average angle is given by $\Phi_{average} = (\phi_1 + \phi_2 + \phi_3) / 3$ --- (4), where Φ_j ($j = 1, 2, 3$) denotes the angle of the fissure segment

between two adjacent anchor points. So the left and right oblique fissures are removed from the isotropic input CT images by this algorithm.

3. RESULTS AND DISCUSSION

The slice of CT input image from the online database in Harvard University is shown in Figure 5(a) and before the left and right lung segmentation by the bounding box, the result of connected component labeling is shown in Figure 5(b). The outcome of fissure sweep and recognized fissure section in right lung is shown in Figure 5(c) and 5(d).



Figure 5 (a) Original Image (b) Bounding box (c) Fissure Sweep (d) Fissure region

The sequences of outputs from the fissure extraction algorithm after applying DTCWT are shown in Figure 6(a) to 6(d).

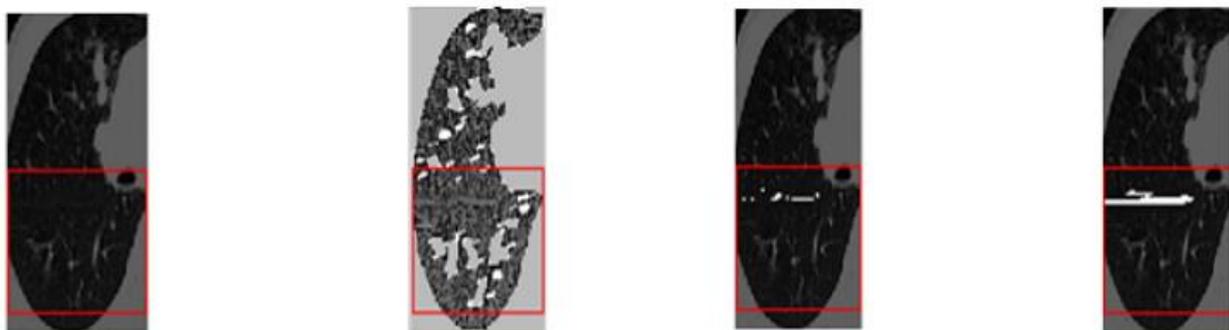


Figure 6 (a) Identified Fissure (b) Enhanced Fissure (c) Right Oblique Fissure (before interpolation) (d) Right Oblique Fissure (after interpolation)

The sequences of outputs from the left lung are shown in Figure 7(a) to 7(f)

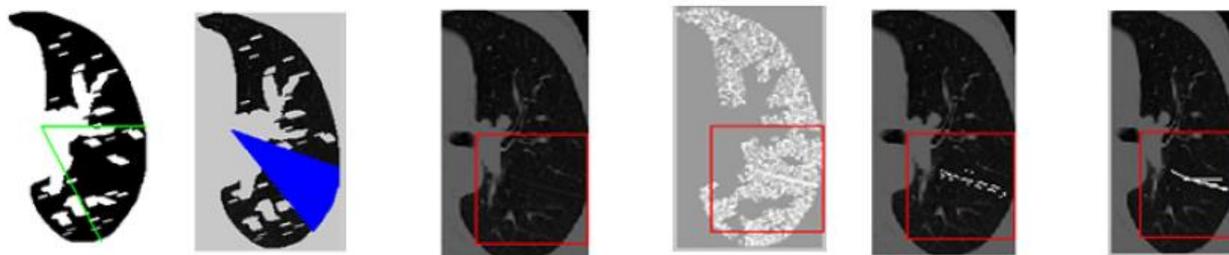


Figure 7 (a) Fissure Sweep (b) Fissure Region (c) Detected Fissure (d) Enhanced Fissure (e) Left Oblique Fissure (before interpolation) (f) Right Oblique Fissure (after interpolation)

The peak signal to noise ratio analysis of lung images from the LOLA database by using two methods are given in the table 1. The analysis is performed with five lung images. From the table, it is identified that the proposed method has the

highest PSNR ratio and the comparison of these three methods indicates that the proposed method is efficient and speedy. The lung images are taken from the LOLA database.

Table 1. PSNR Comparison with three methods

Name of the image	PSNR Ratio		
	FLICM	FBEA -SPQT	PROPOSED METHOD
Lungimage1	64.73	68.34	71.94
Lungimage2	68.55	72.65	74.75
Lungimage3	64.27	67.26	69.54
Lungimage4	66.81	69.94	72.26
Lungimage5	67.11	71.33	73.82

The PSNR analysis charts of different lung images with three methods are shown in Figure 8.

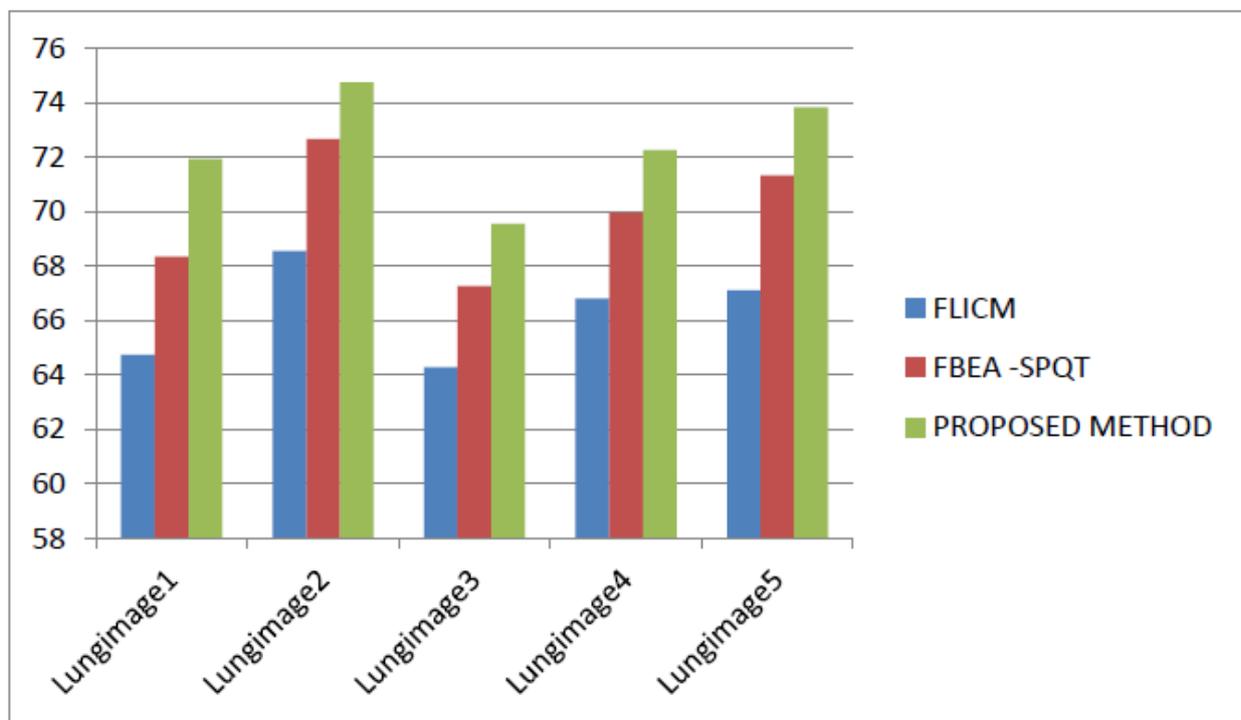


Figure 8. PSNR analysis chart

4. FUTURE WORK AND CONCLUSION

The lung lobe segmented by this algorithm is useful to identify the location of affected regions of CT lung image and helpful for the medical practitioner to identify the proper location of the affected lungs for the surgery. The proposed method is more accurate and speedy compared to the existing method. The horizontal fissures are identified with affected regions. The PSNR ratio of this proposed method is effective compared to the existing method. The advanced concept is applied in order to derive the accurate results of horizontal fissure in the future. The defined three phases are executed and the results are obtained with more accuracy. The concept consumes very less time to get the required results. This result is further used for the major surgery.

REFERENCES

- [1] Dr. Bharathi,N., and Manikandan, T., “ Lobar Fissure Extraction in CT lung image – An application to Cancer identification,” *International Journal of Computer Applications*, Vol.33, No.6, (0975 – 8887), Nov.2011.

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- [2] Emedicinehealth, [online]. Available: http://www.emedicinehealth.com/lung_cancer/article_emptlung_lobes
- [3] Sonka, M., Hlavac, V., and Boyle, R., " *Image processing, Analysis, and Machine Vision. 3rd edition. Thomson Learning,* " 2008.
- [4] Anitha, S., and Sridher, S., "Segmentation of lung lobes and nodules in CT images," *International journal of signal processing and image processing (SIPIJ)*, 1-12, 2010.
- [5] Haralick, R.M., Stenberg, S.R., and Zhuang, X., "Image analysis using mathematical morphology,"
- [6] *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 532–550, 2007.
- [7] Kumar, S.N., and Kavitha, V., "Automatic segmentation of lung lobes and fissures for surgical planning," *Proceedings of ICETECT*, 546-550, 2011.
- [8] R. C. Gonzalez, R. E. Woods, " *Digital Image Processing* ", 2nd ed., Prentice Hall.
- [9] <https://www.google.com/search?q=Histogram+of+a+CT+Lung+image&tbm=isch&tbs=rimg>:
- [10] Aryaz Bhadarani, and Runyi, yu., " A Dual Tree Complex Wavelet with application in image denoising," *IEEE International conference on Signal Processing and communications*, 1203-1206, 2007.