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A COMPARATIVE STUDY ON THRESHOLDING TECHNIQUES FOR GRAY IMAGE BINARIZATION

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Abstract: This work aimed to find a robust thresholding technique to image binarization for the gray level images. Thresholding is a simple method that plays a vital role in image segmentation. This comparative study provides to select the robust thresholding technique for general images and MRI head scans. This paper analyses the five thresholding techniques such as Sauvola thresholding, Niblack thresholding, Ridler and Calvard thresholding, Kittler and Illingworth thresholding and Otsu Thresholding for general gray images, normal and abnormal MRI head scans. The performance analysis was carried out by using the region non-uniformity parameter. Experiments were done using the mixture of gray images chosen form popularly available image databases.

Keywords: Gray Images, Image Segmentation, MRI Head Scans, Thresholding

1. INTRODUCTION

Image binarization is technique that uses a threshold to partition the image into two classes in which one class contains the gray values above the threshold value and another one contains the remaining pixels. It is an important preprocessing tool in medical image processing pipeline in order to proceed an accurate and segmentation studies. Medical images are usually gray images in nature. Binarization of gray images is a challenging task because both are approximately have similar intensity characteristics [1]. The important variations between gray image and binary image is intensity values of pixels i.e. gray image a particular pixel takes an intensity value lying between 0 to 255 and binary image it could take only two values either black (0) or white (1).

A popular method used in image binarization is thresholding and it is a simplest method. Thresholding converts any higher scale images where it's assigned into two levels of pixels that are above or below that specified parameter, is called threshold value [2] [3]. Thresholding techniques are classified into two types: global and local thresholding. Global thresholding means a single threshold value, which is used in the whole image. Local thresholding finds the threshold value of each pixel by using the information in the region of pixel. Advantage of thresholding is minimum storage space, processing speed is high and manipulation is simple. Several popular thresholding techniques were developed and used in digital image processing applications [4].

Sauvola and Pietikainen proposed a new technique to document image binarization and used two algorithms in order to calculate a different threshold for each pixel [5]. This method used test images with ground truth and quantitatively verified the evaluation metrics for binarization of textual and synthetically generated document images. Niblack method used local mean and standard deviation for find the threshold [6]. A method by Bernsen proposed the local threshold using neighbors [7]. Kapur et al., thresholding method calculated a threshold value from gray level histogram and using entropy concept from information theory [8]. Nikolaos and Dimitris proposed a binarization algorithm for historical manuscripts gives good result for historical documents [9]. Shaikh et al., used a iterative partitioning method that produces good results for degraded graphic documents [10]. Sezgin and Sankur give a brief survey of image binarization and concept of performance metrics [11].

This paper aimed to compare the performance of popular methods Sauvola thresholding (ST), Niblack thresholding (NT), Kittler and Illingworth thresholding, Ridler and Calvard thresholding (RCT) and Otsu thresholding (OT) for binarizing the gray images. The detail description of these thresholding methods are given in the forth coming section. Experiments were done by using MRI head scans and general gray images selected from popular imaging pools. The comparison is done by using the region-non uniformity parameter (RNU). This is a unique parameter does not require ground truth information. The paper is organized as follows: methods are explained in section 2, the evaluation parameter is given in section 3, the results and discussion is given in section 4 and conclusion is given in section 5.

2. METHODS

2.1.1. Niblack's Thresholding

Niblack's Thresholding [6] calculates a pixel-wise threshold by sliding a rectangular window over the gray level image. The computation of threshold is based on the local mean m and the standard deviation s of all the pixels in the window and is given below:

$$T_N = m + k * s \quad (1)$$

$$T_N = m + k\sqrt{\frac{1}{NP}\sum(p_i - m)^2} \quad (2)$$

$$= m + k\sqrt{\frac{\sum p_i^2}{NP} - m^2} = m + k\sqrt{B} \quad (3)$$

where NP is the number of pixels in the gray image, m is the average value of the pixels p_i, and k is fixed to -0.2 by the authors. Advantage of NT is that it always identifies the text regions correctly as foreground but on the other hand tends to produce a large amount of binarization noise in non-text regions also.

2.1.2. Sauvola's Thresholding

Sauvola's thresholding [12] claims to improve NT method by computing the threshold using the dynamic range of image gray-value standard deviation, R:

$$T_S = m * \left(1 - k * \left(1 - \frac{s}{R}\right)\right) \quad (4)$$

where k is set to 0.5 and R to 128. This method outperforms NT in images where the text pixels have near 0 gray-value and the background pixels have near 255 gray-values. However, in images where the gray values of text and non-text pixels are close to each other, the results degrade significantly.

2.1.3. Ridler and Calvard's Thresholding

This method is called as an iterative approach method [13]. First compute the initial threshold of given image. Initial threshold (T_0) is the mean of the intensity values of pixels. It separates image into background and foreground classes respectively. The mean of the foreground and background classes as μ_{fg} and μ_{bg}. The mean values of two classes are threshold value for foreground T_{fg} and threshold value for background T_{bg}. The improved threshold value T_1 is given below:

$$T_1 = \frac{(T_{bg} + T_{fg})}{2} \quad (5)$$

The new threshold value T_1 is taken as T_0 and this process continues iteratively until $T_1 = T_0$. Finally T_1 is taken as threshold value T. The algorithmic steps are as follows:

Step 1: Assuming no knowledge about the exact location of objects, consider, as first approximation, the four corner values of given image contain background pixels only and remainder contains object pixels.

Step 2: At step T_0, compute the μ_{fg} and μ_{bg}, the mean of the foreground and background pixels.

Step 3: μ_{bg} is mean of below T_0 and μ_{fg} is mean of above T_0. T_1 is computed as:

$$T_1 = \frac{\mu_{bg}(T_0) + \mu_{fg}(T_0)}{2} \quad (6)$$

T_1 now provides an updated background-object distinction.

Step 4: If $T_1 = T_0$ then stop the process, otherwise let $T_0 = T_1$ and go to step 2.

2.1.4. Kittler and Illingworth's Thresholding

Kittler and Illingworth's thresholding method also called as minimum error thresholding (MET) method [14]. The algorithm is based on the Bayesian classification rule. This method first computes the bi-model histogram of the gray level image $h(g)$ that is normally distributed. Then estimates the priori probability (p_i) of gray level of histogram $h(g)$ and find the mean of total probability. It is the initial threshold (T) of given image and separates the image into foreground and background classes $(i = 1, 2 \ldots)$. The probability (p_i), the mean (μ_i) and standard deviation (σ_i) are calculated by the following equations.

$$P_i(T) = \sum_{g=a}^{h} h(g) \quad (7)$$

$$\mu_i(T) = \frac{1}{P_i(T)}\sum_{g=a}^{h} h(g) \quad (8)$$

$$\sigma^2(T) = \frac{1}{P_i(T)}\sum_{g=a}^{b}\left(g - \mu_i(T)\right)^2 h(g) \quad (9)$$

where, $a = \begin{cases} 0 & i = 1 \\ T+1 & i = 2 \end{cases}$ and $b = \begin{cases} T & i = 1 \\ n & i = 2 \end{cases}$ (10)

The criterion function is,

$$J(T) = 1 + 2\left[P_1(T)\log\sigma_{bg}(T) + P_2(T)\log\sigma_{fg}(T)\right] \\ -2\left[P_1(T)\log p_1(T) + P_2(T)\log p_2(T)\right] \quad (11)$$

The criterion function $J(T)$ can be computed easily and finding its minimum error threshold is relatively simple task and finds the threshold T_2 as given below,

$$T_2 = arg_{1\le t\le n} \min J(T) \quad (12)$$

2.1.5. Otsu's Thresholding

Otsu's method involves all possible threshold values and calculates the pixel levels in each side of the threshold value [15] [16]. Threshold value separates the foreground or background of pixels. This algorithm classifies the image into two classes of pixels such as within class and between class variance. The within class variance is used in this research work which is the weighted sum of the variances of each foreground and background. It is defined as,

$$\sigma_{within}^2(T) = W_{bg}(T)\sigma_{bg}^2(T) + W_{fg}(T)\sigma_{fg}^2(T) \quad (13)$$

where,

$$W_{bg}(T) = \sum_{i=0}^{T-1} p(i), \; W_{fg}(T) = \sum_{i=T}^{N-1} p(i) \quad (14)$$

$p(i)$- is the probability of occurring of pixel value x_i,

The variance of background $\sigma_{bg}^2(T)$and foreground $\sigma_{fg}^2(T)$ pixels,

$$\sigma_{bg}^2(T) = \frac{1}{W_{bg}(T)}\sum_{i=0}^{T-1}\left(i - \mu_{bg}(T)\right)^2 p(i) \quad (15)$$

$$\sigma_{fg}^2(T) = \frac{1}{W_{fg}(T)}\sum_{i=T}^{N-1}\left(i - \mu_{fg}(T)\right)^2 p(i) \quad (16)$$

The mean of background $\mu_{bg}(T)$ and foreground $\mu_{fg}(T)$ pixels,

$$\mu_{bg}(T) = \frac{1}{W_{bg}(T)}\sum_{i=0}^{T-1} ip(i) \quad (17)$$

$$\mu_{fg}(T) = \frac{1}{W_{fg}(T)}\sum_{i=T}^{N-1} ip(i) \quad (18)$$

3. EVALUATION MEASURE

The segmented images are evaluated using the performance measure Region Non-Uniformity (RNU) and processing time. For NU, ground truth information is not requiring for this measure [17]. The measure is defined as,

$$RNU = \frac{|F_{fg}|}{|F_{fg}+B_{bg}|}\frac{\sigma_{fg}^2}{\sigma^2} \quad (19)$$

where σ^2 is represent the variance of whole image and σ_{fg}^2 is represent the variance of foreground. A well segmented image will have RNU close to 0. In worst case, RNU=1 that corresponds to an image in which the background and foreground are indistinguishable up to second order moments.

4. RESULTS AND DISCUSSION

To analyze the performance criterion, experiments were carried out by using some general gray images, normal and abnormal MRI head scans. General gray images were selected from segmentation evaluation database maintained by Department of Computer Science and Applied Mathematics, Weizmann Institute of Science, Israel [18]. The normal and abnormal MRI head scans were selected from the “The Whole Brain Atlas” website maintained by Harvard Medical School, USA [19].

The comparisons of these five thresholding methods are done by using the final binary images produced by them. In Fig.1, the general gray images (GGI) are given in column 1, the results of NT method are given in column 2, the results of ST method are given in column 3, the results of RCT method are given in column 4, the results of MET method are given in column 5 and the results of OT method are given in column 6. In Fig.2, the normal MRI head scans (NHS) are given in column 1, the results of NT method are given in column 2, the results of ST method are given in column 3, the results of RCT method are given in column 4, the results of MET method are given in column 5 and the results of OT method are given in column 6. In Fig.3, the abnormal MRI head scans (AHS) are given in column 1, the results of NT method are given in column 2, the results of ST method are given in column 3, the results of RCT method are given in column 4, the results of MET method are given in column 5 and the results of OT method are given in column 6. The performance measure RNU is computed for GGI and values are shown in Table 1. RNU value of well segmented image is close to 0. MET provides well segmented images by having RNU value is 0.1229 and it has more close to 0 while comparing with other thresholding methods. The RNU values of NHS are shown in Table 2. In this case, RNU of RCT value is similar to the OT, but higher than OT RNU value. RNU value of OT is 0.3213 and its close to 0. This thresholding method given best results for NHS. The RNU values of AHS are shown in Table 3. RNU of OT is close to 0 while comparing with other thresholding methods for AHS.

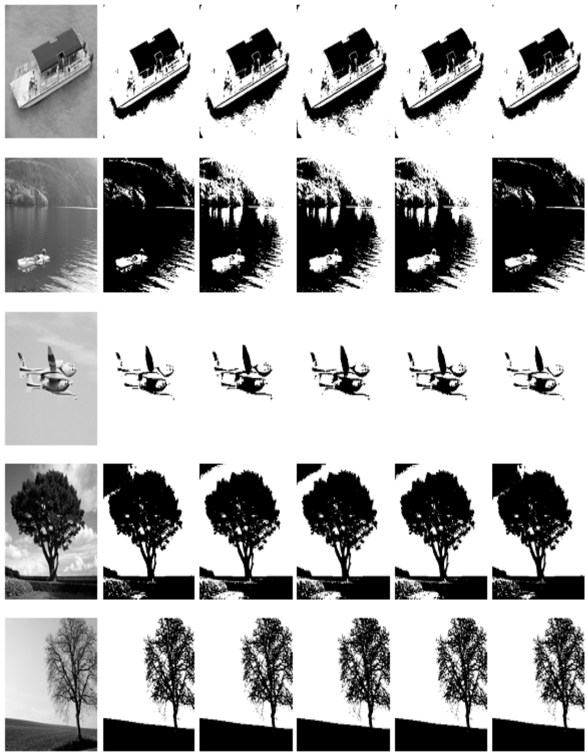

Figure 1. The original GGI images are in column 1, the results of NT method are given in column 2, the results of ST method are given in column 3, the results of RCT method are given in column 4, the results of MET method are given in column 5 and the results of OT method are given in column 6.

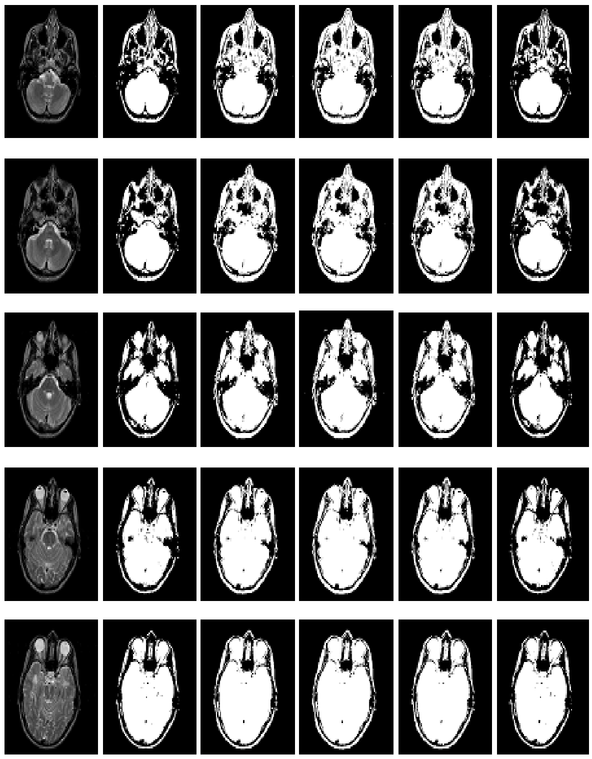

Figure 2. The original NHS images are in column 1, the results of NT method are given in column 2, the results of ST method are given in column 3, the results of RCT method are given in column 4, the results of MET method are given in column 5 and the results of OT method are given in column 6.

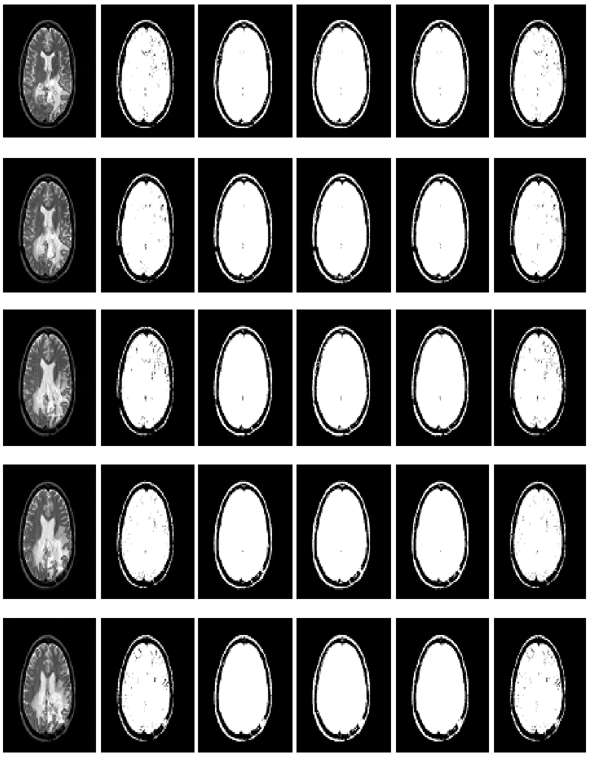

Figure 3. The original AHS images are in column 1, the results of NT method are given in column 2, the results of ST method are given in column 3, the results of RCT method are given in column 4, the results of MET method are given in column 5 and the results of OT method are given in column 6.

Table 1: RNU values of GGI

General Images	NT	ST	RCT	MET	OT
GGI_1	0.1168	0.1286	0.0916	0.1747	0.0893
GGI_2	0.1068	0.1068	0.1057	0.0922	0.1057
GGI_3	0.004	0.0041	0.0047	0.0042	0.0048
GGI_4	0.4399	0.4435	0.4551	0.22	0.4551
GGI_5	0.1614	0.1537	0.2648	0.0332	0.2648
GGI_6	0.2931	0.2919	0.6622	0.1512	0.6488
GGI_7	0.8443	0.8405	0.7189	0.5834	0.7189
GGI_8	0.0042	0.0042	0.0042	0.0044	0.0042
GGI_9	0.4545	0.4439	0.6287	0.2219	0.6069
GGI_10	0.0759	0.0782	0.0729	0.0993	0.0729
GGI_11	0.1829	0.1658	0.4538	0.09	0.4538
GGI_12	0.1446	0.3071	0.3231	0.109	0.3082
GGI_13	0.0468	0.0554	0.0546	0.0118	0.0546
GGI_14	0.4112	0.4135	0.3345	0.2046	0.3345
GGI_15	0.0372	0.0468	0.0265	0.0222	0.0268
GGI_16	0.0253	0.0263	0.0295	0.0273	0.0295
GGI_17	0.3747	0.3758	0.4945	0.0889	0.2594
GGI_18	0.1047	0.1143	0.1201	0.0752	0.1184
Mean	**0.2126**	**0.2222**	**0.2691**	**0.1229**	**0.2531**

Table 2: RNU values of NHS

Normal MRI Head Scans	NT	ST	RCT	MET	OT
NHS_1	0.7467	0.6971	0.5511	0.7876	0.5455
NHS _2	0.6331	0.5709	0.4063	0.6797	0.3995
NHS _3	0.5974	0.5693	0.4184	0.6726	0.4053
NHS _4	0.5777	0.541	0.4168	0.6474	0.4076
NHS _5	0.4909	0.4566	0.32	0.5933	0.3125
NHS _6	0.4187	0.3787	0.3266	0.5201	0.3183
NHS _7	0.3494	0.3222	0.2896	0.4563	0.2738
NHS _8	0.2906	0.2809	0.2534	0.3912	0.2412
NHS _9	0.2514	0.2411	0.2169	0.3562	0.2086
NHS _10	0.2723	0.2646	0.2518	0.3669	0.2443
NHS _11	0.28	0.2717	0.2705	0.3751	0.2682
NHS _12	0.3041	0.2984	0.2946	0.3891	0.2891
NHS _13	0.3374	0.3325	0.328	0.4106	0.317
NHS _14	0.3005	0.2884	0.2824	0.372	0.2773
NHS _15	0.294	0.279	0.2863	0.3542	0.2582
NHS _16	0.3075	0.2921	0.2862	0.3646	0.2762
NHS _17	0.3753	0.3531	0.3466	0.4236	0.3391
NHS _18	0.4531	0.4343	0.4144	0.4847	0.4031
Mean	**0.4044**	**0.3817**	**0.3311**	**0.4802**	**0.3213**

Table 3: RNU values of AHS

Abnormal MRI Head Scans	NT	ST	RCT	MET	OT
AHS_1	0.8374	0.7942	0.73	0.9288	0.7256
AHS _2	0.8083	0.7722	0.6735	0.9121	0.6753
AHS _3	0.7073	0.6768	0.5907	0.8562	0.5853
AHS _4	0.6775	0.648	0.5517	0.8228	0.5517
AHS _5	0.6763	0.6159	0.5443	0.8195	0.5443
AHS _6	0.6129	0.5772	0.4899	0.7706	0.4899
AHS _7	0.5275	0.4841	0.413	0.7052	0.413
AHS _8	0.538	0.4919	0.4258	0.7084	0.4221
AHS _9	0.5001	0.4686	0.4158	0.6781	0.4083
AHS _10	0.4411	0.4094	0.3588	0.6137	0.355
AHS _11	0.4174	0.3826	0.3344	0.5876	0.3325
AHS _12	0.3974	0.3623	0.3147	0.562	0.3114
AHS _13	0.3572	0.3386	0.2902	0.5326	0.284
AHS _14	0.3658	0.34	0.312	0.5273	0.3075
AHS _15	0.3934	0.3704	0.3502	0.5696	0.3459
AHS _16	0.411	0.393	0.3749	0.5671	0.3712
AHS _17	0.429	0.3969	0.3925	0.6018	0.3932
AHS _18	0.4089	0.3891	0.4048	0.603	0.4035
Mean	**0.5281**	**0.4950**	**0.4426**	**0.6870**	**0.4399**

We observed some different features by comparing these thresholding methods. Each thresholding methods have merits and demerits for their developed algorithm. Kittler and Illingworth's thresholding given well segmented images for general gray images. This thresholding is not providing good results for both NHS and AHS. OT method is given well segmented images for both NHS and AHS.

5. CONCLUSION

This paper analyse the five thresholding methods to select robust thresholding technique for gray image binarization. Experiments were done on general images, normal and abnormal MRI head scans. The outputs generated by these methods were compared using RNU measure. Kittler and Illingworth's thresholding technique provides better results for general gray images. Otsu's thresholding finds to produce better quality of results when compared to other methods while considering both normal and abnormal MRI head scans.

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