Segmentation of Lung Nodules in CT scan Using Four Direction Thresholding Approach

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Abstract - Computed tomography technology is one of the important technology techniques, which shows the inside part of the human body through scanning the specific area. FDT Technique aims to augment the precision of the CT image thresholding by implementing an advanced thresholding approach from four different directions. Based on the FDT technique, the foreground and back ground pixel values of the adjacent pixel intensity value. Based on the intensity value, final decision is made based on all four directions. FDT method has been evaluated on different CT images with an aspect that the neighbor pixels in precision of thresholding. The effectiveness of FDT technique is demonstrated by means of the new approach Four Directional Thresholding (FDT) technique. This FDT technique segments the pulmonary parenchyma in Computed-Tomography (CT) images using the Similarity-Based Segmentation (SBS). This FDT technique aims to augment the precision of the CT image thresholding by implementing an advanced thresholding approach from four different directions. In which the determination of pixels' value as being either on foreground or background .With the phenomenon that background pixel's intensity highly dependent on its adjacent value and the final decision is made based on all four directions' thresholding results. In this study the precision of thresholding with FDT technique is implemented and the importance of neighbor pixels in it is demonstrated. The effectiveness of FDT method has been evaluated on different CT images.

Index Terms – CT Images, FDT, Thresholding,

1. INTRODUCTION

The lung nodule detection, segmentation, and classification problem is a challenging endeavor especially when the focus is early detection and classification of lung cancer. Computer vision and machine learning approaches have been used to create computerized methods of diagnosis, commonly called computer-assisted diagnosis (CAD), from various imaging modalities. In reading the chest CT, for example, radiologists are able to differentiate changes in image intensities or Hounsfield Units (HU) of physiological tissues and abnormalities. Radiologists use observable shape, intensity, texture and size as measures of discrimination between the anatomies of healthy lung tissues and various abnormalities.CAD models are built to mimic the radiologists and aim at enhancing the quality of the diagnosis for early detection of lung cancer. Lung cancer is a leading cause of death worldwide [1], and the best chances for survival come with early detection. CAD systems involve nodule detection, categorization and segmentation. It is a very important area of biomedical image analysis in which computer vision, image processing, visualization, and machine learning approaches have played major roles in the development and validation of these systems[2]–[4]. Object segmentation is a traditional task in image analysis, in this paper lung nodules are the objects that will be segmented. Real world objects are hard to model precisely; hence the segmentation process is never an easy task. It is even more of a challenge with the lung nodules due to the size constraints when the nodule is less than 1 cm. Segmentation will allow radiologists to measure and follow up lung nodules size which is one of the most reliable indicators of malignancy of some nodule types [5], [6]. The lungs are a complex organ which includes several structures, such as vessels, fissures, bronchi or pleura that can be located close to lung nodules. Also, the main "head" of the nodule is what radiologists consider when computing the size. In the case of detached nodules (i.e. well-circumscribed nodules) the whole segmented nodule is considered in size computations and growth analysis. Intensity-based segmentation [17], [21] has been applied to the nodule segmentation problem using local density maximum and thresholding algorithms. These classes of algorithms are primarily effective for solitary nodules (well-circumscribed), however, fail in separating nodules from juxtaposed surrounding structures, such as the pleural wall (i.e. Juxta-Pleural and Pleural-Tail nodules) and vessels (Vascular), due to their similar intensities.

2. RELATED WORK

2.1. Automated Lung Nodule Detection Method for Surgical Preplanning

Nowadays, the main challenge of medical field is Lung cancer. The very low survival Computer Aided Diagnosis (CAD) helps reducing the burden of radiation by improving the accuracy of abnormality detection during CT image interpretation.The lung lobes and nodules in CT image are segmented using adaptive fissure sweep and adaptive thresholding. A segmentation system in order to assist the surgeons to remove the portion of lung for the treatment of certain illness such as lung cancer, and tumours. The fissures of lung lobes are not seen by naked eyes in low dose CT image, there is a proposal for automatic segmentation system The lung lobes and nodules in CT image are segmented using two stage approaches such as modified adaptive fissure sweep and adaptive thresholding.

2.2. Integrated Atlas Based Localisation Features in Lungs Images

Segmentation of the pulmonary lobes is relevant in clinical practice and particularly challenging for cases with severe diseases or incomplete fissures. An automated segmentation approach is presented that performs a transformation on computed tomography (CT) scans to subdivide the lungs into lobes. Complementary information from past cases with confirmed diagnoses, to lung tissue classification and quantification in CT images.

2.3**.** An Enhanced Framework for Automated Segmentation of the pulmonary lobes from chest CT scans using Level Set Approach

The level set approach for segmentation of the lobe in chest CT images. A Novel multi region level set method for lobe segmentation. The fissures were detected using supervised enhancement filter, and level set method for lobe segmentation given the better results than watershed segmentation. The fissure extraction method to identify the cancer in the lung. Dual tree complex wavelet Transform (DTCWT) to extract the fissures which helps the surgeon to identify the cancer part easily. After extracting the fissure the cancer part was detected and it helps the surgeon to remove the tumor part while surgery. The lobe segmentation using marker based watershed transformation method.

Wiener filter has been applied in the preprocessing step to remove noise from CT image and then the lung segmentation was done using the similarity pixel of the seed point. The nodule was detected using adaptive threshold method, and the fissure was identified using fissure sweep technique. The automatic method for lung segmentation in X-ray CT images. The dynamic programming method was presented to detect the anterior and posterior junctions of each lung. The morphological operation was performed to smooth the boundary of the lung to get the clear and accurate results. The region growing algorithm for automatic segmentation of lung in CT image.

3. PORPOSED MODELLING

The FDT algorithm performs thresholding on CT image in four different directions, in which any direction's result can affect the final step of thresholding process. The FDT technique involves 5 steps in which the image is threshold from four different directions and then their results are matched base on the algorithm decision.
Calculate threshold value for the given input.
Calculate pixel intensity value in four directions.

From left to right pixels.
From right to left pixels.
From top to bottom pixels.
From bottom to top pixels.

After calculating the pixel intensity value and compare the value with the first obtained threshold value.

Last step so-called decision-making, ponders on every individual directions to make the final decision for thresholding.

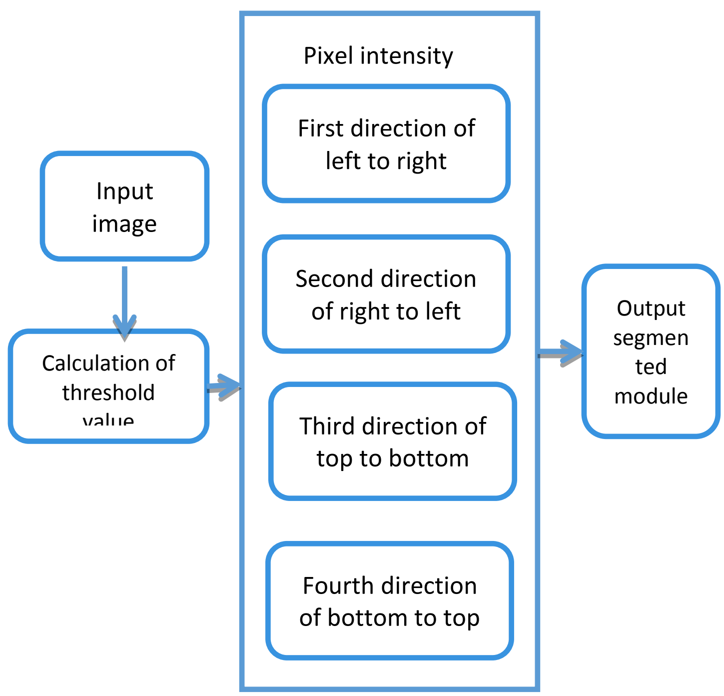

Fig: Architecture diagram

First the input image sample is taken and then the mean threshold value is taken and given for pixel intensity value is calculated from all the four direction. And the PIV is compared with the threshold value. Finally the lung nodule is segmented is produced in the output. The second is more efficient than the former but more difficult to achieve high performance due to the limited amount of information available for the non-target structures.

3.1. Preprocessing

Extract lung tissue from surrounding pleural surface using various approaches found in the literature including the statistical intensity based approach found in [4]. Perform lung nodule detection to obtain candidate nodule locations. The approach found in [5] and [9] is used to compute the positions of the candidate nodules followed by a post processing stage that provides the cropped regions of interest of nodule candidates [11]. Cropping here means from the detection process only nodules confirmed with provided ground truth information as being actual nodules have the segmentation approach analyzed on.

Computation of the initialization parameters used for the segmentation approach and generation of the signed distance representation of the shape model, and 3. Perform the shape based level set algorithm where correct convergence occurs when the nodule "head" is completely extracted. Different image segmentation examples are shown in Fig. 3 in addition to the signed distance function representation *φg*. of the non-lung tissues. From the results, we can see that the proposed approach overcomes the in homogeneities found in either the lung or non-lung tissues

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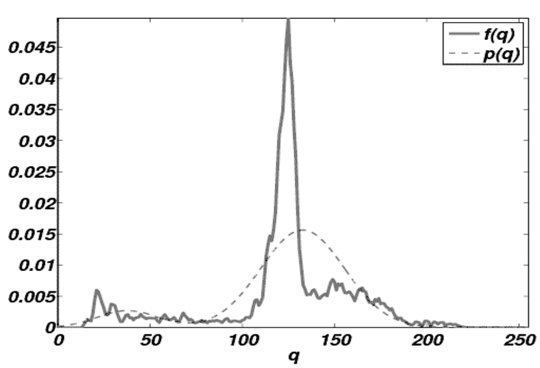
3.2. Initialization

Compute the initial probability distributions of the object and background intensities as Gaussian functions using the expectation maximization (EM) algorithm. Use this information to mark the object and background regions and compute the signed distance function, *φg* (more details in [4]).

Initialize λ and μ and compute the prior probabilities using Equation and the probability density functions for the object and background for each intensity levels using equation (Note that $\sigma = 1$).

Solve Equation to compute the intensity segmentation region implicitly represented by φg.



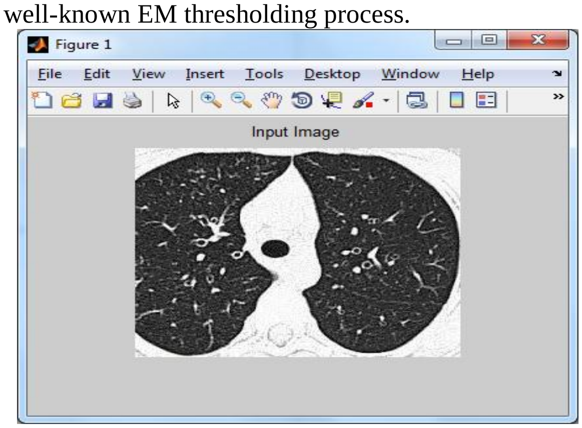
Repeat the computations iteratively until *φg* reaches saturation level. If *φg* does not saturate to a level of minimum change, repeat the steps. Initialize the transformation parameters to *sx*= 1, *sy*= 1, $\theta = 0$. (Arbitrary values chosen).

Construct the initial prior shape model and corresponding signed distance representation, *φp*. The input nodule image size provides the initial size information necessary of the created elliptical model.

4. RESULTS AND DISCUSSIONS

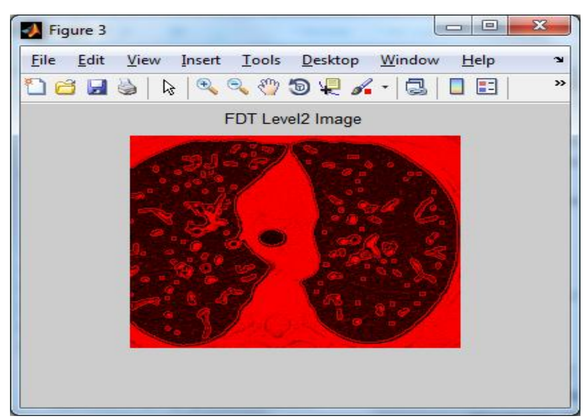
4.1. Input Image

The proposed approach uses a region of interest image that contains the lung nodule in the center as input. The EM algorithm is used initially to estimate the probability density function for the lung and non-lung tissues in the ROI image .The probability density functions are assumed to be Gaussian and used to initialize the level set function by computing the signed distance transform of the resulting binary image from the well-known EM thresholding process.

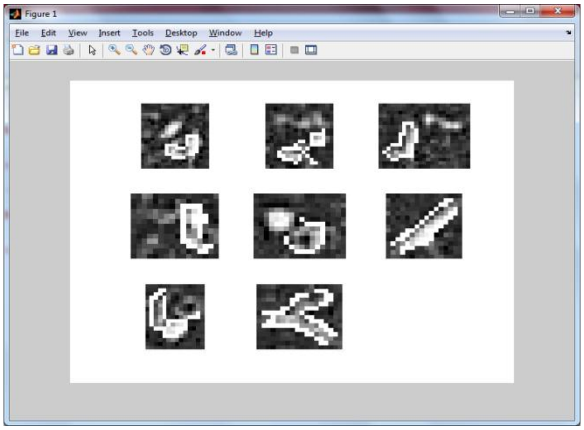


4.2. FDT Technique Result Image

First the input image sample is taken and then the mean threshold value is taken and given for pixel intensity value is calculated from all the four direction. And the PIV is compared with the threshold value. Finally the lung nodule is segmented is produced in the output.



4.3. Output Image



Calculate threshold value for the given input. Calculate pixel intensity value in four directions. The pixel intensity value and compare the value with the first obtained threshold value. Decision-making, ponders on every individual directions to make the final decision for thresholding.

5. CONCLUSION

FDT algorithm is used and it performs thresholding in four different directions on the CT image. Determination of pixels' value as being either on foreground or background is highly dependent on its adjacent pixel's intensity value. Neighbour pixels in precision of thresholding with FDT technique is demonstrated and the effectiveness of FDT method has been evaluated on different CT images. The FDT algorithm performs thresholding on CT image in four different directions. The FDT technique involves 5 steps in which the image is threshold from four different directions. Calculate threshold value for the given input. Calculate pixel intensity value in four directions. The pixel intensity value and compare the value with the first obtained threshold value. Decision-making, ponders on every individual directions to make the final decision for thresholding. The registration process incorporates a prior shape model as well as image intensity information in implicit spaces. The approach is tested and validated on nodules obtained from four different databases. Our technique is not dependent on nodule size or location. Using the prior shape model allowed the problem of nodules attached to the lung walls and vessels to be overcome. Despite the low quality of some of the LDCT images used in our experimentation, the proposed approach is successful with a rate more than 94%. The technique was also tested on 3D nodules with multiple patient follow-up scans. The resulting nodule sizes across the scans gives a possible indication about nodule(s) malignancy. Our results are consistent with those of expert radiologist's diagnosis. For future considerations: convex optimization will be investigated in order to have unique solution and different initializations. Also, automating the initialization process will be investigated. Further extensions include incorporating 3D shape priors to the proposed method.Calculate threshold value for the given input. Calculate pixel intensity value in four directions. The pixel intensity value and compare the value with the first obtained threshold value. Decision-making, ponders on every individual directions to make the final decision for thresholding.

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