The CSI Journal on
Computer Science and Engineering
Vol. 16, No. 1, 2018
Pages 32-44
Regular Paper

Improving Image Dynamic Range for an Adaptive Quality Enhancement Using Gamma Correction

Hamid Hassanpour[1] Sekineh Asadi Amiri[2]

[1]Faculty of Computer Engineering & IT, Shahrood University of Technology, Shahrood, Iran
[2]Faculty of Technology and Engineering, University of Mazandaran, Babolsar, Iran

Abstract

This paper proposes a new automatic image enhancement method via improving the image dynamic range. The improvement is performed via modifying the Gamma value of pixels in the image. Gamma distortion in an image is due to the technical limitations in the imaging device, and imposes a nonlinear effect. The severity of distortion in an image varies depending on the texture and depth of the objects. The proposed method locally estimates the Gamma values in an image. In this method, the image is initially segmented using a pixon-based approach. All of the pixels in each segment have similar characteristics in terms of the need for Gamma correction. Then, the Gamma value for each segment is estimated by minimizing the homogeneity of co-occurrence matrix. This feature can represent image details. The minimum value of this feature in a segment shows maximum details of the segment. The quality of an image is improved once more details are presented in the image via Gamma correction. In this study, it is shown that the proposed method performs well in improving the quality of images. Subjective and objective image quality assessments performed in this study attest the superiority of the proposed method compared to the existing methods in image quality enhancement.

Keywords: Image Enhancement; Gamma Correction; Segmentation; Co-Occurrence Matrix; Homogeneity.

1. Introduction

Image enhancement is an important pre-processing stage in most image processing applications. In face recognition systems, for example, without image enhancement the algorithms may fail to recognize the faces correctly due to possible differences between illumination of the image with the one stored in the database [1,2]. Due to technical limitations, many devices used for capturing, printing or displaying the images generally apply a transformation, called power-low [3, 4], on each pixel of the image, which has a nonlinear effect on luminance:

$$g(x, y) = f^{\gamma}(x, y). \quad (1)$$

In the above equation $f(x, y) \in [0,1]$ denotes the image pixel intensity at the location of coordinate (x, y), $g(x, y)$ is the processed pixel and γ is a positive constant introducing the Gamma value. The value of γ can typically be determined experimentally, by passing a calibration target with a full range of known luminance values through the imaging device [5]. When the value of γ is known, inverting this process is trivial:

$$f(x, y) = g^{1/\gamma}(x, y). \quad (2)$$

Often, such calibration or information about the imaging device may not be available once an image is downloaded from the web. Also, most commercial digital cameras may change the Gamma value in an image [5]. Hence an algorithm is needed to enhance an image for its Gamma value without any prior knowledge about the imaging device.

In addition to this problem, in practice, these nonlinear effects aren't consistent across all regions of the image. In other words, the value of Gamma for an image may change from one region to another. It mainly depends on the relative illumination reflection of objects in the image. Since an image contains objects with a variety of texture and depth, Gamma distortion may not be the same for all objects. Hence, an adaptive approach is needed to enhance the Gamma distortion. Also, it is possible that a scene contains a large illumination range that an imaging device may not able to thoroughly capture the scene. Thus, especially in very dark or bright regions of an image, some details may merge within a small intensity range [6]. Global enhancement techniques can improve the global contrast, but they may simply cause the loss of details in brighter or darker regions [7]. Hence a local enhancement process is needed to adjust the image quality in different regions in a way that the human viewers grasp these details.

As mentioned above, imaging devices apply the power-low transformation on each pixel of the image; hence Gamma correction is required to enhance the image. In [5] a blind inverse Gamma correction technique was developed exploiting the fact that Gamma correction introduces specific higher-order correlations in the frequency domain. In this approach the Gamma values from 0.1 to 3 are applied to image pixels, so that the best Gamma value is the one that minimizes those higher order correlations. This method used a global Gamma correction. With global correction, it is not possible to accommodate both lowlight and highlight detail simultaneously.

Another global Gamma correction method based on texture analysis has been introduced in [8]. Although this method is faster than the one presented in [5], because of using global Gamma correction this method may not succeed at enhancing images that require local Gamma correction. In [2] a mapping function is considered to correlate Gamma values with pixel values. In fact, the algorithm is a nonlinear transformation that makes pixels with low values brighter, whereas pixels with high values become darker. This transformation leaves midtons with less correction or even no correction. This approach is a pixel-wise operation that may be successful in reducing the illumination on the scene. Since local information of the pixels is not used, this approach may lead to image distortion in natural scene images.

Another local Gamma correction method was presented in [9] which is based on the nearest neighbor algorithm with two feature vectors: pixel intensity histogram and dispersion-versus-location distribution. This method only works on grayscale images. In [10], the image is divided into overlapping windows and then the Gamma value of each window is estimated by trained neural network. For training the neural network, some images and their known Gamma values are needed. Although this method produces satisfactory results, but it may have blocking effects on smooth regions of the image. Improved version of this method has been introduced in [11]. In this method, a number of features that characterize content of the images are computed from its pixel intensity histogram, gray level co-occurrence matrix (GLCM), and discrete cosine transform domain. This method can better estimate the Gamma values for different parts of the image, but its performance depends on the database and blocking effects exist to some extent in smooth regions of the image.

The method proposed in [12] has overcome the problem of database dependency. In [12] after dividing the image into overlapping windows, the Gamma value of each window is estimated by minimizing the homogeneity of GLCM. Similar to previous methods, this method may cause blocking effects on smooth regions of the enhanced image. In [13], a Gamma correction method is proposed to enhance palatoglossal air space error that may occur in digital panoramic radiograph.

In addition to gamma correction, un-sharp masking is another approach for image enhancement. Purpose of using this method is contrast enhancement via boosting high frequency regions, such as image edges [14]. In the classic un-sharp masking technique, at first, the high frequency components of the input image is extracted by using a linear high pass filter; then via adding a scaled amount (the gain factor) of these components to the input image, a sharper image is obtained. The gain factor has an important influence on un-sharp masking results. Indeed, undesirable gain values may lead to an over sharpening problem or a negligible influence on the image quality.

In [15], an un-sharp masking method has been proposed, which is based on intensity of the input image and the extracted edges. In this method, the intensity of the input image and the extracted edges are applied to a hyperbolic tangent function to determine the gain factor automatically. In [16], the particle swarm optimization (PSO) algorithm is employed to determine the gain factor.

This paper proposes a new technique for estimating the Gamma values without any calibration information or knowledge of the imaging device. For the local Gamma correction, an input image is segmented into several disjoint regions and each region is individually enhanced. For image segmentation, first, wavelet thresholding technique is applied to the image to obtain better results via slightly smoothing the image. Then, the pixons are extracted and finally the Fuzzy C-Means (FCM) algorithm is used for image segmentation. To determine the Gamma value of each region, initially different Gamma values are applied to each segment. Then, gray level co-occurrence matrix is calculated for each segment with different Gamma values (luminance). Finally, the best Gamma value of each segment is estimated by minimizing the homogeneity of GLCM. This feature indicates how details of objects are visible in the image, the lower value of this feature leads to more visibility of the image details. Using the homogeneity feature of the co-occurrence matrix to measure the visibility of image details, a proper Gamma value will be assigned to each segment. This technique can be used to enhance both gray and color images. The HSV (Hue Saturation Value) color model is adopted in processing color images. In practice, the value (V) is only processed with the proposed method. Then the HSV color model with the modified V is transformed into the RGB (Red Green Blue) color model.

In the next section, pixon-based image segmentation is described. In Section 3, gray level co-occurrence matrix is briefly described. Image quality assessment is introduced in Section 4. The proposed algorithm is presented in Section 5. Section 6 shows the results, and Section 7 contains the conclusions.

2. Image Segmentation

Image segmentation is a process of partitioning an image into several disjoint regions with similar characteristics in terms of intensity, color, or texture. Recently, the pixon-based approaches for image segmentation have received considerable attention among researchers. The pixon concept is a set of disjoint regions with constant shapes and variable sizes. In [17], initially a wavelet thresholding technique is used to smooth the image and prepare it to form the pixons. Utilizing the wavelet thresholding leads to elimination of image details and results in a smaller pixon number and faster performance. As the next step, the pixons are constructed. Finally, the FCM algorithm is used for image segmentation. In the following, wavelet thresholding technique and pixon scheme are described.

2.1. Wavelet Thresholding Technique

After applying the wavelet transform to the image matrix, this matrix is divided into four sub-bands: LL, HL, LH and HH. Thresholding is a simple nonlinear technique which operates on the wavelet coefficients. If the coefficients are smaller than the threshold, it is set to zero; otherwise it is kept or modified by considering the thresholding method. Whereas these small coefficients are often considered as image details, they can be cut without any effect on the significant features of the image.

Using the soft thresholding method, all coefficients less than the threshold are replaced with zero and the values above it are decreased by the amount of the threshold. The following equation implies the soft thresholding function:

$$\eta(Y) = \begin{cases} sign(Y)(|Y| - T), & if\ |Y| > T \\ 0, & otherwise \end{cases} \tag{3}$$

where Y is the arbitrary input matrix, $|.|$ represents the absolute value, $sign(Y)$ returns the sign of Y value, $\eta(Y)$ is the soft thresholding function and T indicates the threshold value. In [17] global thresholding is applied on all of the wavelet sub-bands to smooth the image. Threshold value is determined using a penalization method.

2.2. Description of Pixon Scheme

The main idea of the pixon concept is that at each point in the image there is the finest spatial scale of interest and that there is no information content below this scale. The size, shape and position of all pixons over an image are collected into a pixon map, which provides an adaptive scale description of the image with various spatial scales. Since different parts of an image often do not display a uniform spatial resolution, the pixon map, as an adaptive scale representation language, is suggested. It provides the finest spatial scale at each portion of the image [18].

In [18], a pixon definition scheme has been defined which can be described as follows:

$$I = \bigcup_{i=1}^{n} P_i, \tag{4}$$

where I is the pixon-based image model, n is the number of pixons, P_i is a pixon, which is made up of a set of connected pixels and symbol $\cup$ represents the union. The mean value of the connected pixels making up the pixon is defined as the pixon intensity. Both the shape and size of each pixon vary according to the observed image. After the pixon-based image model is defined, the image segmentation problem is transformed into a problem of labeling pixons.

3. The Gray Level Co-occurrence Matrix

The co-occurrence matrix is often used for feature extraction in texture analysis of an image. The co-occurrence matrix of a gray level image is regarded as a two dimensional matrix. Its size is proportional to the number of gray levels in an image. For instance, the images used in this paper have 256 gray levels; thus, their GLCM is a matrix of size 256×256 [19]. In contrast to histogram, GLCM describes the relationship between the values of neighbouring pixels. It measures the probability that a pixel of a particular gray level occurs in a specified direction and a distance from its neighbouring pixels. This can be calculated by the function $P(i.j, d, \theta)$, where i is the gray level at location of coordinate (x, y), j is the gray level of its neighbouring pixel at a distance d and a direction θ from the location (x, y) [19]. θ usually ranges from: 0, 45, 90, to 135. This is mathematically defined by Equation 5:

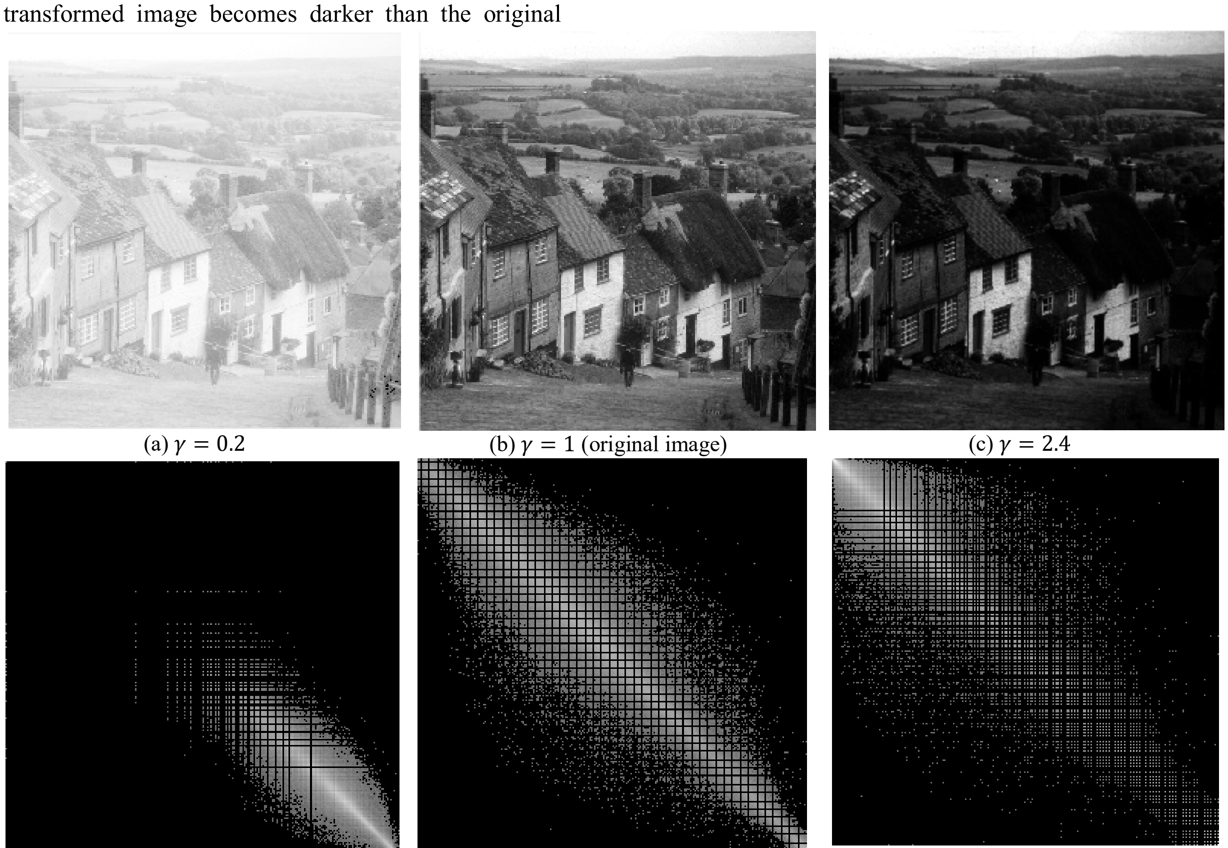
$$P(i, j, d, \theta) = \# \{(x_1, y_1)(x_2, y_2) | f(x_1, y_1) = i, \\ f(x_2, y_2) = j, |(x_1, y_1) - (x_2, y_2)| = d, \\ \angle((x_1, y_1), (x_2, y_2)) = \theta\}. \tag{5}$$

In this equation, $\#$ represents the number of times a particular gray level occurs in a specified direction and its distance from neighbouring pixels, $|.|$ is absolute value and $\angle$ represents the angle. In [20], fourteen different features of GLCM have been defined. These features consist of texture information, but, there may be correlations between them. In this paper, homogeneity feature is extracted from co-occurrence matrix, this feature is illustrated below:

$$H(i,j,d,\theta) = \sum_{i=1}^{256}\sum_{j=1}^{256}\frac{P(i,j,d,\theta)}{1+|i-j|}. \tag{6}$$

Homogeneity returns a value that measures the closeness of distribution of GLCM's elements to the GLCM diagonal, and its range is from 0 to 1. In other words, it describes how uniform the texture is [12]. Figure 1 shows three images with different Gamma condition along with their co-occurrence matrix. As it can be conceived from the images, when the amount of γ is less than one, the transformed image becomes lighter than the original image (see Figure 1(a)), and when the amount of γ is greater than one, the transformed image becomes darker than the original image (see Figure 1(c)). When the Gamma value is one, there is no change of the pixels value (see Figure 1(b)).

It needs to be noted that extracted homogeneity feature from the associated co-occurrence matrix reveals that this feature has the minimum value for image under good Gamma conditions. As discussed above, this feature represents how uniform the texture is. Figures 1(a) and 1(c) are two distorted images that their details are not clearly revealed. The details can be clearly seen in Figure 1(b), and the homogeneity value in Figure 1(e) indicates that the image is not uniform as the other two images.



(a) $\gamma = 0.2$ (b) $\gamma = 1$ (original image) (c) $\gamma = 2.4$

(d) $H = 0.39$ (e) $H = 0.26$ (f) $H = 0.35$

Fig. 1. Three images with different Gamma condition and their associated gray level co-occurrence matrix with extracted homogeneity feature.

4. Image Quality Assessment

The two types of image quality assessment approaches are the subjective method, which involves human beings to evaluate the quality of the images; and the objective method, which numerically computes the image quality [24]. Since human kind is the ultimate receiver in most image processing applications, subjective evaluation is the most reliable way of assessing the quality of an image. In a subjective test, we asked the observers to determine if the enhanced images display more details and convey other useful information that are not clearly visible in the original images. But, it is not usually useful for real world applications because this method is expensive and time consuming [24]. Objective image quality assessment is desired to automatically estimate the quality of an image. Thus, it aims to measure the quality of an image as closely as possible to the subjective assessment. In other words, these numerical measures should correlate well with human subjectivity.

Mean square error and peak signal to noise ratio are the two common objective methods, but they do not correlate well with the subjective assessment. They depend only on the difference between the original reference image and the enhanced image, and do not measure whether the enhanced version contains more visual information or not [6]. Thus, a lot of objective image quality assessments have developed in the past few decades to replace them. The structural similarity metric (SSIM) [24, 25] is one of such measures which correlates with the human visual system. Let I, J be the original and the test images, respectively. SSIM is defined as:

$$SSIM = \frac{\sigma_{IJ}}{\sigma_I \sigma_J} \times \frac{2\bar{I}\bar{J}}{(\bar{I})^2 + (\bar{J})^2} \times \frac{2\sigma_I \sigma_J}{\sigma_I^2 + \sigma_J^2} = S(I,J) \times L(I,J) \times C(I,J), \quad (7)$$

S is the correlation coefficient between I and J, which measures the degree of linear correlation between them. L measures how much I and J are close in luminance. C measures the similarities between the contrast of the images.

Where:

$$\bar{I} = \frac{1}{N}\sum_{i=1}^{N} I_i \; , \bar{J} = \frac{1}{N}\sum_{i=1}^{N} J_i, \quad (8)$$

$$\sigma_I^2 = \frac{1}{N-1}\sum_{i=1}^{N}(I_i - \bar{I})^2, \quad (9)$$

$$\sigma_J^2 = \frac{1}{N-1}\sum_{i=1}^{N}(J_i - \bar{J})^2, \quad (10)$$

$$\sigma_{IJ}^2 = \frac{1}{N-1}\sum_{i=1}^{N}(I_i - \bar{I})(J_i - \bar{J}). \quad (11)$$

In the above equations, N is the number of pixels in the image. The dynamic range of SIMM is [0, 1]. The best value ,1 , is achieved if $I = J$.

5. Proposed Method

As mentioned earlier, the goal of the present research is to estimate the Gamma values of an input image using an adaptive approach. Figure 2 exhibits the flowchart of the proposed image enhancement method. The basic idea is the fact that Gamma correction causes specific homogeneity values in the spatial domain. These homogeneity values can be calculated via co-occurrence matrix. The amount of Gamma correction is then estimated by minimizing these homogeneities. In the proposed method, for local Gamma correction, pixon-based image segmentation is used to segment an image into several distinct sub-regions, and each segment is enhanced individually. The number of sub-regions depends on the complexity of the image. Figure 3 shows an example of this segmentation result. This image was segmented into four different sub-regions.

To find a proper Gamma value for each region, we apply a range of inverse Gamma values from 0.1 to 3, 0.1 intervals in each region. To find the best Gamma value for each region, we compute the co-occurrence matrix from each region to extract the homogeneity feature. Then, the Gamma value associated with the minimum homogeneity is considered as the best Gamma value for enhancement. In this approach, each segment in the image has its own Gamma value. In practice this simple search strategy is effective because the function being minimized is typically well-behaved, i.e., contains a single minimum. This is illustrated in Figure 3(c), where the homogeneity values for Region A in Figure 3(b) are plotted as a function of inverse Gamma values. The Gamma value associated with the least homogeneity offers the most suitable one for enhancing this segment. In this example, homogeneity value reaches a unique minimum at $\gamma^{-1} = 0.6$. Consequently, each segment has its own Gamma value. In other words, the matrix M of Gamma values with the same size as the image is achieved.

To enhance the image, according to Equation (2) the Gamma values are applied to each pixel. The differences between the Gamma values of the two adjacent segments may have undesirable blocking effects on the enhanced image (see Figure 3(d)). In this step, to eliminate the blocking effects, first, we apply average filter on matrix M containing the Gamma values. Then the filtered Gamma values are applied to the image for Gamma correction. Figure 3(e) shows this result. As can be seen, the blocking effects have been removed.

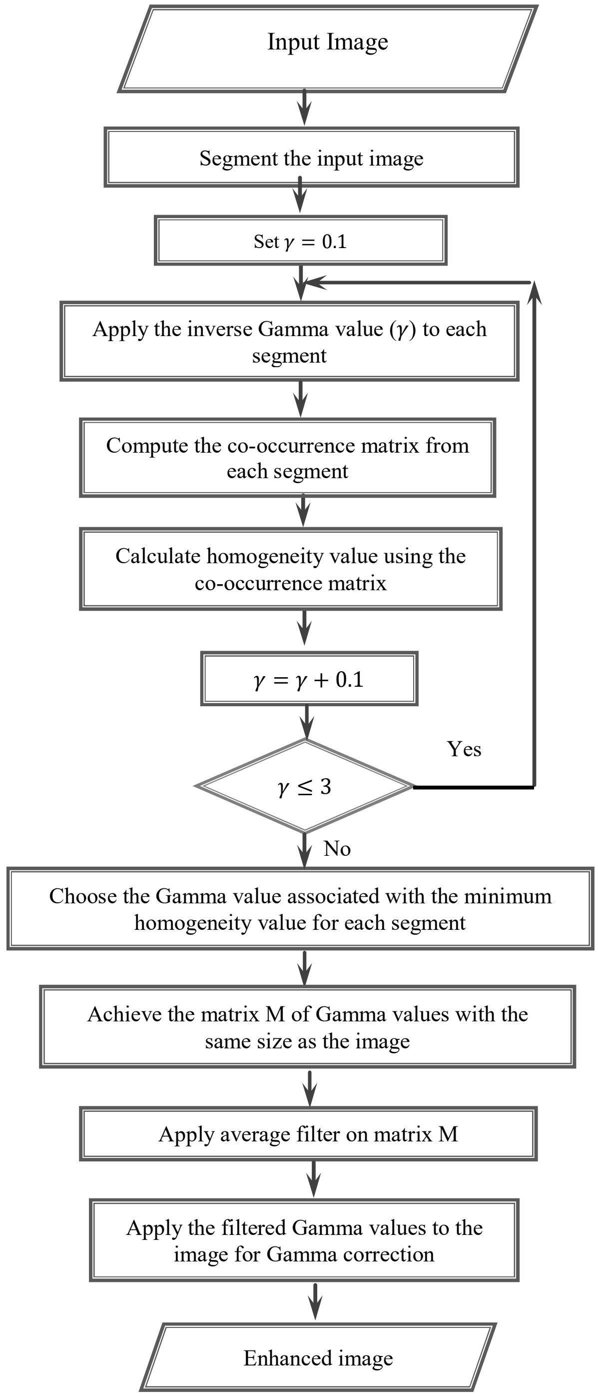
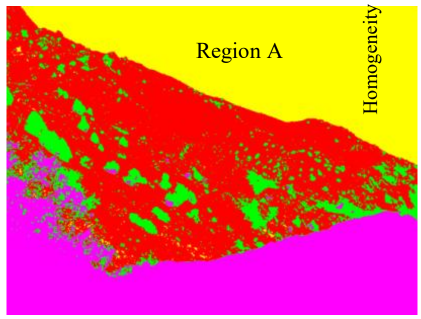
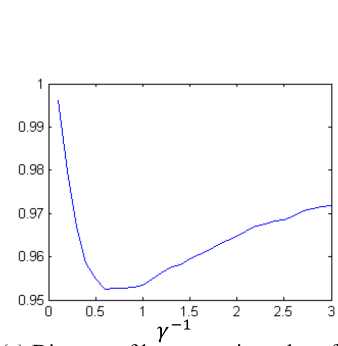


Fig. 2. Flowchart of the proposed image enhancement method.

(a) Original image



(b) Segmentation result into four sub-regions



(c) Diagram of homogeneity values for thirty different inverse Gamma images, (the deep point reaches a unique minimum at $\gamma^{-1} = 0.6$)

(d) Blocking effects due to Gamma correction (these areas have been depicted by the ellipses)

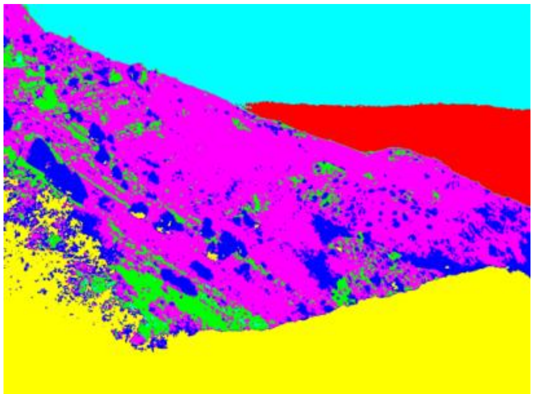
(e) Image enhancement without the problem of blocking effects

Fig. 3. An example of image enhancement by our proposed method.

6. Experimental Results

In this paper, we have proposed a technique for estimating the Gamma values without any calibration information or knowledge of the imaging device. The presented method was implemented using MATLAB 2013. As mentioned before, the images are segmented into disjoint regions for a local Gamma correction in each segment. The appropriate number of segments depends on the image. In an experiment, Figure 3(a) was segmented into six segments and the results are shown in Figure 4. Although Figure 4(b) is better than the original image, Figure 3(a), the quality of the image is not better than the one in Figure 3(e) (segmented into four regions).

We consider the subjective and objective image quality assessment to demonstrate performance of the proposed algorithm. We also compare the results of our proposed method with those generated by four other methods [2, 12, 15, 16] (see Figures 5 to 7). These figures are outdoor images with a high contrast under sunlight. Using the proposed method, the enhanced images effectively improve the visual perception in darker and brighter regions, and bring out much more details. In other words, the proposed method can accommodate both lowlight and highlight detail simultaneously. But, the methods presented in [2, 15, 16] do not have these capabilities and undesirable blocking effects are still visible in some parts of smooth regions in the enhanced image produced by [12]. The subjective assessment in these figures indicates that the enhancement results using the proposed method have a better performance compared to the existing approaches. In fact, the enhanced images using our proposed method look closer to real natural scenes, clearer with more details, and more visually pleasing.



(a) Segmentation result into six sub-regions

(b) Image enhancement by our proposed method

Fig. 4. An example of the proposed method with segmentation into six sub-regions.

(a) Original image

(b) Proposed method

(c) Method proposed in [2]

(d) Method proposed in [12]

(e) Method proposed in [15]

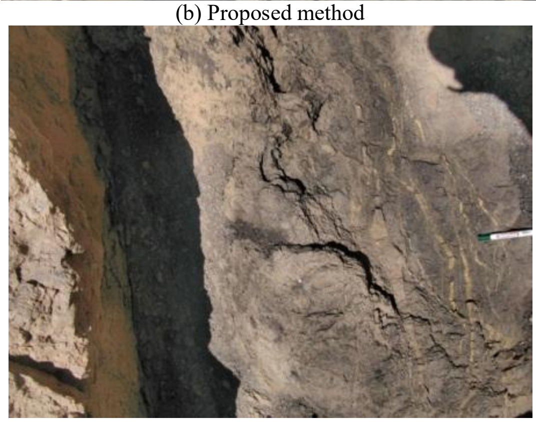
(f) Method proposed in [16]

Fig. 5. Comparison between the proposed method and the methods proposed in [2, 12, 15, 16] (subjective quality assessment, Sample 1).

(a) Original image

(b) Proposed method

(c) Method proposed in [2]

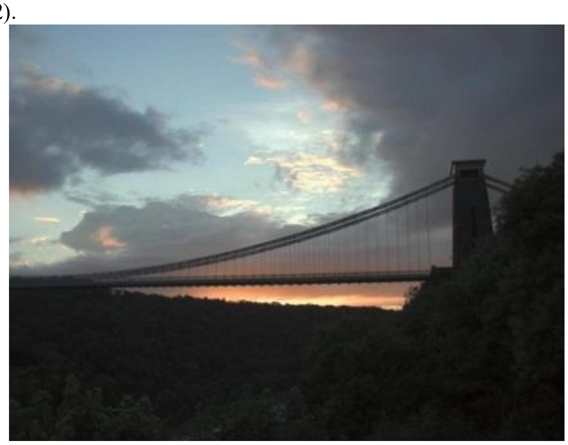


(d) Method proposed in [12]

(e) Method proposed in [15]

(f) Method proposed in [16]

Fig. 6. Comparison between the proposed method and the methods proposed in [2, 12, 15, 16] (subjective quality assessment, Sample 2).

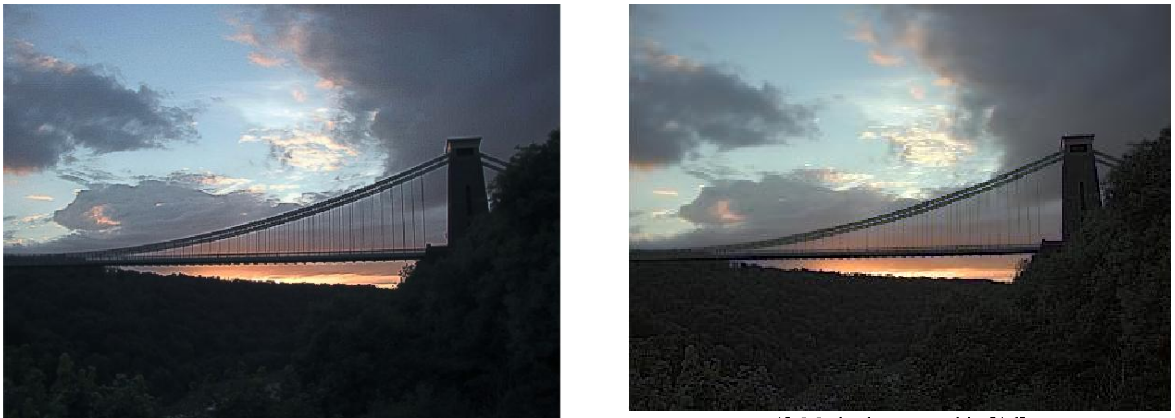


(a) Original image

(b) Proposed method

(c) Method proposed in [2]

(d) Method proposed in [12]



(e) Method proposed in [15]

(f) Method proposed in [16]

Fig. 7. Comparison between the proposed method and the methods proposed in [2, 12, 15, 16] (subjective quality assessment, Sample 3).

(a) Original image

(b) Damaged image via changing the Gamma values, SSIM=0.55

(c) Proposed method, SSIM=0.978

(d) Method proposed in [2], SSIM=0.788

(e) Method proposed in [12], SSIM=0.942

(f) Method proposed in [15], SSIM=0.8423

(g) Method proposed in [16], SSIM=0.9261

Fig. 8. Comparison between the proposed method and the methods proposed in [2, 12, 15, 16] (objective quality assessment).

Numerical assessment has also been performed to show the performance of the proposed method. We have used SSIM measure as the full reference numerical image quality assessment. Since the reference versions of the images were not available for the quality assessment, a standard image with the size of 256×256 was used. First, quality of this image was damaged by random Gamma values, then this image was applied to the three algorithms to restore. Figure 8 shows the SSIM values of different approaches in restoring this image. As it is shown in Figure 8, SSIM gives the highest score to the proposed algorithm, hence outperforms the other two algorithms in enhancing the images.

7. Conclusions

The research in this paper introduced a new efficient Gamma correction method to improve the image dynamic range in an adaptive approach. In this approach, the image is initially segmented using the pixon concept. Then the Gamma value of each segment is individually estimated. Depending on the texture and depth of the objects, different regions of an image might be under different Gamma values.Using the segmentation method, the image is partitioned into several disjoint regions. Then the appropriate Gamma value for each region is estimated.

As a future work, image segmentation can be done according to the depth of the objects in the image or texture information of the image. Also, image sharpening method such as unsharp masking can be applied on the Gamma corrected image. Indeed, image sharpening method and Gamma correction can improve the image quality per se, employing both of them can further increase the improvement.

References

[1] M.Y. Nam, and P.K. Rhee, “An efficient Face Recognition for Variant Illumination Condition,” *The International Symposium on Intelligent Signal Processing and Communication Systems*, pp. 111-115, 2004.

[2] Y. Shi, J. Yang, and R. Wu, “Reducing Illumination Based on Nonlinear Gamma Correction,” *The IEEE International Conference on Image Processing, San Antonio*, pp. 529-532, 2007.

[3] R.C. Gonzalez, and R. E. Woods, Digital Image Processing, Prentice Hall, Upper Saddle River, *NJ 07458*, 2002.

[4] M. Tiawari, S. S. Lamba, and Bh. Gupta, “An approach for visibility improvement of dark color images using adaptive gamma correction and DCT-SVD,” *International Workshop on Pattern Recognition,* 2016.

[5] H. Farid, “Blind Inverse Gamma Correction,” *IEEE Transactions on Image Processing*, vol. 10, no. 10, pp.1428-1433, 2001.

[6] S. Lee, “Content-based Image Enhancement in the Compressed Domain based on Multi-scale α-rooting Algorithm,” *Pattern Recognition Letters*, vol. 27, no. 10, pp. 1054-1066, 2006.

[7] Q. Chen, X. Xu, Q. Sun, and D. Xia, “A Solution to the Deficiencies of Image Enhancement,” Signal Processing, vol. 90, no. 1, pp. 44-56, 2010.

[8] S. Asadi Amiri, H. Hassanpour, and A.K. Pouyan, “Texture Based Image Enhancement Using Gamma Correction,” *Middle-East Journal of Scientific Research*, vol. 6, pp. 569-574, 2010.

[9] M. Farshbaf Doustar, and H. Hassanpour, “A Locally Adaptive Approach for Image Gamma Correction,” *Signal Processing and their Applications*, pp. 73-76, 2010.

[10] H. Hassanpour, and S. Asadi Amiri, “Image Enhancement Using Gamma Information,” *Journal of Signal and Data Processing,* vol. 1, no. 15, pp. 25-32, 2012.

[11] H. Hassanpour, and S. Asadi Amiri, “Image Quality Enhancement Using Pixel Wise Gamma Correction via SVM Classifier,” *International Journal of Engineering*, vol. 24, no. 4, pp. 301-311, 2011.

[12] H. Hassanpour, and S. Asadi Amiri, “A Preprocessing Approach for Image Analysis Using Gamma Correction,” *International Journal of Computer Applications*, vol. 38, no. 12, pp. 38-46, 2012.

[13] S. Asadi Amiri, and E. Moudi, “Image Quality Enhancement in Digital Panoramic Radiograph,” *Journal of AI and Data Mining*, vol. 2, no. 1, pp. 1-6, 2014.

[14] Z. Mortezaie, H. Hassanpour, and S. Asadi Amiri, "Image Enhancement Using an Adaptive Un-Sharp Masking Method Considering the Gradient Variation", *International Journal of Engineering (IJE)*, vol. 30, no. 8, pp.1118-1125, 2017.

[15] S.C.F. Lin, C.Y. Wong, G. Jiang, M.A. Rahman, T.R. Ren, N. Kwok, H. Shi, Y.H. Yu, and T. Wu, "Intensity and edge based adaptive unsharp masking filter for color image enhancement", *Optik-International Journal for Light and Electron Optics*, vol. 127, no. 1, pp.407-414, 2016.

[16] N. Kwok, H. Sm, G. Fang, and Q. HA, “adaptive scale adjustment design of unsharp masking filters for image contrast enhancement,” *International Conference on Machine Learning and Cybernetics*, pp. 14-17., 2013

[17] H. Hassanpour, and H. Yousefian, “An Improved Pixon-Based Approach for Image Segmentation,” *International Journal of Engineering*, vol. 24, no. 1, pp. 25-35, 2011.

[18] F. Yang, and T. Jiang, “Pixon-based Image Segmentation with Markov Random Fields,” IEEE Transactions on Image Processing, vol. 12, no. 12, pp. 1552-1559, 2003.

[19] R. Jobanputra, and D. Clausi, “Preserving Boundaries for Image Texture Segmentation using Grey Level Co-Occurring probabilities,” *Pattern Recognition*, vol. 39, no. 2, pp. 234-245, 2006.

[20] R.M. Haralick, K. Shanmugan, and I. Dinstein, “Textural features for image classification,” *IEEE Transactions on Systems, Man, and Cybernetics,* vol. 3, no. 6, pp. 610-621, 1973.

[21] Z. Wang, and A.C. Bovik, “Mean Squared Error: Love It or Leave It? A New Look at Signal Fidelity Measures,” *IEEE Signal Processing,* vol. 26, no. 1, pp. 98-117, 2009.

[22] Zh. Wang, L. Li, Sh. Wu, Y. Xia, Zh. Wan, and C. Cai, “A New Image Quality Assessment Algorithm based on SSIM and Multiple Regressions,” *International Journal of Signal Processing, Image Processing and Pattern Recognition,* vol. 8, no. 11, pp. 221-230, 2015.

Hamid Hassanpour received the B.S. degree in Computer Engineering from Iran University of Science & Technology, Tehran, Iran, in 1994, the M.S. degree in Computer Engineering from Amirkabir University of Technology, Tehran, Iran, in 1997, and the Ph.D. degree in signal processing from Queensland University of Technology, Brisbane, Australia. He is currently a professor at Department of Computer Engineering, Shahrood University, Iran.

Email: h.hassanpour@shahroodut.ac.ir

Sekineh Asadi Amiri received the B.S. degree in Computer Engineering from Babol University, Babol, Iran, in 2006, the M.S. degree in Computer Engineering from Shahrood University of Technology, Shahrood, Iran, in 2010, and the Ph.D. degree in Computer Engineering from Shahrood University of Technology in 2016. She is currently an assistant professor at Department of Engineering, University of Mazandaran, Iran.

Email: s.asadi@umz.ac.ir

Paper Handling Data:

Submitted: 01.01.2017
Received in revised form: 27.06.2018
Accepted: 23.08.2018
Corresponding author: Sekineh Asadi Amiri
Faculty of Technology and Engineering, University of Mazandaran, Babolsar, Iran