MULTI-SCALE HESSIAN BASED APPROACH FOR SEGMENTATION OF LUNG VESSEL TREE IN 3-D CTA DATA

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ABSTRACT

In the process of diagnosing illnesses related to lung, knowing the shape and curvature of lung vessels is essential. Automatic segmentation of vessel tree is one of the most important requirements for Computer Aided Diagnosis (CAD) Systems. In this paper one of the existing segmentation techniques, multi-scale Hessian-matrix based approach is used to segment the lung vessels. The Hessian-matrix based approach does not require any user interaction for creating segmentation results. After training the data on expert annotated data, the results showed that multi-scale Hessian-matrix based approach, which is a line structure enhancement Filter, gives accurate segmentation results.

1. Introduction

According to WHO in 2008 the deaths related to lung cancer was around 1.4 million people [1]. In order to prevent the deaths related to cancer early diagnosis of the disease is crucial. Even though there are many methods related to nodule segmentation [2][3], there are less methods for automatic segmentation of lung vessel tree. These publications focus on the region growing [4][5] and level set techniques[6].Recently some methods made use of Hessian matrix based approaches[7].

2. SEGMENTATION ALGORITMS

This section focuses on the preprocessing, segmentation and post processing techniques

2.1. Preprocessing

Before the segmentation of the lung vessel tree, the three dimensional data is filtered with a [3x3x3] median mask filter to remove the noise. Apart from that the lungmasks are used to remove the vessels of the heart.

2.2. Hessian Matrix Based Approach

Hessian Matrix based approaches have been widely used for vessel segmentation purposes in various cases. This approach finds the tubular structures in an image. It uses the cylindrical structure of the vessels and segments them with a line enhancement filter..

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Hessian matrix consists of the second order gradients of the Image. In this work the eigenvalue orientation of this matrix is the basis for the vesselness filter.

$$H = \begin{bmatrix} \partial^2 I/\partial x^2 & \partial^2 I/\partial x\partial y & \partial^2 I/\partial x\partial z \\ \partial^2 I/\partial x\partial y & \partial^2 I/\partial y^2 & \partial^2 I/\partial y\partial z \\ \partial^2 I/\partial x\partial z & \partial^2 I/\partial z\partial y & \partial^2 I/\partial z^2 \end{bmatrix} \quad (1)$$

Where I refers to the image and the values inside the matrix are second order gradients of the three dimensional image. This process is repeated for each point to build a different matrix for each point with different scales.

Using these values a vesselness value can be calculated according to Frangi's article [8].

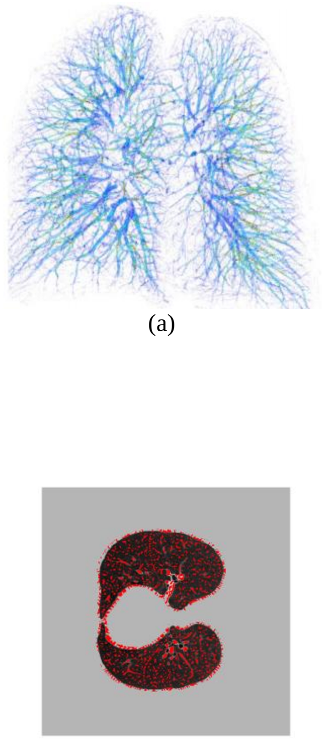
$$R_A = \frac{|\lambda_1|}{|\lambda_2|} \quad (2)$$

$$R_B = \frac{\lambda_1}{\sqrt{|\lambda_2 \lambda_3|}} \quad (3)$$

$$S = \|H\|_F = \sqrt{\sum_{i<3} {\lambda_i}^2} \quad (4)$$

$$V = \begin{cases} 0, & \lambda_2 > 0 \ or \ \lambda_3 > 0 \\ (1 - e^{\frac{{R_A}^2}{2\alpha^2}})\, e^{-\frac{R_B}{2\beta^2}} \left(1 - e^{\frac{s^2}{2c^2}}\right), & otherwise \end{cases} \quad (5)$$

In these equations α,ß and c values represents the weights R_A , R_B and S values calculated from different eigenvalues of the hessian matrix. Equation (5) gives a vesselness normalized value 'V' for each point on the data. This vesselness value is mapped onto a [0-255] intensity interval using a log transformation, which highlights lower values. This result gives a probabilistic vesselness output for each point. The vesselness measure in Equation (5) is analyzed at different scales and the response of the filter will be maximum at a scale that approximately matches the size of the vessel is chosen as the appropriate vesselness value. Figure 1.a shows a three dimensional view of the probabilistic result and Figure 1.b shows a binary two dimensional representation of the segmentation overlaid on the original image



(a)

(b)

Figure. 1 Segmentation Results Visualizations a) Three dimensional probabilistic representation(dark blue represents high intensity values) b) Two-dimensional binary representation overlaid on original image

2.3. Postprocessing

The expert annotations provided are used to train the algorithm for a better segmentation. A maximum scale should be fixed in order to prevent huge computational costs of the multiple different scaled matrices. Thee optimum scale performance and processing timewise is selected as two, with the help of the golden data. For the testing dataset the scale is set to that value for the segmentation.

A log transformation is necessary to highlight the small difference in variance between false positives and true positives, to separate these two groups better.

3. RESULTS

Multi-scale Hessian Matrix approach is a three dimensional efficient automatic method for lung vessel segmentation. The algorithm can be used in multiple scans and has better performance with thinner slices. The execution time of the algorithm on 2.4 GHz processor with an average dataset is approximately seven minutes.

4. REFERENCES

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