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An Automated Method for Brain Tumor Segmentation Based on Level Set

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Abstract

In this paper, an automatic method has been proposed for tumor segmentation. In this method, a new energy function by introducing the feature tumor is determined implemented by level set. Multi-scale Morphology Fuzzy filter is applied to the image and its output determines the tumor feature. The initial contour selection is important in active contour models. Therefor the initial contour has been selected automatically by using Hough transform and morphology function. Experimental results on MR images verify the desirable performance of the proposed model in comparison with other methods.

Keywords: Tumor segmentation; Multi-scale fuzzy filter; feature; energy function; Level set.

1. Introduction

Based on the World Health Organization (WHO), nearly half thousand people suffer from brain tumor each year. The tumors cloud be seen at different location with different intensities and differ in shape and size. As a result, precise segmentation of brain tumors is a very challenging task beside its great interest. Fatality and the rate of spread of tumors fall them into two major categories namely: Benign and malignant brain tumors. Patients suspected of having tumors undergo many diagnostic CT-scans and MRI in hospitals. Tumor identification is extremely hard due to some abnormalities and noise, as a result radiologist face with a challenging operation. Numerous methods have been proposed in the field of tumor segmentation. Lee and his colleagues [1] inspected the use of the support vector machine (SVM) classification method and Markov random fields (MRFs) for brain tumor segmentation and claimed the advantage of SVM-based approach. In [2] by using biologically inspired BWT and SVM, the MR images were analyzed for Brain Tumor Detection and Feature Extraction. Tumor volume in MR images effectively measured by Fuzzy-correctness method [3,4].

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Other common methods used in segmentation of many types of medical image processing are Convolutional Neural Networks (CNNs) and region growing methods [5, 6]. Active Contour is one of the most popular methods used in image segmentation. By minimizing of energy function, the curve stops on the true boundary of the target object.

Active contour models are one of the most effective methods in segmentation of clinical images. Active contours can be categorized as edge-based [7–9] or region-based [10–11]. In region-based models, the statistical information inside and outside of the contour control its evolution. These models have more effective performance in images with weak edges or no edges and are less sensitive to noise. Popular region-based active contour models can segment images with the intensity homogeneity [10–11]. However, intensity inhomogeneity often arises in real images like clinical images.

In magnetic resonance images, intensity inhomogeneity refers to the non-uniform magnetic fields caused by limitations in imaging devices and variations in the object susceptibility. Intensity inhomogeneity must be corrected to remove undesired effects in analysis of MR images.

In [12-16], region-based models were proposed to segment the images with intensity inhomogeneity. For example, Li and his colleagues [12] and Zhang and his colleagues [14] proposed local binary fitting (LBF) and local image fitting (LIF) models, respectively, to combat intensity inhomogeneity by embedding local intensity information into their models. In [16], a novel level set method was proposed for segmentation these images.

In this paper, a new energy function is defined for tumor segmentation by using tumor feature. This energy function is implemented by level set method. First, a multi-scale fuzzy filter is applied to the image. The proposed filter output obtained in a multi-scale framework as tumor feature, determines the probability of each pixel belonging to the tumor structure. This function forces the active contour to coincide with the boundaries of tumor, more precisely. The active contours in [14, 16] have not this ability.

The remainder of this paper is organized as follows: In Section 2, first, we review the most popular region-based active contour models then the proposed method for tumor feature segmentation is described. The experimental results on MR images and discussion are presented and assessed in Section 3. Section 4 is devoted to conclusions.

2. Materials and Methods

2.1. Region -based active contour models

Mumford and Shah defined an optimal piecewise smooth approximation function u of a given initial image I, for energy minimization problem. In practice, it is difficult to minimize the Mumford–Shah functional due to different dimensions of u and contour and also the non-convexity of the functional.

Chan and Vese [10] proposed an active contour, CV model inspired by the Mumford–Shah model. Their proposed energy function is:

$$E^{CV}(C,c_1,c_2)=\lambda_1\iint_{in(C)}|I(x,y)-c_1|^2 dxdy + \lambda_2\iint_{out(C)}|I(x,y)-c_2|^2 dxdy+\mu|C| \quad (1)$$

where λ_1 and λ_2 are positive constants, in (C) and out (C) represent the regions inside and outside the contour C, respectively, c_1 and c_2 are two constants that approximate the image intensity in in (C) and out (C). Thus, in images with intensity inhomogeneity the original image data is not the same with c_1 and c_2. Consequently, the CV model is not applicable to such images.

In [12-15], region-based models were proposed to segment the images with intensity inhomogeneity. For example, in [14] local fitted image (LIF) formulation was defined as follows:

$$I^{LIF}=m_1H_\varepsilon(\phi)+m_2(1-H_\varepsilon(\phi)) \quad (2)$$

where are defined as follow:

$$\begin{cases} m_1=mean(I\in(\{x\in\Omega|\phi(x)<0\}\cap W_k(x))) \\ m_2=mean(I\in(\{x\in\Omega|\phi(x)>0\}\cap W_k(x))) \end{cases} \quad (3)$$

where $W_k(x)$ is a rectangular window function, e.g. a truncated Gaussian window or a constant window. In this experiment, a truncated Gaussian window $K_\sigma(x)$ with standard deviation σ and of size 4k+1 by 4k+1 was chosen, where k is the greatest integer smaller than s. In [14] a local image fitting energy functional by minimizing the difference between the fitted image and the original image was proposed. The formulation is as follows:

$$E^{LIF}(\phi)=\frac{1}{2}\int_\Omega |I(x)-I^{LFI}(x)|^2 dx, \quad x\in\Omega \quad (4)$$

Using the calculus of variation and the steepest descent method [17], $E^{LIF}(\phi)$ was minimized with respect to f to get the Corresponding gradient descent flow:

$$\frac{\partial\phi}{\partial t}=(I-I^{LIF})(m_1-m_2)\delta_\varepsilon(\phi) \quad (5)$$

where $\delta_\varepsilon(\phi)$ is the regularized Dirac function defined in Eq.(11).

In [16] The inhomogeneous objects are modeled as Gaussian distributions of different means and variances in which a sliding window is used to map the original image into another domain, where the intensity distribution of each object is still Gaussian but better separated.

Moreover, since the models only extract local intensity means which are close to the background means in tumor structure, it fails to detect tumors, carefully. Thus, to detect tumors precisely, more accurate characterization of tumors is to be introduced to model as [18]. The goal of this paper is to relieve these drawbacks.

2.2. Determination of tumor features

The tumor tissue mainly appears in brighter colors than the rest of the regions in the brain and mass. Based on these observations, we use a fuzzy Morphology filter to enhance tumor structure in MR images.

In the next, the definition of fuzzy morphology filter is presented, followed by the morphology operator to extract local image information.

2.3. Fuzzy morphology filter

Given an universe U, a map $\mu X : U \rightarrow [0, 1]$, $x \rightarrow \mu X(x) \in [0, 1]$ defines a fuzzy set X on U. Many transfer functions can be used to map an image F into a fuzzy set F'. We use the membership function of the fuzzified image that is calculated as:

$$F'(m,n) = \frac{F(m,n) - F\min}{F\max - F\min} \tag{6}$$

Where $F(m,n)$ is the pixel value at $(m, n)^{th}$ position. F_{min} and F_{max} are the maximum and minimum grey values of the image, respectively. On the normalized image, fuzzy morphological erosion, dilation, opening, closing, and top-hat of F' by A are, respectively, defined as follows [19]:

$$F' \oplus A = E(F', A) \tag{7}$$

$$F' \Theta A = 1 - E(1 - F', A) \tag{8}$$

$$F' \circ A = 1 - E(1 - E(F', A), A) \tag{9}$$

$$F' \bullet A = E(1 - E(F', A), A) \tag{10}$$

Fuzzy erosion can be computed by using different matrices. One of them is the average function

$$E = 1 - \sum |F' - A| / s \tag{11}$$

where s is the number of active pixels in the SE. More detailed explanation about the fuzzy morphological operators can be seen in [19].

In order to obtain the feature of tumors with various sizes, the fuzzy opening acts applied at different scales in a certain range.

The filter is analyzed at different scales SE in a range S. When the scale matches the size of the tumor, the filter response will be maximum. Therefore, the final proposed filter response is

$$\Phi(x,y)=\max_{SE\in S} F'(x,y)\Theta SE \qquad (12)$$

For each pixel (x,y), $\Phi(x.y)$ estimates the measure to be tumor using tumor features extracted by multiscale fuzzy morphology analysis.

The result of the proposed filter for two MR images is shown in Fig.1.

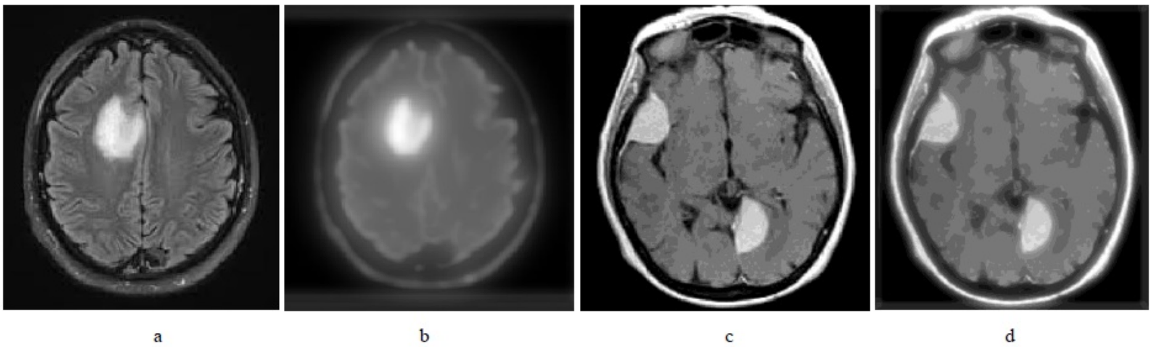

Figure 1: The result of our filter on a MR image (a, c) original images (b, d) The result of our filters

2.4. Proposed active contour model

We define the following energy function of a contour C:

$$E_T(C)=\frac{1}{2}\int\int_{N(C)}\left|f(x,y)-f_I(x,y)\right|^2 dxdy \qquad (13)$$

where N(C) define a narrow band around C, that caused the energy is only calculated in a neighborhood of C. f_I is the feature image defined as:

$$f_I(x,y)=\begin{cases} c_1, & (x,y)\in inside(C) \\ c_2, & (x,y)\in outside(C) \end{cases} \qquad (14)$$

For each pixel (x,y) , $f_I(x.y)$ approximates its intensity according to its feature. c_1 and c_2 of (7) can be viewed as the weighted local averages of the image intensities inside and outside of the contour, respectively.

$$c_1(x,y) = \frac{\iint_{N(C)\cap input(C)} f(x,y) f_\tau(x',y') K_\sigma(x-x',y-y') dx'dy'}{\iint_{N(C)\cap input(C)} K_\sigma(x-x',y-y') dx'dy'},$$

$$c_2(x,y) = \frac{\iint_{N(C)\cap output(C)} f(x,y)(1-f_\tau(x',y')) K_\sigma(x-x',y-y') dx'dy'}{\iint_{N(C)\cap output(C)} K_\sigma(x-x',y-y') dx'dy'}. \quad (15)$$

where K_σ is the Gaussian function with standard deviation σ. The weights are adjusted by $f_\tau(x',y')$ to be high inside the tumor, where the measure $\Phi(x',y')$ is also high, and low otherwise.

$$f_\tau(x',y') = \frac{1}{2}\left(1+\frac{2}{\pi}\arctan\left(\frac{\Phi(x',y')-\tau}{\tau}\right)\right) \quad (16)$$

Therefore, in this model, the intensity for each pixel *(x,y)* is estimated by a weighted average of the pixel intensities in a neighborhood around (x,y). These weights are controlled by f_τ and K_σ functions. Thus, if (x,y) belongs to a tumor, c_1 is high and c_2 is low and if (x.y) belongs to background c_1 is low and c_2 is high. Thus, it can successfully detect tumor in images with intensity inhomogeneity by using local information and tumor features. The proposed energy function is implemented by the level set method described below.

2.5. Level set method

In level set methods, the curve $C \subset \Omega$ is represented by the zero level set of a Lipschitz function $\phi : \Omega \to R$.

we propose to minimize the energy functional:

$$F(\phi) = \lambda E_T(\phi) + \mu\rho(\phi) + \upsilon\vartheta(\phi). \quad (17)$$

The level set evolution equation for minimizing the energy functional (11) becomes:

$$\frac{\partial\phi}{\partial t} = -\delta_\varepsilon(\phi)(\lambda(f - c_1 H_\varepsilon(\phi) + c_2(1-H_\varepsilon(\phi)))(c_1-c_2)$$
$$+\mu(\nabla^2\phi - div(\frac{\nabla\phi}{|\nabla\phi|})) + \upsilon\,\delta_\varepsilon(\phi)div(\frac{\nabla\phi}{|\nabla\phi|}) \quad (18)$$

where δε (φ) is the smoothed Dirac delta function given by (12)

$$\delta_{\varepsilon}(x) = H'_{\varepsilon}(x) = \frac{1}{\pi}\frac{\varepsilon}{\varepsilon^2 + x^2} \tag{19}$$

and c_1 and c_2 are calculated as:

$$\begin{aligned} c_1(x) &= \frac{\int_{N(C)} f(y) f_{\tau}(y) K_{\sigma}(x-y) H_{\varepsilon}(\phi) dy}{\int_{N(C)} K_{\sigma}(y) H_{\varepsilon}(\phi) dy}, \\ c_2(x) &= \frac{\int_{N(C)} f(y)(1-f_{\tau}(y)) K_{\sigma}(x-y)(1-H_{\varepsilon}(\phi)) dy}{\int_{N(C)} K_{\sigma}(y)(1-H_{\varepsilon}(\phi)) dy}. \end{aligned} \tag{20}$$

Here, $f_{\tau}(P)$ is calculated prior and c_1, c_2 and f_I are calculated iteratively.

2.6. Selection of initial contour

Initial contour selection is important in active contour models. The proper initial contour not only increases the speed of convergence but the accuracy of segmentation. In this paper the initial contour is selected by combining of Hough and morphology method. First the image is converted to binary, and then by using closing operator the small objects are removed. According to that tumors are semi-circle, Hough transform imply to image and the objects of circle is determined. As it is shown in fig.2, the algorithm can detect the tumor well from other areas of the brain.

3. Results and Discussion

The proposed algorithm has been tested on MR images to evaluate the results of tumor detection. We used the parameters $\lambda = 1$, $\mu = .5$, $\sigma = 2$, $\tau = 0.1$, $t = 0.1$ as [13] respectively. $\varepsilon = 1$ in all experiments and for each case, υ is chosen manually so that the best segmentation result is obtained. As shown in Fig.2, our method detects tumors in images with inhomogeneity intensity and noise accurately. Another models extract part of background as tumor.

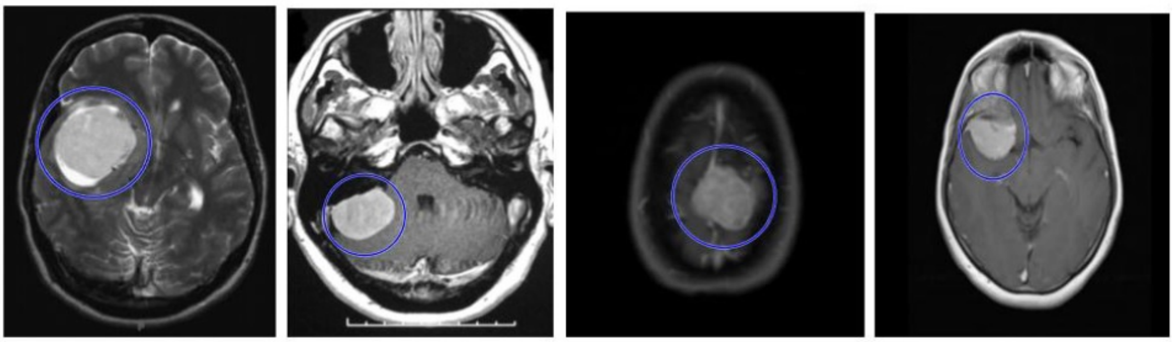

Figure 2: The result of selection of initial contours in MR image

In order to evaluate our method quantitatively, we randomly selected 21 MR images obtained in Hajar Hospital, shahrekord, Iran. These images were segmented manually by an expert at this center as Gold standard.

To compare the performances quantitatively, we used true positive fraction (TPF) and false positive fraction (FPF) indices. TPF, also called 'sensitivity', is the ratio of the number of pixels correctly classified as tumor (TP), to the total number of tumor pixels in the gold standard segmentation

$$TPF = \frac{TP}{P} = \frac{TP}{TP + FN} = sensitivity \tag{21}$$

where FN is the number of pixels incorrectly classified as non-tumor. The ideal TPF is 1. FPF is the number of pixels incorrectly classified as tumor (FP), divided by the total number of non-tumor pixels in the gold standard

$$FPF = \frac{FP}{N} = \frac{FP}{FP + TN} = 1 - specificity \tag{22}$$

Here, TN is the number of pixels correctly classified as non-tumor pixels. The ideal FPF is 0. The accuracy (ACC) for one image is the ratio of the total number of correctly classified pixels (the sum of true positives and true negatives) to the total number of pixels in the image

$$ACC = \frac{TP + TN}{P + N} = \frac{TP + TN}{TP + FN + FP + TN} \tag{23}$$

The ideal ACC is also 1. In Fig.3 (column a) three MR images are shown. The results of CV, LIF, the method in [16] and the proposed method are shown in Fig.3(column b), (column c) , (column d) and ((column e), respectively.

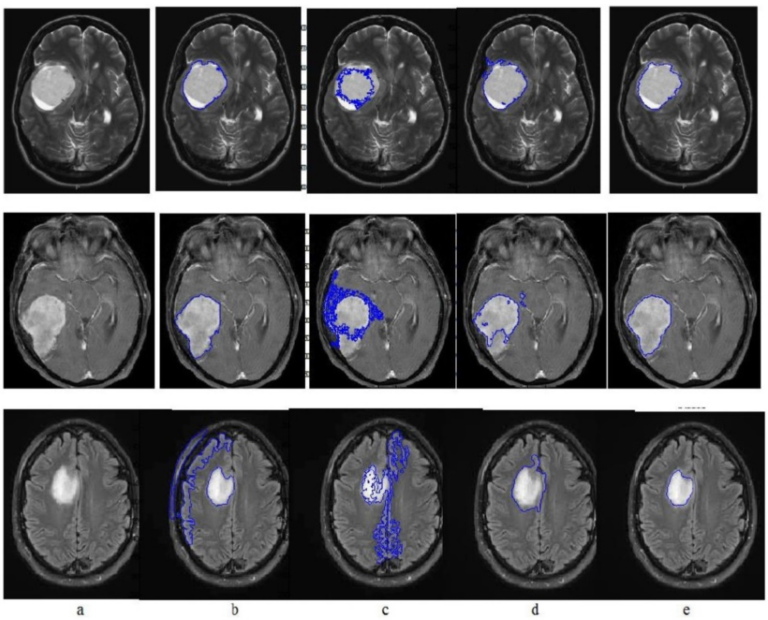

Figure 3: original images and segmentation results of CV, LIF, [16] and proposed method. Column (a) original

Images. Column (b) the results by CV. Column (c) the results by LIF. Column (d) the results by [16]. Column (e) the results by the proposed method.

As shown in Fig. 3b, the CV model is able to extract the tumor, but a part of background is segmented as tumor. The results of LIF and the method in [16] are shown in Fig. 3 (c, d), respectively. It is clear that the methods cannot extract the tumors in images with a complex background accurately. According to Fig3, the great performance of the proposed model in comparison with other methods is obvious.

To evaluate our method quantitatively, we selected 21 MR images from 21 patients obtained from Hajar Hospital, Shahrekord, Iran. One expert at this center segmented these images as ground truth manually. Table 1 shows the average of the accuracy measurements for all 21 images with the proposed method, CV, LIF and the model in [16]. It is apparent that our method outperforms other models in tumor segmentation. For example, it exhibits a very low false positive error, which is very important in medical image segmentation.

Table1: Performance of tumor detection by the proposed active contour

	TPF_1	FPF_1	ACC_1
The proposed model	0.9845	0.0009	0.9987
CV[10]	0.9521	0.0720	0.9768
LIF[14]	0.7123	0.6432	0.3258
[16]	0.8796	0.4562	0.5543

4. Conclusion

In this paper, a new active contour model was proposed by introducing the tumor feature into its energy function for tumor detection on 2-D MR images. The features were determined by applying a multi-scale morphology fuzzy filter. The feature determines the probability of each pixel belonging to the tumor structure. For increasing the speed of convergence and accuracy of segmentation, the initial contour is selected by combining of Hough and morphology method. According to the results, this method is able to detect tumors in images with intensity inhomogeneity and noise, correctly. The proposed method is a more accurate candidate for segmentation of brain tumor in clinical tasks .

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5. Conflict of Interest

There is no conflict of interest regarding the publication of this paper.

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