Annals of **F**uzzy **M**athematics and **I**nformatics
Volume 7, No. 3, (March 2014), pp. 495–518
ISSN: 2093–9310 (print version)
ISSN: 2287–6235 (electronic version)
http://www.afmi.or.kr

Text extraction from low-contrast non-uniform illuminated document images using mathematical morphology and fuzzy operator

(Mrs)Sharmistha Bhattacharya (Halder), Md. Atikul Islam

Received 29 May 2013; Accepted 11 August 2013

Abstract. Document image binarization has been studied for decades and many practical binarization techniques have been proposed for different kinds of degraded document images. Document images captured with electronic devices in low-contrast and non-uniform lightening conditions often cause serious problems in document layout analysis and optical character recognition systems (OCR). In this paper a new efficient method for extraction of text from low-contrast non-uniform illuminated document images is proposed. Morphological operator Bottom-Hat Transform and fuzzy intensification operator are combined to extract text from degraded document images. Experiments are performed using gray-scale and colour document images. Results of proposed method and other methods are shown and discussed.

2010 AMS Classification: 94DXX, 68U10

Keywords: Bottom-Hat transformation, Contrast removal fuzzy operator, Non-uniform illuminated, Document image, Binarization.

Corresponding Author: Md. Atikul Islam(atik.math@yahoo.com)

1. Introduction

Document image binarization to extract text stroke pixels from the background of document image is an active research area and has been studied for decades. Many practical binarization techniques have been proposed. Sezgin and Sankar [41] classified the different techniques into six categories: histogram based methods, clustering based methods, entropy based methods, forground attribute based methods, spatial binarization method. Wen, Li and Sun [52] again divide these methods into three categories: clustering based methods [7, 8, 17, 31], threshold-based methods and hybrid methods. The threshold methods categories into two groups: one is global threshold methods [1, 11, 18, 19, 25, 42] which assign a single threshold for the entire image. However global thresholding methods are usually not suitable for degraded document images, because they do not have a clear bimodal pattern that separates foreground text and background. So the other method local thresholding are better approaches for degraded document images with non-uniform background and foreground distribution. The local threshold method based on the information contained in the neighbourhood of each pixel, or in the region of the image. One drawback of local thresholding approaches is that the thresholding performance depends on the window size and hence the character stroke width. In Bernsen's method [4], the threshold is a function of the highest and lowest gray values. Whereas Niblack [27] and Sauvola [43] threshold value depends on mean and standard deviation of the gray scale. Yanowitz and Bruckstein (YB) [53] were classically locally adaptive methods. Su, Lu and Tan [44] based on local maximum and minimum filters. By shading estimation and compensation Lu and Tan [21] proposed a binarization method for badly illuminated document images. Based on edge information [9, 22, 36, 37], based on gradient information [6, 32, 49] are locally adaptive methods. Kim et al. [20] proposed an effective algorithm based on a water flow model for binarization of degraded document images. They consider document image as a three dimensional terrain. Binarization of images was obtained by thresholding the amount of water filled in valley's (as text). An improved version of Kim's method was proposed by Oh et al. [30]. Valizadeh and Kabir [50] proposed an adaptive water flow model for binarization of degraded document images. They consider image surface as a three-dimensional terrain and pour water on it. The water finds the valleys and fills them. There algorithm controls the rainfall process, pouring the water, in such a way that the water fills up to half of the valley's depth. After stopping the rainfall, each wet region represents one character or a noisy component. To segment each character labeled the wet regions and regarded them as blobs. They used Multilayer Perceptron to label each blob as either text or non-text. Some widely used hybrid models were Gonman [14], Liu [23], Moghaddam [26], Valizadeh [51]. A neuro-fuzzy techniqe was given in [33]. In 2011 Bataineh, Abdulla and Omar [2] was proposed an adaptive local binarization method for document images based on thresholding and dynamic windows. Blayvas [5] method based on threshold surface, threshold surface was determined by successive over relaxation as the solution of Laplace equation. In recent Wen [52] proposed a effective binarization method for non-uniform illuminated document images. Images was decomposed by the Curvelet transformation and the curvelet coefficient were enhanced by non linear function then Otsu's method was combined for binarization. A learning built rules for document images produced by cameras was given by [10]. Image was divided into several regions and decided by learning process how to binarize each region. We may mention some other kind of methods where text was extracted from degraded document images. Morphological-based [12, 13, 15, 28, 38, 45], fuzzy logic based Sattar and Tay [46], Parbathi [34, 39] based on an intensification operator on first and second type of intuitionistic fuzzy sets. Leung [24] in 2005 presented a method based on Generalized Fuzzy Operator, pre-processed with HE and POSHE for low contrast and low illumination document images. The thresholding of document images is still an unsolved problem due to different types of document degradations, such as uneven illumination, image contrast variation, bleeding-through, and smear. The high intensity variation within both the document background and foreground caused by degradations makes it difficult to design an uniform classification method that correctly separates text and background for all kinds of degraded document images. Mathematical morphology [47, 48] offers a unified and powerful approach to numerous image processing problems. It provides powerful tools for extracting geometrical structures and representing shapes in many applications. Morphological feature extraction techniques have been efficiently applied to character recognition and document analysis. It is a problem solving tool for extraction of text from non-uniform illuminated document images.

In this paper we first introduce fuzzy image membership intensification operator and some of its application is given to extract text from images. For the case of proposed method, we first used morphological Bottom-Hat transformation to the image to remove non-uniform illumination from the image. Using fuzzy intensification operator text is extracted from background. We then reconstructed the image using fuzzy transformation. Lastly we remove background noise of the image and enhance the contrast of the text.

The rest of the paper is organized as follows. In section 2, some preliminaries are given. In section 3, the proposed method is introduce. Section 4 details the experiment results. Then in section 5, we present our conclusion.

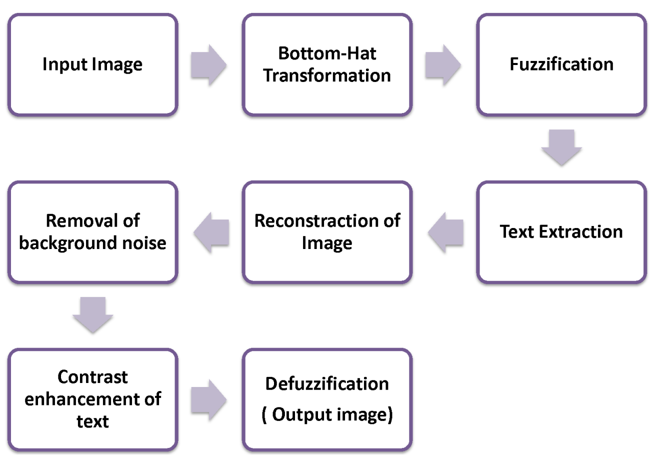

Figure 1. Procedure of the proposed method.

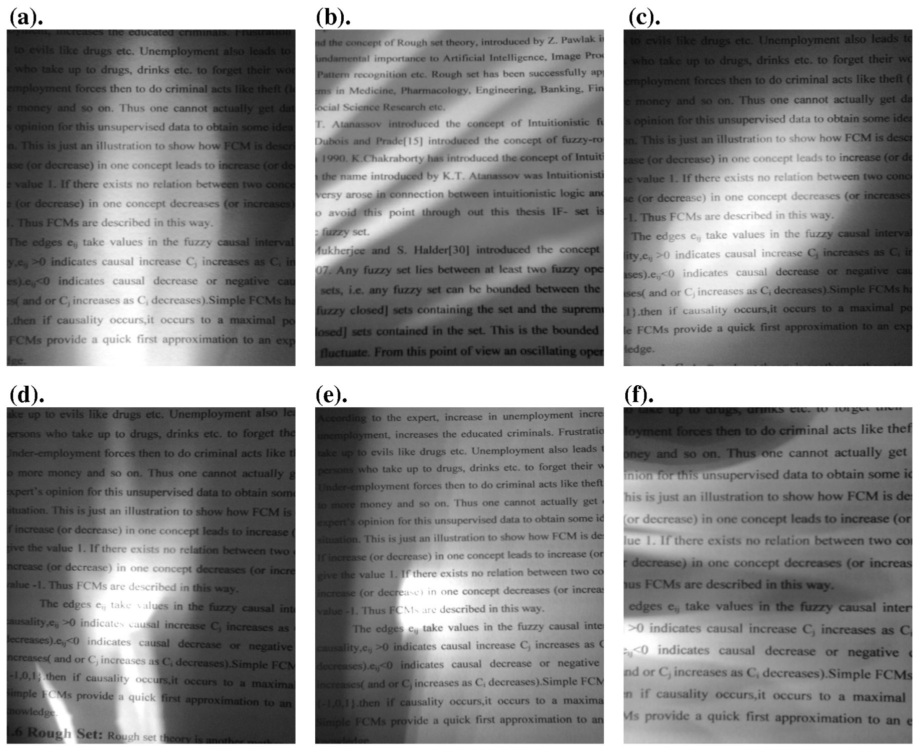

FIGURE 2. Different kind of non-uniform illuminated document images.

2. PRELIMINARIES

In this section the preliminaries necessary for further study are cited.

2.1. **Review of binarization techniques.** A threshold $T(x, y)$ is a value such that

$$b(x,y) = \begin{cases} 1, & T(x,y) < I(x,y) \\ 0, & I(x,y) \leq T(x,y) \end{cases} \tag{1}$$

where $b(x, y)$ is the binarized image and $I(x, y) \in [0, 1]$ be the intensity of a pixel at location (x, y) of the image I. It is clear that a fixed value of the threshold surface $T(x, y) = const$ cannot yield satisfactory binarization results for images obtained under non-uniform illumination and/or with a non-uniform background. Otsu [29] calculates a global threshold by accepting the existence of two classes, foreground and background, and choosing the threshold that minimizes the interclass variance of the thresholded black and white pixels. Rosenfeld and Kak [40] select global threshold from the histogram of 2D image. They assume that gray values of each object are possible to cluster around a peak of the histogram of 2D image and try to compute the location of valley or peaks directly from the histogram. Kittler and Illingworth [18] present an algorithm that is based on the fitting of the mixture of Gaussian distributions and it transforms the binarization problem to a minimum-error Gaussian density fitting problem. A local technique Kapur et al. [19] is the maximization of the entropy of the thresholded image and is interpreted as indicative of maximum information transfer. The image foreground and background are considered as two different signal sources, so that when the sum of the two class entropies reaches its maximum, the image is said to be optimally thresholded.

2.1.1. *Niblack's Technique* [27]. In this method the local threshold value $T(x, y)$ at (x, y) is calculated within a window of size $w \times w$ as :

$$T(x, y) = m(x, y) + k\delta(x, y) \tag{2}$$

where $m(x, y)$ and $\delta(x, y)$ are the local mean and standard deviation of the pixels inside the local window and k is a bias. The result is satisfactory at $k = -0.2$ and $w = 15$. The local mean $m(x, y)$ and standard deviation $\delta(x, y)$ adapt the value of the threshold according to the contrast in the local neighborhood of the pixel. The bias k controls the level of adaptation varying the threshold value.

2.1.2. *Sauvola's Technique* [43]. In Sauvola's binarization method, the threshold $T(x, y)$ is calculated using the mean $m(x, y)$ and standard deviation $\delta(x, y)$ of the pixels within a window of size $w \times w$ as:

$$T(x, y) = m(x, y)(1 + k(\frac{\delta(x, y)}{R} - 1) \tag{3}$$

where R is the maximum value of the standard deviation ($R = 128$ for a gray-scale document), and k is a bias, which takes positive values in the range [0.2, 0.5]. The local mean $m(x, y)$ and standard deviation $\delta(x, y)$ adapt the value of the threshold according to the contrast in the local neighborhood of the pixel. When there is high contrast in some region of the image, $\delta(x, y) \sim R$ which, results in $T(x, y) \sim m(x, y)$. This is the same result as in Niblack's method. However, the difference comes in when the contrast in the local neighbourhood is quite low. In that case the threshold $T(x, y)$ goes below the mean value thereby successfully removing the relatively dark regions of the background. The parameter k controls the value of the threshold in the local window such that the higher the value of k, the lower the threshold from the local mean.

2.1.3. *Bernsen's Technique* [4]. In this method the local threshold value $T(x, y)$ at (x, y) is calculated within a window of size $w \times w$ as:

$$T(x, y) = 0.5(I_{Max(i,j)} + I_{Min(i,j)}) \tag{4}$$

where $I_{Max(i,j)}$ and $I_{Min(i,j)}$ are maximum and minimum gray values within the local window, provided contrast

$$C(x, y) = I_{Max(i,j)} - I_{Min(i,j)} \geq 15 \tag{5}$$

In this method, the threshold is set at the mid range value, which is the mean of the maximum and minimum gray values in a local window of size $w \times w$. A value of $w = 31$ gives the satisfactory results. However, if the contrast $C(i, j)$ is below a certain threshold (15), then that neighborhood is said to consist of only one class, foreground or background, depending on the value of $T(x, y)$. There is no bias to control the threshold value.

2.2. **Mathematical Morphology.** Mathematical Morphology is a geometric approach in image processing and analysis with a strong mathematical flavour. Originally it was developed as a powerful tool for shape analysis in binary and, later grayscale images mathematical morphology was firstly introduced by Matheron and Serra [47, 48] as a methodology for image processing. The language of mathematical morphology is set theory. As such morphology offers a unified and powerful approach to numerous image processing problems. Sets in mathematical morphology represent objects in an image. Morphological operators transform the original image into another image through the interaction with the other image of certain shape and size, which is known as the structure element. By translating the structuring element over an image and by applying basic set operations, such as intersections or union, the basic morphological operations (Dilation, Erosion, Opening, Closing) are obtained. Gray-scale mathematical morphology is a natural extension of binary mathematical morphology into gray-scale images.

2.2.1. *Structuring element.* Structuring element in gray-scale morphology perform the same basic functions as their binary counterparts: They are used as "probes" to given image for specific properties. This simple "probe" is called structuring element, and is itself a binary image (i.e., a subset of the space or grid. Here are some examples of widely used structuring elements (denoted by B):

- Let B is an open disk of radius r, centered at the origin.
- Let B is a 3×3 square, that is, $B = (-1, -1), (-1, 0), (-1, 1), (0, -1), (0, 0), (0, 1), (1, -1), (1, 0), (1, 1)$.
- Let B is the "cross" given by: $B = (-1, 0), (0, -1), (0, 0), (0, 1), (1, 0)$.

2.2.2. *Gray-scale morphological operations.* In terms of gray-scale morphology erosion and dilation are, respectively,

$$(G\Theta S)(x) = min_{y\epsilon F}\{G(x + y) - S(y)\} \tag{6}$$

$$(G \oplus S)(x) = max_{y\epsilon F,(x-y)\epsilon E}\{G(x - y) + S(y)\} \tag{7}$$

where $x, y\epsilon Z^2$ are the spatial co-ordinates; $G : E \to R$ is the gray-scale image; $S : F \to Z$ is the gray-scale structuring element; and $x, y\epsilon Z^2$ are the domains of the gray-scale image. The definitions of gray-scale opening and closing are, respectively,

$$G \circ S = (G\Theta S) \oplus S \tag{8}$$

$$G \bullet S = (G \oplus S)\Theta S \tag{9}$$

2.2.3. *Top-Hat and Bottom-Hat Transformation.* Let $G : E \to R$ be a gray-scale image. Let $S : F \to Z$ be a gray- scale structuring element. Then, the white top-hat transform of G is given by

$$T_w(G) = G - G \circ S \tag{10}$$

where $\circ$ denotes the opening operation. The black top-hat transform (Botom-Hat transform) of G is given by

$$T_b(G) = G \bullet S - G \tag{11}$$

where $\bullet$ is the closing operation.

Definition 2.1 ([35]). An image G of size $m\times$n and L gray levels k ranging between 0 to $L-1$ can be consider as an array of fuzzy singletones, each having a value of membership denoting its degree of brightness relative to some brightness lavels. For an image G, we can write in the notion of fuzzy sets as

$$G = \{< G_k(i,j), \mu_{G_k}(i,j) > | i = 1, 2, ...m, j = 1, 2, ..., n\} \tag{12}$$

where G$_k$(i,j) is the value of G at position (i,j) at any gray level k, $\mu_{G_k}(i,j)$ denotes the degree of brightness possessed by the gray level intensity $G_k(i,j)$ of the (i,j)th pixel.

3. Text Extraction by proposed method

Before entering into Our proposed method we introduce contrast removal fuzzy operator (CRFO) and we give some of its application to remove background noise of document images.

3.1. Contrast removal fuzzy operator CRFO [3].

In a low-contrast image most of the gray level lies in the lower luminance range (typically under 0.5 on closed interval [0,1]) and fewer gray level lies in the upper luminance range (typically above 0.5 on closed interval [0,1]). A higher contrast in an image can be achieved by darkening the gray level in the lower luminance range and brightening the ones in the upper luminance range. Moreover in the case of over-contrast, over-bright images all gray level lies in the lower and upper luminance range respectively. Fuzzy membership values of such images lies in a tiny interval which can be seen from Fig.3(c). To get a good contrast enhanced images we must distribute membership values of the image in lower and upper luminance range. Here we introduce CRFO to distribute membership values from small interval to larger interval in [0,1] for the case of low contrast, high contrast and over bright images, So that the maximum contrast enhancement is possible. We define Contrast Intensification Fuzzy Operator (CRFO) for enhancement of low contrast images and to remove background noise of images. A mathematical expression of such function $CRFO$:$[0,1] \to [0,1]$ can be expressed as

$$CRFO\left(\mu_{G_k}(i,j)\right) = \mu^{/}_{G_k}(i,j) = \{1 - e^{-\alpha\mu^2_{G_k}(i,j)}, 0 \le \mu_{G_k}(i,j) \le 1 \tag{13}$$

where $\mu_{G_k}(i,j)$ denotes the degree of brightness possessed by the gray level or colour level intensity $G_k(i,j)$ of the (i,j) th pixel, $\mu^{/}_{G_k}(i,j)$ is the modified membership value of $\mu_{G_k}(i,j)$ by CRFO and α is an intensification parameter which can range from 1 to infinity.

Then we generate new gray level or colour level $G^{/}_k(i,j)$ for $G_k(i,j)$ by the following way

$$G^{/}_k(i,j) = (L-1)\left(\mu^{/}_{G_k}(i,j)^{\frac{\sigma}{\tau}}\right) \tag{14}$$

where L is the highest gray level or colour level of the image, $\sigma > 0$ and $\tau \ge 1$ are arbitrary parameters. Here image enhancement is done by applying the equation (13) and (14) on images by setting suitable parameters.

3.1.1. *Property.* When $\alpha \to \infty$,

$$\mu^{/}_{G_k}(i,j) = \begin{cases} 1, & \text{if } \mu_{G_k}(i,j) \neq 0 \\ 0, & \text{if } \mu_{G_k}(i,j) = 0 \end{cases} \tag{15}$$

3.1.2. *Property.* When $\alpha \geq 1$,

$$\mu^{/}_{G_k}(i,j) = \begin{cases} (0,1], & \text{if } \mu_{G_k}(i,j) \neq 0 \\ 0, & \text{if } \mu_{G_k}(i,j) = 0 \end{cases} \tag{16}$$

In fuzzy image processing a binarized image is obtain by changing the membership values from closed interval $[0,1]$ to $\{0,1\}$(0 for forground and 1 for background. In Fig.3 and Fig.4 we show extraction of text from document images. The images of Fig.3 is obtained by capturing in low-illumination condition by 2 mega pixel camera. Fig.3(a) shows the document image of dimension 600×323 is in high contrast condition. It can be seen from the Fig.3(c) membership values of the image lies in tiny interval [0,0.1] and no membership values in upper luminance range. So to extract text form the dark background we removed high contrast of the image by applying CRFO operator at parameter $\alpha = 6000$, σ =80 and $\tau = 2$. Fig.3(b) shows the image after extraction of text where as Fig.3(d) (membership histogram) shows after binarization membership values are only o or 1. Now consider the document image (d) of Fig.3 of dimension 796×726. The document image consist of gray background with text. Fig.3(g) shows the image has no dark pixel, no white pixel and maximum membership values lie in $[0.5, 0.8]$ and few membership values in the range $[0.1, 0.6]$. Binarized image is shown in Fig.3(f) after removing noisy background.

Extraction of text by preserving the colour information is always a challenging task. Many binarization algorithms was proposed earlier for extraction of text from colour document images based on thresholding. But extraction of text preserving the colour information is still unsolved problem for low-contrast colour document images. Fig.4(a), (e) shows two colour document images of dimension 435×246 and 472×468 pixel respectively. The first image consist of dark background with colour and black text. In Fig.4(c) the red, green and blue colour lines shows membership histogram of red green and blue colour channel. Here maximum number of membership value lies in [0.3,0.7] for each channel red, green and blue and not a single membership value greater than 0.7. Hence the image is in low-contrast condition. The resulting image of Fig.4(b) is obtained by giving $\alpha = 30$, $\sigma = 5$ and $\tau = 2$. Fig.4(d) shows the membership histogram of extracted image(b). Here it can seen from the graph that after processing the image maximum membership values distributed from closed interval [0.3,0.7] to the upper and lower luminance range. Hence a good text extracted image preserving the colour information. Text extraction of another document image with noisy background is shown in Fig.4(e), (f), (g), (h). Text colour in this case is black, so removal of background noise is much easier than the previous one.

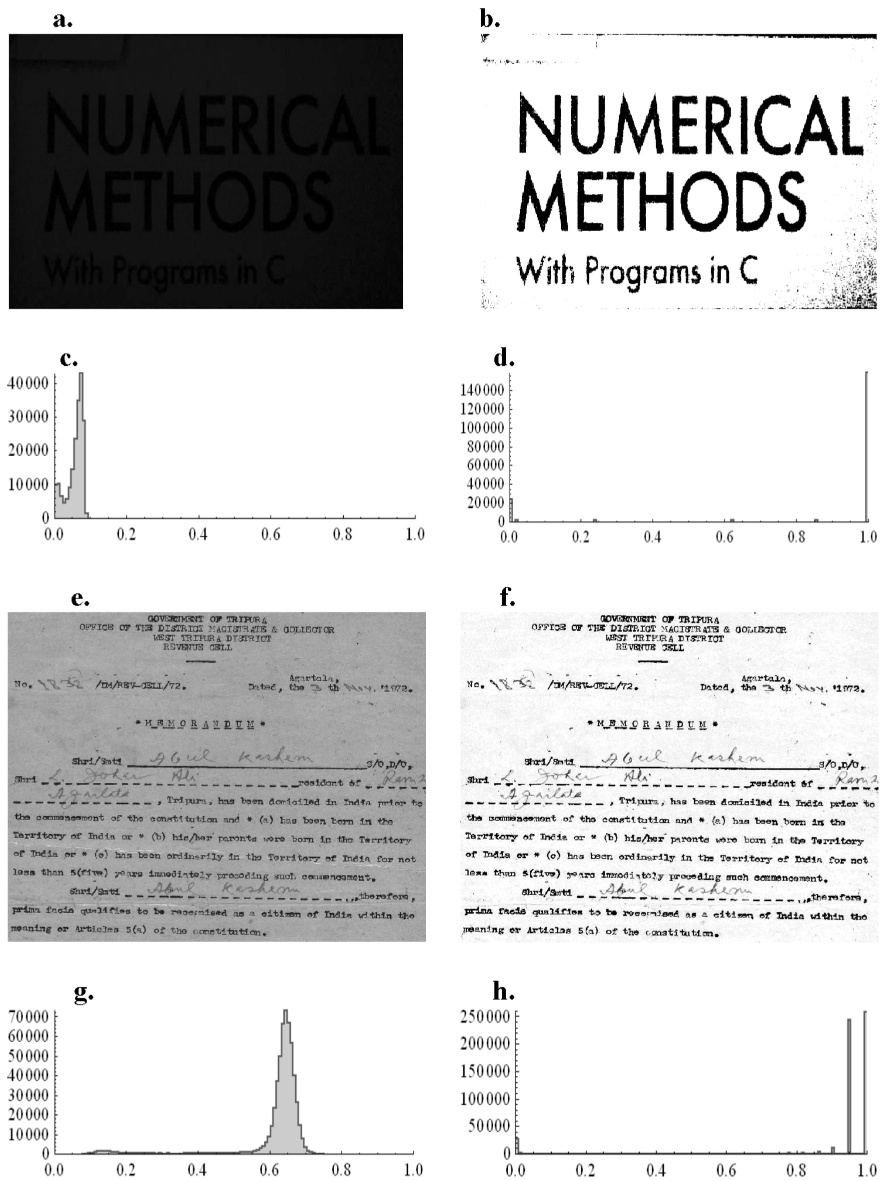

FIGURE 3. (a),(e) Original image. Text extraction by CRFO (b) at α =6000, σ =80 and τ = 2 (f) α = 15, σ = 25 and τ = 2. Membership histogram : (c), (g) Before extraction of text; (d), (h) After extraction of text.

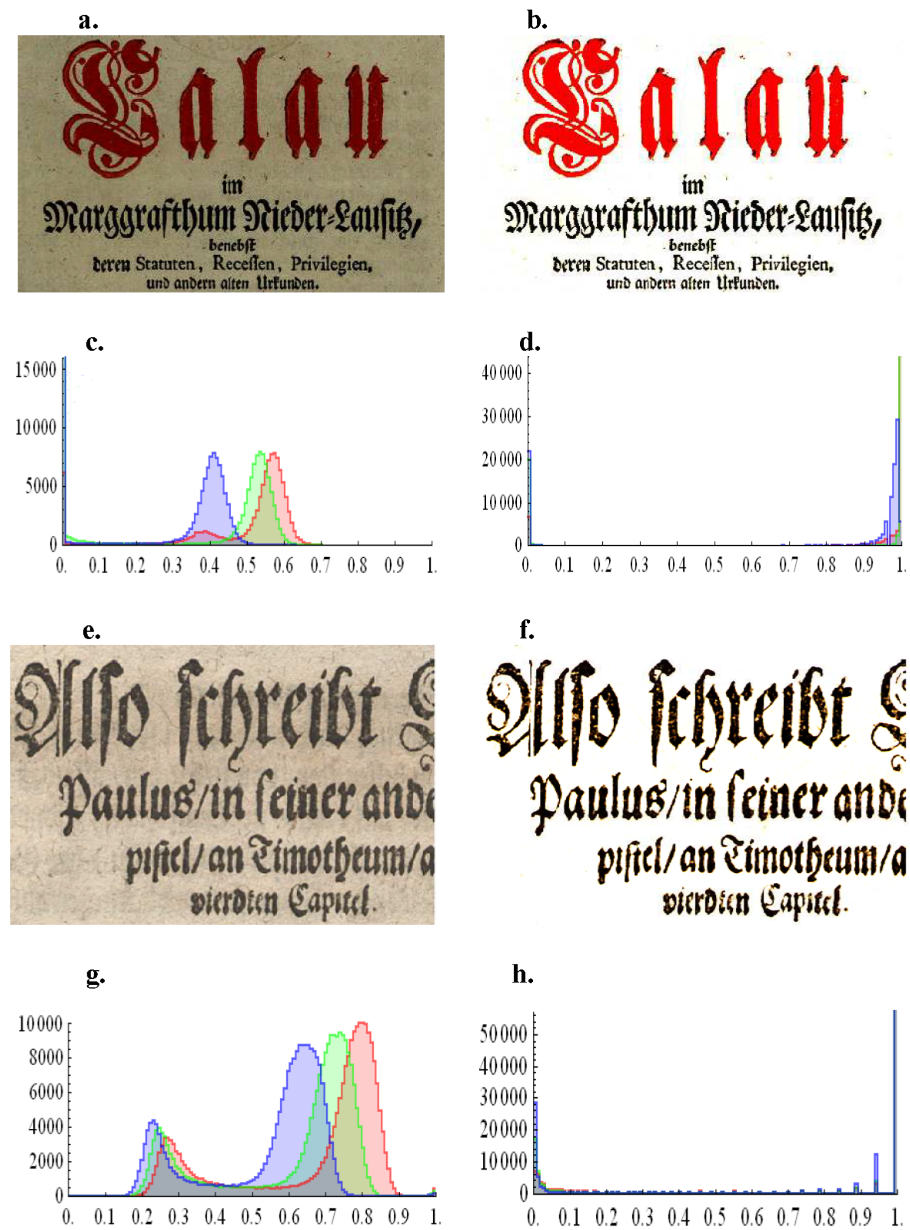

FIGURE 4. (a), (e) Original image. Text extraction by CRFO : (b) at α =30, σ =5 and τ = 2 (f) α = 20, σ = 30 and τ = 2. Membership histogram : (c), (g) Before extraction of text; (d), (h) After extraction of text.

3.2. **Proposed method.** Our new method includes seven steps (i) Image preparation. (ii) Removal of non-uniform illumination and uneven object. (iii) Fuzzification of image. (iv) Text Extraction. (v) Re-construction of image. (vi) Background noise removal. (vii) Contrast enhancement of the text.

(i) **Image preparation.** The low-contrast non-uniform illuminated images shown in Fig.2 are acquired by camera of resolution 1600×1200, and the experimental image consisted of 600×450 pixels. To test our method, different non-uniform illumination effects are applied on printed document. The document was composed of text region and blank region. To test our method, the text and blank regions are all under non-uniform illumination. Some patterns of low-contrast non-uniform illuminated images used fare are shown in Fig. (2). These images has low contrast ratio in a certain region, which makes global and local method generally a bad result. To show the step by effect we consider an image $I(i,j)$ of dimension 600×450 pixels shown in Fig.5(a).

(ii) **Removal of non-uniform illumination and uneven object.** Global and local threshold techniques, which are often the first step in object measurement, cannot be applied to unevenly illuminated images. To overcome this problem we used here morphological operator to even out the lighting in the image. One principal application of Top-Hat and Bottom-Hat transforms is in removing objects from an image by using a structural element in the opening and closing that does not fit the objects to be removed. The difference then yields an image with only the removed objects. We here used Bottom-Hat transformation to extract black pixels from image. Al the images shown in Fig.2 are consist of gray background with black text. A gray scale Bottom-Hat transformation only visualise those pixels whose intensity values are nearer to zero. The structuring element used here is either disk of certain radius or square. The extraction of text depend on the structuring element, as big as the structuring element text will be extracted more as a bright object. Fig.5(b) shows the image after step (ii). Here structuring element is taken as a disk of radius 15.

(iii) **Fuzzification of image.** A gray-scale image can be consider as a fuzzy set [35] and also colour image can be consider as a fuzzy set [16]. There are so many method for fuzzification of an image . We describe image $I(i,j)$ in fuzzy environment as follows

$$I=\{<I_k(i,j),\mu_{I_k}(i,j)>|i=1,2,...m,j=1,2,....,n\} \tag{17}$$

where $I_k(i,j)$ is the intensity value of I at position (i,j) at any gray level or colour level k ranges from 0 to 255, $\mu_{I_k}(i,j)=\frac{I_k(i,j)}{L-1}$ denotes the degree of brightness possessed by the gray level or colour level intensity $I_k(i,j)$ of the (i,j)th pixel.

(iv) **Text Extraction.** After pre-processing with morphological transformation and after fuzzification of intensity values we get image with dark background and text as a white object. Since one main characteristic of CRFO operator is that as parameter α grows up its gives modified membership values nearer to 1 except membership values near about zero. That is, membership values increases as α increase except for 0. To extract text as maximum as possible we then apply CRFO defined in eqn.(13) on the resultant image. We modified membership values of image $I(i,j)$ at gray or colour level k as follows:

$$\mu_{I_k}^{(i)}(i,j) = \{1 - e^{-\alpha\mu_{I_k}^{2}(i,j)}, 0 \le \mu_{I_k}(i,j) \le 1 \tag{18}$$

So by setting larger value of parameter α (which ranges from 1 to infinity) we get image with modified membership values, which leads extraction of text from the image shown in Fig.5(c). Here parameter α is taken as 150.

(v) **Re-construction of image.** After step. (iv) we get image which has text as a white object. Since our main aim is to binarized the image, so that the text can extract easily. We reconstruct the resulting image applying fuzzy transformation such a way that the text will converted in black mode and background will be in white mode. The fuzzy transformation is defined as follows:

$$\mu_{I_k}^{(ii)}(i,j) = 1 - (\mu_{I_k}^{(i)}(i,j))^{\frac{\lambda}{\gamma}}, 0 \le \mu_{I_k}^{(i)}(i,j) \le 1 \tag{19}$$

Here $\mu_{I_k}^{(i)}(i,j)$ are membership values defined in (18), $\lambda \ge 0$ and $\gamma > 0$ are arbitrary parameter. Fig.5(d) is the reconstructed image obtain by setting $\lambda = 1$ and $\gamma = 2$. The image of Fig.5(d) shows that there are large number of background noise with text. So to get noise free image we remove noise from the image by the following way.

(vi) **Background noise removal.** To remove background noise we again apply CRFO operator as follows:

$$\mu_{I_k}^{(iii)}(i,j) = \{1 - e^{-\beta\mu_{I_k}^{(ii)}(i,j)}, 0 \le \mu_{I_k}^{(ii)}(i,j) \le 1 \tag{20}$$

Here β is an intensification parameter which ranges from 1 to infinity. Fig.5(e) shows the result after step (vi) with parameter $\beta = 15$.

(vii) **Contrast enhancement of the text.** To give more contrast in the image we then apply fuzzy transformation which is defined as follows:

$$\mu_{I_k}^{(iv)}(i,j) = 1 - (1 - (\mu_{I_k}^{(iii)}(i,j))^{\frac{\omega}{\delta}}), 0 \le \mu_{I_k}^{(iii)}(i,j) \le 1 \tag{21}$$

Here $\omega \ge 0$ and $\delta > 1$ are arbitrary parameter. Fig.5(f) is the final binarized image obtain by setting $\omega = 3$, $\delta = 2$ and generating new gray level by defuzzifying the image as follows:

$$G_k^{/}(i,j) = (L-1)\,\mu_{I_k}^{(iv)}(i,j) \tag{22}$$

where L is the maximum intensity value of the image I.

4. Result and discussion

In this section to show the effectiveness of our method we compared with seven different methods from the literature like Otsu's method, Kapur's method, Kittler's method, Mean threshold method, Median threshold method, Niblack's method, Sauvola,s method. We worked under Wolfram Mathematica version 8 with windows 7 operating systems, 2 GB RAM, Pentium 2.30 GHz Dual core processor. The results of our method and other methods mention here are shown in Fig.6, 7, 8, 9, 10, 11. To test the generality of proposed method, not only the low-contrast non-uniform illumination images but also other type of grayscale and colour degraded images some results were shown in Fig.12, 13.

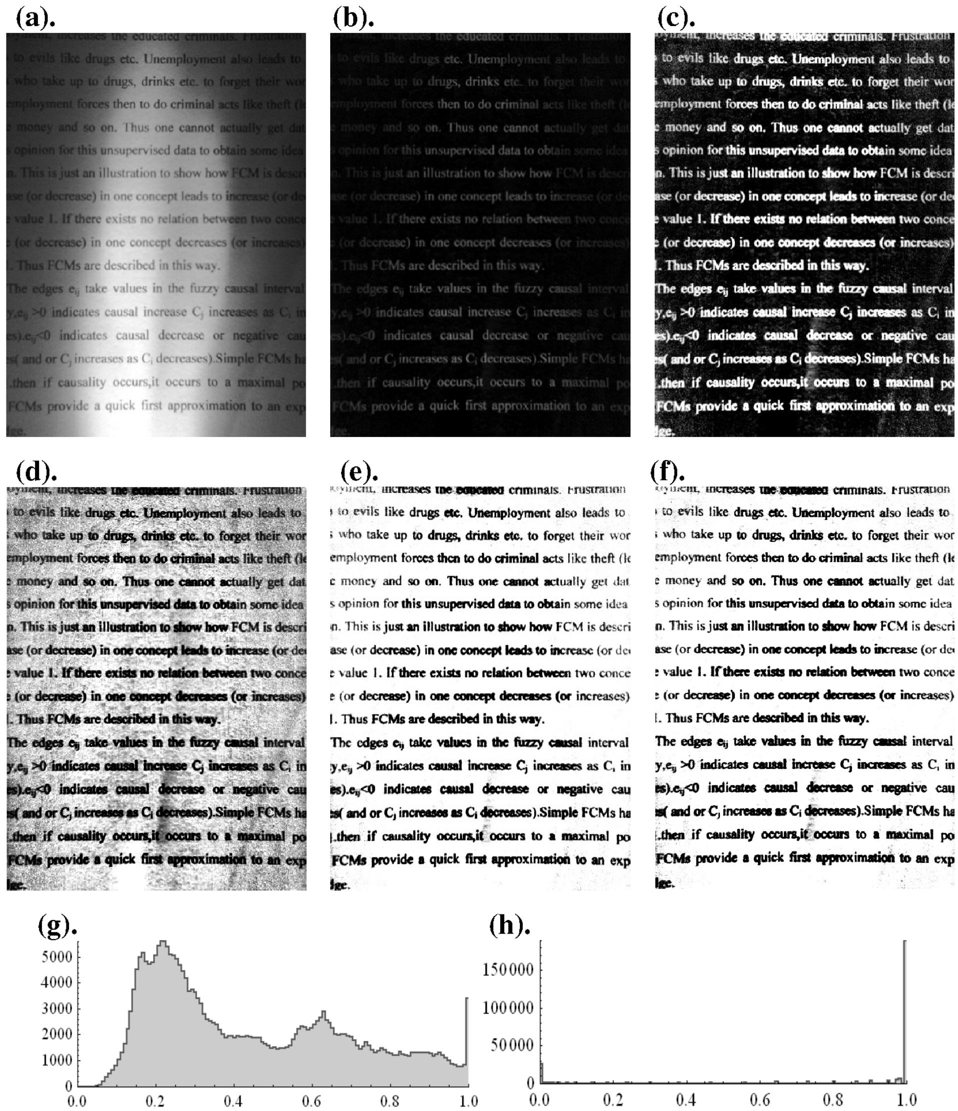

FIGURE 5. Step by step result of proposed method:(a) Original image, (b) After Bottom-Hat transformation, (c) After applying CRFO,(d) After reconstruction, (e) After applying CRFO, (f) After contrast enhancement of the text, (g) Membership histogram before extraction of text, (h) membership histogram after extraction of text.

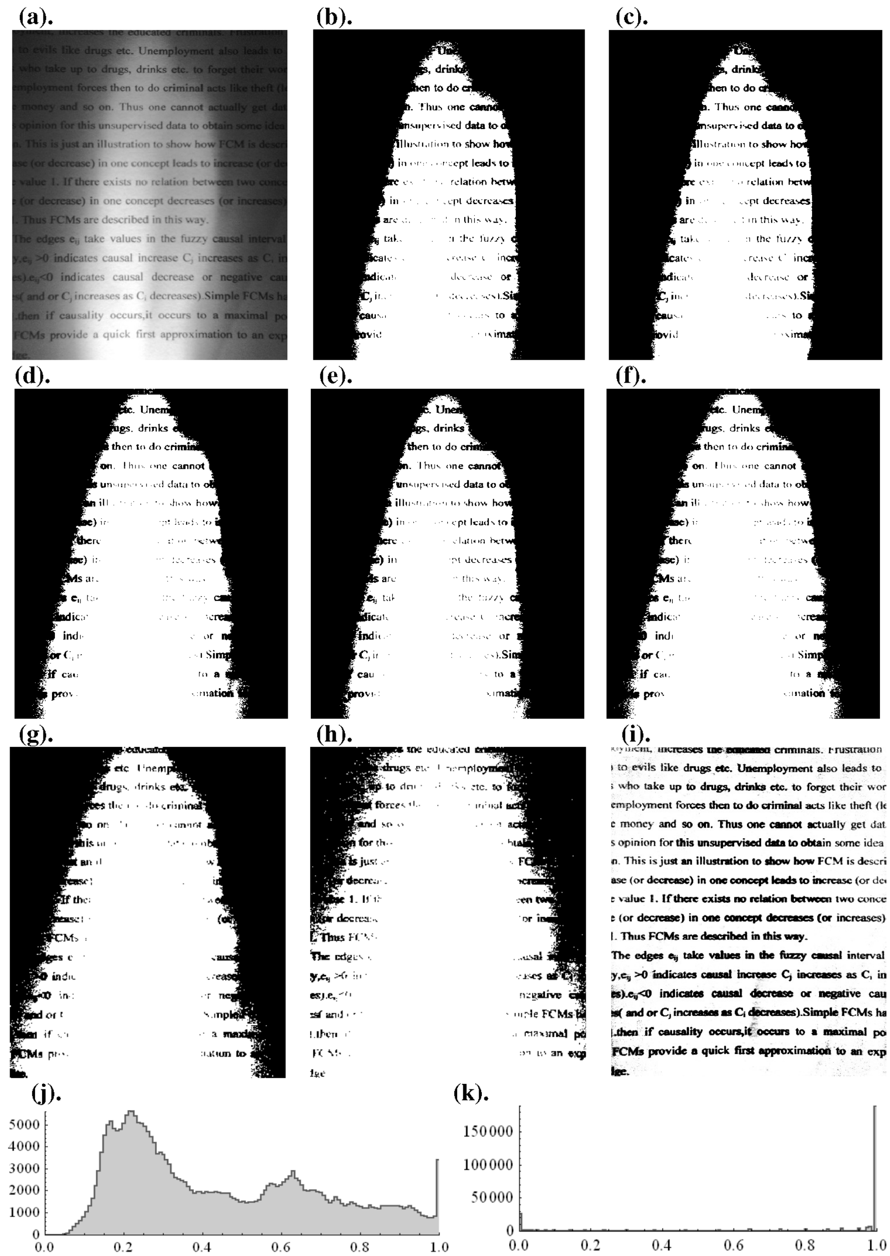

Figure 6. (a) Original image. Extraction of text by: (b) Otsu's method, (c) Kapur's method, (d) Kittler's method, (e) Mean threshold method, (f) Median threshold method, (g) Niblack's method, (h) Sauvola's method, (i) Our method. Membership histogram: (j) Before extraction of text, (k) After extraction of text.

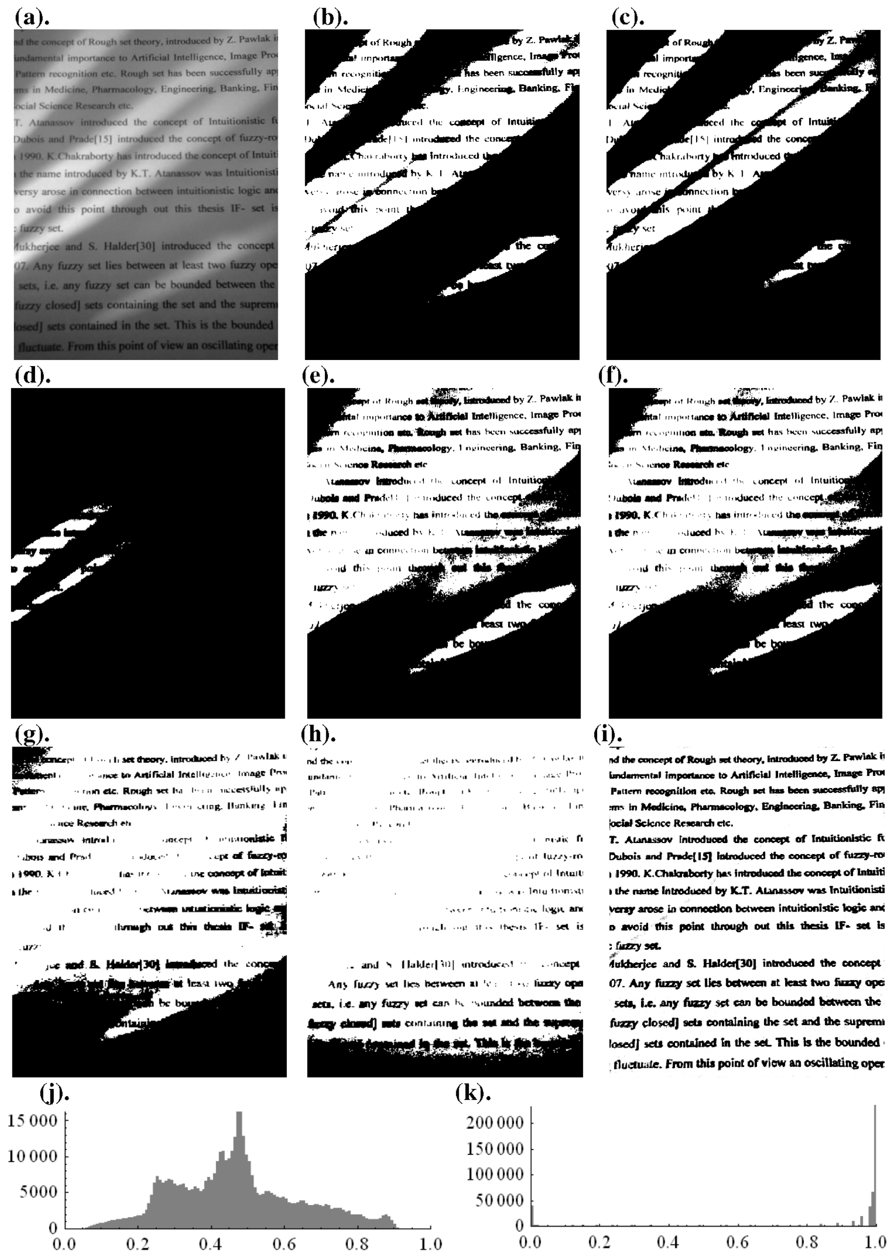

FIGURE 7. (a) Original image. Extraction of text by: (b) Otsu's method, (c) Kapur's method, (d) Kittler's method, (e) Mean threshold method, (f) Median threshold method, (g) Niblack's method, (h) Sauvola's method, (i) Our method. Membership histogram: (j) Before extraction of text, (k) After extraction of text.

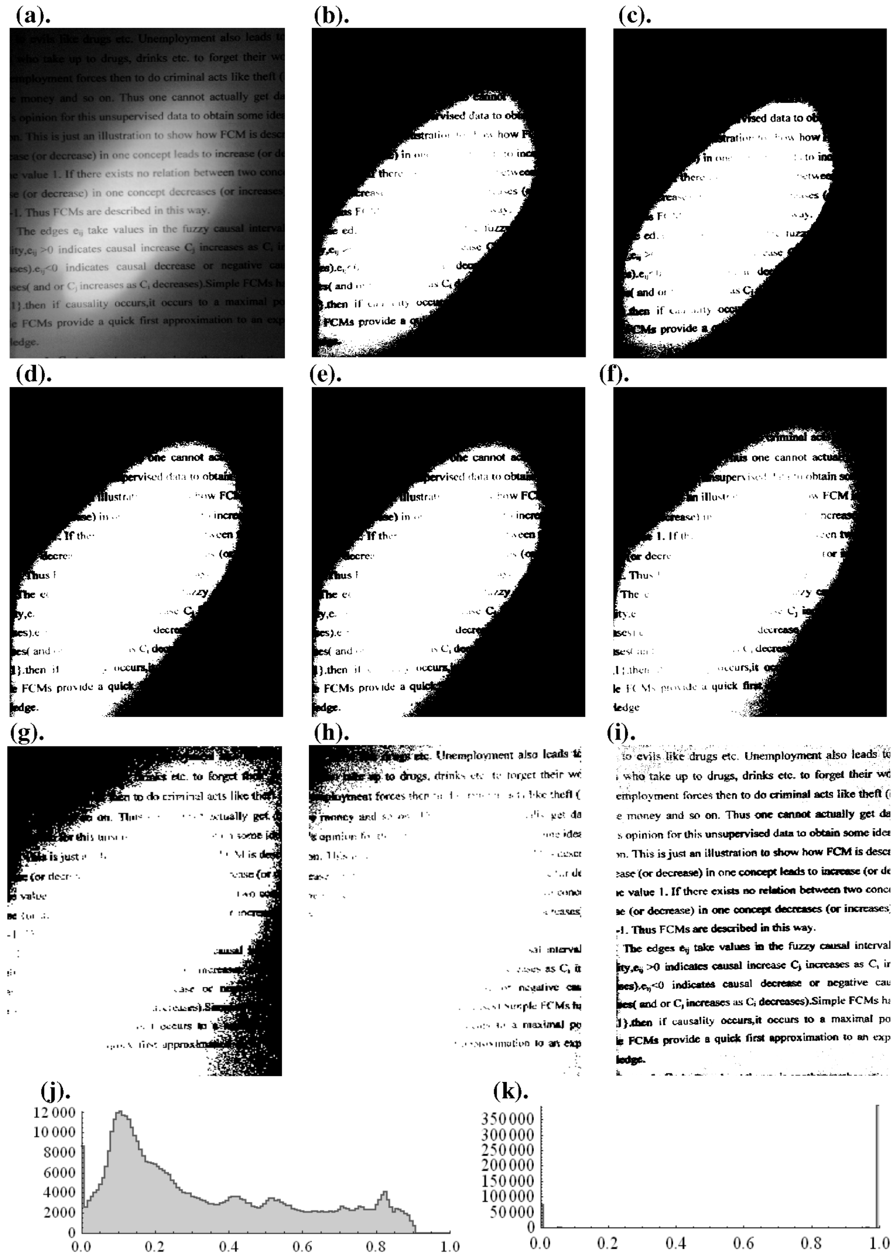

FIGURE 8. (a) Original image. Extraction of text by: (b) Otsu's method, (c) Kapur's method, (d) Kittler's method, (e) Mean threshold method, (f) Median threshold method, (g) Niblack's method, (h) Sauvola's method, (i) Our method. Membership histogram: (j) Before extraction of text, (k) After extraction of text.

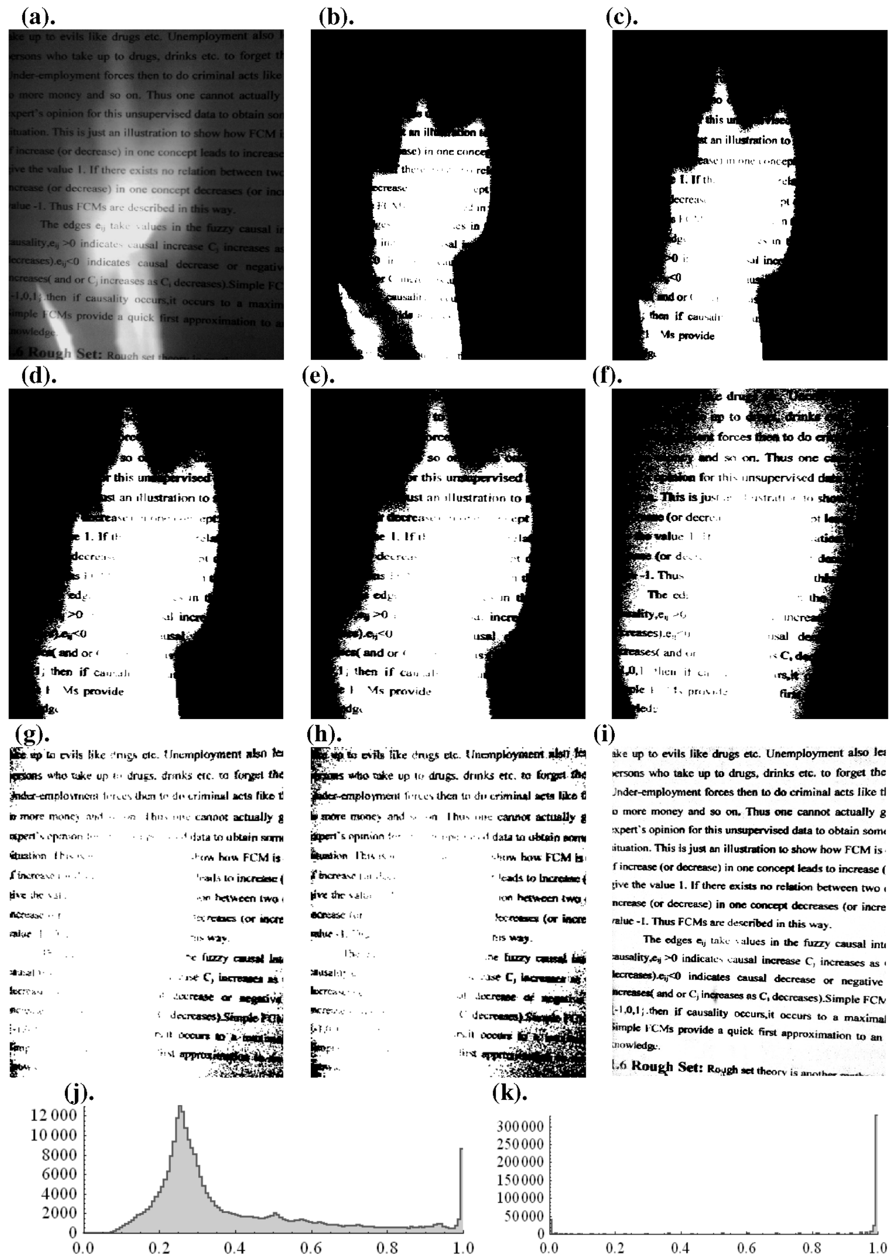

FIGURE 9. (a) Original image. Extraction of text by: (b) Otsu's method, (c) Kapur's method, (d) Kittler's method, (e) Mean threshold method, (f) Median threshold method, (g) Niblack's method, (h) Sauvola's method, (i) Our method. Membership histogram: (j) Before extraction of text, (k) After extraction of text.

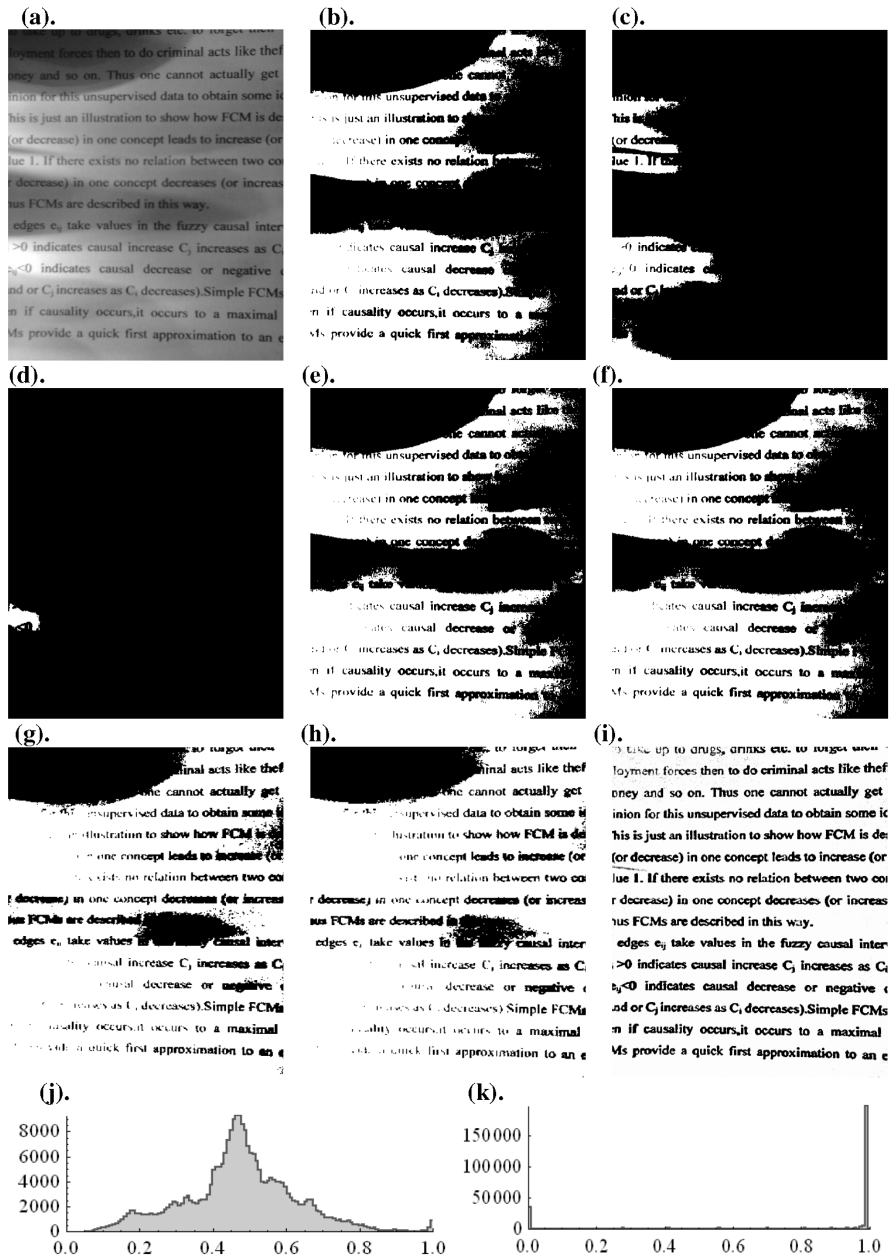

FIGURE 10. (a) Original image. Extraction of text by: (b) Otsu's method, (c) Kapur's method, (d) Kittler's method, (e) Mean threshold method, (f) Median threshold method, (g) Niblack's method, (h) Sauvola's method, (i) Our method. Membership histogram: (j) Before extraction of text, (k) After extraction of text.

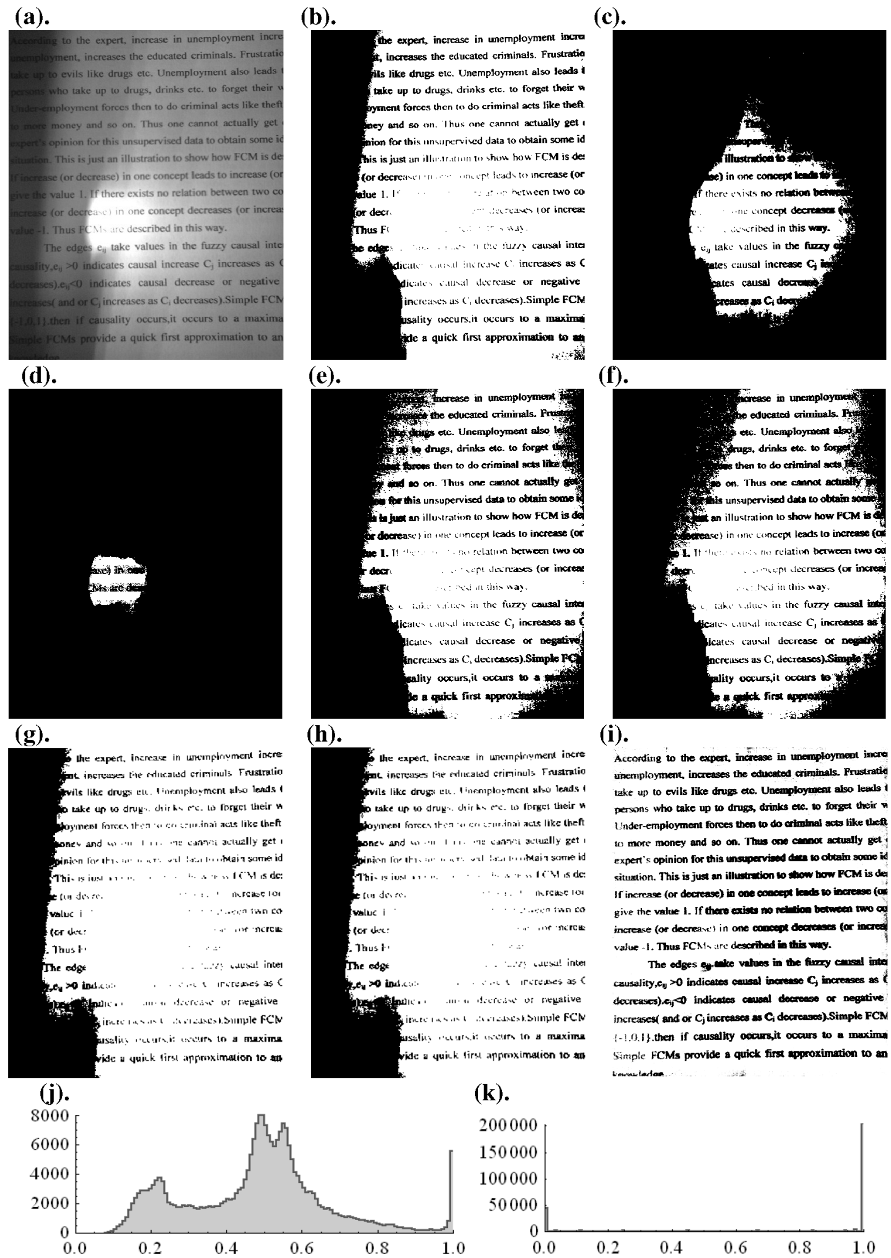

Figure 11. (a) Original image. Extraction of text by: (b) Otsu's method, (c) Kapur's method, (d) Kittler's method, (e) Mean threshold method, (f) Median threshold method, (g) Niblack's method, (h) Sauvola's method, (i) Our method. Membership histogram: (j) Before extraction of text, (k) After extraction of text.

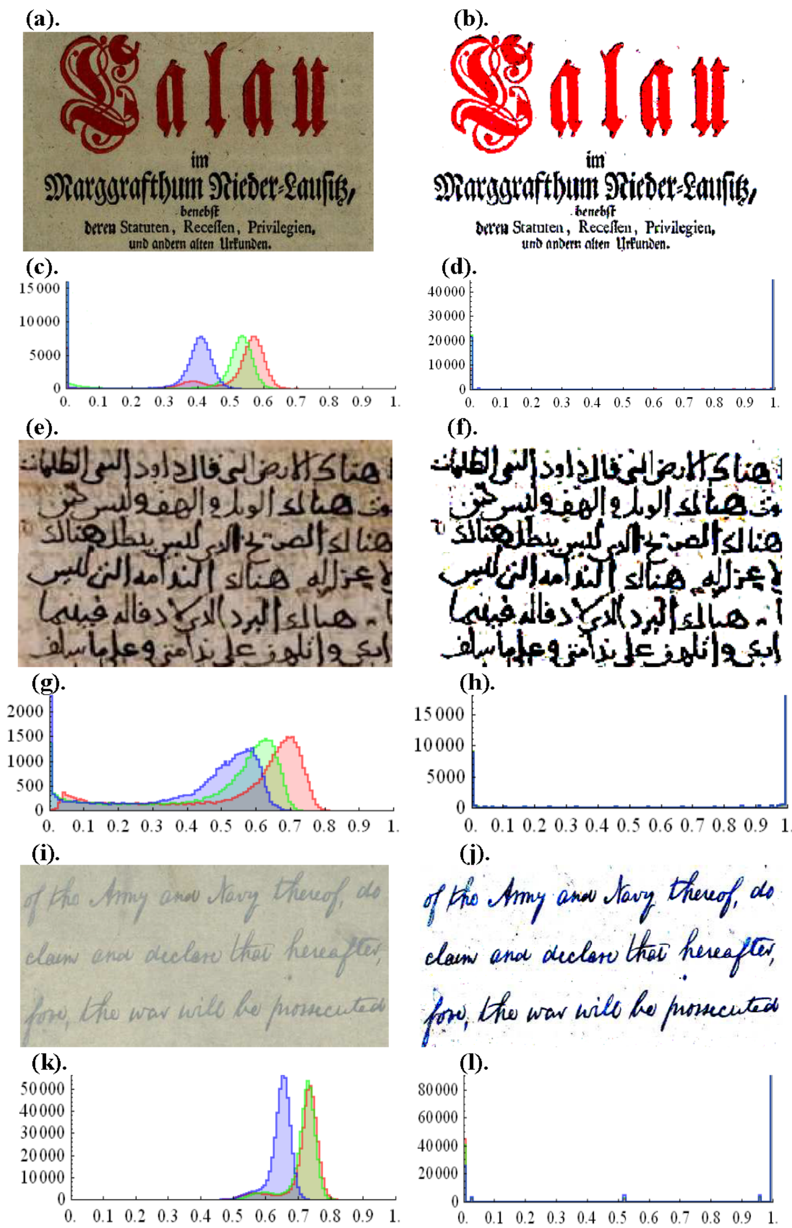

FIGURE 12. (a), (e), (i) Original image. (b), (f), (j) Extraction of text by the Proposed method. Membership histogram:(c), (g), (k) Before extraction of text;(d), (h), (l) After extraction of text.

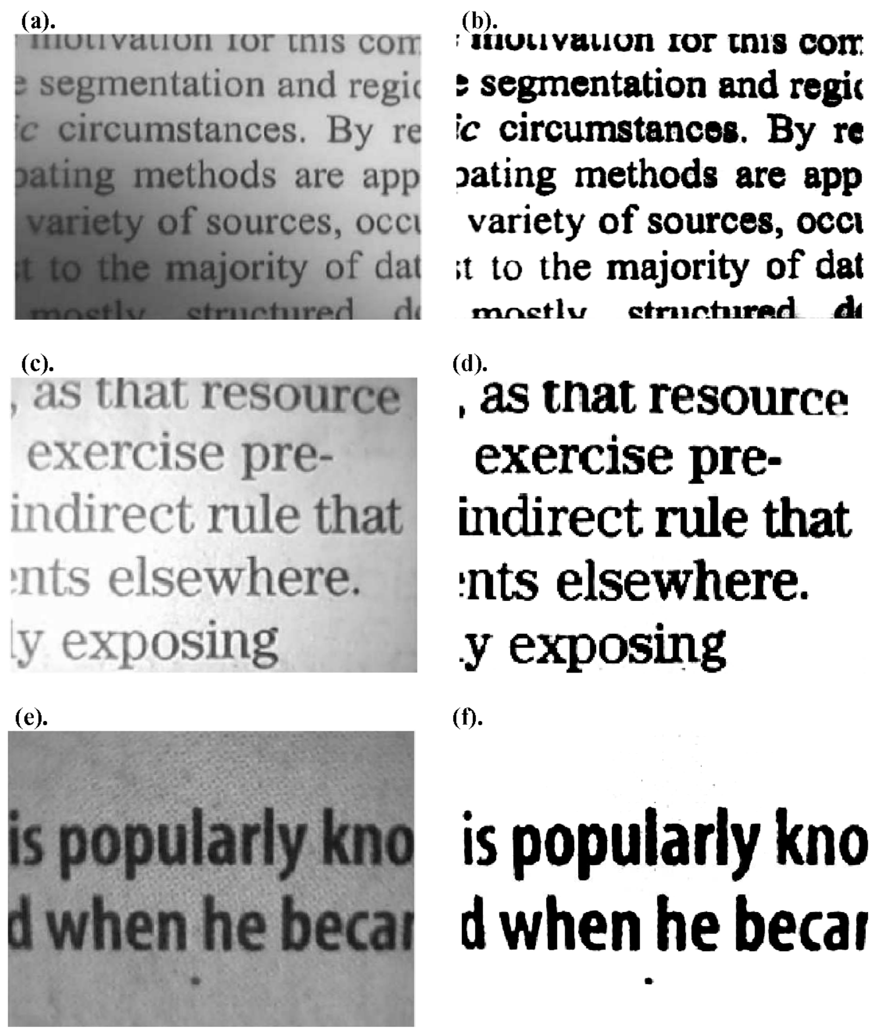

FIGURE 13. (a), (e), (i) Original image. (b), (d), (f) Extraction of text by the Proposed method.

5. Conclusions

In this paper we have proposed text extraction method for the case of low-contrast non-uniform illuminated document images based on morphological operator combined with fuzzy operator (CRFO). Comparative study shows that the proposed method has achieved best performance for extraction of text over the other method for non-uniform illuminated document images. We conclude that the proposed method attains the most improvement in readability of characters in low-contrast non-uniform illuminated document images.

Acknowledgements. I would like to thank UGC, New Delhi,India for the financial support to doing this work under the scheme of **Maulana Azad National Fellowship for Minority students to pursue M.Phil/Ph.D Degree 2010-11**.

References

[1] A. S. Abutaleb, Automatic thresholding of gray-level pictures using two-dimensional entropy, Comput. Vision Graph. Image Process. 47(1) (1989) 22–32.
[2] B. Bataineh, S. N. H. S.Abdullah and K. Omar, An adaptive local binarization method for document images based on a novel thresholding method and dynamic windows, Pattern Recogn. Lett. 32 (2011) 1805–1813.
[3] S. Bhattacharya and A. Islam, Contrast removal fuzzy operator in image processing, Ann. Fuzzy Math. Inform. 6(2) (2013) 401–413.
[4] J. Bernsen, Dynamic thresholding of gray-level images, in:Proceedings of the Eighth International Conference on Pattern Recogn., Paris, IEEE Computer Society Press, France (1986) 1251–1255.
[5] I. Blayvas, A. Bruckstein and R. Kimme, Efficient computation of adaptive threshold surfaces for image binarization, Pattern Recogn. 39 (2006) 89–101.
[6] I. Blayvas, A. Bruckstein and R. Kimme, Efficient computation of adaptive threshold surfaces for image binarization, Pattern Recogn. 39 (2006) 89–101.
[7] H. D. Cheng and Y. H. Chen, Fuzzy partition of two-dimensional histogram and its application to thresholding, Pattern Recogn. 32(5) (1999) 825–843.
[8] L. Cinque, S. DiZenzo and S. Levialdi, Image thresholding using fuzzy entropies, IEEE Trans. SMC 28(1) (1998) 15–23.
[9] Q. Chen, Q. S. Sun, P. A. Heng and D. S. Xia, A double-threshold image binarization method based on edge detector, Pattern Recogn. 41(4) (2008) 1254–1267.
[10] C. -H. Chou, W. -H. Lin and F. Chang, A binarization method with learning-built rules for document images produced by cameras, Pattern Recogn. 43 (2010) 1518–1530.
[11] H. S. Don, A noise attribute thresholding method for document image binarization, IJDAR 4(2) (2001) 131–138.
[12] M. P. Dhore, V.M.Thakre and K.V. Kale, A novel morphological technique for segmentation of document images in NIST database, Int. J. Mach. Intell. 3(5) (2011)172-180.
[13] A. Farahmand, A. Sarrafzadeh and J. Shanbehzade h, Document noises and removal methods, Preceeding of the International Multi Conference of Engineers and Computer Scientists (IMECS2013)(1)(March 13-15, 2013).
[14] Gorman, Binarization and multithresholding of document images using connectivity, Graph. Mods. Image Process 56(6) (1994) 494–506.
[15] B. Gangamma, S. Murthy and A. B. Sing, Restoration of degraded historical document images, Journal of Emerging Trends in Computing and Information Sciences 3(5) (2012) 792–798.
[16] H. J. Jimmermann, Fuzzy Set Theory and its Applications, second ed. Kluwer Academic Publishers Dordrecht, 1991.
[17] S. H. Kwon, Threshold section based on cluster analysis, Pattern Recogn. Lett. 25(9) (2004) 1045–1050.

[18] J. Kittler and J. Illingworth, On threshold selection using clustering criteria, IEEE Trans. Systems Man Cybernet 15 (1985) 652–655.

[19] J. N. Kapur, P. K. Sahoo and A. K. Wong, A new method for gray-level picture thresholding using the entropy of the histogram, Comput. Vision Graphics Image Process 29(3) (1985) 273–285.

[20] I. K. Kim, D. W. Jung and R. H. Park, Document image binarization based on topographic analysis using a water flow model, Pattern Recogn. 35 (2002) 265–277.

[21] S. J. Lu and C. L. Tan, Binarization of badly illuminated document images through shading estimation and compensation, Int. Conf. on Document Anal. and Recogn. (2007)312–316.

[22] Y. Li, C. Y. Suen and M. Cheriet, A threshold selection method based on multiscale and gray level co-occurrence matrix analysis, in:ICDAR'05:Proceedings of the Eighth International Conference on Document Analysis and Recognition, IEEE Computer Society, Washington, DC, USA (2005) 575–579.

[23] Y. Liu and S. N. Srihari, Document image binarization based on texture characteristics, IEEE Trans. Pattern Anal. Mach. Intell. 19(5) (1997) 540–544.

[24] C. -C. Leung , K. -S. Chan, H. -M. Chan and W. -K. Tsui, A new approach for image enhancement applied to low-contrast-low-illumination IC and document images, Pattern Recogn. Lett. 26 (2005) 769–778.

[25] J. M. Monte, R. D. Lins and R. Wachenchauzer, A new and efficient algorithm to binarize document images removing back-to-front interference, J. UCS 14(2) (2008) 299–313.

[26] R. F. Moghaddam and M. Cheriet, A multi-scale frame work for adaptive binarization of degraded document images, Pattern Recogn. 43 (2010) 2186–2198.

[27] W. Niblack, An Introduction to Digital Image Processing, Prentice-Hall, Englewood Cliffs, NJ (1986) 115–116.

[28] S. Nomura, K. Yamanaka, T. Shiose, H. Kawakami and O. Katai, Morphological preprocessing method to threshold degraded word images, Pattern recogn. Lett. 30(8) (2009) 729–242.

[29] N. Otsu, A threshold selection method from gray level histogram, IEEE Trans. on Sys. Man. Cyber. 191 (1978) 62–66.

[30] H. -H. Oh, Kil-TaekLim and Sung-IlChien, An improved binarization algorithm based on a water flow model for document image within homogeneous backgrounds, Pattern Recogn. 38 (2005) 2612–2625.

[31] N. Papamarkos, A technique for fuzzy document binarization, in:Proceedings of the 2001 ACM Symposium on Document Engineering, Atlanta, Georgia, USA, ACM (2001) 152–156.

[32] J. R. Parker, Gray level thresholding in badly illuminated images, IEEE Trans. on Pattern Analysis and Machine Intelligence 13 (1991) 813–819.

[33] Papamarkos, A neuro-fuzzy technique for document binarization, Neural Comput. Appl. 12(3-4) (2003) 190–199.

[34] R. Parvati, S. Jayanti, N. Pallaniappan and S. Devi, Intuitionistic fuzzy approach to enhance text documents, Proceedings 3rd IEEE International Conference on Intelligent Systems(IEEE1S,06) (2006) 733–737.

[35] S. K. Pal and R. A. King, Image enhancement using smoothing with fuzzy sets, IEEE Trans. Sys. Man Cybern. SMC-11 (1981) 494–501.

[36] M. A. Rami'rez-Ortego'n and E. Tapia, Transition pixel:a concept for binarization based on edge detection and gray intensity histograms, Pattern Recogn. 43 (2010) 1233–1243.

[37] M. A. Rami'rez-Ortego'n and E. Tapia, et al., Transition thresholds and transition operators for binarizatio nand edge detection, Pattern Recogn. 43 (2010) 3243–3254.

[38] H. Rajace, Enhancement of document images by morphological operator, 12th International conference of computer society of Iran, 2007.

[39] P. Rangasamy, J. Kuppannan, K. T. Atanassov and G. Gluhchev, Role of fuzzy and intuitionistic fuzzy contrast intensification operators in enhancing images, Twelfth Int. Conf. on IFSs, Sofia, NIFS 14 (2) (2008) 59–66.

[40] A. Rosenfeld and A. C. Kak, Digital Picture Processing, 2nd ed. New York: Academic, 1982.

[41] M. Sezgin and B. Sankur, Survey over image thresholding techniques and quantitative performance evaluation, Journal of Electronic Imaging 13(1) (2004) 146–165.

[42] Y. Solihin and C. Leedham, Integral ratio: A new class of global thresholding techniques for handwriting images, IEEE Trans. on Pattern Analysis and Machine Intelligence 21(8) (1999) 761–768.
[43] J. Sauvola and M. Pietikainen, Adaptive document image binarization, Pattern Recogn. 33(2) (2000) 225–236.
[44] B. Su, S. Lu and C. L. Tan, Binarization of historical handwritten document images using local maximum and minimum filter, International Workshop on Document Analysis Systems (2010) 303–314.
[45] J. Said, M. Cherict and C. Suena, Dynamical morphological processing:a fast method for base line extraction, ICDAR (1996) 8–12.
[46] F. Sattar and D. B. H. Tay, Enhancement of document images using multiresolution and fuzzy logic techniques, IEEE Signal process. Lett. 6 (1992) 249-252.
[47] J. Serra, Mathematical Morphology, Academic Press, London, UK 1, 1982.
[48] J. Serra, Image Analysis and Mathematical Morphology, Theoritical Advances, Academic Press, London, UK, 1982.
[49] O. D. Trier and T. Taxt, Improvement of integrated function algorithm for binarization of document images, Pattern Recogn. Lett. 16(3) (1995) 277–283.
[50] M. Valizadeh and E. Kabir, An adaptive water flow model for binarization of degraded document images, IJDAR, Springer-Verlag, 2012 (20 January).
[51] M. Valizadeh, N. Armanfard and M. Komeili, et al., A novel hybrid algorithm for binarization of badly illuminated document images, Computer Conference, Tehran (1-4) (2009).
[52] J. Wena, S. Li and J. Sun, A new binarization method for non-uniform illuminated document images, Pattern Recogn. 46 (2013) 1670–1690.
[53] S. D. Yanowitz and A. M. Bruckstein, A new method for image segmentation, Comput. Vision Graph. and Image Process. 46(1) (1989) 82–95.

(Mrs)Sharmistha Bhattacharya (Halder) (halder_731@rediffmail.com)
Reader,Department of Mathematics, Tripura University, Suryamaninagar, Agartala-799022, Tripura, India

Md. Atikul Islam (atik.math@yahoo.com)
Research scholar, Department of Mathematics, Tripura University, Suryamaninagar, Agartala-799022, Tripura, India