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Evaluation and Performance Analysis of Brain MRI Segmentation Methods

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***Abstract* -** Image segmentation is very important in computer vision for image recovery, visual summary, image base modeling, and for many other purposes. Despite many years of research and substantial contributions, image segmentation is still a very challenging task to suit for range of applications. Brain Magnetic Resonance Image (MRI) segmentation is one of the most challenging and time consuming task in the field of medical imaging. But by nature medical images are complex and noisy. This leads to the necessity of processes that reduces difficulties in analysis and improves quality of output. Even though several methods and encouraging results are obtained in medical imaging area, reproducible segmentation and grouping of abnormalities are still a thought provoking task due to the different shapes, locations and image intensities of different types of tumors. This paper critically reviews recent brain MRI segmentation methods along with their detailed analysis, and evaluation on the basis of various parameters. The study and evaluation is useful in improving the performance of existing methods as well as helpful in the development of new methods.

Keywords- Image Segmentation, Brain MRI, Graph Cuts

I. INTRODUCTION

Image segmentation plays an important role in medical imaging for extraction of features, image measurements and its display [1]. Segmentation of the brain structure from magnetic resonance imaging (MRI) has received paramount importance as MRI distinguishes itself from other modalities and MRI can be applied in the volumetric analysis of brain tissues such as multiple sclerosis, schizophrenia, epilepsy, Parkinson's disease, Alzheimer's disease, cerebral atrophy, etc. [2]. Brain Magnetic Resonance Image (MRI) segmentation is still a challenging problem in the field of medical imaging even though lot of methods are proposed in the literature. Segmentation is the process of dividing an image into several small regions or objects, it is an essential tool in medical image processing [3]. Segmentation for MR image of human brain divides soft tissues into grey matter, white matter and cerebrospinal fluid. As an initial step segmentation can be used for visualization and compression. Threshold based, region based, connectivity preserving relaxation based methods, and graph theory based are generally used for image segmentation [4]. Local pixel information is used in threshold techniques and this method is more active for the intensity levels of the object that falls outside the predefined range. But spatial information is ignored and leads to blurred region boundaries. In region based methods, the image is subdivided into connected regions by grouping together adjacent pixels of same intensity and then neighboring regions are combined together depending on some measures such as uniformity or sharpness of region borders. A connectivity preserving relaxation based segmentation method starts with specific primary boundary shape characterized in the form of spline curves and then energy functions based shrink or expansion operations are used to alter the shape iteratively. In Graph based methods, image is characterized by undirected weighted graph in which the nodes are pixels or pixel regions. Graph based methods for image segmentation have been widely investigated within the fields of image processing. In these methods, segmentation problems by analogy are translated into graphs and solved as the graph partitioning problem. In each method, an image is represented as weighted undirected graph, $G = (V, E)$ where V is the set of nodes called as pixels and an edge set E contains edges formed by joining every pair of nodes [5]. Weight of each edge $w(m, n)$ is function of similarity between nodes V_m and V_n . Partition the set of nodes into disjoint sets $V_1, V_2, V_3, \dots V_k$ such that the nodes in V_m has strong affinities between them. Partitioning to attain segmentation poses many challenges such as the precise criteria for good partition and its efficient computation. These graph based methods can be classified as Graph Cut based, Minimal Spanning Tree based, and Shortest Path based methods. Graph cuts is one of the image segmentation techniques which is originated by collaborative or automated identification of one or more points representing the 'object'. In this technique one or more points representing the 'background' are called seeds and serve as segmentation hard constraints whereas the soft constraints reflect boundary and/or region information. An important feature of this technique is its ability to interactively improve a previously obtained segmentation in an efficient way.

This paper discusses in depth review of existing segmentation methods for brain MRI. The study is done on the basis of classification of various segmentation algorithms. It deals the detailed analysis and comparison of their performances. The rest of the paper is organized as: Section II describes various image segmentation methods, in Section III, the performance evaluation of these methods is presented and finally the paper is concluded in Section IV.

II. METHODS

Several image segmentation methods have been proposed over the last several decades. Accurate formulation for image segmentation problem and computationally efficient implementations are very crucial. This Section covers the reported formulations and implementation strategies for each class of segmentation methods. The distinctive point of these methods in a way they define the desirable quality of segmentation and how they achieve using different image properties.

A. Threshold Based Segmentation

Thresholding is one of the simplest approaches for image segmentation based on intensity levels. Threshold based technique works on the assumption that the pixels falling in certain range of intensity values represents one class and remaining pixels in the image represents the other class. Thresholding can be implemented either locally or globally [6]. For global thresholding brightness threshold value is to be selected to segment the image into object and background. It generates binary image from given input image. The pixels satisfying threshold test are considered as object pixels with binary value '1' and other pixels are treated as background pixels with binary value '0'.

$$g(u,v) = \begin{cases} 1, & f(u,v) \geq T \\ 0, & Otherwise \end{cases} \quad (1)$$

Where T is predefined threshold.

Selection of threshold is very crucial in image segmentation process. Threshold value can be determined either by an interactive way or can be the outcome of automatic threshold selection method [7]. N. Otsu method is optimal for thresholding large objects from the background [8]. Threshold based approaches are computationally inexpensive fast and can be used for real time applications. A single global threshold partitions image into objects and background, but objects may have different characteristic grey value. In such situations multiple threshold values are needed, for applying over different areas of the image. Threshold value for each region is local threshold and the process is multilevel thresholding [9] which helps to detect different objects in an image separately.

Steps for multilevel thresholding are:

- Divide image into subparts.
- Select local threshold for each subpart of image.
- Compare the pixels for individual subpart and segment the region.
- Repeat the process for each subpart and stop when all subparts are segmented.

Let us consider an image with two different objects, then identify two thresholds T_1 and T_2 such that

$$\left.\begin{array}{r} T_1 \leq f(u,v) \leq T_2 \quad for\ one\ object \\ f(u,v) \geq T_2 \quad for\ the\ other\ object \\ f(u,v) \leq T_1 \quad for\ the\ background \end{array}\right\} \quad (2)$$

Fig 1 (a) represents thresholding of an image with one light object and shady background, and fig 1 (b) two different light objects and dark background.

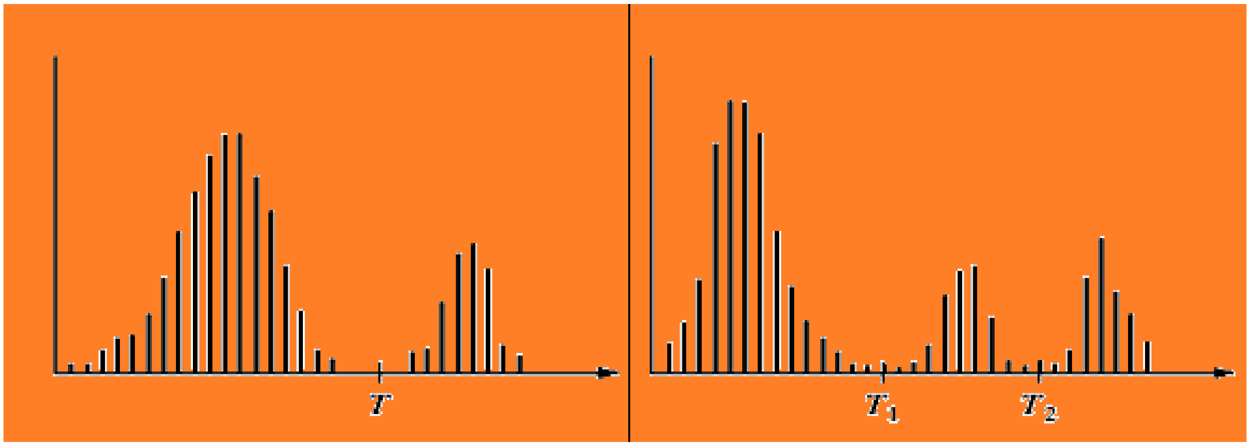

Fig. 1 (a) Threshold for Image with one object   Fig. 1 (b) Threshold for Image with two objects

Kim et. al. [10] have proposed an image segmentation technique to identify the tumor from the brain magnetic resonance imaging (MRI). Several existing thresholding techniques have produced different result in each image. Thus, to produce a satisfactory result on brain tumor images, they have proposed a technique, where the detection of tumor was done uniquely.

B. Region Based Segmentation

In region based segmentation regions are constructed by associating or dissociating neighbor pixels. It works on the principle of homogeneity, by considering the fact that neighboring pixels inside a region possess similar characteristics and dissimilar to the pixels in other regions. Each pixel is compared with its neighboring pixel for similarity check such as grey level, color, texture, shape. If the result is positive then that particular pixel is added to the pixel to grow the region.
If complete image is denoted as region *R*, then for segmentation compose it into *n* disjoint regions S_1, S_2, $S_3, \ldots\ldots$, S_n such that

$$\left.\begin{array}{c} \cup S_i = S, \quad S_i \cap S_j = \emptyset, \quad if\ i \neq j \\ Prop\ (S_i) = True, \quad if\ i = 1,2,3,\ldots,n \\ Prop\ (S_i \cup S_j) = False, if\ i = 1,2,3,\ldots,n \end{array}\right\} \qquad (3)$$

Where $Prop\ (S_i)$ is defined in terms of feature values over region *R*. These regions are connected disjoint and homogeneous in nature [11].
Region based method is classified in two categories such as region growing and region split and merge.

Region Growing Method

In this method pixels in a region are labeled with a unique label which is different from the labels of other regions [12]. This method can further be classified as Seeded Region Growing (SRG) and Unseeded Region Growing (UsRG). SRG is semiautomatic method and UsRG is fully automatic method [13].

- **Seeded Region Growing (SRG)**
  It is proposed by R. Adam [14]. SRG is robust, rapid and is free from tuning parameters. The process starts by selecting a seed pixel within the image. The proper choice of seed is very crucial in this method, since it is concerned with overall segmentation quality.
  General steps in SRG algorithm are:

- Select seed pixel within image to start segmentation process.
- Decide criteria to grow the region.
- Include pixel in the region if it is 8 – connected to at least one of the pixel in the region.
- Label all the regions, after testing all the pixels for allocation.
- Merge regions if two different regions get same label.

- **Unseeded Region Growing (UsRG)**
  This method is based on pixel similarities within the region. UsRG is flexible, fully automatic and does rely on tuning parameters. General steps in UsRG algorithm are:
- Initialize segmentation process with region S_1 containing single pixel and eventually results in $S_1, S_2, \ldots, S_n$ regions after completion.
- For pixel allocation, difference measure of the test pixel with the mean value of the statistics is considered.
- Allocate the pixel to the specific region say S_i, if difference value is less than certain threshold; otherwise allocate the pixel to new region S_j.
- Repeat above steps for all remaining pixels.

Region Split and Merge Method

This method proposed by B. Penetal [15] works on the basis of quad tree with main objective to distinguish the homogeneity of the image. In this method entire image is considered as one single region and then divide the image into four different quadrants based on certain predefined criteria. Fig. 3 illustrates the method.

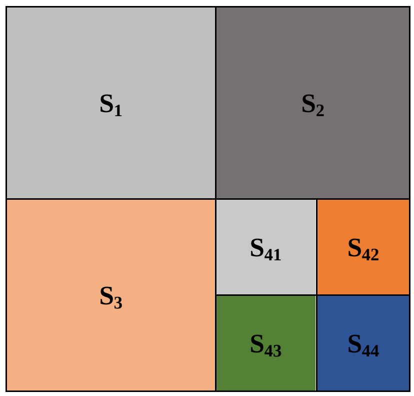

Fig. 2: Region Split and Merge method

General steps in this method are:
- Define homogeneity condition.
- Create pyramid data structure for image.
- Form a quad tree with level numbers and form fragment number at node
  Repeat the process until no more splitting or merging is possible.

Koley et. al. [16] have proposed a consistency based self-merging (CSM) algorithm to segment brain MRI for finding the precise area of brain tumor. This approach has produced satisfactory results in less computational time by reducing the effect of noise, in comparison with region merging approaches.

C. Discontinuity Based Segmentation

Segmentation by this method is based on the principle of intensity variations among the pixels. Object boundaries leads to formation of edges. The significant sudden changes in the intensity levels among neighboring pixels in certain direction are termed as edges and results in the discontinuity in the pixels. Smoothing, detection and localization are the steps involved in edge detection [17]. Edges are usually found by applying masks over the image. Edges in the given image are detected by using gradient or the zero crossing technique. The convolution between mask and the image determines the edge set for image. Edge detection operators are first derivative operator and second derivative operator [18].Gradient for first derivative operator is

$$\nabla f = G[f\ (u,v)] = \begin{bmatrix} \frac{\partial f}{\partial u} \\ \frac{\partial f}{\partial v} \end{bmatrix} \quad (4)$$

direction of gradient is $\theta = \tan^{-1}\left[\frac{f_v}{f_u}\right]$ where θ is measured with respect to X – axis. Operators used in this type are Robert's operator, Prewitts operator, Sobels operator etc. Second order derivative operator works on zero crossing detection, gradient for this operator is

$$\nabla^2 = \frac{\partial^2 f}{\partial u^2} + \frac{\partial^2 f}{\partial v^2} \quad (5)$$

where $\frac{\partial^2 f}{\partial u^2} = f(u, v+1) - 2f(u,v) + f(u, v-1)$

$\frac{\partial^2 f}{\partial v^2} = f(u+1, v) - 2f(u,v) + f(u-1, v)$,

operators used in this type are Laplacian of Gaussian and Canny Edge operator.

D. Clustering Based Segmentation

In cluster based segmentation, data is combined into groups such that the data with similar features will fall in one group whereas the data clusters are being different from each other [19]. The *k*-means algorithm is commonly used for determining the organization of the data [20].This unsupervised clustering approach has a strong affinity to get trapped into local minima while generating an optimal solution and hence it makes clustering wholly dependent on the primary cluster centers distribution. Hence, the proper choice of correct initial parameters is most challenging as well the clustering algorithms needs thorough study to identify correct input parameters for getting optimal or suboptimal clustering results.

- ***k*-means algorithm**

  In this algorithm number of desired clusters needs to be decided initially. *k*-means algorithm minimizes the total distance between data points and cluster centre. Steps involved in *k* – means algorithm are:

- Decide number of desired clusters *k*, randomly set the *k* – cluster centers at different initial locations in the image.
- Assign each pixel to the cluster having center nearest to that respective pixel.
- Compute new cluster center, which should be average co-ordinates of data points.
- Repeat the process until no more changes are required.

The system for brain tumor diagnosis and tumor region extraction is proposed by Quratul Ain et al. [21], naive bayes classification approach is used in this method. After the diagnosis, the K-means clustering and boundary detection techniques have been applied to extract the exact brain tumor region. Experimental results have revealed that the proposed system has extracted accurate tumor region and around 90% of the accuracy for diagnosis. H. Khotanlou et al. [22] have proposed a technique for segmenting the brain tumors in 3D magnetic resonance images. The proposed approach is suitable to different kinds of tumors. In the first phase brain image has been segmented using the and then the suspicious areas have been selected with respect to the approximate brain symmetry plane and fuzzy classification for tumor detection.

E. Normalized Cut Methods:

Any graph $G = (V, E)$ can be partitioned into two disjoint sets *A*, *B* provided that $|V|$ is greater than 1. The degree of dissimilarity between the sets *A* and *B* is sum of all the weights of edges between nodes in *A* to nodes in *B* called as cut value.

$$Cut(A, B) = \sum_{u \in A, v \in B} w(u, v) \quad (6)$$

The optimal bi-partitioning of a graph is the one that minimizes the cut value. By considering every possible partition, minimum cut for a graph can be obtained, but it is very complex problem. Finding minimum cut is well studied problem and there exists efficient algorithms for solving it. Wu *et al.* [23] proposed a clustering method based on minimum cut criterion. However, this criterion is suitable for cutting of small sets of isolated nodes in the graph, and can give a bad segmentation. This is because by using (6), cut value increases if the numbers of crossings between the two partitioned segments are more. If two partitions are equally sized they will be related by more edges than the unequally sized partitions. To avoid unnatural bias for partitioning, Kapade *et al.* proposed a new measure of disassociation, the normalized cut *Ncut* [24].

Given graph partition, $G = A \cup B$ the normalized cut cost is

$$Ncut(A, B) = \frac{Cut(A, B)}{Volume(A)} + \frac{Cut(A, B)}{Volume(B)} \quad (7)$$

where $Cut(A, B)$ is the sum of weights of edges removed to split the graph and $Volume(A)$ and $Volume(B)$ are respectively the sum of weights of edges in the nodes of *A* and *B* to all nodes in the original graph *G*. The best normalized cut in a graph is one which minimizes the *Ncut* value. Finding minimum *Ncut* has a NP-hard complexity [25].

min *Ncut* for a graph with N nodes is calculated as below:

- Let $d(i) = \sum w(i, j)$ weight of all the edges connecting node *i* to all other nodes *j*.
- Let *D* be *N x N* diagonal matrix with $d = \{d(1), d(2), \dots, d(N)\}$ as diagonal entries and *W* is *N x N* symmetric matrix with $W_{ij} = w(i, j)$.

$$\min Ncut\ (A,B) = min\frac{y^T(D-W)y}{y^T\ Dy} \tag{8}$$

where y is orthogonal to seconds smallest eigenvectors $v_1, v_2, v_3, \dots, v_n$ of $\left[\frac{D-W}{D}\right]$. (8) is called as Rayleigh Quotient [26].

- If $y \in R$ then Rayleigh Quotient is minimized by solving the generalized Eigen value problem,

$$(D-W)y = \lambda y \tag{9}$$

The second smallest eigen vector v_2 gives the solution of the normalized cut problem.

To split graph, the graph nodes are partitioned into two subsets using threshold value. The cut can recursively be obtained in two partitioned parts and stops when it reaches to previously given *Ncut* value. This technique is known as recursive two-way cut and follows the steps:

i. For given weighted graph *G*, write the weight matrix *W* and degree matrix *D*.
ii. Solve $(D-W)y = \lambda D_y$.
iii. For threshold $v_{2,}$ calculate *Ncut*.
iv. Repeat steps for each subgraph if *Ncut* in Step ***iii*** is below threshold v_2.

Finally to partition the graph, one can perform a simple thresholding on this eigen vector. Shi *et al.* [27] discussed multi-class partitioning in which an iterative process of two-way partition is implemented on the graph till satisfactory result is achieved. This technique is computationally expensive and also *Ncut* tends to produce equally sized regions which rarely occur in natural images.

F. Minimal Spanning Tree based Methods:

The Minimal Spanning Tree (MST) is an important concept in graph theory. A spanning tree T of graph G = (V, E) is a tree T such that T = (V, E') where E' $\subseteq$ E. Each graph may have several spanning tree but minimal spanning tree is the tree with minimum weight. In MST of a graph, nodes are pixels and edges represents affinities between the nodes that it connects. There are several algorithms to construct minimal spanning tree. In Prim's algorithm, MST is constructed by adding the frontier edge with smallest weight. This algorithm is greedy style and runs in polynomial time. MST based segmentation is related to graph based clustering where the data is represented by undirected adjacency graph. Different clusters that have stronger inherent affinities could be obtained by suitably removing the lowest weight edges. Most of the MST based approaches for segmentation emphasizes the importance of Gestalt theory [28]. Earlier MST based methods perform image segmentation in an implicit way, which is based on the inherent relationship between MST and cluster structure. Morris *et al.* [29] used MST to hierarchically partition images based on the principle that most similar pixel should be together and dissimilar pixels should be separated. They also proposed recursive MST algorithm which splits up MST built from an image into many sub-trees representing homogeneous regions such that each sub-tree should have certain number of nodes and neighboring sub-trees should have significantly dissimilar average gray levels. It yields low quality result in case of noisy images since wrong configuration of MST as an object might be contained in more than one sub-tree due to noise. An advanced work on MST based algorithm is proposed in [30] using both the differences across the sub-graph and the differences inside the sub-graph. The internal difference of a segment is the highest weight in the minimal spanning tree of the segment which is given by the relation $int(S) = Max(W_e)$ where *e* = MST *(S, E)*. An edge with minimum weight among edges connecting to the two segments represents the differences between segments. Two segments can be merged if difference between them is less than or equal to minimum of any of the internal differences of two segments. The formal definition for merging criterion is

$$|e_t| < \min\left(Int(C_1) + \frac{K}{|C_1|}, Int(C_2) + \frac{K}{|C_2|}\right) \tag{10}$$

where K is constant, $|C_1|$ and $|C_2|$ are the sizes of components C_1 and C_2 respectively. $Int(C)$ is the largest weight in the MST of C. $|e_t|$ is the edge with smallest weight which connects C_1 and C_2. From (14) we can see that algorithm is sensitive to edges in smooth areas and less sensitive to areas with high variability. Felzenszwalb *et al.* [31] showed that segmentation produced by this method is neither too coarse nor too fine. Since two segments are merged on the basis of single low weight edge between them, there are possibilities that the result could be considerably affected by noise if initial filtering of image is not done properly. In practical scenario, it is difficult to acquire images without noise due to perplexed imaging environment. Since MST based methods are very much susceptible to noise, therefore for noisy images without preprocessing such as filtering may yield unacceptable segmentation.

G. Shortest Path based Methods:

Finding the shortest path between two nodes is a classical problem in graph theory. For connected weighted graphs, shortest path between pair of nodes is the path whose total edge weight is minimum. The most well-known algorithm to find shortest path is Dijkstra's algorithm [32]. For a directed graph $G = (V, E)$ with edge length $l(e) \geq 0$, e is an edge in E and a vertex $u \in V$ is called as source. To find shortest path from u to each vertex $v \in V$ steps are as below:

i. Set $U = V$, $L(u) = 0$, $L(v) = \infty$ for $v \in V - \{u\}$.

ii. Set $W = arg\ min\{L(v)/\ v \in U\}$ and $X = U - W$.

iii. If $X = \emptyset$, then stop; for $v \in V$, $L(v)$ is the shortest path length from u to v.

iv. Set $U = X$. For $v \in U$ new label is,
$L(v) = \min\{L(v), \min\{L(u) + l(u, v)/(u, v) \in E, u \in W\}\}$.
Repeat step ***ii***.

To find shortest path between nodes u and v, grow Dijkstra's tree starting at the node u, after each iteration add frontier edge whose non-tree end point is close to v. After each iteration, node set of Dijkstra's tree will be added with nodes to which shortest path from u have been obtained.

In case of shortest path based segmentation methods, the problem of finding best boundary segment is converted into finding the path with minimum cost between the two nodes. In Live-wire method, initial point is selected by user and the subsequent point is selected in such a way that the shortest path between initial point and current position should be best fit to the object of interest [33]. Sequence of oriented pixel edges represents the boundary, where each oriented edge has single cost value to measure the quality of boundary. The boundary wraps around the object at real time speed. In comparison with tedious manual tracing, Live-wire provides more accurate segmentation. Selection of proper initial seed near the desired boundary is difficult tasks. Hence for blurred images or weak boundaries implementation of Live-wire is difficult. While segmenting high resolution images, Live-wire needs large number of computational resources to search the shortest path over the whole graph. Live lane [34] overcomes this limitation by liming the searching space in much smaller range of 5 to 100 pixels and largely reducing the computational time. Falcao *et al.* [35] exploited some known properties of graphs to avoid the unnecessary shortest path computation and proposed a fast algorithm called Live-wire-on-the-fly. The speeding up of path searching is based on the fact that the results of computation from the selected point can make use of the previous position of arrow. It has advantage that there is no restriction on the shape or size of the boundary and also the boundary can be oriented so that it has well defined inner and outer parts of the boundary.

In comparison with MST based methods, the shortest path can well describe certain nature of the object boundaries in an image since MST based methods focuses on clustering property of a segment. To control segmentation process, Live-wire provides more freedom to the user. Shortest path method might be more suitable for extracting complex objects with relatively explicit boundaries than other graph based methods.

H. Other Methods:

Badran *et al.* [36] have proposed a computer-based technique for recognizing the tumor section precisely in the brain via MRI images. The steps involved in the proposed algorithm were preprocessing, image segmentation, feature extraction and image classification via neural network techniques. Finally, using the region of interest technique, the tumor area has been located.

Chandra, S et al. [37] have proposed a Particle Swarm Optimization (PSO) based clustering algorithm. The centroids of number of clusters, where each cluster has grouped together the brain tumor patterns, obtained from MR Images. In the performance analysis it has been shown that the qualitative results of proposed model are comparable with SVM.

Kapade et al. [38] have proposed a robust image segmentation technique, which combines discrete PSO and multilevel graph partitioning algorithm to minimize undesirable over-segmentation. Greedy graph growing partition is used, which is based on employing the region adjacency graph to improve the quality of segmentation. The performance of the proposed technique is evaluated through quantitative and qualitative validation experiments on benchmark images.

Even though many algorithms are available for brain MR image segmentation, the detection rate is still not satisfactory. Also, accurate partitioning of an image into meaningful regions is essential key to success or failure of image classification.

III. Analysis of Image segmentation methods

Table 1 summarizes the advantages and disadvantages of image segmentation methods proposed in the literature.

Table 1 Advantages and Disadvantages of Image Segmentation Methods

Method	Advantages	Disadvantages
Threshold based Method	• Does not require prior information of the image. • Computationally inexpensive. • Fast and simple for implementation. • Can be used in real time applications.	• For an image with broad and flat valleys or without any peak, it doesn't works well. • Neglects spatial information of an image, cannot guarantee that the segmented regions are contiguous. • Highly noise sensitive. • Selection of threshold is crucial, wrong choice may result into over or under segmentation.
Region based Method	• Gives better result in comparison with other segmentation methods. • Provides flexibility to choose between interactive and automatic technique for image segmentation. • Flow from inner point to outer region generates clearobject boundaries. • Proper selection of seed gives accurate result than any other method.	• Sequential by nature and quite expensive in both computation time and memory. • To decide stopping criteria for segmentation is difficult task. • Scan order dependencies may be yielded in SRG and can have considerable impact on minute regions. • Selection of noisy seed by user leads to flawed segmentation.
Discontinuity based Method	• Works well for images having good contrast between regions. • Second order differential operator gives reliable result.	• For all type of images, single operator doesn't suits. • Size of operator and computational complexity are proportional to each other. • Generally boundaries determined are discontinuous.
Cluster based Method	• For small values of *k*, *k*- means is computationally faster. • Eliminates noisy spots. • Reduces false blobs. • More homogeneous regions are obtained.	• Difficult to predict k with fixed number of clusters. • Sensitive to initialization condition of cluster number and center. • Computationally expensive. • Doesn't works well with non-globular clusters.
Graph based Method	• Interactively improves previously obtained segmentation. • Unsupervised and converges very well. • Very effective in medical image segmentation • Some methods neglects noisy regions	• Some of the graph based methods are computationally expensive. • To decide stopping criteria for segmentation is difficult task.

Comparative study of these methods using some standard parameters such as: spatial information, region continuity, speed, computation complexity, automaticity, noise resistance, multiple object detection and accuracy is done. Table 2 presents analysis of all the methods.

Table 2: Comparison of Image Segmentation Methods

Parameter	**Threshold based Method**	**Region based Method**	**Discontinuity based Method**	**Cluster based Method**	**Graph Based Method**
Spatial Information	Ignored	Considered	Ignored	Considered	Considered
Region Continuity	Reasonable	Good	Reasonable	Reasonable	Good
Speed	Fast	Slow	Moderate	Fast	Moderate
Computation Complexity	Less	Rapid	Moderate	Rapid	Moderate
Automaticity	Semiauto	Semiauto	Interactive	Automatic	Automatic
Noise Resistance	Less	Less	Less	Moderate	Moderate
Multiple Object Detection	Poor	Fair	Poor	Fair	Fair
Accuracy	Moderate	Fine	Moderate	Moderate	Moderate

IV. CONCLUSION

Numerous image segmentation methods have been developed in the last few decades for segmenting MRI brain images, but still it is a challenging task. A segmentation technique developed may perform well for one MRI brain image but not for the other images of same type. Hence neither the single segmentation method is applicable to all type of images nor do all the segmentation methods perform well for one specific image. In this paper, we have presented the in-depth review of recent image segmentation methods and their deviations. These methods are studied analytically and comparison is carried out on the basis of distinct parameters. The state-of-the review will be useful in selection of the appropriate segmentation method. Such study and evaluation is also essential for refining the performance of existing segmentation algorithms and for developing new powerful segmentation algorithms. Their performance can be enhanced by use of hybrid approach and correct optimization.

REFERENCES

[1]. Acton, S.T., Mukherjee, "Scale space classification using area morphology," IEEE Trans Image Process 9(4):623–635, 2000.
[2]. Ahmed, M.N., Yamany, S.M., Mohamed, N. "A modified fuzzy c-means algorithm for bias field estimation and segmentation of MRI data," IEEE transaction medical imaging, Vol.21, No.3, pp.193-199, 2002.
[3]. Abdullah, N., Ngah, U.K., Aziz, "Image Classification of brain MRI using Support Vector Machine," Imaging systems and Techniques (IST), IEEE International conference on 17-18 May 2011.
[4]. J. Tou and R. Gonzalez, *Pattern Recognition Principles.* Addison-Wesley, 1974.
[5]. C. C. Hung, "Competitive learning networks for unsupervised training," Int. J. of Remote Sensing, vol. 14, no. 12, pp. 2411-2415, 1993.
[6]. S. Nagabhushana, "Computer Vision and Image Processing," New Age International Publishers, 2005.
[7]. W. Hongzhi and D. Ying, "An Improved Image Segmentation Algorithm Based on Otsu Method," International Symposium on Photo electronic Detection and Imaging 2007: Related Technologies and Applications, Vol. 6625, 2008.
[8]. Nobuyuki Otsu, "A Threshold Selection Method From Gray-Level Histograms," IEEE Transactions on Systems, Man, And Cybernetics, Vol. 9, No. 1, 1979.
[9]. Tranos Zuva, Oludayo O. Olugbara, Sunday O. Ojo and Seleman M. Ngwira, "Image Segmentation, Available Techniques, Developments and Open Issues," Canadian Journal on Image Processing and Computer Vision, Vol. 2, No. 3, 2011.
[10]. Bhattacharyya, D., Tai-hoon Kim, "Brain Tumor Detection Using MRI Image Analysis", Communications in Computer and Information Science, Vol: 151, pp. 307-314, 2011.
[11]. Bryan S. Morse, Lecture 18: Segmentation (Region Based), Brigham Young University, 1998.
[12]. H.S.Prasantha, H. Shashidhara, and Madhavi Lata, "MEDICAL IMAGE SEGMENTATION", (IJCSE) International Journal on Computer Science and Engineering Vol. 02, No. 04, 2010.
[13]. Dzung L. Pham, Chenyang Xu, and Jerry L. Prince, "Current Methods in Medical Image Segmentation," Annu. Rev. Biomed. Eng., Vol. 02 pp. 315–37. 23, 2000.

[14]. Rolf Adams and Leanne Bischof, “Seeded Region Growing,” IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.16, No. 6, 1994.
[15]. Bo Peng, Lei Zhang, and David Zhang, “A Survey of Graph Theoretical Approaches to Image Segmentation,” IEEE Transactions on Image Processing, Vol. 7, No. 12, December 2001.
[16]. Koley, S., Majumder, "Brain MRI segmentation for tumor detection using cohesion based self-merging algorithm", Proceedings of the IEEE 3rd International Conference on Communication Software and Networks (ICCSN), Xi'an, pp: 781 – 785, 2017.
[17]. Ravi S and A M Khan, “Operators Used in Edge Detection: A Case Study,” International Journal of Applied Engineering Research, Vol. 7 No. 11, 2012.
[18]. N. Senthil kumaran and R. Rajesh, “Edge Detection Techniques for Image Segmentation – A Survey of Soft Computing Approaches,” International Journal of Recent Trends in Engineering, Vol. 1, No. 2, 2009.
[19]. http://www.cs.uu.nl/docs/vakken/ibv/reader/chapter10.pdf.
[20]. K.Duraiswamy and V. Valli Mayil “Similarity Matrix Based Session Clustering by Sequence Alignment Using Dynamic Programming,” Computer and Information Science journal, Vol. 1, No.3, 2008.
[21]. Qurat-ul Ain., Irfan Mehmood., Naqi, M. Syed., Arfan Jaffar, M "Bayesian Classification Using DCT Features for Brain Tumor Detection", Lecture Notes in Computer Science, Vol:6276, pp. 340-349, 2016.
[22]. Rogowska, J (2009): “Overview and Fundamentals of medical image segmentation,” Handbook of medical imaging: Processing and Analysis Management, I.Bankman, Ed.pp.69-85, 2009.
[23]. F. Benezit, T. Cour, and J. Shi, “Spectral segmentation with multi-scale graph decomposition,” in Proc. IEEE Computer Society Conference on Computer Vision and Pattern Recognition, vol.2, pp.1124-1131, 2005.
[24]. S. D. Kapade, S. M. Khairnar, B. S. Chaudhari, “Enhanced Graph based Normalized cut Methods for Image Segmentation,” ICTACT Journal on Image and Video Processing, vol. 5, no. 2, pp. 907 - 911, November 2014.
[25]. G. Csurka, C. Bray, and L. Fan, “Visual categorization with bags of key points,” Conf. on Statistical Learning in Computer Vision, 2004.
[26]. R. Fergus, P. Perona, and A. Zisserman, “Object class recognition by unsupervised scale - invariant learning,” in Proc. of the IEEE Conf on Computer Vision and Pattern Recognition, 2003
[27]. S. Yu and J. Shi, “Object-specific figure-ground segregation,” in Proc. IEEE Computer Society Conf on Computer Vision and Pattern Recognition, vol.2, pp. 39-45, 2003.
[28]. Shi and J. Malik, “Normalized Cuts and Image Segmentation,” IEEE Trans. on Pattern Analysis and Machine Intelligence, vol.22, no.8, pp. 888-905, 2000.
[29]. I. J. Cox, S.B. Rao, and Y. Zhong, “Ratio Regions: a technique for image segmentation,” in Proc. of the Int. Conf. on Pattern Recognition, pp. 557-564, 1996.
[30]. A.X. Falcao, J.K. Udupa, and F.K. Miyazawa, “An ultra-fast user-steered Image segmentation paradigm: live wire on the fly,” IEEE Trans. on Medical Imaging, vol.19, no.1, pp. 55-62, 2000.
[31]. X. Bai and G. Sapiro, “A geodesic framework for fast interactive image and video segmentation and matting,” in Proc. of Int. Conf. on Computer Vision, pp.1-8, 2007.
[32]. L. Grady, “Minimal surfaces extend shortest path segmentation methods to 3D,” IEEE Trans. on Pattern Analysis and Machine Intelligence, pp. 321-334, vol.32, no.2, 2010.
[33]. V. Ramos V. and F. Almeida, “Artificial ant colonies in digital image habitats - a mass behaviours effect study on pattern recognition,” in Proc. Second Int. Workshop on Ant Algorithms, pp. 113-116, 2000
[34]. H. Nezamabadi, S. Saryazdi, and E. Rashedi, “Edge detection using ant algorithms,” Soft Computing, vol.10, pp. 623-628, 2006.
[35]. Aydın, “A modified ant-based approach to edge detection,” ICCCI – LNAI, vol. 5796, pp. 620 – 628, 2009.
[36]. Badran, E.F., Mahmoud, E.G., Hamdy, "An algorithm for detecting brain tumors in MRI images", Proceedings of the International Conference on Computer Engineering and Systems (ICCES), Cairo, pp: 368 – 373, 2010.
[37]. Chandra, S., Bhat, R., Singh, "A PSO based method for detection of brain tumors from MRI", Proceedings of the World Congress on Nature & Biologically Inspired Computing, Coimbatore, pp: 666 – 671, 2009.
[38]. S. D. Kapade, S. M. Khairnar, B. S. Chaudhari, “Image Segmentation using min- cut and swarm intelligence,” International Journal of mathematical Sciences and Engineering Applications, vol. 9, no. I, pp. 165 - 177, March 2015.

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