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On the Performance of Image Quality Measures with Application to Multifocused Image Fusion

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Abstract

Due to limited depth of field of machine vision cameras, multifocused image fusion is finding importance to produce a single image called fused image from various images of the same scene being imaged. To have focused images of all the objects in the scene, the fused image is formed by combining important features of various images. This in turn increases the importance of ability to assess the quality of the fused image more accurately. To be accurate, a typical image quality measure should be independent of image content, robust to noise, monotonic with respect to image blur and calculated with minimal computation complexity. In this paper, the performance of nine image quality measures were assessed through various experiments by applying image blur, adding image noise, changing image contrast and image saturation level. Experiments were also conducted on six sets of images to find the best image quality measure for multifocused image fusion.

Keywords: *Image Quality Measure, Multifocused Image Fusion, Depth of field*

1. Introduction

Due to the limited Depth of Field (DOF) lenses used in machine vision cameras, it is possible to take clear image of the objects which are in focus only. The remaining objects in the scene will be out of focus [2]. The acquisition of all in focus images is very difficult. This is a major issue in many engineering applications. Multifocus image fusion produces a single image called fused image from various images of the same scene being imaged. To have focused images of all the objects in the scene, the fused image is formed by combining two or more images of the same scene with different focus points [12]. The performance of multifocus image fusion is measured by comparing the fused image with the reference image using image quality measures. To be more accurate, a typical image quality measure should be independent of image content, robust to noise, monotonic with respect to image blur, and calculated with minimal computation complexity. It should be maximized when the fused image is equal to the reference image. When blurring is applied to any one of the source image, the quality of the fused image should degrade and the quality measure should decrease. If the blurring is more severe, the degradation will be more severe and the quality measure should decrease proportionally. In this paper, nine image quality measures have been chosen among a lot of measures available in the literature and they are applied to measure the performance of multifocused image fusion in spatial domain. The performance of the selected image quality measures has been assessed through experiments carried out under different conditions by applying image blur & adding noise at various level, changing image contrast and image saturation level of source images. Experiments were also conducted on several sets of images to find the best quality measure for multifocused image fusion.

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2. Image Quality Measures

This paper deals with two classes of image quality measures. The first class of image quality measures is widely used common measures such as Normalized Absolute Error, Root Mean Square Error and Peak Signal to Noise Ratio [12]. The second class of quality measures considers Spatial Frequency [18], Normalized Cross Correlation, Pearson Correlation Coefficient, Structural Content, Quality Index [11] and Structural Similarity Index [14]. The mathematical expressions to calculate these two classes of image quality measures are presented in the following Table I. This paper evaluates the performance of these quality measures under different conditions by applying image blur, adding image noise, changing image contrast and image saturation level.

Table I. Mathematical Expressions for Image Quality Measures

Image Quality Measures	Mathematical Expressions
Normalized Absolute Error	$NAE = \sum_x \sum_y \lvert F(x,y) - R(x,y) \rvert \Big/ \sum_x \sum_y \lvert R(x,y) \rvert$
Root Mean Square Error	$RMSE = \sqrt{\sum_x \sum_y R(x,y) - F(x,y) / N^2}$
Peak Signal to Noise Ratio	$PSNR = 10 \log_{10} (255)^2 \Big/ (RMSE)^2$
Spatial Frequency	$SF = \sqrt{RF^2 + CF^2}$ where $RF = \sqrt{\sum_x \sum_y [f(x,y) - f(x,y-1)]^2 \Big/ M*N}$ & $CF = \sqrt{\sum_x \sum_y [f(x,y) - f(x-1,y)]^2 \Big/ M*N}$
Normalized Cross Correlation	$NCC = \sum_x \sum_y [F(x,y) * R(x,y) \Big/ \sum_x \sum_y R(x,y)^2$
Pearson Correlation Coefficient	$PCC = \dfrac{\sum_i [F(i) - F_m] * [R(i) - R_m]}{\sqrt{\sum_i [F(i) - F_m]^2} * \sqrt{\sum_i [R(i) - R_m]^2}}$
Structural Content	$SC = \sum_x \sum_y F(x,y)^2 \Big/ \sum_x \sum_y R(x,y)^2$
Quality Index	$QI = 4 * \sigma_{RF} \mu_R \mu_F \Big/ (\mu_R^2 + \mu_F^2)(\sigma_R^2 + \sigma_F^2)$ where μ_R & μ_F are mean of images R and F, σ_{RF} be covariance of R & F, $\sigma_R{}^2$, $\sigma_F{}^2$ be the variance of image R,F.
Structural Similarity Index	$SSI = \dfrac{(2 * \mu_R * \mu_F + c_1) * (2 * \sigma_{RF} + c_2)}{(\mu_R^2 + \mu_F^2 + c_1) * (\sigma_R^2 + \sigma_F^2 + c_2)}$

3. Evaluation of Image Quality Measures

The performance of the above selected image quality measures are assessed under different conditions by applying image blur, adding image noise, changing image contrast and image saturation level to a set of six test images[7].

3.1. Sensitivity to Image Blurs

In this section, the sensitivity of selected image quality measures are evaluated by applying different blurs namely square blur, radial blur, motion blur and Gaussian blur. The square blur was applied by convolving a set of six test images (shown in Figure 1) with the averaging mask of size 3X3, 5X5, 7X7 and 9X9.

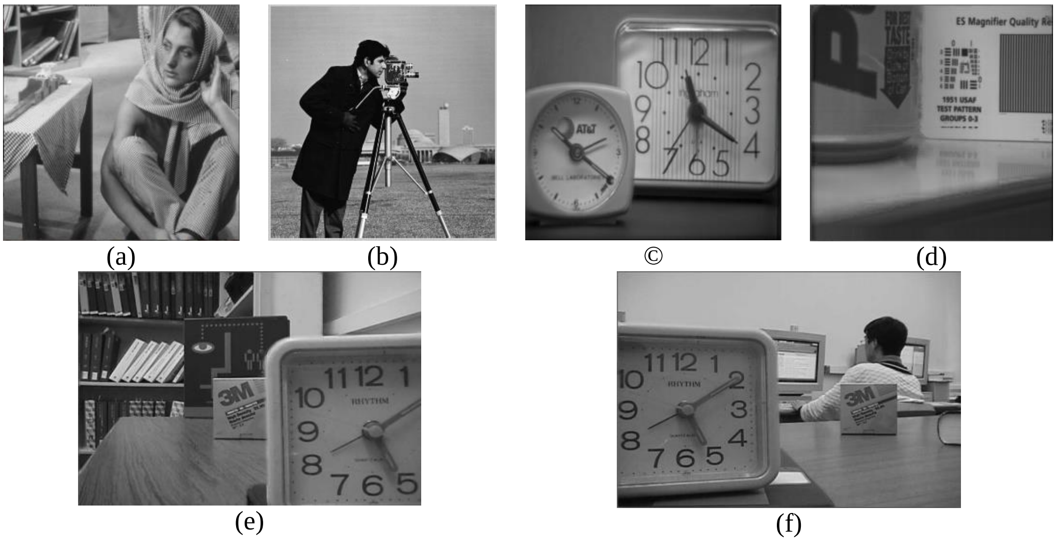

Figure 1. Test Images (a) Lena (b) Cameraman (c) Clock (d) Pepsi e) Disk (f) Lab

In the similar manner, the radial blur was introduced to the test images by convolving the source image with the averaging mask of radius 11, 21, 31 and 41 pixels. Motion blur is the results due to the movement of objects or camera during image acquisition process. This blur was introduced by the linear motion of a camera by 5 & 10 pixels, with an angle of 5 & 10 degrees in a counterclockwise direction. Gaussian blur was applied to the test images by passing through a rotationally symmetric Gaussian low pass filter of size 3X3, 5X5, 7X7 & 9X9 with standard deviation of 0.3, 0.5, 0.7 & 0.9 respectively. Thus, a total of 96 images with different blurs were generated. The selected image quality measures were measured for each and every blurred image. The image quality measures were then averaged to plot the results in 2D column charts which are shown in Figure 2. From the Figure, it is inferred that if the blur increases, the image quality measure value decreases.

3.2. Sensitivity to Image Noises

This section evaluates the sensitivity of selected image quality measures in the presence of image noise. Image data sets collected by the imaging sensors are generally corrupted by noise. Imperfect instruments, problems with the data acquisition process and interfering natural phenomena can all introduce noises in the captured image. Furthermore, noises can be introduced by transmission errors and compression. All selected focus measures are evaluated with three different noises namely Salt & Pepper, Gaussian and Speckle with different noise levels. The salt and pepper noise with noise density of 0.1, 0.2, 0.3 &0.4, Gaussian and Speckle noise of variance 0.01, 0.02, 0.03

&0.04 were added with the test images separately to generate 72 noisy images. The selected quality measures are measured for each and every noisy image and averaged to plot the graphs as shown in Figure 3. From these graphs, one can infer that the value of quality measures increases as the noise level increases.

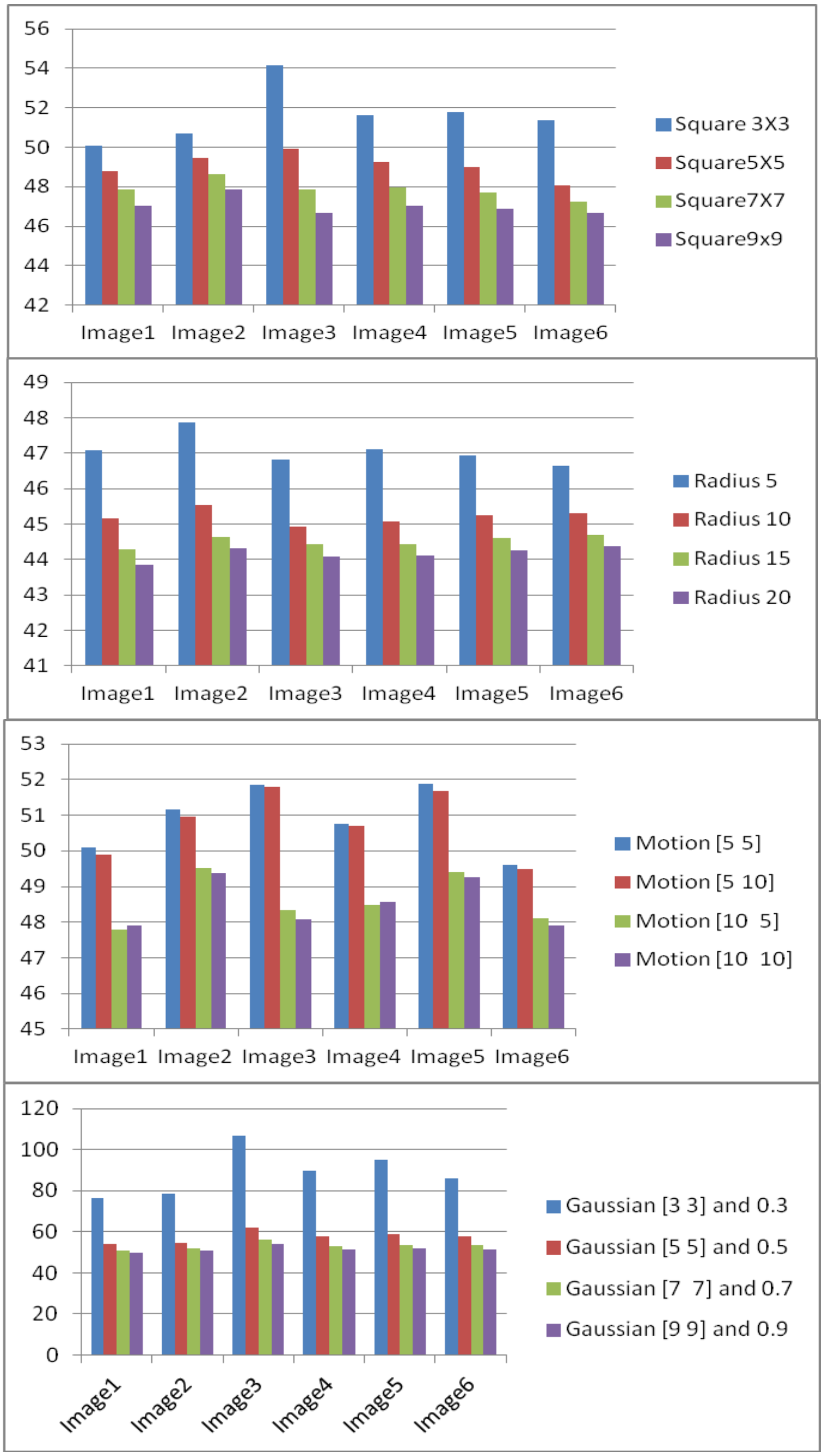

Figure 2. Sensitivity to Image Blurs

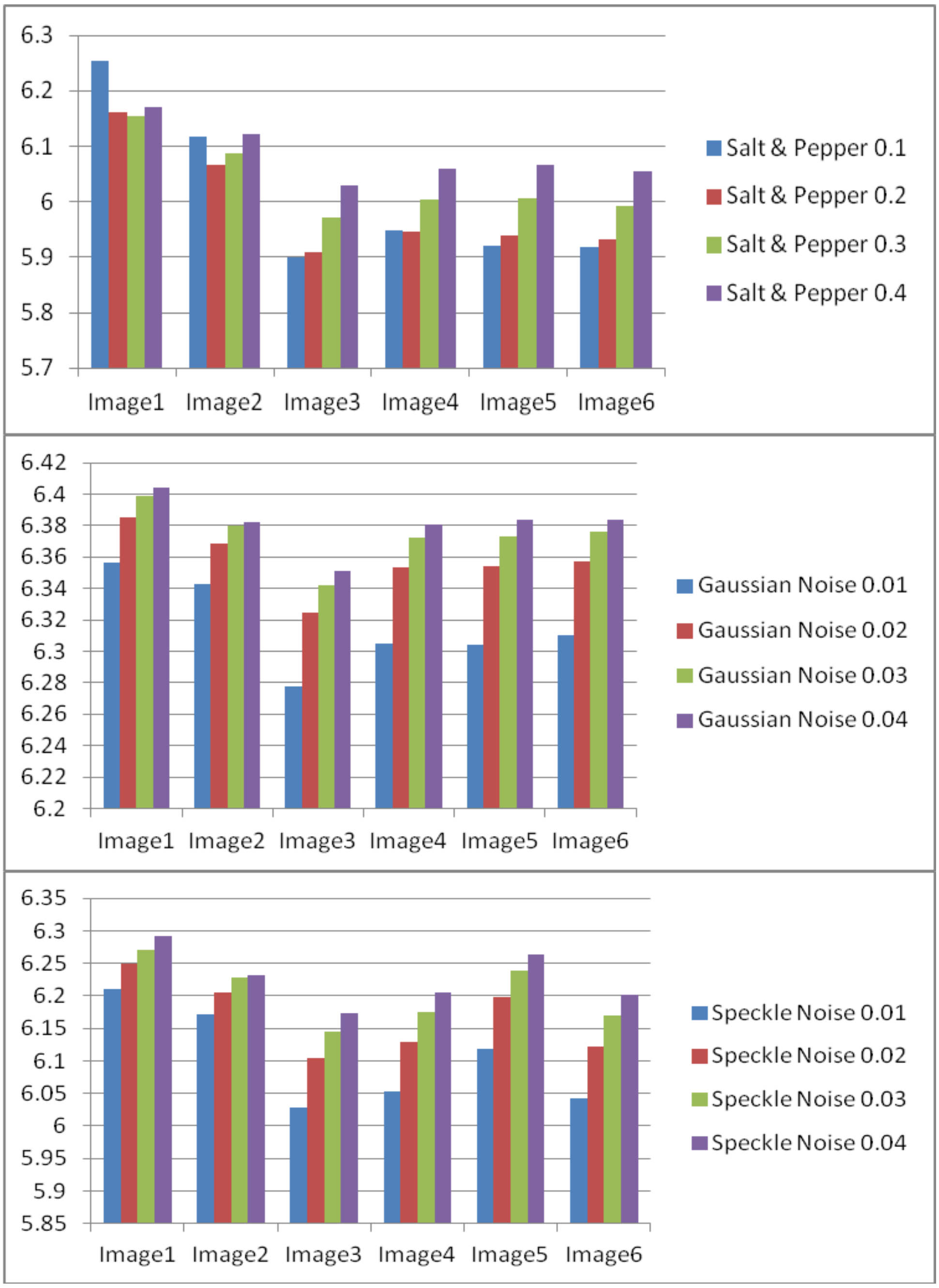

Figure 3. Sensitivity to Image Noise

3.3 Sensitivity to Image Contrast

The sensitivity of selected image quality measures to image contrast is presented in this section. Image contrast is one of the image feature related to the image content that affects the performance of focus measure. Low contrast images contain only smooth details and thus increases the difficulty in determining the degree of focus. In order to study the sensitivity of selected focus measures to low contrast images, the experiments were repeated by pre-processing the test images to reduce their contrast. The contrast of the test images were reduced by compressing their histograms using the following formula,

$$f(x, y) = c(f(x, y) - 128) + 128 \tag{1}$$

where c is the histogram compression ratio. In the above equation, the value of c is changed from 0.6 to 1.0 with increments of 0.1 to generate a total of 30 images from the set of six test images. The selected focus measures were calculated for each and every image and averaged to plot the graph as shown in Figure 4. From the graph, it is inferred that as the histogram compression ratio increases the value of quality measures also increases.

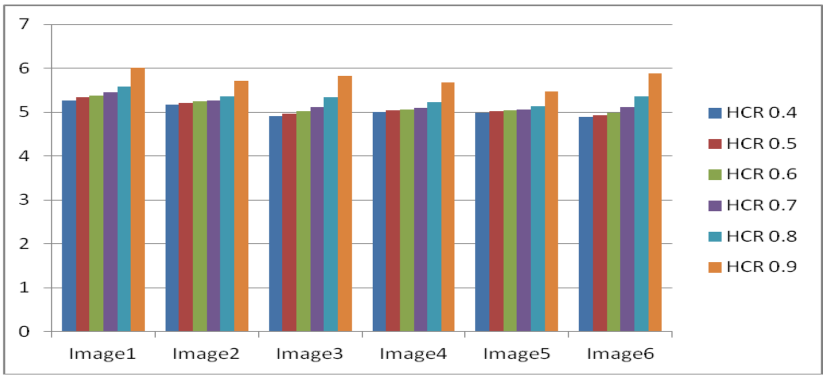

Figure 4. Sensitivity to Image Contrast

3.4 Sensitivity to Image Saturation

Image saturation is another feature of image that affects the performance of focus measure. Image saturation was evaluated by adding a constant offset to the original image as given in the following equation

$$f_s(x,y) = f(x,y) + S \qquad (2)$$

where S is the saturation level. The values of S are 0 to 128 in order to obtain the saturation level of 10% to 50%. Here also, a total of 30 images were generated from the set of six test images by varying the saturation level from 10% to 50% with increments of 10%.The selected quality measures were calculated for each and every images and averaged to plot the graph as shown in Figure 5. From the graph, it is inferred that the value of quality measures also decreases as the value of saturation level increases.

4. Multifocused Image Fusion

Multifocus image fusion is the process of combining two or more images of the same scene with different focus points to form the fused image. The objective of image fusion is to produce the fused image in which all the pixels in the image are in focus. To find the pixels with good focus, the modified laplacian focus measure is applied.

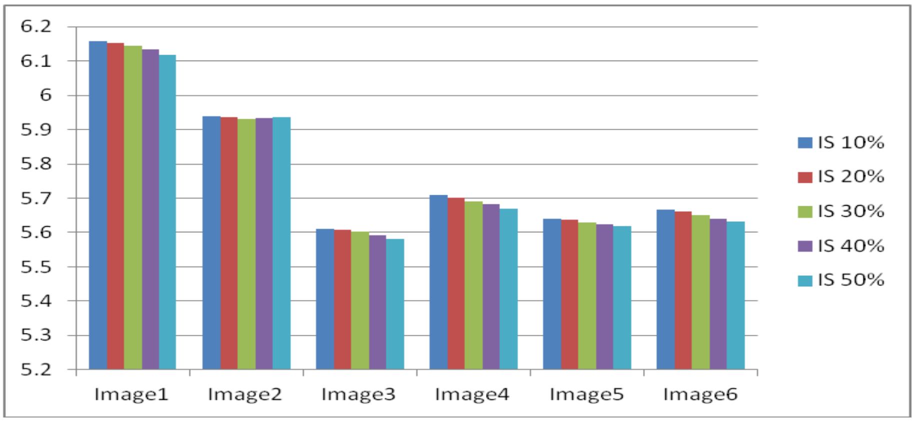

Figure 5. Sensitivity to Image Saturation

Let there are two source images A & B and they are assumed to be registered spatially. In the first step, each source image is divided into (2N+1) X (2N+1) window of overlapping regions. Let $W_{i,j}^{2N+1}$ is a window of size (2N+1) X (2N+1) centered at the pixel $X_{i,j}$. Then, the modified laplacian focus measure of the window $W_{i,j}^{2N+1}$ for the two source images A and B (denoted as $F_{XA}(i,j)$ and $F_{XB}(i,j)$) are calculated using the formulae [6],

$$\text{Modified Laplacian} = \frac{1}{\text{MXN}} \sum_{x} \sum_{y} [\text{abs}(Lx(x,y)) + \text{abs}(Ly(x,y))] \tag{3}$$

where L_x and L_y are the X and Y image gradients computed by convolving the image f(x,y) with the mask M = [-1 2 -1]. Then, the fused image F was produced by combining two source images as

$$F(i,j) = \begin{cases} A(i,j) & \text{if} \quad F_{XA}(i,j) \geq F_{XB}(i,j) \\ B(i,j) & \text{if} \quad F_{XB}(i,j) \geq F_{XA}(i,j) \end{cases} \tag{4}$$

In order to study the effect of window size on the performance of multifocused image fusion, the window size is varied from 3X3 to 7X7 by changing the value of N from 1 to 3. To evaluate the quality of the obtained fused image with the reference image, all the selected image quality measures were used. The results of image fusion using modified laplacian focus measure with variable window size are tabulated in Table II and shown in Figure 6.

5. Conclusion

In this paper, nine image quality measures were chosen to study about their sensitivity towards blur, noise, and contrast and image saturation level. From these analyses, it is inferred that value of image quality measure decreases with increase in image blur & saturation and increases with increase in histogram compression ratio & noise level. Experiments were also conducted for these nine image quality measures using six sets of images to find the best measure to assess the quality of fused image from multifocused image fusion. From these experiments, it is also inferred that the spatial frequency shows no effect on the window size and the common quality measures NAE, RMSE and PSNR give better assessment in analysis of quality of fused image from multifocused image fusion.

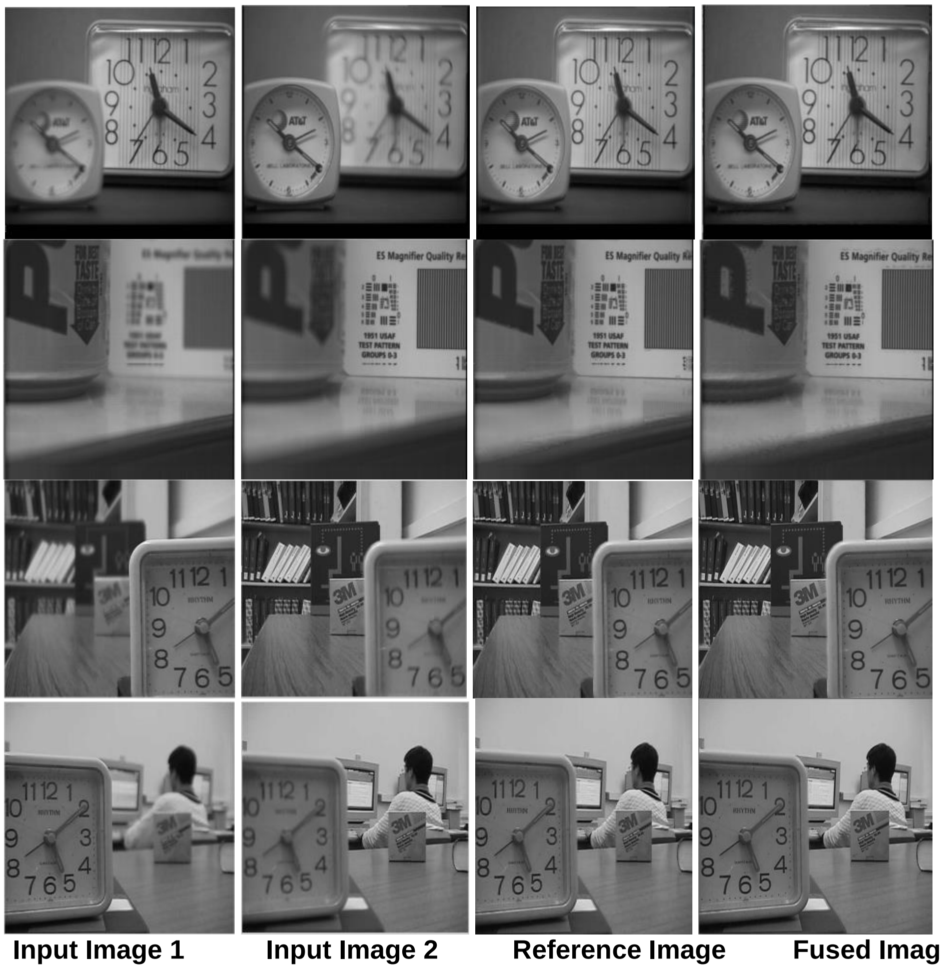

Figure 6. Results of Image Fusion using Modified Laplacian with Window Size 7X7

Table II. Results of Multifocused Image Fusion

Image	Barbara			Camera man			Clock		
	3X3	5X5	7X7	3X3	5X5	7X7	3X3	5X5	7X7
NAE	0.00200	0.00002	0.00000	0.00950	0.00058	0.00020	0.03220	0.02940	0.02900
RMSE	1.5851	0.083	0.0156	6.2509	0.8846	0.535	6.46	5.9756	5.8502
PSNR	44.1299	69.7538	84.2544	32.212	49.1956	53.564	31.9262	32.6032	32.7874
SF	36.6052	36.6052	36.6052	28.916	28.916	28.916	9.8102	9.8102	9.8102
NCC	1.0005	1	1	1.0011	1	1	1.011	1.0086	1.0084
PCC	0.9994	1	1	0.9951	0.9999	0.9999	0.9922	0.9934	0.9937
SC	0.9988	1	1	0.9957	0.9999	1	0.9751	0.9803	0.9806
QI	0.9917	0.9999	1	0.9537	0.9865	0.9944	0.8134	0.8131	0.809
SSI	0.9965	1	1	0.9708	0.9973	0.9991	0.9532	0.9648	0.9653
Image	Pepsi			Disk			Lab		
	3X3	5X5	7X7	3X3	5X5	7X7	3X3	5X5	7X7
NAE	0.01830	0.01390	0.01280	0.02510	0.01730	0.01620	0.01590	0.01220	0.01140
RMSE	4.5891	3.5287	3.2704	6.6197	4.4399	4.2266	4.8328	3.217	2.8445
PSNR	34.8962	37.1785	37.8388	31.7141	35.1834	35.6109	34.4468	37.9818	39.0507

SF	13.7649	13.7649	13.7649	15.25	15.25	15.25	12.826	12.826	12.826
NCC	1.0042	1.0004	0.9992	1.0022	1.0031	1.0032	1.0073	1.0065	1.0063
PCC	0.9949	0.997	0.9974	0.9899	0.9956	0.996	0.995	0.9979	0.9984
SC	0.9898	0.9981	1.0007	0.9919	0.9921	0.9921	0.9843	0.9866	0.9872
QI	0.8413	0.8622	0.8753	0.8021	0.8465	0.8579	0.8042	0.8254	0.8345
SSI	0.9362	0.9556	0.9627	0.9356	0.9649	0.9693	0.9668	0.9811	0.9841

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