A New Efficient Binarization Method for MRI of Brain Image

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ABSTRACT

This paper proposes a new image binarization method that uses a simple standard deviation approach and gives us very good results for MRI of brain images. The problem of binarization of gray MRI images due to the black background and large intensity variation has been overcome by our proposed method. This method is very useful to extract the objects of interest from an image and, hence, to distinguish the foreground (brain) from the background (black background). The threshold of the image is determined by standard deviation multiplied by a heuristic value. The paper describes the details including the heuristic value used as well as the performance of this method along with some other well known image binarization method.

KEYWORDS

Image Binarization, Performance Evaluation Metrics, Reference Image, Threshold Value, MRI of Brain.

1. INTRODUCTION:

Gray scale image and Binary image are two important variations among digital images. In a gray scale image a particular pixel takes a intensity value lying between 0 to 255 where as a binary image it could take only two values either 0 or 1.The procedure to convert a gray scale image into a binary image is known as image binarization. Image binarization has wide popularity in many research areas especially in case of document image analysis, medical image process and scene processing.

Binarization by Threshold Segmentation of a brain from MRI images is a challenging task. Segmentation and quantification of brain tumor, edma and other disease from MRI of brain need binarization technique as a pre-processing or any other useful steps, so binarization is a very important task for us. There are several binarization techniques or methods which produce very good results for degraded documents, arial image, texture images, and graphic image and shaded image etc, but for MRI many of the existing methods fail due to the large difference of foreground and background intensity. Background part of the image is totally black which have no information and foreground part of the image, the actual brain part have lot of information. In simple cases, binarization can be achieved by thresholding the image, i.e., by assigning all the pixels with gray-level lower than a given threshold to either the background or the foreground, and all the remaining pixels to the other set. However, often more refined processes are required. This is the case when regions with noticeably different gray-levels are all regarded as of interest,

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or when regions with the same gray-level can be regarded as belonging to the foreground or to the background, depending on the local context. To binarized MRI images most of the method produces very shocking output. The use of binary images decreases computational load for the overall application. As after binarization we do some needful work for brain edma, tumor detection and quantification like morphological operation, watershed segmentation etc. Thus if poor binarization results produces then their results affect reflected on segmentation. Thus we need techniques which produce meaningful binarization i.e. meaningful information. In this situation i.e. for MRI of brain tumor images our proposed methods gets very good results and produce meaningful information compare to the other well-known method like Otsu [1], Savala[2], Niblack[3], Bernsen[4], Kapur[5] and Otsu as a frame[6] work in iterative partition.

2. BRIEF REVIEW

Binarization is the processes of translating a gray-scale image to a binary image by choosing threshold selection method to categorize the pixels of an image into either one of the two classes. Most of the technique are divided into two category global thresholding and local thresholding techniques, in the global thresholding method threshold of the entire image is unique and local thresholding method choose threshold value locally and binarization also local. Otsu[1] and Kapur[5] are two very popular method for global thresholding method and Savala [2], Niblack[3], Bernsen[4] are most popular local thresholding methods. Soharab Hossain Shaikh et all [6] proposed a iterative partitioning method as a framework which produce good results for degradead, graphic documents. Except that Ntogas nikolaos et all [7] proposed a binarization a binarization algorithm for historical manuscripts which produce good result for historical documents. Mehmet Sezgin et all [8] gives a brief survey of image binarization and concept of performance metric. We compare our technique with other well known popular algorithms which are shortly describe.

Otsu Thresholding method, as proposed in [1], is based on discriminate analysis. In this method, the threshold operation is regarded as the partitioning of the pixels of an image into two classes C_0 and C_1, (e.g., objects and background) at gray level t. That is, $C_0 = \{0,1,. . . , t\}$ and $C_1=\{t+l,t+2,...,1-L\}$, where L = maximum intensity. Let σ_W^2 , σ_B^2 and σ_T^2 be the within-class variance, between-class variance, and the total variance, respectively. An optimal threshold can be determined by minimizing one of the following (equivalent) criterion functions with respect to t:

$$\lambda = \frac{\sigma_B^2}{\sigma_W^2}, \eta = \frac{\sigma_B^2}{\sigma_T^2}, K = \frac{\sigma_T^2}{\sigma_W^2} \tag{1}$$

And

Of these three criterion functions, η is the simplest. Thus, the optimal threshold t^* is,

$$t^* = \text{Arg} \underbrace{\text{MIN}}_{t \in G} \eta \tag{2}$$

where

$$\sigma_T^2 = \sum_{i=0}^{l-1} (i-\mu_T)^2 P_i , \quad \mu_T = \sum_{i=0}^{l-1} iP_i \tag{3}$$

$$\sigma_B^2 = w_0 w_1 (w_0 w_1)^2, \quad w_0 = \sum_{i=0}^{t} P_i , \quad w_1 = 1 - w_0 , \tag{4}$$

$$\mu_1 = \frac{\mu_T - \mu_t}{1 - w_0}\ ,\ \ \mu_0 = \frac{\mu_t}{w_0}\ ,\ \ \ \mu_T = \sum_{i=0}^{t} P_i\ , \tag{5}$$

Kapur's algorithm [5] is an extension of Otsu's method. In this method two probability distributions (e.g. object distributions and background distributions) are derived from the original gray level distributions of the image as;

$$\frac{P_0}{P_t}, \frac{P_1}{P_t}, \ldots, \frac{P_t}{P_t} \text{ and } \frac{P_{t+1}}{1-P_t}, \frac{P_{t+2}}{1-P_t}, \ldots, \frac{P_{l-1}}{1-P_t} \tag{6}$$

Where t is the threshold value

$$P_T = \sum_{i=0}^{t} P_i \tag{7}$$

And

$$H_b(t) = -\sum_{i=0}^{t} \frac{P_i}{P_t} \log_e \frac{P_i}{P_t}, \quad H_w(t) = -\sum_{i=t+1}^{L-1} \frac{P_i}{1-P_t} \log_e \frac{P_i}{1-P_t} \tag{8}$$

Then the optimal threshold $\mathbf{t}^*$ is defined as the gray value which maximizes $H_b(t) + H_w(t)$, that is,

$$t^* = \text{Arg Max}_{t \in G} \{H_b(t) + H_w(t)\}$$

Niblack [3] proposed an algorithm that calculates a pixel wise thresholding by shifting a rectangular window across the image. This method varies the threshold over the image, based on the local mean and local standard deviation. Let the local area b*b. Also the threshold $T_{nib}(x,y)$ at pixel f(x,y) is determined by the equations:

$$\text{Tnib}(x,y) = \mu\text{nib}(x,y) + K\,\text{nib} * \sigma\_\text{nib}\hat{}2\ (x,y) \tag{9}$$

Where,

$$\mu\text{nib}(x,y) = \frac{1}{b^2}\left[\sum_{j=y-b/2} \left(\sum_{i=x-b/2} f(i,j)\right)\right] \tag{10}$$

and

$$\sigma^2_{nib}(x,y) = \frac{1}{b^2}\left[\sum_{j=y-b/2}^{y+b/2} \left(\sum_{i=x-b/2}^{x+b/2} \{\mu_{nib}(x,y) - f(i,j)\right)\right] \tag{11}$$

Here, $\mu_{nib}(x,y)$ & $\sigma^2_{nib}(x,y)$ are the local mean and the standard deviation values of local area. The local window size b, should be small enough to reflect the local illumination level accurately and adequately large to include both objects and background.

Bernsan's algorithm [4] that method calculates the local threshold value based on the mean value of the minimum and maximum intensities of pixels within a window. If the window is centered at the pixel (x,y) the threshold for (x,y) is defined by: $T(x,y) = \frac{Z_{max} + Z_{min}}{2}$ where Z_{max} and Z_{min} are the maximum and minimum intensity of the window. This threshold works properly only when the contrast is large. Contrast is defined, $C(x,y) = Z_{max} - Z_{min.}$ if the contrast is less that a specific value K, the pixels within the window may be set to background or to foreground according to the class that most suitably describes the window. This algorithm is dependent on K value and also on the size N of window N * N.

Sauvola and Pietikainen [2] devised a method that solves Niblack's problem by hypothesizing on the gray values on objects and background pixels, resulting in the following formula for the threshold:

$$T_{sa}(x,y) = \mu_{sa} + (1 - K_{sa}(1 - \frac{\sigma_{sa}^2(x,y)}{R})) \tag{12}$$

Where μ_{sa} and σ_{sa}^2 are the local mean and the standard deviation values of local area, R denotes the dynamics of the standard deviation fixed to 128 and K_{sa} refers to a fixed value usually set to 0.5.

In spite of the global and local thresholding approaches, we use the partitioning approach [13]. This partitioning method calculates the number of peaks P in a histogram. If P>=2then it subdivides the image into four equal sub-images and repeats the tasks until the sub- image becomes bimodal. This task is recursive and reappearance is controlled by a partition parameter partition parameter. If a sub-image has perfectly bimodal histogram then a global thresholding procedure like Otsu [1] is applied on that sub-image.

Mehmet Sezgin and Bulent Sankur [8] gives a survey over image thresholding method which gives to measure by performance metrics and brief discussion about local thresholding, global thresholding, adaptive, non adaptive type of binarization. There are several research on graphic image, degradead text, documented image some of them gives very good results but for MRI of brain images most of the images produces insensitive results. MRI images gives meaningful information for diagonistic purpous. Thus the focus of our paper is to produce an efficient algorithms for MRI of brain images which produce better results than other existing well known algorithms.

3. PROPOSED METHODOLOGY

In the proposed methods we used standard deviation to select the threshold intensity of the image. Ultimate selection of threshold has done by multiplying a constant value with the threshold intensity of the image using standard deviation. We use the threshold intensity as global value i.e. the threshold intensity of the entire image is unique. The standard deviation of the image pixel of a image I(x,y) or matrix element for I(x,y) is given by :

$$S = (\frac{1}{2}\sum_{i=1}^{n}(x_i - x')^2)^{1/2} \tag{13}$$

Where

$$x' = (\frac{1}{n}\sum_{i=1}^{n} x_i) \tag{14}$$

The algorithms are written below.

3.1 Algorithm

Input: MRI of Brain Image.

Output: Binarizes MRI of Brain Image.

Step1: Take an MRI image I(x,y).

Step2: If it is color image then convert it into gray scale image $I_g(x,y)$.

Step3: Calculate standard deviation of the image and store the intensity value in T_S.

Step4: calculate the threshold value by product of standard deviation and a predefine constant H, i.e.

Threshold intensity value $T= T_S*H$.

Step5: Scan left to right and top to bottom, each pixel of the gray image $I_g(x,y)$.

Step6: Find a binary image I_B from the gray image $I_g(x,y)$ in the following way,

$I_B(x,y) = 1 \quad I_g(x,y) >= T$

$I_B(x,y) = 0 \quad I_g(x,y) < T$

Step7: I_B is the output binary image.

Our proposed method is a new binarization technique of MRI of brain that so MRI of brain is used as an input. As the binarization technique can be applied only to grayscale images. We convert RGB image to its corresponding grayscale image. A RGB image has three components red, green and blue and converts it into on component i.e. gray value which lies between 0 to 255 intensity values. Then we calculate the standard deviation of the matrix elements (image pixels).Thus by using standard deviation we select the random intensity values as the standard deviation values will be less than 100 and hence we multiplied the deviated value by a constant value. Here we choose this constant value H=3. Although H=3 is choosen, in few images H= 2.5 also produce good results .Here we also gives a comparative study why we choose constant H equal to 3. Here we use visual inspection as well as quantative measurement to choose the constant. Visual inspection may be biased but together with quantative measurement [8] such as ME, RAE, Precision, Recall, F-measure and visual are very effective. Thus after getting the threshold intensity we compare each pixel of the gray image to find out whether it is greater than or less than the threshold intensity value. If the pixel intensity is greater than the threshold value then that pixel value is set to 1 otherwise it is set to 0. Thus the whole image is transformed into 0 or 1 i.e. a binary image is generated from the gray image where the foregrounds are marked as 1 and backgrounds are marked as 0.

As there is no proper reference image creation methodology for MRI of brain image we initially select majority voting scheme as a reference image creation but it has been observed that using majority voting scheme improper reference images are produce in MRI of brain image datasets. So, for MRI of brain images the reference images have been created manually with the help of Software photo editor. From this reference image we measure the parameter like ME, RAE, Recall, Precision, F-Measure which has been describe in the next section. The output of our proposed methodology with different constant value i.e. H=2, H=2.5, H=3, H=3.5 are shown in figure 3; figure 4, figure5, figure 6. Input MRI and its corresponding reference image is shown in figure 1 and figure2.

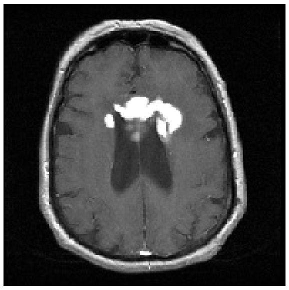

Figure1: MRI of Brain

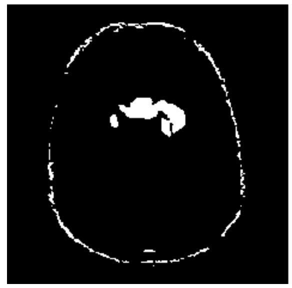

Figure2: Reference image

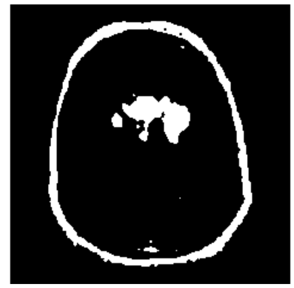

Figure3: Binarize output with H=2

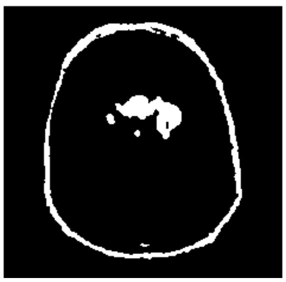

Figure4: Binarize output with H=2.5

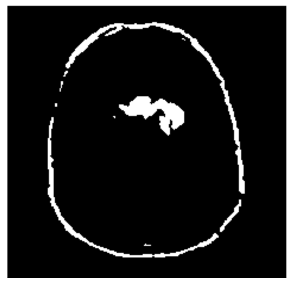

Figure5: Binarize output with H=3

Figure6: Binarize output with H=3.5

3.2. Evaluation techniques for constant H selection

We can select constant H from visual observation but visual observation may be biased so we use some metric such as ME, RAE, Precision, Recall, F-measure.
Misclassification error (ME): Misclassification error [8] gives us the percentage of background pixels wrongly assigned to foreground, and conversely. ME can expressed in the following equation of the two-class segmentation problems:

$$ME = 1 - \frac{|\mathrm{BO} \cap \mathrm{BT}| + |\mathrm{FO} \cap \mathrm{FT}|}{|\mathrm{BO}| + |\mathrm{FO}|} \qquad (15)$$

where B0 and F0 denote the background area pixel and foreground area pixels of the original reference image and BT and FT denote the background area pixel and foreground area pixels in the test image, and | . | is the cardinality of the set. Thus lesser the ME for a technique better is the result.

Relative Foreground Area Error (RAE): Relative Foreground Area Error (RAE) [8] is based on a measure for the area ; the RAE is stated below in the following equation:

$$RAE = \begin{cases} \frac{\mathrm{A0} - \mathrm{AT}}{\mathrm{A0}} & \text{if AT} < A0 \\ \frac{\mathrm{AT} - \mathrm{A0}}{\mathrm{AT}} & \text{if AT} \geq \mathrm{A0} \end{cases} \qquad (16)$$

Here, A0 is the area of original reference image, and AT is the area of thresholded binarized image. Thus lesser RAE means better binarization.

Recall, Precision and F-measure [8]: In the context of binarization, the recall, precision and F-measure are defined as ,

N_Relevant = Number of object pixels in the Reference Image.
N_Retrieved = Number object pixels in the Binary Image.
A = Number of object pixels intersect between Reference and the Binary Image.
B = N_Relevant – A , C= N_Retrieved – A and Recall = $\frac{A}{A+B}$, Precision = $\frac{A}{A+C}$

A measure that combines precision and recall is the harmonic mean of precision and recall, the traditional F-measure. It is defined as follows:

$$F\text{-}measure = \frac{2 \times \text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \quad (17)$$

A higher value of F-measure indicates better performance.

Thus the table for ME, RAE, Precision, Recall, F-measure on different MRI of brain is shown below.

Table 1: ME measurement

Image name	H=2	H=2.5	H=3	H=3.5
MRI_1	0.0702	0.0331	0.0245	0.0168
MRI_2	0.0252	0.0340	0.0524	0.0841
MRI_3	0.2608	0.0292	0.0051	0.0081
MRI_4	0.0500	0.0253	0.0117	0.0344
MRI_5	0.2188	0.0332	0.0051	0.0195
MRI_6	0.1058	0.0176	0.0090	0.0236
MRI_7	0.3358	0.0246	0.0098	0.0116
MRI_8	0.0608	0.0385	0.0221	0.0098
MRI_9	0.1091	0.0470	0.0108	0.0180
MRI_10	0.1077	0.0340	0.0210	0.0273
MRI_11	0.2075	0.0483	0.0086	0.0048
MRI_12	0.3144	0.0954	0.0265	0.0361
MRI_13	0.1745	0.0964	0.0225	0.0056
MRI_14	0.1387	0.0168	0.0053	0.0159
MRI_15	0.0532	0.0153	0.0252	0.0411
MRI_16	0.0212	0.0157	0.0071	0.0155
MRI_17	0.0844	0.0433	0.0077	0.0217

Table 2: RAE measurement

Image name	H=2	H=2.5	H=3	H=3.5
MRI_1	0.7401	0.5622	0.4475	0.2543
MRI_2	0.0217	0.2419	0.4415	0.7260
MRI_3	0.9588	0.7222	0.4578	0.7193
MRI_4	0.3646	0.2005	0.0445	0.3984
MRI_5	0.6829	0.2424	0.0131	0.1908
MRI_6	0.7444	0.3136	0.0916	0.6501
MRI_7	0.9570	0.5735	0.0010	0.7737
MRI_8	0.6515	0.5364	0.3506	0.1670

MRI_9	0.6494	0.4387	0.0840	0.3050
MRI_10	0.8090	0.5695	0.3982	0.2757
MRI_11	0.9382	0.7793	0.3838	0.2546
MRI_12	0.8849	0.6880	0.0257	0.8818
MRI_13	0.9533	0.9186	0.7250	0.3939
MRI_14	0.8380	0.3846	0.1986	0.5948
MRI_15	0.3990	0.0448	0.3447	0.5614
MRI_16	0.2566	0.2039	0.1041	0.2514
MRI_17	0.6610	0.4997	0.1783	0.5007

Table 3 : Recall measurement

Image name	H=2	H=2.5	H=3	H=3.5
MRI_1	100	97.0916	90.9035	83.0446
MRI_2	88.0501	73.2279	55.2964	27.4045
MRI_3	100	99.7275	54.2234	28.0654
MRI_4	99.7705	97.8817	90.9797	60.1589
MRI_5	99.8044	99.6389	98.1342	80.8607
MRI_6	100	98.6140	83.0323	34.9853
MRI_7	91.9470	84.9134	67.2783	22.6300
MRI_8	100	98.7336	93.0582	76.5478
MRI_9	100	99.1708	95.4133	69.4480
MRI_10	99.4582	99.0367	91.6315	32.2697
MRI_11	100	99.8884	99.6652	99.6652
MRI_12	100	93.6218	66.2812	11.8239
MRI_13	100	100	100	100
MRI_14	100	100	80.1366	40.5236
MRI_15	96.8952	87.3099	65.5345	43.8633
MRI_16	100	100	100	74.3358
MRI_17	100	100	82.1705	49.9295

Table 4 : Precision measurement

Image name	H=2	H=2.5	H=3	H=3.5
MRI_1	25.9932	42.5088	50.2222	61.9289
MRI_2	90.0067	96.5937	99.0092	100
MRI_3	4.1174	27.7063	100	100
MRI_4	63.3988	78.2529	95.2152	100
MRI_5	31.6445	75.4902	96.8518	99.9256
MRI_6	25.5637	67.6852	91.4008	100
MRI_7	3.9515	36.2174	67.2098	100
MRI_8	34.8537	45.7708	60.4325	91.8919

MRI_9	35.0563	55.6655	87.3962	99.9254
MRI_10	18.9929	42.6387	55.1449	44.5553
MRI_11	6.1810	22.0498	61.4168	74.2928
MRI_12	11.5148	29.2132	68.0322	100
MRI_13	4.6671	8.1407	27.5049	60.6061
MRI_14	16.1980	61.5412	100	100
MRI_15	58.2342	91.4049	100	100
MRI_16	74.3358	79.6088	89.5931	100
MRI_17	33.9028	50.0264	100	100

Table 5 : F – measure

Image name	H=2	H=2.5	H=3	H=3.5
MRI_1	41.2613	59.1295	64.6994	70.9490
MRI_2	89.0176	83.3034	70.9612	43.0196
MRI_3	7.9091	43.3649	70.3180	43.8298
MRI_4	77.5309	86.9736	93.0493	75.1240
MRI_5	48.0530	85.8996	97.4888	89.3879
MRI_6	40.7183	80.2735	87.0158	51.8357
MRI_7	7.5773	50.7772	67.2440	36.9077
MRI_8	51.6911	62.5464	73.2779	83.5210
MRI_9	51.9136	71.3061	91.2289	81.9447
MRI_10	31.8950	59.6122	68.8532	37.4302
MRI_11	11.6424	36.1251	76.00	85.1287
MRI_12	20.6517	44.5312	67.1453	21.1474
MRI_13	8.9179	15.0558	43.1433	75.4717
MRI_14	27.8800	76.1925	88.9731	57.6752
MRI_15	72.7472	89.3105	79.1793	60.9791
MRI_16	85.2789	88.6469	94.5109	85.6210
MRI_17	50.6379	66.6902	90.2128	66.6040

Thus from visual inspection and metric dependent evaluation we choose the H=3 as the constant value but some images which have low intensity may have to choose H = 2.5 as a constant. For H=2 some extra portion are binarized and for H=3.5 binarization are not effective due to high threshold value.

4. RESULT & COMPARISON WITH OTHER WELL-KNOWN METHODOLOGY

We compare our proposed methodology with other existing well known binarization like Otsu, Niblack, Otsu as a partition framework, Savala, Bernsen, and Kapur methods visually as well as metric wise. Our proposed method produces very good results for MRI of brain. Most of the image produce result or binaries the total image but MRI of brain proceeds by a dark background, we want to binarize the actual brain portion. The global threshold segmentation Kapur produce good results and global thresholding methods Otsu satisfactory but local thresholding method like Savala, Niblack are not suitable for this type of image. For some of the images local thresholding method Bernsen produce satisfactory results. Partitioning framework method do not produce good results. Our proposed method is a global thresholding methods produces very good results for MRI of brain. From the metric ME, RAE is less in our proposed method and F-measure are greater value which is expected. Thus our proposed method is very good and efficient algorithms for binarization of MRI of brain. We show the output of different method for the image shown in figure 1 and also shown below proposed method with other existing method for other images.

Figure 7: Otsu

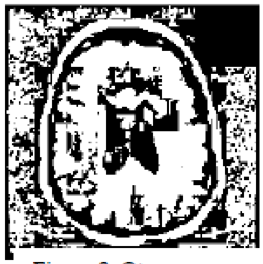

Figure 8: Otsu as a partition

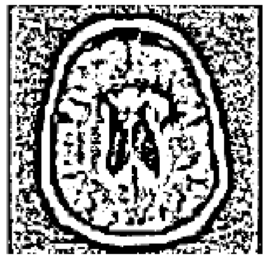

Figure 9: Niblack

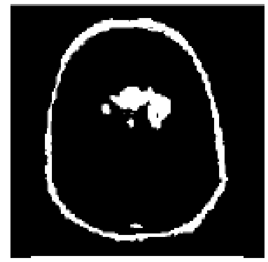

Figure 10: Bernsen

Figure 11: Savala

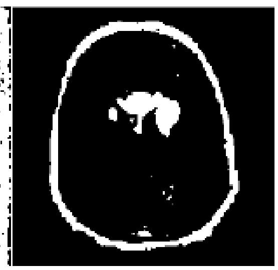

Figure 12: Kapur

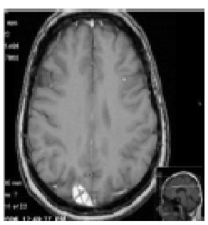

Figure 13: MRI of Brain

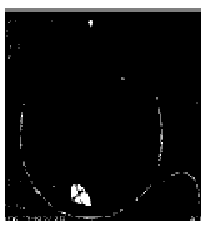

Figure 14: Reference image

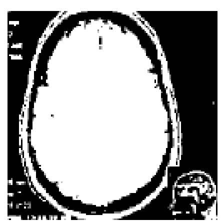

Figure 15: Otsu

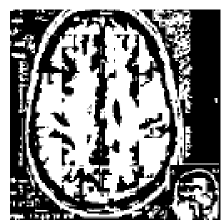

Figure 16: Otsu as a partition

Figure 17: Niblack

Figure 18: Bernsen

Figure 19: Savala

Figure 20: Kapur

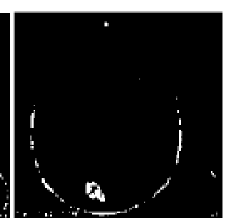

Figure 21: Proposed

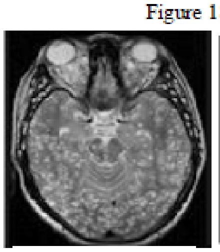

Figure 22: MRI of Brain

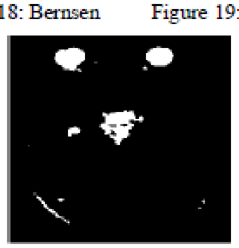

Figure 23: Reference image

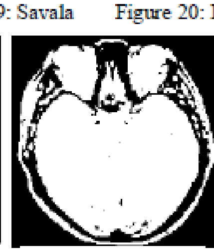

Figure 24: Otsu

Figure 25: Otsu as a partition

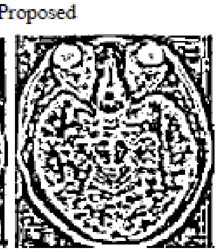

Figure 26: Niblack

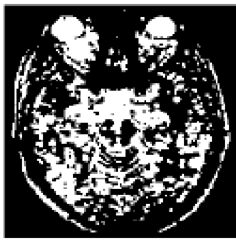
Figure 27: Bernsen


Figure 28: Savala

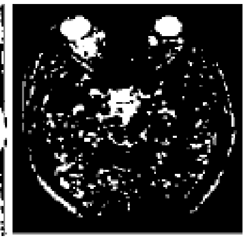
Figure 29: Kapur

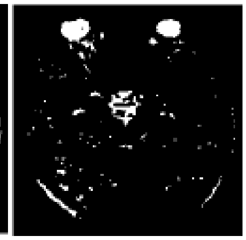
Figure 30: Proposed

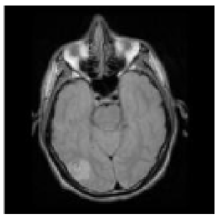
Figure 31: MRI of Brain

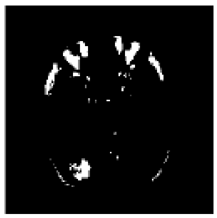
Figure 32: Reference image


Figure 33: Otsu


Figure 34: Otsu as a partition

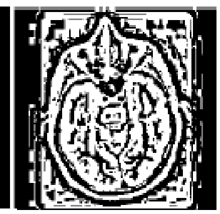
Figure 35: Niblack

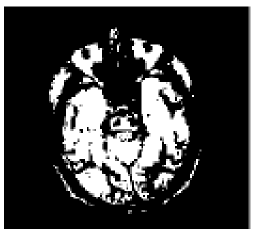
Figure 36: Bernsen


Figure 37: Savala


Figure 38: Kapur

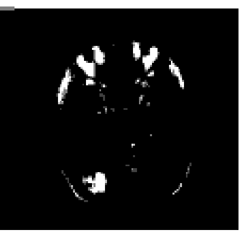
Figure 39: Proposed

Table 6 : ME Measurement

Image name	Kapur Method	Otsu as a partition	Otsu Method	Niblack Method	Bernsen Method	Savala Method	Proposd Method
MRI_1	0.0424	0.3763	0.3621	0.4527	0.0399	0.6975	0.0242
MRI_2	0.0403	0.4183	0.0272	0.3426	0.0255	0.6957	0.0514
MRI_3	0.0051	0.4373	0.3783	0.4773	0.3250	0.8811	0.0044
MRI_4	0.0665	0.4171	0.0442	0.4879	0.0526	0.6907	0.0113
MRI_5	0.5156	0.4333	0.4496	0.4849	0.2280	0.7004	0.0043
MRI_6	0.0376	0.2553	0.3969	0.2844	0.1207	0.4175	0.0090
MRI_7	0.0255	0.4399	0.5172	0.4777	0.3332	0.6460	0.0053
MRI_8	0.0627	0.4633	0.3939	0.5184	0.0475	0.7412	0.0218
MRI_9	0.0857	0.5142	0.6194	0.4839	0.0971	0.7719	0.0105
MRI_10	0.0485	0.5418	0.3674	0.4088	0.0296	0.8716	0.0226
MRI_11	0.0110	0.4013	0.3515	0.5228	0.0290	0.8778	0.0103
MRI_12	0.0695	0.4360	0.5460	0.5063	0.2354	0.7459	0.0265
MRI_13	0.0149	0.3914	0.2874	0.5441	0.0473	0.8522	0.0267
MRI_14	0.0203	0.3661	0.4300	0.3818	0.1344	0.5000	0.0047
MRI_15	0.0440	0.2691	0.2807	0.3429	0.0759	0.4161	0.0149
MRI_16	0.0461	0.1984	0.0236	0.2979	0.0327	0.4618	0.0071
MRI_17	0.0105	0.4257	0.1507	0.4993	0.0117	0.7222	0.0077

Table 7 : RAE Measurement

Image name	Kapur Method	Otsu as a partition	Otsu Method	Niblack Method	Bernsen Method	Savala Method	Proposed Method
MRI_1	0.6470	0.9378	0.9363	0.9363	0.6160	0.9662	0.4475
MRI_2	0.2535	0.7969	0.1247	0.7127	0.1159	0.8585	0.4415
MRI_3	0.3075	0.9782	0.9713	0.9766	0.9669	0.9875	0.4578
MRI_4	0.4280	0.8481	0.3227	0.8510	0.3646	0.8918	0.0445
MRI_5	0.8345	0.8120	0.8195	0.8252	0.6902	0.8746	0.0131
MRI_6	0.4834	0.8713	0.9169	0.8850	0.7935	0.9206	0.0916
MRI_7	0.5735	0.9680	0.9720	0.9700	0.9579	0.9780	0.0010
MRI_8	0.6574	0.9377	0.9243	0.9414	0.6094	0.9597	0.3506
MRI_9	0.5988	0.8977	0.9133	0.8915	0.6147	0.9294	0.0840
MRI_10	0.6531	0.9554	0.9359	0.9408	0.5457	0.9719	0.3982
MRI_11	0.4452	0.9705	0.9627	0.9743	0.6470	0.9848	0.3838
MRI_12	0.5996	0.9118	0.9303	0.9240	0.8518	0.9480	0.0257
MRI_13	0.5566	0.9784	0.9707	0.9844	0.8344	0.9900	0.7250
MRI_14	0.2778	0.9300	0.9400	0.9327	0.8227	0.9481	0.1986
MRI_15	0.2995	0.7779	0.7864	0.8188	0.4674	0.8469	0.3447
MRI_16	0.4283	0.7521	0.2774	0.8201	0.5324	0.8825	0.1041
MRI_17	0.2435	0.9077	0.7768	0.9201	0.2692	0.9434	0.1783

Table 8 : Recall Measurement

Image name	Kapur Method	Otsu as a partition	Otsu Method	Niblack Method	Bernsen Method	Savala Method	Proposed Method
MRI_1	99.9381	98.6386	100	100	99.5668	100	90.9035
MRI_2	97.6680	93.0435	95.2174	89.6047	82.8063	99.8682	55.2964
MRI_3	96.5940	90.4632	100	98.6376	100	100	54.2234
MRI_4	99.8941	96.1518	99.5587	93.3098	99.7705	100	90.9797
MRI_5	99.8947	98.1794	99.8646	97.3819	99.8044	99.8345	98.1342
MRI_6	99.9580	97.6900	100	94.4141	100	100	83.0323
MRI_7	84.9134	93.9857	97.8593	96.1264	92.1509	98.8787	67.2783
MRI_8	100	97.5610	100	98.6867	99.9531	100	93.0582
MRI_9	100	99.3003	100	99.8445	100	100	95.4133
MRI_10	99.0367	99.6388	100	90.6081	99.0367	100	91.6315
MRI_11	99.6652	100	100	92.4107	99.8884	100	99.6652
MRI_12	89.8545	83.9239	100	89.1085	99.6270	100	66.2812
MRI_13	100	100	100	100	100	100	100
MRI_14	100	100	100	100	100	100	80.1366
MRI_15	95.5407	96.2909	100	98.4788	97.8120	99.3749	65.5345
MRI_16	100	90.3202	100	85.6540	46.7610	100	100
MRI_17	75.6519	99.9648	100	98.8724	73.0796	100	82.1705

Table 9 : Precision Measurement

Image name	Kapur Method	Otsu as a partition	Otsu Method	Niblack Method	Bernsen Method	Savala Method	Proposed Method
MRI_1	35.2774	6.1400	6.3695	5.1980	38.2367	3.3808	50.2222
MRI_2	72.9124	18.8965	83.3468	25.7477	93.6662	14.1310	99.0092
MRI_3	66.8868	1.9709	2.8729	2.3037	3.3103	1.2491	100
MRI_4	57.1385	14.6032	67.4319	13.8999	63.3988	10.8171	95.2152
MRI_5	16.5293	18.4541	18.0206	17.0231	30.9173	12.5205	96.8518
MRI_6	51.6381	12.5771	8.3075	10.8610	20.6451	7.9404	91.4008
MRI_7	36.2174	3.0070	2.7381	2.8831	3.8777	2.1777	67.2098
MRI_8	34.2600	6.0760	7.5724	5.7877	39.0436	4.0338	60.4325
MRI_9	40.1185	10.1566	8.6704	10.8334	38.5322	7.0604	87.3962
MRI_10	34.3567	4.4394	6.4104	5.3654	44.9945	2.8100	55.1449
MRI_11	55.2941	2.9505	3.7346	2.3705	35.2640	1.5217	61.4168
MRI_12	35.9821	7.4033	6.9702	6.7721	14.7651	5.1994	68.0322
MRI_13	44.3389	2.1590	2.9292	1.5580	16.5582	0.9976	27.5049
MRI_14	72.2154	7.0020	6.0007	6.7256	17.7331	5.1876	100
MRI_15	66.9245	21.3886	21.3574	17.8441	52.0977	15.2179	100
MRI_16	57.1733	22.3911	72.2561	15.4097	100	11.7494	89.5931
MRI_17	100	9.2311	22.3218	7.9047	100	5.6569	100

Table 10: F Measure Measurement

Image name	Kapur Method	Otsu as a partition	Otsu Method	Niblack Method	Bernsen Method	Savala Method	Proposed Method
MRI_1	52.1472	11.5604	11.9761	9.8823	55.2541	6.5405	64.6994
MRI_2	83.4938	31.4132	88.8875	40.0012	87.9021	24.7587	70.9612
MRI_3	79.0412	3.8577	5.5854	4.5022	6.4085	2.4674	70.3180
MRI_4	72.6957	25.3555	80.4049	24.1955	77.5309	19.5224	93.0493
MRI_5	28.3651	31.0685	30.5318	28.9802	47.2100	22.2505	97.4888
MRI_6	68.0973	22.2850	15.3405	19.4809	34.2245	14.7125	87.0158
MRI_7	50.7772	5.8275	5.3271	5.5983	7.4422	4.2615	67.2440
MRI_8	51.0353	11.4396	14.0786	10.9341	56.1528	7.7547	73.2779
MRI_9	57.2637	18.4284	15.9572	19.5460	55.6292	13.1896	91.2289
MRI_10	51.0157	8.5000	12.0485	10.1309	61.8770	5.4664	68.8532
MRI_11	71.1270	5.7318	7.2003	4.6223	52.1258	2.9979	76.000
MRI_12	51.3865	13.6063	13.0320	12.5876	25.7185	9.8848	67.1453
MRI_13	61.4372	4.2267	5.6916	3.0682	28.4120	1.9755	43.1433
MRI_14	83.8663	13.0875	11.3220	12.6036	30.1243	9.8636	88.9731
MRI_15	78.7124	35.0023	35.1975	30.2135	67.9846	26.3940	79.1793
MRI_16	72.7519	35.8858	83.8938	26.1202	63.7240	21.0282	94.5109
MRI_17	86.1384	16.9015	36.4969	14.6390	84.4463	10.7080	90.2128

Figure below shows the graphical representation of ME, RAE, Recall, Precision, F measure of different method with different color representation. Vertical axis represent measurement value and horizontal axis represent different image with different methods.

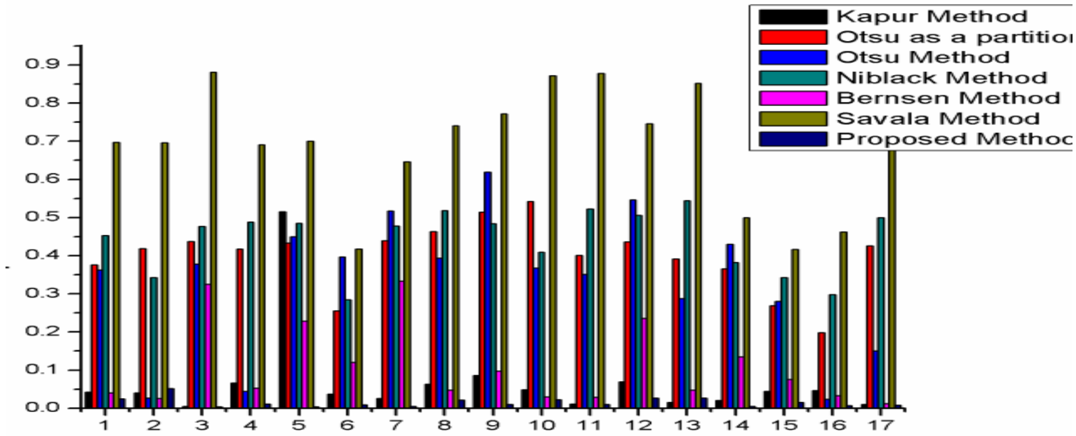

Figure 40: ME measurement graph

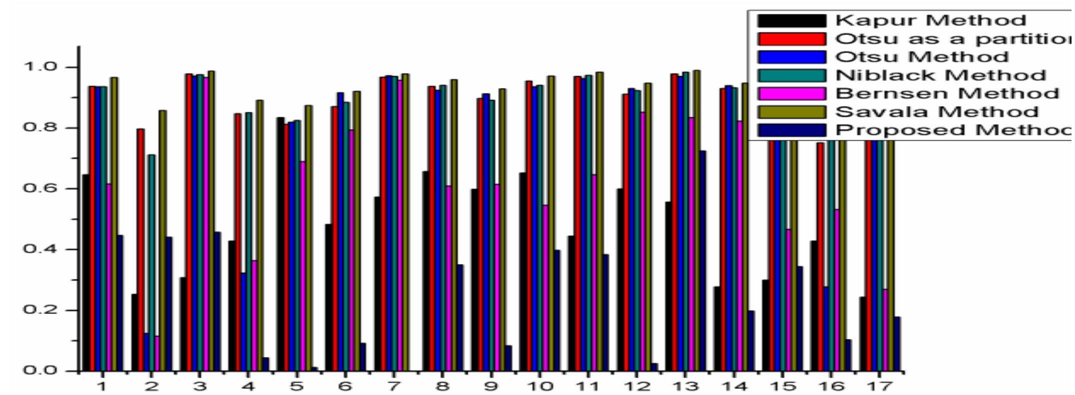

Figure 41: RAE measurement graph

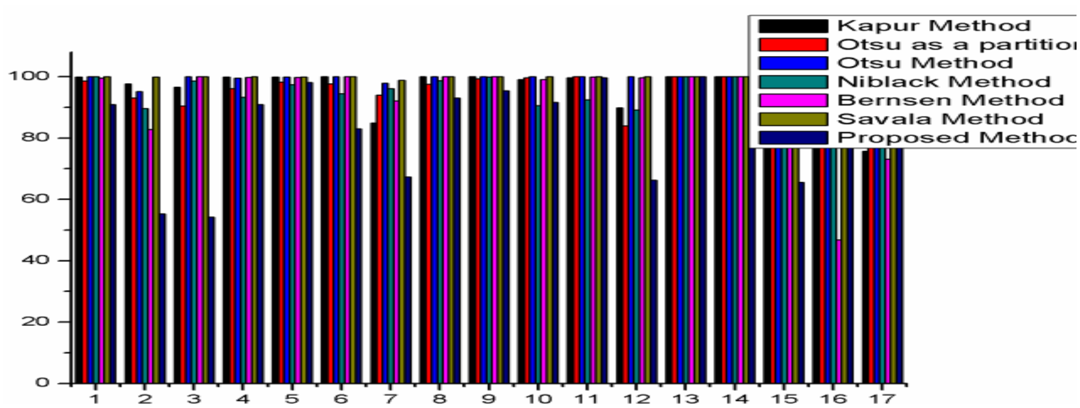

Figure 42: Recall measurement graph

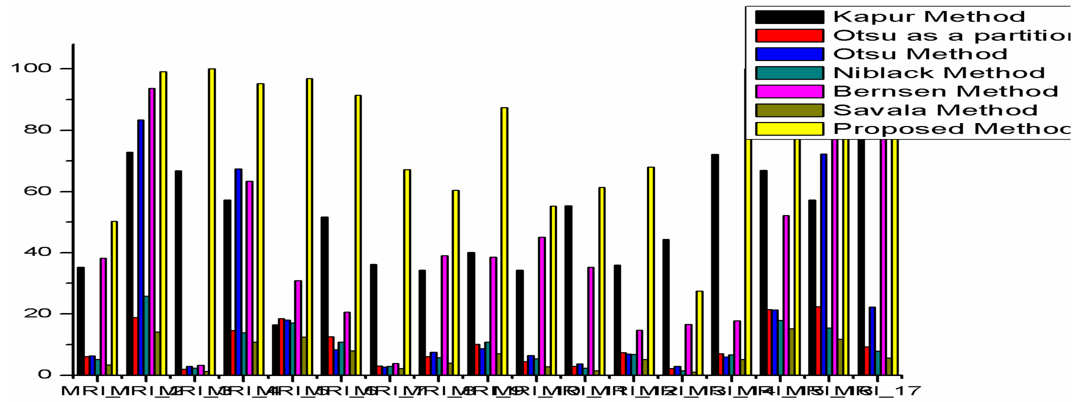

Figure 43: Recall measurement graph

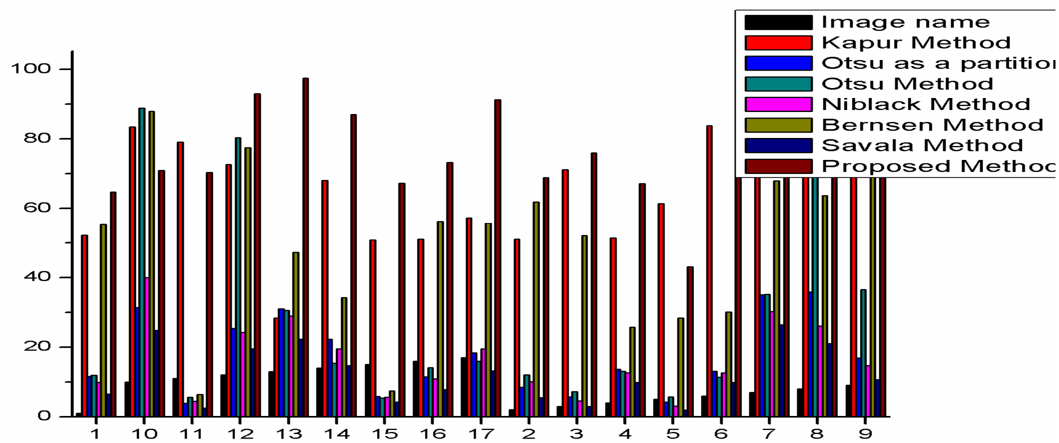

Figure 44: F measure measurement graph

5. CONCLUSIONS AND FUTURE WORK:

When different binarization method is being applied on MRI of brain data base the most of the algorithms binarized whole image without properly detecting the region of interest and the black background, so some method fails to give appropriate binarization. Thus the problem of variation of intensity level foreground to the background is totally overcome. Our proposed methods produce very good results for all type of MRI of brain images. We also proved that our proposed method produces better results visually as well as metric wise compare to the other established image binarization. Our method is very much simple it can be easily implement in any platform.

Here we create reference image manually because there is no suitable method of reference image creation for MRI of brain images thus in future we to develop a reference image creation methodology for MRI of Brain which will produce good reference image.

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