Multi-focus image fusion is the area of image fusion techniques in which effect due to limitation of depth of focus of various camera systems is considered. This paper presents a quantitative analysis of some available image fusion algorithm on multi-focus images. A statistical comparison to analyze the quality of fused image Root Mean Square Error (RMSE) and Special Frequency (SF) has been taken as assessment parameters. This paper also suggests a modification on existing multifocus image fusion algorithm to improve the fusion process.

**Keywords:** RMSE, MI, multifocus

1. **INTRODUCTION**

The best description of an object is its image. Images of objects are acquired from different camera systems for different applications in various fields. The camera systems usually have a limited depth of field. The objects which are within the depth of field of camera are well focused in acquired image, while others are blurred. The clear image of blurred areas of objects can be acquired with different camera setting. An image with every object of the scene in focus can be obtained by fusing different images taken from different camera settings under same viewpoint.

Image fusion is the process of combining two or more images into a single fused image retaining the important feature into a single image from set of different images. Image fusion can be done for various applications, like fusion of visible and IR images for military applications, fusion of spectral images in remote sensing, fusion of X-ray CT and MR images in medical images etc. This paper is limited to fusion of multi-focus images. Multifocus images can fuse by various algorithms but each algorithm has its own merits and demerit. The performance of these algorithms can be evaluated by quantitative parameters such as RMSE and SF.

This paper organized as follows. Section 2 gives a brief description of various image fusion algorithms, section 3 gives proposed modified method of image fusion and in section 4 results of proposed algorithm for better fusion results are discussed.

2. **IMAGE FUSION ALGORITHMS**

Various research works are going on from last few years in the area of multifocus image fusion. The image fusion algorithms can be classified into two major domains:

1. **Image Fusion in Spectral Domain**
2. **Image Fusion in Spatial Domain**

2.1 **Image Fusion in Spectral Domain**

In spectral domain image fusion, multiple images of the object are first decomposed into its spectral coefficients based on some transformation method. Then by applying some fusion rules these coefficients are fused and inverse transformation method is applied to get the fused image. In this domain following methods can be used.

2.1.1 **Pyramidal Transformation Method**

In this method Multi resolution image pyramids are constructed by successive filtering and downsampling of an image. An image pyramid is first constructed for each source images, and then a pyramid is formed for the composite image by selecting coefficients from the source pyramid. Finally, the composite image is recovered through an inverse pyramid transform.

There are several variations on pyramid-based fusion. These differ in the type of pyramid transform used, and in the rules used to select transform coefficients that carry “salient” information for inclusion in the composite image. Burt (1993) presented an extension to the pyramid approach to fusion by defining two distinct modes of combination: *selection* and *averaging*. At sample locations where the source images are distinctly different, the combination process selects the most salient component pattern from the source pyramids and copies it to the composite pyramid, while discarding less salient patterns. But at sample locations where the source images
are similar, the process averages the source patterns. Again, selection avoids double exposure artifacts in the composite. Averaging reduces noise and provides stability where source images contain the same pattern information. Pattern selective image fusion is guided by two measures: a match measure that determines the mode of combination at each sample position (selection or averaging), and salience measures that determine which source pattern is chosen in the selection mode. The modifications introduced were intended to further improve stability and noise immunity, to overcome the pathological case of patterns with opposite contrast.

2.1.2 Wavelet Transformation

Wavelet transform fusion is more formally defined by considering the wavelet transforms \( \omega \) of the two registered input images \( I_1(x, y) \) and \( I_2(x, y) \) together with the fusion rule \( \Phi \). Then, the inverse wavelet transform \( \omega^{-1} \) is computed, and the fused image \( I(x, y) \) is reconstructed:

\[
I(x, y) = \omega^{-1}(\Phi(\omega(I_1(x, y), \omega(I_2(x, y))))
\]

(1)

The wavelet schemes have more advantages over pyramid schemes, such as increased directional information, better signal-to-noise ratio, improved perception and no blocking artifacts that often occur in pyramid fused images. The performance of wavelet transform deteriorates if there is any misregistration of source images or if there is a movement of object in the source images.

2.1.3 Curvelet Transformation

Nencini et al. (2007) introduced a method of image fusion where each input image is transformed from image space into multi resolution domain by applying Curvelet Transform. An activity level is calculated from the transform coefficient separately or by averaging over a small window at each coefficient location. Larger activity level indicates that the corresponding object is clearer. Then select the coefficient with the larger activity level at each pixel location from multiple transformed coefficients replace the coefficient at that location in the fused image. Fused image is reconstructed by performing inverse transform.

2.1.4 Combining wavelet and Curvelet Transformation

DWT and CT reveals very different features of the source images. Wavelets do not restore long edges while Curvelet are challenged with small features. Li and Yang (2008) introduced image fusion by combining wavelet and Curvelet transform. In this method each of the source images is decomposed by Curvelet transform into Curvelet coefficients. Each pair of coefficients is fused by using wavelet transform. The largest absolute value coefficients are selected to obtain the fused wavelet coefficients. Curvelet coefficients are obtained by inverse wavelet transform. By applying inverse Curvelet transform fused image is formed. This method can preserve more useful information compared with DWT and CT-based fusion methods.

2.2. Image Fusion in Spatial Domain

In this method of image fusion; fusion rules are applied directly on pixel values or focus measures of multiple images of the object to get the fused image. Different focus measures had been proposed such as Energy of Gradient, Energy of Laplacian etc. Based on focus measure value best focused image portion in source images is used for fusion. These methods can further classified as follows.

2.2.1. Weighted Average

This method is based on pixel values of all source images at each pixel location. A weight factor is added to each pixel value and an average of weighted pixel values is used for the fused image at same pixel location. This method produces unsatisfactory results because the features that appear in one source image but not in others are rendered in the composite image at reduced contrast or superimposed on features from other images as in photographic double exposure effect.

2.2.2. Partition Fusion Algorithm

Li et al. (2001) introduced a method based on the selection of image blocks from source images. The basic idea underlying the method is to choose the clearer image blocks from source images to construct the fused image. Spatial frequency (SF) is used to distinguish the focused image blocks from the defocused image blocks. The problem with transform domain approach was mainly during the case of movement in object during imaging. This problem will not appear in partition fusion method because of the selection of image block. Thus the method proposed by Li et al. (2001) was able to avoid the problem of shift-variant, caused by DWT.

3. MODIFIED PARTITION FUSION ALGORITHM

The purpose of this paper is to provide a solution for modification in existing image fusion method for better performance. The above discussed image fusion methods provide good results in various types of images but in different methods there are some limitation also. As in the case of transform domain approach if there is any movement in the object while taking sequence of images for different camera settings the performance will deteriorate. To overcome the problem spatial domain approach as partition fusion method is used. But while measuring the focus quality of the source images these focus measures are affected with noise.
This paper presents the modification in terms of preprocessing the image by FIR low pass filter. This processing makes the image fusion process by partition fusion algorithm; more robust to noise. Subbarao (1993) suggest most of the focus measures based on the idea of emphasize high frequencies of the image and measure their quantity. This comes from an idea that blurring suppresses high frequencies regardless of the particular PSF. But during this process of emphasizing high frequencies robustness towards noise becomes low. To make the process robust this paper suggests the use of FIR LPF to remove the noise from high frequency component of image and then calculate the focus measure for partition fusion algorithm.

For quantitative Evaluation of the different image fusion methods following parameters are used:

### 3.1. RMSE

It is a measure of mean difference between the desired (reference) image and resultant (fused) image. It is defined as:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{M} \sum_{j=1}^{N} (R(x,y) - F(x,y))^2}{M \times N}}$$

Where $R(x,y)$ is the reference image and $F(x,y)$ is the fused image.

### 3.2 Spatial Frequency (SF)

Spatial frequency is used to measure the overall activity level of an image. For an $M \times N$ image the gray value at pixel position $(x,y)$ is denoted by $F(x,y)$. The spatial frequency is defined as

$$SF = \sqrt{RF^2 + CF^2}$$

Where $RF$ and $CF$ are the row frequency and column frequency respectively. This is defined as

$$RF = \sqrt{\frac{1}{MxN} \sum_{i=1}^{M} \sum_{j=1}^{N} (F(x,y) - F(x,y-1))^2}$$

$$CF = \sqrt{\frac{1}{MxN} \sum_{i=1}^{M} \sum_{j=1}^{N} (F(x,y) - F(x-1,y))^2}$$

### 3.3 Mutual Information

For objective assessing various methods, mutual information is used as the objective standard to estimate the performance of different methods. In fact, image fusion is used to fuse a variety of multi-source images and aims at creating a fused image that acquires as much information from each of the source images as possible.

The more information obtained from source images, the better the effect of fusion there is. Then, mutual information can measure the similarity between two images. If both sides are similar, the value of mutual information is larger. Hence, mutual information can exactly measure the performance of different methods. Between the reference image $R$ and the fused image $F$, the corresponding mutual information is defined as

$$MI = \sum_{i=1}^{L} \sum_{j=1}^{L} h_{R,F}(i,i) \log_2 \frac{h_{R,F}(i,i)}{h_R(i)h_F(i)}$$

Here, $h_{R,F}$ is the normalized joint gray level histogram of images $R$ and $F$, $h_R$, $h_f$ are the normalized marginal histograms of the two images, and $L$ is the number of gray levels. Notice that MI measures the reduction in uncertainty about the reference image due to the knowledge of the fused image, and so a larger MI is preferred.

### 4. EXPERIMENTAL RESULTS AND DISCUSSION:

Two different sets of images has been taken to evaluate the performance of seven image fusion algorithms described in section 2 and section 3. Fig. 1 shows the two reference images. Fig. 2 shows the fusion results of various method of image fusion while considering one image to be left focused and other right focused on first image of fig. 1. Fig. 3 shows the fusion results while considering left, middle and right focused parts of second image of fig. 1. The quantitative comparison of these algorithms are summarized in table-1

In order to assess the fusion algorithms Root Mean Square Error (RMSE) and Special Frequency (SF) and Mutual Information has been used in this paper, but SF and MI gives the same results so only SF is shown in the table. The results have been provided in quantitative way in table 1 shows performance of different algorithms. The performance of these algorithms depends on images of different natures. In the partition fusion algorithm the results depends on the block size of the partitioned images. In this paper results of block size 8 x 8 have been used.

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>for toy images</th>
<th>for clock images</th>
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<td>RMSE</td>
<td>SF</td>
<td>RMSE</td>
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<tr>
<td>Pyramid Transform</td>
<td>5.645</td>
<td>7.955</td>
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<tr>
<td>Wavelet transform</td>
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<td>10.830</td>
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<td>Curvelet transform</td>
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<td>CT+DWT</td>
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<td>10.910</td>
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<td>Averaging</td>
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<td>9.854</td>
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<td>Partition fusion</td>
<td>3.938</td>
<td>10.543</td>
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<td>Modified partition fusion</td>
<td>1.9301</td>
<td>10.145</td>
</tr>
</tbody>
</table>
5. CONCLUSION

Image fusion is used to combine complementary information from different images of the same objects in the scene. The resultant image is in more suitable form for human and/or machine perception. The image fusion process for multi focus images, in majority consist of finding clearer component available in different image to be used in fused image. Comparing spatial domain method with spectral domain methods, it is reflected from the results that spatial domain approach outperforms the spectral domain approach especially in the case of multifocus images because focus measures play important role in this type of images. The results of table-1 shows that using low pass filter overcome the problem of robustness of noise in focus measure parameter and provide better results with improved values of RMSE and SF.

REFERENCES


