

## Multi Focus Image Fusion Using Statistical Approaches

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### Abstract

Pictures of the long focal lengths cameras, suffer from the problem of limited depth of field. Consequently, it is often difficult to obtain good focus for all objects in the picture. In this work, the problem of multi focus is solved by taking several pictures with different focus points, and then fusing them together to form a single image using image fusion method. Contrast of the source images is used as a measure to select the proper pixels (pixels with high focus) to obtain the fused (output) image. This work suggests using three statistical measures of contrast to calculate the pixels gradient magnitude. Those three measures are applied and compared with the traditional method of gradient magnitude measures (Sobel and Perwit) in Multi focus Image Fusion. The results show that the modified methods gave better results than Sobel and Perwit methods.

**Keywords:** Multi Focus Image, Image Fusion, Statistic

### دمج الصور ذات التركيز المتعدد باستخدام الطرق الاحصائية

#### الخلاصة

الصور في الكاميرات ذات الابعاد البؤرية العالية تعاني من مشكلة محدودية عمق حقل الصورة (Depth of Field). نتيجة لذلك يكون من الصعب الحصول على تركيز جيد لكل المكونات (objects) الموجودة في الصورة. في هذا البحث تم حل مشكلة التركيز المتعدد من خلال اخذ عدد من الصور لنفس المشهد ولكن بتراكيز مختلفة لمكونات هذه الصور حيث يظهر في كل صورة احد المكونات بشكل اوضح من باقي المكونات وبعد ذلك تدمج هذه الصور مع بعضها باسلوب دمج الصور (Image Fusion) فيتم الحصول على صورة واحدة تكون فيها كل المكونات بنفس الدرجة من الوضوح. تم استخدام التباين (Contrast) كمقياس لاختيار النقطة (pixel) المناسبة (ذات الوضوح الاعلى) للحصول على الصورة الناتجة بعد عملية الدمج. في هذا البحث تم اقتراح استخدام ثلاث مقاييس للتباين عن طريق حساب نسبة الزيادة او النقصان في قيمة النقطة (Pixel gradient magnitude) باسلوب احصائي. هذه المقاييس تم تطبيقها عمليا وتمت مقارنتها مع الطرق المعروفة (Sobel و Perwit) في حساب الـ gradient magnitude في مشكلة التركيز المتعدد, وقد اثبتت نتائج عملية المقارنة ان الطرق المعدلة افضل من طرق (Sobel و Perwit).

### 1. Introduction

The low depth-of-field is one of the optic systems fundamental limitations; it is often difficult to

obtain good focus for all objects in the picture because certain objects at particular distance are focused while

other objects are blurred to a degree depending on their distances from the camera. This problem which is called multi focus is encountered in photography and of the microscopy. Different approaches are suggested to solve the multi focus problem; one of these approaches is image fusion. The source images are fused together to produce an image of the scene. All the objects of the fused image (resultant image) should have the same degree of clarity and sharpness [MAR07].

Multi focus has been performed using many approaches. The first approach block by block image fusion depends on composing the source images into blocks of equal size and fuse the corresponding blocks from the source images to select the best blocks depending on the sharpness criterion of this blocks. The fused blocks from the different images are mosaiced or blended to form the final fused image. Goshtasby [GOS07] used the block by block comparison and selected the block with highest contrast. Also, Li [LIS01] select the fused block. The second approach for multi focus fusion based on multi \_scale decomposition method. Kannan and Perumal [Kan07] described the optimal level of decomposition of discrete wavelet transform for image fusion. The third approach based on region by region comparison to construct the fused image. In region based approach, the source images are initially divided into regions by segmentation. The segmentation process either based on objects connectivity or based on focal connectivity. Hariharan, Koschan and Abidi [Har07] based on focal connectivity segmentation and used intelligence to select the sharpest region. Hence, multi focus image

fusion may be performed in spatial domain or frequency domain.

In spatial domain, multi focus image fusion is performed using region based or block based approaches as mentioned previously. The main drawback of region based approach is that it requires segmentation process of the source images which means we have to preprocess the source images before image fusion process which means consuming time. Besides, this approach will produce an image where the boundary between two adjacent region may appear very different in contrast [MAR07].

On the other hand, block based approach required dividing the source images into blocks of equal size (16\*16, 32 \* 32,... ), the gradient magnitude of the pixels of each blocks are calculated and a comparison is made among the gradient magnitude of the corresponding source images blocks. The block with higher gradient magnitude will be selected as the candidate block and the original pixels of the source image that correspond to the candidate block will be copied to the output image. This approach may be speeded up by comparing selected pixels of the corresponding block. Also, the block by block approach is effected by the size of the blocks, that is the smaller blocks leads to slower processing while larger blocks may miss smaller but high contrast region in the image. Although this approach will speed up the algorithm but will cause lose of precision [GOS07].

In this work, another approach is suggested for multi focus image fusion which depends on pixel by pixel gradient magnitude (as a measure of contrast) comparison. There are different traditional

methods to compute the gradient as an example of these methods are Sobel and Perwit methods which are depends on horizontal and vertical masks. These methods are applied and compared with the modified method. Three statistical measures of contrast measure are suggested to be used to calculate the pixels gradient magnitude.

## 2. Depth of Field

Depth of field refers to the region of proper focus that is available in any photographic image. When the camera is focused, it is not possible to get a paper-thin region of proper focus in an image; instead, there's some distance in front and behind the subject that will also be in focus. This entire region of sharp focus is called the depth of field, or sometimes the depth of focus. The region that is out of depth of field will be blurry. There are three factors determining the depth of field [JOH02]:

- **Aperture** which means the size of the lens opening that determines how much light reaches camera's imaging sensor.
- **Focal length** is the second factor which means a measure of the lens's ability to magnify a scene.
- **Subject distance** is the distance from the subject determines how much depth of field can be obtained in the scene.

These three factors work together in any shooting situation. Hence, depth of field is an extremely important element in the overall composition of photographs. Using depth of field, a subject can be isolated by making sure it is the only sharply focused person or object in the frame. Alternately, depth of field can be increased to make the entire image

from foreground to background as sharp as possible [JOH02].

## 3. Image Fusion

Information fusion has long been studied in various areas of computer science and engineering, and the number of applications for this class of techniques has been steadily growing. Image fusion is the process of combining images from two or more sources into highly informative fused image. The objective of image fusion is to increase information for later processing or applications of these images [MAN08].

There are two approaches for image fusion. The first approach works in the spatial domain by processing the corresponding pixels from the different source images and fusing them together to obtain the pixel in the fused image. The second approach work in the frequency domain of the source image by transforming the source image to be represented at multi scale. The most common used transform for image fusion at multi scale is Wavelet transform [GOS07] [Kan07].

The technology of image fusion was developed at the same time with the computers development. In recent years there has been a growing interest in image fusion processing to increase the capability of the intelligent machines and systems.

## 4. Contrast

Contrast is the difference in visual properties that makes an object (or its representation in an image) distinguishable from other objects and the background. In visual perception of the real world, contrast is determined by the difference in the color and brightness of the object and other objects within the same field of view. Because the human visual

system is more sensitive to contrast than absolute luminance, we can perceive the world similarly regardless of the huge changes in illumination over the day or from place to place [WIK08].

In this work, three methods that calculate the contrast in images are suggested to be modified. The results of these methods will be used later to compare the contrast of the source images to determine the fuse image. These methods are:

**4.1 Center Variance**

Variance is one of the most important measures of dispersion, which indicates the difference of each value from all other values. Variance is obtained through computing how much each value (pixel in this work) deviate from the average value (mean value) then combining these deviations through averaging (by dividing the result by the number of values), which can be analytically described by [HAN91]:-

$$S^2 = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n - 1} \dots \dots \dots (1)$$

It is obvious that variance is a measure of how data tend to vary around the mean.

In this work, we present a new variance, which is more suitable to image processing operations, because in image processing operations, we almost deal with a sliding window of different sizes (e.g. 3x3, 5x5, 7x7, ...etc.) and we need to compute the contrast of this window in order to find edges or object boundaries. We find that, in order to measure the contrast of a sliding window we need to calculate the deviation of each pixel from the center of the window rather than from the average of the window (as in the ordering variance).

The proposed variance which we call the center variance is given by equation (2):-

$$Center\ Variance = \frac{\sum_{i=1}^n (x_i - C)^2}{n - 1} \dots \dots \dots (2)$$

Where C is the window center and n is the number of values.

When we calculate the contrast for a sliding window, we replace the pixel in the center of the window with the sum of the square of the difference between the center pixel and the 8 neighbors.

**4.2 Center Deviation**

Mean deviation is another important measure of dispersion which is widely used in statistic. Mean deviation is obtained by calculating the difference between the observed value and the mean value, which can be analytically described by equation (3):-

$$Mean\ Deviation = \frac{\sum_{i=1}^n |x_i - \bar{x}|}{n} \dots \dots \dots (3)$$

Mean deviation represent the average of distance (ignoring the directions) of the deviations from the mean value [HAN91].

In this work, we proposed to modify the mean deviation equation to be more suitable for image processing through computing the deviation of the sliding window values from the center of window instead of the mean value as in the ordinary mean deviation. The proposed mean deviation which we call center deviation is given by equation (4):-

$$Center\ Deviation = \frac{\sum_{i=1}^n |x_i - C|}{n} \dots \dots \dots (4)$$

Where C is the window center,  $x_i$  is the value, and n is the number of values.

**4.3 Goodness of Fit**

This test is based on the Chi\_Square  $\chi^2$  distribution. It is a test of consistency between a hypothetical and observed distribution, which is shown in equation (5).

$$\chi^2 = \sum_{i=1}^n \frac{(o_i - e_i)^2}{e_i} \dots \dots \dots (5)$$

Where  $o_i$  is the observed frequencies and  $e_i$  is the expected frequencies.

The  $\chi^2$  value may be considered as a measure of discrepancy between  $o_i$  and  $e_i$ . if there is no discrepancy, then  $\chi^2 = 0$ . The value of  $\chi^2$  increases proportionally to the discrepancy, as the discrepancy become larger, then  $\chi^2$  value becomes larger. If the observed and expected frequencies are quiet close, the  $\chi^2$  will approach to zero.

When this test is applied to a sliding window of an image, we assume that the pixel values of the window represent the observed frequency, and the mean value of that window represents the hypothetical frequency, so that when the resulted  $\chi^2$  is equal to zero or approach to zero, that means this window has no contrast, otherwise, if the resulted  $\chi^2$  is greater than zero, then the window has a big contrast.

**Multi focus Image Fusion using Modified Statistical Measures**

In this work a statistical pixel by pixel approach for multi focus fusion is suggested. The proposed algorithm starts with calculating gradient magnitude for all the pixels of the source images (two image or more) using one of the three proposed statistical measures: Center Variance, Center Deviation, and Goodness of Fit (which will be presented in the next section). The resultant gradient images will be compared pixel by pixel, The pixel with higher gradient magnitude will be selected as the candidate pixel and the original pixels of the source image that correspond to the candidate pixel will be copied to the output image. The proposed approach can be analytically described as follows:

If we have  $i$  source images, the gradient value  $G_{(i)}(x, y)$  is computed for each pixel at each source images, then the gradient values of the corresponding pixels are compared together to obtain the fused pixel value

$$P_{(i)}(x, y) = G_{(i)}(x, y) > G_{(k \neq i)}(x, y) \forall i \in \{1, 2, \dots, N\}, \forall k \in \{1, 2, \dots, N\}$$

The fused image is constructed by the union of the fused pixels:

$$F(x, y) = \bigcup_{n=1}^m (P_{(i)})$$

The proposed approach of multi focus image fusion can be shown in the following algorithm:

Algorithm (1) : Multi Focus Image Fusion using Modified Measures

Input: number (N) of source images have different degree of blurring for the different objects.  
 Output : a fused image where all objects have the same degree of clearness.

Step1: for k=1 to N (N:number of source images)  
 Step2 : for all pixels coordinated i and j do  
 Step 3: calculate the gradient magnitude for each pixel with one of the proposed methods (Center Variance, Center Deviation, and Goodness of Fit).  
 Step 4: obtain N gradient images.  
 Step 5: for k=1 to N (N:number of gradient images)  
 Step6: for all pixels coordinated i and j do  
 Step4: put the pixel (i,j) of all the gradient images in a vector.  
 Step 5: compare the gradient of each pixel value in the vector.  
 Step6: obtain the pixel which has the greater gradient value.  
 Step7: get the pixel (i,j) in the source image which corresponds to the greater gradient value pixel and put this pixel at the coordinate i and j in the output image (fused image) value of the corresponding image.

**5. Evaluation Criteria**

In this work, three evaluation criteria are used. These criteria can be used to measure the amount of error in the reconstructed (manipulated) image. The three evaluation measures are [KAN07]:-

The Root\_Mean\_Square\_Error is computed by taking the square root of the squared error divided by the total number of pixels in the image as shown in equation (6).

$$Root\_MSE = \sqrt{\frac{1}{N^2} \sum_{r=0}^{N-1} \sum_{c=0}^{N-1} [I(r,c) - \hat{I}(r,c)]^2} \dots\dots\dots (6)$$

Where I(r,c)=the original image

$\hat{I}(r,c)$ = the reconstructed image

The smaller the value of the error metric, the better the reconstructed image represents the original image.

The SNR metrics consider the reconstructed image  $\hat{I}(r,c)$  to be the signal and the error to be “noise”, the Root\_SNR is defined as equation (7):

$$Root\_SNR = \sqrt{\frac{\sum_{r=0}^{N-1} \sum_{c=0}^{N-1} [I(r,c)]^2}{\sum_{r=0}^{N-1} \sum_{c=0}^{N-1} [I(r,c) - \hat{I}(r,c)]^2}} \dots\dots\dots (7)$$

With the signal to noise ratio (SNR) metrics, a larger number implies a better result.

The Peak\_SNR is defined as equation (8):

$$Peak\_SNR = 10 \log_{10} \frac{(L-1)^2}{\frac{1}{N^2} \sum_{r=0}^{N-1} \sum_{c=0}^{N-1} [I(r,c) - \hat{I}(r,c)]^2} \dots\dots\dots (8)$$

Where L is the number of gray levels.

In this measure a larger number implies a better result.

**6. Analyze Results**

The proposed Image fusion approach for multi focus problem has been tested on images with different degree of blurring for the different objects in the source images. The multi focus images, the computed gradient values for each of the source images, and the fused image which is obtained by one of the suggested three methods (Center Variance, Center Deviation, and Goodness of Fit) are shown in the figures below.

Figures (1-a and 1-b) show the original multi focus image of the tiger image which have different degree of blurring from region to region in both of them.

Figures 2-a, 2-b, and 2-c show the results of the gradient for the source tiger1 images using the proposed gradient measures. These images show that the gradient image using Center Variance and Center Deviation are approximate. Figure 2-c shows the gradient value of tiger1 image using Goodness of Fit method

which shows the best distinguish among the blurry and clear regions at the same image.

Figures 3-a, and 3-b show the results of the gradient for the source tiger1 images using the conventional methods Sobol and Perwit.

The three modified methods gave better results than conventional methods (Sobel and Perwit).

The Goodness of fit method also gave the best result when it was applied on tiger2 images as follows:

Figures 4-a, 4-b, and 4-c show the results of the gradient for the source tiger2 images using the modified gradient measures.

Figures 5-a, and 5-b show the results of the gradient for the source tiger2 images using the conventional methods Sobol and Perwit.

Figures 6-a, and 6-b show the results of applying the suggested three method to obtain the fused image where all objects have the same degree of clearness.

Another test is made on multi focus phantom image. Figures (7-a and 7-b) show the original multi focus image of the phantom image.

Figures 8-a, 8-b, and 8-c show the result of applying the suggested three method to obtain the fused image where all objects have the same degree of clearness.

Tables 1 and 2 show a comparison among the results of the three modified methods of gradient calculation as they used as a measure of contrast in the proposed multi focus image fusion. Also, the comparison includes the conventional methods to calculate the gradient magnitude: Sobel and Perwit. These methods had been applied onto multi focus tiger images and multi focus phantom images. The resultant images are compared

with a smooth tiger image and phantom image to compute the error ratio according to the evaluation criteria. The values of the evaluation criteria are as in the table (1) for tiger image, and table (2) for the phantom image:

## 7. Conclusion

In this work an Image Fusion approach have been suggested for image multi focus problem. This approach is categorized under the spatial domain approaches for multi focus image fusion. The fused image is obtained using pixel by pixel comparison which resulted in more precise results than other spatial domain approaches.

Three statistical measures are suggested to be used in multi focus image fusion to compute the gradient magnitude of the source images. These measures are: Center Variance, Center Deviation, and Goodness of Fit. The statistical approaches have been applied for multifocus images, the modified statistical measures for image fusion are compared with Sobel and Perwit method and the results show that the suggested statistical image fusion approach is better in solving the multi focus problem than the Sobel and Perwit methods according to the three evaluations criteria (Root\_MSE, Root\_SNR and Peak\_SNR).

Results shows that the modified Center Deviation give superior results in measuring the contrast of the tested images according to the results that are shown in the tables 1 and 2.

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**Table (1) The Results of the Evaluation Criteria after applying the different multi focus methods for the tiger image**

criteria filter	Root_MSE	Root_SNR	Peak_SNR
<b>Center_Variance</b>	<b>3.912</b>	<b>28.912</b>	<b>36.282</b>
<b>Center_Deviation</b>	<b>3.801</b>	<b>29.758</b>	<b>36.531</b>
<b>Goodness of Fit</b>	<b>4.062</b>	<b>27.782</b>	<b>35.953</b>
<b>Sobel</b>	<b>5.800</b>	<b>19.452</b>	<b>32.861</b>
<b>Perwit</b>	<b>5.730</b>	<b>19.689</b>	<b>32.966</b>

**Table (2) The Results of the Evaluation Criteria after applying the different multi focus methods for the phantom images**

criteria filter	Root_MSE	Root_SNR	Peak_SNR
<b>Center_Variance</b>	<b>2.846</b>	<b>68.381</b>	<b>39.054</b>
<b>Center_Deviation</b>	<b>2.314</b>	<b>84.018</b>	<b>40.841</b>
<b>Goodness of Fit</b>	<b>3.691</b>	<b>52.604</b>	<b>36.786</b>
<b>Sobel</b>	<b>5.248</b>	<b>37.015</b>	<b>33.730</b>
<b>Perwit</b>	<b>5.068</b>	<b>38.329</b>	<b>34.033</b>

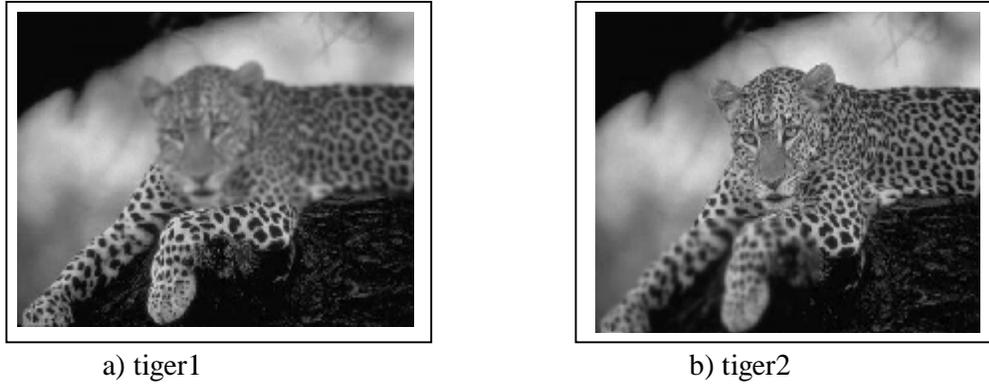


Figure (1) Source Images a) tiger1 b) tiger2

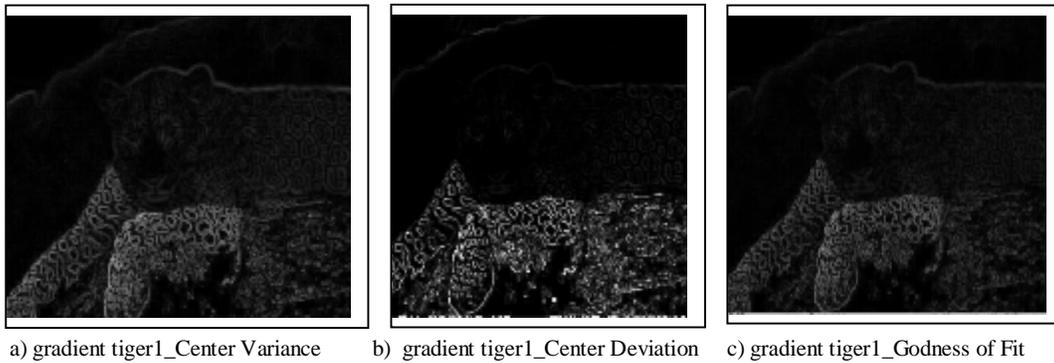
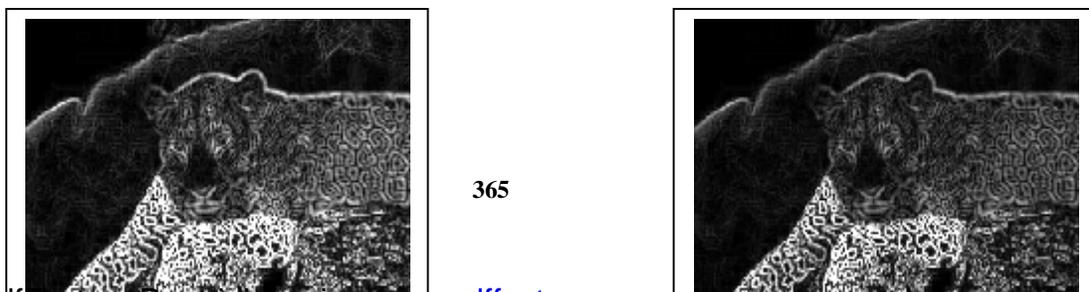


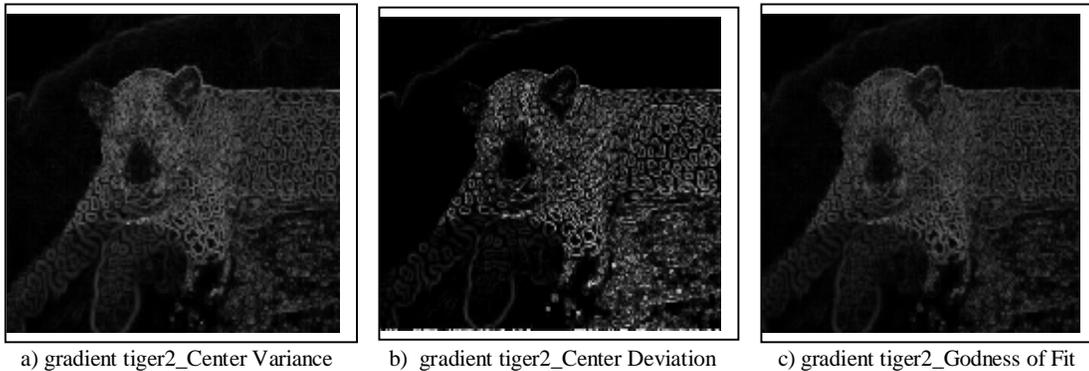
Figure (2) Gradient of (Figure1\_ a) using the proposed gradient measures  
a) gradient tiger1- Center Variance    b) gradient tiger1-Center Deviation



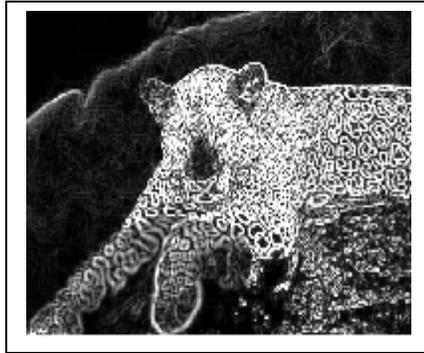
a) gradient tiger1\_Sobol

b) gradient tiger1\_Perwit

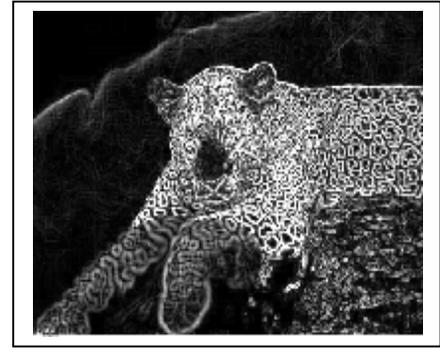
**Figure (3) Gradient of (figure1-a) using conventional methods a) gradient tiger1-Sobol b) gradient tiger1-Perwit**



**Figure (4) Gradient of (Figure1\_ b) using the proposed gradient measures a) gradient tiger1- Center Variance b) gradient tiger1-Center Deviation**



a) gradient tiger2\_Sobol



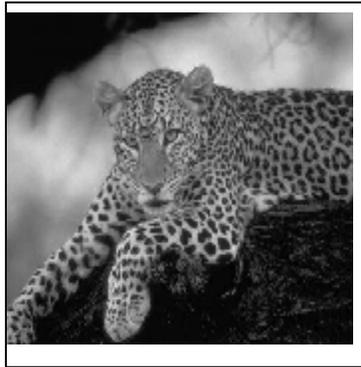
b) gradient

tiger2\_Perwit

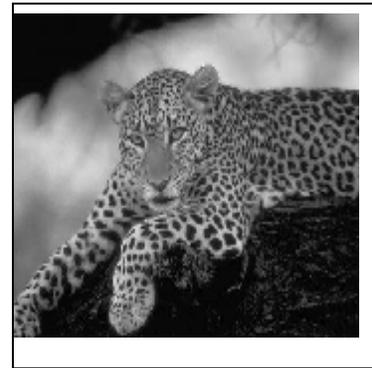
**Figure (5) Gradient of (figure1-b) using conventional methods a) gradient tiger2-Sobol**



a) Fused tiger- Center Variance

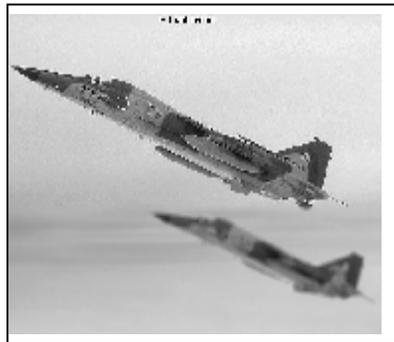


b)Fused tiger- Center Deviation



c)Fused tiger-  
Goodness of Fit

**Figure (6) the fused tiger images using the proposed three methods a) Fused tiger- Center Variance  
b) Fused tiger- Center Deviation c)Fused tiger- Goodness of Fit**

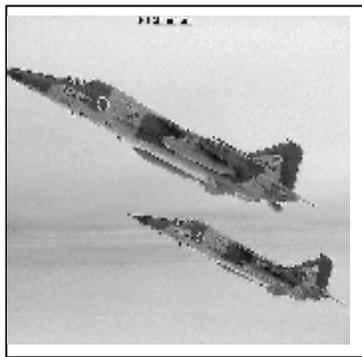


a) phantom 1

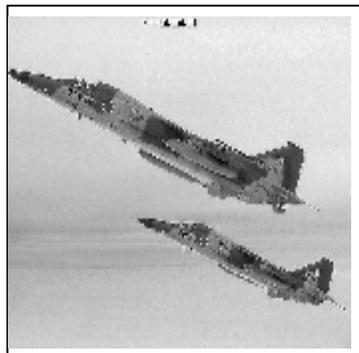


b) phantom 2

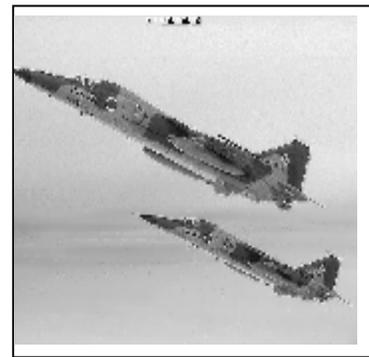
Figure (7) Original Images a) phantom 1 b) phantom 2



a) Fused phantom - Center Variance



b) Fused phantom -Center Deviation



c) Fused phantom -

Figure (8) the fused phantom images using the proposed three methods a) phantom -Center Variance b) phantom-Center