A Comprehensive Review: Segmentation of MRI Images—Brain Tumor

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ABSTRACT: Segmentation of tumors in human brain aims to classify different abnormal tissues (necrotic core, edema, active cells) from normal tissues (cerebrospinal fluid, gray matter, white matter) of the brain. In existence, detection of abnormal tissues is easy for studying brain tumor, but reproducibility, characterization of abnormalities and accuracy are complicated in the process of segmentation. The magnetic resonance imaging (MRI)-based segmentation of tumors in brain images is more enhancing and attracting in current years of research studies. It is due to non-invasive examination and good contrast prone to soft tissues of images obtained from MRI modality. Medical approval of different segmentation techniques depends on the benchmark and simplicity of the method. This article incorporates both fully-automatic and semi-automatic methods for segmentation. The outlook study of this article is to provide the summary of most significant segmentation methods of tumors in brain using MRI. Int J Imaging Syst Technol, 26, 295–304, 2016; Published online in Wiley Online Library (wileyonlinelibrary.com). DOI: 10.1002/ima.22201

Key words: magnetic resonance imaging; segmentation; brain tumor

I. INTRODUCTION

Imaging analysis of tumors in the brain is to obtain the most prominent information, which helps in clinical diagnosis of the patient for better treatment. In image analysis, errors emerge at feature extraction, display and also in image measurements. Segmentation is the foremost level in medical image analysis (MIA). When growth of the cancer cells is uncontrollable then the disease is named as the tumor. This tumor is of different types and has different characteristics, which are cured with various types of treatments (Gupta and Shringirishi, 2013). Medical image segmentation of brain is the labeling process indicating tissue type or anatomical structure of each pixel/voxel. These segmentations have application in conception and interpretation of the disease. Segmentation can be on biological parts of the human body such as the blood vessels, the brain, the pelvis, the heart, the spine, the knee, and the prostate. Segmentation purpose is to extract richer information from the original medical images. The major intention of segmentation is to divide an image into homogeneous and non-overlapping regions of comparable properties such as intensity, depth, color, or texture. The brain segmentation results in either an image of labels that identify the region boundaries in terms of homogeneous regions or a set of contours. The noise, bias field, and partial volume effect are the difficulties and a challenging task in the process of segmenting the brain images. Magnetic resonance imaging (MRI) modality is most popular in obtaining complete details of images of different parts of the brain. Also, it is well-known for analysis and detecting abnormal changes in the tissues with high contrast when compared with other modality named computerized tomography (CT). Acquisition parameters of MRI can be adjusted for different tissues to obtain different gray values. Most of the researchers use MRI images for segmentation in clinical applications. The present study is concentrated on tumors located in brain. In particular, these tumors occur when abnormal tissues are found in some parts of the brain.

Methods of brain segmentation are categorized based on different principles. Brain segmentation of normal tissues is shown in Figure 1. For the medical use, the MRI segmentation methods are grouped as

i. Manual segmentation
ii. Semi-automatic segmentation
iii. Fully-automatic segmentation
iv. Hybrid segmentation.

Manual segmentation refers to that when an expert human operator labels the image and segments the boundaries which are perceptually valid. This segmentation aims to paint the regions of the anatomical structures labeling by hand, it is done in the fashion of slice-by-slice volumetric imagery (Pham et al., 2000). The manual segmentation method is said to be more accurate. This technique is used in brain tumor segmentation to draw the boundaries and structures of interest in detecting lesions with different labels.

Practically manual segmentation is not only plodding and error-prone, but also a time-consuming task for the operator to evaluate the results by intra or inter variability studies. Atlas based segmentation methods of different brain structures use the brain atlas of manual segmentation for basic formations (Murgasova, 2008).To overcome the difficulties of manual segmentation, more advanced methods emerged as semi-automatic and fully automatic segmentation methods.

Automatic segmentation refers to the process to segment boundaries assigned automatically by a computer aided system. The

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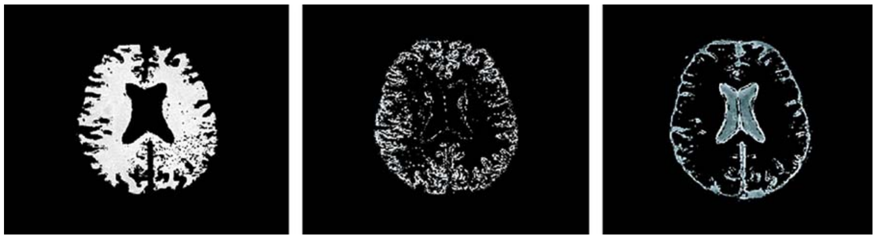

Figure 1. Brain segmentation classes: (i) gray matter (GM), (ii) white matter (WM), (iii) cerebrospinal fluid (Ortiz et al., 2014).

process of semi-automatic segmentation includes manual checking and automatic segmentation while editing the segmented boundaries. In this semi-automatic segmentation, the region of interest is outlined by the operator. The algorithms such as simple interactive object extraction (SIOX) livewire are applied on the image to obtain the results for the best edge fits of the image. Some input parameters are to be given by the human expert in perception analysis of information to obtain the feedback response from the computing software. Initialization, feedback response, and evaluation are the main processes of semi-automatic segmentation (Shi et al., 2011). Better results are produced with fully automatic segmentation methods than the semi-automatic methods.

In fully automatic segmentation method without any human operator assistance the segmentation is determined by the computer. The preceding knowledge and artificial perception are combined in the algorithms in fully automatic segmentation methods. The hybrid segmentation is the combination of any number of segmentation techniques to show the improvised results in terms of accuracy, computational time.

Different segmentation techniques are thresholding, region based, edge based, deformable models and classification methods. These methods are classified into supervised and unsupervised methods. The supervised methods are the representations of classifiers like artificial neural network (ANN), support vector machine (SVM), and Bayes classifiers. The unsupervised methods are the representations of clustering algorithms like K-Means algorithm, fuzzy clustering means (FCM) algorithm, markov random field (MRF) algorithm, and atlas based segmentations. This article is organized as follows. Section describes different conventional segmentation techniques of MRI brain images. Hybrid segmentation methods are elaborated in Section . Finally, article is concluded in Section .

II. SEGMENTATION TECHNIQUES

A. Thresholding. Thresholding is the quiet easiest method of segmentation which includes histogram and gray level features based on their intensities with one or more threshold values. This technique is used as standard method in brain tumor segmentation (Sharma and Aggarwal, 2010). Intensity thresholding is used to achieve segmentation in medical images with region of interest is a challenging task (Harris et al., 1994) due to typical structures of tumors in brain. The local and global thresholding techniques are widely used to detect appropriate location of tumors. When homogeneous intensities between the object and the background are high then the segmentation uses global thresholding. For segmenting images on space region to separate the regions of background and object, thresholding is considered as a powerful approach (Kass et al., 1988). The $O(k,l)$ can be obtained from $I(k,l)$ as,

$$O(k,l) = \begin{cases} 1, & I(k,l) > T \\ 0, & I(k,l) \leq T \end{cases} \quad (1)$$

where T is the threshold value, $O(k,l)$ is the output image, and $I(k,l)$ is the input image.

Local thresholding is to segment different regions around the pixel using intensity histogram. This is used to determine the threshold of mean intensity in T1 weighted images of MRI (Kang et al., 2009). Gaussian distribution is used to determine threshold in T2 weighted images in the normal brain MRI (Park, 2000). The simplest form of segmentation method is thresholding and its value is effective when compared with the region based method of segmentation. In brain MRI, information provided by local or global thresholding is cannot be considered. Because it is sensitive to pre-processing and post-processing techniques like intensity in-homogeneities, bias field correction and it is also sensitive to noise. Thresholding methods fail to determine the intensity distributions in medical images and they are difficult in practice. Over a period of decade, thresholding is combined with other methods of segmentation to obtain more accurate results in terms of gray level features and intensity distributions in medical images.

B. Region Based. Region based segmentation is constructed from the background of homogeneity properties in the image. This examines pixels in an image, by merging neighborhood pixels formed by disjoint regions based on predefined criteria of similarities (Stadlbauer et al., 2004). Region-based segmentation methods are categorized into (i) region growing, (ii) watershed segmentation methods. These methods are generally used in segmentation of brain tumors based on MRI.

B.1 Region Growing. The region growing method is most commonly used and it is the simplest technique of region based segmentation. This method is utilized to obtain bonded region of pixels which are similar to the original image (Mittelhaeusser and Kruggel, 1995; Adams and Bischof, 2004). The process of region growing method begins with a minimum one seed. The neighborhood pixels from the seed of an image are intensified to region-based homogeneity criteria which establish the connected regions. This process is recursive until no more voxels/pixels can be combined to the regions in the image of the brain. These seeds are selected by either manual or automatic seed finding methods (Kaus et al., 2001).The numerical classification of the recursion technique is involved to segment an image based on the intensity value of the signal into different tissue classes in brain. Segmentation of volumetric images is ensured with the region growing as it is composed of outsized connected regions. In medical imaging analysis, region growing is commonly used to segment tissues and lesions in MRI images. In comparison, region based methods are proved to be more efficient approaches with less

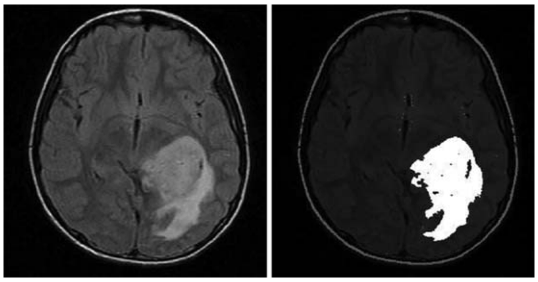

Figure 2. Gradient based genetic algorithm: (i) Original MRI image(ii) Brain tumor segmentation (KumarKole et al., 2012).

computation time over non-region based methods for segmentation of MRI brain images. The major drawback of the region growing for segmentation of the MRI brain images is lack of accuracy in terms of partial volume effect (PVE). As the voxel is represented by more than one type of a tissue class in 3D MRI brain images, the blurring effect of the intensity peculiarity among tissue classes of two tissue types at the borders is referred as PVE. It can be removed and incorporated to produce more accurate gradient information in boundary detection and filling holes appear subsequently with segmentation by using the modified region growing method (MRGM) (Lakare and Kaufman, 2000).

A novel method is proposed using the anisotropic filter as adaptive region growing method in which information of edges with variances along with the gradients inside the curve are preserved (Deng et al., 2010). The edge information can be preserved by using the anisotropic filter. The mean variance of the innermost boundary and the reciprocal of the lateral curve of the mean gradient are chosen by some researchers. The multispectral registration of the images is the foremost in the framework, consists of fuzzy features, prior knowledge, and modifications in the fuzzy region growing. Based on T1, T2, and FLAIR MRI, fast multispectral brain tumor segmentation is possible by probabilistic intensity model. Initially segmentation with the refinement path is followed iteratively. Segmentation of tumor affected areas in brain utilizes dynamic gradient based clustering with a genetic algorithm, to examine the highest average intensity value and asymmetry map of seed located region, as shown in Figure 2 (KumarKole and Halder, 2012).

The drawbacks of this technique are sensitive to noise and seed point initialization. In presence of noise, segmented regions are disconnected. Segmentation results differ when an object of interest in segmented regions is merged. Region growing process is incorporated as refinement path in some segmentation methods (Salman, 2009). This method is used to extract tumor pixels/voxels from brain MRI images.

B.2 Watershed. Watershed is region based segmentation. It uses the concepts of hydrography and geographic structures. Watersheds in image processing are better explained with an example of the catchment height map which comes under gradient based technique. The water drop which is moving along the gradient of an image drifts in the path to reach the local minimum point. Finally, an automatic assistance of watershed resembles the limits of catchment basins of adjacent water drops. A dam is erected in between different bodies of water meets and all focus features in the map are submerged with raise in water, it is accomplished by making use of watersheds segmentation. These dams are referred as watersheds, catchment regions as the segmented regions (Adalsteinsson and Sethian, 1995; Li et al., 2007). Complete contours of the image are produced by watersheds and need of combining contours is avoided. Hierarchical and multiscale watersheds are used by some of the researchers in segmentation of tumors in brain (Cates et al., 2005). Figure 3 shows the comparison of voxel-wise precision analysis between watersheds and manual segmentation methods with high and low operator agreements. In outline detection and region portioning of multiple sclerosis, lesion is carried out by segmentation. Intensity model estimation with spatial information is done using watersheds for brain parcellation and classification of local regions in the brain (Prastawa and Gerig, 2008).

Watersheds are used as the prediction of building blocks in supervised learning methods.T1 MRI segmentation of brain is proposed in (Dam et al., 2004).This method blocks different scales that are build and from which user selects the desired brain anatomical objects from the data obtained. The analysis of qualitative and quantitative segmentation is significantly improved when compared with manual segmentation in terms of precision and time. The major drawback of watersheds is the shaped boundaries generated from the image that may represent any local maximum value and due to which watershed suffers from over segmentation. Over-segmentation can be avoided by using either pre- or post-processing methods to improve the objects layout detection like Fuzzy C-Means clustering algorithm as proposed by (Kong et al., 2006). Detection of tumors in the brain using 3D and 2D MRI images are acquired by a multiparameter and marker-based improved watershed segmentation technique (Salman and Bahrani, 2010). The watershed segmentation is integrated with morphological operations to obtain the segmented region of the tumor and to detect the abnormal brain image with better

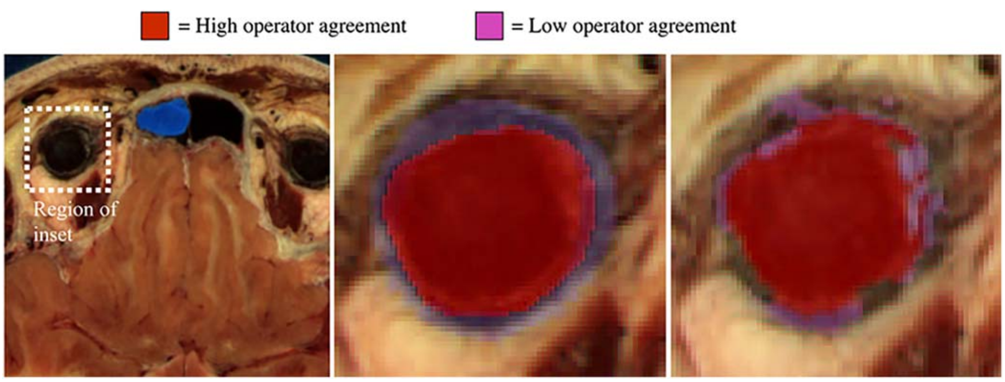

Figure 3. Voxel-wise precision analysis: (i) Original image, (ii) Manual segmentation, and (iii) Watersheds (Cates et al., 2005). [Color figure can be viewed at wileyonlinelibrary.com]

segmentation accuracy (Thirumurugan and Shanthakumar, 2016). The major drawback of the conventional watershed segmentation is over-segmentation, (Kwon et al., 2016) proposed a novel method for segmentation by combining the expectation maximization (EM) algorithm with watershed segmentation. This gives the outcome of effective gradients on segmenting the cerebrospinal fluid (CSF) and gray matter in MRI brain images. In brain segmentation, these methods are used as pre-processing steps. Automatic methods with more advancement are proposed for the requirements in diagnosis of the diseases.

C. Supervised and Unsupervised Methods. The analysis and diagnosis of medical images are effective with the machine learning methods. It helps in learning complex patterns, relationships and makes accurate decisions from the empirical data. Different categories of classification methods are supervised and unsupervised methods of segmentation. Supervised methods of segmentation make use of labeled MRI brain training datasets. Supervised methods aim to reduce the functional relationship of brain datasets which are generalized in testing MRI. In other words, it is a relation in between numerical weights or numerical coefficients and set of equations. Selection of training datasets plays a crucial role in supervised methods because different training datasets cause great inequalities in training time, impacts on the segmentation results (Bezdek et al., 1993). Each sample in the supervised method is comprised of two factors, input features, and output labels. The input features are considered as causes and output labels as effects.

In unsupervised segmentation methods the algorithm specifies the number of classes and numerically grouped with similar pixels/voxels in the brain image. The manually labeled MRI brain training datasets are not used in unsupervised segmentation methods. Thus only input features are available in unsupervised method and those features are caused by suppressed or ignored variables (Hastie et al., 2005). The aim of the unsupervised methods is to reveal the suppressed variables in distinct to the feature samples. A new approach is proposed in Kong et al. (2015) for robust MRI brain image segmentation at supervoxel level on tissues of brain. The information theoretic discriminative segmentation (ITDS) is a clustering method for analysis of discriminating simultaneous data clustering and feature selection of brain tissues at supervoxel level. The ITDS incorporates the maximization of boundaries in different clusters by means of mutual information. This results in tissues heterogeneity with higher confidence when compared with other clustering methods of brain segmentation.

C.1. Fuzzy-C Means (FCM). Fuzzy-C Means is a clustering method, segments the data groups into two or more clusters. It considers only intensity of the segmented image but intensity in noisy images is also appreciably acceptable. FCM algorithm is based on object function minimization. In the medical diagnosis of tumors, standard treatments are available for different characteristics in different diseases. Examination of tumors in different sizes and stages are accurately improved by combining k means and FCM segmentation algorithms (Gupta and Shringirishi, 2013). Segmentation of brain tumor using FCM has become an effective research area and it is given as,

$$X_y = \sum_{i=1}^{n} \sum\nolimits_{j=1}^{m} r_{ij}^{y} d\left(s_i,\ \theta_j\right) \tag{2}$$

where y is the degree of fuzziness in clustering (in general $y = 2$), r is the membership of fuzzy data s_i to θ_j as center of the cluster and, d is the distance between s_i data, and cluster center j, θ_j. The r must satisfy the conditions,

$$\sum_{i=1}^{n} r_{ij}=0 \ \& \ 1 \ < \sum_{j=1}^{n} r_{ij} < n, \ \ r_{ij} \in [0,1](3)$$

The r and θ_j are obtained as

$$\theta_j = \frac{\sum_{i=1}^{N} s_i r_{ij}^{y}}{\sum_{i=1}^{N} r_{ij}^{y}} \tag{4}$$

$$r_{ij} = \frac{1}{\sum_{k=1}^{m} \left(\frac{d\left(s_i, \theta_j\right)}{d\left(s_i,\ \theta_k\right)} \right)^{\left(\frac{2}{y-1}\right)}} \tag{5}$$

The θ_j iterations stops at,

$$\max\{|r_{ij}^{p} - r_{ij}^{(p-1)}|\} \leq \varepsilon \tag{6}$$

where ε is the termination lies between *0* and *1*; p is the number of iteration steps (Kannan et al., 2010).

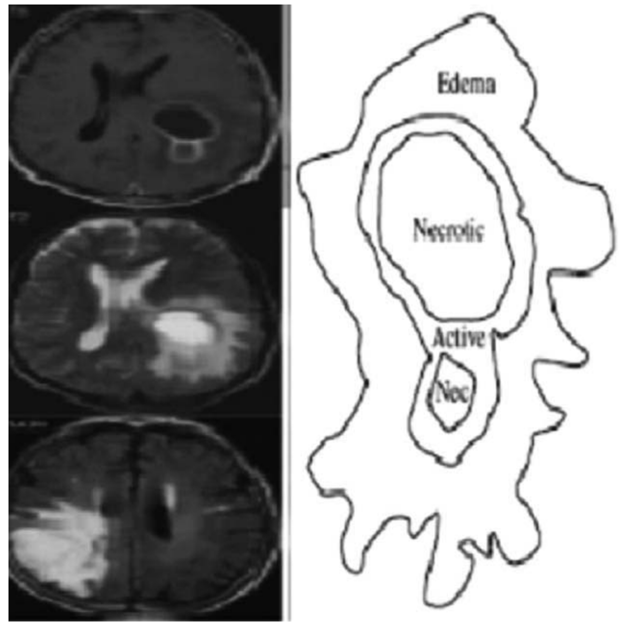

Figure 4. (i) Brain tumor images of T1 MRI with contrast, T2 MRI and FLAIR MRI, (ii) Representation of abnormal tissues in brain (Corso et al., 2008).

In FCM, object function is optimized by membership function and center of cluster updates continuously unless and until threshold is greater than the optimization within the iterations (Pohle and Toennies, 2001). Segmentation of tumors in brain includes normal and abnormal tissues, whereas normal tissues: gray matter, white matter, cerebrospinal fluid, and abnormal tissues: edema, active cells and necrotic core (Corso et al., 2008) as observed in Figure 4. FCM segmentation is used in clinical diagnosis of MRI raw multisequence data to find contrast information of both neuro-pathologic and neuro-anatomic tissues. The exhibited results are of even multi-sequence data with overlapping of normal tissues and intensity distribution (Phillips et al., 1995). A new approach was implemented and proposed to develop the tumor shapes of MRI images with 3D

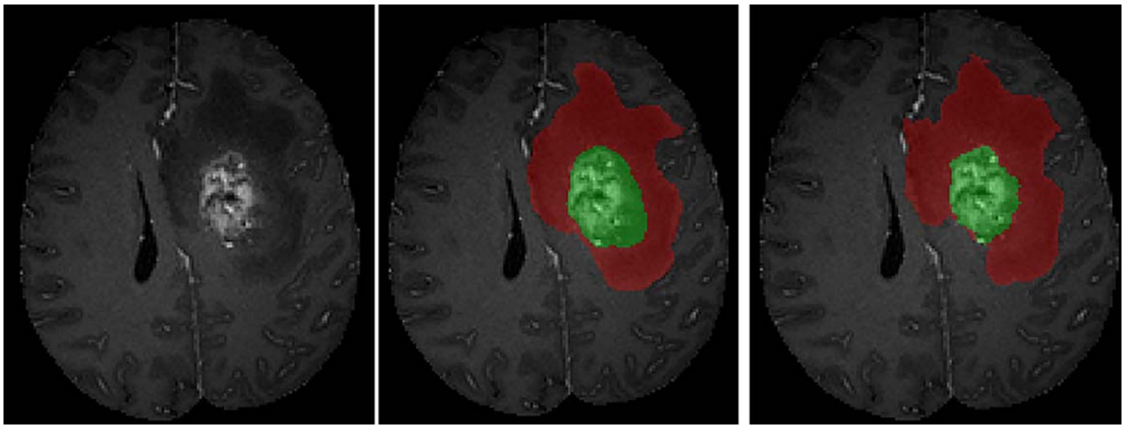

Figure 5. (i)The unlabeled T1C slice, (ii) and (iii) The expert labeling, (red: edema, green: non-edema) (Subbanna et al., 2013). [Color figure can be viewed at wileyonlinelibrary.com]

connected components named as knowledge based fuzzy clustering (Fletcher-Heath et al., 2001), to distinguish non enhancing regions of tumor and healthy tissues in brain. By combining seeded region growing and this fuzzy knowledge segmentation method, a novel approach named fuzzy knowledge based seeded region growing (FKSRG), intended for multispectral MRI images was proposed (Lin et al., 2012). It gives much more accurate results when compared with functional MRI automatic segmentation of brain tumor. In Meena Prakash and Shantha Selva Kumari (2016) FCM segmentation is incorporated with spatial information in order to conquer the drawback of conventional FCM method by convoluting the membership function with $3 \times 3 \times 3$ mean filter. The conventional FCM method lacks in considering the spatial correlation between the neighboring pixels, in-homogenities of intensity and noise sensitivity. In brain segmentation, FCM is considered as an iterative algorithm, which consumes more time. The other developments have been implemented to reduce the execution time by a new approach referred as enhanced FCM by making use of average pre-filters.

C.2. Markov Random Field (MRF). Markov random field belong to unsupervised clustering segmentation methods. It provides assimilated spatial information and related information between pixels of the MR images of brain. MRF technique is mainly preferred because both overlapping of pixels/voxels and effect of noise in the image are reduced in MRI datasets. Different normal and abnormal tissues are segmented with different models in each tissue of T1 and T2 weighted MRI images. These tissues are modeled and trained by MRF with iteration condition modes (ICM) and Gaussian mixture models (GMM). MRF model includes the statistical need for neighborhood voxels/pixels without removal of morphological operations (Capelle et al., 2000). To detect abnormalities of brain, the author proposed a multilayer MRF framework to provide information between layers of brain including intensity of pixels, spatial locations and structural consistency. Low level layers share similarities of strong attributes in presence of tumor for the given voxel which changes to the high level classification. For clinical diagnosis of automatic and enhanced brain tumor segmentation a new technique named spatially accurate weighted Hidden MRF and Expectation maximization is proposed (Nie et al., 2009). The low resolution images incorporate the accuracy of spatial interpolation to evaluate the hidden MRF procedure in segmenting tumors with different resolutions in multichannel MR images. Likewise high resolution data sequences are used together with low resolution data sequences and they show more accurate results. By making use of volumetric MRI images of brain tumor, an automatic method is proposed (Bauer et al., 2011a, 2011b) to segment the tissues of the brain. Volumetric MRI is based on average atlas of non-rigid registration which is combined with the model of tumor growth biomechanically and mass effect of the tumors to justify soft tissues deformations which are simulated. Hierarchically, fully automated probabilistic framework for segmentation of tumors in brain is developed, using MRF adapted framework and Gabor filters with multiwindowing techniques for multispectral brain MRI images (Subbanna et al., 2013). To segment the tumors into edema and non-edema BraTs database are used as shown in Figure 5.

The discriminative random field also known as a conditional random field (CRF) (Lafferty et al., 2001) is proposed to segment and label the of sequence MRI data. The region of segmentation strongly labels the brain as tumor and non-tumor regions, the labeled regions are determined with the help of neighboring pixels/voxels using MRF technique. Brain tumor segmentation using MRF and CRF techniques are having the high accuracy in detecting the complex dependencies of different data sets of MRI images. Classification and segmentation of MRF's are implemented and coupled, based on the knowledge of SVM and CRF techniques. MRF is vastly used in texture segmentation and on the other side it is also used for intensity in-homogeneities of different modeling classes (Zhang et al., 2004). MRF's are computationally expensive and approximations are considered rather than accurate values.

C.3. Support Vector Machine (SVM). The support vector machine is the most common and efficient supervised classifier with statistical patterns and treated as kernel based segmentation method parametrically. SVM is categorized under a machine learning method which is widely employed in recognition of brain tumor approaches, tissue classification and in the segmentation of human brain anatomical structures. SVM classifier is used to separate the two classes of regions with highest boundary hyper-plane in the image. Without any prior knowledge like thresholding, SVM has the familiarity of studying the non-linear distribution of MR image data. Due to the automatic procedure, better segmentation results are obtained in feature extraction of tumors in brain as compared with fuzzy clustering methods and SVM is explored as one class method for segmentation of brain tumor (Zhou et al., 2006). In general SVM classifier is used to segment healthy tissues and most of the new researchers use SVM to even segment the tumor and non-tumor

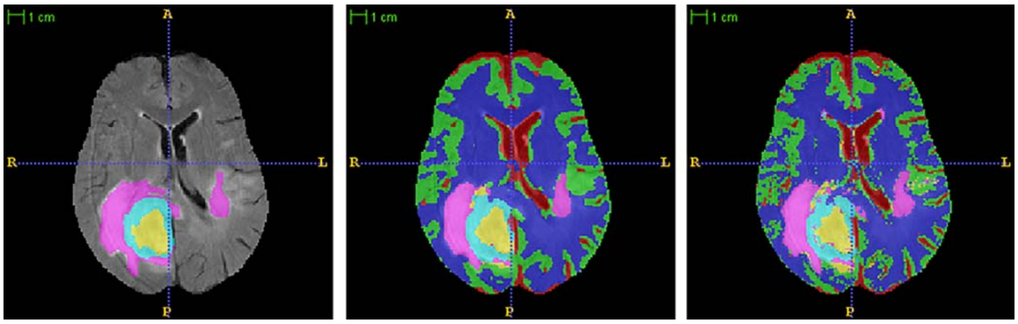

Figure 6. (i) Manual segmentation using SVM, (ii) Hierarchical SVM with CRF-regularization, (iii) Non-hierarchical SVM without regularization (Bauer et al., 2011 MICCAI). [Color figure can be viewed at wileyonlinelibrary.com]

regions into sub-compartments of tissues using voxels intensity based feature vectors (Verma et al., 2008). Novel approach of SVM is used to segment multi sequence brain tumor MR images based on multi-kernels, integrated with both fusion process and feature selection (Zhang et al., 2009). This involves two steps in measuring the distance and maximum likelihood function as classifying brain tumor, amending the contours of the tumor region. When results are compared with one class SVM method, multi-kernel SVM method is more accurate with low error rate. For segmentation of brain tissue (Bauer et al., 2011a; MICCAI), proposed a fully automatic approach, which combines multispectral intensities and hierarchical subsequent regular texture based on CRF for SVM classification. To improve robustness and speed, a hierarchical method is used in different stages at different levels of regularization which can be observed in Figure 6. In MRI images, brain tumor segmentation has great hypothetical and effectiveness in using SVM method of classifiers. Segmentation of brain tumors is an enhancing challenge, which exhibits complex characteristics in the appearance of high diversity and ambiguous boundaries. To overcome this difficulty a new method local independent projection based classification (LPIC) was proposed for segmenting tumors in MRI brain images automatically (Huang et al., 2014). LPIC categorizes each voxel to a different class and results in natural smoothness of the images when compared with other segmentation methods using contextual information without any unambiguous regularization. The drawbacks of SVM classifier and neural networks in providing segmentation accuracy have been overcome by adaptive network-based fuzzy inference system (**ANFIS**) classifier (Thirumurugan and Shanthakumar, 2016). This ANFIS classifier combines the fuzzy rules and feed forward back propagation neural network to improve the segmentation accuracy. This helps in training the extracted features from MRI brain images and classifies them into either normal or abnormal brain images. In Rajaguru et al. (2016) SVM classifier is combined with EM algorithm, to obtain good segmentation accuracy and large values of performance index when compared with other combinations of SVM classifier with k-means, particle swarm optimization (PSO), FCM segmentation methods.

C.4. Artificial Neural Networks (ANN). Artificial neural network is the clustering based segmentation technique. The series of nodes are feed by this ANN classifier, input nodes are modified with help of mathematical operations to set the absolute output nodes. Implementation of ANN involves more complexity and time consuming task in segmentation of brain tumors. In network more number of images is essential for training datasets which makes the network size large and its training time will be more.

D. Deformable Models. Deformable model is defined as surfaces or curves in image domain, which are influenced by the internal and external forces in deformation of the image. In the process of deformation, an internal force is to maintain the smoothness and same features of curve, whereas external forces are responsible to attract the structure of interest and relate with adjacent regions in the curve of an image. Deformable models extract elements with similar structure and integrate the boundaries to be consistent and coherent structures. It has become a challenging method segmentation of 3D MRI data. Deformable models are categorized into (i) Parametric deformable models and (ii) geometric deformable models.

D.1. Parametric Deformable Models. Parametric deformable models are well-known as snakes, explicit deformable models and active contour models. The most important step in segmentation of brain tumors using this model is to detect the boundaries of tumor in brain. Snakes are widely used because of their sensitivity in finding the tumor boundaries. They can even trace the object contours with proper initialization, due to which better resolution results are obtained when compared with traditional edge detection segmentation like Sobel and Laplacian (Xu and Prince, 1998). External force of snakes in homogenous regions is minimum positive value and observed as zero at edges, due to which performance of the snakes can be improvised using balloon and gradient vector flow models in T1 MRI segmentation of brain tumor (Luo et al., 2003). A balloon model allows enlarging the capture range obtained using snakes, whereas gradient vector flow is to trace the inabilities in short capture range of boundaries. By combining deformable models with expectation maximization algorithm (Gooya et al., 2011), incorporates the growth of glioma. In brain scan, seeding atlas is modified to detect tumor or edema when compared with normal atlases used in estimating tissue labels with various posterior probabilities in registered space. A parametric deformable model needs manual location of boundaries to avoid wrong converging of boundaries. To calculate the volumetric measurements of brain tumors a new method is proposed (Al-Tamimi et al., 2015) that uses active contour model for segmentation in MR images. The volume of the tumor is obtained from its contours using alpha shape theory, gives more precise results because this technique involves the affected tissues. The concepts of alpha shapes are validated for the spatial sets of points from the natural perception of "shape," mathematically well-defined for specific set of points in geometric models. Figure 7 represents the set of points in specified form using concepts of convex hull, where every convex hull represents α- shape but α- shape does not represent the convex hull. The novel set approach is proposed (Wang and Pan, 2014) for MRI images corrupted with intensity in-homogeneities and bias field correction to improve the correction accuracies by uniting

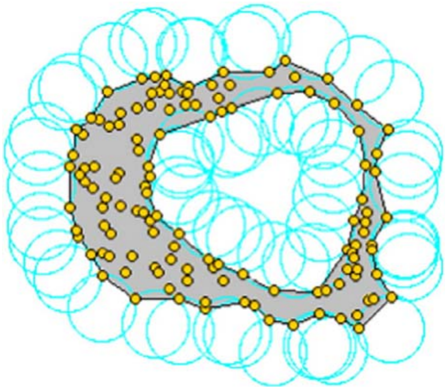

Figure 7. Set of points representing α-shape (Al-Tamimi et al., 2015). [Color figure can be viewed at wileyonlinelibrary.com]

the tissue segmentation and bias field to a single Bayesian framework and obtains better results when compared with other segmentation methods. The main drawback of the parametric deformable models is that they are not good enough to handle changes in splitting and merging of contours in the 3D MRI images.

D.2. Geometric Deformable Models. Geometric deformable models are also known as implicit deformable models, level sets. The level set snakes define higher-dimensional surfaces and that are formulated in evolving the surfaces or contours over image domain. Level set snakes are more advantageous than mathematical morphology and usual statistical classifications (Kichenassamy et al., 1995). In segmentation of brain tumors, variable level set snakes are formulated with new approach named as region-based active contours, in which sides of the contours are approximated locally with image intensities from which curve equation is evolved for minimization of energy (Li et al., 2008). Evolution of level set snakes and bias field estimation are considered as interleaved process in achieving energy minimization. The segmentation accuracy and robustness are improved by using the multiplicative intrinsic component optimization (MICO) (Li et al., 2014), which combines the tissue segmentation and bias field estimation in MRI brain images with new formulae of energy minimization. Figure 8 represents the result of corrected bias fields. The new approach is designed for segmentation of tumor affected brains which combine evolution of level sets with automatic cellular tumor segmentation, to improve spatial smoothness in probability map of tumor (Hamamci et al., 2012). These deformable models are not used alone, but they are combined with other algorithms like FCM, MRF, ANN, etc., due to which accuracy is improved in segmentation of brain tumor in MRI images.

E. Other Segmentation Techniques. *E.1. Atlas Based Segmentation.* The most powerful and commonly used method of segmentation in medical images is atlas-based segmentation. In this method registration algorithms are used to locate one-to-one mapping between input image and the pre-segmented image to determine the segmentation result. Atlas based segmentation algorithms of brain are investigated, atlases of brain can provide the difference in measured data of tumor segmentation between abnormal brains and normal brains (Iglesias et al., 2013). The limitation of this method is apparent at complex structure segmentations like variable size, shapes and properties of medical images. The perspective of segmentation in MRI brain structure of humans, multi-atlas segmentation methods are used to pre-processing tasks like skull stripping, tissue classification, and segmentation of tumors. This segmentation is engrained with the theory widely applied to the structures of brain (Iglesias and Sabuncu, 2015). Thus professional knowledge is needed in building the training datasets of MRI images.

E.2. Gaussian Mixture Model. Gaussian Mixture Model (GMM) uses the probability density function (PDF) estimate distribution functions in each class. In class, i is PDF of GMM (Dokur, 2008) is given as,

$$p(\boldsymbol{x}|i)=\sum_{m=1}^{M} p_m * G_m(\boldsymbol{x}) \tag{7}$$

where M is the number of Gaussian components, $\boldsymbol{x}$ is the data, p_m is the priori probability of Gaussian component m, G_m is the PDF of Gaussian component m.

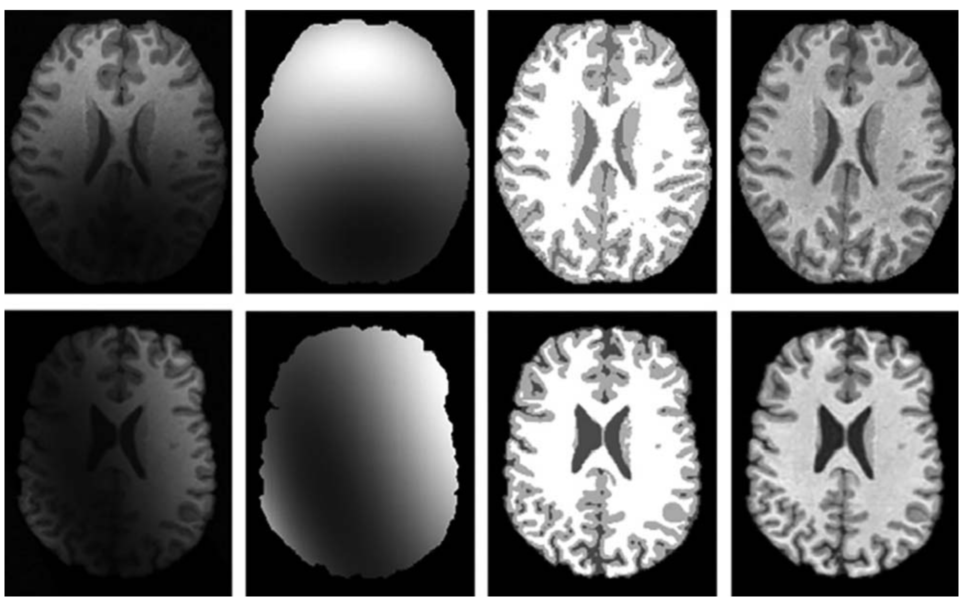

Figure 8. (i) input image with severe intensity in-homogeneity, (ii) estimated bias fields,(iii) segmentation results, and (iv) corrected bias field results (Li et al., 2014).

For all the classes,

$$G_m(\boldsymbol{x}) = \frac{1}{(2\pi)^{\frac{n}{2}} \; |\Sigma_m|^{\frac{1}{2}}} \; e^{-\frac{1}{2}(\boldsymbol{x}-y_m)' \sum_m^{-1} (\boldsymbol{x}-y_m)} \tag{8}$$

where y_m and Σ_m are the mean and covariance matrix of the training datasets belonging to Gaussian component m, n is the dimension of data $\boldsymbol{x}$.

A fully automatic method for segmentation named GMM for 3-layer framework is proposed in (Liu and Chen, 2014).The GMM is employed to segment tissues of brain in MR images by making use of spatial information. It is mainly intended to separate the model of spatial structure information, intensity information and intensity spatial feature vectors.

III. HYBRID TECHNIQUES

In MRI segmentation of the brain, new problems are emerging with specific applications and new methods are proposed to find easy solutions for applications in medical imaging. The appropriate technique has to be chosen and it is a troublesome task, combination of any two or more techniques aims to attain much better results when compared with usage of single technique. Hybrid segmentation methods are used in brain segmentation of MRI images to overcome the disadvantages of individual method and improve the accuracy.

Some of the hybrid methods are:

i. Combination of multi-region with multi-reference framework to obtain lower standard deviations and higher tissue overlapping rates (Phillips et al., 1995).
ii. Combination of EM segmentation and active contours with binary mathematical morphology is used to segment adult brain using 2D MRI for segmenting different brain tissues (Kapur et al., 1996).
iii. Combining thresholding, active contours with T1 and T2 weighted MRI the volume of newborn brain can be segmented (Despotovic et al., 2010).
iv. Support Vector Machines are combined with the conditional random field to achieve low computational times of segmentation with multispectral datasets among different patients (Bauer et al., 2011aa, 2011b).
v. Based on ANN hybrid segmentation of T2 and FLAIR MRI is proposed (Vijayakumar and Chandrashekhar Gharpure, 2011) to segment normal tissues, edema, cysts, and tumor lesions.
vi. Combination of kernel feature selection with SVM is used achieve to low computational time and better results in testing T1W and T2W MRI (Zhang et al., 2011).
vii. Combining K-means with FCM is used to obtain better reproducibility and accurate results (Gupta and Shringirishi, 2013).
viii. Self-organizing maps are combined with entropy-gradient clustering method to improve brain segmentation in MRI images (Ortiz et al., 2014).
ix. Integration of modified Particle Swarm Optimization with fuzzy entropy based segmentation provides the maximum entropy while segmenting tumors in brain with less computation time (Remamany et al., 2015).

To achieve good and efficient qualitative results hybrid segmentation should be eruditely and carefully designed. Large number of parameters and low computational time are included in each specific application. But the main drawbacks of these hybrid segmentation methods are increase in the complexity when compared with the single method of segmentation.

IV. CONCLUSION

The different methods of segmentation of brain tumor using MRI modality are presented in this article. Each method claims its own advantages over other segmentation methods to achieve better results. Thresholding is the trouble-free and simple method in implementation but it's sensitive to noise. Region growing is treated as the fastest method in finding high contrast regions but depends on the seed point initialization. Watersheds use morphological operations and helps in improvement of capture range, but results in over-segmentation. Deformable models are advantageous for their contour connectivity but computationally expensive. The supervised methods reduce the functional relationship of brain datasets and unsupervised methods reveal the suppressed variables in distinct to the feature samples. These methods lack the segmentation accuracy and can be improved by using hybrid segmentation methods. Hybrid segmentation results in good accuracy and gives better results in terms of validity and robustness. Different segmentation algorithms are developed by many researchers and it is still treated as the most challenging task. There is a massive scope for future research to improve the accuracy, precision, complexity, speed, and efficiency of segmentation methods.

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