No-Reference Quality Assessment of the Gaussian Blur Image Depending on Local Standard Deviation

Hazim G. Daway
AL – Mustansiriyah University Physics Department, College of Science

Abstract

No-reference measurement of blurring artifacts in images isa difficult problem in image quality assessment field. In this paper, we present a no-reference blur metric to estimatethe quality of theimages. These images are degraded using Gaussian blurring. Suggestion method depends on developing the Mean of Locally Standard deviation this method is called Blur Quality Metric (BQM) and itcalculatesby using gamma correction and reblurring the image again And the BQM is compared with the No-reference Perceptual Blur Metrics (PBM)and the Entropy of the First Derivative (EFD) Image; the BQM is a simple metric and gives good accuracy in metrics the quality for theGaussian blurred image if it compared with another algorithms. The BQM satisfied high correlation coffecion compared with another method.

Keywords: No-referencequality assessment, Gaussian blurring, Standard deviation, mean.

1. Introduction

Measurement of image quality is significant for many imageprocessing applications, such as acquisition, compression, restoration, and enhancement. The image quality metrics can be broadly classified into two categories, subjective and objective. A large numbers of objective image quality metrics have been developed during the last decade. Objective metrics can be divided [1], [2], [3] in three categories: Full Reference, Reduced Reference and No Reference. For the existing no-reference image quality metrics that existed in the literature, most of these are developed for measuring image blockiness[4].In [5],[6] A blur metric relies on measuring the spread of edges in animage. And [7] suggested the no reference perceptual Gaussianblur metric using the image gradients along local image structures.In this paper, we are focusing on the no- reference image quality assessment for estimatethe Gaussian blurring. The Blur Quality Metric (BQM)wasinspired from the Mean of Locally Standard deviation and Mean of the image (MLSD) model by calculated the area under the curve form this relation.

2. GaussianBlurring

In digital image there are three common types of Blur effects: average blurs,Gaussianblur and motion blur [2]. The Gaussian blur is one type of image-blurring filter , that is uses a Gaussian function (which also may beexpressed in the normal distribution in statistics) for find the transformation to apply to each pixel in the image. The equation of the Gaussian blur function in one dimension is[2]:

$$G(x) = \frac{1}{\sqrt{2\pi s^2}} e - \frac{x^2}{2s^2} \quad (1)$$

In two dimension

$$G(x, y) = \frac{1}{\sqrt{2\pi s^2}} e - \frac{x^2+y^2}{2s^2} \quad (2)$$

Where xbeing the distance from the origin of the kernel in the horizontal direction, ybeingthe distance from the originof the kernel in the vertical direction, and S is the standard deviation of the Gaussian function. When applied theGaussian functionin two dimensions, this functionproduces a surface that contours are concentric circles with a Gaussian from the center point. Values from this distribution are used to build a convolution matrix which is applied to the original image. Each pixel is approximately equal the new value is set to a weighted average of that pixel's neighborhood. The original value of the pixelhave the highestweight (have the high Gaussian value) and neighboring pixels havelowerweights as their distance to the original pixel increases.The blurring image is given by:

$$\mathrm{Ib} = \mathrm{I} * \mathrm{G} \tag{3}$$

Where Ib being the blurring image and G is the Gaussian function

Figure(1) shows the different burring image with deferent values of S.

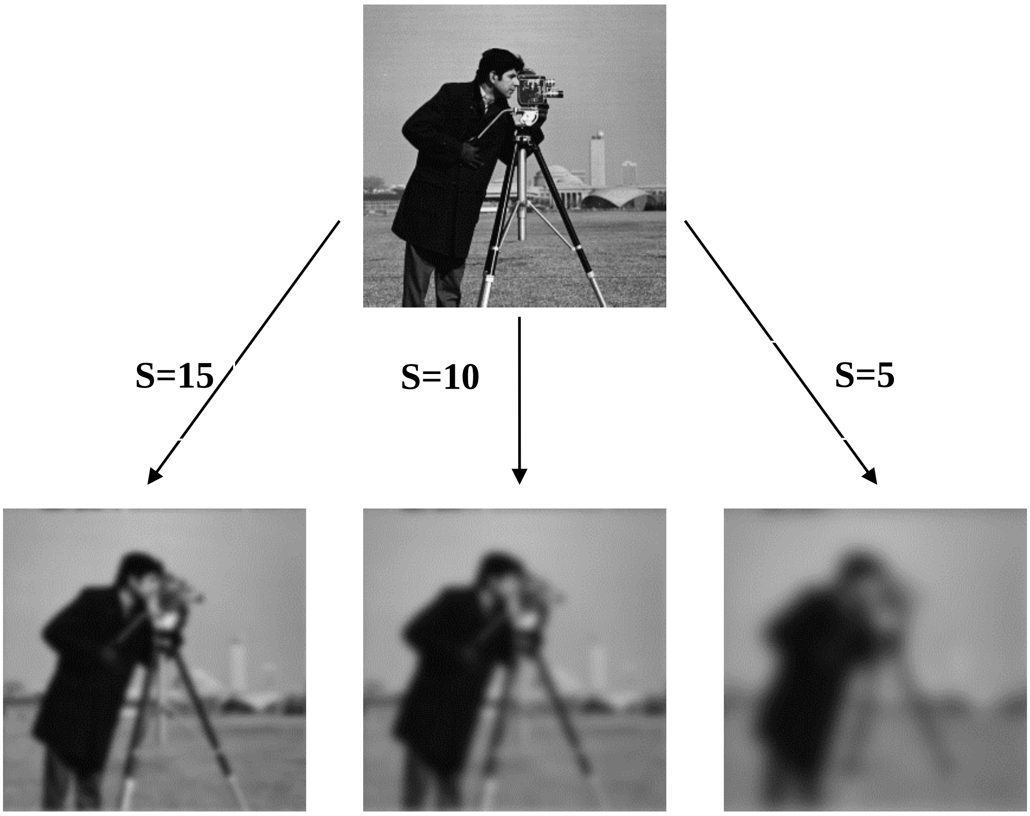


Figure (1): Original image is degraded with Gaussian blurring at different value of sigma (S).

3.Universal Quality Index (UQI)

Instead of using error metrics, Wang and Boviksuggested a method to model any image distortion by a combination of three components: luminance distortion, loss of correlation, and contrast distortion and named it like Universal Quality Index (UQI) [8].

$$\mathrm{UQI} = \frac{4\bar{\mathrm{I}}\bar{\mathrm{I}}_n \sigma_{\mathrm{II}_n}}{(\bar{\mathrm{I}}^2+\bar{\mathrm{I}}_n^{\,2})(\sigma_{\mathrm{I}}^2+\sigma_{\mathrm{I}_n}^{\,2})} \tag{4}$$

Where $\bar{I}$ and $\bar{I}_n$ being the mean of the original and processing(or noisy) image , σ_I and σ_{I_n} is the standard deviation of the original and processing(or noisy) image and σ_{II_n} is the covariance that is given by:[8]

$$\sigma_{II_n} = \frac{1}{N-1}\sum_{i=1}^{N}(I-\bar{I})(I_n-\bar{I}_n) \quad (5)$$

Or

$$UQI = \left(\frac{\sigma_{II_n}}{\sigma_{I_n}\sigma_I}\right)\left(\frac{2\bar{I}\bar{I}_n}{(\bar{I}^2+\bar{I}_n{}^2)}\right)\left(\frac{2\sigma_{I_n}\sigma_I}{\sigma_I{}^2+\sigma_{I_n}{}^2}\right) (6)$$

4. No-Reference Perceptual Blur metric

This method uses advantage of the possibility to access to specific variations representatives of the blur effect locally. The Figure 2 illustrated the flow chart that is describe the steps of the algorithm description and refers to the following equations for No-reference perceptual blur metric [9],to find the blur annoyance of gray image the first step content in blurred it due to obtain a blurred image B. The horizontal and a vertical strong low-pass filter have been chooseto model the blur effect and to create $B_{ver}$and B_{Hor} ,where the average low bass kernel in the vertical direction is[9] :

$$h_v = \frac{1}{9}\times[111111111] \quad (7)$$

And in the horizontal direction:

$$h_h = \text{transpose}(h_v) = h_v' (8)$$

And image filters are:

$$B_{ver} = h_v * F \quad , \quad B_{Hor} = h_h * F \quad (9)$$

Then, in order to study the variations of the neighboring pixels, we compute the absolute difference images $D\_F_{ver}, D\_F_{Hor}, D\_B_{ver}$ and D_B_{Hor}[9]:

$$D\_F_{ver}(i,j) = Abs\big(F(i,j) - F(i-1,j)\big)$$

$$for\ i = 1\ \ to\ \ m-1, j = 0\ \ to\ n-1 \quad (10)$$

$$D\_F_{Hor}(i,j) = Abs\big(F(i,j) - F(i,j-1)\big)$$

$$for\ j = 1\ \ to\ \ n-1, i = 0\ \ to\ m-1 \quad (11)$$

$$D\_B_{ver}(i,j) = Abs\big(B_{ver}(i,j) - B_{ver}(i-1,j)\big)$$

$$for\ i = 1\ \ to\ \ m-1, j = 0\ \ to\ n-1 \quad (12)$$

$$D\_B_{Hor}(i,j) = Abs\big(B_{Hor}(i,j) - B_{Hor}(i,j-1)\big)$$

$$for\ j = 1\ \ to\ \ n-1, i = 0\ \ to\ m-1 \quad (13)$$

The variation of the neighboring pixels in the local region after the blurring step is analyzed the, If this variation is high, the initial image or frame was sharp whereas if the variation is slight, the initial image or frame was already blurred. This variation is estimated only on the absolute differences which have decreased where[9]

$$V_{Ver} = Max\big(0, D\_F_{ver}(i,j) - D\_B_{ver}(i,j)\big)$$

$$for\ i = 1\ to\ \ m-1, j = 0\ to\ n-1 \tag{14}$$

$$V_{Hor} = Max(0, D\_F_{Hor}(i,j) - D\_B_{Hor}(i,j)$$

$$for\ i = 1\ to\ \ m-1, j = 0\ to\ n-1 \tag{15}$$

Then, by comparing the variations from the initial image, we find the sum of the coefficients are[9]:

$$S\_F_{Ver} = \sum_{i,j=1}^{m-1,n-1} D\_F_{ver}(i,j) \tag{16}$$

$$S\_F_{Hor} = \sum_{i,j=1}^{m-1,n-1} D\_F_{Hor}(i,j) \tag{17}$$

$$S\_V_{Ver} = \sum_{i,j=1}^{m-1,n-1} D\_V_{ver}(i,j) \tag{18}$$

$$S\_V_{Hor} = \sum_{i,j=1}^{m-1,n-1} D\_V_{Hor}(i,j) \tag{19}$$

And the Normalize Perceptual Blur Metric (PBM) in a defined range from 0 to 1 is given by[9]:

$$PBM = Max\left|(b_{F_{ver}}, b_{F_{Hor}})\right| \tag{20}$$

where

$$\left.\begin{aligned} b\_F_{Ver} &= \frac{S\_F_{Ver} - S\_V_{Ver}}{S\_F_{Ver}} \\ b\_F_{Hor} &= \frac{S\_F_{Hor} - S\_V_{Hor}}{S\_F_{Hor}} \end{aligned}\right\} \tag{21}$$

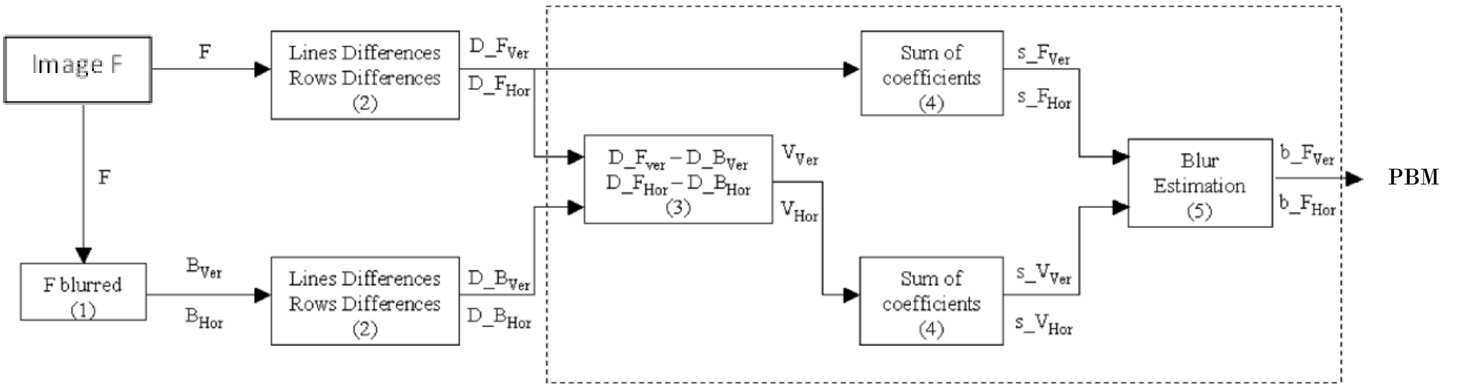


Figure (2):Flow chart of the PBM algorithm[9].

5.The Entropy

This method dependent on the first derivative of an image can be shown by the following formula:

$$I_d(x,y) = \frac{\partial^2 I(x,y)}{\partial x \partial y} \tag{22}$$

The entropy of the first derivativeis defined as follows [10]:

$$H(\chi) = \sum_{k=1}^{n} P(x_k)\, log_2(\frac{1}{P(x_k)}) \tag{23}$$

Where χ is a discrete random variable with possible results x_1, x_2,... x_n; $P(x_k)$is the probability of the resultsx_k. The outcome is understood as a gray level in the lightness image, and its probability is calculated by:

$$P(x_k) = \frac{n_k}{Nt} \quad (24)$$

Where $k = 1, 2, \ldots n$, n is the total number of possible lightness in the image, Nt is the total number of pixels, and n_k is the number of pixels that have lightness levelx_k. The higher entropy value denotes a better contrast in the image.

6. Suggestion algorithm of No reference Quality of Blurring Image

This metric is depends on standard deviation values (in the regions) of image, generally the standard deviation of the image increases if the texture details or edge regions increasing in the image or in high quality image. Whereas, in the blurring image the standard deviation well be small. First step in this metric is used Gamma correction to correct the contrast in the image ,this transform given by:

$$I_t(x, y) = [I(x, y)]^n (25)$$

Where I(x,y) is the original image with position x,y , I_t is transform image and n is the Gamma correction value . After using Gamma correction, the image had been dividedinto non overlapping blocks that are 40×40 pixels or less (depending on the image size)., For each block the standard deviation (g) are computed then taken mean value where:

$$Q = \frac{\sum_{i=1}^{n} g_i}{n} (26)$$

n being the number of blocks. And Q is quality factor, In the image with higher quality (low blur) the BQM being high. And in the blurring image Q will be low due to insufficient contrast in the image. figure (4) shows the Qvalue for Lena image and (7 database images) after it degraded by the Gaussian from this figure we can defined the general faction is power function :

$$S = a + b\left(\frac{\sum_{i=1}^{n} g_i}{n}\right)^c (27)$$

Where a,b and c are general constants ,depending on the contrast and mean in the images. And this function is the best fit of these curves. We can used this function as Point separated function (PSF) for image restoration.In this metric the standard deviation in the region of image preoperational directed with the Q, and the BQM of the images is where:

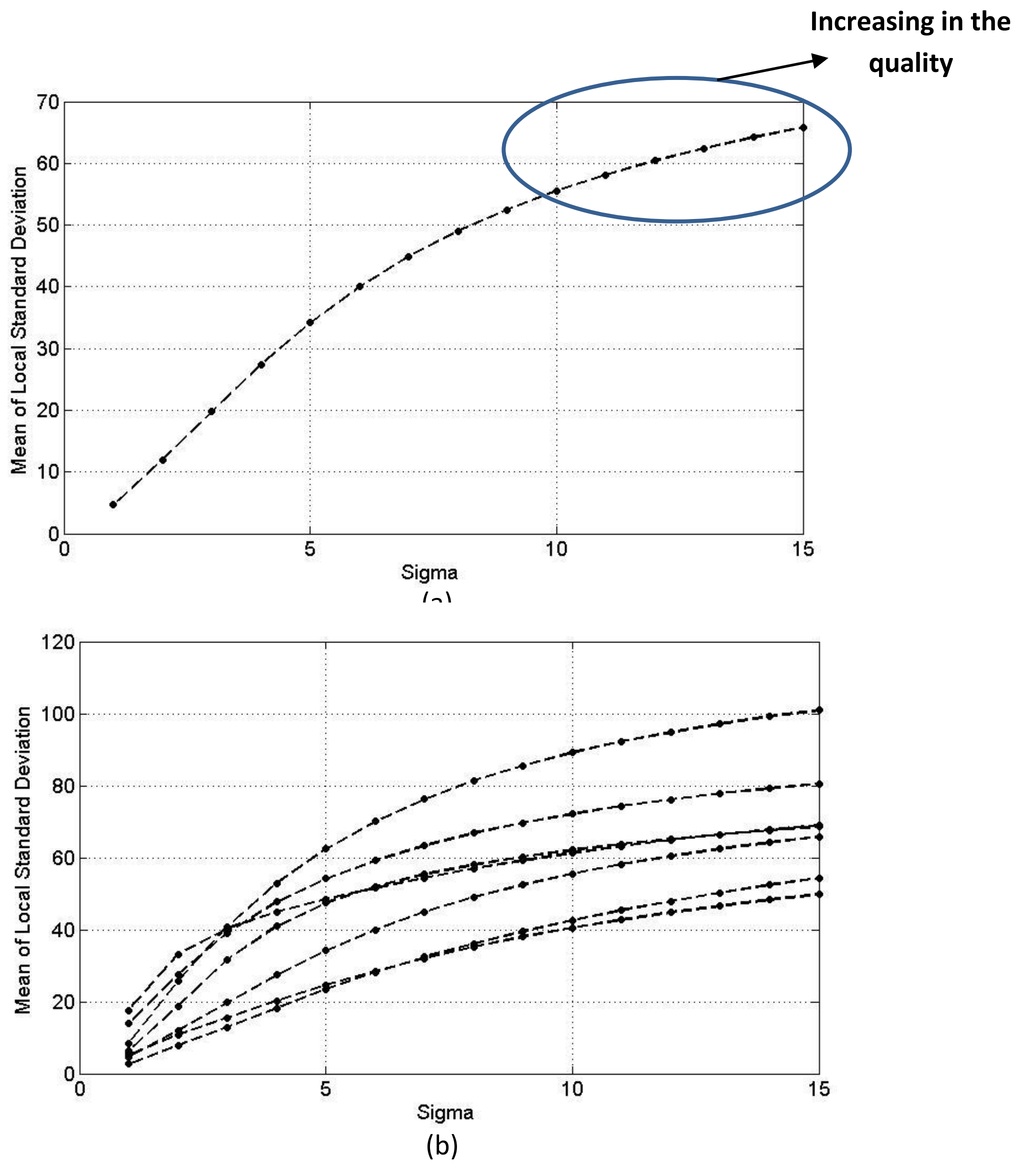
$$QBM = \frac{\sum_{s=1}^{5} \frac{\sum_{i=1}^{n} g_{i,s}}{n} + Q}{6} (28)$$

The term $\sum_{s=1}^{5} \frac{\sum_{i=1}^{n} g_{i,s}}{n}$ represent mean of the standard division for re-blurring for blur image with Q quality. In figure(5) the blurring image is represented BQM value for deferent blur factor(s=3,7,11,13) images is increasing in blurring at five value of (S=5,4,3,2,1) for each point.

BQM has been fined from the following steps:

1. Input degradation blurring image Io(x,y)
2. Find Gamma Correction at n=12 for Io(x,y).
3. Increasing blurring in image It(x,x) in five value of sigma by using Gaussian blurring (S=5,4,3,2,1) getting five image(I_5,I_4, I_3, I_2,I_1).
4. Find BQMCalculate Mean of locally (40*40)all images in the step 3

5.



Figure(4): The Q factor in (a) the original (Lena) image and Gaussian blurring of this image with different value of s (from 1 to 15) and (b) same metric for data images.

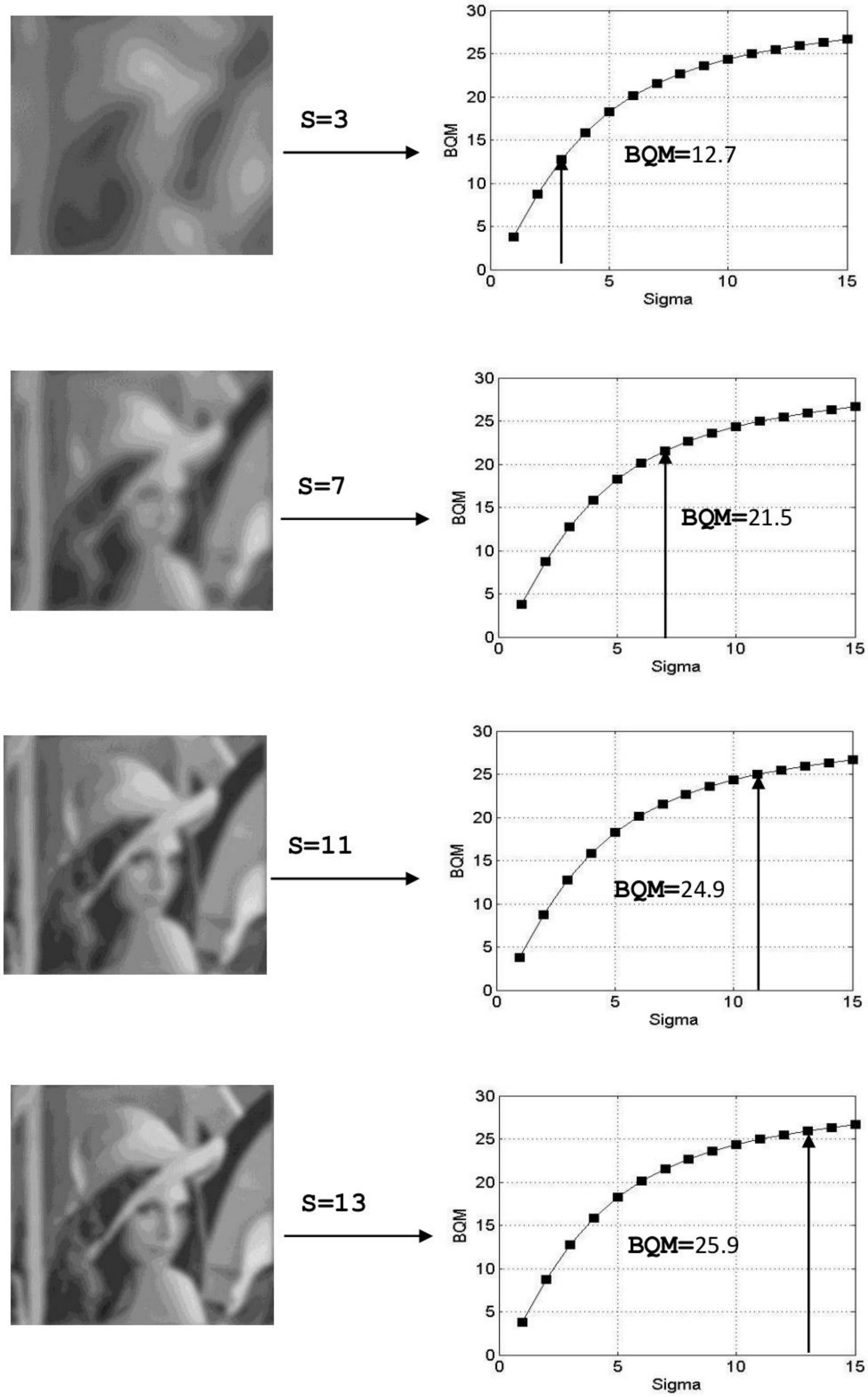


Figure (5): The BQM for blurring lena images at different values of sigma, these value direct proportional with the BQM after they reblurring at (S=3,7,11,13).

7. Experiment Results

In our approach, several images had been used as a data to test our metrics (all gray images with size 512×512), see figure 6, the Gaussian blurring are added for each image form (S=15) of the low blurring to (S=1) the highest blurring.Figure 7 illustratedthe(UQI, BQM,PBM and EFD) in normalization(0-1) state as function of blurring factor (Sigma).the normalization. From this figure we can see the BQM curve (no reference quality) nearestfrom UQI (reference quality) curve if it is compared with PBM method and EFD, follows the EFD .whereas the PBM is not success to measure the no reference quality in the in the low blurring levels.

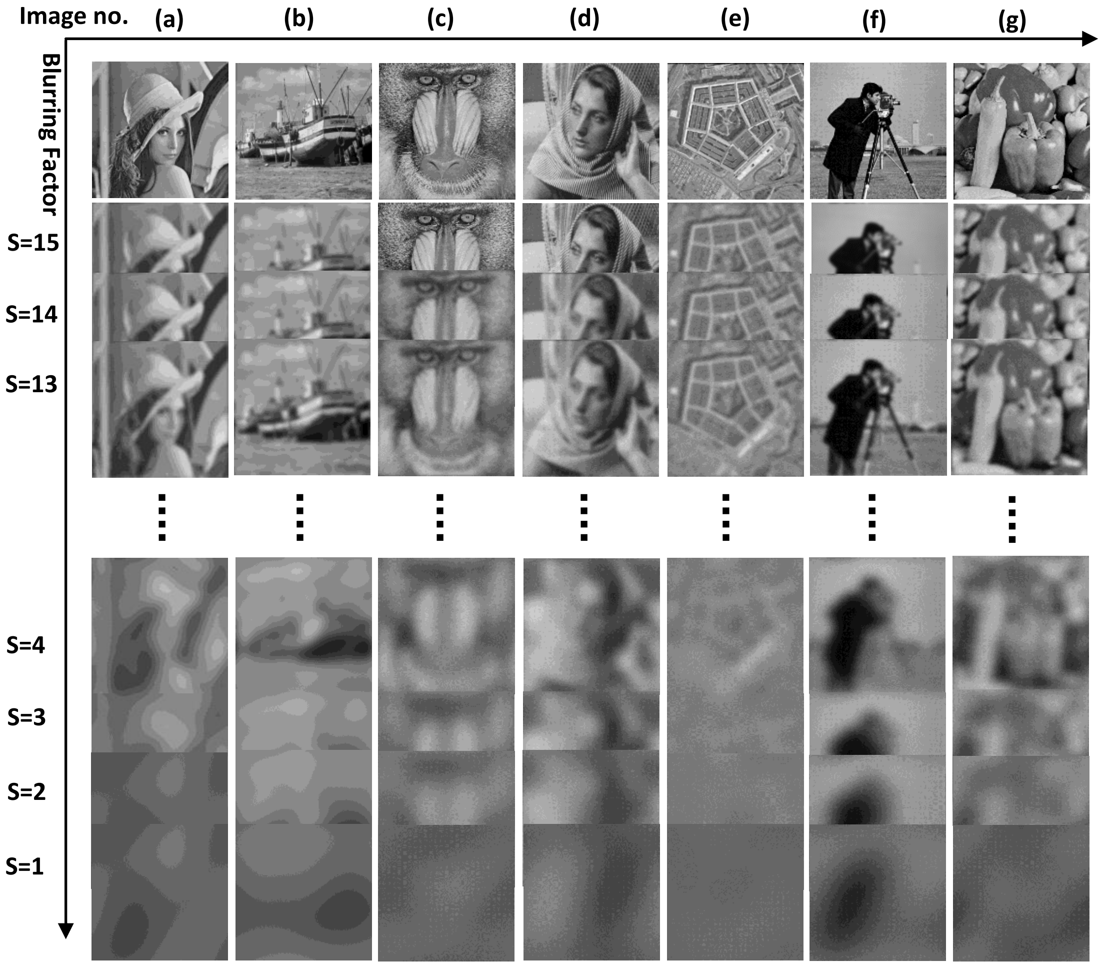
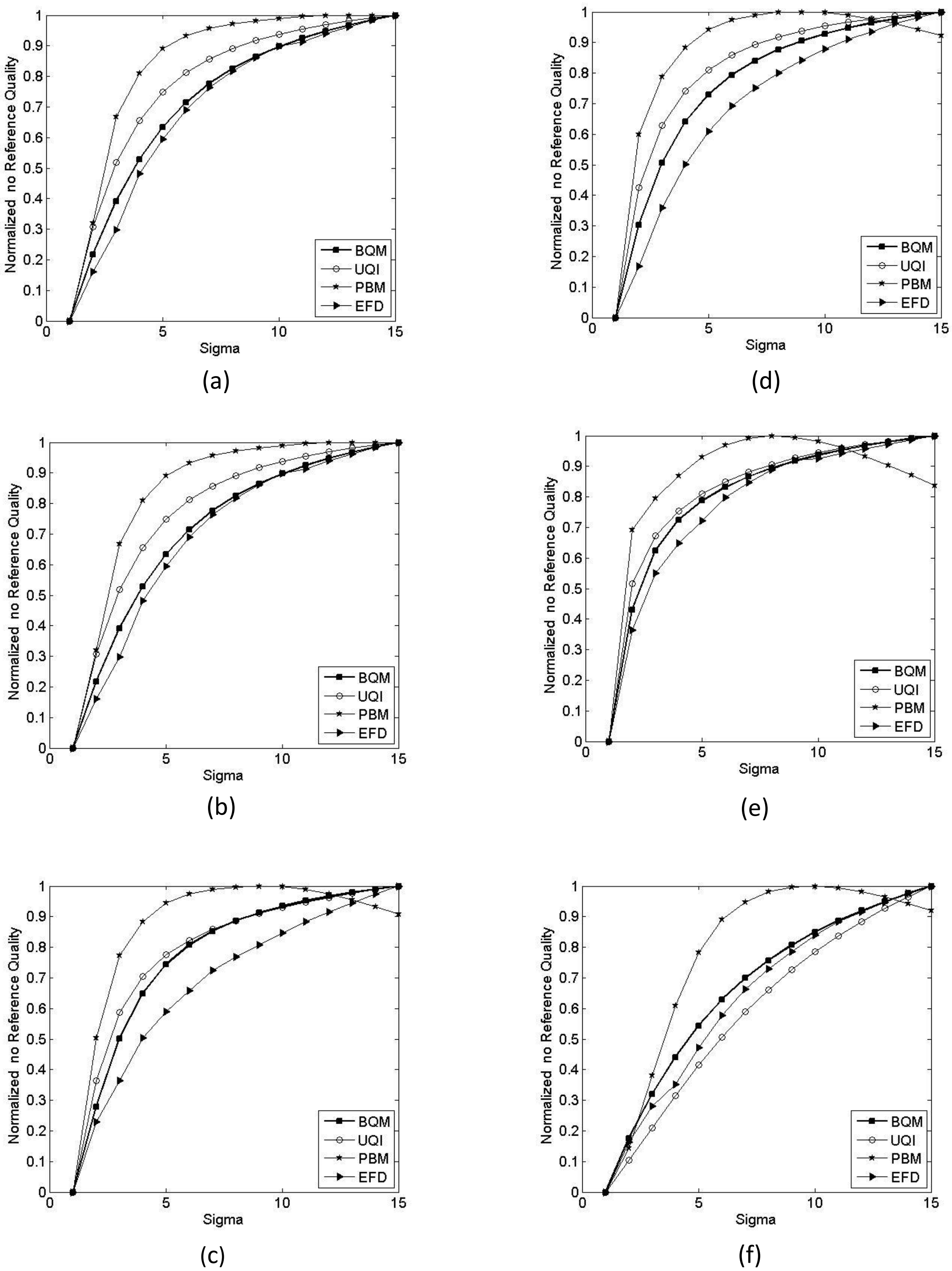


Figure (6): The test images are blurred from S=15 to S=1.



Figure(7) : Relationship between blurring factor (sigma) and the normalized No reference quality assessment (BQM , PBM and EFD) and (UQI) as a reference quality assessment for all tested data images.

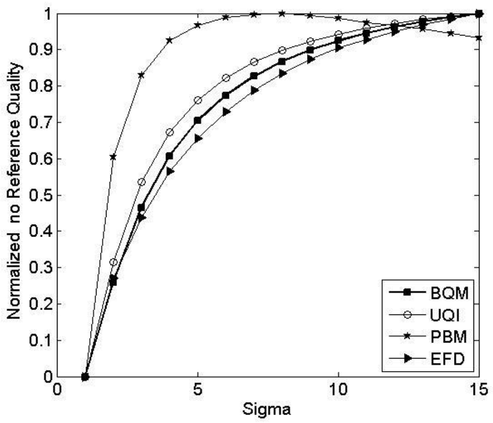


Figure (7): Continued.

This behavior was reflected in the table (1), that is illustrated the correlation coefficient between the reference quality metric UQI and noreference quality. From this value we can see the best correlation in the curves (in the figure 7) was occurred in suggestion methodBQM.

Table (1):correlation coefficient between no referance (BQM , PBM and EFD) and (UQI) as a reference quality assessment for all tested data images.

Image	EFD	PBM	BQM
a	0.9899	0.9600	0.9921
b	0.9737	0.9928	0.9872
c	0.9684	0.9472	0.9953
d	0.9539	0.9581	0.9896
e	0.9969	0.8883	0.9904
f	0.9853	0.9231	0.9968
g	0.9913	0.9052	0.9968

7. Conclusion

In This paper we suggested a no reference quality assessment for measuring Gaussian blurring in the various gray-scale images. This method is developed form MLSD model. From the result we can say the BQM method is simple method, gives numerical value and more accurate from MLSD model. And the suggestion method is belter then PBM and EFD, to metrics the no reference quality of blurring image.

Reference

[1] A. M. Eskicioglu and P. S. Fisher, “Image quality measures and their performance,” IEEE Trans. Communication. , vol. 43, pp. 2959–2965, Dec. 1995.

[2] Z. Wang and A. C. Bovik, “A universal image quality index,” IEEE Signal Processing Letters , vol. 9, pp. 81–84, Mar. 2002.

[3] D. A. Silverstein and J. E. Farrell, “The relationship between image fidelity and image quality,” in Proc. IEEE Int. Conf. Image Processing, pp. 881–884, 1996.

[4] Zhou Wang, Alan C.Bovik, and Brian L.Evans,“Blind measurement of blocking artifacts in images”,IEEEProc.ICIP, Vol.3, pp.981-984,2000.

[5] P. Marziliano, F. Dufaux, S. Winkler and T. Ebrahimi ,A no-reference perceptual blur metric,” in Proc. IEEEICIP , pp. 57-60, 2002 .

[6]L. Liang, J. Chen, S. Ma, D. Zhao, W. Gao, “A no-reference perceptual blur metric using histogram of gradient profile sharpness,” in Proc. IEEE ICIP, pp .4369-4372, 2009.

[7]Luhong Liang, Jianhua Chen, Siwei Ma, Debin Zhao, Wen Gao: A no-reference perceptual blur metric using histogram of gradient profile sharpness. ICIP: 4369-4372, 2009.

[8]Z. Wang and A. C. Bovik.. A universal image quality index,” IEEE Signal Processing Letters, vol. 9, pp. 81–84,2002.

[9] F. C. Roffet, T. Dolmiere, P. Ladret, and M. Nicolas, “The Blur Effect:Perception and Estimation with a New No-Reference Perceptual Blur Metric,” inSPIE proceedings SPIE Electronic Imaging Symposium ConfHuman Vision and Electronic Imaging, n Jose United States,vol. XII, pp. EI 6492–16, 2007.

[10]ThuyTuong Nguyen, Xuan Dai Pham, Dongkyun Kim and Jae WookJeon," Automatic Exposure Compensation for Line Detection Applications" ,IEEE International Conference on Multisensor Fusion and Integration for Intelligent SystemsSeoul, Korea, 2008.

[11] D. J. Jabson, Z. Rahman, G. A. Woodell, “Retinex processing for automatic image enhancement,” Journal of Electronic Imaging, Vol. 13(1), PP.100–110, January 2004.