# Text/ Background separation in the degraded document images by combining several thresholding techniques

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*Abstract:* - Extract the text from the background is an important step in all process of document analysis and recognition. If this extraction is easy for document images of good quality by applying simple techniques of global thresholding, the images of degraded documents require a more accurate analysis and we have recourse in this case to local methods. Indeed, these latter are generally more efficient and provide better results than the global methods but they are very slow because of the threshold calculation which is performed separately for each pixel based on the information of its neighborhood. In this article, we try to solve this problem by proposing a hybrid thresholding technique which combines the advantages of the two families of methods, speed and performance. The idea is to precede a thresholding in two passes: globally in order to class the most of pixels and then locally on the remaining pixels. The approach has been tested on a standard collection and compared with well known methods, and the results are encouraging.

*Key-Words:* - Binarization, Degraded Documents, Document Preprocessing, Combination of Thresholding Methods, Evaluation of Binarization Methods, Hybrid Thresholding.

## 1 Introduction

The libraries, museums and other institutions in pedagogic or sociopolitic matters contain significant collections of documents, mostly handwritten. Historical documents of old civilizations and public archives are typical examples of such abundance which represent the patrimony, and nation's history. Indeed, these documents incur a progressive degradation because they are not preserved in good conditions, and consequently, they are threatened with a real danger of disappearance. A method of preservation is to scan the documents and to save them as image format. But alone, digitalization is not sufficient; it must be accompanied by tools and techniques allowing their automatic processing and analysis.

In most cases, automatic processing and analysis of document images pass through a binarization step. Binarization has as goal to reduce the amount of information present in the image (remove background and noise) and keep only relevant information (text, figures, tables), which allow us to use simple methods of analysis opposite to color or gray scale images. In fact, image binarization is critical in the sense that bad separation will cause the loss of pertinent information and/or add useless information (noise), generating wrong results. This difficulty increases for old documents which have various types of damages and degradations from the digitization process itself, aging effects, humidity, marks, fungus, dirt, etc. making the automatic processing of these materials difficult at several levels.

A great number of techniques have been proposed in the literature for the binarization of gray-scale or colored documents images, but, no one between them is generic and efficient for all types of documents.

The binarization techniques of grayscale images may be classified into two categories: global thresholding and local thresholding [1] [2]. Another category of hybrid methods can be added [3]. Global methods compute a single threshold for the whole image. They are usually fast and give good results for document images of good quality. When the document image is of poor quality, global methods become ineffective. Local methods calculate a different threshold for each pixel based on the information of its neighborhoods. These methods generally give better results than the global ones but they are very slow because of the threshold calculation which is done for each pixel by considering its neighborhoods. Hybrid methods combine global and local information for segmenting the image.

In this paper, we propose a combination of thresholding methods for binarizing images of historical documents. The proposed approach combines the advantages of the two families of techniques: execution rapidity and efficiency. The remainder of this paper is organized as follows. In Section 2, we present some existing binarization methods. Then in Section 3 we describe the proposed approach. The experiments performed and the results will be shown in Section 4, before concluding.

## 2 State of the Art

Sezgin et al. [4] established a classification of binarization methods according to the information that they exploit in 6 categories:

- Histogram-based methods: the methods of this class perform a thresholding based on the form of the histogram.
- Clustering-based methods: These methods assign the image pixels to one of the two clusters: object and background.
- Entropy-based methods: These algorithms use the information theory to obtain the threshold.
- Object attribute-based methods: Find a threshold value based on some similarity measurements between original and binary images.
- Spatial binarization methods: find the optimal threshold value taking into account spatial measures.
- Locally adaptive methods: These methods are designed to give a new threshold for every pixel. Several kinds of adaptive methods exist. We find methods based on local gray range, local variation, etc.

We present in this section some binarization methods the most frequently cited in the literature.

### 2.1 Global methods

Noting *I* the grayscale image of which the intensities vary from 0 (black) to 255 (white), and *H* its histogram of intensities. The number of pixels having a gray level *i* is noted *H(i)*.

#### 2.1.1 Otsu method

Otsu method [5] tries to find the threshold *T* which separates the gray-level histogram in an optimal way into two segments (which maximize the inter-segments variance or which minimize the intra-segments variance). The calculation of the inter-classes or intra-classes variances is based on the normalized histogram $H_n = [H_n(0) \dots H_n(255)]$ of the image where $\sum H_n(i)=1$.

The inter-classes variance for each gray level *t* is given by:

$$V_{inter} = q_1(t) \times q_2(t) \times [\mu_1(t) - \mu_2(t)]^2 \quad (1)$$

Such as:

$$\mu_1(t) = \frac{1}{q_1(t)} \sum_{i=0}^{t-1} H_n(i) \times i$$

$$\mu_2(t) = \frac{1}{q_2(t)} \sum_{i=t}^{255} H_n(i) \times i$$

$$q_1(t) = \sum_{i=0}^{t-1} H_n(i) \text{ and } q_2(t) = \sum_{i=t}^{255} H_n(i)$$

#### 2.1.2 ISODATA method

Thresholding using ISIDATA [6] consists to find a threshold by separating iteratively the gray-level histogram into two classes, with the apriority knowledge of the values associate to each class. This method starts by dividing the interval of non-null values of the histogram into two equidistant parts, and next we take $m_1$ and $m_2$ as the arithmetic average of each class. Repeat until convergence, the calculation of the optimal threshold *T* as the closest integer to $(m_1 + m_2) / 2$ and update the two averages $m_1$ and $m_2$ .

#### 2.1.3 Kapur et al. method

Kapur's method [7] is an entropy based method which takes into account the foreground likelihood distribution $P_f$ and the background likelihood distribution ($P_b = 1 - P_f$) in the determination of the division entropy. The binarization threshold *T* is chosen for which the value: $E = E_f + E_b$ be maximal, such as:

$$E_f = -\sum_{i=0}^{t} \frac{P_i}{P_f} \times log\left(\frac{P_i}{P_f}\right) \quad (2)$$

$$E_b = -\sum_{i=t+1}^{255} \frac{P_i}{1-P_f} \times log\left(\frac{P_i}{1-P_f}\right) \quad (3)$$

Where $P_i$ is the occurrence probability of the gray level *i* in the image, and $P_f = \sum_{i=0}^{t} P_i$

#### 2.1.4 Chen et al. method

Cheng and al. method is based on the maximal entropy principle and the fizzy C-partition, for choosing the threshold [8]. Consider two fuzzy sets *Foreground* and *Background* of which the membership functions are defined by:

$$\varphi_f = \begin{cases} 1, & x \le a \\ (x-c)/(a-c), & a<x<c \\ 0, & x \ge c \end{cases} \qquad \varphi_b = \begin{cases} 0, & x \le a \\ (x-a)/(c-a), & a<x<c \\ 1, & x \ge c \end{cases}$$

In this method, the binarization threshold is chosen as the gray-level of which the membership function=0.5, and so it is the center of the interval [$a_{opt}$, $c_{opt}$], such as $a_{opt}$ and $c_{opt}$ are the values of $a$ and $c$ maximizing the division entropy.

The partitioning entropy is given by:

$$H = - P_f \log (P_f) - P_b \log (P_b) \qquad (4)$$

### 2.1.5 Li and Lee method

Li and Lee proposed a thresholding technique where the grouping of gray-levels in two classes (foreground and background) is based on the crossed entropy minimization [9]. Note $\mu_1(t)$ and $\mu_2(t)$ the means of the two classes according to the gray-level $t$. Li and Lee established that the optimal threshold $T$ is calculated in order to minimize $E(t)= E_f(t)+ E_b(t)$ where:

$$E_f(t) = \sum_{i=0}^{t-1} i\, H(i) \log\left(\frac{i}{\mu_1(t)}\right) \qquad (5)$$

$$E_b(t) = \sum_{i=t}^{255} i\, H(i) \log\left(\frac{i}{\mu_2(t)}\right) \qquad (6)$$

$$\mu_1(t) = \frac{\sum_{i=0}^{t-1} i\, H(i)}{\sum_{i=0}^{t-1} H(i)} \quad and \quad \mu_2(t) = \frac{\sum_{i=t}^{255} i\, H(i)}{\sum_{i=t}^{255} H(i)}$$

### 2.1.6 Iterative global thresholding

The proposed method selects a global threshold to the entire image based on an iterative procedure [19]. At each iteration $i$, the following steps are performed:

a. Calculating the average gray level ($T_i$) of the image,
b. Subtracting $T_i$ from all pixels of the image,
c. Histogram equalization to extend the pixels over the whole gray levels interval.

The algorithm stops when: $|T_i - T_{i-1}| < 0.001$.

## 2.2 Local methods

Local methods compute a local threshold for each pixel by sliding a square or rectangular window over the entire image.

### 2.2.1 Bernsen method

It is an adaptive local method [10]. Thus for each pixel of coordinates ($x$, $y$), the threshold is given by:

$$T(x,y) = \frac{Z_{low} + Z_{high}}{2} \qquad (7)$$

Such as $Z_{low}$ and $Z_{high}$ are the lowest and the highest gray-level respectively in a squared window $w \times w$ centered over the pixel $(x, y)$.

However, if the local contrast $C(x, y) = (Z_{hight} – Z_{low})$ is below a threshold $l$ ($l$ = 15), then the neighborhood consists of a single class: *Foreground* or *Background*.

### 2.2.2 Niblack method

The local threshold $T(x, y)$ is calculated using the mean $m$ and standard deviation $\sigma$ of all pixels in the window (neighborhood of the pixel in question) [11]. Thus, the threshold $T(x, y)$ is given by:

$$T(x,y) = m + k \times \sigma. \qquad (8)$$

Such as $k$ is a parameter used for determining the number of edge pixels considered as object pixels, and takes a negative values ($k$ is fixed -0.2 by authors) .

### 2.2.3 Sauvola and Pietikainen method

Sauvola et al. algorithm [3] is a modification of that of Niblack, in order to gives more performance in the documents with a background containing a light texture or too variation and uneven illumination. In the modification of Sauvola, the local binarization threshold is given by:

$$T = m.(1 - k.(1 - \frac{\sigma}{R})) \qquad (9)$$

Where $R$ is the dynamic range of the standard deviation $\sigma$, and the parameter $k$ takes positives values in the interval [0.2, 0.5].

### 2.2.4 Wolf et al. method

In order to address to Sauvola et al. algorithm problems (low contrast, disparity of gray-level, etc.), Wolf et al. [12] proposed to normalize the contrast and the image gray-level mean, and calculate the threshold by:

$$T(x,y) = (1-k)*m + k*M + k*\frac{\sigma}{R}(m-M) \qquad (10)$$

Such as $k$ is fixed to 0.5, $M$ is the minimum gray-level of the image and $R$ is the maximum standard deviation of gray-levels obtained over all windows.

### 2.2.5 Nick method

This method improves considerably the binarization of lighted images and low contrasted images, by downwards moving, the threshold of binarization [2]. The threshold calculation is done as follow:

$$T(x,y) = m + k\sqrt{\frac{(\sum p_i^2 - m^2)}{NP}} \quad (11)$$

Such as: $k$ is the Niblack factor and vary between -0.1 and -0.2 according to the application need, $m$: the average gray-level, $p_i$: the gray-level of pixel $i$ and $NP$ is the total number of pixels. In their tests, the authors used a window of size 19 × 19.

#### 2.2.6 Sari et al. method
This method uses an artificial neuron network of type multilayer Perceptron (MLP) to classify the image pixels into two classes: *Foreground* and *background* [18]. The MLP have one hidden layer, 25 inputs, and one single output. To assign a new value (black or white) to a pixel, the MLP takes as input a vector of 25 values corresponding to the intensities of the pixel in a 5×5 window centered on the processed pixel. The MLP parameters (structure, the input statistics, etc.) have been chosen after several experiments.

#### 2.2.7 Peng et al. method
In order to extract the text from old manuscripts, Peng et al. proposed a novel adaptive binarization method [20]. Starting with the assumption that the background intensity is consistent within the local area of document image, the proposed method calculate a local threshold *T(x,y)* for each pixel using the local mean *m(x,y)* and the local variance $\delta_{x,y}$ calculated over a $m \times n$ window, and the minimal and maximal variance in the whole image $\delta_{min}$ and $\delta_{max}$.

$$T(x,y)=m(x,y)\left[\frac{1-k}{\left(1+e^{-B\left(\frac{\delta_{x,y}-\delta_{min}}{\delta_{max}-\delta_{min}}-M\right)}\right)^{1/\upsilon}}+k\right] \quad (12)$$

The parameters $k$, $B$, $M$ and $\upsilon$ takes the values 0.97, 25, 0.005 and 20 respectively.

#### 2.2.8 Romen Singh et al. method
Romen Singh et al. [21] calculate the local thresholds basing on the integral sum images which accelerate the binarization considerabely. The first step of this technique is the calculation of the integral sum image $g$ defined as follow:

$$g(x,y) = \sum_{i=0}^{x}\sum_{j=0}^{y} I(i,j)$$

The local binarization threshold is determined later on by using the local mean *m(x,y)* and the average deviation *δ(x,y)* in a window $w \times w$ centred on the pixel *(x,y)*.

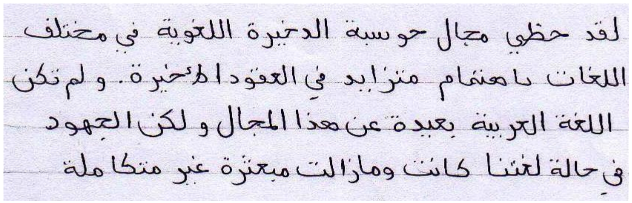
$$T(x,y) = m(x,y)\left[1 + k\left(\frac{\delta(x,y)}{1-\delta(x,y)} - 1\right)\right] \quad (13)$$

Such as: *δ(x,y)= I(x,y) - m(x,y)* and $k$ a parameter in [0, 1] and suggested 0.06 by the authors.

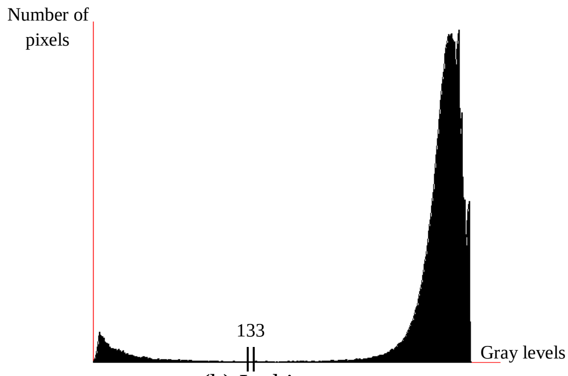
Noting *d=w/2*, the local mean *m(x,y)* is calculated using the integral sum image by:

$$m(x,y) = \frac{1}{w^2} g(x+d-1, y+d-1) + g(x-d, y-d) - [g(x-d, y+d-1) + g(x+d-1, y-d)] \quad (14)$$

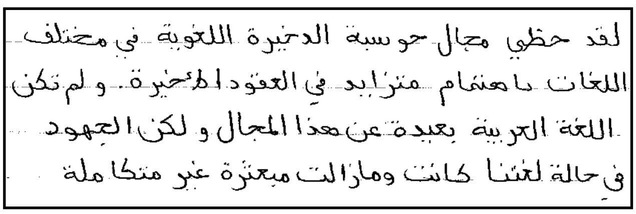
## 3 Proposed Technique
As we said earlier, the global thresholding techniques are generally simple and fast algorithms which tend to calculate a single threshold in order to eliminate all background pixels, with preserving all foreground pixels. Unfortunately, these techniques are applicable only when the original documents are of good quality, well contrasted, with a bimodal histogram. Fig. 1 shows an example.




(a) Gray-level image,




(b) Its histogram,

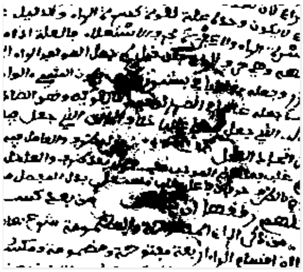



(c) Thresholding result with Otsu method

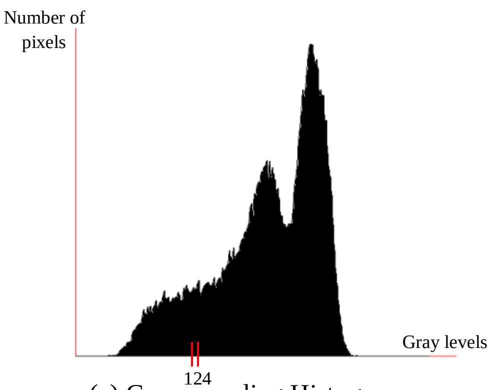
Fig.1. Global thresholding of a bimodal image

When the documents are of poor quality, containing different types of damage (stains, transparency effects, etc.), with a textured background and uneven illumination, or when the gray levels of the foreground pixels and the gray levels of the background pixels are close, it is not possible to find a threshold that completely separates the foreground from the background of the image (Fig. 2).

(a) Original image



(b) Otsu thresholding result




(c) Corresponding Histogram

Fig. 2. Global thresholding of degraded image

In this case, a more detailed analysis is needed, and we have recourse to local methods. Local methods are more accurate and may be applied to variable backgrounds, quite dark or with low contrast, but they are very slow since the threshold calculation based on the local neighborhood information is done for each pixel of the image. This calculation becomes slower with a high size of sliding window.

To solve this problem, we propose a hybrid thresholding approach that will be fast and at the same time effective as well as local methods, and that by combining the advantages of both families of binarization methods. The proposed technique uses two thresholds *T1* and *T2*, and it runs in two passes. In the first pass, a global thresholding is performed in order to class the most of pixels of the image. All pixels having a gray-level higher than *T2* are removed (becomes white) because they represent the background pixels. All pixels having a gray-level lower than *T1* are considered as foreground pixels and therefore they are kept and colored in black. The remaining pixels are left to the second pass in which they are locally binarized by combining the results of several local thresholding methods to select the most probable value.

We details in the following the processing steps.

## 3.1 Estimation of two thresholds *T1* and *T2*

The first step in the binarization process is the calculation of the two thresholds *T1* and *T2*. Since the thresholding purpose is to divide the image into two classes: foreground and background, and since a single threshold is not able to accomplish this task, the use of two thresholds seems be a solution.

These two thresholds are estimated from the gray-levels histogram of the original image and represent the average intensity of the foreground and background respectively.

To obtain these two thresholds, we first compute a global threshold *T* using a global thresholding algorithm which can be Otsu algorithm, Kapur, or any other global algorithm. In our approach, we chose Otsu algorithm because this technique has shown its efficiency and overcome other global methods in several comparative studies [13] [15]. *T* separates the gray-levels histogram of the image into two classes: foreground and background.

*T1* and *T2* are estimated from *T*. Noting $\Delta T$ the minimum distance between the average intensity of the foreground represented by the first half of the histogram and the average intensity of the background represented by the second half.

$$T1 = T - \frac{\Delta T}{2}, \quad (15)$$

$$T2 = T + \frac{\Delta T}{2} \quad (16)$$

The value of $\Delta T$ is chosen by experiments. After several tests, we adopted $\Delta T = 40$.

## 3.2 Global image thresholding using *T1* and *T2*

After the estimation of the two thresholds *T1* and *T2*, all pixels having a gray-level higher than *T2* are transformed into white which eliminates most of the image background, and those whose gray level is less than *T1* are colored in black. These pixels are certainly foreground pixels. The resulting image still contains noise but all the foreground information are preserved.

### 3.3 Local thresholding of the remaining pixels

The pixels unprocessed in the previous step (those with a gray level between *T1* and *T2*) may belong to the foreground, and they must be preserved, likewise they may be background or noise pixels and in these both cases they must be eliminated. The decision to assign the remaining pixels to one of two classes: foreground or background is performed using a local process by examining the neighborhood of these pixels. To ensure a more correct classification, we proposed to apply several local thresholding methods. In our experiments, we chose the following methods: Niblack, Sauvola and Nick, since these methods were ranked in first places in several previous comparative studies [2] [16] [17].

For each pixel *p* not yet classified, we calculate locally its new binary values (0 for black and 255 for white) obtained by applying Niblack, Sauvola and Nick methods. Noting *b1*, *b2*, *b3* these values respectively.

The final pixel value (*b*) is that resulted of at least two of the three methods.

In general, if we apply *n* methods, the new values assigned are denoted *b1*, *b2*, ..., *bn*. The new value *b* is given as follows:

$$b=\text{round}\left(\frac{\sum_{i=1}^{n} bi}{n\times 255}\right)\times 255 \qquad (17)$$

*Round* returns the integer closest integer to a real number.

## 4 Experiments and Results

In order to estimate the performance of our approach, we applied them over a test set and compared them with well known methods, including Otsu method, Kapur et al., Niblack, Sauvola and Pietikainen, and Nick. The comparison concerns both the binarization quality and the execution time. A series of experiments was first performed in order to determine the best parameter values of the local methods (Table 1).

Table 1. Best parameters values of the local methods

| Method | Parameters |
|---|---|
| Bernsen | *w*=27×27 and *l*=15 |
| Niblack | *k*= -0.2 and *w*=27×27 |
| Sauvola and Pietikainen | *k*= 0.2, *R*= 128 and *w*=27×27 |
| Nick | *k*=-0.2 et *w*=27×27 |

### 4.1 Test base

We used in our test the collections of images proposed within the context of the competitions DIBCO 2009[1], H-DIBCO 2010[2], DIBCO 2011[3], et H-DIBCO 2012[4]. DIBCO the acronym of *Document Image Binarization Contest* is an International competition of document images binarization, emerged in 2009 in the context of ICDAR 2009 conference. The goal of this competition is to follow the progress in the field of documents binarization and to evaluate their performance using quantitative measures and on the same test base.

The images of the 4 collections contain representative degradations which appear frequently (e.g. variable background intensity, shadows, smear, smudge, low contrast, bleed-through). The images are in grayscale and color, handwriting and printed, real and synthetic with their corresponding ground truth image. Fig. 3 shows some examples of test images:

Fig. 3. Examples of images from the 4 test collections

The test collection consists of 50 document images handwritten and printed.

[1]http://users.iit.demokritos.gr/~bgat/DIBCO2009/benchmark/
[2]http://www.iit.demokritos.gr/~bgat/H-DIBCO2010/benchmark
[3]http://utopia.duth.gr/~ipratika/DIBCO2011/benchmark
[4] http://utopia.duth.gr/~ipratika/HDIBCO2012/benchmark

### 4.2 Evaluation measures

In addition to the execution time, the qualitative assessment is performed in terms of three standard evaluation measures used in DIBCO 2009, H-DIBCO 2010, DIBCO 2011, and H-DIBCO 2012: F-measure, PSNR, and NRM.

Noting *TP, TN, FP, FN* the True positive, True Negative, False positive and False negative values, respectively.

**a) F-Measure**

$$FMesure=\frac{2\times Recall\times Precision}{Recall+Precision} \quad (18)$$

Where: $Recall=\frac{TP}{TP+FN}$

$$Precision=\frac{TP}{TP+FP}$$

**b) PSNR**

PSNR is a similarity measure between two images. However, the higher the value of PSNR, the higher the similarity of the two images.

$$PSNR=10\log\left(\frac{C^2}{MSE}\right) \quad (19)$$

Where : $MSE=\frac{\sum_{x=1}^{M}\sum_{y=1}^{N}(I(x,y)-I2(x,y))^2}{MN}$

$I$ and $I_2$ represents the two images matched. $M$ and $N$ there height and width respectively. $C$ the difference between foreground and background (here 255).

**c) NRM (Negative Metric rate)**

$$NRM=\frac{NR_{FN}+NR_{FP}}{2} \quad (20)$$

Where : $NR_{FN}=\frac{FN}{FN+TP}$ *and* $NR_{FP}=\frac{FP}{FP+TN}$

Contrary to Fmeasure and PSNR, The better binarization quality is obtained for lower NRM value.

**d) MPM (Misclassification Penalty Metric)**

The Misclassification penalty metric *MPM* evaluates the binarization result against the Ground Truth on an object-by-object basis.

$$MPM=\frac{MP_{FN}+MP_{FP}}{2} \quad (21)$$

where : $MP_{FN}=\frac{\sum_{i=1}^{FN}d_{FN}^{i}}{D}$ and $MP_{FP}=\frac{\sum_{j=1}^{FP}d_{FP}^{j}}{D}$

$d_{FN}^{i}$ and $d_{FP}^{j}$ denote the distance of the $i^{th}$ false negative and the $j^{th}$ false positive pixel from the contour of the Ground Truth segmentation. The normalization factor $D$ is the sum over all the pixel-to-contour distances of the Ground Truth object. A low MPM score denotes that the algorithm is good at identifying an object's boundary.

### 4.3 Results and discussion

The results obtained over the test images are summarized in the following Table 2.

Table 2. Obtained Results

| | Execution time (*ms*) | F-mesure (%) | PSNR | NRM | MPM |
|---|---|---|---|---|---|
| Otsu | 624.3 | 78.51 | 35.12 | 0.05 | 2.8783 |
| Kapur et al. | 639.7 | 72.28 | 34.80 | 0.051 | 3.3474 |
| Niblack | 78504.1 | 79.46 | 37.64 | 0.1247 | 4.178 |
| Sauvola and Pietikainen | 81392.2 | 84.92 | 37.56 | 0.08 | 2.2288 |
| Nick | 74119.9 | 81.848 | 36.268 | 0.123 | 2.5658 |
| Proposed Approche | 3223.12 | 85.719 | 37.88 | 0.06 | 1.8475 |

From the above table, our method achieved the performance of local methods (ranked 1st before Sauvola and Pietikainen method) and simultaneously accomplished the task within a very reasonable time equal almost five times the execution time of global methods. So, it is very fast compared to local methods, which enabled us to earn more than 90% of the execution time.

## 5 Conclusion

In this paper we presented our hybrid approach of degraded document images binarization. The proposed approach is based on the combination of several global and local thresholding methods to obtain a fast and efficient method combining the advantages of the two families of techniques. A step of global thresholding is first performed on the entire image in order to classify the most of pixels. The remaining pixels are then processed locally based on their neighborhood information. Since the number of pixels processed locally is very small compared to the total number of pixels, the time required for the binarization is reduced considerably without reducing the performance. To validate our approach, we compared it with methods in the literature and the results obtained on a standard test collection are encouraging and confirm our proposal.

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