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Robust Document Image Binarization Technique for Degraded Document Images

Subba Rao Nasina
M.tech Student,
PBR VITS,
Kavali, Nellore(D.t), A.P

A Suman Kumar Reddy
Associate Professor,
PBR VITS,
Kavali, Nellore(D.t), A.P

Abstract: *Libraries and archives around the world store an abundance of old and historically important documents and manuscripts. These documents accumulate a significant amount of human heritage over time. Segmentation of text from badly degraded document imagesis a very challenging task due to the high inters/intravariation between the document background and the foreground text of different document images. In this paper, we propose a novel document image binarization technique that addresses these issues by using adaptive image contrast. The adaptive image contrast is a combination of the local image contrast and the local image gradient that is tolerant to text and background variation caused by different types of document degradations. In the proposed technique, an adaptive contrast map is first constructed for an input degraded document image. The contrast map is then binarized and combined with Canny's edge map to identify the text stroke edge pixels. The document text is further segmented by a local threshold that is estimated based on the intensities of detected text stroke edge pixels within a local window. The proposed method is simple, robust, and involves minimum parameter tuning. It has been tested on three public datasets that are used in the recent document image binarization contest (DIBCO) 2009 & 2011 and handwritten-DIBCO 2010 and achieves accuracies of 93.5%, 87.8%, and 92.03%, respectively that are significantly higher than or close to that of the best performing methods reported in the three contests. Experiments on the Bickley diary dataset that consists of several challenging bad quality document images also show the superior performance of our proposed method, compared with other techniques.*

Keywords: *optical character recognition (OCR), document analysis, document image processing, post processing, degraded document image binarization and pixel classification.*

1. INTRODUCTION

Documents image binarization is performed in the preprocessing stage for document analysis and it aims to segment the foreground text from the document background. A fast and accurate document image binarization technique is important for the ensuing document image processing tasks such as optical character recognition (OCR). Though document image binarization has been studied for many years, the thresholding of degraded document images is still an unsolved problem due to the high inter/intra variation between the text stroke and document background across different document images. Many environmental factors, improper handling, and the poor quality of the materials used in their creation cause them to suffer a high degree of degradation of various types. Today, there is a strong move toward digitization of these manuscripts to preserve their content for future generations. The huge amount of digital data produced requires automatic processing, enhancement, and recognition. A key step in all document image processing workflows is binarization, but this is not a very sophisticated process, which is unfortunate, as its performance has a significant influence on the quality of OCR results. Many research studies have been carried out to solve the problems that arise in the binarization of old document images characterized by many types of degradation including faded ink, bleed-through, show-through, uneven illumination, variations in image contrast, and deterioration of the cellulose structure. There are also differences in patterns of hand-written and machine-printed documents, which add to the difficulties associated with the binarization of old document images.

As illustrated, the handwritten text within the degraded documents often shows a certain amount of variation in terms of the stroke width, stroke brightness, stroke connection, and document background. In addition, historical documents are often degraded by the bleedthrough where the ink of the other side seeps through to the front. In addition, historical documents are often degraded by different types of imaging artifacts. These different types of document degradations tend to induce the document thresholding error and make degraded document image binarization a big challenge to most state-of-the-art techniques.

Fig.1. *Five degraded document image examples (a)–(d) are taken from DIBCO series datasets and (e) is taken from Bickley diary dataset.*

The recent Document Image Binarization Contest held under the framework of the International Conference on Document Analysis and Recognition (ICDAR) 2009 &2011. We participated in the DIBCO 2009 and our background estimation method performs the best among entries of 43 algorithms submitted from 35 international research groups. We also participated in the H-DIBCO 2010 and our local maximum-minimum method was one of the top two winners among 17 submitted algorithms. In the latest DIBCO 2011, our proposed method achieved second best results among 18 submitted algorithms. This paper presents a document binarization technique that extends our previous local maximum-minimum method and the method used in the latest DIBCO 2011. Many thresholding techniques have been reported for document image binarization. As many degraded documents do not have a clear bimodal pattern, global thresholding is usually not a suitable approach for the degraded document binarization. Adaptive thresholding which estimates a local threshold for each document image pixel, is often a better approach to deal with different variations within degraded document images. For example, the early window-based adaptive thresholding techniques estimate the local threshold by using the mean and the standard variation of image pixels within a local neighborhood window. The main drawback of these window-based thresholding techniques is that the thresholding performance depends heavily on the window size and hence the character stroke width. The local image contrast and the local image gradient are very useful features for segmenting the text from the document background because the document text usually has certain image contrast to the neighboring document background. They are very effective and have been used in many document image binarization techniques. This paper presents a document binarization technique that extends our previous local maximum-minimum method and the method used in the latest DIBCO 2011. The proposed method is simple, robust and capable of handling different types of degraded document images with minimum parameter tuning. It makes use of the adaptive image contrast that combines the local image contrast and the local image gradient adaptively and therefore is tolerant to the text and Background variation caused by different types of document degradations. In particular, the proposed technique addresses the over-normalization problem of the local maximum minimum Algorithm. At the same time, the parameters used in the algorithm can be adaptively estimated.

2. Literature Survey

Binarization techniques have been developed in the document analysis community for over 30 years and many algorithms have been used successfully. On the other hand, document analysis tasks are more and more frequently being applied to multimedia document such as video sequences. Due to low resolution and lossy compression, the binarization of text included in the frames is a non trivial task. Existing techniques work without a model of the spatial relationships in the image, which makes them less powerful. They introduce a new technique based on a Markov Random Field (MRF) model of the document. The model parameters (clique potentials) are learned from training data and the binary image is estimated in a Bayesian frame work. The performance is evaluated using commercial OCR software. A new method is presented for adaptive document image binarization, where the page is considered as a collection of subcomponents such as text, background and picture. The problems caused by noise, illumination and many source type-related degradations are addressed. Two new algorithms are applied to determine a local threshold for each pixel. The proposed algorithms were tested with images including different types of document components and degradations.

2.1 Existing Systems

Document images often suffer from different types of degradation that renders the document image binarization a challenging task is based on the observations that the text document usually have a document background of the uniform color and texture and the document text within it has a different intensity level compared with the surrounding document background. Different types of document degradation are then compensated by using the estimated document background surface. The text stroke edge is further detected from the compensated document image by using L1-norm image gradient. Finally, the document text is segmented by a local threshold that is estimated based on the detected text stroke edges.

2.2 Disadvantages of Existing System

This method is simple, but cannot work properly on degraded document images with a complex document background. This method can deal with document bleeding-through. But when the back-side text is as dark as or even darker than the front -side text, the proposed method cannot differentiate the two types of character strokes properly.This technique is designed for the binarization of scanned document images that have no or weak slanting. But for the document text captured by digital cameras that may have severe slanting. The polynomial smoothing it cannot handle the sharp variation of small size within the document background such as the one resulting from the document folding.

3. PROPOSED SYSTEM

This section describes the proposed document image binarization techniques. Given a degraded document image, an adaptive contrast map is first constructed and the text stroke edges are then detected through the combination of the binarized adaptive contrast map and the canny edge map. The text is then segmented based on the local threshold that is estimated from the detected text stroke edge pixels. Some post-processing is further applied to improve the document binarization quality.

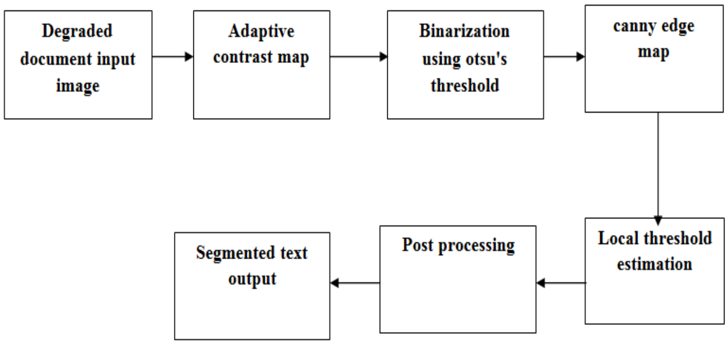


Fig 2. *Block diagram of proposed system.*

3.1 Contrast Image Construction

The purpose of the contrast image construction is to detect the stroke edge pixels of the document text properly. The constructed contrast image consists of a clear bi-modal pattern. It can be used to detect the text stroke edges of the document images that have a uniform document background. While, it often detects many non stroke edges from the background of degraded document that perhaps contains certain image variations because of uneven lighting, noise, bleed-through etc. For proper extraction of only the stroke edges, the image gradient needs to be normalized to compensate the variation in the image within the document background. The local contrast evaluated by the local image maximum and minimum is used to suppress the background variation as described in below Equation. In particular, the numerator (i.e. the difference between the local maximum and the local minimum) captures the local image difference that is similar to the traditional image gradient .The denominator is a normalization factor that suppresses the image variation within the document background. For pixels of image within bright regions, it will generate a greater normalization factor to neutralize the numerator and accordingly result in a relatively low image contrast. For the pixels of image within dark regions, it will generate a small denominator and accordingly result in a relatively high image contrast.

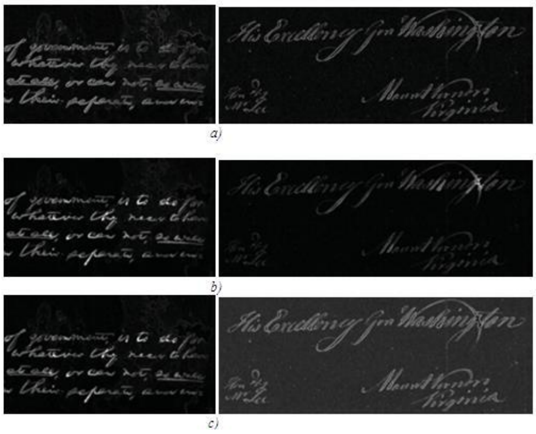


Fig.3. *Contrast Images constructed using (a) local image gradient, (b) local image contrast, and (c) our proposed method of the sample document images in Fig. 3 (b) and (d)*

3.2 Text Stroke Edge Pixel Detection

We get the stroke edge pixels of the document text properly from contrast image construction. The constructed contrast image consist a clear bi-modal pattern [5]. The local image gradient is evaluated by the difference between the maximum and minimum intensity in a local window, the pixels at both the sides of the text stroke will be selected as the high contrast pixels. Binary map is then constructed. In the combined map, we keep only pixels that appear within both the high contrast image pixel map and canny edge map. Accurate extraction of the text stroke edge pixels is helped out by this combination.

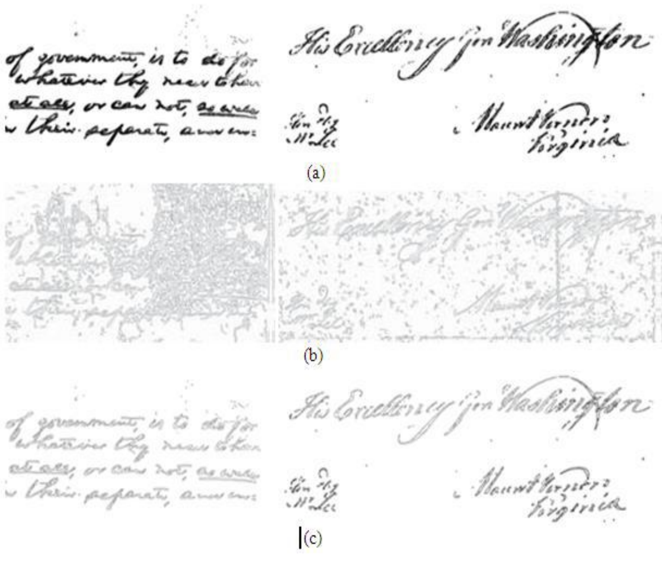


Fig. 4. *(a) Binary contrast maps, (b) canny edge maps, and their (c) combine edge maps of the sample document images in Fig. 3(b) and (d), respectively.*

3.3 Local Threshold Estimation

Subsequent extraction of the text from the document background pixels is carried out once the high contrast stroke edge pixels are detected properly. Two characteristics can be observed from different kinds of document images first, the text pixels are close to the detected text stroke edge pixels. Second, the distinct intensity difference between the high contrast stroke edge pixels and the surrounding background pixels. The text within the document image can therefore be extracted based on the detected text stroke edge pixels. In this we are calculating the mean value. Here we are using the Edge width estimation algorithm is as follows:

ALGORITHM2

Ensure: The Estimated Text Stroke Edge Width EW

1. Get the width and height of I

2. for Each Row i = 1 to height in Edge do

3. Scan from left to right to find edge pixels that meet the following criteria:

a) its label is 0 (background);

b) the next pixel is labeled as 1(edge).

4. Examine the intensities in I of those pixels selected in Step 3, and remove those pixels that have a lower intensity than the following pixel next to it in the same row of I.

5. Match the remaining adjacent pixels in the same row into pairs, and calculate the distance between the two pixels in pair.

6. end for

7. Construct a histogram of those calculated distances.

8. Utilize the most frequently occurring distance as the estimated stroke edge width EW.

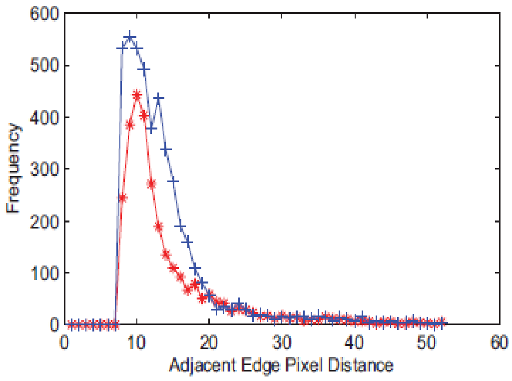


Fig.5. *Histogram of the distance between adjacent edge pixels. The "+++"line denotes the histogram of the image in Fig. 1(b). The "***" line denotes the histogram of the image in Fig. 1(d).*

3.4 Post Processing

After deriving the initial binarization result from above the method that binarization result can further is improved as described in below Post processing procedure algorithm. Require: The Input Document

ALGORITHM2

Image I , Initial Binary Result B and Corresponding Binary Text Stroke Edge Image Edge

Ensure: The Final Binary Result B

1. Look for all the connect components of the stroke edge pixels in Edge

2. Eliminate those pixels that are not connected with other pixels.

3. for Each remaining edge pixels (i, j): do

4. Get its neighborhood pairs: (i − 1, j) and

(i + 1, j);(i, j − 1) and (i, j + 1)

5. if the pixels in the same pairs belong to the same class (both text and background) then

6. Allot the pixel with lower intensity to foreground class (text), and the other to background class.

7. end if

8. end for

9. Eliminate single-pixel artifacts along the text stroke boundaries after the document thresholding.

10. Store the new binary result to B.

First, the isolated foreground pixels that do not connect with other foreground pixels are filtered out to make the edge pixel set precisely. Second, the neighborhood pixel pair that lies on symmetric sides of a text stroke edge pixel should belong to different classes (i.e., either the document background or the foreground text). A single pixel out of the pixel pair is therefore labeled to the other category if both of the two pixels belong to the same class. At last, certain numbers of single-pixel artifacts along the text stroke boundaries are filtered out by using several logical operators.

4. Experiments and Discussion

A few experiments are designed to demonstrate the effectiveness and robustness of our proposed method. We first consider the presentation of the proposed technique on public datasets for parameter selection. The proposed technique is then tested and compared with state-of-the-art methods over on three well-known competition datasets: DIBCO 2009dataset, H-DIBCO 2010 dataset, and DIBCO 2011 dataset. Finally, the proposed technique is further evaluated over a very challenging Bickley diary dataset. The binarization performance are evaluated by using F-Measure, pseudo F-Measure, Peak Signal to Noise Ratio (PSNR), Negative Rate Metric (NRM), Misclassification Penalty Metric (MPM), Distance Reciprocal Distortion (DRD) and rank score that are adopted from DIBCO 2009, H-DIBCO 2010 and DIBCO 2011. Due to lack of ground truth data in some datasets, no all of the metrics are applied on every images.

4.1 Parameter Selection

In the first experiment, we apply different γ to obtain different power functions and test their performance under the DIBCO 2009 and H-DIBCO 2010 datasets. The γ increases from 2−10 to 210 exponentially and monotonically as shown in Fig. 4(a). In particular, α is close to 1 when γ is small and the local image contrast C dominates the adaptive image contrast Ca in Equation 3. On the other hand, Ca is mainly influenced by local image gradient when γ is large. At the same time, the variation of α for different document images increases when γ is close to 1. Under such circumstance, the power function becomes more sensitive to the global image intensity variation and appropriate weights can be assigned to images with different characteristics as shown in Fig. 4(b), Our proposed method produces better results on DIBCO dataset when the γ is much smaller than 1 and the local image contrast dominates. On the other hand, the F-Measure performance of H-DIBCO dataset improves significantly when γ increases to 1. Therefore the proposed method can assign more suitable α to different images when γ is closer to 1. Parameter γ should therefore be set around 1 when the adaptability of the proposed technique is maximized and better and more robust binarization results can be derived from different kinds of degraded document images. Another parameter, i.e., the local window size W, is tested in the second experiment on the DIBCO 2009, H-DIBCO 2010 and DIBCO 2011 datasets. W is closely related to the stroke width EW. Fig. 5 shows the thresholding results when W varies from EW to $4EW$. Generally, a larger local window size will help to reduce the classification error that is often induced by the lack of edge pixels within the local neighborhood window. In addition, the performance of the proposed method becomes stable when the local window size is larger than $2EW$ consistently on the three datasets. W can therefore be set around $2EW$ because a larger local neighborhood window will increase the computational load significantly.

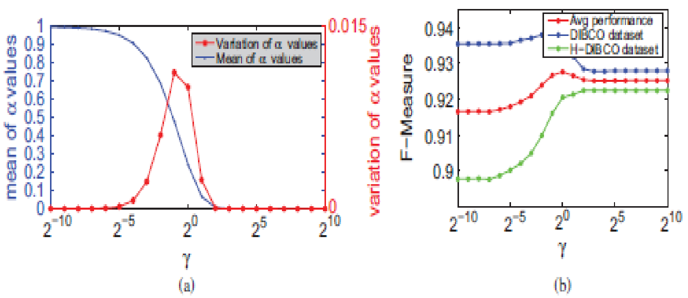


Fig.4. *(a) Means and variations of the values of the twenty imageson DIBCO and H-DIBCO dataset under different γ values. (b) F-measure performance on DIBCO 2009 & H-DIBCO 2010 datasets using different γ power functions.*

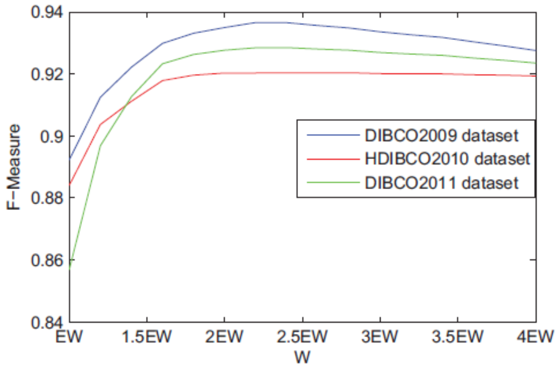


Fig.5. *F-measure performance on DIBCO 2009, H-DIBCO 2010, and DIBCO 2011 datasets using different local window size W (the EW denotes the estimated text stroke width).*

4.3 Testing on Competition Datasets

In this experiment, we quantitatively compare our proposed method with other state-of-the-art techniques on DIBCO 2009, H-DIBCO 2010 and DIBCO 2011 datasets. These methods include Otsu's method (OTSU), Sauvola's method (SAUV), Niblack's method (NIBL), Bernsen's method (BERN), Gatos et al.'s method (GATO), and our previous methods (LMM, BE). The three datasets are composed of the same series of document images that suffer from several common document degradations such as smear, smudge, bleed-through and low contrast. The DIBCO 2009 dataset contains ten testing images that consist of five degraded handwritten documents and five degraded printed documents. The H-DIBCO 2010 dataset consists of ten degraded handwritten documents. The DIBCO 2011 dataset contains eight degraded handwritten documents and eight degraded printed documents. In total, we have 36 degraded document images with ground truth. Based on this ranking score scheme, the performance of our proposed method is relative to other methods to compare. It's clear that our proposed method extracts the text better than the other comparison methods. Besides the comparison methods mentioned above, our proposed method is also compared with the top three algorithms, namely Lelore et al.'s method (LELO), the method submitted by our team (SNUS) and N. Howe's method (HOWE) for the DIBCO 2011 dataset. The quantitative results are shown in Table 4.3. As Table 4.3 shown, our proposed technique performs the best in terms of DRD and MPM, which means that our proposed technique maintains good text stroke contours and provides best visual quality. In addition, out proposed method also performs well when being evaluated in pixel level.

Table 4.1. *Evaluation Results of the dataset of DIBCO 2009*

Methods	F-Measure(%)	PSNR	NRM($\times10^{-2}$)	MPM($\times10^{-3}$)	Rank Score
OTSU[12]	78.72	15.34	5.77	13.33	196
SAUV[18]	85.41	16.39	6.94	3.2	177
NIBL[19]	55.82	9.89	16.4	61.5	251
BERN[14]	52.48	8.89	14.29	113.8	313
GATO[21]	85.25	16.5	10	0.7	176
LMM[5]	91.06	18.5	7	0.3	126
BE[4]	91.24	18.6	4.31	0.55	101
Proposed method	93.5	19.65	3.74	0.43	100

Table 4.2. *Evaluation Results of the dataset of H-DIBCO 2010*

Methods	F-Measure(%)	Pseudo F-Measure(%)	PSNR	NRM($\times10^{-2}$)	MPM($\times10^{-3}$)	Rank Score
OTSU[12]	85.27	19.83	17.51	9.77	1.35	188
SAUV[18]	75.3	84.22	15.96	16.31	1.96	225
NIBL[19]	74.1	85.4	15.73	19.06	1.06	263
BERN[14]	41.3	44.4	8.57	21.18	115.98	244
GATO[21]	71.99	74.35	15.12	21.89	0.41	284
LMM[5]	85.49	92.64	17.83	11.46	0.37	216
BE[4]	86.41	88.25	18.14	9.06	1.11	202
Proposed method	92.03	94.85	20.12	6.14	0.25	178

4.3 Testing on Bickley Diary Dataset

In the last experiment, we evaluate our method on the Bickley diary dataset to show its robustness and superior performance. The images from Bickley diary dataset are taken from a photocopy of a diary that is written about 100 years ago. These images suffer from different kinds of degradation, such as water stains, ink bleed-through, and significant foreground text intensity and are more challenging than then previous two DIBCO and H-DIBCO datasets. We use seven ground truth images that are annotated manually using Pix Labeler [46] to evaluate our proposed method with the other methods. Our proposed method achieves average 78.54% accuracy in terms of F-measure, which is at least 10% higher than the other seven methods. Detailed evaluation results are illustrated in Table 4.3.

Table 4.3. *Evaluation results of bickley diary dataset*

Methods	F-Measure(%)	PSNR	NRM($\times10^{-2}$)	MPM($\times10^{-3}$)
OTSU[12]	50.42	7.58	21.41	196.98
SAUV[18]	64.60	11.62	23.26	28.97
NIBL[19]	67.71	9.79	9.52	105.17
BERN[14]	52.97	7.71	18.86	193.35
GATO[21]	69.13	11.44	21.89	36.57
LMN[5]	66.44	10.76	17.50	72.08
BE[4]	34.65	3.54	40.78	370.15
Proposed method	78.54	13.15	12.92	16.71

5. Simulation Results

The proposed paper discusses a document image binarization technique. It involves only minimum number of parameters. It has been tested on various images in DIBCO datasets and Bickley diary datasets. The proposed document image binarization technique combines the local image contrast and local image gradient. The binarization performance of the proposed method is evaluated in terms of F-measure, PSNR, Negative Rate Matric (NRM), and Miss Classification Penality Metric (MPM). PSNR of proposed method is considerably higher than the previous methods. The evaluation measures are adapted from the DIBCO report including F-measure, peak signal-to-noise ratio (PSNR), negative rate metric (NRM), and misclassification penalty metric (MPM). In particular, the F-measure is defined as follows:

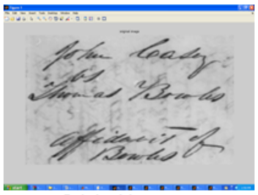
$FM= 2*RC*PRRC+PR$

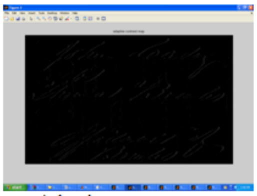
Where RC and PR refer the binarization recall and the binarization precision, respectively. This metric measures how well an algorithm can retrieve the desire pixels. The PSNR is defined as follows:

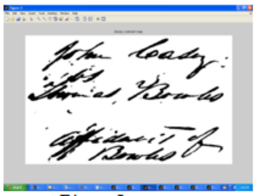
$PSNR=10\log (C2MSE)$

Where MSE denotes the mean square error and C is a constant and can be set at 1. The normalization factor D is the sum over all the pixel-to-contour distances of the ground truth object. This metric measures how well the result image represents the contour of ground truth image.

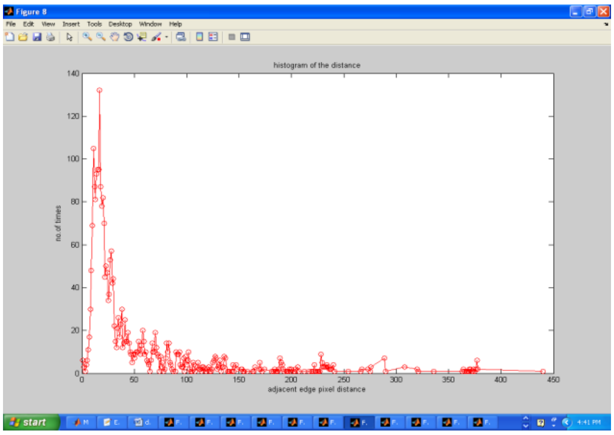
6. Screen Shots


Original image

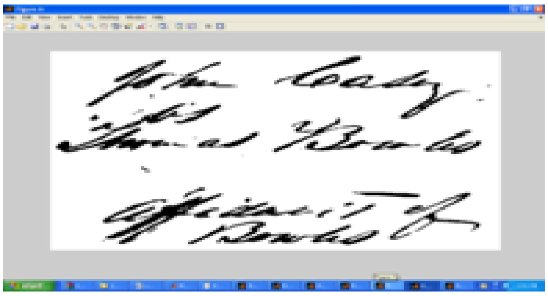

Adaptive contrast map


Binary Image


Using Canny Edge Map



Histogram of edge pixel



characters segmented

Input Image with character Segmented using bounding

7. Conclusion

This system presents an adaptive image contrast based document image binarization technique that is tolerant to different types of document degradation such as uneven illumination and document smear. The proposed technique is simple and robust, only few parameters are involved. Moreover, it works for different kinds of degraded document images. The proposed method has been tested on the various datasets. Experiments show that the proposed method outperforms most reported document binarization methods in term of the F-measure, pseudo F-measure, PSNR, NRM, MPM and DRD. The proposed paper discusses a document image binarization technique. It involves only minimum number of parameters. It has been tested on various images in DIBCO datasets and Bickley diary datasets. The proposed document image binarization technique combines the local image contrast and local image gradient. The binarization performance of the proposed method is evaluated in terms of F-measure, PSNR, Negative Rate Matric(NRM), and Miss classification Penality Metric(MPM). PSNR of proposed method is considerably higher than the previous methods. Hence the proposed method extracts the text better than previous methods. Value of F-measure, MPM and NRM are more close to the previous best performing methods. The proposed method also solve the over binarization problem in the previous paper.

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