RESEARCH ARTICLE OPEN ACCESS

A Novel Classification Algorithm based on Contextual Information using FCM Classifier for Brain Tumor Diagnosis using MR Images

Dinesh Babu G L[1], Hariharan G[2]
[1](PG Scholar, Department of Computer Science and Engineering, PSN Engineering College, Tirunelveli)
[2] (Department of Computer Science and Engineering, PSN Engineering College, Tirunelveli)

----------------------------------*************************----------------------------------

Abstract:

The identification and localization of a brain tumor is a complex work. The proposed method allows to assess the anatomical location, morphology and extent of the tumor with high spatial resolution. A modified Fuzzy C-Means (FCM) Classifier is introduced to identify and locate the tumor effectively with minimal duration. The brass tacks of the classifier is carried out by incurring the contextual information from the brain tissues. The clustering is used to classify the tissues expeditiously and the standing of specifying the cluster size is user customizable. Due to the intricateness of the human brain the tumor may overlaps with the healthy brain tissues in Magnetic Resonance (MR) images. FCM works on an ingeminating fashion to discriminate the tumor from normal tissues.

Keywords: **- Fuzzy C- Means (FCM), Clustering, MR images.**

----------------------------------*************************----------------------------------

I. INTRODUCTION

Medical imaging is the technique, process and art of creating visual representations of the interior of a body for clinical analysis and medical intervention. Medical imaging seeks to reveal internal structures hidden by the skin and bones, as well as to diagnose and treat disease.

A magnetic resonance imaging instrument (MRI scanner) produces a detectable signal which is spatially encoded, resulting in images of the body. The particular frequency of resonance is called the Larmour frequency and is calculated based on the particular tissue being imaged and the strength of the main magnetic field. MRI uses three electromagnetic fields: a very strong static magnetic field to polarize the hydrogen nuclei, called the static field; a weaker time-varying field(s) for spatial encoding, called the gradient field(s); and a weak radio-frequency (RF) field for manipulation of the hydrogen nuclei to produce measurable signals, collected through an RF antenna.

The majority of the brain is separated from the blood by the blood-brain barrier (BBB) which exerts a restrictive control as to which substances are allowed to pass. Therefore many tracers that reach tumors in the body very easily would only reach brain tumors once there is a disruption of the BBB. Therefore the disruption of the BBB (blood-brain-barrier), which can be detected by a MRI and CT, is regarded as the main diagnostic indicator for malignant gliomas, meningiomas, and brain metastases.

Swelling, or obstruction of the passage of cerebrospinal fluid (CSF) from the brain may cause (early) signs of increased intracranial pressure which translates clinically into headaches, vomiting, or an altered state of consciousness, and in children changes to the diameter of the skull and bulging of the fontanels. More complex symptoms such as endocrine dysfunctions should alarm doctors not to exclude brain tumors.

A bilateral temporal visual field defect (due to compression of the optic chiasm) or dilatation of the pupil, and the occurrence of either slowly evolving or the sudden onset of focal neurologic symptoms, such as cognitive and behavioral impairment (including impaired judgment, memory loss, lack of recognition, spatial orientation disorders), personality or emotional changes, hemiparesis, hypoesthesia, aphasia, ataxia, visual field impairment, impaired sense of smell, impaired hearing, facial paralysis, double vision, or more severe symptoms such as tremors, paralysis on one side of the body hemiplegia, or (epileptic) seizures in a patient with a negative history for epilepsy, should raise the possibility of a brain tumor.

II. RESEARCH BACKGROUND

[1] "**Automated Segmentation of MRI of Brain Tumors**", Michael R Kaus, Ferenc A Jolesz have proposed an automated brain tumor segmentation method was developed and validated against manual segmentation on 3D-MRI of 20 patients with meningiomas and low grade gliomas. The automated method allows the rapid identification (5-10 minutes operator time) of brain and tumor tissue with accuracy and reproducibility comparable to manual segmentation (3-5 hours operator time) making automated segmentation practical for low grade gliomas and meningiomas. This software produces good accuracy.

[2] "**Model-Based Brain and Tumor Segmentation**", Nathan Moon, Elizabeth Bullitt, Koen van Leemput have implemented a method which uses a probabilistic geometric model of sought structures and image registration serves both initialization of probability density functions and definition of spatial constraints. A strong spatial prior, however, prevents segmentation of structures that are not part of the model. In practical applications, it encounters either the presentation of new objects that cannot be modelled with a spatial prior or regional intensity changes of existing structures. A scheme for high dimensional warping of multichannel probability data to get a better match between atlas and deformed patient images need to be developed.

[3] "**Atlas-Based Segmentation of Pathological Brain MR Images",** M. Bach Cuadra, C. Pollo, A. Bardera, O. Cuisenaire, J.-G. Villemure and J.-Ph. Thiran have proposed a method for brain atlas deformation in presence of large space-occupying tumors, based on an *a priori* model of lesion growth that assumes radial expansion of the lesion from its starting point. First, an affine registration brings the atlas and the patient into global correspondence. Then, the seeding of a synthetic tumor into the brain atlas provides a template for the lesion. Finally, the seeded atlas is deformed, combining a method derived from optical principles and a model of lesion growth (MLG). Results show that the method can be applied to the automatic segmentation of structures and substructures in brains with gross deformation, with important medical applications in neurosurgery, radiosurgery and radiotherapy. This method overcomes the limitation such as the *seed* size dependence.

[4] "**A brain tumor segmentation framework based on outlier detection**", Marcel Prastawa, Elizabeth Bullitt, Sean Ho have proposed automatic brain tumor segmentation from MR images. The detection of edema is done simultaneously with tumor segmentation, as the knowledge of the extent of edema is important for diagnosis, planning, and treatment. Whereas many other tumor segmentation methods rely on the intensity enhancement produced by the gadolinium contrast agent in the T1-weighted image, the method proposed here does not require contrast enhanced image channels. The only required input for the segmentation procedure is the T2 MR Image channel, but it can make use of any additional non-enhanced image channels for improved tissue segmentation. The technique uses a concept that detects difference from normal and uses non-parametric estimates for distributions

rather than traditional mixture Gaussian models. The technique also makes use of other features besides intensity: the shape of brain tumor and location of edema. This method does not deal with wide varieties and hence in near future the process can be tried without edema.

[5] "**Segmenting Brain Tumors using Pseudo-Conditional Random Fields**", Chi-Hoon Lee1, Shaojun Wang, Albert Murtha, Matthew R. G. Brown have used a method for locating Brain tumor segmentation within MR images to the treatment of brain cancer. This segmentation task requires classifying each voxel as either tumor or non-tumor, based on a description of that voxel. Unfortunately, standard classifiers, such as Logistic Regression (LR) and Support Vector Machines (SVM), typically have limited accuracy as they treat voxels as independent and identically distributed.

[6] "**A Discriminative Model-Constrained Graph Cuts Approach to Fully Automated Pediatric Brain Tumor Segmentation in 3-D MRI**", Michael Wels, Gustavo Carneiro, Alexander Aplas, Martin Huber proposed a fully automated approach to the segmentation of pediatric brain tumors in multi-spectral 3-D magnetic resonance images. It is a top-down segmentation approach based on a Markov Random Field (MRF) model that combines Probabilistic Boosting Trees (PBT) and lower-level segmentation via graph cuts. The entire processing of one multi-spectral data set does not require any user interaction, and takes less time than previously proposed methods.

[7] **"3D brain tumor segmentation in MRI using fuzzy classification, symmetry analysis and spatially constrained deformable models"** Hassan Khotanlou, Olivier Colliot, Jamal Atif, Isabelle Bloch have implemented a new general method for segmenting brain tumors in 3D magnetic resonance images. This method is applicable to different types of tumors. First, the brain is segmented using a new approach, robust to the presence of tumors. Then a first tumor detection is performed, based on selecting asymmetric areas with respect to the approximate brain symmetry plane and fuzzy classification. Its result constitutes the initialization of a segmentation method based on a combination of a deformable model and spatial relations, leading to a precise segmentation of the tumors. Imprecision and variability are taken into account at all levels, using appropriate fuzzy models. The results obtained on different types of tumors have been evaluated by comparison with manual segmentations. This approach has some advantages such as automation (in the symmetry analysis method, a reduced interaction is required to select the appropriate peaks in the difference histogram), and more generality with respect to the wide range of tumors. A limit of this approach is that the symmetry analysis may fail in the case of a symmetrical tumor across the mid-sagittal plane.

[8] "**Level-set Segmentation of Brain Tumors in Magnetic Resonance Images**", Sima Taheri has implemented Three-dimensional segmentation is reliable approach to achieve an accurate estimate of the tumor volume. This estimate is useful for several applications such as assessing tumor growth, assessing treatment responses, planning radiation therapy, and constructing tumor growth models. Among all possible methods for this purpose, the level set is a powerful tool which implicitly extracts the tumor surface. The major challenge of the level set algorithms is to set the equation parameters, especially the speed function. These approaches are examined on 16 MR images and the experimental results confirm their effectiveness.

[9] **"Brain Tumour Detection from MRI Images Using MATLAB",** Rajesh C. Patil, Dr. A. S. Bhalchandra in International Journal of Electronics, Communication & Soft Computing Science and Engineering (ISSN: 2277-9477, Volume 2, Issue 1) have proposed strategy to detect & extraction of brain tumour from patient's MRI scan images of the brain. This method incorporates with some noise removal functions,

segmentation and morphological operations which are the basic concepts of image processing. Detection and extraction of tumour from MRI scan images of the brain is done by using MATLAB software.

[10] **“Quick Detection of Brain Tumors and Edemas: A Bounding Box Method Using Symmetry”,** Baidya Nath Saha, Nilanjan Ray, Russell Greiner, Albert Murtha proposed a novel automated, fast, and approximate segmentation technique brain tumor or edema segmentation from MR modalities. This method is based on an unsupervised change detection method that searches for the most dissimilar region (axis-parallel bounding boxes) between the left and the right halves of a brain in an axial view MR slice. This change detection process uses a novel score function based on Bhattacharya coefficient computed with gray level intensity histograms. It has been proved that this score function admits a very fast search to locate the bounding box. The average dice coefficients for localizing brain tumors and edemas, over ten patient studies, are 0.57 and 0.52 respectively, which significantly exceeds the scores for two other competitive region-based bounding box techniques.

[11] **"A novel content-based active contour model for brain tumor segmentation,"** J. Sachdeva, V. Kumar, I. Gupta, N. Khandelwal, and C. K. Ahuja, A. Hamamci, N. Kucuk, K. Karaman, K. Engin, and G. Unal, Intensity-based active contour models such as Gradient Vector Flow (GVF), Magneto static Active Contour (MAC) and Fluid Vector Flow (FVF) have been proposed to segment homogeneous objects/tumors in medical images. In this study, extensive experiments are done to analyze the performance of intensity-based techniques for homogeneous tumors on brain Magnetic Resonance (MR) images. They also have pre-convergence problem in case of false edges/saddle points. However, the presence of weak edges and diffused edges (due to edema around the tumor) leads to over segmentation by intensity-based techniques. Therefore, the proposed method Content-Based Active Contour (CBAC) uses both intensity and texture information present within the active contour to overcome above-stated problems capturing large range in an image.

[12] “**Context-sensitive Classification Forests for Segmentation of Brain Tumor Tissues**”, D. Zikic, B. Glocker, E. Konukoglu, J. Shotton, A. Criminisi, have implemented a method for tissue-specific segmentation of high-grade brain tumors. The main idea is to cast the segmentation as a classification task, and use the discriminative power of context information. The idea by equipping a Classification Forest (CF) with spatially non-local features to represent the data, and by providing the CF with initial probability estimates for the single tissue classes as additional input (along-side the MRI channels). This method is fully automatic, with segmentation run times in the range of 1-2 minutes per patient. This method is fully automatic, with segmentation run times in the range of 1-2 minutes per patient.

[13] “**Decision Forests for Tissue-specific Segmentation of High-grade Gliomas in Multi-channel MR**”, D. Zikic, B. Glocker , E. Konukoglu, A. Criminisi, C. Demiralp, J. Shotton have proposed a method for automatic segmentation of high grade gliomas and their sub regions from multi-channel MR images. Besides segmenting the gross tumor, it also differentiated between active cells, necrotic core, and edema. The accuracy of our method is evaluated quantitatively on a database of 40 high-grade glioma patients to our knowledge, the largest annotated database of this kind so.

[14] “**Segmentation of Brain Tumor Images Based on Integrated Hierarchical Classification and Regularization**”, Stefan Bauer, Thomas Fejes, Johannes Slotboom have proposed a method fully automatic method for brain tumor segmentation, which integrates random forest classification with hierarchical conditional random field regularization in an energy minimization

scheme. It has been evaluated on the BRATS2012 dataset, which contains low- and high-grade gliomas from simulated and real-patient images. The method achieved convincing results (average Dice coefficient: 0.73 and 0.59 for tumor and edema respectively) within a reasonably fast computation time (approximately 4 to 12 minutes).

[15] "**3D brain tumor segmentation in multimodal MR images based on learning population- and patient-specific feature sets**", Jun Jiang, Yao Wu, Meiyan Huang, Wei Yang, Wufan Chen, Qianjin Feng have proposed a method to construct a graph by learning the population- and patient-specific feature sets of multimodal magnetic resonance (MR) images and by utilizing the graph-cut to achieve a final segmentation. The probabilities of each pixel that belongs to the foreground (tumor) and the background are estimated by global and custom classifiers that are trained through learning population- and patient-specific feature sets, respectively. The encouraging evaluation results obtained, i.e., DSC (84.5%), Jaccard (74.1%), sensitivity (87.2%), and specificity (83.1%), show that the proposed method can effectively make use of both population- and patient-specific information. This method does not focus on lesion contouring.

III. Methodology

The classification method requires no explicit regularization because the patch feature contains the contextual information of a voxel in the image. This method leads a natural smoothness to the segmentation results without explicit regularization by using this contextual information

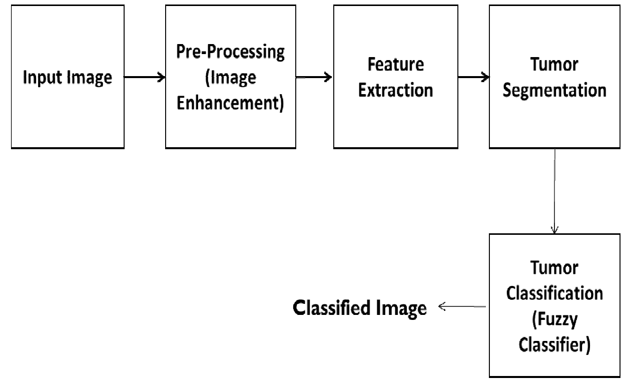

Fig 1: Proposed Fuzzy Framework

.

A very popular unsupervised method for medical image segmentation is fuzzy c-means (FCM) clustering algorithm. The Fuzzy Cluster Means algorithm is concerned with the spatial or contextual information considered for the generation of tissue classes.CM has motivated a significant amount of research in the context of MRI brain tumor segmentation. Specifying number of clusters is a trivial task, since the tumor presents a heterogeneous intensity pattern that overlaps with healthy brain tissues. This determines that in different clusters that represent different healthy tissues, e.g., white matter, gray matter, etc. Other contextual features may be added as a proposed work to improve the classification accuracy.

A. Preprocessing

Pre-processing generally means removing noise and improving or altering image quality to suit a purpose. Image enhancement and noise reduction techniques were implemented. The image enhancement yields the result of more prominent edges and a sharpened image, noise will be reduced thus reducing the blurring or salt paper effect from the image that might produce errors.

After image enhancement, image segmentation will be applied. This step is vital as the improved and enhanced image will yield better results when detecting edges and improving the quality of the overall image. Edge detection will lead to determining and understanding the outline shape of the tumor.

1) ***Noise Removal:*** There is a wide range of filters available to be used to remove the noise from the images. Linear filters present on Matlab with simple line of code can also serve the purpose such as Gaussian and averaging filters. Salt and pepper noise is a common noise present in original captured images. Average filters for example, can remove these noise but with the sacrifice of sharpness of image. Median filter is also another example of a filter used to remove the noise like salt and pepper. In the median filter value of pixel is determined by the median of the values of its neighboring pixels. This filter however, is less sensitive to the outliers.

2) ***Image Sharpening:*** Sharpening is generally achieved by using high pass filters. After applying low pass filters (noise removing step), the image need to be sharpened and ensuring that edges are kept. This is important as edges will detect and highlight the tumor for us. Gaussian filter (a high pass filter) is used to enhance the boundaries of the objects.

B. Feature Extraction

Feature Extraction is a method of capturing visual content of images for indexing & retrieval. The issue of choosing the features to be extracted should be guided by the following concerns: the features should carry enough information about the image and should not require any domain-specific knowledge for their extraction. They should be easy to compute in order for the approach to be feasible for a large image collection and rapid retrieval. They should relate well with the human perceptual characteristics since users will finally determine the suitability of the retrieved images. Color feature is one of the most widely used feature in Image Retrieval. Color Histogram is the most used in color feature representation. Textures features can be rough or smooth, vertical or horizontal etc. Generally they capture patterns in the image data (or lack of them), e.g. repetitiveness and granularity.

C. Segmentation

Edge detection is the most vital part in tumor detection. It is used to determine the boundaries of the object. In this step, canny edge filter is used. "Five steps in canny filter: 1.Filters out noise in original image 2.Smoothing the image using filters 3.Finding the edge directions with library of orientation 4. Relate to a direction that can be traced in an image 5.After edge directions are known, non-maximum suppression is done to thin out of remove edges based on threshold values determined."

D. Classification – FCM Classifier

Fuzzy c-means (FCM) algorithm is the most popular method used in image segmentation because it has robust characteristics for ambiguity and can retain much more information than hard segmentation methods. Although the conventional FCM algorithm works well on most noise-free images, it has a serious limitation: it does not incorporate any information about spatial context, which cause it to be sensitive to noise and imaging artifacts. To compensate for this drawback of FCM, the obvious way is to smooth the image before segmentation. However, the conventional smoothing filters can result in loss of important image details, especially image boundaries or edges.

The Fuzzy C-Means (FCM) clustering algorithm is an iterative clustering method that produces an optimal c partition by minimizing the weighted within group sum of squared error objective function,

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^{m} \left\| x_i - c_j \right\|^2 \qquad 1 \le m < \infty$$

where m is any real number greater than 1, u_{ij} is the degree of membership of xi in the cluster j, xi is the ith of d-dimensional measured data, c_j is the d-dimension center of the cluster, and ||*|| is any norm expressing the similarity between any measured data and the center.

Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership u_{ij} and the cluster centers c_j by:

$$u_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|}\right)^{\frac{2}{m-1}}}, \qquad c_j = \frac{\sum_{i=1}^{N} u_{ij}^m \cdot x_i}{\sum_{i=1}^{N} u_{ij}^m}$$

1. Initialize U=[u_{ij}] matrix, $U^{(0)}$

   A new matrix is initialized to store the pixels.

2. At k-step: calculate the centers vectors $C^{(k)}$=[c_j] with $U^{(k)}$

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^m \cdot x_i}{\sum_{i=1}^{N} u_{ij}^m}$$

3. Update $U^{(k)}$, $U^{(k+1)}$

$$u_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|}\right)^{\frac{2}{m-1}}}$$

4. If $\| U^{(k+1)} - U^{(k)}\| < \varepsilon$ then STOP; otherwise return to step 2.
5. Calculate weight so as to provide good accuracy in case of noise data as,

$$w_{ji} = \exp[(-x_j - v_i)^2 / (\sum(x_j - v_i)^2 * (c/n))]$$

The data is first presented according to example pictures of the image processes involved in the system. The image used is of grayscale MRI brain scans. First we acquire the images and pre-processes it.

Next the edges of the images are specified with the various edge detection techniques.

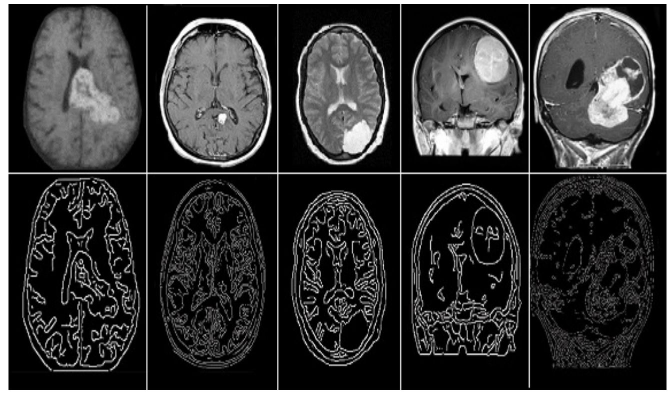

Fig 1: Extracted Edge Features

The edges are extracted to discriminate the tumor tissues and their presence on the folding of brain tissues. The above Fig 1. Shows the input image and their corresponding detected edge using the Canny Feature edge detector.

The formation of clusters are designed and the cluster size is specified. The FCM works recursively to obtain the accurate tumor region.

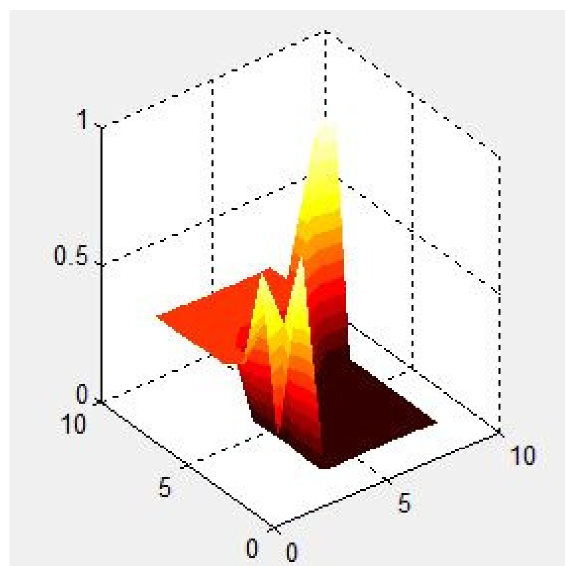

Fig 2: Tumor affected region in 3D graph representation

Depending on the size of the cluster each time the membership function varies and a 3D graph is generated to show the tumor region which is represented in Fig2.

Finally the tumor is segmented after the successful classification by the FCM classifier. Fig3. Shows the final segmented image.

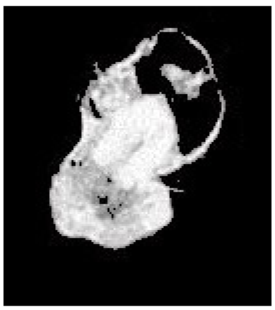

Fig 3: Segmented Tumor

IV. Conclusion

The proposed work integrates the Fuzzy C-Means and segmentation techniques and successfully detects the tumor, even in the brain. Compared with the ground truth, this quantifiable method shows a feasible detection rate and good accordance. The system, therefore, demonstrates high potential for practical clinical use, and may assist medical experts with tumor location, volumetric estimation, therapeutic planning and follow-up. The preliminary results also demonstrate the efficacy and efficiency of our four-step brain tumor detection and localization approach and motivate us to extend this framework to detect and localize a variety of other types of tumors in other types of medical imagery.

Future aims include the improvement of the system's calculation loading, exploring the potential use of other MR modalities, and experimenting with the 3D image format.

REFERENCES

[1] M. R. Kaus, S. K. Warfield, A. Nabavi, P. M. Black, F. A. Jolesz, and R. Kikinis, "Automated segmentation of MR images of brain tumors," Radiology, vol. 218, no. 2, pp. 586-91, Feb 2001.

[2] N. Moon, E. Bullitt, K. V. Leemput, and G. Gerig, "Model-based brain and tumor segmentation," in 16th International Conference on Pattern Recognition, 2002.

[3] M. B. Cuadra, C. Pollo, A. Bardera, O. Cuisenaire, J. G. Villemure, and J. P. Thiran, "Atlas-based segmentation of pathological MR brain images using a model of lesion growth," IEEE Transactions on Medical Imaging, vol. 23, no. 10, pp. 1301-1314, 2004.

[4] M. Prastawa, E. Bullitt, S. Ho, and G. Gerig, "A brain tumor segmentation framework based on outlier detection," Med Image Anal, vol. 8, no. 3, pp. 275-83, Sep 2004.

[5] C.H. Lee, S.Wang, A. Murtha, M.R. Brown, and R. Greiner, "Segmenting brain tumors using pseudo-conditional random fields," presented at the Med Image Comput Comput Assist Interv, 2008.

[6] M. Wels, G. Carneiro, A. Aplas, M. Huber, J. Hornegger, and D. Comaniciu, "A discriminative model-constrained graph cuts approach to fully automated pediatric brain tumor segmentation in 3-D MRI," presented at the Med Image Comput Comput Assist Interv, 2008.

[7] H. Khotanlou, O. Colliot, J. Atif, and I. Bloch, "3D brain tumor segmentation in MRI using fuzzy classification, symmetry analysis and spatially constrained deformable models," Fuzzy Sets and Systems, vol. 160, no. 10, pp. 1457-1473, 2009.

[8] S. Taheri, S. H. Ong, and V. F. H. Chong, "Level-set segmentation of brain tumors using a threshold-based speed function," Image and Vision Computing, vol. 28, no. 1, pp. 26-37, 2010.

[9] D. Bhattacharyya and T. H. Kim, "Brain tumor detection using MRI image analysis," Communications in Computer and Information Science, vol. 151, pp. 307-314, 2011.

[10] B. N. Saha, N. Ray, R. Greiner, A. Murtha, and H. Zhang, "Quick detection of brain tumors and edemas: A bounding box method using symmetry," Computerized Medical Imaging and Graphics, vol. 36, no. 2, pp. 95-107, 2012.

[11] J. Sachdeva, V. Kumar, I. Gupta, N. Khandelwal, and C. K. Ahuja, "A novel content-based active contour model for brain tumor segmentation," Magnetic Resonance Imaging, vol. 30, no. 5, pp. 694-715, Jun 2012.

[12] D. Zikic, B. Glocker, E. Konukoglu, J. Shotton, A. Criminisi, D. H. Ye, C. Demiralp, O. M. Thomas, T. Das, R. Jena, et al., "Context-sensitive classification forests for segmentation of brain tumor tissues," in Proceedings of MICCAI-BRATS 2012, France, 2012.

[13] D. Zikic, B. Glocker, E. Konukoglu, A. Criminisi, C. Demiralp, J. Shotton, O. M. Thomas, T. Das, R. Jena, and S. J. Price, "Decision forests for tissue-specific segmentation of high-grade gliomas in multi-channel MR," presented at the Med Image Comput Comput Assist Interv, 2012.

[14] S. Bauer, T. Fejes, J. Slotboom, R. Wiest, L.-P. Nolte, and M. Reyes, "Segmentation of brain tumor images based on integrated hierarchical classification and regularization," in Proceedings of MICCAI-BRATS 2012.

[15] J. Jiang, Y. Wu, M. Huang, W. Yang, W. F. Chen, and Q. J. Feng, "3D brain tumor segmentation in multimodal MR images based on learning population and patient specific feature sets," Computerized Medical Imaging and Graphics, vol. 37, no. 7-8, pp. 512-521, Jun 28 2013.