Lobar Fissure Extraction in Isotropic CT Lung Images - An Application to Cancer Identification

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Abstract - The essential organ for respiration and inspiration of human beings are Lungs. It consists of five distinct lobes which are separated by three fissures (the boundaries of lung lobes are the areas containing fissures and having absence of bronchial trees). They are two oblique (left and right) fissures and one horizontal fissure. The left lung consist of left oblique fissure which separates the superior and middle lobes. The right lung consist of right oblique fissure which separates superior and middle lobes and right horizontal fissure which separates middle and inferior lobes. The identification of the lobar fissures in isotropic Computed Tomography (CT) images are very difficult even for the experienced surgeons because of its variable shape and appearance along with low contrast and high noise association with it. Further the fissure thickness is observed to be around 2 pixels (approximately 1.2mm) complicates the fissure identification. The identification of lobar fissure in CT images will be helpful for the surgeon to identify the cancer location before they plan for surgery. The surgical removal of the diseased lung is the final stage for treating the lung cancer. Therefore it is necessary to find the cancer location at the early stage to treat it. This paper presents an automated method to extract the left and right oblique fissures from the CT lung images. The proposed method is implemented in two phases. In the first phase, the fissure region is located. In the second phase, the found lobar fissures are extracted. The obtained results show that the proposed work can help the surgeon to identify the cancer location.

Keywords-Computed Tomography (CT), Dual Tree Complex Wavelet Transform (DTCWT), Filter Bank and Discrete Wavelet Transform (DWT).

1. INTRODUTION

The lungs are the very important organ for the human beings for respiration. The cells in human body are normally divided and grow in a control manner. When the tissues start expanding and the control process is lost then the situation is called cancer. Lung cancer is the deadliest cancer in the world for both men and women. Lung cancer has surpassed breast cancer as the leading cause of cancer deaths in women [1]. The cells form a mass or tumour that differs from the surrounding tissues from which it arises. The tumours take oxygen, nutrients, and space from healthy cells and because destroy the ability of normal tissues to function hence it is very dangerous. The diagnosis process of tumour is based on whether a pulmonary nodule is benign (normal) or malignant (cancerous). The most common way to differentiate the benign and malignant nodule is by examining the growth rate of nodule. The cancerous nodules can double in size on average every four months (some as slowly as 15 months, some as quickly as 25 days). Benign nodules, on the other hand, do not grow much if at all. Growth can be evaluated through the serious of CT or X-ray scans over the period of time. Another most common way to differentiate the malignant nodule from the benign is development based on its shape and surface. Cancerous nodules more likely to have irregular shapes and rougher surfaces and color variations. Benign nodules tend to be smoother and more regularly shaped, with more even color throughout. In most of the cases, CT scan or X-rays provide adequate information to make a reliable diagnosis. The doctors might choose to retrieve cells from the suspected nodules for a biopsy. The anatomy of human lungs are shown in Fig. 1. It consists of five distinct lobes that are separated by three fissures namely, left oblique fissure, right oblique fissure and right horizontal fissure respectively. The CT slice which shows the Right Oblique Fissure (ROF), Right Horizontal Fissure (RHF) and Left Oblique Fissure (LOF) are shown in Fig. 2.

The surgical removal of the diseased lung is the final stage of treating the lung cancer. It is very important to find it at the early stage to limit the danger. The lung cancer identification is done by extracting the lobar fissure from the CT images. However the extraction of fissure region in isotropic

CT images is very challenging even for the experienced surgeons.

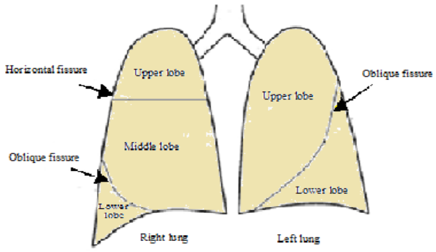

Fig. 1 Anatomy of human lungs

In clinical settings the surgeons examine the stack of 2D clinical CT images for surgical planning to identify the diseased lung lobes but it takes long time to start the surgical procedure. To reduce the surgical planning time we proposed the automatic lobar fissure (boundaries of lobes) extraction by Dual Tree Complex Wavelet Transform (DTCWT). The proposed method first identifies the fissure region then extracts the identified lobar fissures.

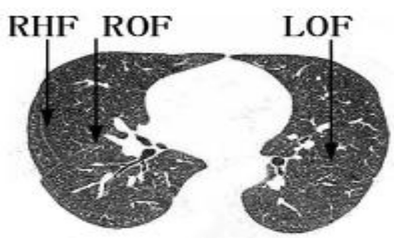

Fig. 2 A CT slice

This paper is organized as follows: Section 2 deals the related work, Section 3 describes the methodology and Section 4 gives the results and discussion. Finally the section 5 draws the conclusion and future work.

2. RELATED WORK

The lobar fissure in CT images appears to be blurred boundaries with low contrast. The Automatic and semi automatic fissure extraction methods were proposed by the different research groups. The three-dimensional (3-D) watershed algorithm proposed by Kuhnigk et al. [2] to detect the lobar fissures on a cost image, which was computed from a combination of the original data and the distance map performed on a previously generated vessel mask. The authors show the low variability of their method with different manual initializations. Further their method was sensitive to the vessel segmentation it complicates the fissure extraction. Ukil and colleagues took a similar approach, but with anatomic information of both vascular and airway trees to segment CT images [3]. However the drawback of their approach was requirement of manually placing the anchor points for guidance. The user intervention is needed for these algorithms which prevents during busy clinical settings. The algorithm proposed by Qiao Wei et. al [4] for surgical planning show that the three-dimensional (3D) visualization of lung cavities has distinct advantage over traditional CT images. In their autonomous algorithm the fissure region was found by adaptive fissure sweep and watershed transform to refine the location and curvature of fissures within the found fissure regions. However the accuracy of the extracted fissure was poor. In their later approach [5] to improve the accuracy of the extracted fissures lobe segmentation algorithm makes use of adaptive fissure sweep to identify the fissure region and DWT to extract the identified fissures. In this paper the automatic extraction of lobar fissure from isotropic CT image is discussed using Dual Tree Complex Wavelet Transform.

3. METHODLOGY

The extraction of lobar fissure from CT images involves two phases. In the first phase the fissure region is identified by adaptive fissure sweep technique. In the second phase, the lobar fissures are extracted by DTCWT. The flow diagram of the proposed method is shown in Fig. 3. The steps involved in extracting the lobar fissure are acquisition of CT images, mean filtering, adaptive fissure sweep, DTCWT and interpolation.

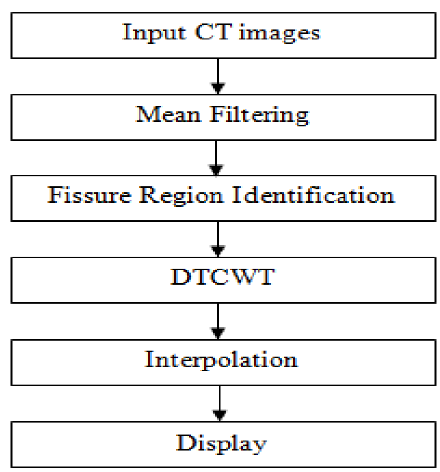

Fig. 3 Flow diagram of fissure extraction

i. Adaptive fissure sweep

The adaptive fissure sweep is used in the first stage of the lobe segmentation algorithm to find the fissure regions in the isotopic CT images after acquisition of CT images. The step before to adaptive fissure is pre-processing the input CT image. More noise is associated with isotropic image than the clinical counterpart. Hence pre-processing is performed on the input CT image after acquisition, which is aimed mainly to remove the noise. Here mean filter is used for primary noise removal. Mean filter replaces the each input pixel by weighted average of its neighbourhood pixels. Since noise in CT images follows Gaussian distribution the mean filter is employed. The filter size of 3x3 is selected to balance between the noise removal and over blurring. The lung region is segmented from the background by histogram analysis and connected component labelling [6], currently there is an extensive amount of literature for lung segmentation, which combines thresholding, region growing, mathematical morphology operation, [7], [8]. The threshold value (T_r) is first computed based on the histogram of the input image to remove the fat and muscles surrounding the lungs according to the following equation.

$$T_r = \frac{I_{FM} - I_{BL}}{2} + I_{BL} \qquad (1)$$

Where, I_{FM} and I_{BL} are the average pixel intensity values of peaks corresponding to the fat/muscles and back ground/lung parenchyma, respectively.

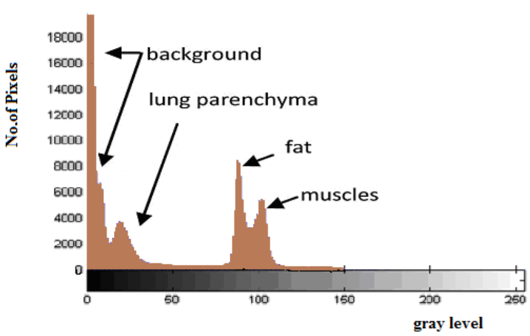

Fig. 4 Histogram of a CT image

The algorithm then performs a connected component labelling and bounding box to extract the two lungs. After the extraction of lung the boundaries of lungs are irregular due to the presence of vascular and bronchial tree. The solution for the above problem is by applying the circular morphological closing operator to the lungs [7]. The filter size of 10 × 10 (pixels) is used to ensure smooth lung boundaries to store the original lung shape. Then adaptive fissure sweep is performed on the segmented each lungs. Within the segmented lungs, the adaptive fissure sweep locates the fissure region (the boundaries of lung lobes are the areas containing fissures and having absence of bronchial trees). To enhance the bronchial and vascular trees the morphological dilation operator [8] is employed. This approach allows an optimized framework for finding the fissure region in the isotropic CT images.

ii. Dual Tree Complex Wavelet Transform

In the second phase, the DTCWT is employed to extract the found fissures from the isotropic CT images. The Dual-tree complex wavelet transform (DTCWT) calculates the complex transform [9] of an image using two separate DWT decompositions (tree a and tree b), which is shown in Fig. 5. If the filters used in one are specifically designed different from those in the other it is possible for one DWT to produce the real coefficients and the other the imaginary. This redundancy of two provides extra information for analysis but at the expense of extra computational power. It also provides approximate sift in-variance (unlike the DWT) yet still allows perfect reconstruction of the image.

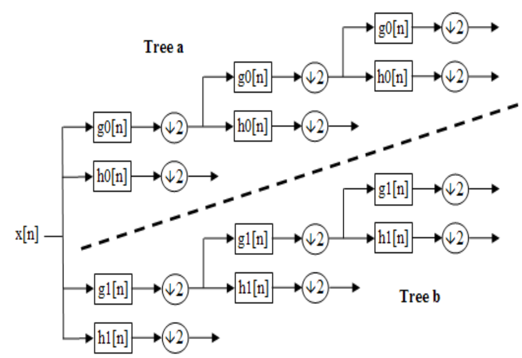

Fig. 5. Filter bank structure for DTCWT

The design of the filters is particularly important for the transform to occur correctly and the necessary characteristics are:

1. The low-pass filters in the two trees must differ by half a sample period
2. Reconstruction filters are the reverse of analysis
3. All filters from the same orthonormal set
4. Tree a filters are the reverse of tree b filters
5. Both trees have the same frequency response

In image processing technique, to produce the detail coefficients of an image the stationary DWT uses low-pass and high-pass filters to simultaneously decompose the input image [10]. A 2-D DTCWT implies 1-D DTCWT to transform the rows and the columns. The two dimensional DTCWT yields four sub-images consists of three high-pass filtered images: horizontal, vertical, and diagonal and a low-pass version of the original image, unlike stationary two dimensional conventional DWT. This space invariance property allows our algorithm to find the fissure location and curvature using the detail coefficient of images. The horizontal detail of the sub-image is used for further analysis because most lobar fissures appear horizontally across the fissure regions. This is due to find the adaptive fissure sweep that orients the fissure regions along with the direction of the fissures. To provide the best contrast for the fissures our algorithm uses two-level decompositions to generate the horizontal detailed images. The lobe segmentation algorithm uses a fissure search technique to find out the longest continuous lines crossing the fissure regions to identify the actual fissure locations and curvatures. The fissure search technique conducts pixel-by-pixel analysis and automatically placing anchor points at a distance of 5 pixels apart along to identify the fissures. The fissures verify technique is used following the fissure search, which validates the correctness of a current fissure by comparing its anchor points with their counterparts on a previous adjacent fissure. The changes between fissures in two adjacent isotropic CT images are very small, the following criteria define a correct fissure

$$\begin{aligned}&(\frac{1}{M}\sum_{M}^{j-1} z_j,1 - z_j,2 \le 3\,piexls\\ &and \\ &z_j,2 - z_j,1 \le 9\,pixels)\end{aligned} \qquad (2)$$

Where M is the number of anchor points used for a fissure and Z_j is the z-coordinate of the j^{th} anchor point. The fissures between adjacent CT images tend to change mostly in the vertical direction. Hence Z coordinate is used instead of Euclidean distance. To find the correct fissure, the last three CT slices are considered by applying the anchor points of this fissure to guide the fissure search in the next adjacent CT slice. The found fissures are discontinuous rather continuous pixels. Therefore the linear interpolation yields continuous fissures. The average angle for the extension of a fissure by using the last three anchor points of the fissure, which is given by,

$$\varphi_{average} = \frac{1}{3}(\phi_1 + \phi_2 + \phi_3) \qquad (3)$$

Where φ_j (j = 1, 2, 3) is the angle of the fissure segment between two adjacent anchor points. Thus the proposed algorithm extracts the left and right oblique fissures automatically from the isotropic CT images.

4. RESULTS AND DISCUSSION

The series of steps involved in identification of fissure region from the isotropic CT image is shown in Fig. 6. The input CT image used for fissure extraction algorithm is shown in Fig. 6(a). The noise from the input CT image is removed by applying median filtering technique. Then threshold is calculated based on equation 1, which is applied on the filtered image to remove the fat and muscles from the original lung image. Before segmenting the left and right lungs by bounding box [see Fig. 6(c)] the connected component labelling is applied on the thresholded image, which is shown in Fig. 6(b). The fissure region is identified by adaptive fissure sweep is shown in Fig. 6(g). Prior to the identification of lobar fissures the dilation and edge detection techniques are performed on the segmented lung image, which is shown in Fig. 6(d)-(e).

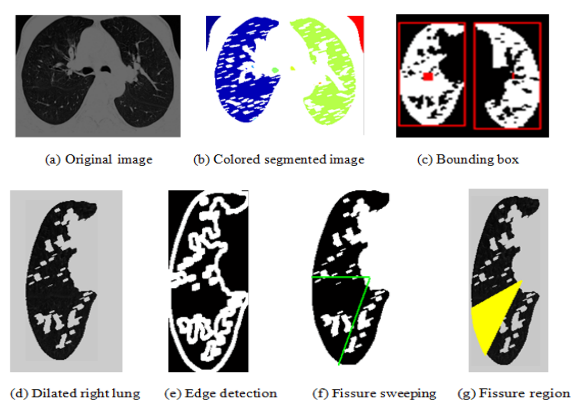

Fig. 6 Series of steps in fissure detection (right lung)

After the identification of fissure region, the DTCWT is applied to extract the lobar fissures. The series of outputs involved in fissure extraction algorithm is shown in Fig. 7.

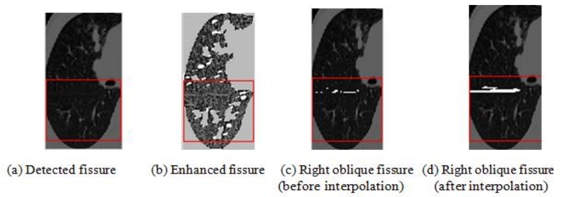

Fig. 7 Series of steps in fissure extraction (right lung)

The found fissure is discontinuous [see Fig. 7(c)] rather continuous. Hence Gaussian smoothing is performed on the resultant image to get the continuous pixels for the extracted fissures, which is shown in Fig. 7(d). Thus the right oblique fissure is extracted from the isotropic CT image by employing fissure region identification followed by fissure extraction. The same procedure is repeated for the left lung for extracting the left oblique fissure. The series of steps involved in identification of fissure region in the left lung is shown in Fig. 8.

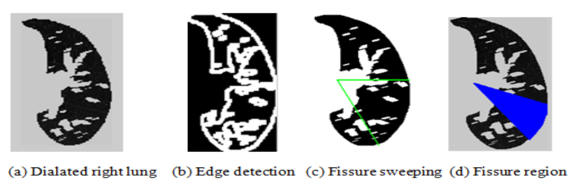

Fig. 8 Series of steps in fissure detection (left lung)

The series of steps involved in fissure extraction from the left lung is shown in Fig. 9. Thus the oblique fissures (left and right) are extracted using adaptive fissure sweep and DTCWT.

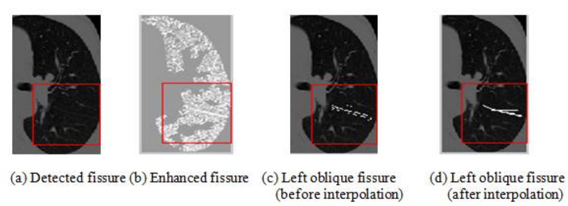

Fig. 9 Series of steps in fissure extraction (left lung)

5. CONCLUSION AND FUTURE WORK

The important tasks in analyzing the computed tomography images for identification of several diseases are segmentation and detection of abnormality. It requires efficient automatic method to perform segmentation and detection. The identification of tumour region involves extraction of lobar fissures from the input CT images which make use of two phases. In the first phase, the fissure region is identified. In the second phase, the found fissures are extracted. The result obtained show that the proposed work can help the surgeons to identify the lobar fissures (left & right oblique) correctly to locate the tumour region before they plan for the surgery. In this paper the extraction of left and right oblique fissures are discussed. The future research involves the extraction of horizontal fissure from CT images by applying superior image processing techniques before applying DTCWT.

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