Edge Enhanced Optimum Automatic Thresholding

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Abstract

The thresholding process has been widely used to segment one or several objects from their background.

The automatic thresholding requires that, the image formation be of two well-segmented homogeneous regions, and there exists a threshold value that separates these regions. The separation deteriorates when the objects are not homogenously illuminated. In this paper a new algorithm is proposed for the optimum automatic thresholding of digital images in the presence of non-homogenous illumination. The algorithm is based on determining an optimum threshold value that maximizes an edge similarity function of the binary and the original gray level images. Experimental results to compare the proposed algorithm to the various thresholding techniques are also presented.

1-INTRODUCTION

Threshoding or binarization is one of the basic image-segmentation operations[1-3]. It is the process of separating objects from their background.

An optimum threshold value is the value at which the maximum amount of information about the object of interest is revealed and the minimum amount of information is lost.

In general, the automatic determination of optimum threshold values is a difficult task in digital image processing. It has been extensively studied for its obvious practical importance as well as its theoretical interest. Many thresholding techniques have been proposed to solve the segmentation problem. Such techniques optimize a criterion function based on information obtained from either the image histogram or its spatial distribution.

The problem becomes simple when the gray-levels occupied by the objects and their background are sufficiently separated. This separation is normally represented in the gray level histogram by a valley and two peaks. One can then select a threshold value at the bottom of this valley[4].

Otsu[5] describes a method based on obtaining an optimum threshold value that maximizes a class of separability measure based on the variance of the normalized histogram.

Misclassification may result when parts of the object are classified as background or vice versa. An obvious optimization procedure would be to choose a threshold value that minimizes the misclassification error. In general, the two peaks may differ greatly in size and/or may lie close to each other. The histogram may then be unimodal, with one of the two peaks being absorbed by the other, making it difficult to define a threshold value separating the two populations[6,7]. To handle this situation a variety of techniques[8-11] has been proposed to produce a transformed gray-level histogram in which the valley is deeper. These methods generally make use of the gray-level magnitude in conjunction with the gray-level itself. The poor performance of histogram based methods can be attributed to the fact that the gray-level histograms of noisy images do not have distinct modes or valley points which can be used to locate the optimum threshold value. There are techniques, which do not use the gray-level histogram for threshold selection and hence avoid the problems associated with the histogram analysis.[12-13].

In this paper, we investigate the thresholding problem and present a new technique to automatically threshold the gray level images in the presence of non- uniform illumination. This technique is based on selecting an optimum threshold value that maximizes a similarity measure between the edges of the objects in the original gray level image as well as the thresholded image. The proposed algorithm does not require the bimodality of the image histogram. The performance of this novel technique has been verified experimentally on both clean and noisy images. The results revealed that the new algorithm achieved the best overall performance

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among several popular threshoding techniques. The problem of non-homogenous or weak illumination has little effect on the proposed technique.

Section 2 presents a brief description of the process of digital image segmentation using thresholding. The proposed algorithm is explained in details in Section 3. In Section 4, experimental results are presented to compare the proposed algorithm with the main thresholding algorithms reported n the literature. Conclusions derived from this study and suggestions for future work are presented in Section 5.

2-Image segmentation using Thresholding

The segmentation process is used to segment the image into several parts or regions. Each region can then be identified as having its own uniform appearance[14].

The process of segmenting the image into objects and background is very important in many image processing and pattern recognition applications. Finding a suitable threshold value that could separate or segment the gray level image into objects and background is the core of the thresholding operation. A proper way of analyzing the gray level distribution of an image is to construct its histogram. An image *histogram* is a representation of a discrete function $h(t)$ that gives the population of pixels in each gray-level in an image. A typical image histogram is shown in Fig.1.

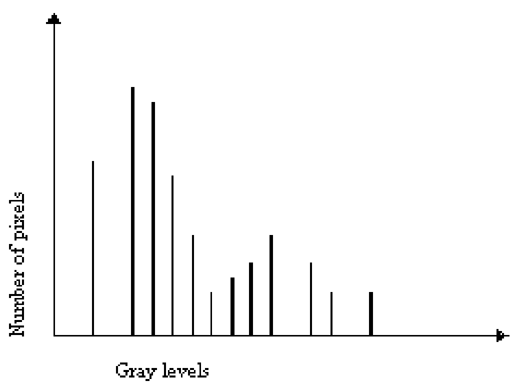

Fig.1 Atypical image histogram.

An image histogram function is:

$$h(t) = n_t \qquad \textbf{(1)}$$

where n_t is the number of pixels in the image with gray level *t*.

The *normalized* histogram is given by:

$$h_n(t) = n_t \,/\, \boldsymbol{N} \qquad \textbf{(2)}$$

where ***N*** is the total number of the pixels in the image.

A gray-level histogram is one of the most useful tools for manipulating gray-level images. The idea behind the histogram-based thresholding techniques is to compare each pixel in the image to a threshold value, and a pixel is classified as an object or background depending on whether the threshold value is exceeded or not. Most of these techniques are dependent on the spatial information available about the objects. In the next section we will introduce a technique that utilizes the edge information as well as the spatial information in order to arrive at a reasonable choice for the threshold value.

3-Edge Similarity Technique

In this section a new technique is presented. This technique is based on finding the optimum threshold value that will maximize the edge similarity between an edge enhanced gray level image and the edges of the thresholded binary image.

As discussed previously the histogram based technique is dependent on the success of estimating the threshold value that separates the two homogenous regions of the object and background, of an image. This requires that, the image formation be of two homogeneous and well-separated regions, and there exists a threshold value that separates these regions.

The above algorithm performance deteriorates when there are several homogenous regions or there is a variable illumination effect. An example of this scenario would be an image with many objects with different gray levels. In this case, portions of the object may be merged with the background or portions of the background may appear as an object.

From the above discussion the histogram based technique (**HDT)** is suitable for images with *large* homogenous and *well*-separated regions. These conditions are fully satisfied for edge-enhanced images, where all areas of objects and background are homogenous except the area that falls between the objects and background. This area is small and has a distinct gray-level value. The performance of the **HDT** algorithm when applied to edge-enhanced images, is expected to improve due to two reasons. The first is the availability of two *large* homogenous areas (i.e., the area inside the object *plus* the area inside the background). The second is the regions are *well* separated as a result of using a gradient operation to create the edge-enhanced image. To get the optimum threshold value based on the above observations the edge-enhanced image is obtained using the following operation:

$$g(x,y)=\sum_{j=-1}^{j=0}\sum_{i=-1}^{i=0}A_{ij}\,f(x+i,y+j)$$

where $A_{-1,0}= A_{0,-1}=-1$, $A_{-1,-1}=0$ and , $A_{0,0}=2$.

The edge enhanced image can be obtained by comparing the value of g(x,y) to a threshold value T according to:

If g(x,y) > T then $f_{oth}(x,y) = 1$.

Otherwise: $f_{oth}(x,y)=0$.

For each threshold value, the edges of the binary image f_{th}**(x,y)**, are obtained as follows:

$e_1(x,y)=1$ if the gray levels of f(x,y) and f(x,y-1) are different,

$e_1(x,y)=0$ otherwise. **(3)**

$e_1(x,y)=1$ if the gray levels of f(x,y) and f(x-1,y) are different,

$e_1(x,y)=0$ otherwise. **(4)**

From (3) and (4) the edges of the binary image f_{th}**(x,y)** are obtained as follows:

$f_{eth}(x,y)= 1$ if either $e_1(x,y)$ or $e_2(x,y)=1$

$f_{eth}(x,y)= 0$ otherwise. **(5)**

The optimum threshold value is defined as the value that maximizes the *similarity* between the edge-enhanced original binary image f_{oth}**(x,y)** and the edges of the binary image f_{eth} ***(x, y)*** at each threshold value.

The similarity ***S*** between these images is defined as follows:

$$S(t) = [\, 2\sum\sum(f_{oth}(x,y)\, f_{eth}(x,y))]/[\, \sum\sum(|f_{oth}(x,y)|^2+|\, f_{eth}(x,y)|^2)] \quad \textbf{(6)}$$

S(t): is the similarity measure.

f_{eth} ***(x, y)***): represents the edges of the binary image at **t** threshold value.

f_{oth}**(x,y)**: is the binary image resulted from applying the **HDT** algorithm on the edge-enhanced image.

The optimum threshold value is the value that gives a maximum value of ***S(t)***. The above algorithm is abbreviated as **EST** (**E**dge **S**imilarity **T**echniques).

4- Experimental Results

An experimental test images have been prepared to cover a variety of situations and conditions.

A set of noisy and clean images was used to evaluate the performance of the proposed algorithms as well as some of the popular algorithms presented in the literature. All images are of 128 x128 pixels array with gray-level ranged between 0 and 255.

The test images were selected such that they cover one or more of the following situations:

•Unimodal, bimodal, and multimodal histograms.
•Shadowy and non-homogenous background.
•Disproportional histogram peaks.
•Reflections due to strong illumination.
•Noisy images.
•Non uniformly illuminated images.

The performance of the new techniques is compared with the performance of the following techniques:

•The Histogram Dependent Thresholding (HDT) technique[5].
•The Laplacian Histogram Dependent Thresholding (LHDT) technique[8].
•The Quad Tree Thresholding (QTT) technique[7].
•The Edge Thresholding (EDT) technique[13].
•The Perimeter Maximization Thresholding (PMT) technique[12].

The main comparison criterion is the absolute error ratio. The absolute error is defined as the absolute difference in the number of pixels between the optimally thresholded image and the thresholded image obtained by each method. The error rate can then be computed by dividing the absolute difference by the total number of pixel for each image.

The first part of these results deals with clean images and is shown in figure (2) to figure (8). These figures show the original gray-level image, histogram of the image, the optimally thresholded image (manually), modified histogram using Laplacian operator, modified histogram using quad-tree, and thresholded image using each method.

The optimum thresholding, which has been obtained manually using the visual inspection, and the *deviation* from the optimum threshold value for each algorithm are shown in Table (1).

In most cases, as shown in figure (2) to figure (8), thresholding based on the other techniques gave higher error rates in comparison with the proposed technique, this can be noticed form the error rates, presented in Table (1).

Figure (2) shows an image for four toys occupying different gray-levels. Most of the algorithms failed to extract the darker toy from its background. On other hand, the EST, extracted all four toys.

Figurer (5) shows an image with *unimodal* histogram, this is the case when an object has a gray-level value close to its background. All the algorithms were unable to correctly segment this image, with the exception of the EST algorithm. The only way to segment this type of image is to use the Edge information of the original image, which represents a distinct feature of the EST.

An interesting observation about the EST algorithm is that a gray level image can be transformed into a bilevel image even if its histogram is not bimodal. This is very apparent from the histograms shown in figure (2) and figure (4).

Small variation in gray-level due to shadows do not present a problem for the proposed algorithm which can be seen in figure (6), and figure (7)

Although the **PMT** did very well in most cases it has failed to produce the optimum threshold value for the image in Fig.3, due to the fact that this image contains shadowy background.

Histogram modifications fail to transform the multimodal histogram into bimodal one as shown in figure (3).

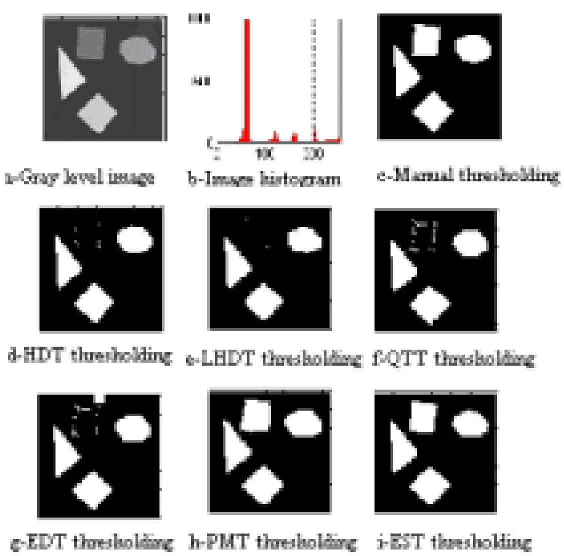

Figure.2 An image with multi peaks.

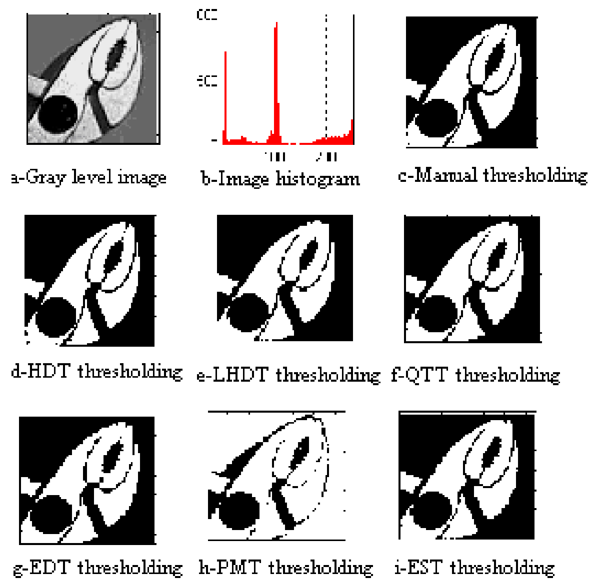

Figure.3 An image of pliers with three-peak histogram

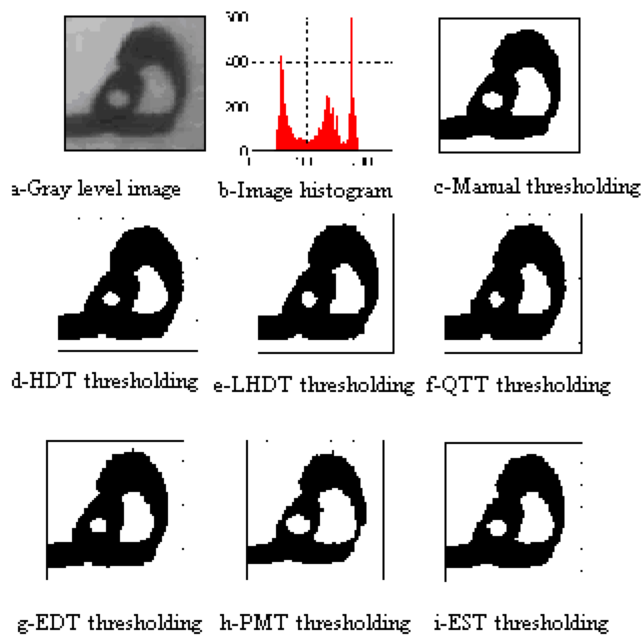

Figure.4 Image with three-peak histogram.

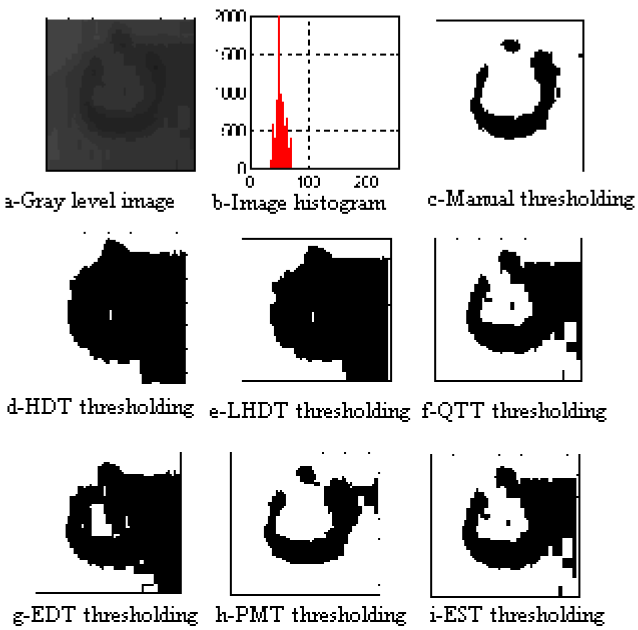

Figure.5 Image with unimodal histogram.

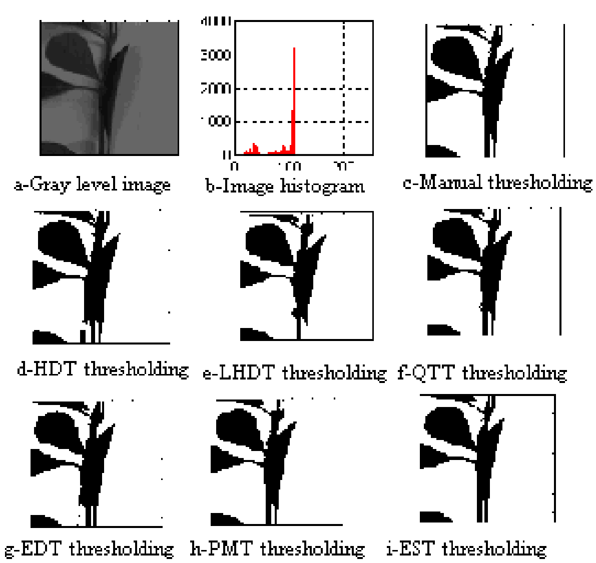

Figure.6 Shadowy image.

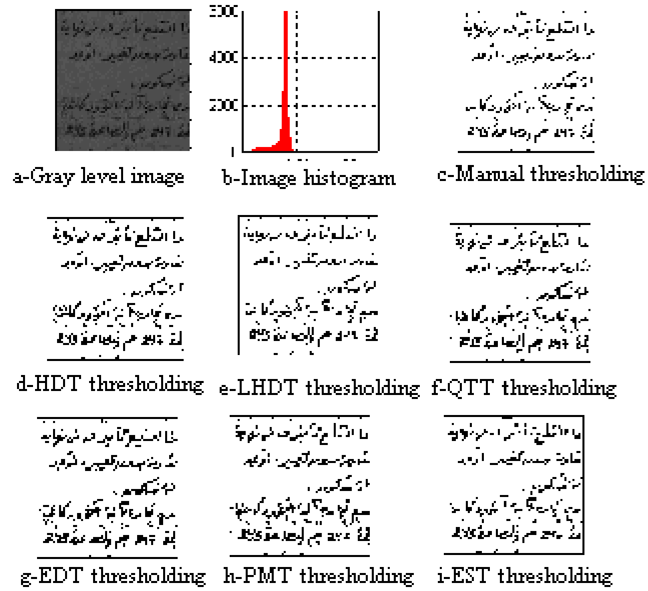

Figure.7 Arabic text with undefined peaks.

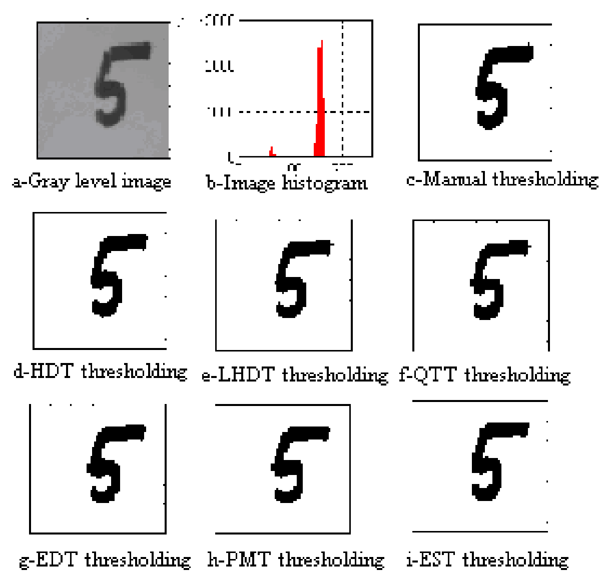

Figure.8 An image with well separated object.

The performance of the algorithms in the presence of noise is studied using a set of real and synthetic images. Two types of noise, which is usually encountered in images, are used. The first group of these sets is corrupted by a Gaussian additive noise of zero mean and standard deviation of 32. A signal to noise ratio of value 2 has been used for all samples.

The second group of images contains *low* frequency noise (multiplicative noise) caused by non-homogenous illumination covering the whole image area.

All the previous thresholding algorithms were tested using the generated set of noisy images. The results of these tests are shown in figure (9) to figure (14). The error rate for each algorithm is shown in Table (2).

The second group of results indicates that the performance of algorithms that depend on image boundaries (**EDT, QTT, LHDT, HDT**) has deteriorated. The noise in the background for the images of figure (9) and figure (10) has been detected as object edges by these algorithms. Unlike the other techniques, the **EST** algorithm has performed well despite the noise in the background. The averaging of the non-edge pixels in the enhancement process enables the EST algorithm to converge to the optimum threshold value that minimize the noise effect.

As far as the second group of noisy images is concerned (corrupted with multiplicative noise), the proposed algorithm preformed very well in the presence of such noise. In the case of non-uniform illumination, the performance of the EST algorithm has been superior to the rest of the other algorithms, as shown in figure (11). The non-uniform illumination as well as the noise effect can actually determine the difference in performance between all algorithms due to the fact that they all performed well in the absence of such noise, as shown in figure (8).

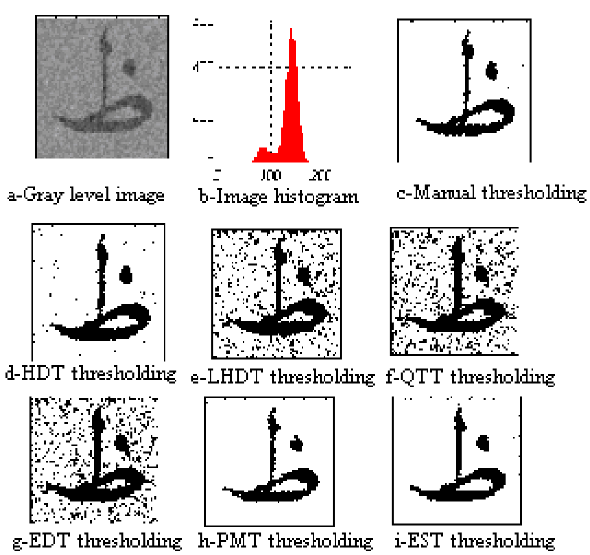

Figure.9 Arabic character with added Gaussian noise

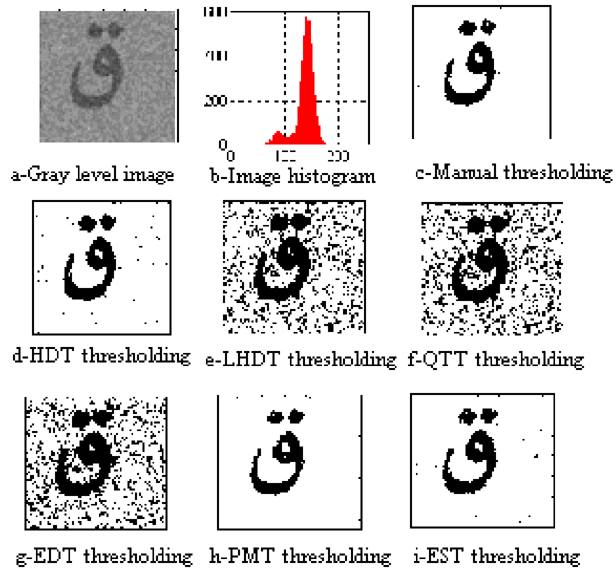

Figure.10 Arabic character with added Gaaussian noise

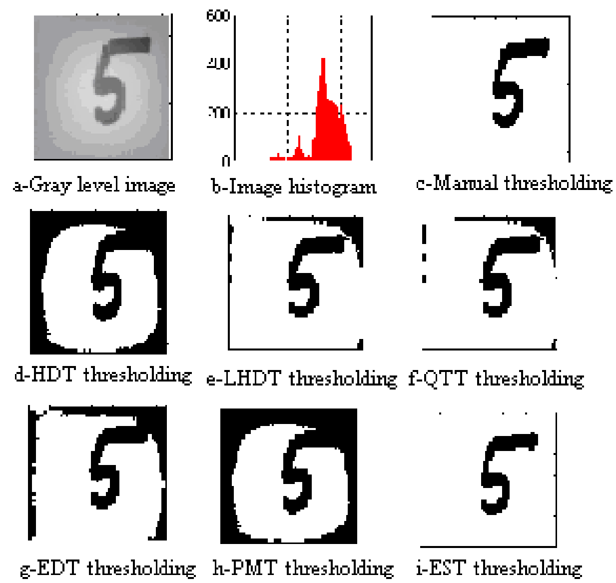

Figure.11 Numerals 5 in non-uniform illumination

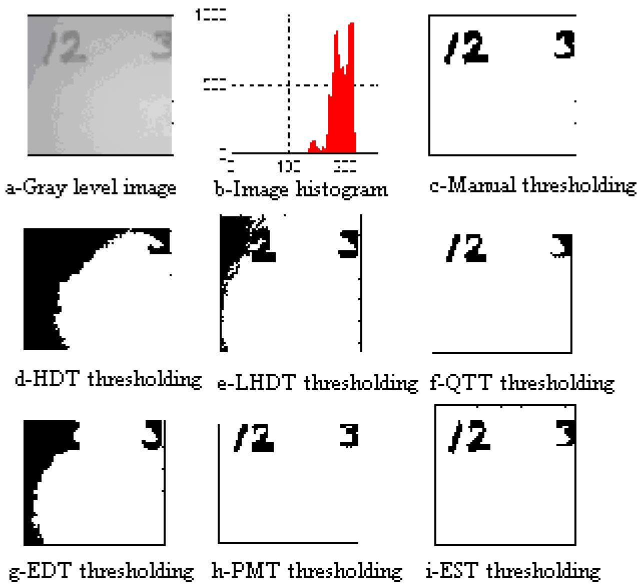

Figure.12 Numerals 1,2 and 3 in non-uniform illumination

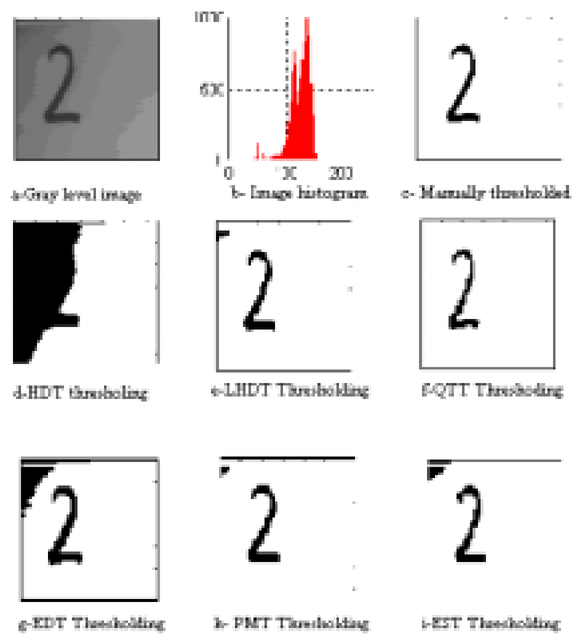

Fig.13. Numeral 2 in non-uniform background.

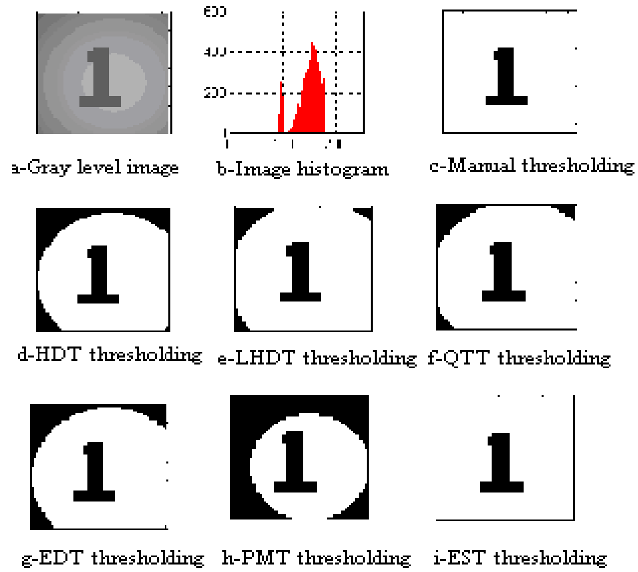

Figure.14 Object with non-uniform illumination.

5-Conclusions

Image segmentation using threshoding has been attempted. A brief review and comparison of several popular thresholding algorithms to produce an optimal binary or bilevel image has been presented. The problems associated with selecting an optimum single threshold value (Global Thresholding) have been addressed.

Various automatic thresholding algorithms have been explored. The problem of illumination effects on an image histogram has been illustrated. It has been shown that the illumination effect can be reduced by histogram modification techniques. These techniques may in general result in transforming an image histogram into a strongly bimodal histogram with two peaks comparable in size and separated by deep valley.

A new technique for automatic thresholding of images has been introduced. This technique, abbreviated as EST, is based on maximizing the similarity of edges between the gray-level image and the thresholded image. The EST technique has been tested against most of the popular thresholding algorithms and experimentally proven to be superior.

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Table.1 the error percentage for each algorithm

Figure	HD	MH	QT	ED	PM	ES
2	5.3	5.7	4.9	5.2	1.3	0.0
3	0.4	8.8	7.9	0.5	4.0	0.9
4	4.9	3.4	4.6	3.7	4.6	0.7
5	44	44	19	36	1.6	19
6	3.5	1.9	0.7	2.4	0.4	0.2
7	2.6	1.1	4.3	4.3	4.3	1.4
8	0.9	1.2	1.0	0.8	1.2	0.6

Table.2 the error percentage for noisy images.

Figure	HD	MH	QT	ED	PM	ES
9	0.2	0.2	1.8	1.8	0.6	0.3
10	1.8	30	23	23	0.3	0.1
11	37	7.6	7.6	16	37	0.0
12	39	8.9	0.2	19	0.5	0.0
13	31	1.5	2.0	6.1	0.3	2.2
14	15	4.7	4.7	15	42	0.0