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ANALYSIS ON THE PERFORMANCE OF BILATERAL FILTERS IN MULTI FOCUSED IMAGE FUSION

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Abstract

Multi focused image fusion combines two or more images focusing different objects in the same scene to produce all-in-one focus image without artifacts and noises. Among two scale edge preserving filters used in multi focused image fusion, Bilateral Filters plays a vital role since it preserves edge information and avoids staircase effect. This paper analyses the performance of Standard Bilateral Filter (SBF) and its variant Robust Bilateral Filter (RBF) and Weighted Bilateral Filters (WBF) in fusing multi focused images in terms of Quality Index and Mutual Information.

Keywords:

Image Fusion, Multi focused Images, Bilateral Filters, Quality Index and Mutual Information

1. INTRODUCTION

Due to limited Depth of Field (DOF) in CCD and CMOS cameras used in industries, it is only possible to capture the clear image of the objects that are in focus. The remaining objects in the scene which are not in focus will be blurred. 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 an all-in-one focus image. This all-in-one focus image is called as Multi focus image. In this image, all objects in the scene will be in focus with clear visibility. This image provides a comprehensive information about the scene which is useful for human perception and machine vision applications.

A good multi focused image fusion method is expected to have the following properties:

- It should preserve useful and relevant information from multiple individual images in Multi focused image;
- It should not produce artifacts and noises; and
- It should be robust enough to perform above imperfect conditions like shifting, scaling, misregistration and noises.

Many literatures related to multi focus image fusion methods are reported by the research community, and yet there is a requirement for novel image fusion methods for feature extraction and target recognition. Among the literatures available for Multi focus image fusion, multi scale decomposition methods are very successful and are showing good results. They use different data representation and different image fusion rules to produce all-in-one focus image. But, in these methods, artifacts were introduced into the Multi focus image. To avoid these artifacts, optimization based fusion methods were proposed. Optimization methods took multiple iterations to generate Multi focus image which in turn removed the edge details.

To preserve edge details in the Multi focus image, edge preserving fusion methods were introduced. These methods use two scale decomposition edge preserving filter for the purpose of fusion. A popular two scale decomposition edge preserving filter is the anisotropic diffusion filter [18]. Though edge details are preserved by this filter, it reflects the staircase effect. To avoid this staircase effect during denoising, bilateral filter [21] [24] and Guided filter [8]-[10] were proposed.

Bilateral filters use the nonlinear combination of nearby image values to smooth images while preserving edges. It combines gray levels based on both geometric closeness and photometric similarity, and prefers near values to distant values in both domain and range. This paper compares and presents the performance of Standard Bilateral Filter (SBF) and its variant Robust Bilateral Filter (RBF) and Weighted Bilateral Filters (WBF) [1]-[3] in fusing multi focused images in terms of Quality Index and Mutual Information.

The ensuing sections of this paper are purposed as follows: Section 2 overviews SBF, RBF and WBF as proposed in [21]. Section 3 presents the multi focused fusion methodology. Section 4 discusses the performance of SBF, RBF and WBF. Finally, section 5 summarizes this paper along with the presentation of the conclusion.

2. OVERVIEW OF BILATERAL FILTER

Edge-preserving filters have been hot research topic in image processing recently. One of the most widely used filters to remove the noise while preserving edges is bilateral filter. Averaging filters and Gaussian filters work well in applications where the amount of noise present is small. However, when the noise present is large and it is required to average more pixels to remove the noise, the above two filters over-smooth sharp edges and corners. The over-smoothing can be avoided using anisotropic diffusion filter, where the amount of smoothing is controlled using the image features.

A classic example of anisotropic diffusion filter is the Partial Difference Equation based diffusion Filter developed by Perona and Malik [18]. An alternative to this diffusion filter is Bilateral Filter was proposed by Tomasi and Maduchi [21]. In this work, the suitability of Standard Bilateral Filter (SBF) which uses Gaussian kernel for range filtering and spatial filtering is studied. The output $f_{BF}(i)$ Bilateral Filtering of an input image $\{f(i){:}i\in I\}$, where I is some finite square or rectangular domain of Z^2 and is given by

$$f_{BF}(i)=\frac{\sum_{j\in\Omega} g_{\sigma_s}(j)\, g_{\sigma_r}\left(f(i-j)-f(i)\right) f(i-j)}{\sum_{j\in\Omega} g_{\sigma_s}(j)\, g_{\sigma_r}\left(f(i-j)-f(i)\right)} \tag{1}$$

where, $g_{\sigma_r}=\exp\left(-\frac{t^2}{2\sigma_r^2}\right)$ and $g_{\sigma_s}=\exp\left(-\frac{\|1\|^2}{2\sigma_s^2}\right)$

The Gaussian Kernels for range and spatial filtering consists of The spatial domain of Gaussian kernel in a square window, Ω

$= [-W,W] \times [-W,W]$ where $W=\sigma_s$. From the equation relating the input and output of Bilateral Filters, it is clear that direct computation of output requires $O(W^2)$ operations per pixel. To reduce this computational complexity, researchers came with several fast algorithms which are based on approximation which in turn provide compromise between speed and quality of approximation.

Chaudhury [1] presented a novel algorithm to decompose the bilateral filter into a series of spatial convolutions and this filter is called Robust Bilateral Filter (RBF). The fundamental difference between the earlier algorithms and RBF is that RBF algorithm directly approximates the translated Gaussians instead of approximating and then translating the approximation in range space.

The computational advantages obtained using RBF are:

a) For a fixed approximation order, RBF requires only half the number of spatial filtering required by the approximations in other fast filters.
b) RBF does not involve the transcendental functions. It involves only polynomials, in which, the rounding error is small and it may be efficiently implemented on hardware.

The output $f_{RBF}(i)$ Robust Bilateral Filtering of an input image $\{f(i): i\in I\}$, where I is some finite square or rectangular domain of Z^2 and is given by

$$f_{RBF}(i) = \frac{\sum_{j\in\Omega} g_{\sigma_s}(j)\, g_{\sigma_r}\left(\bar{f}(i-j) - \bar{f}(i)\right) f(i-j)}{\sum_{j\in\Omega} g_{\sigma_s}(j)\, g_{\sigma_r}\left(\bar{f}(i-j) - \bar{f}(i)\right)} \quad (2)$$

where, $\bar{f}(i) = \frac{1}{(2L+1)^2} \sum_{j\in\{-L,L\}} f(i-j)$

The amount of smoothing induced by the box filter is controlled by L and it is suggested that $L=1$ provides optimal results. Since RBF uses box filter as pre-processing, better performance may be achieved if SBF and RBF combined. The linear combination of these estimate results Weighted Bilateral Filter (WBF) whose output can be expressed as

$$f_{WBF} = \theta_1 f_{SBF} + \theta_2 f_{RBF},\ (i\in I) \quad (3)$$

The weights θ_1 and θ_2 can be done hypothetically by minimizing the MSE between f_{WBF} and $f(i)$.

3. PROPOSED METHODOLOGY

The proposed method to perform multi focused image fusion using bilateral filters needs three steps as shown in the Fig.1. In the first step, each input image is decomposed into approximation and detail images by employing edge preserving SBF, RBF and WBF. In the next step, approximation and detail images are fused by employing separate fusion rules and the different fusion methods are given below. Finally, the fused image is reconstructed by combining the final fused approximation and detail images.

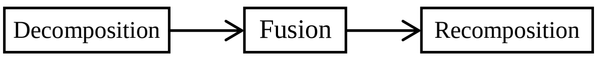

Fig.1. Method of Multi Focused Image Fusion

Let the source images be $In(x,y)$, 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 SBF, RBF and WBF. Each input image is decomposed into base layer and detail layer by bilateral filtering. The base layer of each input image is obtained by

$$B_n(x,y) = I_n(x,y)*Z \quad (4)$$

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

$$D_n(x,y) = I_n(x,y)-B_n(x,y) \quad (5)$$

The base layer consists of average image information called low frequency bands, whereas the detail layer consists edge information called as high frequency bands [11] [12] [17]. 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 Fig.2.

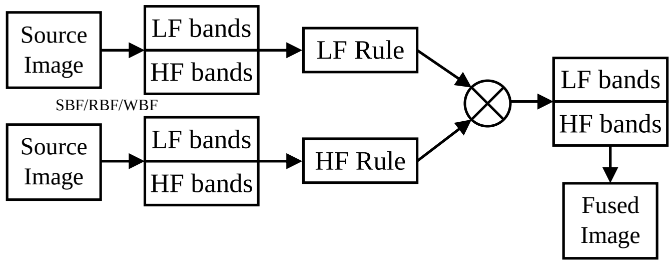

Fig.2. Proposed Multi Focused Image Fusion

Method 1: 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.

Method 2: In this method, the salience match measure based fusion rule is applied to the low frequency bands and high frequency bands. The salience of low and high frequency band is computed as a local energy in the neighbourhood of a coefficient. The salience of coefficient p of band A over a window is denoted as $E(A,p)$ and calculated as:

$$E(A,p) = \sum_{\phi=Q} W(q)\, C_j^2(A,q) \quad (6)$$

where $w(q)$ is a weight and $\sum_{\phi=Q} W(q) = 1$.

At a given decomposition level j, this fusion scheme uses two distinct modes of combination namely Selection and Averaging. In order to determine whether the selection or averaging is to be used, the match measure $M(p)$ is calculated as:

$$M(p) = \frac{2\sum_{\phi=Q} W(q)\, C_j(A,q)\, C_j(B,p)}{E(A,q)+E(B,p)} \quad (7)$$

If $M(p)$ 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. It is implemented as:

$$C_j(F,p)=\begin{cases}C_j(A,p),\ E(A,p)\geq E(B,p)\\ C_j(B,p),\ E(B,p)>E(A,p)\end{cases} \tag{8}$$

If $M(p)\geq T$, then averaging mode is used to form the composite coefficient. It is implemented as:

$$C_j(F,p)=\begin{cases}W_{\max}C_j(A,p)+W_{\min}C_j(B,p), E(A,p)\geq E(B,p)\\ W_{\max}C_j(B,p)+W_{\min}C_j(A,p),\ E(B,p)>E(A,p)\end{cases} \tag{9}$$

where,

$W_{\min}=0.5-0.5\left(\frac{1-M(p)}{1-T}\right)$ and $W_{\max}=(1-W_{\min})$.

A binary decision map is used to record the coefficient selection results. If the coefficient is from image '*A*', the logic value '1' is stored in the map. Otherwise, logic value '0' is stored. Then, consistency verification is applied to this binary decision map. The fused coefficient map is generated based on the new binary decision map.

Method 3: 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 maximum absolute value with consistency check as activity measure to fuse low frequency bands and high frequency bands.

Method 4: This method uses maximum value as activity measure to fuse low frequency bands and high frequency bands.

4. RESULTS AND DISCUSSIONS

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, RBF and WBF is implemented using MATLAB simulation package.

These approaches are tested with 10 pairs of input images [26]. One image of the pair focuses on the right side and the other image focuses on the left side of the scene. All test images are said to be registered spatially. The factors considered for analysis are Quality Index (QI) [13] [14] [25] and Feature Mutual Information values based on Gradient (FMIG) and Edges (FMIE) [22].

The results of Multi focused image fusion is given in Fig.3. The performance metrics Quality Index (QI) and FMIG and FMIE of Multi focused image fusion using SBF, RBF and WBF for all 10 sets of input images are shown in Table.1.

From the Table.1 it is inferred that Robust Bilateral Filter performs well for all sets of input images in terms of QI and MI. The impact of implementation RBF Filter is also examined using the time required for Multi focused image fusion by Intel Pentium Processor CPU4417U at 2.3GHz as given in Table.1.

(a) (b) (c) (d) (e)

Fig.3. Results of Multi Focused Image Fusion using SBF, RBF and WBF (a) Input Image 1 (b) Input Image 2 (c) Fused Image using SBF (d) Fused Image using RBF (e) Fused Image using WBF

Table.1. Results of Multi Focused Image Fusion using SBF, RBF and WBF

Method	**1**	**2**	**3**	**4**
Filter	**Quality Index**			
SBF	0.7712	**0.80668**	0.79296	**0.75458**
RBF	**0.7802**	0.80257	**0.79634**	0.74987
WBF	0.7567	0.79882	0.78639	0.73894
	Mutual Information based on Gradient			
SBF	0.5881	**0.62672**	0.63897	**0.56525**
RBF	**0.5887**	0.62564	**0.64804**	0.55679
WBF	0.5762	0.62155	0.63526	0.5577
	Mutual Information based on Edge			
SBF	0.8936	0.90465	0.90586	0.89293
RBF	**0.8996**	**0.90466**	**0.90711**	**0.89797**
WBF	0.8905	0.90379	0.90549	0.88925
	Computation Time (Sec)			
SBF	2.172114	2.163558	2.15405	2.278025
RBF	**1.770394**	**1.754973**	**1.736169**	**1.786256**
WBF	3.624585	3.612708	3.55498	3.62066

5. CONCLUSION

In this paper, we perform multi focused image fusion using bilateral filters. Initially, each input image is decomposed into approximation and detailed images by employing edge preserving SBF, RBF and WBF. Secondly, approximation and detail images are fused by employing separate fusion rules. Finally, the fused image is reconstructed by combining the final fused approximation and detail images.

The results show that the proposed method is effective in fusing the image with high quality index, mutual information based on gradient, mutual information based on edge and reduced computational time.

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