Extraction of Cerebral Vasculature from Anatomical MRI

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The purpose of our research



What we focus on

3D MRI data (selected cross-section)



The 3D vascular model



Knowledge-Based Extraction of Cerebral Vasculature from Anatomical MRI

The algorithm

Multiscale vessel enhancement

 Gaussian filtering
 Hessian matrix computation
 Vesselness function

 Center-line extraction

 a. 3D Segmentation
 Skeletonization

 Skeletonization

with tube-like deformable models

Gaussian Filtering

 Derivatives of image L is a convolution with derivatives of Gaussian:

$$\frac{\partial}{\partial \mathbf{x}} L(\mathbf{x}, s) = s^{\gamma} L(\mathbf{x}) * \frac{\partial}{\partial \mathbf{x}} G(\mathbf{x}, s)$$

Where γ is a normalization parameter and s is a scale parameter $s_{\min} \le s \le s_{\max}$. For a typical diameter of a vessel $s_{\min}=0.2$, $s_{\max}=2$.

The *D*-dimensional Gaussian is defined:

$$G(\mathbf{x},s) = \frac{1}{\sqrt{2\pi s^2}} e^{-\frac{\|\mathbf{x}\|^2}{2s^2}}$$

Multiscale vessel enhancement

 A Taylor expansion of the image L in the neighborhood of point x₀

$$L(\mathbf{x}_0 + \delta \mathbf{x}_0, s) \approx L(\mathbf{x}_0, s) + \delta \mathbf{x}_0^T \nabla_{0,s} + \delta \mathbf{x}_0^T \mathbf{H}_{0,s} \delta \mathbf{x}_0$$

where:

 $abla_{0,s}, H_{0,s}$ is a gradient and Hessian matrix of an image computed at $\mathbf{x_0}$ coordinates, at scale *s*.

Multiscale vessel enhancement

 Hessian matrix computed H at coordinates x₀:

• Eigenvalues are sorted

 The eigenvector of the highest eigenvalue indicate a direction of the vessel at coordinates x₀

$$= \begin{bmatrix} L_{xx} & L_{xy} & L_{xz} \\ L_{yx} & L_{yy} & L_{yz} \\ L_{zx} & L_{zy} & L_{zz} \end{bmatrix}$$

 $\left|\lambda_{3}\right| \leq \left|\lambda_{2}\right| \leq \left|\lambda_{1}\right|$



Multiscale vessel enhancement

Blob like structures:

3D 2D $R_{B} = rac{\left|\lambda_{1}
ight|}{\left|\lambda_{2}\cdot\lambda_{3}
ight|} \qquad R_{B} = rac{\lambda_{1}}{\lambda_{2}}$

Plate-like structures: $R_A = \frac{|\lambda_2|}{|\lambda_2|}$

Hessian norm:



Vesselness function

Vesselness function :

3D case:

 $\lambda_2 > 0$ and $\lambda_3 > 0$

$$V_0(s,\gamma) = \begin{cases} 0 \\ \left(1 - \exp\left(-\frac{R_A^2}{2\alpha^2}\right)\right) \exp\left(-\frac{R_B^2}{2\beta^2}\right) \left(1 - \exp\left(-\frac{S^2}{2c^2}\right)\right) \end{cases}$$

2D case:

$$V_0(s,\gamma) = \begin{cases} 0 & \lambda_2 > 0\\ \exp\left(-\frac{R_B^2}{2\beta^2}\right) \left(1 - \exp\left(-\frac{S^2}{2c^2}\right)\right) & \lambda_2 > 0 \end{cases}$$

Finally:

$$V_0(\gamma) = \max_{s_{\min} \le s \le s_{\max}} V_0(s, \gamma)$$

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Multiscale Filtering Results



Slide before filtering

Vesselness function representation

Multiscale Filtering Results





Axial, coronal and sagittal planes of the multi-scale enhancement filtered volume. Maximum intensity projections through the 3D volume.

3D Visualization Results

Visualisation of a selected vessel after 3D vesselness function thresholding and data segmentation with flood-fill (seed growing) algorithm.

The surface is rough and uneven. Applying a surface smoothing methods is needed.



Center-line extraction results

the first step for surface smoothing with deformable models



Vesselness function

after masking and thresholding after applying a skeletonization algorithm

Plans for the future work

- Improving a 3D data filtering algorithm,
- Applying tube-like deformable models for surface smoothing,
- Modelling a viscosity, blood flow and pressure drop.

References:

 Knowledge-Based Extraction of Cerebral Vasculature from Anatomical MRI – L.R.
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Multiscale vessel enhancement filtering

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Thank you for your attention