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Qualitative Comparison of Threshold based Segmentation Techniques

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***Abstract*—Threshold Segmentation is a kind of important image segmentation method and one of the important preconditioning steps of image detection and recognition, and it has very broad application during the research scopes of the computer vision. Thresholding is the simplest approach to separate object from the background. Object background classification is the basic problem of object tracking in the computer vision area. The solutions using thresholding techniques become more complex when the image is blurred or low contrast. In this paper, four different thresholding methods, for partitioning images into different regions are analyzed and compared. The different methods for thresholding for image segmentation have been simulated using MATLAB. Experiments on images demonstrate that block processing method, morphological image thresholding works better as compared to simple and Otsu thresholding.**

***Index Terms*— Image segmentation, Local thresholding, Morphological operation, Non-destructive testing, Optical character recognition.**

I. Introduction

In many applications of image processing, the gray levels of pixels belonging to the object are substantially different from the gray levels of the pixels belonging to the background. Thresholding then becomes a simple but effective tool to separate objects from the background. Examples of thresholding applications are document image analysis, where the goal is to extract printed characters,[1,2] logos, graphical content, where lines, legends, and characters are to be found[3] scene processing, where a target is to be detected[4] and quality inspection of materials,[5,6] where defective parts must be delineated. The output of the thresholding operation is a binary image whose one state will indicate the foreground objects, that is, printed text, a legend, a target, defective part of a material, etc., while the complementary state will correspond to the background. Depending on the application, the foreground can be represented by gray-level 0, that is, black as for text, and the background by the highest luminance for document paper, that is 255 in 8-bit images or conversely the foreground by white and the background by black. Various factors, such as non stationary and correlated noise, ambient illumination, busyness of gray levels within the object and its background, inadequate contrast, and object size not commensurate with the scene, complicate the thresholding operation. A document image analysis system includes several image-processing tasks, beginning with digitization of the document and ending with character recognition and natural language processing. The thresholding step can affect quite critically the performance of successive steps such as classification of the document into text objects, and the correctness of the optical character recognition OCR. Improper thresholding causes blotches, streaks, erasures on the document confounding segmentation, and recognition tasks. The merges, fractures, and other deformations in the character shapes as a consequence of incorrect thresholding are the main reasons of OCR performance deterioration. Segmentation of various image modalities is for nondestructive testing NDT applications, such as ultrasonic images [7]. In NDT applications, the thresholding is again often the first critical step in a series of processing operations such as morphological filtering, measurement, and statistical assessment. In contrast to document images, NDT images can derive from various modalities, with differing application goals. Furthermore, it is conjectured that the thresholding algorithms that apply well for document images are not necessarily the good ones for the NDT images, and vice versa, given the different nature of the document and NDT images.

The thresholding techniques can be divided into bi-level and multilevel category. In bi-level thresholding, a threshold is determined to segment the image into two brightness regions, one brightness level correspond to background and another brightness region represent the object within the image. In case of multilevel thresholding, more than one threshold is determined to segment the image into certain brightness regions. Image segmented by using multilevel thresholding techniques represents to one background and several objects of the image. In some cases, however, the existence of some undesired disturbance in thresholding may generate false result. One of the primary disturbance sources that affect the segmentation result is uneven lighting, which often exists in the capturing of an image, especially during field operation. The main causes for uneven lighting are: (a) the light may not be always stable and (b) the object is so large such that it creates an uneven distribution of the light, and (c) the scene is unable to be optically isolated from shadows of other objects [8]. In last two decades a number of methods have been proposed for image segmentation but most of them are not much suitable for uneven lighting images. We describe four different

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thresholding algorithms with the idea underlying them, categorize them according to the information content used, and describe their thresholding functions in a streamlined fashion.

The rest of this paper is organized as follows. Section 2 describes the theory of simple thresholding, and Section 3 describes the theory and implementation of the review of Otsu algorithm. Section 4 describes the theory and implementation of the review of morphological thresholding. Section 5 describes the theory and implementation of the review of thresholding based on block processing. Experimental results are reported in Section 6, and conclusions are drawn in Section 7.

II. SIMPLE THRESHOLDING

Threshold is one of the widely used methods for image segmentation. It is useful in discriminating foreground from the background [9]. By choosing an adequate threshold value T, the gray level image can be transform in to binary image. Given an input image f(x), thresholding may be viewed as an operation that involves tests against a function of t(x). Assuming that we are interested in detecting a light foreground which we refer to as objects or light objects for the remainder of the paper, on a dark background a thresholded image g(x) is defined as

$$g(x) = \begin{cases} 1 \ \ if \ \ t(x) \geq 0 \\ 0 \ \ if \ \ t(x) < 0 \end{cases} \qquad (2.1)$$

In other words, pixels labeled 1 (or any other convenient intensity level) correspond to light objects, whereas pixels labeled 0 correspond to the dark background. A similar definition can be introduced when objects of interest are represented by dark pixels and the background light pixels, as in the case of OCR applications.

III. OTSU THRESHOLDING

Converting a gray scale image to monochrome is a common image processing task. Otsu's method, named after its inventor Nobuyuki Otsu, is one of many binarization algorithms. Otsu is used to automatically perform clustering-based image thresholding [10], or, the reduction of a gray level image to a binary image. The algorithm assumes that the image contains two classes of pixels following bi-modal histogram (foreground pixels and background pixels), it then calculates the optimum threshold separating the two classes so that their combined spread (intra-class Variance) is minimal, or equivalently (because the sum of pair wise squared distances is constant), so that their inter-class variance is maxima [11]. This method is considered as a variation of iterative thresholding method. It is a clustering method based upon maximizing the between class variance. It is based upon defining well defined threshold classes as clusters with clusters lying tightly adjacent to each other and there is a minimal overlap [12].

An image can be represented by a 2D gray-level intensity function f(x, y). The value of f(x, y) is the gray-level, ranging from 0 to L-1, where L is the number of distinct gray-levels. Let the number of pixels with gray-level i be n_i and n be the total number of pixels in a given image, the probability of occurrence of gray-level i is defined as

$$p_i = \frac{n_i}{n} \qquad (3.1)$$

The average gray-level of the entire image is computed as:

$$\mu_T = \sum_{i=0}^{L-1} i p_i$$

In the case of single thresholding, the pixels of an image are divided into two classes

$C_1 = \{0, 1, \ldots, t\}$ and $C_2 = \{t+1, t+2, \ldots, L-1\}$, where t is the threshold value.C_1 and C_2 are normally corresponding to the foreground (objects of interest) and the back ground. The probabilities of the two classes are

$$\omega_1(t) = \sum_{i=0}^{t} p_i \quad and \quad \omega_2(t) = \sum_{i=t+1}^{L-1} p_i \qquad (3.2)$$

The mean gray-level values of the two classes can be computed as:

$$\mu_1(t) = \sum_{i=0}^{t} {ip_i}/{\omega_1(t)} \quad and \quad \mu_2(t) = \sum_{i=t+1}^{L-1} {ip_i}/{\omega_1(t)} \qquad (3.3)$$

Using discriminant analysis, Otsu (1979) showed that the optimal threshold t^* can be determined by maximizing the between-class variance; that is

$$t^* = ArgMax_{0 \leq t < L} \{\sigma_B^2(t)\} \qquad (3.4)$$

Where the between-class variance σ_B is defined as:

$$\sigma_B^2(t) = \omega_1(t)(\mu_1(t) - \mu_T)^2 + \omega_2(t)(\mu_2(t) - \mu_T)^2 \qquad (3.5)$$

An equivalent, but simpler formulation for the Otsu method is given in Liao et al. (2001). The simplified formula for obtaining optimal threshold t* is computed as follows:

$$t^* = ArgMax_{0 \leq t < L} \{\omega_1(t)(\mu_1(t))^2 + \omega_2(t)(\mu_2(t))^2\} \qquad (3.6)$$

The Otsu method works well when the images to be thresholded have clear peaks and valleys in other words, it works for images whose histograms show clear bimodal or multimodal distributions Otsu's method exhibits the relatively good performance if the histogram can be assumed to have bimodal distribution and assumed to possess deep a and sharp valley between two peaks. But if the object area is small compared with the background area, the histogram no longer exhibits bimodality [13]. And if the variances of the object and the background intensities are large compared to the mean difference or the image is severely corrupted by additive noise, the sharp valley of the gray level histogram is degraded. Then the possibly incorrect threshold determined by Otsu's method results in the segmentation error. (Here we define the object size to be the ratio of the object area to the entire image area and the mean difference to be the difference of the average intensities of the object and the background)

From the experimental results, the performance of global thresholding techniques including Otsu's method is shown to be limited by the small object size, the small mean difference, the large variances of the object and the background intensities, the large amount of noise added, and so on[14]. Threshold is separating foreground or object from the background into no overlapping sets [15].

IV. MORPHOLOGICAL APPROACH FOR IMAGE THRESHOLDING

We first determine the shape and size of the desired mask for morphological transforms. Achieving suitable result and reducing computation time in morphology-based methods depend on the shape and size of a mask; so, the selected mask for a problem should be in appropriate shape and size. Generally, the desired mask is selected arbitrarily. Since disk-shaped mask is independent of changes in rotation, it is more commonly used in medical imaging compared to type of masks. The size of mask is also dependent on input image and can take different values for different images; therefore, in the proposed method, we use a disk-shaped mask to apply morphology transforms whose initial size is determined through trial and error and based on the input image. Then, exfoliation process is done by applying a filter of Top-Hat transforms using different masks in various radii. We will have an enhanced image per each mask.

4.1. Top hat morphological

Methods of mathematical morphology act based on the structural properties of objects. These methods use mathematical principles and relationships between categories to extract the components of an image, which are useful in describing the shape of zones. Morphological operators are nonlinear, and two sets of data are their input. The first set contains the original image and the second one describes the structural element (mask). The original image is binary or in gray level and the mask is a matrix containing zero and one values [16].It is after applying the final image to the morphological operators that a new value for each pixel is obtained through sliding the mask on the original image. Value 1 in each mask indicates effectiveness and value 0 indicates ineffectiveness in the final image. Different formats can be selected to form a mask. A disk-shaped mask with radius of 4 is as shown below.

$$\begin{matrix} 0 & 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 1 & 1 & 0 \\ 0 & 0 & 1 & 1 & 1 & 0 & 0 \end{matrix}$$

Disk-shaped structural element (mask) with radius of 4

4.2. Morphological operators

If A (x, y) and B (u, v) describe the gray-level image matrix and the structural element matrix respectively, erosion and dilation operators are defined as (4.2.1) and (4.2.2):

$$A \Theta B = \min_{x,y}\{A(x+u, y+v)-B(u, v)\} \qquad (4.2.1)$$

$$A \oplus B = \max_{x,y}\{A(x-u, y-v)+B(u, v)\} \qquad (4.2.2)$$

The erosion operator reduces the size of objects. This operator increases the size of holes in an image and removes very small details of that image. Removing bright areas under the mask makes the final image looks darker than the original image. The dilation operator acts in reverse; in other words, it increases and decreases the size of objects and holes in the image respectively. The opening operator is equivalent to the application of the erosion and dilation operations on the same image respectively (Eq. (4.2.3)) while the closing operator acts in reverse (Eq. (4.2.4)):
The opening operator removes weak connections between objects and small details while the closing operator removes small holes and fills cracks.

$$A \circ B = (A \Theta B) \oplus B \qquad (4.2.3)$$

$$A \cdot B = (A \oplus B) \Theta B \qquad (4.2.4)$$

4.3. Selecting a proper mask

Selecting a mask in proper shape and size to take morphological actions has a key role in achieving desired results and reducing calculation time. In general, the shape and size of a mask are arbitrarily selected; however, the selected mask should be in appropriate shape and size for various diagnosis purposes. Disk-shaped masks (Fig. 1) are more commonly used for medical images than other masks. As stated before, since disk-shaped masks are independent of changes in rotation they are chosen for medical images. Since big or small masks strengthen or weaken various parts of an image, it is impossible to gather detailed information on the contrast of different images using only one structural element. This is why one mask in a particular shape and size may not appropriate for other applications [17]. In the proposed method, the change in shape and size of the mask continues until an appropriate result obtained. It should be mentioned that past experiences have key roles in selecting proper masks to take morphological actions.

4.4. Top-Hat transforms

These transforms are used to enhance the contrast of images through morphological methods and are in two general types:
Top-Hat transform is obtained by subtracting the opening of the original image from the image itself (Eq. (4.4.1)), and Bottom-Hat transform is obtained through subtracting the original image from its closing (Eq. (4.4.2)) [18]:

$$\text{Top-Hat}(A) = A_{TH} = A-(A \circ B) \qquad (4.4.1)$$

$$\text{Bottom-Hat}(A) = A_{BH} = (A \cdot B)-A \qquad (4.4.2)$$

Top-Hat and Bottom-Hat transforms are generally known as Open Top-Hat or White Top-Hat and Close Top-Hat or Black Top-Hat respectively. In many papers, Top-Hat is used to refer to both kinds of hat transforms. According to Eq. (4.4.1), since the opening operator leaves a background of the image, it is expected that Top-Hat transform removes the image background. This transform acts like a high-pass filter and extracts the bright areas of the image (with contrast not less than h) which are smaller than the mask. Bottom-Hat transform also removes the background of the image and leaves some dark areas of the image which are smaller than the mask itself [19].It is possible to add the bright areas (the results of the opening operator) to the image and subtract the dark areas (the results of the closing operator) from it. As a result, there will be an enhancement in the contrast between bright and dark areas.

4.5. Contrast improvement

Contrast which is defined as the difference in visual properties of pixels makes an object distinguishable from other objects and the background. In gray-scale images, contrast is determined by the difference in the brightness of the object and its surroundings.

4.6. Morphological transform based thresholding

1. Taking the input image and determining the shape and size of the mask. We use a disk-shaped mask with the initial. The size of the radius is increased arbitrarily according to the size of the original image
2. Top-Hat transforms which first calculates the morphological opening and then subtracts it from the original image.
3. ***Increase the Image Contrast using Enhancement technique***
4. Create a new binary image by thresholding the adjusted image

V. BLOCK PROCESSING APPROACH FOR IMAGE THRESHOLDING

Images with non-uniform contrast distribution where considerable background noise or non-uniform illumination exists, the pixels that cannot be easily classified as foreground or background based on pixel intensities. In case of block size technique, threshold value not only depends upon the pixel values or the intensity values of the pixels in the image, it also depends upon the position of the pixel in the image. So, the threshold for different pixels in the image will be different. Threshold value is calculated based on standard deviation of pixel intensity values of each M x N sub block.

5.1.1. Algorithm

The proposed approach for image segmentation is based on threshold, performing some steps over it.

1. Read the image.
2. Image is divided in to sub-blocks of size M x N
3. For each sub block, standard deviation is calculated to increase intensity of image object.
4. Global threshold is applied for each sub block which has standard deviation as greater than one.
5. The above process is repeated for each and every sub block of entire image.

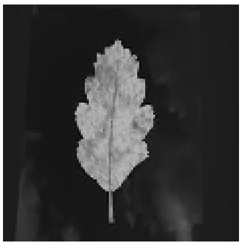
5.1.2. Block processing approach for image thresholding

In distinct block processing, image matrix is divided into m-by-n sections. These sections, or distinct blocks, overlay the image matrix starting in the upper left corner, with no overlap. If the blocks do not fit exactly over the image, padding can be added to the image with partial blocks on the right or bottom edges of the image.

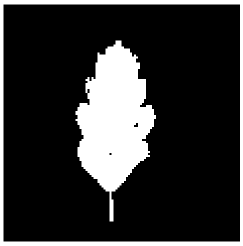
The block processing function extracts each distinct block from an image and passes it to a function which is specified for processing. The block processing function assembles the returned blocks to create an output image.

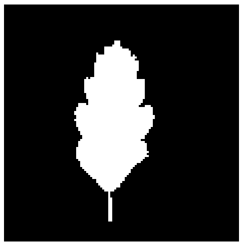
VI. EXPERIMENTAL RESULTS

To evaluate the performance of the different threshold based segmentation methods, real world images were chosen as testing samples. The original images, leaf, nano particle, palm leaf document and field images are shown in Fig 1(a), Fig 2(a), Fig 3(a), Fig 4(a). Threshold based segmentation results of simple, Otsu, morphological and block processing are shown in (Fig. 1(b)–(e)), (Fig. 2(b)–(e)), (Fig. 3(b)–(e)) and (Fig. 4(b)–(e)) respectively. Block processing gives better result for palm leaf document and field images. Otsu method gives better result for leaf and nano particle images.

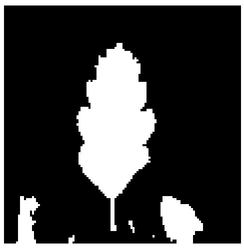


(a) Original Image





(b) Simple Threshold (c) Otsu method



(d) Morphological (e) Block Processing

Fig 1: Original leaf image and its threshold based segmentation results

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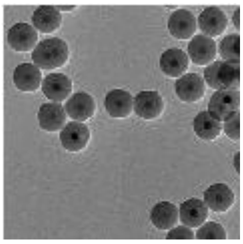
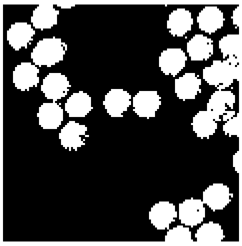
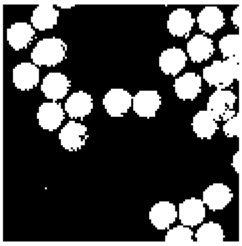


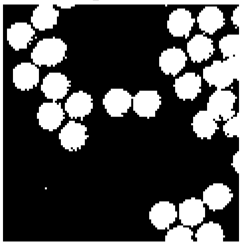
(a) Original Image



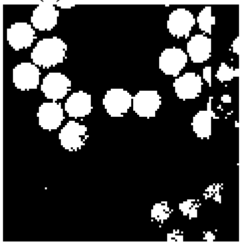
(b) Simple Threshold



(c) Otsu method

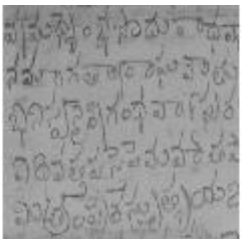


(d) Morphological

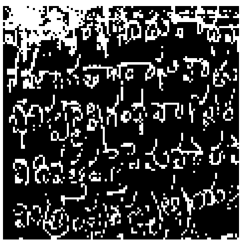


(e) Block Processing

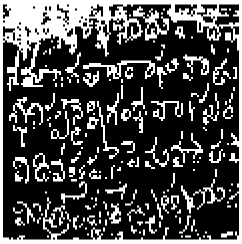
Fig 2: Original nano particle image and its threshold based segmentation results



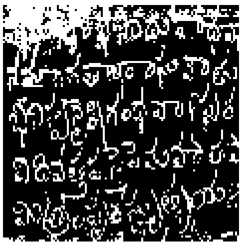
(a) Original Image



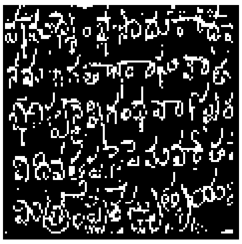
(b) Simple Threshold



(c) Otsu method

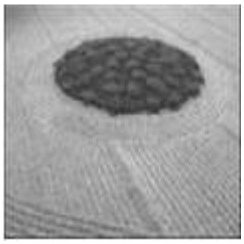


(d) Morphological



(e) Block Processing

Fig 3: Original palm leaf document image and its threshold based segmentation results.



(a) Original Image

(b) Simple Threshold

(c) Otsu method

(d) Morphological

(e) Block Processing

Fig 4: Original field image and its threshold based segmentation results

VII. CONCLUSION

Simple and Otsu thresholding techniques are unable to consider spatial contextual information for selecting the optimum threshold and are effective only for bi-level thresholding. Otsu's method is best in segmentation with respect to uniformity and shape features. In this article four thresholding techniques are presented that block processing based and morphological based thresholding mitigate both these limitations. Morphological thresholding is to enhance the quality and contrast of medical images. We compared four threshold methods exist in the literature by using four different images. In this comparison, we observed that the morphological image thresholding, block processing method gives better results as compared to the Simple thresholding, Otsu thresholding techniques.

Table 1
Qualitative comparison on PSNR for the images:

	Leaf	***Nano-particle***	***Palm leaf document***	***Field Image***
Simple Thresholding	49.55	52.76	52.53	51.73
Otsu method	62.66	55.33	55.92	57.36
Morphological thresholding	61.98	52.83	52.83	51.73
Block processing	59.43	55.31	56.05	58.10

Experimental results are listed in Table 1. In addition, the table compares PSNR for four different images with simple, Otsu, morphological and block processing based thresholding techniques. A larger PSNR value indicates better value of thresholding. Moreover by analyzing the results reported in Table 1, Leaf image PSNR value is more in Otsu method than other methods. Nano particle image PSNR value is more in Otsu method than other methods. Palm leaf document image PSNR Value is more in block processing technique than other methods. Field image PSNR value is more in block processing technique than other methods.

Table 2
Qualitative comparison on MSE for images

	Leaf	***Nano particle***	***Palm leaf document***	***Field Image***
Simple Thresholding	0.73	0.35	0.37	0.44
Otsu method	0.04	0.19	0.17	0.12
Morphological thresholding	0.04	0.34	0.36	0.44
Block processing	0.07	0.19	0.16	0.11

Table 2 provides comparison results of MSE obtained by four methods for different images. A larger MSE value indicates poor quality of the image. Moreover by analyzing the results reported in Table 2, Leaf image MSE value is less in Otsu method and Morphological than other methods. Nano particle image MSE value is less in Otsu and block processing than other methods. Palm leaf document image MSE value is less in block processing technique than other methods. Field image MSE value is less in block processing technique than other methods.

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