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A review on brain tumor segmentation techniques

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ABSTRACT

Brain tumor segmentation is the vital requirement on preplanning of surgical treatments that may aid the pathologists to accomplish successful surgical operations on the human brain. In present days brain tumor surgical operations are progressed in the manual approach on hospitals that intakes excess time. Manual brain tumor segmentation is tedious and much depends on the individual operator that may not an advisable one. The literature on brain tumor segmentation consists of many papers related to tumor detection. This paper is a review paper to analyze the recent five papers related to human brain tumor segmentation. This paper analyses them invariant potential ways to help green researchers to find their research area.

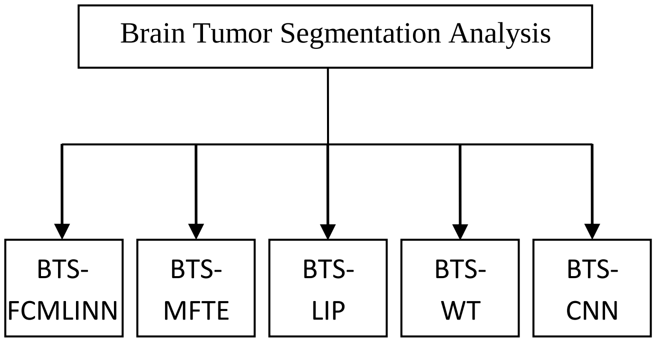
Keywords— *Magnetic resonance image, Brain tumor segmentation, Deep learning*

1. INTRODUCTION

Medical image processing is a gift to human beings for preplanning their medical treatments. The brain tumor disease is a dangerous disease for human life-cycle because it emerges as a dominant disease in all over the world [1][2]. The advanced medical diagnosis system detects the brain tumor in patients through MRI scanning, but in some cases, the radiologist can't detect tumors even though they may be experienced pathologist [3][4]. The main challenges of brain tumor segmentation are its various sizes, shapes, and appearance at different locations. The deformation of surrounding structures in the brain due to mass effect or edema also complicates the brain tumor segmentation [5]. The artifacts and noise are other obstacles in brain tumor segmentation [6][7]. For the segmentation pattern recognition technique is widely used [8]. The tumor can be segmented as the outlined of the tissues. The tumor mass effect can change the normal tissues. The segment of gliomas is important for treatment. Images can be tested by using magnetic resonance imaging (MRI) or Computed Tomography (CT) scan. Accurate classification of medical imaging is needed for clinical diagnosis [9][10]. Many papers are explored on this topic with solutions and many of the researchers do not know about which is the best paper to continue their new research. This paper progressed with a solution to elaborate on the information about the recent state-of-the-art papers which may help young researchers.

2. BRAIN TUMOR SEGMENTATION METHODOLOGIES

- Brain Tumor Segmentation using Fuzzy C- Means clustering with Local Information and Neural Networks (BTS-FCMLINN) [11]
- Brain Tumor Segmentation using Multi-Fractial Texture Estimation (BTS-MFTE)[12]



2.1 Brain tumor segmentation in fuzzy C-Means clustering with local information and kernel metric for image segmentation

In this paper, image segmentation is performed by using Fuzzy C-Means Algorithm (FCMA). FCMA is good for noise-free images and BTS performance. FCMA categorized into two factors weighted fuzzy factor and kernel metric factor.

(i) By the weighted fuzzy weighted factor neighbour pixels can be estimated accurately. The input MR image is of 128 x 128 pixels. The types of the images are synthetic images, nature images, and medical images. To weight the pixel in two cases (i) The mid of the pixel is not noise some pixel within the windows corrupted by noise (ii) The mid of the pixel is noise and the remaining pixels are not corrupted by noise. FCMA factor is parameter free. This is designed to control spatial relationship to speed up BTS enhanced the linear weighted image is sum with the neighbor pixel with the original image. The need for the parameter to control noise and effectiveness. The parameter selection is not an easy task. The index terms are a gray-level and spatial constraint.

(ii) Kernel metric factor enhances the image. BTS-FCMLINN function is introduced for spatial neighbour pixels having mean and median filtered images. BTS cluster algorithm based on kernel method is used. Kernel method solves the problem of dimensional spaces. The Gaussian filter is adapted for fast bandwidth selection. Test the algorithm with Gaussian, Salt, and Pepper levels. Normally noise level is 20% and 30%. For this experiment choose Brain web data. The original image is divided into four stages background, white matter, gray matter, and cerebrospinal fluid. The proposed algorithm improves the performance of the BTS. In recent year kernel method adopted the machine learning technique. The advantage of this work is to reduce the complexity of segmentation, Reduce the computational cost. The drawback of this work is Non-robust to noise, Time consuming process, Hardware implementation is high cost. The distance measured in the original data space by non-Euclidian methods. All process performed on a Pentium IV (3 GHz) under Windows XP Professional using MATLAB.

2.2 Multi-fractal texture estimation for detection and Segmentation of Brain Tumors

This method proposed a brain tumour MR Image texture. To evaluate a texture of brain tumour multi fractral resolution method is introduced. The texture is calculated using a Multifractional Brownian Motion (MFBM).BTS is extended using a scheme of AdaBoost algorithm. BRATS2012 dataset segmentation is more consistent. Brain tissues from the surrounding area are masked and combined with the atlas registration and classifications. The disadvantage is atlas-based segmentation. The proposed segmentation method is Discriminative Random Field (DRF). By this method multiscale image and alignment of the image are segmented.

Conditional Random Field (CRF) model has employed for cascade the classifier, each classifier use set of features. However, the proposed technique studied to build a statistical model for tissues. The new technique is initialized for boundary leakage artifacts. Standard Classification Forest (CF) and Random Forest (RF) scheme are used for Brain Tumor Segmentation (BTS). For texture feature extraction fractal analysis technique is shown a success rate. To select different texture pattern Multi Fractional Brownian Motion (MFAM) technique is included. In this work, we propose a Multi Fractral Dimension (MFD) for texture extraction and the intensity of the tumor and non -tumor tissues. AdaBoost (Adaptative Boosting) is the method which is highly trained to boost the texture of various patients.

To enhance the AdaBoost algorithm depends on the weight of the classifier. Add the Neural Network (NN) Classifier. If more components are adding the classifier becomes weak, so is known as a weak learner. An AdaBoost framework is not dependent on the weak learner. The dataset used is T1 weighted, T2 weighted and FLAIR type of tumor image. In pre-processing to slice the image SPM8 toolbox is used for each patient. To separate tumor tissues from skull BET toolbox is used. The hardware implementation is using MATLAB 2011a on windows 64 bit 2.26 GHz Intel(R) Xeon(R) processor, with 4GHz RAM. In future AdaBoost, classification can be modified.

2.3 Brain tumor segmentation based on local independent projection-based classification

In this paper, to enhance the tumour segmentation various methods are developed. Tumor images have high diversity in their boundaries. We proposed an automated Brain Tumor Segmentation (BTS) for MR images using a Local Independent Projection (LIP) classification. LIP classification has different regression model, which improve the performance. By this method contrast of tumor, tumor core is completely segmented. In the case of glioma, the tumor area is divided into necrosis, enhanced tumor, non-enhanced tumor, and edema. LIP method highlights the contrast region and edema region. Size and shape of tumor vary. To find the tumor edge is the challenging task in the medical field. The binary image is classified into edema region then it is inputted using the connected component algorithm. At last each edgma region is separated and compare with the tumor region for the result. Further noise and artifacts in tumor image make difficult in segmentation. So we design the automated segmentation approach. To improve the robustness multi-resolution framework are proposed. In present patch based technique is used for image extraction. In future cubic patch based technique can be used for MRI images. The LIP method is used for solving linear weight reconstruction.

Many algorithms have been developed to detect the brain tumor. Intensity-based method, surface evaluation method, asymmetric analysis, interactive algorithm, atlas-based method, supervised and unsupervised learning method. The advantage of this method is to reduce computation cost; the multi-resolution framework is embedded and improves the robustness. It classifies the voxels for processing. Voxel-based is implemented for multi-core CPUs, therefore, the processing time decreases. For testing the algorithm run in a single thread. The drawback of this method is to improve the classification of Sofmax Regression Model (SRM). SRM is not applicable for synthetic data groups.SRM select the neighbouring data which increase the computational cost. It does not regularize the contextual information.

2.4 Segmentation of tumor and edema along with healthy tissues of the brain using wavelets and neural networks

In this paper, a segmentation algorithm is difficult to analyze the tumor tissues and edema. We introduce a new Tissue Segmentation Algorithm (TSA). TSA detect the diseased tissues and healthy tissues separately. We develop an algorithm using Self Organizing Map (SOM). SOM algorithm segment edema, white matter, gray matter, and cerebrospinal fluid, the accuracy of white matter is 91%, gray matter is 87%, and cerebrospinal fluid is 96%. Input Gaussian filter to soften the image. Set a global threshold value for the intensity of the pixels. Convert black/white images using Otsu methods.

In adults, most of the case glial tumor occurs with a high mortality rate. Glial cells of the brain show the progressive growth in healthy tissues. Image segmentation is the process of dividing the image into subclasses according to the feature enhancing background area. The input brain image is of 512x512 sizes, computerized algorithm diagnosis the disease of the brain tissues and structure. In the case of glial tumor segmentation is a more tedious process to identify dead cells and active cells. Existing we use wavelets and SOM for segmentation. In proposed we segment healthy and pathological tissues. The advantage is its tolerance fault and optimum searching. The non-linear filter is used to eliminate the noise. Skull stripping is the important process to remove the non-cerebral tissue. SOM is used for multilayer segmentation. SOM has two layer input in the first layer and output in the second layer. The output obtained by the system is compared manually selected by the physician. The drawback discrete wavelet transform for the variant. The BRATS2012 dataset is used. In the future, we can change the shape and model of the image. In the future, the segmentation ratio can be done accurate and efficient by changing the shapes and models. For skull stripping IBRS database algorithm is performed. Skull stripping algorithm is developed by a Brain Surface Extractor (BSE), Brain Extraction Tool (BET).

2.5 Brain tumor segmentation using convolutional neural networks in MRI images

In this paper, we proposed an automated segmentation method use of 3x3 kernels. The disadvantage is manual segmentation is required if a number of MRI image is used. The database used is BRATS2013 which find the core and region of the dice. It is a challenging task for a dataset of BRATS2015.

Neoplasm is graded into Low-Grade Gliomas (LGG) and High-Grade Gliomas (HGG). Nowadays treatment includes surgery, chemotherapy, radiotherapy. Several methods use the parametric or non-parametric model of data. The tumor can be segmented like the outline of the tissue and shapes of the tumor. The growth of the tumor is measured by its mass, improved atlases neighborhood voxels. Histogram-based estimation is used for segmentation of super voxel images. The drawback is during the training stage brain tumor does not match the pattern. The various features proposed is encoding context, Fractal based texture, brain symmetry and some of the physical properties. The recent classifier is Support Vector Machines (SVM) and Random Forest (RF). RF handles multi-level problems. The advantage is CNN uses raw data, it works on patches using kernel. Most of the authors work on the 2D filter. But the disadvantage of using a 3D filter is loaded computational cost. Evaluation is done by use of two-pathway networks one network is used for bigger patches and the one is larger context view. Evaluate each component by studying improving performance. CNN use two layers for separation fully connected layer and softmax layer. The output of the FC layer with softmax layer is separated by RF classifier.

In the pre-processing stage, MRI image is corrected by bias field distortion. The intensity of the tissues varies in images. By normalization method, we find the intensity and standard deviation of the sequence of patches. Convolutional layer train the FC layers. Since the kernel is used for all the images, different location of the same matter is identified. By the use of kernel, neighborhood information is taken as context information. The following are the context information initialization, activation, pooling, Regularization, loss of function, and data argument. The proposed architecture includes more layers and weight. To train the CNN Gradient optimization algorithm is used for MRI image. Brain tumors are highly variable in spatial location.

3. RESULT ANALYSIS

This analysis part makes the tables by filling the analysed results of the five methods such as BTS-FCMLINN, BTS-MFTE, BTS-LIP, BTS-WT, and BTS-CNN. It also projects the publisher and year of publishing to know about the methods towards a better way.

Table 2: Analysis of the five methods

Method Name	Input Type	Database used	Segmentation Accuracy
BTS-FCMLINN [11]	CT image, the synthetic image	FLAIR, BRATS 2012	98.98%
BTS-MFTE[12]	MRI image	BRATS 2012	Nil
BTS-LIP[13]	MRI image	BRATS 2013	94
BTS-WT[14]	MRI image	IBRS, BRATS 2013	95.34%
BTS-CNN[15]	MRI image	BRATS 2013	97.02%

Table 1 describes the main contribution, merits, and demerits of the five methods targeting tumor segmentation for humans. The Table 2 deals with the input type, the name of the database used and segmentation accuracy of the five methods in detail.

4. CONCLUSION

This survey analyses the five methods such as BTS-FCMLINN, BTS-MFTE, BTS-LIP, BTS-WT and BTS-CNN related to brain tumor segmentation against Segmentation-accuracy. This study effectively deals with the main contribution, advantage, and disadvantage of the concerned five methods. This study finally end-up with the conclusion that the BTS-FCMLINN and BTS-WT methods are best for human brain tumor segmentation. This study reproduces knowledge among young researchers about which kind of method is the better solution for tumor segmentation.

Table 1: Analysis of constraint, advantage, and disadvantages for five methods

Method Name	Year of Publishing	Publisher	Main contribution	Advantage	Disadvantage
BTS-FCMLINN [11]	2013	IEEE Transactions on Image Processing	Gray-level, spatial constraint	Reduce computational cost, reduce the complexity of segmentation	Nonrobust to noise
BTS-MFTE [12]	2013	IEEE Transactions on Bio-Medical Engineering	Multi-resolution wavelet	Decrease the computation complexity	Atlas-based segmentation
BTS-LIP [13]	2014	IEEE Transactions on Bio-Medical Engineering	Local independent projection	reduce computation cost, improves the robustness	Not applicable for synthetic data group
BTS-WT [14]	2015	IEEE Journal of Biomedical and Health Informatics	Stationary wavelet transform	Tolerance fault and optimum searching.	Segmentation ratio is not accurate and efficient.
BTS-CNN [15]	2016	IEEE Transactions on Medical Imaging	Convolutional Neural Network	It works on patches using kernel.	For 3D filter increase the computational cost

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