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Lung Vessel Segmentation in CT images Using Graph-cuts

Introduction

- Lung vessel detection is a key research topic in pulmonary CT image processing, since accurate vessel segmentation is an important step in extracting imaging bio-markers of vascular lung diseases.
- Hessian-based filters are popular and perform well in lung vessel enhancement, according to the VESSEL12 challenge [2]. However, global or local thresholding the vesselness does not provide accurate binary results.
- Graph-cuts [1] methods consider the segmentation a labeling problem. As it incorporates neighborhood information and combines features easily, we implemented graph-cuts for lung vessel segmentation.

Datasets

In-house data

Clinical image data was acquired of two patients on a Toshiba Aquilion 16 detector row CT scanner, without contrast media. Two sub-volumes on the boundary of pulmonary lobes were extracted. The size of sub-volumes are around 70·70·120 with voxel size of 0.65·0.65·0.5mm^3. Vessels, bronchi and fissures were manually labeled by an expert.

VESSEL12 challenge data

CT scans of 20 patients were collected by the VESSEL12[2]. The CT scan size was around 512·512·400, with voxel size around 0.7·0.7·0.7mm^3. The scan data and lung masks were provided by the organizers. Manual labeling was performed on pre-generated points, and only those points were kept, that obtained equal labels from three independent observers. There were nine categories in the reference standard to perform a comprehensive evaluation of vessel segmentation.

Conclusions

- A graph-cuts based segmentation method was proposed to extract the pulmonary vessels in thoracic CT images.
- A new cost function was designed by combining appearance and shape features.
- An efficient strategy was adopted to cope with the memory requirements of a graph representation.
- A competitive performance was obtained from the evaluation of in-house data and VESSEL12 challenge data.

Methods

Vessel enhancement filter

The response of traditional Hessian-based vesselness filters is low at the vessel bifurcations and boundaries, due to an overly simplified cylindrical model. To remedy this, we used the strain energy filter [3], which is based on strain energy density theory from solid mechanics.

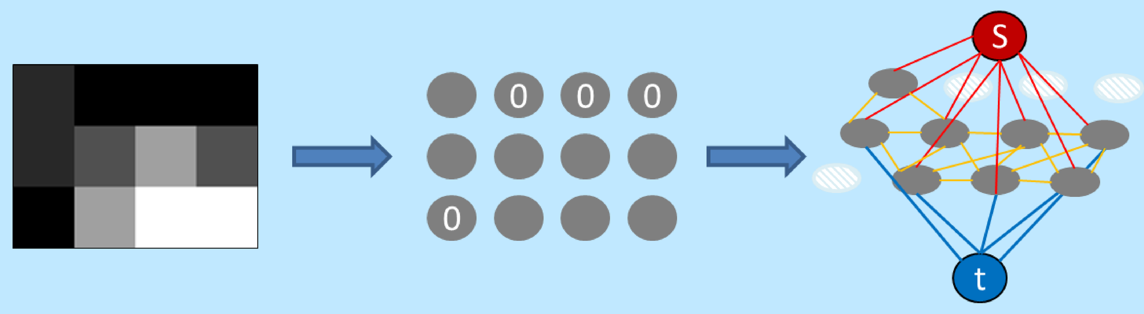


Figure 1: Graph structure representation of the proposed method.

Graph-cuts for lung vessel segmentation

- **Graph representation**

  The memory requirements of graph representation for high resolution pulmonary CT scans is very high. A thresholding strategy was adopted to cope with the memory requirements, by excluding voxels from the background (Figure 1). The sparse adjacency matrix analysis method was designed to determine the n-edges in a memory-efficient way.
- **Graph-cuts cost function**

  A new cost function was designed by combining appearance and shape features. For the cost function optimization we used GCMex 1.9 from Matlab [1].

Graph-cuts energy function

$$E(L) = \sum_{p \in P} \left(\omega D_p^{CT}(L_p) + (1-\omega) D_p^{vsl}(L_p)\right) + \gamma \sum_{\substack{(p,q) \in N, \\ L_p \neq L_q}} V_{p,q}(L_p, L_q)$$

with data terms

$$D_p^{CT}(I_p | L_p = l) = \frac{1}{1 + e^{-\alpha_l^{CT}(I_p - \beta_l^{CT})}}, \text{for image Intensity;}$$

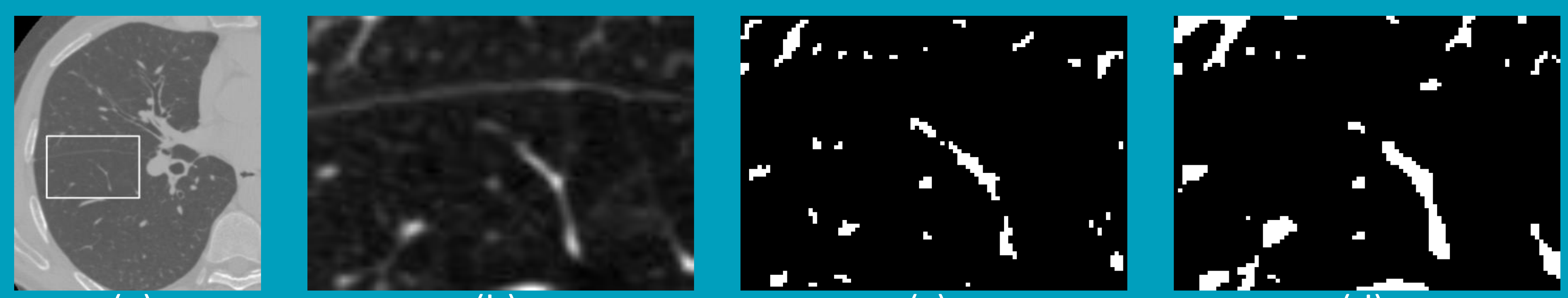
$$D_p^{vsl}(I_p | L_p = l) = \frac{1}{1 + e^{-\alpha_l^{vsl}(I_p - \beta_l^{vsl})}}, \text{for vesselness;}$$

with neighborhood term

$$V_{p,q}(L_p, L_q) = \begin{cases} e^{-\frac{|I_p - I_q|}{dist(p,q)})}, & if\ L_p \neq L_q\ and\ (p,q) \in N \\ 0, & otherwise \end{cases}$$

and γ is a positive coefficient for adjusting the smoothness.

Results



(a) (b) (c) (d)

Figure 2: Segmentation result on a reference region, (a) reference region in the CT, (b) one slice of the extracted region, (c) manually segmented reference standard (vessels only), (d) segmentation result of the proposed method.

Table 1: Evaluation results of methods on reference standard data sets.

		Data1			Data2		
Enhancement	binarization	Recall	Precision	F1 score	Recall	Precision	F1 score
Frangi	threshold	0.734	0.508	0.601	0.629	0.515	0.566
Freiman's method [4]	graph-cuts	0.823	0.478	0.605	0.643	0.487	0.554
Strain energy	threshold	0.708	0.729	0.718	0.622	0.712	0.664
Strain energy	graph-cuts	0.733	0.792	0.761	0.667	0.715	0.690

Table 2: Evaluation results of the VESSEL12 data-set: Az score, Specificity and Sensitivity of our submission across all categories. (Categories 1: Principal, 2: Small Vessels, 3: Medium Vessels, 4: Large Vessels, 5: Vessel/Airway Wall, 6: Vessel/Dense Lesion, 7: Vessel/Mucus-filled bronchi, 8: Vessel-in-lesion/Lesion, 9: Vessel/Nodules).

	1	2	3	4	5	6	7	8	9
Az	0.975	0.953	0.977	0.993	0.867	0.481	0.331	0.661	0.238
Specificity	0.910	0.865	0.910	0.979	0.588	0.239	0.112	0.451	0.038
Sensitivity	0.929	0.966	0.953	0.960	0.929	0.929	0.929	0.829	0.929

References

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[4] M. Freiman, et al., "Vessels-cut: a graph based approach to patient-specific carotid arteries modeling," in Modelling the Physiological Human, 1–12(2009).

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