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Segmentation of vascular structures around brain tumors using region growing on Frangi vesselness

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Abstract

A segmentation of 3D vascular structures based on vesselness associated with a region growing algorithm is presented in this paper. The blood vessels segmentation is still important in the diagnosis of diseases related to their forms, surfaces and volumes. The extraction of vascular structures is commonly achieved with angiographic data set, but our contribution in this work is to perform this task with standard available data in the context of brain tumor. This is a big challenge because of the variation of pixels intensity and the low contrast in cT1MR (contrast T1 Magnetic Resonance). We propose a method starting by the enhancement of tubular structures using a vesselness filter, and then the region growing algorithm is performed slice by slice in a 3D volume defines by a ROI (Region Of Interest) for segmenting blood vessels.

Brain tumor, Image segmentation, Region Growing, Vascular structures, Vesselness.

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Introduction

The analysis of vascular structures in medical image is useful in the diagnostic process of specific diseases or in the planning of surgeries with the goal to keep them intact. The segmented vessels can be used directly by surgeon for a checking or for other purposes such as registration carried out with vessels as landmarks. Despite remarkable efforts developed in recent years, medical image segmentation is still one of the problem not solved in general, because there are difficulties due to low contrast, noise, and other imaging ambiguities [1]. Radiologists and medical experts spend most of the time segmenting manually medical images. Moreover, the final result is affected by the user fatigue or missing manual steps. Several techniques were introduced to automate the process in order to handle a large number of cases with the same accuracy and high speed.

The simplest approach for segmentation is the thresholding [2, 3], but there are also improved method such as region growing [4]. The first method suffer of many drawbacks such as: it fails in the presence of smooth edge, varying intensity and sensible to the noise. The second one has the problems of leakage when the boundary is blurred and the difficulty to set a threshold value confining the target. Other techniques are used for this purpose such as hybrid genetic algorithm and Artificial Neural Network Fuzzy (ANFIS) [5] in brain tumors segmentation, graph cut with shape priors [6, 7] and active contour model introduced by [8] which used an explicit type of curve representation.

The level set approach [9] was proposed to address the curve parameterization issue of the last method.

Vessels segmentation also can be achieved with vessel enhancement filters by using the Hessian operator as presented by Frangi [10] and by Krissian et al. [11]. Krissian proposed a model which combine the Hessian matrix and the gradient based structure tensor to get a robust technique to extract tubular structures [12].

In this work, we developed a visualization tool to enhance the blood vessels in 3D MR data during brain tumor surgery with the goal to keep them intact. Tumor resections are commonly guided using a navigation system based on contrasted cT1MR data. The contrast agent highlights the brain tumor and the vascular structures as well. Especially those around the brain tumor are of interest for the surgeon. However, these blood vessels are thin and few contrasted. We tested therefore a vessel enhancement filter known as Frangi vesselness will be associated with a region growing algorithm to enhance the vascular structures in order to increase the contrast between vascular structures with other anatomical structures. The pixel intensity obtained after the vesselness is suitable for an automatic thresholding using Otsu method. This paper is organized as follows: section II describes the algorithm used for blood vessels segmentation and the proposed methodology to extract vessels around brain tumors is explained in section III. Preceded by the results section of tests performed on the patient data, the last one concludes the analysis.

Background

Region Growing

The basic idea of the Region Growing method is to start the segmentation from a given seed point selected in the target to be segmented.

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The object is segmented by a recursive search among the voxels in the neighborhood of the starting point to find those that meet a membership criterion to the region. Usually, the threshold value is used as a criterion of belonging to the region. The final partition segmented R is defined by the mathematical formulation:

$$\bigcup_{i=1}^{n} R_i = R$$
$$R_i \cap R_j = \emptyset$$
$$P(R_i) = True$$
$$P(R_i \cup R_j) = false \quad (1)$$

Where Ri is the connected points satisfying the predicat P.

Vesselness

The use of other segmentation methods is not adequate for the segmentation of cT1MR data. Usually, they are used on angiographic data. The vesselness based Hessian matrix is useful to enhance vascular structures and to allow the visualization of vessels relative to the tumor.

The filtering based on hessian matrix allows to extract vascular structure in medical images by calculating the eigenvalues λ1, λ2, λ3 (|λ1 | < |λ2 | < |λ3 |) of Δ2 I, and their corresponding eigenvectors e_1, e_2, e_3.

$$H = \begin{bmatrix} \frac{\partial^2 I}{\partial x^2} & \frac{\partial^2 I}{\partial x \partial y} & \frac{\partial^2 I}{\partial x \partial z} \\ \frac{\partial^2 I}{\partial x \partial y} & \frac{\partial^2 I}{\partial y^2} & \frac{\partial^2 I}{\partial y \partial z} \\ \frac{\partial^2 I}{\partial x \partial z} & \frac{\partial^2 I}{\partial y \partial z} & \frac{\partial^2 I}{\partial z^2} \end{bmatrix} \quad (2)$$

Having this eigenvalues and eigenvectors, the intensity and the direction of vascular structures can be found.

In 3D, the Hessian matrix H is composed by the second order partial derivatives of the image I at a point (x, y, z).

To control the width of the extracted centerline, the partial second derivatives of I in (2) will be replaced by the partial second derivatives of Gaussian as:

$$\frac{\partial^2 I_\sigma}{\partial x^2} = \left\{ \frac{\partial^2}{\partial x^2} G_\sigma \right\} * I$$
$$\frac{\partial^2 I_\sigma}{\partial x \partial y} = \left\{ \frac{\partial^2}{\partial x \partial y} G_\sigma \right\} * I$$
$$G_\sigma = \frac{1}{\sqrt{(2\pi\sigma^2)^3}} \exp(-\frac{x^2+y^2+z^2}{2\sigma^2}) \quad (3)$$

Where G_σ is a Gaussian function with a standard deviation σ.

Using the eigen values, the dissimilarity measure is described as follows:

$$R_A = \frac{|\lambda_1|}{|\lambda_2|} \quad (4)$$
$$R_B = \frac{\lambda_1}{\sqrt{|\lambda_2 \lambda_3|}} \quad (5)$$
$$S = \sqrt{\sum_{i=1}^{3} \lambda_i^2} \quad (6)$$

The vesselness function can be calculated as described in [10]:

$$v_o(\sigma) = \begin{cases} 0 & if\ \lambda_2 > 0\ or\ \lambda_3 > 0 \\ (1-\exp(-\frac{R_A^2}{2\alpha^2}))\exp(-\frac{R_B^2}{2\beta^2}) & \\ (1-\exp(-\frac{S^2}{2c^2})), & otherwise \end{cases} \quad (7)$$

Where α, β, and c are thresholds which control the sensitivity of the filter to the measures R_A , R_B , and S. By applying a multiple scales, the maximum response v_I is the final estimate of vesselness and also the enhanced image which corresponds to line like structures.

$$v_I = \max_{\sigma_{min} \le \sigma \le \sigma_{max}} v_o(\sigma) \quad (8)$$

In this equation σ_{min} and σ_{max} values represent respectively the minimum and maximum scales wherein the structures are expected to be found.

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They are chosen in order to cover the range of the vessels widths.

Methods

The low contrast in MR images does not facilitate the segmentation task in medical application. By using the simple region growing, the result obtained is not adequate because of the leakage in the segmentation due to the close intensity value of vessels and other structures. On the other hand, this technique is more sensitive to the initialization seed point and without an appropriate choice of this starting point, the extraction of the target fails. Because the segmentation carried out by a region growing method is based intensity, the optimal threshold value that could be chosen will extract inappropriate structures such as head bones and soft tissues. To overcome this drawback we propose first to enhance de vascular structures with a Frangi vesselness filter. Based on eigenvalues of the Hessian matrix, the filter will find the vesselness maximum response which corresponds to the tubular forms in the image. The goal of this step is to highlight the vessels in comparison with other structures. With an improved contrast between our target structures with others, an automatic thresholding algorithm such as the Otsu technique could be used to perform the segmentation. By assuming that the image to be thresholded contains two classes of pixels, the algorithm calculates the optimum threshold for separating them in order to minimize the intraclass variance and to maximize the interclass variance.

The proposed segmentation methodology, allows not only extract the vascular structures, but also our approach presents the result in a 3D model for a good evaluation.

For a 3D model, a centerline is calculated as local maximal distances for getting skeletons presented in Figure 1.

Results

The results of the proposed method are illustrated in this section. The implementation was done with an Intel Celeron, 1.5 Ghz and 2 GB of memory using Mevislab tool.

Figure 1 Skeletons

An accurate segmentation carry out manually that could be considered as reference becomes more difficult in the 3D images used. With a goal to extract vessels among different structures, our results were validated by experts based on a visual inspection as described in [13]. Fig .2(a) and Fig .3(a) show the slices of a region of interest from a cT1MR images with blood vessel to be segmented and located in the neighbour of the brain tumor. In the Fig .2(b) and Fig .3(b) the results obtained with our segmentation method are presented.

The task has been carried out with a multi scale vesselnes to extract vascular structures in the image slices. We choose $\sigma = [1, 3]$ for the first case, $\sigma = [1, 2]$ for the second case and the number of scales equal to 3 in the both cases.

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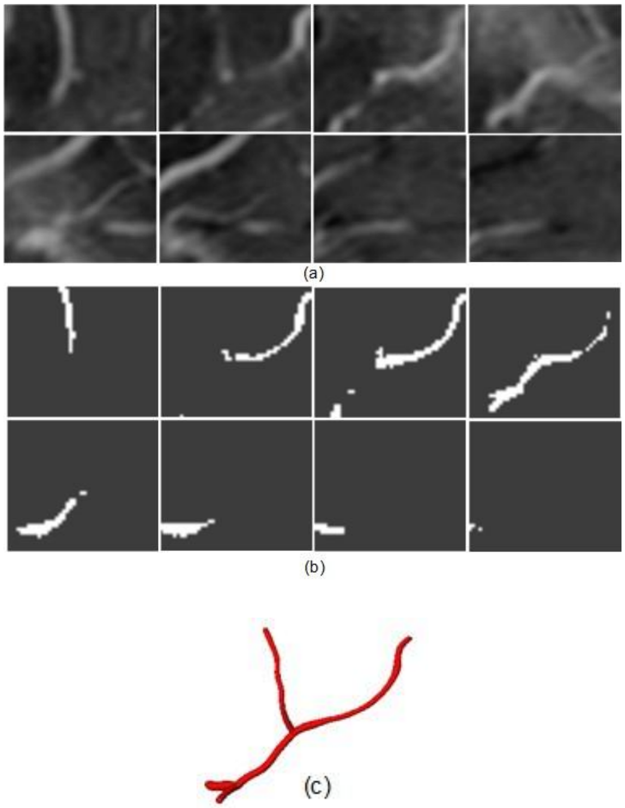

Figure 2 (a) 4 slices of a MR image with blood vessels, (b) The result segmentation of vascular structures in (a), (c) representation of the segmented vessel from the set of 8 previous slices

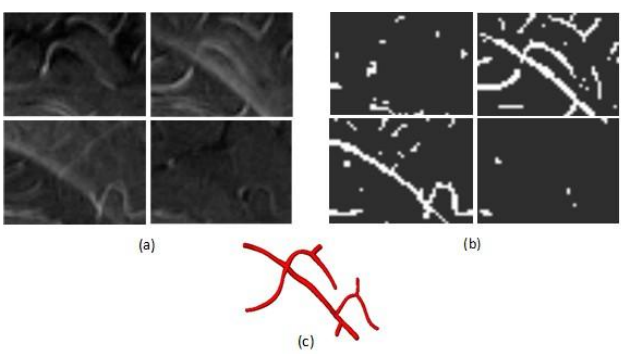

Figure 3 (a) 8 slices of a MR image containing blood vessels, (b) The result segmentation of vascular structures in the image slices (a), (c) representation of the segmented vessel from the set of 8 previous slices

Conclusion

In this paper a region growing method applied to Frangi vesselness is proposed in the context of segmentation of vascular structures around the tumor. Despite the difficulty of using this kind of data not oriented vessels visualization, the results of the proposed method have shown the capability to enhance and extract vascular structures. The 3D reconstruction is a suitable mean for surgeon in the planning step or during brain tumor surgery when the risk of damaging blood vessels should be reduced.

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