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Detection and Classification of Pleural Plaque using ACM and ELM Algorithm Model

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Abstract : The diagnosis of lung cancer in the early stages is very much inevitable to overcome that. The serious illness of a person due to the lung problems can be found by the type of pleural plaques in the lungs. Pleura is a membrane around the lungs which supports the breathing process. The plaques developed on the layers of pleura leads to cause the defects which reduce the functionality of the lungs. The plaque affects both the parietal pleura which as well as visceral pleura. The early detection of the development of plaque helps in detecting the major lung diseases. For lung image segmentation, many clustering and threshold techniques have been proposed. Here initially the image is pre-processed using anisotropic diffusion filter. Then pleural plaque is detected and segmented using region growing approach followed by layer refinement using active contour model (ACM). Finally the segmented image is classified so as to yield normal and abnormal set using Extreme Learning Machine (ELM). Segmentation is carried using chest CT images to evaluate the effectiveness of the proposed technique.

***Keywords* :** Pleural plaque, Region growing, Active contour model, ELM classifier.

1. INTRODUCTION

Pleural diseases are widely known problems irrespective of the age groups. The pleura can be classified into two types namely parietal pleura which lining the thoracic region and visceral pleura, the covering of the lungs. The parietal pleura becomes visceral pleura by folding back at the root of the lung. Pleural plaques are formed of discrete portions of hyaline fibrosis of the parietal pleura and rarely present in the visceral pleura[1,2]. The major reason for the development of pleural plaques is exposure to asbestos. This is due to the environmental setup of industries and work places.

Plaques consist of conglomerations of collagen fibres with medium to high densities set in a basket-weave pattern[3]. If this continuously happens, the deposits often become partly calcified.

Pleural calcification also occurs due to healed pleural tuberculosis and thoracic trauma[4]. The detection and extraction of pleural plaques for analysis is a challenging task for the correct diagnosis of the lung issues. Though various methods are used, the detection is effective when the Computed tomography (CT) imaging modality is used.

Pleural plaques of increased levels are asymptomatic although and it can engender anxiety that stimulates dyspnoea and chest tightness[5-7]. In advanced stages it can cause pleural thickening, pleural effusion, lung cancer, bronchial carcinoma, mesothelioma etc. Wide-ranging and confluent plaques are unusual and leads to a restrictive ventilator defect[8-10]. So segmentation of pleural plaque is given more emphasis here.

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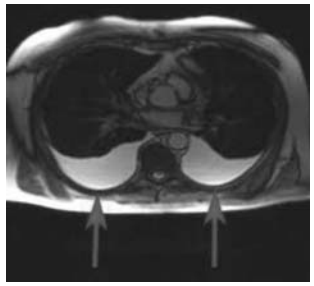

Fig. 1. Pleural plaque Image

The proposed section is structured as follows. Firstly, proposed framework is given including the pre-processing, lung segmentation, feature extraction and classification. Finally, results and conclusion are depicted along with future scope.

2. PROPOSED FRAMEWORK

This section describes the process of proposed system which is shown in Figure 2. It includes pre-processing, lung segmentation for pleural plaque detection, layer refinement and classification. The aim of this project is performing the segmentation of pleural plaque on the CT scan image using MATLAB software.

Pre-Processing

The primary purpose of pre-processing is to denoise the image and to improve the image quality. The images obtained may be comparatively low quality images. So it might be little hard to get the useful information and extract the noise affected portion exactly. Usually the contrast of the medical images are less as the amount of radiation used controlled not more than an allowed level. If the radiation dose is reduced, the image quality also reduced as the noise in the image will be more. If the radiation dose of ionizing radiation is increased it will cause the cancer in the exposed area. So in order to enhance the image, pre-processing stage plays a vital role prior to segmentation.

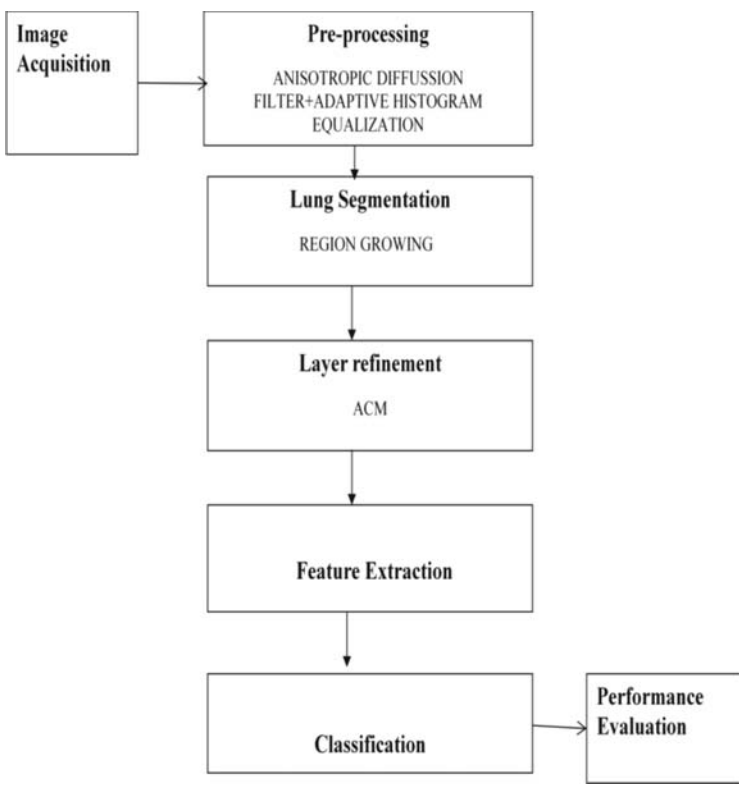

Fig. 2. Schematic of proposed method

Here an anisotropic diffusion is applied to remove the high frequency noises without affecting the edge information. The loss of information is de to filtering is reduced by controlling the number of iterations of the anisotropic diffusion. Pixel intensities are slightly changed with respect to the average of the neighbouring region. Following the filtering is the contrast limited adaptive histogram equalization (CLAHE) technique which is helps in altering the local contract of CT image.CLAHE method works basically on a small cells in the image which is named as a tile. It modifies the contrast of each tile and also the contrast of the adjacent tiles. These adjacent tiles are that are then included by using bilinear interpolation.

At first the input CT-lung image is estranged into different non overlapping continuous regions known as contextual regions. The histogram ofthese contextual regions are separately calculated and they are clipped individually.

Lung Segmentation

In order to detect the pleural plaque, segmentation algorithm is performed by using region growing method followed by active contour model. The basic limitation of region detection is it is histogram-based so that histograms will not provide any spatial information and it gives information about only the allocation of gray levels. Region-growing utilizes the nature of pixels are similar when the pixels are closely together as clusters.

Region growing algorithm begins with an origin pixel known as seed. Gradually it adds more new pixels with respect to the similarity index.It includes seed point selection and checking and adding the neighbouring pixels with the seed point based on the predefined rules in the algorithm. This process of including the new pixels with the seed point is continued. As the region grows it covers the entire neighbouring pixel area with similar properties and it segments the required portion of the image. The process of including pixels stops when no more points are added. This gives the segmented output.

The properties of the portions to be segmented can be defined by the user with respect to the need of the application. Region growing methods can correctly separate the regions that have the same properties already defined and also it hs the original image quality unaffected with clear edges. The advantage of this method is that it is simple. The noise interference is minimized using specific filter masks and thus the presence of noise is almost eliminated as it seems it never existed.

Layer Refinement

In order to extract the pleural plaque accurately, the pleura has to be refined. Pleura here are the lung layers mentioned in section I. Layer refinement is done using active contour model (ACM).

An active contour model gives the edges based on some salient image features like shapes of parametric curve and that is made allowed to bend from the initial shape to the expected final shape. The difficulty in finding the correct final shape is that it radiate as energy minimization. There is also a problem with the purpose that the final contour yields a local minimum of an associated energy functional (E) and it is defined such that the energy of the contour attains a local minimum when the contour is spatially aligned with the shape or object boundary of interest in the image.

The contour is defined as a curve in the (x, y) plane $v(s) = (x(s), y(s))$, where s is a parameter which increases as it goes around the contour and is related to arc length. By specifying the contour as $v(s)$, the designed model is defined with total energy terms which are classified as follows in the continuous spatial domain.

1. **Internal Energy :** Internal energy is a function of the contour $v(s)$. It denotes the tension and smoothness of the curve and it depends on the internal characteristics of the snake.
2. **External energy :** It is obtained from the image used for the process and it consists of the local minima at the edges or at boundaries.
3. **Constraint energy :** Constraint energy acts on the contour only if an interactive interpretation and feedback given by a user, automatic attention mechanism or a higher- level process. The mathematical model with the energy terms is

$$E_{snake} = E_{int} + E_{ext} + E_{con} \tag{1}$$

If the limitation of this equation are determined and a function is fitted, layer refined segmented output will be gained. Next interpretation of this equation is to consider it to be a force balance equation of a system

$$F_{int} + F_{ext} = 0 \tag{2}$$

Where $F_{int} = \alpha v_{ss} - \beta v_{ssss}$ and $F_{ext} = -\nabla E_{image}$

The internal forces restrict the stretching and bending while the external force draws the snake towards the desired image edges. Thus the original contour evolves and deforms into the final contour $F_{int} = -F_{ext}$. For every point along the curve the internal and external forces are equal and act in opposite direction to each other to provide a stable state.

The final contour is the one that satisfies the force equation which is given as

$$\alpha v_{ss} - \beta v_{ssss} - \gamma \nabla E_{image} = 0 \tag{3}$$

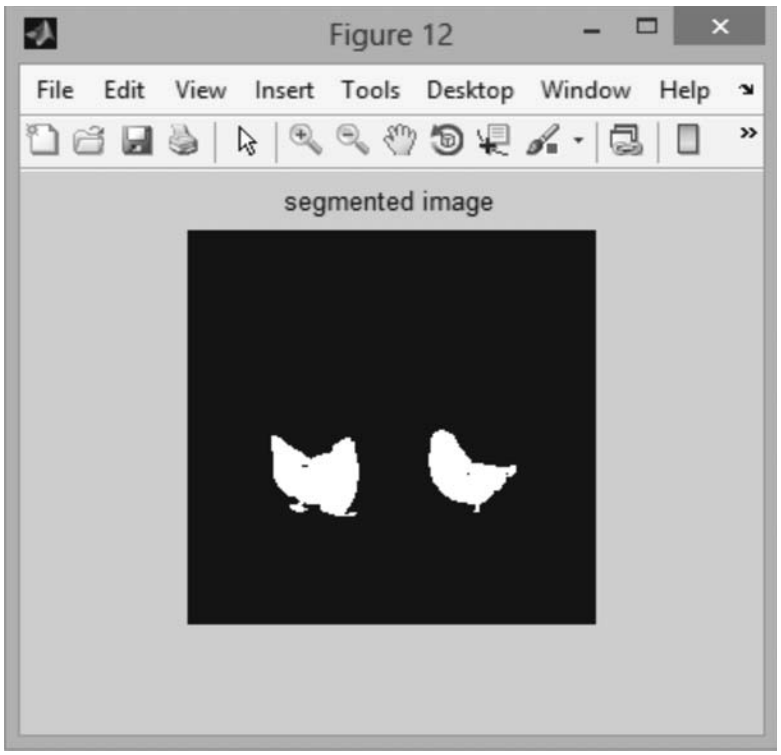

Fig. 4. Segmented pleural plaque

Feature extraction

To detect pleural plaque feature extraction is based on Texture features that are extracted according to the statistics of gray-level co- occurrence matrix (GLCM).

GLCM is a statistical approach to find the texture that has the spatial relationship between pixels. It is otherwise called as the gray-level spatial dependence matrix. It characterizes the features of an image by measuring the incidents of pairs of pixel with predefined values. It also consists of specific spatial relationship in an image which creates a GLCM followed by extracting the statistical features from the matrix. The size of the GLCM is based on the number of gray levels in the image.

Medical images are basically classified using the texture information. The most fundamental features are contrast and homogeneity. Contrast deals with the local variations of gray-level co-occurrence matrix. It proceeds with a measure of the intensity contrast between a given pixel and its neighbour over the whole image. Contrast also captures the gray levels that are in dynamic range presented in an image. Contrast is 0 for a constant image.

Homogeneity measures the proximity of the allocation of elements in the GLCM. Its range is from 0 to 1. Homogeneity is 1 for a diagonal GLCM. Another feature is entropy E = entropy (I) a scalar value representing the entropy of gray scale image I. It is a measure of randomness of a gray level distribution that can be used to describe the consistency of the input image. Entropy is high if the gray levels are distributed randomly throughout the image. For computational purpose, the averages of every point over neighbourhoods are manipulated.

Classification

Extreme learning machine (ELM) is used for single-hidden layer feed-forward neural networks (SLFNs) . The core kernel of ELM is the note that the hidden layer of SLFNs are not be tuned. It selects the input weights and determines the output weights by calculations. ELM inclined to give a better performance at the increased speed of the learning process.

Here extreme learning machine approach is used for the classification of pleural plaque in chest ct images. Classification results categorize into two classes namely normal and abnormal. And then specificity, sensitivity, accuracy and precision rate is evaluated suing the true positive, true negative, false positive and false negative values.

3. CONCLUSION

This study aimed at the detection and segmentation of pleural plaque using region growing and active contour model. The images are pre-processed using anisotropic diffusion filter and contrast limited adaptive histogram equalization. And then segmented and layer refinement is done. Classification is done using extreme learning machine to categorize output as normal and abnormal. Performance evaluation is done in terms of accuracy, specificity, sensitivity and precision with a data sample set of 60 patients. Automatic segmentation of the same can be a scope for future work. It can be tried out using Vector flow convolution in future.

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