Brain Tumor Segmentation Methods-A Survey

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Abstract--- The objective of this article is to throw light on contemporary and existing brain tumor identification and segmentation methods from MRI brain images. An aberrant proliferation of cells in the brain is referred to as brain tumor. The brain tumors are classified as benign and malignant (cancerous tumor). Identifying the malignant tumor(s) in the early stage becomes challenging for the physicians. Hence, the automated brain tumor segmentation algorithms were evolved to overcome the dilemma in identifying and locating the brain tumors. In this article, the authors presented the contemporary and existing brain tumor segmentation algorithms and techniques evaluated on real time and standard datasets with its performance measures.

Keywords--- Brain Tumor, Segmentation, MRI, Cancerous Cells, Clustering Algorithm, Classification.

I. Introduction

The brain tumor is defined as the aberrant proliferation of cells in the brain. According to [1], the brain tumor is classified as primary (starts growing within the brain) and secondary tumor (starts growing from another part of the body and then spread to the brain through the bloodstream). The primary brain tumor is categorized as benign and malignant tumors.

The features of benign tumors are not cancerous, slow growth and do not affect nearby cells whereas the malignant tumors are cancerous cells which grow fast and affects nearby tissues very quickly. Some of the common primary brain tumors are summarized from [1] includes glioma, Primitive Neuroectodermal Tumor (PNET), pineal gland tumors, pituitary tumor, Craniopharyngioma, Schwannoma, Meningioma and Central Nervous System lymphoma.

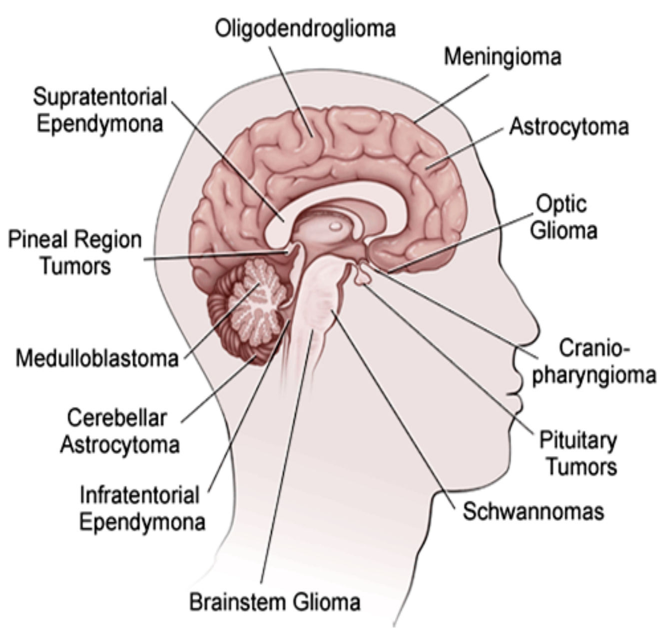

Figure 1: Different Locations of Brain Tumors (Courtesy [1])

The secondary brain tumors are also referred as metastatic brain tumor is graded as Lung Cancer, breast cancer, melanoma, colon cancer and Kidney cancer. Figure 1 shows the various locations of tumor possibilities in the brain depicted from [1].

II. Brain Tumor Segmentation

Figure 2 shows the necessary steps in identifying and locating the tumors in the MRI brain images. The input MRI brain image is enhanced, and intensity is normalized to improve the clarity of the input image. Further, the enhancement process aids in removing or reducing the noise and blurring effect and reveals the content with excellent clarity. Then follows the segmentation, feature extraction and classification methods. During the classification stage, the input image is compared with the trained data to validate the presence of tumor. During the abnormal scenarios (in the presence of a tumor), the tumor location is accurately identified, located and segmented in the input image.

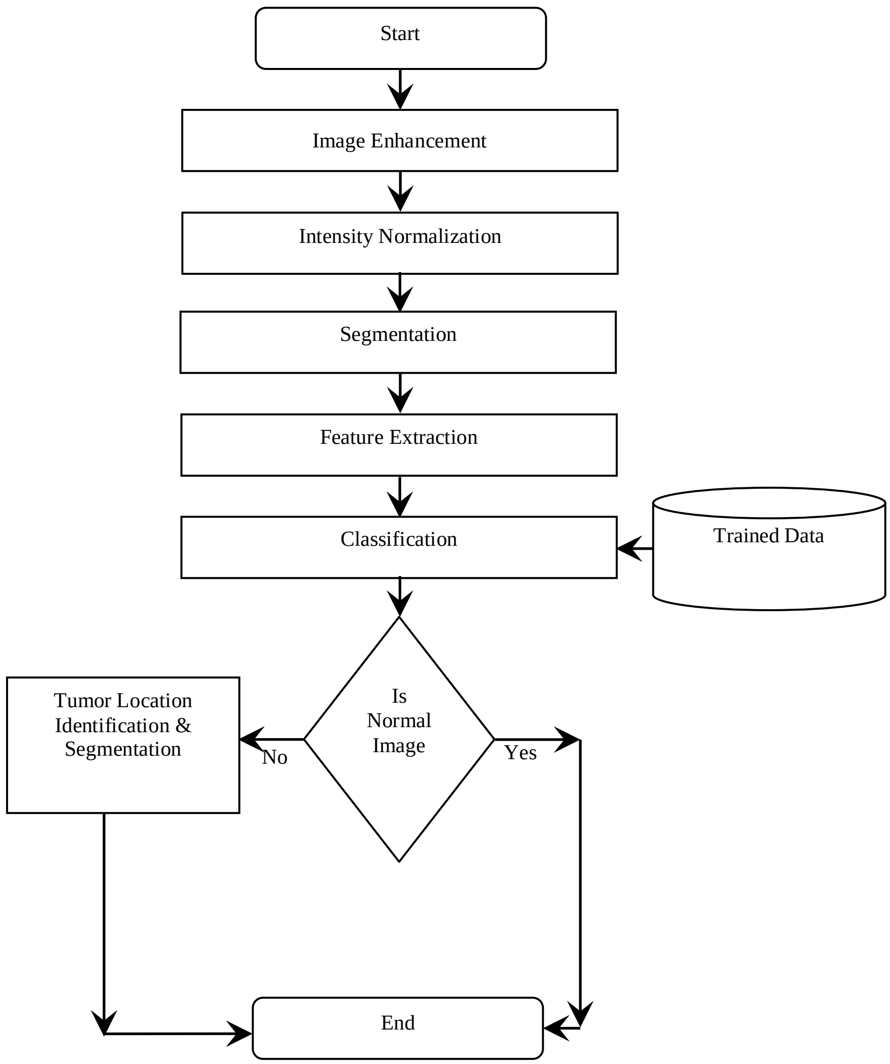

Figure 2: Steps in Brain Tumor Segmentation

In this paper, Section 3 deals with the existing and contemporary methods in brain tumor segmentation methods. The general discussion about the brain tumor identification and localization is provided in section 4. Section 5 draws the conclusion

III. Existing Methods of Brain Tumor Segmentation

This section provides the overview of existing and contemporary brain tumor segmentation methods evaluated with various datasets.

Neda and Hamid [2] determined an automated method for segmentation of brain tumors in MRI. This proposed method includes removal of the skull, other non-brain tissues and projection of the tumor image to determine ROI or primary region. The identified primary region was grown to segment the tumor. The proposed automatic method was tested on 12 patients with Gd-enhanced areas in their brain tumors and was acquired from 3 Tesla GE systems with multi-parametric images. The segmentation results showed excellent correlations with expert radiologists. The method was tested on the images from 12 patients (3 female and 9 male) and not with standard data sets.

Ehab F.Bhadran, Nadder Hamdy, Esraa Galal Mahmoud [3] proposed an algorithm to classify the brain into two categories as healthy or a brain with tumor. After identification of tumor, it is further classified into benign or malignant tumor. When compared to other algorithms, this algorithm used LOG – Lindeberg algorithm and Harris – Laplace algorithm in feature extraction process. This method was evaluated with 102 images collected from the World Wide Web and not tested with any of the standard datasets. Experiment results from both the techniques (Canny edge detection with Harris and Adaptive threshold with Harris) resulted in error free tumor identification.

Gondal and Ahmed Khan [4] highlights the strengths and limitation of contemporary segmentation techniques in Brain tumor detection using MRI images. Anjum analyzed (13 algorithms of) 13 different authors and their proposed/ contemporary technique of detecting Brain tumor. Normally image segmentation is a fundamental step in tumor detection carried out with different methods. The author neither introduced a new technology nor highlighted the best method for segmentation.

Dhivya, Preethi and Kirthika [5] presented an overview of brain tumor segmentation methods using Fuzzy C Means algorithm in MRI of brain images. The various segmentation methods discussed in this paper includes thresholding, region growing, mean shift, Clustering and Fuzzy means techniques. The refinement of FCM algorithm such as Fast Generalized FCM, automatic modified FCM, Fuzzy Probabilistic C-Means approach and bias Corrected FCM were discussed in detail. Moreover, the authors failed to represent the dataset and the corresponding segmentation accuracy.

David [6] proposed tissue segmentation with linear “Eigen image” filtering and normalization. The method was compared with the contemporary segmentation techniques using T1 Weighted MRI in 5 subjects. The database was a collection of several, thick slice; fast spin echo images (ESE) of different contrast. Application to single voxel spectroscopy was also possible by using this method.

Murthi and Shameer [7] proposed a two-stage method for detecting the brain tumor in the MRI images. The two stages were modified K-Means Clustering approach and Hierarchal Centroid Shape Descriptor (HCSD) method. As the K-Means Clustering leads to time-consuming process, Modified K-Means Clustering approach was used. HCSD was used to identify the location of the tumor for better results. This method is evaluated with the real-time T1 weighted scanned images of brain MRI images. The metrics used to evaluate the proposed method were Jaccard Dice indices. When compared with the earlier methods such as K-Means, HCSD multilevel Otsu and HCSD K-Means, the proposed method (Modified K-Means along with HCSD) resulted in higher similarities with expert’s opinion. Though the authors specify the percentage of similarity measure with other methods, they failed to specify the time duration to detect the tumor in brain MRI images.

Naveen and Velmurugan [8] proposed K-Means Algorithm to identify the tumor in MRI images using Clustering technique. The pixels in an MRI brain image were clustered to fortify the quality of clustering algorithm. The algorithm, when applied on MRI brain image, identified the tumor correctly. Though the algorithm used Point Outliers from MRI imagery, no standard dataset was used to test the method. Moreover, the number of pixels differs when the number of clusters taken was 8 and 16. The variation in clusters and pixels ensured that the proposed method needs further refinement.

Shanmugapriya and Ramakrishnan [9] compared the two Kernel function of the Support Vector Machine (SVM) to process and analyze the bulk images for the diagnosis and treatment procedure of Brain tumors. The segmentation accuracy and segmentation error were compared for both the Kernel function polynomial and RBF. The results depicted that RBF Kernel outperformed than the earlier method. This method was evaluated with the brain MRI images collected from the Scan center and failed to present the number of images used for evaluating the proposed method.

Zeljkovic, Druzgalski, Zhang, Zhu, Xu, Zhang and Mayorga [10] proposed an automated algorithm for brain tumor detection. The enhanced brain MR images showed the skull and meninges in pure white color and are removed. On applying global threshold segmentation and superimposing, the tumor part on the original brain diagnosis becomes easier. The method was tested on 120 images (60 brain images with tumor and 60 healthy brain images). The method resulted in 93.33% accuracy in abnormal images and 100% accuracy on healthy brain MR images. The possibility of human error and misdiagnosis were reduced by the proposed method.

Phooi and Frank [11] proposed a concept and simple classification method using multi-parameter features on supervised block to classify brain images. The proposed method classified tumor areas in T2 Weighted medical brain images. The edge, contrast and gray values were the three parameters used to detect the tumors in the brain images. When this method is tested on T2 Weighted MRI brain images captured under different technical conditions and clinical scenarios, the abnormalities were detected very clearly within the response time of 176 milliseconds. Even though the authors evaluated this method on the Whole Brain Atlas V.1.0 dataset, but failed to specify the number of images used for evaluation and tumor detection accuracy.

Mikula [12] proposed a segmentation method of brain tumor in MR images where the tumor portion is separated into individual parts namely actual tumor, the surrounding edema and the necrotic tissue. During perfusion imaging, the edema mask was applied.

The author described a technique where the segmentation is interpreted as multidimensional data set, which was further classified into predefined classes based on a training set.The results of tumor segmentation indicated the lower sensitivity of the method. Experimental results concluded that this method had inaccurate segmentation when compared with the ground truth segmentation results. The major pitfall of this method lies in the extensive training phase to improve the segmentation accuracy.

Anahita Fathi Kazerooni, Alireza Ahamadian, Nassim Dadashi Seraj, Hamidreza Saligheh Rad, Hooshang Saberim, Hossein Yousefi, Parastoo Farina [13] proposed Multi-Scale Gradient Vector Flow (MSGVF) for medical image segmentation of tumor.

The traditional Gradient Overflow method and Bspline snake were modified in MSGVF method. To segment the brain tumor in MRI images, multiscale was applied to traditional GVF algorithm and to evolve active contour Bspline snake was used by applying a threshold based edge detector to the GVF algorithm.

The improved MSGVF algorithm was tested on the datasets of Surgical Planning Lab at Harvard Medical School website. The patients with “oligoastocytoma” and “Glioblastoma” brain tumors were used for evaluation. The validation of the result was accurate as it was compared to the ground truth obtained from radiologists. MSGVF algorithm yielded 92.8% accuracy in 15.2 sec with 95.4% sensitivity.

Even though the algorithm was tested on mild noise images, the robustness of this algorithm needs improvement in high noise environments.

Zafer Iscan, Zumray Dokur, Jamer Olmez [14] proposed a novel method to detect tumor in MR brain images. 2D continuous Wavelet Transform was applied on brain images followed by Segmentation using the Incremental Supervised Neural Network (ISNN) and wavelet-bands, determination of symmetry and asymmetry on those segmented tissues using Zernike moments on the sagittal plane. The method was tested on one phantom and 20 original MR brain images and 50 healthy brain images. This method accurately identified the 20 tumor brain images.

Varsha and Panchal [15] compared two contemporary methods of segmentation in tumor detection namely K-Mean Clustering and Fuzzy C-Means Clustering methods.

The efficacy of both the methods was compared based on execution time and accuracy in identifying the tumor region.

The results revealed that the K-Means Clustering method outperformed the other because it worked without any preprocessing and supervision with lesser iterations. The author claimed to test the algorithm in 100 MRI brain images with 95% efficacy in K-Means method.

IV. Discussion

This section deals with the summary of the existing brain tumor segmentation methods discussed in section 2. Table 1 shows the overview of algorithms used for identification and segmentation of brain tumor. Even though some of the previous algorithms ([2], [3], [10], [12] and [15]) resulted in better segmentation accuracy, it lacks with processing time.

In contrast, the algorithms with less processing time lacks with segmentation accuracy. Hence, these two factors (segmentation accuracy and processing time) have to be managed equally for the algorithm to be very efficient. By considering most the factors in the existing algorithms, the authors would like to focus on refining the Fuzzy C-Means clustering algorithm for dynamic localization of tumors in the brain images.

Table 1: Summary of Existing Methods

S.No.	Year	Author Name	Methodology adopted	Dataset	Accuracy
1	2012	Neda Behzadfar, Hamid Soltanian [2]	ROI or primary region	Henry Ford Health System, Detroit, MI,USA(9 male and 3 female of age 36-66)	Correlation = 0.968
2	2010	Ehab Bhadran, Nadder Hamdy, Esraa Galal Mahmoud [3]	LOG – Lindeberg algorithm and Harris – Laplace algorithm	102 images from World Wide Web	Method I : 100% Method II : 93.75%
3	2013	Anjum Hayat Gondal,Muhammad Naeem Ahmed Khan [4]	Comparison of contemporary brain tumor detection techniques	Not applicable	Not applicable
4	2016	Dhivya, Preethi, Krithika [5]	Fuzzy C Means algorithm	Not specified	Not specified
5	2005	David Bonekamp, Alena Horka, Michael Jacob, Atilla Arslanoglu, Peter Barker [6]	Eigen image filtering and normalization; T1 Weighted MRI	ESE images of five healthy subjects with prior protocol	Gray Matter correlation =0.893 White Matter Correlation= 0.892
6	2016	Murthi and Shameer [7]	Hierarchal Centroid Shape Descriptor(HCSD)	Images from Govt. Mohan Kumaramangalam Medical College, Salem, TN, India.	HCSD Modified K Means - Dice index=0.93
7	2015	Naveen and Velmurugan [8]	Clustering Technique; Point Outliers	DICOM images	Attained maximum efficiency when no: of clusters= 16 in K-Means algorithm
8	2014	Shanmugapriya, T.Ramakrishnan [9]	Support Vector Machine, Kernel Function Polynomial & RBF	Images from Scan center	Segmentation accuracy =81.94(AVG) Segmentation error = 6.24(AVG)
9	2014	Zeljkovic, Zhang, Zhu, Xu, Zhang, Mayorga [10]	Global Threshold Segmentation and Superimposing	120 images	100 % on healthy brain images and 93.3% accuracy in abnormal images
10	2005	Phooi Yee Lau, Frank Voon, Shinji Ozawa [11]	Edge, Gray & Contrast parameter	Whole Brain V.1.0 dataset	Not specified
11	2013	Jan Mikulka, Radim Burget, Kamil Riha, Eva Gescheidtova [12]	Perfusion imaging-edema mask	105 MR images of patients	Accuracy=99.71(avg) Sensitivity = 0.83 (avg)
12	2011	Anahita Fathi Kazerooni, Alireza Ahamadian, Nassim Dadashi Seraj, Hamidreza Saligheh Rad, Hooshang Saberim, Hoosein Yousefi, Parastoo Farina [13]	Multi Scale Gradient Vector Flow	Datasets of Surgical Planning Lab at Harvard Medical School website	92.8% accuracy
13	2010	Zafer Iscan, Zumray Dokur, Jamer Olmez [14]	2D continuous Wavelet Transform, Incremental Supervised Neural Network(ISNN), Zernike moments on the sagittal plane	70 MR images (20 original MR bain images ; 50 healthy brain images)	Segmentation performance =100%
14	2015	Varsha and Panchal [15]	Comparison of K-Mean Clustering and Fuzzy C-Means Clustering methods	100 MRI images	95% efficacy

V. Conclusion

In the past decades, the image segmentation process played a vital role in the medical analysis and interpretations. Further, the image segmentation is the first stage in almost all the image analysis methodologies. Even though there exists some state-of-the-art algorithms in the brain tumor segmentation methods, that algorithm needs improvement and refinement in the parameters like precision, accuracy and processing time. Upon presenting the study of various existing and contemporary brain tumor segmentation methods, authors would like to work on improving the accuracy with less processing time by using Fuzzy C-Means clustering algorithm in the future implementation phase.

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