

MELBS ALGORITHM FOR BACKGROUND BRIGHTNESS BALANCING IN TEXT IMAGES

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Abstract: The first part of the paper describes an algorithm for balancing the background brightness of text images (ELBS algorithm). After that, the algorithm is modified by implementing the Gravity Edge Detection Algorithm. The second part of the paper describes an experiment in which the performance of ELBS and MELBS algorithms is determined. Performance is determined through MSE and PSNR measures. The results are presented by tables and graphs. A comparative analysis of the results showed a higher efficiency of the MELBS algorithm.

Key words: adaptive processing, light balance, uneven illumination, histogram

1. INTRODUCTION

Today, intensive work is being done on the digitalization of important documents in order to preserve culture, art, history, technology, etc. Digitized documents can be permanently saved. In addition, digitized documents can be made available to the general public via the Internet. The process of digitizing documents is the transformation of physical material (paper) into digital form using a camera or scanner [1]. Uneven brightness distribution of digitized documents is the result of incomplete contact between the material (paper) and the scanner. In addition, uneven light distribution may be due to uneven lighting conditions during the photocopying process. Shadow, caused by uneven lighting distribution, degrades the visual quality of text images and makes it difficult to recognize content. In order to enable efficient digital image processing, with the aim of detecting lines and contours in the image, text recognition, etc., the scanned document is translated into a binary document. The efficiency and precision of digital image processing directly depends on the quality of the binary document. Therefore, special algorithms are used to increase the quality of the scanned document.

Algorithms for balancing the brightness in the image are intensively applied [2]-[4]. An algorithm for classifying regions of scanned images into: a) textual and b) non-textual ones is described in [2]. The described algorithm is based on the thresholding method. After that, the binarization of textual regions is performed by histogram analysis, while binarization of non-textual regions is realized by applying soft decision based methods. The results of the application of the adaptive thresholding method for text binarization are presented in [5]. An algorithm for balancing the brightness of text images, which is based on dividing the image into regions, estimating the brightness of the region and linear interpolation between neighbor regions, is presented in [6]. Adaptive brightness correction is applied to each pixel. Determining of the decision threshold for classification is not precise enough when the luminances of text pixels are approximately the same as the luminances of background pixels.

The algorithm, based on an efficient edge-based light balancing scheme (ELBS), is presented in [1]. The ELBS algorithm is used to increase the contrast, and for that purpose, the Sobel algorithm for detecting edges in the image was applied. After that, the text regions in the image are located. Finally, the brightness in the background of the text regions are balanced.

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In this paper, the ELBS algorithm is described in detail and, after that, its modification is performed. The modification was performed with the aim of increasing the efficiency in balancing the background brightness of the text image (MELBS algorithm). The modification was performed by implementing an algorithm for estimating edges and contours, based on the Newton gravitational model (GA algorithm) [7]. In the second part of the paper, the experiment, within which the efficiency of the ELBS and MELBS algorithms was tested, is presented. A test database, which is composed of text images in which the background brightness is purposefully deformed, was formed. Background brightness of the test images was balanced by ELBS and MELBS algorithms. The results of the action of the algorithms, expressed by mean squared error (MSE) and peak signal-to-noise ratio (PSNR), are presented using tables and graphs. The efficiency of the algorithms was tested by comparative analysis of the results. Detailed analysis indicated greater efficiency of the MELBS algorithm.

The rest of the paper is organized as follows. Section 2 describes the ELBS and MELBS algorithms. Section 3 presents the experiment and a comparative analysis of the results. Section 4 is the conclusion.

2. ALGORITHMS FOR BACKGROUND BRIGHTNESS BALANCING

2.1. ELBS algorithm

An algorithm for balancing the uneven distribution of brightness in the background is shown in [1]. The algorithm is realized through five phases: a) contrast enhancement phase, where the text is emphasized in relation to the background, b) edge detection phase, where edge detection is performed using the Sobel edge algorithm, c) text location phase, d) light distribution phase, where the background brightness is balanced by applying interpolation, and e) light distribution phase, where a background-like image is formed by applying interpolation. The ELBS algorithm is realized in the following steps:

Input: Image I , dimension $h \times w$.

Output: LBI image with balanced background.

Step 1: compute the histogram h of image I .

Step 2: compute the accumulation of the brightness intensity of the pixel hp_i in the range $(i * 100 - (i + 1) * 100)$, where $i = 0, 1, \dots, 25$.

Step 3: Find the first i that $hp_i > \lfloor \sqrt{h \cdot w} \rfloor$, where $i = 0, 1, \dots, 25$, and determination of the histogram reduction factor $hr = 10 * i$.

Step 4: compute contrast enhanced image, CEI:

$$CEI(pv_j) = 2(I(hp_j) - (hr + 50 \cdot c)), \quad (1)$$

where pv_j is the j -th pixel of the image $I_j = 1, \dots, h * v$, and $c = 0 - 1$ is the brightness correction factor. In underflow and overflow cases contrast enhanced image is:

$$CEI(pv_j) = \begin{cases} 0, & \text{ako je } CEI(pv_j) \leq 0 \\ 255, & \text{ako je } CEI(pv_j) \geq 0 \end{cases}, \quad (2)$$

Step 5: generate four edges images (EI_1, EI_2, EI_3, EI_4) by filtering the image I using the Sobel filter for directions: $0^\circ, 45^\circ, 90^\circ$ i 135° , respectively.

Step 6: the resulting averaged image with prominent edges is:

$$EI_{avg} = \frac{1}{4} \sum_{n=1}^4 \sum_{i=1}^{h \times w} EI_n(pv_j), \quad (3)$$

Step 7: create a histogram $h_{EI_{avg}}$ of the image EI_{avg} .

Step 8: determination of the decision threshold th_e (mean between two dominant peaks in histogram $h_{EI_{avg}}$).

Step 9: generate a binary image:

$$EI_{bin}(pv_j) = \begin{cases} 0, & \text{if } EI_{avg}(pv_j) < th_e \\ 255, & \text{if } EI_{avg}(pv_j) \geq th_e \end{cases}. \quad (4)$$

Step 10: create a binary image CEI_{bin} from the image CEI :

$$CEI_{bin}(pv_j) = \begin{cases} 255, & \text{if } CEI(pv_j) < th_c \\ 0, & \text{if } CEI(pv_j) \geq th_c \end{cases}, \quad (5)$$

where the decision threshold th_c is determined as the mean of the two dominant peaks in the histogram of the image CEI , and $j = 1, \dots, h \times v$.

Step 11: the text location image TLI is generated according to CEI_{bin} and EI_{bin} .

$$TLI(pv_j) = \begin{cases} 0, & \text{if } EI_{bin}(pv_j) = 255 \text{ or } CEI_{bin}(pv_j) = 255 \\ 255, & \text{otherwise} \end{cases}, \quad (6)$$

where $j = 1, \dots, h \times v$.

Step 12: morphology erosion of the TLI image is performed using the erosion mask.

Step 13: the luminances of all pixels of the TLI image were analyzed. If the luminance of the pixel is 0, then the corresponding pixel of the image CEI is potentially a text pixel. Otherwise, the pixel is considered the background.

Step 14: an analysis of the CEI image pixel column is performed, starting from the left to the right. Each column specifies the pixel sections that belong to the text. The first pixel of the section text is marked as *head* and the last as *end*.

Step 15: each pixel of the text section is replicated using interpolation:

$$II(pv_{head+m}) = CEI(pv_{head-1}) + \frac{mpv_{end} - mpv_{head}}{n} (m+1), \quad (7)$$

where m is the m -th pixel in the text section, $m = 0, 1, \dots, n-1$, and n is the number of pixels in the text section, and mpv_{head} and mpv_{end} are defined as:

$$mpv_{head} = \text{MAX}(CEI(pv_{head-k})), \quad mpv_{end} = \text{MAX}(CEI(pv_{end+k})), \quad (8)$$

where $k = 0, 1, \dots, 4$.

Step 16: light distribution image LDI was obtained by filtering the image II using a mean filter dimension 11×11 .

Step 17: the final result is a light balanced image LBI , which is created according to:

$$LBI(pv_j) = \begin{cases} \frac{bl}{LDI(pv_j)} \times CEI(pv_j), & \text{if } TL_{bin}(pv_j) = 0 \\ \frac{bl \times 1.5}{LDI(pv_j)} \times CEI(pv_j), & \text{otherwise} \end{cases}, \quad (9)$$

where bl is the luminance level adjustment parameter, and $j = 1, \dots, h \times v$.

The result of applying the ELBS algorithm is shown in Fig. 1: a) image I with uneven brightness distribution, b) histogram h of the image I (Step 1), c) histogram hp_i (Step 2), d) contrast enhanced image, CEI (Step 4), e) averaged image with prominent edges EL_{avg} (Step 6), f) histogram $h_{EL_{avg}}$ of the image EL_{avg} (Step 7), g) binary image EL_{bin} (Step 9), h) binary image CEI_{bin} (Step 10), i) interpolation image II (Step 15), j) light distribution image LDI (Step 16), k) light balanced image LBI (Step 17).

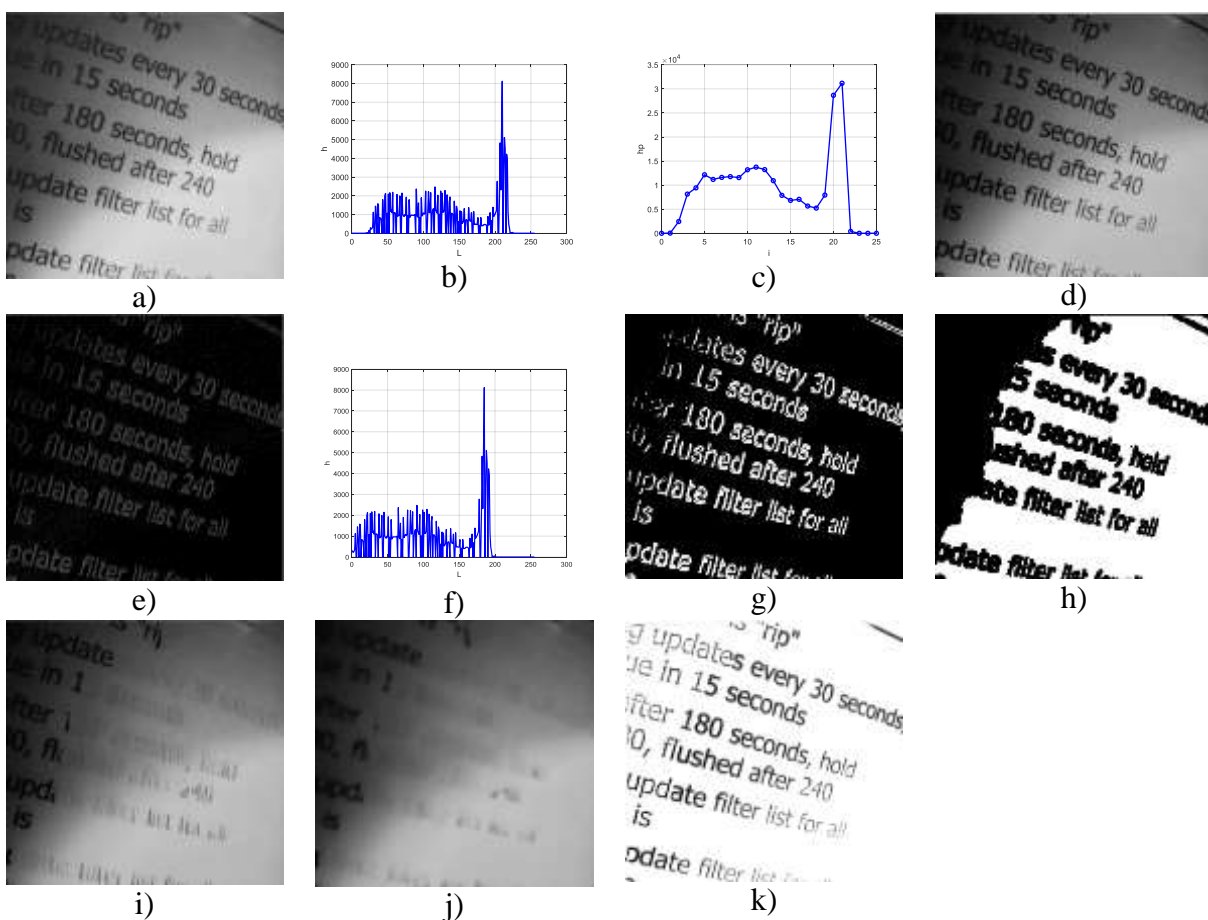


Figure 1 –a) image I with uneven brightness distribution, b) histogram h of the image I , c) histogram hp_i , d) contrast enhanced image, CEI, e) averaged image with prominent edges EL_{avg} , f) histogram $h_{EL_{avg}}$ of the image EL_{avg} , g) binary image EL_{bin} , h) binary image CEI_{bin} , i) interpolation image II , j) light distribution image LDI , k) light balanced image LBI

2.2. MELBS algorithm

In order to increase efficiency, the authors have created a modified ELBS algorithm (MELBS). The modification was done in steps 5 and 6. The Gravity Algorithm (GA) was used to detect the edges in the image [7]. According to Newton's law of universal gravitation, every object in the universe attracts every other object by mechanical force of gravity. The force of gravity, whose direction lies on the same line as the centers of the two objects, is

proportional to the product of their masses, and inversely proportional to the square of the their distance. The force acting on the mass m_1 and the consequence of the action of the mass m_2 is:

$$\overrightarrow{F_{1,2}} = G \frac{m_1 \cdot m_2}{\|\overrightarrow{r_{2,1}}\|^2} \cdot \hat{r}_{2,1}, \quad (10)$$

where $\overrightarrow{F_{1,2}}$ is force vector by which the body m_1 acts on the body m_2 , and G is the gravitational constant. An analogy between the mass and luminance of the pixels, as well as the gravitational force and the distance between the pixels, were introduced. A decision about the affiliation of the analyzed pixel to the edge between the two regions, by calculating the interaction of the neighbors pixels of the analyzed pixel, is made.

3. EXPERIMENTAL RESULTS AND ANALYSIS

3.1. Experiment

The ELBS (Section 2.1, Sobel Algorithm) and MELBS (Section 2.3, Gravity Algorithm) algorithms were applied to the test images from the test database, with the aim of examining the efficiency of text highlighting and backlight balancing. The efficiency of the algorithms, for some values of the parameters c and bl , was measured using MSE and PSNR

$$MSE(c, bl) = \frac{1}{MN} \sum_{i=1}^h \sum_{j=1}^w (I_{i,j}(c, bl) - LBI_{i,j}(c, bl))^2, \quad (11)$$

$$PSNR(c, bl) = 10 * \log_{10}(255^2 / MSE(c, bl)), \quad (12)$$

where I (image with black text and a white background, Fig. 2a), LBI (light balanced image), and $h \times w$ are the dimensions of the image. MSE and PSNR errors are calculated for various mean background brightness $L_m = (L_{min} + L_{max}) / 2$. By minimizing the MSE and maximizing the PSNR errors, the optimal values of the parameters c and bl were found. The quality of the algorithms was determined by comparative analysis of the results. The experiment was realized with $c = -1 : 0.1 : 0$, $bl = 200 - 260$, $L_{min} = 120 - 150$, $(L_{max}) = 255$.

3.2. Image database

The test image database consists of text documents suitable for testing. First, an image, with black text and a white background, was created (Fig. 2a). After that, a background image, with a continuous increase in brightness, starting from the left (L_{min}) to the right (L_{max}), was created (Fig. 2b). Finally, by merging the image with the text and the background image, a test image is formed (Fig. 2c).

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a).

b).

c)

Figure 2 – a) image with black text and a white background, b) background image i c) test image

3.3. Results

The values of MSE (c, bl) are shown in: a) Fig. 3a (ELBS algorithm) and b) Fig. 3b (MELBS algorithm). The values of PSNR (c, bl) are shown in: a) Fig. 3c (ELBS algorithm)

and b) Fig. 3d (MELBS algorithm). The MSE(c) for the optimal value of bl is shown in Fig. 4a (ELBS algorithm). The MSE(bl) for the optimal value of c is shown in Fig. 4b (MELBS algorithm). The PSNR(c) for the optimal value of bl is shown in Fig. 4c (ELBS algorithm). The PSNR(bl) for the optimal value of c is shown in Fig. 4d (MELBS algorithm). A graphical representation of the dependence of MSE and PSNR errors on mean background brightness is shown in Fig. 5. The optimal values of c and bl and MSE_{min} are shown in Table 1. The optimal values of c and bl and $PSNR_{max}$ are shown in Table 2.

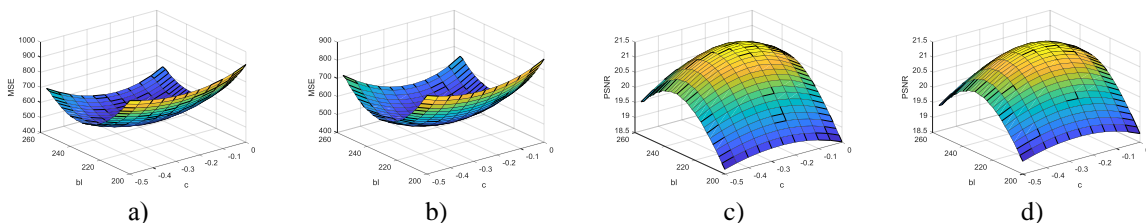


Figure 3 – MSE(c , bl): a) ELBS algorithm, b) MELBS algorithm. PSNR(c , bl): c) ELBS algorithm, d) MELBS algorithm.

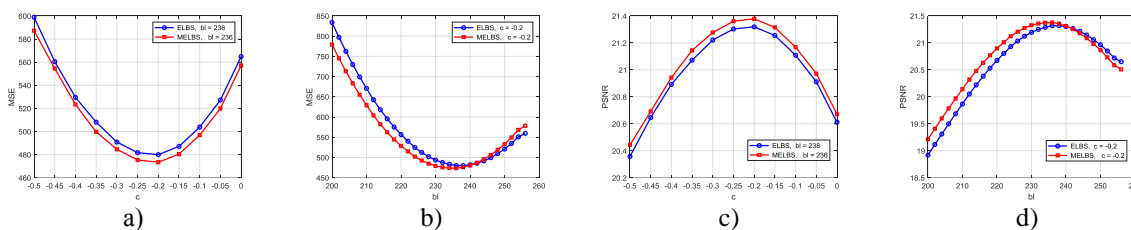


Figure 4 – MSE: a) ELBS algorithm, b) MELBS algorithm. PSNR: c) ELBS algorithm, d) MELBS algorithm.

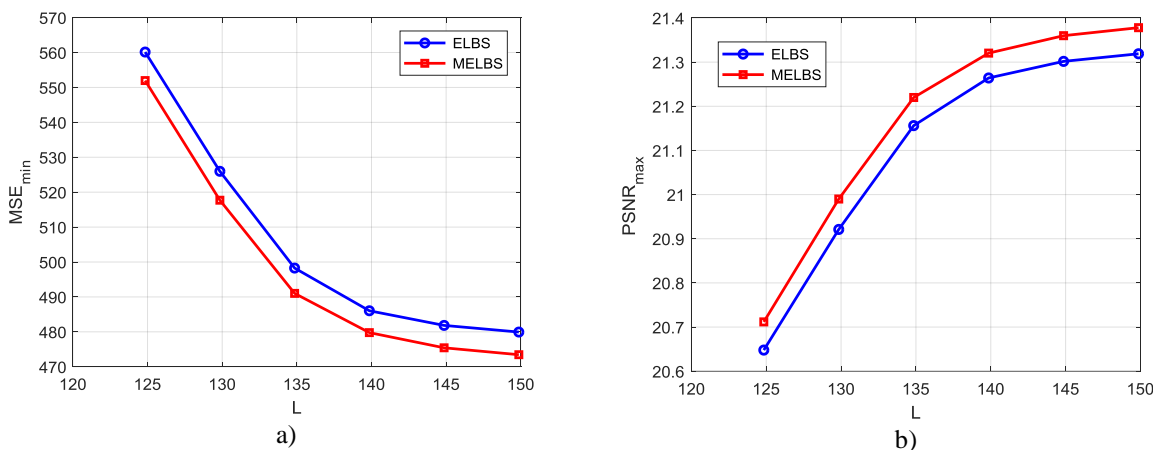


Figure 5 – MSE and PSNR errors depending on mean background brightness: a) MSE and b) PSNR.

Table 1 – Optimal values of parameters c , bl and MSE_{min} .

L_m	L_{min}	ELBS algorithm			MELBS algorithm		
		c_{opt}	bl_{opt}	MSE_{min}	c_{opt}	bl_{opt}	MSE_{min}
149.8706	50	-0.2	238	479.9397	-0.2	236	473.4521
144.8642	40	-0.2	238	481.8443	-0.2	236	475.4296
139.8577	30	-0.2	236	486.0361	-0.2	236	479.7783
134.8512	20	-0.15	238	498.2646	-0.15	234	491.0153
129.8448	10	-0.15	238	525.9757	-0.15	236	517.6988
124.8383	0	-0.05	240	560.1353	-0.05	236	551.9679

Table 2 – Optimal values of parameters c , bl and $PSNR_{max}$

L_m	L_{min}	ELBS algorithm			MELBS algorithm		
		c_{opt}	bl_{opt}	$PSNR_{max}$	c_{opt}	bl_{opt}	$PSNR_{max}$
149.8706	50	-0.2	238	21.3189	-0.2	236	21.3780
144.8642	40	-0.2	238	21.3017	-0.2	236	21.3599
139.8577	30	-0.2	236	21.2641	-0.2	236	21.3204
134.8512	20	-0.15	238	21.1562	-0.15	234	21.2199
129.8448	10	-0.15	238	20.9211	-0.15	236	20.9900
124.8383	0	-0.05	240	20.6479	-0.05	236	20.7117

3.4. Analysis of results

Based on the results shown in Fig. 2-5 and Tables 1 and 2, it is concluded that:

- the increase of the mean value of the background brightness L_m led to a decrease of the MSE, that is, to an increase of the PSNR.
- the optimal value of the parameter c , determined as the mean value of the parameters c_{opt} (Tables 1 and 2), is $c_{\mu} = \overline{c_{opt}} = -0.1583$.
- the optimal value of the parameter bl , determined as the mean value of the parameters bl_{opt} (Tables 1 and 2), is $bl_{\mu} = \overline{bl_{opt}} = 238$.

By the comparative analysis of the errors in the application of ELBS and MELBS algorithms, it was concluded that:

- the mean squared error in MELBS algorithm is $\overline{MSE}_{ELBS} / \overline{MSE}_{MELBS} = 505.3659 / 498.2237 = 1.0143$ times higher, i.e. 1.4133%, and
- the peak signal-to-noise ratio is less than $\overline{PSNR}_{ELBS} / \overline{PSNR}_{MELBS} = 21.1016 / 21.1633 = 0.997$ times, i.e. 0.2924%.

Based on the presented results, the application of the MELBS algorithm is recommended.

4. CONCLUSION

The paper presents a modified MELBS algorithm for balancing background brightness in text images. Compared to the original ELBS algorithm, where the Sobel edge detection algorithm is implemented, the MELBS algorithm implements the Gravity Edge Detection Algorithm. A detailed analysis of the experimental results showed that, when applying the MELBS algorithm, compared to the ELBS algorithm, the mean squared error is smaller, i.e. the peak signal-to-noise ratio is higher. Therefore, it is recommended to use the MELBS algorithm to balance background brightness in text images.

5. REFERENCES

- [1] Kuo-Nan Chen, Chin-Hao Chen, Chin-Chen Chang (2012), *Efficient illumination compensation techniques for text images*, Digital Signal Processing Vol. 22, pp.726–733.
- [2] J. Sauvola, M. Pietikäinen (2000), *Adaptive document image binarization*, Pattern Recogn. Vol. 33, No. 2, pp. 225–236.

- [3] E. Kavallieratou, E. Stamatatos (2006), *Improving the quality of degraded document images*, in: Proceedings of the Second International Conference on Document Image Analysis for Libraries, Lyon, France, pp. 340–349.
- [4] S.C. Hsia, M.H. Chen, Y.M. Chen (2006), *A cost-effective line-based light-balancing technique using adaptive processing*, IEEE Trans. Image Process. Vol. 15, No. 9, pp. 2719–2729.
- [5] W. Niblack (1986), *An Introduction to Image Processing*, Prentice–Hall, EnglewoodCliffs, NJ, pp. 115–116.
- [6] Shih-Chang Hsia, Ming-Huei Chen, and Yu-Min Chen (2006), *A Cost-Effective Line-Based Light-Balancing Technique Using Adaptive Processing*, IEEE Transactions On Image Processing, Vol. 15, No. 9, pp. 2719 - 2729.
- [7] G. Sun, Q. Liu, Q. Liu, C. Yuan and X. Li (2007), “*A Novel Approach for Edge Detection Based On the Theory of Universal Gravity*”, Pattern Recognition, Vol. 40, No. 10, pp. 2766-2775.