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Study Algorithms which Assessed Quality of the Blurred Images

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Abstract

No-reference measurement of blurring artifacts in images is a difficult problem in image quality assessment field. In this paper, we present a no-reference blur metric to measure the quality of the images. These images are degraded using Gaussian blurring. Suggestion method depends on developing the Mean of Locally Standard deviation and Mean of the image (MLSD) model, this method is called Blur Quality Metric (BQM) and it calculates from numerical integral of the function in this model. 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 the Gaussian blurred image if it compared with another algorithms.

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

دراسة الخوارزميات التي تخمن جودة الصور المشوية ضبابيا

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الخلاصة

تخمين جودة الصور المشوبة ضبابيا بدون وجود صورة مرجعية مهمة صعبة . في هذا البحث تم اقتراح مقياس غير مرجعي لقياس جودة الصورة التي تم تشويهها بالضبابية الكاوسية .الطريقة المقترحة تعتمد على تطوير نموذج المعدل (لكل من المعدل الموضعي والانحراف المعياري الموضعيMLSD)، هذه الطريقة سميت بمقياس الجودة بالاعتماد على الضبابية (BQM) وتم استنتاجها عن طريق حساب التكامل العدددي لنموذج MLSD . ان طريقة BQM تم مقارنتها مع مقاييس اخرى غير مرجعية هما مقايس الادراك الحسي للضبابية (PBM) ومقياس حساب الانتروبي المشتقة الاولى (EFD) للصورة . ان طريقة BQM هي طريقة سهلة وقدمت نتائج جيدة في قياس جودة الصور المشوبة ضبابيا مقارنة مع الخوارزميات الاخرى.

1. Introduction

Measurement of image quality is very important for many image processing algorithms, such as acquisition, compression, restoration, enhancement and other applications. Image quality assessment is a very important activity for many image applications. 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 an image. And [7] suggested the no reference perceptual blur metric using the image gradients along local image structures. In this paper, we are focusing on the no reference image quality assessment for measuring the Gaussian blurring. The Blur Quality Metric (BQM) was inspired 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. Gaussian Blurring

In digital image there are three common types of Blur effects: average blurs, Gaussian blur and motion blur [2]. The Gaussian blur is a type of image-blurring filter that uses a Gaussian function (which also expresses the normal distribution in statistics) for calculating the transformation to apply to each pixel in the image. The equation of a Gaussian 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 x is the distance from the origin in the horizontal axis, y is the distance from the origin in the vertical axis, and S is the standard deviation of the Gaussian distribution. When applied in two dimensions, this formula produces a surface whose contours are concentric circles with a Gaussian distribution 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 pixel receives the heaviest weight (having the highest Gaussian value) and neighboring pixels receive smaller weights as their distance to the original pixel increases. This results in a blur that preserves boundaries and edges better than other, more uniform blurring filters. The blurring image is given by:

$$Ib = I * G \quad (3)$$

Where Ib being the blurring image and G is the Gaussian function Figure(1) shows the different burring image with deferent values of S.

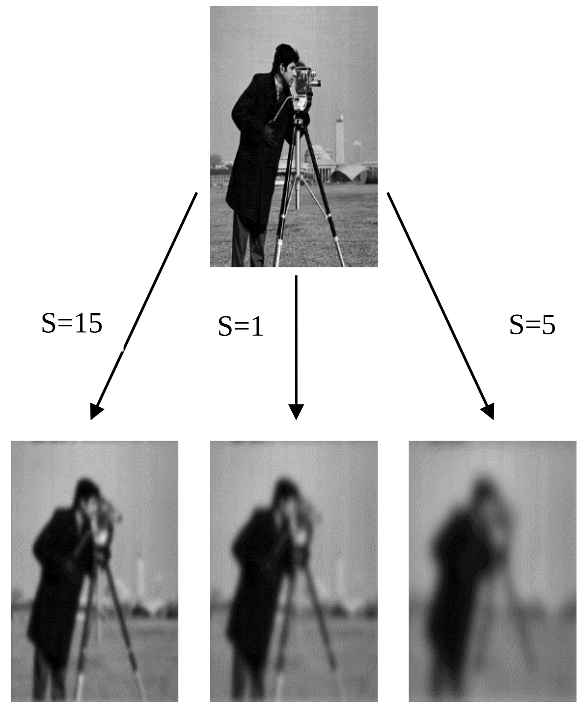


Figure (1): Original image is degraded with Gaussian blurring at different value of sigma (S).

3. The Structural Similarity Index (SSIM)

The SSIM metric is based on the evaluation of three different measures, the luminance, contrast, and structure comparison measures are computed as[8]:

$$l(x,y) = \frac{2\mu_X(x,y)\mu_Y(x,y) + C_1}{\mu_X^2(x,y) + \mu_Y^2(x,y) + C_1} \quad (4)$$

$$c(x,y) = \frac{2\sigma_X(x,y)\sigma_Y(x,y) + C_2}{\sigma_X^2(x,y) + \sigma_Y^2(x,y) + C_2} \quad (5)$$

$$s(x,y) = \frac{\sigma_{XY}(x,y) + C_3}{\sigma_X(x,y)\sigma_Y(x,y) + C_3} \quad (6)$$

Where X and Y correspond to two different images that we would like to match, i.e. two different blocks in two separate images, μ_x, σ_x^2, and σ_{xy} the mean of X, the variance of X, and the covariance of X and Y respectively where[9]:

$$\mu(x,y) = \sum_{p=-P}^{P} \sum_{q=-Q}^{Q} w(p,q) X(x+p, y+q) \qquad (7)$$

$$\sigma^2(x,y) = \sum_{p=-P}^{P} \sum_{q=-Q}^{Q} w(p,q)[X(x+p,y+q) - \mu_X(x,y)]^2 \qquad (8)$$

$$\sigma_{XY}(x,y) = \sum_{p=-P}^{P} \sum_{q=-Q}^{Q} w(p,q)[X(x+p,y+q) - \mu_X(x,y)] [Y(x+p,y+q) - \mu_Y(x,y)] \qquad (9)$$

Where $w(p,q)$ is a Gaussian weighing function such that:

$$\sum_{p=-P}^{P} \sum_{q=-Q}^{Q} w(p,q) = 1 \qquad (10)$$

And C_1 , C_2, and C_3 are constants given by $C_1 = (K_1 L)^2$, $C_2 = (K_2 L)^2$, and $C_3 = C_2/2$. L is the dynamic range for the sample data, i.e. $L = 255$ for 8

$$SSIM(x,y) = [l(x,y)] \cdot [c(x,y)] \cdot [s(x,y)] \qquad (11)$$

4.No-Reference Perceptual Blur metric

This method takes advantage of the possibility to access to specific local variations representatives of the blur effect. The flow chart in Figure 2 describes the steps of the algorithm description and refers to the following equations of No-reference perceptual blur metric [9],To estimate the blur annoyance of gray image the first step consists in blurred it in order to obtain a blurred image B. We choose an horizontal and a vertical strong low-pass filter to model the blur effect and to create B_{ver} and B_{Hor} ,where the average low bass kernel in the vertical direction is [9] :

$$h_v = \frac{1}{9} \times [111111111] \qquad (12)$$

And in the horizontal direction:

$$h_h = transpose(h_v) = h_v' \qquad (13)$$

And image filters are :

$$B_{ver} = h_v * F \quad , \quad B_{Hor} = h_h * F \qquad (14)$$

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]:

$$D\_F_{ver}(i,j) = Abs(F(i,j) - F(i-1,j))$$
$$for\ i = 1\ to\ m-1, j = 0\ to\ n-1 \qquad (15)$$

$$D\_F_{Hor}(i,j) = Abs(F(i,j) - F(i,j-1))$$
$$for\ j = 1\ to\ n-1, i = 0\ to\ m-1 \qquad (16)$$

$$D\_B_{ver}(i,j) = Abs(B_{ver}(i,j) - B_{ver}(i-1,j))$$
$$for\ i = 1\ to\ m-1, j = 0\ to\ n-1 \qquad (17)$$

$$D\_B_{Hor}(i,j) = Abs(B_{Hor}(i,j) - B_{Hor}(i,j-1))$$
$$for\ j = 1\ to\ n-1, i = 0\ to\ m-1 \qquad (18)$$

To analyze the variation of the neighboring pixels after the blurring step. 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 blur. This variation is evaluated only on the absolute differences which have decreased where [9]

$$V_{Ver} = Max(0, D\_F_{ver}(i,j) - D\_B_{ver}(i,j))$$
$$for\ i = 1\ to\ m-1, j = 0\ to\ n-1 \qquad (19)$$

$$V_{Hor} = Max(0, D\_F_{Hor}(i,j) - D\_B_{Hor}(i,j)$$
$$for\ i = 1\ to\ m-1, j = 0\ to\ n-1 \qquad (20)$$

Then, in order to compare the variations from the initial image, we compute the sum of the coefficients are [9]:

$$S\_F_{Ver} = \sum_{i,j=1}^{m-1,n-1} D\_F_{ver}(i,j) \qquad (21)$$

$$S\_F_{Hor} = \sum_{i,j=1}^{m-1,n-1} D\_F_{Hor}(i,j) \qquad (22)$$

$$S\_V_{Ver} = \sum_{i,j=1}^{m-1,n-1} D\_V_{ver}(i,j) \qquad (23)$$

$$S\_V_{Hor} = \sum_{i,j=1}^{m-1,n-1} D\_V_{Hor}(i,j) \qquad (24)$$

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

$$PBM = Max|(b_{F_{ver}}, b_{F_{Hor}})| \qquad (25)$$

where

$$\left.\begin{aligned} b\_F_{Ver} &= \frac{S\_F_{Ver} - S\_V_{Ver}}{S\_F_{Ver}} \\ b\_F_{Hor} &= \frac{S\_F_{Hor} - S\_V_{Hor}}{S\_F_{Hor}} \end{aligned}\right\} \qquad (26)$$

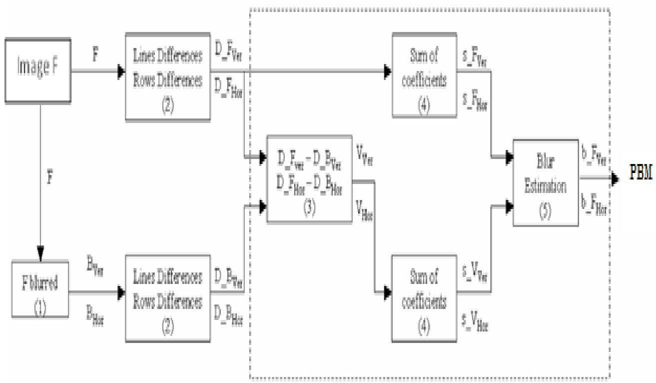


Figure (2): Flow chart of the PBM algorithm [9].

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

$$I_d(x,y) = \frac{\partial^2 I(x,y)}{\partial x \partial y} \qquad (27)$$

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

$$H(\chi) = \sum_{k=1}^{n} P(x_k) \log_2\left(\frac{1}{P(x_k)}\right) \qquad (28)$$

Where χ is a discrete random variable with possible outcomes x1, x2,... xn; $P(x_k)$is the probability of the outcome x_k. The outcome is understood as a gray level in the lightness image, and its probability is calculated by:

$$P(x_k) = \frac{n_k}{Nt} \qquad (29)$$

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 nk is the number of pixels that have lightness level x_k. The higher entropy value denotes a better contrast in the image.

5. Suggestion algorithm of No reference Quality of Blurring Image

The Mean of locally (standard deviation, mean) or MLSD model, proposed the idea that good visual representations seem to be based upon some combinations of high regional visual lightness and contrast[11]. To compute the regional parameters, we divided the image into non overlapping blocks that are 50×50 pixels or less (depending on the image size). For each block, the mean (m) and a standard deviation (g) are computed, and then taking the mean of them (m) and (g) as shown in figure (3). If the points tend to visual optimal region the image has higher quality of lightness and contrast, whereas if g (without m) is increased, it makes image having insufficient lightness, but if m (without g) is increased it makes insufficient contrast in the image. if Gaussian blurring has been applied on the original image with different value of S (from 1 to 15) and then applied this model as demonstrated in the figure (4,a) we can see the quality of these image are increased if S have a maximum value and it near with the optimal region(due to increasing contrast), whereas decreasing value in S makes images in the visual optimal. From this relation we can see:

$$g = f(m) \qquad (30)$$

figure (4,b) shows the MLSD model for (7 database images) after it degraded by the Gaussian from this figure we can defined the general faction is :

$$g = ce^{\left(a+\frac{b}{m}\right)} \qquad (31)$$

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. From the curves in the figure (4-b), the area under the curve represent the Blur Quality Metric (BQM), and this value has been simply numerically circulated without find a ,b and c constant by using trapezoidal method where:

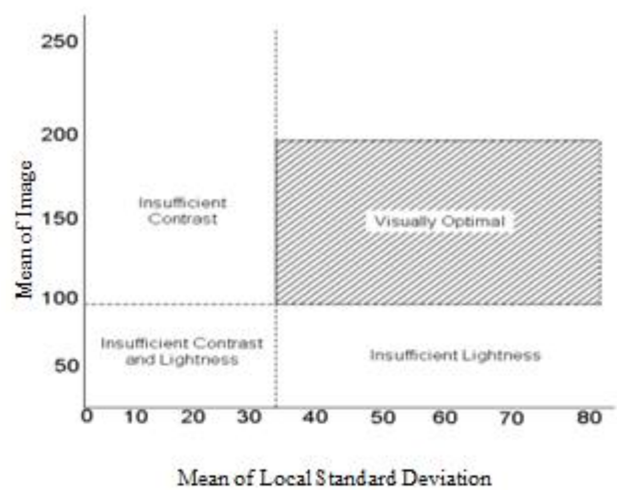
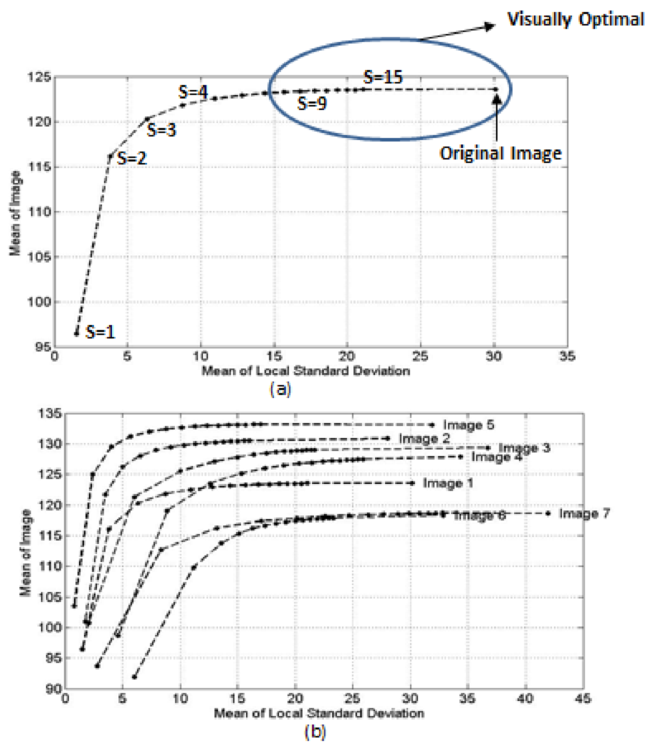


Figure (3): Image quality description according to MLSD model [11].

$$BQM = \int_{m-m1}^{m=m2} f(m)\, dm \qquad (32)$$

m1and m2 are the minimum and maximum mean value. In this metric the area under the curve preoperational directed with the BQM, figure (5) is show increasing the quality of the image according to incising the S value and this value is depending on the area under the curve of the shadow region. In figure(5-b) the blurring image is represented the point in the curve is staring of the shadow region then the images is increasing in blurring at five value of (S=5,4,3,2,1) ,this mean that the shadow region limited between m1 at S=1 (very blurring image) and m2 is the mean of the blurring image (image need to know your quality). And the total curves have the same behavior in the figure (5).



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

BQM has been calculated from the following steps:

1. Input degradation blurring image Io(x,y).
2. Increasing blurring in image Io(x,x) in five value of sigma by using Gaussian blurring (S=5,4,3,2,1) getting five image(I5,I4, I3, I2,I1).
3. Calculate Mean of locally (m ,g) for all image in the step 1,2
4. Find BQM using numerical integration

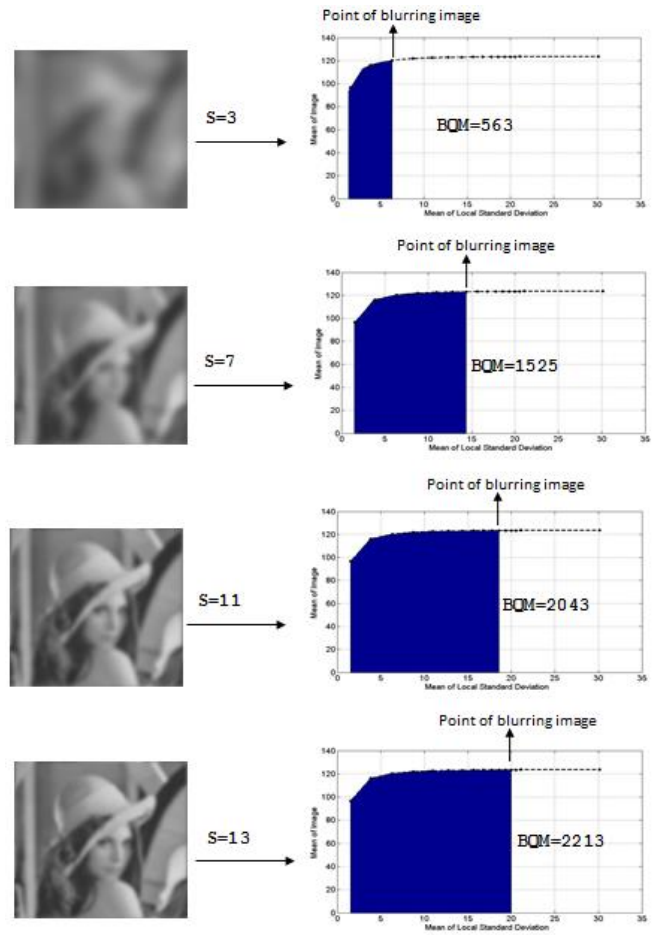


Figure (5): The BQM for blurring lena images at different values of sigma, these value direct proportional with the area under the curve in the (m, g) mode after they reblurring at (S=3,7,11,13).

6. Experiment Results

In our approach, several images were 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 illustrated the(SSIM, BQM,PBM and EFD) in normalization (0-1) state as function of blurring factor (Sigma).the normalization had been done by $Qn = \frac{Q-\min(Q)}{\max(Q)-\min(Q)}$, Where Q is the matching (SSIM, BQM,PBM and EFD) .from this figure we can see the BQM curve (no reference quality) nearest from SSIM (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 level.

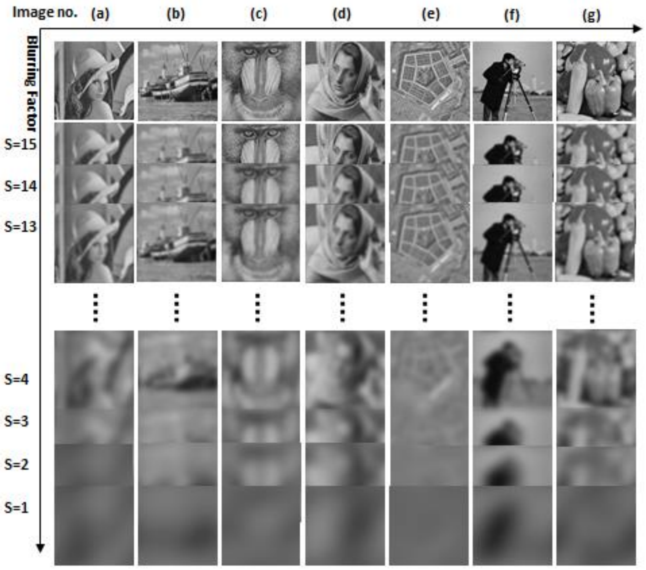
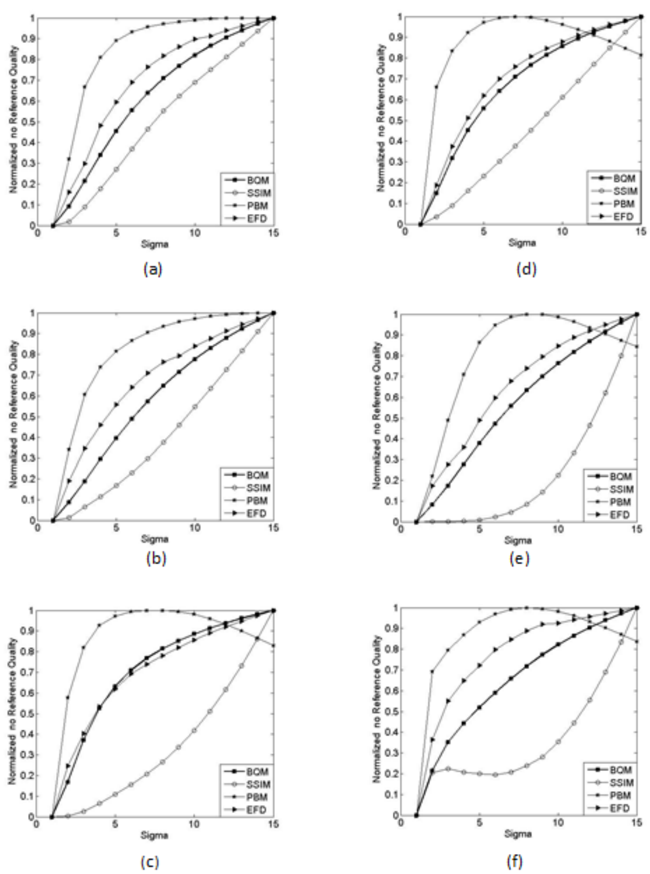
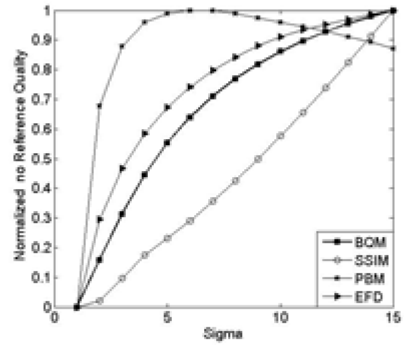


Figure (6): The test images are blurred from S=15 to S=1.



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



(g)

Figure (7): Continued.

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.

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