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Review on Brain Tumor Segmentation and Classification Techniques

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***Abstract:-* Magnetic resonance imaging (MRI) is an advanced medical imaging technique providing rich information about the human soft tissue anatomy. Segmentation plays the vital role in the medical image processing. There are several typical MRI segmentation approaches such as Thresholding techniques, Edge-based methods, Region-based segmentation, Cooperative hierarchical computation approach, Statistical approaches, and ANN image segmentation techniques. One more important phase in the medical sciences is Brain tumor classification, the images acquired from different modalities such as CT, MR that should be verified by the physician for the further treatment, but the manual classification of the MR images is the challenging and time consuming task. The main aim of this research and review paper is to explore the existing segmentation and classification techniques in the medical image processing.**

Keywords: MRI, ANN, CT.

I. INTRODUCTION:

Segmentation subdivides an image in to number objects from which we can find the Region of Interest (ROI) for the specific task to perform. Also, Segmentation of MR images into different tissue classes, especially gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF), is an important task[1] .There are several typical MRI segmentation approaches as follows:

Threshold techniques: where the classification of each pixel depends on its own information such as intensity and color information. Those techniques are efficient when the histograms of objects and background are clearly separated.

Edge-based methods: which are focused on detecting contour, they fail when the image is blurry or too complex to identify a given border.

Region-based segmentation: in which the concept of extracting features (similar texture, intensity levels, homogeneity or sharpness) from a pixel and its neighbors is exploited to derive relevant information for each pixel.

Cooperative hierarchical computation approach: Use pyramid structures to associate the image properties to an array of father nodes, selecting iteratively the point that average or associate to a certain image value.

Statistical approaches: This type of method labels pixels according to probability values, which are determined based on the intensity distribution of the image. With a suitable assumption about the distribution, statistical techniques attempt to solve the problem of estimating the associated class label, given only the intensity for each pixel. Such an estimation problem is necessarily formulated from an established criterion.

ANN image segmentation techniques: originated from clustering algorithms and pattern recognition methods. They usually aim to develop unsupervised segmentation algorithms. For sometimes the above segmentation approaches are overlapped and can be combined [2].

II. SEGMENTATION TECHNIQUES:

Xiao Xuan, Qingmin Liao (2007) have presented Statistical Structure Analysis in MRI Brain Tumor Segmentation in which a statistical structure analysis based tumor segmentation scheme is presented, which focuses on the structural analysis on both tumorous and normal tissues. Firstly, 3 kinds of features including intensity-based, symmetry-based and texture-based are extracted from structural elements. Then a classification technique using AdaBoost that learns by selecting the most discriminative features is proposed to classify the structural elements into normal tissues and abnormal tissues. Experimental results on 140 tumor-contained brain MR images achieve an average accuracy of 96.82% on tumor segmentation [3].

Shan Shen et.al.(2005) have given MRI Fuzzy Segmentation of Brain Tissue Using Neighborhood Attraction With Neural-Network Optimization in which they have presented A robust segmentation technique based on an extension to the traditional fuzzy c-means (FCM) clustering algorithm. A neighborhood attraction, which is dependent on the relative location and features of neighboring pixels, is shown to improve the segmentation performance dramatically. The degree of attraction is optimized by a neural-network model. Simulated and real brain MR images with different noise levels are segmented to demonstrate the superiority of the proposed technique compared to other FCM-based methods. This segmentation method is a key component of an MR image-based classification system for brain tumors, currently being developed [4].

Tao Wang et.al. (2009) have proposed Fluid Vector Flow and Applications in Brain Tumor Segmentation in which they call the “fluid vector flow” (FVF) active contour model to address problems of insufficient capture range and poor convergence for concavities. With the ability to capture a large range and extract concave shapes, FVF demonstrates improvements over techniques like gradient vector flow, boundary vector flow, and magnetostatic active contour on three sets of experiments: synthetic images, pediatric head MRI images, and brain tumor MRI images from the Internet brain segmentation repository [5].

Andac Hamamci et.al. (2012) have proposed Tumor-Cut: Segmentation of Brain Tumors on Contrast Enhanced MR Images for Radiosurgery Applications in which they present a fast and robust practical tool for segmentation of solid tumors with minimal user interaction to assist clinicians and researchers in radiosurgery planning and assessment of the response to the therapy. Particularly, a cellular automata (CA) based seeded tumor segmentation method on contrast enhanced T1 weighted magnetic resonance (MR) images, which standardizes the volume of interest (VOI) and seed selection, is proposed. First, they establish the connection of the CA-based segmentation to the graph-theoretic methods to show that the iterative CA framework solves the shortest path problem. In that regard, they modify the state transition function of the CA to calculate the exact shortest path solution. Furthermore, a sensitivity parameter is introduced to adapt to the heterogeneous tumor segmentation problem, and an implicit level set surface is evolved on a tumor probability map constructed from CA states to impose spatial smoothness. Sufficient information to initialize the algorithm is gathered fromthe user simply by a line drawn on the maximum diameter of the tumor, in line with the clinical practice [6].

Shaheen Ahmed et.al. (2011) have given Efficacy of Texture, Shape, and Intensity Feature Fusion for Posterior-Fossa Tumor Segmentation in MRI in which they systematically investigate efficacy of using several different image features such as intensity, fractal texture, and level-set shape in segmentation of posterior-fossa (PF) tumor for pediatric patients. They explore effectiveness of using four different feature selection and three different segmentation techniques, respectively, to discriminate tumor regions from normal tissue in multimodal brain MRI. They further study the selective fusion of these features for improved PF tumor segmentation. Their result suggests that Kullback–Leibler divergence measure for feature ranking and selection and the expectation maximization algorithm for feature fusion and tumor segmentation offer the best results for the patient data [7].

Yongyue Zhang et.al. (2001) have proposed Segmentation of Brain MR Images Through a Hidden Markov Random Field Model and the Expectation-Maximization Algorithm, in which they propose a novel hidden Markov random field (HMRF) model, which is a stochastic process generated by a MRF whose state sequence cannot be observed directly but which can be indirectly estimated through observations. Mathematically, it can be shown that the FM model is a degenerate version of the HMRF model. The advantage of the HMRF model derives from the way in which the spatial information is encoded through the mutual influences of neighboring sites. Although MRF modeling has been employed in MR image segmentation by other researchers, most reported methods are limited to using MRF as a general prior in an FM model-based approach. To fit the HMRF model, an EM algorithm is used. They show that by incorporating both the HMRF model and the EM algorithm into a HMRF-EM framework, an accurate and robust segmentation can be achieved [8].

Javad Alirezaie et.al.(1997) have proposed Neural Network-Based Segmentation of Magnetic Resonance Images of the Brain, in which they presents a study investigating the potential of artificial neural networks (ANN's) for the classification and segmentation of magnetic resonance (MR) images of the human brain. In this study, they present the application of a learning vector quantization (LVQ) ANN for the multispectral supervised classification of MR images. They have modified the LVQ for better and more accurate classification. They have compared the results using LVQ ANN versus back-propagation ANN. This comparison shows that, unlike back-propagation ANN, their method is insensitive to the gray-level variation of MR images between different slices. It shows that tissue segmentation using LVQ ANN also performs better and faster than that using back-propagation ANN [9].

Su ruan et.al. (2007) have proposed the Tumor Segmentation from a Multispectral MRI Images by using Support Vector Machine classification, in which they present a supervised system aimed at tracking the tumor volume during a therapeutic treatment from multispectral MRI volumes. Four types of MRI are used in their study: T1, T2, Proton Density (PD) and Fluid Attenuated Inversion Recovery (FLAIR). For decreasing the processing time, the proposed method employs a multi-scale scheme to identify firstly the abnormal field and extract then the tumor region. Both steps use Support Vector Machines (SVMs). The training is carried out only on the first MRI examination (at the beginning of the treatment). The tracking process at the time point *t* takes the tumor region obtained in the examination at *t-1* as its initialization. Only the second step is performed for others examinations to extract the tumor region. The results obtained show that the proposed system achieves promising results in terms of effectiveness and time consummating [10].

Herng-Hua Chang (2007) have proposed a Segmentation of Brain MR Images Using a Charged Fluid Model in which they developed a new deformable model, the charged fluid model (CFM), that uses the simulation of a charged fluid to segment anatomic structures in magnetic resonance (MR) images of the brain. Conceptually, the charged fluid behaves like a liquid such that it flows through and around different obstacles. The simulation evolves in two steps governed by Poisson's equation. The first step distributes the elements of the charged fluid within the propagating interface until an electrostatic equilibrium is achieved. The second step advances the propagating front of the charged fluid such that it deforms into a new shape in response to the image gradient. This approach required no prior knowledge of anatomic structures, required the use of only one parameter, and provided subpixel precision in the region of interest. They demonstrated the performance of this new algorithm in the segmentation of anatomic structures on simulated and real brain MR images of different subjects. The experimental results in different types of MR images indicate that the CFM algorithm achieves good segmentation results and is of potential value in brain image processing applications [11].

Yutaka Hata et.al.(2000) have proposed an Automated Segmentation of Human Brain MR Images Aided by Fuzzy Information Granulation and Fuzzy Inference in which they proposes an automated procedure for segmenting an MR image of a human brain based on fuzzy logic. An MR volumetric image composed of many slice images consists of several parts: gray matter, white matter, cerebrospinal fluid, and others. Generally, the histogram shapes of MR volumetric images are different from person to person. Fuzzy information granulation of the histograms can lead to a series of histogram peaks. The intensity thresholds for segmenting the whole brain of a subject are automatically determined by finding the peaks of the intensity histogram obtained from the MR images. After these thresholds are evaluated by a procedure called region growing, the whole brain can be identified. A segmentation experiment was done on 50 human brain MR volumes. A statistical analysis showed that the automated segmented volumes were similar to the volumes manually segmented by a physician [12].

III. CLASSIFICATION TECHNIQUES

Marlene Huml et.al. (2013), have proposed Brain Tumor Classification Using AFM in Combination with Data Mining Techniques, in which they have proposed a methodology based on atomic force microscopy (AFM) derived images made from histopathological samples in combination with data mining techniques. By comparing AFM images with corresponding light microscopy images of the same area, the progressive formation of cavities due to cell necrosis was identified as a typical morphological marker for a computer-assisted analysis. Using genetic programming as a tool for feature analysis, a best model was created that achieved 94.74% classification accuracy in distinguishing grade II tumors from grade IV ones. While utilizing modern image analysis techniques, AFM may become an important tool in astrocytic tumor diagnosis. By this way patients suffering fromgrade II tumors are identified unambiguously, having a less risk for malignant transformation. They would benefit from early adjuvant therapies [13].

A. Jayachandran et.al. (2013) have proposed Brain Tumor Detection and Classification of MR Images Using Texture Features and Fuzzy SVM Classifier, in which they have given a hybrid algorithm for detection brain tumor in Magnetic Resonance images using statistical features and Fuzzy Support Vector Machine (FSVM) classifier. Brain tumors are not diagnosed early and cured properly so they will cause permanent brain damage or death to patients. Tumor position and size are important for successful treatment. The proposed technique consists of four stages namely, Noise reduction, Feature extraction, Feature reduction and Classification. In the first stage anisotropic filter is applied for noise reduction and to make the image suitable for extracting features. In the second stage, obtains the texture features related to MRI images. In the third stage, the features of magnetic resonance images have been reduced using principles component analysis to the most essential features. At the last stage, the Supervisor classifier based FSVM has been used to classify subjects as normal and abnormal brain MR images. Classification accuracy 95.80% has been obtained by the proposed algorithm. The result shows that the proposed technique is robust and effective compared with other recent works [14].

A.Padma et.al. (2011) have proposed Automatic Classification and Segmentation of Brain Tumor in CT Images using Optimal Dominant Gray level Run length Texture Features, in which their method deals with an efficient segmentation algorithm for extracting the brain tumors in computed tomography images using Support Vector Machine classifier. The objective of their work is to compare the dominant grey level run length feature extraction method with wavelet based texture feature extraction method and SGLDM method. A dominant gray level run length texture feature set is derived from the region of interest (ROI) of the image to be selected. The optimal texture features are selected using Genetic Algorithm. The selected optimal run length texture features are fed to the Support Vector Machine classifier (SVM) to classify and segment the tumor from brain CT images. An avearage accuracy rate of above 97% was obtained usinh this classification and segmentation algorithm [15].

AmirEhsan Lashkari (2010) has given A Neural Network-Based Method for Brain Abnormality Detection in MR Images Using Zernike Moments and Geometric Moments, in which he has introduced one automatic brain tumor detection method to increase the accuracy and yield and decrease the diagnosis time. The goal is classifying the tissues to two classes of normal and abnormal. *MR* images that have been used here are *MR* images from normal and abnormal brain tissues. Here, it is tried to give clear description from brain tissues using *Zernike* Moments, Geometric Moment Invariants, energy, entropy, contrast and some other statistic features such as mean, median, variance and correlation, values of maximum and minimum intensity. It is used from a feature selection method to reduce the feature space too. This method uses from neural network to do this classification. The purpose of this project is to classify the brain tissues to normal and abnormal classes automatically, that saves the radiologist time, increases accuracy and yield of diagnosis [16].

Pauline John (2012) proposed Brain Tumor Classification Using Wavelet and Texture Based Neural Network, in which he introduces an efficient method of brain tumor classification, where, the real Magnetic Resonance (MR) images are classified into normal, non cancerous (benign) brain tumor and cancerous (malignant) brain tumor. The proposed method follows three steps, (1) wavelet decomposition, (2) textural feature extraction and (3) classification. Discrete Wavelet Transform is first employed using Daubechies wavelet (db4), for decomposing the MR image into different levels of approximate and detailed coefficients and then the gray level co-occurrence matrix is formed, from which the texture statistics such as energy, contrast, correlation, homogeneity and entropy are obtained. The results of co-occurrence matrices are then fed into a probabilistic neural network for further classification and tumor detection. The proposed method has been applied on real MR images, and got the best accuracy of classification using probabilistic neural network [17].

Yi-hui Liu et.al. (2011) have proposed Classification of MR Tumor Images Based on Gabor Wavelet Analysis, in which Gabor wavelet analysis is used to extract the texture features of magnetic resonance (MR) tumor images to differentiate between primary central nervous system lymphoma (PCNSL) and glioblastoma multiforme (GBM). Gabor wavelet transform with eight orientations and various frequencies is performed on contrast-enhanced T1-weighted MR images to extract the discriminant features, including tumor shape information. A classification model is built based on the extracted features. Experiments show that the proposed hybrid method, which uses wavelet analysis, Gabor wavelet analysis, a support vector machine classifier, and linear discriminant analysis, can distinguish different diagnosis categories of tumor images [18].

Simon Duchesne et.al. (2008) have proposed MRI-Based Automated Computer Classification of Probable AD Versus Normal Controls, in which the accuracy of
their ACC (Automated Computer Classification) methodology is assessed when presented with real life, imperfect data, i.e., cohorts of MRI with varying acquisition parameters and imaging quality. The comparative methodology uses the Jacobian determinants derived from dense deformation fields and scaled grey-level intensity from a selected volume of interest centered on the medial temporal lobe. The ACC performance is assessed in a series of leave-one-out experiments aimed at separating 75 probable AD (Alzheimer’s dementia) and 75 age-matched normal controls. The resulting accuracy is 92% using a support vector machine classifier based on least squares optimization. Finally, it is shown in the Appendix that determinants and scaled grey-level intensity are appreciably more robust to varying parameters in validation studies using simulated data, when compared to raw intensities or grey/white matter volumes. The ability of cross-sectional MRI at detecting probable AD with high accuracy could have profound implications in the management of suspected AD candidates [19].

Omar S. Al-Kadi et.al. (2008) have proposed Texture Analysis of Aggressive and Nonaggressive Lung Tumor CE CT Images, in which the potential for fractal analysis of time sequence contrast-enhanced (CE) computed tomography (CT) images to differentiate between aggressive and nonaggressive malignant lung tumors (i.e., high and low metabolic tumors). The aim is to enhance CT tumor staging prediction accuracy through identifying malignant aggressiveness of lung tumors. As branching of blood vessels can be considered a fractal process, the research examines vascularized tumor regions that exhibit strong fractal characteristics. The analysis is performed after injecting 15 patients with a contrast agent and transforming at least 11 time sequence CE CT images from each patient to the fractal dimension and determining corresponding lacunarity. The fractal texture features were averaged over the tumor region and quantitative classification showed up to 83.3% accuracy in distinction between advanced (aggressive) and early-stage (nonaggressive) malignant tumors. Also, it showed strong correlation with corresponding lung tumor stage and standardized tumor uptake value of fluorodeoxyglucose as determined by positron emission tomography. These results indicate that fractal analysis of time sequence CE CT images of malignant lung tumors could provide additional information about likely tumor aggression that could potentially impact on clinical management decisions in choosing the appropriate treatment procedure [20].

Lena Gorelick et.al. (2013) proposed Prostate Histopathology: Learning Tissue Component Histograms for Cancer Detection and Classification, in which they describe and evaluate their system for automatic prostate cancer detection and grading on hematoxylin & eosin-stained tissue images. Their approach is intended to address the dual challenges of large data size and the need for high-level tissue information about the locations and grades of tumors. Their system uses two stages of AdaBoost-based classification. The first provides high-level tissue component labeling of a super-pixel image partitioning. The second uses the tissue component labeling to provide a classification of cancer versus non-cancer, and low-grade versus high-grade cancer. They evaluated their system using 991 sub-images extracted from digital pathology images of 50 whole-mount tissue sections from 15 prostatectomy patients. They measured accuracies of 90% and 85% for the cancer versus non-cancer and high-grade versus low-grade classification tasks, respectively [21].

M. G. Kounelakis et.al. (2011) proposed Strengths and Weaknesses of 1.5T and 3T MRS Data in Brain Glioma Classification, in which they provides a method consisting of three steps first, to show that the diagnostic value of the information extracted from two different MRS scanners of 1.5T and 3T is significantly influenced in terms of brain gliomas discrimination. Second, to statistically evaluate the discriminative potential of publicly known metabolic ratio markers, obtained from these two types of scanners in classifying low-, intermediate-, and highgrade gliomas finally, to examine the diagnostic value of new metabolic ratios in the discrimination of complex glioma cases where the diagnosis is both challenging and critical. Their analysis has shown that although the information extracted from 3T MRS scanner is expected to provide better brain gliomas discrimination; some factors like the features selected, the pulse-sequence parameters, and the spectroscopic data acquisition methods can influence the discrimination efficiency [22].

Behnood Gholami et.al. (2013) proposed a Statistical Modeling Approach for Tumor-Type Identification in Surgical Neuropathology Using Tissue Mass Spectrometry Imaging, in which they have given a method for computer-aided histopathological evaluation using mass spectrometry imaging. Specifically, mass spectrometry imaging can be used to acquire the chemical composition of a tissue section and, hence, provides a framework to study the molecular composition of the sample while preserving the morphological features in the tissue. The proposed classification framework uses statistical modeling to identify the tumor type associated with a given sample. In addition, if the tumor type for a given tissue sample is unknown or there is a great degree of uncertainty associated with assigning the tumor type to one of the known tumor models, then the algorithm *rejects* the given sample without classification. Due to the modular nature of the proposed framework, new tumor models can be added without the need to retrain the algorithm on all existing tumor models [23].

D. Jude Hemanth et.al.(2010) have proposed an Application of Neuro-Fuzzy Model for MR Brain Tumor Image Classification in which the application of Adaptive neuro-fuzzy inference systems (ANFIS) for MR brain tumor classification has been demonstrated. Abnormal brain tumor images from four classes namely metastase, meningioma, glioma and astrocytoma are used in this work. A comprehensive feature set and fuzzy rules are selected to classify an abnormal image to the corresponding tumor type. Experimental results illustrate promising results in terms of classification accuracy and convergence rate. A comparative analysis is performed with the representatives of ANN and fuzzy systems to show the superior nature of ANFIS systems [24].

IV. CONCLUSION:

As we presented various segmentation and classification techniques in the field of medical image processing. Most of the research is done on magnetic resonance imaging which give clear cut insight of human anatomy which is helpful for the physician for the further treatment.

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