

# SEGMENTATION OF BLOOD-VESSEL TREE IN WHOLE-BODY MRI DATA

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**Abstract:** The aim of this paper is to introduce a method of blood-vessel tree segmentation in 3D volume and the visualization of the processed data. The method is based on the detection of tubular structures which the blood-vessels resemble. The processing is based on the information that is carried in the derivatives of the original volume. Second derivatives of each voxel are computed and organized into a Hessian matrix. The used method is based on the calculation of the eigenvalues of this matrix for each voxel. Those eigenvalues carry the information of the structure shape. Based on this information, a new parametric volume is created that represents the 'vesselness' of each voxel. The processed volume is visualized with Visualization ToolKit.

**Keywords:** segmentation, blood-vessel tree, MRI, Hessian matrix, eigenvalues

## 1 INTRODUCTION

The goal of this work is to segment blood-vessel tree and allow its visualization with the possibility to measure the distances within the segmented blood-vessel tree. The original volume comes from a whole-body MRI data set. In the first part of this paper, the acquisition of the blood-vessel tree MRI data is described. Second part elaborates the method used for the segmentation. In the third part of this paper, the visualization with Visualization ToolKit is described. The possible 3D visualization allows the user to determine how a certain blood-vessel progresses throughout the body and to establish more precisely the exact location. With the visualized information, the user is able to mark the significant point in the arterial system and draw out the lengths of individual arteries.

## 2 BLOOD-VESSEL TREE AS MRI DATA

The desired segmented blood-vessel tree constitutes of the main vessels of the arterial system. The arterial system is possible to detect due to the set up during acquisition. To distinguish the arteries from vessels, the direction of the flow is set during acquisition. The acquisition is synchronized with the ejection phase of the heart to provide a certain uniformity within the blood-vessel tree. The used MRI scan is GE Discovery MRI750 3.0T. The whole-body sequence that is processed comes from several acquisition sequences of separate parts of the body. Most commonly stored in a 256x256 matrix with the voxel size of 1.875x1.875x25 mm. The whole-body MRI sequence is stored in DICOM images that provide information for the possible reconstruction, such as the slice location or the spacing between slices.

## 3 THE HESSIAN MATRIX EIGENVALUE METHOD

The detection of the arterial system is based on the second derivatives of the intensity of the original image. Second derivatives carry the information of the shape, magnitude and the orientation.[3] Furthermore, the assumption that the blood-vessel's profile in the cross-section is of a Gaussian shape

is made and the intensity does not change with the propagation of the vessel throughout the volume. Unfortunately, the second derivatives calculation enhances the noise in the image. For the noise suppression, a Gaussian filter is used in preprocessing. The second derivatives are computed with the central difference formulas because the original image consists of a discrete data set. The computation is realized through convolution with masks interpreting following formulas. [1]

$$f_{x,x}(x_i, y_j, z_k) \approx \frac{1}{h_x^2} (f_{i+1,j,k} - 2f_{i,j,k} + f_{i-1,j,k}) \quad (1)$$

And the mixed partial derivatives

$$f_{x,y}(x_i, y_j, z_k) \approx \frac{1}{4h_x h_y} (f_{i+1,j+1,k} - f_{i-1,j+1,k} - f_{i+1,j-1,k} + f_{i-1,j-1,k}) \quad (2)$$

where  $f_n$  is a partial derivative with respect to  $n$ ,  $h_n$  is the spacing in direction of  $n$  for  $n \in \{x, y, z\}$  and  $f_{i,j,k}$  is  $f(x_i, y_j, z_k)$ . Similarly for  $f_{y,y}$ ,  $f_{z,z}$ ,  $f_{y,z}$  and  $f_{z,x}$ . From the equation 2, the assumption of  $f_{i,j} = f_{j,i}$  can be made. Moreover, the second partial derivatives are organized into a symmetrical Hessian matrix  $H$

$$H = \begin{pmatrix} f_{x,x} & f_{x,y} & f_{x,z} \\ f_{x,y} & f_{y,y} & f_{y,z} \\ f_{x,z} & f_{y,z} & f_{z,z} \end{pmatrix} \quad (3)$$

By calculating the eigenvalues of  $H$  for each voxel, each data point from the original volume is represented with three parameters being the three eigenvalues. The following Table 3 shows image structure properties based on the Hessian matrix eigenvalues.[2]

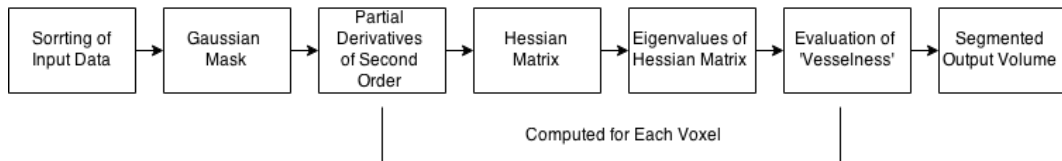
**Table 1:** Structure properties dependency on the eigenvalues

$\lambda_1$	$\lambda_2$	$\lambda_3$	structure shape
L	L	L	noise
L	L	H	sheet-like structure
L	H	H	tubular structure
H	H	H	blob-like structure

where  $L$  stands for low values and  $H$  stands for high values of the computed eigenvalues that are sorted descendingly, therefore  $\lambda_1 \geq \lambda_2 \geq \lambda_3$ . The high values in the original volume are negative. That is based on the relation between the structure intensity and the background intensity (bright to dark). Applied on the segmentation of the blood-vessel tree, the voxels are assigned a value based on the resemblance to the expected properties of a tubular structure.

### 3.1 IMPLEMENTATION

The Hessian matrix eigenvalue method was implemented in MATLAB. The block diagram of the volume processing algorithm is shown in Figure 1. The original volume data is sorted to acquire



**Figure 1:** Block diagram of the implemented method

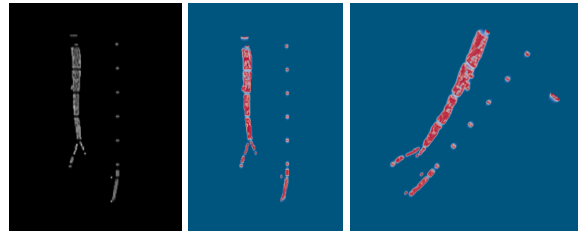
the z-slice sequence only. The smoothening with a Gaussian mask suppresses the noise. The size of the mask is chosen according to the vessel cross-section and the resolution of the original slice. The calculation of the second partial derivatives is done by convolution with operators that represent the second partial derivatives. The computed second derivatives are organized into a Hessian matrix and the eigenvalues are calculated and sorted in the descending order. According to Table 1, for a sorted vector of eigenvalues  $u = (\lambda_1, \lambda_2, \lambda_3)$  of a voxel of a vessel the assumption of  $\lambda_1 \approx 0$  is made. The remaining eigenvalues  $\lambda_2$  and  $\lambda_3$  are of a negative high value. To create a parametric image that represents the 'vesselness' of the voxel, a function  $f(\lambda_1, \lambda_2, \lambda_3)$  is defined

$$f(\lambda_1, \lambda_2, \lambda_3) = \sqrt{\lambda_2^2 + \lambda_3^2} \quad (4)$$

The criterion for a voxel to be assigned any value in the resulting image is the value of  $\lambda_1 \approx 0$ . And the resulting intensity is dependent on the remaining eigenvalues.

#### 4 VISUALIZATION

For the 3D visualization the VTK was used. This data carry the information about each voxel's 'vesselness' in the form of a value from 0 to 1. Figure 2 shows part of a processed volume data and the options visualization with VTK offers.



**Figure 2:** 3D visualization of part of the arterial system

#### 5 CONCLUSION

The segmentation of the desired blood-vessel tree and its 3D visualization helps to distinguish many anatomical properties. The placement of certain location can be better specified when a whole volume is available and therefore it can allow greater precision with the measurements of the lengths of the arteries. The Hessian matrix eigenvalue method does have little false negatives, however some acquisition artefacts can cause a false positive detection. The knowledge of the anatomy and the visualization within the body can help to mark these false detections and contribute to a very precise arterial system segmentation.

#### REFERENCES

- [1] MOHLENKAMP, M. and YOUNG, T.: Introduction to Numerical Methods and Matlab Programming for Engineers. In *Numerical Differentiation*. Ohio University, Department of Mathematics. 2014.
- [2] FRANGI, F. A., et al.: Model-Based Quantitation of 3-D Magnetic Resonance Angiographic Images. *IEEE Transactions of Medical Images.*, October 1999, vol. 18, no. 10, p. 945-948.
- [3] QINFENG, L.: *Enhancement, Extraction and Visualization of 3D Volume Data*. [Dissertations. No. 824] Linköping, Sweden: Institute of Technology, Linköping University, 2003. 213 p.