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Improved Edge Detection Algorithm for Brain Tumor Segmentation

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Abstract

Image segmentation is used to separate objects from the background, and thus it has proved to be a powerful tool in bio-medical imaging. In this paper, an Improved Edge Detection algorithm for brain-tumor segmentation is presented. It is based on Sobel edge detection. It combines the Sobel method with image dependent thresholding method, and finds different regions using closed contour algorithm. Finally tumors are extracted from the image using intensity information within the closed contours. The algorithm is implemented in C and its performance is measured objectively as well as subjectively. Simulation results show that the proposed algorithm gives superior performance over conventional segmentation methods. For comparative analysis, various parameters are used to demonstrate the superiority of proposed method over the conventional ones.

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Keywords: Brain Tumor Segmentation; Closed Contour Algorithm; Improved Sobel Edge Detection; Sobel Edge Detection.

1. Introduction

Image segmentation is one of the most challenging aspects of image processing, and is widely used in many applications like sports, bio-medical, remote sensing satellites, security purposes etc. Segmentation procedures subdivides an image into its constituent parts or objects. The separation of tumor from magnetic resonance imaging (MRI) is one of the important application of image segmentation. Manual detection of tumors in MRI need trained radiologists which is a time-consuming process and is also susceptible to errors. Due to large number of patients and scans, manual detection and segmentation of such a large data is too cumbersome. So, there is a need to automate this process and segmentation techniques play an important role in achieving this goal.

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In the technical literature many segmentation techniques are proposed for the separation of objects. These are based on region growing approach[1,2,3], threshold approach[4,5], watershed approach[6], fuzzy approach[7,8,9], graph-based methods[10], etc.

This paper presents an improved edge detection method to extract brain tumor in MRI images. Most of the existing edge detection methods[11,12,13] detect object boundaries in the image. In this paper the edge detection method is modified so that it can be extended for object segmentation, which can be efficiently used for separation of tumor in the images. The proposed approach is based on Sobel operator combined with automatic thresholding to extract edges of a tumor. Then closed contour algorithm is applied to these edges to find closed regions in images. Finally, brain tumors are extracted from the MRI images. Experiments are performed on a set of images. Comparative analysis is performed, by comparing the performance in terms of gray level uniformity measure (GU), Q-parameter and relative ultimate measurement accuracy (RUMA), which demonstrate effectiveness of the proposed method.

The remainder of the paper is organized as follows. A brief overview of existing edge detection techniques appears in Section-2. Details of proposed edge-detection based segmentation are presented in Section-3. Simulation results & comparisons are given in Section-4. Concluding remarks and avenues for future work appear in Section-5.

2. Background

Edge detection is the approach most widely used for detecting edges and is based on detecting abrupt local changes in the intensity of image. Edge pixels are those pixels at which the intensity of an image function changes abruptly. The earliest operator in the field of edge detection is Roberts cross-gradient operator[11]. It computes the gradient of an image by using 2-D masks and gives preference to diagonal edges. In order to be symmetric about the center point, the smallest metric should be of size 3×3 dimensions. The extensions of 2D masks to 3D masks gives a new operator known as Prewitt's Operator[11]. Sobel Operator, shown in Fig. 1a is a modified form of Prewitt's operator in which the central column/row are multiplied by a factor of 2. This is equivalent to combining smoothing operation with Prewitt method.

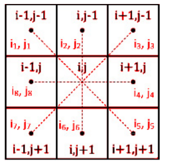
-1	-2	-1
0	0	0
1	2	1

-1	0	1
-2	0	2
-1	0	1

(a) Sobel 3×3 mask

z_1	z_2	z_3
z_4	z_5	z_6
z_7	z_8	z_9

(b) 3×3 region



(c) 8-connected neighbor

Fig. 1: 3×3 mask of Sobel Operator, part of image and 8-connectivity neighborhood

The *Canny edge detection* algorithm[12] is another approach used for edge detection. It has three salient characteristics: low error rate, edge points should be well localized, and single edge point response. The Canny edge detector first smooths the image to eliminate noise, and then it finds the image gradient. Also it requires threshold for detecting edges and thinning thereafter. It is more complex and has a relatively higher execution time and sometime gives false edges. In addition to edge-based techniques, region growing techniques are also used for image segmentation. The *watershed transform*[13], which is a region growing approach, is based on visualizing an image in three dimensions with (x,y) coordinates on x and y axes and intensity on the z axis. In the topographic view of image, height of mountains is proportional to intensity values. Catchment basins are then constructed by flooding of water, where water level rises from bottom to top, *i.e.* from lower intensity to higher intensity. The points at which water between two catchment basins is about to merge, a dam is constructed through dilation. Finally, these dam lines work as the edges of objects. One of the advantage of watershed segmentation is that it always gives closed contours. But for complex images such as MRI scans, it is over-sensitive and results in too many closed contours.

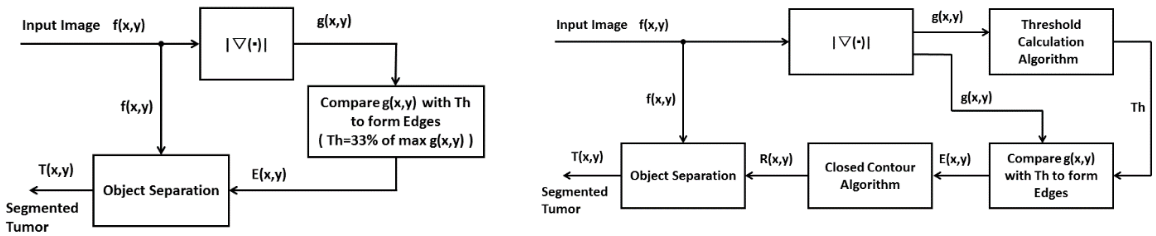
From the above discussion, it may be noted that edge detection algorithms are simple, but they do not guarantee closed contours and are sensitive to the threshold. On the other hand, watershed transform gives closed contours, but are over sensitive for complex images. In this paper an improved edge detection algorithm for tumor extraction is proposed.

3. The Proposed Segmentation Algorithm

The proposed segmentation algorithm uses the following four steps and is based on automatic threshold calculation:

1. Finding gradient image using Sobel Operator
2. Calculate image dependent threshold iteratively
3. Apply Closed-Contour Algorithm
4. Object segmentation based on pixel intensity within closed contour.

The block diagram of the above approach with convention algorithms are shown in Fig. 2b.



(a) Conventional Algorithm (b) Proposed Algorithm

Fig. 2: Block Diagram of Conventional and Proposed Algorithm

3.1. Sobel Operator

Sobel Operator uses a 3×3 mask shown in Fig. 1a and applied on part of the image shown in Fig. 1b. Given an image *f (x, y)*, its gradient along x and y-axis are calculated according to (1) and (2).

$$g_x = \frac{\delta f}{\delta x} = (z_7 + 2z_8 + z_9) - (z_1 + 2z_2 + z_3) \tag{1}$$

$$g_y = \frac{\delta f}{\delta y} = (z_3 + 2z_6 + z_9) - (z_1 + 2z_4 + z_7) \tag{2}$$

Then the gradient of image is defined as:

$$\nabla f(x,y) = \frac{\delta f}{\delta x}\hat{\imath} + \frac{\delta f}{\delta y}\hat{\jmath} = g_x\hat{\imath} + g_y\hat{\jmath} \tag{3}$$

where, $\hat{\imath}$ & $\hat{\jmath}$ are unit vectors along *x* and *y* axis respectively. The magnitude of gradient is given by,

$$g(x,y) = |\nabla f(x,y)| = \sqrt{{g_x}^2 + {g_y}^2} \tag{4}$$

3.2. Threshold Algorithm

After finding the image gradient, the next step is to automatically find a threshold value so that edges can be determined. The algorithm to automatically determine image dependent threshold is as follows:

1. Let the initial threshold be Th^0 which is equal to the average intensity of gradient image *g(x, y)*, as defined in (5).

$$Th^0 = \frac{\sum_{j=1}^{h}\sum_{i=1}^{w} g(x,y)}{h \times w} \tag{5}$$

where, *h* and *w* are height and width of the image under consideration.

2. Set iteration index $l = 0$, separate *g(x,y)* into two classes, where the lower class consists of those pixels of *g(x,y)* which have gradient values less than Th^l, and the upper class contains rest of the pixels.
3. Compute the average gradient values m_L and m_H of lower and upper classes respectively.
4. Set iteration $l = l+1$ and update threshold value as:

$$Th^l = \frac{m_L + m_H}{2} \tag{6}$$

5. Repeat steps 2 to 4 until $|Th^l - Th^{l-1}| \le \epsilon$ is satisfied, where $\epsilon \to 0$ and take Th^l as final threshold and denote it by *Th*.

Once the final threshold is obtained, each pixel of gradient image *g(x,y)* is compared with *Th*. The pixels with gradient higher than *Th* are considered as edge point and is represented as a white pixel; otherwise it is designated as black. The edge-mapped image *E(x,y)*, thus obtained is:

$$E(x,y) = \begin{cases} 255 & g(x,y) \ge Th, \\ 0 & otherwise \end{cases} \tag{7}$$

That is, a pixel at (*x,y*) having *g(x,y)* less than *Th*, is called a *background point*; otherwise, it is an *edge point*.

3.3. Closed Contour Algorithm

The proposed closed region algorithm first finds a seed pixel of each region, then it expands that region with the help of its 8-neighbours as shown in Fig. 1c. It scans the image pixel by pixel, to find the pixel that can be inside a region (if it does not lie on any edge). Then the algorithm checks for 8-connected neighbors; *i.e.* if they belong to this region or not (that is, if they are not the member of other regions and are not the edge pixels), then they can be the part of this region. The same process is repeated iteratively for neighbors of neighbors and so on. It is a recursive procedure. Meanwhile it also checks for the boundary of other regions by considering a 5×5 window around every pixel, where it stops if any pixel in the window is a boundary pixel. Although it gives a slightly shrunk region because it find closed contours 2 pixels away from the boundary of regions, it has the advantage of finding closed contours in all cases. The proposed algorithm is presented below.

Consider the image after thresholding as a two-dimensional matrix *E(i, j)* with '*h*' rows and '*w*' columns. The algorithm scans *E(i, j)* and segments it into *r* regions. Thereafter, it associates each pixel with one of the *r* (say) regions. Let R_k denote the k^{th} region and initialize *r* with 0 in the main of closed-contour algorithm discussed below. Now first pixel of a particular region R_r is known, then to find more pixels of this region, a search procedure, called closed-contour **Search**(i_0, j_0) is developed.

Closed-Contour Main

```
1.  for i = 1 to h
2.    for j=1 to w
3.      if E(i,j)=0
4.     {  for k = 1 to r
5.          if( E(i,j) ∈ region R_k)
6.              { goto step 1 to scan next pixel
7.              }
8.        r =  r + 1 //increment the region index by 1
9.        E(i, j) → Rr //insert element in region R_r+1
10.       call Search(i,j)
11.    }
```

Closed-Contour Search(i_0, j_0)

```
1.  for n = 1 to 8 neighbours of pixel (E(i_0, j_0))
2.    { for k = 1 to r
3.       { if(E(i_n, j_n) ∈ region R_k)
4.          { goto step 1 to scan next neighbour
5.          }
6.       }
7.    for x = −2 to 2
8.      for y = −2 to 2
9.         if(E(i_n + x, j_n + y) = 255) goto step 1
10.   E(i_n, j_n) → R_r //insert element in region R_r
11.   call search(i_n, j_n)
12. }
```

3.4. Object Separation

It is expected that after the previous three steps, all closed contours are detected. The next step is the extraction of tumor from image. The brain tumor is extracted from the regions image *R(x,y)* by detecting the most active region of the brain MRI. Active region is recognized by brighter color area. The following equation is used for finding the tumor.

$$Tumor = R_k | \mu_k = \max \{\mu_1, \mu_2, \ldots, \mu_r\} \tag{8}$$

where R_i denotes i^{th} region, and μ_i denotes average intensity of pixels of MRI that overlap with region R_i.

Consider the image generated after separating regions be *R(x,y)* and original image is *f(x,y)*. Create new image *T(x,y)* of tumor. The algorithm is as follows:

1. for $t = 1$ to r where $R_t \in R(x, y)$
2. { count number of pixels $(i, j) \in R_t$ as n_t
3. set sum $S_t = 0$.
4. for all pixels $(i, j) \in R_t$
5. $S_t = S_t + f(x, y)$
6. $\mu_t = S_t / n_t$
7. }
8. find R_k such that $\mu_k = \max \{\mu_1, \mu_2, \ldots, \mu_r\}$
9. set all pixels $T(i,j) \leftarrow 0$
10. for all pixels $(i, j) \in R_k$
11. $T(i, j) = f(i, j)$

4. Simulation Results

Subjective as well as numerical comparisons are performed to demonstrate the superiority of proposed method over the Sobel edge detection and watershed in identifying the brain tumors. For numerical comparison three parameters, defined below, are considered in this work.

1. Gray level Uniformity measure (GU)[14]: The gray level uniformity measure is based on inter-region uniformity. On the basis of variance evaluated for every pixel of a particular region, the gray level uniformity of that region can be computed. Lower value of GU is desirable. For an image f(x,y), GU can be calculated using (9).

$$GU = \sum_i \sum_{(x,y)\in R_i} \left[f(x, y) - \frac{1}{A_i} \sum_{(x,y)\in R_i} f(x, y) \right]^2 \tag{9}$$

2. Q-parameter[15]: The Q-parameter is based on three criteria: (*i*) region must be uniform (*ii*) region's interior does not have too many holes, (*iii*) adjacent regions must have non-uniform characteristics. Here also lower value means better performance. The function Q(I) for performing this task is:

$$Q(I) = \frac{1}{1000(N \times M)} \sqrt{R} \sum_{i=1}^{R} \left[\frac{{e_i}^2}{1 + \log A_i} + \left(\frac{R(A_i)}{A_i} \right)^2 \right] \tag{10}$$

3. Relative Ultimate Measurement Accuracy (RUMA)[14]: The Relative Ultimate Measurement Accuracy (RUMA) can be computed only for segmented object. It is based on features of extracted object. It is defined as:

$$RUMA = \frac{|R_f - S_f|}{R_f} \times 100 \tag{11}$$

where R_f denotes the feature value obtained from the reference image and S_f denotes the feature value measured from the segmented image, lower is the value of RUMA, better is the performance of segmentation algorithm.

The performance of the proposed algorithm is evaluated for seven MRI images (Tumor 1 to 7) in terms of GU, Q and RUMA, and shown in Fig. 3a, 3b and 3c respectively. For comparison purpose, the values of those parameters are also evaluated for Sobel based and watershed methods.

It can be observed from Fig. 3a that for almost all tumor images, the values of GU using the proposed algorithm are lower than that of Sobel and Watershed method. Although for Tumor-2 and Tumor-6 proposed method GU value is slightly greater than conventional method, because it measures only uniformity of an area, and does not include other factors like open contours. However, subjective comparison show that the final segmented image obtained through the proposed method is better than that obtained using both Sobel and Watershed method. Similarly from Fig. 3b, it can be seen that proposed method values are much lower than the Sobel and watershed segmentation method Q-value except for Tumor-2 image. Also from Fig. 3c, it can be observed that RUMA values obtained from proposed algorithm are much lower than corresponding values of comparison methods for all images.

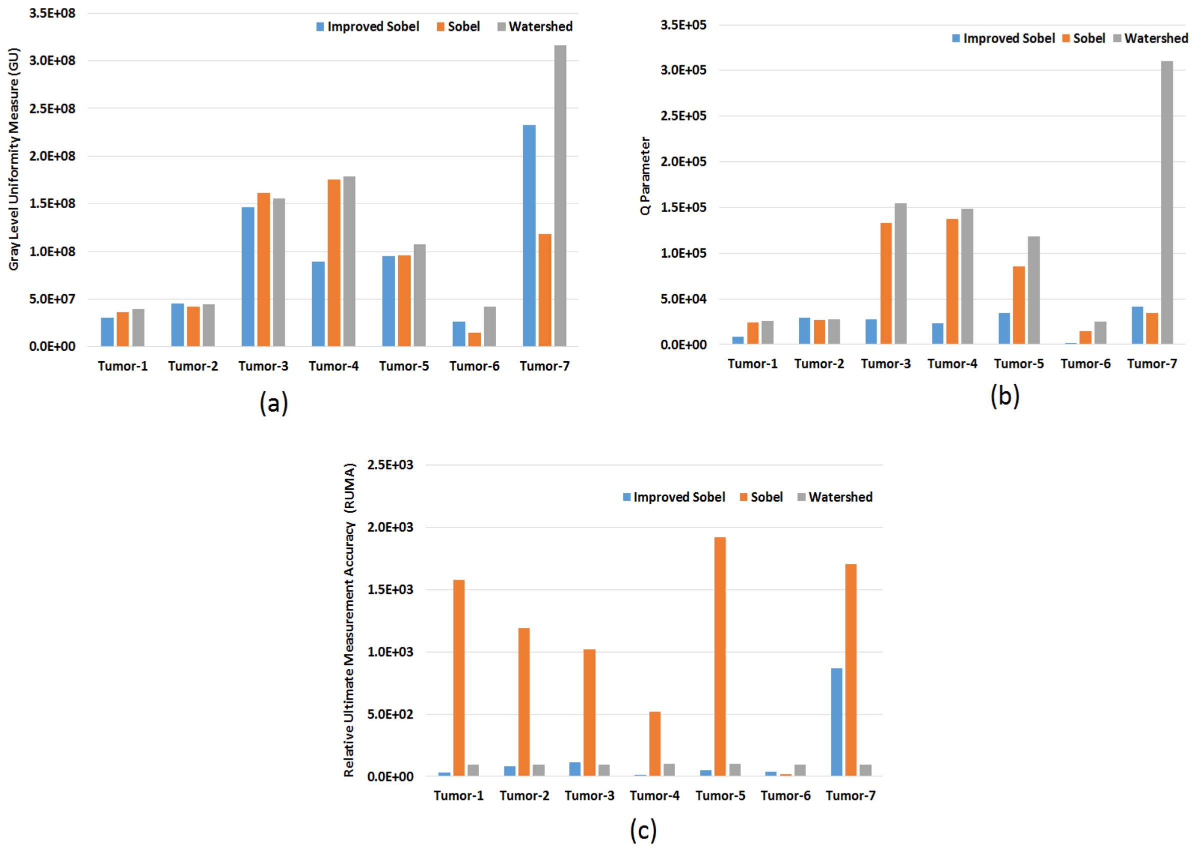
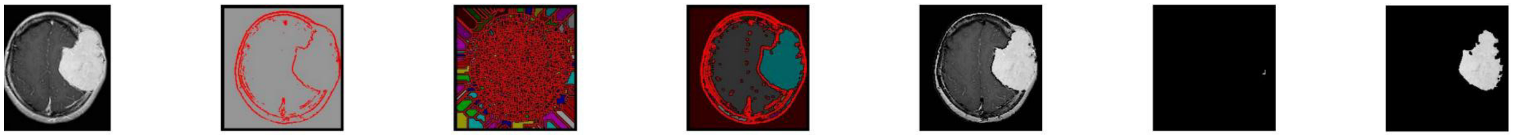


Fig. 3. Performance comparison in terms of (a) Gray level Uniformity measure (GU); (b) Q-parameter; (c) Relative Ultimate Measurement Accuracy (RUMA).

For the purpose of subjective quality evaluation, the results of region formation step, using sobel and proposed algorithm and extracted contours of four test images (Tumor-1, Tumor-4, Tumor-5 and Tumor-6 of bar-graphs) are shown in Fig. 4, 5, 6 and 7 respectively. Due to scarcity of space, it is not possible to show the results of all images. Observing Fig. 4 it can be seen that, the regions of sobel edge detection does not give closed contour (Fig. 4b), resulting in false tumor (Fig. 4e) on the other hand watershed segmentation gives too many closed contours because of its over-sensitive nature (Fig. 4c) which gives very small size tumor (Fig. 4f). While proposed method generates closed contours (Fig. 4d) which are separated from each other by fine boundaries and different colors. Thus the extracted tumor (Fig. 4g) from proposed method is very close to the original tumor.

(a) (b) (c) (d) (e) (f) (g)

Fig. 4: (a) Original Image(Tumor-1), (b) Regions formed using Sobel Method, (c) Regions formed using Watershed Method, (d) Regions formed using Proposed Method, (e) Extracted Tumor from Sobel Method, (f) Extracted Tumor from Watershed Method, and (g) Extracted Tumor from Proposed Method



(a) (b) (c) (d) (e) (f) (g)

Fig. 5: (a) Original Image(Tumor-4), (b) Regions formed using Sobel Method, (c) Regions formed using Watershed Method, (d) Regions formed using Proposed Method, (e) Extracted Tumor from Sobel Method, (f) Extracted Tumor from Watershed Method, and (g) Extracted Tumor from Proposed Method

(a) (b) (c) (d) (e) (f) (g)

Fig. 6: (a) Original Image(Tumor-5), (b) Regions formed using Sobel Method, (c) Regions formed using Watershed Method, (d) Regions formed using Proposed Method, (e) Extracted Tumor from Sobel Method, (f) Extracted Tumor from Watershed Method, and (g) Extracted Tumor from Proposed Method

(a) (b) (c) (d) (e) (f) (g)

Fig. 7: (a) Original Image(Tumor-6), (b) Regions formed using Sobel Method, (c) Regions formed using Watershed Method, (d) Regions formed using Proposed Method, (e) Extracted Tumor from Sobel Method, (f) Extracted Tumor from Watershed Method, and (g) Extracted Tumor from Proposed Method

Similar effect is observed in Fig. 5, in which regions generated by Sobel edge detection (Fig. 5b) have openings of one to ten pixels and therefore they are merged as a single region. So the brain tumor extracted (Fig. 5e) from this region comprises of almost the whole brain when superimposed on original image while the watershed segmentation (Fig. 5c) for this tumor results in a point size extracted tumor (Fig. 5f). The regions generated by proposed method (Fig. 5d) are better than Sobel and therefore it successfully identified the tumor (Fig. 5g) which is more close to the original one, and better than the conventional method. Finally, similar results are obtained in Fig. 6 and Fig. 7 with slightly shrunk size of extracted tumor (Fig. 6g) from proposed method as compared to the extracted tumor (Fig. 6e) of Sobel technique.

The edges detected by Sobel technique gives open contours while watershed gives too many closed contours, so it is not possible to detect where a tumor is located. The results of improved-edge algorithm are not always closed contours in intermediate steps but they are almost closed near the brain-tumor. So after applying closed contour algorithm given in Section–3 to the detected edges, tumors can be extracted from the original image.

5. Conclusion

In this paper, an improved version of Sobel edge detection for brain tumor segmentation of MR image is proposed. The edges generated by proposed method have less false edges and have closed contours. Thus the brain tumors extracted from proposed approach are better than the tumors extracted using sobel edge detection. Furthermore, in terms of three parameters the proposed method is found to be superior compared to conventional methods. In future, the closed contour algorithm can be improved to increase the region area and decrease the thickness of boundary lines of regions.

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