Article

Improved methods for analyzing MRI brain images

Jyotsna Dogra, **Navdeep Prashar**, **Shruti Jain**, **Meenakshi Sood**
Department of Electronic and Communication Engineering, Jaypee Institute of Information Technology, Solan-173234, India
E-mail: jyotsnadogra1989@gmail.com, nav.prashar@gmail.com, shruti.jain@juit.ac.in, meenakshi.sood@juit.ac.in

Received 13 October 2017; *Accepted 20 December 2017*; *Published 1 March 2018*

Abstract
Image segmentation is a part of image processing for region or object extraction from the background area. Owing to the complex background, contrast of the infected portion, low intensity difference values, intricate inner body parts etc.; the problem of region extraction in segmentation is very challenging. Among various image segmentation techniques, thresholding is one of the simplest techniques, in which the region of interest is extracted from the background by comparing the pixel values with the threshold value. The threshold value is obtained from histogram of the image. The technique presented in the paper involves graph cut method in which the initial centroids are automatically selected by exploiting the symmetrical nature of the MRI images. The results obtained by the thresholding technique in this research work shows that any abnormality can be localized easily in horizontal divided MRI brain image rather than in vertical divided MRI image. Graph cut results show better segmentation than thresholding technique which is justified by PSNR and SSIM values.

Keywords segmentation; fuzzy c-mean clustering; k-mean clustering; split and merge; graph-cut.

Network Biology
ISSN 2220-8879
URL: http://www.iaees.org/publications/journals/nb/online-version.asp
RSS: http://www.iaees.org/publications/journals/nb/rss.xml
E-mail: networkbiology@iaees.org
Editor-in-Chief: WenJun Zhang
Publisher: International Academy of Ecology and Environmental Sciences

1 Introduction

Since evolution, the most effective and convenient medium for the understanding of information is through images. With the advent of time the different techniques for different images got exploited for the image analysis as per the applications such as: medical application, satellite imaging for identification of various objects like land (Ballestores and Qiu, 2012; Hussain, 2014; Seljuq and Hussain, 2014), body, building and river, robot navigation, remote sensing, detecting tumors and malign tissue finger print recognition, face recognition, iris recognition etc (Pham et al., 2000). Image processing popularity resulted due to its versatile method and low cost (Sonka et al., 2014). In digital image processing the image undergoes with fast computers for signal analysis various phases: Data acquisition, Pre-processing, Image enhancement (Bhusri et al., 2016; Sharma et al., 2017; Wang et al., 1983), Information Extraction (Amandeep et al., 2017; Bhusri et al., 2016; Rana et al., 2016; Sharma et al., 2017), and Classification (Dhiman et al., 2016; Jain et al., 2011; Sood, 2017; Sood et al., 2015). Further, for information extraction images go through three levels: image analysis, image processing and image segmentation as shown in Fig 1. Image analysis involves the extraction of the meaningful information contained in the image. Image processing includes manipulation of images to enhance the quality of image: as removing noise, histogram equalization, processing RGB values etc (Sood et al., 2014). The process includes image as input in terms of pixels with intensity values and output may be an image or any characteristic or property of image (Soille, 2013). The various techniques that conclude for image segmentation are: detecting edges, counting objects, finding shapes and area of the objects in binary image (Pal et al., 1993).

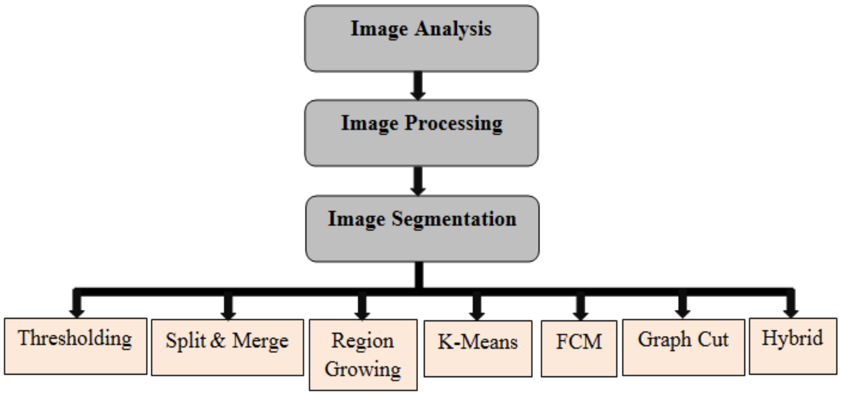

Fig. 1 Classification of image segmentation

In this research work different steps of image analysis, especially Medical Imaging is dealt with. Medical imaging comprises of techniques and process of creating visual representation of human body to reveal, diagnose and examine the disease for clinical application. It has been acknowledged to be most significant advancement over other medical technologies (Suetens, 2017). Some of the techniques encompassed by medical imaging are Positron emission tomography (PET), Medical resonance imaging (MRI), Computed tomography (CT) and more. Among all the MRI is one of the popular ways for non-invasive imaging of human body providing rich information about the human soft tissue anatomy. In comparison to X-ray, CT images, MRI shows more detailed image (Ferrari, 2005; Zhang, 2018).

Segmentation of brain MRI's is an important image processing procedure for both the physician and the brain researcher as it offers a valuable evaluation method for pre-and-post surgical after effects. A great deal of research is going on number of segmentation methods and lot of literature is available to segment images based on various criteria. Therefore, it is necessary to develop algorithms to obtain robust image segmentation. Thresholding is one of the oldest technique in image segmentation in which at an optimum threshold value the complete image is separated in object region and background image when the intensity of pixels is above or below the calculated threshold value. The limitation arises as it is not easy to find an appropriate threshold which can separate the image into two different groups.

Graph cut was first proposed byBoykov. It is an interactive segmentation. In this paper we have performed automatic centroid selection and returned the actual pixel value to the object region. The energy function responsible for the optimum cut in the graph comprises of the regional and the boundary term.

This research paper has been divided into following sections: Section II gives the description of Image Segmentation. Section III discusses the histogram thresholding and Section IV gives the results and discussions followed by conclusion.

2 Image Segmentation

Image segmentation plays a vital role in image processing by providing partitioning of image into region, measuring the area and shape, identification of region of interest in the image so that it becomes more meaningful and can be analysed (Comaniciu et al., 1997). Any image comprises background and the object region and image segmentation separates these two regions to provide the region of interest for its analysis. Main task of segmentation is the extraction of region of interest from the given image (Cheng et al., 2015). On similarity and discontinuity basis image segmentation is categorized in the categories as discussed in the following section.

a) *Thresholding*: One of the simplest and oldest techniques for segmentation of gray image is thresholding. An image described as f (x, y) is composed of light object and a dark background, such that the pixels are distributed in two dominant modes. A threshold value is decided to group the pixels and extract the images for segmentation. Kallergi et al. (1992) have performed image segmentation in three levels: image pre-processing, local thresholding and region growing.
b) *Split and Merge*: In split and merge procedure, the image is divided into regions based on the homogeneity criterion. If the pixels in the region have different intensity value then the region is divided until no more splitting is required and a complete homogenous region is achieved. The regions are merged if the divided regions have same intensity value. Borges et al. (2000) have proposed a method in which prototype based fuzzy clustering algorithm in split and merge framework. Split and merge technique is also applied for bimodality detection and 3D image segmentation(Chaudhuri et al., 2010; Damiand et al., 2003).
c) *Region Growing*: In this technique the growth of region depends upon the homogeneous neighbouring pixels around the seed. The homogeneity criterion depends not only on the problem under consideration, but also on type of image data available. To increase the effectiveness of region growing, Pavlidis et al. (1990) and Gambotto (1993) have presented different approaches for integrating edge detection and region growing.
d) *Clustering*: Clustering is the organization of data with high intra cluster similarity and low inter cluster similarity. To find the similarity or dissimilarity between two data points i.e. the distance between image pixels is calculated. This distance can be the intensity difference between two pixels. It reflects the degree of separation or closeness among the data points. Coleman et al. (1979) presented the approach of clustering for image segmentation. The most commonly used clustering methods:
   I. *K-mean Clustering*: K-mean Clustering also known as hard clustering is based on iterative process that divides the image into different clusters. The data points or the pixels are grouped in an exclusive way such that if a data point belongs to a certain cluster then it will not belong to any other cluster. K-mean assumes Euclidean distance on the basis of which the similarity and dissimilarity is measured and the clustering is performed. Chen et al. (1998) have proposed an adaptive K-mean algorithm for the segmentation of regions with the smooth varying intensity distribution which is applied on cardiac CT volumetric images.
   II. *Fuzzy C mean Clustering*: In FCM clustering the clusters of similar pixel is formed by giving membership value to the assigned pixel, these membership values give the degree of similarity. But the algorithm lacked in the initialization as the final result is depended solely on the input or the initial values. FCM technique is also known as soft clustering because it does not put any hard constraints on the pixel in forming the clusters. Clark et al. (1994) proposed a hybrid method in which the fuzzy clustering has been used to detect the tumor and then label the clusters formed. Clark, et. al. provides an automatic segmentation of MR Images. Ahmed et al. (2002) proposed a method to modify the objective function of

the conventional FCM so that the spatial information of the neighbourhood pixel could be used for the labelling of neighbourhood pixel (Chuang et al., 2006).

e) *Graph Cut method* Boykov et al. (2006) and Khanna et al. (2012) have given a technique in which the image is treated as binary and making a hard constraint for performing the image segmentation. Graph cut is an interactive technique which provides global optimal segmentation of N-dimensional images. The cost function defines the properties of boundary and region/object in the image. Felzenszwalb et al. (2004) have proposed an algorithm that measures the boundary between two regions in such a way that it satisfies two properties. Pauchard et al. (2016) have introduced graph cut for the interactive graph cut segmentation for fast creation of femur finite element models and observed that the proposed algorithm corresponded well to the manual segmentation.

f) *Hybrid Method*: Due to innovation in technology, the image segmentation techniques have become more application specific and the judgment of the most appropriate technique useful for a particular application is a difficult task. Therefore, hybrid or combined segmentation methods have been extensively used in different application specific biomedical image segmentation. The MRI segmentation method proposed by Ortiz et al. (2013, 2014) is based on Self-Organizing Maps (SOMs) and Genetic Algorithm (GAs). Sepas-Moghaddam et al. (2014) have presented a hybrid algorithm combining PSO, K-mean and learning automata based on multilevel thresholding are applied on standard test images.

3 Thresholding

Thresholding is the one of the simplest technique which has been based on the similarity index. Function f represents the complete image and $f(x, y)$ is the pixel intensity at the point (x, y). Single threshold value segments the image in two intensity values i.e. 0 (black) & 255 (white), resulting in extraction of region of interest inside the brain. Increase in the threshold values gives the increased number of intensity values in the segmented image. For application of thresholding based segmentation technique, it is required to apply the correct threshold values in order to achieve proper segmentation results.

Algorithm 1: Histogram Thresholding

Input: Image $f(x,y)$.

Output: Segmented image.

BEGIN

Step 1: Divide the MRI image in two halves (horizontal, vertical).

Step 2: Calculate the histogram for both images

Step 3: Difference between histograms (two halves) is calculated.

Step 4: Calculate the threshold value T from the difference value in step 3.

Step 5: Segment the image as per:

$$f(x,y) \geq T;\ \text{Background}$$

$$f(x,y) \leq T;\ \text{Object}$$

END

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4 Graph Cut Segmentation

Graph cut is an interactive technique which provides the global optimal segmentation of N-Dimensional images. In this technique, image is expressed ina binary form where it is partitioned inobject and background regions, which restricts the segmentation to have a hard constraint. In Boykov et al. (2001), the authors have demonstrated the following hypothesis which are employed in this paper:

a. Combination of hard and soft constraint.
b. If the hard constraint are added or changed optimal segmentation can still be recalculated.
c. In case initial segmentation is not perfect the user can define additional seed points from the result and can be adjusted to the current segmentation without any re-computation. Hence it becomes time efficient.

As explained by Boykov et al. (2006), an image is represented in graphical form G, which comprises of set of nodes V and edges $\mathcal{E}$ which connect the nodes.

$$G = < V, \mathcal{E} >$$

Where nodes V consists of source s and the sink t; source s represents the set of nodes that belong to the segmented region of interest and sink t represents the set of nodes that belong to the segmented background region.

$$\mathcal{V} = \{s, t\} \cup \mathcal{P}$$

An edge $\mathcal{E}$is described as a $t-$link, if it connects the non terminal node with a terminal node; and as a $n-$link if it connects two non-terminal nodes. Partition in an image is executed when edges which connect nodes are broken or cut; which require knowledge of boundary and region properties. The cost function defines these properties and provide optimal cut for the segmentation. Among the various strategies for optimizing energy function, in this paper authors have used the following energy function which was initially explored by Greig et al. (1989):

$$E(R) = \gamma U_p(R) + B_p(R)$$
$$U(R) = \sum_{p \epsilon P} U_p(r_p)$$
$$B(R) = B_{p,q} = e^{-\left(\frac{|I_p - I_q|}{\sigma}\right)}$$

where R gives the label to the image pixel, $U_p(R)$ is the regional term that gives the measure of assigning R to p (whether its object pixel or background pixel), $B_p(R)$calculates the boundary term and $\gamma$is the relative importance factor.

Algorithm 2: Graph Cut Segmentation
Input: MRI Brain Image.
Output: Segmented image.
BEGIN
Step 1: Divide the MRI image in two halves.
Step 2: Calculate the pixel difference between the two halves to obtain maximum difference value.
Step 3: A range of is taken above and below the maximum value.
Step 4: From step 4. Obtain the centroids for the background and the object region
Step 5: Calculate object terminal and background terminal.
Step 6: Label the all pixel with the respect to the degree of belongingness.
Step7: Segment the region of interest by calculating the minimum cut.
Step 8: Segmented image is obtained.
END

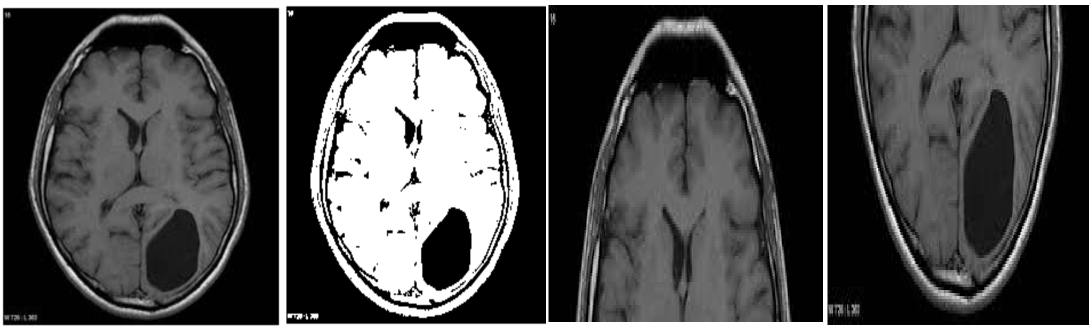
5 Simulation Results and Discussions

In this section we have analyzed and compared the MRI image segmentation by two methods: a. Histogram Thresholding & b. Graph cut. Three MRI images are used among which thresholding is done on the first image and graph cut is implemented using other two MRI images. The two techniques proposed are explained in the following:

a. *Histogram Thresholding*:

MRI image used for experiment is infected with a tumor region in the temporal lobe. The MRI brain has been divided into two halves: vertical half and horizontal half. Brain is having the similar shape around the central axis, so any change in any half of the brain will result in high difference value in the pixel intensities. The histogram for the both upper and lower half portion of horizontally divided MRI image is plotted and compared. The optimum threshold value is obtained from this histogram. In our implementation we have used only one threshold value. The difference between both the histogram has been calculated and analyzed. Finally segmented image has been based on the threshold value, T = 0.4980 which has been calculated from the difference values of the histogram.

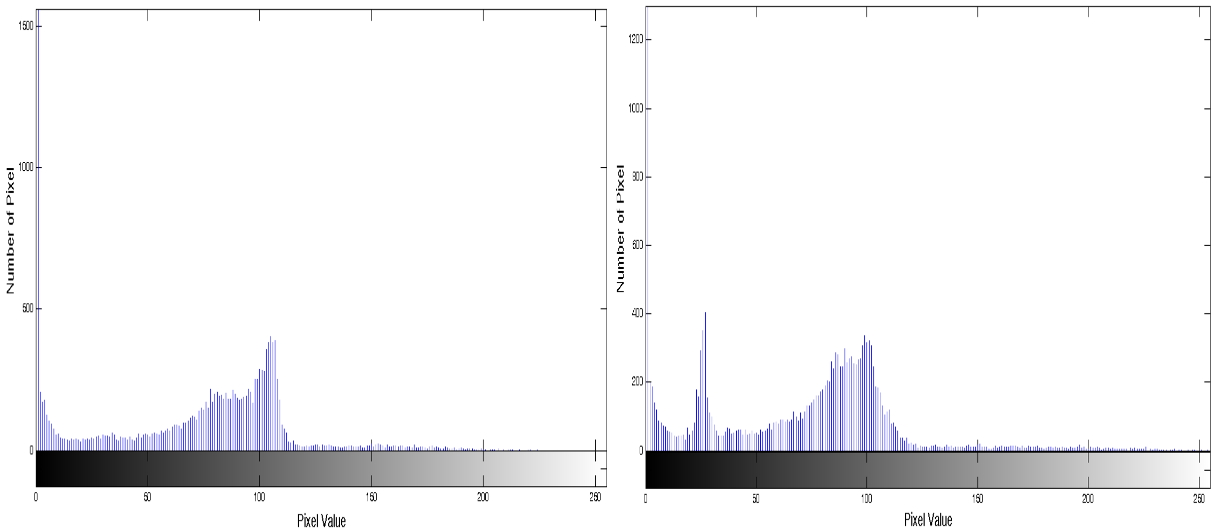
In this paper we have used only one threshold value so as to extract the infected portion from the brain. The final segmented image contains two intensity values and the infected portion has been clearly segmented.



(a) (b) (c) (d)

Fig. 2 (a) Original Image, (b) Output Image, (c) Upper half MRI, (d) Lower half MRI

Upper half and lower half of horizontally divided MRI image have been shown in Fig. 2(c) & 2(d) respectively, and histograms corresponding to Fig. 3 is shown in Fig. 3(a) & 3(b). In Fig. 4 it has been observed that number of pixel for the pixel values greater than 130 to 255 are zero. Higher difference has been seen for the pixel-value near to zero i.e. the tumor may contain these pixel intensity. Same procedure has been followed for the vertically divided MRI image.



(a) (b)

Fig. 3 (a) Histogram of Fig. 2 (c), Histogram of Fig. 2 (d).

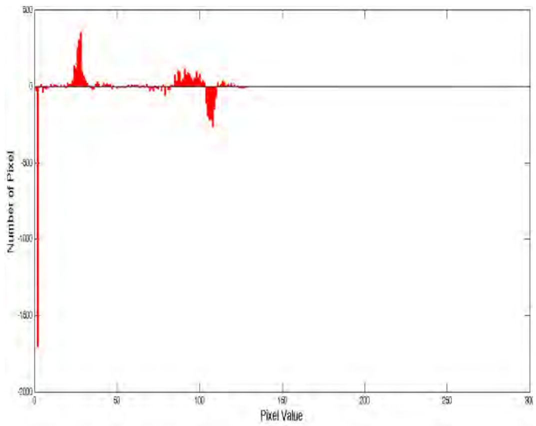
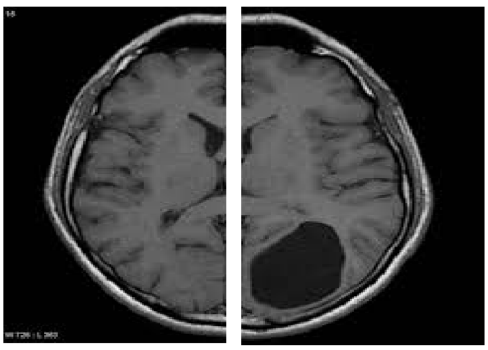


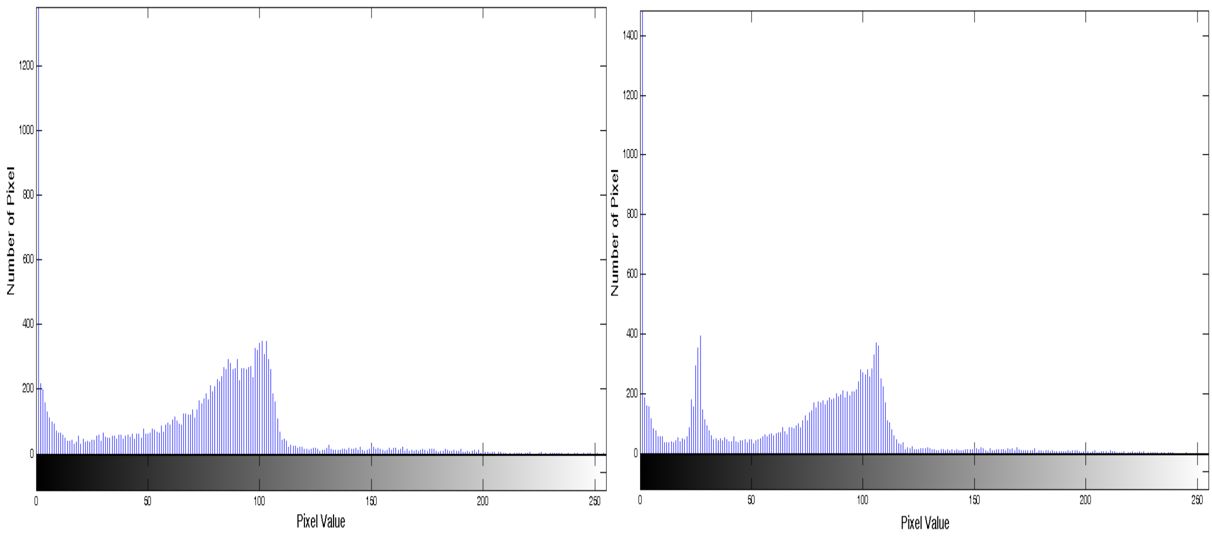
Fig. 4 Difference in histograms.

Right half and left half of the vertically divided MRI image have been shown in Fig. 5(a) & 5(b) respectively, and histograms corresponding to Fig. 6 is shown in Fig. 6(a) & 6(b). It has been observed from Fig. 4 to Fig. 7 that the difference values of the horizontally divided MRI image are low as compared to the vertically divided MRI image.



(a) (b)

Fig. 5 (a) Right half MRI image, (b) Left half MRI image



(a) (b)

Fig. 6 Histogram of Fig. 6 (a), Histogram of Fig. 6 (b).

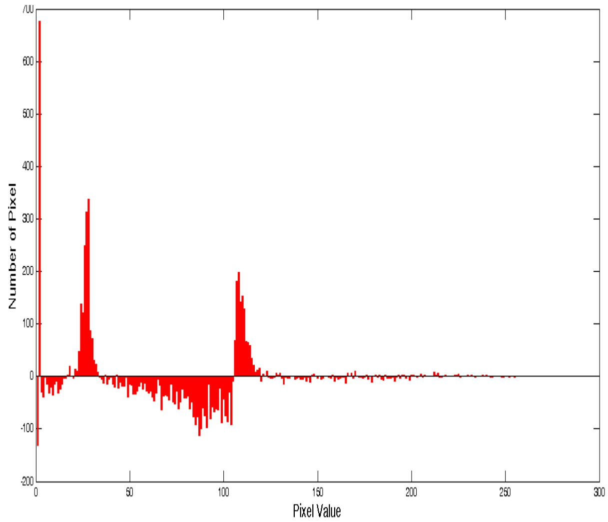
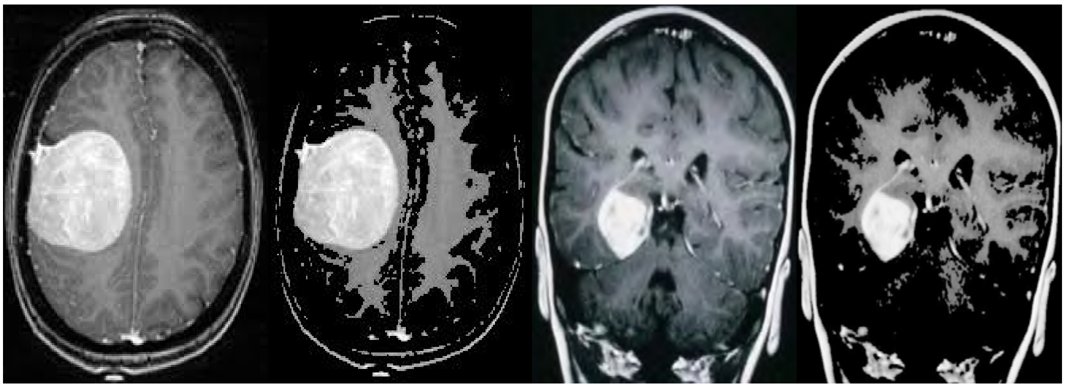


Fig. 7 Difference in histogram.

b. *Graph Cut segmentation:*

Initial centroids have been obtained by dividing the MRI Image in two halves (horizontal and vertical) and calculating the pixel difference. These difference values are responsible for evaluating the centroids from which the object and the background terminals are obtained. Hence the entire image is segmented in regions with homogeneous property. Image displayed in Fig. 8(a) is infected from tumor (URL: https://bigpictureeducation.com). Fig. 8(c) is astrocytoma infected brain and the image is taken from (URL: https://in.mathworks.com/matlabcentral.com). The corresponding segmented images are displayed in Fig. 8(b) and 8(d). The infected region is extracted from the background region and it is observed that they are not restricted to binary intensity values. The segmented region holds the original pixel values as in original image instead of intensity value 0. To measure the quality of the image parameters such as PSNR and SSIM are calculated for both the images. The values obtained for tumor affected segmented image is PSNR=22.28 dB, SSIM=0.75 and for astrocytoma affected segmented image is PSNR=18.80 dB, SSIM=0.90.



(a) (b) (c) (d)

Fig. 8 Segmented output images: (a) and (c) original MRI; (b) and (d) segmented images using Graph cut.

6 Conclusion

In this paper two methods are presented and an improved segmentation is acquired by the graph cut method. The process of finding the difference in intensity values in thresholding method is blended in the graph cut method for evaluation of centroids in this research work. This leads to an automatic selection of centroids. The PSNR and SSIM parameter values also imply that presented graph cut segmentation method is an effective way to detect tumor of any irregular shape holding the properties of segmented region.

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