Detection of pulmonary vessels in 3D lung CT using improved Graph Cut

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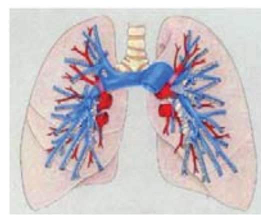
***Abstract*— The problem of pulmonary vessel detection from 3D pulmonary CT Scan is a very challenging one. The identification of vessels is important for clinical evaluation. In this paper, we proposed a vessel segmentation technique based on improved graph cut algorithm by designing the energy function. First of all, the enhanced image is modeled with adaptive k-means algorithm to give the regional parameter of the energy function. Then the improved energy function is given to graph cut algorithm for vessel segmentation. Graph cut algorithm creates a graph which is cut using minimum cut theory. The segmentation is done with the data provided in VESSEL12 site. This automatic segmentation gives quite satisfactory results.**

Keywords—Pulmonary vascular trees, adaptive k-means, graph cut

I. INTRODUCTION

With advancement of 3D volumetric CT (computed tomography) techniques which offers high resolution imaging, many image processing techniques have been proposed. This facilitates radiologists with necessary information. There are different therapeutic approaches (modalities) namely MRI, CT Scan, Ultrasound, Nuclear Medicine (PET), Radiography (X-ray) which are imaging techniques to diagnose and/or treat diseases. Computed Tomography (CT) can be taken in Axial (transverse), Coronal or Sagittal planes. Further CT Scans can be standard, high resolution, low dose or CT angiography. Even pulmonary vascular trees branches can be visualized with CT imaging techniques. Earlier radiologists use to trace vessels manually slice by slice which was very time taking and cumbersome but with the help of automatic pulmonary vascular tree identification; radiologists/physicians are able to detect pulmonary disorders and vascular diseases in very less time. It helps them in treatment of pulmonary emboli, lung nodules, interstitial lung diseases and grading of stenoses.

Lungs broadly consist of respiratory and pulmonary vascular systems. Respiratory system consists of airway tree which run along artery vessels in lungs as shown in Fig 1. Correct pulmonary vessel segmentation is still a bottleneck due to geometrical complexity, partial volume effect and high density air walls. Especially in non-contrast images, vessel detection becomes very challenging due to complex anatomy and limited imaging quality. Otherwise also vessels have complex pattern, tiny size and a huge number of ramifications. The contrast between vessels and other tissues are considerably degraded by noise caused by volume effect. Also the segmentation of small vessels results in erroneous results. A number of different approaches have been reported to deal with the problem but no one is fully successful in doing so.



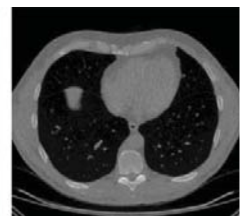


Fig 1: Lungs showing respiratory and vascular systems
Fig 2: Axial CT image (courtesy: School of medicines, university of Virginia)

This paper is articulated as follows: Section II lists the work done by various authors. The details of the data and annotations are mentioned in section III. The various method used are in short mentioned in section IV. Section V lists the proposed methodology used for this work on axial CT images as shown in Fig 2. Details of data evaluation criteria and results are mentioned in section VI. Conclusion is made in section VII. Finally references are in section VIII.

II. RELATED WORKS

Numerous semi-automatic and automatic vascular detection techniques have been proposed to deal with the problem. A challenge was put up by R. Rudyanto et al [1], VESSEL12 study in which works of different participants were compared. Mostly the methods used so far for pulmonary vessel segmentation can be broadly classified in the following ways:

(i) Morphology and Intensity based methods
(ii) Region Growing methods
(iii) Hessian based methods
(iv) Graph cut and level set methods
(v) Machine learning approach

Earlier for vessel segmentation, intensity based approaches were used. But due to volume effects and improper contrast, this method fails to give good results. Improvements have been done in this regard using adaptive approach. J. N. Kaftan et al. [2] have given fuzzy seed point based approach which can be adapted to the sensitivity/ specificity of the application. Samet. R et al. [3] used some morphology for pre-processing followed by vessel tracking algorithm with continuity checking. Adaptive modeling with Hough and Euclidean distance has been applied by M. Feuerstein et al. [4] on both contrast and non-contrast images for pulmonary artery segmentation after vessel detection. The evaluation was based on sensitivity, specificity, Jaccard index, and minimum mean distance.

Region Growing is a very popular segmentation technique. Conventional region growing is based on information of pixels, region and intensity ie their homogeneity criteria. 3D region growing have been efficiently used for vessel segmentation. J Lai et al. [5] first acquired lung volume using thresholding technique followed by adaptive seed acquisition. Then 3D region growing have been applied for vascular segmentation. Variational region growing have been used by M. Orkisz et al. [6] to segment vascular pulmonary trees in 3D CT images. Data from VESSEL12 framework has been used to evaluate the work. Probabilistic submission was made under VESSEL12 challenge. It fails to detect small vessels. Work by A. Fabijanska [7] consists of random walk method for seed points in the slices, then vascular tree segmentation using 3D region growing techniques. Initially both thoracic trees (vascular trees and airway trees) were extracted and then airway walls removed.

Hessian based enhancement techniques have been used by many scholars due to its ability to detect vascular structures. Hessian matrix helps in enhancement or detection of tubular structures by computing features from the eigenvalues of matrix. Eigen values of the Hessian matrix help to find the principle direction of the tubular structures. A. F. Frangi et al [8] designed a frangi multiscale filter based on Hessian parameters. Vesselness function formulated gives the estimates of vessel according to different criteria. Complex structures like bifurcations could not be detected using traditional Hessian based filters. C. Xiao et al [9] introduced stress-strain principles to incorporate the problem. Shape-tuned strain energy density function presented measures the vessel likelihood in 3D medical images and efficiently enhanced vessel bifurcations. False positive cases in airway walls were decreased by D. J. Carretero et al [10] using frangi filter for lung vessel and airway detection method. The evaluation has been done on VESSEL12 data. M. Helmberger et al [11] worked on automatic detection of lung vessels from contrast-enhanced thoracic CT scans and quantify it's tortuosity to evaluate the severity of pulmonary hypertension. Firstly lungs were segmented using morphological operations followed by airway removal by detecting a point in trachea and applying 3D region growing algorithm. Vessel enhancement filter was used to segment vessels.

There are some literatures about Graph cut and level set which take care of vessel bifurcations and vessel boundaries and provide more accurate segmentation. Work by Z. Zhai et al [12] designed an energy cost function which is minimized using graph cut optimization framework for vessel segmentation. The work was done on 20 CT scans of VESSEL12 data. X.Zhu et al [13] proposed a Vascularity-Oriented Level Set algorithm (VOLES) in which the traditional level set constant has been regulated to take care of vascular curvatures.

Machine learning methods are becoming popular day-by-day. R. Kiros et al [14] worked on multiscale feature learning were learned feature vectors from each voxel were passed to logistic regression classifier which probabilistically predicted the occurrence of vessel. This work was a part of VESSEL12 challenge. Labhuman [15] participated in VESSEL12 challenge where they conducted segmentation of vessels using K-means classifier after morphological preprocessing step. Later 3D filtering removed spurious elements like tumor.

The vessel segmentation work done by different scholars has been tabulated for better vision in Table 1.

III. DATA AND ANNOTATIONS

The Data for proposed vessel segmentation work has been taken from VESSEL12-challenge which was organized with IEEE International symposium on Biomedical Imaging (ISBI 2012) held in Barcelona, Spain. There are 20 CT scans of normal lungs and also with abnormalities like emphysema, nodules or pulmonary embolisms. Most scans are isotropic with 1 mm (max) spacing between slices. Three example pulmonary CT volumes have been provided along with respective masks and annotations of few slices. Data extraction work has been carried out using Mevislab software. As manual marking of all the vessels in every slices is almost an impossible task, only 3 slices of each data sets show few annotations

The validation of pulmonary vascular tree segmentation is extremely difficult task. Marking vessels manually on slices is a very cumbersome and time consuming task. There is no gold standard for reliably and accurately assessing the vessels segmented. In general, experts mark limited number of vessels and non-vessels on few slices and based on theses, evaluation is done. Results are verified with the help of radiologists.

IV. THEORETICAL BACKGROUND

Adaptive K-means

K-means is a simple clustering technique. It helps to partition image into K (predefined) clusters based on some similarity. The technique is highly dependent on initial seed points. To improve its performance, adaptive technique is used. Here number of clusters is not to be defined as it automatically rearranges the clusters which best represents the partitions. The algorithm starts with a single seed and stops when the number of seeds required for partitions is fulfilled.

Graph Cut

Graph cut technique is basically a labeling optimization problem. It is based on graph theory where several pair of objects connected by links represents a graph. In a graph G = (V, E), V and E are the vertices and edges of G, respectively. An s-t graph is a weighted directed graph with two nodes, the source s and the sink t. There are two types of

TABLE 1. Different works and their performances

S.No.	Author	Publication	Algorithm type	Data	Evaluation with	Results	Time	Comments
1.	R. Saket et al	Nicograph international 2016	Vessel continuity and vessel tracking	133 images of LIDC and 3 datasets of ELCAP	With the help of radiologist	Sensitivity=0.9815 Specificity=0.9825 Accuracy=0.96		
2.	J. Kaftan et al	Medical Imaging 2008	Fuzzy vessel segmentation	10 Clinical PE cases from radiologist	58 ROIs from 10 patients from radiologist	Sensitivity=0.89 Specificity=0.98 DSC = 0.846	38 sec	Method leaks into non-vessel structures
3.	M. Feuerstein et al	SPIE Medical Imaging 2010	Adaptive model based hough transform	10 contrast and 30 non-contrast patient datasets	Manual segmentation	Sensitivity=0.93 Specificity=0.98 Jaccard index=0.87	5 min	Could not fully extract the lumen
4.	M. Orkisz et al	Elsevier Masson 2013	Variational region growing	20 CT scans from VESSEL12 and 3 example scans	Manually marked by radiologists. Training data annotations from VESSEL12	Sensitivity=0.772 Specificity=0.967 AUC=0.879		Fails to detect small vessels
5.	A. Fabijanska	Elsevier 2015	3D region growing with morphological processing	10 cases from EXACT'09 challenge data	Manually marked by radiologists.	Sensitivity=0.9 Specificity>0.89 DICE= 0.82	10 min	Accuracy low in detecting small vessels
6.	J. Lai et al	Sens Imaging, Springer 2016	Multiseed 3D region growing	10 low dose CT scan dataset	Centerlines of the vessels by skeleton algorithm	Could segment vessels in few cases upto 10 levels	16 sec	Couldn't go beyond 7th level in few due to diseases
7.	C. Xiao et al	Elsevier 2011	Strain energy filter function based on Hessian matrix	Synthetic data,	Artificially defined references on sub-volumes		20 sec for 80 slices dataset	
8.	J. P. Charbonnier et al	Medical Imaging, IEEE transactions 2016	Frangi vesselness filter for vessel segmentation, artery vein classification	55 non-contrast low dose from ANODE challenge	annotations by experts	Accuracy>0.84 in most cases Cohen's K . 0.76	6 min	False positives in periphery reduced accuracy
9.	M. Helmberger et all	CoRR 2013	3D region growing	VESSEL12 20 datasets and 24 patients	VESSEL12 and experts annotations	Az = 0.677 to 0.951 Specificity =0.439 to 0.971 Sensitivity = 0.585 to 0.909	5 - 10 min	Small vessels misclassified as noise
10.	A. F. Frangi et al	Springer Verlag 1998	Vessel enhancement filter	2D DSA and 3D MRA images				Only vessel enhancement
11.	Z. Zhai et al	Medical imaging 2016	Graph cut optimization	20 CT Scans of VESSEL12	2 manually labeled sub-volumes	ROC = 0.975 Az = 0.993(max) Specificity = 0.979(max) Sensitivity = 0.966(max)		Airway wall and nodule removal could improve performance
12.	X. Zhu et al	Biomedical Imaging 2009	Level set algorithm (VOLES)	10 contrast enhanced CT Scans	Manual annotations	Sensitivity = 0.962 Specificity = 0.985		An adaptive approach
13.	R. Kiros et al	Machine learning in medical imaging, Springer 2014	Multiscale feature learning and logistic regression classifier	MICCAI, VESSEL12 and BRATS2012 data	VESSEL12 and expert annotations	Score in VESSEL12 challenge = 0.986		Domain independent approach
14.	Labhuman	VESSEL12 challenge	K - -means classifier	VESSEL12 dataset	VESSEL12 and expert annotations	Score in VESSEL12 challenge = 0.652	< 1min	Problem in tumor ramification area

Note: Many submissions have been made in VESSEL12 challenge held at International Symposium on Biomedical Imaging(ISBI) 2012, Barcelona , Spain. Few are included in this table.

links namely n-links (between pixels) and t-links (between pixel and terminal). The cost of cut is the weights of the links cut. When there is no path from source to sink, an s-**t cut is made. Every pixel is assigned a label *f* and the goal is to find labeling *f* based on links. The goal is achieved by energy minimization where $E(f) = E_{data}(f) + E_{smooth}(f)$. Here the max**-flow min-cut theorem is used for computing the mincut/maxflow of the graph. The theorem states that the maximum value of an s-t flow is equal to the minimum weight of an s-t cut.

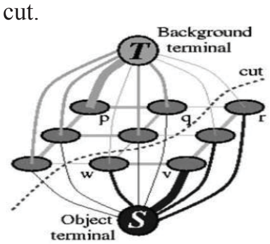


Fig 3: Pictorial view of Graph cut

V. PROPOSED METHOD

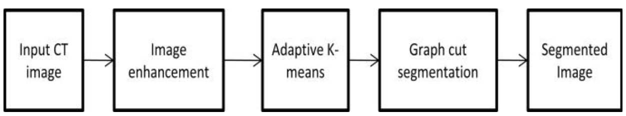


Fig 4: Block diagram

The proposed method have been explained through block diagram in fig 4. Here :

1. The pulmonary CT data in RAW format is converted to jpeg using Mevislab.
2. The CT images were enhanced using block-wise enhancement technique.
3. Adaptive K-means is used to find the $E_{data}(f)$ **for the** Graph cut segmentation step.
4. Graph cut technique has been used for vessel segmentation based on the work done by Y. Boykov and O. Veksler [16], min-cut/max-flow algorithm by Y. Boykov and V. Kolmogorov [17][18] and Matlab wrapper by Shia Bagon.

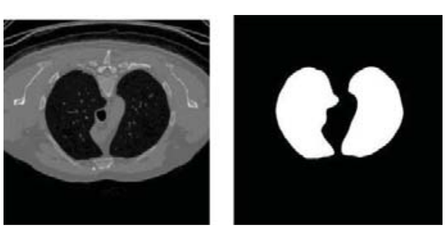


Fig 5: Pulmonary CT axial view and its masked image

VI. RESULTS AND DISCUSSION

This work has been implemented on MATLAB with visual studio and C++. Images and annotations have been worked on using Mevislab. The proposed methodology is applied on VESSEL12's three example scans.

We have tried to segment vessels on many images using our proposed methodology and few results are given below in Fig 6-8.

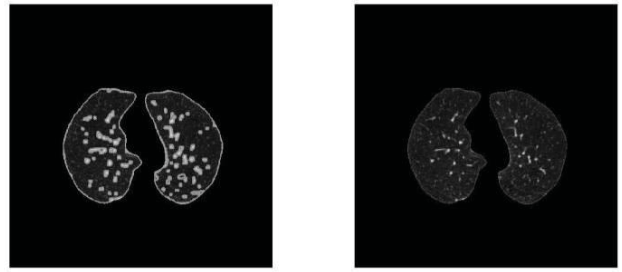


Fig 6: Segmented result with its masked image

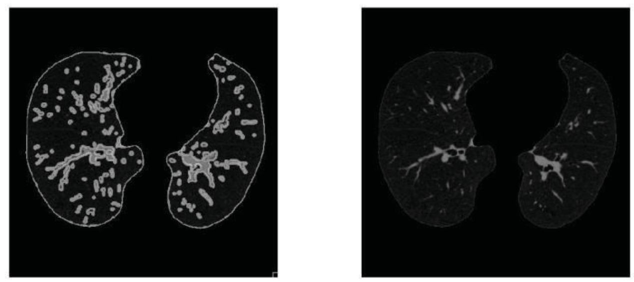


Fig 7: Segmented result with its masked image

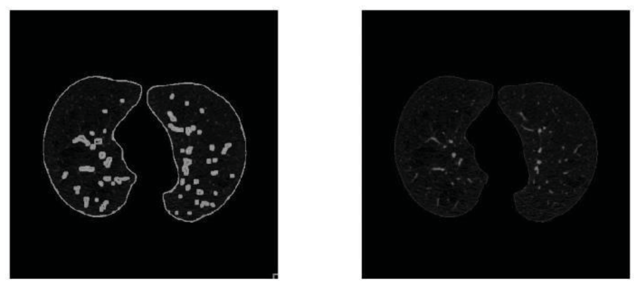


Fig 8: Segmented result with its masked image

VII. CONCLUSION

In this proposed work, improvisation on graph cut is presented for vessel segmentation. The work seemed to be suitable for the intended project. However, as the annotations on images given by VESSEL12 were very few (specially the false positive cases), evaluation was difficult. In future, experts/radiologists marked annotated data will be used to evaluate the work. Work will be improved using other techniques like multiscale, texture enhancement scheme and machine learning tool.

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