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Segmentation and 3D Visualization of Volumetric Image for Detection of Tumor in Cancerous Brain

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***Abstract*—Development of an accurate three dimensional (3D) model of human skull showing the shape and relative position of a tumor inside the cancerous brain is crucial for taking pre-surgical or pre-therapy measures. This paper presents a new method for automatic segmentation of volumetric image which is a collection of series of spatially distributed slice images of a cancerous brain. The proposed method provides a 3D visualization in order to identify the position, shape, and size of a tumor inside the brain of a skull. Each of the images of the series is segmented using a level-based segmentation method using the histogram of image intensities. Such a segmentation of single image in the series results in spurious regions which may cause misleading 3D shapes of tumors. In order to obtain an accurate 3D model of the tumor inside the brain, both the intra- and inter-slice area-based thresholds are exploited for removing the spurious regions from the initially segmented images. The proposed segmentation scheme not only removes the false regions regarding the segmentation of tumor, but also effectively maintains the size and shape of the original tumor. Extensive experimentations on a number of volumetric images reveal that the proposed method can provide minimum volumetric noise in the extraction process of a tumor as compared to the recently introduced vector flow method.**

***Index Terms*—Segmentation of tumors, 3D visualization, volumetric noise.**

I. Introduction

In the last two decades, applications of a number of three dimensional (3D) imaging techniques such as the magnetic resonance (MR) and computed tomography (CT) imaging are quite common in medical science for mapping the anatomy of a subject without biopsy. In these 3D imaging techniques, a series of cross-sectional or slice images that are commonly referred to as the volumetric images, are created for an organ. A suitable 3D visualization technique is used to have a 3D view of the organ using these volumetric images captured from the CT or MR imaging machines. In medical diagnosis, it is often necessary to obtain a 3D segmented view and quantify the volume of a part of the organ, since the shape, volume or position of the concerned part of the organ plays vital roles for determining a treatment plan. The segmentation process of volumetric images varies widely with the resolution of images determined by the imaging modalities or with the characteristics of the part of the organ to be segmented. In this paper, we are dealing with the automatic segmentation of tumors from volumetric MR images of a cancerous brain with a view that the position, shape, and size of the tumors would be helpful for accurately determining the alignment and doses of radioactive therapy.

In order to segment a tumor from a cancerous brain, a number of methods are proposed in the literature. These methods may be broadly classified into two categories, viz., supervised and unsupervised methods. Supervised segmentation methods use images of tumors or healthy brains to train a set of parameters of a segmentation method and then use these set of parameters to identify the existence of a tumor or to segment the tumors that exist in the images of a brain under the test. For example, in [1] a method is developed and then extended in [2] to segment the MR brain images of the patients having tumors of low-grade glioma (LGG) and meningioma (MG) by using a spatially varying statistical classification method. Corso *et al.* [3] integrate a Bayesian formulation into the segmentation by a weighted aggregation algorithm to identify glioblastoma multiforme (GBM) brain tumors. This algorithm uses voxel intensities in a neighborhood to compute an affinity among the surrounding voxels to train the segmentation model parameters and then classify the edema and GBM tumor in the testing phase. However, the efficacy of this method in segmenting other types of brain tumors such as LGG and MG, is not reported.

Unsupervised methods are also developed for segmentation of volumetric images to avoid the use of patient-specific training. In [4], a new set of fuzzy rules are developed to segment tumors from the brain MR images using human expert intervention and analysis of histogram of pixels. Ratan *et al.* [5] adopts an watershed approach for 2D image segmentation to provide an approximate shape of the tumor in terms of a number of disks. Karayiannis *et al.* [6] formulate the segmentation of MR images as an unsupervised vector quantization process using the feature vectors obtained from local relaxation parameters of the MR imaging technique. Ho *et al.* [7] use segmentation based on level-set snake evolution and a probability model to isolate tumors from a MR brain image. In [8], a Bayesian classifier is first used to identify the initial location of a tumor in a brain and then a fluid vector flow algorithm is employed to estimate the shape of the tumor. In most of the existing segmentation techniques, the 2D visualization is considered, and thus an idea about the position and shape of the tumor may not be realized with satisfaction. Further, in such scenarios the parameters with regard to segmentation process cannot be controlled by an expert through an interactive mode.

In this paper, a method is developed to segment the MR image series into three sections, namely, skull, brain and tumor, and visualize the shape and position of these sections in 3D. The proposed segmentation method is a successive operation of a level-based segmentation of 2D image followed by removal of spurious voxels using intra- and inter-slice area-based logical operations. In order to visualize the three sections in the brain, a platform of 3D Slicer [9] is used. The

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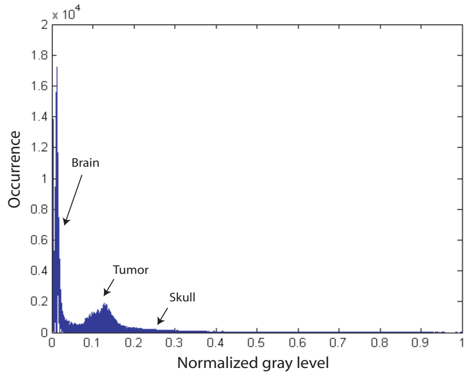


Fig. 1. Histogram of pixel intensities of entire set of slices of the MR images of a cancerous brain.

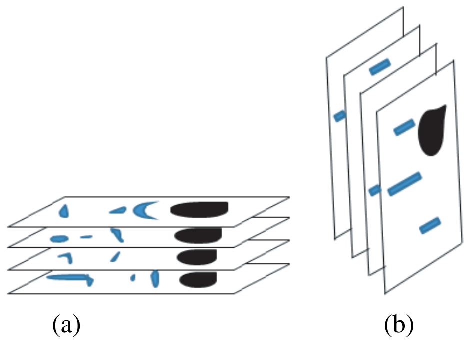


Fig. 2. Selection of segmented region for a tumor using the proposed intra- and inter-slice thresholding: (a) segmented region in the xy-plane and (b) segmented region in the yz-plane.

proposed visualization provides a better exposure of the tumor, its location, size and shape to facilitate tumor surgery, radiation therapy, chemotherapy or other treatments.

The paper is organized as follows. In Section II, the proposed segmentation scheme and the process of removal of spurious voxels are presented. In Section III, experimental results on segmentation and 3D visualization of commonly-used MR image series are presented. Finally, some concluding remarks are provided in Section IV.

II. Proposed Segmentation Method

Let I_{xyz} be the intensity of a voxel in a volumetric image series of size $(X \times Y \times Z)$ at the 3D spatial location (x, y, z), where $x = 1, 2, \cdots, X$, $y = 1, 2, \cdots, Y$, and $z = 1, 2, \cdots, Z$. It is considered that each of the slice remains on the xy-plane and there are Z number of slices in the volumetric image series, wherein the inter-slice distance is ℓ_z. The image series represents the skull, brain, and tumor as a whole in the 3D space. In order to segment these regions from the volumetric image series, first a level-based thresholding is applied on each of the slices, i.e., on xy- plane, to separate the skull from the whole brain. This step also provides a preliminary estimate of the regions of the tumor inside the brain. Next, a new intra- and inter-slice area-based logical operation is used on the binary image series to estimate the accurate region of the tumor inside the brain.

A. Level-Based Segmentation of 2D Slices

Since the tumors exist inside the brain, the first step of the proposed segmentation method is to isolate the skull from the whole brain by using a level-based thresholding on the xy-plane of the volumetric image series. The binary image series for skull is obtained as

$$S_{xyz} = \begin{cases} 1 & \text{if } I_{xyz} \geq \tau_s \\ 0 & \text{if } I_{xyz} < \tau_s \end{cases} \tag{1}$$

where τ_s is a suitable skull-threshold level depending on the intensity of pixels. A histogram of the pixel intensities of the entire set of slices for MR images of a typical cancerous brain is shown in Fig. 1. In order to obtain the histogram, the bin width is chosen as $\sqrt{XYZ}$, since such a choice provides a good statistical contrast in data [10]. It is seen from the histogram that the pixel intensities of the skull and tumor in an MR image is significantly higher than that of the brain. Thus, a thresholding may be applied to an MR image series to obtain a pixel in the binary image series that include both the skull and tumor given by

$$ST_{xyz} = \begin{cases} 1 & \text{if } I_{xyz} \geq \tau_{st} \\ 0 & \text{if } I_{xyz} < \tau_{st} \end{cases} \tag{2}$$

where τ_{st} $(\tau_{st} < \tau_s)$ is a suitable skull-tumor-threshold. From these two binary image series defined by the voxels S_{xyz} and ST_{xyz}, the voxels of the binary image series of the brain and tumor are obtained as

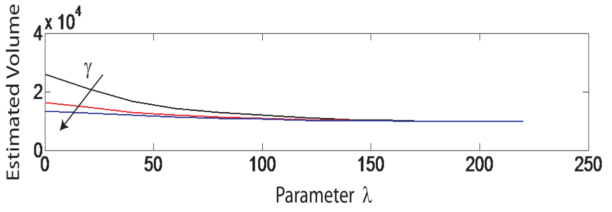
$$\text{Brain}: \quad B_{xyz} = 1 - ST_{xyz} \tag{3}$$

$$\text{Tumor}: \quad T_{xyz} = ST_{xyz} - S_{xyz} \tag{4}$$

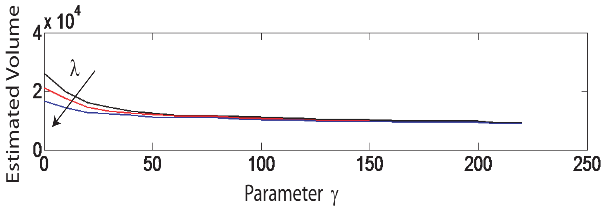
In most cases, the segmented regions obtained in both the binary image series of brain and tumor by the proposed thresholding technique are discontinuous. To connect these disjoint regions, morphological operations such as dilation, followed by erosion, are performed on each image in the series. In the proposed method, dilation is performed using a diamond-shape object denoted as D_ν, where ν $(\nu > 1)$ is the distance of any edge of the shape from the origin in terms of pixels. This operation not only joins the discontinuous segmented regions but also extends the shape of the individual regions in all sides. To remove these unwarranted extensions, the erosion operation is performed with line object L_μ, where μ $(\mu > 1)$ is the length of the line in terms of pixels. Such a dilation operation, followed by an erosion is often called a closing operation [11]. It is found that the proposed closing operation is sufficient for obtaining disjoint segmented regions of good quality in the binary images of brain and tumor.

B. Intra- and Inter-Slice Thresholding

The level-based thresholding on the xy-plane is sufficient for isolating the whole brain from the skull. At the same time, it gives an initial estimate of the regions of probable candidates of tumor inside the brain. Thus, a refinement is required to remove the spurious segmented regions and find the accurate position and shape of the tumor. Let the number of disjoint regions obtained for tumors in the xy-plane in a slice be p_z $(p_z \geq 1)$ and that for yz-plane be q_x $(q_x \geq 1)$. Let the areas of regions in the xy-plane be denoted as $\mathcal{A}_z^m$ $(m = 1, 2, 3, \cdots, p_z)$ and those in the yz-plane as $\mathcal{A}_x^n$ $(n = 1, 2, 3, \cdots, q_x)$. Since tumors in the volumetric image would have a significant volume both in the xy- and yz-planes, we may consider those regions to be tumors provided the areas of both these planes are significant. The level of significance



(a)



(b)

Fig. 3. The variations of estimated volume with respect to the intra- and inter-slice area-based threshold parameters. The variations are (a) in terms of λ when γ is fixed and (b) in terms of γ when λ is fixed.

that a region corresponds to a tumor may be expressed in terms of logical values given by

$$\Upsilon_{xy} : \mathcal{A}_z \geq \lambda \tag{5}$$

$$\Upsilon_{yz} : \mathcal{A}_x \geq \gamma \tag{6}$$

where λ and γ are area-based intra- and inter-slice thresholds defined for the xy- and yz-planes, respectively. In the proposed method, only the segmented regions are treated as tumor for which Υ is true such that

$$\Upsilon : \Upsilon_{xy} \wedge \Upsilon_{yz} \tag{7}$$

A typical example of disjoint regions in the horizontal xy-plane and vertical yz-plane is shown in Fig. 2. It is seen from this figure that the large segmented regions that exist in both the horizontal and vertical planes, selected from the proposed thresholding technique, may be considered as tumor.

To obtain suitable values of the two area-based threshold parameters, viz., λ and γ, we have estimated the total volume of the 3D shapes resulting from the segmented regions by varying these parameters. The total volume of the 3D shapes is estimated as

$$\mathcal{V} = \frac{1}{2} \sum_{z=1}^{Z} \left(\sum_{m=1}^{p_z} \mathcal{A}_z^m + \sum_{m=1}^{p_{z+1}} \mathcal{A}_{z+1}^m \right) \ell_z \tag{8}$$

It is noted that the estimated volume varies with the threshold parameters λ and γ as the $\mathcal{A}_z^m$ and p_z depend on the condition set by Υ. Fig. 3 shows the variations of estimated volumes of 3D shapes by varying one of the two parameters while keeping the other fixed. It is seen from this figure that initially the estimated volume decreases with the value of these parameters, but at a higher value of these parameters the volume becomes almost fixed. Since the 3D shapes may include the tumors as well as the spurious regions, any values of λ and γ may be chosen while the estimated volume does not change significantly with the variations of these parameters.

III. Experimental Results

Extensive experimentations have been carried out in order to evaluate the performance of the proposed method as compared to the existing methods. In the experiments, MATLAB is used for image processing and the 3D Slicer is for visualization. The volumetric MR images of cancerous brains are obtained from the sources given in [9]. The brain images of 10 patients having MG or LGG type tumors are considered in the experiments. Each set of volumetric images consists of 112 slices. The physical distance between two slices, i.e., ℓ_z, is 1.4 mm. Each of the slices is a 16-bit grayscale image of size 256×256 stored in 'dicom' format. In the experiments, the graylevels of all images are normalized between 0 and 1. In the level-based thresholding, the values of τ_s and τ_{st} are chosen as 0.20 and 0.10, respectively. The results presented in this section are obtained using $\nu = 2$ and $\mu = 3$ for the dilation and erosion operations, respectively. The values of the intra- and inter-slice threshold parameters λ and γ are chosen by estimating the volumes of the segmented objects and using an interactive visualization by 3D Slicer.

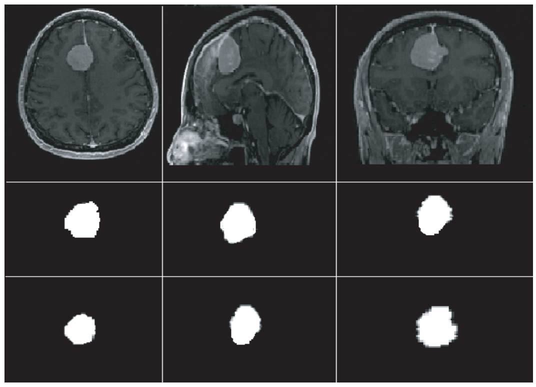


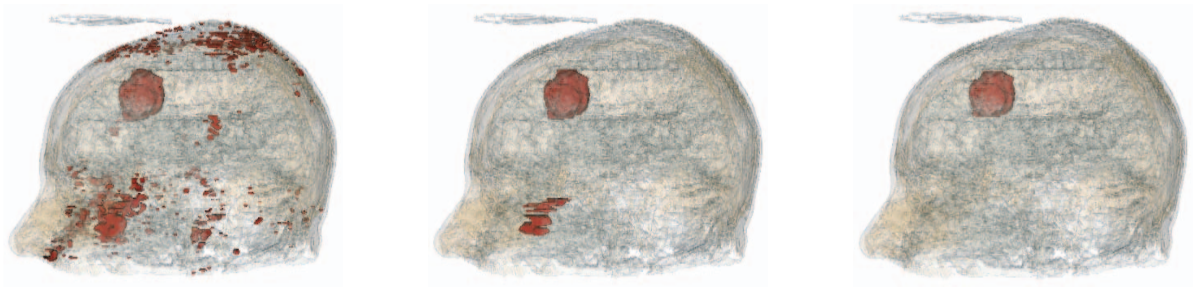
Fig. 4. Comparisons on results concerning the 2D segmentation of tumors from the cancerous brain. Columns from left to right indicate the axial, sagittal, and coronal views, respectively. Top row provides the original images. The middle and bottom rows show the segmentation results for [8] and the proposed methods, respectively.

TABLE I
ESTIMATED VOLUMES OF SEGMENTED 3D SHAPES WITH THE VARIATIONS OF THE INTRA- AND INTER-SLICE AREA-BASED THRESHOLDS.

Parameter λ (pixel)	Parameter γ (pixel)	Volume $\mathcal{V}$ (pixel^2-mm)
0	0	1,071,400
50	50	1,021,100
150	150	989,530

Fig. 4 shows a 2D axial, sagittal, and coronal views of a typical slice of MR brain images that possess a tumor. This figure also shows a 2D view of the segmented regions of the tumor using the fluid vector flow method [8] and the proposed method. From this figure, it may be seen that the proposed method maintains the 2D shape of the tumor in all three views better than that is maintained by the method of [8].

After obtaining three different series of images for skull, brain, and tumors using the proposed thresholding technique, the 3D Slicer is used to visualize them altogether so that position and shape of the tumors can be investigated interactively. Figs. 5 and 6, respectively, show the side-view and top-view of the 3D model constructed by the Slicer using three different values of the intra- and inter-slice threshold parameters λ and γ. Table I shows the volume of the segmented regions in terms of pixel^2-mm estimated for the 3D shapes obtained by varying these parameters. From the figures as well as from the tabular results, it is found that a value of 150 for the intra- and



(a) (b) (c)

Fig. 5. 3D side-view of the estimated tumors inside a cancerous brain obtained using the proposed segmentation method. The parameters are (a) $\lambda = \gamma = 0$, (b) $\lambda = \gamma = 50$, and (c) $\lambda = \gamma = 150$.

(a) (b) (c)

Fig. 6. 3D top-view of the estimated tumors inside a cancerous brain obtained using the proposed segmentation method. The parameters are (a) $\lambda = \gamma = 0$, (b) $\lambda = \gamma = 50$, and (c) $\lambda = \gamma = 150$.

inter-slice threshold parameters is a good choice to estimate a tumor without any spurious shapes in the 3D visualization. In summary, the proposed method not only provides the shape and relative position of the tumor inside brain and skull but also the actual size of the tumor in terms of pixel^2-mm.

IV. Conclusion

Automatic segmentation and 3D visualization of tumors inside the cancerous brain are crucial for diagnosis and treatments in medical science. In this paper, an automatic segmentation method has been developed for MR images of cancerous brain based on the fact that their intensity levels vary due to their tissue structures. A simple level-based threshold estimated from the intensity histogram isolates the skulls from the brain that includes the tumor. The level-based thresholding provides an initial estimate of the segmented region of tumors inside the brain. In order to remove the volumetric noise from the estimated regions of tumors, intra- and inter-slice area-based thresholds have been proposed. It has been shown that the area-based thresholding sufficiently removes the spurious regions and provides an accurate 3D shape and position of a tumor inside the brain. Thus, the proposed segmentation method results in three sets of image series, namely, skull, brain, and tumor. These image series have been used to build a 3D model for interactive visualization. In the experiments, it has been shown that the proposed segmentation method performs better than the recently proposed fluid vector flow method. In addition to providing a position and shape of the tumor in the 3D visualization, the proposed method gives an estimate of the volume of the tumor in terms of pixel^2-mm. Further, it is worth mentioning that being a threshold-based technique the proposed method is very fast in implementation.

References

[1] S. K. Warfield, M. Kaus, F. A. Jolesz, and R. Kikinis, “Adaptive template moderated, spatially varying statistical classification,” *Med. Image Anal.*, vol. 4, no. 1, pp. 43-55, 2000

[2] M. Kaus, S. K. Warfeld, A. Nabavi, P. M. Black, F. A. Jolesz, and R. Kikinis, “Automated segmentation of MRI of brain tumors,” Radiology, vol. 218, pp. 586-591, Feb. 2001.

[3] J. J. Corso, E. Sharon, S. Dube, S. El-Saden, U. Sinha, and A. Yuille, “Efficient multilevel brain tumor segmentation with integrated Bayesian model classification,” *IEEE Tran. Med. Imaging*, vol. 27, no. 5, pp. 629-640, 2008.

[4] N. Gordillo, E. Montseny, and P. Sobrevilla, “A new fuzzy approach to brain tumor segmentation,” in *Proc. IEEE Int. Conf. Fuzzy Systems*, 2010, Barcelona, Spain, pp. 1-8.

[5] R. Ratan, S. Sharma, and S. K. Sharma, “Brain tumor detection based on multi-parameter MRI image analysis,” *ICGST Int. J. Graphics, Vision and Image Processing*, vol. 9, no. 3, pp. 9-17, 2009.

[6] N. B. Karayiannis and P.-I Pai, “Segmentation of magnetic resonance images using fuzzy algorithms for learning vector quantization,” *IEEE Tran. Medical Iimaging*, vol. 18, no. 2, pp. 172-180, 1999.

[7] S. Ho, E. Bullitt, and G. Gerig, “Level-set evolution with region competition: Automatic 3-D segmentation of brain tumors,” in *Proc. IEEE Int. Conf. Pattern Recog.*, 2002, Quebec City, vol. 1, pp. 532-535.

[8] T. Wang, I. Cheng, and A. Basu, “Fully automatic brain tumor segmentation using a normalized Gaussian Bayesian classifier and 3D fluid vector flow,” in *Proc. IEEE Int. Conf. Image Processing*, 2010, Hong Kong, pp. 2553-2556.

[9] Available online, Official web-site: http://www.slicer.org/

[10] J. S. Simonoff, *Smoothing Methods in Statistics*, 1st ed. New York: Springer-Verlag, 1996.

[11] R. C. Gonzalez and R. E. Woods, *Digital Image Processing*, 2nd ed. Singapore: Pearsons, 2002.