Analysis of Graph Cut Technique for Medical Image Segmentation

Jyotsna Dogra(✉), Shruti Jain, and Meenakshi Sood

Department of Electronics and Communication,
Jaypee University of Information Technology, Solan, India
Jyotsnadogra1989@gmail.com, jain.shruti15@gmail.com,
meenusood9@gmail.com

Abstract. Segmentation plays an important role in image analysis as it is used to identify and differentiate foreground and background regions. Image segmentation in brain MRI analysis performs several roles like extraction of abnormal region for better diagnosis of the disease aiding in the therapy planning. Various brain tumors comprise diverse properties like their shapes, intensity distribution and location, hence reducing the possibility of developing a single general algorithm. In this paper authors have illustrated two methods for performing extraction which includes histogram thresholding and centroid based graph cut segmentation. On the basis of their potential, advantages and limitation comparison is made, that emphasize better performance of centroid based graph cut segmentation method. To measure the performance some quality parameters are evaluated. This paper also solves the problem of initial seed selection by using graph cut segmentation technique.

Keywords: Segmentation · Threshold · Fuzzy C-Mean clustering · K-mean clustering · Split and merge · Graph-Cut

1 Introduction

In the last few decades one of the most growing technique for providing the non-invasive image analysis for the diagnosis is Magnetic Resonance Imaging (MRI) technology. The huge amount of data analysis with good quality aids the expert radiologist in the study of brain anatomy. This huge brain data analysis maybe tedious with various difficulty due to the complex brain stricture but MRI is the most convenient and useful application in the imaging technology.

The formation of brain tumors is due to the irregular growth of the tissue mass that destroys the brain cells. The early diagnosis of tumor helps in increasing the survival rate [1]. Different growth rate of the tumor distributes the tumor in various grades belonging to the benign and malignant classes [2]. All these classes comprise different intensity distribution, locations and vary in size [3]. Brain tumor are one the most fatal disease and a high death rates have been observed in the developed countries [4]. Various Computer aided diagnosis methods provided for benefitting the clinicians with better diagnosis and testing are developed. Among them image segmentation is popularly used as it segments the image into different fragments generating a better

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diagnosis of targeted region. Some of the conventional methods employed redundantly are intensity based, clustering based and some hybrid techniques.

A binary conversion of the MR image is done in threshold based segmentation [5–7] method. The iterative methods such as split and merge, region growing [8] are intensity dependent and only considers uniformity of the homogenous regions. Region growing method initializes with seed points and grouping is performed through pre-defined criteria such as similar intensity, color and texture. The selection of seed points is a hurdle and many algorithms are illustrated by researchers [9, 10]. The second iterative method is the split and merge technique [11] divides the complete image in smaller region and merges all the homogenous region to form one single targeted region. Some of the hybrid approaches studied by the authors [12, 13] include region growing and edge detection. The popular and most generally used clustering methods are: k-mean Clustering and Fuzzy clustering. A membership function is given to all the pixels that provide amount of degree present in an element in the fuzzy clustering also known as soft clustering [14]. On the other hand in k-mean Clustering [15] popularly also known as hard clustering generates different grouping of the image in such a way that each group shall depict highest similarity or minimum Euclidean distance from the mean value of every group. These techniques are completely dependent on the initial points that is the biggest struggle [16–18] and are iterative in nature. Due to the iterative nature, these methods are time consuming and face the problem for the initial seed point selection.

One of the prominent technique used is the graph based method proposed by Boykov *et al.* [19]. In graph cut technique minimum value of the objective function is obtained on the formation of the segmented image. Authors in [20] developed a graphical representation of the image that used cost function enabling the division of the images. The objective function introduced by authors [21–24] provided identical segmentation even though different combinatorial algorithm are used for evaluating minimum cut. Authors analyzed the efficiency in [23] for illustrating all the problems involved when both the 2D and 3D images are used for segmentation. Graph cut extends up to ND segmentation of images due to its ability of integrating the regional and boundary term. Other techniques like live wire and intelligent scissor [25, 26] evaluate the lowest weighted edge for the partition.

In this research paper we have compared two segmentation technique and evaluated the performance metric. The first technique is one of the simplest technique that is thresholding. The second technique is graph cut segmentation that has limitation of seed selection for the initialization of the algorithm. This limitation is avoided in the proposed framework by developing an automatic graph cut segmentation.

The organization of the paper is given as: detail explanation along of the two techniques along with their algorithms and mathematical explanation are described in Sect. 2. The simulation result, image database is described in Sect. 3. Quality measure of the segmented image is verified by four parameters which are briefly described and the values calculated are framed. Conclusion for obtained results from the proposed framework is explained in the Sect. 4.

2 Methodology

In this section flow diagram, algorithm and a detail explanation for the threshold segmentation and proposed framework for graph cut segmentation is provided. In the histogram thresholding method threshold value is evaluated from the histogram of difference intensity values. These values project the pixel location where the tumor may have occurred then, partition is done based on the threshold value and binary values are assigned to different regions. Many region based methods face problem for the initialization of seed points. To overcome this problem, graph cut segmentation explains image in a graphical form and automatic centroid/seed values are evaluated by exploiting the symmetrical nature of the brain. Different labelling is done for the object and the background region. Partition is performed by breaking the edges with lower thickness and s-t graph is formulated. Both methods are compared using mean square error (MSE), peak-signal-to-noise ratio (PSNR), similarity index (SSIM) and dissimilarity index (DSSIM). Experimental results show that our approach of centroid based graph cut segmentation outperforms the histogram thresholding technique.

2.1 Histogram Thresholding

Thresholding technique is one of the popular techniques due to its simplicity. It converts MR image into a binary image, distinctly displaying the segmented region. Complete process of thresholding relies on the selection of the threshold value. This value is evaluated by means of number of pixels corresponding to a particular pixel value which are obtained by histogram. There are three types of thresholding technique: global threshold, variable threshold and regional threshold. In this paper global thresholding is employed and a single threshold value is evaluated by Otsu's method for the entire image.

Flow diagram of the histogram thresholding algorithm is given in Fig. 1. The MR image which is in RGB form is converted into gray scale image. Single threshold value is calculated for the entire image in two steps: the image is divided vertically, then, difference in the pixel intensity between the vertical sections is calculated and their histogram is computed. Using Otsu's method, the difference value is used to calculate the threshold value. All the pixels are compared about the threshold value. Pixels are labelled as '1' (representing white intensity value) if they belong to object region and as '0' (representing black intensity value) if they belong to background region. Hence, this algorithm provides a binary partition of the MR images. This partition is only possible if the accurate knowledge of the threshold value is obtained. If a single threshold value is selected, then the image is partitioned in binary form but on selecting higher value of the threshold the number of regions formed also increase. Therefore, the accurate knowledge of the threshold value is of critical importance. After the pixels are labelled the targeted tumor region is extracted from the MRI image and finally the segmentation is done.

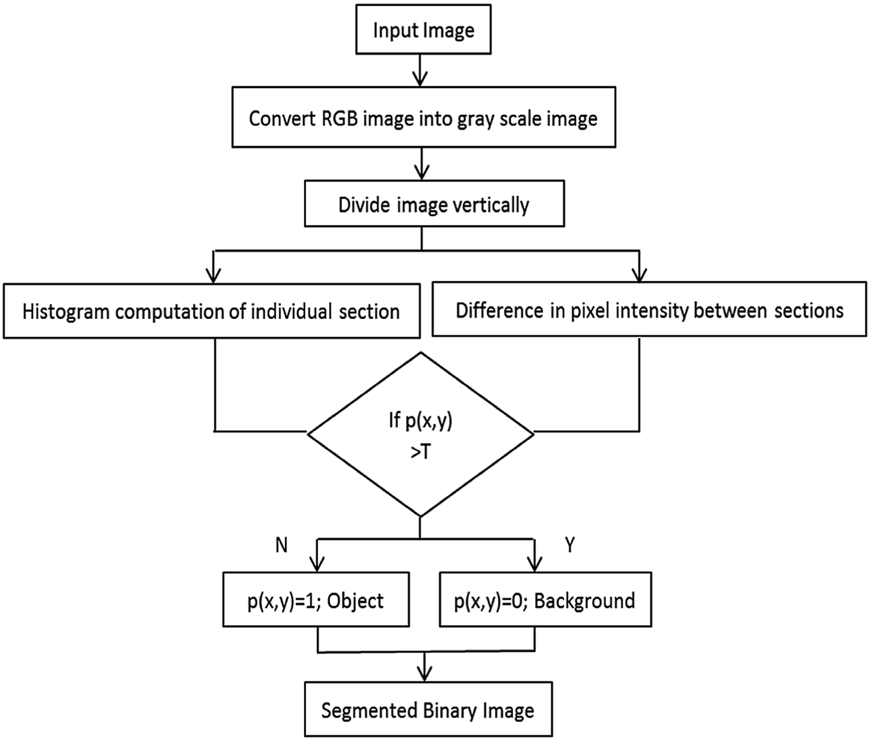


Fig. 1. Flow diagram of overall algorithm

2.2 Graph Cut

This segmentation technique divides the complete set of the image in two subgroups in such a way that the targeted region is presented as the foreground and the remaining as the background region. Graph cut represents the image in a graphical form such that each pixels are represented as nodes, illustrated in Figs. 2 and 3.

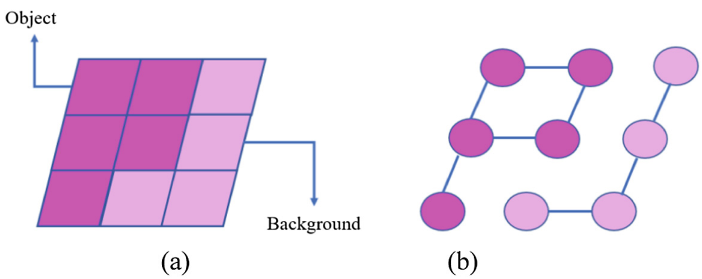


Fig. 2. (a) Graphical form of image (b) segmented image.

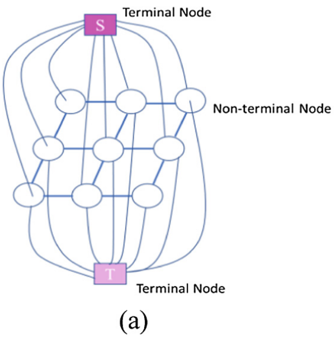


Fig. 3. (a) Source terminal and sink terminal (b) cut to segment object and background.

The basic representation of the image in the graphical form is given in Fig. 3(a) was proposed by Boykov *et al.* in [27] as:

$$G = < V, E > \tag{1}$$

$$\mathcal{V} = \{s, t\} \cup \mathcal{P} \tag{2}$$

where, graph G contains nodes/pixels $\mathcal{V}$ and edges/neighboring distance $\mathcal{E}$. The pixels $\mathcal{P}$ are nodes and the seed values are the non-terminal nodes (s, t) (s: source/object terminal; t: sink/background terminal) that are connected to each other via link. There are two types of links present: $t - link$ and. The $t - link$ connects the terminal nodes to the non-terminal nodes and $n - link$ connects all the neighboring nodes to each other. The partition takes place when two homogeneous regions are formed that show the highest similarity with the terminal nodes. This cut is shown in Fig. 3(b) that provides two exclusive regions. The flow diagram of this methodology is depicted in Fig. 4. The RGB image is converted into gray scale image and the image is divided in vertical sections as previously done in histogram thresholding. Both the symmetrical halves are compared and the pixel values with highest difference are obtained. These are the centroid points that provide the seed point for initializing the graph cut segmentation. Once the seed points are known the segmentation is performed by assigning the weights and labels are assigned corresponding to them.

3 Simulation Results and Discussion

3.1 Study Area and Dataset

The experiments were performed on MATLAB 2013a on the standard database [28, 29]. The clinical data was provided from radiology department of PGI Chandigarh as shown in Fig. 5(c). The sizes of three images are 180 × 218, 800 × 450 and 960 × 1280 respectively as given in Fig. 5(a), (b) and (c).

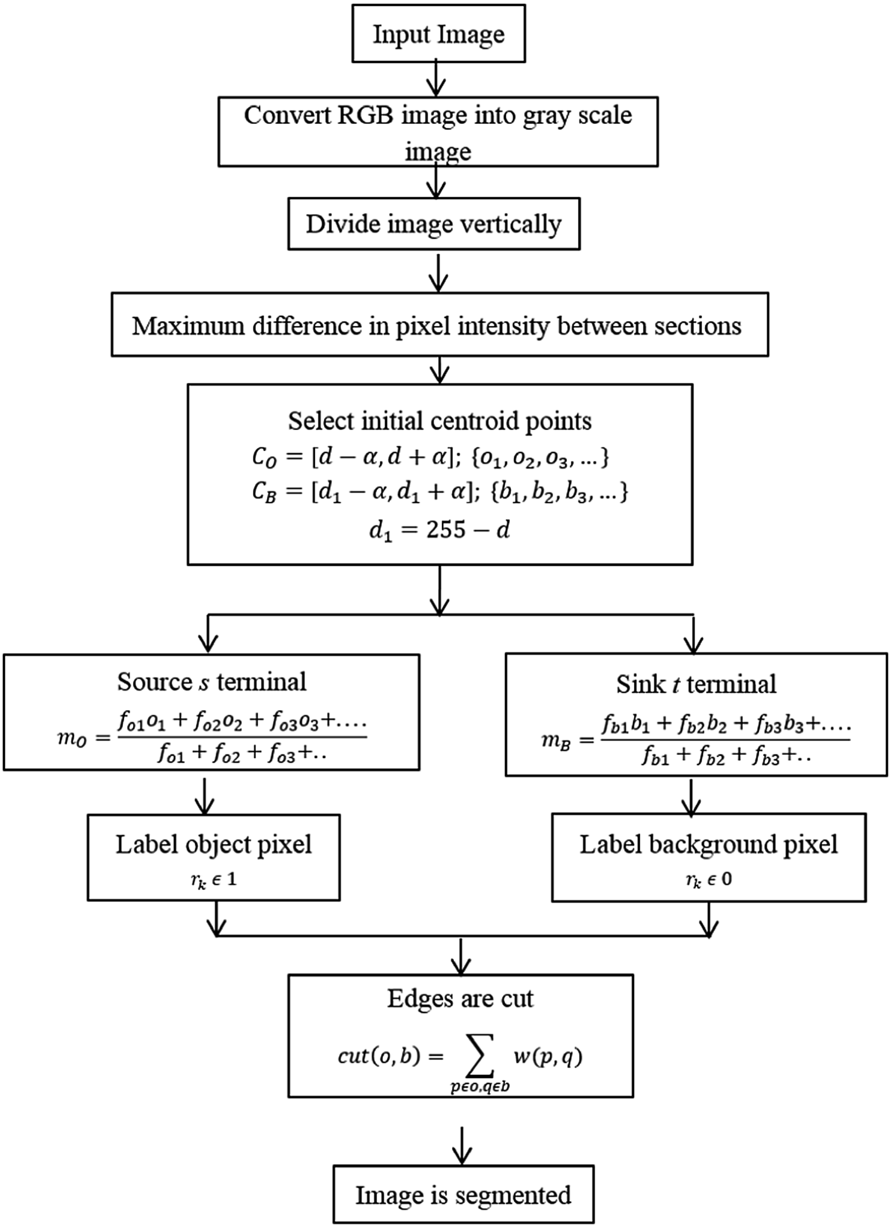
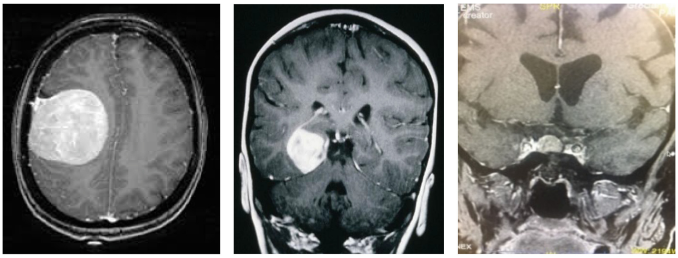


Fig. 4. Flow chart of automatic graph cut.



(a) (b) (c)

Fig. 5. Different set of original images (a), (b) and (c)

3.2 Quality Measure

For the performance analysis and quality measurement of the image, following parameters obtained from literature are evaluated: Peak Signal to Noise Ratio (PSNR), Structural Similarity Index (SSIM) and Dissimilarity Index (DSSIM).

3.2.1 Mean Square Error

MSE measures the average difference of the pixels throughout the image. Higher value implies greater difference of the segmented image from the original image. It is calculated as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(I_{xi} - I_{yi}\right)^2 \tag{3}$$

where, n, is the total no of pixel, I_{xi} is the intensity value of the original image and I_{yi} is the intensity value of the segmented image.

3.2.2 Peak Signal to Noise Ratio

PSNR computes how much noise is present in the resultant image due to segmentation and it is measured in decibel. It is computed as follows:

$$PSNR = 10 \log \frac{255 * 255}{MSE} \tag{4}$$

Ideally the PSNR value is infinite but practically it is 20 to 30 dB.

3.2.3 Structural Similarity Index (SSIM)

Authors in [30] presented SSIM as a quality measure parameter that calculates any disturbance in the segmented region of interest if created by the simulation. It correlates the local patterns of pixel intensities that are normalized.

$$SSIM = \frac{\left(2m_x m_y + K_1\right)\left(2\sigma_{xy} + K_2\right)}{\left(m_x^2 + m_y^2 + K_1\right)\left(\sigma_x^2 + \sigma_y^2 + K_2\right)} \tag{5}$$

where, $\boldsymbol{m_x}, \boldsymbol{m_y}$ are the mean value of the original region of interest (infected region in the original image) and the segmented region of interest (infected region in the segmented image) respectively, σ_x, σ_y are the variance respectively. K_1, K_2 are the substitution values, in this paper we have taken these values 0.01 and 0.03 which are calculated by Wang *et al.* in [30]. The values should range between 0 and 1, exhibiting higher similarity if the values are nearby 1 and lower similarity for values nearby 0.

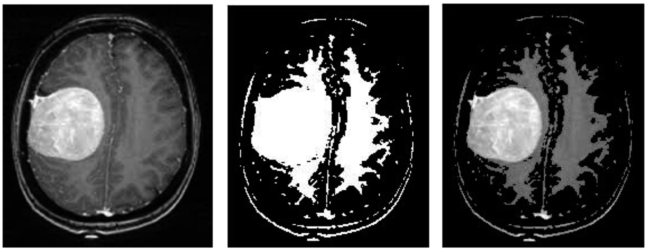
3.2.4 Dissimilarity Index

This parameter evaluates the pixels that have dissimilar intensity value from the original image. It computes adverse effect from the SSIM. Similar to SSIM its value also range between **0** and **1** but differs in the implications. For values near to **0** represent lower dissimilarity and value near to **1** show higher dissimilarity. This value is calculated as follows:

$$\boldsymbol{DSSIM} = \mathbf{1} - \boldsymbol{SSIM} \tag{6}$$

3.3 Results and Discussion

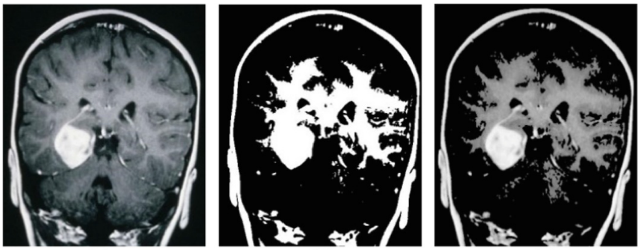
In this research work, tumor affected MRI image is segmented by thresholding and graph cut method as shown in Fig. 6. In threshold segmentation resulting image is binary image that is segmented at threshold value of T = 0.489. It is observed that region of interest is extracted but erroneous pixels also get included and it is difficult to differentiate between tumor region and other part of the brain. Whereas, the brain segmented by graph cut technique has a clear visibility of the tumor region. The segmented image is not binary, and extracted region's intensity values are similar to the tumor region in the original image.



(a) (b) (c)

Fig. 6. Segmentation results of Image 1 (a) original image, (b) thresholding, (c) graph cut

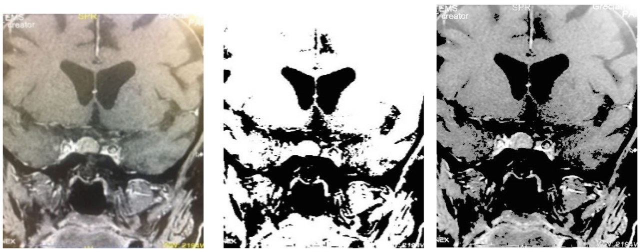
Segmented results of the Image-2 are shown in Fig. 7. The original MRI image is of a young child who is diagnosed by astrocytoma which occurs due to the astrocyte cells. Image segmented by threshold technique is a binary image. Tumor region is not extracted properly due to inclusion of pixels whose intensity value is close to the pixels in the tumor region. On the contrary, image obtained by graph cut segmentation has a clear picture of tumor region and no erroneous pixels are included in the ROI.



(a) (b) (c)

Fig. 7. Segmentation results of Image 2 (a) original image, (b) thresholding, (c) graph cut

In Fig. 8 segmented results of the third image are shown using both the techniques. Image obtained by thresholding technique is binary but it is very difficult to locate the tumor region. Most of the region are holding the value 1 hence majority region in the image is white.



(a) (b) (c)

Fig. 8. Segmentation results of Image 3 (a) original image, (b) thresholding, (c) graph cut

This implies that majority region in the original image are of high contrast. Tumor is successfully segmented by the proposed Graph cut segmentation technique. From the results it is observed that resultant image obtained by thresholding process extracts the tumor portion completely comprising of binary intensity values i.e. 0 and 1.

Threshold value of $T = 0.4980$ is obtained by calculating difference between two horizontal half of the image. Although this technique is one of the fast, simplest and oldest but the infected tumor region loses its original intensity value and returns value **0** or black color in the infected region. In the second method object and background centroid are automatically initialized, where 20 seed points for object/tumor region and 40 seed points for the background region are selected in this method. Variation in number of seed points results in similar mean/centroid value. It is observed from the images that the ROI/tumor region hold their original pixel value which is an advantage for the clinical application where the pixel intensity of the region of interest is measured to calculate the various parameter for the diagnosis of tumor. To analyze performance of the two methods MSE and PSNR quality measure are evaluated and are tabulated in Table 1. It is observed that MSE values for threshold segmentation method are very high for all three images. High MSE signifies that difference level between resultant images and original images is very high. The results also show very low PSNR value for threshold segmented images which ideally should be between 20 to 30 dB. However, results of graph cut segmented images show better result as the MSE is low and PSNR value is between 20 to 30 dB. These quality measures illustrate that graph cut method gives better result than threshold segmentation method.

Table 1. MSE and PSNR values of segmented images (by Threshold and Graph Cut method).

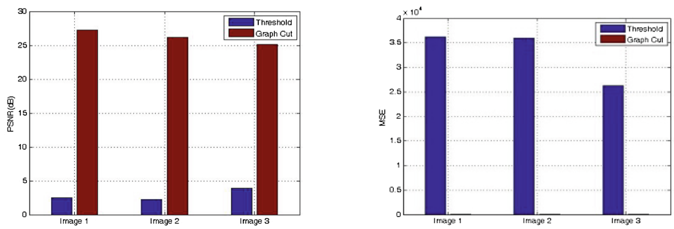
	Image-1		Image-2		Image-3	
Parameter	Threshold	Graph cut	Threshold	Graph cut	Threshold	Graph cut
MSE	36252.75	29.284	36018.45	37.506	26307.72	48.78
PSNR	2.503	27.202	2.218	26.197	3.895	25.125

In Table 2 similarity and dissimilarity index of the three images are evaluated. It is observed that SSIM values for threshold segmented images have very low similarity index and a very high dissimilarity index. This implies that the extracted image is quite different from the original image. Whereas, graph cut method shows high similarity index and low dissimilarity index as shown in Table 2.

Table 2. SSIM and DSSIM values of segmented images (by Threshold and Graph Cut method).

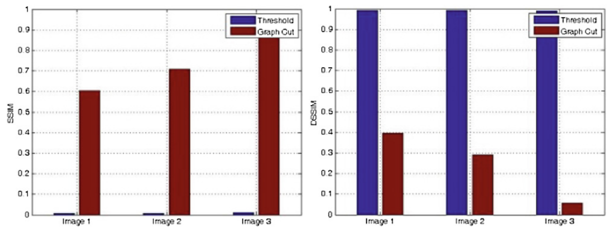
	Image-1		Image-2		Image-3	
Parameter	Threshold	Graph cut	Threshold	Graph cut	Threshold	Graph cut
SSIM	0.603	0.007	0.709	0.008	0.058	0.009
DSSIM	0.397	0.993	0.291	0.992	0.942	0.991

For ease of better clarification and understanding of performance of both techniques on the basis of quality measure are represented in graphical representation. The comparison of the two techniques with respect to the parameters in Tables 1 and 2 are shown in Figs. 9 and 10 respectively.



(a) (b)

Fig. 9. Comparison of threshold and graph cut segmentation on the basis of parameter (a) MSE and (b) PSNR



(a) (b)

Fig. 10. Comparison of threshold and graph cut segmentation on the basis of parameter (a) SSIM and (b) DSSIM.

4 Conclusion

In this paper we have proposed two techniques for image segmentation and evaluated the effectiveness on the basis of quality measure parameters. In the first technique single threshold value is used for segmenting the three images and corresponding binary images are obtained it is observed that tumor region is not clearly visible for all three images. This is because erroneous pixels are included in the infected region which may result in false diagnosis. This is validated by the evaluated MSE and PSNR. Better segmentation is observed from the second technique of automated graph cut method that generates the seed points resulting in the efficient and most accurate segmentation. The quality measure evaluated for the validation of automated graph cut method for MSE, PSNR parameter are 29.3, 27.2 for image 1; 37.5, 26.2 for image 2 and 48.8, 25.1 for image 3 respectively. The SSIM and DSSIM values obtained are 0.007, 0.993 for image 1; 0.008, 0.992 for image 2 and 0.009, 0.991 for image 3 respectively. The evaluated results imply effectiveness of the proposed graph cut segmentation irrespective of any irregular tumor shape and a clear visibility of extracted tumor.

References

1. Kotsas, P.: Non-rigid registration of medical images using an automated method, pp. 199–201. IEC, Prague (2005)
2. Nagalkar, V., Asole, S.: Brain tumor detection using digital image processing based on soft computing. J. Signal Image Process. **3**, 102–105 (2012)
3. Mirajkar, G., Barbadekar, B.: Automatic segmentation of brain tumors from MR images using undecimated wavelet transform and gabor wavelets. In: 17th IEEE International Conference on Electronics, Circuits, and Systems (ICECS), pp. 702–705 (2010)
4. Lin, C.-T., Yeh, C.-M., Liang, S.-F., Chung, J.-F., Kumar, N.: Support-vector-based fuzzy neural network for pattern classification. IEEE Trans. Fuzzy Syst. **14**, 31–41 (2006)
5. Cheriet, M., Said, J.N., Suen, C.Y.: A recursive thresholding technique for image segmentation. IEEE Trans. Image Process. **7**, 918–921 (1998)
6. Sezgin, M., Sankur, B.: Selection of thresholding methods for nondestructive testing applications. In: Proceedings of International Conference on Image Processing, pp. 764–767 (2001)
7. Li, Z., Liu, G., Zhang, D., Xu, Y.: Robust single-object image segmentation based on salient transition region. Pattern Recogn. **52**, 317–331 (2016)
8. Manousakas, I., Undrill, P., Cameron, G., Redpath, T.: Split-and-merge segmentation of magnetic resonance medical images: performance evaluation and extension to three dimensions. Comput. Biomed. Res. **31**, 393–412 (1998)
9. Adams, R., Bischof, L.: Seeded region growing. IEEE Trans. Pattern Anal. Mach. Intell. **16**, 641–647 (1994)
10. Fan, J., Yau, D.K., Elmagarmid, A.K., Aref, W.G.: Automatic image segmentation by integrating color-edge extraction and seeded region growing. IEEE Trans. Image Process. **10**, 1454–1466 (2001)
11. Hancer, E., Karaboga, D.: A comprehensive survey of traditional, merge-split and evolutionary approaches proposed for determination of cluster number. Swarm Evol. Comput. **32**, 49–67 (2017)
12. Gambotto, J.-P.: A new approach to combining region growing and edge detection. Pattern Recogn. Lett. **14**, 869–875 (1993)
13. Pavlidis, T., Liow, Y.-T.: Integrating region growing and edge detection. IEEE Trans. Pattern Anal. Mach. Intell. **12**, 225–233 (1990)
14. Pal, N.R., Pal, S.K.: A review on image segmentation techniques. Pattern Recogn. **26**, 1277–1294 (1993)
15. Jain, A.K.: Data clustering: 50 years beyond k-means. Pattern Recogn. Lett. **31**, 651–666 (2010)
16. Dhanachandra, N., Chanu, Y.J.: Image segmentation method using k-means clustering algorithm for color image. Adv. Res. Electr. Electron. Eng. **2**(11), 68–72 (2015)
17. Despotovic, I., Vansteenkiste, E., Philips, W.: Spatially coherent fuzzy clustering for accurate and noise-robust image segmentation. IEEE Signal Process. Lett. **20**, 295–298 (2013)
18. Chuang, K.-S., Tzeng, H.-L., Chen, S., Wu, J., Chen, T.-J.: Fuzzy c-means clustering with spatial information for image segmentation. Comput. Med. Imaging Graph. **30**, 9–15 (2006)
19. Boykov, Y., Funka-Lea, G.: Graph cuts and efficient ND image segmentation. Int. J. Comput. Vis. **70**, 109–131 (2006)
20. Wu, Z., Leahy, R.: An optimal graph theoretic approach to data clustering: theory and its application to image segmentation. IEEE Trans. Pattern Anal. Mach. Intell. **15**, 1101–1113 (1993)

21. Ford Jr., L.R., Fulkerson, D.R.: Flows in Networks. Princeton University Press, Princeton (2015)
22. Goldberg, A.V., Tarjan, R.E.: A new approach to the maximum-flow problem. J. ACM (JACM) **35**, 921–940 (1988)
23. Boykov, Y., Kolmogorov, V.: Computing geodesics and minimal surfaces via graph cuts. In: null, p. 26 (2003)
24. Heimowitz, A., Keller, Y.: Image segmentation via probabilistic graph matching. IEEE Trans. Image Process. **25**, 4743–4752 (2016)
25. Mortensen, E.N., Barrett, W.A.: Interactive segmentation with intelligent scissors. Graph. Models Image Process. **60**, 349–384 (1998)
26. Falcão, A.X., Udupa, J.K., Miyazawa, F.K.: An ultra-fast user-steered image segmentation paradigm: live wire on the fly. IEEE Trans. Med. Imaging **19**, 55–62 (2000)
27. Boykov, Y.Y., Jolly, M.-P.: Interactive graph cuts for optimal boundary & region segmentation of objects in ND images. In: Proceedings of Eighth IEEE International Conference on Computer Vision, pp. 105–112 (2001)
28. Stubberfield, L.: Big Picture. https://bigpictureeducation.com
29. MathWorks. https://in.mathworks.com/matlabcentral.com
30. Wang, Z., Bovik, A.C., Sheikh, H.R., Simoncelli, E.P.: Image quality assessment: from error visibility to structural similarity. IEEE Trans. Image Process. **13**, 600–612 (2004)