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Brain tumor and vascular structures segmentation applied in computer assisted surgery

ILUNGA-MBUYAMBA, Elisee*† and AVIÑA-CERVANTES, J. G.

Universidad de Guanajuato, Division de Ingenierias, Campus Irapuato-Salamanca. Valle de Santiago km 3.5+1.8, Communidad de Palo Blanco, 36885 Salamanca, GTO, Mexico

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Abstract

A possible treatment of brain tumor consists in a surgery performed by neurosurgeons who open the skull (called craniotomy). By navigating through the brain, they reach the tumor tissues and try to remove the maximum possible. The task is tricky because of the small operation field delimited by the craniotomy, also because of the difficulty to differentiate the brain healthy tissue surrounding the tumor and the brain shift that occurs. Furthermore, the use of an ultrasound contrast agent does not allow to distinguish the tumor remnant with other hyperechogenic structures after resection. An additional tool for intraoperative imaging represents therefore a crucial element to guide the navigation through the brain safely and improve the resection task.

Brain tumor, image segmentation, vascular structures, vesselness.

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* Correspondence to Author (email: avina@ugto.mx)
† Researcher contributing first author.

Introduction

The operation involving blood vessels requires the segmentation of vascular structures in medical image (CTA, MRA, CEUS, and Color Doppler) for a good diagnostic. The extracted region can be examined by its form, its superficies or its volume in 3D. Despite remarkable efforts consented in recent years, segmentation is still one of the problem not solved in general. Radiologists and medical experts spend most of the time manually segmenting medical images. However, computational application performs the segmentation with the least possible error and in a record time. Several techniques was proposed for this purpose. The simplest approach for segmentation is the thresholding [1, 2] followed by its sophisticated version, region growing [3]. The first method suffer of many drawbacks such as: it fails in the presence of smooth edge, of 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. To overcame the limitation of the firsts methods, several techniques are used such as hybrid genetic algorithm and Artificial Neural Network Fuzzy (ANFIS) [4] in brain tumors segmentation, graph cut with shape priors [5,6] and active contour model introduced by [7] which used an explicit type of curve representation. The level set approach [8] was proposed to address the curve parameterization issue of the last method. Vessels segmentation is achieved also by using the Hessian operator as presented in [9]. Krissian et al. proposed a model which combine the Hessian matrix and the gradient-based structure tensor [10] to get a robust technique to extract tubular structure. Several research have proposed different possibilities for the correction of brain displacement that happens during tumor resection [11-13]. In [14, 15], this problem is addressed based on vessels segmentation.

In this work, we tested different segmentation methods for the extraction of vascular structures in image data involved in tumor resection surgeries. Three applications are presented in this context, firstly, the visualization of the blood vessels in cT1MR (contrast T1-weighted MR) data for the surgery planning, secondly the brain shift evaluation and finally the vascular structure tracking in intraoperative US data. One visualization tool was implemented for this purpose to assess the correction of the brain shift, to identify the vascular structures after resection and to differentiate them with residual tumors. This report is organized as follows: section II describes the segmentation methods, in section III, the methodologies proposed and based on blood vessels segmentation are applied to medical applications.

The section IV presents the results of tests performed on the phantom and patient data set. Preceded by a discussion section, the last one concludes the analysis.

Background

A. Thesholding

The thresholding is the simplest method to partition a grayscale image into two classes. The result obtained after segmentation is called binary image. By setting a threshold value, the pixels are classified in one of the two classes as described following:

$$I_t(x,y,z) = \begin{cases} 0, & if\ I(x,y,z) < t \\ 1, & if\ I(x,y,z) > t \end{cases} \quad (1)$$

Where $I_t(x, y, z)$ and $I(x, y, z)$ represent respectively the voxels of the segmented image and those of the original image at the coordinate point (x, y, z), and t is the threshold value.

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B. Region Growing

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

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:

$$\bigcup_{i=1}^{n} R_i = R$$

$$R_i \cap R_j = \emptyset$$

$$P(R_i) = True \tag{2}$$

Where Ri are the connected points satisfying the predicate P.

C. Vesselness

The use of other segmentation methods is not adequate for the segmentation of MRT data.

Usually, those models 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 method consist to extract the brain from MRT1 as preprocessing step, to segment blood vessels and the tumor. The 3D surface rendering presents all structures together, what is interesting for neurosurgeons.

The filtering based on hessian matrix allows to extract vascular structure in medical images by calculating the eigenvalues $\lambda_1, \lambda_2, \lambda_3$ $(|\lambda_1| < |\lambda_2| < |\lambda_3|)$ of $\nabla^2 I$, and the corresponding eigenvectors e_1, e_2, e_3.

$$H = \begin{bmatrix} \partial^2 I/\partial x^2 & \partial^2 I/\partial x\partial y & \partial^2 I/\partial x\partial z \\ \partial^2 I/\partial x\partial y & \partial^2 I/\partial y^2 & \partial^2 I/\partial y\partial z \\ \partial^2 I/\partial x\partial z & \partial^2 I/\partial y\partial z & \partial^2 I/\partial z^2 \end{bmatrix} \tag{3}$$

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 (3) will be replaced by the partial second derivatives of Gaussian as:

$$\frac{\partial^2 I_\sigma}{\partial x^2} = \left\{\frac{\partial^2}{\partial x^2} G_\sigma\right\} * I$$

$$\frac{\partial^2 I_\sigma}{\partial x\partial y} = \left\{\frac{\partial^2}{\partial x\partial y} G_\sigma\right\} * I$$

$$G_\sigma = \frac{1}{\sqrt{(2\pi\sigma^2)^3}} exp\left(-\frac{x^2+y^2+z^2}{2\sigma^2}\right) \tag{4}$$

Where $G\sigma$ is a Gaussian function with a standard deviation σ.

Using the eigenvalues, the dissimilarity measure is described as follows:

$$R_A = \frac{|\lambda_1|}{|\lambda_2|} \tag{5}$$

$$R_B = \frac{\lambda_1}{\sqrt{|\lambda_2 \lambda_3|}} \tag{6}$$

$$S = \sqrt{\sum_{i=1}^{3} \lambda_i^2} \tag{7}$$

The vesselness function can be calculated as described in [9]:

$$v_0(\sigma) = \begin{cases} 0, if\ \lambda_2 > 0\ or\ \lambda_3 > 0, \\ \left(1 - \exp\left(-\frac{R_A^2}{2\alpha^2}\right)\right) exp\left(-\frac{R_B^2}{2\beta^2}\right) \left(1 - \exp\left(-\frac{S^2}{2c^2}\right)\right), otherwise \end{cases} \tag{8}$$

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

$$v_l = \max_{\sigma_{min} \leq \sigma \leq \sigma_{max}} \{v_0(\sigma)\} \tag{9}$$

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

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

Methods

A. Segmentation of cerebral vascular structures driven by vesselness

Despite the contrast agent used in cT1MR data, blood vessels are still little contrasted, and othe anatomical structures are visible and represented with similar gray intensities. The segmentation becomes more complex than in CTA or MRA data, where only the vascular structures are represented.

To improve the visualization of vessels in the preoperative planning step, the vesselness method has been adopted for the segmentation task. Due to the skull noises affecting the result, a preprocessing was carried out to extract the brain using Brain Surface Extraction tool (BSE). Secondly, the vesselness was applied on the brain to enhance the visualization of vascular structures. In the method illustrated in the Fig. 1, the vesselness was performed with a single scale σ = 1 and the extracted target was filtered by a 3x3 median filter to reduce noises.

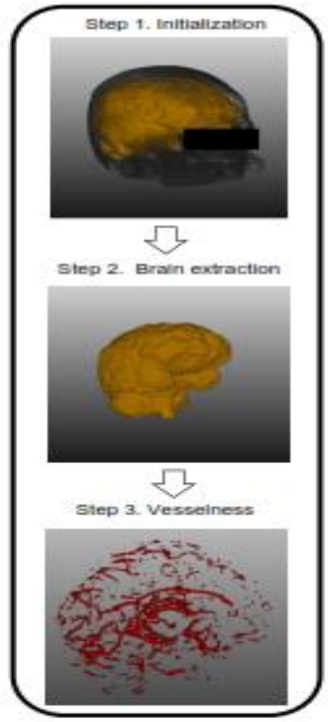

Figure 1 Image segmentation process proposed

B. Vessels-based registration for brain shift correction Since a brain displacement occurs after the craniotomy and during tumor resection, the correction of the initial registration is required. The vascular structures was used as a reference to achieve the correct alignment during surgery. The first tests have been performed on the phantom data.

With a CEUS image a little misaligned to the CT image, we used the vascular structures to perform the alignment. The method consist firstly by a segmentation of vascular structures in both modalities, and followed by a registration task of these segmented elements. The registration provided a transformation matrix that allows the overlapping of images. When this matrix is applied to the CT image, the alignment error converge to zero.

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The methodology for correcting the brain shift is illustrated in Fig. 2, where the segmentation in step 1 was effected with a simple thresholding method.

The registration on the second step has been performed using the Normalized Cross Correlation (NCC) as similarity measure. In the third step, the corrected alignment of the CT and CEUS images is presented. The computation iteration time was of 34.9 seconds and the images size 88, 40, 111 in 3D.

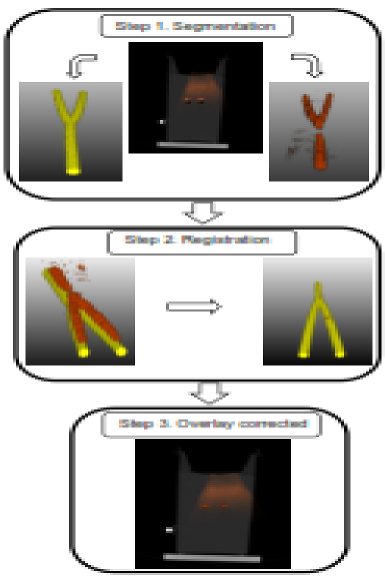

Figure 2 Proposed methodology for correcting Misalignment

This correcting process can be described as follows:

1. Manually definition of the Region of interest (ROI) on the images,
2. Define the Threshold value by the user and compute the segmentation,
3. Start the registration of the segmented structures, The similarity measure is calculated as:

$$NCC = \frac{1}{\sigma_x \sigma_y} \sum_i (x_i - \bar{x})(y_i - \bar{y}) \qquad (10)$$

4. Display the final solution

Our contribution is the evaluation of the accuracyand of the computation time relative to the shapeand the pattern size. By reducing the ROI size, the segmented structures also are reducing in order toimprove the response time of the algorithm. Thecomputation iteration time decreased to 1.2 seconds (image size: 84, 37, 34), what means 29 times fasterthan in the first case or an improvement of 96.56 percent.

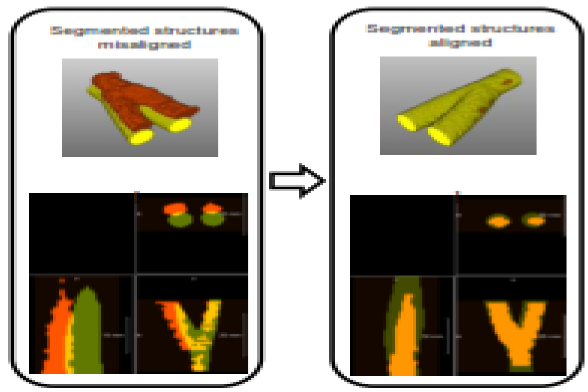

Figure 3 Overview of the computation time Improvement

The registration using small structures is computed with a reduced iteration time, and the choice of a bifurcation helps to make the algorithm robust to noises and less sensible to errors related to the confusion in identification of targets.

Given that this proposed scheme has shown its capability to remedy the misalignment of images, it have also tested on real data.

C. Tracking of vascular structures in intraoperative US

The patient image dataset includes a preoperative contrast T1 MR data and 3D intraoperative contrast enhanced ultrasound (3D-iCEUS) data acquired before and after tumor resection.

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The use of a contrast agent enhances the visualization not only the tumors, but also the vascular structures. On the other hand, to differentiate the remnant tumor with the blood is a complex task in CEUS after resection.

Our method proposes to track vessels in CEUS data using a pattern extracted in cT1MR data, and the identification of the vessels avoids the confusion between vessels and residual tumor in CEUS images. Therefore, with the implemented tool, the user defines a ROI in the preoperative MR data including a blood vessel perfusing the tumor to

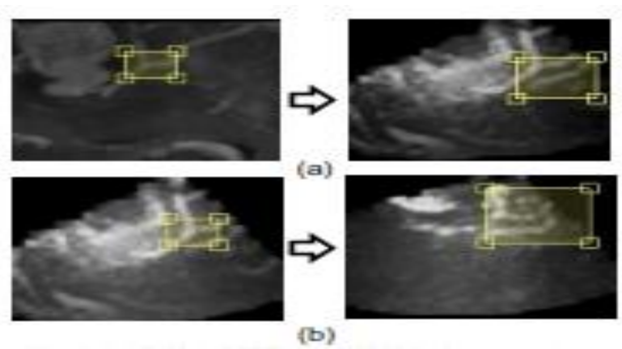

Figure 4 (a) ROI in MRT and CEUS before resection, (b) ROI CEUS before and after resection

Track the vessels intraoperatively based on the proposed methodology as shown in Figure 6 and 7.

Using a rigid registration method, the selected pattern is searched in the 3D-iCEUS data before resection within a larger region because of the brain shift (Fig. 4). The detected blood vessel becomes then the new pattern to identify the same vascular structure in the 3D-iCEUS data after resection. The extracted blood vessels are finally segmented using a vesselness method and visualized.

Results

This section shows the results obtained in each application, and the implementation was done with an Intel Celeron, 1.5 Ghz and 2 GB of memory. The algorithms have been implemented using MeVisLab tool and ITK C++ (Insight Segmentation andRegistration).

A. Visualization of blood vessels for brain tumor resection planning

The figure 5 illustrates how the vascular structures are displayed together with tumor data to facilitate the surgery planning task by the visualization. The tumor was segmented using a region growing threshold connecting.

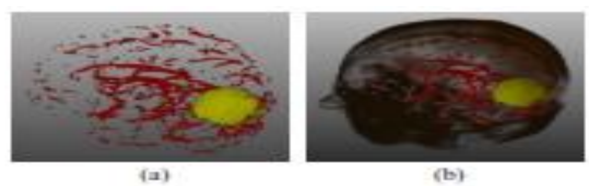

Figure 5 (a) Blood vessels image merged with a tumor, (b) Segmented structures displayed in the skull

B. Correction of the brain deformation based onvascular structures

Since the brain shift can be corrected using blood vessels, some results of the tests performed on a patient data set is presented below.

At the same position, the figure 8 (a) and (b) shows the misalignment between the MRT image and the CEUS data occurred during brain tumor resection. By applying the method of vessels-based registration to correct the brain shift, the result obtained is illustrated in the figure 8 (c).

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Furthermore, in the figures 9, the first one shows the overlay of preoperative and intraoperative data when there is a brain deformation. In the second one, the result obtained by the proposed methodology is presented.

C. Blood vessel tracking in intraoperative CEUS

Our method was tested on patient data in the context of a brain tumor operation.

It was validated by registering the preoperative MR data with the 3D-iCEUS data using the transform matrix obtained in the registration method.

The correct overlapping of anatomical structures, especially the vessels, was visually checked in the 3D-iCEUS data before and after resection.

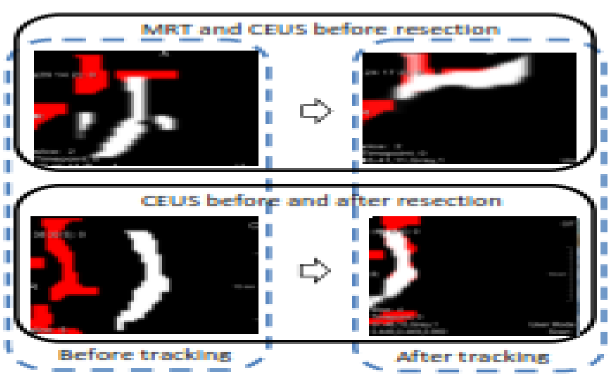

Figure 6 Tracking process flow

Discussion

Application 1: for the planning stage, the segmentation performed with the vesselness method gives an output with noises and should be validated by many specialists. The future work will be to test other vesselness method as described in [16].

Application 2: in this work, we used a rigid transformation model that allows to correct the brain shift in a local volume. Due to the elastic deformation of the brain, an elastic registration method is needed to perform the task.

Application 3: the big issue in the segmentation task in iCEUS for tracking vessels data still the quality of available data. The image quality is important in order to get an expected result with the proposed tool and method. The future work could be focused on the image quality enhancement as preprocessing step to overcome some flaws that occurred in the tracking process.

MRT and CEUS before resection
CEUS before and after resection
Before tracking
After tracking

Conclusion

Various segmentation methods are used on a patient data set in medicine. In this work, three medical applications based on segmentation of vascular structures have been presented in the context of brain tumor surgery. The obtained results indicate that the vesselness method is a suitable approach to help neurosurgeons in a planning stage of brain tumor resection. With a 3D visualization, they can choose the least invasive trajectory to reach their target. Intraoperative CEUS modality is a cheaper and easy method to check the brain deformation and to identify the tumor tissues. The use of blood vessels as a reference pattern has shown its capability to correct the misalignment of cerebral structures and to track a vessel after resection in CEUS data to differentiate it with the remnant tumor.

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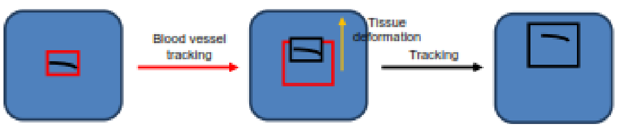

Figure 7 Tracking vessels

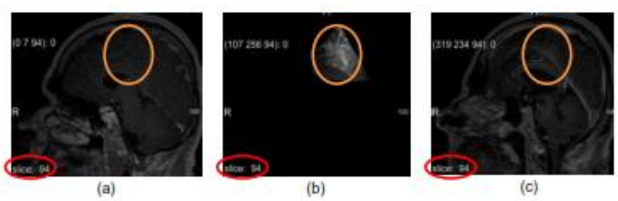

Figure 8 (a) Initial MRI data, (b) iCEUS and (c) MRI data with a brain shift corrected

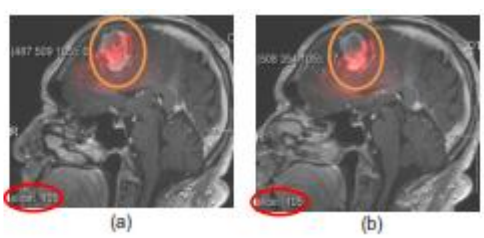

Figure 9 (a) Overlay of MRI and iCEUS data with brain deformation, (b) MRI and iCEUS data superimposed after the correction of brain shift

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