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A Method for Lung Boundary Detection

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ABSTRACT

In computerized analysis of chest radiographs is the detection of the lung field boundaries. Once the boundaries of the lung fields are identified,   physiological measurements of the lung features are possible. The properties of the boundary are determined by edge detection along with suitable filter algorithms. The aim of proposed work is to develop an experimental system which segmented and analysis of the lung boundaries in chest X-ray images. This paper presents boundary detection of lung using algorithms and results obtained quite satisfactory.   This is tried to make a sharp distinction between the lung region and the exterior of the lung.

Keywords: *Medical image, Edge detection, Segmentation, lung, infections, physiological measurements*

I. INTRODUCTION

Many image processing techniques have been developed over the past two decades to help radiologists in detection of lung boundary. Most studies conducted have proven that an early measurement of physiological parameters may help detection of diseases related to lung. Bronchopneumonia or bronchial pneumonia or "Bronchogenic pneumonia" (not to be confused with lobar pneumonia) is the acute inflammation of the walls of the bronchioles. It is a type of pneumonia characterized by multiple foci of isolated, acute consolidation, affecting one or more pulmonary lobes. It is one of two types of bacterial pneumonia as classified by gross anatomic distribution of consolidation (solidification), the other being pneumonia. The detection of the lung field boundaries becomes even more difficult in the presence of bacterial pulmonary infections. The most common radiographic manifestation of such infections is foci of consolidations [1]. These are visible as bright shadows interfering with the interior lung intensities and can lead to weak lung field boundaries, difficult to distinguish even by experienced physicians. Therefore, a computational approach that would robustly detect the boundaries of the lung fields would be an asset to the medical community.

Images of abnormal anatomy pose a problem for all automated analysis schemes, particularly cases where expected anatomical structures are missing, or altered to the point where they cannot be detected by the available segmentation routines.

Lobar and lobular, are the classic anatomic categories of bacterial pneumonia, in clinical practice the types are difficult to apply, as the patterns usually overlap. Bronchopneumonia (lobular) often leads to lobar pneumonia as the infection progresses. The same organism may cause one type of pneumonia in one patient, and another in a different patient. From the clinical standpoint, far more important than distinguishing the anatomical subtype of pneumonia, is identifying its causative agent and accurately assessing the extent of the disease. Lung anatomy is shown in figure 1.
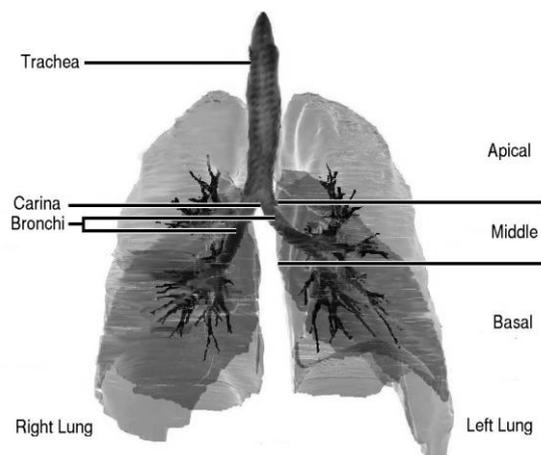
Fig. 1: Lung Anatomy, modified from original [2]

Automatic lung segmentation from High Resolution Computed Tomography (HRCT) images is used in Computer Aided Diagnosis (CAD) systems for the lung. Automatic segmentation of the lungs into left and right lungs is a relatively straight forward task. The task of labelling separate regions within the lung poses more of a challenge. The segmentation of the lung into Apical, Middle and Basal regions is essential for the differential diagnosis of diffuse lung diseases, as it helps radiologists to identify the distribution of the disease patterns.

In this paper we present initially pre-processing of X-ray image after digitization and then anatomical segmentation of lung Region of Interest (ROI) is used. Further we use Divide and Conquer Homogeneity algorithm, followed by   edge detection. We obtain the lung boundary by using our proposed algorithm.

2. REVIEW WORKS

The treatment of lung cancer and tuberculosis (TB) is easier in initial stages but very difficult in the advanced stages of the diseases. Computerised analysis of lung X-ray images

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can help these diseases in their early stages. Most cancer and TB cases start with the appearance of small nodules. Nodule pixels are often brighter than the surrounding areas but in some cases, the difference in grey levels is not at all significant. Furthermore, ribs and pulmonary arteries, which often have higher grey levels, also contribute to the complexity of lung tissue and make often some nodules undetectable.

In the past two decades several algorithms were developed to extract the contour of homogeneous regions within digital image. The basic image processing techniques such as Erosion, Median Filter, Dilation, Outlining, Lung Border Extraction and Flood-Fill algorithms are applied to the CT scan image in order to detect the lung region.

Computed Tomograph (CT) is efficient than X-ray [3], the latter is more generally available. Therefore preliminary diagnosis for TB and lung cancer, currently performed by medical doctors, is mainly based on chest Xray images. This is a time-costly process, and the quantity of images to be examined is at an unmanageable level, especially in populous countries with scarce medical professionals. When radiologists examine X ray image, they first need to recognise the two lungs and then find any obvious abnormality.

Hence segmentation is an essential process. Image segmentation is often based on the Watershed method [4] or the energy-minimization technique. The Watersnakes method [5], which uses the Watershed as a starting point, tries to make a link between the two segmentation approaches with the introduction of an adjustable energy function to change the smoothness of the boundary of a segmented area. However the Watersnakes method may be not suitable for lung segmentation on image.

The basic diagnostic task is to detect abnormality. To isolate lung objects, radiologists need to know both the structures within the mediastinum forming the mediastinal margins and the lobes of the lungs forming the margins of the lungs along the mediastinum and chest wall. Some abnormality may be recognised easily, but some may need careful examination as well as accurate measurement.

Medical image analysis is a complex task in which a human expert makes extensive use of the knowledge of anatomy and imaging techniques. Specially, the automatic segmentation of chest radiographs is challenging problem from a computer vision point of view. Because there are large anatomical variations from person to person and the most important problem is that radiographs are projection images and thus contain superimposed structures.

To interpret the chest radiographs, the radiologists often employ local properties like perceived intensity, uniformity, roughness, regularity, directionality, coarseness, smoothness and granulation [2]. Most of the proposed computer-aided diagnosis systems (CAD systems) adopt a two-step pattern recognition approach, which is a combination of a feature extraction process and a classification process using neural network classifier or statistical classifier. The performance of the classifier depends directly on the ability of characterization of candidate regions by the adopted features.

Many kinds of features have been proposed for discriminating between normal tissues and abnormal ones. However, there have been a few researches on comparing the effectiveness of those features [6-10]. The numbers of features used in those researches are not sufficiently large. The purpose of our research is to find the optimal feature set from a large number of features which enable a CAD system for lung cancer screening to take large step toward a practical application.

3. PRE-PROCESSING OF IMAGE

X-Ray Lung images are medical images requires a preparation phase in order to improve the image. Our objective during this process is to improve the quality of the image to make it ready for further processing by removing the irrelevant and unwanted parts in the background of the X-Ray.

The   image is transformed, so that the chest wall location, i.e., the side of the image containing the pectoral muscle, is on the upper left corner of the image. In order to determine the chest wall location, the decreasing pixel intensity of the breast tissue near the skin-air interface is used. This tissue is estimated by employing the Minimum cross-entropy threshold selection technique twice in the original image. After determining the chest wall location we determine the top of the image. We extract the vertical centroid of the image.

There are different types of noises, which appear in images. High intensity noise is characterized by high values of optical densities, such as labels or scanning artifacts. Tape artifacts are markings left by tapes, or other shadows presenting themselves as horizontal running strips. Such noise must be replaced by black pixels.

The Gaussian smoothing operator is a 2-D convolution operator that is used to `blur' images and remove detail and noise. In theory, the Gaussian distribution is non-zero everywhere, which would require an infinitely large convolution kernel, but in practice it is effectively zero more than about three standard deviations from the mean, and so we can truncate the kernel at this point. Once we obtain a suitable kernel, then the Gaussian smoothing can be performed using standard convolution methods. In our proposed method we have taken 5×5 kernel as a convolution filter. The following steps are required:

Step 1.   Calculate Gaussian Kernel values to create a convolution filter.
Step 2.   Convolution of the mammogram image starting from Left Topmost pixel to Bottom Rightmost pixel.
Step 3.   Perform matrix multiplication between calculated Gaussian filter values and pixel intensity.

4. PROPOSED METHODS

The edge detection process is done in three passes. In the first pass the scanning of image is done horizontally in the x direction i.e in a row major order. The algorithms start from the leftmost pixel of the first row and traverse all pixels on the first

row to reach the last pixel of the first row. Then we repeat the scanning of pixel from the next row and continue to subsequent rows till we reach the last pixel in the last row of the two dimensional image data array.

An adaptive threshold value is taken for pixel intensity comparison. The threshold value changes depending on the intensity of the pixels in the surrounding region. During the scanning of pixels the algorithm compares the intensities of subsequent pixels. If a change in intensity is observed between two pixels that exceed the threshold value then the algorithm marks the last pixel as edge and adds this pixel location to the horizontal edge map image.

For further processing it is of utmost importance to extract the boundary of the lung. In this   paper we now proposed a method for extraction of the lung boundary.

We start with the output image of the edge extraction process with the objective to identify the outermost edge line that constitutes the edge of the lung. We scan the image from the right side of the image to locate the rightmost point at the first row of the image, which is the starting point of the processing. We then consider all the surrounding pixels in a clockwise priority and consider the pixel with the highest priority. We store the pixel traversed in a Plotting List to be used later for drawing the boundary. The pixels that surrounded the starting pixel, but are of lower priority are stored in a Backtrack Stack to be used only if the traversal process reaches a dead end. If a dead end is reached, we pop out from the Backtrack stack a lesser priority pixel and continue with the traversal process. The traversal continues to the next pixel and continues till it reaches the baseline or the bottom of the image, indicating the end of the lung region. The Plotting list contains the lung boundary pixels that are plotted after smoothening for further processing.

Algorithm to Detect lung Boundary:

Step 1. Scan the image from the Left side of the image to locate the leftmost pixel of the lung region.

Step 2. Draw a vertical line along this pixel from top to bottom representing the Left baseline or boundary.

Step 3. Scan the edge map from the right side to left, from the first row.

Step 4. Obtain a pixel that is black indicating an edge path, traverse the pixel path by considering all the surrounding pixels in a clockwise priority and consider the pixel with the highest priority.

Step 5. The pixels that surrounded the edge pixel, but are of lower priority are stored in a Backtrack Stack to be used only if the traversal process reaches a dead end.

Step 6. If a dead end is reached, pop out from the Backtrack stack a lesser priority pixel and continue with the traversal process.

Step 7. Store the pixels traversed in a Plotting List to be used later for drawing the Lung boundary.

Step 8. Traversal continues to the next pixel till it reaches the left baseline or the bottom of the image.

Step 9. If the bottom of the image or the left baseline is not reached the path is discarded, the plot list is erased and continue from Step4.
Else Get pixels from the Plotting List at a discrete interval.

Step 10. Plot the first pixel.

Step 11. Draw a simple curve between two consecutive pixel position separated by the discrete interval. Continue plotting till the last pixel in the Plotting List is plotted.
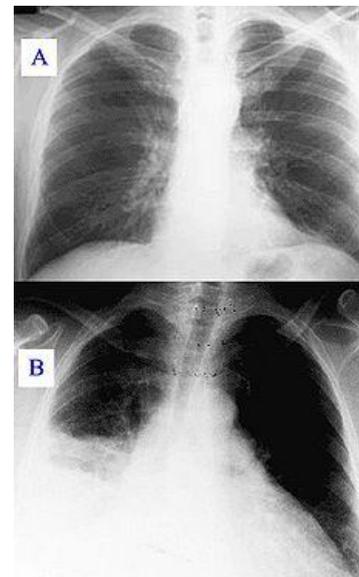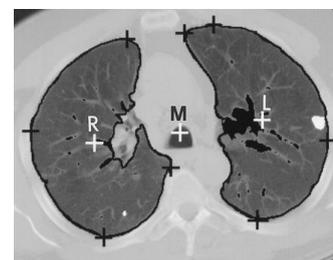

Figure 3: Lung Consolidation

Figure 4 output of the algorithm (Lung Border)

5. CONCLUSIONS

Further research will combine our method with the knowledge-based method to select the accurate boundary. Our system will also continue to diagnose the lung diseases based

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on all the information such as boundary, rib shadow and the location of the abnormal nodules of the lung.

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