IJCSE International Journal of Computer Sciences and Engineering Open Access

Research Paper Vol.-6, Issue-12, Dec 2018 E-ISSN: 2347-2693

Probability based Watershed Segmentation Algorithm for Multiple Brain Tumor Detection

Srikanth Busa[1*], E.S. Reddy[2]

[1]Department of CSE, Acharya Nagarjuna University., Guntur, A.P, India
[2]Department of CSE, A.N.U. College of Engineering & Technology, Acharya Nagarjuna University., Guntur, A.P, India

**Corresponding Author: srikanth.busa@gmail.com,*

Available online at: www.ijcseonline.org

Accepted: 25/Dec/2018, Published: 31/Dec/2018

***Abstract*—** Automatic tumor detection is one of the difficult tasks in medical image diagnosis due to variations in size, type, shape and location of tumors. In the traditional brain tumor detection models, intra and inter slice resolutions may affect the segmentation accuracy. In addition, brain tumors have different intensities overlapping with normal tissue. In this paper, we have proposed an automatic tumor detection framework to detect the multiple tumors in brain tumor databases. This system has three main phases, namely image preprocessing, iterative threshold image enhancement and multi tumor segmentation algorithm. Experimental results show that our proposed system efficiently detects multiple tumors at different locations in the brain tumor image dataset.

***Keywords*—** PWS, Brain, Tumor, Noise reduction, MRI Images.

I. INTRODUCTION

Brain tumor is an abnormal behaviour of the cells within the brain. Brain tumor classifier is based on the location of the tissue, type of tissue, malignant and other features. In the last few years, many approaches have been proposed by researchers to locate and detect structure from different modalities such as CT scan, X-ray and Magnetic Resonance Imaging (MRI). MRI images are more convenient than X-ray and CT scan images for diagnosis. MRI images use a high powerful radio frequency, magnetic field and a computer to generate a detailed information regarding the human organs. At present there exist several methods for segmentation and classification of MR images. Manual segmentation is a process of segmenting an image to find the essential information. Manual segmentation is not only time consuming and tedious, but also produces inaccurate segmentation [1].

A large number of segmentation methods have been proposed with advantages and limitations. Different tumor segmentation approaches are classified as shown in Figure 1.

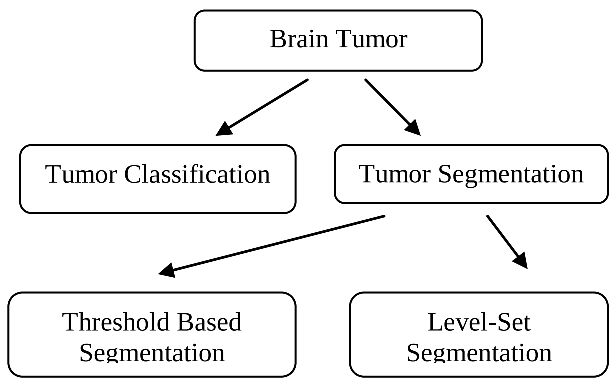


Figure 1: Brain Tumor Detection Steps

Tumor thresholding: Thresholding based mechanism is based on choice of threshold and determines an intensity value to classify the image into desired values called a threshold. Failing to find such a threshold may lead to poor classification or segmentation.

Tumor Segmentation: Segmentation is dividing the image data into groups of similar object classes. Each group indicates the cluster, which may contain the objects of similar type or features. The performance of the traditional segmentation algorithms is based on initial random assignments and similarity metrics.

Level Set Segmentation: Level set models use dynamic boundary variations for image segmentation. In this model, initial segmentation is performed using one of the traditional algorithms such as K-means, FCM, and KFCM etc. with trial and error basis. The parameters of the level set segmentation control the initial gradient level set function and spread of Gaussian smoothing function [2-3].

Problem Statement: The segmentation of brain tumor images is challenging with respect to several factors. It is common for many tumors, such as glioma, which exhibit irregular boundaries. Also, subregions can only be partitioned when several modalities are merged, which requires an efficient registration process in the preprocessing step. In the traditional brain tumor detection models, intra and inter slice resolutions may affect the segmentation accuracy. In addition, brain tumors have different intensities overlapping with normal tissue. Due to the partial volume effect, inherent noise, wide range of image features and spatial constraints, conventional models fail to detect the exact location and segmentation of the multiple brain tumors[3,4].

The rest of this paper is organized as follows, Section II describes the literature study of segmentation models, threshold based models, classification models, Section III describe the tumor image preprocessing, Section IV describe the proposed framework for detecting multiple tumors, Section V describes the experimental results and in Section VI we conclude with the model.

II. Related Work

Segmentation of brain tumor images is required for many diagnoses like radiation treatment, volume visualization of tumor ROI, tumor or stroke boundary extraction, etc. Brain images are used to analyse the behaviour of the tumors or strokes. Regarding the appearance and nature of the brain tumors, one sequence of MRI is not enough for segmentation of the brain tumor including the area. In recent years, a large number of techniques have been implemented for image segmentation and tumor detection. In most of the brain tumors automatic segmentation is being carried out using pixel classification and neighbourhood information [5].

In paper [2], they proposed a combination of wavelet co-occurrence texture and wavelet statistical features to classify the abnormal brain tissues malignant. They proposed framework that has four phases: Segmentation, Discrete wavelet decomposition, feature selection and classification. However, the main problem of this system is that, it needs new training for SVM classifier whenever there is change in image tumors. As the distribution of the intensity in tumor is complex, traditional methods become difficult to process. Since fuzzy c-means clustering does not require training data and parameter initialization,[2-5] implemented an automatic brain tumor classification and segmentation using an unsupervised fuzzy method.[6] proposed a tumor segmentation using context domain fuzzy method to find the tumor detection in static images.[7] integrates random forest classifier with dynamic region estimation in an efficient manner.

- **Unsupervised Segmentation**:

Brain tumor unsupervised segmentation models [7-9] use an optimization function to segment the image into meaningful regions, one of which is edema or tumor. These models are limited to segmentation of tumor areas due to the hard processing of visual data and features information of the tumors. These models, partition the image into homogeneous blocks using image based characteristics such as textures and intensities. The major limitations of traditional unsupervised models are the number of regions to be segmented needs to be predefined, tumors can be located at different positions and tumors may not have clear intensity or tumor boundaries.

- **Supervised Segmentation:**

Supervised classification is implemented using both a labeled training data to learn a model and the unlabeled test data to assign labels based on the extracted features. The source of the training data and test data has a major influence on the efficiency of the supervised model. The main challenge of this model is tumor images often suffer from the patient specific training data.

III. Methodology

A. Preprocessing

Preprocessing of brain tumor images is the primary step in medical diagnosis, which performs noise reduction methods and image enhancement to optimize the image quality.

- **Noise removal:**

In most of the MRI and CT scan images multiplicative noise is involved with unknown noise variance. Most of the traditional denoising models work for the additive noise, so in order to convert the multiplicative noise to additive logarithmic function is applied to the image as follows.

$$\log\ mul(x,y)=\log I(x,y)+\log addgnoise(x,y)$$

The noise component add-ons can be considered as additive Gaussian noise with mean.

[5] Proposed a variational tumor segmentation technique which incorporates both prior probability method and learned statistical models for healthy tissue and tumor detection.The logistic regression and Gaussian approximation were evaluated for tumor estimation.[6] proposed a level-set segmentation model using a new hybrid speed function with gradient vector flow and region based level sets.[6] Proposed an adaptive level set, where both edge based and region based terms are used for the segmentation of tumors.

- **Adaptive median filter:**

An adaptive median filter is used to enhance the image quality as well as remove the poison noise from the images. In the adaptive median filter, a window moves along the image and the computed median value of the window pixels becomes the output. It preserves the edges and reduces the noise in the image. Each pixel is replaced by a median value neighbourhood of the input pixels.

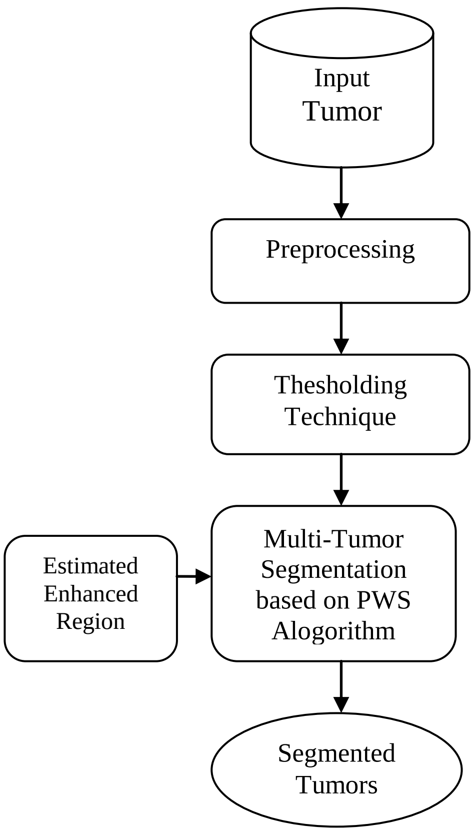


Figure 2: Proposed Framework

B. Image Segmentation

- **Probability Segmentation Iterative Threshold Algorithm:**

Step 1: Partition the image into two classes Cls_1 and Cls_2 with foreground level fl and background level bl with the image mean value Th such that

$fl = \{0,1,2...Th\}$ And

$bl = \{Th+1, Th+2, Th+3...\mathrm{N}-1\}$ where N is the total number of levels.

$$Th = \min\{\sum_{x=0}^{N-1} x^2 * prob(\mathrm{x})\}$$

where $prob(x) = v_x / |\mathrm{v}|$

$$prob(\mathrm{x}) \geq 0,$$

$$\sum_{x=0}^{N-1} prob(x) = 1$$

Step 2: Computing the lower threshold as

The variance of foreground level $fl = \{0,1,2...Th\}$ is

$$T_1 = \sum_{x=0}^{Th} prob(x) * (\sum_{x=0}^{Th} (\mathrm{x}* prob^2(x) - x^2 * prob) / |\,\mathrm{N}\,|$$

Step 3: Compute highest Threshold .

$$T_2 = \sum_{x=Th+1}^{N-1} prob(x) * \sum_{x=Th+1}^{N-1} (\mathrm{x}* prob^2(x) - x^2 * prob(\mathrm{x})) / |\,\mathrm{N}\,|$$

Step 4: Compute the inter-class and intra-class variance of each block

$$\sigma^2_{intercls_1} = \sum_{x=0}^{Th} (\mathrm{x} - (\sum_{x=0}^{Th} \mathrm{x} * n_x / |\,\mathrm{n}_x\,|) * \sum_{x=0}^{Th} n_x / |\,\mathrm{n}_x\,|)$$

$$\sigma^2_{intercls_2} = \sum_{x=Th+1}^{N-1} (\mathrm{x} - (\sum_{x=Th+1}^{N-1} \mathrm{x} * n_x / |\,\mathrm{n}_x\,|) * \sum_{x=Th+1}^{N-1} n_x / |\,\mathrm{n}_x\,|)$$

Step 5: Intra-class variance can be calculated using

$$\sigma^2_{intra} = \sigma^2_{intercls_1} + \sigma^2_{intercls_2}$$

Step 6: Repeat steps 2 to 5 until the condition is satisfied.

After enhancing the given image using a threshold based algorithm, the next step is to find the tumors in the enhanced image using segmentation algorithm.

- **Watershed segmentation Algorithm:**

The main aim of the segmentation algorithm is to partition an image into homogeneous regions (classes) with respect to one or more characteristics. Proposed segmentation algorithm is based on probabilistic estimation of the tumors and non-tumor regions. In this tumor detection algorithm, the basic watershed algorithm is applied on the preprocessed image for initial segments. Initial segments have a large number of over segmented regions which are very difficult to detect or process the tumors in the image. In order to overcome this issue, the probabilistic estimation method is applied in the over-segmented regions to extract the tumors by merging the estimated regions.

Watershed segmentation Algorithm:

1. Compute a segmentation function. This is an image whose dark regions are the objects that are to be segmented.
2. Compute foreground markers. These are connected blobs of pixels within each of the objects. 3. Compute background markers. These are pixels that are not part of any object.
4. Modification of segmentation functions such that it only has minima at the foreground and background marker locations.
5. Compute the watershed transformed of the modified segmentation function.

- **Optimized Region Merging Tumor Segmentation Algorithm**

Input: Enhanced Threshold Image,
Output: Brain Tumors.

Segmented regions S_i; Tumor estimated Segmented Region S'_i

S_i =Apply Watershed Algorithm
Set i=0.
For each pair of adjacent S_i
L=Calculate the segmented region along with the area.
Done
Calculate average area of all the regions in List L as φ .
For each pair of adjacent segmented regions
do
α =RegionrArea(A).
β =RegionArea(B).
If($(\alpha \| \beta) < \varphi$)
Then
e_x =edgeset of first region X .
e_y =edgeset of second region Y.
p_x =pixelset of X.
p_y =pixelset of Y.

Refined confidence measure C is the acceptance factor for regions merging.

$$threshold = prob(p_x / p_y) = prob(p_y / p_x).prob(p_x) / p_y$$

$$\text{Conf}=|E \cap \{e_x \cup e_y\}| / (\min(e'_x, e'_y) * |\{e_x \cup e_y\}|$$

Where

$$e'_x = |E \cap \{p_x\}| / |\{p_x\}| \quad \text{and} \quad e'_y = |E \cap \{p_y\}| / |\{p_y\}|$$

End if
If (Conf <= $threshold$)
Then
Merge (p_x , p_y)
Else
Break.
End if
done.

- **Tumor Segmentation Algorithm Framework:**

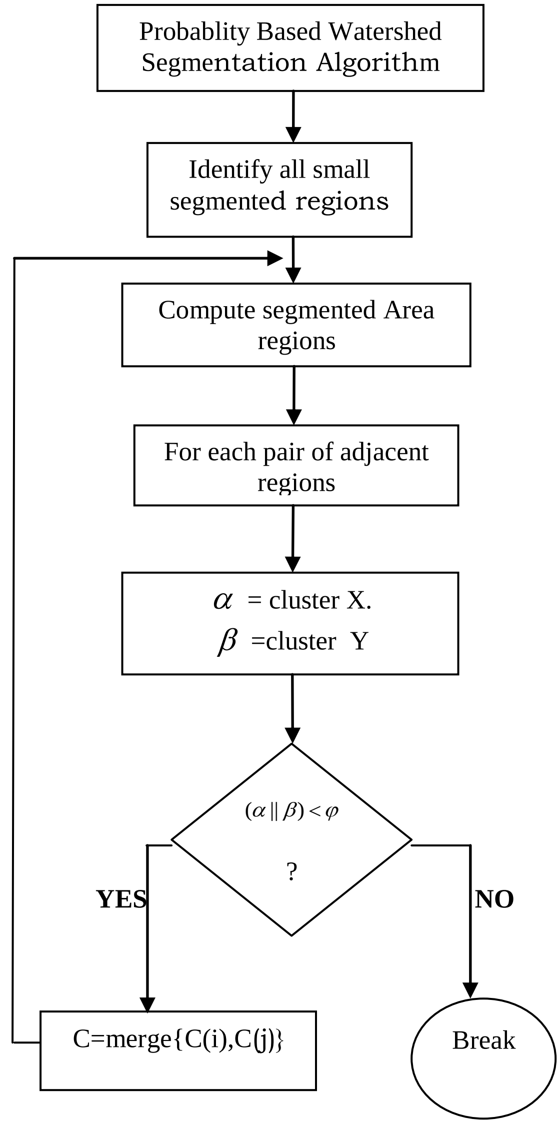


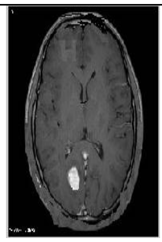
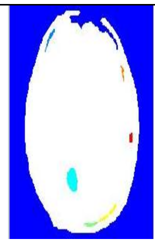
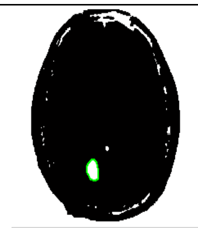
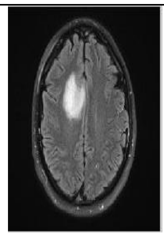
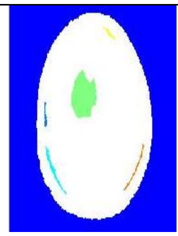
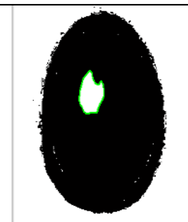
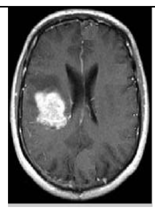
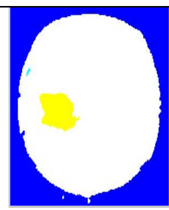
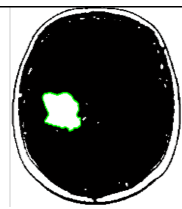
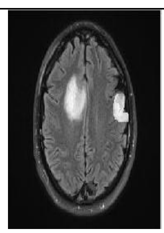
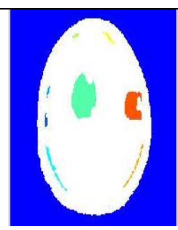
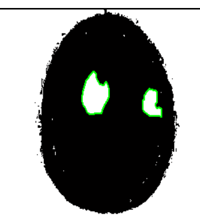
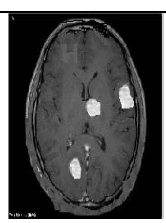
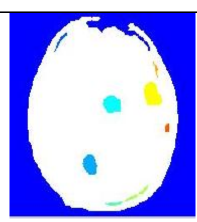
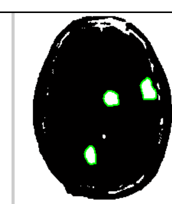
Figure 3: Multi Tumor Segmentation Algorithm

IV. Results and Discussion

The experimental database consists of 20 brain tumor patients' images of different tumor locations and pulse sequences. The evaluation of the proposed model was compared to different traditional segmented models in terms of tumor detection accuracy and statistical measures as shown below:

Table1: Single and Multi-Tumor detection results

Sno	Tumor Images	Initial Tumor Segmented	Final Tumor segmented Result

1			
2			
3			
4			
5			

The table1 shows the image which is used for segmentation and its tumor detection results. In case of traditional models small regions of false detection rate exist. But these small regions are completely eliminated using the proposed model. Proposed model shows accurate detection of tumor regions without false detection rate.

Table 2: PSNR and MSE comparison of Various Algorithms with Proposed Algorithm

Method	PSNR	MSE
Histogram Based Classifier	68.22	1.357
Normal Watershed	71.18	0.98
Proposed Model	85.68	0.195

Table 3: Region Segmented comparison of Various Algorithms with Proposed Algorithm

Method	**Normal Images** **No. of Regions Segmented**	**Noise Images** **No. of Regions Segmented**
Histogram Based Classifier	**4**	**3**
Normal Watershed	**5**	**4**
Proposed Model	**7**	**7**

V. Conclusion and Future Scope

In the traditional brain tumor detection models, intra and inter slice resolutions may affect the segmentation accuracy. In addition, brain tumors have different intensities overlapping with normal tissue. Algorithms for each model is discussed and developed in MATLAB programming environment. Experimental results of each model are also discussed in this paper. Results also show that proposed model have high PSNR and high accuracy compare to traditional models for single or multi-tumor detection. In future, a novel classifier to predict the dynamic tumor classification and segmentation will be implemented on a large tumor dataset.

References

[1] Amsaveni, V.; Singh, N. Albert," Detection of brain tumor using neural network" Institute of Electrical and Electronics Engineers – Jul 4, 2013.
[2] Tulsani, Saxena, Mamta," Comparative study of techniques for brain tumor segmentation", IEEE, Nov 23,2013.
[3] Dhage, Phegade, Shah," Watershed segmentation brain tumor detection", IEEE, 2015.
[4] Francis, Premi," Kernel Weighted FCM based MR image segmentation for brain tumor detection",IEEE,2015.
[5] Badmera, Nilawar, Anil," Modified FCM approach for MR brain iamge segmentation", IEEE,2013.
[6] Hanuman Verma, Ramesh, " Improved Fuzzy entropy clustering algorithm for MRI Brain image segmentation", IJIST, 2014.
[7]S.Luo, "Automated Medical image segementation using a new deformable surface model", IJCSNS,2006.
[8] Gordiallo, Eduard," State of the art survey on MRI Brain tumor segmentation" , Magnetic resonance imaging,2013.
[9] Tang, Welping,"Tumor segmentation form single constrast MR images of human brain", IEEE,2015.

Authors Profile

Mr. B. Srikanth received the B.Tech. degree in CSE from V.R. Siddhartha Engineering College, Acharya Nagarjuna University in 2005, M.Tech. degree in CSE from University Campus, Acharya Nagarjuna University in 2009. He is a research student of Dr E. Sreenivasa Reddy. Currently he is Associate Professor at KHIT, Guntur. His research interests are in Image Processing and Data Mining.

Dr. E. Sreenivasa Reddy received the B.Tech. degree in Electronics & Communication Engineering from Nagarjuna University, India in 1988, M.S. degree from Birla Institute of Technology and Science, India in 1997, M.Tech. degree in Computer Science from Visveswaraiah Technological University, India in 2000 and PhD in computer science from Acharya Nagarjuna University, India in 2008. He is the senior member of IEEE. Currently, he is Principal & professor at Acharya Nagarjuna University, Guntur. His research interest includes image processing, biometrics and pattern recognition.Mr. B.Srikanth