Hepatic vessel segmentation based on an improved 3D region growing algorithm

Huahai Zhang¹, Peirui Bai¹*, Xiaolin Min¹, Qingyi Liu¹, Yande Ren², Hui Li¹ and Yixuan Li¹

¹College of Electronic and Information Engineering, Shandong University of Science and Technology, Qingdao, Shandong, 266590, China
²Department of Radiology, Affiliated Hospital of Qingdao University, Qingdao, Shandong, 265000, China
*Corresponding author’s e-mail: bprbjd@163.com

Abstract. Hepatic vessel segmentation of CT image is of great importance in the computer aided diagnosis. This paper proposes an automatic segmentation method of 3D vessel CT images to obtain better segmentation results. First, the single Gaussian kernel of Hessian matrix in Jerman’s algorithm is replaced by bi-Gaussian kernel. Then, a histogram-based method is adopted to adaptively estimate the threshold value of the region growing. Finally, a new scheme is proposed for automatically searching seed points of the region growing. The experimental results show that the proposed method achieves a significant enhancement of hepatic vessels segmentation with an average accuracy 98.1%.

1. Introduction

3D segmentation of vascular CT images is an important part of computer-aided treatment system [1]. However, the low contrast, edge blur and other factors of CT images make accurate segmentation of hepatic vessels a difficult problem[2]. Therefore, it is important to develop an automatic and efficient segmentation method for hepatic vessels. In most methods of hepatic vascular segmentation, vascular structures are enhanced usually by designing effective filters[3]. The most commonly used vascular filters are based on Hessian filters such as the filters in Ref Frangi[4], Sato[5] and Erdt[6]. Recently, Jerman et al. improved the performance of vascular enhancement algorithms by applying a loose constraint ratio to the vessel shape to achieve a better near-uniform response in vascular nodules and branches[7]. Currently, hepatic vascular segmentation methods are divided into roughly four categories. The first category is “regional growth and thresholding” [8]. For example, Zeng et al. used a 3D region growing algorithm to segment fine blood vessels[9]. Yang et al. also used empirical threshold intervals to extract seeds and then used regional growth method to perform vascular segmentation[10]. Their researches all provided a reliable basis for accurate segmentation of blood vessels. The second is based on the active contour model such as the level set methods. Cheng et al. proposed an active contour model for vessel segmentation that accurately segmentes low-contrast blood vessels[11]. The third is based on the method of graphic cutting. Sangsefid et al. defined an equilibrium data items of the graph cut to improve the segmentation of hepatic vessels[12]. In addition to methods listed above, Oliveira et al. adopted a morphological and Gaussian mixture model to segment hepatic vessels[13]. However, the segmentation of hepatic vessels remains a challenge problem. On one hand, it is difficult to detect the fine blood vessels accurately because of the wide range of blood vessels, on the other hand, false...
detections are easily occurred due to the highly curved blood vessels and pathological structures. In this paper, an improved region growing algorithm is proposed to enhance the segmentation performance of 3D CT hepatic vessels.

The remainder of this paper is organized as follows. Section 2 describes the background of the vessel enhancement algorithm. Section 3 presents the details of the proposed hepatic vascular segmentation method. In Section 4, the experiments and results are presented, and Section 5 concludes the paper.

2. Background

2.1 Principle of vessel enhancement algorithm

Currently, the Hessian matrix i.e. a multi-scale 3D filter is commonly used as a vessel enhancement tool. It can distinguish droplets, tubes and planar structures in medical images:

\[ H_\theta(x, \sigma) = \sigma^2 I(x) * \frac{\partial^2}{\partial x_i \partial x_j} G(x, \sigma) \]  

(1)

where \( x = [x_1, x_2, \ldots, x_n] \) presents the spatial coordinate of the n-dimensional image voxel, \( G(x, \sigma) \) is a Gaussian function, \( \sigma \in [\sigma_{\min}, \sigma_{\max}] \) indicates the size of the vessel structure to be enhanced. The corresponding eigenvalues of \( H_\theta(x, \sigma) \) are indicated by \( \lambda_1, \lambda_2, \) and \( \lambda_3 \) respectively. In the ideal vascular structure \( \lambda_2 \approx \lambda_1 \) and \( \lambda_2 \approx 0 \), it is assume that \( |\lambda_3| \geq |\lambda_2| \geq |\lambda_1| \) in this paper.

2.2 Jerman’s vascular enhancement algorithm

Jerman et al. constructed a novel vascular enhancement response function that greatly improved the performance of the vascular enhancement algorithm [7]. The Hessian matrix eigenvalues should be reversed if the vascular grayscale in the image is higher than the background for computational simplicity. Usually, the value of \( \lambda_2 \) and \( \lambda_3 \) in the vascular edge or the low-order vascular region are low when applying the traditional vascular enhancement algorithm. It means that they cannot match the eigenvalue relationship of the Hessian matrix related to the ideal vascular structure. Thus, a significant response attenuation of the conventional vascular enhancement algorithm will be produced. In addition, the traditional vascular enhancement algorithms are less effective in identifying the tubular structures. In order to solve these problems, Jerman et al. compensated the lower-valued eigenvalues sectionally to obtain an optimized eigenvalues \( \lambda^*_\mu \):

\[
\lambda^*_\mu(\sigma) = \begin{cases} 
\lambda_3, & \text{if } \lambda_2 > \tau \max_i \lambda_3(x, \sigma) \\
\tau \max_i \lambda_3(x, \sigma), & 0 < \lambda_2 \leq \tau \max_i \lambda_3(x, \sigma) \\
0, & \text{else} 
\end{cases}
\]  

(2)

A compensation was carried out for the ellipsoid structure: \( \lambda_2 \geq \lambda^*_\mu / 2 > 0 \). The final improved Jerman’s vascular enhancement algorithm could be expressed as follows:

\[
v_k = \begin{cases} 
0, & (\lambda_2 \leq 0 \lor \lambda^*_\mu \leq 0) \\
1, & (\lambda_2 \geq \lambda^*_\mu / 2 > 0) \\
\lambda_2^2 (\lambda_2 - \lambda_2) \left[ \frac{3}{\lambda_2 + \lambda^*_\mu} \right], & \text{else} 
\end{cases}
\]  

(3)

3. The proposed method

The proposed hepatic vascular segmentation algorithm mainly includes three steps. First, a pre-processing operation is implemented to locate the liver region and enhance the contrast of the image. Then, We improve the Jerman’s algorithm by bi-Gaussian kernel to enhance the structure of hepatic vessels. Finally, we adopt automatically selected seed points to drive the 3D region growing algorithm to obtain accurate structure of the hepatic vessels.
3.1 Preprocessing of hepatic image

First, a hepatic image $I_{ROI}$ is obtained by performing a logical "AND" operation on the hepatic mask (predefined manual segmentation) and the 3D CT image of the abdominal region $I_{CT}$.

$$I_{ROI} = I_{CT} \cap I_{Mask} \tag{4}$$

To reduce the influence of noise and artifacts, a contrast enhancement operation is implemented by using an adaptive sigmoid filter:

$$I(x) = (1 + \exp(-\frac{I_{ROI} - \beta}{\alpha}))^{-1} \tag{5}$$

where $\beta$ and $\alpha$ represent the central gray scale range of the vascular structure to be enhanced.

The nonlinear anisotropic diffusion filter is then used to remove the noise and preserve the vessel boundaries:

$$\frac{\partial I(x)}{\partial t} = \text{div} \exp[-\|\nabla I\|/b^2] \cdot \nabla I$$

where $\text{div}$ is the divergence calculator and $\nabla$ is the gradient operator, $b$ is the heat transfer coefficient which is used to control the sensitivity of the edge and it was set to 70.

3.2 Vessel enhancement algorithm

The Hessian matrix usually involves a convolution operation on the second derivative of the image and the Gaussian kernel. Since the Gaussian kernel adopts a single scale in both the foreground and the background, the Jerman's algorithm is interfered with the hepatic parenchyma and the contours of the hepatic region, which resulted in a false enhancement for the hepatic vessels.

In order to solve this problem, we use a bi-Gaussian kernel instead of a single Gaussian kernel to improve the Jerman’s algorithm. The bi-Gaussian kernel is obtained by combining two traditional Gaussian nuclei with different proportions [14]:

$$BG(x, \sigma, \sigma_b) = \begin{cases} \gamma \cdot G(\sigma_b, x - \sigma_b + \sigma), x \leq -\sigma \\ G(\sigma, x) + e^{-\frac{1}{2}}(\frac{\sigma_b}{\sigma} - 1) \cdot \frac{1}{\sigma} |x| < \sigma \\ \gamma \cdot G(\sigma_b, x + \sigma_b - \sigma), x \geq \sigma \end{cases} \tag{7}$$

where $\sigma_b$ is the background scales, $\gamma$ is a coefficient and set as 0.2. The modified Hessian matrix $H_{BG}(\sigma, x)$ can be written as:

$$H_{BG}(x, \sigma) = \sigma^2 I(x) \ast \frac{\partial^2}{\partial x_i \partial x_j} BG(x, \sigma) \tag{8}$$

where $I_{BG}(\sigma, x) = BG(x, \sigma, \sigma_b) \ast I(x)$.

The steps of the enhancement algorithm in this paper are as follows:

step 1. Calculate the corresponding matrix element that related to the voxel of the image $I(x)$ at the spatial position $\mathbf{x}$, the scale $\sigma$ according to the improved Hessian matrix $H_{BG}(x, \sigma)$. The values of feature $\lambda_i$ are obtained from the eigenvalue decomposition.

step 2. Sort the eigenvalues $\lambda_i$ and perform the inverse operation, which lead to $\lambda_1 < \lambda_2 < \lambda_3 < 0$. According to equation (2) to obtain $\lambda_v(\sigma)$, then according to equation (3) to obtain the vascular enhanced response $v_i$.

step 3. Obtain the maximum response at all scales of the vessels, and define it as the final vascular enhancement response:

$$\varphi(x) = \max \{ v_i(x, \sigma), \sigma_{min} \leq \sigma \leq \sigma_{max} \} \tag{9}$$

where the scale ranges $\sigma_{min}$ and $\sigma_{max}$ are set to 1 and 4, respectively.
An example result of the improved vascular enhancement algorithm is shown in Figure 1.

Figure 1. An example result of vascular enhancement. (a) original image, (b) vascular enhancement result using Jerman’s method, (c) vascular enhancement result using our method.

### 3.3 Hepatic vascular segmentation using 3D region growing algorithm

A given threshold is required in the region growing algorithm to distinguish the region of interest (ROI) from background. Commonly, the threshold value is selected manually. In Ref.[8], a histogram-based method is proposed to estimate the threshold. First, the histogram is obtained by convoluting the enhanced image (intensity range of 1024 bins) with a low-pass filter. Then, the background intensity is estimated by fitting the Gaussian distribution to the histogram. Finally, the minimum threshold $L_{th}$ and the maximum threshold $M_{th}$ can be obtained as follows:

$$L_{th} = p + \frac{1.75}{2(2\log 2)^{1/2}}(h_l + h_r) + \mu(h_r - h_l)$$

$$M_{th} = p + \frac{3(h_l + h_r)}{2(2\log 2)^{1/2}}$$

where $p$ is the position of the highest peak of the histogram, and $h_l$ and $h_r$ are the half widths of the half peaks on the left and right sides of the histogram, respectively. $\mu$ is the threshold and it is set to 2.

Appropriate selection of seed points can improve the accuracy of the region growing algorithm. In order to ensure there is only one vascular structure in the region, the seed point for the hepatic vessels is usually selected in a local region of 5 mm × 5 mm × 3 mm [15]. Since the vascular structure is brighter in the CT image after enhancement, the voxel $x_0$ with the strongest intensity in the local region is selected as the seed point for the region growth. Then, the similarity criterion is used to judge whether the $n$th voxel $x_n$ belongs to the seed points:

$$|\varphi(x_n) - \varphi(x_0)| < M_{th}$$

$$\varphi(x_n) > L_{th}$$

The pixel that satisfies the condition will be the new seed point until there are no new pixels. According to the seed point selection criterion, it is judged whether the voxel of the input CT data belongs to the seed point, and if so, the flag is marked until no new voxel satisfies the condition, the region growth is stopped, and the segmentation of the hepatic blood vessel is finally completed.

### 4. Experiments and results

The public dataset 3Dircadb provided by the French Institute of Digestive Cancer Therapy (https://www.ircad.fr/research/3dircadb/), is employed to validate our proposed method. We selected 14 volume data from the dataset to validate the proposed method. The slice number of different volume data is different which is ranged from 64 to 502. The size of each slice is 512×512. The data set contains the true hepatic vascular contours manually labeled by the radiologists. The representative segmentation results of four volume data (from left to right, the index number of the volume data is 2, 4, 8 and 14) are shown in Figure 2. The first row is the manual segmentation results. It will be used as the ground truth to evaluate the performance. The second row is the segmentation results obtained from the method in Ref. [16]. The third row is the segmentation results of using Jerman’s enhancement method [7]. The fourth row is the segmentation results obtained by our method.
method. It can be seen that the segmented hepatic vessels using our algorithm have more detail information than the other compared methods.

We also make a quantitative comparison between the above algorithms. Table 1 lists three indices i.e., accuracy, sensitivity and specificity of the compared algorithms. The values are the means of the 14 test examples. It can be seen that our proposed method has a better accuracy and sensitivity. The average accuracy of our method can achieve 98.1%, which is 1.2% and 0.9% higher than that of method in Ref.16 and Jerman's method respectively.

![Segmentation Results](image)

**Figure 2.** The representative segmentation results of four liver CT volume data, which are displayed in columns from left to right. The first to fourth row show the segmentation results of manually labeled, the method in Ref.16, the Jerman's method and our method respectively.

| Methods       | Accuracy | Sensitivity | Specificity |
|---------------|----------|-------------|-------------|
| Method in [16]| 96.9%    | 72.1%       | 98.3%       |
| Jerman’s      | 97.2%    | 76.7%       | 96.5%       |
| Our method    | 98.1%    | 78.5%       | 98.0%       |

5. **Conclusion**

In this paper, a hepatic vessel segmentation method based on the improved 3D region growing algorithm is proposed. By adopting bi-Gaussian kernel into the vascular enhancement algorithm, and automatic searching of seed points, the proposed algorithm show superior performance than the traditional region growing algorithm. In the future work, we will study how to improve the accuracy of vascular segmentation, and hope to get more ideal results.

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