A Novel Fusion Method for Noisy Multifocused Images

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Abstract: This paper presents a novel multi focus image fusion approach, aiming at obtaining a fused image of multi focus images corrupted by noise. Focused objects or regions would usually be sharp and hold more information. On the other hand, defocused areas contain very less information which causes the effect of blurring and information loss in the image. However, in real time situation, images produced by sensors are normally contaminated by noise signals. In our proposed approach, Firstly, the noisy multifoused images are denoised by bilateral filter which preserves edges while smoothing the noisy images. Secondly, each denoised image is decomposed by Discrete Stationary Wavelet Transform (DSWT) approach in order to construct an intermediate fused image used to build the final fused image based on RMSE. By this method, the region to be selected for fusion is determined by comparing the Root Mean Square Error (RMSE) values of corresponding regions of the input images. Finally, the fused image with full focus can be obtained by using a binary matrix.

Keywords: multifocus, fusion, RMSE, DSWT, noise

1. Introduction

Image fusion is the process of producing a composite image constructed from one or more images and is widely used in several areas such as machine vision, medical, surveillance and military [3]. The primary aim of fusion is to obtain complete information that would be more powerful and more useful in human-machine interaction. Images captured by different sensors cannot be focused all areas in a scene due to the lack of limited depth of fields. So, same scene captured by different focal length provides two different images focused in different areas (Fig. 2). So, the de-focused area in the image results blurring effects. One possible solution to overcome this problem is a fusion of blurring and de-blurring images and which becomes more important research topic [2].

Focused objects or regions would usually be sharp and hold more information. On the other hand, defocused areas contain very less information which causes the effect of blurring and information loss in the image [9]. When the image is captured by the devices, points on the surface of the scene at a particular distance will not be focused by differing degree from the lens. Therefore, fusion over two or more defocused images of the same scene needs to be improved as everywhere-in-focus image [4].

In order to fuse the defocused images, plenty of approaches have been adopted based on pixel level fusion in which intensities are taken from source images to find local average. But, in this approach, the quality of fusion is degraded due to introducing side effects such as loss of contrast. To overcome this problem, recently, multiresolution based pyramids have been used such as Discrete Wavelet Transform (DWT) [10][3][6], Laplacian[6] and Gaussian pyramid [8]. In frequency domain, DWT is a well known popular method for image fusion. But, it introduces artifacts due to its characteristics of shift variance. So, an alternative, DSWT has widely been used. It is to DWT except that the signals are not sub sampled during the process of decomposition [12]. Moreover, the DSWT is shift –invariance, which causes the drawback in traditional DWT and Stationary Wavelet Transform (SWT) when relates to image fusion. Though the size of different sub-bands is similar, it is not much difficult to identify the relationships among them which are advantage

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of implementing fusion rules. Therefore, in this paper, DSWT is proposed to get an efficient multifocus fusion algorithm.

Although, it may different techniques, be in the literature, the source input images are considered to be noise free, but, indeed, in real time situation, images produced by sensors normally contaminated by noise signals. So, the input noisy images must be denoised before to fusion, because the noise can statistically degrade the quality of the focused regions.

Section 2 gives a short review of DSWT. The mechanism of edge preserving by the bilateral filter can be explained in section 3. The proposed fusion algorithm is given in section 4. Results and discussion are carried over in section 5.

2. Discrete Stationary Wavelet Transform

In this section, a stationary wavelet transform, a modified version of a DWT algorithm can be explained. The notion behind this is very simple. Before getting into DSWT method, in the wavelet domain, it is assumed that a dyadic sampling is referred by sets of dilation and translation factors of a signal. In a particular scale, number of operations can be involved to acquire a finite number of scaling and wavelet coefficients [1]. This can be represented in a signal decomposition which can be defined as

$$f(x)=\sum_{j} S_{ij}\phi_{ij}(x)+\sum_{i=1}^{i}\sum_{ij} w_{ij}\Psi_{ij}(x) \quad (1)$$

Where, S_{ij} and w_{ij} are scaling and wavelet coefficients respectively. In the above equation, the approximation is represented by lowpass subband in the first term and the detailed information is represented by highpass subbands in given from the original down to current resolution in the second term of the equation. During the decomposition, a process of eliminating one out of every row and columns, and making it half the original resolution is called down-sampling. When it is iterated, the size of the image is shifted into small called shift-variant; the overall system gets a pyramid shape. These two factors lead artifacts when come into the picture of image fusion.

To make a shift–invariant for DWT that means multiresolution without reducing the size of the image in the dilation process, it can be modified slightly and is called SWT. It is achieved through by making upsampling the filters by adding zeros among the smoothed coefficients. Therefore, the coefficients derived as one lowpass and three highpass subbands are having the same size with different resolutions. So, the structure, constructed in multiresolution decomposition shows as parallelepiped instead of pyramid shape. By applying the inverse transformation, the immediate previous approximation and scale can be obtained similar to forward construction but in the reverse orders.

3. Bilateral Filtering

Bilateral filtering presents an efficient direction to smooth an image while protecting its discontinuities. It provides a beneficial path to distill image structures of different scales [11]. In this process, smoothing can be achieved by a weighted average of neighborhood pixels through convolution in both spatial and range domains [5] in related to retrieve the edges. Basically, it derives from Gaussian low-pass filter and combines with an edge stop function. However, determining the weights of a pixel depends not only on nearby pixel values but also on the pixel's range values.

During the smooth function, the center pixel value x can be replaced by the Bilateral filter by

$$F_x=\frac{1}{n(x)}\sum_{x^1\in\Omega} g_s\left(\left\|x^1-x\right\|\right)g_r\left(I_p-I_{p^1}\right)I_{p^1} \quad (2)$$

where, n(x) is normalization factor and is exposed as

$$n(x)=\sum_{x^1\in\Omega} g_s\left(\left\|x^1-x\right\|\right)g_r\left(I_p-I_{p^1}\right) \quad (3)$$

In the above expression, for calculating weight, the distance between the pixels in the spatial domain is fixed by the function g_s, at the same time; the function g_r fixes the weight in the range domain. It is well known that the supreme quality of images can be acquired from bilateral smoothing response in determining the way how properly the parameters of domain and range would be assigned values [11]. By fluctuating the parameter values, different kind of images can be constructed with various spatial and spectral details such as cartoon and residual images. Increasing the value of domain

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parameter provide cartoon like images on the other hand, increasing the parameter value of range domain results over smoothed images.

To acquire more spectral information of the input image, the process of filtering by the bilateral filter can be performed repeatedly. The iteration process makes the result, almost piecewise invariant. Even though the bilateral filter results, smoother images, the result is not similar from enhancing the spatial and range arguments. The effect of enhancing spatial argument depends on the range argument. Unless either parameter is increased or decreased the rest cannot be affected.

To measure and calculate the error of the noisy image, which can be separated. During this process, a most knowledgeable residual image can be derived by performing a subtraction between noisy and filtered images. It is possible to make use of the residuals in terms of estimating, constructing noise model as well as retrieving fine details.

4. Proposed Multi Focus Image Fusion Method

As we know, the noise model required to restore the original image is defined by original and error images [2]. According to the noise model, if η represents noise in the location (x, y) of the original image $o(x, y)$ then the association among them results a noisy version $n(x, y)$ of the original image.

$$n(x, y) = o(x, y) + \eta(x, y) \tag{4}$$

In order to obtain the restored image from the noisy background, the most popular bilateral filter is noticed to be the best one for preserving edges in the images [11]. Therefore, we suggest bilateral filter to remove noise in the input images for the proposed multi-focus algorithm. In order to perform the intermediate fusion of multifocus images, wavelet based image fusion approach can be utilized to fuse the noise-free input images, previously, the corrupted version of the sources would be denoised by bilateral filter.

To reduce the complexity in deriving the intermediate fused image of the proposed method, a pictorial representation of the fusion scheme is illustrated in fig. 1. Where S_1 and S_2 are input images to be fused and F is an intermediate output image containing the sharp information from both different focus images. As the input images are corrupted by noise, it is essential to perform a pre-process. In pre-processing, the input images are denoised by bilateral filter. To get intermediate fusion, the denoised source images are decomposed into a low-pass subband and three high pass subbands by DSWT (Discrete Stationary Wavelet Transform) as more than one level. Each subband has different directions and scales. To retrieve the de-blurred information from the input images, selective fusion rules can be applied to fuse the low and high pass subband coefficients. At last, to obtain the intermediate fused image, the inverse DSWT can be employed to the coefficients derived from the former step.

When the image is involved in the DSWT multiresolution scheme, the input image is decomposed into a lowpass subband coefficient epresented the approximation of the input image and three highpass subband coefficients represented larger absolute values such as edges, linear lines, textures and curves. From this system, fusion can be conducted on both lowpass and highpass subband coefficients individually. In this method, average fusion rule, shown in eqn. (5), has been chosen for lowpass subbands for obtaining coarsest details and MAX-CHOOSE rule, exposes in eqn. (6), is determined for highpass subbands to obtain the high frequency details to be localized in fused coefficients.

$$L_F(x, y) = 0.5 * \left(D_1 L(x, y) + D_2 L(x, y)\right) \tag{5}$$

$$H_F^m(x, y) = \begin{cases} D_1 H^m(x, y) & if \quad \left|D_1 H^m(x, y)\right| \geq \left|D_2 H^m(x, y)\right| \\ D_2 H^m(x, y) & if \quad \left|D_1 H^m(x, y)\right| < \left|D_2 H^m(x, y)\right| \end{cases} \tag{6}$$

An intermediate fused image can be constructed using inverse DSWT. In order to perform multifocus image fusion, identifying focused regions in the source images is the most important task. Regarding this, the pixel similarity between the denoised images and the intermediate fused image is considered as pixels located in focused regions. Based on this assumption, it is possible to identify the focused regions of the denoised images by computing RMSE between the sources

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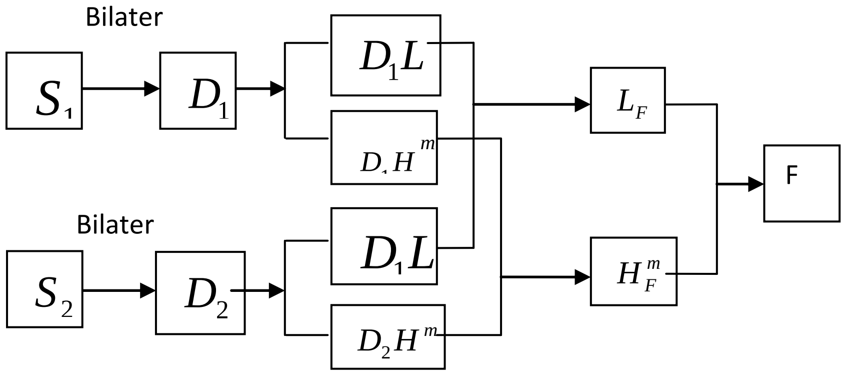

Fig. 1. Image fusion scheme for intermediate fused image

denoised images and the intermediate fused image. The value of RMSE can be calculated for denoised image a and b within a $M \times N$ window by

$$R_{D_1}(x,y)=\sqrt{\frac{\sum_{a=-M}^{M}\sum_{b=-N}^{N}\left(F(x+a,y+b)-D_1(x+a,y+b)\right)^2}{(2M+1)\times(2N+1)}} \qquad (7)$$

$$R_{D_2}(x,y)=\sqrt{\frac{\sum_{a=-M}^{M}\sum_{b=-N}^{N}\left(F(x+a,y+b)-D_2(x+a,y+b)\right)^2}{(2M+1)\times(2N+1)}} \qquad (8)$$

Where D_1, D_2 and F represent the pixel values at (x, y) of denoised images and intermediate fused image. A binary image can be built to determine which pixel is being focused on the source images by accomplishing a comparison between the two RMSE values.

$$Map(x,y)=\begin{cases}1 & if \quad R_{D_1}(x,y)\le R_{D_2}(x,y)\\ 0 & if \quad R_{D_1}(x,y)> R_{D_2}(x,y)\end{cases} \qquad (9)$$

In the binary array Map, the values 1 and 0 are used to indicate the selection of focused pixel from the source images. Logically, the value 1 direct the fusion system to pick the pixel from denoised image D1 and the value 0 leads the fusion system to select the focused pixel from the denoised image D_2. It indicates that the pixel with lowest RMSE is having more probability in focused region.

Along with a binary matrix contained label indicators of the focused image pixels which are obtained from the input denoised images, the final restored cum fused multi focused image can be constructed by

$$FF(x,y)=\begin{cases}D_1(x,y) & if \quad Map(x,y)=1\\ D_2(x,y) & if \quad Map(x,y)=0\end{cases} \qquad (10)$$

Where, Map represents as a label indicator, D_1, D_2 and the FF are the pixel values of the denoised input and final fused images at position (x, y). Here, FF contains the mutual information from both defocused images. The advantage of our fusion approach is that it is able to resolve fusion as well as restoration simultaneously.

5. Results and discussion

To evaluate the proposed approach, three pairs of multi focus input images with Gaussian noise, as shown in fig. 2, are used to examine the algorithm. In order to show the effectiveness of the proposed method, the traditional wavelet based multiresolution methods like DWT based method, LSWT based method and DSWT based method are employed for the purpose of comparison. In DWT based method, the noise images are smoothed by the 5×5 average window before the fusion done by DWT. At the same time, to acquire a fused image based on LSWT method, bilateral filter has previously been used to smooth the source corrupted images. The same procedure has been applied in fusing of the noise source images by the DSWT based method.

The first experiment is conducted on books image sets as shown in fig. 2, in which, the right side is focused, in the first image, the left side is focused in the second image. To contaminate the original image, Gaussian noise with 50 of a standard deviation is added to the book images for showing the excellent benefit of the proposed

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method. The denoised image using a bilateral filter is shown in fig. 3. Fig. 4 shows the fused versions of the comparison methods and proposed approach. The robustness of the proposed method can be seen visually by looking at the visibility of the letters on the books. The letters would not display clearly due to the blurring effects in DWT based fusion. In fact, the performance of the DSWT based method is quite better than the previous, but the letters are being displayed in overlapping manner and still noise has been retained in the result image. However the proposed method outperforms the DWT and DSWT method with respect to clearing noise as well as merging details of the sources.

In the second experiment, the clock source images, shown in fig. 2, focused right and left of the first and second input images respectively, are corrupted with Gaussian noise with standard deviation 20, which is shown in fig. 2. The noise removal images filtered by the bilateral are illustrated in fig. 3. while comparing with the other two methods, the fused image of the recommended method makes the image more brighter and free of noise which is demonstrated in fig. 4.

Fig. 2. Original and corrupted images
First Row: right focused book, left focused book and gaussian corrupted with sigma=50
Second Row: right focused clock, left focused clock and Gaussian corrupted with sigma=20
Third Row: right focused pepsi, left focused pepsi and Gaussian corrupted with sigma=30

The third experiment examined over the Pepsi multi focused images is conducted by adding Gaussian noise of standard deviation 30 to the original images blurred in two different places of the original images. The figure shows the noisy and denoised images respectively. The power of the proposed method's excellent edge preserving feature

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can be shown in fig. 4, where the barcode of the Pepsi tin can clearly visible without smudging in the fused image of the proposed method. But, the bar code displayed in the merged images of the other two approaches would slightly fat in terms of the overlapping manner of DSWT and slightly blur due to the information overload feature to DWT approach.

Fig. 3. Denoised images filtered by bilateral filter:
From top to bottom : noise-free book,noise-free clock and noise-free pepsi, respectively

In order to show the ability of the proposed method, some statistical metrics can be utilized in terms of highlighting the fusion results. In order to measure the information transferred from source images in fused image, the metric Mutual Information MI can be calculated between each input image and fused image. Q_{AB}^{F}, another important metric used to measure the edge details transferred to fused image is computed by the mathematical equation [11].

Fig. 4. Fused images of DWT-based, DSWT-based and proposed algorithms

$$Q_{AB}^{F} = \frac{\sum_{i=1}^{N}\sum_{j=1}^{M} Q^{AF}(n,m)W^{A}(n,m)Q^{BF}(n,m)W^{B}(n,m)}{\sum_{i=1}^{N}\sum_{j=1}^{M} W^{A}(i,j)+W^{B}(i,j)} \quad (11)$$

Generally, mean and standard deviation employed in the fused image to judge the standard image. A given M by N size image is involved to calculate standard deviation by the following equation which needs mean to be calculated earlier.

$$\sigma = \sqrt{\frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}\left(f(n,m)-\mu\right)^{2}} \quad (12)$$

In related with counting the number of information available in the fused image, entropy given in the equation format is used.

$$E = -\sum_{l=0}^{L-1} P_l \log_2 P_l$$

Table 1. Evaluation of Fusion Results

Images	Algorithms	Entropy	Mean	Std	MI	Q_{AB}^{F}	VIF
Book	DWT	7.4003	0.3310	0.2245	6.4716	0.5072	0.7098
	DCWT	7.4340	0.3322	0.2298	7.8356	0.5651	0.8257
	Proposed	7.4423	0.3424	0.2305	8.6650	0.5707	0.8435
Pepsi	DWT	7.0535	0.3764	0.1678	6.2895	0.4415	0.6579
	DCWT	7.0073	0.3831	0.1690	7.8893	0.4917	0.7019
	Proposed	7.0179	0.3934	0.1795	8.4583	0.5176	0.7232
Clock	DWT	7.3636	0.3793	0.1911	6.1524	0.4023	0.6504
	DCWT	7.3575	0.3815	0.1897	7.0092	0.4743	0.6866
	Proposed	7.3616	0.3918	0.1905	7.9760	0.4956	0.7096

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The examined values of mean, SD, entropy, MI and Q_{AB}^{F} of Fig. 4 are given in the table.1. The recommended method leads to the best operation and it exceeds the comparison methods in terms of reaching highest value of all the metrics except entropy. Because the nature of entropy is providing the number of information existed in the image. So, the DWT and DSWT based fusion image retain noise information along with original information. That is why the entropy value of the fused image in the proposed approach yields a less value than other two.

6. **Conclusions**

This paper provides a fusion algorithm for multi focus noisy images based on RMSE and DSWT. This algorithm proves that the performance of both the denoising and fusion can be superior to the comparison methods. In order to show the ability of the proposed method, plenty of parameters are employed in performance evaluation of the proposed algorithm with comparison algorithms. It exceeds the conventional state-of-art methods includes DWT and DSWT based methods in terms of visual as well as objective evaluation methods.

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