

Image Quality Enhancement Based on Fusion using Cross Bilateral filter and Wavelet Transform

Neelam Yadav, Abhinav Jain

SR Group of institution, Jhansi, Uttar Pradesh, India

ABSTRACT

The images are widely used in various applications such as medical field. The quality of images should be improved so that better image analysis can be predicted. For that, image fusion concept is one of the popular techniques, where images are improved using more than one similar images. In this paper, a technique is proposed based on the concept of image fusion. In proposed technique, two input images are used where cross bilateral filter and wavelet based fusion are processed. The cross bilateral filter is used in such a way so that most of the image features can be obtained and fused. Wavelet based fusion is performed based on the DCT and PCA. The proposed scheme is tested on various images. In experimental evaluation, the PSNR and mean square error are obtained to analyze the experimental results. From result analysis, it was analyzed that most of the times; the proposed scheme is giving better outcomes.

Keywords : Wavelet Transform, Image Fusion, Bilateral Filter.

I. INTRODUCTION

Digital images are very important in various applications such as medical field and others. If the quality of images are not up to mark then these kinds of images are referred as degraded images. These degraded images may have blurring problems which is not good for image analysis. There are various solutions to sort out this problem. Image fusion is one of the solutions to solve the problem of blurring [1].

The application of wavelet transform to multimodality medical image fusion was proposed by [2]. The result of image fusion is a single image which is more suitable for human and machine perception or further image-processing tasks. In [3-5], proposed a method for fusing multi-exposure images of a static scene taken by a stationary camera into an image with maximum information content. An image is considered best-exposed within an area if it carries more information about the area than any other image. Information content will be measured using entropy. The method partition the image domain into uniform blocks and for each block selects the image that contains the most

information within that block. A novel approach for solving the perceptual grouping problem in vision was rather than focusing on local features and their consistencies in the image data, in [6-8] approach aims at extracting the global impression of an image. In [9-10], proposed a novel approach for solving the perceptual grouping problem in vision. Rather than focusing on local features and their consistencies in the image data, our approach aims at extracting the global impression of an image. They treat image segmentation as a graph partitioning problem and propose a novel global criterion, the normalized cut, for segmenting the graph. The normalized cut criterion measures both the total dissimilarity between the different groups as well as the total similarity within the groups. In [11-12], described an adaptive and parameter-free image fusion method for multiple exposures of a static scene captured by a stationary camera.

With the motivation from wavelet transforms, the proposed scheme is designed to get the enhanced image from degraded images. This paper has the following structure: section 2 is about cross bilateral filtering, section 3 gives information on the proposed algorithm

employed for the fusion process, section 4 represents the results and discussion and section 5 concluded the paper.

II. METHODS AND MATERIAL

1. Cross Bilateral Filter:

Bilateral filtering is a local, nonlinear and non-iterative technique which combines a classical low-pass filter with an edge-stopping function that attenuates the filter kernel when the intensity difference between pixels is large. As both gray level similarities and geometric closeness of the neighboring pixels are considered, the weights of the filter depend not only on Euclidian distance but also on the distance in gray/color space. The advantage of the filter is that it smoothes the image while preserving edges using neighboring pixels. It can be mathematically expressed as:

$$A_F(p) = \frac{1}{W} \sum_{q \in S} G_{\sigma_s}(\|p - q\|) \times G_{\sigma_r}(|A(p) - A(q)|) A(q) \quad (1)$$

Where, $G_{\sigma_s}(\|p - q\|) = e^{-\frac{\|p - q\|^2}{2\sigma_s^2}}$ is the geometric closeness, $G_{\sigma_r}(|A(p) - A(q)|) = e^{-\frac{|A(p) - A(q)|^2}{2\sigma_r^2}}$ is gray level similarity and $W = \sum_{q \in S} G_{\sigma_s}(\|p - q\|) G_{\sigma_r}(|A(p) - A(q)|)$ is the normalization constant.

2. Proposed Architecture of Image Fusion

We have proposed a new approach for efficient and reliable image fusion in multi-focus images, which is a challenging task due to blurring effect.

The first aspect of this work is to use cross bilateral filter to get the sharp and smooth images over the both input images. Further, input images are subtracted from the bilateral filtered images. To more enhance results, Wavelet transform, where multi-scale analysis and extraction of features oriented in different directions are used. The decomposition level of the wavelet transform is decided by the imagery details which we need. In this work first level decomposition is satisfactory to preserve the details. The Second and important aspect of this work is to extract the features from *low frequency sub bands and high frequency sub bands using DCT and PCA*, respectively. Lastly, results are added with cross bilateral filtered images to gain the final outcome.

The propose scheme is processed using following steps:

Step 1: Two input images (X and Y) are taken which are defocused.

Step 2: Over the both input images, cross bilateral filter.

Step 3: Subtract outcome of step 2 with both input images.

Step 4: Over the both subtracted images, perform Wavelet Transform (DWT).

Step 5: Apply Discrete Cosine Transform (DCT) over the approximation parts of both input images.

Step 6: Compute average pixel by pixel of both DCT coefficients obtained by step 3.

Step 7: Apply Inverse Discrete Cosine Transform (IDCT) to obtain filtered approximation part.

Step 8: Perform PCA over the detail parts (LH1, HL1, HH1, LH2, HL2 and HH2) of both input images.

Step 9: Obtained principal components (PCs) of the detail parts are multiplied with their respective sub bands.

Step 10: Both modified detail parts are added with their respective sub bands to obtain filtered detail part.

Step 11: To obtain fused image, apply inverse DWT over filtered approximation parts (obtained from step 7) and filtered detail parts (obtained from step 10).

Step 12: Lastly, Perform addition of both results obtained from Step 2 and Step 11 and perform the average to get the final results as fused image.

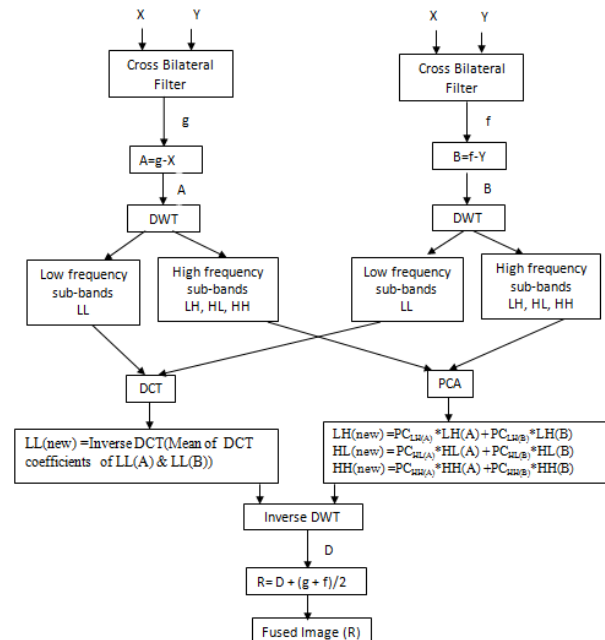


Figure 1: Block diagram for proposed method

III. RESULTS OF EXPERIMENT AND ANALYSIS

The proposed method is tested on various images of size 512×512 . The results are tested using images as shown in figs. 2(a)-(b), 3(a)-(b) and 4(a)-(b). In fig. 2-3, the images 2(a) and 3(a) are highly concentrated on the right part and 2(b) and 3(b) highly concentrated on left part. Whereas in fig. 4 (a) the image is focused on the front leaves and 4(b) is focused on background leaves. The noisy images are obtained by adding salt and pepper noise. Over the input images, the fusion is performed based on cross bilateral filter and DCT as discussed in proposed methodology. The resultant fused images of proposed scheme are shown in figs. 2(c), 3(c) and 4(c). The visual quality of results is good in compare of input images. To measure the quality of proposed scheme in terms of MSE and PSNR, the results are compared with existing schemes, as shown in table 1. For comparison, the existing schemes are DWT with maximum, DWT with minimum, DWT with average and DWT with PCA.

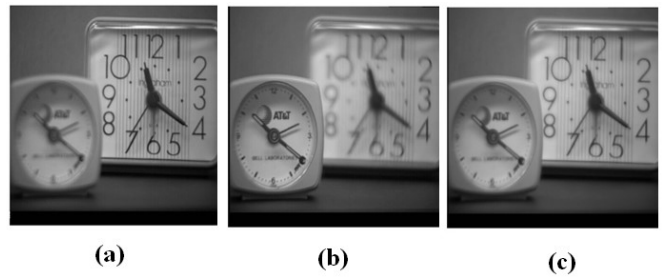


Figure 2: Clock images: (a) first input image (b) second input image (c) fused image

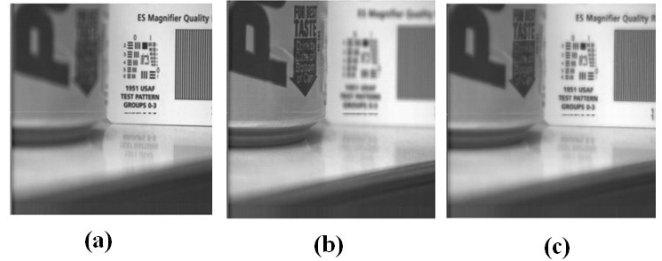


Figure 3: Pepsi images: (a) first input image (b) second input image (c) fused image

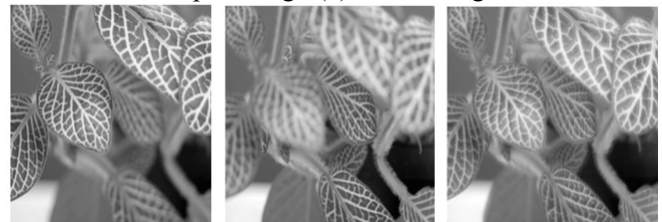


Figure 4 : Leaves images: (a) first input image (b) second input image (c) fused image

Table 1: PSNR and MSE

Input Images	Fusion methods	PSNR with first input image	PSNR with second input image	MSE with first input image	MSE with second input image
Clock (512x512)	DWT + maximum method	34.95	33.19	29.46	29.42
	DWT + minimum method	33.18	34.90	29.32	29.87
	DWT + average method	36.22	36.92	29.58	29.11
	DWT + PCA	36.04	36.90	29.35	29.33
	Proposed Method	38.01	37.88	28.11	28.01
Pepsi (512x512)	DWT + maximum method	35.91	37.10	29.77	29.08
	DWT + minimum method	36.99	35.89	29.37	29.73
	DWT + average method	39.04	39.42	29.41	29.22
	DWT + PCA	39.66	39.31	29.71	29.01
	Proposed Method	39.95	39.54	27.77	27.07
	DWT + maximum	28.69	31.34	30.21	29.34

	method				
Leaves (512x512)	DWT + minimum method	31.33	28.61	29.71	29.23
	DWT + average method	32.82	32.88	30.32	29.24
	DWT + PCA	32.58	32.84	29.34	29.24
	Proposed Method	34.17	34.25	27.64	27.31

Peak Signal to Noise Ratio (PSNR) is the ratio between the maximum possible value of a signal and the power of distorting noise that affects the quality of its representation. The PSNR is usually expressed in terms of the logarithmic decibel scale. Higher PSNR value indicate high quality image and our approach is to increase the PSNR.

$$PSNR = 10 \log_{10} \left(\frac{255^2}{MSE} \right)$$

$$MSE = \frac{1}{mn} \sum_{x=0}^{\infty} [I(i, j) - P(i, j)]^2$$

Where, $I(i, j)$ is the input image of size $m \times n$ and $P(i, j)$ is processed image.

IV. CONCLUSION

In this research work, attention was drawn towards the current trend of the use of multi-resolution image fusion techniques, especially approaches based on cross-bilateral filter. Due to cross-bilateral filter, results of fused images are very impressive in terms of sharp and smooth images. Similarly, DWT also helps to get results that are more accurate. PSNR and MSE also get good results for proposed methodology.

The number of decomposition levels in the Multi-resolution analysis has a great impact on image fusion performance. However, using more decomposition levels do not necessarily implies better results. Therefore, methods for selection of optimized number of decomposition levels can be explored.

V. REFERENCES

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