ICDAR 2013 Document Image Binarization Contest (DIBCO 2013)

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***Abstract* - DIBCO 2013 is the international Document Image Binarization Contest organized in the context of ICDAR 2013 conference. The general objective of the contest is to identify current advances in document image binarization for both machine-printed and handwritten document images using evaluation performance measures that conform to document image analysis and recognition. This paper describes the contest details including the evaluation measures used as well as the performance of the 23 submitted methods along with a short description of each method.**

I. INTRODUCTION

Document image binarization is of great importance in the document image analysis and recognition pipeline since it affects further stages of the recognition process. The evaluation of a binarization method aids in verifying its effectiveness and studying its algorithmic behaviour. To this end, following the success of DIBCO 2009 [1] and DIBCO 2011 [2] organized in conjunction with ICDAR 2009 and 2011 respectively, as well as H-DIBCO 2010 [3] and H-DIBCO 2012 [4] organized in conjunction with ICFHR 2010 and 2012 respectively, the follow-up of these contests, namely DIBCO 2013 is organized in the framework of ICDAR 2013. 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. 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 (8 machine-printed and 8 handwritten images with the associated ground truth) along with the evaluation software are publicly available at the following link:
(http://utopia.duth.gr/~ipratika/DIBCO2013/benchmark).

II. METHODS AND PARTICIPANTS

Eighteen (18) research groups have participated in the competition with twenty three (23) distinct algorithms (one participant submitted two algorithms and each of two other participants submitted three algorithms). Brief descriptions of the methods are given in the following (the order of appearance is the chronological order of submission of the algorithm).

1) University of Tebessa and Badji-Mokhtar University of Annaba, Algeria (*Chawki Djeddi and Labiba Souici-Meslati*): The proposed algorithm is based on three processing steps, namely, preprocessing, thresholding and post-processing, while details are given in [5]. In preprocessing, conditional noise removal and edge-based processing is performed. The thresholding step involves a computation of final threshold for background and text segmentation based on an average value computed through multiple thresholds (based on 4 different thresholding formulas inspired by Niblack [6]). In the final step, post processing comprises conditional noise removal and constrained morphological operations which are performed to get the final binarized image.

2) Tata Consultancy Services, Innovation Lab, Kolkata, India (Ramu Vempada Reddy, *Tanushyam Chattopadhyay and Utpal Garain*): The proposed method is based on the selection of a set of one or more binarization techniques suitable for different regions of the document. This selection is completely automatic and guided by the machine learning approaches used beforehand. In this method, the image is initially segmented into k regions and m different methods are applied on each of these segments and concatenate all possible combinations (m^k) of binarized images. Each of these binarized images are compared against the ground truth to check which one gives better performance in terms of recall, precision, F-Measure and select it as a candidate for learning set. The system is trained using SVM. The trained data are used to predict the best

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DOI 10.1109/ICDAR.2013.219

binarization technique for each of the segments in a test image. Details of the method are given in [7].

3) Smith College, MA, USA (*Nicholas R. Howe*): The technique is described in [8]. Briefly, it employs a base algorithm that minimizes a global energy function based upon the Laplacian image, with peer pressure between neighboring pixels modulated by the location of Canny edges. It then automatically determines promising settings for peer pressure and Canny parameters by applying a stability criterion to the resulting binarizations.

4) Osaka University, Japan (*Hiromi Yoshida*): The proposed binarization method uses mathematical morphology along with a multi-resolution methodology. At a first step, an input image is preprocessed for noise reduction by median filter and top-hat operation, and two images are generated which have different resolution based on a Gaussian pyramid. A low resolution image can be obtained by using Gaussian blur and high resolution one is obtained by Gaussian up-sampling and adding the estimated high-frequency component based on Laplacian pyramid. The high resolution image is expected to contain character region in a detail with much noise while the low resolution one is expected to contain general character region with little noise. At the second step, these two images are binarized by any threshold method (in this work, discriminant analysis method is used). At the third step, after up-sampling or down-sampling these two images to the size of input image, the output image is obtained by conditional dilation of them. Here, the condition image is the high resolution image, and the target image of dilation is the low resolution image. This process is expected to achieve an output image which includes character region in a detail with little noise.

5) University of Quebec, Canada and Smith College, MA, USA (*Reza Farrahi Moghaddam, Fereydoun Farrahi Moghaddam, Nicholas R. Howe and Mohamed Cheriet*): In this entry the Laplacian-energy binarization method introduced in [8] is combined with the Ensemble-of-Expert (EoE) framework [9]. The Laplacian-energy method, inspired by a Markov random field model, defines the binarization as a minimization problem for a global energy function. The fidelity term of this function is defined based on the intensity Laplacian that is highly contrast- and intensity-independent. Moreover, the edge information is used to ensure that the binarization boundaries are aligned with them. In this entry, four parameters of the Laplacian-energy method are used: The hysteresis thresholds of the Canny edge map, the radius of the Gaussian filter, and the mismatch penalty. In addition, the endorsement-weighted EoE variation is used [9].

6) University of Quebec, Canada (*Reza Farrahi Moghaddam, Fereydoun Farrahi Moghaddam, and Mohamed Cheriet*): This binarization method results from the application of the Ensemble-of-Expert (EoE) framework [9] along with the Grid-based Sauvola method [10]. The EoE framework accepts the outputs of various (an ensemble) binarization methods for an input document image. Then, it creates the confidence map of every expert and also the endorsement graph among the experts. Using two highly objective principles, the EoE framework identifies the relevant experts for that input document image, and combines their associated outputs to generate the final output. The two principles are saturated expert opinions and schools of experts. In this entry, the endorsement-weighted EoE variation is used [9]. In this variation, soft weight-based combination is used instead of hard pruning of the irrelevant experts of the original EoE approach. The EoE framework can be used along any binarization method. In this entry, the Grid-based Sauvola method has been used. This method has three parameters, similar to Sauvola's method [11], and uses the grid-based modeling to reduce the computational complexity associated to large patch sizes. At the end of the process, a texture-based post-processing step is applied to the final output.

7) University of Quebec, Canada (*Reza Farrahi Moghaddam, Fereydoun Farrahi Moghaddam, Hossein Ziaei Nafchi and Mohamed Cheriet*): This entry comprises the Ensemble-of-Expert (EoE) framework [9] and the phase congruency binarization method [12]. The phase congruency binarization method uses a combination of phase feature maps, such as maximum moment of phase congruency covariance (MMPCC) and local weighted mean phase angle (LWMPA), regional minima feature map, and also adaptive Gaussian and median filtering in order to provide a robust and consistent binarization performance for various types of degradation. In this entry, only three of its parameters are considered: the number of scales, the number of orientations of the wavelet transform, and also the threshold of noise standard deviation. The endorsement-weighted EoE variation is used [9].

8) Kobe University, The Graduate School of Maritime Sciences, Japan (*Akihiro Okamoto, Yuichi Nakata, Naoki Tanaka*): This research group has submitted **three** algorithms : **(a)** For this entry, in a first step, the character stroke width of each image is roughly estimated which is used to the estimation of the structuring element size for the applied morphological operations. The subsequent process is the same as the group's method which was proposed in H-DIBCO 2012 [4]. **(b)** This entry is composed of several steps, estimating stroke width of character, generating marker image and mask image and reconstructing text region with such marker and mask. The Distance Reciprocal Distortion (DRD) Metric is introduced to estimate the character stroke width. This process is achieved with DRD to comparing tentatively binarized images which are obtained by applying Otsu's method [13] to images which are generated by varying the structuring element in top-hat transform operation. The grayscale input image is transformed with morphological top-hat transformation to remove unwanted background intensity fluctuations. In this operation, the structuring element is determined by the value of the estimated stroke width. The marker image is obtained by applying Canny edge detector to the previous image. The parameters of Canny edge detector are set based on the gradient intensity distribution. The mask image is obtained by binarizing with locally adaptive method only in relation to the character contours which have high gradient values. Finally, morphological reconstruction is conducted using marker and mask images. **(c)** This method first sharpens the original image and binarizes it by local method (Niblack's method [6] with parameters k=-0.2 and w=13.) The binarized image, however, contains many non-character regions which should be removed. A sharpening process (weighted sum of original image and its Laplacian) makes character regions well-separated from noisy background. Therefore, noise regions can be distinguished from target regions by the mean value of gradient magnitude in boundary pixels of each region. A gradient magnitude value is estimated using the Sobel operator. The final value is obtained through the subtraction of the gradient magnitude of blurred image from that of original image, which reduces effectiveness of blunt edges that often appear as a boundary of a character on reverse side. Foreground regions of the binarized image are labeled and those pixels are filled with the gradient value of their boundary (background pixels are filled with zero). The final output of the method is the binarization of this region gradient image with Otsu's method [13].

9) University of Quebec, Canada (*Hossein Ziaei Nafchi,Reza Farrahi Moghaddam and Mohamed Cheriet*): This method is a modified version of the method proposed in [12]. It uses phase-derived features of images to model background and foreground. These features are: i) Denoised image with phase preserved, ii) Maximum moment of phase congruency covariance and iii) Locally weighted mean phase angle. Also, adaptive median and Gaussian filters are applied for further enhancement.

10) Tlemcen University, Algeria and Qatar University, Qatar (*Yazid Hassaine, Abdelaali Hassaine and Somaya Al Maadeed*): This research group has submitted **three** algorithms: **(a)** This method was adapted from a technique for restoration of optical soundtracks of old movies [14] in which the text part is considered as the opaque region of the optical soundtrack. **(b)** This method classifies the edges of the Otsu binarization method [13] as true or false edges using the geometric features introduced in [15]. Regions are eliminated if the majority of their edges are classified as false edges. **(c)** This method combines the two above methods and trains them on all DIBCO databases as well as the QUWI handwriting database [16].

11) Federal University of Pernambuco, Brazil (*Edward Roe, Carlos A.B.Mello and Saulo C.S.Machado*): The binarization is achieved after three main steps: the first step removes undesirable degradation artifacts using a local image equalization and Otsu binarization algorithm [13]. The second step uses global image equalization and an extended difference of Gaussian (XDoG) edge detection operator to binarize the text. The final step combines the two previous steps, performing a cleanup to remove remaining degradation artifacts and fixing possible missing text or area, to produce the final result.

12) National University of Sciences and Technology (NUST), Pakistan (*Syed Ahsen Raza*): The algorithm is based on three steps: preprocessing, thresholding and postprocessing. In preprocessing, conditional noise removal is done using a cascade of filtering operations followed by edge-based processing. The thresholding step involves a computation of final threshold for background and text segmentation based on an average value computed through multiple thresholds (based on 4 different Niblack [6] inspired thresholding formulas). In the final step of post processing, conditional noise removal and constrained morphological operations are performed to get the final binarised image.

13) University of South Toulon Var, France (*Thibault Lelore, Frederic Bouchara*): This entry is based on the algorithm described in [17]. In a first step, the input image is upscaled (x2) using linear interpolation. A robust detection of areas containing text is performed by combining the result of a clustering algorithm achieved around edge detected with two different thresholds. From this merging, we identify problematic areas where some differences occur between the two images. The final binary image is then obtained by recalculating the class of pixels around these problematic areas using an asymmetric neighborhood.

14) Ecole Superieure d'Informatique, Algeria, Université des Sciences et des Technologies Houari Boumedienne, Algeria and Ecole des Technologies Superieurs, Canada (*Abdenour Sehad, Youcef Chibani, Mohamed Cheriet and Yacine Yaddaden*): The method is a pixelwise adaptive thresholding technique based on texture features. The latter is computed by using a descriptor based on a co-occurrence matrix. Some relevant Haralick's parameters are computed, such as the contrast and the mean. The binarization equation is inspired from the the Niblack's method [6].

15) National University of Singapore and Institute for Infocomm Research, Singapore (*Bolan Su, Shijian Lu, Shangxuan Tian and Chew Lim Tan*): This research group has submitted **two** algorithms. **(a)** This entry comprises four main steps. First, the input image is smoothed by a wiener filter, and then the image background is estimated using a previously defined polynomial smoothing method [18]. Second, the input image is then subtracted by the estimated background, and binarized by the adaptive binarization method presented in [19]. Third, the binarization result of the original input image is also obtained using [19]. Finally, the binary images obtained in the previous two steps are combined, and some post-processing work is applied to produce better results. **(b)** This entry consists of four main steps. First, local image contrast which is evaluated by local maximum and minimum and local image gradient are combined using an exponential function with an adaptive factor. Second, the local image contrast is combined with the edge map to extract an accurate text character edge image. Third, the document image is binarized by a local threshold which is decided based on the constructed edge map and estimated stroke width. At last, some post-processing work is applied to produce better results.

16) University of Bern, Switzerland (*Anguelos Nicolaou*): This method is a slightly modified version of a previous submission in H-DIBCO 2010 [3]. The method uses a local version of Otsu thresholding [13]. Using the integral image of histograms, we can obtain the histogram of any rectangular region in constant complexity. For each pixel, the Otsu threshold of a square window with the size of the minimum dimension of the grayscale image is attributed. As long as it is classified as 'foreground' the window is reduced by a factor of 11/20 up to 6 times. Then all connected components become filtered out with a size less than 25 pixels assuming they are salt and pepper noise.

17) Technische Universität Braunschweig, Germany and University of Guadalajara, Mexico, Freie Universität Berlin, Germany (*Marte A. Ramírez-Ortegón, Volker Märgner, Erik Cuevas and Raúl Rojas*): This entry has 3 modules. The first module detects the regions of interest (ROI) based on gray-intensity variances. Then, an improved version of the transition method is computed subjected to the ROI [20-21]. Lastly, the binary image is post-processed for several operators to restore contours [22] and remove binary artifacts [23].

18) Federal University of Pernambuco, Brazil (*Renata F. P. Neves, Cleber Zanchettin, C. A. B. Mello*): This entry deals with complex background images, illumination and aspect variants, back-to-front interference, variation of brightness and different positioned shadows. The proposed algorithm is divided into two phases. The first phase uses morphological and edge operations to identify the text of the image. The second phase uses the positions of the text to define the threshold value in an adaptive process.

III. EVALUATION MEASURES

For the evaluation, the measures used comprise an ensemble of measures that are suitable for evaluation purposes in the context of document analysis and recognition. These measures consist of (i) F-Measure (*FM*), (ii) pseudo-FMeasure (F_{ps}), (iii) *PSNR* and (iv) Distance Reciprocal Distortion (*DRD*).

A. F-Measure

$$FM = \frac{2 \times \text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \qquad (1)$$

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

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

B. pseudo-FMeasure

Pseudo-FMeasure $\boldsymbol{F_{ps}}$ is introduced in [24] and it uses pseudo-Recall $\boldsymbol{R_{ps}}$ and pseudo-Precision $\boldsymbol{P_{ps}}$ (following the same formula as F-Measure). The pseudo Recall/Precision metrics use distance weights with respect to the contour of the ground-truth (GT) characters. In the case of pseudo-Recall, the weights of the GT foreground are normalized according to the local stroke width. Generally, those weights are delimited between [0,1]. In the case of pseudo-Precision, the weights are constrained within an area that expands to the GT background taking into account the stroke width of the nearest GT component. Inside this area, the weights are greater than one (generally delimited between (1,2]) while outside this area they are equal to one. It is worth to mention that pseudo-FMeasure $\boldsymbol{F_{ps}}$ is different from the pseudo-FMeasure ***p-FM*** used in H-DIBCO 2010 [3] and H-DIBCO 2012 [4].

C. PSNR

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

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. The higher the value of $PSNR$, the higher the similarity of the two images. Note that the difference between foreground and background equals to C.

D. Distance Reciprocal Distortion Metric (DRD)

The Distance Reciprocal Distortion Metric (DRD) has been used to measure the visual distortion in binary document images [25]. It properly correlates with the human visual perception and it measures the distortion for all the $\boldsymbol{S}$ flipped pixels as follows:

$$DRD = \frac{\sum_{k=1}^{S} DRD_k}{NUBN} \quad (3)$$

where NUBN is the number of the non-uniform (not all black or white pixels) 8x8 blocks in the GT image, and DRD_k is the distortion of the k-th flipped pixel that is calculated using a 5x5 normalized weight matrix $\boldsymbol{W_{Nm}}$ as defined in [25]. DRD_k equals to the weighted sum of the pixels in the 5x5 block of the $\boldsymbol{GT}$ that differ from the centered kth flipped pixel at (x,y) in the binarization result image $\boldsymbol{B}$ (Eq. 4).

$$DRD_k = \sum_{i=-2}^{2}\sum_{j=-2}^{2} |GT_k(i,j) - B_k(x,y)| \times W_{Nm}(i,j) \quad (4)$$

IV. EXPERIMENTAL RESULTS

The DIBCO 2013 testing dataset consists of 8 machine-printed and 8 handwritten images resulting in a total of 16 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 collections that belong to the IMPACT project [26], the Library of Congress [27] and the TranScriptorium project [28]. The selection of the images in the dataset was made so that representative degradations appear. The evaluation was based upon the four distinct measures presented in Section III. The detailed evaluation results along with the final ranking are shown in Table I. The final Ranking was calculated after first, sorting the accumulated ranking value for all measures for each test image. The summation of all accumulated ranking values for all test images denote the final score which is shown in Table I at column

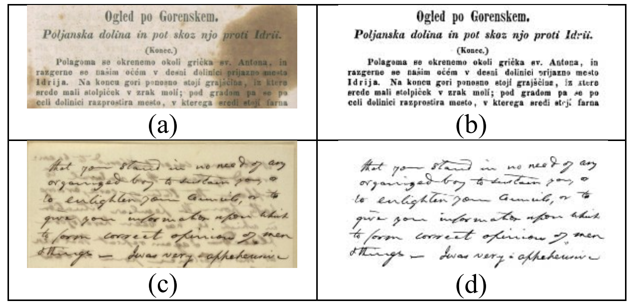

Figure 1. Representative samples and corresponding binarization results from the winner algorithm of DIBCO 2013 (a) Original machine printed image; (b) The binarization result of (a); (c) Original handwritten image; (d) The binarization result of (c).

TABLE I. DETAILED EVALUATION RESULTS FOR ALL METHODS SUBMITTED TO DIBCO 2013.

Rank	Method	Score	FM	F_{ps}	PSNR	DRD
1	15b	322	92,12	94,19	20,68	3,10
2	3	342	92,70	93,19	21,29	3,18
3	5	362	91,81	92,67	20,68	4,02
4	13	408	91,69	92,16	20,54	3,59
5	17	636	90,92	92,82	19,32	3,91
6	10c	642	89,77	90,36	19,26	4,31
7	7	646	89,79	91,53	18,99	4,24
8	9	688	88,95	90,61	18,74	5,06
9	10b	716	89,46	89,95	19,05	4,72
10	18	725	89,29	92,56	18,50	4,64
11	11	749	89,05	91,40	18,73	4,36
12	8b	752	88,58	90,81	18,66	4,66
13	2	757	88,45	88,91	18,66	6,36
14	10a	759	89,54	89,57	18,99	4,62
15	8a	774	89,06	89,98	18,81	4,67
16	4	800	87,35	91,80	18,34	4,40
17	16	935	83,24	86,59	17,64	6,45
18	15a	963	87,21	86,90	18,20	4,93
19	8c	984	85,23	91,80	17,30	5,61
20	12	1072	86,16	86,36	17,29	6,51
21	6	1084	84,90	87,41	17,02	8,25
22	14	1199	78,73	86,82	15,25	11,30
23	1	1349	64,62	65,35	11,10	46,09
-	Otsu	-	83,94	86,52	16,63	10,98
-	Sauvola	-	85,02	89,77	16,94	7,58

"Score". Additionally, the evaluation results for the widely used binarization techniques of Otsu [13] and Sauvola [11] are also presented. Overall, the best performance is achieved by ***Algorithm 15(b)*** which has been submitted by ***Bolan Su, Shijian Lu, Shangxuan Tian and Chew Lim Tan*** affiliated to ***the National University of Singapore and the Institute for Infocomm Research, Singapore***. Example binarization results of this algorithm are shown in Fig. 1(b),(d).

Acknowledgement

The research leading to these results has received funding from the European Union's Seventh Framework Programme (FP7/2007-2013) under grant agreement n° 600707 – tranScriptorium.

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