Comparative Experiments of Brain Tumor Segmentation Methods in MRI image

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Abstract

The detection of brain cancer without human interfering is a major problem in the domain of medicinal image processing. The segmentation of brain images of MRI is a technique used as a first step to extract different characteristics of these images for analysis, appreciative and understanding. The main function of brain segmentation by MRI is to detect the type of brain abnormality. Many segmentation techniques are proposed in the literature. In this comparative paper, we will discuss the behaviors of tested segmentation methods. Otsu thresholding, Region growing, Particle swarm optimization and Interactive graph cut segmentation methods are analyzed and compared in this paper. After segmented with these methods, the morphological operation is used to get exact shape and size of tumors. As a benchmark dataset, BRATS dataset is used to test segmentation results.

1. Introduction

Magnetic Resonance Imaging (MRI) is a medical imaging technique used in the radiology department and forms images of the anatomy of the body and physical processes in organized health and disease. Magnetic resonance imaging is broadly used in hospitals and clinics for medicinal diagnosis, disease production and monitoring without uncovering the body to ionizing radiation. It is used to find problems such as tumors, hemorrhages, injuries, vascular diseases or infections. Tumors are a group of abnormal cells that form masses or growths. Image segmentation is the method of dividing a digital image into numerous segments. Image segmentation is usually used to locate objects and boundaries (lines, curves, etc.) in an image. Several types of segmentation techniques can be found in any application, including the detection, recognition and measurement of objects in an image. The foremost purpose of tumor segmentation is to detect and approximation the tumor size and shape. The segmentation accuracy will help to identify the classification accuracy of tumor and more determine the types of tumor.

In this comparative paper, Otsu thresholding, Region growing, Particle Swarm Optimization and Interactive graph cut segmentation methods are implemented and they are experienced on 72 flair images in BRATS dataset. As the evaluation methods, Ture positive rate (TPR), True negative rate (TNR), Accuracy and Jaccard Similarity index are used. This paper describes also the runtime duration of each method.

2. State of the Arts

Jianwei Liu and Lei Guo proposed the paper with the title "An Improved K-means Algorithm for Brain MRI Image Segmentation" in 2015. In this paper, an improved K-means algorithm is proposed. The conventional traditional K-means algorithm ignores the relationship between the pixels and takes into account only the gray value of the brain image. In this article, to reduce the influence of noise, it is necessary to adopt the minor neighborhood of each image pixel and the average value of the gray value of the image according to the characteristic of the adjacent pixel of the MRI image of the brain that most likely belongs to the same class, Accuracy of the cluster that makes up the points The experimental results demonstrate that the improved algorithm of K-means can effectively improve the segmentation accuracy of noisy brain MRI images. In this paper, the jaccard similarity index is used in evaluation experimental results. The experimental results presented that the segmentation accuracy of improved K-means algorithm was higher to the traditional K-means algorithm for noised brain MRI images [1].

The next paper is "A Hybrid Approach Based Segmentation Technique for Brain Tumor in MRI Images". This paper was proposed by D. Anithadevi and K. Perumal. Manual and semiautomatic segmentation techniques need extra time and knowledge. However, although these shortcomings have been overcome by automatic segmentation, it is still necessary to develop more suitable methods for segmentation of medical images. Therefore, the authors proposed segmentation of images based on a hybrid approach, using the complex features of the method of expanding the area and threshold division. In this article, we use a median filter for image pre-processing. As a result, the assessment was performed using several performance indicators, such as DICE, similarity, accuracy, sensitivity, specificity and similarity with Jaccard. These measures of similarity are widely used for the analysis by the truth of the terrain of each processed image and the results are compared and analyzed. The experimental results show the hybrid segmentation gives improved result on seeing the overall enactment than two approaches (Thresholding and Region growing). The extension of the work would be the classification of tumor types with the new improved features [2].

M. Kazi et al. described the paper with the title " MRI Brain Image segmentation using Adaptive Thresholding and K-means Algorithm" in 2017. In this article, we apply an adaptive threshold value to obtain cerebrospinal fluid (CSF), gray matter (GM), white matter (WM), etc. And a new method based on K –means clustering algorithm. In addition, although the threshold determination method image dividing is accepted because the fixed threshold is not suitable for splitting, the adaptive threshold method is suitable for the case when the background is dense and the K-means clustering algorithm is an MR image of the brain. According to the results of this document, the adaptive thresholds and K-means clustering is best performed to generate different groups of input MRI images [3].

R.Kotteswari and K.G Sathiya proposed the paper with title is "Analysis of Foreground Detection in MRI Images using Region Based segmentation". To identify brain tissue at an early stage, the authors proposed a robotization scheme using images from multispectral cameras. This multispectral camera is important for capturing images with higher resolutions. This can be done using a region-based segmentation (RBS) algorithm. There are two main stages. The first stage consists of segmentation of the input image using anisotropic diffusion filtering and pre-processing performed by segmentation of the region. In the second stage, classification processing is included using the SVM (Support Vector Machine) classifier, and its main contribution is the detection of Sobel edges and the extraction of characteristics. Experimental analysis shows that the suggested method obtains a specific result and runs in a diverse data set when testing scenes that contain an irregular or related foreground. This segmentation shortens the processing time and elapsed time, analyzes the maximum signal-to-noise ratio (PSNR) for a sophisticated background and foreground, and reaches a value of 61.48 dB. This processed image is executed to classify the first plane of the segmented image made by the SVM classifier using MATLAB, which achieves an accuracy of 62.3% [4].

G. Evelin Sujji et al. presented the paper with title is "MRI Brain Image Segmentation based on Thresholding". This paper discussed about the detail of Thresholding base segmentation methods. In this paper, authors presented about Global thresholding, Local thresholding and Adaptive thresholding. And then, the selection of thresholding value is also more important in thresholding based segmentation. Therefore, a threshold selection based on a histogram was discussed. Select a threshold based on iteration, select an Otsu threshold, and select a threshold based on clustering. The main limitation of the threshold method is that only two classes are generated and cannot be used for multichannel images. The threshold approach is sensitive to the uniformity and intensity of noise. Depending on the application, it can choose a combination of one or more methods to obtain the desired segmented output [5].

A. Chaudhari, V. Choudhari and J. Kulkarni presented the paper with title is "Automatic Brain MR Image Tumor Detection using Region Growing". Seed region growing is a very common and attractive algorithm for image segmentation. In the proposed study, conventional region growing algorithms are used to segment the brain tumor core. Selection of automatic seed points is done using fuzzy C mean algorithm. Here authors describe the Region growing algorithm and the fuzzy c mean algorithm together with the proposed method. Experiments on tumor segmentation are performed on a flair image from the publicly available BRATS database. Verification of divided images using the proposed method is performed using the ground truth image provided from the same database. Experts show average accuracy of 97%, sensitivity 70%, specificity 98% [6].

S. Sushma, R. Devi Kala proposed the article with the title is "Brain Tumor Segmentation and Classification using Graph Cut Segmentation and DRLBP". In this document, authors implemented BPN for the classification of MR brain images. The method is incorporated into a segmentation system that provides interactive 2D based on graph- cut method. When applying the appropriate method, image preprocessing, edge and border detection, histogram threshold processing, graphics segmentation are performed. Classification Normal and abnormal brains are presented using ANN-Back propagation neural networks. To examine the accuracy of the classifier, the BPN classifier and the test were run in different sets of images. The developed classifiers were observed under different diffusion values as smoothing coefficients. The experimental results show that the BPN classifier is executable with a precision that ranges between 100% and 73% according to the dispersion value [7].

R.Punidha, S.Sakthivel, V.Nehru, C.Gunasundari presented the paper with the title is "Segmentation of Brain Tumor MRI Based on Particle Swarm Optimization". In this work, authors have proposed brain tumor segmentation based on particle group optimization (PSO). Particle Swarm Optimization is a calculation method based on optimization used to optimize the problem by iteratively refining the candidate solution for a given quality measurement. In preprocessing, the high luminance values of the film artifacts and other undesirable information are removed from the MRI brain image. The area of the tumor can be extracted according to the optimization technique of the particle group. Next, the approximate inference method is used to calculate the area of the tumor. Depending on the area of the tumor, classification results are obtained. In future research, tumor detection can be performed based on other optimization techniques and performance can be compared. This algorithm is also implemented for 3D images [8].

2. Background Theory

In this paper, Otsu's Thresholding, Region growing, Particle swarm optimization and Interactive graph cut methods are tested. In this section, all comparison method of theoretical information will be described.

2.1 Otsu's Thresholding

Assuming the segment has relatively the same gray level value and the threshold T can be selected to minimize the dispersion of the gray level in the segment or minimize the adjustment between the object and the background k. This method makes the most of the variance between classes and is based on calculations accomplished on the image histogram.

Otsu's algorithm is as follows:

1. Compute the standardized histogram of the input image. The components of the histogram is denoted by $P_i = n_i / MN$, where i=0, 1, 2, L-1 and $MN = n_0+n_1+n_2+\ldots+n_{L-1}$
2. Compute the cumulative sums $P_1(k)=\sum_{i=0}^{k} Pi$, for k= 0,1,2,…, L-1
3. Compute the aggregate means,
4. Compute the global intensity mean, m_G
5. Compute the between-class variance,
6. Get the threshold Otsu k * as the maximum value of k. If the maximum is not unique, k * is obtained by averaging the values of k corresponding to the various maximum values found.
7. Obtain the separability measure, * η

The main disadvantage of choosing the Otsu threshold is that the histogram is bimodal. This method differs in size in two classes and fails in the case of variable lighting [5].

2.2. Region Growing

Let R denote the entire image region. We may view segmentation as a process that barriers R into 'n' sub regions, R_1, R_2,….Rn such that ,

(a) $\bigcup_{i=1}^{N} Ri = R$

(b) R_i is a connected region, i = 1,2,…..,n.

(c) $R_i \cap R_j = \emptyset$ for all, i = 1,2,…,n.

(d) $P(R_i)$ = TRUE for I = 1,2,…,n.

(e) $P(R_i \cap R_j)$ = FALSE for $i \neq j$.

Here, $P(R_t)$ is a logical predicate defined over the points in set R_t, and Ø the null set. Condition (a) indicates that the segmentation must be widespread; that is, every pixel must be in a region. Condition (b) requires that points in a region must be connected in some predefined sense. Condition (c) shows that the regions must be disjoint. Condition (d) has a property that must be satisfied by pixels in a segmented area. For example, if all pixels Ri have the same gray level, P (Rt) = TRUE. Finally, condition (e) directs that the domains Rt and Rj differ in the sense of the predicate P [6].

2.3. Particle Swarm Optimization

PSO has particles determined from a natural group by combining self-experience and social experience, using communication based on iterative calculation. In the PSO algorithm, the candidate solutions are presented as particles. To look for global optimal values, we use a collection of flying particles (changing solutions) and a movement to a promising area in the search area (current and possible results). PSO is heuristic because it assumes little about the optimization of the problem, so it can look for a large candidate solution space. More specifically, PSO does not use the gradient of the problem that is being optimized. It is similar to the classical optimization method, such as the gradient descent method and the quasi-Newton method. PSO does not need to distinguish between optimization problems. Consider a scenario where a group of birds are finding for food in a random area. There is only one food in the search area. Each bird does not know the exact location of the food, but after each iteration knows the distance of the food. Therefore, the best strategy to approach food is to follow the birds closest to the food. PSO takes this state and uses this state to resolve the optimization problem. In PSO, each individual solution is a "bird" in the search space called "particles." All particles have an estimated fitness value using the fitness function to adapt and have a velocity to direct the flight of the particles. The particles (solutions) fly through the problematic space by tracking recent optimal particles. PSO is modified as a group of random particles, updating the generations and looking for the best. In each iteration, each particle is modernized according to two "best" values. The first value is the best solution (aptitude) that system has achieved so far. This value is called p better. Another "best" value followed by the particle group optimizer is the best global and is called g best. After judging the two best values, the particle evaluates its speed and position [8].

2.4. Interactive Graph Cut

The graph cut is an interactive method that arrange for global optimal segmentation of N-dimensional images. In this method, the image is communicated in binary form, divided into an object and a background area, and limits the segmentation to rigid constraints. Boykov et al. (2001), this system proved the following hypothesis.

a. Grouping 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 used to the current segmentation without any re-computation. Hence it becomes time efficient. As explained by Boykov et al. (2006), an image is signified in graphical form G, which involves of set of nodes V and edges which join the nodes. If node V contains source s and receiver t, source s denotes the set of corresponding nodes in the segmented area of interest, and sink t is the set of nodes belonging to the segmented background area [7] represent.

3. Dataset Description

In this research paper, the MRI images for brain are got from Brats dataset. In this dataset, MRI images are stored as .mha format. But the system emphasized on the .jpeg format. So, MRI cro and MITK standard toolbox are used to convert .mha format to .jpeg format. There are four types of MRI sequences in this dataset. They are Flair, T2, T1c and T1. Comparative methods are tested on only flair sequence. Figure (1) describes about the sample image of each sequence.

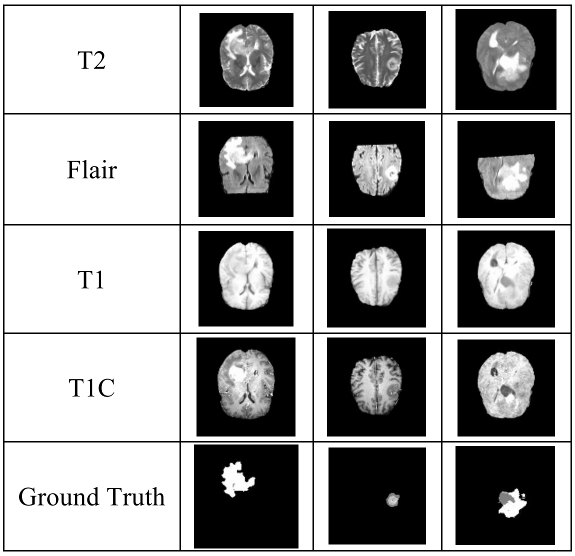


Figure 1. Sample images of MRI sequences

4. Research's Method and Methodology

In this paper, first step is image acquisition, second step is preprocessing, third step is image segmentation, fourth step is morphological operation and final step the system generates the segmented image. In second step, median filter is used to eliminate the noise and it can be more shaper the images than the original image. In third step, the comparative methods (such as Otsu thresholding, Region growing, Particle swarm optimization and

Interactive graph cut) are used to segment. In this research paper, Opening and Closing operations are used. Opening is the dilation shadowed erosion and Closing is the erosion shadowed dilation. The structured element of Opening is [1 1 1 1 1 1 1 1 1 1 1] and Closing is [1;1;1;1;1;1]. The figure (2) describes about the architecture of system.

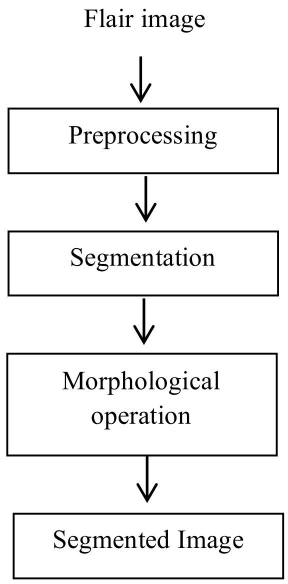


Figure 2. Architecture of the System

5. Experimental Results Comparison

In this paper, two types of statistical analysis method are used in experimental results comparison. First group is True Positive Rate (TPR), True Negative Rate (TNR) and Accuracy (A). Second is Jaccard similarity index. The formulation of each method is as follow:

$$TPR = \frac{TP}{TP+FN} \quad (1)$$

$$TNR = \frac{TN}{TP+FP} \quad (2)$$

$$A = \frac{TP+TN}{TP+FP+TN+FN} \quad (3)$$

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} \quad (4)$$

Table (1) and figure (3) describe about the experimental results of 72 flair images without morphological operation for all comparative methods. According to tested result, the Region growing and particle swarm optimization methods got the results better than Otsu's thresholding and interactive graph cut segmentation.

Table 1. Averege results of 72 Flair image without Morphological operation

Methods	TPR (%)	TNR (%)	A (%)
RG	73.64	99.28	97.42
PSO	56.1	99.39	95.13
Otsu	56	99.39	95.08
IGC	42	92.64	86.2

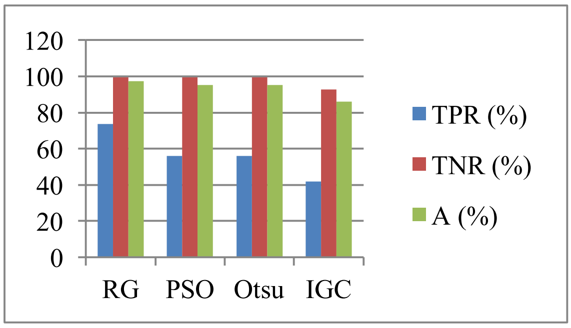


Figure 3. Average results of 72 Flair image without Morphological operation

Table (2) and figure (4) show the experimental results of 72 flair images with morphological operation. According to tested results, morphological operation is more effected in Otsu's thresholding. So, Otsu's thresholding results are better than other comparative methods.

Table 2. Average results of 72 Flair image with Morphological operation

Methods	TPR (%)	TNR (%)	A (%)
Otsu	73.57	99.24	97.26
RG	79.2	99.11	97.88
PSO	73.57	99.19	97.27
IGC	67.26	92.23	90.35

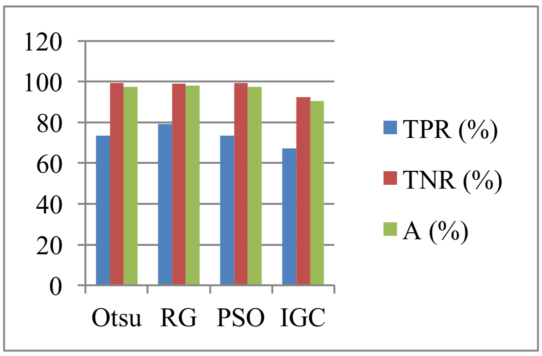


Figure 4. Average results of 72 Flair image with Morphological operation

Table 3 shows about the jaccard similarity index of comparative methods in 72 flair image segmentation. Min value refers to the minimum segmentation result of 72 flair images and max refers to maximum segmentation result. In jaccard similarity, region growing segmentation results better than other comparative methods.

Table 3.Average results of 72 Flair image with Jaccard Similarity Index

Methods	Jaccard Similarity Index (%)	
	Without Morphological	With Morphological
RG	0.647(min= 0.1124, max=0.87)	0.6691(min= 0.1472, max=0.8614)
PSO	0.513(min= 0.0672, max=0.834)	0.6467(min= 0.0808, max=0.8661)
Otsu	0.51(min= 0.0699, max=0.834)	0.6433(min= 0.0953, max=0.867)
IGC	0.393(min= 0, max=0.840)	0.5693(min= 0, max=0.867)

Table (4) and figure (5) discuss about the run-time duration of all methods. According to results, Otsu's thresholding method is faster than other methods. Table (5), (6) and (7) present about the segmented image of expression methods.

Table 4. Run-Time Duration of Methods

Methods	Time (sec)	
	Without Morphological	With Morphological
RG	2.21231	2.43891
PSO	3.39532	3.55405
Otsu	0.15237	0.43558
IGC	3.77659	3.91609

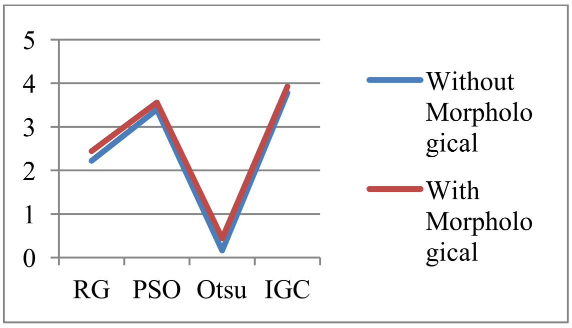


Figure 5. Run-Time Duration

Table 5. Sample Segmented image of Methods with Morphological operation

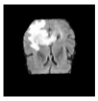
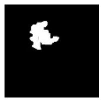
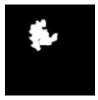
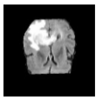
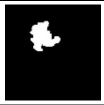
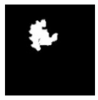
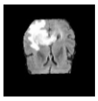
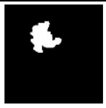
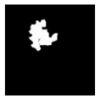
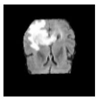
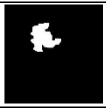
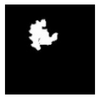
Methods	Original Image	Segmented Image	GT
RG			
PSO			
Otsu			
IGC			

Table 6. Sample Segmented image of Methods with Morphological operation

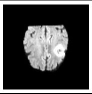
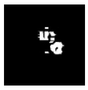
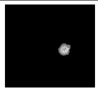
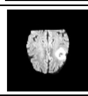
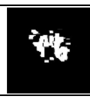
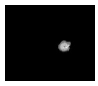
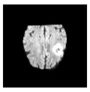
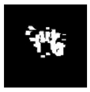
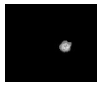
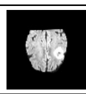
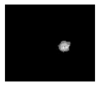
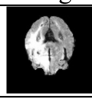
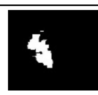
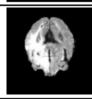
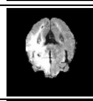
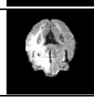
	Original Image	Segment	GT
RG			
PSO			
Otsu			
IGC			

Table 7. Sample Segmented image of Methods with Morphological operation

Methods	Original Image	Segment	GT
RG			
PSO			
Otsu			
IGC			

5. Conclusion

In this work, we have compared the mentioned methods. All of the experimental results are experienced on 72 flair images in BRATS dataset. According to tested result, Region growing segmentation is more accurate than other methods in without morphological operation. That fact indicates this method can segment well without morphological operation. With morphological operation, Otsu's thresholding method got better result than other methods. Particle swarm optimization's segmentation results are not highly difference with region growing in MRI image segmentation. Interactive graph cut segmentation spend more time and less accuracy when comparing another method in MRI image segmentation. Finally, threshold based method is better than other region based methods and graph based segmentation methods.

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