Image Pair Fusion using Weighted Average Method

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Abstract

Image fusion is a process of combining complimentary details from multiple input images such that the new image give more information and more suitable for the purpose of human visual perception. Noisy and Blurred image pairs have been considered as a solution to provide high quality images. In this paper it is proposed to decompose the input images into two layers namely the base layer and the detail layer and it fuses the input images by weighted average using the weights computed from the detail layer that are extracted from the input images using Cross Bilateral Filter (CBF).

Keywords: Base Layer, cross bilateral filter, detail layer, image fusion, multi focus, multi sensor, pixel significance

I. INTRODUCTION

Image fusion is a process of combining the relevant information from a set of images of the same scene into a single image and the resultant fused image will be more informative and complete than any of the input images. Input images could be multi sensor, multimodal, multifocus or multitemporal. There are some important requirements for the image fusion process [1], the fused image should preserve all relevant information from the input images and the image fusion should not introduce any artifacts which can lead to a wrong diagnosis. High camera gain or long exposure time can lead to noise or blurring artifacts on captured images. Even with state-of-the-art denoising and deblurring methods [2], [3], high-quality image acquisition in low lighting conditions remains a challenging problem. To solve this issue, various types of image pairs that are captured twice consecutively for the same scene have been widely used [4]–[5]. Noisy and blurred image pairs [3] can be acquired by controlling the amount of exposure; in other words, by using relatively short and long shutter speeds during shooting. In this way, an image captured with a short exposure will contain some noise but can avoid blurring artifacts, while an image captured with a long exposure will have blurring artifacts due to camera shake but will have clean color tones.

The image fusion methods can be divided into pixel-level, feature-level, and symbolic-level fusion methods [6], [7]. In pixel-level fusion methods, a fused image is generated by combining individual pixel or small regular regions of pixels from multiple input images based on fusion decision algorithms [8],[9]. In feature-level fusion methods, multiple input images are initially segmented into regions which are then fused according to various properties of all related regions [10], [11]. In symbolic-level fusion methods, abstractions are extracted from all input images followed by combining these abstractions to a fused image [6]. Feature-level fusion methods are also named region-based methods. Compared with pixel-level fusion methods, region-based fusion methods have a number of perceived advantages including reducing sensitivity to noise, decreasing artifacts or inconsistencies in the fused images, preserving significant features of the input images, and increasing flexibility in choosing intelligent fusion rules.

Generally, one image of a complex scene does not contain enough information because of limitations in the system. Like, it is difficult to get all the objects in focus in a single image due to limited depth of focus by optical lens of a CCD camera. But, a series of images obtained by progressively shifting the focal plane through the scenery can be fused with a best fusion rule to produce an image with a quasi-infinite depth of field. This gives rise to the problem of multifocus image fusion. Similarly, the images obtained by CCD camera give information only in visible spectrum whereas Infrared (IR) camera in IR spectrum, and hence, the multispectral data from different sensors often present complementary information about the region surveyed, scene or object. In such scenarios, image fusion provides an effective method to enable comparison, interpretation, and analysis of such data, as the fused image facilitates improved detection and unambiguous localization of a target (represented in IR image) with respect to its background (represented in the visible image). Hence, the fusion of IR and visual images is gaining momentum in surveillance applications.

A suitably fused representation of IR and visible images provides a human operator a more complete and accurate mental representation of the perceived scene, which results in a larger degree of situational awareness. Likewise in medical imaging, the MRI image shows brain tissue anatomy, whereas CT scan image provides details about bony structures. The integration of these medical images of different modalities into one image with the merits of both source images provides both anatomical and functional information, which is important for planning surgical procedure. The aim is to achieve better situation assessment and/or more rapid and accurate completion of a predefined task than would be possible using any of the sensors individually.

The objective of the paper is to improve the fusion performance by combining all the important visual information contained in the individual source images using the weights computed from the detail images of the cross bilateral filter (CBF).Here weights are computed by measuring the strength of details of detail layer.

II. RELATED WORK

Carper et al [12] describes multispectral image fusion based on intensity-hue-saturation method and that based on Laplacian pyramid mergers in Toet [13]. Haeberli [14] proposed multifocus image fusion uses the fact that the focused area of the image will have highest intensity compared to that of unfocused areas. Du [15] and Wang [16] exploited the energy compaction and multiresolution properties of a wavelet transform (WT) for image fusion. In Qu et al. [15], the medical images are fused based on the WT modulus maxima of input images at different bandwidths and levels. Ranjith and Ramesh [17] proposed lifting-based wavelet decomposition instead of convolution-based wavelet decomposition, to reduce the computational complexity with less memory requirements.

Li and Kwok [18] learnt image fusion by averaging approximation subbands of the source images which blurs the fused image and is reduced by combining approximation subbands based on the edge information present in the corresponding detail subbands. Here mean and standard deviation over 3 × 3 windows are used as activity measurement to find the edge information present in detail subbands. Hao and Arivazhagan [19] [20] proposed a pixel-level image fusion by decomposing the source images using wavelet, wavelet packet, curvelet and contourlet transform. Due to non ideal characteristics of the imaging systems, the source images will be noisy, and hence, fusion of these images requires a hybrid algorithm which addresses both image denoising and fusion. Shah [21] discusses the concept of contrast-based fusion of noisy images using discrete wavelet transform (DWT).

Tomasi and Manduchi [22] introduced the concept of bilateral filter which has many applications in image denoising, flash photography enhancement, image/video fusion and so on. Petschnigg [23] and Eisemann [24] proposed a variant of BF, Joint/Cross BF, which uses a second image to shape the filter kernel and operate on the first image, and vice versa. Both of these papers address the problem of combining the details of images captured with and without flash under ambient illumination. Kotwal and Chaudhuri [25] proposed the application of BF for hyperspectral image fusion which separates the weak edges and fine textures by subtracting the BF output from the original image. The magnitude of this difference image is used to find the weights directly.

III. PROPOSED METHOD

For blurred and noisy image pairs, the proposed image fusion algorithm decomposes the input image pairs into base layer and detail layer and directly fuses two source images of a same scene using weighted average. The proposed method differs from other weighted average methods in terms of weight computation and the domain of weight average. The weights are computed by measuring the strength of details in a detail layer obtained by subtracting Cross bilateral filter (CBF) output from original image. The weights computed are multiplied directly with the original source images followed by weight normalization.

A. *Cross Bilateral Filter (CBF).*

Bilateral filter is a non-linear, edge-preserving and noise-reducing smoothing filter for images. The intensity value at each pixel in an image is replaced by a weighted average of intensity values from nearby pixels. This weight can be based on a Gaussian distribution. Crucially, the weights depend not only on Euclidean distance of pixels, but also on the radiometric differences (e.g. range differences, such as color intensity, depth distance, etc.). This preserves sharp edges by systematically looping through each pixel and adjusting weights to the adjacent pixels accordingly.

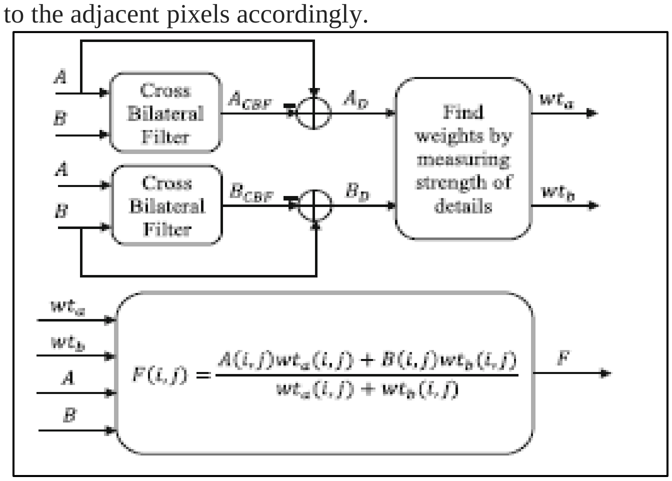

Fig. 1: Weight computation for the proposed image fusion framework

B. Detail Image.

The detail image is obtained by subtracting CBF output from the respective original images. For image A and B the detail image is given by

$$A_D = A - A_{CBF} \qquad (1)$$
$$B_D = B - B_{CBF} \qquad (2)$$

where A_D and B_D is the detail image of image A and image B and A_{CBF} and B_{CBF} are the cross bilateral filter output images of image A and image B.

In multifocus images, unfocused area in image A will be focused in image B and the application of CBF on image B will blur the focused area more compared to that of unfocused area in image B. This is because the unfocused area in image A anyway looks blurred with almost similar gray values in that area thereby making the filter kernel close to Gaussian. Now, the idea is to capture most of the focused area details in detail image B_D such that these details can be used to find the weights for image fusion using weighted average. Similarly, in multi-sensor images, the information in image B is absent in image A and the application of CBF on image B will blur the information in image B. This is because as the information in A is absent, the gray levels in that region has similar values thereby making the kernel as Gaussian.

Fig. 2: Simulated multifocus lady source images in (a) and (b), CBF output images in (c) and (d), and detail images in (e) and (f).

A window of size W×W around a detail coefficient $A_D(i,j)$ or $B_D(i,j)$ is considered as a neighborhood to compute its weight. This neighborhood is denoted as matrix X. Each row of X is treated as an observation and column as a variable to compute unbiased estimate $c_h^{i,j}$ of its covariance matrix [15], where i and j are the spatial coordinates of the detail coefficient $A_D(i,j)$ or $B_D(i,j)$.

$$\text{Covariance}(X) = E[(X - E[X])(X - E[X])^T \qquad (3)$$

$$c_h^{i,j} = \frac{\sum_{K=1}^{W}(x_k - x^-)(x_k - x^-)^T}{(W-1)} \qquad (4)$$

where x_k is the k-th observation of the w-dimensional variable and x^- is the mean of the observations. It is observed that the diagonal of matrix $c_h^{i,j}$ gives a vector of variances for each column of matrix X. The Eigen values of matrix $c_h^{i,j}$ is computed and the number of Eigen values depends on size of $c_h^{i,j}$. Sum of these Eigen values are directly proportional to horizontal detail strength of the neighborhood and are denoted as HdetailStrength. Similarly, an unbiased covariance estimate $c_v^{i,j}$ is computed by treating each column of X as an observation and row as a variable (opposite to that of $c_h^{i,j}$), and the sum of Eigen values of $c_v^{i,j}$ gives vertical detail strength VdetailStrength. The weight given to a particular detail coefficient is computed by adding these two respective detail strengths. Therefore, the weight depends only on the strength of the details and not on actual intensity values.

$$\text{wt}(i,j) = \text{HdetailStrength}(i,j) + \text{VdetailStrength}(i,j) \qquad (5)$$

IV. RESULTS

The proposed method is applied to two input images. In input 1 the foreground pixels (flower) is more clear compared to background pixels (leaf). In input image 2 the background pixels (leaf) is more clear compared to foreground pixels (flower).

The fusion of these two input images give a better high quality image which includes both foreground and background pixels more clear compared to input images.

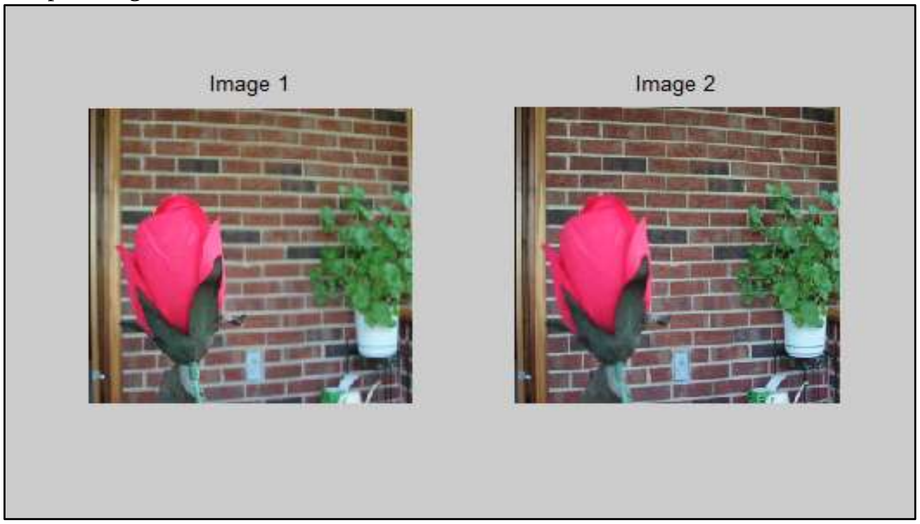

Fig. 3: Input images

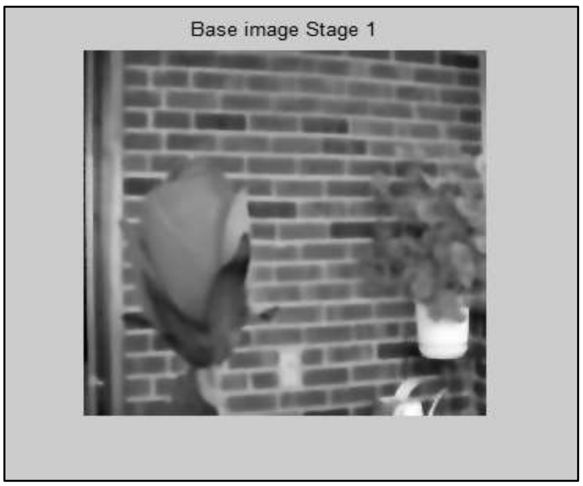

Fig. 4: Base image of input image1

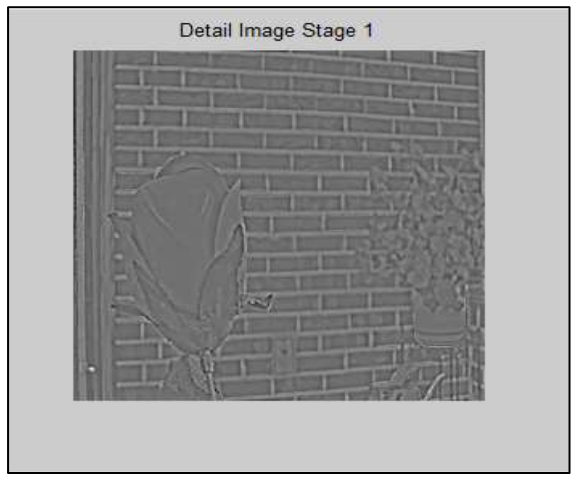

Fig. 5: Detail image of input image 1

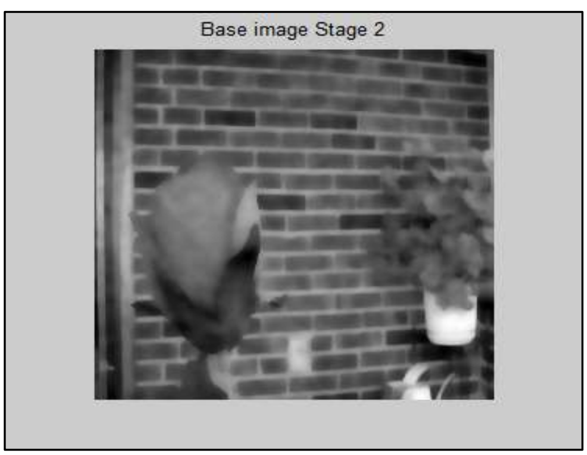

Fig. 6: Base image of input image 2

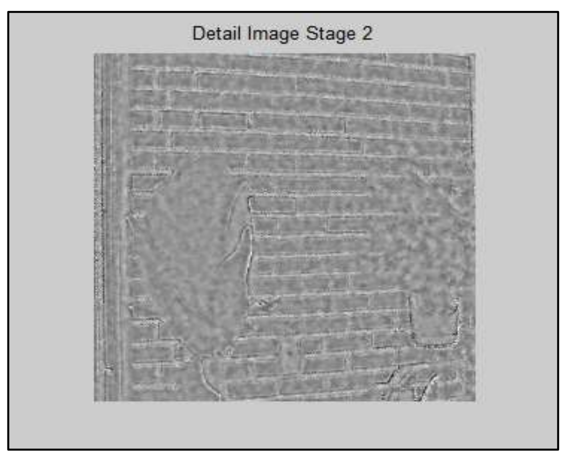

Fig. 7: Detail image of input image 2

Fig. 8: Weight image of input image 1

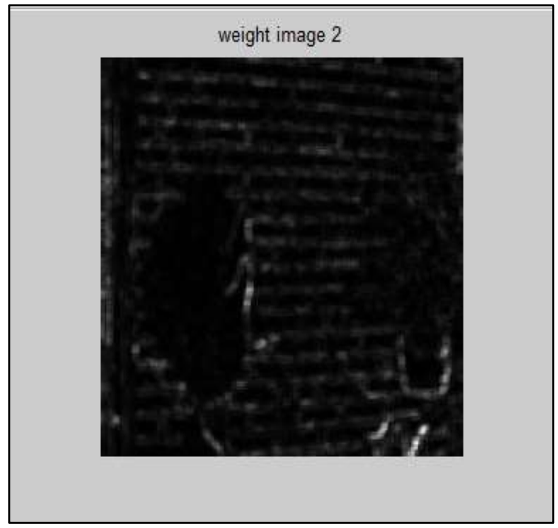

Fig. 9: Weight image of input image 2

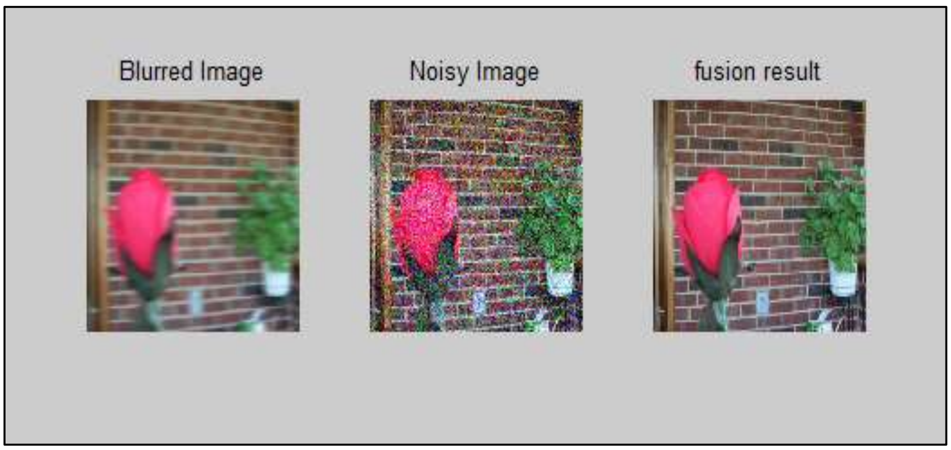

Fig. 10: Fused image by proposed method.

The general requirement of an image fusing process is to preserve all valid and useful information from the source images, while at the same time it should not introduce any distortion in resultant fused image. Performance measures are used essential to measure the possible benefits of fusion. Performance measures such as Peak Signal to Noise Ratio (PSNR), Average Pixel Intensity (API), Standard Deviation (SD) and Average Gradient (AG) is calculated for the fusion output.

Table – 1
Performance measures for the proposed method.

Parameters	*Proposed method*
Peak signal to noise ratio (PSNR).	*37.44*
Average Pixel Intensity (API).	*108.93*
Standard Deviation (SD).	*9.26*
Average Gradient (AG).	*11.61*

V. CONCLUSIONS

In this paper, it was proposed to fuse blurred image and noisy image by using detail images extracted from the source images by CBF for the computation of weights .The application of other nonlinear filters instead of CBF for detail image extraction is left as future work and will inspire further research toward image fusion. Also, the performance of the proposed method could be improved by exploring the other methods of weight computation and the domain of weighted average to reduce the fusion artifacts. Further, it can be extended to fuse multiple source images.

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