

Automatic CT Image Segmentation of the Lungs with Region Growing Algorithm

Nihad Mesanovic¹, Mislav Grgic², Haris Huseinagic³, Matija Males⁴, Emir Skejic⁵, Muamer Smajlovic¹

¹ IT Sector, University Clinical Center, Trnovac bb, Tuzla, Bosnia and Herzegovina

² University of Zagreb, Faculty of Electrical Engineering and Computing, Unska 3, Zagreb, Croatia

³ Radiology Department, University Clinical Center, Trnovac bb, Tuzla, Bosnia and Herzegovina

⁴ Croatian Control Ltd., Zagreb-Airport, Pleso bb, POB 45, Croatia

⁵ University of Tuzla, Faculty of Electrical Engineering, Franjevačka 2, Tuzla, Bosnia and Herzegovina

Abstract - Computer aided diagnosis of lung CT image has been a revolutionary step in the early diagnosing of lung diseases. The best method of implementing computer aided diagnosis for medical image analysis is first to preprocess the image in order to segment it. The first step in computer aided diagnosis of lung computed tomography patient image is generally to first segment the region of interest, in this case lung, and then analyze separately each area obtained, for a tumor, cancer, node detection or other pathology for diagnosis. This is generally much easier approach, because the area used for setting the right diagnosis, is getting smaller with the process of segmentation, so the radiologist can focus his observation only on specific data inside the specific region. In this paper we proposed lung segmentation technique to accurately segment the lung parenchyma of lung CT images, which can help radiologist in early diagnosing lung diseases, but the algorithm can also be used to early diagnose other benign or malignant pathologies in other organs, such as liver, brain or spine.

Keywords - Computer Aided Diagnosis, Lung Extraction, Region Growing Algorithm

I. INTRODUCTION

Cancer, tumor and nodules that are to be examined are located within the lungs parenchyma, in an area which is usually no more than half of the area of the computed tomography (CT) image slice: this means that a lot of processing time can be saved if the segmentation algorithms only run on this inner part of the lungs area. Moreover, the number of false detection of lesions found in a segmented image is dramatically lower than that found in the same image without segmentation, because no signals at all will be found outside of the lungs. Lung segmentation is a common preprocessing step of lung CAD systems and in general of lung image analysis systems. CT datasets can contain over 1000 images, therefore manually segmenting the lungs is tedious and prone to inter observer variations. The radiology department of the university hospitals of Tuzla produces currently more than 40.000 CT images per day. That is why we implemented and tested an automatic segmentation algorithm for lung extraction from CT patient image.

II. LUNG DISEASE

Lung diseases [1] are some of the most common medical conditions worldwide. Tens of millions of people suffer from lung disease worldwide. Smoking, infections, and genetics are responsible for most lung diseases. Some of the common lung disease can be divided in these groups:

- Lung Diseases Affecting the Airways;
- Lung Diseases Affecting the Air Sacs (Alveoli);
- Lung Diseases Affecting the Interstitium;
- Lung Diseases Affecting Blood Vessels;
- Lung Diseases Affecting the Pleura;
- Lung Diseases Affecting the Chest Wall.

Most occurred ones are: asthma, acute bronchitis, cystic fibrosis, emphysema, pneumonia, tuberculosis, emphysema, pulmonary edema, lung cancer, sarcoidosis, and different kind of pulmonary edemas.

A. Lung Imaging

Imaging plays a vital role in the diagnosis of lung cancer, with the most common modalities including chest radiography, CT, PET, magnetic resonance imaging (MRI), and radionuclide bone scanning [2], but in this work, we primarily used CT images for analysis.

X-Ray imaging will show most lung tumors, but CT is used because it is more sensitive in finding tumor size and the presence of lymph node metastases. However, with CT imaging, it is not always easy to distinguish the limits between tumor and normal tissue, especially when the dense pathology is present. Recent advances in Computed Tomography (CT) technology have enabled its use in diagnosing and quantifying different diseases [3]. In particular, the expanding volume of thoracic CT studies along with the increase of image data, bring in focus the need for CAD algorithms to assist the radiologists [4]. Several lung diseases are diagnosed by investigating the patterns of lung tissue in pulmonary CT images, therefore segmentation and analysis is one of the important parts of CAD systems [5, 6].

B. CT Scan

CT or computer axial tomography, uses special X-ray tube to obtain image data from different angles around the body, and then uses computer processing of the data to show a cross-section of body tissues and organs. Some of the basic ideas underlying CT are reconstruction from projections that means that the patient data is getting measured at many positions and angles. CT modalities can show various types of tissues, lung, soft tissue and bones, and using specialized equipment and expertise to create and interpret CT scans of the body, radiologists can more easily diagnose tumor, cancer or other lesion, and to measure its size, precise location, and the extent of the tumor's involvement with other nearby tissue. The images received from a CT scanner can reveal some soft tissue and other structures that cannot even be seen in conventional X-rays.

C. Computer-Aided Diagnosis

Computer aided diagnosis of lung CT image has been a remarkable and revolutionary step, in the early and premature detection of lung abnormalities. The CAD systems include systems for automatic detection of lung nodules and 3D reconstruction of lung systems, which assist the radiologists in their final decisions. Advanced image processing algorithms are applied on the images to clarify and enhance the image and then to separate the region of interest from the whole image. The separately obtained region is then analyzed for nodule detection, tumor or cancer to diagnose the disease [7]. Efficient lung segmentation technique helps to raise the accuracy and higher decision confidence value of any lung abnormality identification system.

Computer-aided diagnosis may serve as a second reader by analyzing nodules, lesions or tumor and providing a malignancy estimate using computer vision and machine learning techniques. CAD may address some of the issues in diagnosis characterization, such as the increasing demand on radiologist's time caused by the increasing data volume, radiologist fatigue or distraction, and differences in radiologists' experience. Computers are playing an increasingly large role in radiology. In conventional radiography, X-ray images were recorded on screen-film systems, while today's radiologists view digital radiographs on display monitors. Computers have been vital in the development of medical imaging technology - without computerized reconstruction, CT and MRI imaging would not be possible. The next role for computers may be in the interpretation of images. A CAD system comprises segmentation, feature extraction, feature selection, and classification components. We aim to develop an effective CAD system that will assist radiologists in setting the right diagnosis.

CAD systems for medical images typically involve the steps of segmentation the image, extraction of various region of interest and classification of that area. Various algorithms from different authors can be found for medical image

segmentation such as thresholding [8], region growing [9, 10]. These methods may be effective for specific types of disease, segmentation of lungs is always a challenging problem due to changes in pathology in the parenchym area, or in shape and anatomic connection to neighboring pulmonary structures, such as blood vessels or pleura.

Different window width and level settings can also effect the image reconstruction [11]. These factors contribute to inaccuracies in the measured volume [12], resulting in inconsistency and uncertainty in detecting volume change in serial CT scans. Even for the identical imaging conditions, CT images will contain difference in image data, sometimes from the detector itself, noise received from the CT modality or the detectors, noise from the patient itself, or from the different procedures of the technician that is performing the scan. One example is that the starting scan position or sometimes the standard table height of the CT scanner is not always reproducible, as well as the slice locations relative to the anatomical structures are therefore not identical in repeated scans. In clinical CT exams, variabilities such as patient motion and the change in pitch size or topogram characteristics over time will further degrade the reproducibility between exams.

III. RELATED WORK ON IMAGE SEGMENTATION

Some authors explored the segmentation techniques in medical imaging depending on the region of interest [13]. The most relevant ones for our problem are atlas-guided techniques and region growing segmentation methods [14, 15]. Some of them use a semi-automatic algorithm and still need some user interaction, while others are fully automatic and the user has only a verification role.

Numerous of articles can be found regarding lung CT segmentation. Hu et al. [16] describe a method of global thresholding for that purpose. Pohle and Toennies [17] suggest adaptive region growing for segmentation of medical images. In this paper region growing is discussed using automatic tools, where the region growing algorithm learns its homogeneity criterion automatically from characteristics of the region to be segmented, and it allows a segmentation of individual structures. Segmentation of pulmonary X-ray computed tomography (CT) images is a precursor to most pulmonary image analysis applications [18]. Results in these articles are showing some limitations on test database [19], but give good results for segmentation.

Manual segmentation of lung images is extremely time consuming for users, labor intensive and prone to human errors and hence an automated technique with proven algorithm is the only road to success in CAD applications. There is no generally applicable automatic segmentation technique that will work for all images as the images itself are quite complex and unique depending upon the domain application. This paper presents an efficient region growing segmentation algorithm that can segment a region of interest into a more meaningful set of regions and objects. Our

algorithm combines automated region growing approach with optimized elimination of false edges to arrive at more meaningful segments.

In our work, we developed an automatic approach based on a region growing algorithm technique in order to segment the lung area. As it showed good results we tested it for other organs like the parotid glands (risk areas) and even on tumors with also encouraging results. After introducing the region growing method, we will present the results and limitation of the proposed method and make a discussion on future work and improvements.

In some applications segmentation may be useful to classify image pixels into anatomical regions, such as bones, muscles, and blood vessels, while in others into pathological regions, such as cancer, tumor, tissue deformities and multiple sclerosis lesions.

Image segmentation is the process of partitioning an image into regions by grouping together neighborhood pixels based on the some predefined similarity criterion. The similarity criterion can be determined using specific properties or features of pixels representing objects in the image. In other words, segmentation is a pixel classification technique that

allows the formation of regions of similarities in the image [20].

Segmentation is an important tool in medical image processing and it is been widely used in many medical diagnostic applications, such as measuring tumor volume and its response to therapy, detection of micro calcification on mammograms automated classification of blood cells, studying brain development, image registration, etc [21].

IV. MATERIALS AND METHODS FOR SEGMENTATION ALGORITHM

The main source of data for implementation of this algorithm is images from the Picture Archiving and Communication System (PACS), a system that is used for transferring the images from the modalities directly to servers, and is available immediately to users, regardless to their location. Our segmentation algorithm is composed of six main steps. We started with taking the image from the PACS, and because PACS is already doing the noise reduction of the source image, smoothing algorithm is not used. Basic algorithm can be seen on the Figure 1.

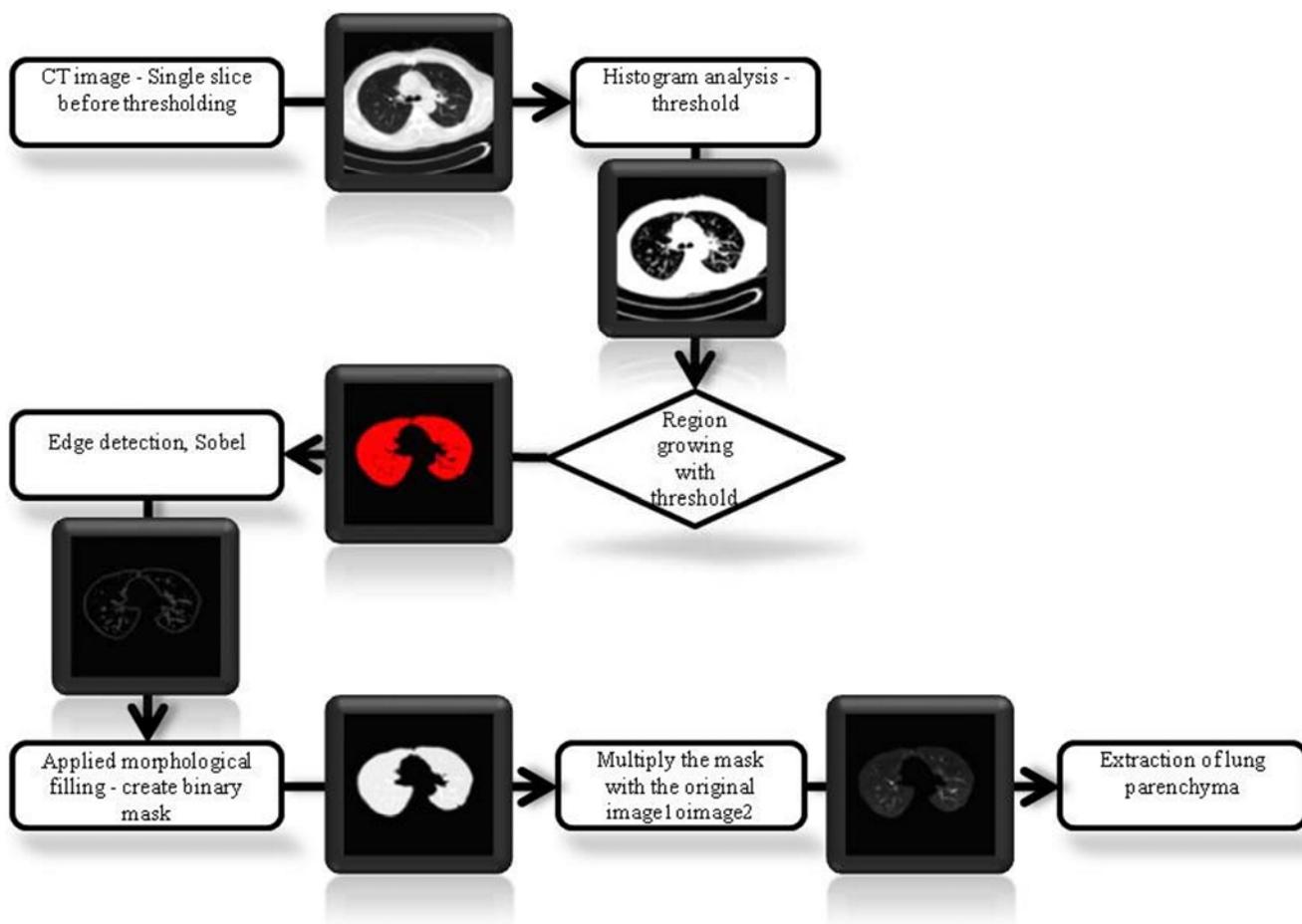


Figure 1. Segmentation process

A. Preprocessing step for the Segmentation of CT image

The first step was to convert the image to gray scale. So by converting the image to gray scale, the processing time is reduced and a faster algorithm is produced. For the removal of the table, we used a fast marching level set method and a rapid change in gradient magnitude for the segmentation. Essentially, we created a map of the biggest area, and keep only that one, after that we apply it on the image and get only thorax extracted.

B. Histogram Thresholding

Histogram thresholding is used for determination of the actual binary masks for the lung area. Binary masks are generated from input gray-level CT data using an iterative thresholding algorithm [22], a better method than the conventional thresholding algorithm, in which the threshold is simply chosen as the minimum between the two maxima of the gray level histogram [23]. The image histogram is initially divided into two parts using a starting threshold value, which can be for example half the maximum of the dynamic range of the current image, or the conventional threshold value just described.

Afterwards, the sample mean of the gray values associated with the foreground pixels and the sample mean of the gray values associated with the background pixels are computed, and a new threshold value is determined as the average of these two sample means. The process is repeated until the threshold value does not change any more.

Optimal thresholding is the first step in thresholding the image. A thoracic CT contains two main groups of pixels: high intensity pixels located in the body and low intensity pixels that are in the lung and the surrounding air. Due to the large difference in intensity between these two groups, thresholding leads to a good separation. Since our algorithm needs to handle JPEG as well as DICOM images, the proposed threshold proposed by Kemerink et al. [24] is not applicable. The method applied in our algorithm is the optimal thresholding proposed by Hu et al. [16]. This iterative procedure computes the value of a threshold so that the two groups of pixels are well separated. It works as follows: Let Th^i be the threshold value at step i and t_b , t_n be the average intensity value of body pixels, t_b with intensity higher than Th^i , and t_n intensity lower than Th^i . The threshold for step $i + 1$ is: $Th^{i+1} = (t_b + t_n) / 2$. This procedure is repeated until convergence. The initial threshold Th^0 is set to 120 which is the median gray level. When convergence is reached, the image is thresholded at value T^k . Every pixel with intensity higher than T^k is set to 0, pixels belong to body, and all other pixels are set to 1 which belongs to surrounding air.

C. Region Growing Algorithm

Region growing algorithm starts with a seed pixel, examines other pixels that surrounds it, determines the most similar one, and, if it meets certain criteria, it is included in the region.

This process is followed until no additional pixels can be added.

The region is iteratively grown by examining all unallocated neighboring pixels to the region. The difference between a pixels intensity value and the regions mean is used as a similarity measure. The pixel with the smallest difference measured this way is allocated to the iteratively grown region. This process is finished when the intensity difference between region mean and new pixel is larger than a certain threshold. Essentially, a seed pixel must be selected from which the region growing may commence. Since the aim of the lung segmentation process is the removal of the dark areas that does not belong to the actual lungs, a seed pixel must be selected from the dark region. The approach selected here finds the minimum pixel from the image on the boundary. This is a dark pixel in most cases.

Once the dark pixel coordinates are selected (background air), region growing commences in the form of marking all the pixels which lie in the 4-connected neighborhood of the seed pixel. The process is repeated for each pixel until all the black pixels are marked in the image which adjoin the areas of the lung parenchyma. This will delete the dark regions that are connected to the border of the whole image. Since the goal of the segmentation process is to segment the lung cavities, we have full liberty in assigning the same grey-level intensity to the adjoining black pixels as the lung parenchyma. To distinguish between the white regions already present in the lung parenchyma and the white regions generated because of the background air volume, the white regions of the lung parenchyma are tagged before region growing commences. This is because if the region-growing algorithm was only moderated according to gray-levels, the region growing algorithm would extend on the complete image. The enclosing property of the white parenchyma is retained by tagging the white parenchyma before region growing commences from the border regions towards the inside. After the region-growing based 4-connectivity analysis of the image, the original gray-scale image has been segmented into the lungs and trachea. The results are shown in Figure 2.

D. Edge Detection

After the region growing algorithm is finished, we applied the edge detector on the image, to create a mask for the extraction of the lungs. An edge operator is a neighborhood operation which determines the extent to which each pixel's neighborhood can be partitioned by a simple arc passing through the pixel where pixels in the neighborhood on one side of the arc have one predominant value and pixels in the neighborhood on the other side of the arc have a different predominant value. Usually operators like Sobel, Laplacian and zero-crossing operators are used for edge detection. Edge detection operators are often implemented with convolution masks and discrete approximations to differential operators. These operators may return magnitude, and some operators may return magnitude and direction information.

E. Binary Mask and Image Filling

After edge detection, morphological binary closing [25] is applied to each mask to close the borders of the edges, we conclude that the mask will not be created properly if this is not done, sometimes few pixels are missing, usually caused by noise. The structuring element is a disk of radius 1. Finally edges outside the lung region are filled. Extraction is done by combining the regions of binary map of the entire lung (BW1) and from binary map of just its edges (BW2).

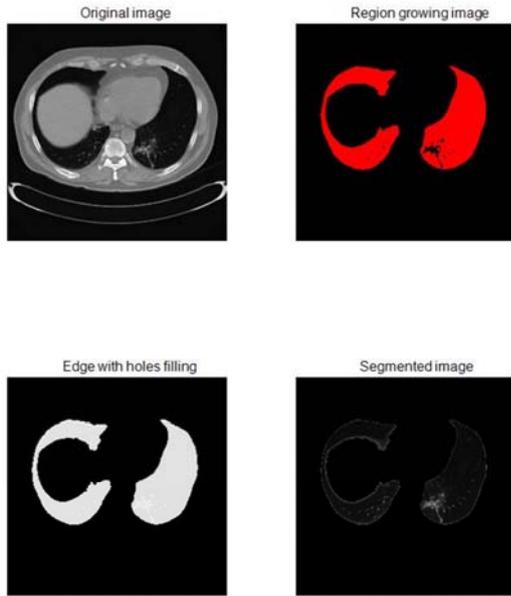


Figure 2. Result of the proposed method

V. RESULTS

The thorax CT image data for this work was acquired on one 64-slice Siemens Sensation 64 and one 6-slice Siemens Sensation 6 CT scanners using a standard contrast enhanced imaging protocol with slice thickness between 1 - 5 mm. The data are composed of 50 patients, representing a range of patients and pathology. All lungs were automatically segmented by an experienced radiologist and confirmed by another radiologist, as reference for evaluation purposes. Segmentation program was performed using Intel Xeon 5140 2.33 GHz server with 4 GB RAM. The computational time for each segmentation varied from 5 s to 20 s per slice. Results can be seen in the Figure 3.

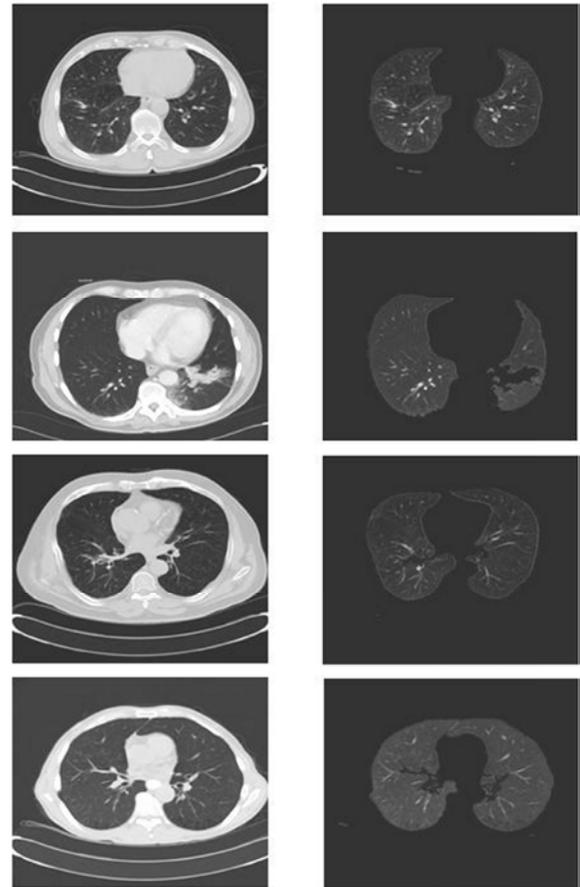


Figure 3. Some results of the proposed method

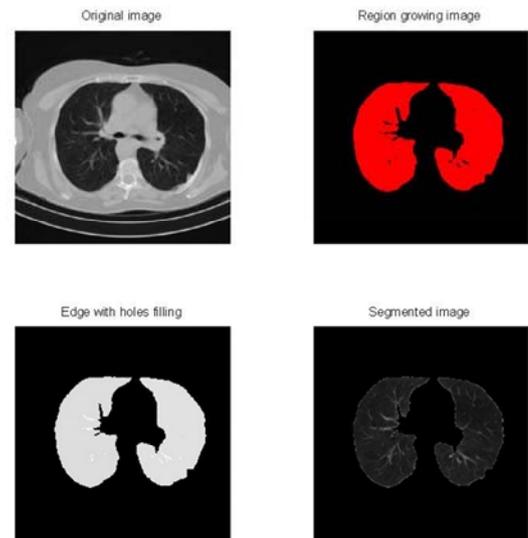


Figure 4. Example of the limitation of the proposed method. Lung nodule attached to the right ribs is not detected.

After applying region growing algorithm on the images shown in Figure 1, we applied this algorithm on the images received from AGFA PACS, Public Health Institution Tuzla, Bosnia and Herzegovina. However, the results shown in Figure 3 depict that the algorithm does not give the satisfied results. Figure 3 shows that a portion of the lungs, where the lung nodule is found, and the algorithm is not accurately finished with the segmentation process on the image, or at least it missed it. So we can conclude that in case of the lesions attached to pleura, this algorithm is not precise.

VI. CONCLUSION

The segmentation algorithm starts off with choosing the seed pixel from the dark side of the image. In case that the thorax is touching the edges of the image, one pixel is added to the edge of the image as the border, to ensure the segmentation process to finish exactly. In other case, we need to make sure that for each region of background that touches the border, we need to choose a seed pixel for the region growing algorithm. The optimum threshold for each patient CT set depends on the following basic factors, tissue and air volume, density units of tissue, image acquisition methodology and contrast in the image for the lung parenchyma. Also, the optimum threshold is selected for each image in each from the selected series.

Segmentation process of the lungs from thorax CT images is shown to be helpful to radiologist, because the focus for the analyzing the images is set only to the lungs, so users can pay their attention only on the region of interest. However, in the area where the lesion is touching the pleura, it is shown that the algorithm can be more precise, so that all the pixels will be included in the region of interest. This approach can be evaluated in the future studies.

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