MSIO: MultiSpectral Document Image BinarizatIOn

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***Abstract*—MultiSpectral (MS) imaging enriches document digitization by increasing the spectral resolution. We present a methodology which detects a target ink in document images by taking into account this additional information. The proposed method performs a rough foreground estimation to localize possible ink regions. Then, the Adaptive Coherence Estimator (ACE), a target detection algorithm, transforms the MS input space into a single gray-scale image where values close to one indicate ink. A spatial segmentation using GrabCut on the target detection's output is computed to create the final binary image. To find a baseline performance, the method is evaluated on the three most recent Document Image Binarization COntests (DIBCO) despite the fact that they only provide RGB images. In addition, an evaluation on three publicly available MS datasets is carried out. The presented methodology achieved the highest performance at the MultiSpectral Text Extraction (MS-TEx) contest 2015.**

I. Introduction

The number of channels and therefore the spectral resolution is increased if MultiSpectral (MS) imaging is used instead of conventional color (RGB) imaging. In addition, objects such as documents are imaged outside the visual range which renders faded-out or scraped-off ink legible again [1]. Document image binarization is a pre-processing step in document analysis systems which makes subsequent processing steps such as HandWriting Recognition (HWR) applicable or more efficient [2]. This paper deals with a binarization that makes use of MS data. We will show that binarization algorithms, which make use of the additional information, gain better performance than traditional methods that are designed for gray-scale or color methods.

Historical documents contain faded-out ink, background clutters and inhomogeneous writing. The Document Image Binarization COntest (DIBCO) [3] is an annual event where algorithms especially designed for binarizing historical documents are put to the test. Su et al. [4] present a binarization technique that combines local edge maps with image gradients. While their method is good at rejecting large homogenous noise regions such as ink stains, it is heavily dependent to a uniform stroke width within a document image. Howe et al. [5] propose a method which applies Energy Minimization (EM) to a Laplacian image. In order to smooth the EM, knowledge gained by the Canny edge detection is incorporated.

While the majority of document image binarization techniques is designed for conventional gray-scale or RGB images, binarization techniques which use MS input data have become more mature recently [1]. Mitianodis and Papamarkos [6] use image fusion techniques such as the Independent Component Analysis (ICA) combined with a k-harmonic means classifier in order to binarize document images. Mogghadam and Cherit [7] reduce the multi-dimensional MS data by means of subspace selections and their output is then fed to state-of-the-art gray-scale binarization algorithms.

Hedjam et al. [8] propose a self-referencing strategy which is applied to a target detection algorithm such that a specific ink's legibility is improved in MS document images. The proposed method relies on the same principles with a few improvements and a strong focus on binarization.

Our approach roughly finds locations where ink is present in order to statistically estimate its spectral signature. In contrast to Hedjam et al. [8] we propose to use the Adaptive Coherence Estimator (ACE), which is a non-linear target detector, to boost ink pixels. The ACE reduces MS pixel vectors to a scalar which is close to one if a pixel vector is similar to the target signature. While we introduced this strategy in [1], the method is further improved in this paper by adding a spatial segmentation which forms the final binary image. In this processing stage the GrabCut [9], a semi-automated Graph-Cuts based segmentation, is fed with the results of the foreground estimation and the target detection rather than manual input.

The paper is organized as follows. The next section introduces the MS document image binarization. An empirical evaluation which benchmarks the proposed methods and compares it to state-of-the-art techniques is presented in Section III. The paper is concluded in Section IV.

II. Methodology

The proposed method consists of three consecutive steps (see Fig. 2). First a binarization is carried out on one of the visible channels to roughly localize ink. A statistical measure (see Eq. 1) further reduces the number of false positives based on the assumption that at least 50% of the foreground pixels found are actually ink. In the second step, the spectral information is transformed such that pixels which match the target signature become one. The target signature itself is estimated from the foreground estimation. Finally, a spatial segmentation is performed which is guided by information gained during the previous steps. Figure 2 shows all processing stages with their respective results.

A. Pre-Processing

The signature wavelength of the iron gall-based ink is varying between different images [1]. That is why a rough

Fig. 1: A detail from the MS-TEx MSI 1 database (*z97*). A pseudo color image a), the binarization result b) and the foreground estimation c). While yellow pixels indicate definitive foreground, violet pixels are marked as uncertain and thus not used for the ACE signature estimation.

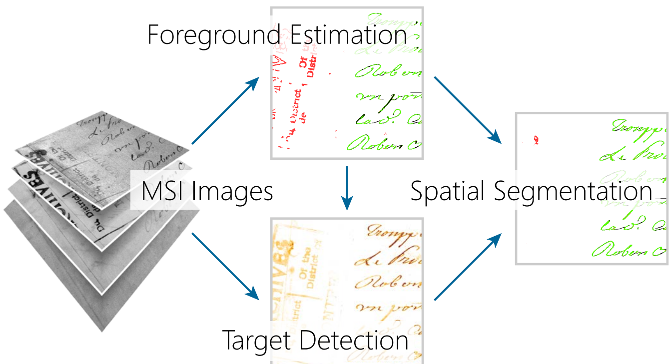

Fig. 2: Method outline

localization of potential ink pixels is performed prior to signature computation. The F2 channel ($500nm$) [10] is chosen for the initial ink detection. It is chosen since it is in the visible range and has therefore a high contrast between ink and supporting material. Tests on the MS-TEx database showed, that choosing any of the visible channels (F2-F4) results in a very similar performance. Iron gall ink is invisible in the IR channel while ruptures or stains are still visible. To reduce such noise, the infrared (IR) channel (F8) is subtracted from the visible channel.

To binarize the image, we apply the technique proposed by Su et al. [2]. While we chose the Su et al. binarization which won the DIBCO in 2009 and 2013 [11] any binarization technique could be used for this step. It is only important that the binarization has a high precision rather than a high recall since false positives are more crucial for the signature estimation. The Su et al. method has the advantage, that it incorporates the idea of a stroke width which guarantees that no large areas such as ink stains are binarized.

Figure 1 illustrates the ink detection. The pseudo color image in a) consists of a mean, a standard deviation and the F2 channel. It shows that the document is written using two different inks (bright pink and dark pink). While text written in dark ink is iron gall-based ink the bright pink text is written using a different ink and should therefore not be binarized. In addition, background clutter is present in the image. The algorithm proposed by Su et al. [2] handles most of the background clutter (see Figure 1 b). But it cannot distinguish between both two inks.

In order to improve the ink detection, a rough spectral analysis is performed. Spectral inliers or iron gall ink pixels are considered to be those pixels who are detected by the binarization and fulfill:

$$f_i(x) = q_{25} - w \cdot iql < f(x) < q_{75} + w \cdot iql \tag{1}$$

with $f(x)$ being the 8 dimensional pixel vector at location x, q_{25} and q_{75} being the first and the third quartiles respectively and iql being the interquartile range $q_{75} - q_{25}$. The weight w is chosen to be $w = 1.5$. By these means up to 50% of the initially detected foreground pixels can be rejected because of an inconsistent spectral signature. Figure 1 c) shows rejected foreground pixels. Dark violet pixels are rejected because of their spectral signature while yellow pixels are considered to be iron gall ink $f_i(x)$. Note that the second ink has a similar spectral signature at a character's border while central pixels are rejected correctly.

B. Target Detection

The target detection estimates if a data vector x_i is similar to a target signature s. Hence, it transforms the data x such that signature-like vectors become 1 while dissimilar vectors are set to 0. In order to estimate the signature, the harmonic mean of all definitive foreground pixels previously found is calculated.

Target detection can be performed using different transformations such as the Constrained Energy Minimization (CEM) [12] or the Adaptive Matched Filters (ACM) [13]. While these target detectors apply a linear transform to the data, the ACE applies a non-linear transformation based on second-order statistics. We are using ACE for target detection, since it proved to be superior to the afore mentioned methods [14], [1]. It is defined as

$$y(x) = \frac{(\bar{s}^T \Sigma^{-1} \bar{x}) \| \bar{s}^T \Sigma^{-1} \bar{x} \|}{(\bar{s}^T \Sigma^{-1} \bar{s})(\bar{x}^T \Sigma^{-1} \bar{x})} \tag{2}$$

$$y_{ACE}(x) = \begin{cases} 0 & \text{if } y(x) < 0 \\ 1 & \text{if } y(x) > 1 \\ y(x) & \text{else} \end{cases} \tag{3}$$

where $\bar{s}$ is the mean normalized signature $(s - \mu)$, $\bar{x}$ are the mean normalized data vectors (pixel values) and Σ^{-1} is the inverted covariance matrix with $\Sigma = (x^T x)/(N-1)$. The inverse is computed by means of a Singular Value Decomposition (SVD). In the resulting image $y_{ace}(x)$ pixels, which have a similar spectral signature to the target signature s (iron-gall ink pixels), have values close to 1.

Figure 3 shows the target detection's result. Note that 1672 is written in a different ink and should therefore not be segmented. The figure shows, that the target detection b) is conservative since faded-out ink (e.g. the stroke of the P) is not boosted very much. But it correctly rejects most of the second ink (light yellow).

Fig. 3: The F2 channel ($500nm$) from the MS-TEx MSI 1 database a) and the resulting target detection image b)

C. Spatial Segmentation

Having applied the target detection, the MS data is transformed such that pixels having a spectral signature which is similar to the iron gall ink are enhanced. The resulting image could be directly thresholded with a global threshold or combined with the initial binary image [1]. However, images (e.g. document images but also natural scene images) have a spatial correlation between neighboring pixels [15]. Hence, when binarizing an image, the fact that all neighbors of a pixel $f(x, y)$ are labeled as foreground increases the likelihood of the observed pixel to be foreground. Because of this assumption, a spatial segmentation is used to generate the final binary image.

We exploit the interactive GrabCut segmentation proposed by Rother et al. [9]. The GrabCut is an extension of Graph Cuts segmentation proposed by Boykov and Jolly [16]. The Graph Cut segmentation combines texture information with edge information. While it is proposed for grayscale images, GrabCut utilizes Gaussian Mixture Models (GMM) to model the color information of objects and background. Moreover, the EM is performed iteratively which allows us to interact with the spatial segmentation based on knowledge gained during the previous stages.

Since the GrabCut is designed for color images, the MS data is converted to a pseudo-color image using:

$$p_b(x, y) = f_2(x, y) - f_8(x, y) \tag{4}$$

$$p_r(x, y) = \mu(x, y) \tag{5}$$

$$p_g(x, y) = \sigma(x, y) \tag{6}$$

with $\mu(x, y)$ and $\sigma(x, y)$ being the spectral mean and standard deviation respectively. The blue channel ($p_b(x, y)$) is a cleaned image where f_2 represents the F2 channel (500nm) and f_8 the IR channel. Note that the result of the target detection is not added to the pseudo color image since it would emphasize the spectral information too much. Thus, the benefit of spatial segmentation would be lost.

As previously mentioned, we feed the GrabCut with the results of the spectral processing gained during target detection. Hence, a mask is created which marks definitive/potential foreground and background regions. The mask is created by combining the result of the target detection with the initial binary image:

$$m(x, y) = \begin{cases} \mathrm{F} & \text{if } y(x, y) > t_f \wedge b(x, y) = 1, \\ \mathrm{B} & \text{if } y(x, y) < t_b \wedge b(x, y) = 0, \\ \mathrm{PF} & \text{if } y(x, y) > t_{pf} \vee b(x, y) = 1, \\ \mathrm{PB} & \text{else.} \end{cases} \tag{7}$$

with $y(x, y)$ being the result of the target detection/classification, $b(x, y)$ the initial binary image and $m(x, y)$ the resulting mask. Pixels in the mask image are labeled as Foreground (F), Potential Foreground (PF), Potential Background (PB), and Background (B). The thresholds ($t_f = 0.3, t_b = 0$, and $t_{pf} = 0.1$) are empirically found on the MS-TEx MSI 1 database. Note that the performance is not too crucial with respect to varying these thresholds.

After initializing the GrabCut, the EM is performed with a stroke width control. Hence, after each EM step, the mask's binary image (F $\vee$ PF) is eroded until its overlap is less than 5% of the initial binary image $b(x, y)$. Remaining foreground pixels of this eroded image are set to definitive background (B). If there are no remaining pixels, the EM iteration is stopped. This strategy incorporates Su et al.'s [2] *stroke width* idea. Hence, the GrabCut is guided such that it does not segment large areas as foreground. Moreover, if the GrabCut segments a large area as potential foreground, removing only a few pixels from this area, results in the whole area being labeled as potential background. After the GrabCut's EM, the final binary image is set to be true (255) for all potential and definitive foreground pixels of the mask.

Figure 4 illustrates different stages of the spatial segmentation. An image from the MS-TEx MSI 2 dataset (z43) is chosen to show the segmentation if background clutter and a stamp are present in the image. The first image a) shows the pseudo color image which is the basis for the GrabCut's color segmentation. The initial mask which is generated by combining the target detection with the initial binary image (see Equation 7) can be seen in b). Note that violet pixels indicate F, pink PF, yellow PB, and white B. After only one iteration c), most pixels are labeled correctly. Solely, a part of the stamp is still labeled as potential foreground. The final mask after applying the GrabCut guided with the afore mentioned stroke width control is shown in d). The resulting binary image is shown in e).

Figure 5 illustrates all major steps of the proposed methodology. Green pixels indicate true positives (**tp**), white pixels true negatives (**tn**), red pixels false positives (**fp**) and

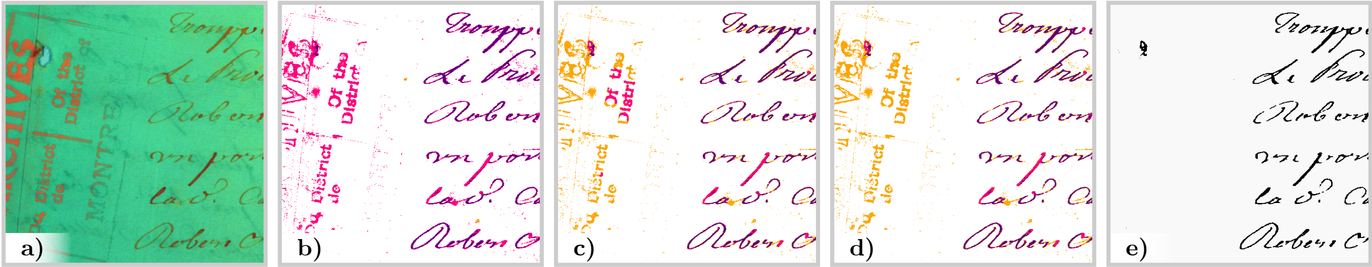

Fig. 4: Pseudo color image which is provided as RGB image to the GrabCut a). Initial mask gained from combining the target detection with the binary image b). First GrabCut iteration c) and final mask d) with the resulting binary image e).

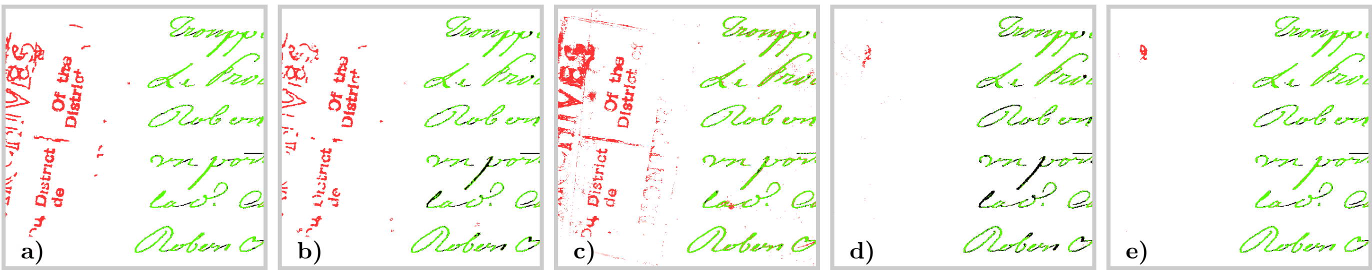

Fig. 5: All major stages of the proposed method (green=**tp**, white=**tn**, red=**fp**, and black=**fn**). Initial binarization a), foreground estimation b), target detection thresholded with t_{pf} c), with t_f d), and the resulting image after applying the GrabCut e).

black pixels false negatives (**fn**). In a), the binarization of the F2 channel is shown if Su et al.'s [2] is used. Using the information of only one channel does not allow for a distinction between e.g. stamps and iron gall ink. The proposed foreground estimation b) reduces the false positives while introducing only a few false negatives (e.g. the black stroke in the 4$^{\text{th}}$ line). Thresholding the result of the target detection with t_{pf} results in c). Note that the stamp could not be removed because of the false positives in b). Applying the 'definitive' foreground threshold t_f to the target detection results in hardly any false positives (see d) but introduces some false negatives. After applying the GrabCut in e) the false negatives are reduces without increasing the false positive rate. Note, that the Su et al. [2] binarization illustrated in a) cannot distinguish between ink and the stamp.

III. Evaluation

The presented method was thoroughly evaluated on different datasets. Although the method is especially designed for MS data, it is compared to the most recent binarization contests namely H-DIBCO 14 [3], DIBCO 13 [11], and H-DIBCO 12 [17]. This evaluation demonstrates the method's performance when binarizing RGB images.

While the evaluation on the DIBCO datasets aims at finding the baseline performance, the method is additionally evaluated on three MS datasets namely HISTODOC1 [18], MS-TEX MSI 1 [10], and MS-TEX MSI 2. In order to evaluate and compare the proposed methodology, the following well-known evaluation metrics are used:

- F-Measure (FM) [3]
- pseudo F-Measure (p-FM) [3]
- Peak Signal-to-Noise Ratio (PSNR) [3]
- Distance Reciprocal Distortion Metric (DRD) [3]
- Negative Rate Metric (NRM) [10]

A. Baseline Evaluation on DIBCO

The Document Image Binarization COntest DIBCO [3] is an annual binarization contest which is organized in conjunction with the ICDAR and ICFHR conferences. The last three years datasets consist of 10 to 14 document images which are labeled on a per-pixel level. The documents range from historical prints to modern handwritten images. Every year, between 8 and 24 methods joined the competition. Note that 20% of all DIBCO images are gray-scale documents. For these images the proposed methodology cannot take a benefit at all.

Table I summarizes the results of the proposed method if it is applied to the last three DIBCO datasets. For comprehensibility, only the best performing methods and the Sauvola binarization as baseline are listed in the table. The full evaluation results can be found in the respective papers [3], [11], [17]. In addition to the best performing method, the results of Howe's binarization [5] are listed for every contest, since the performance of this method is also evaluated on the MS-TEX MSI 2 dataset [10].

Figure 6 shows two samples from the DIBCO datasets. The first sample a) (HW03 DIBCO 13 [11]) shows limitations of the proposed method. Since the method is designed to find a specific ink in documents, the second (red) ink is hardly detected at all and thus increases the false negative rate b). In contrast to this, the second sample c) (H07 H-DIBCO 14) shows an image region, where a stain is almost entirely removed by the proposed method d).

TABLE I: Results on the last three DIBCO datasets.

Author	Rank	FM	p-FM	PSNR	DRD
H-DIBCO 12					
Howe	1	89.5	90.2	21.8	3.44
Sauvola	-	82.9	88.0	16.7	6.59
Proposed	-	90.2	92.6	19.2	3.22
DIBCO 13					
Su	1	92.1	94.2	20.7	3.10
Howe	2	92.7	93.2	21.3	3.18
Sauvola	-	85.0	89.8	16.9	7.58
Proposed	-	89.2	92.6	19.1	3.54
H-DIBCO 14					
Mesquita	1	96.9	97.7	22.7	0.90
Howe	2	96.6	97.5	22.4	1.00
Sauvola	-	86.8	91.8	17.6	4.89
Proposed	-	92.6	95.3	19.1	2.30

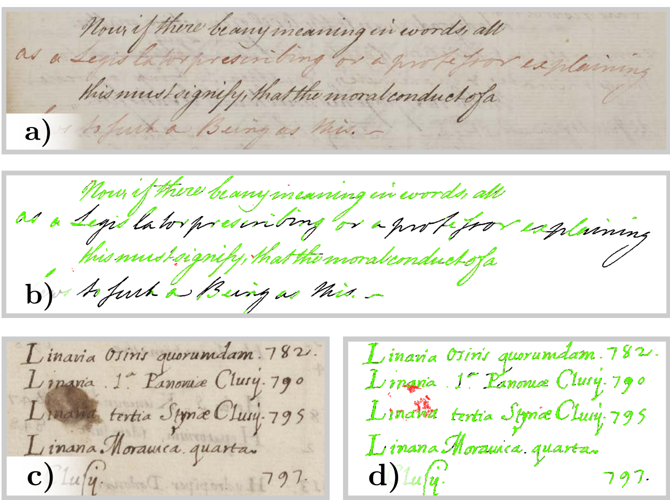

Fig. 6: A sample from the DIBCO 13 and the H-DIBCO 14 datasets.

B. Evaluation on MS Data

The method is evaluated on three publicly available MS datasets namely HISTODOC1[1], MS-TEX MSI 1[2] [10], and MS-TEX MSI 2. The MSI 1 and the MSI 2 datasets are used as train and test set for the MultiSpectral Text Extraction Contest [10]. All images are collected with the same camera and illumination system which reduces the variability between the different datasets.

HISTODOC1*:* The HISTODOC1 is the smallest and oldest dataset. It was introduced by Hedjam et al. [18] and consists of 9 comparably small image patches which have on average 200000 pixels. Figure 7 shows the average F-Measure of the proposed method compared to state-of-the-art MS binarization methods. The gray bars indicate the standard deviation between F-Measures of different images. The proposed method is shown by the cyan bar. The dark cyan illustrates the base method proposed by Hollaus et al. [1] while yellow indicates results presented by Mitianoudis and Papamarkos [6]. The remaining results are studies conducted by Hedjam and Cheriet [18]. Table II shows detailed results including the NRM and DRD measures. There, the results are compared to our previous approach and to the currently best performing method.

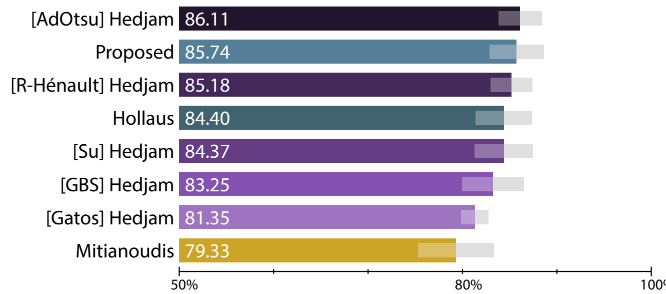

Fig. 7: Average F-Measures gained on the HISTODOC1 dataset.

MS-TEX *MSI 1:* This dataset is the largest among the evaluated. It contains a total of 21 images which are on average twice as large as those of the HISTODOC1 database. It has been used to evaluate our previous method [1] and also by Mogghaddam et al. [19] (see Table II).

MS-TEX *MSI 2:* Although, this dataset is smaller than than the MSI 1 with a total of 10 images, it is the most challenging dataset (the F-Measure of the proposed method drops by 3.7%). It was used for the MS-TEX evaluation [10]. In this contest, a total of five methods were submitted which are designed for MS binarization. In addition, the state-of-the-art binarization methods are evaluated. Figure 8 shows the average F-Measure of all methods evaluated within the contest. While cyan bars represent the results of our methods, violet bars show the results of all other MS-TEX participants and yellow bars illustrate the results of the state-of-the-art binarization methods at DIBCO. A more comprehensive discussion about the results and the respective methods can be found in [10].

Table II shows detailed error metrics. For MSI 2, the performance of Howe et al. [5] is compared with the proposed approach. The results suggest, that MS imaging enriches the information content. Moreover, if the spectral information is exploited, the binarization performance can be increased.

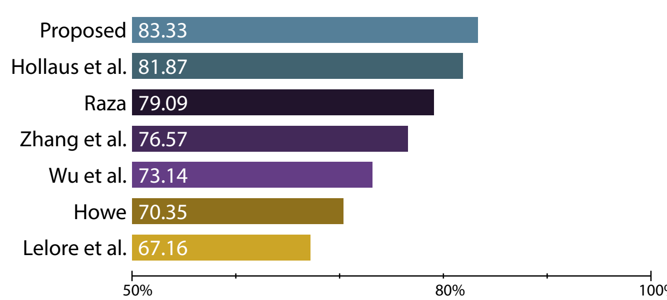

Fig. 8: Average F-Measures gained on the MS-TEX MSI 2 dataset.

[1] http://www.synchromedia.ca/databases/HISTODOC1
[2] http://www.synchromedia.ca/databases/MSI-HISTODOC

Histodoc1 1				MS-TEx MSI 1				MS-TEx MSI 2			
Author	FM	NRM	DRD	Author	FM	NRM	DRD	Author	FM	NRM	DRD
Proposed	85.7	8.49	2.92	Proposed	**87.0**	7.33	3.09	Proposed	**83.3**	9.25	4.24
Hollaus	83.7	9.87	3.35	Hollaus	85.8	8.11	3.51	Hollaus	81.9	10.1	4.74
Hedjam	**86.1**	-	-	Moghaddam	80.8	-	-	Howe	70.4	12.1	8.60

TABLE II: Comparison to our previous approach and to the best performing method found in the literature.

IV. Conclusion

A fully automated approach for MS image binarization was presented in this paper. The approach extends a previously published method [1]. Three processing stages consider three different aspects of MS document images. The first stage localizes potential ink regions. Since it is needed to form a target signature, potential false positives are strictly rejected. A target detection then transforms the input vectors to scalar values such that ink pixels are close to 1 while other elements become 0. After this stage, the ink is enhanced and the results could be presented to humans to decipher the text. However, further processing such as HWR need reliable segmentation techniques. That is why, the target detection's result is used to automate a semi-automated Graph Cuts segmentation technique. We showed that this final processing stage improves the binarization quality by $\approx 2\%$.

Though, the method achieves the best performance on the MS datasets evaluated, there is still room for improvements. First, the initial foreground estimation is crucial for the overall system performance. The proposed approach relies on Su et al.'s [2] method which requires homogeneous stroke widths throughout a document image. Though binarizing in this stage is a convenient engineering approach since it speeds up subsequent processes, it would be more desirable to estimate the ink's target signature by means of stochastic approaches. The GrabCut [9] is designed for RGB images. That is why we reduce the MS data to a three dimensional vector by means of first and second order statistics. However, modeling the color GMMs on the full MS dimensionality would enrich the information content provided to the GrabCut and therefore possible improve its performance. The proposed method is available at https://github.com/diemmarkus/MSTEx-CVL.

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