Contrast Enhancement in Digital Images Using an Adaptive Unsharp Masking Method

Z. Mortezaie, H. Hassanpour, S. Asadi Amiri

Abstract—Captured images may suffer from Gaussian blur due to poor lens focus or camera motion. Unsharp masking is a simple and effective technique to boost the image contrast and to improve digital images suffering from Gaussian blur. The technique is based on sharpening object edges by appending the scaled high-frequency components of the image to the original. The quality of the enhanced image is highly dependent on the characteristics of both the high-frequency components and the scaling/gain factor. Since the quality of an image may not be the same throughout, we propose an adaptive unsharp masking method in this paper. In this method, the gain factor is computed, considering the gradient variations, for individual pixels of the image. Subjective and objective image quality assessments are used to compare the performance of the proposed method both with the classic and the recently developed unsharp masking methods. The experimental results show that the proposed method has a better performance in comparison to the other existing methods.

Keywords—Unsharp masking, blur image, sub-region gradient, image enhancement.

I. INTRODUCTION

MANY defectives may be imposed on the captured image. These imposing defectives occur due to technical reasons such as inappropriate environmental conditions and limitations on devices used to capture an image. These defectives sometimes degrade the high frequency component (edge) of an image which is named contrast degradation. Contrast is one of the important properties of an image that has effects on the quality of the image; hence, to have a high quality image, we should improve the contrast of the image using image enhancement methods.

There are different methods to enhance an image in literature [1]-[5]. Among the existing methods, unsharp masking is a popular method due to its simplicity in implementation and computation. This method improves the image contrast by boosting the high frequency components such as image edges. In the classic unsharp masking, at first, a linear high pass filter is used to extract the high frequency components of the input image; then to obtain a sharper image, a scaled amount (the gain factor) of these components are added to the input image. The quality of the enhanced image is highly dependent on the selected gain factor. Indeed,

undesirable gain values may lead to an over sharpening problem or a negligible influence on the image quality.

A number of methods have been introduced in literature to improve the classic unsharp masking technique. The method introduced in [6] initially segments the image into three different areas: low contrast, medium contrast and high contrast areas. Based on these three segments, appropriate gain factors are applied on each segment. In this method, the gain factors for each segment are determined experimentally. Due to the influence of image segmentation on the quality of resulted image, the method in [7] has tried to improve the segmentation approach in [6]. Similar to [6], in [7] the gain factor for each segment is determined experimentally. In [8], an unsharp masking technique has been proposed to enhance the dark region details of an image similar to the bright regions which matches the response of the human visual system well. In this method by applying the negative operation, the dark regions are transformed to the bright regions. Then to reduce the noise effect, a mean weighted high pass filter is used to extract the regions edges. In this method, a constant gain factor is applied on all input images. A method, using the discrete wavelet transform (DWT), was proposed in [9] for reducing the over sharpening. In this method, a set of wavelet coefficients are obtained by applying the DWT on the input image. To reduce the over sharpening problem, the wavelet coefficients which are related to extra details are trimmed. By applying the inverse discrete wavelet transform (IDWT) on the rest of the coefficients, the image containing the edges of the input image is obtained. Then, the scaled value of this image is added to the input image for enhancing. The method in [10] has combined DWT with the method in [6] to enhance the satellite images. In these two last methods, which are based on DWT, the gain factors are chosen as a constant value throughout the input image.

In all of the above mentioned approaches, the gain factors are chosen without considering the quality and the content of the input image. There are some approaches that choose the gain factor by considering these issues. In [11], the particle swarm optimization (PSO) has been used to automatically find the gain factor for gray-level input images. In this method the optimization is based on maximizing the enhanced image entropy. But maximizing the entropy may lead to an over sharpening problem. In [12], the same idea has been proposed to determine the gain factor for color input images. In this approach the PSO is used based on maximizing the enhanced image entropy and minimizing the number of over ranged pixels to overcome the over sharpening problem. Time consuming is an important problem in [11], [12]. In [13] a fast

Z. Mortezaie is with the Department of Computer Engineering, Shahrood University of Technology, Shahrood, Iran (corresponding author, phone: 023-32300251; e-mail: zm.mortezaie@gmail.com).

H. Hassanpour is with the Department of Computer Engineering, Shahrood University of Technology, Shahrood, Iran (e-mail: h_hassanpour@yahoo.com).

S. Asadi is with the Faculty of Engineering and technology, Mazandaran University, Babolsar, Iran (e-mail: asadi_amiri@yahoo.com).

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 on a hyperbolic tangent function to determine the gain factor automatically. This method causes an over sharpening problem on some images.

In this paper, we propose an adaptive unsharp masking method. Since quality of an image may not be the same throughout the image, we compute the gain factor for individual pixels of the image. Indeed, we consider the gain factor as a matrix rather than a fixed scalar value which is commonly used. The gradient variations in the image are considered to compute the gain factor.

This paper is structured as follows: the classic unsharp masking method is reviewed in Section II. The proposed method is presented in Section III. The experimental results and conclusion are presented in Sections IV and V, respectively.

II. THE CLASSIC UNSHARP MASKING

In classic unsharp masking, the sharp image is obtained as follows:

$$y(n,m) = x(n,m) + \frac{1}{\lambda} \times z(n,m), \qquad (1)$$
$$z(n,m) = x(n,m) - x(n,m) * f,$$

where $y(n,m)$ is a sharp image, $x(n,m)$ is the input image, $z(n,m)$ represents high frequency components, λ is the gain factor and $*$ indecates the convolution operator, and f is simply a low pass filter like an average filter. Indeed, by applying the linear high pass filter on $x(n,m)$, $z(n,m)$ is obtaind; hence, $z(n,m)$ involves high frequency components of $x(n,m)$. High frequency components are scaled via the gain factor.

The small gain value causes an over sharpening problem, and a large gain value has a little influence on the images quality. Hence, the image contrast can be increased via choosing an appropriate value for this parameter. In classic unsharp masking, this factor is chosen as a constant.

III. PROPOSED METHOD

As mentioned earlier, the quality of an image may not be the same throughout; hence, for enhancing the contrast of an image, the enhancing parameter (i.e. gain factor) should be adaptively computed for different regions. Since sharp regions have a higher gradient than a blurred one, we consider the gradient variations in different regions of the image to set gain factor.

For a better description of the proposed method, we first analyze the gradient variation by applying 30 different gain factors (from 0.1 to 3 interval 0.1) on a sub-region; hence, we have 30 processed images of each sub-region. All of the processed images in a sub-region are sharper, and thus with a higher gradient value than the associated sub-region in the input image. The sub-region may be over sharpened by employing a small gain value. The chance of the over sharpening problem is decreased by increasing the gain value.

This relationship between the gain value and the gradient variation is used in our proposed method to choose an appropriate gain factor for each sub-region. For increasing the accuracy of the proposed method, the sub-regions have 50% overlap and the gradient variation is considered as three forms: 1-norm gradient in horizontal direction, 1-norm gradient in vertical direction, and the 1-norm of the second order gradient as:

$$S = \left(\frac{\|FX\|}{\|fx\|}\right) \times \left(\frac{\|FY\|}{\|fy\|}\right) \times \left(\frac{\|FXY\|}{\|fxy\|}\right), \qquad (2)$$

where FX, FY and FXY are respectively, the sub-region gradients in horizontal direction, vertical direction and second order gradient associated with the sub-region. Similarly, fx, fy and fxy represent the same meaning for the processed image of the sub-region, and $\|.\|$ indicates 1-norm.

In this equation, FX, FY and FXY are independent of the gain factor. But, fx, fy and fxy depend on the gain factor. As mentioned before, the 1-norm gradient is increased for the small value of gain factor; whereas this value is decreased for a large value of gain factor. Hence, increasing the gain factor causes an increase in the S value. Moreover the gradient of the over sharpened sub-regions is large, and these sub-regions cause a decrease in the S value. Therefore, for avoidance of the over sharpening problem, increasing the S value is desirable.

As mentioned before, 30 different processed images of the sub-region are obtained via considering 30 different gain values. Most of these gain values cause a little variation in S value. Indeed, some of these gain values cause the over sharpening problem in the processed images and some of them have a little influence on quality of the input sub-region. One of the gain values causes that S has a maximum increment; indeed, the smaller gain values cause an over sharpening problem and the larger gain values have no significant influence on the sub-region quality. So, we should choose the gain value that causes the maximum increment in S value, as the most appropriate gain value and apply it on all of the intended sub-region pixels. In our proposed method, the gradient of S value is used to find the maximum increment in the S value. The gain value that causes this increment is determined accordingly.

The values of S for 30 different gain factors and the gradient of S are indicated in Figs. 1 (a) and (b), respectively. In part (a) of this figure, the horizontal and vertical axes indicate 30 different gain values and the S value variation, respectively. In part (b) of this figure, 30 different gain values and the gradient of S value are indicated by the horizontal and vertical axes, respectively.

IV. EXPERIMENTAL RESULTS

To enhance an image using the proposed adaptive unsharp masking method, the image is windowed (size 32×32) with 50% overlap.

Our proposed method can be applied on color images. The HSV (Hue Saturation Value) color model is adopted in the

processing color images. In this model, the H channel describes the pure color, the S channel represents the degree of pure color which is diluted by white light, and the V channel depicts colorless intensity; the V channel is an important

component to describe color sensation [14]. So, in practice, this channel is only processed with the proposed method. Then the HSV color model with the modified V is transformed into the RGB color model.
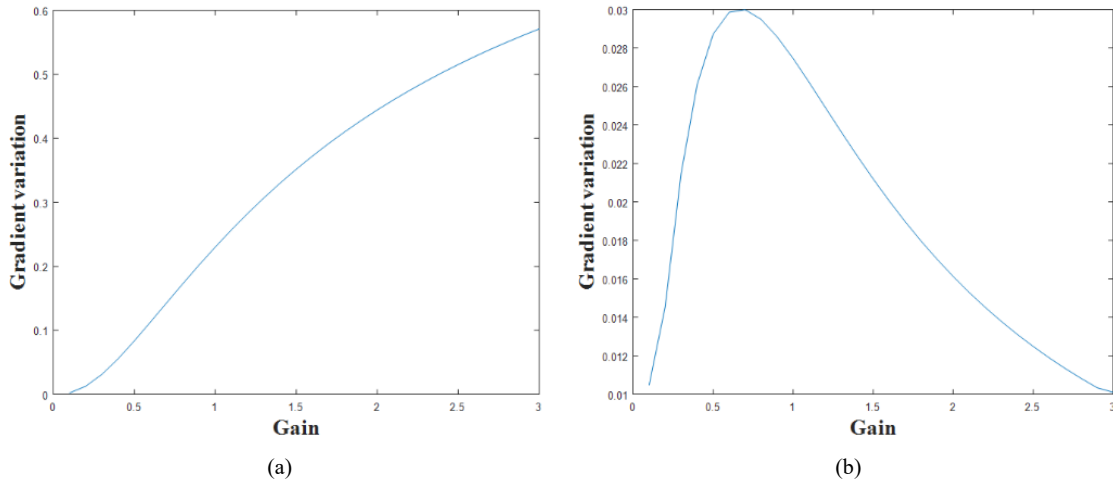

(a)   (b)

Fig. 1 The values of *S* for 30 different gain factors (a) and its gradient (b)

FOM [15], [16] and SSIM [17], [18] measures are two types of objective measures. In this paper, we use these measures to evaluate the performance of our proposed method. The FOM measure is based on the edge similarity between two images, and the SSIM is a measure to assess image quality as closely as human visual system. The output of these measures is a value in the interval [0-1]. The bigger value of these measures represents a higher similarity between the two images.

We also compare the results of the proposed method with the classic unsharp masking method and the method proposed in [13] in the CSIQ database [19]. This database includes 30 reference images (size: 512×512) and various blurred images with different levels of blurriness. Figs. 2 and 3 illustrate two instance results of the proposed method in comparison with the results obtained using the classic unsharp masking method, as well as, the method proposed in [13]. As it is shown in these figures, the enhanced images using the proposed method are more visually pleasing; while the classic unsharp masking method and the method proposed in [13] cause an over sharpening. Objective evaluation represents that our proposed method provides a better FOM and SSIM values than the classic unsharp masking method and the method proposed in [13] (see Table I).

Our method, the classic unsharp masking method and the method proposed in [13] were applied on 90 different blurred images of CSIQ database. The mean and variance of FOM and SSIM which are obtained from these methods are shown in Table II:

TABLE II
SUMMARY OF FOM AND SSIM RESULTS

	Blur images	The proposed method	Classic unsharp masking	The method proposed in [13]
FOM Mean	0.8742	0.9188	0.8631	0.8469
FOM Variance	0.0139	0.0174	0.0104	0.0103
SSIM Mean	0.9346	0.9535	0.7058	0.7357
SSIM Variance	0.00076	0.0013	0.0120	0.0186

As it is shown in Table II, the FOM means and SSIM means of these three methods have significant difference. Thus, it is clear that the mean of SSIM and the mean of FOM for the proposed method outperform the classic unsharp masking method and the method proposed in [13].

V. CONCLUSION

In this paper, a local adaptive unsharp masking method was proposed. Indeed, the proposed method locally estimates the gain factors in an image. First, the image is divided to overlapping windows and then the gain factor of each window is estimated by gradient variation. This feature can represent image details, hence the appropriate gain factor can be chosen with this feature. The subjective and objective results show the superiority of the proposed method compared to the existing methods in image enhancing using unsharp masking.

TABLE I
FOM AND SSIM RESULTS (SAMPLE 1 AND 2)

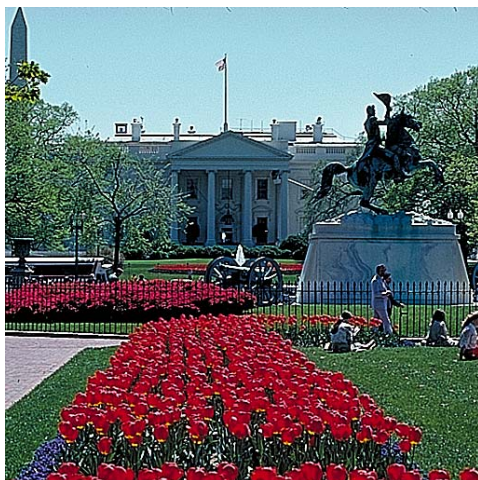|	Blur images	The proposed method	Classic unsharp masking	The method proposed in [13]
FOM (sample 1)	0.9427	0.9896	0.8871	0.8484
FOM (sample 2)	0.9511	0.9858	0.8546	0.8331
SSIM (sample 1)	0.9560	0.9895	0.6728	0.6982
SSIM (sample 2)	0.9546	0.9881	0.5490	0.6335

(a)

(b)

(c)

(d)

(e)

Fig. 2 Comparison between the proposed method, classic unsharp masking and the method proposed in [13] (subjective and objective quality assessment, Sample 1). Reference image (a); blurred image (b); enhanced image by the proposed method (c); enhanced image by classic unsharp masking (d); enhanced image by the method proposed in [13] (e)

(a)

(b)

(c)

(d)

(e)

Fig. 3 Comparison between the proposed method, classic unsharp masking and the method proposed in [13] (subjective and objective quality assessment, Sample 2). Reference image (a); blurred image (b); enhanced image by the proposed method (c); enhanced image by classic unsharp masking (d); enhanced image by the method proposed in [13] (e)

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