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Comparison of the Methods of Image Slicing After Initial Image Processing Using the Statistical Confidence Limits Technique

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Abstract. The use of image segmentation in image processing is of great importance in analyzing and extracting information from images, and one of the most important segmentation techniques is the threshold technique, which is considered one of the simplest techniques of image division in image processing. The statistical methods play an important role in the process of image segmentation. Statistical confidence in image processing, preliminary processing, as it removed noise from the images, and here the obscure noise was used. After that, the resulting images were cut, the initial processing process with the global Otsu threshold technology and a group of local techniques, namely Niblack, sauvola and local Bernsen, and the split image quality was measured by statistic measures namely Jaccard Similarity Coefficient and Maximum Signal to Noise Ratio (PSNR). as was the application of the methods mentioned on the images and the comparison between the methods of treatment in order to obtain the best results that appear in the image in which it appears and reduce noise.

Keywords: image processing, initial processing process, global threshold, Local threshold, Niblack’s, Sauvola’s, Bernsen's Thresholding Technique

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1. Introduction

Image division is an important stage of image processing, it is the process of dividing or dividing the image into interconnected or homogeneous regions (Homogenous regions), and these parts or pieces are similar to some characteristics or characteristics, and thus be more useful and clearer in the analysis process, so the main goal of the process of dividing Images is to get useful information from the original image by converting the image into something clearer and softer. There are several uses for image segmentation, as it is used in many studies of pre-processing of engineering images such as medical applications, video retrieval, pattern recognition, manufacturing inspection, and diagnosing structural errors. In general, image cutting methods can be divided into three main types: The first type depends on Pixel-based method, the second type depends on region-based methods, while the third type depends on the use of edges or borders in the image. (Edge-based method). The first type is considered one of the simplest types in image cutting in practical terms, as it has many important uses in digital image analysis applications, because this type is one of the most sensitive types of noise. (susceptible to noise) As for the second and third types, one of them uses the opposite of the second in the slicing process, where the second type uses the concept of similarity, while the third type uses the concept of difference. In digital image cutting, these techniques determine the image threshold of the grayscale level with a specified limit for each image unit separately. The method of confidence limits was also used, which was suggested by researchers (Buenestado and Acho) [3] in (2018), who worked on developing the (Otsu) Otsu Method on which the research idea was adopted, and the limits of confidence [12] are the range. Which falls within the population parameter with a probability of (1-∝) and is known as an estimation. (1-∝)% is defined as the confidence level, which is the percentage of confidence limits that are likely to contain the true (value) of a parameter of a probability model. Also, note that when the sample size is large, the estimate is better for the relevant community criteria. After that, an opaque noise [17] was added to the image, which often occurs due to the scattering and scattering of the waves in different directions due to the presence of particles, minutes, or impurities of relatively small diameters present in the vicinity and equipment of the imaging system itself, or it may be caused by thermal noise in the signal transmission system or Recorded, and this noise is usually represented by the normal distribution, which takes the shape of a bell and is called the caustic distribution. For the purpose of measuring quality (quality measurement) and comparing the results and knowing which techniques are better, the Jaccard scale and the PSNR scale were used.

According to the experiments conducted on the images that were cut using the techniques, it was concluded that the Niblack technology in normal conditions is better than other techniques, and the quality of other techniques in the cutting process is also not less. The research aims to find a suitable method in the image segmentation process for image processing by comparing the techniques of slicing the threshold using statistical confidence limits in an initial image processing. [8,16].

2. Threshold

The threshold technique [4,11] is one of the simplest image division techniques in image processing, which is used to segment the image, whether it is a gray scale image, a color image, or a multi-spectral image. The resulting image is binary images. (Binary Image) The image is divided into two areas, which are the foreground and the other background, so it takes black and white colors, so each image point bears either a zero or one. The most common way to convert a gray level image to a binary image is to specify a single threshold value.

The threshold methods are classified into two main categories, namely, global and local thresholding. There are a large number of threshold algorithms, mainly based on graph, spatial analysis, entropy, object characteristics and clustering.

The division of the image into the front and the background is clear through the following equation:

$$g(x,y)=\begin{cases}1, & \text{if } f(x,y) \text{is foreground pixel}\\ 0, & \text{if } f(x,y) \text{ is background pixel}\end{cases}$$

With many real-world applications the graphing is more complex, with many peaks and not clear valleys so it is not always easy to determine the value of T.

$$g(x,y) = \frac{0\ f(x,y) < T}{1\ f(x,y)\ \geq T} \tag{1}$$

3. Global thresholding

The global threshold [9,12] is based on the assumption that the image has a bimodal histogram, so the object can be extracted from the background by a simple process that compares the image values with a threshold value of [132, 32]?? T. The global threshold method (single) is used when it is a distinction between the density distribution of organisms fore and aft. That is, when the differences between the foreground and background objects are very clear, a single Threshold value can be used to distinguish between the two objects. Thus, the value of Threshold T depends on the picture unit characteristic and the gray level value of the image only. Among the more common global threshold methods are Otsu, Entropy (1) based threshold, etc.

4. Otsu method for selecting a threshold value

The Otsu [2,5,13] method is considered an efficient and simple way to set the value of the threshold automatically. One of the classes is represented in the image, and it is widely used in digital image processing, especially in the field of remote sensitivity and in the medical fields.

The threshold value is determined depending on the histogram shape of the image, where the image is assumed to be composed of two or more classes. In the event that the image is composed of two categories, then these two categories will usually represent the background of the image and the foreground. An example of this is the study of a specific area that may consist of desert and sea water areas or agricultural and mountainous areas. The best threshold value will be that which will achieve the lowest value of variance within each class (minimizing within class variance). The theoretical basis is based on the histogram and is as follows:

$$q_1(t) = \sum_{i=1}^{t} p(i) \tag{2}$$

$$q_2(t) = \sum_{i=t+1}^{I} p(i) \tag{3}$$

where $q_1(t)$ and $q_2(t)$ both represent histograms for each category. The variance is calculated as follows:

$$\sigma_1^2(t) = \sum_{i=1}^{t} (i - \mu_1(t))^2 \frac{ip(i)}{q_1(t)} \tag{4}$$

$$\sigma_2^2(t) = \sum_{i=1}^{t} (i - \mu_2(t))^2 \frac{ip(i)}{q_2(t)} \tag{5}$$

where $\mu_2(t)$, $\mu_1(t)$ represent the arithmetic mean of each category and it is calculated as follows:

$$\mu_1(t) = \sum_{i=1}^{t} \frac{ip(i)}{q_1(t)} \tag{6}$$

$$\mu_2(t) = \sum_{i=1}^{t} \frac{ip(i)}{q_2(t)} \tag{7}$$

I : Well represented the intensity of illumination for each point of the image, and the final form of the process is as follows:

$$\begin{aligned}(t) &= \sigma^2 - \sigma^2(t) \\ &= q_t[1 - q_1(t)]q_1(t)[\mu_1(t) - \mu_2(t)]^2\end{aligned}$$

Therefore, Otsu technology is based on creating an optimal threshold that works to reduce the degree of implicit variance (minimizing intra-class variance) or increase the internal variance (maximizing intra-class variance). The image may consist of more than two distinct regions, so one of the researchers developed the Otsu method. And converting it to (method Thresholding level-Multi) to divide the bright points of the image (Pixels) into more than two classes. If the histogram of the image contains three peaks, then the image can be segmented using two threshold values. These two values divide the image into three non-intersecting regions (regions overlapping-non.) If we have f (x, y) an image and have thresholds value $k_1 \ldots k_n$ $Thresholds\ value$ where $k_1 > \cdots > k_n$ Determine threshold values according to the nature of the visual used and the type of application. Thus, the image is divided into (n + 1) categories or regions.

5. Local threshold

The basic idea of this method [9] is to divide the image into sub-images m × m and then choose the threshold value, which depends on determining the value of k, which plays a major role in determining the threshold value, where we note that the small value of k makes the threshold value large, but if the value of k is large, the threshold value is small. Local threshold can be used effectively when the dithering effect is small in relation to the size of the selected sub-image. Local threshold technique, the threshold value T depends on the gray levels of f (x, y) and some local image properties of adjacent image units such as mean or contrast (3). Therefore, the threshold term function T (x, y) is written as follows:

$$\begin{aligned} g(x,y) &= 0, \quad \text{if } f(x,y) < T(x,y) \\ &= 1, \ \text{if } f(x,y) \geq T(x,y) \\ T\,(x,y) &= f\,(x,y) + T \end{aligned} \tag{8}$$

First, the sub-image gray plane graph is approximated by adding two Gaussian distributions, and then the minimum is obtained by reducing the classification error related to the threshold value. The most common local threshold method is the.

5.1. Niblack's thresholding technique

Niblack [6,10,15] depends on the arithmetic mean and variance, as they are calculated within a window size of w x w, as follows:

$$T_{Niblack}(x,y) = m(x,y) + k\sigma(x,y) \tag{9}$$

where m (x, y) the arithmetic mean and σ (x, y) the standard deviation of the picture unit inside the window, k is the amount of bias and its value is always k = -0.2, which works to control the level of adaptation with changing the threshold value The local window size is w = 15.

5.2. Sauvola's thresholding technique

Sauvola's [7,14,15] threshold is calculated using the mean and standard deviation of the pixel intensities in a window size w x w about the picture unit (x, y), and written as follows:

$$T_{Sauvola}(x,y) = m(x,y)(1 - k(1\text{-}\frac{\sigma(x,y)}{R})) \tag{10}$$

where m (x, y) is the arithmetic mean and σ (x, y) the standard deviation of the image unit inside the window, R is the maximum standard deviation (R = 128 for a gray scale document)), and k is a parameter that takes positive values in the range [0.5] [1]

5.3. Bernsen's thresholding technique

The Princeton [13,14,16] technique uses the local gray range technique, where it uses the range between the upper and lower limit of the range of the gray visual unit within the local window to determine the threshold value as follows:

$$\mathrm{T}_{\mathrm{Bernsen}}(\mathrm{x},\mathrm{y}) = 0.5(\mathrm{I}_{\max(\mathrm{i,j})}+\mathrm{I}_{\min(\mathrm{i,j})}) \tag{11}$$

where $(I_{min(i,j)})$, $(I_{(i,j)})$ is the maximum and minimum gray level value in the w x w window, which is centered at (x, y) respectively, the threshold depends on the local variance value and can therefore be expressed as:

$$C(x,y) = (I_{max(i,j)}\text{-}I_{min(i,j)}) < L \tag{12}$$

If the contrast scale is $C(x,y) < L$ then a contrast neighborhood only consists of one class or from the foreground or background (class, foreground or background). In addition, the values for w and L differ depending on the images and regions used.

6. Image segmentation based on statistical confidence interval approach

The confidence limit algorithm is a modern algorithm for slicing the image based on statistical theories. According to our numerical experiments, this method provides better performance compared to the standard process. The boundary of the confluence gives an area where the mean value of the group is likely to exist. It is found through the following mathematical explanation: [1,8,15] .

$$p\left(-Z_{\frac{1-\alpha}{2}} < \frac{\underline{x} - A_k(i,j)}{\frac{\sigma}{\sqrt{\overline{i_a j_a}}}} < +Z_{\frac{1-\alpha}{2}}\right) = 1 - \alpha \tag{13}$$

By simplifying the probability period, he obtained:

$$p\left(\underline{x} - Z_{\frac{1-\alpha}{2}} * \frac{\sigma}{\sqrt{\overline{i_a j_a}}} < A_k(i,j) < \underline{x} + Z_{\frac{1-\alpha}{2}} * \frac{\sigma}{\sqrt{\overline{i_a j_a}}}\right) = 1 - \alpha \tag{14}$$

The method can be represented by the following algorithm:

1. The image is entered, which converts into a gray-scale image. Then the standard deviation () is calculated taking into account the density of each pixel as a raster datum.
2. The original image is separated into n_p from the sub-image.
3. Through the Cartesian coordinate $A_k(i,j), k = 1, \dots, n_p$ which represents the gray scale image unit density for each given sub-image, the arithmetic mean $\underline{x}$ is calculated.
4. For each sub-image $A_k(i,j), k = 1, \dots, n_p$ the confidence limits are calculated:

$$p\left(\underline{x} - Z_{\frac{1-\alpha}{2}} * \frac{\sigma}{\sqrt{i_a j_a}} < A_k(i,j) < \underline{x} + Z_{\frac{1-\alpha}{2}} * \frac{\sigma}{\sqrt{i_a j_a}}\right) = 1 - \alpha \qquad (15)$$

5. Reconstruct the previously processed image by configuring the resulting sub-images from above.
6. Applying the threshold process to the image obtained from step (5) to obtain the final image. The following diagram shows the work of the above-mentioned techniques:

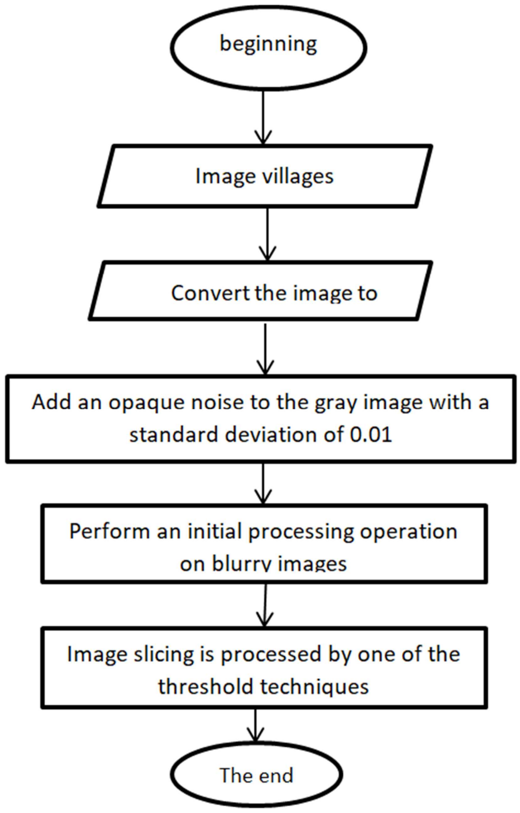


Figure 1: Illustrates the steps and structural work

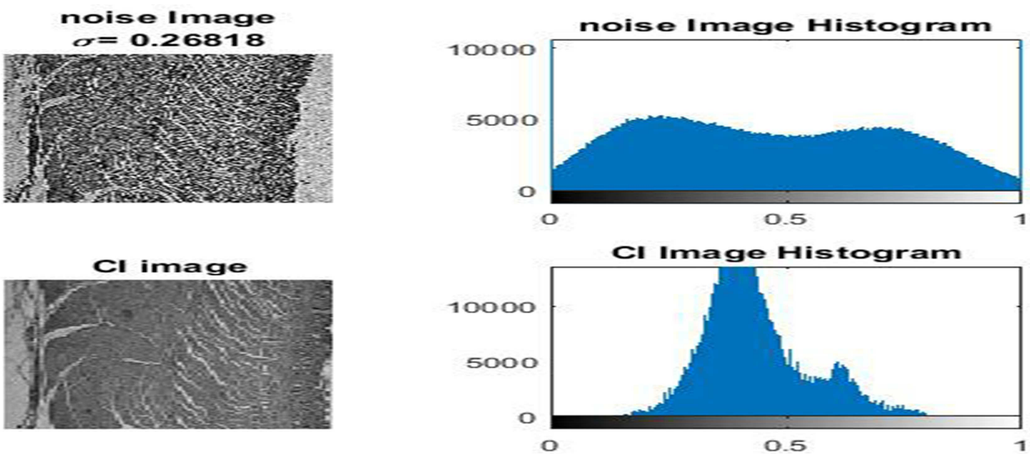
7. The practical aspect

In order to know the performance of the threshold methods mentioned in the theoretical side, which works to separate or divide the approved image into only two front and back regions, these methods were applied in the MATLAB2017a program, where the global threshold Otsu and a group of local threshold methods were compared, namely Sauvola, Niblack and Bernsen. The techniques were applied to a group of the aforementioned images.

Image 1 Image 2 Image 3

Figure 2: The original images

Most of the aforementioned threshold techniques share the same implementation steps with the difference in the mechanism for calculating the threshold value. When the image is entered, it is converted to gray, and then the obsessive noise is added as shown below.



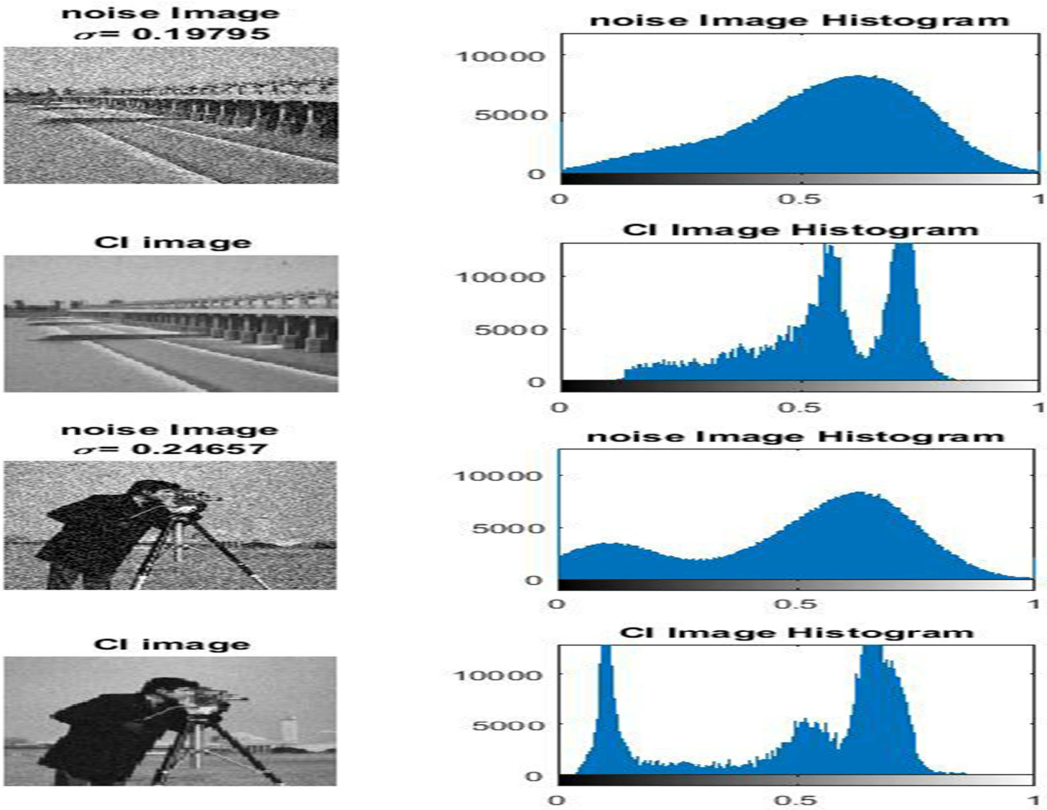


Figure 3: The images with added Gaussian noise and the images processed by the CI method with the histogram of the blurry image and the processed image

After that, a preliminary treatment is performed on the image in the manner of statistical confidence limits, after which the cutting process is carried out by the methods mentioned in the theoretical side, as shown below:

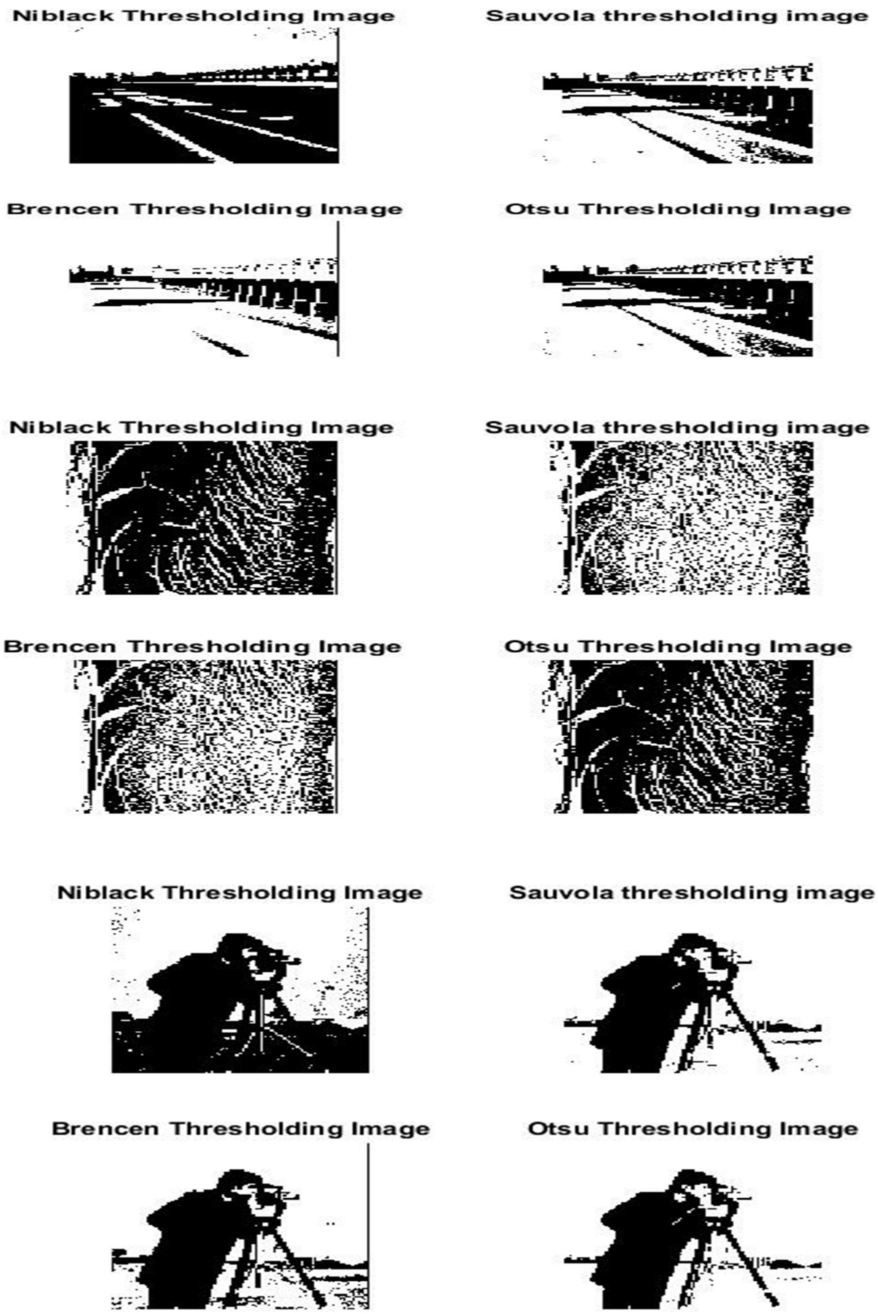


Figure 4: The images obtained from the threshold technique methods after performing an initial treatment on the blurry images

After performing the cutting process, we notice that the resulting images are black and white (binary images).

To find out which methods gave better results, the Jaccard scale and the PSNR scale were used, and the values are shown in Table (1).

	Methods	**Jaccard**	**PSNR**
Image1	Niblack	0.7521	54.1812
	Sauvola	0.3449	49.9882
	Bernsen	0.4554	50.2166
	Otsu	0.7326	53.8824
Image2	Niblack	0.6065	52.1769
	Sauvola	0.2718	49.5189
	Bernsen	0.1702	48.9541
	Otsu	0.2825	49.5841
Image3	Niblack	0.5163	51.2910
	Sauvola	0.3121	49.7548
	Bernsen	0.3475	49.9543
	Otsu	0.2970	49.6559

Table 1: The Jaccard and PSNR scale values for all methods

We notice in Table (1) that the local Niblack technique has higher values when using the Jaccard scale and the PSNR scale of the three images compared to Otsu technology, as it showed its efficiency in showing the most prominent features.

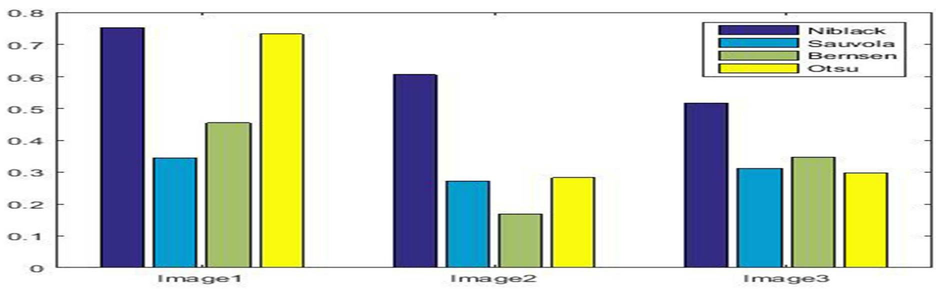


Figure 5: Comparison of images use Jaccard

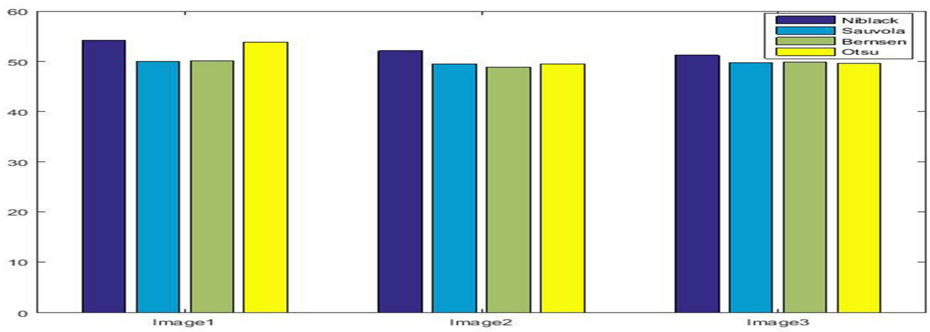


Figure 6: Comparison of images use PSNR

8. Conclusion

Through the results obtained from the practical side, it was found that the initial treatment using statistical confidence limits removed the obsessive noise from the blurry image, thus it gave clearer images. Also, it was concluded that the local Niblack threshold technique was better because it took the highest value when using a scale Jaccard and the PSNR standard, and this does not mean that the other methods are bad or unfit for cutting, as the global Otsu threshold technology has been distinguished by its efficiency in working and its speed in implementation, as well as the rest of the local threshold methods.

9. Recommendations

We recommend using threshold techniques other than those mentioned and knowing the best one in the shredding process. We also recommend using other processing methods other than the statistical confidence limits and using the methods of slicing and comparing images mentioned in the research or other methods not mentioned.

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Conflict of interest. The authors declare that they have no conflict of interest.

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