AUTOMATIC THRESHOLDING TECHNIQUES FOR OPTICAL IMAGES

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ABSTRACT

Image segmentation is one of the important tasks in computer vision and image processing. Thresholding is a simple but most effective technique in segmentation. It based on classify image pixels into object and background depended on the relation between the gray level value of the pixels and the threshold. Otsu technique is a robust and fast thresholding techniques for most real world images with regard to uniformity and shape measures. Otsu technique splits the object from the background by increasing the separability factor between the classes. Our aim form this work is (1) making a comparison among five thresholding techniques (Otsu technique, valley emphasis technique, neighborhood valley emphasis technique, variance and intensity contrast technique, and variance discrepancy technique)on different applications. (2) determining the best thresholding technique that extracted the object from the background. Our experimental results ensure that every thresholding technique has shown a superior level of performance on specific type of bimodal images.

KEYWORDS

Segmentation, Thresholding, Otsu Method, Valley Emphasis Method, Neighborhood Valley Emphasis Method, Variance and Intensity Contrast Method, & Variance Discrepancy Method.

1. INTRODUCTION

Segmentation is one of the difficult research problems in the machine vision industry and pattern recognition [1,2]. Its performance based on partition an entire image into a group of objects or regions in order to simplify and/or modify the representation of an image in a way to make it more understandable and easy for analyze. Usually, segmentation techniques are depended one of two main attributes of intensity: discontinuity and similarity [1]. In the first class, the segmentation techniques separate an image according to abrupt changes in intensity like the edges in an image, while in the second class the segmentation techniques divide an image into similar areas depended on a set of predefined criteria. Region splitting and merging, and region growing and thresholding are examples of techniques in this class. Thresholding is one of the most commonly used techniques for segmenting images. It is a simple but effective technique to separate objects from the background [2]. The output of the thresholding operation is a binary image whose gray level of 0 (black) indicates a pixel related to the background, and gray level of 255 indicates a pixel related to the object, or vice versa. Thresholding has become the most important component of image analysis. Therefore, many researchers presented different thresholding techniques such as: in 1979 Nobuyuki Otsu proposed a thresholding technique based on between class variance. Otsu selected the optimal threshold which extracted the object of interest from the background by maximizing between class variance [3]. Later many thresholding methods have been constructed to revise Otsu technique. Each method improves Otsu technique in a specific way; such as Hui-Fuang Ng presented a new method named valley-emphasis technique. This method succeeds in detection both large and small objects from the background [4]. On other side, Jiu-Lun Fan improved valley-emphasis technique. This technique computes the sum of probabilities of occurrences for both the threshold point and its neighborhood [5]. Also, Yu Qiao suggested another idea to develop Otsu technique named (Thresholding based on variance and intensity contrast). The presented method used both within-class variance and the intensity contrast of the image. This technique extracted the small objects from difficult homogeneity background [6]. Finally, Zuoyong Li introduced a new method. This method used for images have big variance discrepancy of the object and background. The formula of this method calculates two factors to select the optimal threshold: the variance sum and the variance discrepancy between the object and background [7].

This paper is organized as follows: Section 2 defined the formulation used in thresholding. Section 3 describes Otsu method, and the techniques related to it. Section 4 is about the thresholding evaluation methods. Section 5 defines the Statistical Distribution . Section 6 defines the experimental results. Conclusion appears in Section7.

2. FORMULATION

To analyze and process any image we should know that an image is generated from a set of pixels denoted as$n$; for each image level there are a set of pixels denoted as n_i . Therefore, the total number of pixels is defined as:

$$n=\sum_{i=0}^{L-1} n_i \tag{1}$$

Grey level histogram is normalized and regarded as a probability distribution:

$$h_i=\frac{n_i}{n} \tag{2}$$

The grey level of an image is [0… L-1].Where the grey level 0 is the darkest and the grey level L-1 is the lightest.

The probability of occurrence of the two classes can be denoted as the following:

$$w_1(t) = \sum_{i=0}^{t} h(i) \qquad w_2(t)=\sum_{i=t+1}^{L-1} h(i) \tag{3}$$

The mean and variance of the foreground and background are denoted respectively as the following:

$$\mu_1(t) = \sum_{i=0}^{t} i\, h(i)\, , \sigma_1^2(t) =\sum_{i=0}^{t}(i-\mu_1(t))^2 h(i) / w_1(t) \tag{4}$$

$$\mu_2(t)= \sum_{i=t+1}^{L-1} i\, h(i), \sigma_2^2(t) =\sum_{i=t+1}^{L-1}(i-\mu_2(t))^2 h(i) / \quad w_2(t) \tag{5}$$

It worth to mention that in each image there is a specific thresholding algorithm used to get an optimal threshold, which separated the object from the background.

3. OTSU TECHNIQUE

In 1979 Nobuyuki Otsu[3] presented his idea in extraction the object from the background by maximizing between class variance equivalent (minimizing within class variance). The following equations represent the within-class variance, and the between -class variance respectively.

$$\sigma_W^2(t)=\omega_1(t)\sigma_1^2(t)+\omega_2(t)\sigma_2^2(t) \tag{6}$$

$$\sigma_B^2(t)=\omega_1(t)(\mu_1(t)-\mu_T(t))^2+ \omega_2(\mu_2(t)-\mu_T(t))^2 \tag{7}$$

The final form of between-class variance can also be denoted as the following :

$$\sigma_B^2(t)=\omega_1(t)\omega_2(t)\big(\mu_2(t)-\mu_1(t)\big)^2 \quad (8)$$

The algorithm of Otsu technique is as the following :

1) Compute the histogram.
2) Start from t=0….unitl 255 (all possible thresholds).
3) For each threshold:
    i. Compute $\omega_i(t)$and $\mu_i(t)$.
    ii. Compute $\sigma_B^2(t)$.
4) Desired threshold is a threshold that maximums $\sigma_B^2(t)$.

The following techniques are used to develop Otsu technique:

3.1 Valley Emphasis Technique

Hui-Fuang Ng [4] presents a revised technique of Otsu technique; this technique succeeds in detection both large and small objects. It applies a new weight to ensure that the optimal threshold located at the deepest point between two peaks for (bimodal histogram), or at the bottom rim of a single peak for (unimodal histogram). In addition , it increases the variance between the classes as much as possible like in Otsu method.

The valley-emphasis equation is as in [10].

$$t_{opt}=\arg \max_{0\le t\le L-1}\{(1- h(t)(\omega_1(t)\mu_1^2(t)+\omega_2(t)\mu_2^2(t))\} \quad (9)$$

3.2 Neighborhood Valley Emphasis Technique

Jiu-Lun Fan [5] improves the prior technique (valley-emphasis technique) by taking into account the neighborhood information (gray values) of the threshold point. It calculates between class variance σ_B^2 for both the threshold point and its neighborhood. Neighborhood valley emphasis technique is suitable to choose optimal threshold for images with big diversity between object variance and background variance.

The sum of neighborhood gray level value $\bar{h}(i)$ is in Eq.(10) within the range n=2m+1 for gray level i , n represents the number of neighborhood that should be odd number.
If the image has one dimensional histogram h(i) ; the neighborhood gray value $\bar{h}(i)$ of the gray level i is denoted as the following :

$$\bar{h}(i)=[h(i-m)+\ldots+h(i-1)+h(i)+h(i+1)+\ldots+h(i+m)] \quad (10)$$

The neighborhood valley emphasis method is denoted as the following:

$$\xi(t)=(1-\bar{h}(t))((\omega_1(t)\mu_1^2(t)+\omega_2(t)\mu_2^2(t)) \quad (11)$$

The optimal threshold is in Eq. (12). The first part refers to the largest weight of the threshold and its neighborhood, while the second part refers to the maximum between class variance.

$$t_{opt}=\arg \max_{0<t<L-1}\{(1-\bar{h}(t)(\omega_1(t)\mu_1^2(t)+\omega_2(t)\mu_2^2(t))\} \quad (12)$$

3.3 Thresholding Based on Variance and Intensity Contrast

Yu Qiao [6] introduced a new formula to isolate small objects from difficult homogeneity background. The performance of this technique based on the information of the weighted sum of both within-class variance and the intensity contrast at the same time.

The proposed formula is defined as the following:

$$J(\lambda,t)=(1-\lambda)\sigma_W(t)-\lambda\,|\mu_1(t)-\mu_2(t)| \quad (13)$$

In this technique λ plays a central role. It is a weight that determines and balances the contribution of (within class variance , intensity contrast) in the formula. λ Values should be in interval [0, 1).

1) When $\lambda = 0$ the new technique based only on within class variance.
2) λ =1 made the optimal threshold is determined only from the intensity contrast .

In Eq. (13) $\mu_1(t)$, $\mu_2(t)$ are the mean intensities of the object and background. $\sigma_W(t)$ Represents the square root of within-class variance. $\sigma_W(t)$ is formulated from the following equation:

$$\sigma_w^2(t)=\omega_1(t)\ \sigma_1^2(t)+\omega_2(t)\sigma_2^2(t) \quad (14)$$

Where the first part represents the probability of occurrence and the standard deviation (variance) of the background, while the second part represents the probability of occurrence and the standard deviation (variance) of the object.

3.4 Variance Discrepancy Technique

Zuoyong Li [7] introduces a new technique to segment images have large variance discrepancy between the object and background. The new method takes into consideration both the class variance sum and variances discrepancy simultaneously. It is formulated as the following:

$$J(\alpha, t) = \alpha(\sigma_1^2(t)+\sigma_2^2(t)) + (1-\alpha)\sigma_D(t) \quad (15)$$

Where

$$\sigma_D(t)=\sigma_1(t)\sigma_2(t) \quad (16)$$

and, $\sigma_1^2(t)<=\sigma_D(t)<=\sigma_2^2(t)$ or $\sigma_2^2(t)<=\sigma_D(t)<=\sigma_1^2(t)$. $\sigma_D(t)$ Is a measurement of variance discrepancy of (object, background). $\sigma_1^2(t)$,$\sigma_2^2(t)$ are the standard deviation of the two classes.

In this technique α is an effective parameter; it balances the weight of class variance sum and variance discrepancy in the method. The values of α is within the range [0,1]. The smaller α , the larger weight of variance discrepancy in the method, and this means a limited effect of variance sum. On the contrary, if α is large, the technique will be based on variance sum ,and the effect of variance discrepancy will be ignored.

4. THRESHOLDING EVALUATION METHODS

The quality of thresholding technique is a critical issue. In order to analyze the performance of the thresholding techniques, there are different evaluation methods used to measure their robustness and efficiency. In our study we used two evaluation methods Region Non-Uniformity (NU) and Inter–Region Contrast (GC). Then, we compare the results of the five thresholding techniques to determine which technique is the best in determination the region of interest (object) from the background.

4.1 Region Non-Uniformity (NU)

This method measures the ability to distinguish between the background and object in the thresholded image. A good thresholded image should contain higher intra region uniformity, which is related to the similarity attribute about region element. In the following NU Equation (17): $\sigma^2(t)$ denotes to the variance of the whole image, while $\sigma_o^2(t)$ denotes to the variance of the object (foreground). $w_o(t)$ denotes to the probability of occurrence of the object. NU equal to zero denotes to well thresholded image, but NU = 1 denotes to incorrect thresholded image [8].

$$NU = \frac{w_o(t)\,\sigma_o^2(t)}{\sigma^2(t)} \tag{17}$$

4.2 Inter –Region Contrast (GC)

This method is very important in measure the contrast degree in the thresholded image. A good thresholded image should have higher contrast across adjacent regions. In the following GC Equation(18) the object average gray-level is known as $\mu_o(t)$, and the background average gray–level is known as μ_b (t) [8].

$$GC = 1 - \frac{\mu_o(t) - \mu_b(t)}{\mu_o(t) + \mu_b(t)} \tag{18}$$

5. STATISTICAL DISTRIBUTION

A histogram is the best and simple way to represent the distribution of image pixels. It determines pixels intensity distribution in an image by gathering the number of pixels intensity at each gray level. In our work, we took two kinds of distributions (Gaussian and Gamma). For symmetric mode Gaussian distribution is suitable to determine the optimal threshold value, whereas for the non- symmetric mode; it is better to use Gamma distribution to represent it. All the presented thresholding techniques are applied on images using Gaussian distribution. But in our applications we will use the techniques with the two distributions (Gaussian and Gamma distributions).

5.1 Gaussian Distribution

Gaussian distribution is a continuous probability distribution. Its form is concentrated in the center, then it decreases on either side taking a form as a bell shape. Each variable in (Gaussian distribution) has a symmetric distribution about its mean [9]. We will represent the classes of the original image by using the histogram. Gaussian distribution used to estimate the mean values of the image modes Gaussian distribution. The probability density function is:

$$f(x, \mu, \sigma^2) = \frac{1}{\sigma\sqrt{2\pi}}\, e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{19}$$

Where Π is approximately 3.14159 and *e* is approximately 2.71828.

The following figure 1 displayed the form of Gaussian distribution.

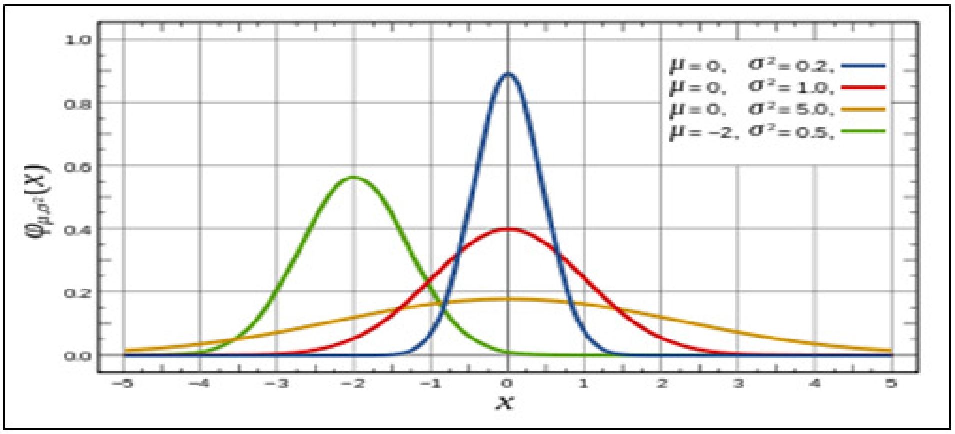


Figure 1 Gaussian distribution.

In Gaussian distribution there are two main parameters the mean (μ , average) and the variance (σ^2, standard deviation squared). Both of them are used to determine the shape of distribution. The mean determines the position of the center, and the standard deviation identifies the height and the width of the bell.

In our experiments we used Gaussian distribution for the following reasons:

1. It used for modeled symmetric data.
2. In Gaussian distribution and based on central limit theorem; the mean of a large number of random variables independently are distributed normally.
3. This type of distribution is flexible analytically. In plus, it is easy to apply mathematically.

5.2. Gamma Distribution

Gamma distribution used to represent image data with symmetric and non–symmetric distribution. It based on some parameters of continuous probability distributions, and they are shown in the following equation :

$$f(x, \mu, N) = \frac{2q}{\mu\,\Gamma(N)}\frac{N^N}{}\left(\frac{qx}{\mu}\right)^{2N-1} e^{-N\left(\frac{qx}{\mu}\right)^2} \tag{48}$$

1. X is the intensity of the pixel.
2. μ represents the mean value of the distribution.
3. N is the shape parameter of Gamma distribution. The shape of the Gamma distribution can be symmetric or skewed to right.

Gamma distribution used to estimate the mean values of the image modes and then find the optimal threshold value with different shape parameter N values. Figure. 2 displays the Gamma distribution for one mode with different shape parameter and same value of mean μ.

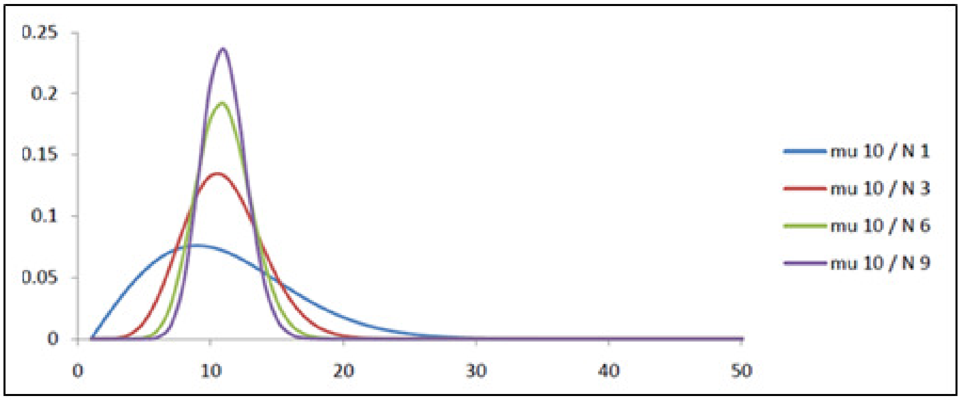


Figure2 Different gamma distribution.

6. EXPERMENTAL RESULTS

This section has a number of images with different problems such as the small object size, the big variance discrepancy between the objects and background, and the existence of small objects in complex homogeneity background.

Figure.3 (a) number image is the last example in this section. This image has a noise distributed non uniformly in the center.

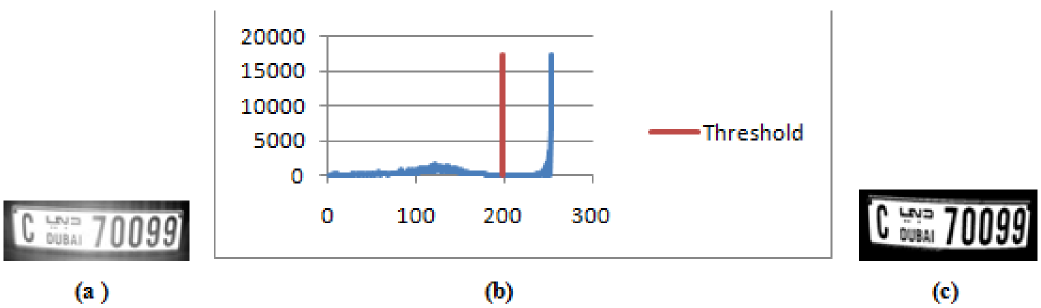


Figure 3 (a)shows the original , (b) the histogram (c) the best thresholded image is obtained from variance discrepancy (Gaussian) T=199.

By using Gaussian distribution, Otsu technique with T=173 did not extract the object well, as shown in the (Figure.4 (b)) Otsu technique is not (suitable for image has large diversity between the object variance and background variance). Its formula based on maximized the variance between the classes. Valley emphasis technique T= 188 detected the object by using the gray information of the threshold point (smaller probability of occurrence to detect the small object) Figure. 4(c). Neighborhood valley emphasis technique T = 203 gave the best thresholded images; it separated the object clearly. It used the smaller probability of occurrence of the threshold point and the neighborhood to isolate number the background (Figure. 4(d)). The last technique variance discrepancy also produced good thresholded image. It maximized the variance discrepancy and minimized the variance sum to obtain the optimal threshold T =199 (Figure.4 (f)).

Figure 4: Example 1 number image (Gaussian) (a) original image, (b) Otsu technique T = 173, (c) valley emphasis technique T = 188 . (d) neighborhood valley emphasis T = 203, n = 11 , (e) variance and intensity contrast T = 183 , (f) variance discrepancy T =199, α = 0.7 .

In Gamma distribution, Otsu technique T= 165 performed badly; it presented inaccurate thresholded image (Figure 5(b)). Valley emphasis technique with T= 254 did not detect the object; it presented incorrect thresholded image (Figure 5(c)). Neighborhood valley emphasis technique with T = 17 and n = 11 presented the worst thresholded image; it did not detect the object at all (Figure 4.50 (d)). Variance and intensity contrast technique with T = 173 and λ = 0.5 gave image with unclear objects, (Figure 5(e)). Finally, variance discrepancy technique with T= 199 and α = 0.7 presented the best thresholded image, it used the variance sum and the variance discrepancy to get the optimal threshold (Figure 5 (f)).

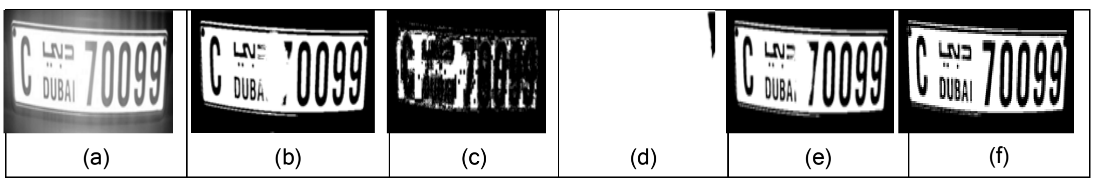


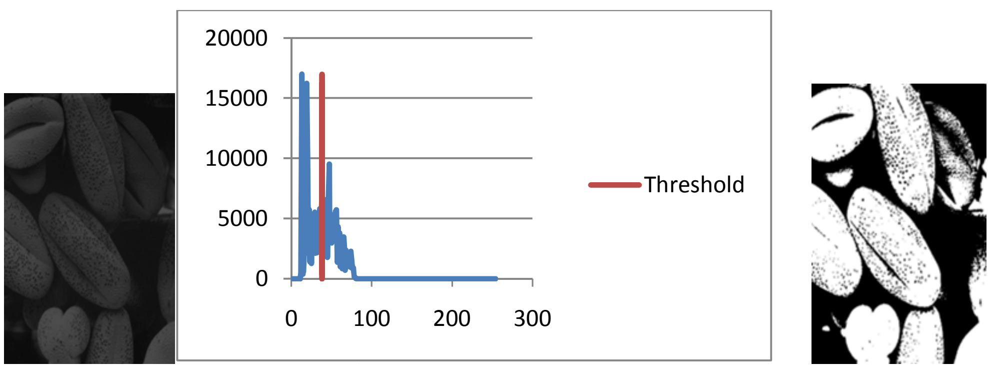
Figure 5 Example 1 number image (Gamma) (a) original image, (b) Otsu technique T = 165. (c) valley emphasis technique T = 254. (d) neighborhood valley emphasis technique T = 17 , n = 11 , (e) variance and intensity contrast T = 173 , λ = 0.5 (f) variance discrepancy technique T = 199, α = 0.7.

According to Table the smallest region non uniformity value NU = 0.004092 is presented from neighborhood valley emphasis technique, while the smallest inter region contrast value GC = 0.603502 is obtained from valley emphasis technique using Gaussian distribution. In this example, the smallest average value AVG = 0.305098 is introduced from variance discrepancy technique using Gaussian distribution, which makes this technique is the best among all other thresholding techniques; not only because it gave the smallest average value, but also it succeeded in presenting even the small details of the object in the image.

Table1 Shows the values of (T, NU, GC, AVG) for only the successful thresholding techniques.

Valley (Gaussian)	T	188
	NU	0.0085156
	GC	0.603502
	AVG	0.306009
Neighborhood valley (Gaussian)	T	203, $n = 11$
	NU	0.004092
	GC	0.606463
	AVG	0.305277
Variance discrepancy technique (Gaussian)	T	199, $\alpha = 0.7$
	NU	0.00488681
	GC	0.605309
	AVG	0.305098
Variance discrepancy technique (Gamma)	T	199, $\alpha = 0.7$
	NU	0.00736052
	GC	0.631274
	AVG	0.319317

Example 2 image has complex structure, because it has a large variance discrepancy between the object and background classes. In plus, it has many objects with difficult details; in addition, the background has a noise.



(a) (b) (c)

Figure 6 (a)shows the original , (b) the histogram (c) the best thresholded image is obtained from Otsu(Gamma) T= 35.

Using Gaussian distribution as seen in Fig.7 (b, c, d, e, f) the five thresholding techniques separate the objects from the background. Otsu technique has optimal threshold T =38. Otsu technique maximized the variance between the large objects and the background. Valley Emphasis Technique T = 43 used the smaller probability of occurrence of the threshold point. So that it worked well in detection all the objects (the small and large objects). Neighborhood valley emphasis T = 31 used the smaller probability of occurrences for both the threshold and its neighborhood. This technique gave more accurate results. Variance and Intensity contrast T= 38, $\lambda = 0.35$ also gave good thresholded image. It used within class variance and the intensity contrast to select the optimal threshold. Variance Discrepancy technique with T =35, $\alpha = 0.9$ succeeded in detection all the objects. This technique the variance sum and variance discrepancy of the image.

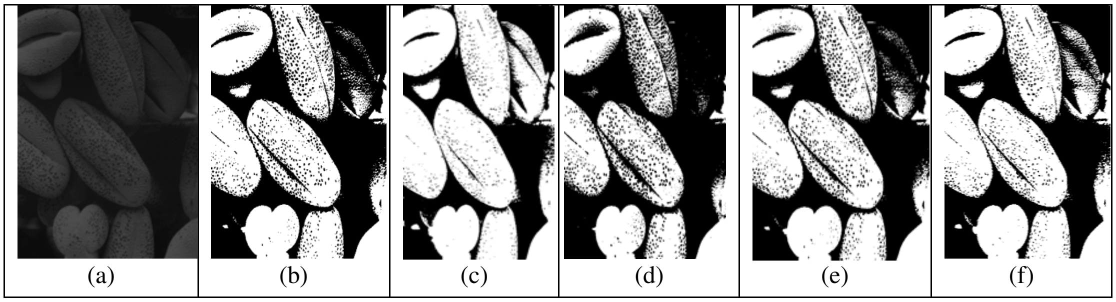


Figure 7 Example 2 small pieces image (Gaussian) (a) original image,(b) Otsu technique T= 38. (c) valley emphasis technique T = 43. (d) neighborhood valley emphasis T =31, (e) variance and intensity contrast T = 38 , λ = 0.35 , (f) variance discrepancy T =35 , α = 0.9.

In Gamma distribution, we have three thresholding techniques succeeded in isolation the objects from the background. Otsu technique T= 35 worked well in detection all the objects from the background. It increased the variance between the classes to get the optimal threshold Fig. 8(b) . Valley emphasis technique failed in detection the objects. It presented black image Fig.8(c). Neighborhood valley emphasis technique did not detect the objects at all. This technique detected only the small objects (in Gamma) Fig. 8(d). Variance and intensity contrast technique T =38 reported a good threshold. This technique detected all the objects Fig.8(e). Variance discrepancy technique T= 38 also presented a good thresholded image Fig.8(f). It used the variance sum and variance discrepancy to obtain the optimal threshold.

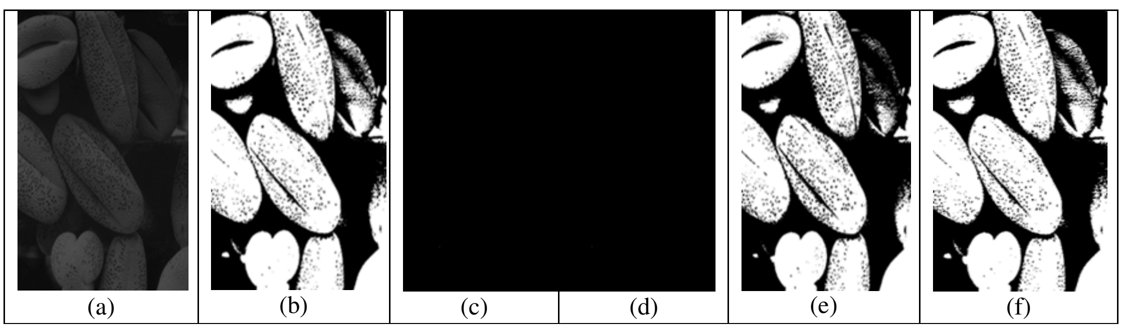


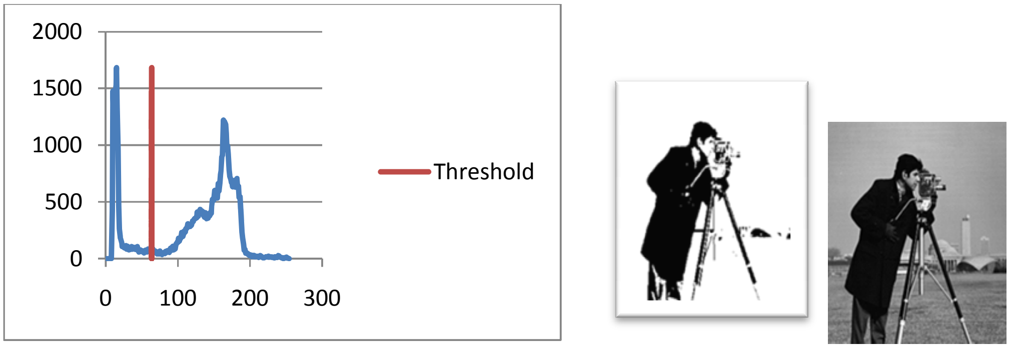
Figure 8 Example 2 small pieces image (Gamma) (a) original image, (b) Otsu technique T= 35. (c) valley emphasis technique T =82. (d) neighborhood valley emphasis T = 82, (e) variance and intensity contrast T= 38, λ =0.45 , (f) variance discrepancy T = 35, α =0.9 .

The quality of the thresholded images are compared based on region non uniformity and inter region contrast, and we found that the smallest value of region non uniformity is presented from Otsu technique NU= $3.60167*10^{-8}$ using Gamma distribution, while the smallest value of inter region contrast is obtained from neighborhood valley emphasis Technique GC =0.571076 using Gaussian distribution. Among all the thresholding techniques; Otsu technique Gamma distribution is the best technique in this example, not only because they present smallest average AVG = 0.338201 but also they present less background noise with more objects details as shown in Fig.8 (b). Table 2 lists the (T, NU, GC, AVG) values of the five thresholding techniques using Gaussian and Gamma distributions.

Table 2 Shows the values of (T, NU, GC, AVG) for the successful thresholding technique.

		Example 2
Otsu (Gaussian)	T	38
	NU	0.17035
	GC	0.605769
	AVG	0.388059
Otsu (Gamma)	T	35
	NU	$3.60167*10^{-8}$
	GC	0.676403
	AVG	0.338201
Valley (Gaussian)	T	43
	NU	0.1152
	GC	0.638108
	AVG	0.376654
Neighborhood valley (Gaussian)	T	31, n=3
	NU	0.277654
	GC	0.571076
	AVG	0.424365
Variance and intensity contrast (Gaussian)	T	38, $\lambda = 0.35$
	NU	0.17035
	GC	0.605769
	AVG	0.388059
Variance and intensity contrast (Gamma)	T	38
	NU	0.177642
	GC	0.619594
	AVG	0.398618
Variance discrepancy technique (Gaussian)	T	35, $\alpha = 0.9$
	NU	0.217957
	GC	0.588298
	AVG	0.403128
Variance discrepancy technique (Gamma)	T	35, $\alpha = 0.9$
	NU	0.222356
	GC	0.596649
	AVG	0.409502

Figure 9 (a) represents camera man image. This image has complex structure; it has many objects with difficult details. The image objects are the man, building, sky, grassland. Also, this image has large variance discrepancy between the object and the background.



(a) **(b)** **(c)**

Figure 9 (a) shows the original, (b) the histogram and (c) the best thresholded of the image T=64.

As seen in Figure.10 (b, c, d, e, f) the five thresholding techniques separated the objects from the background using Gaussian distribution. Otsu technique with optimal threshold T= 89 separated the large objects from the background. It maximizes the variance between the objects and background. Valley emphasis technique T = 87 used for detection bimodal and unimodal distribution (it succeeded in detection both large and small objects). Neighborhood valley emphasis technique T = 78 used the smaller probability of occurrence for the threshold point and the neighborhood, so that it separate all the objects. Variance and intensity contrast technique T= 64 and λ = 0.6 detected all the objects from the background; it gave all the objects details. The work of this technique based on maximizes the intensity contrast between the classes and minimizes the within class variance of each class. Camera man image has large variance discrepancy between the objects and the background, so that variance discrepancy technique with T = 64 and α = 0.8 gave good thresholded image. This technique selected the optimal threshold by computing the variance sum and the variance discrepancy at the same time.

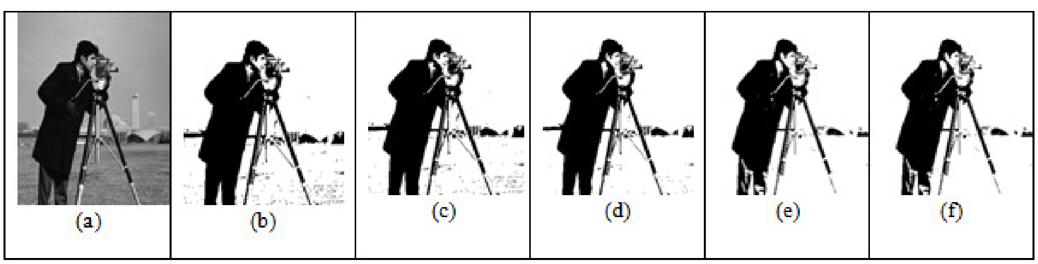


Figure 10 cameraman image (Gaussian results) (a) original image, (b) Otsu technique T= 89. (c) valley emphasis technique T = 87 . (d) neighborhood valley emphasis T = 78 , (e) variance and intensity contrast T= 64, λ = 0.6, (f) variance discrepancy T = 64, α = 0.8 .

On the other side, by using Gamma distribution, there are only three thresholding techniques worked well in separation the objects from the background (Figure.11 (b, e, f)). Otsu technique has optimal threshold T= 58; it separated all the objects from the background by increasing the variance between the classes as much as possible. Variance and intensity contrast technique T= 49 and λ = 0.5 separated the different objects from the background by using both within class variance and the intensity contrast at the same time. Variance discrepancy technique T= 51 detected all the objects, because this technique is presented for this type of images (images has large discrepancy of the object and the background). Other techniques valley emphasis technique T= 245 and neighborhood valley emphasis technique T= 245 failed in extraction the objects from the background; they only detected the small dots in the lower part of the image, (Figure11 (c, d)).

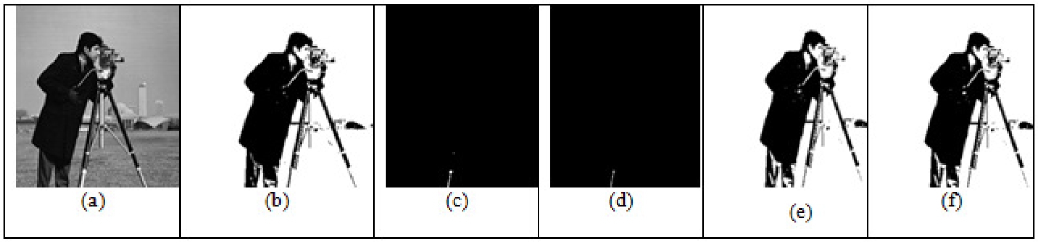


Figure 11 cameraman image (Gamma results) (a) original image, (b) Otsu technique T= 58 . (c) valley emphasis technique T = 245 , (d) neighborhood valley emphasis T = 245, (e) variance and intensity contrast T= 49 , $\lambda = 0.5$, (f) variance discrepancy T=51, $\alpha = 0$.

Based on the values of region non uniformity and inter region contrast; we found that the smallest value of region non uniformity NU= $9.65511*10^{-8}$ is presented from Otsu technique using Gamma distribution. This means Otsu (Gamma) proved its ability to distinguish between the objects and the background class. While the smallest value of inter region contrast GC = 0.217206 is obtained from variance and intensity contrast technique (Gamma). The largest GC means the maximum contrast of the objects and the background. Among all the successful thresholding techniques; variance and intensity contrast technique (Gaussian) with T = 64 and $\lambda = 0.6$ and variance discrepancy technique (Gaussian) with T = 64 and $\alpha = 0.8$ are the best techniques in isolation the objects from the background, not only because they gave the smallest average value AVG = 0.189964, but also they presented less background noise with more objects details. Variance and intensity contrast technique minimizes the within class variance of the objects and background, and it increases the intensity contrast between the classes. While variance discrepancy technique computes the variance sum and the variance discrepancy at the same time. Therefore, this technique is the best technique for images have large variance discrepancy between the object and the background.

Table 3 shows the values of (T, NU, GC, AVG) for the thresholding technique**s**

Otsu (Gaussian)	T	89
	NU	0.12409
	GC	0.267821
	AVG	0.195956
Otsu (Gamma)	T	58
	NU	$9.65511*10^{-8}$
	GC	0.692798
	AVG	0.346399
Valley (Gaussian)	T	87
	NU	0.126882
	GC	0.263233
	AVG	0.195057
Neighborhood valley (Gaussian)	T	78 , $n = 11$
	NU	0.136788
	GC	0.246478
	AVG	0.191633

Variance and intensity contrast (Gaussian)	T	64, $\lambda = 0.6$
	NU	0.157261
	GC	0.222667
	AVG	0.189964
Variance and intensity contrast (Gamma)	T	49, $\lambda = 0.5$
	NU	0.197347
	GC	0.217206
	AVG	0.207277
Variance discrepancy technique (Gaussian)	T	64, $\alpha = 0.8$
	NU	0.157261
	GC	0.222667
	AVG	0.189964
Variance discrepancy technique (Gamma)	T	51, $\alpha = 0.5$
	NU	0.192938
	GC	0.222016
	AVG	0.207477

7. CONCLUSION

Automatic thresholding has been widely utilized in image analysis and pattern recognition. Otsu technique is the simplest and the most standard one to select thresholding automatically. It performs well for images with clear valleys and peaks, in other word it gives satisfactory results in detection large objects. However, Otsu technique has some limitations represents with the small object detection, variance, intensity contrast. So that over the past years many thresholding techniques have been proposed to modify Otsu technique, but their concept are based on maximize between class variance, and their aim are selecting the optimal threshold. One of these techniques solved the problem of small objects like the first technique Valley Emphasis technique. Its optimal threshold applied a largest weight on images with both bimodal and unimodal distribution, and in this way it succeed in thresholded both large and small objects. Secondly, Neighborhood Valley Emphasis technique which computes between class variance for the threshold point and its neighborhood. This technique solves the problem in thresholded images have big diversity between the object variance and the background variance. Thirdly, we have variance and intensity contrast technique. It based on exploring the knowledge about the intensity contrast. This technique succeeded in isolation small objects from large and complex homogeneity background. The last technique is variance discrepancy technique. Its performance based on used both variance sum and variance discrepancy at the same time. This technique performed well in thresholded images have large variance discrepancy between the object and background. All the experiments are simulated on PC with VC++ 2010, Intel Core 2.53 GHz CPU , and 4 G memory. As a result, we found that our experimental results ensure the efficiency of the five thresholding techniques in thresholded difficult bimodal images. Each technique is suitable for a specific type of images. We aim as a future work to apply the five thresholding techniques on other images to solve other image processing and computer vision problems and applications.

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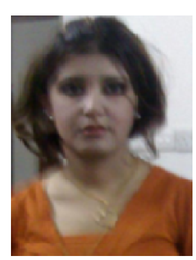

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