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Comparative Analysis of Segmented brain MR images using Different Thresholding Techniques

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ABSTRACT

In medical image processing, image segmentation playing very important role in processing of images. In a medical diagnosis MR images playing very crucial role. Generally, brain MR images are complex its nature is inhomogeneous to converting inhomogeneous into homogeneous are very difficult. In this paper, we have proposed an efficient segmentation technique that can differentiate normal and abnormal tissues i. e white matter, gray matter, cerebrospinal fluid and tumor in brain MRI. This technique can be compared with different thres holding techniques in terms of signal to noise ratio (SNR) and quality metric. Finally results are shown numerically and graphically.

Keywords:- Image segmentation, MR images, White matter, Gray matter, cerebrospinal fluid, SNR.

1.INTRODUCTION

Partition an image into number of regions or objects is called image segmentation. In MR image Segmentation, it is very difficult to separation of tumor in brain. Segmentation accuracy determines the eventual success or failure of the computerized analysis procedures [1]. Segmentation algorithms are area oriented instead of pixel-oriented. The result of segmentation is the splitting up of the image into connected areas. The primary step of Image segmentation is analysis, understanding, and interpretation and recognition of objects in the image. Segmentation is the most important step in automated recognition system which has numerous applications in the field of medical imaging, satellite imaging, movement detection, security, surveillance etc. [2].

2. SEGMENTATION TECHNIQUES

The region represents meaningful areas in an image or be the set of border pixels grouped into structures such as line segments, edges etc. The segmentation has two objectives: (i) to decompose an image into regions for further analysis, (ii) to perform a change of representation of an image for faster analysis [2]. Different types of segmentation techniques are used for segmentation. Based on the application, a single or a combination of segmentation techniques can be applied to solve the problem effectively. Based on gray level values of pixels perform the segmentation. There are mainly three types of segmentation techniques (1) Edge based segmentation (2) Threshold Based Segmentation (3) Region Based Segmentation. In this paper, we proposed Standard Normal variate technique for selection of thresholding value for segmenting the image.

3. THRESHOLD BASED IMAGE SEGMENTATION

Main purpose of thresholding techniques is to identify a region based on the pixels with similar intensity values. This technique provides boundaries in images that contain solid objects on a contrast background [3]. Thresholding technique gives a binary output image from a gray scale image. This method of segmentation applies a single fixed criterion to all pixels in the image simultaneously [3].

3.1 Global Thresholding

Suppose the histogram of an image f (x, y) is composed of light objects on a dark background. The pixel intensity levels of the object and the background are grouped into two dominant modes. In global thresholding, a threshold value T is selected in such a way that it separates the object and the background. The condition for selecting T is given as follows:

$$g(x,y) = \begin{cases} 1 & \text{if } f(x,y) > T \\ 0 & \text{if } f(x,y) \le T \end{cases} \quad (1)$$

Equation (1) has no indication on selecting the threshold value T. The threshold T separates the object from the dark background. Any point (x,y) for which f(x, y) ≥ T is called an object point. After thres holding operation, the image is segmented as follows: Pixels labeled 1 corresponds to object whereas pixels labeled 0 corresponds to the background. In global thresholding, the threshold value T depends only on gray levels of f(x, y). Global thres holding technique will not produce the desired output when pixels from different segments overlap in terms of intensities [3]. The overlapping of intensities may be caused due to (a) noise (b) variation in illumination across the image. In the first case, minimum-error method can be used to estimate the underlying cluster parameters and the threshold is chosen to minimize the classification error. Variable thresholding technique is used for the latter case. Global thresholding is popular due to simplicity and easy implementation [5][6].

3.2 Local Thresholding

Global thresholding method is not suitable whenever the background illumination is uneven. In local thresholding technique, the threshold value T depends on gray levels of f(x, y) and some local image properties of neighboring pixels such as mean or variance [2]. The threshold operation with a locally varying threshold function T(x, y) is given by

$$g(x,y) = \begin{cases} 1 & \text{if } f(x,y) \geq T(x,y) \\ 0 & \text{if } f(x,y) < T(x,y) \end{cases} \quad (2)$$

Where

$$T(x\ y) = f_0(x,\ y) + T_0 \quad (3)$$

f0(x, y) is the morphological opening of f, and the constant T0 is the result of function gray thresh applied to f0 [1]. Local thresholding is superior to the global threshold method in the case of poorly illuminated images.

3.3 Adaptive Thresholding

Adaptive thresholding technique is used when images are captured under unknown lightning condition and it is required to segment a lighter foreground object from its background or whenever the background gray level is not constant and object contrast varies within an image. This technique allows the threshold value T to change based on the slowly varying function of position in the image or on local neighboring hood statistics. Threshold T depends on the spatial coordinated (x, y) themselves.

4. THRESHOLD SELECTION

The key parameter in image segmentation using thresholding technique is the choice of selecting threshold value T. In case of manual thresholding method, the threshold value T can be selected by the user with the help of image histogram. This method is generally accomplished by a tool that allows the user to select the threshold value T based on choice. In case of automatic threshold selection method, the value of T can be chosen based on histogram, clustering, variance, means etc.

4.1 Histogram based Threshold Selection

An image having an object on a contrasting background has a bimodal histogram. The two peaks correspond to the relatively large number of points inside and outside the object. The valley is commonly used to select the threshold gray level. If the image containing the object is noisy and degraded due to illumination artifacts the histogram itself will be noisy and will not be sharp. This can introduce error in selecting the threshold value T. This effect can be overcome to some extent by smoothing the histogram using either a convolution filter or the curve-fitting procedure [3]. Histogram based thresholding is applied to obtain all possible uniform regions in the image [7]. Let P1 and P2 be the gray value of the peaks of the histogram. The threshold value T is given by

$$T = \frac{P_1 + P_2}{2} \quad (4)$$

Or T may be the gray level at the minimum between the two peaks.

$$T = \min_{u \in [P_1, P_2]} H(u) \quad (5)$$

where H(u) is the histogram value at gray level u between P1 and P2

4.2 Iterative based Threshold Selection

Iterative methods give better result when the histogram doesn't clearly define valley point. This method doesn't require any specific knowledge about the image. Iterative method has the ability to improve the anti-noise capability.[4].

Gonzalez and Woods [2002] describe the following iterative procedure:

1. Select an initial estimate for the threshold value (T). This can be done by selecting the midpoint between the minimum and maximum intensity values in the image.
2. Segment the image using T. This will produce two sets of pixels G1 and G2. G1 contains all pixels with intensity values ≥ T and G2 contains pixels values <T.
3. Compute average intensity values m1 and m2 for each set of pixels.

m1 = average value of G1
m2 = average value of G2
4. Compute new threshold value

$$T = \frac{1}{2}(m_1 + m_2)$$

5. Repeat steps 2 through 4 until the difference in T in successive iteration is smaller than a predetermined parameter ΔT. This iterative algorithm is a special one dimensional case of K-means clustering that converges at a local minimum. But the main disadvantage is, a different initial estimate for T may give a different result.

4.3 Threshold Selection based on Otsu's method

A segment is assumed to have relatively homogeneous gray level values, then a threshold value T can be selected in such a way that it minimizes the variance of the gray levels within the segment or T can be selected that minimizes the variance between objects and background or a method that attempts to optimize „within‟ and „between‟ segments variance [2]. This method maximizes the between-class variance and is based on computations performed on the histogram of an image. Otsu‟ s algorithm is as follows:

1. Compute the normalized histogram of the input image. The components of the histogram is denoted by Pi = ni / MN, where i=0, 1, 2, L-1 and MN = n0+n1+n2+…+nL-1
2. Compute the cumulative sums $p_1(k)$, where

$$P_1(k) = \sum_{i=0}^{k} P_i \text{, for } k = 0,1,2,\ldots, L-1$$

3. Compute cumulate means

$$m(k) = \sum_{i=0}^{k} i P_i \text{, for } k=0,1,2,\ldots,L-1$$

4. Compute the global intensity mean, mG

$$\text{using } m_G = \sum_{i=0}^{L-1} i P_i$$

5. Compute the between-class variance,

$$\sigma^2 B(k), \text{for } k = 0,1,2,\ldots,L-1 \text{ where}$$

$$\sigma^2 B(k) = \frac{[m_G P_1(k) - m(k)]^2}{P_1(k)[1 - P_1(k)]}$$

6. Obtain the Otsu threshold, k*, as the value of k for which σ^2 B(k) is maximum. If the maximum is not unique, obtain k* by averaging the values of k corresponding to the various maxima detected.
7. Obtain the separability measure, η*

$$\eta(k^*) = \frac{\sigma^2_B(k^*)}{\sigma^2_G}$$

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The main drawback of Otsu‟ s method of threshold selection is that it assumes that the histogram is bimodal. This method fails if two classes are of different sizes and also with variable illumination.

4.4 Proposed threshold selection method

In this method the selection of threshold consisting of following steps:

Step 1: Initially select the gray scale image.

Step 2: Find mean (μ) and standard deviation (σ) of given image.

Step 3: Compute standard normal variate Z, where Z=x-μ/σ.

Step 4: Take standard normal variate Z as threshold value.

Step 5: Finally, segment the image using Gaussian function i.e f(x)= 1/Z $e^{-z2/2}$.

5.EXPERIMENTAL RESULTS

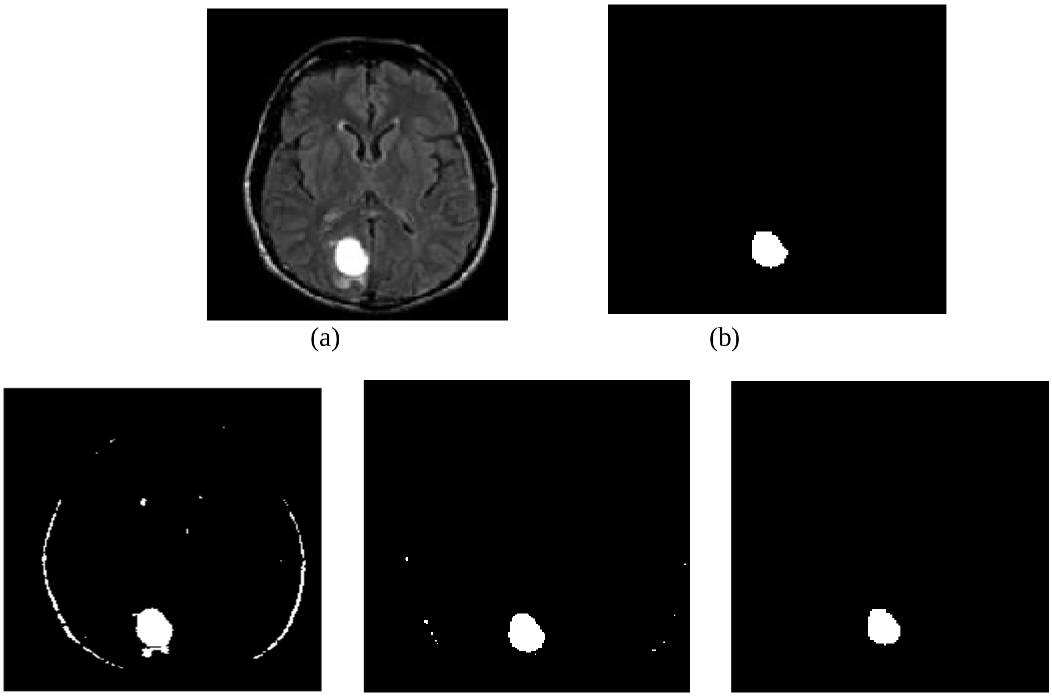
The proposed selection of thresholding is compared with Histogram thresholding and Ostu's thresholding methods in terms of Signal to noise ratio (SNR) and Quality metric i.e Jaccard coefficient. The noise function defined as

$$SNR_{dB} = 10\log_{10}\left(\frac{1}{N^2}\sum_i \frac{x_i^2}{\sigma^2}\right)$$

Jaccard Coefficient

The first measure similarity is the Jaccard Index known as Jaccard similarity coefficient, which is very popular and used mostly as similarity indices for binary data. The area of overlap Aj is calculated between the original image Bj and its corresponding gold standard image Gj as shown in equation

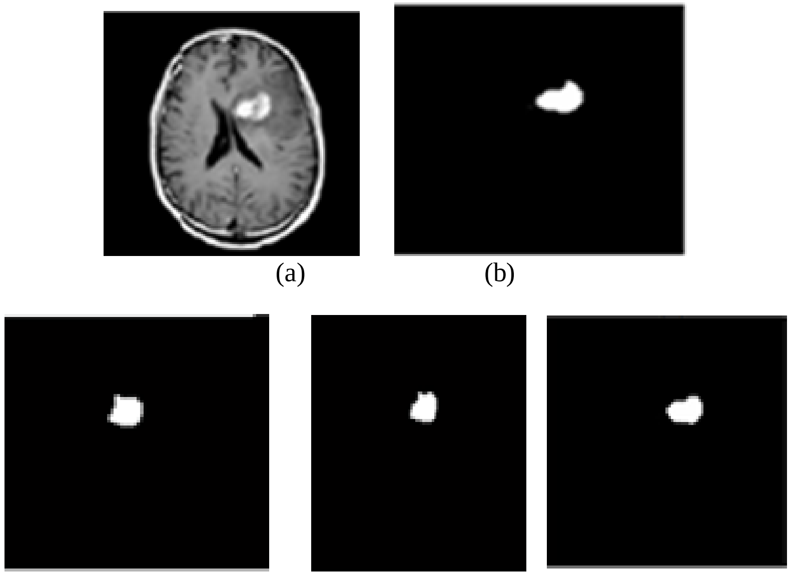
$$A_i = \frac{|B_i \cap G_i|}{|B_i \cup G_i|}$$



(a) (b)

© (d) (e)

Figure 1: Image Segmented results for tumor (a) original image (b) ground truth image (c) Histogram thresholding (d) Ostu;s thresholding and (e) Standard normal variate threshold.



(a) (b)

© (d) (e)

Figure 2: Image Segmented results for tumor (a) original image (b) ground truth image (c) Histogram thresholding (d) Ostu;s thresholding and (e) Standard normal variate threshold.

Table 1: Jaccard coefficient for Histogram thresholding, Ostu's thresholding and Standard normal variate method.

	Histogram thresholding	Ostu's thresholding	Standard normal variate	Standard limit
Img 1	0.6234	0.7188	0.7811	0 to 1
Img 2	0.6155	0.7377	0.7796	0 to 1

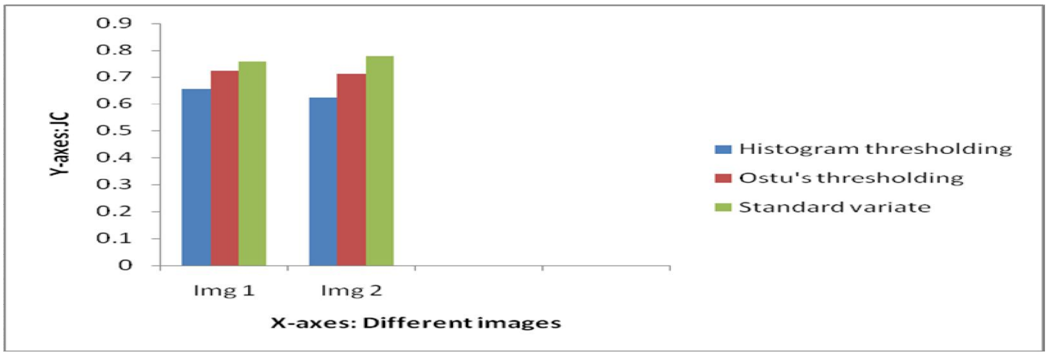


Figure 3: Jaccard coefficient for Histogram thresholding, Ostu's thresholding and Standard variate.

Table 2: Signal to noise ratio results for Histogram thresholding, Ostu's thresholding and Standard normal variate method.

	Historam thresholding	Ostu's thresholding	Normal variate
3%	3.24	3.15	2.23
5%	4.56	3.88	2.98
7%	5.53	4.78	3.57

Table 3: Signal to noise ratio results for Histogram thresholding, Ostu's thresholding and Standard normal variate method.

	Historam thresholding	Ostu's thresholding	Normal variate
3%	3.67	3.22	2.89
5%	4.78	3.95	3.32
7%	4.92	4.34	3.78

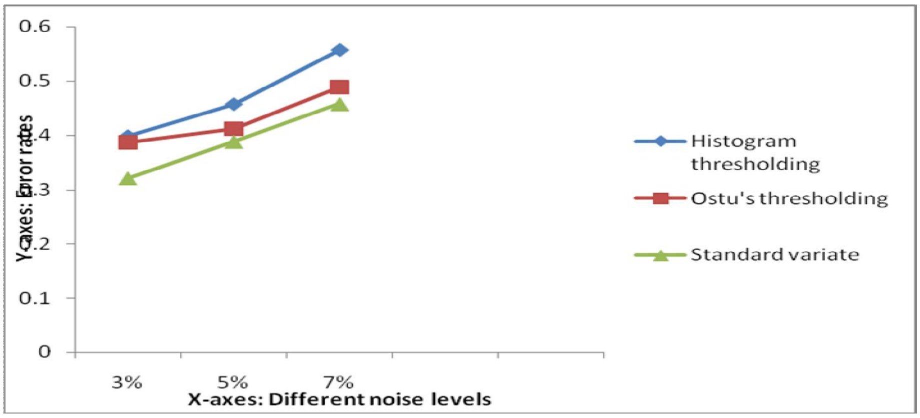


Figure 4: Noise reduction for Histogram thresholding, Ostu's thresholding and Standard variate method.

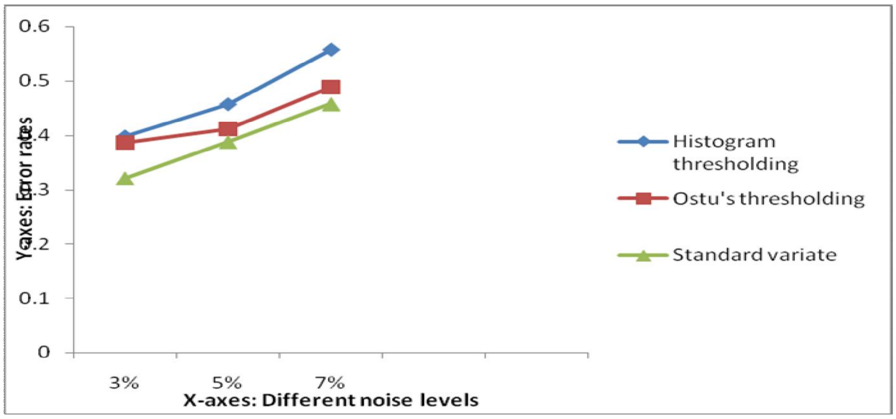


Figure 5: Noise reduction for Histogram thresholding, Ostu's thresholding and Standard variate method.

We can observe above figures and tables quantitatly and qualitatively, proposed method gives better segmentation results than different thresholding segmented results. And also reduce noise for each brain MR image.

6.CONCLUSION

In this paper, novel standard threshold based segmentation for brain MR images has been discussed. This approach yields good results than Histogram thresholding and Ostu;s thresholding. For segmentation of MRI brain images can help in the proper detection of the region of interest in abnormality in the brain.. The main limitation of this approach is cannot be used for multi-channel images. But in medical image segmentation accuracy and boundaries are very crucial, for that purpose in future we will develop an hybrid models for better segmentation.

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