Lodz University of Technology Faculty of Electrical, Electronic, Computer and Control Engineering Institute of Electronics

PhD Thesis

Application of level set based method for segmentation of blood vessels in angiography images

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1. Introduction

Automatic segmentation of blood vessels from 3D angio-graphic images significantly supports a diagnosis and surgical treatment planning of circulatory system diseases. An extracted vascular network enables modeling of vessel architecture and a blood flow. Quantitative information obtained from such models is very important in an analysis of vessel pathologies like stenosis or intraoperative guidance.

The rapid development of angiographic imaging techniques has led to the emergence of competition for contrast computed tomography, considered as a standard for visualizing brain blood vessels. Recently, MR angiographic sequences have been able to substitute angio-CT imaging providing high quality reproductions of a vascular network. MR ToF (time of flight) sequence does not require any contrast agent and offers high resolutions of acquired images (when modern 3T scanners are used) detecting vessels with a relatively small diameter. Another approach used e.g. for characterization of complex arteriovenous anatomy of upper extremity vascular disorders is T2-weighted MR imaging with an application of blood pool contrast agent. Both techniques enable construction of accurate models based on segmented vasculature.

The level sets are actually the most common methods used in blood vessel network extraction. This article is part of a current trend, presenting our own extension of the LS based approach introduced in [1]. There, a Chan–Vese [2] mathematical model is enhanced by additional energy terms to ensure more accurate vessel extraction. However, this is limited to a single scale that corresponds to a given vessel diameter. Since vessels sizes vary in the real angiographic images, our contribution further improves Forkert model by introducing a multiscale analysis. The proposed method was tested on artificial and real data, including brain and upper extremities vessel images obtained for different imaging modalities and acquisition protocols.

The thesis statement was formulated as follows:

Multiscale vesselness function information used for level set based segmentation allows detection of blood vessels with a wider diameters range in comparison to the single scale function.

2. Materials and methods

2.1. Analyzed images

To evaluate performance of discussed image segmentation techniques, from qualitative as well as quantitative points of view, numerical phantoms were designed. To model real vessel trees, cylinders of different diameters were connected together. To generate such vascular tree images, a computer simulator of tree growth was developed and implemented in [3].

Also, the following medical images were analyzed, acquired for volunteers and patients with circulatory disorders:

- 1. MR hand contrast (Vasovist) images. For image acquisition, the 3D MR T2 sequence was applied (Siemens Avanto 1.5T).
- 2. Two MR brain angiography provided by Friedrich Schiller University in Jena, Germany.
- 3. Five CT brain angiography with a contrast agent (Ultravist 370).

2.2. Vesselness function

For all analyzed datasets a vesselness function (VF) was evaluated before further segmentation. The purpose of VF is to enhance vessel structures with an eventual goal of vessel segmentation. The vessel enhancement is a filtering process that searches tubular structures in the image. There are several approaches to vessel enhancement filtering, yet the most commonly used method is a filtering process presented by Frangi et al. in [4]. This method was used in presented research.

2.3. Level set based segmentation

The basic idea of such segmentation techniques is to iteratively evolve a curve (or surface in 3D), which is controlled by some parameters estimated from the image. The curve evolves toward image objects and should stop at their boundaries. In this work the level set method proposed by Forkert in [1] is used, which is an extension of a well-known Chan–Vese approach. This is an energy minimization based segmentation and the motion of the curve is obtained by solving a curve evolution partial differential equation (PDE). Firstly, a vesselness function is estimated, which quantifies the likeliness of each voxel to belong to a bright tubular structure as described in a previous chapter. The essential step for further processing is to calculate eigenvector e_1 which is obtained from the first Hessian eigenvalue λ_1 . The first extension to the classic level set approach is adding weight to the internal energy equation which is locally adapted based on the eigenvector e_1 obtained from the vesselness function. The standard Chan–Vese level set equation can be written as:

$$F_1(C) + F_2(C) = \int_{inside(C)} |I_0(x) - c_1|^2 dx + \int_{outside(C)} |I_0(x) - c_2|^2 dx$$
(1)

The external energy can be denoted as:

$$E_i(\phi,\omega^{\phi}) = \int_{\Omega} \omega^{\phi}(x) |\nabla H(\phi(x))| dx = \int_{\Omega} \omega^{\phi} \cdot \delta_0(\phi(x)) \cdot |\nabla \phi(x)| dx$$
(2)

and:

$$\omega^{\phi}(x) = \mu \cdot \left(1 - \cos^2(\alpha(x))\right) \tag{3}$$

where $cos(\alpha(x))$:

$$\cos(\alpha(x)) = \frac{e_1 \cdot \nabla \phi}{|e_1| \cdot |\nabla \phi|} \tag{4}$$

The second improvement proposed in [1] means adding an additional term to the level set formulation which represents so called vesselness force. This additional energy term is used to drive the contour along the vessels more actively. Additional Energy term is defined by:

$$\vartheta(\phi) = \omega^V \int_{\Omega} H(\phi(x)) \cdot \cos^2(\alpha(x)) \cdot \sqrt{VF(x)} \, dx \tag{5}$$

To correctly emphasize vessels with different sizes by the vesselness function a multiscale analysis should be per-formed. Thus, VF should be calculated for multiple Hessian filters with different s values. The selection of the number of implemented filters and their corresponding s values depend on distribution of vessel radii in the analyzed image. The main idea of our improvement of Forkert framework is to use information from a multiscale vesselness function and adapt it to the equations presented in the previous point. Firstly, a multiscale effect should also be reflected in the weight estimation. The eigenvector e_1 should be calculated for corresponding eigenvalue λ_1 for every selected scale s. After that the vesselness function value is calculated and a final value is chosen as follows:

$$V(x) = \max_{s_{min} \le s \le s_{max}} V(s, x)$$
(6)

This maximum vesselness function value is calculated for every voxel in the image and it is used in the vesselness force in Eq. (5).

3. Results

3.1. Artificial tree image

An artificial tree image, after estimation of VF, was analyzed according to Eqs. (1)-(6) for the scale 1.2. Next, the analysis was repeated using a proposed improvement (consideration of multiple scales in Eqs. (6)). The scales used in this case were equal to {1, 1.2, 1.4}. Even though only three scales with small ratio between them was used, it was enough to expose both thin and thick vessels in the artificial tree.

For quantitative evaluation of segmentation results, the Jaccard coefficient was estimated. It expresses the similarity between a segmented image and a binarized version of the undistorted tree phantom. Its value varies from 0 to 1 where the highest one represents the perfect segmentation. J values are given in Table 1.

Table 1. Estimated J coefficients along with TP, FP and FN values for different segmentation methods.

Metoda	Jaccard	ТР	FP	FN
Jedna skala (LS2)	0.51	83234	216	79127
Wiele skal (LS3)	0.55	91117	411	71321
Wiele skal (LS3) +	0.54	89041	112	73767
bi-Gauss FU				



Fig. 1. Segmentation results: single scale – red vessels, multiscale – red and blue vessels.

3.2. MRA images

For brain images, to compare both segmentation techniques better, only a continuous vessels network is presented. Thus fragments of thinner vessels, not connected to main branches were omitted. In these Figures red color was used to mark vessels obtained by means of a single scale segmentation while blue shows additional vasculature obtained after application of a multi- scale approach.



Fig. 2. Segmentation results: single scale – red vessels, multiscale – red and blue vessels.

4.Conclusion

This paper presents an improvement to the level set framework proposed in [1]. The introduction of an energy term to the LS model that considers a multiscale vesselness function enables the correct detection of branches with different diameters. This leads to a better characterization of the segmented vasculature resulting in a more precise brain or hand vessel geometric model. The efficiency of this approach was demonstrated on a number of medical images acquired by different modalities. The proposed method should be further verified on digital vessel phantoms obtained by means of simulated MR angiography. Preliminary segmentation results were considered by radiologists as promising, however further qualitative and quantitative assessment of the developed method is much needed. All aforementioned issues, along with works aimed at automation of preprocessing algorithms, will be topics of further research.

References

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