Neurocomputing 162 (2015) 234–244

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Extraction of vessel networks based on multiview projection and phase field model

Shifeng Zhao [a,b,*], Mingquan Zhou [a,b], Yun Tian [a,b], Pengfei Xu [a,c], Zhongke Wu [a,c], Qingqiong Deng [a,c]

[a] College of Information Science and Technology, Beijing Normal University, Beijing 100875, China
[b] Beijing Key Laboratory of Digital Preservation and Virtual Reality for Cultural Heritage, Beijing, China
[c] Engineering Research Center of Virtual Reality and Applications, Ministry of Education, China

ARTICLE INFO

Article history:
Received 24 August 2014
Received in revised form
11 December 2014
Accepted 12 March 2015
Communicated by Pingkun Yan
Available online 3 April 2015

Keywords:
Segmentation
Blood vessel
Level set
Projection

ABSTRACT

The precise segmentation of cerebral vessels is essential for detecting cerebral diseases. This work proposed a novel method for automatic extraction of blood vessels. The proposed framework includes three steps: (a) projection from 3D volume to 2D plane: in order to make up the small percentage vessels occupy in each slice and to avoid overlapping between vessels, the volume dataset is projected from different directions; (b) extraction on 2D plane: a new energy model is proposed using phase-field and statistical information which is based on the Allen–Cahn equation with a double well potential and statistical data fitting terms. The segmentation is based on curve evolution. This model is effective in extracting blood vessels with low contrast, multi-branch structure and intensity inhomogeneity from projection images; (c) projecting back from 2D plane to 3D volume: the pixels segmented from previous step will be projected back into the volume dataset, and the corresponding voxels in the volume will be reserved to construct the blood vessels in three-dimensional space. Experimental results illustrate that the performance of the methods is better than existing techniques.

1. Introduction

Vascular diseases are among the most important public health problems in developed countries. The vessel segmentation provides an equipment to understand the relation between vessels and diseases. In clinical applications, blood vessel extraction is often a necessary preprocessing step for three-dimensional (3D) reconstruction, quantitative analysis and computer aided diagnosis. The development from two dimensional X-ray images to the possibility of creating three dimensional representations of the body has helped significantly when it comes to detecting diseases [1]. However, given the size and complexity of modern angiography acquisitions, segmentation task is of key importance to the accurate visualization, diagnosis and quantification of vascular pathologies [2].

While most of the arterial anatomy can be shown clearly in MRA (Magnetic Resonance Angiography) images, this is often not for thinner ones. Thinner vessels containing low or complex flow and are poorly represented in images. The presence of disease such as an aneurysm could cause significant vascular signal loss in image with some intensity levels approximately equal to those of background signal, thereby producing a heterogeneous intensity pattern with other tissues. Therefore, segmentation is a challenging task and generally requires sophisticated algorithms and human intervention.

The distribution of gray level values corresponding to one structure may vary throughout the structure and may also overlap those of another structure. These inhomogeneous subregions pose a challenge for robust vascular segmentation. This work was motivated by the need to develop a fully automatic segmentation algorithm that could reliably segment the vasculature including other regions of low or complex flow from MRA images.

2. Related work

The problem of vascular structures extraction has received considerable attention in the computer vision and medical imaging communities [3]. Lesage et al. [4] reviewed 3D vessel segmentation techniques about the models, features and extraction schemes. However, the complex 3D structure of cerebral vessels and the low contrast of thin vessels in images make precise

* Corresponding author at: College of Information Science and Technology, Beijing Normal University, Beijing 100875, China.
E-mail address: zhao_shifeng@bnu.edu.cn (S. Zhao).

http://dx.doi.org/10.1016/j.neucom.2015.03.048
0925-2312/

segmentation difficult. Some blood vessels are so thin that may even not be recognized by human eyes. To the best of our knowledge, no effective solution is currently available for the automatic and multimodal segmentation of cerebral vasculature.

Typical brain blood vessel segmentation was widely investigated in the past. A common approach for blood vessel segmentation is based on deformable models, which detect the boundary of the object through minimizing an energy associated to the current contour as a sum of an internal and external energy. A popular way to numerically implement such an active contour evolution is through the level set framework. Gradient and geodesic implemented with level set techniques offer flexible topological adaptability to segment MRA images [5].

Intensity inhomogeneity and thin vascular regions in the angiograms are not easy to handle in the segmentation process. To deal with this problem, a number of approaches have been proposed. In the low-contrast regions, rather than using the unreliable intensity gradient alone, contours can also be evolved based on shape prior [6]. Region information is also efficiently used in such models to deal with intensity inhomogeneity problem. For example, Li et al. [7] proposed an efficient region-based level set method by introducing a local binary fitting (LBF) energy weighting by a kernel function. Other hybrid methods combining both edge and region information can perform the segmentation efficiently. For example, Wang et al. [8] proposed the local and global intensity energy (LGIF) model combining the advantages of both CV and LBF model by taking the local and global intensity into account. Wang et al. [9] introduced a local Chan–Vese (LCV) model which also utilized both global and local information for segmentation. Tian et al. [10] combined both region and edge information to construct a signed pressure force function to improve the segmentation results. However, such methods have limited success in dealing with low contrast problems. Zhao et al. [11] modified the length term and combined the statistical information into the energy function, they could extract more thin and low contrast blood vessels.

Apart from using the active contour models, image segmentation methods using the statistical information have been an active research area. In statistical models, the input volume is classified into either vascular voxels or nonvascular voxels [12]. Such model ensures the local structural coherence of the vascular surface and constrains the binary segmentation within the Bayesian framework. Such probabilistic framework for estimating the posterior probability is based on the product of observation model and prior model. The observation model embodies the knowledge of image formation and noise properties. The prior model represents the prior beliefs about the image [13]. This gives better delineation of the blood vessel boundary between vascular regions and background regions.

The statistical approaches for extracting blood vessels from the MRA data were proposed by some groups [14], using similar research principles based on different statistical mixture models. Experimental results show that the proposed statistical mixture models can provide a better modeling of the statistical properties of the underlying background and vascular signals. Hassouna et al. [15] proposed a cerebrovascular segmentation method from TOF (Time of flight) using stochastic models. They use one Gaussian distribution to fit the vascular voxels, two Gaussian distribution and one Raleigh distribution function to model the brain tissue region. Salem et al. [16] proposed a segmentation method for blood vessels from color retinal images by using a novel clustering algorithm with a partial supervision strategy. It is experimentally shown that these models could improve the robustness of the segmentation methods when SNR (Signal-to-noise ratio) is low in the images. But their accuracy depends on underlying probability models.

Roy et al. [17] introduced a Rician Classifier which was based on Rician mixture model with an expectation maximization (EM) for segmentation. They showed the Rician Classifier using EM (RiCe) yielded better performance compared with finite Gaussian mixture model. Gao et al. [18] introduced a fast automatic segmentation algorithm based on statistical model and also improved curve evolution for extraction the 3D cerebral vessels from MRA dataset. They modeled cerebral vessels using Gaussian distribution and other brain tissue using combination of Rayleigh and Gaussian distributions. Tian et al. [19] proposed an active contour model by combing the image intensity distribution and the vessel shape information. Such model could obtain some of the thin vessels. The experimental results are promising but not for thin blood vessels.

Farag et al. [20] proposed an approach using level sets in the 3D volume. The classification approach depends on initializing the level sets in the 3D volume, and the level sets evolve with time to yield the blood vessels. This work introduced a high quality initialization for the level set functions, allowing extraction of the blood vessels in 3D and elimination of non-vessel tissues. The results demonstrate good accuracy for vessels with significant size but not for those with small size compared to the voxel size. Some methods allow for good segmentation of certain vessels, such as the common carotid vessels and the carotid bifurcation, as presented by Cuisenaire [21] and Freiman [22]. Adel et al. [23] proposed a tracking method based on statistical model for linear structure detection, especially for vessel segmentation. Although this method yields better results in easier cases, it fails to detect the smaller vessels.

Despite the tremendous amount of past and on-going dedicated research, extracting thin blood vessels automatically and accurately remains a challenging task due to the variety of shapes, the complexity of the topology, the presence of noise in a complicated background, and the diversity of imaging techniques. The MRA images are multi-modal in the sense that particular modes of the marginal probability distribution of signals are associated with regions-of-interest.

In this present work, we introduce an algorithm of blood vessel segmentation for MRA data. The single generic active contour model, as well as the statistical model alone, is inadequate for extracting the whole part of the vessels. That is because of the image property of the MRA, where the intensity of each pixel on the blood area depends on the amount of blood flow. Moreover, thin vessels are affected by the partial volume effect which reduces the intensity of vessel parts as the low pass filtering effect. So the range of the intensity of the blood vessel is not restricted in a small interval but spread widely. Therefore, the new approach combines distribution information with the active contour model in a level set formulation to extract blood vessels.

The reminder of this paper is organized as follows: Section 3 gives the details of the proposed method. Experimental results and comparisons with several other methods are presented in Section 4. The paper concludes with a discussion on the direction for future work.

3. The framework of the proposed method

Some of the main steps to be carried out when dealing with vascular segmentation have a generic nature or, in other words, can be found in all general purpose image analysis systems. Fig. 1 shows the flowchart of the proposed method. However, the specific features of the blood vessels as well as the particular acquisition techniques, which are used, have led to targeted methods. More attention will be given to the projection and segmentation-characterization stage.

3.1. Projection from volume to the plane

Vessels occupy a very small area in each slice. They just look like a few white dots of varying sizes, or different thickness ranging of bending curves, two examples are shown in Fig. 2(a, b). The small percentage makes segmentation on each slices time consuming and