Survey of Segmentation Techniques for CT Lung Scans

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***Abstract*— A survey of important papers in the area of lung and lobe segmentation is presented. The selected works focus on the use of image processing technique to solve the segmentation problem. The method and significant result of each work is given, with comparisons where appropriate.**

Keywords—lung segmentation, image processing, computed tomography, survey

I. Introduction

This paper presents a survey of methods for lung and lobe segmentation of lung scans. This investigation is limited to non-deep learning methods, focusing instead of traditional image processing techniques. The papers are presented in chronological order, with significant dependencies between works noted.

Methods in the earlier papers are tested on very small datatsets, which provide few quantitative results for evaluation. Many of the papers published after 2010 make use of the dataset from the LObe and Lung Analysis 2011 (LOLA11) challenge [1]. This dataset consists of 55 CT scans for which the lobe labeling had been performed. The scans include a number of abnormal cases, making the task more difficult than one using only scans from healthy patients, thus perhaps providing a better “real world” test. The labeled data is not publicly available, rather a researcher can submit a set of labeled scans to the LOLA11 organization and receive a mean overlap score (intersection over union). This provides the community with a larger labeled dataset than had been previously available as well as a consistent scoring method for comparing segmentation systems.

II. Method for Segmenting Chest CT Image Data Using an Anatomical Model: Preliminary Results [2]

Brown et al. developed an automated knowledge-based system for segmentation of lung CT datasets. This system makes use of classic Artificial Intelligence techniques of an inference engine backed by a blackboard architecture for inter-component communication. The system is designed to identify the various structures in and around the lungs, as well as isolating and segmenting pulmonary nodules. Although the system was tested on a small number of scans, several useful conclusion were drawn from this project.

The method presented here was later evaluated against the LOLA11 dataset in [8].

A. Approach

The system architecture is composed of four major components. An anatomical model was created using a frame-based semantic network. This model encodes a description of the relevant anatomical structures, such as the lung tissue, chest wall, mediastinum, and central tracheobronchial tree. Fuzzy sets are used to account for anatomical variations.

The anatomical model is used to drive the image processing module. This component uses techniques such as gray-scale thresholding, 3D region growing, and mathematical morphology to extract areas of interest from the 3D image data. The image processing routines generate lists of candidates for each structure of interest.

An inference engine is used to couple the image-based information with the anatomical model to select the anatomical structure from among the candidates produced. The model contains information about the expected parameters of each structure as well as knowledge about the relationships between structures. For example, the model knows there should be two lungs, and the tracheobronchial tree should be located roughly between them.

The final component is a control system which schedules and coordinates the processing of the anatomical, image processing, and inference engine models. The control system module also manages the blackboard, which is used for communication between the four parts of the system.

B. Dataset

The system was tested on scans from seven subjects, two healthy individuals, and five patients with emphysema.

C. Evaluation

The results from the system were evaluated subjectively by experienced thoracic radiologists. In the absence of a larger, annotated dataset, this is a reasonable approach for a preliminary investigation, though the authors do state that a more rigorous approach is desired.

The authors are able to segment the tested scans with some degree of success. As part of the evaluation, the authors identify four issues that must be dealt with to solve the segmentation problem, which are still relevant today.

1. Structures to be segmented are not continuous in 3-D. This can be caused by structures being parallel to the scan plane, or if the voxel spacing is too large. This discontinuity

can be problematic for the identificatioin of blood vessels and airways.

2. Structures cannot be segmented by available low-level algorithms. Although the authors were able to use morphology and thresholding to isolate the structures in the lung area, they are concerned that segmenting structures which do not exhibit such a wide variation as that between air and soft tissue elements will prove difficult using existing techniques.

3. There may be an unusual orientation or ordering of the images. The anatomical model developed for this project assumes the scan is created in a particular orientation. If the orientation was to be altered the anatomical model would have to be revised.

4. The set of features may be unable to precisely discriminate between structures. One example given of this is the inability of the system from distinguishing between a nodule on the chest wall and a soft tissue area just outside the cell wall.

III. Automatic Lung Segmentation for Accurate Quantitation of Volumetric X-Ray CT Images [3]

In this paper Hu et al. describe a procedure for segmenting the two lung areas from a CT chest scan. The methods presented here have withstood the test of time and form the basis of the image processing steps of later works [4], [10], and [13]. The system is tested on a small number of CT scans and compared with manual segmentation results.

A. Approach

The method involves four major steps. First gray scale thresholding separates the lung volume from the surrounding tissue. This is followed by connected component analysis to identify the two lung areas. Then the left and right lungs are separated using a dynamic programming algorithm. Finally a set of morphological operations are used to smooth the boundary and fill internal holes, which provides a better match to the manually segmented data.

One difficulty in using thresholding to separate the air filled lung tissue from the chest wall is the selection of an appropriate threshold. Hu uses an iterative procedure to determine an optimal threshold. The threshold is determined by comparing the mean gray level of the pixels above and below the current threshold.

After thresholding, 3D connected component analysis is used to extract the lung tissue from other structures such as the trachea and main bronchi.

The result of the connected component analysis will often produce a lung mask in which the left and right lungs are connected. To separate the two lungs each axial slice of the 3D image is processed. A dynamic programming algorithm finds the maximum cost path across the image, effectively splitting the two lungs at the junction point.

The left and right lung masks are then independently smoothed using a morphological opening operations. This step also removes the large airways. The left and right masks are dealt with separately to avoid rejoining the two lungs.

B. Dataset

The system was evaluated on CT scans from eight normal subjects. Three sets of scans were taken, at approximately two week intervals, for a total of 24 scans.

C. Evaluation

The performance of the system was evaluated by comparing the generated segmentation with manual analysis. Two image annalists manually traced the left and right border on every fifth slice for 12 of the image data sets. The mean, root mean squared (rms), and maximum distance between the generated segmentation border and the manually defined border is used to evaluate the system.

The results are shown in Fig. 1 and 2 (reproduced from the original paper). The system was able to reliably produce the same outline as the human analysts to within a few pixels. The results with smoothing are more accurate, although there is a danger that smoothing parameters empirically derived to match the observer performance may not be generally applicable.

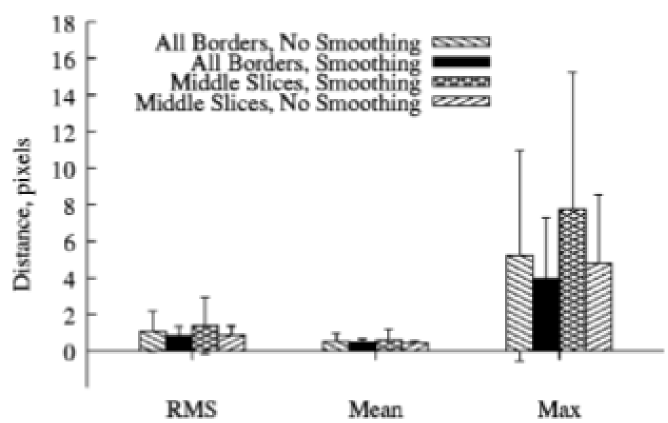

Fig. 1. Border position accuracy for automatic method versus observer 1

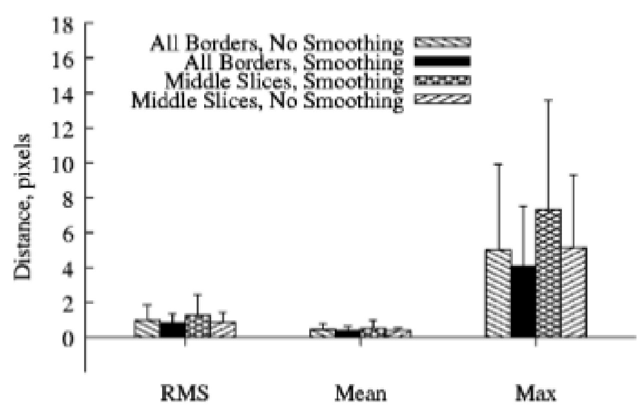

Fig. 2. Border position accuracy for automatic method versus observer 2

IV. Lung lobe segmentation by anatomy-guided 3D watershed transform [4]

This work uses an interactive watershed algorithm to segment the lung lobes. Although not a fully automated process, the methods developed here serve as a foundation for later works.

A. Approach

The system starts with a process similar to that described in [3] for separating the lungs from the surrounding tissue. The major contribution of this work is using that result as a starting point for the lobe segmentation.

The gray scale image data is not sufficient to directly allow a watershed algorithm to separate the lung lobes. Additional anatomic information was supplied by segmenting the blood vessels within the lungs, and developing a distance map from each voxel to the nearest blood vessel.

This distance map was combined with the image data to develop the cost function used as input to an interactive watershed algorithm. The interactive nature of the algorithm allows a user to provide input to guide the segmentation when the cost function does not provide sufficient information to identify the lobe boundaries.

B. Dataset

The system was tested on CT scans of 24 patients, many with abnormal scans containing tumors, emphysema, fibrosis, and atelectasis.

C. Evaluation

The method was successfully applied to each of the 24 scans, without undue interaction from the user. The authors were not able to acquire manually generated segmentation results for comparison. An intra-observer study was performed to demonstrate consistent results using the developed method.

V. Adaptive Border Marching Algorithm: Automatic Lung Segmentation on Chest Ct Images [5]

In this paper, Pu et al. demonstrate an interesting method for dealing with one particular aspect of the lung segmentation problem, that of correctly segmenting nodules attached to the chest wall. These juxtapleural nodules appear as bumps in the otherwise smooth border between the lung and the chest wall. Without addressing these nodules as a special case, an algorithm may either under segment the lung and not include the nodule, or over segment non-lung structures, including more of the chest wall than is necessary. Under segmenting has the potential to miss identifying a tumor, while over segmenting increases the computational burden of any following steps.

A. Approach

Before applying the adaptive border marching (ABM) algorithm, a CT scan is first processed to separate the lung region from the surrounding tissue. This is accomplished by first applying a Gaussian smoothing filter, followed by a gray scale thresholding, and a region floodfill algorithm to remove any small non-lung regions.

The ABM algorithm is then applied to each axial slice of the scan. First, the border between the lung and cell wall is identified using an inner border tracing algorithm. Then the marching algorithm traces around the border, matching areas that appear as small bumps in the border. One key to this algorithm is that the step size around the border is adapted to include hemispherical structures. These structures are identified by measuring the width to height ratio, allowing the inclusion of nodules while excluding other structures. Fig. 3 shows one such structure and the resulting border found by the ABM algorithm.

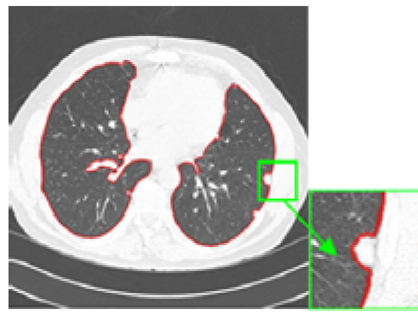

Fig. 3. Juxtaplueral lung nodule included by ABM

B. Dataset

The system was tested on a dataset of 20 CT scans. The scans were evaluated by a panel of three radiologists, who identified 67 juxtaplueral nodules. The contours where manually segmented by one radiologist and this was used as the reference standard.

C. Evaluation

The authors used three measures for evaluating their procedure: inclusion ratio of the juxtaplueral nodules, per-voxel over segmentation and under segmentation rates.

The ABM algorithm was able to identify and include all 67 juxtaplueral nodules. The algorithm produced an average over segmentation error of 0.43% and an under segmentation rate of 1.63%, which was deemed to be a reasonable result.

The key takeaway from this work is that although general methods such as thresholding and smoothing can accomplish much of the segmentation problem, there are subproblems particular to lung segmentation that may need very specific solutions.

VI. Lung and Lung Lobe Segmentation Methods at Fraunhofer MEVIS [6]

This short paper describes the authors approach to the LOLA11 challenge, building on the work first presented in [4]. The work is further extended in [10].

A. Approach

In this paper the authors present an automated method for lung segmentation, followed by three methods for lobe segmentation. The lung segmentation method follows the same model described in [3] and [4]. This approach uses a combination of image processing techniques to identify the two lung areas.

All three lobe segmentation methods presented are based on watershed segmentation using the image data, segmented blood vessels, and airways. The methods vary in the amount of automation provided. The authors compare a fully automated method, a semi-automated method which allows the user to manipulate the seed points used by the watershed process, and a iterative process in which the user can modify the lobar boundary directly where necessary.

B. Dataset

This work was evaluated using the LOLA11 dataset.

C. Evaluation

The LOLA11 challenge provides a comparison with ground truth data. The measure used for evaluation is mean overlap between the labeled scan and the ground truth. The authors report a 97.3% mean overlap for the lung segmentation. For the lobe segmentation mean overlap scores of 88.1%, 91.8%, and 92.3% are given for the fully automated, semi-automated, and iterative methods.

VII. Keuhkot: A Method for Lung Segmentation [7]

This paper presents a method for lung segmentation using the LOLA11 dataset. The segmentation method uses a slightly different approach from that described in [3] and [4].

A. Approach

The described method consists of a sequence of several steps. The first step, patient extraction, consists of thesholding and connected component analysis to remove the patients soft tissue and areas outside the body.

This is followed by a localization of the trachea by looking for an elliptical region of the expected size, in or near the expected area. The trachea location is then used as a seed point for a region growing algorithm to segment the airway tree.

Once the airway tree is removed, a graph-cut algorithm is used to separate the two lung volumes. This is followed by a morphological opening operation to smooth the final lung mask.

B. Dataset

This method was tested against the LOLA11 dataset.

C. Evaluation

The authors report a mean overlap score of 94.8% for the lung segmentation. They note that dealing with the variations in the images, due to either imaging artifacts or anatomical anomalies, created significant difficulties.

VIII. Historic Automated Lung Segmentation Method: Performance on LOLA11 Data Set [8]

In this work the authors apply the method described by Brown, et al. [2] to the LOLA11 dataset.

A. Approach

The system evaluated is an implementation of the system described in above in the discussion of [2].

B. Dataset

The system was tested using the 55 scans of the LOLA11 dataset.

C. Evaluation

The authors report a mean overlap score of 96.3% for the lung segmenation, which compares favorably with other techniques.

IX. Automated 3-D Segmentation of Lungs With Lung Cancer in CT Data Using a Novel Robust Active Shape Model Approach

This work focuses on the problem of segmenting diseased lungs. In particular, the dataset used contains CT scans with large cancerous regions which introduce non-trivial problems to the segmentation task.

A. Approach

To deal with the problem of identifying the lung tissue in the presence of large cancerous regions, which may appear similar to the soft tissue outside the lung area, the ribs are used as a first clue to the lung location. A rib detection algorithm is used to define the outside border for the possible lung region.

A robust active shape model (RASM) approach is then used to roughly find the lung boundaries. This is followed by a smoothing algorithm to produce the final segmentation.

B. Dataset

The system was tested on 30 CT scans which contain 20 normal lungs and 40 cancerous left/right lungs.

C. Evaluation

The authors report a Dice coefficient score of 97.5% and a mean absolute surface distance error of 0.84 mm. This work is another example of how solving the lung segmentation problem may require additional or novel information, such as the rib location, especially for abnormal cases.

X. Automatic Segmentation of the Pulmonary Lobes From Chest CT Scans Based on Fissures, Vessels, and Bronchi [10]

This work describes a fully automated extension of the work presented in [6]. The lobe segmentation is accomplished using a marker-based watershed algorithm. The authors show a high level of success on the LOLA11 dataset, as well as a second dataset consisting of 20 CT scans from healthy subjects.

A. Approach

Segmentation of the two lungs is performed using the same approach as the earlier works by this group of researchers ([3], [4], and [6]). The novelty of this work is in the fully automated lobe segmentation.

In order for the watershed segmentation algorithm to succeed, an accurate cost function is required. The authors construct such a cost function by combining information from the original image with other pieces of anatomical information.

To construct a model of the fissure locations, the Eigen values of the Hessian matrix of the image are computed. The fissures create a sheet-like structure, which can be identified by comparing the magnitude of the three Eigen values. For voxels which are part of a fissure, we expect the magnitudes of λ_1 and λ_2 to be very small and that of λ_3 to be relatively large. Based on this observation a somewhat complicated formula is constructed to estimate a fissure-ness measure.

The second piece of anatomical information used is the location of the blood vessels. Blood vessels generally do not cross the lobe boundaries, so the distance to a vessel can be used as an additional measure for locating fissures. The contrast difference between blood vessels and the lung tissue is sufficiently large to allow segmentation of the vessels using a thresholding technique.

The location of the bronchial tree is the final piece of information used. Like the blood vessels, the bronchial tree does not cross lobe boundaries. After segmenting the airways, a distance map is created to identify potential fissure locations.

The final watershed cost image is constructed by combining the original image data, the fissure-ness map, the blood vessel distance map, and the airway distance map. The locations of the ends of the major bronchial tree segments are used as seed points for the watershed algorithm, as each lobe is fed by a different segment. By making use of all the available data the watershed algorithm is able to successfully divide the lungs into the component lobes.

B. Dataset

The system was evaluated on two datasets, the LOLA11 dataset and a collection of 20 CT scans which have been manually segmented.

C. Evaluation

At the time this paper was published the authors had achieved the highest score for lobe segmentation on the LOLA11 challenge. The scores are shown in Table 1.

TABLE I. MEAN, STANDARD DEVIATION (SD), MINIMUM, MAXIMUM, AND MEDIAN OVERLAP SCORES ON THE LOLA11 DATASET

Lobe	mean	SD	min	max	Median
LUL	0.92	0.16	0.20	1	0.98
LLL	0.89	0.23	0	1	0.96
RUL	0.92	0.09	0.60	1	0.96
RML	0.77	0.30	0	0.99	0.89
RLL	0.91	0.18	0	1	0.97
LOLA score	0.88				

Overall the approach seems able to provide reasonable results. The scores do point out some difficulties. Segmentation of the smaller right middle lobe is particularly difficult, with only a 77% mean overlap and at least one scan missing the lobe entirely. The minimum values of 0 for both lower lobes also indicate that these lobes were not identified in some scan. The high median score shows that for most scans the algorithm was able to generate a reasonable segmentation. Most likely the few severely abnormal cases in the LOLA11 dataset resulted in failed segmentation, accounting for the missing lobes.

XI. AUTOMATIC LUNG LOBE SEGMENTATION AND FISSURE EXTRACTION USING ITEMPLS METHOD ON COMPUTER TOMOGRAPHY IMAGES [11]

This brief paper describes a method for lobe segmentation based on a supervised, iterative approach to identifying the fissure locations. The fissure locations are used to train a fissure model from the population which can be used to guide further segmentation. This idea has some overlap to the method developed in [13].

The LOLA11 dataset was used to develop the system, although no results from the LOLA11 challenge are given.

A. Approach

The authors present a detailed algorithm for performing an adaptive thresholding to find an initial lung mask. This is followed by morphological operations to remove blood vessels and air holes.

To identify the fissures, the image is presented to the user in a log scale. This highlights the relatively bright fissures against the darker background. A Euclidean distance transform based on previous training data is also used to guide the user in selecting the fissure locations. Once the fissures have been identified a region growing algorithm is used to label the lobes.

B. Dataset

The system was developed using the LOLA11 dataset.

C. Evaluation

The authors state that the system is able to segment the scans of the LOLA11 dataset, although no quantitative data is presented.

Two interesting contributions of this work are the adaptive thresholding algorithm which may compare favorably from that used in [3] and [4], and the use of fissure locations from previous scans to guide future segmentations.

XII. 3-D Lung Segmentation by Incremental Constrained Nonnegative Matrix Factorization [12]

This paper presents a method for lung segmentation of 3-D data using matrix operations rather than more standard image processing techniques.

A. Approach

Rather than using a gray scale thresholding based technique for segmentation, this work proposes using matrix factorization to identify the transformations implicit in the image data.

An initial preprocessing step is used to remove the background. Then each axial slice is processed independently. Although the math can be done in 3 dimensions, the computational cost is prohibited and a slice-by-slice approach is used instead.

The authors present a detailed construction of the matrix operations making up their Incremental Constrained Non-negative Matrix Factorization. Ultimately, each voxel is represented by a context vector based on its 3-D neighborhood. Based on how the context vector is constructed, the values should form two clusters in the n-dimensional space, one for lung voxels and one for non-lung voxels. Once all the voxels have been processed a simple clustering algorithm is used to identify the lung voxels. The final 3-D lung volume is refined using a connected component analysis.

B. Dataset

The method presented was evaluated on two datasets, the LOLA11 dataset and another dataset consisting of CT images from 17 patients.

C. Evaluation

On the full LOLA11 dataset this method scored 96.5%. Some of the severely abnormal scans cause this method to struggle. Removing nine worst case scans, the method achieved a mean overlap score of 98.6% on the remaining 46 scans.

These results demonstrate that the approach has promise. In the more difficult task of lobe segmentation, incorporating this approach may improve the performance of existing approaches.

XIII. Pulmonary Lobe Segmentation With Probabilistic Segmentation of the Fissures and a Groupwise Fissure Prior [13]

This work uses an approach similar to that of [10] to perform lobe segmentation. After an initial segmentation of the lungs, a watershed algorithm is used to segment the lobes. A major problem in lobe segmentation is incomplete or missing fissures in the image data. The key innovation of this work is the use of a probabilistic fissure prior to provide a reasonable approximation of the fissure location in the absence of clear image data.

A. Approach

The first step in the process is segmentation of the lungs using the approach given by Hu, et al. in [3]. Next, the blood vessels and airways are segmented and removed from the lung mask.

A map of the fissure locations is created using the Eigen values of the Hessian matrix of the image data. This is similar to the approach in [10], although a different measurement is developed for identifying the fissure voxels. In this work the measure is viewed as a probability of the voxel belonging to a fissure.

Another innovation of this work is the creation of a groupwise average fissure model. The fissure locations of previously processed scans are averaged together after a registration process. The result is also viewed as a probability map, providing a probabilistic prior. This map provides a clue to the most likely fissure locations in the case where a fissure is incomplete or missing in the original image data.

The watershed cost image is created by combining the fissure measure with the groupwise prior, the vessel and airway distance maps, and the image data. The exact formulation is inspired by but slightly different from that used in [10]. The airway branches are used to generate the seed points for starting the watershed algorithm.

B. Dataset

Two datasets were used for this project; the LOLA11 dataset and 30 scans from patients from the chronic obstructive pulmonary disease COPDGene study.

C. Evaluation

At the time this paper was published the authors report the highest score among fully automated methods in the LOLA11 lobe segmentation challenge. The mean and median overlap scores are shown in Table 2.

TABLE II. Mean and Median Score on the LOLA11 Dataset

Lobe	Mean	Median
LUL	0.906	0.975
LLL	0.880	0.962
RUL	0.928	0.980
RML	0.799	0.891
RLL	0.908	0.976
Overall	0.884	0.950

As stated, these results are higher than previous works. The trends between the various lobes remain the same, with the right middle lobe being the most difficult.

XIV. Conclusion

We can draw some interesting conclusions from this review of the literature on lung and lobe segmentation. Traditional image processing techniques such as thresholding, connected component analysis, and morphological operations seem sufficient to perform segmentation of the lungs in many cases. However, as shown in [9], for severely abnormal scans more information, such as a segmentation of the rib cage, may be needed.

Lobe segmentation is much more difficult than lung segmentation. The pulmonary fissures that define the lobe boundaries are difficult to find consistently in the image data. The preferred approach to this problem seems to be using a watershed algorithm and including as much information as possible into the cost function. Including clues from the locations of blood vessels and airways [10] and data from previously segmented cases [13] achieved the best results on the LOLA11 challenge. However, the lobe segmentation results are still far below the results for lung segmentation, leaving much room for improvement.

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