ICDAR 2009 Document Image Binarization Contest (DIBCO 2009)

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Abstract

DIBCO 2009 is the first International Document Image Binarization Contest organized in the context of ICDAR 2009 conference. The general objective of the contest is to identify current advances in document image binarization using established evaluation performance measures. This paper describes the contest details including the evaluation measures used as well as the performance of the 43 submitted methods along with a short description of each method.

1. Introduction

Document image binarization is an important step in the document image analysis and recognition pipeline. Therefore, it is imperative to have a benchmarking dataset along with an objective evaluation methodology in order to capture the efficiency of current document image binarization practices. To this end, we organized the first International Document Image Binarization Contest (DIBCO 2009) in the context of ICDAR 2009 conference. In this contest, we focused on the evaluation of document image binarization methods using a variety of scanned machine-printed and handwritten documents for which we created the binary image ground truth following a semi-automatic procedure based on [1]. The authors of submitted methods registered in the competition and downloaded representative samples along with the corresponding ground truth. At a next step, all registered participants were required to submit their binarization executable. After the evaluation of all candidate methods, the testing dataset (5 machine-printed and 5 handwritten images with the associated ground truth) along with the evaluation software became publicly available (http://www.iit.demokritos.gr/~bgat/DIBCO2009/benchmark).

The remainder of the paper is structured as follows: Each of the methods submitted to the competition is briefly described in Section 2. The evaluation measures are detailed in Section 3. Experimental results are shown in Section 4 while in Section 5 conclusions are drawn.

2. Methods and participants

Thirty five (35) research groups have participated in the competition with forty three (43) different algorithms (several participants submitted more than one algorithm). Brief descriptions of the methods are given in the following (The order of appearance is based upon the order of submission of the algorithm).

1) The Generations Network, Inc. USA (*D. Curtis*): The "Generations Network Binarization algorithm" referenced in [2].

2) Meisei University, Japan (*Y. Shima*): Adaptive binarization technique that relies on the detection of background using a filtering process that applies a mapping of the original grey level value based on a predefined threshold table.

3) Democritus University of Thrace, Greece (*M. Makridis, N. Papamarkos*): The technique focuses on degraded documents with various background patterns and noise. It is based on [3]. It involves a pre-processing local background estimation stage. The estimated background is used to produce a new enhanced image having uniform background layers and increased local contrast. The new image is a combination of background and foreground layers. Foreground and background layers are then separated by using a new transformation which exploits efficiently, both grey-scale and spatial information. The final binary document is obtained by combining all foreground layers.

4) South University of Toulon-Var, France (*F. Bouchara, T. Lelore*): The algorithm is based on a statistical model of the image in which the text and the background are assumed to be Gaussian processes. The different parameters of the two processes, and the label of each pixel (text or background), are estimated

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due to both EM algorithm and Maximum Likelihood rule. Heuristics rules are applied as a post processing to remove stamps and noise.

5) University of the Aegean, Greece (*E. Kavallieratou*): A hybrid approach that combines global and local thresholding. It is an improved version of [4]. First, a global binarization technique based on an iterative procedure is applied. Then, the areas that still contain noise are further processed independently. The main idea for detecting the areas with remaining noise is based on the fact that such areas will include more black pixels on average in comparison with other areas. These areas are separately re-processed based on local thresholding.

6) University of Groningen, The Netherlands (*A. Brink*): An algorithm based on heuristics and the knowledge that the signal consists of high frequencies. First, gradual intensity variations of the background are removed using high pass filtering. Then, Otsu thresholding [5] is applied in two phases. In the first phase, a threshold value is determined using Otsu's method. In the second phase, pixels are categorized as "surely foreground", "surely background" or "undecided". For the "undecided" pixels, before proceeding to thresholding, the original greyscale value is increased by a correction based on the fraction of sure foreground pixels in a 21x21 neighborhood. Finally, part of the remaining noise is removed by flipping isolated pixels.

7) Institute of Space Technology, Pakistan – (*K. Khurshid*): The proposed approach [6] is based on Niblack's algorithm. It considerably improves binarization for "white" and light page images by shifting down the binarization threshold. The submitted algorithm has the variations in the following:

a. The window size equals to 19

b. The window size equals to 45

c. The thresholding formula instead of being applied on a local window, it is applied to the whole image.

8) East China Normal University, China (*G. Gu*): An illumination compensation algorithm is used to convert the unevenly lighted document to an evenly lighted document. The visual model used is physically realistic and the estimation can be iteratively implemented for higher accuracy. The compensated image is then binarized by applying an improved locally adaptive approach based on Otsu.

9) Université de Lyon, INSA, France (*C. Wolf*) :

a. The proposed algorithm [7] is based on sliding a rectangular window over the document image calculating the mean and standard deviation of the grey values in each window. The minimum mean and the maximum standard deviation over all windows is calculated. Thereafter, sliding a rectangular window is again applied over the document image, and the threshold surface is calculated. Finally, the Sauvola et al. equation [8], is modified by the minimum mean and maximum standard deviation.

b. A binarization algorithm based on Markov random fields and a modified version of Sauvola et al. algorithm. The submitted algorithm (i) uses a different calculation of the threshold in order to adapt to images which do not satisfy the original hypothesis of having text grey levels close to 0 and background grey levels close to 255 and (ii) regularizes the threshold decision through a MRF Potts model.

10) Tsinghua University, China, (*X. Shen*): The method is based on (i) edge detection, (ii) connected component extraction from the edge image in order to have a draft text detection result, (iii) an iterative method to find a global threshold for the text areas and (iv) a pruning to adjust the binary image using line structure in the document image.

11) Centre de Morphologie Mathématique, France (*B. Marcotegui, J. Hernández*): The method is based on the ultimate attribute closing. A variant of this operator, the ultimate attribute closing with accumulation is used in order to improve the results on blurred images. This operator filters out potential illumination changes, as well as noise inside characters. Noise is filtered out as long as it is less contrasted than the character itself with respect to its background. The obtained contrast information is then thresholded using the Otsu binarization method. Finally, small connected components are removed.

12) Google R&D Bangalore, India (*A. Jain*): In the proposed technique, the tiled-LOG (Laplacian-of-Gaussian) based binarization is first used to detect the foreground edge components and then an adaptive Sauvola binarization is used to detect the background. A post-processing is applied to fill holes inside characters.

13) University of Sfax, Tunisia (M. Chakroun, M. Charfi, M.A. Alimi): The approach is based on combining two thresholding methods, a local thresholding method based on wavelet transform and a global thresholding using Otsu's binarization.

14) Université Pierre et Marie Curie & CMM, France (*J. Fabrizio, B. Marcotegui*): The proposed algorithm is based on the toggle mapping operator [9]. The image is first mapped on the corresponding morphological erosion and dilation. Then, if the pixel value is closer to the erosion, it is marked as background otherwise it is marked as foreground. To avoid salt and pepper noise, pixels whose erosion and dilation are too close, are excluded from the analysis. Pixels are then classified into three classes: foreground, background and homogeneous. Finally, homogeneous regions are assigned to foreground or background according to the class of their boundaries. A hysteresis threshold is also used in order to reduce the critical effect of the threshold parameter.

15) Freie Universität Berlin, Germany (*M.Block, R.Rojas*): The proposed Local Contrast Segmentation (LCS) method [10] is based on positive and negative pixel energies using the Laplacian of the image. After a filtering step and applying morphological operations, the local contrast segmentation method is able to detect connected components.

16) Universidade Federal de Pernambuco, Brazil (*D.M. Oliveira, R.D. Lins*): The algorithm is based on (i) image splitting into blocks, (ii) RGB histogram computation taking into account an area around the blocks, (iii) merging regions when considered Narrow Gaussian (NG) Blocks with similar colors, (iv) defining the background by analyzing the NG blocks and (v) applying Otsu's method to obtain the final binary image.

17) University of Joensuu, Finland (*M. Chen, Q. Zhao, T. Kinnunen, R. Saeidi and P. Franti*): The proposed algorithm is based on (i) applying Otsu's method to detect potential object pixels, (ii) performing local surface fitting using the background, (iii) thresholding using the differential image between the original and fitted surface image, (iv) performing a two step binarization based on Otsu as well as on a edge-based method and (v) filling holes, removing artifacts and applying a post-processing.

18) Centre de morphologie mathématique, France (*J. Hernández, B. Marcotegui)*: The proposed method is based on the morphological operator ultimate opening (UO) [11]. First, ultimate attribute openings (UAO) of height and width attributes are carried out in order to extract the most contrasted structures in both directions. The contrast output of UAO is binarized by the classical Otsu algorithm. Finally, small and isolated structures are eliminated.

19) Freie Universität Berlin, Germany (*M. Ramirez, E. Tapia and R. Rojas*): The main idea is to compute transition values using pixel-intensity differences in a neighborhood around the pixel of interest [12]. Two subsets are considered in the neighborhood corresponding to high positive and negative transition values, called transition sets. These sets are refined by morphological operators in the transition image. The binarization threshold is computed over the pixels in the transition sets using a statistical model to generate a preliminary binary image. Finally, stains are removed using several morphological operators while erroneous connected components are detected and removed using contextual rules.

20) University of Quebec, Canada (*R. Hedjam, R. F. Moghaddam and M. Cheriet*): The method uses Markovian-Bayesian segmentation to convert the input image into many coherent regions which represent the strokes of the text and also the background. The obtained regions are merged based on a metric which can differentiate between regions of the text and the others regions representing the rest of the document image. Finally, the resulting regions are classified as either text or as regions that form the background and correspond to existing defects on the document.

21) Universidade Federal de Pernambuco, Brazil (*R.D. Lins, J.M.M. da Silva*): The proposed algorithm [13] takes into account several global statistical measures which result in the calculation of the a posteriori probability distribution of the grey values in the image. The desired threshold is equal to the required number of additions so that the summation of a priori distribution probabilities becomes as close as possible to the a posteriori probability distribution.

22) The Neat Company, PA, USA (*H. Ma*): The approach consists of four steps: (i) Foreground detection; (ii) Cleaner image generation; (iii) Niblack Adaptive binarization [14] and (iv) Post-processing.

23) University of Sfax, Tunisia (*F. Drira, F. LeBourgeois*): The algorithm is the application of a pre-processing procedure using a tensor based diffusion process [15] followed by the binarization algorithm proposed by Wolf et al. [16]. The use of the pre-processing step has many useful properties mainly a noticeable improvement of the visual text quality, the preservation of the stroke connectivity and the reinforcement of character discontinuity.

24) University of Quebec, Canada (*D. Rivest-Hénault, R.F. Moghaddam and M. Cheriet*): The method takes advantage of local probabilistic models and the calculus of variation [17][18]. The statistics of the input image are used for the automatic estimation of the stroke width. Based on this, very small regions with small confidence scores are removed. The produced stroke map is eroded using a curve evolution approach implemented in the level set framework using an energy term which measures the fitness of the stroke pixels with respect to the stroke grey level map.

25) University of Quebec, Canada (*R.F. Moghaddam*): The core of the method is based on the multi-level classifiers [17] [18] which are capable to extract and identify information on different levels from local to global. On each level, a set of parameters is used as the a priori information of the document image. These parameters are estimated by analysis of the input image automatically.

26) Institute for Infocomm Research, Singapore (*S. Lu, C.L. Tan*): The algorithm includes four parts, which deal with document background extraction, stroke edge detection, local thresholding, and post-processing, respectively. The local threshold is estimated by averaging the detected edge pixels within a local neighbourhood window.

27) University of Sfax, Tunisia (*A. Bougacha, W. Boussellaa, A.M. Alimi*): The algorithm comprises a pre-processing step in which an histogram equalisation is applied and a segmentation step which is based on Maximum Likelihood with a parameter estimation using the EM algorithm where the underlying probability distributions follow the Raleigh law.

28) Google R&D Bangalore, India (*K. Chaudhury, A. Jain, S. Thirthala, V. Sahasranaman, S. Saxena and S. Mahalingam*): The algorithm tries to identify foreground using local contrast. It does not use any absolute global or local threshold value explicitly. Specifically, this is a dome detection-based document image binarizer. The dome detection is implemented using grey scale image reconstruction. The final binarization result is refined by a post-processing step.

29) University of Malta (*A. Bonnici, K.P. Camilleri*): The algorithm makes Bernsen's original algorithm adaptive by applying the following modifications [19]: (i) The contrast threshold is evaluated for sub-regions within the image, rather than using a fixed pre-defined value. This captures the different contrasts that may be present within the image and between different images that require binarization; (ii) The window size is evaluated adaptively based on the size of the strokes in the image, allowing adjustable window sizes for images containing different stroke thickness.

30) University at Buffalo, SUNY, USA (*Z. Shi, S. Setlur, V. Govindaraju*): The algorithm is based on adaptive document image normalization [20][21]. Finally, Otsu's global algorithm is applied on the normalized image to get the binary result.

31) Pune Institute of Computer Technology, India (*S.D. Shelke*): The method first passes the image through a 3x3 averaging filter that bridges small gaps in the character. Then, a grey level classification operation is performed which classifies the pixel values into four distinct classes. The image after classification was then passed to an adaptive binarization technique to obtain the final result.

32) Universitat Autonoma de Barcelona, CVC (*R. Coll*): Initially, a blurring operation is performed over the greyscale image. After that, the AINDANE algorithm [22] is applied to the image to increase the contrast and enhance the luminance. The edges of the resulting image are extracted using Canny edge detection. Thereafter, the edges are dilated and smoothed to achieve a probability matrix where, once normalized, each position represents the probability that the pixel belongs to foreground or background class. Using this probability matrix, a luminance enhanced greyscale image is computed in which morphological operations are performed to extract the detected background. Finally, the remaining foreground is binarized using the Otsu's method.

33) Google, Inc., Mountain View, USA (*D. Bloomberg*):

a. Image binarization using a local background normalization, followed by a global threshold.

b. Image binarization using a local background normalization, followed by a modified Otsu approach to get a global threshold that can be applied to the normalized image.

c. Image binarization using a local background normalization with two different thresholds. For the part of the image near the text, a high threshold can be chosen, to render the text fully in black. For the rest of the image, much of which is background, use a threshold based on the Otsu global value for the original image.

34) Boise State University, USA & Telecom ParisTech, France & Math dept., UCLA, USA (*E. H. Barney Smith, L. Likforman and D. Jerome*): There are two submissions :

a. The method is based on the total variation image regularization procedure.

b-d The method is based on Non-local Means that enter the competition with three variations. The variation concerns the parameter β which is used in the corresponding energy term. The values used for β are 20, 30, 40, respectively.

For both these methods, the binarization depends on regularizing the grey scale image to reduce variations in the vicinity of the characters themselves. Then the background shading of the image is estimated with an envelope detector and subtracted from the image. A global threshold determined by the Otsu method is then applied to perform the actual binarization.

35) Google, Inc., Mountain View, USA (*R. Romano*): The algorithm is a data-driven thresholder combiner: it runs six thresholding algorithms with fixed parameters (Sauvola, Otsu, Niblack, and three distinct locally-adaptive thresholders) on the input image and for each pixel creates a feature vector of each thresholder's output value at that pixel and the thresholder outputs at each of its 4 neighbors (top, bottom, left, right). It then runs a binary linear classifier on the 30-dimensional feature vector to decide whether the given pixel should be labeled foreground or background. The classifier used for this entry was trained only on the 4 example images supplied by the DIBCO organizers (for lack of additional ground truth data).

3. Evaluation Measures

For the evaluation, the measures used comprise an ensemble of measures that have been widely used for evaluation purposes. These measures consist of (i) F-Measure; (ii) PSNR; (iii) Negative Rate Metric and (iv) Misclassification Penalty Metric.

3.1. Definitions

- F-Measure

$$FMeasure = \frac{2 \times \text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \tag{1}$$

where $\text{Recall} = \dfrac{TP}{TP + FN}$, $\text{Precision} = \dfrac{TP}{TP + FP}$

TP, FP, FN denote the True positive, False positive and False Negative values, respectively.

- PSNR

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

where $MSE = \dfrac{\sum_{x=1}^{M}\sum_{y=1}^{N}(I(x,y) - I'(x,y))^2}{MN}$

PSNR is a measure of how close is an image to another. Therefore, the higher the value of PSNR, the higher the similarity of the two images. We consider that the difference between foreground and background equals to *C*.

- Negative Rate Metric (NRM)

The negative rate metric NRM is based on the pixel-wise mismatches between the GT and prediction. It combines the false negative rate NR_{FN} and the false positive rate NR_{FP}. It is denoted as follows:

$$NRM = \frac{NR_{FN} + NR_{FP}}{2} \tag{3}$$

where $NR_{FN} = \dfrac{N_{FN}}{N_{FN} + N_{TP}}$, $NR_{FP} = \dfrac{N_{FP}}{N_{FP} + N_{TN}}$

N_{TP} denotes the number of true positives, N_{FP} denotes the number of false positives, N_{TN} denotes the number of true negatives, N_{FN} denotes the number of false negatives.

In contrast to F-Measure and PSNR, the binarization quality is better for lower NRM.

- Misclassification penalty metric (MPM)

The Misclassification penalty metric MPM evaluates the prediction against the Ground Truth (GT) on an object-by-object basis. Misclassification pixels are penalized by their distance from the ground truth object's border.

$$MPM = \frac{MP_{FN} + MP_{FP}}{2} \tag{4}$$

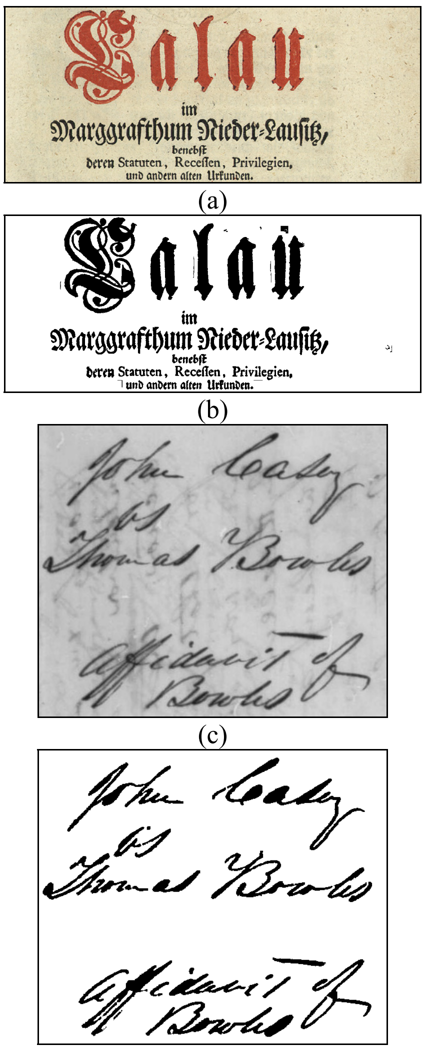
where $MP_{FN} = \dfrac{\sum_{i=1}^{N_{FN}} d_{FN}^i}{D}$, $MP_{FP} = \dfrac{\sum_{j=1}^{N_{FP}} d_{FP}^j}{D}$

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 GT segmentation. The normalization factor *D* is the sum over all the pixel-to-contour distances of the GT object. A low MPM score denotes that the algorithm is good at identifying an object's boundary.

4. Experimental Results

The DIBCO testing dataset consists of 5 machine-printed and 5 handwritten images resulting in a total of 10 images for which the associated ground truth was built for the evaluation. A representative example of the dataset is shown in Fig. 1(a),(c). The documents of this dataset originate from the collections of the following libraries: The Goettingen State and University Library (UGOE), The Bavarian State Library, the British Library and the Library of Congress. The selection of the images in the dataset was made so that should contain representative degradations which appear frequently (e.g. variable background intensity, shadows, smear, smudge, low contrast, bleed-through and show-through).

The evaluation was based upon the four distinct measures presented in Section 3. The final ranking as shown in Table 1 was calculated after sorting the accumulated ranking value for all measures. At Table 1, the detailed performance for each algorithm is also given. We further provide graphs that show the performance of the binarization algorithms in terms of F-Measure and PSNR (see Fig. 2). Overall, the best performance is achieved by ***Algorithm 26*** which has been submitted by S. Lu and C.L. Tan of the Institute for Infocomm Research in Singapore. Example binarization results of this algorithm is shown in Fig. 1(b),(d).



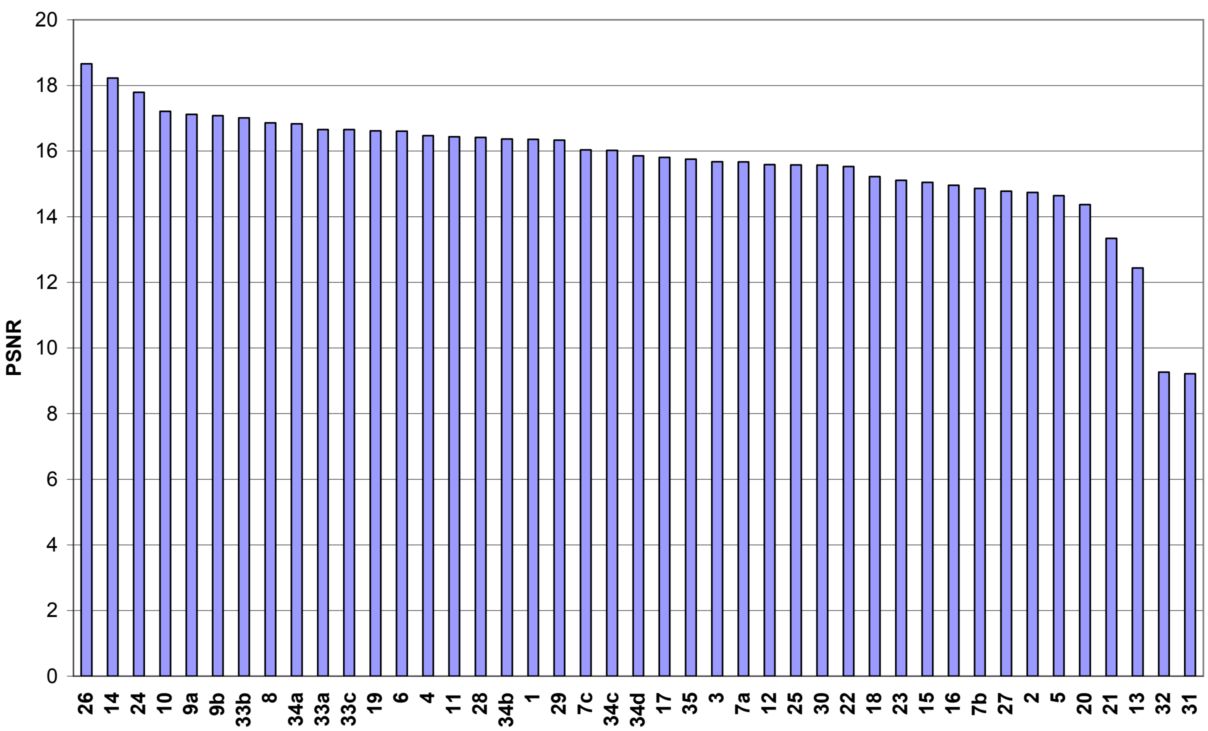
(a) (b) (c) (d)

Figure 1. Representative samples and corresponding binarization results from DIBCO 2009 testing dataset (a) Original printed image; (b) Binarized machine printed image; (c) Original handwritten image; (d) Binarized handwritten image.

Table 1. Evaluation results wrt to the measures used for all methods submitted to DIBCO 2009.

Rank	Method	F-Measure (%)	PSNR	NRM ($x10^{-2}$)	MPM ($x10^{-3}$)
1	**26**	91,24	18,66	4,31	0,55
2	**14**	90,06	18,23	4,75	0,89
3	**24**	89,34	17,79	5,32	1,90
4	**10**	87,03	17,21	7,03	0,57
5	**9a**	87,89	17,12	7,73	0,97
6	**8**	87,71	16,86	5,99	2,19
7	**33c**	86,35	16,66	6,03	1,45
8	**9b**	87,16	17,08	8,5	0,74
9	**4**	86,53	16,47	5,41	1,76
10	**34a**	87,49	16,83	7,76	1,57
11	**33b**	85,66	17,01	11,37	0,52
12	**6**	86,93	16,61	7,29	2,58
13	**11**	85,72	16,44	8,94	1,12
14	**34b**	85,99	16,37	8,28	1,46
15	**35**	85,11	15,75	5,38	2,22
16	**33a**	84,59	16,66	11,48	0,61
17	**1**	85,06	16,36	6,49	3,78
18	**34c**	84,78	16,02	8,73	1,50
19	**25**	83,99	15,58	4,18	4,60
20	**3**	85,30	15,68	7,59	4,18
21	**7c**	85,17	16,04	9,93	1,93
22	**17**	83,98	15,81	4,51	5,48
23	**34d**	84,03	15,86	8,78	1,40
24	**29**	84,69	16,33	7,96	3,83
25	**18**	83,74	15,22	4,62	3,86
26	**23**	82,50	15,11	4,47	3,62
27	**12**	83,53	15,59	4,91	5,34
28	**22**	83,54	15,53	7,62	3,54
29	**7a**	84,57	15,67	7,81	5,84
30	**28**	84,25	16,42	9,13	7,46
31	**30**	83,62	15,57	7,67	5,53
32	**2**	83,10	14,74	5,18	7,11
33	**19**	79,71	16,62	9,93	4,55
34	**7b**	80,74	14,86	5,98	9,60
35	**5**	80,90	14,64	8,17	4,22
36	**15**	74,12	15,05	18,07	2,57
37	**16**	82,27	14,96	8,04	41,30
38	**21**	75,86	13,34	15,45	2,51
39	**20**	80,43	14,37	8,21	7,70
40	**27**	82,74	14,78	10,12	56,22
41	**13**	35,28	12,44	36,60	2,68
42	**31**	61,48	9,22	14,69	86,03
43	**32**	58,77	9,27	18,77	118,02

(a)



(b)

Figure 2. Graphs that show the performance of the binarization algorithms submitted in DIBCO 2009 in terms of (a) F-Measure and (b) PSNR.

5. Conclusions

The DIBCO 2009 Document Image Binarization Contest attracted 35 research groups that are currently active in document image analysis. The increased interest in this competition is a two-fold proof: first, it shows the importance of binarization as a step towards an effective document image recognition and second, the need for pursuing a benchmark that will lead to a meaningful and objective evaluation.

Our hope is that DIBCO 2009 will become a reference benchmark for binarization which will serve the evolution of research in the next years.

References

[1] K. Ntirogiannis, B. Gatos and I. Pratikakis, "An Objective Evaluation Methodology for Document Image Binarization Techniques", In *Proc. of the 8th International Workshop on Document Analysis Systems (DAS'08)*, Nara, Japan, September 2008, pp.217-224

[2] D.B. Curtis, "Evaluating Binarization Techniques for Optical Character Recognition," IS&T Archiving 2007 Proceedings, pp. 110 – 112.

[3] M. Makridis and N. Papamarkos, "An adaptive layer-based local binarization technique for degraded documents", *International Journal of Pattern Recognition and Artificial Intelligence*, to appear.

[4] E.Kavallieratou, E.Stamatatos, "Improving the quality of degraded document images", *Proc. of the Second International Conference on Document Image Analysis for Libraries (DIAL'06)*, 2006, pp. 340-349.

[5] N. Otsu, "A threshold selection method from gray-level histograms", *IEEE Trans. Systems Man Cybernet.* Vol. 9 (1), 1979, pp. 62–66.

[6] K. Khurshid, I. Siddiqi, C. Faure, N. Vincent, "Comparison of Niblack inspired binarization techniques for ancient document images", *16th International conference on Document Recognition and Retrieval*, 2009, to appear.

[7] C. Wolf, J-M Jolion and F. Chassaing, "Text Localization, Enhancement and Binarization in Multimedia Documents", In *Proc. of the International Conference on Pattern Recognition (ICPR)*, volume 4, 2002, pp. 1037-1040.

[8] J. Sauvola, M. Pietikainen, "Adaptive document image binarization", *Pattern Recognition*, Vol. 33, 2000, pp. 225–236.

[9] J. Serra, "Toggle mappings, from pixels to features" J.C. Simon (ed.), Elsevier, 1998.

[10] M.Block, R.Rojas, "Local Contrast Segmentation to Binarize Images", In *Proc. of the 3rd International Conference on Digital Society (ICDS 2009)*, Vol.1, No.1, Cancun/Mexico, 2009, pp.294-299.

[11] T. Retornaz and B. Marcotegui, "Scene text localization based on the ultimate opening" In *Proc. of the 8th International Symposium on Mathematical Morphology (ISMM'07)*, Vol. 1, 2007, pp. 177-188.

[12] M. Ramirez, E. Tapia, M. Block, R. Rojas, "Quantile linear algorithm for robust binarization of digitalized letters", In *Proc. of the 9th International Conference on Document Analysis and Recognition (ICDAR '07)*, 2007, pp. 1158–1162.

[13] J. M. M. da Silva, R. D. Lins, F. M. J. Martins, R. Wachenchauzer, "A New and Efficient Algorithm to Binarize Document Images Removing Back-to-Front Interference" *Journal of Universal Computer Science*, v. 14, 2008, pp. 299-313.

[14] W. Niblack, "An Introduction to Digital Image Processing", Prentice-Hall, 1986, pp. 115–116.

[15] F. Drira, F. LeBourgeois and H. Emptoz, "Document images restoration by a new tensor based diffusion process: Application to the recognition of old printed documents", In *Proc. of the 10th International Conference on Document Analysis and Recognition (ICDAR)*, 2009, Spain, to appear.

[16] C. Wolf, J.-M. Jolion and F. Chassaing, "Text Localization, Enhancement and Binarization", In *Proc. of the International Conference on Pattern Recognition (ICPR)*, Canada, volume 4, 2002, pp. 1037-1040.

[17] R.F. Moghaddam and M. Cheriet, "EFDM: Restoration of Single-sided Low-quality Document Images", *ICFHR'08*, 2008, pp. 204-209.

[18] D. Rivest-Henault and M. Cheriet, "Image Segmentation Using Level Set and Local Linear Approximations", *ICIAR 2007*, pp. 234-245.

[19] A. Bartolo, K.P. Camilleri, J.C. Borg and P.J. Farrugia, "Adaptation of Brensen's Thresholding Algorithm for Sketched Line Drawings", In *Proc. of the Eurographics 2004 Workshop on Sketch-based Interfaces and Modelling*, Grenoble, France, pp. 81-90.

[20] Z. Shi and V. Govindaraju, "Historical Document Image Segmentation Using Background Light Intensity Normalization", *SPIE Document Recognition and Retrieval XII*, 2005, San Jose, California, USA.

[21] Z. Shi, S. Setlur and V. Govindaraju, "Digital Enhancement of Palm Leaf Manuscript Images using Normalization Techniques". In *Proc. 5th International Conference On Knowledge-Based Computer Systems*, Hyderabad, India, December 19-22, 2004.

[22] L. Tao, V.K. Asari, "Adaptive and integrated neighborhood-dependent approach for nonlinear enhancement of color images", *Journal of Electronic Imaging*, 2005.