ISSN: 2321-7782 (Online)
Volume 3, Issue 4, April 2015
International Journal of Advance Research in Computer Science and Management Studies
Research Article / Survey Paper / Case Study
Available online at: www.ijarcsms.com

MRI based Brain Tumor Segmentation Methods: A Critical Review

Swati Khurana[1]
Mtech,CSE
DIT University, Dehradun
India

Dr. M. L. Garg[2]
HOD (CSE)
DIT University, Dehradun
India

***Abstract:** In recent years Magnetic Resonance Imaging (MRI) based brain tumor segmentation methods are getting more and more attention and coming closer to clinical acceptance, as it provides non-invasive (MR) images with high resolution and excellent contrast between different soft tissues. The brain is made up of white matter (WM), gray matter (GM), as well as cerebrospinal fluid (CSF). The ultimate goal of brain tumor segmentation is to extract different tumor tissues such as active cells, necrotic core, and edema from normal brain tissues. As per the survey studies, brain tumors can be easily detected from the brain MR images, but disease analysis and classification relies on level of accuracy of segmentation, indeed segmentation is one of the most crucial step in medical imaging. The purpose of this paper is to provide review for MRI based brain tumor segmentation methods. Firstly, a brief introduction to brain tumors and imaging modalities. Then, proceeding with the comparison in different imaging modalities .Finally the brief discussion of the current state is performed and the qualities of different approaches are critically reviewed.*

***Keywords:** Magnetic Resonance Imaging (MRI);CT-SCAN; PET; imaging modalities; brain tumor; segmentation;*

I. INTRODUCTION

Brain tumor is an uncontrolled growth of cells which leads to development of intracanical lesion which occupies space with the skull and tends to cause intracanical pressure. Brain tumor is one of the most common brain diseases, has devastated many lives.

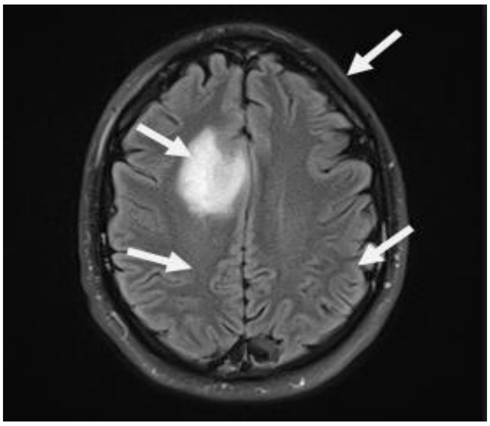


Fig.1. MRI image of a patient having brain tumor. In the left most top arrow indicates the tumor, bottom arrow indicates the white matter. In the right most top arrow indicates the skull, bottom arrow indicates the grey matter.

Therefore the early detection and treatment of brain tumor have become necessity. According to International Agency for Research on Cancer(IARC) approximately, more than 126000 people are diagnosed for brain tumor per year around the world, with more than 97000 mortality rate [1]. Tumors are of different types and have different characteristics and different treatments [2]. There are 120 types of brain and centeral nervous system tumors. Brain tumor are classified as primary and metastatic brain tumors. The former begin in the brain and tends to stay within the brain, the later begin in another part of the body and

© 2015, IJARCSMS All Rights Reserved

spreading to the brain. Brain tumor divided into two types: benign and malignant. The former is least aggressive, slow growing, non cancereous, the later considered as life threatening as consist of cancer cells, rapidly growing. The most widely used grading scheme has been issued by the World Health Organisation (WHO) [3]. It classifies brain tumor into grade I to IV .In general, grade I (Pilocytic Astrocytoma) and grade II (Low-Grade Astrocytoma) are benign tumor(low-grade); grade III (Anaplastic Astrocytoma) and grade IV (Glioblastoma) are malignant brain tumor(high-grade).

Along with the advancement in medical images analysis, imaging modalities plays a vital role in radiology to investigate the physiology of body in both health and disease. Since the brain is safeguarded by the skull, an early detection of brain tumor is only possible when diagnostic tools are directed at intracranical cavity [4]. Recent years, new emerging modalities Such as X-Ray, Computed Tomography (CT), Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI), Magneto Encephalo Graphy (MEG), Electo Encephalo Graphy (EEG), Single-Photon Emission Computed Tomography (SPECT) these modalities not only visualize complete aspects of the brain, but also makes the investigation of type of brain disease easier for clinical doctors after which they can adopt the best method of therapy among surgery , chemotherapy , and radiation for the patients.

As Bhandarkar states [5] The main objective of image segmentation is to partition an image into mutually exclusive regions such that each region is spatially contiguous and the pixel within the region are homogeneous with respect to predefined criterion. So the main key aspect of image segmentation in case of brain tumor is to extract the region of interest (ROI) i.e extraction of tumor cells from the normal brain tissues. Due to large amount of brain tumor images are generated for a single patient, it is not possible for clinical doctors to segment the tumor and analyze it in a reasonable time. Hence, automatic segmentation methods requirement has become inevitable. In recent years researchers made significant advancement in brain tumor segmentation methods in field of medical imaging and soft computing. Some of the segmentation methods are clinically accepted and provides fruitful results, but still some challenges exist in accurate segmentation results for tumor due to non rigid boundaries, variety of shapes, location and non homogeneous intensities of different tumors. Since for clinical doctors or radiologist accurate brain tumor segmentation is a key issue for monitoring, treatment planning and diagnosing, this paper focuses on MRI based different segmentation methods adopted with their critical evaluation.

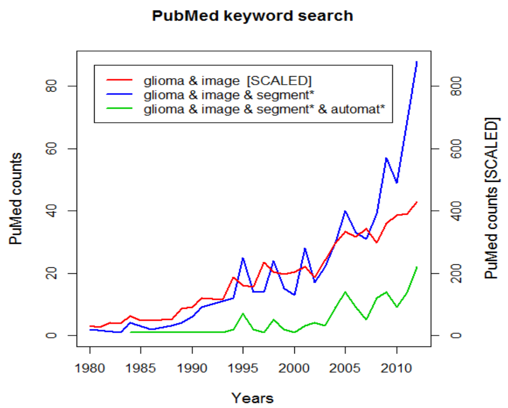


Fig. 2 Results of PubMed searches for brain tumor (glioma) imaging (red),tumor quantification using image segmentation (blue) and automated tumor segmentation (green). While the tumor imaging literature has seen a nearly linear increase over the last 30 years, the number of publications involving tumor segmentation has grown more than linearly since 5-10 years. Around25% of such publications refer to "automated" tumor. [6]

The rest of this paper is organized as follows. We briefly introduced different imaging modalities techniques and their comparison in Section 2.We then discussed the current different brain tumor segmentation algorithms including conventional methods, pixel classification, statistical model methods and deformable model methods in section 3. In section 4, the current state-of-the-art in manual and automated tumor segmentation are reviewed with their critical analysis in tabular form .Finally the paper conclusion are summarized in section

II. Modalities And Techniques

Before the presentation of the brain tissues segmentation methods, the imaging modalities are introduced as modalities play an important role in the evaluation of patient with brain tumor and have a significant impact on patient care. Once a brain tumor is clinically suspected, radiologic analysis is required to determine the tumor location, the extent of the tumor and its relationship to its surroundings. This information is very important and critical for clinical researchers in deciding between the different forms of therapy such as surgery, radiation, and chemotherapy to be adapted. The water and bones are primary body constituents. Elements like iodine, iron etc are trace elements and present in specific parts of the body. The principle behind imaging lies in the fact of efficiently using those body constituents. The medical imaging modalities can be classified into two categories[7]:

a) Anatomical or structural imaging modalities

They have ability to discriminate different constituents of the body such as Water, bone, soft tissue, etc. This category includes X-ray imaging, computed tomography (CT), ultrasound, and Magnetic Resonance Imaging (MRI).

b) Functional or metabolic imaging modalities

They have ability to discriminate different levels of metabolism caused by specific biochemical activity. This category includes Functional Magnetic Resonance Imaging (fMRI), Single Photon Emission Computed Tomography (SPECT),Positron Emission Tomography(PET).

TABLE I.

COMPARISON IN DIFFERENT IMAGING MODALITIES

Sr.No	IMAGING MODALITIES	PRINCIPLES	ENERGY USED	RESOLUTION	APPLICATION	CHARACTERISTICS
1	CT	X-ray for tomographic imaging	X-ray	50100um; Min	Anatomical, Functional	1. It allows accurate detection of calacification and metal foreign bodies. 3.Provides multiplanar reformatted imaging depending upon the task 2.Over utilization of CT scan can cause tissue damage and cancer 3.In CT X-rays blocked by some form of dense tissues and leads to poor image quality of soft tissues 5.Poor definition of edema
2	MRI	Nuclear magnetic resonance property	Resonance frequency Hence non ionizing	80-100um; s-h	Functional, anatomical, biological	1.MRI provide excellent range of available soft tissues contrast. 2.It is more sensitive and specific for abnormalities within brain. 3.Allows the evaluation of structure obscured by artifacts from bone. 4.Multiplanar capability 5.poor detection of calcification and bone

						erosion 6.Define precise extent and location of the tumor
3	PET	Simultaneos detection of two 511ke V photons in an opposite direction	Annihilation	1-2mm;min	Functional	1.Examine organs activity for diagnostic information in 3 dimensions that can not be acquired in any other way. 2.Poor resolution of anatomical details. 3.PET resolution is better than SPECT
4	SPECT	Detection of gamma radiation	ϒ-photons	1-2mm;min	Functional, biological	1. It can be used to provide information about localised function in internal organs 2.Poor resolution for human brain images

III. Brain Tissues Segmentation Methods

Based on the degree of required human interaction, brain tumor segmentation methods can be classified into three categories as described by Yao[8] ,Olabarriga et al. [9] and Foo et al [10]: manual segmentation, semiautomatic segmentation, and fully automatic segmentation.

a) Manual Segmentation

In manual segmentation, the experts of the brain tumor must master the information presented in an images and an additional knowledge such as brain anatomy because manual segmentation involves manually drawing the boundaries of the tumor and structures of interest or painting the region of anatomic structures with different labels [8]. Clinical researchers requires software tools with sophisticated graphical user interfaces to facilate drawing region of interest (ROI). In practice, manual delineation is error prone and very time consuming task for the experts and yields poor results. Therefore more advanced segmentation methodologies such as semi-automatic and fully automatic segmentation methods will present a clear advantage over manual segmentation trade-offs.

b) *Semiautomatic Segmentation*

In semiautomatic brain tumor segmentation, the human interaction is needed to initialize the methods, and is responsible for analyzing the result or providing manual feedback to correct the segmentation results. According to Olabarriga et al. [9] the main components of an interactive brain tumor segmentation methods are computational part, interactive part and the user interface. The computational part is set of algorithms capable of generating a delineation of the tumor. The interactive part is in charge of displaying the output produced by computational part and accepting the feedback from the users as method parameters. The semiautomatic brain tumor segmentation were divided into three main processes by: Foo et al [10] initialization, intervention or feedback response and evaluation. Since semiautomatic brain tumor segmentation relies on the clinical experts, as they control the initialization and feedback to the computation part. Although semiautomatic methods provides better results than manual segmentation, but it shows result variations when segmentation carried out by different clinical experts in the same environment. Hence fully automatic brain tumor segmentation methods are required to address this problem.

© 2015, IJARCSMS All Rights Reserved

c) Fully automatic Segmentation

In fully automatic segmentation methods, the computational part does not require human interaction for delineation of the tumor. The methods incorporate human intelligence and prior knowledge in the algorithms. Currently, fully automated segmentation methods are desirable in processing large batch of images. Since they are not gaining wide clinical acceptance due to lack of transparency in segmentation process.

IV. CONVENTIONAL METHODS

A wide variety of segmentation methods has been proposed. However, there is no standard approach which yields successful results for MRI brain segmentation or clinically acceptable. In general segmentation techniques are divided into four categories

a) Threshold based techniques

Thresholding is one of the simplest and oldest method for image segmentation. In the process of thresholding the objects of an image are classified by comparing the intensities with one or more intensity thresholds. Thresholding methods are classified into global and local thresholding.

In global thresholding, image is compared pixel by pixel with the selected threshold intensity. If the pixel intensity is higher than the threshold, the pixel is set to white in the output. If the pixel intensity is less than the threshold, the pixel is set to black. Thresholding takes a gray image as an input and produce a binary image as an output. Global thresholding is the best choice of segmenting an image, if image contains objects with homogeneous intensity and with high background intensity.

Local thresholding can be determined by estimating a threshold value for the different regions from the intensity histogram. Prior knowledge is required for estimating the threshold values. Threshold values can also be determined by calculating the partial volumes of each region or by using the local statistical properties.

However threshold based segmentation methods are not capable of exploiting the detailed information provided by MRI, since used in pre-processing stage of medical image segmentation.

b) Region-based techniques

Region-based segmentation techniques examine pixels in an image and form disjoint regions by merging neighborhood pixels with homogeneity based on a predefined similarity criterion thereby resulting in a connected region [11]**.** The region based technique needs to satisfy the following conditions for image segmentation.

Assume R as a complete image,segmented into sub regions R_i where i=1….n.

1. $_{i=1}U^{n}$ R=R, union of sub regions will return the complete image R without any loss

2. $R_i \cap R_j=\phi$ for all $i\neq j$,intersection of two sub regions must needs to be null.

3. $P(R_i)$= True, homegeneity predicate is satisfied by each region.

4. $P(R_i \cup R_j)$= False , No two adjacent regions can have same homogeneity predicate.

5. R_i must be a connected region.

Region Growing is a simplest technique to extract a region of the image based on predefined criteria. It starts with seed point which can be selected manually or provided by automatic seed finding procedure. The regions are grown by comparing unallocated pixels to the region. The procedure iterates until no more pixels can be added to the region.

Region merge and splitting technique does not require seed points, user can divide an image into a set of unconnected multiple regions and than merging process is carried out in an attempt to satisfy the conditions of image segmentation.

© 2015, IJARCSMS All Rights Reserved

1. Initially the complete image is considered if $P(R_i)$=false, the image is further segmented into quadrants,if P=false for any quadrant further splitting into sub quadrants is done, until no further splitting is possible.

2. Merging process is carried out simultaneously with splitting process for regions $P(R_i \cup R_j)$=true, the process ends when no further merging of regions is possible.

Watershed algorithm can be explained by a metaphor based on the behavior of water in a landscape. When it rains, drops of water will fall in different regions and will tend to follow the landscape downhill and end up at the bottom of the valleys. For each valley there will be a unique catchment basin. The water drops coming down from different basin will meet. The dam will be built at that points. When the water level reach the highest peak in the landscape, the process is stopped. As a result, the landscape partitioned into regions separated by dams, called watershed lines.

c) Pixel Classification or clustering technique

Another type of segmentation algorithms proposed so far are based on pixel clustering or classification. Pixels attributes like gray level, local texture and color components can be used for representing pixels of an image in feature space. The methods are constrained to the use of supervised or unsupervised classifier to cluster the pixels in feature space. Clustering involves the task of dividing data points into homogeneous clusters so that the items in the same cluster are as similar as possible and the items in different clusters are as dissimilar as possible depending upon the similarity criteria.

***1. K-Means Clustering* :** The most commonly used non hierarchical unsupervised clustering technique is the K-means method, which clusters n data points into k clusters (k less than n) [12]. This algorithm selects the number of clusters k , then randomly generate clusters and determines the cluster centres. The next step is to assign each data point to the nearest cluster centre and then recomputing the new cluster centres. These two steps are iterated until the minimum variance criterion is achieved. The main objective behind the algorithm is to achieve a minimum intra-cluster variance V. The complexity of an algorithm is O(ndkt) where ,

n = no of data points

d= dimensionality of feature space

k= no of clusters

t= no of iterations

2. Fuzzy C-Means Clustering : In many situations, it is not easy to determine wether a pixel belongs to a region or not. This is because of unsharp transitions at region boundaries. To address this problem Bezdek [13] proposed fuzzy concept as in case of clustering technique Fuzzy c-means clustering. Fuzzy partition is carried out through an iterative optimization of the objective function, with the update of the membership function and cluster centre. The nearer the data to the cluster centre the more possible its membership towards the particular centre is. FCM proves better results for overlapped region and data point can belong to one or more cluster. The brain tumors segmentation using FCM approach is becoming a fruitful research area. The time complexity of an algorithm is $O(ndk^2t)$ where

n = no of data points

d= dimensionality of feature space

k= no of clusters

t= no of iterations

© 2015, IJARCSMS All Rights Reserved

d) Statistical models

Statistical classification methods usually solve the segmentation problem by either labeling a pixel to which it belongs or by estimating the relative amounts of the various tissue types within a pixel. Statistical inference enables us to make statements about which element(s) of this set are likely to be the true ones.

1. Markov Random Field Algorithms : MRF algorithms falls under the category of unsupervised clustering method. In the particular case of brain tumor segmentation, if a region is strongly label as brain tumor or non brain tumor, MRF will easily determine that its neighbor region will have brain tumor or non brain tumor label. Most of the clustering techniques do not consider spatial information of the pixels in an image, however MRF provides a way of integrating clustering process with the spatial information of pixels. In many cases it reduces the problem of noise effect and overlapping in resulting clusters.

e) Artificial Neural Networks

Artificial Neural Networks follows a computational paradigm that is inspired by the structure and functionality of the brain. It consists of a processing element, a number of inputs and weight edges connecting each input to the processing element. The mathematical operations are applied to the input nodes and classification is done at the final output node. The ‘hidden’ layers allows the modeling of non linear dependencies in the features. These neurons works together in a distributed manner to learn from the input information, to coordinate internal processing and to optimize its final output [14]. The neural network segmentation includes two steps feature extraction and image segmentation. Feature extraction is one of the crucial step in which features are extracted from an image and are feed as input data for the neural network. All of the selected features compose of highly non-linear feature space of cluster boundary. The training step for this technique aims of minimizing the networks overall output error by iteratively adjusting the neuron connection weights. On the basis of architecture neural network can be categorized into 2

- » Feed forward neural networks
- » Feed-Backward neural networks

1. Self -Organising Maps : SOM is a non parametric unsupervised neural network used for data representation, visualization and clustering, it works on the principle of competitive nets. The unique feature of SOM is the capability of maintaining the topology of the inputs while reducing the dimensionality. Network consists of the input layer and competitive layer. It is used to cluster patterns of length m into n clusters which should have m number of input units and n number of output units, these output units may be arranged in one, or two dimensional arrays. Each input is fully connected to all units and each connection from an input neuron to a competitive layer is assigned with weight factor. SOM functions in two steps. Firstly, finding the winning neuron i.e. the cluster with the least distance is the winner, and secondly, updating the weight of winning neuron and its neighborhood pixels based on input.

f) Model-based technique

Deformable model based segmentation methods including Parametric Deformable Model and Geometric Deformable Model were proposed to address the problem of segmenting volumetric (3D) image data. In model based segmentation, prior knowledge of object like shape, location and orientation are required for constructing a connected and continuous model for a specific anatomic structure. These models are physically motivated for detecting region boundaries by using closed parametric curve that deform under the influence of internal and external forces. To extract ROI in an image, firstly a curve must be placed near the desired boundary and then be allowed to undergo an iterative relaxation process. The most challenging task is to extract the boundary elements and to integrate these elements into a model of the structure. Existing deformable models can be broadly divided into two categoried: parametric and geometric

© 2015, IJARCSMS All Rights Reserved

1. Snakes Models : The snake models were also known as active contour models and parametric deformable model. The most challenging task in brain tumor segmentation is edge detection. Snakes have been widely used for sensitivity in detecting the boundary of tumor region. The procedure followed, firstly the snake in place near contour of Region of interest (ROI), the shape and location of snake is controlled by image internal and external forces and snake is attracted towards ROI ,the internal forces are responsible for the tension and rigidity where as external forces responsible for the contour guidance towards contour of ROI, lastly the energy function is constructed to calculate the appropriateness of contour of ROI. The above explained snakes model is an iterative process. These models support highly intuitive interaction mechanism that allow medical scientist and practitioners to bring their expertise to bear on model based image interpretation task when necessary [15].

The steps followed in active contour:

Step1: Snake is placed near the contour of Region of Interest (ROI).

Step2: The Snake is attracted towards the target by an iterative process (by various internal and external

forces within the image) [Karch et al. (2009)].

Step3: An energy function is constructed which consisting of internal and external forces is constructed to

measure the appropriateness of the Contour of ROI

Step4: Minimize the energy function

$$E_{snake} = E_{in} + E_{ex}$$

Where E_{in} = elasticity force and E_{ex} = bending force

2. Level set Models : Level set models or Geometric deformable models were proposed to handling the topological changes for the splitting and merging of contours very easily. The basic idea of the model is to represent the curves or surfaces as the zero level set of a higher dimensional hyper surface.The new component of the level set model is the implicit representation of the interface. If the interface is given by Γ,Γ is represented as the level set of a function ϕ. The function is a surface defined over the image area with the following property [16].

$\phi(x,y,t=0)=\pm d(x,y)$, where d is the distance function ± for the points outside the initial interface

V. Review Of Various Techniques Adopted

R. R. Krishnapuram and J.M Keller [17] presented an extension of FCM algorithm is called possibilistic c-means (PCM). In FCM objective function have only one term, in PCM second term is included, forcing the data point membership to be as high as possible without any limit constraint of one. PCM shows advantageous results over FCM in noisy environment. The major drawback of PCM is that it has an undesirable tendency to create coincident clusters, and clustering stuck to one or more cluster without traversing all the data points, in short PCM leads to “worthless” partition.

Clark et al. [18] presented fully automatic system that segments and labels glioblastoma-multiforme tumor in MRI of the human brain.The initial step in segmentation was performed by an unsupervised clustering algorithm. The resulted image was provided as an input to a rule-based expert system which extracts the intracranial region. The final tumor labeling was done by using regional analysis. The results of the proposed system was correspond well to ground truth, both on a per slice basis and in tracking total volume during treatment over time.

Kaus et al. [19] adopted a general algorithm called adaptive template-moderated classification. This technique involved iteration of statistical classification to divide an image into different five tissues classes namely: background, skin, brain, ventricles and tumor. The classification was carried out on the basis of the signal intensity value. Objects of interest were identified on the classified images with local segmentation operations (mathematic morphology and region growing). This automated method (operator time,5–10 minutes) allowed rapid identification of the brain and low grade gliomas, meningiomas tumor tissues with an accuracy and reproducibility comparable to those of manual segmentation operator time 3-5 hours.

[20] Finitie mixture (FM) model is the most commonly used model for statistical segmentation of brain MR images. However FM does not consider spatial information of the images,which make this model suitable only for well defined images with low level of noise, under these conditions FM model produces unreliable results. To address this problem Y Zhang et al. proposed HMRF embedded with EM framework (through which robust and accurate segmentation can be achieved). This framework can be easily combined with other techniques.

Pham [21] introduced a new approach of FCM, called robust fuzzy c-means algorithm (RFCM) .The objective function of conventional FCM was to modified for incorporating spatial context. The RFCM controls the tradeoff between conventional objective function and smooth membership functions.

Marroquin et al. [22] highlight the significance of 3D segmentation of Brain MRI. For classifying data points on the basis of intensity it used the parametric models. The non rigid transformation was calculated using atlas employed with robust registration , and was further used in segmenting brain tissues from non brain tissues, computing prior probabilities and finding the automatic initialization and finally MPM-MAP algorithm was implemented to find out the optimal solution. MPM-MAP algorithm is computationally efficient as it considered only the solutions of linear systems. The previous study show that MPM-MAP algorithm is comparatively robust than EM.

[23] To further agument the advancement made for Brain MRI segmentation is done by Ahmed et al. by modifying Fuzzy C-means algorithm. The proposed algorithm was articulated by modifying the objective function of conventional FCM algorithm. This alteration leads to compensation of intensity in homogeneities and allows labeling of a pixel to be influenced in its immediate neighborhood. This algorithm is advantageous over FCM and EM as it requires less iteration to converge and to produce accurate classification. The BCFCM algorithm has ability to cope up in segmenting scans corrupted by salty and paper noise. There were certain tradeoffs as this proposed algorithm is restricted to a single feature input.

[24] Many tumor segmentation methods rely on the intensity enhancement produced by the gadolinium contrast agent in the T1- weighted image. Prastawa et al. proposed method that did not required contrast enhanced image channel, it only required T2 MR image channel as an input for segmentation. The segmentation procedure was carried out in 3 steps. Initial stage was detecting the abnormal regions using a registered brain atlas, where the intensity characteristics deviate from the expectation. Second stage, was to test the presence of edema with tumor in abnormal regions. Finally, reclassification with spatial and geometric constraints was carried out to the detected tumor and edema regions.

J Zhang et al. [25] proposed a novel and user friendly tumor segmentation approach by exploring one class SVM. SVM has the ability of learning the non linear distribution of the tumor data. In the proposed framework, the only requirement was to fed one-class SVM classifier with a chosen image sample over a tumor area as the query for performing segmentation. Then, accurate boundary of the tumor region was optimally generated by the framework without using any prior knowledge. The final segmentation results was obtained after region analysis.

Corso et al. [26] introduced a new methodology for automatic segmentation of heterogeneous images data which fills the gap between bottom-up affinity based segmentation methods and top-down generative model based approaches. The main contribution of the authors were Bayesian formulation for making complex calculations on soft models. Previously the weighted aggregation algorithm was employed for multilevel segmentation, followed by the various techniques for the task of detection, segmentation in multichannel magnetic resonance (MR) volumes. The method gives more comparable or improved results than current state-of-the-art techniques.

Nie et al. [27] in their paper presented an algorithm to deal with multi channel images with different resolutions, to improve the quality of tumor segmentation in clinical applications where low resolution sequences are commonly used with high resolution images. The proposed algorithm was based on spatial accuracy-weighted Hidden Markov random field and expectation maximization (SHE), a spatial accuracy represents the spatial-resample accuracy of each volex of the re-sampled low resolution images. Initially the low-resolution images were aligned onto T1-weighted images and then SHE algorithm was applied to segment the tumor using the EM algorithm. The volexs were treated equally, which leads to more accurate tumor segmentation results.

Ratan et al. [28] emphasized on designing an automated tool for brain tumor quantification using MRI image data sets. The proposed framework was a simple supervised block based and image based technique. Initially the MRI image was fed into MATLAB and multiple clips of an image was combined to get a single clip. Afterwards multiple-parameter calculations was carried out to address different aspects of analyzing image into an anatomical and pathologically meaningful regions. Followed by watershed algorithm for tumor segmentation and 2D visualization of the tumor region. Author's investigated various segmentation methods, but watershed algorithm is marked out best of all others.

[29] The authors make use of hybrid approach genetic algorithms and particle swarm optimization simultaneously to determine the optimized values of neighborhood attraction parameters in IFCM clustering algorithm. The algorithm was designed so that the GAs facilitate a global search to reach a near optimal solution and and PSO enhance the search for the optimal solution, However, unprecedented improvement in segmentation results was achieved by the BS-based method.

S. D. Salman [30] proposed a new method of tumor line detection and segmentation which is based on watershed algorithm with marking the region of interest as well as background in grey image. The marking was done by using morphology operation technique called opening by reconstruction and closing by reconstruction to clean up the image. Finally the resulted image was super imposed on original image to get the final image differentiable and coloured. This method was very useful for clinical researchers for planning the surgery or treatment.

S Bauer et al. [31] claimed to be able to segment tumor and healthy tissues including sub-compartments based on SVM classification with integrated hierarchical CRF regularization. The CRF regularization introduced spatial constraints to classifier and which assumes volexs independent from their neighbors. The hierarchical approach was adopted for classifying and sub-classifying the normal and tumor tissues. The proposed fully automatic approach provides outstanding results in terms of segmentation details and computational time.

Hamamci et al. [32] emphasize on segmentation tool for solid tumors with minimal user interaction. Firstly to show that the iterative cellular automata (CA) framework solves the shortest path problem, connections were made between the CA based segmentation and graph-theoretic methods. The state transition functions of the CA modified to calculate the exact shortest path solution. Furthermore to deal with heterogeneous tumor segmentation problem sensitivity parameter was introduced and implicit level set surface was evolved on CA states tumor probability map for spatial smoothness. The algorithm required an initialization from the clinical researcher by drawing a line on the maximum diameter of the tumor.

Roy and Bandyopadhya [33] claims that segmentation of brain MR images is one of the essential step in medical area, manual segmentation is very time consuming and tedious task ,hence it is associated with many challenges, so visually study of MRI is adopted as it is more fast and less erroreneous. They carried tumor detection approach using symmetry analysis . The first step was tumor detection, followed by segmentation and than qualitative analysis of tumor. The qualitative analysis is an essential requirement for medical clinic researchers to determine the advancement in the disease. The proposed technique have provided better results even in complex situations using multi-step modular approach.

[34]To further agument the advancements made image segmentation, Padole and Chaudhari proposed an efficient segmenting technique for complex MRI brain images. The technique incorporated the combination of two standard algorithms i.e Mean shift Clustering and Normal cut (Ncut) which provides the simplicity as well as speed. The concept of Mean shift Clustering is discussed by Cheng Yizong [35] and image segmentation approach based on Normalized cut (Ncut) has been

proposed by Shi and Malik [36] .Preprocessing was carried out as the first step using mean shift algorithm to find insignificant clusters and generate the input data for Ncut. In the next step region nodes werve processed by Ncut algorithm. In the last connect component extraction analysis (CCE) was applied for various image features calculation.

[37] As manual segmentation is very time consuming task for clinical researchers so Paul and Badyopadhya emphasized the automation process for the brain tumor segmentation. They proposed two-step automated procedure for brain MRI segmentation process in which, image was enhanced by using 3 by 3 'unsharp' contrast enhancement filters which will results in sharpened picture by removing blurred areas from itself. The two dimensional array was used to hold the output values. For skull stripping mask was generated from the original image using Otsu's method which is an automatic histogram shape based thresholding technique. If thresholding was successful, we get a binary image with skull as the main outline. This generated mask was used over original images for skull erosion. Finally, advanced k-means algorithm based segmentation was performed by two level granularity oriented grid based localization process to segment an images into gray matter, white matter and, tumor region. After completion of above task post-processing was done, in which histogram was calculated for each segmented region and we obtain different peaks of histogram for gray, white and tumor region corresponding to pixel gray values, on the basis of histogram tumor region was extracted. Finally, line scan method was applied to know the maximum length and breadth of the tumor. This nobel approach shows quite satisfactory results and high success rates.

[38] A generative approach combining segmentation and deformable registration of brain scans of glioma to a normal atlas was presented by A Gooya et al. . The method was based on Expectation Maximization (EM) algorithm that iteratively refines the estimates of the posterior probabilities of tissue labels using deformation field and the tumor growth model parameters. The EM algorithm incorporates a glioma-growth model for atlas seeding, a process which modify the normal atlas into one with a tumor or edema. The modified atlas was registered into the patient space and utilized for the posterior probability estimation of various tissue labels. Author's claim that GLISTR can produce promising results even in presence of large mass-effects, necrosis and edema.

P.Buendia et al. [39] developed fully automated MRI brain segmentation model based on enhanced version of the original Grouping Artificial Immune Network called GAIN. The model captured the main concepts by which the immune system recognizes pathogens and models the process in a numerical form. The GAIN was adapted to support a variable number of input patterns for training and segmentation, and to adapted to train multiple images. Bit grouping was carried out to improve the training speed and segmentation accuracy. GAIN performance was evaluated on BRATS 2013 data sets.

Doyle et al. [40] in their paper intoduced an adaptive scheme for brain tumor segmentation using multiple MR sequences. The approach was fully automatic and requires no training. The model parameters were using MRF constraints instead of estimated using a variational EM algorithm and the inclusion of a priori probabilistic maps to provide a stable parameter trajectory during optimization.

N subbanna et al. [41] carried out their work on MRI images acquired from real patients using fully automated multistage graphical probabilistic framework. An initial computation was focused where the probability of tumor was deemed high using Bayesian tumor classification based on Gabor texture features. For classify the tumor subclasses an iterative multistage Markov Random Field (MRF) frame work was devised. The model was designed to combine the strengths of both a local, voxel-based MRF and a contextual, regional MRF, in order to penalize implausible regional labels and label combinations, while also attaining accurate boundaries The results demonstrate that the proposed method achieves the top performance in the segmentation of tumor cores and enhancing tumors, and performs comparably to the winners in other tumor categories.

Table 2

Critical review of current state of art techniques. Empty cell indicates no reported information. Dim stands for dimensionality, FA means fully automatic, SA means semi automatic. SNR means signal to noise ratio, MCR means misclassification rate.

AUTHOR NAME	ALGORITHM	ACCURACY	SPEED	DIM	TYPE	IDENTIFIED PROBLEM
Clark (1998)	Knowledge base technique	0.69-0.99 (% match)		2D	FA	The method do not rely on intensity enhancements provided by the use of contrast agents and require training phase prior to segmenting a set of images
Kaus (2001)	Adaptive template Moderate Classification	95% (Accuracy)	5-10 min	3D	FA	
Y Zhang (2001)	Hiden markov random field + Expectation maximization		<10 min	3D	FA	This algorithm is computationally infeasible for directly solving the maximization problem.
D L Pham (2001)	Robust Fuzzy C-Means (RFCM)	0.52% (MCR)	4-12 min for B estimation 40s to 3.5 min for final clustering	3D	FA	Modification of the objective function results in complex variation of membership function.
J.L Marroquin (2002)	MPM-MAP	0.66-0.68 (overlap)	248 sec	3D	FA	
M N Ahmed (2002)	BCFCM	93.7-99.25 (SNR)		3D		Limited to single features input.
Prastawa (2004)	Outlier detection	0.70-0.80 (Jaccard)	1hr 30min	3D	FA	In case of large deformation the brain atlas algorithm may lead to incorrect sampling and hence MCD algorithm may yiels incorrect results.
J Zhang (2004)	One – Class SVM	Around 90% (Match)	6.58 sec	3D	SA	
J.J Corso (2008)	Weighted aggragation algorithm	0.62-0.69 (Jaccard)	< 1 min	3D	FA	
Nie (2009)	Spatial accuracy weighted HMRF +Expectation maximization	0.72-0.76 (Jaccard)	20-25 min	3D	FA	
Ratan (2009)	Watershed		10-15 min	3D	SA	
Mohamad Forouzanfar (2010)	GA+PSO+IFCM	0.44-0.92 (Similarity index)		3D	FA	
S. D Salman (2010)	Watershed			3D	FA	
S. Bauer (2011)	Hierarichal SVM + CRF	(77-84)% (Dice)	< 2 min	3D	FA	
Hamamci (2012)	Cellular Automata	0.8-0.89 (Dice)	1s-16 min	3D	SA	User interaction for optimal initialization
Padole (2012)	Meanshift + Normalized cut		9.23sec: Sagittal 9.55sec: frontal lobe	3D	FA	

T.U Paul (2012)	Advance k-means	96% cases tumor detection.	12.36 sec:Coronal 12.40 Saiggital (>9 sec)	2D *	FA	
A Gooya (2012)	GLISTR			3D	FA	
P. Buendia (2013)	GAIN	0.73:complete tumor 0.61:tumor core 0.64:enhancing tumor region (dice)	21 sec single case	3D	FA	
S. Doyle (2013)	Hidden Markov field + Variational EM	0.84:high grade 0.81:low grade (dice)	30 min per patient	3D	FA	
N Subbana (2014)	Iterative MRF	0.73-0.86 (Dice)	75 min per volume	3D	FA	

VI. Conclusion

This article has provided a critical review of the state of the art MRI-based tumor segmentation methods. It is not possible to draw general conclusion about the accuracy of the different methods as they have been all evaluated on different data sets. One major goal of all the methods is to locate tumor from MRI in an efficient, accurate and reproducible way. Segmentation methods have been applied according to the characteristics that allow distinguishing tumors from the normal brain tissues.

Although promising results have been reported on brain tumor segmentation, still there is a certain distance in clinical acceptance. One of the principal reasons might be lack of interaction between the clinicians and researchers as clinicians still rely on manual segmentation for brain tumor. Another reasons could be the due to lack of standardized procedures, computational time and robustness of proposed method.

Medical image analysis is a very active and fast growing field that has evolved into an established discipline. Along with the advancement of studies in the area, brain tumor segmentation techniques have already shown great potential in detecting tumors and this trend will undoubtedly continue in future.

References

1. Ferlay J, Shin HR, Bray F, Forman D, Mathers C and Parkin DM, GLOBOCAN 2008 v2.0, Cancer Incidence and Mortality Worldwide, International Agency for Research on Cancer, Lyon, France, 2010. http://globocan.iarc.fr, Accessed on: November 13, 2011.
2. M. P. Gupta and M. M. Shringirishi, " Implementation of brain tumor segmentation in brain mr images using k-means clustering and fuzzy c-means algorithm," International Journal of Computers & Technology, vol. 5, no. 1, pp. 54-59, 2013.
3. D. N. Louis, H. Ohgaki, O. D. Wiestler, W. K. Cavenee, P. C. Burger, A. Jouvet, B. W. Scheithauer, and P. Kleihues, "The 2007 who classification of tumours of the central nervous system," Acta Neuropathologica, vol. 114, no. 2, pp. 97-109, 2007.
4. Anjum Hayat Gondal and Muhammad Naeem Ahmed Khan , " A review of fully automated techniques for brain tumor detection from MR images," I.J modern education and computer science, february 2013.
5. S. Bhandarkar, J. Koh, and M. Suk, "Multiscale image segmentation using a hierarchical self organizing map," Neurocomputing, Vol.14, pp.241-272, 1997.
6. B. Menze, A. Jakab, S. Bauer, J.- K. Cramer, K. Farahani, et al., " The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS)," IEEE Transactions on Medical Imaging, Institute of Electrical and Electronics Engineers (IEEE), pp.33, 2014.
7. Image Processing with Biomedical Applications ELEG-475/675 Prof. Barner.
8. J. Yao, "Image processing in tumor imaging," New techniques in oncologic imaging, pp. 79-102, 2006.
9. S. Olabarriaga and A. Smeulders, "Interaction in the segmentation of medical images: a survey," Medical Image Analysis, vol. 5, pp 127-42, 2006.
10. J. L. Foo, "A survey of user ineraction and automation in medical image segmentation methods," Tech rep ISUHCI20062, Human Computer Interaction Department, Lowa State University, 2006.
11. K. P. Wong, "Medical image segmentation: Methods and applications in functional imaging," Handbook of Biomedical Image Analysis, Springer, pp. 111-182, 2005.
12. A. K. Jain and R. C. Dubes, "Alorithms for clusterin Data," Prentice Hall, 1988.

13. J. C. Bezdek, "Pattern Recognition with Fuzzy Objective Function Algorithms," Kluwer Academics Publishers, 1981.

14. J.Jiang, P. Trundle and J. Ren, "Medical image analysis with artificial neural networks," Computerized Medical Imaging and Graphics, vol. 34, pp. 617-631, 2010.

15. T. Mclnerney and D. Terzopoulos, "Deformable models," Handbook of medical imaging and processing and analysis, San Diego, CA:Academic Press, pp. 127-145, 2000.

16. N. Gordillo, E. Montseny and P. Sobrevilla, "State of the art survey on MRI brain tumor segmentation," Magnetic Resonance Imaging (2013), http:/dx.doi.org/10.1016/j.mri.2013.05.002.

17. R. R. Krishnapuram and J.M Keller, " A probalistic approach to clustering," IEEE Trans. Fuzy Syst., vol. 1, no. 2, pp. 98-110, May 1993.

18. M. Clark, L. Hall, D. Goldgof, R. Velthuizen, R. Murtagh, and M. Silbiger, "Automatic tumor segmentation using knowledge-based techniques," IEEE Transactions on Medical Imaging, vol. 17, pp. 187–201, 1998.

19. [M. Kaus, S. Warfield, A. Nabavi, P. Black, F. Jolesz, and R. Kikinis, "Automated segmentation of MR images of brain tumors," Radiology, vol. 218, no. 2, p. 586, 2001.]

20. Y. Zhang, M. Brady, and S. Smith, "Segmentation of brain MR images through a hidden markov random field model and the expectation maximization algorithm," IEEE Transactions on Medical Imaging, vol. 20, pp. 45–57, 2001.

21. D. L. Pham, "Spatial models for fuzzy classification," Computer Vision and Image Understanding, vol. 84, pp. 285-297, 2001.

22. J. L. Marroquin, B. C. Vemuri, S. Botello and F. Calderon, "An accurate and efficient Bayesian method for automatic segmentation of Brain MRI," Proceedings of the 7th European Conference on Computer Vision, London, August 2002.

23. M. N. Ahmed, S. M. Yamany, N. Mohamed and T. Moriarty, "A modified fuzzy c-means algorithm for bias field estimation and segmentation of MRI data," Proceedings of the IEEE transaction on Medical Images, KY, USA, March2002.

24. M. Prastawa, E. Bullitt, and G. Gerig, "A brain tumor segmentation framework based on outlier detection," Medical Image Analysis, vol. 8, no. 3, pp. 275–283, 2004.

25. J. Zhang, K. Ma, M. Er, and V. Chong, "Tumor segmentation from magnetic resonance imaging by learning via one-class support vector machine," in International Workshop on Advanced Image Technology, pp. 207–211, 2004.

26. J. J. Corso, E. Sharon, S. Dube, S. El-Saden, U. Sinha and A. Yuille, "Efficient Multilevel Brain Tumor Segmentation With Integrated Bayesian Model Classification," IEEE Transactions on Medical Imaging, Volume. 27, Issue. 5, pp. 629-640, May 2008.

27. J. Nie , Z. Xue, T. Liu , G. Young , K. Setayesh , L. Guo and S. TC Wong, "Automated Brain Tumor Segmentation Using Spatial Accuracy- Weighted Hidden Markov Random Field," Computerized Medical Imaging and Graphics, Volume. 33, Issue. 6, pp. 431-441, 2009.

28. R. Ratan, S. Sharma2 and S. K. Sharma, "Multiparameter segmentation and quantization of brain tumor from MRI images," Indian Journal of Science and Technology, Volume. 2, Issue. 2 , Feb 2009.

29. M. Forouzanfar, N. Forghani and M. Teshnehlab, "Parameter optimization of improved fuzzy c-means clustering algorithm for brain MR image segmentation," Engineering Applications of Artificial Intelligence, Volume. 23, pp. 160-168, 2010.

30. S.D. Salman and A.A. Bahrani, "Segmentation of tumor tissue in gray medical images using watershed transformation method," Intl. Journal of Advancements in Computing Technology, Vol. 2, No. 4, 2010, pp.123-127.

31. S.Bauer, L-P. Nolte, and M. Reyes, "Fully automatic segmentation of brain tumor images using support vector machine classification in combination with hierarchical conditional random field regularization," Medical image Computing and Computer-Assisted Intervention-MICCAI 2011. Springer, pp. 354-361, 2011.

32. A. Hamamci, N. Kucuk, K. Karaman, K. Engin and G. Unal, "Tumor-cut: Segmentation of brain tumors on contrast enhanced mr images for radiosurgery applications," Medical Imaging, IEEE Transaction on, Volume. 31, No. 3, pp. 790-804, 2012.

33. S. Roy and S. K. Bandyopadhya, "Detection and Quantification of Brain Tumor from MRI of Brain and it's Symmetric Analysis," International Journal of Information and Communication Technology Research, KY, U89SA, June 2012.

34. V. B. Padole and D. S. Chaudhari, "Detection of Brain Tumor in MRI Images Using Mean Shift Algorithm and Normalized Cut Method," International Journal of Engineering and Advanced Technology, June 2012.

35. Cheng Y., "Mean shift, mode seeking, and clustering",IEEE Trans. On Pattern Analysis and Machine Intelligence, Vol. 17, no. 8, pp. 790-799, 1995.

36. Shi J and Malik J. "Normalized cuts and image segmentation", IEEE Trans. on PAMI, Vol. 22, no. 8, pp. 888-905, 2000.

37. T. U. Paul and S. K. Bandyopadhyay, "Segmentation of Brain Tumor from Brain MRI Images Reintroducing K-Means with advanced Dual Localization Method," International Journal of Engineering Research and Applications, June 2012.

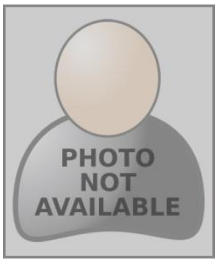
38. A Gooya, K. M. Pohl, M. Bilello, G. Biros, and L Cirillo "GLISTR: Glioma Image Segmentation and Registration," IEEE Transaction on, Medical Imaging, Volume 31, No. 10, pp. 1941-1954, 2012.

39. P. Buendia, T. Taylor, M. Ryal and N. John, "A Grouping Artificial Immune Network got segmentation of Tumor Images," Proceeding of NCI MICCAI-BRATS 2013.

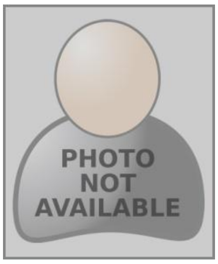
40. S. Doyle, F. Vasseur, M. Dojat and F. Forber , " Fully Automatic Brain Tumor Segmentation from Multiple MR sequence using Hidden Markov Fields and variational EM," Proceedings of NCI MICCAI-BRATS 2013.

41. N. Subbanna, D. Precup and T. Arbel, "Iterative Multilevel MRF Leveraging Context and Voxel Information for Brain Tumour Segmentation in MRI," Computer Vision and Pattern Recognition (CVPR), 2014 IEEE Conference on page.400-405.

AUTHOR(S) PROFILE



Swati khurana, received B-tech degree in Computer Science and Engineering from RIEIT, Ropar in 2012 and pursuing post-graduation in M.Tech, Computer Science at DIT University, Dehradun



Dr. M.L.Garg, received P.hd degree from Thapar Institute of Engg & Technology in 1992 , M.S engineering from Panjab University, Chandigarh in 1979, B.E(Hons) from Panjabi University, Patiala in 1974. Worked as an Assistant Professor in Computer Science & Engineering at Philadelphia University, Amman, Jordan from September 1995 to September 1998 and as Principal Lecturer in Computer Science & Engineering at University Tenaga Nasional (Uniten), Kajang, Malaysia from September 2002 to June 2006. He has an experience of 18 years in UG and PG teaching and research, and 23 years experience in industrial and administrative work. Currently he is Head of the Departement of Computer science and engineering at DIT University, Dehradun.

© 2015, IJARCSMS All Rights Reserved