Multi-Focus Image Fusion Using Variance Based Spatial Domain and Wavelet Transform

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Abstract— **Image fusion combines information from multiple images of the same scene to get a composite image that is more suitable for human visual perception or further image-processing tasks. In this paper, we present a novel hybrid approach for multi-focus image fusion using traditional Discrete Wavelet Transformation (DWT) and a variance based spatial domain fusion method. Some evaluation measures are suggested and applied to compare our method with those of fusion based on spatial domain method and WT-based one. The PSNR and the correlation function and WT-based one. The PSNR and the correlation coefficient value indicate that the performance of the proposed method is better than others. It also enhances the visual effect.**

INTRODUCTION

Image fusion is a process of integrating complementary information from multiple images of the same scene such that the resultant image contains a more accurate description of the scene than any of the individual source images. The image focusing everywhere contains more information than those which just focus one object [1]. This kind of images is useful in many fields such as digital imaging, microscopic imaging, remote sensing, computer vision and robotics. Unfortunately, optical lenses, particularly those with long focal lengths, suffer from the problem of limited depth of field. It is impossible to get an image in which all containing objects appear sharp. The objects in front of or behind the focus plane would be blurred. A popular way to solve this problem is image fusion, in which one can acquire a series of pictures with different focus settings and fuse them to produce an image with extended depth of field. In broad sense image fusion is performed at three different processing levels according to the stages at which the fusion takes place, namely pixel level fusion, feature level fusion and decision level fusion [2].

Image fusion at pixel level means fusion at lowest level, referring to the merging of measured physical parameters. It generates a fused image in which each pixel is determined from a set of pixels in various sources and serves to increase the useful information content of a scene such that the performance of image processing task such as segmentation and feature extraction can be improved.

Feature level fusion first employs feature extraction for example by segmentation procedures separately on each source image and then performs a fusion based on the extracted features. Those features can be identified by characteristics such as contrast, shape, size and texture.

Symbol level fusion allows the information from multiple images to be effectively used at highest level of abstraction. The input images are usually processed individually for information extraction and classification.

In the past decades, pixel-level image fusion has attracted a great deal of research attention. Generally, these algorithms can be categorized into spatial domain fusion and transform domain fusion [2]. The spatial domain techniques fuse source images using local spatial features, such as gradient, spatial frequency, and local standard derivation [1]. For the transform domain methods, source images are projected onto localized bases which are usually designed to represent the sharpness and edges of an image. Therefore, the transformed coefficients (each corresponds to a transform basis) of an image are meaningful in detecting salient features [5].

In spatial domain multi-focus image fusion (SDMIF) algorithm [12] the fundamental idea is that a fused image is constructed by choosing the sharper image blocks within the source images. The methods involved in this algorithm are shift-invariant and can avoid the problem of moving objects and mis-registration of source images. SDMIF techniques require an analytic criterion function to evaluate the sharpness of the blocks of the source images.

The wavelet transform offers certain advantages over the other transform domain techniques. It provides directional information and supply spatial orientation in the decomposition [6]. Moreover since wavelet basis functions are chosen orthogonal, the information of each layer of decomposition is unique. Thus it appears to be an efficient information preserving method from implementation point it

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incorporates mismatch in contrast of the corresponding components. So the proposed fusion scheme combines the efficacies of both transform (DWT) and spatial (Sharpness) domain based fusion schemes.

The paper is organized as follows. In section 2, we briefly introduce variance based spatial domain fusion scheme. The proposed fusion scheme is described in section 3. Section 4 contains the experimental results.

II. VARIANCE BASED SPATIAL DOMAIN IMAGE FUSION

The fundamental idea of this method is that it constructs a fused image by choosing the sharper image blocks within the source images (Fig.1). It requires an *analytic criterion function* to evaluate the sharpness of the blocks of the source images.

A. Criterion Functions

To measure the sharpness of focus in an image area, a metric or criterion of ‘‘sharpness” must be formulated. The level of defocus varies inversely with the amount of high frequency energy present in the spatial power spectrum. Most of the criterion functions make use of the amount of high frequency information in an image corresponding to edge information. Because well-focused images contain sharper edges, they would be expected to have higher frequency content than those that are defocused. As a result, this information can be exploited to measure the sharpness of an image. Spatial frequency [12], variance[12] and sum-modified Laplacian [12] are some of the criterion functions of which variance is used in this section .Let *f*(i,j) be the gray level intensity of the pixel (i,j):

The gray level image variance can also be employed as a criterion function and can be computed by subtracting the mean gray level intensity value from the gray level of each pixel. The focus measure in this case is computed as:

$$\mathrm{VAR} = \frac{1}{\mathrm{M \times N}} \sum_{\mathrm{i}} \sum_{\mathrm{j}} (f(\mathrm{i,j}) - \bar{f})^2 \qquad (1)$$

Where $\bar{f}$ is the average gray level over the image region:

$$\bar{f} = \frac{1}{M \times N} \sum_i \sum_j f(i,j) \qquad (2)$$

III. PROPOSED HYBRID APPROACH OF IMAGE FUSION

This method merges the detail information of the two focused images and also preserves the spectral information of the source images. In this approach; fusion is done at pixel level. A prerequisite for successful image fusion is that the original images have to be registered correctly so that the corresponding pixels are co-aligned. Figure 2 is a framework illustration of image fusion based on DWT and spatial domain algorithm.

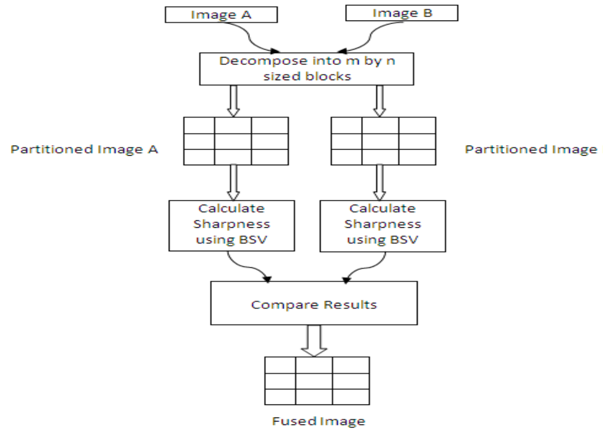

Figure. 1: Steps in Sharpness based Image Fusion

- In the initial step both the registered source images are processed through DWT , so we obtain low frequency approximate parts $S^k A(2^j; x, y), S^k B(2^j; x, y)$ and high frequency detail parts as $W_k^s A(2^j; x, y), W_k^s B(2^j; x, y)$ .J denotes the maximum decomposition level, k=1,2,3,4…..four decomposition parts of the resolution s.
- Thereafter, we have applied the sharpness based fusion technique for each of the detail part coefficients separately by considering each detail high frequency sub-image as a block.
- Let the *i*th detail sub-image blocks of A and B source images are referred to as A_i and B_i respectively.
- Then the criterion function on A_i and B_i can be applied for calculating the sharpness value of the blocks and the results of A_i and B_i are denoted as BSV_i^A and BSV_i^B respectively.
- The sharpness values of two corresponding blocks A_i and B_i are compared to determine the sharper image block and thus the high frequency detail parts after fusion is:

$$F_i = \begin{cases} A_i & \text{if } \mathrm{BSV}_i^A > \mathrm{BSV}_i^B \\ B_i & \text{if } \mathrm{BSV}_i^A < \mathrm{BSV}_i^B \\ (A_i + B_i)/2 & \text{otherwise} \end{cases} \qquad (3)$$

and the low frequency approximate part is

$$S^k(2^j; x, y) = k1S^k f(2^j; x, y) + k2S^k g(2^j; x, y) \qquad (4)$$

where k1, k2 are the weighted coefficients and they satisfy the equation k1+k2=1.

- Eventually the resulted image was obtained by transforming all frequency components of the fused image by inverse DWT transform.

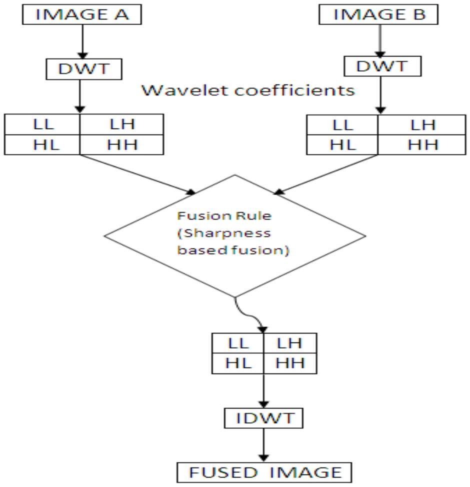

Figure. 2: Proposed Hybrid Approach of Image Fusion.

IV. EXPERIMENTAL RESULT AND PERFORMANCE COMPARISON

This approach takes into account at least two multi-focused source images. As a preprocessing condition, those images have to be co- registered using image to image registration process. This process ensures that the same pixel in both images refers to the same area. Then the two images are merged as per the fusion process explained in fig 2. In this paper, we have checked the performance of the proposed method over 2 pairs of different source images, of size512x512 namely, book and clock as shown in fig. 4, 5 and fig. 9, 10 respectively. The fused image using the proposed method is shown in fig 7 and 12, and the fused image using traditional variance based spatial domain method is fig 5 and 10; fig 6 and 11 is the fused image using pixel based WT fusion method. Some statistical parameters like PSNR, deviation constant and correlation coefficient are calculated as a factor of performance evaluation. Definition of those parameters are stated as follows

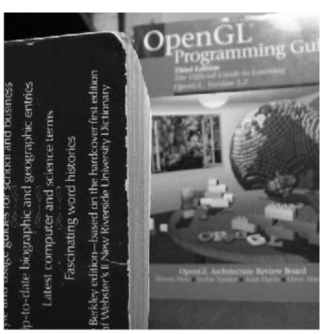
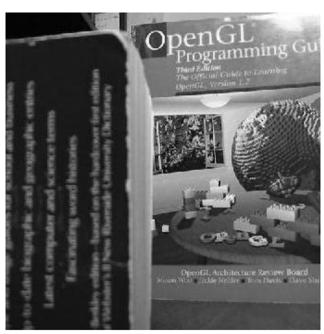

Figure.3, 4: Left focused and Right focused source book images.

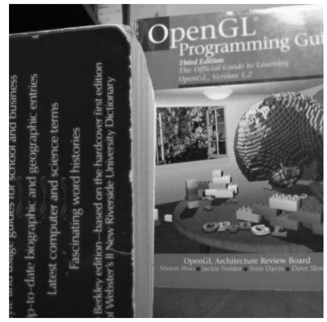
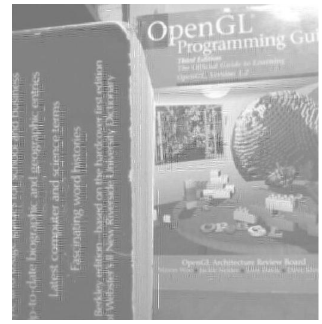

Figure. 5, 6: Fused images based on Sharpness and DWT approaches

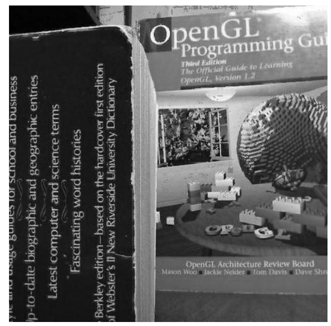

Figure.7:Hybrid fused image.

Figure.8: Left focused clock image

Fig.ure 9: Right focused clock image

Figure. 10: Sharpness based fused image

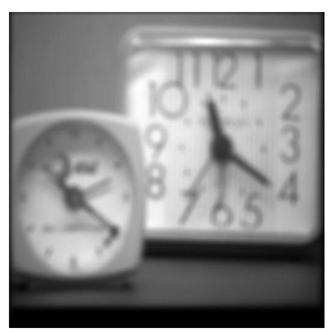

Figure.11:DWT based fused image

Figure.12:Hybrid fused image

1. Peak Signal to Noise Ratio (PSNR)

Quality assessment of fused images is traditionally carried out by visual analysis. So in this work we have taken peak to peak signal-to-noise ratio (PSNR). As pr this if R is the standard reference image and F is the fused image, the root mean square error is defined as

$$RMSE = \sqrt{\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left[R(i,j)-F(i,j)\right]^2}{M\times N}} \tag{5}$$

$$PSNR = 10\times \ln\left(\frac{p_{\max}\times p_{\max}}{RMSE^2}\right) \tag{6}$$

Where $p_{\max}$ is the maximum gray value of the pixels in the fused image. Thus bigger the value of PSNR, better the fusion process.

2. Deviation Index (DI):

It is defined as follows

$$DI = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{\left|I(i,j)-I'(i,j)\right|}{I(i,j)} \tag{7}$$

Where, I denotes the intensity value of the reference uniformly focused image and I' denotes the intensity value of the fused image in the position (i,j). The lesser the value of deviation index, better the fusion process.

3. Correlation Coefficients (CC):

It reflects the correlation extent between the original and fused image. It's defined as

$$C(f,g) = \frac{\sum_{i,j}\left[(f_{i,j}-\mu_f)\times(g_{i,j}-\mu_g)\right]}{\sqrt{\sum_{i,j}(f_{i,j}-\mu_f)^2\times\sum_{i,j}(g_{i,j}-\mu_g)^2}} \tag{8}$$

where $f_{i,j}, g_{i,j}$ denotes the gray value in the position (i,j) of the two fused and reference images and μ_f, μ_g is the mean of the two images respectively.

Table 1: Performance statistical parameters for book image

Method	PSNR	Correlation Coefficient	Deviation Index
Wavelet(DWT)	25.7203	0.9149	1.0084
Variance based spatial domain	36.1248	0.9793	0.1782
Proposed Hybrid	44.8914	0.9970	0.0140

Table 2: Performance statistical parameters for clock image

Method	PSNR	Correlation Coefficient	Deviation Index
Wavelet(DWT)	13.1262	0.9645	1.2564
Variance based spatial domain	32.7139	0.9926	0.9802
Proposed Hybrid	47.1393	0.9932	0.0475

V. CONCLUSION

The proposed algorithm preserves the spectral information in the fused image. This approach also merges the spatial details of the two images. So the performance of this fusion method is improved greatly as compared to other methods. The new algorithm not only enhances the fused image's ability to express the spatial details but also can preserve spectral information of the source image.

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