

Vessel Segmentation Using Prior Shape Based on Tensor Analysis for Inhomogeneous Intensity and Weak-Edge Images

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Abstract—Blood vessel segmentation is a key component for various clinical applications. In this paper, we present a novel method for vessel segmentation by using a prior shape based on tensor analysis and then incorporate it in a level-set-based segmentation method. We firstly introduce the prior shape via tensor analysis, which formulates the fractional anisotropy and anisotropic character of the mechanical tensor. Comparing to conventional statistical prior shape models, the main advantage of the proposed prior shape is that it directly derives from the given clinical images via tensor analysis, instead of statistical shape from a training sample set, leading to a simple and practice method for complex vascular structures. We subsequently explicitly incorporate the prior shape in our hybrid energy function, which enforces the segmentation depending on the joint influence of the region-homogeneity, gradient (edge), and the proposed prior shape. We validate our method both on the synthetic images and multimodal clinical images, which shows that our method outperforms the competing methods.

Keywords—vessel segmentation; prior shape; tensor analysis; intensity inhomogeneity; level set

I. INTRODUCTION

Blood vessel segmentation is a key component for various clinical applications, such as diagnosis of vascular diseases, surgery planning and blood flow simulation. The level set framework has received increasing attentions due to its good performance on vessel segmentation. Broadly speaking, the existing level set methods may be categorized as region-base segmentation, edge-based segmentation and prior-shape-based segmentation.

Region-based methods assume that image intensities are statistically homogeneous in each region, such as the well-known Chan-Vese (CV) model [1]. Zhao *et al.* [2] proposed a vessel segmentation algorithm using infinite perimeter active contour model with hybrid region information for application on retinal images. A novel region-based method utilizing both global and local image information complementarily was proposed by Bai *et al.* [3]. Wang *et al.* [4] proposed a multi-scale local region to segment images with intensity inhomogeneity. Hossain *et al.* [5] provided a semiautomatic method with edge, region, smoothness energy and a novel stopping criterion for atherosclerotic carotid artery segmentation. Hong *et al.* [6] provided a localized

hybrid method, which integrates both boundary feature and local region information. Ukwatta *et al.* [7] proposed a method for carotid atherosclerosis in ultrasound images, which incorporated regional/boundary image statistics and expert-based initializations. Liu *et al.* [8] presented a two-level-set model, which is the generalization of distance regularization on level set models.

The intensity and edge statistics are insufficient for detecting the complex vascular structures. Consequently, masses of existing approaches focus on prior shape knowledge of vessels for accurate and robust segmentation. Wang *et al.* [9] provided a shape-driven method in level set framework by consequently utilizing the shape priors of position, scale and angle information of vessel-like structures. Mezghich *et al.* [10] incorporated geometric shape prior into an edge-based level set model in order to improve its robustness to partial occlusions, low contrast and noise. Qiu *et al.* [11] proposed a prostate segmentation, which contained shape-constraint and local-region-based energies for handling weak edges. Song *et al.* [12] reported a novel approach for multi-object segmentation that incorporated both shape and context prior knowledge in a 3D graph-theoretic framework. Saito *et al.* [13] provided a theoretical framework for accurately estimating all possible shapes by using statistical shape models.

The rest of this paper is organized as follows. In section 2, we reveal an intrinsic relationship between Hessian matrix and mechanical tensors, and later introduce our vascular structure function by using the proposed prior shapes. In the section 3, we qualitatively and quantitatively evaluate our method and the competing approaches on artificial images and various multi-modal clinical images, which intuitively show the power of the proposed method.

II. PROPOSED METHOD

A. Mechanical Stress Tensor

The Hessian matrix is a popular method to formulate both of the local structure and orientation. It is worth note that, mathematically, Hessian matrix and mechanical stress tensor are equivalent to each other for image analysis applications. Consequently, we associate Hessian matrix and mechanical stress tensor, and further analyze the feature of Hessian matrix through analyzing fractional anisotropy and anisotropic character of the mechanical stress tensor, which

breaks restrictions of the traditional cylindrical model on vessel segmentation. A common decomposition of the mechanical stress tensor T is formularized as $T=T_{\text{iso}}+T_{\text{an}}$, where $T_{\text{iso}}=tr(T)/3$ and $T_{\text{an}}=T-T_{\text{iso}}$ respectively denotes the isotropic component and the anisotropic (deviatoric term) component. In the framework of tensor analysis, an orthogonal tensor invariant set $R=\{R_1,R_2,R_3\}$ are defined as $R_1 = \text{norm}(T)$, $R_2=1.5^{0.5} \text{norm}(T_{\text{an}}) / \text{norm}(T)$, $R_3 = 3 \times 6^{0.5} \det(T_{\text{an}}/\text{norm}(T_{\text{an}}))$, where R_1 is a measure of tensor magnitude, R_2 denotes the fractional anisotropy, indicating the ration between anisotropic magnitude of tensor and tensor magnitude. R_2 intuitively reveals the motion speed of an object along the primary vector axes. R_3 is a measure of the anisotropy mode. We later utilize R_2 and R_3 to create the prior shapes of vessel structure and finally incorporate the prior shapes into a hybrid energy function for segmentation.

B. Prior Shape

In our method, we utilize fractional anisotropy and anisotropic model component of mechanical stress tensor to identify the vascular shape. We assume the eigenvalues of the Hessian matrix λ_1, λ_2 , and λ_3 satisfying $|\lambda_1| \geq |\lambda_2| \geq |\lambda_3|$, and reformulate

$$R_2 = \frac{\sum_{i=1}^3 (\lambda_i - \bar{\lambda})^2}{\sum_{i=1}^3 (\lambda_i^2)}$$

and

$$R_3 = 3\sqrt{6} \prod_{i=1}^3 (\lambda_i - \bar{\lambda}) / \left(\sum_{i=1}^3 (\lambda_i - \bar{\lambda})^2 \right)^{3/2}$$

Consequently, we propose our vascular structure measure $VP(T_x)$ at the given point x of the clinical images whose intensity in vessels is brighter than the ones in the background

$$VP(T_x) = \exp(-|FA(T_x) - 1| - |\text{mode}(T_x) - 1|) (1 - \exp(-S^2/2c^2)) \quad (1)$$

otherwise

$$VP(T_x) = \exp(-|FA(T_x) - 1| - |\text{mode}(T_x) + 1|) (1 - \exp(-S^2/2c^2)) \quad (2)$$

where $VP(T_x)$ varies from 0 to 1. $VP(T_x)$ is equal or approximate to 1 if x locates at the vessel structure, otherwise $VP(T_x)$ is a small value or even equal to zero if x locates on the non-vascular structure or background. The last term in (1) and (2) indicate the ‘‘second order structureness’’ [14] for eliminating influences of small eigenvalues in background and low contrast regions.

C. Prior Shape for Segmentation

We defines a vessel shape profile $C_{\text{shape}} = \{x | VP(T_x) = \tau\}$ to approximate the ground truth, where $\tau \in (0,1)$ indicates a threshold for vascular prior shapes. Subsequently, we accurately model the vessel shapes by using implicit Euclidean distance transforms in our work. We present an implicit level set to represent C_{shape} and later introduce a

distance function $\Phi(x, C_{\text{shape}})$ by embedding C_{shape} into a higher-dimensional space. We defines $\Phi(x, C_{\text{shape}})$ as the Euclidean distance between the given point x and the vessel shape. $\Phi(x, C_{\text{shape}})$ is a positive value if point x locations inside the vessel shape, while $\Phi(x, C_{\text{shape}})$ is a negative value if x locations outside the shape. Consequently, we could initialize the level set function $\Psi(x, C_{\text{shape}})$ as $\Phi(t_0, x, C_{\text{shape}})$, which represents the approximate shape of the given vessels. In order to finally force the shape approach to the ground truth, we further propose the shape difference term $E_{\text{shape}} = \int_{\Omega} [H(\Phi) - H(\Phi_0)]^2 dx$ to regular the shape evolution, where $H(\cdot)$ is the Heaviside function.

In order to adequately utilize the advantages of gradient, region and our prior shape of in evolution process, we propose a hybrid energy function $E_{\text{vessel}} = \zeta E_{\text{FLUX}} - E_{\text{CV}} - \gamma E_{\text{shape}}$, where E_{CV} denotes the minimum variance term in CV model [1], which model the region information for segmentation; E_{FLUX} is an edge-based term in our method. ζ and γ are positive constants depending on the intensity scale, which are usually optimized empirically in our work. In the practical segmentation tasks, we usually use a large value γ for intensity inhomogeneity and a large value ζ for images with weak vessel boundaries. We then maximize the proposed hybrid energy functional and get the corresponding evolution function.

III. EXPERIMENTS AND RESULTS

A. Prior Shape

We respectively quantitatively and qualitatively estimate the performance of our method and other competing methods on multimodal clinical images. In order to verify the validity of our vessel probability function for obtaining the prior shapes, we examine it on DSA images and retinal vessel image (shown in Figure 1). It is worth to note that the retinal vascular image (the right column in Figure 1) contains abundant textures in the background, which would make the existing methods fail to get a sound prior shape.

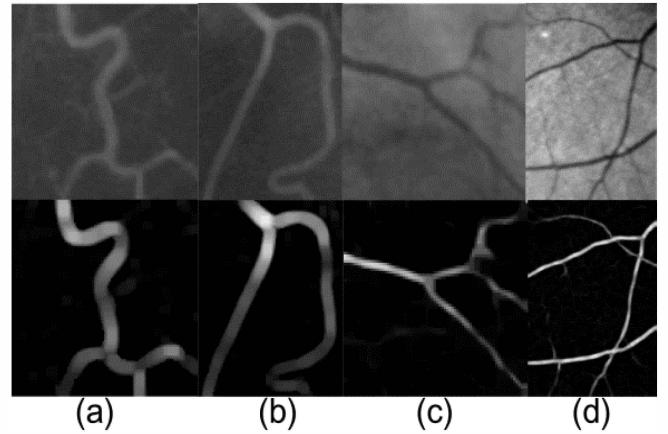


Figure 1. Performance of our method on degenerated clinical images. The top row shows various modal clinical images for evaluation, the middle row shows the performance of our method, and the bottom row demonstrates the initial curves by using our method. (a) DSA, (b) and (c) CTA, (d) retinal vessel image.

B. Vessel Segmentation

We further evaluate our segmentation method on various vessel images (both of synthetic image and multimodal medical images). We execute a quantitative evaluation on synthetic images with various measures and execute qualitative evaluations on multi-modal medical images, which shows the power of the proposed method for images with inhomogeneous intensity and weak-edge.

C. Synthetic Images

In order to quantitatively evaluate the performance of our method, we generated synthetic images containing vessel-like structure, which is shown in Figure 2. Our method successfully gets the synthetic vessel-like shapes, while the competing methods (CV and GCV) fail to approach to the ground truth on intensity inhomogeneity images and weak edge images. In order to quantitatively evaluate the accuracy of segmentation methods, we use area percentage difference AD and relative difference degree RDD . The small value of AD or RDD indicates a good performance of segmentation. Table I shows the quantitative results on the measures of AD and RDD .

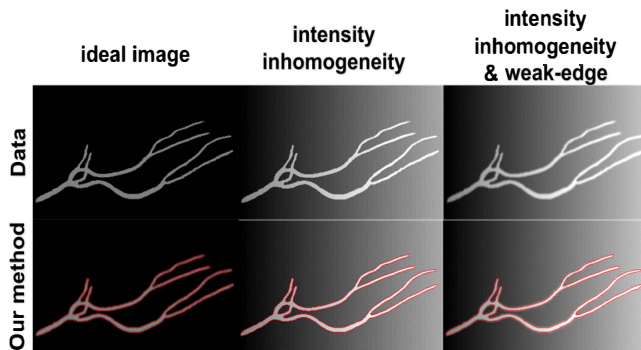


Figure 2. Segmentation on synthetic images. The proposed method gets sound results on intensity inhomogeneity images and weak-edge images.

TABLE I. PERFORMANCE ON DEGENERATED IMAGES

	weak edge	intensity inhomogeneity	weak edge & intensity inhomogeneity
CV	14.4/14.9	449.3/449.5	533.0/540.0
GCV	1.92/16.5	344.7/347.3	371.7/372.4
Our method	1.31/15.0	0.21/10.5	1.69/16.4

D. Clinical Images

In order to further assess the power of our method on clinical images, we perform it on various clinical images with blurred edges and inhomogeneous intensity, which are shown in Figure 3. Figure 3 intuitively shows the performance of our method on multimodal medical images, demonstrating that our method have an ability to handle the degenerations. Our method could accurately and robustly identifies the vascular structures in the degradation images, while other competing approaches fail to get sound vessel shapes.

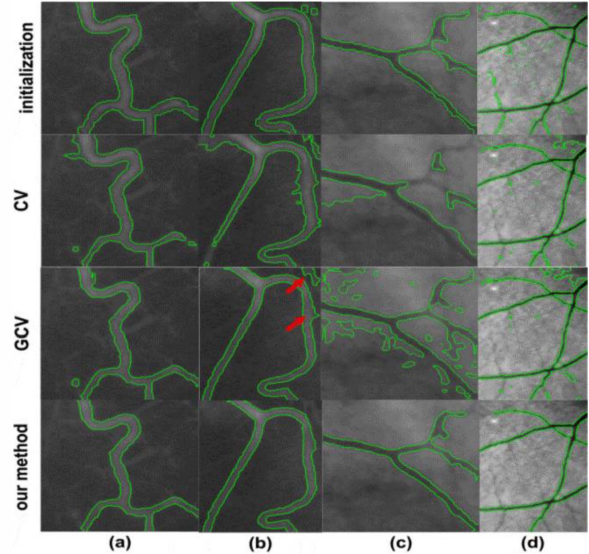


Figure 3. Performance of competing methods and our method for clinical images. First row: prior shape superimposed on the clinical images, representing the initialization for all segmentation methods. The second row to fourth row respectively show performance of CV method, GCV method, and the proposed method.

In order to further reveal the power of the proposed method, we subsequently demonstrate the robustness of our method for various initializations. Figure 4 shows the arbitrary initialization for medical images, where the initialization in the left two images include part of target vessels, while the curves in the right two images exclude the targets. The images in the bottom row demonstrate the good performance of the proposed method and robustness to arbitrary initializations.

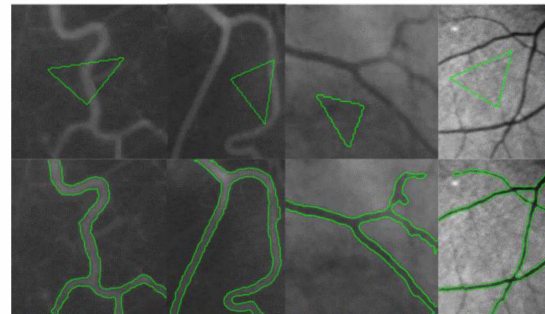


Figure 4. Arbitrary initializations for the proposed method. The left two curves in the top row include part of vessels, while right two curves completely locate on the background.

IV. CONCLUSION AND FUTURE RESEARCH

Blood vessel segmentation is a key component for many clinical applications. In this paper, we proposed a novel vessel segmentation method for medical images with inhomogeneous intensity and weak-edges. In summary, the contribution of our work includes the following aspects. (1) We propose a prior shape via tensor analysis, which formulates fractional anisotropy and anisotropic character (eigenanalysis) of the Hessian matrix. Comparing to

conventional statistical prior shape models, the main advantage of the proposed method is that the prior shapes directly derive from the given clinical images via tensor analysis, instead of statistical shapes from a training sample set, leading to a simple and practice method for complex vascular structures on multimodal images. (2) We explicitly incorporate the proposed prior shapes in our hybrid energy function, which enforces the shape evolution depending on the joint influence of the region-homogeneity, gradient (edge), and the proposed prior shape. Our approach not only preserves the performance of the existing approaches, but also overcomes inabilities of the classical methods to handle inhomogeneous intensity and weak-edge images. We finally validate our method both on the synthetic images and multimodal clinical images, which shows that our method generate the best results, outperforming the competing methods.

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