Brain Tumor Segmentation: A Comparative Analysis

Eman Mohammed[1](✉), Mosab Hassaan[1], Safaa Amin[2], and Hala M. Ebied[2]

[1] Faculty of Science, Benha University, Banha, Egypt
mosab.hassaan@fsc.bu.edu.eg
[2] Faculty of Computer and Information Sciences, Ain Shams University, Cairo, Egypt
{safaa.ameen,Halam}@cis.asu.edu.eg

Abstract. Brain tumor is an abnormal cell population that occurs in the human brain. Nowadays, medical imaging techniques play an essential role in tumor diagnosis. Magnetic resonance imaging (MRI) is a medical imaging technique that uses radio waves and a magnetic field as sound waves are created to produce detailed images of tissues and organs in the human body by computer. In this study, three different methods were reviewed and compared to the tumor's extraction from a set of MRI brain images. These methods are seeded region growing, k-means, and global thresholding. The images used in this study are obtained from the Cancer Imaging Archive (TCIA) and Kaggle. All images are grayscale and in JPEG format. The images from TCIA dataset are 100 images that contain abnormal (with a tumor) brain MRI images while there are 35 images in the Kaggle dataset. The Kaggle dataset contains 20 normal images and 15 abnormal images. The results show that the k-means segmentation algorithm performed better than the others on TCIA dataset according to the Root Mean Square Error (RMSE), the Peak to Signal Noise Ration (PSNR), and Segmentation Accuracy while global thresholding is the best on Kaggle dataset.

Keywords: Image segmentation · Brain tumor · MRI · K-means · Seeded region growing

1 Introduction

Segmentation is the process of dividing an image into regions or classes of non-intersecting meaning. All pixels in the same class must have some common feature. We do this by setting each pixel to be a member of one of the k categories or the smooth regions. Brain tumors are an abnormal mass of tissue in which cells grow and multiply uncontrollably, apparently not under control by the mechanisms that control normal cells. Brain tumors can be malignant or benign [1].

The diffuse brain tumor is cancer that has been deployed from elsewhere in the human body to the brain. Magnetic Resonance Imaging (MRI) is a developed medical imaging technique used to produce high-quality images of the parts contained in the human body MRI is often used when treating ankle, brain, foot, breast, lung, and kidney tumors [2, 3].

A. E. Hassanien et al. (Eds.): AICV 2021, AISC 1377, pp. 505–514, 2021.
https://doi.org/10.1007/978-3-030-76346-6_46

From these high-resolution images, we can derive detailed anatomical information to study the human brain's development and discover defects. Presently, there are many methodologies for categorizing MR images: mysterious methods, neural networks, atlas methods, knowledge-based techniques, and ways to shape and divide differences.

Image segmentation is the primary step in analyzing the image, which is used to segment the input image into meaningful areas. Image segmentation algorithms are based on pixel gray levels, and sudden changes in gray and the similarity between pixel areas is the basis for image segmentation. The image datasets used here can operate on gray-level image segmentation algorithms. Many algorithms are used in image segmentation [4]. The current image segmentation techniques include edge detection segmentation, region-based segmentation, clustering-based segmentation [5], and weakly-supervised learning-based segmentation in the convolution neural network (CNN), etc.

This paper introduces a comparative study between seeded region growing, k-means, and global thresholding. Firstly, two preprocessing techniques are applied to images in general: noise removal and contrast enhancement. Median and Soft weighted median filtering is applied to the MRI images to remove noise from the images. Secondly, the algorithms mentioned above are executed.

The organization of the remaining parts of the paper is as follows. Related works are presented in the second section. The third section describes the image preprocessing. The fourth section describes the segmentation methods. The fifth section shows the results. Finally, the conclusion is introduced in Sect. 6.

2 Related Work

There are several techniques used to segment images. These techniques have their significance and can be classified with one of two basic segmentation categories: the area-based approach and the edge-based approach. Figure 1 shows the different techniques of image segmentation. Each technique can be applied to different images to perform the desired segmentation [6, 7].

Logeswari and Karnan [8] described a two-stage segmentation method. In the first stage, MRI of the brain was obtained from the patient database which noise and artifact were removed in that film. Then, a Hierarchical Self-Organization Map (HSOM) was applied to segment the images. HSOM was an extension of the traditional self-organizing map used to classify an image row by row. In this lower plane of the weight vector, a value of tumor pixels, computation speed was achieved by the HSOM with vector quantization.

Bhide et al. [9] focused on a new brain segmentation algorithm for MRI images using a fuzzy c means algorithm to accurately diagnose the cancer area. In the first step, the authors filtered the noise and then applied the FCM algorithm to only segment the tumor area. In this research, multiple MRI images of the brain used to detect glioma (tumor) growth with advanced diameter technology.

Ilhan et al. [10] developed a method for the clear differentiation of cancer-affected tissues. The proposed approach was used to obtain a segmented tumor area clear enough to be observed by the practicing clinician and give them more detail about the tumor in their prognosis. In the proposed approach, morphological processes, pixel subtraction, threshold-based segmentation, and image filtering techniques are used. The proposed

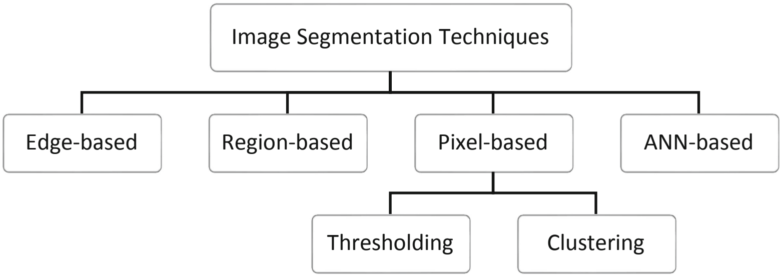

Fig. 1. Image segmentation categories and methods.

approach relied on obtaining clear images of the skull, brain, and tumor. When compared, the proposed approach gave a better result than the other approach.

Dubey et al. [11] compared three different semiautomated techniques: modified gradient magnitude region growing technique (MGRRGT), level set, and a marker-controlled watershed. Methods were implemented to assess their relative performance in tumor segmentation. A study of 9 samples using MGRRGT revealed that all errors were in the range of 6 to 23% compared to the other two methods.

Subashini et al. [12] proposed a clustering-based approach using a Hierarchical Self-Organizing Map (HSOM) algorithm for MR image segmentation. Self-organizing map (SOM) or self-organizing feature map (SOFM) is a type of artificial neural network for unsupervised learning. SOMs operate in two modes: training and mapping. The training is a competitive process, also called vector quantization. Mapping automatically classifies the new input vector. Segmentation is an important process for extracting information from complex medical images.

3 Image Preprocessing

Image segmentation is normally prefixed with the image processing step to enhance the image. Image preprocessing is the first step in image understanding [13]. In general, two preprocessing techniques are applied to enhance the image; noise removal and contrast enhancement. Preprocessing techniques try to reduce the artifacts that introduced by the imaging modality. In this work, the images are loaded and converted into grayscale. Median and soft weighted median filters are applied to the MRI images to remove the image's noise [14].

The medium filter is a non-linear digital filtering technology used to remove signals or noise from the image. Noise reduction is a practical step to improve the results before processing (e.g., edge detection on an image). The soft weighted median filter (SWMF) method is a new way to filter image processing noise. This filter is used for two types of image noise. The first type is fixed value noise (FVN), a type of noise whose value does not change, such as salt and pepper noise. The second type is random value noise (RVN), a type of random-value noise that is to a variable value such as Gaussian and Speckle.

4 Segmentation Techniques

This section describes the seed region growing method, threshold-based segmentation, and k-means Segmentation in the following subsections.

4.1 Seeded Region Growing

Seeded Region Growing is performed on the basis of a set of points known as seeds [15]. The region grows by attaching the seeds to the neighboring pixels. To precisely divide the regions, each component connected to the region must completely meet with one seed. This region growth process will not stop until all pixels in the regions are combined by comparing the initial pixel with all the neighboring pixels.

The main problem you face is choosing the point of the seeds that are determined manually or by automatic seeds criteria for selection and area growth, including a high level of knowledge of segmentation of semantic images to explore seed selection for more accurate segmentation of regions. For interpretation, the image must be divided into meaningful regions associated with the target image's objects. The pixels that are compatible with the object in the image are grouped together and highlighted. Algorithm 1 shows the seed region growing method steps.

Algorithm 1. Seeded Region Growing

1. Choose the seed pixel.
2. **For** every neighboring pixels to the seed **do**
3. Check the neighboring pixels and add them to the region if they are similar to the seed.
4. **Go to** step 2; stop if no more pixels can be added.

4.2 Threshold-Based Segmentation

Threshold-Based Segmentation is the simplest method of segmentation methods. The image is divided directly into regions based on density values with one or more thresholds [16, 17]. Segmenting images containing more than two types of areas corresponding to different objects are a local threshold. Depending on the severity of the image, light objects in the dark background are segmented by specifying a specific threshold value TH, pixels above the threshold are treated as one and those below the threshold are set to zero in the image. Pixels with a value of 1 correspond to the region of interest (ROI) while the remaining pixels that are set to zero correspond to the background of the image. Algorithm 2 describes the Threshold-Based Segmentation method [18].

Algorithm 2. Threshold-Based Segmentation

1. Select the initial value of threshold.
2. Divide the image into sub-blocks of size M × N.
3. For each sub-block, B do
4. Calculate the standard deviation for B.
5. Select the Global threshold as the threshold T that separates an object from the background
6. A Global threshold is applied for B that has a standard deviation greater than one.

4.3 k-means Segmentation

Image segmentation is the classification of an image into different groups. Several types of research have been done in the field of image segmentation using aggregation. One of the most common is the k-means aggregation algorithm [19]. The aggregation algorithm k-means is an unattended algorithm used to split the area of interest from the background. But before applying the k-means algorithm, the first partial expansion improvement is applied to the image to improve the image quality. The aggregate method collects data where you create the midpoint based on the possible value of the data points. Therefore, the molar mass is used to create the initial centroids, and these centroids are used in the k-means algorithm to segment the image. The medial filter is then applied to the split image to remove any unwanted area from the image. Algorithm 3 describes the k-means method. In Algorithm 3, the image p will be clustered into k clusters. Let p(x, y) be any pixel and c_k be the cluster centroid.

Algorithm 3. k-means method

1. Select randomly k pixels as the initial cluster centroids.
2. **For** each pixel of the image, *p(x, y)* **do**
3. Calculate the Euclidean distance $d = \| p(x, y) - c_k \|$
4. Group the pixels based on the min distance.
5. Update centroids by calculate the mean of the pixels in the same group.
6. **Go to** step 2, until no moving of objects between different groups.

5 Experimental and Results

5.1 Dataset

In this paper, we used two datasets. The first one obtained from TCIA (the Cancer Imaging Archive, brain tumor 2017 [20]) namely, TCIA dataset. In TCIA dataset, there are 100 MRI abnormal brain images (with a tumor). The second dataset obtained from kaggle [21] namely, kaggle dataset. It contains 20 normal brain images and 15 abnormal brain images. All images in the two datasets are grayscale 256 × 256 pixels, 8-bit grayscale and in JPEG format.

5.2 Accuracy Criteria

The accuracy is measured by the following equation [22]:

$$Accuracy\,(\%) = \frac{TP + TN}{TP + TN + FP + FN} * 100 \tag{1}$$

where the attributes are used in the calculations are:

TP (True Positive): Existing tumor and detected correctly.
TN (True Negative): Non-existing tumor and not detected.
FP (False Positive): Non-existing tumor and detected.
FN (False Negative): Existing tumor and not detected.

The quality of the segmented image is analyzed using the Peak to Signal Noise Ration (PSNR) [23] and the Root Mean Square Error (RMSE) [24].

5.3 Results

Performance on TICA Dataset
This section discusses the use of k-means, region grow, and threshold algorithms for MRI image segmentation. The experiments are performed using 100 MRI images (TCIA dataset). The first set of experiments was carried out to measure the three segmentation methods' accuracy without using any preprocessing step. Table 1 shows PSNR, RMSE, and segmentation accuracy for three algorithms. It is clear that the segmentation accuracy of the k-means algorithm is better than the others. The PSNR has the highest value with the k-means algorithm. RMSE has the lowest value with the k-means algorithm. Also, the k-means algorithm has the best segmentation accuracy.

The second set of experiments was carried out to measure the effect of using the Median and Soft Weighted Median filters before the segmentation algorithms. Table 2 shows the PSNR, RMSE, and segmentation accuracy for k-means, region grow, and threshold algorithms. When we used the filters, the accuracy of all algorithms becomes better as increased by 1%. Figure 2 shows samples of the segmented images using k-means segmentation, thresholding segmentation, and seeded region growth segmentation on TCIA dataset.

Table 1. Accuracy of k-means, Seeded Region Growing (SRG), and Threshold-based for Segmentation.

Methods	PSNR	RMSE	Segmentation accuracy
k-means	0.3057	0.1021	98.46
Threshold-method	0.2067	0.2036	97.53
SRG	0.2503	0.1804	97.74

Table 2. Effect of Median and Soft weighted Median filters on segmentation accuracy.

Methods	PSNR	RMSE	Segmentation accuracy
k-means	0.4457	0.0621	99.46
Threshold-method	0.2967	0.1436	98.53
SRG	0.3003	0.1404	98.74

Performance on Kaggle Dataset

We discuss the performance of the three algorithms on Kaggle dataset. Table 3 shows PSNR, RMSE, and segmentation accuracy for k-means, region grow, and threshold algorithms (without using any preprocessing step). The threshold-based segmentation algorithm's segmentation accuracy is better than the other two algorithms. Table 4 shows the PSNR, RMSE, and segmentation accuracy for k-means, region grow. Threshold algorithms (with using filters, Median and Soft Weighted Median filters), the accuracy of all algorithms become better. Figure 3 shows 4 samples of the segmented images (3 normal images and one abnormal image) using k-means segmentation, thresholding segmentation, and seeded region growth segmentation on the Kaggle dataset.

Table 3. Accuracy of k-means, Seeded Region Growing (SRG), and Threshold-based for Segmentation.

Methods	PSNR	RMSE	Segmentation accuracy
k-means	0.2663	0.1349	97.89
Threshold-method	0.4207	0.0736	99.59
SRG	0.2218	0.2194	95.92

Table 4. Effect of Median and Soft weighted Median filters on segmentation accuracy.

Methods	PSNR	RMSE	Segmentation accuracy
k-means	0.3590	0.0990	98.20
Threshold-method	0.4396	0.0516	99.73
SRG	0.2575	0.1815	96.43

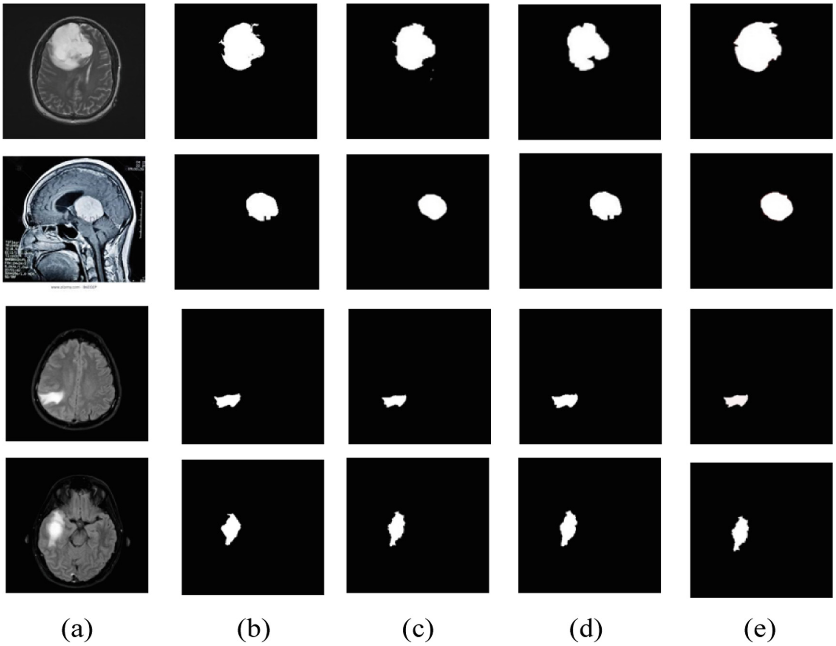

Fig. 2. Segmentation of Kaggle images. (a) Original image, (b) Ground truth, (c) Using k-means segmentation, (d) Using Threshold-based segmentation, and (e) Using Seeded Region Growing segmentation.

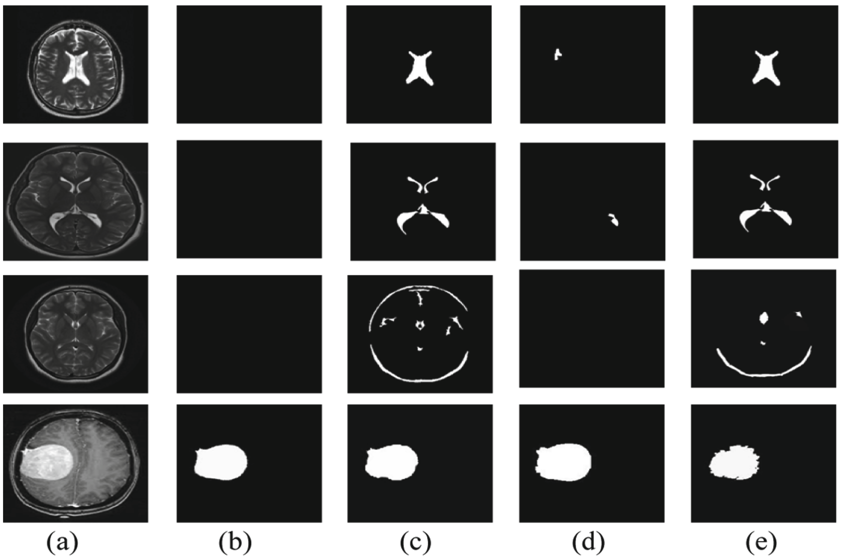

Fig. 3. Segmentation of kaggle images. (a) Original image, (b) Ground truth, (c) Using k-means segmentation, (d) Using Threshold-based segmentation, and (e) Using Seeded Region Growing segmentation.

6 Conclusion

This study aides the medical people to diagnose brain cancer MRI Images. The datasets obtained from The Cancer Imaging Archive (TCIA) and Kaggle are used in this study. A comparative study of three semi-automated methods has been undertaken to evaluate their relative performance in the brain tumor segmentation. These methods are seeded region growing, k-means, and global thresholding. Median and Soft Weighted Median filtering is used before segmentation algorithms to remove any noise from the images. The filters have shown an improvement in image segmentation accuracy. The experimental result shows that the k-means method gives better accuracy than the seeded region growing method and global thresholding method on TCIA dataset. In comparison, global thresholding method gives better accuracy than k-means method and seeded region growing method on kaggle dataset.

Acknowledgment. I would like to thank my supervisor Prof. Dr. Maher Shedid, for his valuable guidance, support, and motivation throughout this research.

References

1. Balafar, M.A., Ramli, A.R., Saripan, M.I., Mashohor, S.: Review of brain MRI image segmentation methods. Artif. Intell. Rev. **33**(3), 261–274 (2010)
2. Mishra, A., Rai, A., Yadav, A.: Medical image processing: a challenging analysis. Int. J. Bio-Sci. Bio-Technol. **6**(2), 187–194 (2014)
3. Osman, A.F.: Automated brain tumor segmentation on magnetic resonance images and patient's overall survival prediction using support vector machines. In: International MICCAI Brain Lesion Workshop, pp. 435–449. Springer (2017)
4. Gordillo, N., Montseny, E., Sobrevilla, P.: State of the art survey on MRI brain tumor segmentation. Magn. Reson. Imaging **31**(8), 1426–1438 (2013)
5. Lakshmi, S., Sankaranarayanan, D.V.: A study of edge detection techniques for segmentation computing approaches. In: IJCA Special Issue on "Computer Aided Soft Computing Techniques for Imaging and Biomedical Applications" CASCT, pp. 35–40 (2010)
6. Zhang, N., Ruan, S., Liao, S.L.Q., Zhu, Y.: Kernel feature selection to fuse multispectral MRI images for brain tumor segmentation. Comput. Vis. Image Underst. **115**(2), 256–269 (2011)
7. Gahukar, S.D., Salankar, S.S.: Segmentation of MRI brain image using fuzzy c means for brain tumor diagnosis. Int. J. Eng. Res. Appl. **4**(4), 107–111 (2014)
8. Logeswari, T., Karnan, M.: An enhanced implementation of brain tumor detection using segmentation based on soft computing. In: 2010 International Conference on Signal Acquisition and Processing, pp. 243–247. IEEE (2010)
9. Bhide, A., Patil, P., Dhande, S.: Brain segmentation using fuzzy c means clustering to detect tumour region. Int. J. Adv. Res. Comput. Sci. Electron. Eng. **1**(2), 85–90 (2012)
10. Ilhan, U., Ilhan, A.: Brain tumor segmentation based on a new threshold approach. Proc. Comput. Sci. **120**, 580–587 (2017)
11. Dubey, R., Hanmandlu, M., Vasikarla, S.: Evaluation of three methods for MRI brain tumor segmentation. In: 2011 Eighth International Conference on Information Technology: New Generations, pp. 494–499. IEEE (2011)
12. Subashini, M., Sahoo, M., Kumar, S.: Brain tumor detection using pulse coupled neural network (PCNN) and back propagation network (2012)

13. Natarajan, P., Krishnan, N., Kenkre, N.S., Nancy, S., Singh, B.P.: Tumor detection using threshold operation in MRI brain images. In: 2012 IEEE International Conference on Computational Intelligence and Computing Research, pp. 1–4. IEEE (2012)
14. Singh, I., Neeru, N.: Performance comparison of various image denoising filters under spatial domain. Int. J. Comput. Appl. **96**(19), 21–30 (2014)
15. Hore, S., Chakraborty, S., Chatterjee, S., Dey, N., Ashour, A.S., Van Chung, L., Le, D.N.: An integrated interactive technique for image segmentation using stack based seeded region growing and thresholding. Int. J. Electr. Comput. Eng. (2088-8708) **6**(6), 2773–2780 (2016)
16. Biswas, B., Soroardi, H.S., Islam, M.J.: Brain tumor detection with tumor region analysis using adaptive thresholding and morphological operation. In: 2018 4th International Conference on Electrical Engineering and Information & Communication Technology (iCEEiCT), pp. 375–380. IEEE (2018)
17. Vijayanagar, V.: Multiscale modeling for image analysis of brain tumor detection and segmentation using histogram thresholding. Int. J. Eng. Comput. Sci. **3**(8), 7525–7534 (2014)
18. Sujan, M., Alam, N., Noman, S.A., Islam, M.J.: A segmentation based automated system for brain tumor detection. Int. J. Comput. Appl. **153**(10), 41–49 (2016)
19. Bennet, M., Babu, G., Lokesh, S., Sankaranarayanan, S.: Testing of Brain Tumor Segmentation Using Hierarchal Self Organizing Map (HSOM) (2015)
20. The Cancer Imaging Archive (2017). https://www.cancerimagingarchive.net/
21. https://kaggle.com/
22. Fawcett, T.: An introduction to ROC analysis (PDF). Pattern Recogn. Lett. **27**(8), 861–874 (2016). https://doi.org/10.1016/j.patrec.2005.10.010
23. Oriani, E.: QPSNR: A Quick PSNR/SSIM Analyzer for Linux. Accessed 6 April 2011
24. Willmott, C., Matsuura, K.: On the use of dimensioned measures of error to evaluate the performance of spatial interpolators. Int. J. Geogr. Inf. Sci. **20**, 89–102 (2006). https://doi.org/10.1080/13658810500286976