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Naturalness Preservation Image Contrast Enhancement via Histogram Modification

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ABSTRACT

Contrast enhancement is a technique for enhancing image contrast to obtain better visual quality. Since many existing contrast enhancement algorithms usually produce over-enhanced results, the naturalness preservation is needed to be considered in the framework of image contrast enhancement. This paper proposes a naturalness preservation contrast enhancement method, which adopts the histogram matching to improve the contrast and uses the image quality assessment to automatically select the optimal target histogram. The contrast improvement and the naturalness preservation are both considered in the target histogram, so this method can avoid the over-enhancement problem. In the proposed method, the optimal target histogram is a weighted sum of the original histogram, the uniform histogram, and the Gaussian-shaped histogram. Then the structural metric and the statistical naturalness metric are used to determine the weights of corresponding histograms. At last, the contrast-enhanced image is obtained via matching the optimal target histogram. The experiments demonstrate the proposed method outperforms the compared histogram-based contrast enhancement algorithms.

Keywords: Image enhancement, contrast enhancement, histogram equalization, histogram specification, naturalness preservation, image quality assessment.

1. INTRODUCTION

With the popularity of digital imaging devices, it is easy to capture images. However, the visual qualities of some images are usually not good, resulting from poor illumination conditions, low quality imaging devices, or unsuitable parameter settings. Image enhancement [1] is an important and challenging technique for dealing with this problem, and has been successfully applied in many related domains, such as camera photographing, video quality improvement [2], medical imaging, and remote sensing imaging [3]. This technique can improve the image quality, which also makes the enhanced image more suitable for high level vision analysis. Contrast enhancement is a kind of image enhancement method for enhancing the contrast, which improves the visibility of the considered image.

There are many different kinds of methods having been proposed for image contrast enhancement. Histogram-based approach is a very popular kind of enhancement method and can be categorized into two subgroups: global methods and local methods. Global methods analyze the global histogram of the whole image, and local methods utilize the information of local histograms in the considered image. Although local methods [4-6] can usually obtain good enhancement results with carefully tuning parameters, these methods are highly depended on the suitable parameter settings. Unsuitable parameters will result in artifacts decreasing the visual quality of the considered images.

One of the most popular global contract enhancement methods is histogram equalization [1, 7], which modifies different kinds of histograms to approximate the uniform histogram and produces higher visual contrast. For some images, traditional histogram equalization will result in unnatural artifacts, which can be clearly seen in Figure 1. Various related methods have been proposed to avoid these kinds of disadvantages. Stark [8] proposed an adaptive image contrast enhancement method based on a generalization of histogram equalization. By setting different forms of mapping functions, this algorithm can result in the corresponding different degrees of contrast enhancement. A more general framework of Stark's method is proposed by Arici et al. [9]. Recently, Xu et al. [10] proposed a generalized equalization model combining white balance and contrast enhancement. Jung et al. [11] proposed an optimized perception tone mapping method for contrast enhancement.

Many previous histogram-based contrast enhancement algorithms, including global methods and local methods, usually need to select the parameters carefully or result in over-enhancement problems. To avoid these issues, a naturalness preservation automatic contrast enhancement approach is proposed in this paper. This method automatically chooses the optimal target histogram considering the image structure and statistical naturalness. Then the target histogram is used to enhance the image contrast via histogram matching methods.

The rest of this paper is organized as follows. The detailed description of the proposed approach is given in Section 2. The numerical experiments and performance comparisons are shown in Section 3. Finally, we give the conclusions in Section 4.

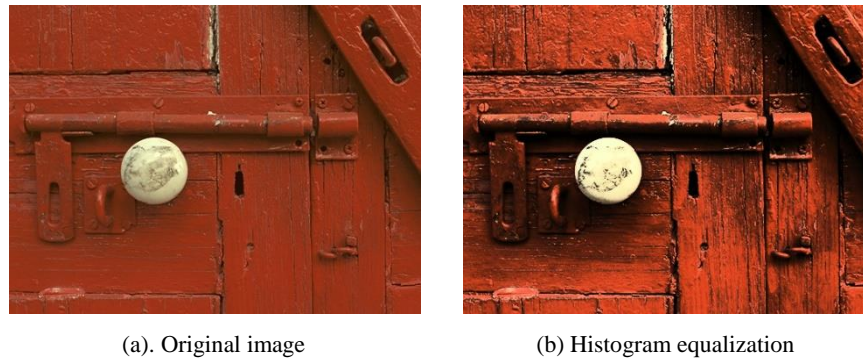


Figure 1. Traditional histogram equalization for a color image. The over-enhancement problem can be observed obviously.

2. THE PROPOSED APPROACH

2.1 Overview

We present the overview of the proposed naturalness preservation contrast enhancement method, which is shown in Figure 2. Given a low contrast image X (RGB color space), it firstly converted to the full value range $[0, 255]$ with the linear stretching. Then the stretched image is converted to HSV color space. The V channel is enhanced with histogram matching methods. Different target histograms can produce different enhanced V_M . The optimal target histogram can be obtained based on the structure measure (between V_M and V_L) and the naturalness measure (for V_M). After computing the enhanced V_E with the optimal target histogram, the final enhancement result Y is produced using HSV-RGB color space conversion.

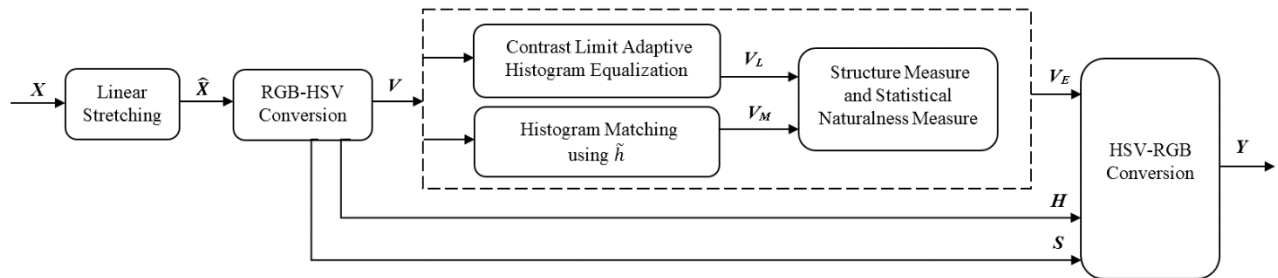


Figure 2. The overall framework of the proposed enhancement method.

2.2 Naturalness Preservation Contrast Enhancement

In section 2.1, we give an overview of the proposed naturalness preservation contrast enhancement approach. Since the linear stretching, RGB-HSV conversion and HSV-RGB conversion are basic image processing techniques, we will not give the detailed description of these operations. In this section, we will present the method obtaining the enhanced V_E with the optimal target histogram and the intensity channel V . The key contributions are the definition of the target histogram and computing the optimal weights of the components of the target histogram.

Considering a gray image V with a total number of N pixels, the normalized histogram is defined by

$$h_v(i) = \frac{n_i}{N}, \quad (1)$$

where $i \in [0, 255]$ is pixel values, n_i is the total number of pixels having the same value i .

Histogram-based contrast enhancement methods use different kinds of histograms to obtain the corresponding mapping functions for modifying the pixel values and enhancing the contrast of the considered image. Traditional histogram equalization algorithm uses the original histogram of the considered image to obtain the mapping function. It tries to create a uniform histogram for the enhanced image via considering a cumulative histogram as the corresponding mapping function. This kind of histogram equalization algorithm often produces over-enhancement problems. To avoid this problem, Arici et al. [9] considered the weight sum of the original histogram and the uniform histogram. The weighted histogram is used to create the mapping function. The over-enhancement problem can be decreased to a certain extent. Inspired by this idea, we consider a more complex histogram modification, which is a weight sum of the original histogram, the uniform histogram and the Gaussian-shaped histogram. In [12], the authors analyzed about 3000 gray images and build a statistical naturalness model. They found that the histograms of the means of these images can be well fitted using a Gaussian function. The similar conclusion can be also found in [13], which adopts a Gaussian curve to assess the well-exposed pixels. So, we adopt the Gaussian-shaped histogram to make the enhancement results more natural.

Based on the above analysis, the modified histogram h should be closer to the normalized uniform histogram h_u and normalized Gaussian-shaped histogram h_g , the residual $h - h_v$ should be also small. We define a target histogram \tilde{h} which can be formulated as the minimization problem:

$$\tilde{h} = \underset{h}{\operatorname{argmin}} ((1 - \alpha - \beta) \|h - h_v\|_2^2 + \alpha \|h - h_u\|_2^2 + \beta \|h - h_g\|_2^2), \quad (2)$$

where h_u is the normalized uniform histogram, h_g is the normalized histogram with the Gaussian curve shape, α and β are the corresponding weights, $\alpha + \beta \in [0, 1]$. In the implement, we use the Gaussian curve $\exp\left(-\frac{(i-0.5)^2}{2\sigma^2}\right)$, $\sigma = 0.2$.

The equation (2) is a quadratic optimization problem, and the solution is given by

$$\tilde{h} = (1 - \alpha - \beta) \cdot h_v + \alpha \cdot h_u + \beta \cdot h_g, \quad (3)$$

The target histogram \tilde{h} is a weighted sum of h_v , h_u , and h_g . There are two parameters α and β to be tuned in this solution. Different α and β can produce different target histogram \tilde{h} , which will generate different contrast enhanced images. Generally speaking, α controls the contrast enhancement, and β controls the naturalness preservation.

Our goal is to automatically enhance the contrast of the considered image. To deal with this automatic problem, we adopt the structure measure and the statistical naturalness measure [12] to guide the optimization. The Contrast Limit Adaptive Histogram Equalization (CLAHE) can produce satisfying local structure of the considered image. We use the CLAHE enhancement result V_L to guide the image structure. And use the statistical naturalness measure to achieve the task of the naturalness preservation. Based on the experience, we can give some candidates of α and β . Each pair of α and β can produce an enhancement result V_M . The corresponding structure measure between V_M and V_L , and the statistical naturalness measure of V_M can be both obtained. Then we can get the optimal α and β based on the best structure measure and the statistical naturalness measure. After determining α and β , the corresponding optimal enhancement result V_E can be found.

3. EXPERIMENTS

We ran the traditional Histogram Equalization algorithm (HE) [1], Contrast Limit Adaptive Histogram Equalization (CLAHE) [1], Histogram Modification Framework (HMF) [9] and the proposed Naturalness Preservation Contrast Enhancement method on five test images from the image dataset TID2013 [14] and CSIQ [15]. For the traditional histogram equalization algorithm, we use the function *histeq* in the MATLAB Image Processing Tool. For the Contrast Limit Adaptive Histogram Equalization algorithm, we use the function *adaphisteq* in the MATLAB Image Processing Tool. For the histogram modification method [9], we reproduce this algorithm and set the parameter $\lambda = 1$ for all experiments. We also implement the proposed method using MATLAB. For all algorithms, the test image is firstly converted from the RGB color space to the HSV color space. Then the *V* channel is processed using the corresponding enhancement algorithms. At last, the enhanced HSV image is converted to the RGB color space.

3.1 Performance Criteria

The quality of the contrast enhanced images can be assessed in many aspects. The performance metrics used in our experiments are Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) [16], which are the most popular metrics to assess image quality and compare the performance of different image enhancement algorithms. In our experiment, we use the metric PSNR to measure the pixel value fidelity between the enhanced images and the corresponding high-quality reference images, and use the metric SSIM to measure the structure fidelity between the enhanced images and the reference images.

Given a test image *A* and a reference image *B*, the PSNR is obtained via

$$\begin{aligned} \text{PSNR}(A, B) &= 10 \cdot \log_{10} \left(\frac{L^2}{\text{MSE}(A, B)} \right), \\ \text{MSE}(A, B) &= \frac{1}{m \cdot n} \sum_{i=1}^m \sum_{j=1}^n (A(i, j) - B(i, j))^2, \end{aligned} \quad (4)$$

where $L=255$ for 8 bits images, m and n are the height and width of the considered images.

The SSIM is computed by

$$\text{SSIM}(A, B) = \frac{1}{N} \sum_{i=1}^N \text{SSIM}(a_i, b_i), \quad (5)$$

where N is the number of local windows for the considered images, and a_i, b_i are the image contents at the i th local window of the image *A* and *B* respectively. SSIM is defined as a combination of luminance, contrast and structure components. The detailed computation of $\text{SSIM}(a_i, b_i)$ is described by

$$\text{SSIM}(a, b) = [l(a, b)]^\alpha \cdot [c(a, b)]^\beta \cdot [s(a, b)]^\gamma, \quad (6)$$

where $l(a, b) = \frac{2\mu_a\mu_b+C_1}{\mu_a^2+\mu_b^2+C_1}$, $c(a, b) = \frac{2\sigma_a\sigma_b+C_2}{\sigma_a^2+\sigma_b^2+C_2}$, $s(a, b) = \frac{\sigma_{ab}+C_3}{\sigma_a\sigma_b+C_3}$, μ_a and μ_b are the mean luminance values of the windows *a* and *b* respectively, σ_a and σ_b are the standard variance of the windows *a* and *b* respectively, σ_{ab} is the auto-covariance between the windows *a* and *b*, C_1, C_2, C_3 are small constants to avoid divide-by-zero error, α, β, γ are constants controlling the weight among the three components. The default settings recommended in [16] are: $C_1 = (0.01L)^2$, $C_2 = (0.03L)^2$, $C_3 = \frac{C_2}{2}$, $L = 255$, $\alpha = \beta = \gamma = 1$. The higher the value of *SSIM* the more similar the structure between the test image and the reference image.

3.2 Result Comparisons

To evaluate the performance of the proposed enhancement method, both qualitative comparisons and quantitative assessments are considered in the following parts.

3.2.1 Qualitative Comparisons

To compare different enhancement algorithms qualitatively, we show some test images and the corresponding enhanced images in Figure 3. The reference images are also given to evaluate whether the corresponding results are over-enhancement or not. HE makes the histograms of the enhanced results as uniform as possible. It produces some regions to be brighter or darker, which makes the results un-natural. These issues can be found in the region of the wall (in Figure 3 (a)), the region of the door (in Figure 3 (b)), the region of the sky (in Figure 3 (c)), the region of the building (in Figure 3 (d)), the regions of the fruit (in Figure 3 (e)). Compared with HE, the results of CLAHE and HMF avoid the over-enhancement (un-naturalness) problem to some extent. However, the slight un-naturalness issue can be observed in the results of CLAHE and HMF. The reason is that these two methods do not consider the naturalness preservation. Compared our results with the others, we can conclude that the proposed method preserves the naturalness better. This conclusion can be also supported by comparing the enhancement results with the high-quality reference images.

3.2.2 Quantitative Comparisons

To compare different enhancement algorithms quantitatively, two widely adopted image quality assessment metrics (PSNR and SSIM) are considered below. The detailed definitions of these metrics are given in section 3.1. The PSNR comparisons of different enhancement algorithms (including HE, CLAHE, HMF and the proposed method) on the five test images are shown Table 1. We can know that the proposed method obtains the best PSNR for all test images, which indicates the ability of image pixel value fidelity. In Table 2, we give the SSIM comparisons of different enhancement methods. The results demonstrate the proposed approach outperforms other enhancement algorithms in terms of SSIM. This indicates the ability of image structure fidelity of our method.

Table 1. The comparison of different enhancement algorithms in terms of PSNR

Algorithms	<i>Image "Wall"</i>	<i>Image "Door"</i>	<i>Image "Lighthouse"</i>	<i>Image "Boston"</i>	<i>Image "Cactus"</i>
HE	16.31	17.90	17.84	17.34	20.33
CLAHE	19.60	27.63	23.94	28.23	25.99
HMF	21.08	24.12	23.94	23.89	26.67
Proposed	25.81	29.92	35.92	34.74	34.90

Table 2. The comparison of different enhancement algorithms in terms of SSIM

Algorithms	<i>Image "Wall"</i>	<i>Image "Door"</i>	<i>Image "Lighthouse"</i>	<i>Image "Boston"</i>	<i>Image "Cactus"</i>
HE	0.7416	0.7690	0.7225	0.7125	0.8887
CLAHE	0.8819	0.9788	0.9439	0.9645	0.9713
HMF	0.9097	0.9442	0.9067	0.9072	0.9752
Proposed	0.9779	0.9818	0.9925	0.9865	0.9941

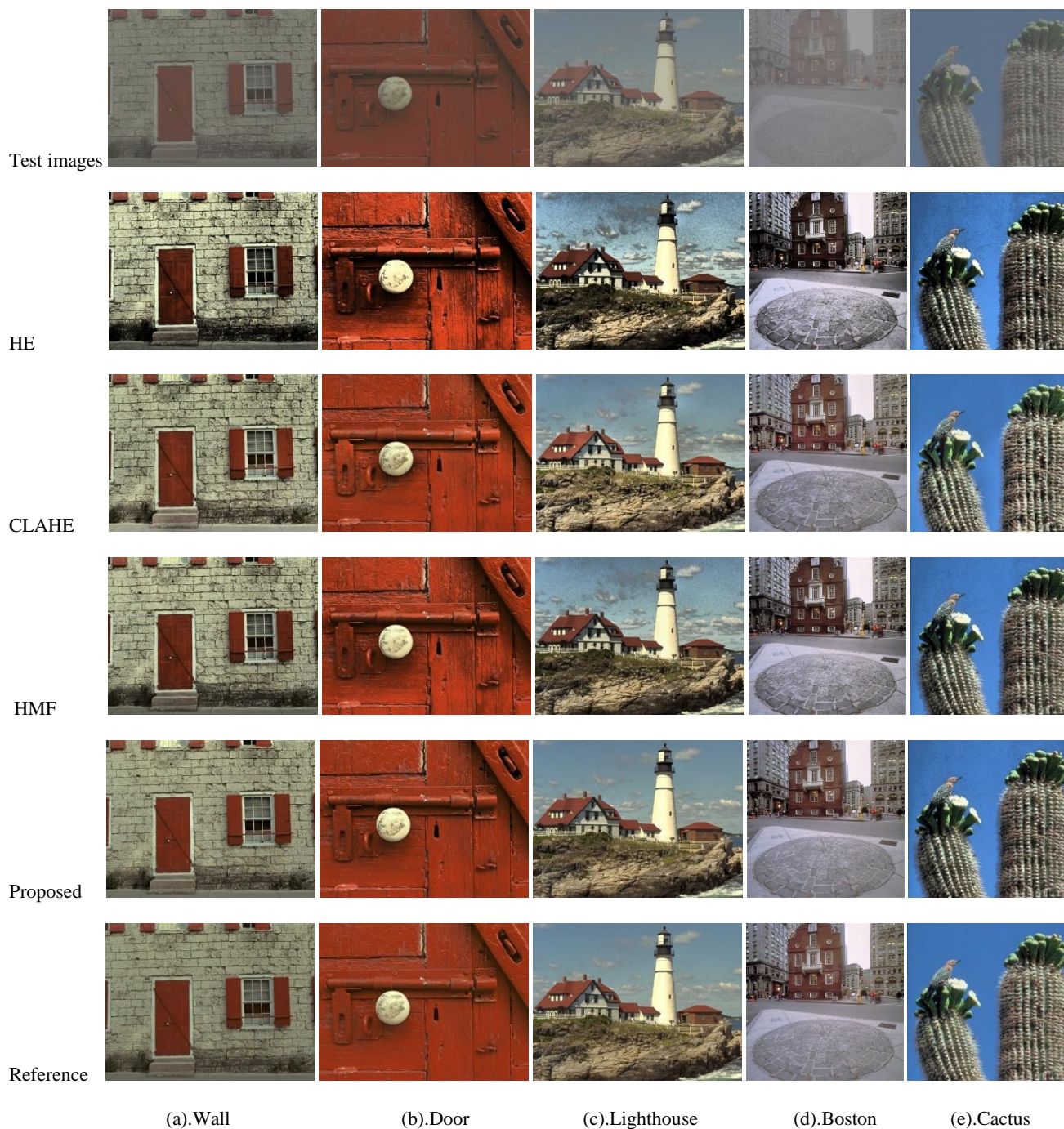


Figure 3. Experimental results of different enhancement algorithms. The first row shows the test low contrast images. The enhancement results by HE, CLAHE, HMF and the proposed method are given respectively in the second row, the third row, the fourth row and the fifth row. In the last row, the reference high contrast images are given.

4. CONCLUSION

In this paper, we have proposed a naturalness preservation automatic contrast enhancement method. The main contributions of this method are: (a). defining the weight sum of the original histogram, the uniform histogram and the Gaussian-shaped histogram as the optimal target histogram for contrast enhancement. (b). using the structure measure and the statistical naturalness measure to determine the optimal parameters. The proposed method considers the trade-off between the contrast enhancement and the naturalness preservation.

We try some candidate parameters to find the optimal target histogram, which is a time-consuming method. In the future work, we will find a more direct and faster way to select the optimal parameters.

REFERENCES

- [1] Gonzalez, R. C. and Woods, R. E., [Digital image processing (3rd Edition)]. Englewood Cliffs, NJ, USA: Prentice-Hall, (2007).
- [2] Wang, Q. and Ward, R.K., "Fast image/video contrast enhancement based on weighted thresholded histogram equalization," *IEEE Transactions on Consumer Electronics*, 53(2), 757-764, (2007).
- [3] Lisani, J.L., Michel, J., Morel, J.M., Petro, A.B. and Sbert, C., "An Inquiry on Contrast Enhancement Methods for Satellite Images," *IEEE Transactions on Geoscience and Remote Sensing*, 54(12), 7044-7054, (2016).
- [4] Kim, J.Y., Kim, L.S., and Hwang, S.H., "An advanced contrast enhancement using partially overlapped sub-block histogram equalization," *IEEE transactions on circuits and systems for video technology*, 11(4), 475-484, (2001).
- [5] Palma-Amestoy, R., Provenzi, E., Bertalmio, M. and Caselles, V., "A perceptually inspired variational framework for color enhancement," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 31(3), 458-474, (2009).
- [6] Pierre, F., Aujol, J.F., Bugeau, A., Steidl, G. and Ta, V.T., "Variational contrast enhancement of gray-scale and RGB images," *Journal of Mathematical Imaging and Vision*, 57(1), 99-116, (2017).
- [7] Pizer, S.M., Amburn, E.P., Austin, J.D., Cromartie, R., Geselowitz, A., Greer, T., ter Haar Romeny, B., Zimmerman, J.B. and Zuiderveld, K., "Adaptive histogram equalization and its variations," *Computer vision, graphics, and image processing*, 39(3), 355-368, (1987).
- [8] Stark, J.A., "Adaptive image contrast enhancement using generalizations of histogram equalization," *IEEE Transactions on Image Processing*, 9(5), 889-896, (2000).
- [9] Arici, T., Dikbas, S. and Altunbasak, Y., "A histogram modification framework and its application for image contrast enhancement," *IEEE Transactions on Image Processing*, 18(9), 1921-1935, (2009).
- [10] Xu, H., Zhai, G., Wu, X. and Yang, X., "Generalized equalization model for image enhancement," *IEEE Transactions on Multimedia*, 16(1), 68-82, (2014).
- [11] Jung, C. and Sun, T., "Optimized perceptual tone mapping for contrast enhancement of images," *IEEE Transactions on Circuits and Systems for Video Technology*, 27(6), 1161-1170, (2017).
- [12] Yeganeh, H. and Wang, Z., "Objective quality assessment of tone-mapped images." *IEEE Transactions on Image Processing*, 22(2), 657-667, (2013).
- [13] Mertens, T., Kautz, J. and Van Reeth, F., "Exposure fusion: A simple and practical alternative to high dynamic range photography." *Computer Graphics Forum*, 28(1), 161-171, (2009).
- [14] Ponomarenko, N., Jin, L., Ieremeiev, O., Lukin, V., Egiazarian, K., Astola, J., Vozel, B., Chehdi, K., Carli, M., Battisti, F. and Kuo, C.C.J., "Image database TID2013: Peculiarities, results and perspectives," *Signal Processing: Image Communication*, 30, 57-77, (2015).
- [15] E. C. Larson and D. M. Chandler, "Most Apparent Distortion: Full-Reference Image Quality Assessment and the Role of Strategy," *Journal of Electronic Imaging*, 19(1), (2010).
- [16] Wang, Z., Bovik, A.C., Sheikh, H.R. and Simoncelli, E.P., "Image quality assessment: from error visibility to structural similarity." *IEEE Transactions on Image Processing*, 13(4), 600-612, (2004).