AUTOMATED 3-D SEGMENTATION OF LUNG WITH LUNG CANCER IN CT DATA USING A NOVEL ROBUST ACTIVE SHAPE MODEL APPROACH

Vaijayanthimala J, Lakkshaya JS, Kanimozhi M, Aswini S, Haridharani S

[1] Assistant Professor, Department of Computer Science and Engineering, Dhirajlal Gandhi College of Technology, Tamilnadu, India

[2,3,4,5]Final Year Student , Department of Computer Science and Engineering, Dhirajlal Gandhi College of Technology, Tamilnadu, India

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Abstract - Segmentation of lungs with (large) lung cancer regions could be a nontrivial problem. Our method consists of two main processing steps. First, a novel robust active shape model (RASM) matching method Applied to roughly segment the outline of the lungs. The initial position of the RASM is found by means of a skeletal structure detection method. Second, an optimal surface finding approach is employed to further adapt the initial segmentation result to the lung. Experiments on the identical 30 data sets showed that our methods delivered statistically significant better segmentation results, compared to 2 commercially available lung segmentation approaches. Additionally, our RASM approach is mostly applicable and suitable for big shape models.

***KeyWords:* lung cancer, lung segmentation, computed tomography, active shape model, lung nodules.**

1. INTRODUCTION

Lung cancer could be a major reason behind cancer-related deaths; it can be detected early by detecting the lung nodules. The main idea of this project is to detect lung nodule and to classify nodules as cancerous and non-cancerous using Genetic Programming-based Classifier (GPC) technique. Thus the lung CT image is subjected to varied processing steps and features are extracted for a collection of images. The processing steps include thresholding, morphological operations and have extraction. By using these steps the nodules are detected and segmented and a few features are extracted. The extracted features are tabulated for future classification.

The x-ray computerized axial tomography (CT) provides a 2D transaxial sectional map of the linear attenuation coefficient mirroring morphological details of the organs under study. Because it is mostly recognized, X-ray CT could be a high spatial resolution and wide dynamic range imaging modality, where, even rather small meaningful density abnormalities are often detected. Contour extraction often occurs as a pre-processing step of a more global image analysis task. It happens to be the case of computer aided analysis of pulmonary X-ray tomograms 1 where many analysis algorithms start by correctly identifying each one of the pulmonary regions. With modern spiral CT machines lung imaging is usually performed at high resolution settings both at the sectional and longitudinal levels. The overall result's an ever-growing volume of data justifying the development of more efficient and accurate segmentation procedures. Fast segmentation procedures also are definitely important for 3D visualization purposes where a batch of slices may need to be prepared for surface or volume rendering. During this work, we present a completely automated and fast method, which is ready to perform pulmonary contour extraction and region identification.

2. EXISTING SYSTEM

The robotic quantification of lung disease requires the segmentation of lung parenchyma in an early giving out step. Normal lungs imaged with CT, a large thickness difference between air-filled lung parenchyma and surrounding tissues. To enable computer-aided cancer treatment preparation (e.g., surgery or radiation treatment) and to make easy the quantitative review of lung cancer loads, robust lung segmentation methods are required. The segmentation of lungs with large cancer area at ability locations. For example, a Bezier surface-based method was proposed in to deal with injury adjacent to the chest wall and mediastinum. “Break-and-Repair” strategy which was use to segment lungs with juxtapleural lung nodules. A new approach for the fully automated segmentation of lungs with lung cancer regions which addresses the limitations of existing methods like robustness or processing speed.we provide a performance comparison with two commercially available methods on the same image data. Both methods are used routinely in the context of lung radiation Treatment planning. Approach addresses this issue the vigorous matching algorithm is specifically designed to take advantage of general-purpose computation on graphics processing units, which reduces the execution time considerably.

2.1 Drawbacks

- ✓ Limitation robustness or processing speed.
- ✓ The lung shape is encountered cannot be explained by using model.

- ✓ Mostly target population is depending upon the missing data.
- ✓ A more dense mesh vertex in combination with an adaption of search profiles is required

3. PROPOSED SYSTEM

Our robust model matching method successfully deals with outliers and other disturbances. The optimal surface finding step after robust ASM segmentation reduces the necessity to feature new lung shapes to the learning set. Pneumothorax or pleural effusion is difficult to segment automatically, and our model-based approach might require some additional processing steps. Performance may be further improved by utilizing more complex cost functions for model matching and optimal surface finding, which might be supported the relative location of shape points moreover as density/gray-value properties and shape features. The detected ribs are only utilized for model initialization, but can provide valuable information for cost function design. The proposed work targets larger cancer masses and is not optimized for handling junta pleural nodules. Left and right lungs are segmented separately, which might cause inconsistencies. We have utilized a straightforward cost function supported gradient magnitude and direction. The performance may be further improved by utilizing more complex cost functions for model matching and optimal surface finding which might be supported the relative location of shape points moreover as density/gray-value properties and shape features.

3.1 Advantages

- ✓ Processing time get raise.
- ✓ Parallel processing.
- ✓ Only one model needs to be matched to volumetric image data instead of several data sets
- ✓ Reduces the execution time

4. IMPLEMENTATION

The implementation contains collection of CT images and processing the images by novel robust active shape model (RASM) approach. The implementation of project includes RIB detection and ASM matching for optimal surface finding.

The noise and other high recurrence segments are evacuated by filters and prepare the datasets for additional processing. It is an optimal filters and has the ability of dealing with noise. The following System is the procedure for process the information.

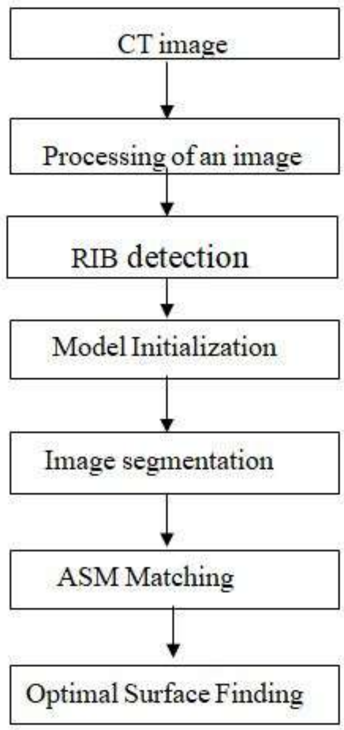

Fig-4(a) Dataflow diagram

5. MODULE DESCRIPTION

5.1 Processing of an image

Processing an image is to enhance the image quality. Preprocessing is the method of include smoothing, sampling, and filtering. In this method we are going to do reduce the noises by using filters. Filtering is used to remove the unwanted noises in an image. A common image processing task is to apply an image processing algorithm to a series of files. This procedure can be time consuming if the algorithm is computationally intensive, if you are processing a large number of files, or if the files are very large. This demo shows how to batch process a set of image files in parallel.

Fig-5(a) Input image

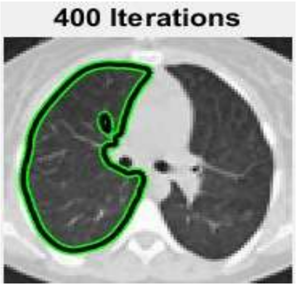

Fig-5(b) preprocessing Image

5.2 Model Intialization

The model initialization method which is based on a novel rib detection approach that is suitable for normal or contrast enhanced CT scans. Initial shape and pose (size, rotation, and location) parameters of the ASM need to be determined.Here in this module we are going to segment the lung cancer image by region segmentation process. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. Threshold method is used to segment the left and right lungs.

Fig - 5(c) Model Initialization

5.3 optimal Surface Finding

The PDM (point distribution model) can be used for lung segmentation by matching the model to the target structure. It has a standard ASM matching framework. An instance of the shape model is generated and placed in proximity to the target structure. The algorithm transforms the segmentation problem into a graph optimization problem, which is solved by means of a maximum-flow algorithm. Here in this module we add the noise to the original image and we remove through denoising process is made through approximation algorithm. After the edge surfaces in the neighborhood are approximated by a surface template, the neighborhood is divided by the surface template into sub neighborhoods.

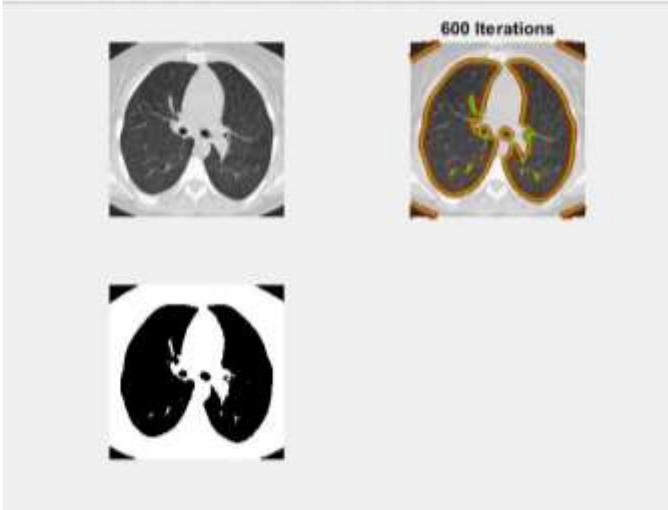

Fig-5(d) Optimal Surface Finding

6. CONCLUSIONS

The fully automated segmentation of lungs with Lung cancer regions was presented. The robustness and effectiveness of our advance was demonstrated on 30 lung scans containing 20 normal lungs and 40 diseased. Lungs where usual segmentation methods frequently fail to deliver usable results. Low segmentation errors were achieved in cases with and without high-density pathology, compared to two clinically utilized methods. The presented approach to lung segmentation exposes new avenues for computer-aided lung image analysis. A core component of our method may be a novel robust ASM matching method. The approach not only allows addressing disturbances but it is also well suitable for large shape models and parallel implementation, allowing low computation times. Our robust ASM framework is additionally applicable to other segmentation problems furthermore as imaging modalities, requiring mainly an adaption of the matching cost function.

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