ISSN 2348-375X

Unique Journal of Engineering and Advanced Sciences

Available online: www.ujconline.net

Research Article

PLEURAL PLAQUE DETECTION USING HYBRID SEGMENTATION ALGORITHM AND ELM CLASSIFICATION

Sruthy K[1*], D Baskar[2], V S Jayanthi[3]

[1]P.G Scholar, Dept of ECE, Hindusthan College of Engineering and Technology, TN, India
[2]Assistant Professor, Department of Electronics and Communication, Hindusthan College of Engineering and Technology TN, India
[3]HOD, Department of Electronics and Communication, Hindusthan College of Engineering and Technology TN, India

Received: 06-03-2013; Revised: 04-04-2014; Accepted: 03-05-2014

*Corresponding Author: **Sruthy K**
P.G Scholar, Dept of ECE, Hindusthan College of Engineering and Technology TN, India. E-mail: sruthymayuram@gmail.com

ABSTRACT

Pleural plaques are by far the most common indication of significant exposure to asbestos and act as a biomarker for the diagnosis of lung cancer in later stages. Plaques can develop on both layers of the pleura, a thin membrane that surrounds the lungs and aids in breathing. They most commonly develop on the parietal pleura, which lines the inside of the rib cage, but can also affect the visceral pleura, which lines the lungs. 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 determine the efficiency of proposed technique.

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

INTRODUCTION

Pleural disease remains a commonly encountered clinical problem for both general physicians and chest specialists. The pleura are membranes lining the thoracic cavity (parietal pleura) and covering the lungs (visceral pleura). The parietal pleura folds back on itself at the root of the lung to become the visceral pleura Pleural plaques are discrete circumscribed areas of hyaline fibrosis of the parietal pleura and occasionally the visceral pleura. The cause of pleural plaques is exposure to asbestos fibres, most commonly in an occupational setting. They comprise dense conglomerations of collagen fibres arranged in a basket-weave pattern. Over time, usually many years, they often become partly calcified.

Pleural calcification may also be seen in other conditions such as healed pleural tuberculosis and healed thoracic trauma. Pleural plaques are the commonest physical manifestation of asbestos exposure. The detection of pleural plaques varies according to the imaging method used. Computed tomography (CT) detects more plaques than x-ray.

Pleural plaques are nearly always asymptomatic although the knowledge that pleural plaques are there can engender anxiety that may produce symptoms that include dyspnoea and chest tightness. In advanced stages it can cause pleural thickening, pleural effusion, lung cancer, bronchial carcinoma, mesothelioma etc. Extensive and confluent plaques are uncommon but can result in a restrictive ventilator defect that results in disability. So segmentation of pleural plaque is given more emphasis here.

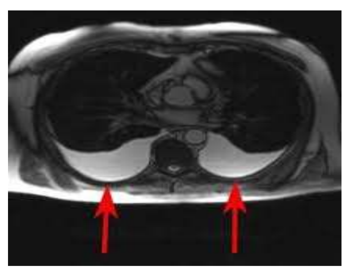

Figure 1: Pleural plaque Image

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.

Proposed Framework

This section describes the process of proposed system. An overview of the method 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 reduce the noise present in the image. The images obtained may be comparatively low quality images. So it might be little hard to get the useful information and extract the part exactly as it may be affected by the noise. Usually medical images are weak in terms of contrast. So in order to enhance the image pre-processing stage plays a vital role prior to segmentation.

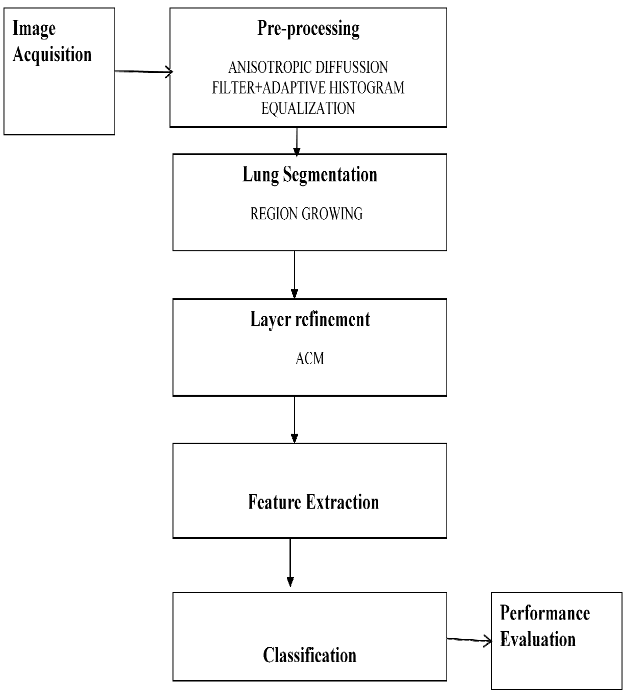

Figure 2: Schematic of proposed method

Here an anisotropic diffusion filter is used to smooth the intensities of the image without blurring edges. Pixel intensities are moved toward the average of the surrounding region. Following the filtering is the CLAHE (contrast limited adaptive histogram equalization) technique which is used to enhance the local contract of a CT-Lung image. CLAHE technique operates on tiles, i.e. a small area in the given image. CLAHE enhances each tile's contrast and the adjacent tiles are then incorporated through bilinear interpolation. Initially the CT-lung image is alienated into conceptual region that are non-overlapping and continuous. Contextual region's histogram is computed and then the histograms of every contextual region are clipped.

Lung Segmentation

In order to detect the pleural plaque, segmentation algorithm is carried out using region growing method followed by active contour model. The fundamental drawback of histogram-based region detection is that histograms provide no spatial information (only the distribution of gray levels).Region-growing approaches exploit the important fact that pixels which are close together have similar gray values.

Region growing starts with a single pixel (seed) and adds new pixels slowly. It includes seed point selection and checking the neighbouring pixels and adds them to the region if they are similar to the seed. Then repeat the checking step for each of the newly added pixels and stop if no more pixels can be added. This gives the segmented output. Region growing methods can correctly separate the regions that have the same properties we define and can provide the original images which have clear edges with good segmentation results. Here the concept is simple. The noise problem is easily by conquered using some mask to filter the holes or outlier. Therefore, the problem of noise actually does not exist.

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 ACM (active contour model).

An active contour model represents an object boundary or some other salient image feature (e.g. shape) as a parametric curve that is allowed to deform from some arbitrary initial shape towards the desired final shape. The problem of finding this final contour is cast as an energy minimization problem with the intention that the final contour yields a local minimum of an associated energy functional (E). The energy functional (E) of the contour 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 in the (x, y) plane of an image as a parametric curve, 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. Having specified the contour as v(s), our model is defined as a sum of energy terms in the continuous spatial domain. The energy terms can be categorized as follows:

1) Internal Energy**:** Internal energy is a function of the contour v(s) itself and it specifies the tension and smoothness of the curve. It therefore depends on the internal properties of the snake.
2) External energy: It is derived from the image under inspection and it possesses local minima at the edges or the object boundaries.
3) Constraint energy: Constraint energy acts on the contour only if we have some sort of interactive interpretation and feedback provided by a user, automatic attention mechanism or a higher-level process.

The mathematical model using above energy terms is

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

Once the constants in 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

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

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

The internal forces discourage stretching and bending while the external force pulls the snake towards the desired image edges. Therefore when the original contour evolves and deforms into the final contour $F_{int} = -F_{ext}$ which means that for every point along the curve the internal and external forces are equal and act in opposite direction to each other giving a stable state.

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

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

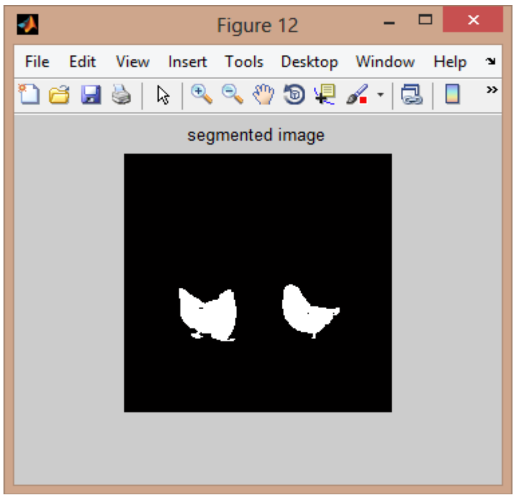

Figure 4: Segmented pleural plaque

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).A statistical method of examining texture that considers the spatial relationship of pixels is the gray-level co-occurrence matrix also known as the gray-level spatial dependence matrix. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM and then extracting statistical measures from this matrix. The number of gray levels in the image determines the size of the GLCM.

Texture plays an important role in classifying the medical images. The most fundamental features are contrast and homogeneity. Contrast measures the local variations in the gray-level co-occurrence matrix. It returns a measure of the intensity contrast between a pixel and its neighbour over the whole image. Contrast captures the gray levels that are in dynamic range presented in an image. Contrast is 0 for a constant image.

Homogeneity measures the closeness of the distribution 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) returns E, a scalar value representing the entropy of gray scale image I. Entropy is a statistical measure of randomness of a gray level distribution that can be used to characterize the texture of the input image. Entropy is expected to be 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 Classification:

Extreme learning machine(ELM) is used for single-hidden layer feed-forward neural networks (SLFNs) .The essence of ELM is that the hidden layer of SLFNs need not be tuned. It randomly chooses the input weights and analytically determines the output weights. ELM algorithm tends to provide better generalization performance at extremely fast learning speed.

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.

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.

REFERENCES

1. Yao J, Bliton J, and Ronald M. Automatic segmentation and measurement of pleural effusions on CT ,in Proc. IEEE Transactions on Biomedical Engineering, 2013; 60(7).
2. Peng B, Zhang L and Zhang D, Automatic image segmentation by dynamic region merging", Hong Kong SAR General Research Fund, 2011.
3. Bridget NJ, and Gowri S,Ameliorate fuzzy c-means: an ameliorate fuzzy c-means clustering algorithm for ct-lung image segmentation, American Journal of Applied Sciences, 2013; 10(11): 1439-1447.
4. Gori I, Fantaccibc ME,An automated system for lung nodule detection in lowdose computed tomography, Eur. Radiol. 2010; 11:1345-1350.
5. Zhang K, Song H, Zhang L, Active contours driven by local image fitting energy, University of Science and Technology of China, Hefei 230027, 2011.
6. Weinheimer O, Achenbach T,et.al, Automatic Lung Segmentation in MDCT Images", Springer-Verlag and Springer, London, 2009.
7. Sridhar KV, Reddy VS,et.al, Automated medical image segmentation for detection of abnormal masses using Watershed transform and Markov random fields, ACEEE Int. J. on Signal and Image Processing,2013; 4(3).

8. Seenivasagam V, A Survey of Image Segmentation Methods using Conventional and Soft Computing Techniques for Color Images", International Journal of Advanced Research in Computer Science and Electronics Engineering (IJARCSEE) 2012; (6).
9. Mai V, Wilson P, et.al, Knowledge driven automated detection of pleural plaques and thickening in high resolution CT of the lung", 19th International Conference, IPMI 2005, Glenwood Springs, CO, USA, 2009;270-285.
10. Wengfeng, kuo, Chiyuan, et.al, Medical image segmentation using the combination of watershed and FCM clustering algorithms, International Journal of Innovative Computing Information and Control 2011;l7(9).

Source of support: Nil, Conflict of interest: None Declared