Comparing Watershed and FCM Segmentation in Detecting Reticular Pattern for Interstitial Lung Disease

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Abstract— Lung is an important organ in human respiratory system. However a group of lung diseases known as interstitial lung diseases (ILD) may affect the tissue and space around the air sacs of the lung that prohibit the transferring of enough oxygen into bloodstream. Presently, ILD patients are diagnosed manually by the medical practitioner based on the clinical findings and High-Resolution Computed Tomography (HRCT) thorax images. The process of diagnosing using HRCT images is time-consuming and the outcomes are subjective in nature. One of the indicators of the ILD is the existence of reticular pattern on the HRCT Thorax images. The severity of ILD basically depends on the coarseness of this reticular pattern. The research focuses on the segmentation of the reticular pattern on the infected region based on the grades given by the ILD scoring index; grade 0 - absent, grade 1 – fine intralobular fibrosis predominating, grade 2 – microcystic pattern with airspace less than 3mm in diameter, and grade 3 – larger cysts 3-6mm in diameter. This paper discussed the two segmentation techniques, watershed segmentation algorithm and Fuzzy C-Means (FCM). The study shows that both methods able to segment the reticular pattern for grade 2 and grade 3 of the disease. FCM yielded better result compared to the watershed in term of having higher accuracy of cyst detection and less over-segmented region.

Keywords- HRCT; Interstitial Lung Disease; FCM; reticular pattern; Watershed

I. INTRODUCTION

Human respiratory is well organized by a very important organ, the lung. However a group of lung diseases known as interstitial lung diseases (ILD) may affect the tissue and space around the air sacs of the lung that prohibit the transferring of enough oxygen into bloodstream. The ILD is caused by a few factors such as infections in lung, toxins in environment, medications, radiation or connective tissue disease whereby without a medical history, ILDs are of unknown cause [1].

The severity of ILD can be identified either by clinical assessment, pulmonary function testing (PFT) or HRCT imaging [2]. The radiologists normally look for the interstitium changes of the lung tissue as the determination for the existence of ILD. One of the changes is represented by the reticular pattern of the lung tissue on the HRCT images. The severity of ILD basically depends on the coarseness of this reticular pattern. The grades on the coarseness score of the reticular pattern in Malaysian scoring index are given as follows:

- Grade 0 - absent,
- Grade 1 – fine intralobular fibrosis predominating,
- Grade 2 – microcystic pattern with airspace less than 3mm in diameter
- Grade 3 – larger cysts 3-6mm.

The grade 2 and 3 reticular pattern can be identified by the presence of the airspace in the lung region. Different grade refers to different size of the airspace. Compared to other regions in the lung, the airspace area has more homogenous surface and surrounded by noticeable boundary (as shown in red arrow in Fig. 1). The segmentation of the reticular pattern may make use of this information. This paper investigates and compares the potential of watershed and FCM segmentation method in segmenting the grade 2 and 3 of reticular pattern.

Figure 1 Example of the reticular pattern

Watershed segmentation is one of the edge-based segmentation method used to identify the regions of interest of an image. The advantage of this method is that the edge information from the gradient surface is used in the region-
growing algorithm [3]. The basic concept of watershed is by flooding the whole image topography through the holes cut in each regional minimum at a uniform rate. A dam is constructed when the rising water is about to merge within the separate catchment basins, in order to prevent the merging. The stage of flooding is counted when only tops of dams are seen above the water line. These dams are the boundaries, which are extracted by watershed segmentation algorithm.

The drawback of the watershed algorithm is that the image will be over segmented. One of the methods to minimize the problem was suggested by M. Frucci [4] by eliminating the non-significant basins and merging the less significant region with the more significant region using the information of properties of particular points of the line which separating the adjacent region. K.N.R. Mohana and A.G. Dempster [5] presented another method that used the morphological area-opening on the distance transforms. Their method was the modification of [6] for objects, which are irregular, touching or overlapping with other objects.

Fuzzy C-Means (FCM) is an unsupervised clustering method, which group similar data to the same cluster by iteratively minimizing the objective function. The objective function is related to the distance between the data to the cluster’s centroid. Similar to the K-Means clustering technique, however, FCM considers the weighted membership information of each data to a particular cluster. The implementation of FCM in medical image segmentation is common and highlighted in [7][8].

This study investigates the ability of watershed and FCM segmentation methods in capturing the reticular pattern on the HRCT images. Both techniques are applied on a preprocessed image which consists of the right and left lung region only. The lung segmentation algorithm is shown in Figure 2 and explained in the next section.

II. METHODOLOGY

This study used watershed algorithm based on Meyer [9] and FCM segmentation proposed by [12] which is presented in [7]. Both methods were applied to 10 of ILD sample images that consisted of reticular pattern of grade 2 and grade 3 only. However, the image is firstly simplified so that it contains fewer unwanted information. It is done in order to eliminate the region other than the lung because the desired pattern is only exists within lung region. This chapter is organized as follows: Firstly, the details on data used are explained. Then, the algorithm to segment the lung region is described based on flowchart in Fig. 2. Next, we presented the watershed segmentation algorithm followed by the FCM method explanation.

A. Data used in the study

The HRCT thorax images of 2 ILD patients were taken from the Radiology Department of Kuala Lumpur Hospital. The images were captured using Siemens Somatom Plus 4 Helical CT scanner, and the reticular pattern of each are observed and graded by three radiologists using Sienet Magicview version 4.2. Each slice was obtained at 10 – 30 mm intervals with patients in supine position with full suspended inspiration.

B. Lung segmentation

The algorithm for the lung segmentation in Fig. 2 is applied to the original image first before proceeding with the watershed and FCM methods. It is done to reduce the unwanted information such as the surrounding tissues and other organ pixels. Note that the lung cyst is an empty space which contains air and can be identified by the darker pixels in the image.

1) Otsu thresholding

The lung regions are visually separable by its darker intensity compared to the other regions. In this study, the Otsu [10] algorithm was used to obtain the optimal threshold value. Given that the original image, \( f(x, y) \) consists of L intensity levels, with total occurrence given by \( n_i \). The total pixels presence in the image is given as \( N = n_1 + n_2 + n_3, ..., n_L \). The
The class variances were also calculated as follow:

\[ \sigma^2_i = \sum_{i=1}^{k} (i - \mu_i)^2 \Pr(i|C_i) = \sum_{i=1}^{k} (i - \mu_i)^2 \frac{P_i}{\omega_i} \]

\[ \sigma^2_0 = \sum_{i=1}^{L} (i - \mu_0)^2 \Pr(i|C_0) = \sum_{i=1}^{L} (i - \mu_0)^2 \frac{P_i}{\omega_0} \]

(7)

The procedures were repeated with different \( k \) until \( \eta \) is maximized by using measurement as shown:

\[ \eta(k) = \sigma^2_B(k)/\sigma^2_T \]

(9)

As explained before, the lung region consists of group of pixels with low intensity value. Thus, Otsu automatically assigned these pixels to black and others to white. For further steps, the output of Otsu is inverted so that the darker region in the original image will be assigned as white and others to black (as shown in Fig. 4).

2) Morphology opening and closing

Then, morphological filtering operation is implemented using 3x3 square structuring element (SE), including opening and closing. The opening refers to the erosion step followed by the dilation while the closing operation is the dilation followed by the erosion. In this work, we first applied the opening operation to remove any small components in the image. Then, the closing operation is applied to fill the gaps between adjacent components that still exist after the opening was implemented. Both results are shown in Fig. 5 and Fig. 6.

3) Connected component analysis

The remaining regions are labeled using 8-connected neighborhood pixels. Based on prior knowledge that the lung region located within the rib of the HRCT, regions attached to the image frame are assumed to be the background (refer Fig. 7). The areas of remaining components are calculated and only the two largest regions are extracted. In this case, the area is calculated by taking the number of pixels enclosed by the region.

4) Filling holes and dilation

Since current concern is the range of lung region, the image is simplified by having all pixels within the obtained region with white. It was done via filling any background pixels located within the object which cannot be accessed from the outside background (see Fig. 8). Then, the solid region is further dilated so that it contains the original lung region with thin surrounding tissues (refer Fig. 9). The surrounding tissues are purposely being included so that the lung region is separable from the background pixel. The original intensity is obtained by simply assigning the original intensity to all white pixels in the image. The lung segmentation output image is shown in Fig. 10.
C. Watershed segmentation

1) Edge Detection
To detect edges of the original image, the gradient magnitude is calculated using Sobel operator of 3-by-3 filters. Firstly, the mask is applied to emphasize horizontal edges using smoothing effect by approximating vertical gradient. The filter is then to emphasize the vertical edges. The gradient is calculated using equation:

\[ \nabla f = \left( G_x^2 + G_y^2 \right)^{1/2} \]  

(10)

The gradient is high at the borders and mostly low at the inside of the object. Fig. 11 shows result of edge detection. The gradient magnitude image cannot be segmented directly to the watershed, as it will result over segmentation so additional preprocessing is needed to limit the number of allowable regions.

2) Foreground Marking
Additional preprocessing step is marking the foreground object by using morphological technique to clean the image. The technique involves image reconstruction where unwanted pixels are removed from the image. The process involves two components, which are the marker image, and the mask. Further explanation of the process is as below:

\[ A \circ B = (A \Theta B) \Theta B \]  

(11)

where \( A \) is the image, \( B \) is the SE, \( \Theta \) is erosion and \( \circ \) dilation. \( A \) was firstly eroded with 3-by-3 of \( B \). Then, the eroded image is called the marker. After that, the marker is repeatedly dilated until it fits the mask image. Here, the mask is the original DICOM image. This whole process is also called opening-by-reconstruction, where the morphological operation is done to the marker image with limit to fit on the characteristic of the mask. Fig. 6 shows the result for opening-by-reconstruction.

\[ A \circ B = (A \Theta B) \Theta B \]  

(12)

The reconstructed image is further dilated with 3-by-3 SE and the output is defined as marker. This marker image is reconstructed again to the output of the opening-reconstruction step, where at this stage, the output of the opening-reconstruction step is known as the mask. This whole process is also known as closing-by-reconstruction. However, as the input of this procedure is the output of the opening-by-reconstruction step, this procedure can also be called opening-closing-by-reconstruction step. Result of opening-closing-by-reconstruction is shown in Fig. 13.

3) Watershed operation
To compute the watershed, the intensity of gradient magnitude image (Fig. 11) is modified using morphological reconstruction so that the regional minimum only occurs when pixel in Fig. 14 is nonzero and shown in Fig. 15. The white pixels represent the locations of seeds where the region-growing or flooding will start. The intensity of Fig. 11 is then modified using morphological reconstruction so it only has regional minima wherever Fig. 14 is nonzero. If value in Fig. 11 is 0, they will be assigned to \(-\text{Inf}\) while else required additional calculation including range and \( h \). Range of gradient magnitude is different between the minimum and maximum value. \( h \) is determined with condition:

If \( \text{range}=0 \), \( h=0.1 \);
If \( \text{range}=a \), \( h=a \times 0.001 \);

Final pixels in Fig. 14 are defined as:

\[ \hat{f}(x,y) = f_{GM} + h \]  

(14)

where \( \hat{f}(x,y) \) is the final pixel, \( f_{GM} \) is the pixel value of the gradient magnitude image and \( h \) is constant.
4) Cyst extraction

In order to extract the cyst region, the average intensity for the watershed labeled regions was investigated. It is noticeable that the cyst region has a darker mean intensity compared to others because it is nearly homogenous. A threshold value was defined to extract only region having mean intensity within specific range.

\[
g(x,y) = \begin{cases} 1 & \text{if } \mu_i < T \\ 0 & \text{if } \mu_i > T \end{cases} \quad f(x_i, y_i) \in R_i
\]

where \( \mu_i \) is the mean intensity of pixels \( f(x_i, y_i) \) within region \( R_i \). At this current stage, the value of the \( T \) was defined empirically and is equal to 90.

D. Fuzzy C-Means (FCM)

1) FCM segmentation

There is various advanced intensity-based segmentation methods that have been proposed in order to compromise the limitations of the simple thresholding method. Among them, Fuzzy C-Means (FCM) is increasingly gaining attention. Unlike the K-Means clustering technique, FCM groups data to a cluster based on the degree of membership assigned to each data. The degree of membership is measured via the distance between the data and the centroid of each cluster. By taking the fuzzy membership value instead of clear-cut binary membership as in K-Means, a new cluster may be formed among pixels with close membership values. The centroid is iteratively recalculate until the objective function as shown in Equation 15 is minimize.

\[
Q = \sum_{i=1}^{n} \sum_{j=1}^{C} u_{ij}^m \| v_i - \mu_j \|^2 \\
\text{with } 1 \leq m < \infty
\]

where \( n \) is the number of data, \( C \) is the number of clusters, \( v_i \) is the \( ith \) measured data, \( m_j \) is the centroid for cluster \( j \) and \( \| * \| \) is the distance measure between the measured data and the cluster centroid. In this study, the Euclidean distance is considered as the distance measure. The alteration to the membership and cluster’s centroid values are obtained through following equation;

\[
u_{ij}^m = \frac{1}{\sum_{k=1}^{C} (\| v_i - \mu_j \|^2)^{\frac{m-1}{2}}} \sum_{k=1}^{C} (\| v_i - \mu_j \|^2)^{\frac{m-1}{2}}
\]

\[
\mu_j = \frac{1}{n} \sum_{i=1}^{n} u_{ij} v_i
\]

In our study, the cluster number is set to 3 and the iteration is performed up to 100 times. However, the iteration may be less, depending on the objective function value. If there is no significant change on the objective function value, the centroid obtained at that particular iteration is optimal and the cluster assigned to each pixel is final. The FCM output image is shown in Fig. 18.

2) Region extraction

The output of the FCM clustering method is an image with pixels labeled with a unique cluster label. Different color represents different cluster and displayed based on the grey level range corresponds to the label. Visual observation shows that the cyst area contains almost total air pixel, which no significant intensity fluctuations. It indicates that the cyst area is filled with air and it is different compared to the other lung area, which has more other information. Due to this reason, the mean intensity in the cyst area should be lower than other detected areas. Thus, using the labeled in FCM output, we calculate the mean intensity of pixels with the same label of FCM and extract only the labeled pixel with lowest mean intensity. The extracted pixel indicates the possible area range of the cyst.
3) Morphological filtering
Morphology erosion was implemented in order to disconnect some noisy pixels that attached together which make them a bigger object. Then, any region with total pixel less than 30 is removed. It is because most of the time, the grade 2 and grade 3 cysts represented by a large region. The remaining regions are dilated to restore the original shape and size corresponds to the original image.

III. RESULT AND DISCUSSION

Results of both methods are shown in Fig. 22. In both cases, the trachea and bronchioles are misclassified as the cyst region. It is due to its similar surface texture and intensity range. The watershed segmentation yielded over segmentation and no signs of cyst area can be notified. Considering the average value of intensity for each region, the cyst area may be predicted and extracted because the cyst area always has lower mean intensity. Fig. 17 shows the results of the extraction of cysts based on the consideration of the mean intensity with threshold value defined at 30. However, it is not agreed by all images due to the variations in the intensity value among different samples. Some cyst regions are missed. Possible merging techniques with similar region could be considered and it is also based on the intensity information. Yet the extraction of cyst region is still issue to be solved. More information to distinguish the cyst region from other area is required.

FCM segmentation yielded better result with higher accuracy of cyst region segmented and less over-segmented region detected. Comparing images in Fig. 22 (a) and Fig. 22 (b), watershed labeled the largest cyst (upper left) as two different regions whereas only one region in FCM output. It is the example where the over-segmentation issue in watershed is more obvious. As stated previously, some merging techniques may be considered to deal with the situation.

The better result may be achieved if the spatial information is considered in FCM. Future work is to apply advanced FCM techniques that consider this factor. The exclusion of the trachea and bronchioles area may be achieved by improving the lung segmentation algorithm. The study also focused on improving the cyst extraction rate by identifying other characteristic of cyst region such as the area, shape and texture feature. The diameter of the cyst will also be measured to identify the grades of the coarseness score of the reticular pattern. Further statistical analysis on the accuracy measure of the cyst extraction will be conducted to evaluate the performance of the methods.

![Figure 20 Color labeled of region extracted from FCM](image)

![Figure 21 region extracted dilated to restore original size and shape](image)

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V. REFERENCE