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# A NEW APPROACH FOR THRESHOLDING FINGER PRINT IMAGES BASED ON SECOND ORDER STATISTICAL METHOD

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## Abstract

Thresholding methods are important in any image processing technique. It is used to convert the input gray level image to binary image. Hence, they are the essential preprocessing methods. The present paper proposes various methods for thresholding based on second order statistics (CTH, ETH, HTH, ATH). The proposed four methods are applied on various finger print images and compared with various first order statistics based methods (max, min, (max-min)/2,standard deviation ,mean). The results clearly indicate the efficiency of the proposed algorithms.

**Keywords:** Preprocessing, Statistics, Gray level, Binary, Segments.

## 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, or musical scores: map processing, 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. Other applications can be listed as follows: cell images [7,8] and knowledge representation [9] segmentation of various image modalities for nondestructive testing applications, such as ultrasonic images[10],eddy current images [11] thermal images [12] x-ray computed tomography [13] endoscopic images [14] laser scanning confocal *microscopy [13] extraction of edge field [15] image segmen*tation [16,17] spatio-temporal segmentation of video images [18] etc. The output of the thresholding operation is a binary image which indicates 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 nonstationary 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. Finally, the lack of objective measures to assess the performance of various thresholding algorithms, and the difficulty of extensive testing in a task oriented environment, has been other major handicaps.

Thresholding is an important technique for image segmentation that tries to identify and extract a target from its background on the basis of the distribution of gray levels or texture in image objects. Most thresholding techniques are based on the statistics of the one-dimensional (1D) histogram of gray levels and on the two-dimensional (2D) co-occurrence matrix of an image. Many 1D thresholding methods have been investigated [19-27]. Locating the thresholds can be proceed in parametric or nonparametric approaches [19, 22, 21]. In parametric approaches, the gray level distribution of an object class leads to finding the thresholds. For instance, in Wang and Haralick’s study [23] the pixels of an image are first classified as either edge non-edge pixels. According to their local neighborhoods, edge pixels are then classified as being relatively dark or relatively bright. Next, one histogram is obtained for those edge pixels which are dark and another for those edge pixels which are bright. The highest peaks of these two histograms are chosen as the thresholds. Moment preserving thresholding is a parametric method which segments the image based on the condition that the thresholded image has the same moments as the original image [21]. In nonparametric approaches, the thresholds are obtained in an optimal manner according to some criteria. For instance, Otsu’s method chooses the optimal thresholds by maximizing the between-class variance with an exhaustive search [20]. In Pun’s method [25] as modified by Kapur et al.

[26] the picture threshold is found by maximizing the entropy of the histogram of gray levels of the resulting classes. Other, some 1D thresholding techniques extend from bi-level threshold selection to multilevel threshold selection [19,23]. In contrast to 1D thresholding methods, 2D methods essentiall do image segmentation by using spatial information in an image [28-33]. Kirby and Rosenfeld proposed a 2D thresholding method that simultaneously considers both the pixel gray level and the local statistics of its neighboring pixels [30]. One particular 2D method is entropic thresholding, which makes use of spatial entropy to find the optimal thresholds. Abutaleb [31] and Pal and Pal [32] proposed that optimal thresholds can be selected by maximizing the sum of the posterior entropies of two classes. However, their method is very time-consuming at determining the 2D total entropy of the resulting two classes. As a result, Chen et al. proposed a two-stage approach to search for the optimal threshold of 2D entropic thresholding so that the computation complexity can be reduced to O(L8/3) for an image with L gray levels [28]. Recently, Gong et al. [29] designed a recursive algorithm for 2D entropic thresholding to further reduce the computation complexity to O(L2). However, it is still inefficient to apply this algorithm to 1D multilevel thresholding selection, owing to their computation of threshold without taking advantage of the recursive structure of entropy measures. The Sahoo et al. study on global thresholding [24] concluded that Otsu's method was one of the better threshold selection methods for general real world images with regard to uniformity and shape measures. However, Otsu's method uses an exhaustive search to evaluate the criterion for maximizing the between-class variance. As the number in classes of an image increases, Otsu's method takes too much time to be practical for multilevel threshold selection. To determine the 1D threshold of an image efficiently, we propose a modified between-class variance for Otsu's method. So, the present paper has attempted to give efficient methods for thresholding. For , this the present paper uses order statistics. The present paper is organized into four sections: section 1 gives the introduction, section 2 gives the methodology, section 3 gives the results and discussions followed by conclusions in section 4.

# II. Methodology

The thresholding methods are used to segment the gray images to binary images. There are various thresholding methods among them statistical methods are popular than other methods. The first order statistics are concentrating on the information related to the distribution of gray levels within the image. Various first order statistics such as max, min, (max-min)/2, standard deviation and mean operations are used for thresholding the gray images. They are described by the equations .The drawback of first order statistics is that they are not concentrating on the information of the positions of gray levels within the image. To overcome this drawback, the present paper proposes new thresholding methods based on the second order statistics. The second order statistics are superior to first order statistics and are concentrated on the locations of gray values also. Among various second order statistics, four measures namely contrast, entropy, homogeneity and ASM (Angular Second Moment) are important. Contrast is a measure of local level variations which takes light values for image of high contrast. Entropy is a measure of randomness and takes low values for smooth images. Homogeneity is a measure of that takes high values for low contrast images.ASM is a feature that measures the smoothness of the image.Together all these features provide in detail information about the gray image. The equations for the proposed second order statistical thresholding methods are given by Equations (1)-(4).

$$CTH = \frac{\sum_{x=1}^{m}\sum_{y=1}^{n}|x-y|^2 \times \left[\log\left(P(x,y)\right)^4\right]}{\alpha} \quad (1)$$

Where CTH defines Contrast based thresholding method, P denotes the gray image with size MxN.

$$\text{ETH}=\frac{\left[\log\left[\sum_{x=1}^{m}\sum_{y=1}^{n} p(x,y) * \log(p(x,y))\right]\right]}{\beta} \quad (2)$$

Where ETH defines Entropy based thrsesholding method, P denotes the gray image with size MxN.

$$\text{HTH}=\left[\log\left[\sum_{x=1}^{m}\sum_{y=1}^{n}\left(\frac{p(x,y}{1+|x-y|}\right)^2\right]\right]\%\gamma \quad (3)$$

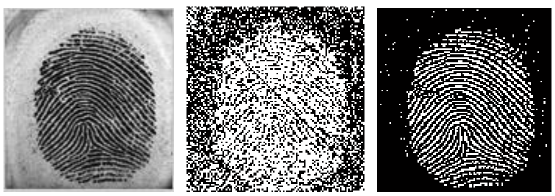
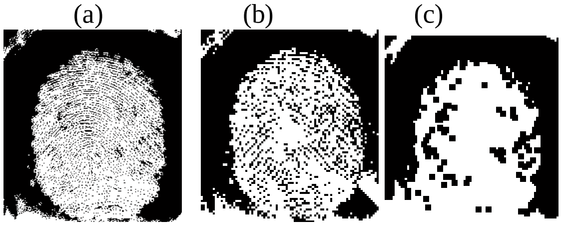
Where HTH defines Homogeneity based thrsesholding method, P denotes the gray image with size MxN.

$$\text{ATH}=\frac{\left[\sum_{x=1}^{m}\sum_{y=1}^{n} p(x,y)^2\right]}{\theta} \quad (4)$$

Where ATH defines ASM based thrsesholding method, P denotes the gray image with size MxN.

# III. Results and Discussions

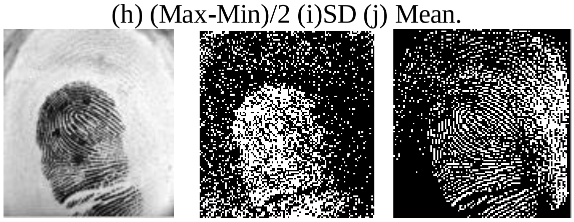
Thresholding plays a vital role in determine the segments of the objects existing in the input image. Though there are various methods for thresholding, among them order based statistics are important than the others. so, the present paper presented various methods based on first order and second order statistics. The present paper has used five first order statistics named as max, min,(max-min)/2,mean and standard deviation measures. The proposed methods are applied on 3X3 local window. For Fingerprint images, the first order statistics are failed to perform thresholding efficiently. To overcome this, we proposed new methods for thresholding based on second order statistics namely Contrast, Entropy, Homogeneity, ASM. The proposed methods are applied on several images taken from database "Fingerprint Verification Competition"


(a) (b) (c)

(d) (e) (f)

(g) (h) (i)

(j)

Figure 1(a) original:DB3 101_1 (b) CTH (c) ETH (d ) HTH (e) ATH(f) Max (g) Min
(h) (Max-Min)/2 (i)SD (j) Mean.


(a) (b) (c)

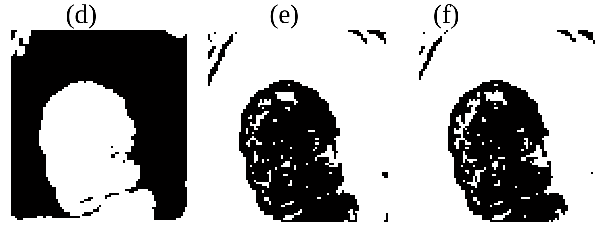
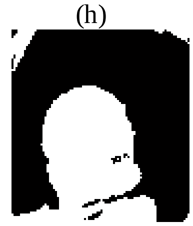
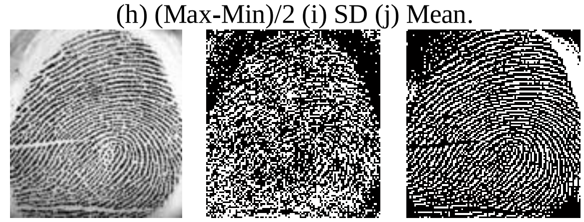
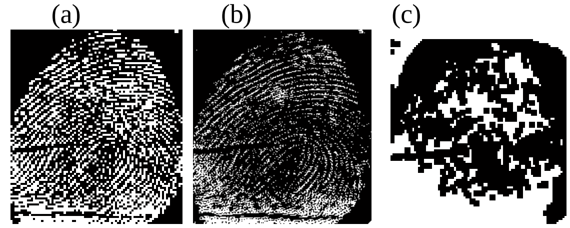
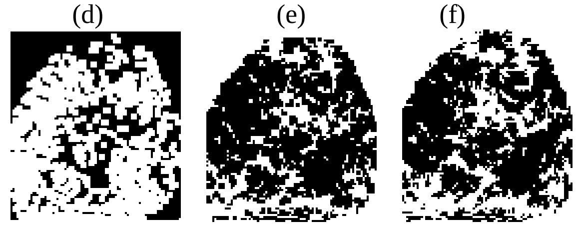
(d) (e) (f)

(g) (h) (i)

(j)

Figure 2(a) original: Db3-110_7 (b) CTH (c) ETH (d) HTH (e) ATH (f) Max (g) Min
(h) (Max-Min)/2 (i) SD (j) Mean.


(a) (b) (c)

(d) (e) (f)

(g) (h) (i)

(j)

Figure 3(a) original:DB3 108_6 (b) CTH (c) ETH (d) HTH (e) ATH (f) Max (g) Min (h) (Max-Min)/2 (i) SD (j) Mean.

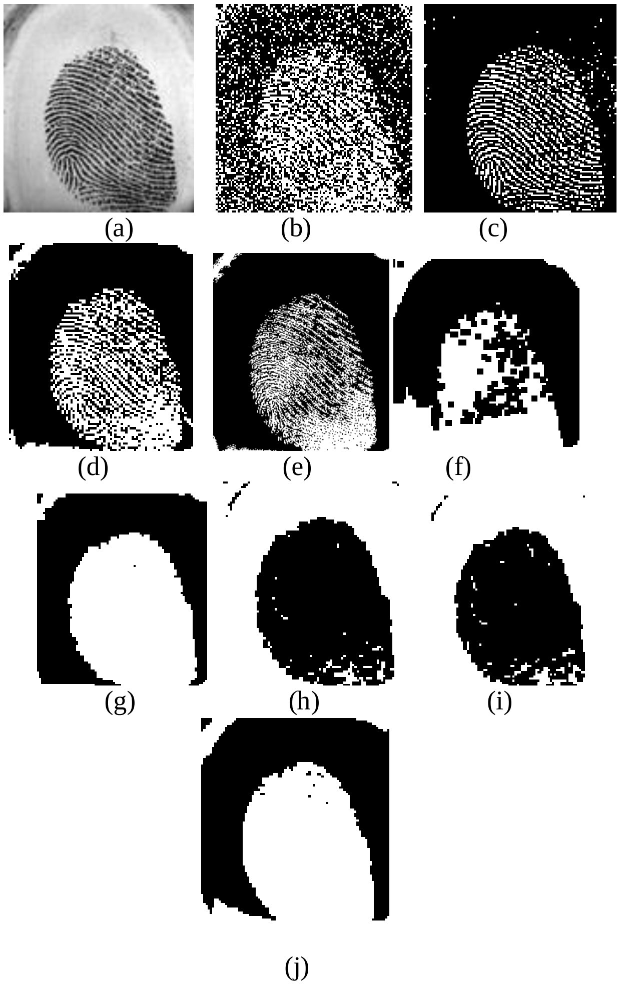
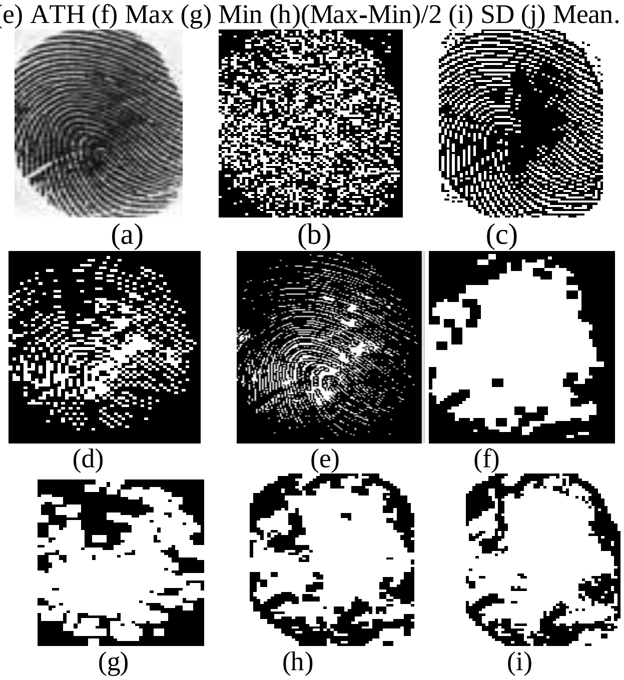



Figure 4(a) original: DB3 101_6 (b) CTH (c) ETH (d )HTH (e) ATH (f) Max (g) Min (h)(Max-Min)/2 (i) SD (j) Mean.



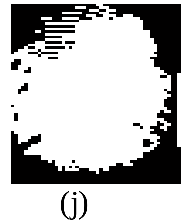




Figure 5(a) original: DB2105_8 (b) CTH (c) ETH (d )HTH (e) ATH (f) Max (g) Min (h) (Max-Min)/2 (i) SD (j) Mean.

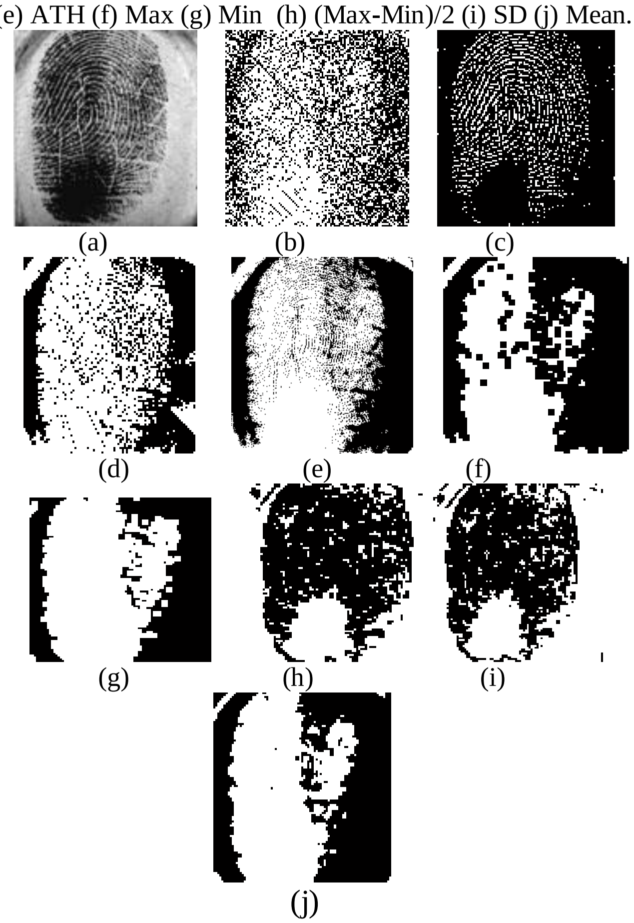
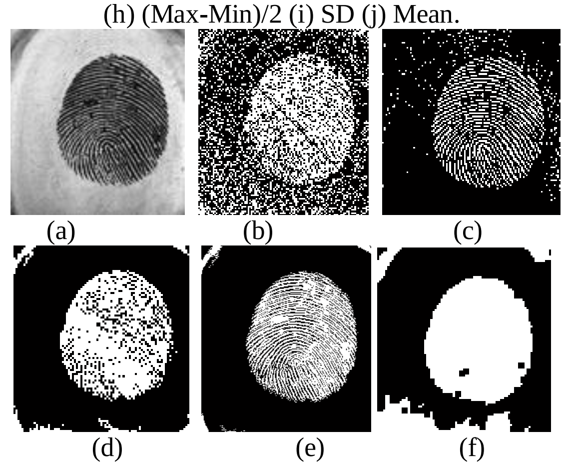



Figure 6(a) original:DB3 102_5 (b) CTH (c) ETH (d )HTH (e) ATH (f) Max (g) Min (h) (Max-Min)/2 (i) SD (j) Mean.



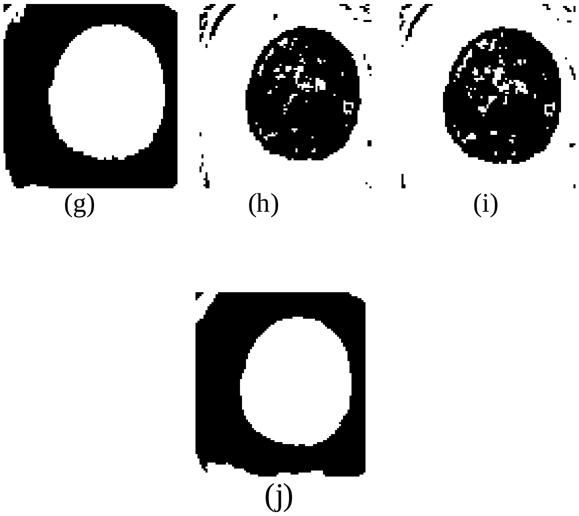



Figure 7(a) original: DB3110_1 (b) CTH (c) ETH (d )HTH (e) ATH (f) Max (g) Min (h) (Max-Min)/2 (i) SD (j) Mean.

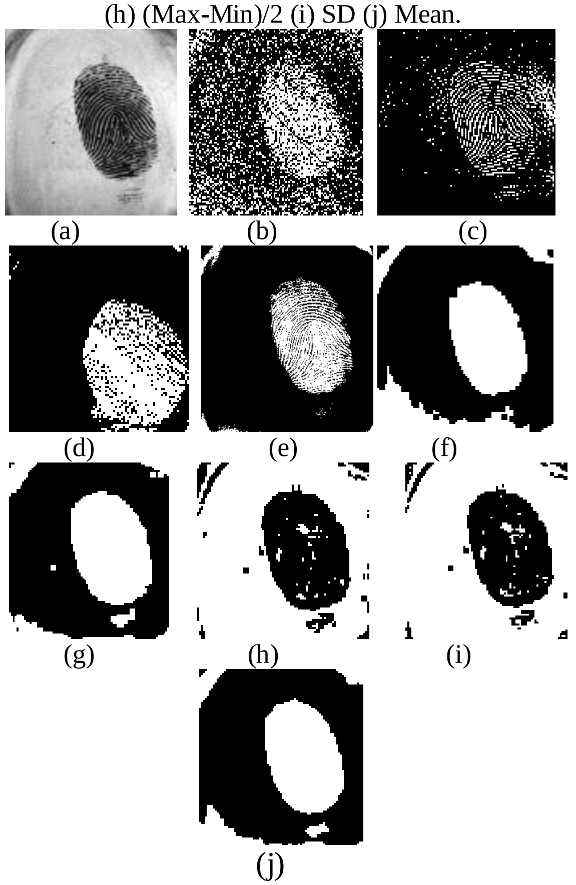
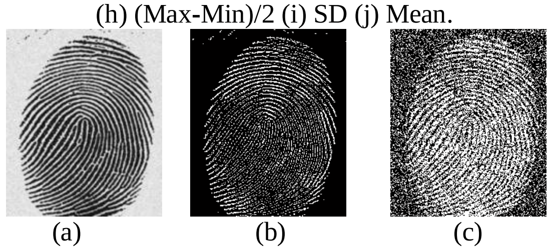



Figure 8(a) original: DB3109_1 (b) CTH (c) ETH (d )HTH (e) ATH (f) Max (g) Min (h) (Max-Min)/2 (i) SD (j) Mean.



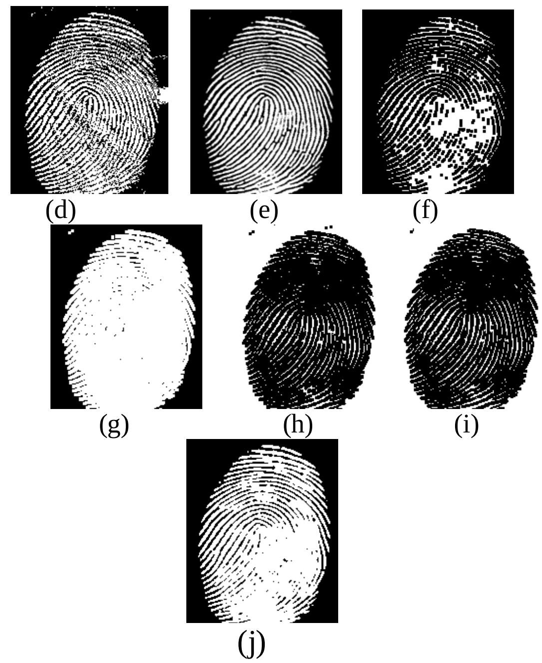




Figure 9(a) original: DB11 05_1 (b) CTH (c) ETH (d )HTH (e) ATH (f) Max (g) Min (h) (Max-Min)/2 (i) SD (j) Mean.

# IV. Conclusions

The present paper has proposed new methods for thresholding based on order statistics. Among them second order statistics based methods (CTH, ETH, HTH, ATH) shown better quality than first order statistics. The proposed methods are applied to various finger print images and proved their capability to preprocess them.

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