An Adaptive Un-Sharp Masking Method for Contrast Enhancement in Images with Non-uniform Blur

Z. Mortezaie[1*], H. Hassanpour[2], S. Asadi Amiri[3]
1- Faculty of Computer Engineering, Shahrood University of Technology, Shahrood, Iran.
Email: zm.mortezie@gmail.com (Corresponding author)
2- Faculty of Computer Engineering, Shahrood University of Technology, Shahrood, Iran.
Email: h_hassanpour@yahoo.com
3- Department of Engineering and technology, University of Mazandaran, Babolsar, Iran.
Email: asadi_amiri@yahoo.com

Received: 2 September 2022 Revised: 27 September 2022 Accepted: 25 Ocober 2022

ABSTRACT:
Un-sharp masking method improves the images contrast without requiring any prior knowledge. In this method, a sharper image can be achieved by empowering the high frequency components of the input image. Un-sharp masking has a parameter named gain factor which has a high effect on the enhanced image quality. In this paper, an approach is proposed to adaptively estimate the appropriate value of this parameter in order to effectively enhance an image with local blur, or an image with non-uniform blur. In proposed method, first, the input image is segmented into blur and non-blur regions. Then the gain factor is estimated for each region adaptively. In this approach, the influence of the image blurriness on its gradient information is used to estimate the value for the gain factor. The image quality assessments are applied to evaluate the performance of proposed un-sharp masking method in image enhancement. Experimental results demonstrate that the performance of our proposed method is better than the performance of existing un-sharp masking methods in image enhancement.

KEYWORDS: Un-Sharp Masking, Contrast Enhancement, Gradient Information, Non-Uniform Blur.

1. INTRODUCTION

The contrast of the captured images may be degraded due to many technical limitations such as poor lens, focus or camera motion. These limitations impose global or local blurriness in the captured images and affect the image contrast. The blurriness leads to eliminate the edges of the images.

Various approaches have been introduced in literature in order to enhance the images contrast. In some image enhancement approaches, prior knowledge about the original images is necessary for improving the contrast of the images [1-4], whereas, this knowledge is not available with a good accuracy. Hence, some approaches try to reduce the need of prior knowledge in image enhancement processes [5-8]. Note that, enhancing the contrast of the images without any prior knowledge is usually time consuming and complex task. Among all these approaches, the un-sharp masking method is used more frequently because it has simple implementation, without need the prior knowledge. In this approach, the contrast of the image is enhanced by empowering high frequency components (i.e., edges) of the image.

In the classic un-sharp masking technique, first, a linear high pass filter is applied for extracting the edges of the input image. Then, the scaled amount of the edges is obtained using the gain factor as a weighing value; by adding the scaled amounts of the edges to the input image, an image with a higher contrast is achieved.

The gain factor has an important effect on the results of un-sharp masking. Inappropriate values for this parameter cause the over sharpening problem or negligence effects on the input image. In classic un-sharp masking, this parameter is considered as a constant value, where, the content of the images and the amount of blurriness are not assessed. Hence, selecting an appropriate value for the gain factor is a crucial challenge. Besides, determining different gain values for the blur and non-blur regions of the image is necessary as the blurriness in the images may not be uniform.

There are some methods for image enhancement which are based on the un-sharp masking technique [9-19]. The considered blurriness in these methods is divided into local and global blurriness. Also, in some

Paper type: Research paper
DOI: 10.30486/mjee.2022.697549
How to cite this paper: Z. Mortezaie, H. Hassanpour and S. Asadi Amiri, “An Adaptive Un-Sharp Masking Method for Contrast Enhancement in Images with Non-uniform Blur”, Majlesi Journal of Electrical Engineering, Vol. 16, No. 4, pp. 139-149, 2022.

of them the gain factor is selected as a constant value and in others this parameter is adaptively achieved. More details of these approaches are described in the following section.

In this paper, an adaptive un-sharp masking is proposed for improving the quality of the images with non-uniform blur. In our proposed method, according to the content of the image and the amount of blurriness in the regions of the image, the gain factor is adaptively achieved. Some information about the contrast of the image can be provided by the image Gradient information. Hence, for enhancing the images with the local blurriness, first, the input image is segmented into two different regions as blur and non-blur. Then, the gradient information of each region is assessed for achieving an appropriate gain value for the region.

The rest of this paper is organized as follows. In Section 2, we briefly review some image enhancement approaches which are based on un-sharp masking. The classic un-sharp masking and the details of our proposed method are respectively explained in Sections 3 and 4. In Section 5, the image quality assessment is introduced. The experimental results and the conclusion are respectively presented in Sections 6 and 7.

2. RELATED WORKS

As mentioned before, there are some global and local image enhancement methods based on un-sharp masking technique. Some of them consider a constant value for gain factor and the others have tried to determine this parameter adaptively. In this section, we briefly review these methods.

In [9], in order to reduce the over sharpening issue, a global un-sharp masking method is proposed based on the Discrete Wavelet Transform (DWT), where, DWT is applied to the input image to achieve a set of wavelet coefficients. Then, the wavelet coefficients corresponded to extra details are trimmed in order to reduce the over sharpening issue. Then, the Inverse DWT (IDWT) is applied to the rest of the coefficients to achieve the image which contains the high frequency components of the input image. Finally, the scaled amount of this image is added into the first image to obtained enhanced image. In this method, a constant gain value is used throughout the input image.

A global un-sharp masking method is proposed in [10], where, negative operation is used to transform the dark regions of the images to the bright regions. Then, the edges of image are extracted using a mean weighed high pass filter. After enhancing the image, the transformed regions are turned into the dark region. Similar to [9], in this approach, a constant gain value is selected throughout the image.

A global un-sharp masking method is proposed in [11], where, the Particle Swarm Optimization (PSO) is used to automatically obtain the gain factor for the input image. In this approach, the PSO is used to maximize entropy of the enhanced image, whereas, maximizing the entropy may lead to an over sharpening problem. The same idea is proposed in [12], to adaptively obtain the gain factor for input images as well as overcome the over sharpening problem. In this global approach, the PSO maximizes the entropy of the enhanced image and, also, minimizes the number of over ranged pixels.

An adaptive un-sharp masking method is proposed in [13] for enhancing images with global blurriness considering the gradient variations of the input image and the image under enhancing, where, the gain factor is obtained depending on the quality of the input images.

A nonlinear unsharp masking approach is proposed in [14] to overcome the issue of out-of-range pixels in the enhanced images using nonlinear transformation. Also, in this approach, the modified hybrid median filter is used in an iterative manner for reducing the halo effect in the result images.

All of the above-mentioned approaches have tried to improve the quality of the images globally, whereas, the blurriness of the images may not be uniform. Hence, it is necessary to improve the quality of the images with local manner.

In [15], a local un-sharp masking method is proposed, where, the input image is segmented into three regions as low, medium, and high contrast regions using the constant thresholds. Then, three constant gain values are used to enhance each region. But the constant thresholds affect the image segmentation and the quality of the result image. The local un-sharp masking approach is proposed in [16] for improving the image segmentation approach by selecting the appropriate thresholds. Similar to [15], in [16], the gain factor for each region is selected as a constant value. Also, in [17], DWT is combined with the method proposed in [15] for enhancing the satellite images. In the above-mentioned approaches, the gain factors are selected without assessing the images content.

In [18], an adaptive block based un-sharp masking approach is proposed, where, the input image is divided into a number of overlapping blocks. In this approach, the gradient information of each block is used in order to determine the appropriate gain factor for the pixels of the block.

A local un-sharp masking approach is proposed in [19], where, it is based on the intensity of input image as well as the extracted edges. In this method, the intensity of the input image and the extracted edges are applied to a hyperbolic tangent function in order to automatically obtain the gain factor for each pixel of the image. This method causes an over sharpening issue on some images.

3. THE CLASSIC UN-SHARP MASKING METHOD

In As mentioned earlier, the classic un-sharp masking method is based on accentuating the edges of images. In this method, the sharp image is achieved using the following equations:

$$h(i,j) = Im(i,j) - Im(i,j) * f, \quad (1)$$

$$f = \frac{1}{9}\begin{bmatrix}1 & 1 & 1\\1 & 1 & 1\\1 & 1 & 1\end{bmatrix}, \quad (2)$$

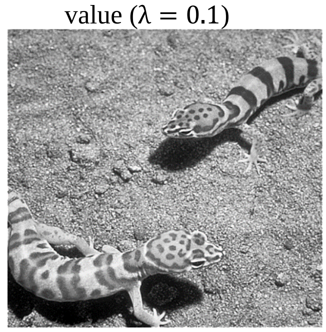
$$Im_s(i,j) = Im(i,j) + \frac{1}{landa} \times h(i,j) \quad (3)$$

Where, $Im_s(i,j)$, $Im(i,j)$, and $h(i,j)$ are the sharp image, the input image, and edges respectively. Also, $landa$ is the gain factor, and $*$ indicates the convolution operation. According to Equation (1), in classic un-sharp masking, first, a linear high pass filter is applied to $Im(i,j)$, in order to achieve $h(i,j)$; hence, $h(i,j)$ contains edges of $Im(i,j)$. Then, according to Equation (3), by adding the scaled edges to the input image, the sharp image is achieved, where, a gain factor is used to scale the edges. Hence, the gain factor has an important effect on the enhanced images quality.

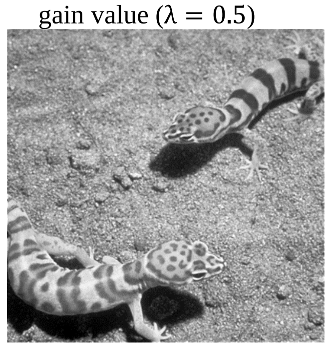
According to Equation (3), using a small gain value (for example, 0.1) leads to an over sharpening in the output image, whereas, using a large gain value (for example, 3) has a little effect on the quality of image. Hence, it is necessary to select an appropriate gain factor to achieve the image with suitable contrast. In the classic un-sharp masking, a constant gain factor is selected throughout the image without considering the content of image and the amount of blurriness in the image. The influence of the gain value on un-sharp masking results is shown in Fig. 1, where, the influence of inappropriate gain values on the image is presented in Fig. 1(b) and 1(c). Also, the image in Fig. 1(d) was achieved by applying an appropriate gain value.

a) Input blur image

b) Enhanced image using low gain value ($\lambda = 0.1$)



c) Enhanced image using appropriate gain value ($\lambda = 0.5$)



d) Enhanced image using high gain value ($\lambda = 3$)

Fig. 1. The outputs of the classic un-sharp masking using different gain values

4. THE PROPOSED METHOD

In In this section, a new adaptive un-sharp masking approach is proposed for improving the image quality. As mentioned earlier, in the un-sharp masking, the gain factor has a significant effect on the quality of the enhanced image. In our proposed approach, the gain factor is computed considering the blurriness of the image. In a blurred image, the edges of the image are weakened, depending on the severity of blurriness. Considering this point, the gradient information of the image can be used to choose the appropriate value for the gain factor. Moreover, the blurriness may not be uniform throughout the image. Hence, in the proposed approach, considering the local blur information of the image, the quality of the image is improved. In this approach, the image blurriness information is used in order to segment the input image into blur and non-blur regions. Then, the gradient information of each region is used to select the appropriate gain factor for the region. In the following sub-sections, we first describe, in more details, the proposed method considering the gradient variation in an image with uniform blurriness. Then the proposed method is generalized to enhance images with non-uniform blurriness.

4.1. Enhancing Images With Uniform Blur

In this section, we initially introduce the base concepts of our proposed method on images with a uniform blurriness (i.e., global blurriness). Then we generalize the proposed method to enhance the images quality with the non-uniform blurriness (i.e., local blurriness).

As mentioned earlier, in the proposed method, an appropriate gain factor is determined considering the gradient information of the image.

Note that, the strength of the edges (i.e., edges and the details) of a blur image is less than the ones in the sharp image. It means that, the gradient l_p norm of a blur image, is lower than the sharp one. Indeed, the blur image has a lower gradient l_p norm than the sharp image. This point is considered in the proposed approach, where, the l_p norm of the gradient information is used to adaptively choose the gain factor. The l_p norm is as follow (4):

$$\|\mathrm{Im}\|_p = \left(\sum_{i,j}|\mathrm{Im}(i,j)|^p\right)^{\frac{1}{p}}, \quad (4)$$

Where, $\mathrm{Im}(i,j)$ is an input image; $|.|$ and $\|.\|_p$ symbols denote absolute value, and l_p norm respectively.

First, for a better description of our proposed approach, the l_1 norm of gradient in an image is analysed by applying different gain factors on it. Hence, 30 different gain factors are considered from 0.1 to 3, with intervals of 0.1. Then, these gain factors are applied to an input image; 30 sharper images than the input image, are achieved accordingly, where, the small gain values may lead over sharpening problem in the output images, but, the big gain values lead negligence effects on the input image.

The l_1 norm of gradient on over sharp images is high. In the processed images, the over sharpening issue is increased by decreasing the gain value, where, the l_1 norm of gradient is increased in these images accordingly.

Fig. 2 presents the relation between the gain factor and the l_1 norm of horizontal direction gradient in an image. In this figure, the horizontal and vertical axes indicate 30 different gain values and the l_1 norm of horizontal direction gradient, respectively.

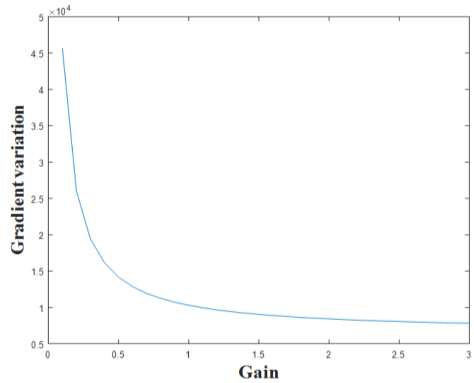


Fig. 2. The l_1 norm of gradient versus gain factor

Similar relations are obtained for both the vertical direction and the second order gradient. As it is shown in this figure, the l_1 norm of gradient in the processed images is increased by decreasing the gain value.

In our proposed approach, the relation between the gradient information of the input image and the gradient information of the processed images are used to adaptively select the image with an appropriate quality as Equation (5):

$$S = \left(\frac{\|GX\|_1}{\|gx\|_1}\right) \times \left(\frac{\|GY\|_1}{\|gy\|_1}\right) \times \left(\frac{\|GXY\|_1}{\|gxy\|_1}\right), \quad (5)$$

Where GX, GY and GXY denote the input image gradients in horizontal direction, vertical direction and the second order gradient, respectively. Meanwhile, gx, gy and gxy denote the similar meaning for the processed image, and $\|.\|_1$ symbol denotes l_1 norm.

Note that, the values of GX, GY and GXY are constant as they denote the input image gradients, whereas, the values of gx, gy, and gxy are changed by applying the different gain factors to the input image.

As mentioned earlier, using the small gain values causes the over sharped images as well as high l_1 norm of gradient information. According to Equation (5), the small gain values decrease the S value, whereas, increasing the gain value decreases the over sharpening issue as well as the l_1 norm of gradient information in the processed images. Besides, according to Equation (5), increasing the gain factor leads to increasing the S value. Hence, the S value is increased to avoid over sharpening issues.

The S value has a maximum increment using one of the gain values, where, the smaller gain values cause an over sharpening issue and the larger ones have no significant effects on the input image quality. Hence, the gain value that causes the maximum increment in the S value, should be chosen as the most appropriate gain value. Also, the most appropriate processed image is achieved accordingly.

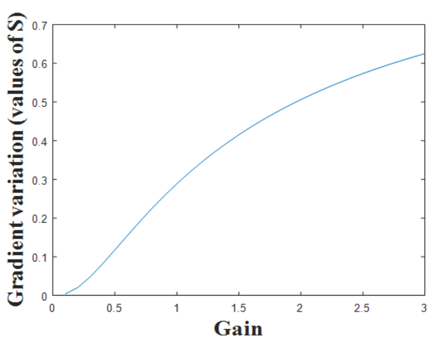
In our proposed approach, to find the maximum increment for the *S* values, the gradient of the 30 obtained S values are used. Also, the gain value that causes this increment is achieved accordingly.

In Fig. 3-a and 3-b, the values of S for 30 different gain factors and the gradient of S are shown respectively. In parts (a) and (b) of this figure, the horizontal axes indicate 30 different gain values and the vertical axes represents the S values and the gradient of *S* values respectively.

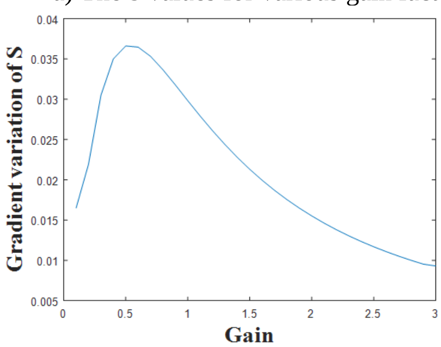
Note that, weak edges of the image have less effect on the S values comparing to the strong ones, by using l_1 norm to select the gain values; but, to select the appropriate gain values, the weak edges are more effective than the strong ones. Hence, to select the appropriate gain factor for an image, the effects of the strong edges should be decreased comparing to the weak ones. In the proposed method, this goal is achieved by applying the exponent values which are smaller than one to the gradient information. In this paper, the exponent 0.8 is used to adjust the influence of the edges. Hence, Equation (5) is rewritten as follow:

$$S = \left(\frac{\|GX\|_{0.8}^{0.8}}{\|gx\|_{0.8}^{0.8}}\right)^2 \times \left(\frac{\|GY\|_{0.8}^{0.8}}{\|gy\|_{0.8}^{0.8}}\right)^2 \times \left(\frac{\|GXY\|_{0.8}^{0.8}}{\|gxy\|_{0.8}^{0.8}}\right)^2, \quad (6)$$

Where GX, GY, GXY, gx, gy and gxy have the similar meaning in Equation (5), and $\|.\|_{0.8}$ symbol indicates $l_{0.8}$ norm.



a) The S values for various gain factors



b) The gradient of the achieved S values in (a)

Fig. 3. The S values achieved by using different gain values and their gradients.

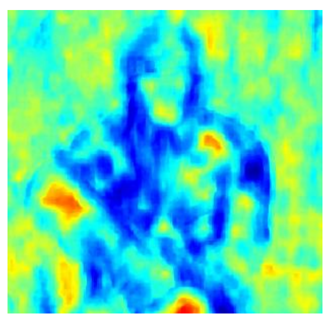
4.2. Enhancing Images With Non-Uniform Blur

As mentioned earlier, the blurriness may occur locally in an image. Hence, it is required to segment blur and non-blur regions of an input image, and determine the appropriate gain value for each segment. Each segment can be enhanced separately using its gradient information.

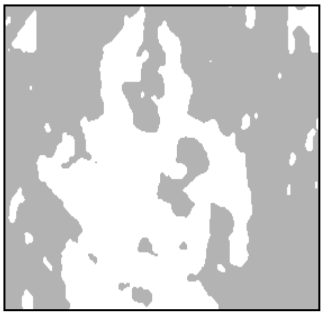
In this paper, the method proposed in [20] is used to segment the input image into the blur and non-blur regions. In this segmentation method, initially, a blur map is provided for the input image by determining the blurriness amount of each pixel. Indeed, a blur map is an image with the same size as the input image. Each pixel of this map represents the estimated amount of blurriness for corresponding pixel from the input image. In the method proposed in [20], the discrete cosine transform (DCT) coefficients are used for determining the blurriness pixels and approximating the blur map accordingly. Finally, the pixon-based segmentation method proposed in [21] is used to segment the achieved blur map into blur and non-blur regions.

A sample image with local blurriness is shown in Fig. 4. In this figure, the background is blurry. Also, the achieved blur map and the segmentation results are depicted in Fig. 5.

Fig. 4. An image with local blurriness.



a) The achieved blur map using the method proposed in [20].



b) Segmentation results using the method proposed in [21].

Fig. 5. The achieved blur map and the segmentation results for the sample image with local blurriness shown in Fig. 4.

Flowchart of our proposed method is shown in Fig. 6. In this flowchart, the input can be an image or a segment of an image with global or local blurriness respectively.

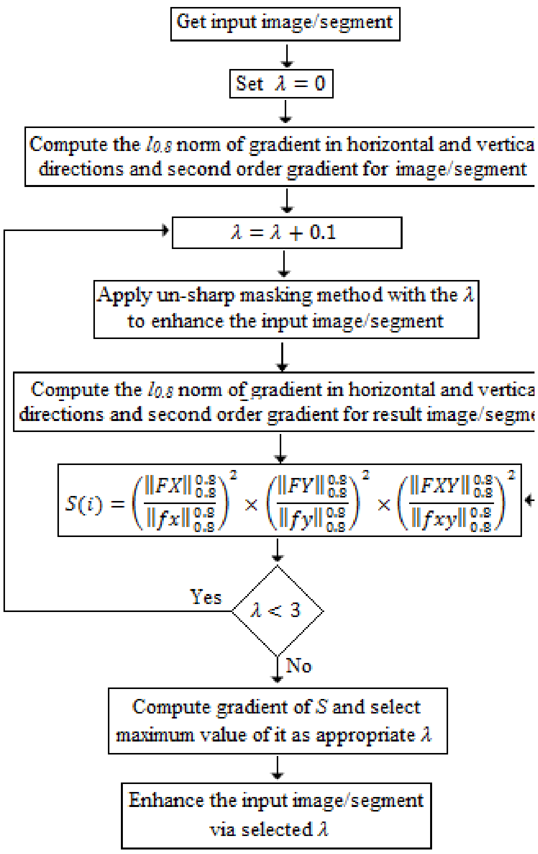


Fig. 6. Flowchart of the proposed method.

5. IMAGE QUALITY ASSESSMENT

Two types of Image Quality Assessment (IQA) are the subjective and objective approaches. The subjective approaches use human beings' evaluations for deciding about the image quality. As the subjective approaches are expensive and time-consuming [22, 23], these approaches are not appropriate for IQA. The objective methods are numerical measures, where, they try to determine the image quality as close as possible to the subjective assessment [24]. In this paper we use two objective IQA approaches, Pratt's Figure of Merit (FOM) [25, 26] and the Structural Similarity Metric (SSIM) [27, 28], to assess the image quality. The output of FOM and SSIM is a value in the interval [0-1], where, a lower value of these measures illustrates less similarity between the two images.

6. EXPERIMENTAL RESULTS

This paper proposes a new adaptive un-sharp masking approach to locally improve the images quality. Our proposed approach can be applied to color images. The HSV (i.e., Hue, Saturation, Value) color space is one of the commonly used color spaces for processing color images [29]. Among the components of HSV, V is an important component to describe color sensation [29]. Hence, in our proposed approach, V component is only processed. Then, the image in HSV color space with the modified V is transformed into the RGB color space.

For evaluating the performance of our proposed approach, a database containing 15 images with local blur is made manually using the images from Berkeley database [30]. Hence, a specified region of these images is blurred manually. These images are enhanced using the proposed approach; the enhanced images are compared with the results of the global and local un-sharp masking method proposed in [13] and [17] respectively.

The results of two instances images are shown in Fig. 7 and Fig. 8. In these figures, the whole images were blurred manually except the man. The segmentation results are shown in part (c) of these two figures. In these images, the blur and non-blur regions are depicted via grey and white colours respectively.

As shown in these figures, the global and local un-sharp masking method proposed in [13], [14], [18] and [19] cause over sharpening issues throughout the images, whereas, the proposed approach improves each region of the image proportional to the amount of blurriness. Hence, in this approach the over sharpening issue does not occur. Besides, according to Table 1, objective evaluations denote the superiority of the proposed local approach comparing to the global and local un-sharp masking approaches proposed in [13], [14], [18] and [19].

Also, the mean and variance of FOM and SSIM achieved from these methods for enhancing the 15 manually blurred images are shown in Table 2.

According to the FOM and SSIM results, the proposed local approach has a better performance compared to the global and local un-sharp masking approaches proposed in [13], [14], [18] and [19].

Table 1. Objective comparison between our proposed approach, classic un-sharp masking, and the un-sharp masking approaches proposed in [13], [14], [18], and [19] on Sample 1 and Sample 2.

		FOM	SSIM
Sample 1	Blur image	0.9077	0.8426
	Our proposed method	**0.9581**	**0.8541**
	Mortezaie et al. [18], (2019)	0.9288	0.8370
	Ngo et al. [14], (2020)	0.8988	0.7469
	Lin et al. [19], (2016)	0.8189	0.6156
	Mortezaie et al. [13], (2017)	0.9550	0.8308
Sample 2	Blur image	0.8725	0.8355
	Our proposed method	**0.9533**	**0.8586**
	Mortezaie et al. [18], (2019)	0.9268	0.8461
	Ngo et al. [14], (2020)	0.9019	0.7734
	Lin et al. [19], (2016)	0.7888	0.5179
	Mortezaie et al. [13], (2017)	0.9455	0.8349

Table 2. Objective comparison between our proposed approach, classic un-sharp masking, and the un-sharp masking approaches proposed in [13], [14], [18], and [19] on manually blurred dataset.

		FOM	SSIM
Blur image	mean	0.9016	0.8654
	var	0.0013	0.0045
Our proposed method	mean	**0.9468**	**0.8673**
	var	3.0739e-04	0.0020
Mortezaie et al. [18], (2019)	mean	0.9199	0.8560
	var	5.6461e-04	0.0024
Ngo et al. [14], (2020)	mean	0.8762	0.6782
	var	0.0015	0.0090
Lin et al. [19], (2016)	mean	0.8417	0.6777
	var	0.0043	0.0198
Mortezaie et al. [13], (2017)	mean	0.9428	0.8542
	var	3.4246e-04	0.0013

a) Reference image;

b) Blur image;

c) Segmentation image by method proposed in [18];

d) Enhanced image by our proposed local approach;

e) Enhanced image by method proposed in [13];

f) Enhanced image by method proposed in [19];

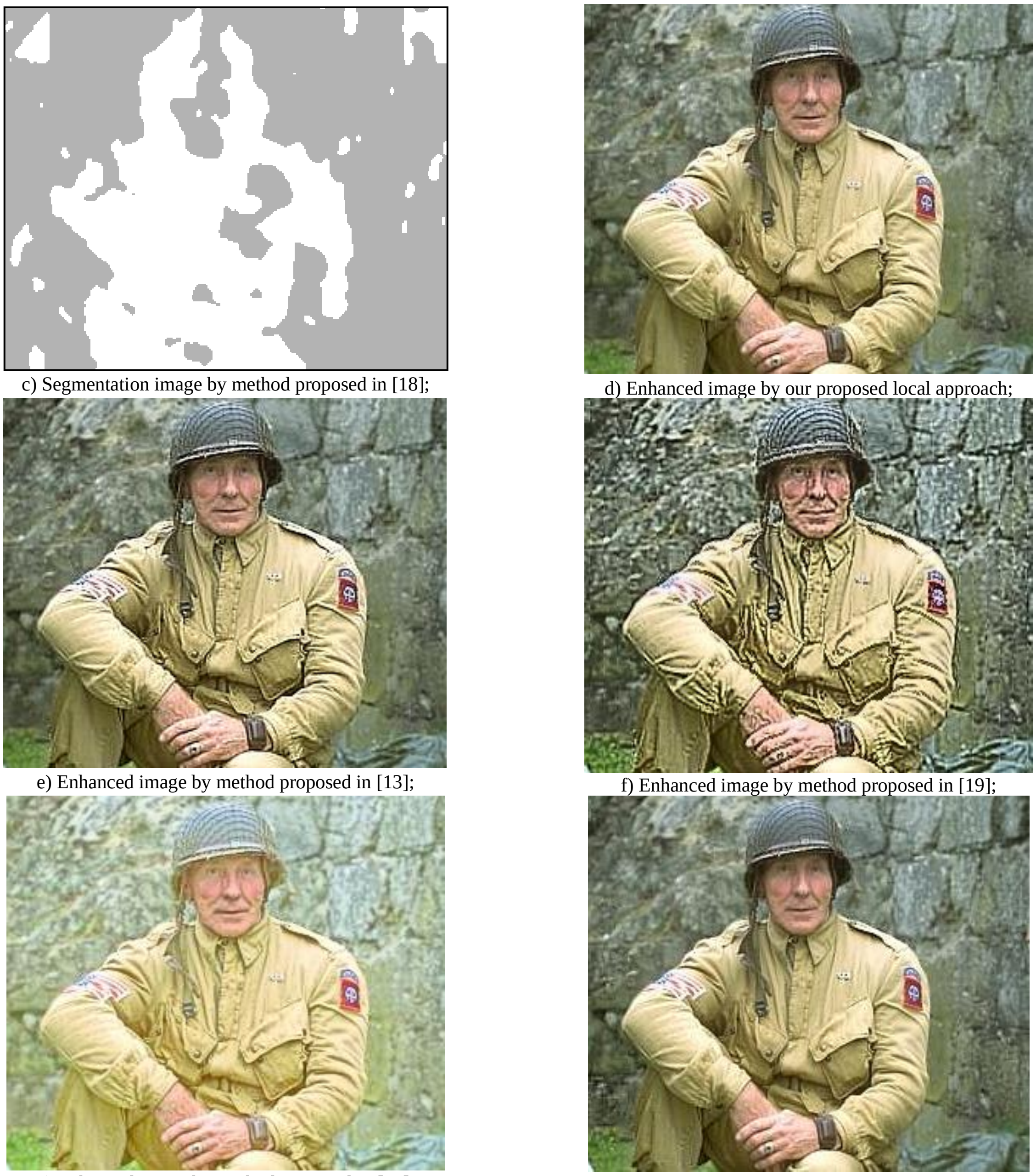
g) Enhanced image by method proposed in [14];

h) Enhanced image by method proposed in [18];

Fig. 7. Comparison between the proposed method and the method proposed in [13], [14], [18] and [19] (subjective and objective quality assessment, Sample 1).

a) Reference image;

b) Blur image;



c) Segmentation image by method proposed in [18]; d) Enhanced image by our proposed local approach;

e) Enhanced image by method proposed in [13]; f) Enhanced image by method proposed in [19];

g) Enhanced image by method proposed in [14]; h) Enhanced image by method proposed in [18];

Fig. 8. Comparison between the proposed method and the method proposed in [13], [14], [18] and [19] (subjective and objective quality assessment, Sample 2)

7. CONCLUSION

In this paper, an adaptive un-sharp masking method is proposed for enhancing images suffering from non-uniform blurriness. In the proposed method, each region of the image is enhanced considering the value of its gain factor. Besides, the blurriness affects the images gradient. Hence, in our proposed method image gradient information is used for selecting the gain value adaptively according to the image content and the amount of blurriness. Our proposed un-sharp masking approach was compared with some of the existing approaches. The subjective and objective results denote superiority of our proposed approach comparing to the other existing methods.

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