Efficient Brain Tumor Segmentation in Magnetic Resonance Image Using Region-Growing Combined with Level Set

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Abstract. Medical image segmentation plays a great role in image processing because it can help human to extract some suspicious regions from a medical image especially brain images. Brain tumor is one of the huge medical problems. It has an influence on our lives. In this paper, we proposed a method for brain tumor segmentation and detection in magnetic resonance image (MRI). The contrast of MRI is enhanced by using histogram equalization and the tumor region is labeled by using the region-growing technique combined with the level set method to create the exact boundary of tumor region and return the segmentation result. The proposed method is better than the other recent methods based on compared results.

Keywords: Tumor · Magnetic resonance · Segmentation · Region-growing · Level set

1 Introduction

In the modern life, MRI is very useful for doctors in diagnosing and determining medical problems. With the support of MRI, doctors can detect brain tumors to treat as soon as possible in order to reduce the mortality rate in the world. However, detection all regions in MRI is not easy if we use pure MRI. Because the brain consists of various tissues such as gray matters (GM), cerebrospinal fluid (CSF), white matter (WM) and other abnormal tissues. In the brain, old cells will be replaced by new cells. If the process runs wrong, new cells will be created while these cells are not required by the body. And old or spoiled cells do not disappear as they should. A mass of tissue is called a tumor that is created by the increase of extra cells.

Recently, a lot of methods are proposed to segment tumors in MRI. Researchers have combined some algorithms together in order to build new better methods. They however cannot solve some special cases, particularly, when the tumor is small and has low sensitivity. Bing [1] and Chuang [2] proposed a method that is combined spatial fuzzy clustering with the level set method to segment medical images. This method is successful in general but its result is not the best because the result of level set method

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depends on the output of Fuzzy C-mean algorithm which may contain more segmented region than the ones of the region-growing technique. In other words, the result of region-growing only contains tumor regions. Salvakumar [3] used K-mean clustering and Fuzzy C-mean algorithm to segment and compute the area of the tumor in MRI. This technique determines a threshold [18] based on intensity values to separate pixels in various classes into two groups. The first group includes the pixels having their intensity value greater than the threshold. And the second one is remained pixels. The technique images can present two colors in black and white. Therefore, it will ignore tumor cells. Kalaiselve [4] proposed a method that is better than Fuzzy c-means because this method bases on intensity values to choose the centroids. Its result however depends on how to set the value for the initial centroid of the regions in gray image. Chenyang [5] formulated a new variation level set. It provides a new kind of level set evolution named distance regularized level set evolution (DRLSE). The DRLSE formulation is effective for image segmentation. Particularly, it is applied to an edge-based active contour model. Chunming [6] presented a framework of level set to segment as well as bias correction of image with intensity in homogeneities. In [6], a minimized energy function is proposed to combine segmentation and bias field estimation. Tran [7] proposed an efficient pancreas segmentation method. Histogram equalization is used to enhance the quality of input images and then the region-growing technique is also applied to segment pancreas. Kailash [8] proposed efficient segmentation methods for tumor detection in MRI images, in which some clustering methods and segmentation algorithms are combined together in order to improve the result. Gopal [9] proposed a method to build an intelligent system which can be used to diagnose brain tumor via MRI by using image processing clustering algorithms. Jichuan [10] proposed a novel local threshold segmentation algorithm with shape information to improve quality. This method is useful for the case, in which, many objects with a similar shape locate in an image. Because most of local threshold algorithms often use intensity value to analyze. Nabizadeh [11] proposed a method to detect and segment brain tumors in MR images. This method shows that statistical features are better than Gabor wavelet features. The result of method however depends on the threshold for the number of mutual information. It has a detectable influence on the size of the tumors. Halder [12] used K-means and Object labeling method to detect tumor in MR images. But the accuracy of the approach is depended on the result of K-means method. Koley [13] used region growing technique to identify the infected regions in brain MR images and then contour detection algorithm is applied to create accurate boundaries of the regions. However, most of these methods are complex.

In this paper, we have proposed an approach to segment tumor in brain MRI using histogram equalization to enhance images and the region growing technique to segment tumor regions if present and then using the level set method to make the exact contour of tumor region based on the previous result. The rest of the paper is organized as follows: we described the background of Jaccard index, the region-based segmentation and level set method in Sect. 2; the proposed method is shown in Sect. 3; the result and conclusion of the paper are presented in Sects. 4 and 5 respectively.

2 Background

2.1 Jaccard Index (J.I)

The similarity between two operational taxonomic units (OTUs) is considered by Jaccard's similarity index. Jaccard's index [19] can be introduced in various ways. One of the popular ways is:

$$\mathrm{J} = \frac{\mathrm{C}}{\mathrm{A} + \mathrm{B} - \mathrm{C}} \tag{1}$$

where *A* and *B* are the amount of attributes present in OTU a and OTU b respectively and *C* is the amount of attributes present in both OTU a and OTU b.

Jaccard's index can also be introduced by:

$$\mathrm{J} = \frac{\mathrm{C}}{\mathrm{A} + \mathrm{B} + \mathrm{C}} \tag{2}$$

in which *A* is the amount of attributes present in OTU a and absent in OTU b, *B* is the amount of attributes present in OTU b and absent in OTU a, and the role of *C* is the same in Eq. (1).

Another approach of introducing Jaccard's index is:

$$J = \frac{C}{N} \tag{3}$$

where *C* holds the role as in Eq. (2) and *N* is the total amount of attributes found in both OTUs together.

2.2 Region-Based Segmentation

The aim of region-based segmentation is to try to split or group regions based on common image characteristics [16]. The characteristics of images include intensity values, textures and spectral profiles.

In region-growing algorithm, intensity value is considered as a property. Combining the seeding and region-growing method to segment pixels set that is made by initially choosing one or more pixels in the image (named the seed points). Those seeds are made by interacting between users and beginning from the growing regions by appending to each seed with its neighbor pixels which satisfy the conditions. In this algorithm, the segmented pixels set will be added by all the pixels which are r-connected to the initial seed pixel and fall the limits of threshold. To be r-connected to another, two pixels must share at least r corner points. The segmented pixel set is added recursively by all the pixels which are connected to the current members of the pixel set. Region growth will stop if no more pixels satisfy the condition for inclusion in that region.

Let: $f(x, y)$ means an array of input image; $S(x, y)$ means a seed array containing two values (1 and 0), the value at the locations of seed points is 1s and 0s elsewhere; and Q means a predication to be applied for each location (x, y). The size of arrays f and S are assumed to be equal. The core of region-growing algorithm based on 8-connectivity should be followed by:

(i) Find all connected components in $S(x, y)$ and erode each one to a pixel and label all pixels found as 1. The other ones in S are assigned 0.
(ii) Build an image f_Q such that, with each pair of coordinates (x, y), if the given predication Q is satisfied at those coordinates then $f_Q(x, y)$ is set to 1; in contrast, it is set to 0.
(iii) Adding to each seed point in S all 1-valued points in f_Q that are 8-connected to the seed point in order to form an image g.
(iv) Various region label is assigned to each connected component in g. The obtaining segmented image is region growing.

And then, a predication must be specified and add all the pixels to each seed. Those pixels are not only k-connected to the seed but also similar to it. Various intensities are used as a measure of similarity, the predication used at each location (x, y) is Q. Q = true if the absolute difference of the intensities between the seed and the pixel at (x, y) is ≤ T where T is a specified threshold. Otherwise, Q = false.

2.3 Level Set Method

The level set method [14, 17] is simple and useful for calculating and analyzing the motion of an interface Γ in two or three dimensions. A region Ω is bounded by the Γ. Its aim is to calculate and analyze the next motion of Γ under a velocity field v. The velocity can be affected by the geometry of the interface, the external physics, time and position. This interface is for the next time as this zero level set of a smooth function φ(x, t). It means that $\Gamma(t) = \{x |\ \varphi(x, t) = 0\}$, φ is positive inside Ω, negative outside Ω, and is zero on $\Gamma(t)$.

The function (φ) of level set includes some properties below:

$$\begin{aligned} \varphi(\mathrm{x}, t) > 0 \ \text{ for } \ \mathrm{x} \in \Omega \\ \varphi(\mathrm{x}, t) < 0 \ \text{ for } \ \mathrm{x} \notin \overline{\Omega} \\ \varphi(\mathrm{x}, t) = 0 \ \text{ for } \ \mathrm{x} \in \partial\,\Omega = \Gamma(t) \end{aligned} \tag{4}$$

3 Efficient Brain Tumor Segmentation in MRI

In this section, we propose an efficient brain tumor segmentation in magnetic resonance that is based on region-growing combined with level set method. The generalized block diagram of the proposed method is given in Fig. 1. The proposed method includes three stages: histogram processing, region-growing segmentation and level set. The stages will be explained in the following subsections.

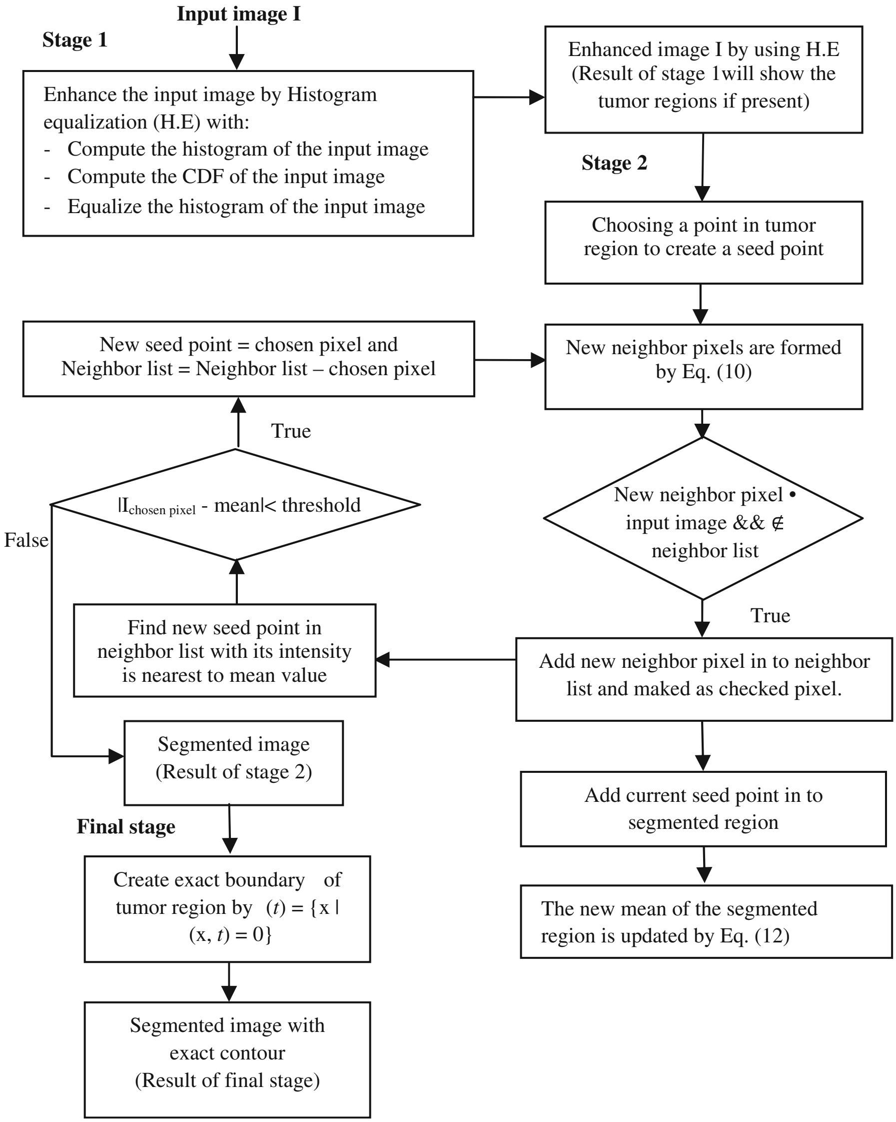

Fig. 1. Block diagram of proposed method.

3.1 Histogram Processing

In the first stage, we apply histogram equalization method to enhance the input image. This task should be done because the real medical image usually has low contrast. With the support of the method, the contrast of output image is improved significantly. As a result, it is easier to recognize the subjects in the image. Especially, the subjects are tumors with low contrast as well as strange shapes. It can be described as follows:

3.1.1 Compute the Histogram of the Input Image

Histogram is a basic processing method in spatial domain. The information can be gotten directly from an image by statistics. The image can be enhanced easily by histogram. The histogram [15] with intensity levels in the range [0, L−1] of an image is a discrete function

$$\mathrm{h}(r_k) = n_k \tag{5}$$

where r_k is the k^{th} value of intensity, n^k is the amount of pixels in the range of intensity r_k and L is the amount of intensity levels. With r is a discrete random variable showing intensity values in the range [0, L−1] and with $p(r_k)$ is the normalized histogram component corresponding to value r_k, and it is considered as an estimate of the probability that intensity r_k happens in the image base on that the histogram is obtained.

3.1.2 Compute the CDF of the Input Image

In a given image the probability $p(r_k)$ of intensity level r_k is computed as

$$p(r_k) = \frac{n_k}{MN} \quad k = 0, 1, 2, \ldots, L-1 \tag{6}$$

where MN is the total amount of pixels.

A function of transformation of special importance in image processing follows the form

$$s = T(r) = (L-1)\int_0^r p_r(w)dw \tag{7}$$

with w is an integration dummy variable. The equation right side is recognized as the Cumulative Distribution Function (CDF) of random variable r. The discrete form of the above transformation follows by:

$$s_k = T(r_k) = (L-1)\sum\nolimits_{j=0}^{k} p_r\left(r_j\right) \;\; k = 0, 1, 2, \ldots, L-1 \tag{8}$$

Therefore, a result image is that each pixel in the input image maps with intensity r_k into a corresponding pixel with level s_k in the result image. This transformation $T(r_k)$ is named a histogram equalization.

3.1.3 The Histogram of the Input Image

is equalized by

$$I_p = T(I_p) \tag{9}$$

Where I_p is intensity value of pixel in the input image.

3.2 Region-Growing Segmentation

In the second stage, the result image of the first stage is used as the input image. This result is very useful for choosing a point on the tumor region being a seed point (*x, y*) because the contrast of among regions in the image becomes higher. We can find out where tumor regions easily. Moreover, the result of region-growing technique is also more accurate because the nature of this technique is based on intensity value of neighbor pixels. The region-growing technique will segment tumor regions. The stage can be described as follows:

(i) The neighbors of each pixel (x, y) are formed by

$$(\mathrm{x}+1,\ \mathrm{y}),\ (\mathrm{x}-1,\ \mathrm{y}),\ (\mathrm{x},\ \mathrm{y}+1),\ (\mathrm{x},\ \mathrm{y}-1) \tag{10}$$

If neighbor pixel $\in$ input image and not belong the neighbor list then this neighbor pixel will be added to the neighbor list and marked as checked pixels.

(ii) The current seed point will be added in to segmented region.

(iii) In the next iteration the new seed point will be chosen by finding the pixel with intensity nearest to mean value of segmented region. The minimum distance depends on the chosen pixel and means value of intensity:

$$min_{distance} = \min_{i=1..n} |I_{i-}m_{mean}| \tag{11}$$

where I_i is an intensity of pixel $\mathrm{p_i}$ in neighbor list, m_{mean} is mean of the segmented region which is computed by:

$$m_{mean} = (m_{mean} * |R| + I_p)/(|R| + 1) \tag{12}$$

where $|R|$ is size of segmented region

(iv) The new mean of the segmented region is updated by Eq. (12) and then the neighbor list = neighbor list\chosen pixel.

(v) While (distance between region and possible new pixels ≤ the certain threshold) do the above processes.

Proposed algorithm will return the segmented region as a logical matrix that contains brain tumor region which has the same properties to seed point.

3.3 Level Set Method

In the final stage, this process needs to use the result of the second stage because this result is the image with intensity homogeneity. In real world, it is not easy for us to get images with intensity homogeneity because of different factors. As a consequence, it causes many problems in image processing. It is considered as hard work for image segmentation especially images with intensity inhomogeneity because of the over-laps among the ranges of the intensities in the regions. It cannot identify the regions based on the pixel intensity value. Meanwhile, the level set method will give a good segmentation result if input data is an image with intensity homogeneity. That is why the region-growing technique is required in the proposed method. Osher [14] gave the level set way to hold topology changes of curves. In the paper, the initial segmentation is run by region-growing technique that makes approximated boundary. The level set method is applied to make the exact boundary. A demonstration of the level set method is when the surface intersects with zero planes to give the curve that depends on the changes of surface. To see the evolution of boundary by tracking the zero level set implicitly with Eq. (4).

4 Experiments and Evaluation

In this section, we implemented the proposed approach in Sect. 3. We applied the proposed method for MRI data that obtained from many cases. We use the Jaccard index (J.I) between an extracted region and a true one [19].

The index ranges from 0 to 100 %, with higher values representing better performance. The resolution of tested images is 512 × 512. The threshold used in experiments ranges from 0.04 to 0.08. We have experimented on image dataset collected from many resources. Here, we report the results of some cases as Fig. 2.

In Fig. 2, the results of the proposed method are better than the other method. The region-growing technique and the method of [3] are based on the threshold to segment brain tumor region. It is not easy to set an ideal threshold value for these methods. If this value is too low the segmented region will lack the pixels which belong to the tumor region. Because the intensity distance between those pixels and mean value is

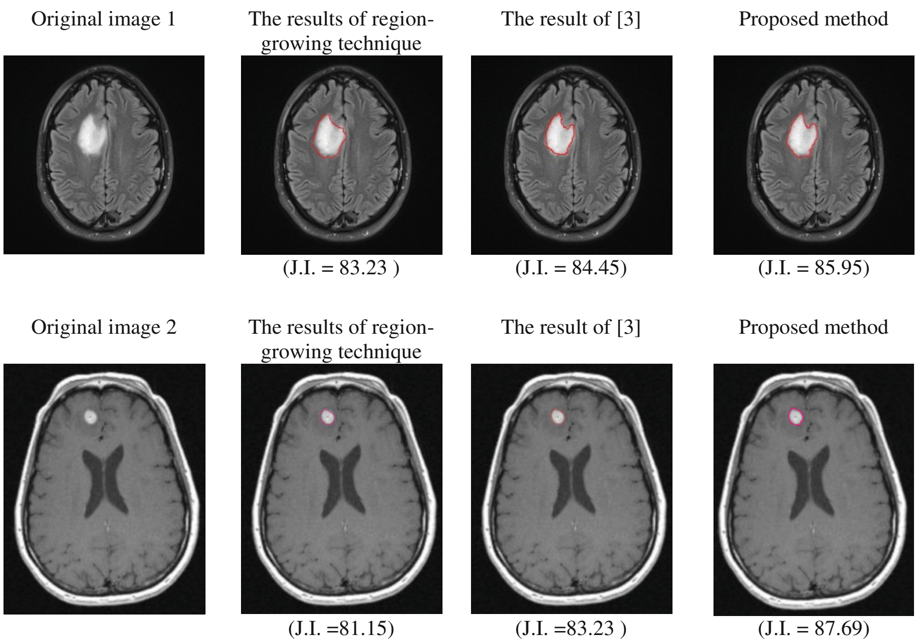

Fig. 2. Some results of the proposed method

higher than the threshold value. In contrast, if the value is too high the segmented region will contain the pixels which belong to other regions. Because the intensity distance between those pixels and mean value is lower than the threshold value. That is reason why those proposed methods need to be improved.

Our method has solved the problem. It means that our results are more exact than the ones of these methods thanks to using the level set method to improve the result of the region-growing technique. The level set method is simple and useful for calculating and analyzing the motion of an interface Γ in two or three dimensions. The tumor region is bounded by the Γ. The method supports to calculate and analyze the next motion of Γ under a velocity field v. The tumor region is get for next time as this zero level set of a smooth function $\varphi(\mathrm{x}, \mathrm{t})$. It means that $\Gamma(t) = \{\mathrm{x} \mid \varphi(\mathrm{x}, t) = 0\}$. The speaking above explains why the result of our method which is evaluated by J.I tool is better than other methods in Fig. 2.

5 Conclusion

Brain tumor segmentation helps the doctors during diagnosis. This is hard work because the brain cells usually have a small size. Therefore, algorithm segmentation must be high. This paper shows an efficient brain tumor segmentation method from MRI. Histogram equalization is applied to improve the contrast of MRI in which a brain tumor region is labeled by using the region-growing technique. And then, the level set method is used to create the exact boundary of the brain tumor region which is labeled in the previous stage. The proposed method performs better because it is easy for us to find out tumor regions thanks to the histogram equalization technique. And only tumor regions are labeled by using the region-growing technique. Finally, the level set method is applied to the output result of the previous stage to create the exact boundary of tumor region. As a result, the proposed method gives a good result which presents segmented tumor regions with the exact contour.

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