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A Survey on Segmentation of Brain Tumors using Supervised Techniques

[1]G.S. Gopika, [2]R.M. Bhavadharini, [3]Dr. S. Karthik

[1]*PG Scholar, Computer Science and Engineering, SNS College of Technology, Box. 641035. Coimbatore. India*
[2]*Assistant Professor (SG), Computer Science and Engineering, SNS College of Technology, Box. 641035. Coimbatore. India*
[3]*Professor and Dean, Computer Science and Engineering, SNS College of Technology, Box. 641035. Coimbatore. India*

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ABSTRACT

Background: The medical images are used to diagnose the diseases. In which the brain tumor detection and segmentation is the critical task. Existing several techniques were proposed by many researchers in the field of medical imaging and soft computing for the segmentation of brain tumors. Its methods are accepted in clinical based on the simplicity and the degree. Segmentation in Magnetic Resonance Images (MRI) involves several stages and it is mostly required in classification. **Objective:** The main aim of this paper is to segment the tumor region using unsupervised Fuzzy C-means clustering. **Results:** The segmentation using unsupervised classification can give better performance when comparing with existing techniques. The supervised methods and its issues are reviewed in this paper. **Conclusion:** Image segmentation is wide research area to identify, detect and segment the complex anatomical structures. Especially, in medical Image Analysis the segmentation is considered as important task for diagnosing the disease whether it is in benign or malignant stage. Normally, Supervised Methods described in section III are used for the segmentation and classification. Each supervised technique that needs the prior knowledge or training data for the classification. Some methods can easily identify low grade tumors when comparing with high grade tumors. In the future, Instead of using supervised an unsupervised classification is done followed by optimization may produce better results.

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INTRODUCTION

In medical image analysis, the MRI images are considered very essential to extract and picture information from medical data. Brain tumor segmentation is one of the major research area in medical imaging and which is very useful for the medical field. The automated techniques were invented for the identification and segmentation of abnormalities from normal healthy brain. Magnetic Resonance Images (MRI) is considered for analysis since it provides the information about the tumor type , size and position. Brain is a very complex structure and it is the important part in our human body. But, Brain which is very sensitive to diseases like abnormal growth of tumor cells and it affects the normal structure and behavior of the brain generally called as brain tumor. Automatic techniques have been developed for the diagnosis of tumors. Frequently, the glioma segmentation and classification is difficult due to large quantity of the MR images and blurred images. However, it is difficult to detect the tumor. Since it is entirely covered by skull. So that it needs more techniques to visualize the interior region of the skull. Magnetic Resonance Images (MRI) provide the Labeled data for classification. For the classification supervised methods are used that will categorize the images based on the features that are taken.

The segmentation is done on the medical images by the following process, Before performing segmentation the image which taken as input should be denoised by passing through some high pass or low pass filter. If an image denoised then it is converted into an binary image after that thresholding is performed. After thresholding the classification is done. Based on the classified results image segmentation is performed. Methods for performing the image segmentation can vary depending on the specific applications, imaging modality, and other factors. For example, the requirements of the segmentation of brain can different from the segmentation of the liver. The artifacts such as the noise, partial volume effects, and motion can also have significant effects on the segmentation algorithms and also there is no single segmentation method to get accurate results in medical image.

Corresponding Author: G.S. Gopika, PG Scholar, Computer Science and Engineering, SNS College of Technology, Box. 641035. Coimbatore. India,
Tel: 9597128061 E-mail: gopikags41@gmail.com

This review contains the various supervised techniques used for classification. It contains four sections, in which after this preface section follows three sections. In the section of related works explanation about the supervised techniques and its issues and the final section describes a relative analysis about various techniques.

Related works:

Modified Adaboost Algorithm:

Atiq Islam *et al*. (2013) anticipated a multifractal feature extraction and also the supervised classification technique for the detection and segmentation of brain tumors. They proposed a modified adaboost algorithm to consider several features across multiple patients MRI images. Multi fractal feature extraction does not require deformable image registration with any predefined atlas. Modified adaboost algorithm is linear and increases along with number of sample times to the number component classifiers. In this approach it needs the manual interaction in the initial stage of classification.

Context Sensitive Classification Forest:

D.Zikie *et al*. (2012) suggested that the segmentation as a classification task and they proposed the method as context sensitive classification forest in which the MRI slices of patients are taken as input after that initial probabilities are assigned for the MRI slices. Context sensitive Features are captured, Simultaneous multi label classification is done based on the features captured. Classification forest allows us to classify the brain points based on high dimensional features but the valuation shows that it performs well in high grade tumors but it is not suitable for low grade tumors. Synthetic data have better performance when comparing with real data.

Level- Set Framework:

Tammy Riklin Raviv *et al*. (2012) proposed a level set framework for the specific segmentation of brain tumors on different MR modalities. Here the joint segmentation problem is solved by using the statistically driven level set framework. In level set framework, cost function is calculated for the energy minimization problem and also the gradient descent function is calculated for the fixed parameters to update each level set function in each iteration. Although the common information is used for the segmentation. However no prior knowledge is used for the segmentation.

Tumor cut method:

Andac Hamamci *et al*. (2012) exploited the tumor cut method for the semi automatic segmentation of brain tumors. In this method it requires the user interaction to draw the maximum diameter of the tumor after that background extraction is done to calculate the tumor strengths and the background strengths. At last, the neocrocratic region is segmented within the tumor. Finally, Total tumor segmentation is done based on the probability that are assigned but it gives lower performance on the low grade stimulated data.

Random Forest Classification:

Stefan Ballen *et al*. (2012) proposed a fully automatic segmentation of brain tumors by integrating the random forest classification with hierarchical conditional random field regularization in an energy minimization scheme. So that this scheme improves the computation time. This method uses the random forest as a classifier instead of Support Vector Machine (SVM). By using this supervised classification technique the accuracy is improved.

Fluid Vector Flow (FVF):

Tav Wang *et al*. (2009) make a new approach called as fluid vector flow to solve the problem of insufficient capture range and poor convergence for concavities. It works better when compared with the previous approaches. Fluid vector flow method it is composed of three stages they are 1.binary boundary map generation, 2.vector flow initialization and 3.Fluid Vector Flow (FVF) computation. In the first stage, filtering is done on the input image and a threshold is set to generate a binary boundary map. In the second stage, the entire contour region is identified by the external force field. At the last stage, a seed point is automatically selected from the object boundary and generates a new external force field to evolve the active contour but the fluid vector flow method does not analyze the 3D-image.

Adaboost SVM Algorithm:

Xuchun Li *et al*. (2008) proposed the adaboostSVM method to solve the imbalanced classification problems. RBFSVM is used as a component classifier along with along with adaboost algorithm in which reweighting technique is used to update the weights of training samples. The adaboostSVM works well when comparing with other techniques and it gives better accuracy obtained by adjusting the kernel parameter to get a set of effective RBFSVM component classifier.

Top down segmentation Approach:

Michael wels *et al*. (2008) proposes the top down segmentation approach it is based on a Markov Random Field(MRF) model that combines both the Probabilistic Boosting Trees(PBT) along with lower level segmentation via graph cut, However this approach is applied for the challenging task of detection and delineation of pediatric brain tumors. some cases like hydrocephalus were the circulation of CSF has nearly come to stand, it is virtually impossible to distinguish voxels within the cystic portion of the tumor from the voxels within the ventricular system from solely the intensities and this will cause the method to generate false positives and false negatives. This method focuses on to detect, to segment and to identify the pathological tissue that occur within the pediatric brain tumors.

Extended graph shifts algorithm:

Jason .J.corso *et al*. (2007) exploited an extended graph shifts algorithm for image segmentation and labeling. This algorithm performs energy minimization by manipulating a dynamic hierarchical representation of image. Extended graph shifts are used for the segmentation of brain tumor and the detection of multiple sclerosis lesions. The advantages of extended graph shifts are speed and robustness and it requires the labeled training data for the segmentation and detection.

Discriminative Variational Method:

Dana Cobzas *et al*. (2007) proposed the variational method for the segmentation of brain tumors. To rectify the problem of segmentation, when the appearance of tumor and the normal tissue overlap. The variational method that evaluates both atlas based priors and the learned statistical model for tumor and healthy tissue. Feature extraction which extracts both the image based features and the alignment based features for the classification of images. In image based features extracting the image intensities alone where the alignment based features defines a distance transform on a labeled template. So that the discriminatively trained conditional model based on Logistic regression gives better performance. When compared with previous traditional generative models the drawback of this method is that the removal of noise is not sufficient when comparing with other techniques.

Support vector Random Fields (SVRF):

Chi-hoon Lee *et al*. (2005) proposed the Support Vector Random Fields (SVRFs) a method that combines the discriminative properties of SVMs along with the random field relaxation properties of DRFs. This method was suggested to perform the tasks includes the enhancement of tumor area, The entire edema region is segmented along with the tumor region and also to segment the Gross Tumor area specified by the radiologist. The problem is very difficult to segment the edema region.

Layered Vision Framework:

David T. Gering *et al*. (2005) projected the framework for the segmentation of brain tumors in MRI images. This approach is mostly used for the identification of irregular shapes and texture which is an extension of Expectation Maximization(EM) algorithm that takes information such as the user input, inter structure relationships, voxel intensities, neighborhood coherence and intra structure properties. A Framework has two stages, In the first stage segmentation is carried for large brain tumors based on the training of healthy brains that deviate from normalcy. The second stage incorporates with the Expectation Maximization (EM) based segmentation along with region– level properties derived from the multilevel Markov Random Fields (MRFs) but here the problem of partial volume effects cannot be fully rectified.

Fractal Analysis for Brain Tumors:

Khan M. Iftekharuddin *et al*. (2003) proposed the novel technique based on the existing fractal analysis of tumors and in which three modified algorithms are used along with fractal analysis. The first method involves thresholding intensity values named as Piece-wise Threshold Box Counting (PTBC). Other two methods are Piece-wise Modified Box Counting (PMBC) and Piece-wise Triangular Prism Surface Area(PTPSA) are used to detect and locate the tumor regions. The major drawback in this techniques cannot be applied in rough surface and higher dimensional images such as cloud and MR images.

Automated Segmenattion:

Michael R. kaus *et al*. (2001) exploited the automated brain tumor segmentation method to reduce the manual segmentation of brain tumors. For this they consider five tissue classes they are skin, brain, ventricles and tumor. The training samples of MR images that contains all the tissues classes are used to train the automated tool. The automated segmentation tool that perform well in low grade gliomas with higher accuracy. For the broader range of brain tumors such as glioblastoma, multiforme the accuracy get degrades.

Shape Based Estimation (SBE) and Force Based Estimation(FBE):

Christos Davatzkos *et al*. (2001) proposed the framework for predicting and modeling anatomical deformations is defined. Two methods are used in the proposed technique in that the first method is Shape Based Estimation (SBE) which is completely shape based and it utilizes the principal modes of co-variation between anatomy and deformation inorder to statistically represent deformability. The second method is Force Based Estimation (FBE) that incorporates both the bio medical model in conjunction with the statistical model. The first approach is used for finding the deformation based on the knowledge of patients anatomy. The major drawback in this technique is clearly, impossible to predict the intra operative deformation without any additional intra-operative data.

Adaptive Template Moderated(ATM), Spatially Varying statistical Classification(SVC):

Simon K.Warfield *et al*. (2000) proposes an Adaptive Template Moderated (ATM), spatially varying statistical classification (SVC) and it is applied to several segmentation problems which contains the quantification of normal anatomy and pathology of various types. The algorithm contains the sequence of iterations on classification and non-linear registration. The drawback of ATM SVC algorithm can't segment structure which has similar characteristics in all feature channels.

Comparative analysis:

In this section it contains the advantages and issues of various supervised techniques.

Table I: Compare and contrast of several techniques.

Author	Proposed Technique	Benefits	Identified problem
Simon *et al*. (2000)	Adaptive Template moderated (ATM), Spatially Varying statistical Classification (SVC).	It identifies the pathology of various types.	It is not suitable to segment structure with similar characteristics.
Christos *et al*. (2001)	Shape Based Estimation (SBE) & Forced Based Estimation (FBE).	The proposed technique identifies if any deformations are present.	It is impossible to predict the intra operative deformation.
Michael *et al*. (2001)	Automated method for brain tumor segmentation.	Manual interaction is reduced.	It is hard to predict in higher range tumors.
Khan *et al*. (2003)	Three algorithms are suggested they are Piece-wise Modified Box Counting (PMBC), Piece-wise Triangular Prism Surface Area (PTPSA), and Piece-wise Threshold Box Counting (PTBC).	To detect and locate the tumor in brain MR images very accurately.	It is not suitable in rough surface and high dimensional images
David *et al*. (2003)	Extended form of Expectation Maximization (EM) algorithm.	Easy to identify the irregular shapes.	Does not reduce the partial volume effects.
Lee *et al*. (2005)	Support Vector Random Fields (SVRF) technique .	Identifies the tumor volume.	Very difficult to segment the edema region
Jason *et al*. (2007)	Extended Graph Shift Algorithm is exploited.	The algorithm improves the speed and accuracy	It requires the large training data.
Xuchun Li *et al*. (2008)	Adaboost SVM algorithm is used for classification	It improves the accuracy.	It requires the linear distribution of data.
Tao Wang *et al*. (2009)	Fluid Vector Flow (FVF) an active contour model is developed.	It reduces the Poor convergence for concavities. Insufficient capture range is minimized.	It does not analyze the 3D-image.
D.Zikie *et al*. (2012)	Level set framework is introduced.	It minimizes the joint segmentation problem.	It provides false positives in results.
Atiq Islam *et al*. (2013)	Multi fractal texture Estimation and an diverse adaboost algorithm is suggested	It does not require deformable image registration.	It requires the user interaction in classification.

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