# REVIEW OF BRAIN MRI SEGMENTATION TECHNIQUES

**A. Farzana [1], Dr.M. Mohamed Sathik [2]**

[1]*Master of Philosophy in Computer Science, Sadakathullah Appa College, Tirunelveli, India*
[2]*Principal & Research Coordinator, Sadakathullah Appa College, Tirunelveli, India*

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**Abstract -** *segmentation is the process of splitting a digital image into constituent parts or meaningful segments which help in extracting quality amount of information in the region of interest. Image segmentation plays a vital role in the construction of clinical diagnostic tools and in the field of medical image processing. The brain MRI can be used to diagnose many diseases such as brain tumor, brain infection, brain vascularity etc. Brain tumor is one of the most perilous disease which affects enormous population. Segmenting the brain MRI becomes mandatory to analyze the brain abnormalities. Because diagnosing the disease in the early stages, increases the chances of survival. This paper provides a review of various segmentation techniques over brain MRI.*

***Key Words:*** *- Brain MRI, Otsu & Adaptive threshold, k means, FCM, Region Growing, Expectation Maximization, Watershed Algorithm*

## 1. INTRODUCTION

### 1.1 Imaging Modalities:

There are several imaging modalities are available to visualize the structure of human anatomy. They are X-Ray, MRI (Magnetic Resonance Imaging), Ultrasound, CT (Computed Tomography), Thermography, PET (positron emission Tomography), endoscopy, SPECT (Single Photon Emission Computed Tomography), elastography, echocardiography, tactile imaging, photo acoustic imaging etc. MRI and CT are the most commonly used neuroimaging modalities. It clearly depicts the structure and function of nervous system. This paper concentrates on MRI images. MRI is a non invasive imaging modality, Noninvasive procedures do not involve tools that break the skin or physically enter the body.MRI uses strong magnetic fields and pulses of radio wave energy to make pictures of organs. The major advantages of MRI over CT images are, MRI provides high contrast for soft tissues than the CT images [5]. The brain MRI contains several information. The common classifications are 1. Grey area 2. White area 3. Cerebrospinal fluid [19]. Brain image segmentation is the tedious and challenging task but it's necessary for diagnosing the disease or abnormalities. Most statistical research depicts that the death rate of people dying because of brain tumors has increased nowadays. It can affect any age group of people. Tumor is nothing but a excessive growth of tissues. The tumor can be of any type benign or malignant. Benign is non cancerous tumor and malignant is cancerous tumor. These type of tumor can appear and grow in anywhere in the brain. It can also affect the healthy brain cells and nerve system and it can cause some secondary disease such as alzimer. To avoid all these problems the tumor should be diagnosed at its early stages and get cured. In this paper we evaluate seven segmentation techniques. These segmentation techniques were applied over brain MRI images. Metrics are used to evaluate the seven segmentation techniques.

## 2. SEGMENTATION TECHNIQUES

The seven segmentation techniques discussed in this paper are,

2.1. Otsu threshold (OT)
2.2. Adaptive threshold (AT)
2.3. K means (KM)
2.4. Fuzzy C Means (FCM)
2.5. Seeded Region Growing (SRG)
2.6. Expectation Maximization (EM)
2.7. Watershed Algorithm (WA).

### 2.1. Otsu Threshold:

Otsu's method was invented by Nobuyuki Otsu. The algorithm assumes an image to be bi modal (foreground and background). Steps involved in Otsu algorithm are:

Step 1: Gray scale image is given as a input
Step 2: Histogram of input image is generated
Step 3: Select threshold based on the histogram.
Step 4: Based on the threshold two clusters have been Generated Cf (foreground), Cb (background)
Step 5: Calculate mean and variance for Cf & Cb
Step 6: Calculate within class variance.
Step 7: Repeat steps 3 to 7 for all possible threshold Values.
Step 8: Final global threshold is computed, and it is Denoted by T .which should minimizes inter Class variance and maximizes intra class Variance.
Step 9: Binary image is segmented based on The threshold T.

Input image is denoted by I total number of pixels denoted by N, pixel intensities ranges from [1, 2, 3... L]. Two clusters Cf and Cb contain pixel ranges from 0 to t and

t to L. At each level I total number of pixels are N=n1+n2+...nL.
For cluster Cb,

$$Weight\ W_b = \sum_{i=1}^{t} \frac{n_i}{N} \qquad Mean\ \mu_b = \frac{\sum_{i=1}^{t} i * n_i}{\sum_{i=1}^{t} n_i}$$

$$Variance\sigma_b^2 = \frac{\sum_{i=1}^{t} (i-\mu_b)^2 * n_i}{\sum_{i=1}^{t} n_i}$$

For cluster Cf,

$$Weight\ W_f = \sum_{i=t+1}^{L} \frac{n_i}{N} \qquad Mean\ \mu_f = \frac{\sum_{i=t+1}^{L} i * n_i}{\sum_{i=1}^{t} n_i}$$

$$Variance\sigma_b^2 = \frac{\sum_{i=t+1}^{L} (i-\mu_b)^2 * n_i}{\sum_{i=1}^{t} n_i}$$

$$Within\ Class\ Variance\sigma_w^2 = W_b\sigma_b^2 + W_f\sigma_f^2$$

## 2.2 Adaptive Threshold:

In global threshold a single threshold value is taken to segment the complete image. Where as in adaptive threshold image was subdivide into smaller regions and for each region a threshold is calculated and based on that threshold that particular region is segmented. Adaptive threshold works well for the images with uneven illumination.

## 2.3 K Means:

It is a simple and unsupervised learning technique. Steps involves in k means clustering are:
Step 1: Input an image with K (number of clusters we want to be in the output image).
Step 2: Randomly select k centroids.
Step 3: Calculate the distance between all the pixels With each centroids.
Step 4: Assign the pixel with appropriate clusters Whose Euclidean distance is minimal.
Step 5: Recalculate new cluster centroids.
Step 6: Repeat the steps 3 to 5 unless and until there Is no reassignment of centroids.
Input image is denoted by I with pixels ranges from X={ x1, x2,...,xn}, clusters K= {k1, k2,...,kK },and centroids C={c1,c2,..ck}
Formula used to calculate Euclidean distance is,

$$\sum_{i=1}^{k} \sum_{X_j} \left\| X_j - C_k \right\|^2 ; x_j \in k_i \qquad [5]$$

New centroid is computed by calculating the mean in that appropriate cluster. The disadvantage of k means clustering is, it segments the input image, only based on the user input k.

## 2.4 Fuzzy C Means:

It was developed by J.C.Dunn in 1973 It is similar to k means clustering. But it has one special concept known as fuzzy. That means when one data point is nearer to two or more clusters, problem arise. So we uses the degree of membership function (fuzzy concept).It clearly depicts which cluster is closer to the particular data point. This helps to segment the input image more accurately. But the disadvantages of k mean clustering is exist here. Fuzzy c means suits well for overlapped data set. Input image is denoted by I with pixels ranges from X={x1, x2... xn}, and clusters C= {c1, c2... ck}, the formula used to calculate degree of membership($u_{ij}$) is,

$$u_{ij} = \frac{1}{\sum_{m=1}^{C} \frac{d_{ij}}{d_{im}\left(\frac{2}{k}-1\right)}}$$

$d_{ij}$ is $\left\| x_i - c_j \right\|$

New cluster centroid $C_j$ is computed using the below formula,

$$C_j = \frac{\sum_{i=1}^{N} x_i u_{ij}^k}{\sum_{i=1}^{N} u_{ij}^k}$$

## 2.5 Seeded Region Growing:

Steps involved in seeded region growing are,
Step 1: Seeded region growing starts with Selecting a seed pixel.
Step 2: Compares the seed pixel with the neighboring Pixel. if it shares the common attributes then It will be added to the seed pixel.
Step 3: Repeat the step 2 until all the pixels are Examined. I.e. no more pixels left. Selection of Seed point can be done manually or Automatically.

## 2.6 Expectation Maximization:

Expectation maximization is an iterative clustering technique similar to k means clustering. The main goal of EM algorithm is to compute the mean and standard deviation for each cluster from these results, probability and likelihood is calculated. Each pixel belongs to a cluster with some probability. The final step is assigning pixel with the cluster which has highest classification probability. The algorithm stops when likelihood in expectation step merges with likelihood in maximization step.

## 2.7 Watershed Algorithm:

Watershed segmentation converts an image into a topographic view. The higher intensity pixels are denoted by mountains and lower intensity pixels are denoted by valleys. Instead of working directly on a image the technique often applied over the gradient of an image.[13].This technique identifies all the three types of points for segmentation process. That is regional minima points, catchment basin of regional minima, and the divide lines or watershed lines. Start filling water from each regional minima, the water level continues to rise in the catchment basin, at particular point, when the water between two or more catchment basin start to merge. Pause the water filling step and construct a dam to avoid water merge at the particular catchment basin. And start the filling process. Stop the process when dam seperates all the catchment basins. Sometimes this may cause oversegmentation problem in an image.

By using marker concept, over segmentation problem is avoided. Two types of markers are used (i) Internal markers (ii) External markers. Internal markers marks the fore ground objects and external markers marks the background markers. External markers are not part of any object. This will help to segment the object more accurately.

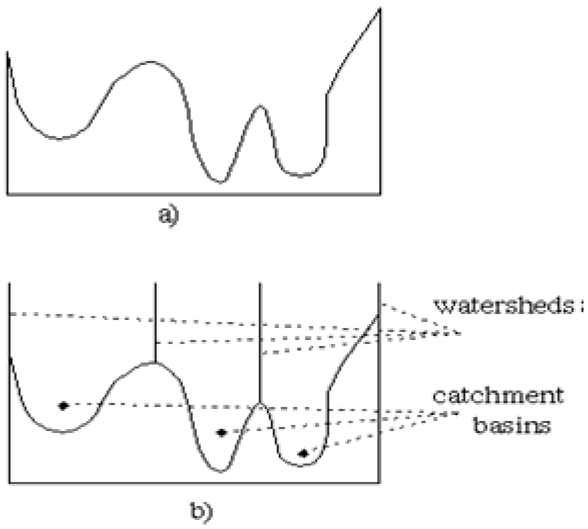



**Fig.[1].** Topographic View Of Watershed Segmentation

## 3. EXPERIMENTAL RESULTS & EVALUATION

Metrics used to evaluate the algorithm are

1. MSE
2. PSNR
3. Sensitivity
4. Specificity
5. Accuracy
6. Precision
7. Hammoude Distance
8. Elapsed Time
9. Border Error

The formula used to calculate MSE and PSNR are

$$MSE = \frac{1}{n}\sum_{i=1}^{n}[\text{seg img- ori img}]^2$$

$$PSNR=10\log_{10}[\text{max intensity}^2 / MSE]$$

$$\text{Sensitivity} = \frac{\#(TP)}{\#(TP)+\#(FN)}$$

$$\text{Specificity} = \frac{\#(TN)}{\#(TN)+\#(FP)}$$

$$\text{Accuracy} = \frac{\#(TP)+\#(TN)}{\#(TP)+\#(TN)+\#(FP)+\#(FN)}$$

$$\text{Hammoude Distance} = \frac{\#(FP)+\#(FN)}{\#(TN)}$$

$$\text{Border Error} = \frac{\#(FP)+\#(FN)}{\#(TP)+\#(FN)}$$

Elapsed time is nothing but time taken to complete the segmentation process.

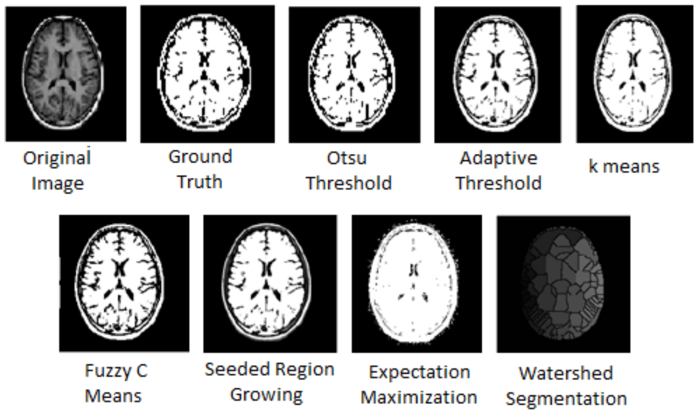



**Fig.[2].** The Seven Segmentation Techniques Applied To Non Tumor Brain MRI Datasets

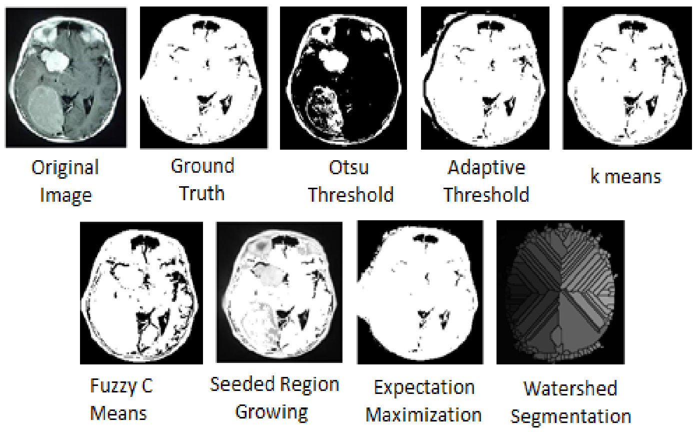



**Fig.[3].** The Seven Segmentation Techniques Applied To Tumor Brain MRI Datasets

**Table [1]:** Performance Analysis of Seven Segmentation Algorithms

| SEG_TECH | MSE | PSNR | SENSITIVITY | SPECIFICITY | ACCURACY | PRECISION | HAM_DIST | BOR_ERR | ELAPSED TIME |
|---|---|---|---|---|---|---|---|---|---|
| OT | 0.1225 | 57.2494 | 65.4662 | 100 | 87.75 | 1 | 18.9842 | 34.5338 | 0.2178 |
| AT | 0.0004 | 81.8469 | 100 | 99.9058 | 99.9575 | 0.99923 | 0.09432 | 0.07741 | 0.6078 |
| KM | 0.0233 | 64.4572 | 100 | 96.3891 | 97.67 | 0.93836 | 3.7461 | 6.5685 | 0.8783 |
| FCM | 0.0311 | 63.2172 | 91.2608 | 100 | 96.91 | 1 | 4.8042 | 8.7392 | 5.8249 |
| SRG | 0.0438 | 61.7161 | 100 | 93.2122 | 95.62 | 0.89009 | 7.2821 | 12.3476 | 1.8402 |
| EM | 0.1061 | 57.8706 | 100 | 83.5458 | 89.3825 | 0.76964 | 19.6949 | 29.9316 | 5.0252 |
| WA | 0.2283 | 54.5443 | 47.9244 | 93.2354 | 77.1625 | 0.79569 | 37.9597 | 64.3809 | 0.2776 |

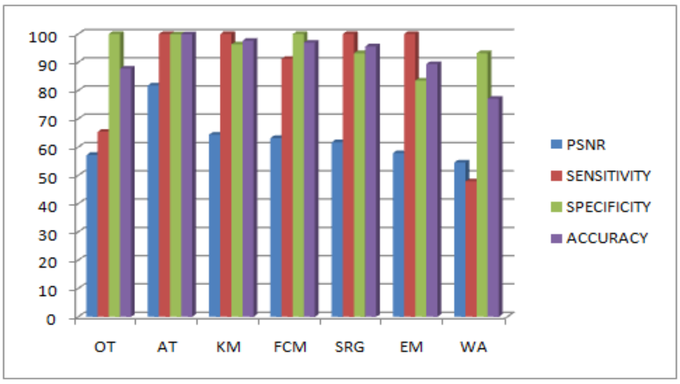



**Chart -1**: PSNR, Sensitivity, Specificity, Accuracy of Seven Segmentation Techniques

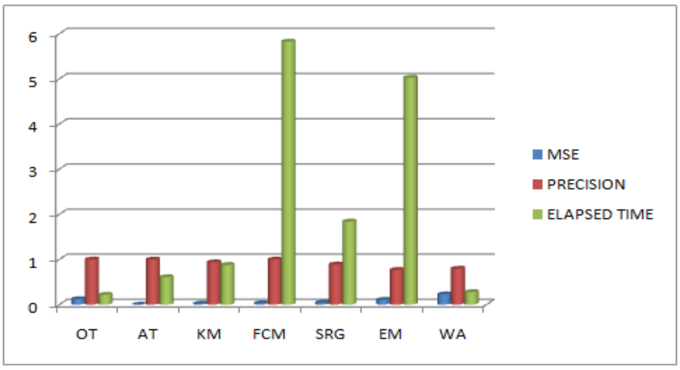
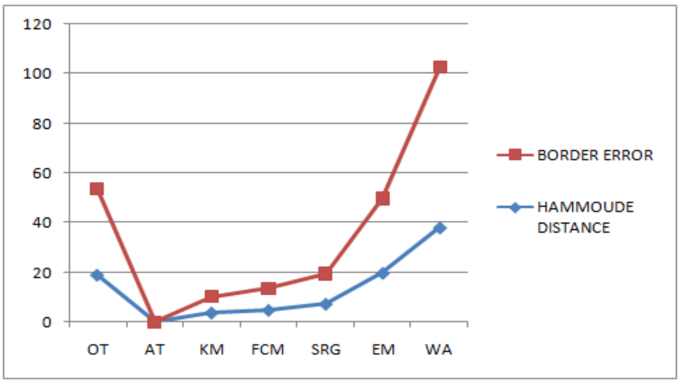



**Chart -2**: MSE, Precision, Elapsed Time for Seven Segmentation Techniques




. **Chart -3**: Hammoude Distance, Border Error for Seven Segmentation Techniques

## 4. CONCLUSION

Seven different segmentation algorithms are compared in this paper. They are Otsu, adaptive, k means, fuzzy c means, seeded region growing, expectation maximization, and watershed algorithm. Brain MRI images are taken to evaluate the seven segmentation algorithms. The metrics used for analyze the segmentation algorithms are MSE, PSNR, specificity, sensitivity, accuracy, precision, hammoude distance, border error, elapsed time. The conclusion derived from the performance analysis is, adaptive segmentation method segment the image efficiently. Its PSNR, sensitivity, specificity, accuracy is high. And hammoude distance, Mean Square Error, border error is very low compared to other segmentation techniques.

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