Int. J. Advanced Networking and Applications 5477
Volume: 14 Issue: 03 Pages: 5477-5481(2022) ISSN: 0975-0290

# Multi focused Image Fusion using Fast Adaptive Bilateral Filter

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**ABSTRACT**

**This paper presents Fast Adaptive Bilateral Filter (FABF) for fusion of Multi Focuses images. Multi Focused image fusion is used to combine one or more input image into single composite image, focusing all objects in the given scene. FABF filter sharpens the image without producing under and over shoot by increasing the edge slope. This paper uses this property to decompose the input image into high and low frequency images so that different fusion rules can be used for high and low frequency images to produce good quality composite image. The performance this FABF filter in Multi focused image fusion is compared with Adaptive Bilateral Filter (ABF) using Root Mean Square Error (RMSE), Spatial Frequency (SF) and Mutual Information (MI).**

Keywords **- Adaptive Bilateral Filter, Fast Adaptive Bilateral Filter, Multi Focused image fusion, Root Mean Square Error, Spatial Frequency and Mutual Information.**

Date of Submission: Aug 12, 2022 Date of Acceptance: Oct 28, 2022

## I. INTRODUCTION

Machine Vision application uses CCD and CMOS cameras in industries to capture the images of object of interest. Due to the limited depth of field in these cameras, it is possible to capture the clear image of the objects which are in focus only. The remaining objects in the scene which are not in focus will appear as blur. In this situation, Multi focus image fusion is used to combine two or more input images of the same scene with different focus to produce composite image in which all the objects in the scene are in focus. This composite image is called as Multi focused image. This image provides more comprehensive information about the scene which is useful for human perception & machine vision applications and reduces the storage capacity. A good multi focused image fusion method is expected to preserve useful & relevant information from multiple input images in Multi focused image. It should avoid artifacts and noises. It should be robust to shifting, scaling and misregistration. Digital Image processing research community reported many literatures related to Multi focus image fusion methods. Even though, there is a requirement of novel image fusion methods for feature extraction and target recognition. Among the literatures, multi scale decomposition methods are very successful and showing good results. They use different data representation and different image fusion rules to produce Multi focused image [19]. But, in these methods introduces artifacts. To avoid these artifacts, optimization based fusion methods were proposed. Optimization methods took multiple iterations to generate Multi focused image which in turn removes the edge details. To preserve edge details in the Multi focused image, edge preserving fusion methods were introduced. These methods use two scale decomposition edge preserving filter for the purpose of fusion [10-14]. Popular two scale decomposition edge preserving filter are anisotropic diffusion filter [20]. This method decomposes each input image into low and high frequency image. Multi focused images are formed by combining manipulated low and high frequency image. Even though edge details are preserved, it reflects the staircase effect. To avoid this staircase effect, fusion using Standard Bilateral filter (SBF) was proposed [17, 18, 21-23]. Unlike convolutional filters, BF uses two Gaussian kernel, one for range and another one for spatial. Even though, BF preserves edges, this filter is non-linear and computation intensive. An adaptive variant of BF, called Adaptive Bilateral Filter (ABF) was introduced for image sharpness enhancement along with noise removal [1], where the center and width of the Gaussian range kernel is allowed to change from pixel to pixel. While several fast algorithms have been proposed in the literature for ABF [2-5], most of them work only with a fixed range kernel. Fast algorithm for adaptive bilateral filtering whose complexity does not scale with the spatial filter width was proposed by Ruturaj G. Gavaskar and Kunal N. Chaudhury and this filter is called as Fast Adaptive Bilateral Filter (FABF) [7]. This paper compares and presents the performance of ABF and FABF in fusing multi focused images in terms of Root Mean Square Error (RMSE), Spatial Frequency (SF) and Mutual Information (MI). The following section overviews ABF and FABF proposed by Buyue Zhang & Jan P. Allebach and Ruturaj G. Gavaskar & Kunal N. Chaudhury respectively. Section 3 presents the multi focused fusion methodology and Section 4 discuss the performance of ABF and FABF. Finally, summary of this paper with conclusion is presented.

## II. ADAPTIVE AND FAST ADAPTIVE FILTER

The bilateral filter proposed by Tomasi and Maduchi is widely used in image processing for removing the noise while preserving the edges. Unlike linear convolutional filters, the bilateral filter uses two kernels namely range kernel and spatial kernel, where both are Gaussian kernels. An adaptive variant of the bilateral filter was introduced by Buyue Zhang & Jan P. Allebach, in which the center and width of the Gaussian range kernel is allowed to change from pixel to pixel. It is used for enhancement of image sharpness along with noise removal.

### 2.1 Adaptive Bilateral Filter

Equation 1 and 2 show the shift variant filtering and impulse response of ABF,

$$\overline{f}[m,n] = \sum_{k}\sum_{l} h[m,n;k,l]g[k,l] \qquad \text{….. (1)}$$

where $\overline{f}[m,n]$ is the input image, $h[m,n;k,l]$ is the response of the filter at [m, n] to an impulse at [k,l] and g[m,n] is the input image.

$$h[m,n;m_0,n_0] = I(\Omega_{mo,no}) r_{mo,no}^{-1} e^{-\left(\frac{(m-mo)^2+(n-no)^2}{2\sigma_d^2}\right)} . e^{-\frac{1}{2}\left(\frac{g[m,n]-g[mo,no]-\xi[mo,no]}{\sigma_r[mo,no]}\right)^2} \qquad \text{….. (2)}$$

where $[m_o,n_o]$ is the center pixel of the window, $\Omega_{mo,no} = \{[m,n]:[m,n]\epsilon[m_o-N,m_o+N] \text{ X } [n_o-N,n_o+N]\}$, I(.) denotes the indicator function and $r_{mo,no}$ normalizes the volume under the filter to unity. Compared with SBF, ABF contains two important changes: First, an offset $\zeta$ is introduced in the range filter. Second, both $\zeta$ and the width of the range filter $\sigma_r$ in ABF are locally adaptive. If $\zeta = 0$ and $\sigma_r$ is fixed, ABF will become SBF.

### 2.2 Fast Adaptive Bilateral Filter

The fast adaptive bilateral filter can be expresses as a weighted average of local pixel intensities similar to classical bilateral filter. The weighted histogram is defined as

$$h_i(t) = \sum_{j\in\Omega} w(j)\delta(f(i-j)-t) \qquad \text{….. (3)}$$

where $\delta$ is the Kronecker delta, $\delta$ (0) = 1 and $\delta$ (t) =0 for t $\neq 0$. Then the output image is given by

$$g(i) = \eta(i)^{-1} \sum_{t\in\wedge_i} t h_i(t)\phi_i(t-\theta(i)) \qquad \text{….. (4)}$$

where $\eta(i) = \sum_{t\in\wedge_i} h_i(t)\phi_i(t-\theta(i))$.

## III. PROPOSED METHODOLOGY

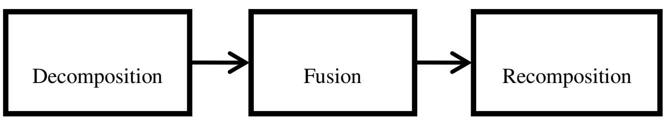


**Figure 1: Method of Multi Focused Image Fusion**

The proposed method to perform multi focused image fusion using ABF and FABF filters needs three steps as shown in the Figure 1. In first step, each input image is decomposed into approximation and detail images by employing edge preserving ABF and FABF. In the next step, approximation and detail images are fused by employing separate fusion rules and the different fusion methods are given below. Final fused image is reconstructed by combining the final fused approximation and detail images. Let the source images be $I_n$(x,y), where n = 1,2 and all source images are assumed to be registered spatially. These images are separated into approximation and detail images by passing through edge preserving ABF and FABF. Each input images are decomposed into approximation and detail images by bilateral filtering. The approximation of each input image is obtained by

$$B_n(x,y) = I_n(x,y) * Z \qquad \text{….. (5)}$$

where Z is the response of the bilateral filter. After obtaining the approximation image, the detail image is obtained by subtracting the approximation image from the input image.

$$D_n(x,y) = I_n(x,y) - B_n(x,y) \qquad \text{….. (6)}$$

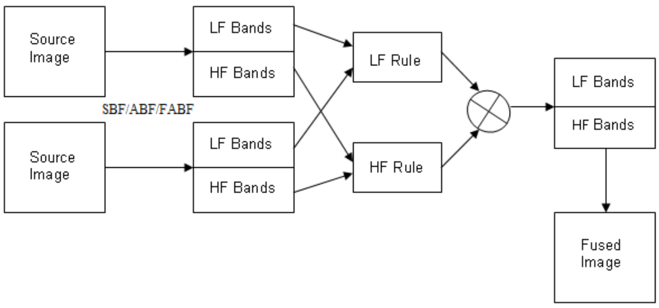


**Figure 2: Proposed Multi Focused Image Fusion**

The base layer consists of average image information called low frequency bands whereas the detail layer consist edge information called as high frequency bands. So, it is necessary to have different feature selection decision mechanism to select the coefficients from the low frequency and high frequency bands as shown in Figure 2. In this paper, to fuse the low frequency bands the absolute of maximum value is used as activity measure in all the methods.

**Method1:** In this method, absolute of maximum value is used as activity measure to fuse the low frequency band and high frequency bands. This activity measure preserves dominant features at each scale in the fused image. Since larger absolute coefficients correspond to sharper brightness changes, the absolute maximum value is used as activity measure for low and high frequency bands.

**Method2:** In this method, the salience measure is used as activity measure to fuse the high frequency bands. The salience of high frequency band is computed as a local energy in the neighborhood of a coefficient.

**Method3:** In this method, the salience and match measure is used as activity measure to fuse the high frequency bands. The salience of high frequency band is computed as a local energy in the neighborhood of a coefficient. This fusion scheme uses two distinct modes of combination namely Selection and Averaging. In order to determine whether the selection or averaging to be used, the match

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measure is calculated. If match measure is smaller than a threshold T, then selection mode is used. In this mode, the coefficient with the largest local energy is placed in the composite transform. If match measure is smaller than a threshold T, then selection mode is used. In this mode, the coefficient with the largest local energy is placed in the composite transform.

**Method 4**: The objective of any image fusion algorithm is to identify, compare and transfer the important visual information from source images into a fused image without any loss. Visual information is conveyed by gradients and edges in images. This method uses gradient of the image with consistency check as activity measure to fuse high frequency bands.

**Method 5:** This method uses maximum value of variance of the image as activity measure to fuse high frequency bands.

**Method 6:** This method uses maximum value of spatial frequency of the image as activity measure to fuse high frequency bands.

**Method 7:** This method uses Principal component of the image as activity measure to fuse high frequency bands. The principal components calculated from the eigen values and eigen vectors of the high frequency bands of the image act as weights to fuse high frequency bands.

## IV. RESULTS

Analysis and Experimental results are provided in this section to find out the strength of bilateral filters to arrive an efficient way to fuse multi focused images. The multi focus image fusion based on SBF, ABF and FABF is implemented using MATLAB simulation package. These approaches are tested with 10 set of pair of input images [30]. One image of the pair focuses right side and other image focuses left side of the scene. All test images are said to be registered spatially. The factors considered for analysis are Root Mean Square Error (RMSE), Spatial Frequency (SF) and Mutual Information (MI) [8-9,15,16,24,27]. These values are tabulated in Table I, II & III and results of Multi focused image fusion are shown in Figure 3.

## V. CONCLUSION

From the Table I, II & III and Figure 3, it is clearly evidence that ABF and FABF can also be used for multi focused image fusion. Comparing the quality metrics, Multi focused image fusion using SBF remains same for all methods. And also, Multi focused image fusion using SBF outperforms ABF and FABF in terms of RMSE. In terms of remaining quality metrics, FABF outperforms SBF and ABF. So, it is concluded that a multi focused image fusion based on ABF and FABF is proposed and these methods able to integrate useful information from input images to form composite images.

**Table I: Root Mean Square Error**

| Method | SBF | ABF | FABF |
|---|---|---|---|
| Method1 | **1.7324** | 3.3318 | 3.8187 |
| Method2 | **1.7324** | 4.0473 | 4.4708 |
| Method3 | **1.7324** | 3.9846 | 4.4193 |
| Method4 | **1.7324** | 3.6543 | 4.7495 |
| Method5 | **1.7324** | 3.7704 | 4.3307 |
| Method6 | **1.7324** | 5.7223 | 5.9934 |
| Method7 | **1.7324** | 3.8408 | 4.8688 |

**Table II: Spatial Frequency**

| Method | SBF | ABF | FABF |
|---|---|---|---|
| Method1 | 27.3013 | 27.2088 | **27.3692** |
| Method2 | 27.3013 | 27.3240 | **27.5454** |
| Method3 | 27.3013 | 27.2861 | **27.5100** |
| Method4 | 27.3013 | 27.1951 | **27.8054** |
| Method5 | 27.3013 | 27.2783 | **27.5970** |
| Method6 | 27.3013 | 28.4386 | **28.6284** |
| Method7 | 27.3013 | 27.9171 | **31.5187** |

**Table III: Mutual Information**

| Method | SBF | ABF | FABF |
|---|---|---|---|
| Method1 | 0.910422 | 0.9042 | **0.9044** |
| Method2 | 0.910422 | 0.9005 | **0.9007** |
| Method3 | 0.910422 | 0.9007 | **0.9009** |
| Method4 | 0.910422 | 0.9020 | **0.9021** |
| Method5 | 0.910422 | 0.9017 | **0.9020** |
| Method6 | 0.910422 | 0.8774 | **0.8917** |
| Method7 | 0.910422 | 0.9036 | **0.9150** |

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**FIGURE 3: RESULTS OF MULTI FOCUSED IMAGE FUSION USING METHOD7**

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