

Active Contour Model for Brain MR Tumor Segmentation and Volume Estimation

G. Anand Kumar, P. V. Sridevi

Abstract: Brain MR tumor segmentation and estimation of volume is a critical task in medical applications. Brain tumors are analyzed by the common test method known as magnetic resonance imaging (MRI) which provides a detail image of brain. The proposed work involves detection of tumor in brain using deep learning based active contour model. Segmentation is the main objective of the proposed work for achieving detailed information about the tumor and accurate volume estimation to detect the size of the tumor. The Euclidean similarity factor (ESF) is used for considering the spatial distances and intensity differences of the region there by preserving all the fine details of the image. 3D convolutional neural network (3DCNN) is used for extracting the features and segmentation to identify the tumor location in the brain. Finally, shoelace method is used to estimate the volume of the tumor, and it provides treatment planning, surgical methods, estimation of dose, etc. The simulation results in this suggested approach could attain effective performance as compared with the existing approaches.

Keywords: Brain tumor, Magnetic resonance imaging, Euclidean similarity factor, Convolutional neural network.

I. INTRODUCTION

In medical image processing, the segmentation of brain tumor and analysis of volume estimation is an essential process focused in research area [1]. Segmentation of tumor and volume estimation also focused on diagnosis and treatment planning. From the past decades, cancer is one of the main diseases that frights the people more. Brain disease is an important challenging malignant tumor to cure [2]. So the technology gives more importance to the estimation of various tumors in brain by oncologist, neurosurgeons and all medical team, they needed to identify the entire information and images of the brain tumors. Moreover the technology associated with more number of images, can't be easily findable by Surgeons or oncologists. Therefore, there is need for segmentation.

Revised Manuscript Received on December 22, 2018.

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The segmentation change the characteristics and estimate the tumor [3]. Solid or active cancer, necrosis and edema are the different tumor matters which is separated, then it segments the standard and abnormal tissues. The typical tissue consist of gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF)[4]. In brain tumor segmentation the normal tissue can detect and separate easily while the abnormal tissue cannot be able to detect easily. The maximum size of tumor detected in boundary box is pixel 1-5035, in which the minimum size is 1-1190 [5]. Among past years, the segmentation are taken through manually, in which physicians and oncologist handle the segmentation. This manual segmentation face more problems such as time consuming and inter-intra rater errors [6]. So automatic or semi-automatic segmentations are used. In automatic segmentation, the tumor tissues automatically segmented without the manual method. The atlas is estimated in the segmentation with different shapes and locations of tissues. Voxels are used through Markov Random Fields (MRF) for smooth segmentation [7]. It also used for the segmentation of the super voxels. Moreover the voxels may be mistakenly segment wrong class and locations. To overcome these Conditional Random Field, and classifier, are used [8-9].

The automatic brain tumor image segmentation is classified as edge based segmentation, regions manipulation segmentation and segmentation by pixel manipulation. The edge based segmentation consist of edge detection and active contours, then the region based is divided as merge/split and graph cut, and the pixel based is subdivide as thresholding and clustering, along it divided as global, adaptive, k-means and fuzzy-c means segmentation respectively [10]. The various techniques and their algorithm are used for the automatic brain tumor segmentations. They are given as; Histogram based method, it's an efficient segmentation method compared to other techniques [11]. Peaks and valleys is used to locate the clusters in histogram. It also used for the measurement of dimensions of image pixels. But it have a limitation as, it is more challenging to find the insignificant of peaks of segmentation and valleys in the certain images. Edge based segmentation, detects and identifies the region of tumor. The edge based segmentation is a common method and it segment the boundaries of images [12]. In edge based segmentation the gray level and color images are used.

It has sobel edge detection, canny edge detection and prewitt edge detection. Region based segmentation known as seed growing method.

This method, considers the input images as seed and it compares with given neighboring pixels. During comparing the smallest difference is compared for each regions. Clustering is an interactive method and portion the image into K clusters. K-means clustering method, each cluster characterized as K. The cluster is chosen randomly from each pixel and calculated using Euclidean function and compare each pixel to all cluster with the above function and moved to the shortest distance and then reestimated it. Fuzzy-C means segmentation, Fuzzy used the process of clustering, in which single section of data used for more clustering. FCM algorithm is applied for noise reduction and increasing the accuracy of segmentation. KNN (Nearest neighbor) segmentation, it has high classification accuracy and voting function in KNN which is employed by Euclidean distance, Hamming distance etc. It also increase the stability. Whereas it has a limitation as slow running segmentation. Watershed segmentation, can segment the tumor with the desired parameters. It's an important method for the tumor segmentation. Thresholding based segmentation, it partition the input image with pixel compared to the threshold values. Atlas base segmentation, based on supervised method and images as in which tissues are segmented by hand. For the segmentation optical flow, finite-element method are used. It can transferred and segmentation. But has a limitations such as time necessary, complicated and rigid registration. Object based segmentation, during segmentation the object based method is an effective and efficient images. Canny based segmentation, in brain tumor segmentation the deformable edge of tumor is detected, Unsupervised clustering, it consist of training and test set. It use the MRI data for the brain tumor segmentation. It has some limitations as registration and segmentation problem.

CNN based segmentation, based on supervised segmentation and used for several object recognition operates in patches using kernels. CNN have an important advantage as it can be used for the raw data. It has two convolutional layers and these layers are separated by Max-pooling technique in segmentation and fully connected layer sequences, a softmax layer. In addition to CNN is mainly used for the smooth segmentation. Simonyan and Zisserman algorithm are used for the kernel and segmentation of MRI images. It has three processing steps as, firstly pre-processing, second classification via CNN and finally post processing operation is done. The intensity is calculated in the preprocessing stage. Sometime the images are occurred more time in the scanner so apply intensity normalization method. Then the convolution method is used to retrieve the accurate results by using the feature maps. In the post processing method the volumetric analysis is applied. The volumetric analysis is used remove clusters in the segmentation. It is also known as the volume estimation. The volume estimation can be estimated by the visual perception by sampling method. It has some techniques such as ABC/2, cavalier method and 3D method, whereas

ABC/2 and cavalier method is worked under 2D, it is used to measure tumor volume by inter-slice spacing with the thickness of slice is 4.5 μ m.

II. RELATED WORK

Ficci et al. [12] proposed the T1, T1c and FLAIR for tumor segmentation in brain. He used FLAIR for estimating the tumor in brain and for calculating the volume the tumor being spread. Then focused on T1 pre gadolinium, T1 Post gadolinium of MRI protocols for segmentation of brain tumor. This work is centered on the automatic brain tumor segmentation. Because of fully automatic in nature, it can be used for all types of tumors. For the detection of normal brain region, fuzzy c, thresholding and skull stripping are applied. As well as the calculation of tumor volume can be done by DICOM header. In proposed method accurate volume can be estimated than the existing approach. It has an advantage as it not need the training dataset in machine learning algorithm. Similarly it had a drawback as latency and security in segmentation. Bandy and Mir [13] proposed semiautomatic technique to segment MR brain images. For the framework of segmented regions the feature map was introduced. Then for the comparison, the Jackard's co-efficient and overlap index was applied. Author proposed and implemented the volume estimation of brain tumor, for that he introduce a Gabor features of ACM based segmentation. In segmentation, volume of tumor is detected by surveyor's algorithm with high accuracy. Then the volume estimation is compared with cavalieri method and ABC/2. The suggested system is more accurate and effective than prevailing system. After the estimation the proposed system has high accuracy as 93.19 \pm 9.20 compared to existing method. Moreover it has some limitations such as limited data and informal analysis of data for segmentation. Somwanshi et al. [14] compared and analyze the segmentation and it was mainly focused on threshold entropy based segmentation method. The various entropy methods are Reniv vajda, kapur and shannon segmentation are applied to MRI images of brain tumors. After segmentation, threshold selection is taken away of the images by entropy method which are highly diagnosis of brain tumor. During comparing and analyzing the simulation, hard chart vat entropy algorithm has high performance than other entropy algorithm. In spite of this technique, it has some drawbacks such as discontinuity of edge, weak edge border etc. Havaei et al [15] presented an automatic segmentation of tumor in brain technique based on Deep Neural Network (DNN). DNN trailed the glioblastomas in MR images. The tumor can appear anyplace of the brain, with different shape, proportions, kind etc. In spite the ordinary segmentation can't be applicable, so the dynamic neural network (DNN) was introduced. The DNN based on the CNN method. Author mainly focused on the GPU implementation in the output layer to get faster magnitude than other methods.

Then he introduced the cascade architecture for accurate segmentation. The proposed DNN method is further accurate and effective than the prevailing manual segmentation method. But it also has some limitations such as, images strongly affected by outliers, poor scaling etc. Soltaninejad et al. [16] presented regarding the detection of tumor and fully automated segmentation of brain tumor. Fluid-Attenuated Inversion Recovery technique in MRI was introduced for detection of tumor in brain images and for segmentation. This method is centered on the superpixel technique for the classification of each superpixel. He also focused on the features of images and intensity based on Gabor textures, curvatures and fractal analysis are designed from superpixel with FLAIR MR. Then the last stage of segmentation compare extremely randomized tree (ERT) classifier to SVM classifier. After comparison the proposed system had greater accuracy of 89.48%, 6% and 0.91 respectively. Even though it has high accuracy but it has some of the limitations such as lack of context, hard to find borders of images. Abdulraqueeb et al. [17] presented the automatic brain tumor segmentation. He used the MRI images for segmentation of tumor in brain. In addition to an algorithm 'devel-oped' was introduced for automated segmentation and determination of brain tumor. Furthermore he proposed the thresholding based segmentation for automatic brain tumor detection. The quality of segmentation was considered by Jaccard index, sensitivity, Dice score, and specificity. The sensitivity of proposed technique had more accurate and sensitive for the segmentation. The specification percentage of sensitivity are 89%-99% in threshold based segmentation. Moreover it has a limitations as computational complicity, poor scaling.

Ghribi et al. [18] proposed a new Multiple Sclerosis (MS) method constructed on cerebral segmentation and documentation using magnetic resonance image (MRI) modalities sequences. The suggested technique was based on the volumetric topographies that can be realized the gray-level co- occurrence matrix (GLCM) and gray-level run length (GLRLM) matrix. While preserving connectivity and spatial information, a new voxel technique was applied in the volumetric estimations. To differentiate the tissues of brain as white matter and gray matter during segmentations, genetic algorithm (GA) was introduced. Thus the proposed system give more accurate segmentation than other existing techniques. Furthermore it possess some limitations as the system is expensive, occurred high noises etc.

III. PROBLEM STATEMENT

Volume estimation for tumor brain segmentation is one of the important method in medical applications. Brain tumor is a dead full diseases, so the technology gives additional significant in medical image processing. Consequently many technologies are developed. Furthermore to achieve detailed information of brain tumor, automatic segmentation is used. It segment the brain tissue and identify the tumor in brain with its

location, shape, size etc automatically. Various algorithms and are used for brain tumor segmentation. After segmentation, the images are predicted as clusters. So the accurate size, and shape cannot be predicted in segmentation process. Volume estimation is introduced to overcome this issue. The thickness of slice is 4.5 μ m and its main aim is to smooth tumor boundaries and to find normal and abnormal tissues. As well as the cavalier method is based on the dimensions of stereological aspects. In which the images are transferred to computer environments with grids. But the accurate specified curves and lines of the images are not seen. For that 3D method is introduced; in this method, surveyor or shoelace technique is introduced, as geometric area is calculated within closed curve. In addition to curves and shapes of the images are easily identified and evaluated. Thus it give better treatment planning, diagnosis etc.

IV. OBJECTIVE

The foremost objective of the suggested system is as follows:-

- To eradicate the need for pre-processing step thereby preserving the details of the image.
- To accomplish great segmentation accuracy and good robustness.
- To estimate the tumor volume that is obtained from the boundaries of smooth tumor.
- To obtain finer segmentation results.

V. PROPOSED WORK

In order to achieve high segmentation accuracy and good robustness by considering the local intensity difference and local spatial information a deep learning based active contour model for segmentation and volume estimation of brain MRI images with high noise level is suggested in this paper. Euclidean similarity factor (ESF) is considered for intensity differences in local region and spatial distances. Our suggested algorithm was adjusted to eradicate the requirement of pre-processing steps that commonly lead to loss of image details.

The proposed work is processed in three stages.

- A. Euclidean similarity factor (ESF)
- B. Segmentation using 3D CNN learning model
- C. Volume estimation

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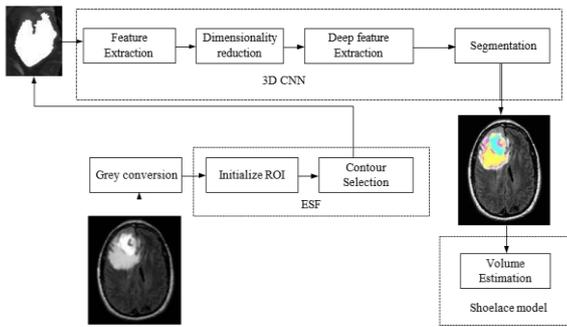


Figure 1: Basic structure of proposed methodology

The original MRI brain image is converted into a gray image in order to correctly initialize the region of interest (ROI). ROI is initialized and the Euclidean similarity factor calculates and extracts the tumor region. ROI is chosen for accurate segmentation and estimation of the brain tumor. Different layers of the 3D convolutional network segments the tumor and the shoelace model estimates the volume of the tumor efficiently.

VI. EXPERIMENTAL RESULT AND ANALYSIS

The experimental results are simulated in MATLAB. The result from this work can be tested using BRATS dataset. The testing dataset has different modalities such as T1, T1c, T2, and FLAIR. The distinctive signature to each tissue type is obtained by calculating the differences between all the said modalities. 3D CNN segments the tumor as necrosis, edema, enhanced and non-enhanced tumor. These segmentations are used to compute the regions as the complete tumor region, enhanced tumor region, and core tumor region. The tumor with all the four tumor structure is considered as the complete tumor region. The tumor with all tumor part, but without the edema part is considered as the core tumor region. The tumor with all tumor structure, including the enhanced tumor is considered as the enhancing tumor region.

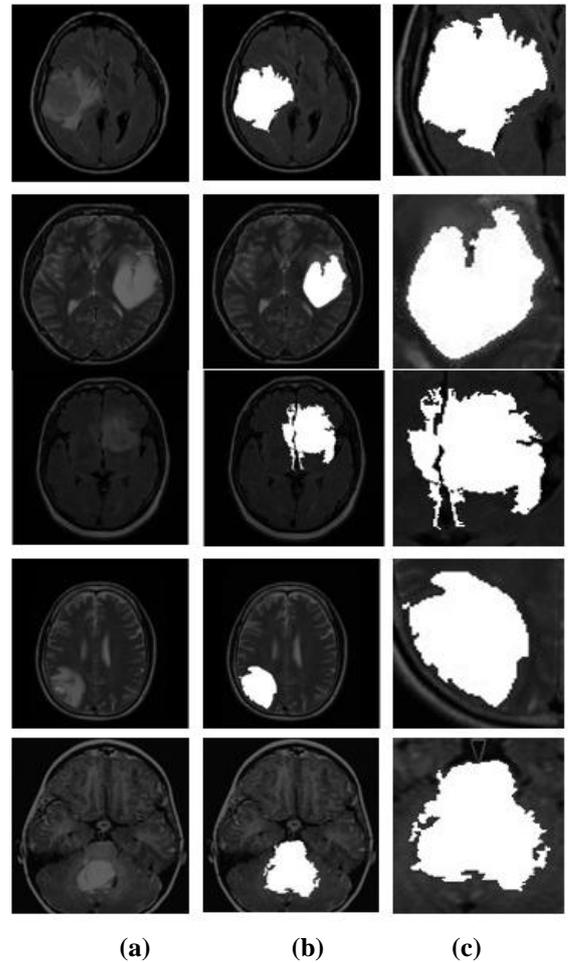


Figure 2: (a) The original brain image, (b) ROI and (c) ESF

Figure 2 shows the original images of brain tumor then the region of interest extraction and the tumor can be detected from original image by using Euclidean similarity factor.

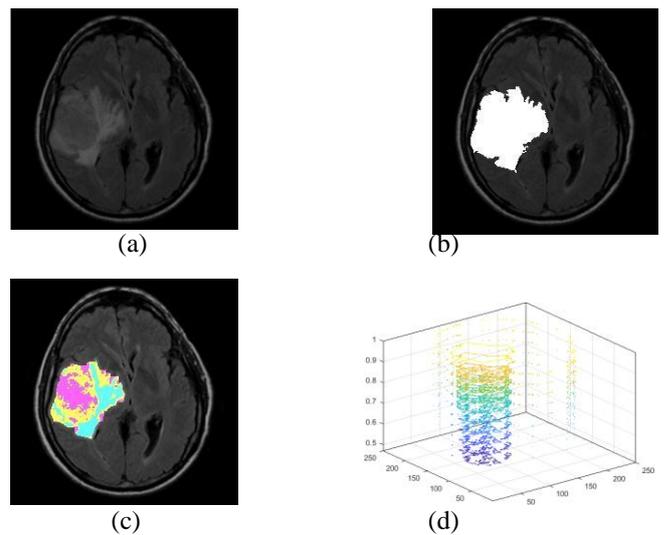


Figure 3: (a) The original gray brain image (b) The detected brain tumor (c) The segmented tumor and (d) The 3D plot for the tumor.

Figure 3 shows that the original MRI image can be converted into a gray image and the region is assumed as the tumor region based on the pixels and ESF calculates the distance for extracting the patch. Then the 3D CNN segments the selected region and the lesion can be segmented into necrosis, edema and the enhanced tumor region. In the figure, yellow denotes the necrosis region, pink denotes the edema region, green denotes the enhancing region and blue denotes the non- enhancing region and it is shown in the 3-dimensional cube.

The segmentation results can be estimated by these following measures.

Dice similarity coefficient (DSC): DSC estimates the segmentation result of the 3DCNN.

$$DSC = \frac{2A}{B + 2A + C}$$

Where variable A, B and C represent the number of true positives (TP), False positives (FP), and false negatives (FN) respectively.

Positive predictive value (PPV): Predictive value computes the amount of true positive (A) and false positive (B).

$$PPV = \frac{A}{A + B}$$

Where A denotes TP and B denotes FP.

Sensitivity (S): The number of detection of true positive (A) and false negative (B) is computed in sensitivity.

$$S = \frac{A}{A + C}$$

Difference in lesion volume (VD):

It is defined as the percentage error in lesion volume in terms of the absolute difference in lesion volume (VD) between manual annotation mask and output segmentation masks.

$$VD = \frac{TP_s - TP_{gt}}{TP_{gt}} \times 100$$

Where TP_s denotes the voxels correspond to correctly identified the lesion in the output segmentation mask and TP_{gt} denotes the correctly identified lesion in the manual annotation mask.

Table 1: A segmentation results for the BRATS dataset

Method	Difference in lesion volume (VD)	Accuracy	Jaccard
ESF based 3D CNN	15.78	92.92	0.912

Table 1 shows segmentation result of the 3D CNN by which results can be given under various parameter. The proposed method achieved segmentation accuracy as 92.92, VD as 15.78 and Jaccard as 0.912 for the BRATS dataset.

Table 2: Volume Estimation for BRATS dataset

Methods	Volume (cm^3)				
	Image 1	Image 2	Image 3	Image 4	Image 5
Proposed method	12.65	11.42	14.24	10.61	4.24
Cavalieri method	16.42	18.47	20.61	13.456	8.28
ABC/2 method	21.11	26.2	25.7	18.24	10.65

VII. CONCLUSIONS

This paper proposes a 3D CNN with an ESF-based active contour model for segmentation and volume estimation. This system accurately fulfills its persistence of segmentation and estimation of the tumor volume. The aim of this approach is the accurate segmentation and precise estimation of volume of the tumor. The active contour model forms the contours of the image without preprocessing and it protects the details of the image. The layers in the 3D convolutional network extract the spatial and temporal features of the image. After segmentation, the volume of the tumor can be estimated using extended Gauss's method in order to provide better treatment and dose estimation. The test results for the anticipated system are evaluated using the BRATS dataset which proves the effectiveness of the segmentation and estimates the volume of MRI tumor. We evaluated the performance of the proposed system with sensitivity, specificity, accuracy, dice coefficients, Jaccard index and difference in lesion volume and we achieved better results.

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