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Efficient illumination compensation techniques for text images

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ABSTRACT

With the great advantages of digitization, more and more documents are being transformed into digital representations. Most content digitization of documents is performed by scanners or digital cameras. However, the transformation might degrade the image quality caused by lighting variations, i.e. uneven illumination distribution. In this paper we describe a new approach for text images to compensate uneven illumination distribution with a high degree of text recognition. Our proposed scheme is implemented by enhancing the contrast of the scanned documents, and then generating an edge map from the contrast-enhanced image for locating text area. With the information of the text location, a light distribution image (background) is created to assist the producing of the final light balanced image. Simulation results demonstrate that our approach is superior to the previous works of Hsia et al. (2005, 2006).

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1. Introduction

Digitization of documents is the process that transforms material into its digital form using digital cameras or scanners. Developed countries digitize important documents in order to preserve cultures, artistry, and histories; these processes are known as digital archives. In this way, digitized documents can be preserved forever and also exhibited conveniently via the Internet. With more valuable documents being digitized for preservation, lightbalance techniques in imaging processing have become a serious concern. The uneven illumination distribution of digitized documents results from an incomplete contact plane between material and scanner or from uneven lighting conditions during the photocopying process. The shadow caused by uneven illumination distribution degrades the visual quality of the text image and makes it difficult to recognize the content, as shown in Fig. 1. Document understanding methods, such as optical character recognition, might be applied to solve this problem, but its requirement of semantic content preservation narrows down its applications.

Some studies have been proposed to deal with the uneven illumination distribution problem [2,3,5,9–11,13–16]. In image binarization, researchers found that adaptive thresholding methods outperform global thresholding ones due to lighting variation. In

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Parametric query optimization: T [1992], Ganguly [1998] and Hulge the selectivity of query parameter—one for each of several different the optimizer, at compile time. Or of the actual selectivities, avoiding Aggregate Optimization: Klug [19] algebra expressions with aggregation is addressed by Yan and Latimization of queries containing

Fig. 1. A scanned text image with uneven illumination distribution.

2000, Sauvola and Pietikäinen proposed a thresholding method [13] in which a hybrid switching was used to classify a scanned image into textual and non-textual regions at first and apply histogram based and soft decision based methods to these textual and non-textual components, respectively. For text binarization, the authors applied an adaptive thresholding method which is a modified version of Niblack's algorithm [12]. In 2001, Seeger and Dance [14] presented a background surface thresholding (BST) method. BST first generates two intermediate images, i.e. block average and block variance images, and then produces a block average image with high variance areas removed to complete text labeling. Then, a continuous background image is created by estimating text areas using interpolating. Afterwards, a binarization image is generated according to the background image by thresholding. The advantage of BST is that it uses adaptive window sizes during text labeling. However, the determination of window size is related to the font

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size and character stroke width. The authors have not mentioned how to deal with a text image with different font sizes and character stroke widths. In 2005, Hsia and Tsai proposed an efficient light balancing technique (ELBT) [3] for text images. The main idea of ELBT is to separate the text part from the background area using block-based processing. Whether a block belongs to a content block or to a background block is determined by computing the block mean variance (BMV). The BMV of a content block is higher than that of a background block. After the text part has been located, new values are substituted for the text pixels by applying linear interpolation to obtain a background-like image. Referring to the background-like image, an adaptive gain control technique is employed to achieve a light balanced text image.

After that, in 2006, Hsia et al. proposed a line-based light-balancing technique (LLBT) [2]. Unlike the block-based ELBT, LLBT generates the background-like image using lines. First, each horizontal line is split into sections. Then, LLBT finds the section level by computing the average value of maximum M pixels in each section. Next, the background-like image can be obtained by adapting interpolation in terms of these section levels. Finally, the light balanced text image is achieved according to the background-like image by employing the adaptive gain control technique in LLBT.

However, most of previous works completed mission by the raw data, i.e. the original scanned files. The threshold determination or object and non-object classification might not work well while the textural pixels were very close to the background pixels. In this paper, we propose an efficient edge-based light balancing scheme (ELBS) for text images. ELBS contains five phases: (1) contrast enhancement phase; (2) edge detection phase; (3) text locating phase; (4) light distribution phase; and (5) light balancing phase. The processes of ELBS are illustrated as follows. The contrast of the original text image is enhanced first. The Sobel technique [4,6] is adapted to generate the edge image from the original text image in order to indicate the text part roughly. The text part can be located more precisely by merging the contrast enhanced and the edge-detected results. The located text pixels are replaced with new values by interpolation according to the background part; this generates the light distribution image. Finally, the light balanced image is constructed in terms of the contrast enhanced and light distribution images. The simulation results show that ELBS outperforms ELBT and LLBT for text images. Our approach not only balances the illumination distribution well but also maintains high visual quality. The details of the proposed scheme are illustrated in Section 2, followed by simulation results in Section 3. Finally, conclusions and further works are stated in Section 4.

2. The proposed scheme

The goals of our proposed scheme are to balance uneven light distribution and to produce content with a high degree of recognition. To achieve these goals, five phases are included in the proposed scheme: contrast enhancement, edge detection, text location, light distribution, and light balancing.

Contrast enhancement [1,7,8] is used to emphasize image characteristics. The contrast of the text image is enhanced to obtain the contrast enhanced image CEI in the first phase. In Phase 2, the Sobel edge detection technique [6] is adapted to obtain an edge image from the original text image. The edge image is then translated into binary edge image EI_{bin} using a predefined threshold. In Phase 3, CEI is translated into binary contrast-enhanced image CEI_{bin} , and the text location image TLI is generated according to CEI_{bin} and EI_{bin} . In Phase 4, the light distribution image LDI is obtained according to CEI and TLI. Finally, the light balanced image

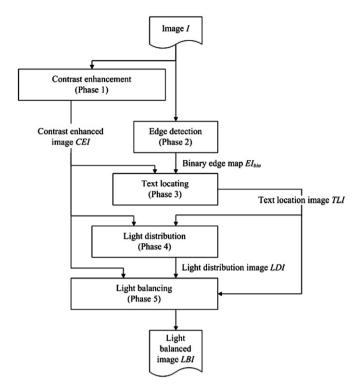


Fig. 2. The flowchart of the proposed scheme.

LBI can be constructed according to CEI, TLI, and LDI. The flowchart of the proposed scheme is shown in Fig. 2.

2.1. Contrast enhancement phase

In the first phase, the contrast is enhanced to increase the luminance difference between the text and background of the original text image. Assume that the original gray-level text image is denoted as I with $h \times w$ pixels. The contrast enhancement procedure is described as follows, and the result is shown in Fig. 3(b).

Step 1. Compute hp_i of I, where hp_i is the accumulation of pixels in a histogram from gray-level $i \times 10$ to $(i+1) \times 10$ for i = 0, 1, ..., 25.

Step 2. Find the first i that $hp_i > \lfloor \sqrt{h \times w} \rfloor$ for i = 0, 1, ..., 25, and then set $hr = i \times 10$, where hr is the histogram reducing value of I.

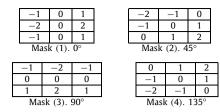
Step 3. Enhance contrast of I to obtain the contrast enhanced image CEI by the following formula:

$$CEI(pv_i) = (I(pv_i) - (hr + 50 \times c)) \times 2, \tag{1}$$

where pv_j is the jth pixel in I for $j=1,2,\ldots,h\times w$, and c is in the interval [0,1] used to further reduce image brightness, and finally multiple a gain factor "2" to enhance image contrast. In underflow and overflow cases, if $CEI(pv_j) < 0$, then set $CEI(pv_j) = 0$; if $CEI(pv_j) > 255$, then set $CEI(pv_j) = 255$.

2.2. Edge detection phase

In the second phase, the Sobel edge detection technique is used to produce an edge image that indicates the text part of the original image. Four edge images are generated according to four different masks in order to detect different directions. The four masks that used in Sobel edge detection are shown as follows:



After the four edge images are generated, the detection result is constructed by computing the average result. The detection result is translated into a binary image according to a predefined threshold. The procedures are listed as follows, and the detection result is shown in Fig. 3(c).

Step 1. Produce four edge images EI_1 , EI_2 , EI_3 , and EI_4 according to I by four Sobel edge masks with four different directions: 0° , 45° , 90° , and 135° .

Step 2. Generate the average edge image EI_{avg} by the following formula:

$$EI_{avg} = \frac{1}{4} \sum_{n=1}^{4} \sum_{i=1}^{h \times w} (EI_n(pv_j)).$$
 (2)

Step 3. Produce the binary edge image EI_{bin} of EI_{avg} by the following formula:

$$EI_{bin}(pv_j) = \begin{cases} 0, & \text{if } EI_{avg}(pv_j) < th_e, \\ 255, & \text{if } EI_{avg}(pv_j) \ge th_e, \end{cases}$$
 (3)

where th_e is a predefined threshold, i.e. the average value of the two peak points in the histogram result of El_{avg} , and $j = 1, 2, ..., h \times w$.

2.3. Text location phase

To create the background-like image of the original text image, the text must be located first. Once the text pixels are found, their pixel values can be replaced with new ones using interpolation. To locate the text pixels in I, images CEI and EI_{bin} are used as requirements. First, CEI is translated into its binary representation, CEI_{bin} , according to the predefined threshold th_c . Next, CEI_{bin} and EI_{bin} are merged to construct the text location image, TLI, according to Eq. (5). Finally, we adopt the morphology erosion operation to TLI according to the erosion mask, which is defined as follows:



The text location result is shown in Fig. 3(e), and the procedure of text location phase is illustrated as follows.

Step 1. Produce CEI_{bin} , the binary representation of CEI, by the following formula:

$$CEI_{bin}(pv_j) = \begin{cases} 255, & \text{if } CEI(pv_j) < th_c, \\ 0, & \text{if } CEI(pv_j) \ge th_c, \end{cases}$$
(4)

where th_c is a predefined threshold generated by calculating the average value of the two peak points in the histogram result of *CEI*, and $j = 0, 1, ..., h \times w$. Fig. 3(d) shows the binary contrastenhanced image CEI_{bin} .

Step 2. Merge EI_{bin} with CEI_{bin} to obtain the text location image TLI by the following equation:

Parametric query optimization: T [1992], Ganguly [1998] and Hulge the selectivity of query parameter—one for each of several different the optimizer, at compile time. Or of the actual selectivities, avoiding Aggregate Optimization: Klug [19] algebra expressions with aggregate tim is addressed by Yan and Latimization of queries containing

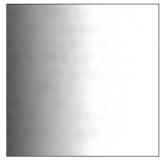
(a) Sampling image

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(c) Binary edge map EI_{bin} ($th_e = 40$)

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(e) Text location image TLI



(g) Light distribution image LDI

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(b) Contrast enhanced image CEI

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(d) Binary contrast enhanced image CEIbin



(f) Interpolated image II

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(h) Light balanced image LBI (bl = 260)

Fig. 3. The gradual outcome.

$$TLI(pv_j) = \begin{cases} 0, & \text{if } EI_{bin}(pv_j) = 255 \text{ or } CEI_{bin}(pv_j) = 255, \\ 255, & \text{otherwise,} \end{cases}$$
 (5)

where $j = 0, 1, \dots, h \times w$.

Step 3. Adopt morphology erosion operation to *TLI* according to the erosion mask.

2.4. Light distribution phase

There are three steps to obtain the background-like image, the light distribution image of *CEI*, in the light distribution phase. The first step is to determine the text pixels in *CEI* according to *TLI*.

A pixel in *CEI* is regarded as a text pixel if the corresponding pixel value in *TLI* is 0; otherwise, it is treated as a background pixel. Next, the values of the text pixels are replaced using interpolation. The interpolated image *II* is generated as shown in Fig. 3(f). The mean filter is then used to smooth the interpolated image in order to produce the light distribution image *LDI*, as shown in Fig. 3(g). The steps of this phase are outlined as follows:

Step 1. Search all pixels in *TLI*; if pixel value 0 is found in *TLI*, then the corresponding pixel in *CEI* is regarded as a text pixel; otherwise, it is treated as a background one.

Step 2. Find text sections in each pixel-column from left to right in *CEI*. If a text section is found, then record the first and last pixel locations as *head* and *end*, respectively. Note that a text section means a vertical line with connected text pixels.

Step 3. Replace text pixel values in each text section to build the interpolated image *II* by the following equation:

$$II(pv_{head+m}) = CEI(pv_{head-1}) + \frac{mpv_{end} - mpv_{head}}{n} \times (m+1), (6)$$

where *head* and *end* are the location of the first and last pixel in a text section, respectively, m means the mth pixel in the current processing section for $m = 0, 1, \ldots, n-1$, and n means the number of pixels in the processing text section. In addition, mpv_{head} and mpv_{end} are defined as follows:

$$mpv_{head} = MAX(CEI(pv_{head-k})), \text{ for } k = 0 \text{ to } 4,$$
 (7)

$$mpv_{end} = MAX(CEI(pv_{end+k})), \quad \text{for } k = 0 \text{ to } 4.$$
 (8)

Step 4. Repeat Steps 1 and 2 until all text sections have been processed.

Step 5. Adapt mean filter with 11×11 matrix to II for generating light distribution image LDI.

2.5. Light balancing phase

The final result of the proposed scheme is generated in the light balancing phase. The light balanced image *LBI* is constructed according to images *CEI*, *TLI*, and *LDI* using the following equation:

$$LBI(pv_{j}) = \begin{cases} \frac{bl}{LDI(pv_{j})} \times CEI(pv_{j}), & \text{if } TLI(pv_{j}) = 0, \\ \frac{bl \times 1.5}{LDI(pv_{j})} \times CEI(pv_{j}), & \text{otherwise,} \end{cases}$$
(9)

where bl is a luminance-level adjusting parameter, and $j = 1, 2, \ldots, h \times w$. The result is shown in Fig. 3(h).

3. Simulation results

To demonstrate the performance of our proposed scheme, scanned images are treated as test images for simulations in Section 3.1. In Section 3.2, we create artificial scanned-liked images as test images to show that the proposed scheme is suitable for various situations. Note that all sampling images are gray-level with 512×512 pixels and that the values of parameters th_e , th_c , and bl are set to be 30, 60, and 260, respectively. In Section 3.3, we discuss how the parameters affect the simulation results. To show the superiority of our scheme, it is compared with previous works [2,3].

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(a) Scanned image S1

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(b) Result of ELBT

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(c) Result of LLBT

(d) Result of the proposed scheme

Fig. 4. The simulation result with physical scanned image S1.

3.1. Simulations with scanned images

We utilized a digital scanner to sample all images from hard copies. It is well known that an incomplete contact plane between material and scanner leads to uneven light distribution of the scanned image and reduces the visual quality. Fig. 4 gives an example to show the performance of previous works and the proposed scheme. Fig. 4(a) depicts scanned image S1, whose image quality is damaged seriously. Figs. 4(b), (c), and (d) are the simulation results of ELBT, LLBT, and the proposed scheme, respectively. It is obvious that the proposed scheme has outstanding performance in both light balancing and text recognition, especially by comparing the marked parts where the image quality is damaged most seriously.

Furthermore, Fig. 5 presents three scanned images with different font sizes and light distribution directions. The simulation results for ELBT are shown in Figs. 5(d) to (f); Figs. 5(g) through (i) are the results of LLBT; Figs. 5(j) to (l) show the results of the proposed scheme with c=0.5. It is clear that our proposed scheme outperforms both ELBT and LLBT in text recognition, especially in the marked parts.

3.2. Simulations with artificial images

To show that the proposed scheme is suitable for various situations, we create artificial images with various uneven light distribution directions. Here, we utilize the peak signal-to-noise ratio (*PSNR*) to measure the image quality. The equation of *PSNR* is shown as follows:

$$PSNR = 10 \times \log_{10} \frac{255^2}{MSE},$$
 (10)

where MSE (mean square error) is defined as

$$MSE = \left(\frac{1}{h \times w}\right) \sum_{i=1}^{h \times w} \left(X_i - X_i'\right)^2,\tag{11}$$

and h and w are the height and width of the image, respectively; X_i and X_i' are the original pixel value and processed pixel value, respectively.

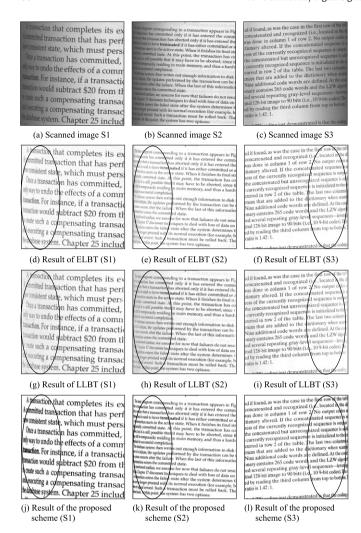


Fig. 5. The simulation results with physical scanned images S1 through S3.

Fig. 6 lists the artificial images (A1 through A6) used for the simulations. Note that each was created by adding shadows to the image translated from a word file, which has perfect light distribution. For example, Fig. 7(a) is the original text image of Fig. 6(a).

Fig. 7 shows that the proposed scheme outperforms ELBT and LLBT in terms of image quality and text recognition. The original text image of A1 is shown in Fig. 7(a). Its corresponding artificial image is shown in Fig. 7(b), whose PSNR value is less than 9 dB. Figs. 7(c) and (d) are the simulation results of ELBT and LLBT, respectively. The simulation result of our proposed scheme is shown in Fig. 7(e). First, the PSNR values are greater than 33.3 dB using the proposed scheme and less than 24.1 dB with the previous works. Moreover, the proposed scheme is better than previous works in terms of text recognition, especially comparing the marked parts where the image quality is damaged most seriously.

All of the artificial images with various shadow directions and their simulation results are listed in Fig. 8. Images R1 through R6 are the simulation results of artificial images A1 through A6, respectively. It can be observed that the proposed scheme is superior for balancing uneven light distribution and improving the degree of text recognition.

Table 1 compares the *PSNR* values of the proposed scheme with those of previous works. It can be observed from Table 1 that the proposed scheme outperforms previous works in all simulations. Furthermore, all PSNR values of the simulation results are more than 30.8 dB using the proposed scheme. On average, the proposed

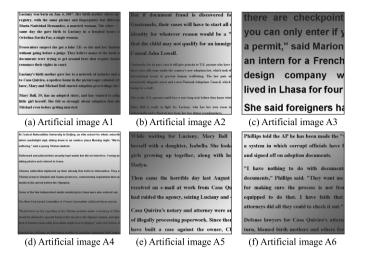
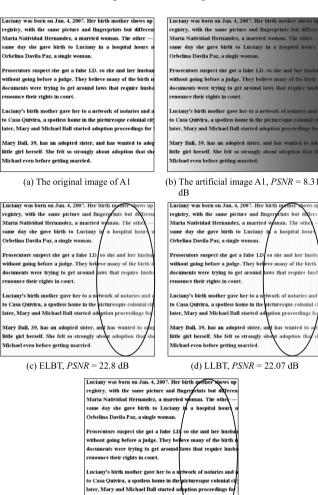


Fig. 6. Artificial test images.



little girl herself. She felt so strongly a Michael even before getting married.

(e) The proposed scheme, PSNR = 33.96 dB

Fig. 7. Simulation results of artificial image A1.

scheme can improve the image quality by 38.37% compared with ELBT and 40.42% compared with LLBT.

We created two artificial images whose quality is so damaged that the text is difficult to be recognized. The original image is

Table 1Comparisons for sampling images.

Schemes	Sampling images (dB)							
	A1	A2	A3	A4	A5	A6	Average	
Artificial image	8.31	7.76	9.23	8.86	9.16	8.59	8.65	
ELBT [3]	22.80	22.53	21.12	24.09	24.79	24.18	23.25	
LLBT [2]	22.07	22.24	20.69	24.09	24.60	23.78	22.91	
Proposed scheme	33.96	31.82	31.70	33.31	30.81	31.47	32.17	

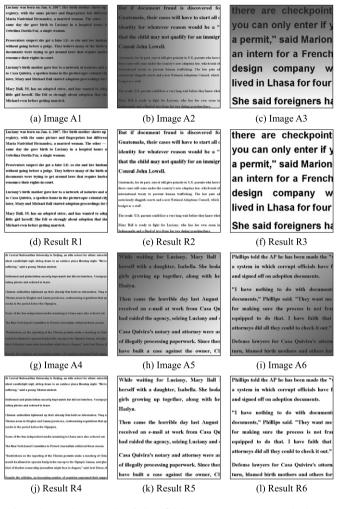


Fig. 8. The simulation results of all artificial images using our proposed scheme.

shown in Fig. 9. Fig. 10(a) is the first special artificial image (SA1), whose *PSNR* value is 6.11 dB, and Figs. 10(b) to (f) show the gradual outcome of our proposed scheme. The simulation results of ELBT and LLBT are shown in Figs. 10(h) and (i), respectively. It can be observed that the result of LLBT is slightly better than that of ELBT, but it is still unsatisfactory. Fig. 10(g) shows the result of the proposed scheme. The text recognition degree is much greater than that with previous works.

Fig. 11 gives another example to show the performance of the proposed scheme. The artificial image used here is SA2 (*PSNR* = 5.289 dB), which is shown in Fig. 11(a). As we can observe from Fig. 11(b), the result is close to a blank image, and it show that ELBT almost cannot work with SA2. The result is also unacceptable for LLBT, as shown in Fig. 11(c). On the contrary, Fig. 11(d) depicts the satisfactory result made by the proposed scheme.

Furthermore, we use 30 historical text images downloaded from the Library of Congress website to test the performance of our pro-



Fig. 9. The original test image of the two special artificial images.



Fig. 10. The simulation results of the first special artificial image SA1.

posed scheme. Table 2 shows an example of a historical text image processed with our proposed and previous schemes, and the average recognition results of 30 historical text images using Google Docs OCR. The experiment results presented in Table 2 show that our proposed scheme has a better performance in text recognition rate compared with previous schemes.

Table 3 lists the comparisons of simulation time within the environment: Intel Core 2 Quad Q9300 2.5 GHz CPU, 4.0 GB main memory, and Java Development Kit 1.6.0_26. The fastest scheme is LLBT [2], the second one is ELBT [3] followed by our proposed scheme. The longer processing time of our proposed scheme is caused by the extra preprocess of raw data (ex: contrast enhancement) which is helpful for generating a good light-balanced result.

Table 2 The comparisons of historical text images.

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burdens from wage-worke "No Anarchist orator, gainst the Constitution framed an indictment of aning judges must be re framed if their re

Mr. and Mrs. J. R. McEif eb. 15th.

Input Image	Our scheme		
Our scheme	98.4 %		
ELBT	95.3 %		
LLBT	96.8 %		



(a) The second artificial image SA2 (PSNR = 5.289 dB)

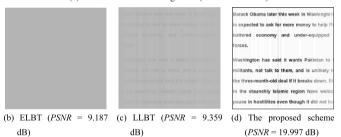


Fig. 11. The simulation results of the second artificial image SA2.

Table 3 The comparisons of simulation time among our proposed and previous schemes.

Schemes	Proposed scheme	ELBT [3]	LLBT [2]
Simulation time (s)	1.197	0.203	0.061

3.3. Discussions

In this section, we discuss how two important parameters, c and bl, affect the image quality of simulation results. For parameter c, we use three artificial images for simulations, and the results are shown in Fig. 12. Note that x- and y-coordinates denote the value of c in the interval [0,1] and the visual quality of the processed images, respectively, where $th_e = 30$, $th_c = 60$, and bl = 260. As shown in Fig. 12, the suggested values of c are from 0.1 to 0.4.

Next, we focus on parameter bl. Fig. 13 shows how the different values of bl affect the visual quality of images, where $th_e = 30$, $th_c = 60$, and c = 0.1. The suggested values of bl are from 200 to 300.

4. Conclusions and further works

In this paper, a novel light balancing scheme for text images based on edge detection technique is proposed. Our approach consists of five phases: contrast enhancement, edge detection, text location, light distribution, and light balancing. Simulation results illustrate that the proposed scheme can achieve superior perforburdens from wage-worke "No Anarchist orator, against the Constitution framed an indictment of ning judges must d if their re

Mr. and Mrs. J. R. McElf ELBT

burdens from wage-worke "No Anarchist orator, against the Constitution framed an indictment of meaning judges must be have framed if their

Mr. and Mrs. J. R. McEif LLBT

• 30 historical text images.

• The distribution of illumination is varied including non-illuminated, bad illumination, and artificial illumination.

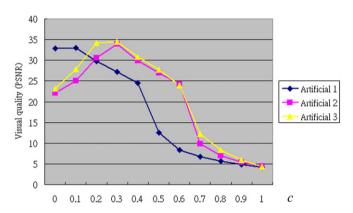


Fig. 12. The simulations of c and the visual quality of processed image.

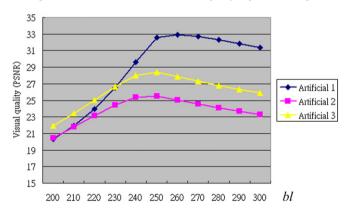


Fig. 13. The simulations of bl and the processed image visual quality.

mance in terms of both balancing uneven light distribution and achieving a high degree of text recognition. In the future, we will focus on developing an efficient scheme to compensate for the uneven illumination problem for all kinds of scanned images, such as text images, text-photo images, and photo images.

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