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Historical document image binarization using background estimation and energy minimization

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***Abstract*—This paper presents an enhanced historical document image binarization technique that makes use of background estimation and energy minimization. Given a degraded historical document image, mathematical morphology is first carried out to compensate the document background with a disk-shaped mask, whose size is determined by the stroke width transform (SWT). The Laplacian energy based segmentation is then performed on the enhanced document image. Finally, the post-processing is further applied to improve the binarization results. The proposed technique has been extensively evaluated over the recent DIBCO and H-DIBCO benchmark datasets. Experimental results show that our proposed method outperforms other state-of-the-art document image binarization techniques.**

Keywords*—Historical document image binarization; document background estimation; stroke width transform (SWT); Laplacian energy minimization

I. INTRODUCTION

Binarization (also referred to as thresholding, foreground/background segmentation) has been a hot research topic in the field of document analysis and recognition for decades. It aims to extract the foreground text from the document background. The performance of this stage directly affects the accuracy of subsequent tasks, such as page layout analysis and *optical character recognition* (OCR). Due to the existence of different types of document degradation, such as page stains, ink bleed through, and artifacts, as shown in Fig. 1, the binarization of degraded historical document images remains challenging.

Numerous document image binarization techniques have been proposed in the literature, and can be roughly classified as global or local[1, 2]. Global thresholding uses a single threshold for the entire image, for instance, the Otsu's method [3] calculates an optimum threshold to separate the foreground and background pixels, so that their intra-class variance is minimum or equivalently their inter-class variance is maximum. Global thresholding gives satisfactory results when the image histogram follows a bimodal distribution. If the image quality is worse, the global thresholding will generally fail.

Locally adaptive thresholding uses neighborhood features to estimate a threshold for each pixel. Niblack's[4], Sauvola's[5], and Wolf's[6] methods use local means and standard deviations, while local contrast is exploited by Bernsen's[7] and Herk's[8] methods. Those sliding window based techniques generally have better performance, but the main drawback is that the thresholding performance depends to a large extent on the sliding window size and hence the text stroke width.

Hybrid approaches have also been developed for historical document image binarization, e.g., edge based method[9, 10], region based method[11, 12], local maximum and minimum method[13, 14], *Markov random field* (MRF) approach[15-18], active contour model based method[19], convolutional neural networks method[20], Gaussian mixture modeling method[21, 22], and multi-spectral imaging method[23]. Since combined different kinds of image information, the hybrid techniques have made some advances, but the time complexity is relatively high.

The *document image binarization competition* (DIBCO 2009[24], 2011[25], 2013[26]) and the *handwritten document image binarization competition* (H-DIBCO 2010[27], 2012 [28], 2014[29], 2016[30]) show recent advances in this effort. We participated in the DIBCO 2017[31] and submitted two distinct algorithms. Our graph cut method (3a) performs the second and tenth prize for handwritten and machine-printed document image binarization, respectively, among 26 algorithms submitted from 18 international research groups. Our locally adaptive thresholding method (3b) performs the ninth prize for both handwritten and machine-printed document image binarization among 26 submitted algorithms.

This paper presents a historical document image binarization technique that extends the method (3a) submitted to the DIBCO 2017. The proposed method is simple and robust to handle different types and levels of degradation based on document background estimation and Laplacian energy minimization. As a matter of fact, the compensation eliminates most of the document degradation and helps to extract foreground text from the document background in the following energy-based segmentation.

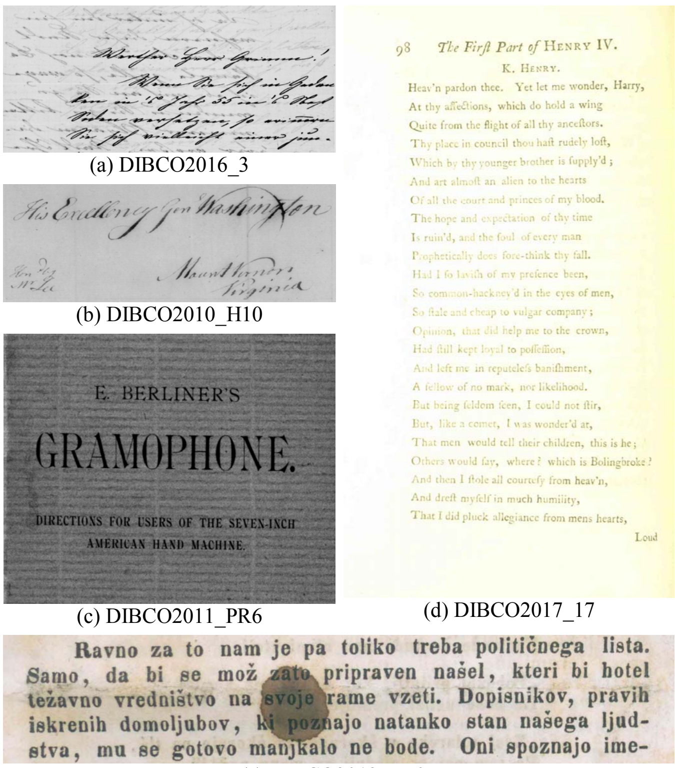
The remainder of this paper is organized as follows: Section II describes the proposed methodology in detail. The experimental results and discussions are reported in Section III, and finally, conclusions are presented in Section IV.

II. PROPOSED METHOD

In this section, we will introduce the proposed historical document image binarization technique. Given an image, the mathematical morphology is first carried out to compensate the document background with a disk-shaped structuring element, whose size is determined by the *stroke width transform* (SWT)[32]. The Laplacian energy based segmentation is then performed on the enhanced document image. Finally, the post-processing stage is adopted to produce better results.

A. Stroke Width Transform (SWT)

We first apply Canny edge detector[33] to produce a text edge map by extracting the principal edge features of the image while reducing irrelevant details as much as possible, such as those aforementioned various types of document degradation. The Canny edge detection includes 3 important parameters, which strongly influence the text edge map output. The Gaussian smoothing filter is used to blur the image, and the degree of blurring is determined by the standard deviation σ of the Gaussian distribution. The two thresholds t_{high} and t_{low} are critical to determine which edges appear or disappear. Since the true text edges usually have higher contrast than noise, e.g., page stains, background texture, ink bleed through, and artifacts, the following choices are empirically valid parameter settings for various document images and can be used as sensible default values in our implementation: $\sigma = 1$, $t_{\text{low}} = 0$, $t_{\text{high}} = 0.4$, the latter two are designated as a fraction of the maximum observed image gradient. Fig. 2(a) shows the text edge map produced by the Canny edge detector with our parameter settings.



(a) DIBCO2016_3

(b) DIBCO2010_H10

(c) DIBCO2011_PR6

(d) DIBCO2017_17

(e) DIBCO2013_PR05

Fig. 1 Examples of degraded historical document images in the DIBCO and H-DIBCO benchmark datasets.

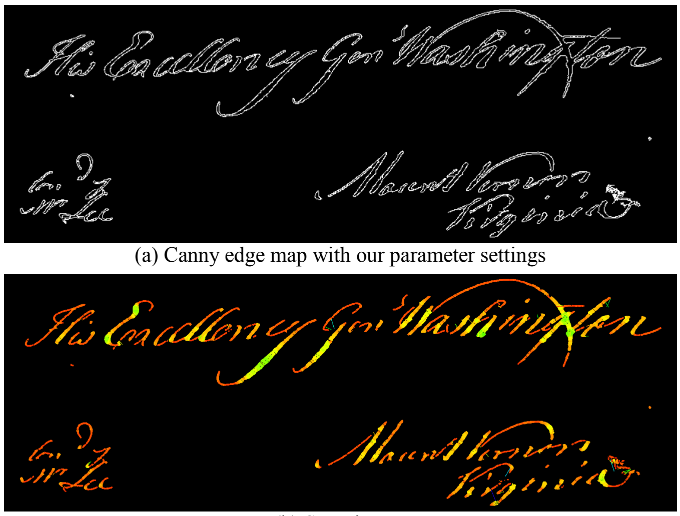
After Canny edge detection, the text stroke width can be estimated from the obtained text edge pixels and directed edge gradients. For each text edge pixel p, a search path in the gradient or counter-gradient direction d_p is generated. We follow the search path until another edge pixel q is located. If the gradient direction d_q at pixel q is approximately opposite to d_p, an edge pair is formed and the Euclidean distance between p and q (namely the text stroke width) is calculated. All pixels lying on the search path between p and q (including these two endpoints) are assigned a corresponding stroke width, unless they already have a lower value. Otherwise, if the matching pixel q is not found, or if the gradient direction of pixel q is not opposite to that of the pixel p, the search path is discarded. For pixels at stroke connections, they generally have wrong stroke width values and need to be corrected. Therefore, the algorithm computes the median value m along each non-discarded search path, and sets all the pixels in its path with values above m to be equal to m. The output is an image where each pixel contains the stroke width value associated with that pixel. Fig. 2(b) shows the corresponding pseudo-color image resulting from the stroke width transform, and different colors denote different stroke width values.

B. Background Estimation and Subtraction

We first estimate the document background via morphological closing with disk-shaped structuring element, the size of which should be no smaller than the estimated stroke width. The closing of the image f by a specific structuring element b, denoted $f \bullet b$, is defined as:

$$f \bullet b = (f \oplus b) \ominus b \tag{1}$$

which means the dilation of f by b, followed by the erosion of the result by b. The gray-scale dilation and erosion are defined,



(a) Canny edge map with our parameter settings

(b) SWT image

Fig. 2 The Canny edge map of Fig. 1(b) using our parameter settings, and the corresponding image produced by the stroke width transform.

respectively, as follows:

$$(f \oplus b)(x,y) = \max\{f(x-x', y-y') \mid (x',y') \in D_b\} \quad (2)$$

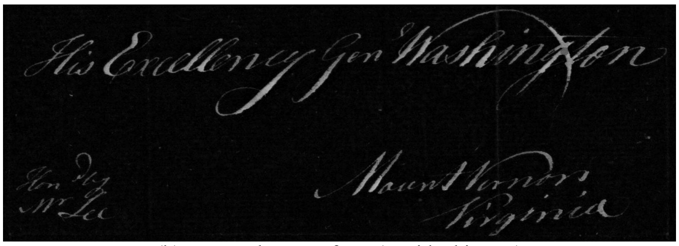
and

$$(f \ominus b)(x,y) = \min\{f(x+x', y+y') \mid (x',y') \in D_b\} \quad (3)$$

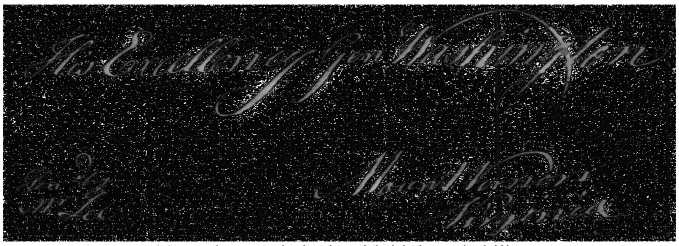
As we can see, gray-scale dilation is a local maximum operator while gray-scale erosion is a local minimum operator, in which the maximum or minimum is taken over a set of pixel neighbors determined by the shape of D_b.

Morphological closing can produce a reasonable estimate of the document background across the entire image, as illustrated in Fig. 3(a). We then perform a bottom-hat transform that

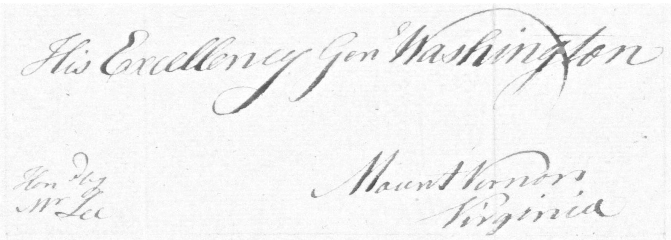
(a) Estimated document background (Closed image)



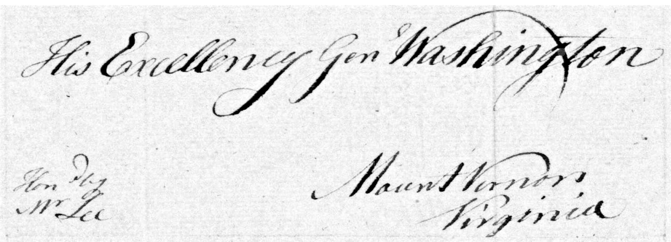
(b) Bottom-hat transform (Residual image)



(c) Background pixels with high probability



(d) Negative image



(e) Enhanced image

Fig. 3 Document background estimation and compensation.

emphasizes the text area and attenuates the document background, as depicted in Fig. 3(b). The morphological bottom-hat transform is defined as the closing of the image minus the gray-scale image. In the residual image, pixels with intensity values equal to zero are referred to as background pixels with high probability, which are converted into white, as demonstrated in Fig. 3(c). The gray-scale complement operation is then applied to the remaining pixels to produce a negative image, as illustrated in Fig. 3(d). Finally, the image contrast is enhanced, as illustrated in Fig. 3(e).

After background estimation and subtraction procedure, the original document background has been normalized and the separation between foreground and background pixels has also been increased, which makes further segmentation easier.

C. Laplacian Energy-based Binarization

The *Markov random field* (MRF) theory can then be used to extract text objects from the enhanced document image. The interest in MRF modeling for degraded historical document image binarization is increasing, as reflected by recent literatures[22, 34, 35].

Howe's method[15, 16] formulates document image binarization as energy minimization over an MRF. The data penalty terms are computed from the image Laplacian, while the smoothness penalty terms are determined by Canny edge detector[33]. An exact minimization of the objective or energy function can be obtained by solving the equivalent max-flow/min-cut problem[36].

We choose to use the Howe's method[16] as part of our proposal, but with some subtle and important differences. The global energy function to be minimized is defined as:

$$\begin{aligned}\mathcal{E}_I(B) = &\sum\nolimits_{i=0}^{m}\sum\nolimits_{j=0}^{n}\left[L_{ij}^0(1-B_{ij}) + L_{ij}^1 B_{ij}\right] \\ &+\sum\nolimits_{i=0}^{m-1}\sum\nolimits_{j=0}^{n} C_{ij}^h (B_{ij} \neq B_{i+1,j}) \\ &+\sum\nolimits_{i=0}^{m}\sum\nolimits_{j=0}^{n-1} C_{ij}^v (B_{ij} \neq B_{i,j+1})\end{aligned} \quad (4)$$

where $B_{ij} \in \{0,1\}$ is the label value (foreground or background) of each pixel indexed at (i,j), L_{ij}^0 and L_{ij}^1 are the cost to assign label 0 or 1 to each pixel, C_{ij}^h and C_{ij}^v are the cost of a label mismatch between B_{ij} and its horizontal or vertical neighbors, respectively.

The pixel label penalties L_{ij}^0 and L_{ij}^1 are set according to the Laplacian of the image intensity:

$$L_{ij}^0 = \nabla^2 I_{ij} \quad (5)$$

$$L_{ij}^1 = \begin{cases} \ell, & \text{background with high confidence} \\ -\nabla^2 I_{ij}, & \text{otherwise} \end{cases} \quad (6)$$

where the Laplacian ∇^2 is a second order differential operator given by the divergence of the image gradient, and background pixels with high confidence in the preceding subsection are set to a large negative constant ℓ. In our implemented system, ℓ is fixed to a negative of two times the maximum pixel value.

The pairwise label mismatch penalties C_{ij}^h and C_{ij}^v are set according to the Canny edge detection:

$$C_{ij}^h = \begin{cases} 0, & E_{ij} \wedge (I_{i-1,j} \geq I_{ij}) \text{ or } E_{ij} \wedge (I_{ij} < I_{i+1,j}) \\ c, & \text{otherwise} \end{cases} \quad (7)$$

$$C_{ij}^v = \begin{cases} 0, & E_{ij} \wedge (I_{i,j-1} \geq I_{ij}) \text{ or } E_{ij} \wedge (I_{ij} < I_{i,j+1}) \\ c, & \text{otherwise} \end{cases} \quad (8)$$

where E_{ij} denotes the Canny edges, and non-edge pixels with label mismatch are set to a positive constant c. Both the high threshold t_{high} for Canny edge detection and the neighbor mismatch penalty c matter most among all the parameters, thus an automatic parameter tuning method has been proposed in [15], based on the stability heuristic criterion under the hypothesis that good parameter values produce low variability in the final binarization with respect to the changes in parameter settings. The binary output of the Howe's method is shown in Fig. 4(a).

D. Post-processing

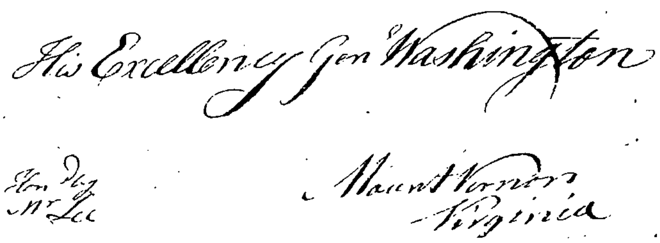
Once the Laplacian energy-based segmentation is derived, we proceed to the final post-processing stage, by removing the isolated text pixels and filling possible breaks, gaps or holes, to eliminate noise and preserve stroke connectivity. Below is a detailed step-by-step description of our post-processing algorithm, which consists of a successive application of connected component analysis.

Step 1: A foreground connected component analysis is used to remove noise from document background. The entire binary image is scanned and each foreground connected component is examined. If p is an unlabeled pixel, then the flood-fill algorithm[37] is used to label all the pixels in the connected component containing p. The actual number of pixels in each connected component is measured, and a binary image B_1 containing only the regions whose areas are greater than N_{th} is created, where N_{th} can be defined experimentally.

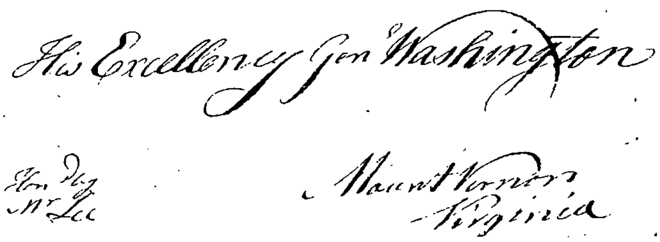
Step 2: A background connected component analysis is used to fill small holes in text strokes. In order to adopt the same analytical framework as described in Step 1, we first perform image complement on B_1, and then follow Step 1 to produce a new binary image B_2 containing only the regions whose areas are less than H_{th}, where H_{th} can also be defined experimentally. The final binary image B is generated as follows:

$$B = B_1 \vee B_2 \quad (9)$$

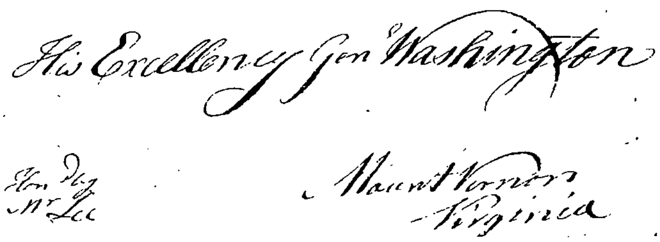
Fig. 4(b) and (c) demonstrate the resulting images after post-processing step 1 and step 2, respectively.



(a) The Howe's binarization image



(b) The resulting image after post-processing step 1



(c) The resulting image after post-processing step 2

Fig. 4 The post-processing stage.

III. Experiments and Discussion

A series of experiments have been carried out to evaluate the performance of our binarization method. The benchmark datasets are DIBCO 2009, 2011, 2013, and H-DIBCO 2010, 2012, 2014, 2016, consisting of 21 machine-printed and 65 handwritten document images. There are a total of 86 historical document images with associated *ground truth* (GT) images. The evaluation measures include *F-measure* (FM), *pseudo F-measure* (F_{ps}), *peak signal-to-noise ratio* (PSNR), *negative rate metric* (NRM), *distance reciprocal distortion* (DRD) metric, and *misclassification penalty metric* (MPM). Readers are suggested to refer to [24-30] for further definition.

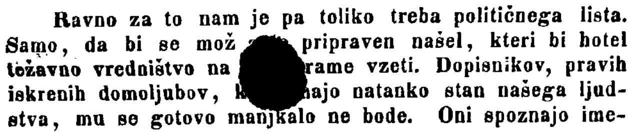
The proposed method has been quantitatively compared with other state-of-the-art techniques, which achieve the TOP 3 performance in annual DIBCO or H-DIBCO competition. The evaluation results are presented in Table 1, and those for the TOP 3 champions of the year are copied from [24-30], respectively. As can be seen from the table, our proposed method achieves the best scores in (almost) all the evaluation measures, except that the FM, PSNR and DRD metrics of our method are just slightly worse than the TOP 1 algorithm under H-DIBCO 2014 benchmark dataset. The result implies that our binarization method has a higher overall accuracy and extracts text strokes better.

Several factors can explain the superior performance of our proposed technique. Firstly, the document background estimation is carried out to properly compensate the variation of historical document background. Secondly, the Laplacian energy based binarization is performed on the enhanced document images. The compensation procedure significantly improves the segmentation of foreground text and document background. Last but not least, the superior performance of our proposed method is also due in part to the two post-processing operations to eliminate noise and preserve stroke connectivity by removing isolated text pixels and filling possible breaks, gaps or holes.

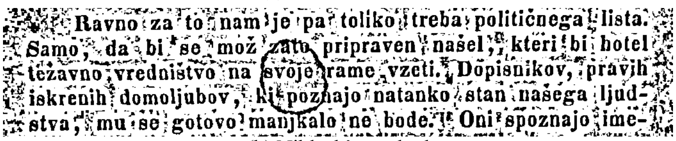
Table 1 Evaluation results of the DIBCO and H-DIBCO benchmark datasets

Dataset	Method	FM (%)	F_{ps} (%)	PSNR	NRM ($\times 10^{-2}$)	DRD	MPM ($\times 10^{-3}$)
DIBCO 2009	TOP 1	91.24		18.66	4.31		**0.55**
	TOP 2	90.06		18.23	4.75		0.89
	TOP 3	89.34		17.79	5.32		1.90
	Proposed	**94.18**		**20.32**	**2.61**		0.57
H-DIBCO 2010	TOP 1	91.50	93.58	19.78	5.981		0.492
		89.70	95.15	19.15	8.180		0.288
	TOP 2	91.78	94.43	19.67	4.771		1.334
	TOP 3	89.73	90.11	18.90	5.776		0.412
	Proposed	**93.97**	**95.39**	**21.15**	**3.482**		**0.252**
DIBCO 2011	TOP 1	80.86		16.13		104.48	64.43
	TOP 2	85.20		17.16		15.66	9.07
	TOP 3	88.74		17.84		5.36	8.68
	Proposed	**90.60**		**18.87**		**4.60**	**7.88**
H-DIBCO 2012	TOP 1	89.47	90.18	**21.80**		3.440	
	TOP 2	92.85	93.34	20.57		2.660	
	TOP 3	91.54	93.30	20.14		3.048	
	Proposed	**94.21**	**94.95**	21.65		**2.080**	
DIBCO 2013	TOP 1	92.12	94.19	20.68		3.10	
	TOP 2	92.70	93.19	21.29		3.18	
	TOP 3	91.81	92.67	20.68		4.02	
	Proposed	**93.50**	**94.42**	**21.36**		**2.79**	
H-DIBCO 2014	TOP 1	**96.88**	97.65	**22.66**		**0.902**	
	TOP 2	96.63	97.46	22.40		1.001	
	TOP 3	93.35	96.05	19.45		2.194	
	Proposed	96.83	**97.72**	22.63		0.908	
H-DIBCO 2016	TOP 1	87.61	91.28	18.11		5.21	
	TOP 2	88.72	91.84	18.45		**3.86**	
	TOP 3	88.47	91.71	18.29		3.93	
	Proposed	**89.70**	**93.62**	**18.73**		3.99	

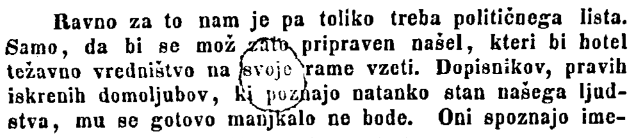
Fig. 5 further shows the resulting binary images of Fig. 1(e) produced by different techniques. As shown in the figure, the Niblack's method fails to produce reasonable results. Otsu's, Sauvola's, Wolf's, and Su's BESE methods remove too much text strokes. Su's LMM method tends to produce hollow text strokes near page boundary and fails to extract low-contrast text strokes. Compared to Howe's and Mesquita's techniques, our proposed method preserves text strokes better and produces better visual quality.



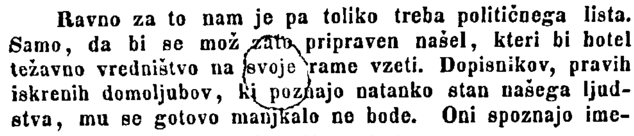
(a) Otsu's method



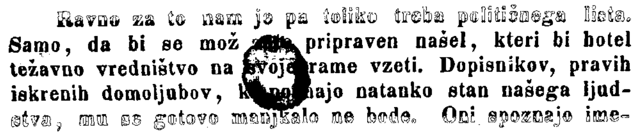
(b) Niblack's method



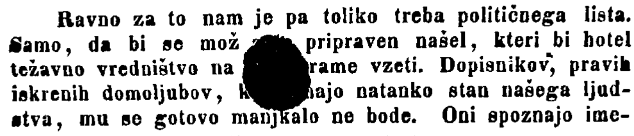
(c) Sauvola's method



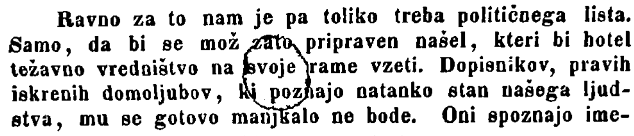
(d) Wolf's method



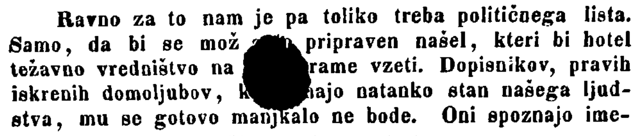
(e) Su's LMM method



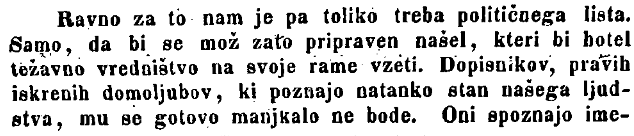
(f) Su's BESE method



(g) Howe's method



(h) Mesquita's method



(i) Our proposed method

Fig. 5 Resulting binary images of Fig. 1(e) produced by Otsu[3], Niblack[4], Sauvola[5], Wolf[6], LMM[13], BESE[9], Howe[15], Mesquita[17], and our proposed methods.

IV. CONCLUSION

In this paper, we present an enhanced historical document image binarization technique, which is robust against different types and levels of degradation. The proposed method makes use of document background estimation and Laplacian energy minimization. Such a combined method leads to high accuracy when applied to degraded historical document images, and our proposed method outperforms other state-of-the-art document image binarization techniques.

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