

An Efficient Adaptive Fusion Scheme for Multifocus Images in Wavelet Domain Using Statistical Properties of Neighborhood

Parul Shah, Shabbir N. Merchant
Department of Electrical Engineering
IIT Bombay, India
Email: parul,merchant@ee.iitb.ac.in

Uday B. Desai
Director
IIT Hyderabad, India
Email: ubdesai@iith.ac.in

Abstract—In this paper we present a novel fusion rule which can efficiently fuse multifocus images in wavelet domain by taking weighted average of pixels. The weights are adaptively decided using the statistical properties of the neighborhood. The main idea is that the eigen value of unbiased estimate of the covariance matrix of an image block depends on the strength of edges in the block and thus makes a good choice for weight to be given to the pixel, giving more weightage to pixel with sharper neighborhood. The performance of the proposed method have been extensively tested on several pairs of multifocus images and also compared quantitatively with various existing methods with the help of well known parameters including *Petrovic and Xydeas* image fusion metric. Experimental results show that performance evaluation based on entropy, gradient, contrast or deviation, the criteria widely used for fusion analysis, may not be enough. This work demonstrates that in some cases, these evaluation criteria are not consistent with the ground truth. It also demonstrates that *Petrovic and Xydeas* image fusion metric is a more appropriate criterion, as it is in correlation with ground truth as well as visual quality in all the tested fused images. The proposed novel fusion rule significantly improves contrast information while preserving edge information. The major achievement of the work is that it significantly increases the quality of the fused image, both visually and in terms of quantitative parameters, especially sharpness with minimum fusion artifacts.

Keywords: Image Fusion, Multifocus Images, Wavelet Transform.

I. INTRODUCTION

Due to the limited depth-of-focus of optical lenses in CCD devices, it is often not possible to get an image that contains all relevant objects 'in focus'. In order to view all relevant objects 'in focus', we have to change the focus setting of a camera to obtain a sequence of images that are differently focused. However, storing all these images consumes memory and correlation among different parts of the object is not direct. One way to overcome this problem is image fusion, in which several images with different focus points are combined to form a single image with all objects fully focused. During the fusion process, all the important visual information found in the input images must be transferred into the fused image without introducing any artifacts [1].

A lot of work has been done in area of multi-focus image fusion [2]- [8]. Several algorithms have been proposed for im-

age fusion for various other applications as well, mainly in the field of remote sensing and medical images [9]- [32]. In [14] fusion of visible and thermal images has been performed for surveillance application. In [15] cloud covering denoising is done through image fusion.

II. RELATED WORK

Image fusion can be as simple as taking pixel-by-pixel average of the source images, but that often leads to undesirable side effects such as reduced contrast. Fusion can broadly be classified as, fusion in frequency domain and in spatial domain. It can be implemented using various fusion rules e.g. '*mean*' or '*max*' where fused coefficient is average or maximum of source coefficients respectively. One can also take '*weighted average*' instead, where fused coefficient is weighted average of source coefficients as proposed by [2], [3].

Frequency domain algorithms can use transforms like Discrete Cosine Transform (DCT) or Discrete Fourier Transform (DFT). As long as the coefficients at each frequency are determined, inverse transform can be computed to construct the fused image in which all parts are focused. This type of algorithm can avoid the discontinuity in the transition zone, but it is computationally expensive. Besides, the frequency algorithm may also bring in so called artifacts such as Gibbs phenomenon. Various multiscale transforms based methods have been proposed, such as Laplacian pyramid, contrast pyramid, gradient pyramid, ratio-of-low-pass pyramid, discrete wavelet transform (DWT) [4], [11], [16]- [23].

In recent years, some extensions to the classical wavelet transform have been used for image fusion. The discrete multiwavelet transform based image fusion methods are proposed in [24], [25] for multisensor image fusion. Multiwavelet offers the advantages of combining symmetry, orthogonality, and variable support, which cannot be achieved by scalar two-channel wavelet systems at the same time. This method is suitable for hardware implementation because of its simple arithmetic operations, however, artifacts may be formed in the fused image. In [26] multisensor remote sensing image fusion using stationary wavelet transform is proposed whereas

[27] uses symmetric non-separable wavelet. Choi et al [9] proposed fusion of remote sensing images using Curvelet transform. Similarly, [32] and [14] have used weights based on local mean and energy to fuse medical and surveillance images respectively in wavelet-packet domain. Soad Ibrahim et. al [33] have fused surveillance images using contourlet using 'maximum' fusion rule. In [31], authors have taken weighted average in wavelet domain using fixed weights (0.6 for CT and 0.4 for PET) to fuse medical images. Yong Chai et al [12] also proposed CT and MRI image fusion using Contourlet. In [32] instead of wavelet, wavelet packet transform was used for medical fusion of CT and MRI images. In [14], authors have proposed fusion of surveillance images in infrared and visible band using curvelet, wavelet and wavelet packet transform.

Ishita De proposed a decomposition scheme which is based on a nonlinear wavelet constructed with morphological operations and presented a multifocus image fusion algorithm using this decomposition scheme [4]. S. Arivazhagan et. al [3] proposed a wavelet based fusion method for multifocus images using weighted average fusion rule in which, weights are based on local statistical features like mean and standard deviation. Shtao et al [2] proposed a method combining Curvelet and Wavelet transform for multifocus image fusion using 'maximum' fusion rule. The basic idea in all these transform based method is to perform a multiresolution decomposition on each source image, then integrate all these decompositions to form a composite representation, and finally reconstruct the fused image by performing an inverse multiresolution transform.

Fusion technique developed for one class of images can be investigated for other classes, but it may not perform equally well for them. In this work, besides comparing the proposed method with recently published multifocus fusion techniques, we have also compared it with methods earlier proposed for other class of images like medical and multispectral.

In this paper, we propose an effective algorithm especially for combining multifocus images of a scene by taking their *weighted average* in wavelet domain. The weights are decided adaptively using the statistical properties of the neighborhood. The main idea is that the eigen value of covariance matrix of an image block depends on the strength of edges in the block and thus makes a good choice for weight to be given to the center pixel, giving more weightage to pixel with sharper neighborhood.

The remainder of this paper is organized as follows. Section III describes the proposed fusion rule followed by the proposed fusion technique. All the evaluation indices used are illustrated in Section IV. The results and quality assessment are discussed in Section V. Conclusions are drawn in Section VI.

III. PROPOSED IMAGE FUSION SCHEME USING STATISTICAL PROPERTIES OF NEIGHBORHOOD

Fusion using weighted average has been proposed by many [2], [9], [12]- [14], but finding the optimum weights for

fusion is still a challenge. Here we propose to find weights adaptively using statistical properties of the neighborhood of the pixel/wavelet coefficient.

A. Proposed Novel Fusion Rule

To compute weight to be given to a pixel (i, j) , we consider its neighborhood by taking a window of size say $w * w$ around the pixel. For this work we experimented with $w = 3, 5, 7, 9$. We call this image block as matrix X . We then treat each row of X as an observation and column as a variable and compute unbiased estimate C_h of its *covariance* matrix [30].

$$\text{covariance}(X) = E((X - E(X))(X - E(X))^T) \quad (1)$$

$$C_h = \frac{\sum_{i=1}^w (x_i - \bar{x})(x_i - \bar{x})^T}{(w - 1)} \quad (2)$$

Where x_i is the i -th observation of the w -dimensional variable and \bar{x} is the mean of observations. Diagonal of matrix C_h is a vector of variances for each column of matrix X . Now we calculate *eigenvalues* of matrix C_h . As the size of C_h matrix is $w * w$, there are w eigen values. Authors observed that sum of these w eigen values is directly proportional to the strength of horizontal edges of the image block, so we call this sum *edgeStrength_h*. To take care of vertical edges, we now treat each column of X as an observation and row as a variable and compute unbiased estimate C_v of its *covariance* matrix and then eigen values of matrix C_v . Sum of these eigen values *edgeStrength_v* is measure of strength of vertical edges. Now we take sum of *edgeStrength_h* and *edgeStrength_v* as the weight to be given to the pixel into consideration as shown below. This way the weight depends only on the strength of the edges and not the actual intensity values.

$$\text{edgeStrength}_h = \sum_{i=1}^w \text{eigen}_i \text{ of } C_h \quad (3)$$

$$\text{edgeStrength}_v = \sum_{i=1}^w \text{eigen}_i \text{ of } C_v \quad (4)$$

$$(5)$$

$$\text{weight} = \text{edgeStrength}_h + \text{edgeStrength}_v \quad (6)$$

where eigen_i is the i^{th} eigen value of the unbiased estimate of *covariance* matrix. Once the weights for all the pixels for both the registered source images are computed, we take the weighted average of both to get the fused image pixel.

Let weight_a and weight_b be the weight for the pixels at position (i, j) of source *imageA* and *imageB* respectively, then fused pixel value is computed as shown in Equation 7.

$$f(i, j) = \frac{a(i, j) * \text{weight}_a + b(i, j) * \text{weight}_b}{(\text{weight}_a + \text{weight}_b)} \quad (7)$$

Here $a(i, j)$ and $b(i, j)$ are intensity value of pixel at position (i, j) of *imageA* and *imageB* respectively and $f(i, j)$ is the intensity of fused pixel.

B. Proposed Wavelet Domain Fusion Scheme (WDF)

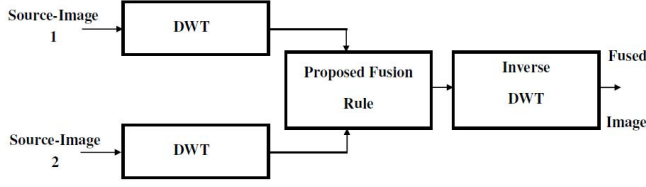


Fig. 1. Proposed Wavelet Domain Fusion

As shown in Fig. 1 both the source images are first subjected to decomposition using discrete wavelet transform till level 3, giving us one approximate and nine detail bands. Now each coefficient of all the bands, is fused using fusion rule discussed in section III-A to get fused image in wavelet domain; inverse wavelet transform of which eventually gives fused image in spatial domain.

IV. QUANTITATIVE EVALUATION INDICES OF IMAGE FUSION

Generally, fusion is a complex process of information transfer and information representation. A fusion artifact introduced into the fused image by the fusion process could lead to a benign object being classified as a threat or a valid target; so an efficient fusion method is one that introduces minimum artifacts. Performance evaluation of fusion is a challenge as in most of the applications, ground truth is not available. Researchers have used and proposed various parameters [1]-[36], *Petrovic Metrics* being one of the recent one [34]. To make the exhaustive study, we have considered several classical evaluation parameters so far reported in literature, which are as follows:

- 1) *Average Pixel Intensity (API)* or mean (\bar{F}): an index of contrast.
- 2) *Average Gradient (\bar{G})*: a measure of sharpness and clarity degree.
- 3) *Spatial Frequency (SF)*: a measure of sharpness and clarity degree.
- 4) *Standard Deviation (SD)*: this is the square root of the variance, which reflects the spread in the data.
- 5) *Entropy (H)*: an index to evaluate the information quantity in an image.
- 6) *Mutual Information (MI)* or *Fusion Factor*: a measure of correlative information content in fused image with respect to source images.
- 7) *Fusion Symmetry (FS)* or *Information Symmetry*: an indication of how much symmetric the fused image is with respect to source images.
- 8) *Normalized Correlation (CORR)*: a measure of relevance of fused image to source images.
- 9) *Petrovic Metric Parameter Q_{ABF}* : an index of edge information preservation.
- 10) *Petrovic Metric Parameter L_{ABF}* : a measure of loss of edge information.

- 11) *Petrovic Metric Parameter N_{ABF}* : a measure of noise or artefacts added due to fusion.
- 12) *Mean Square Error (MSE)*: an index of how close is fused image to the ground truth; as ground truth is not available in real life scenario, one can compute this only in simulated environment.

The first eight parameters are computed using equations 8 to 17, assuming $(m \times n)$ image size. All the *Petrovic Metrics* are computed as described in [34].

$$API = \bar{F} = \frac{\sum_{i=1}^m \sum_{j=1}^n (f_{i,j})}{m \times n} \quad (8)$$

Here $f_{i,j}$ is pixel intensity for position (i, j) of image F .

$$\bar{G} = \frac{\sum_i \sum_j ((f_{i,j} - f_{i+1,j})^2 + (f_{i,j} - f_{i,j+1})^2)^{1/2}}{m \times n} \quad (9)$$

$$Entropy = - \sum_{f=0}^{255} p_F(f) \log_2 p_F(f) \quad (10)$$

Where $p_F(f)$ stands for probability of intensity value f in image F .

$$MI_{AF} = \sum_a \sum_f p_{A,F}(a, f) \log_2 \frac{p_{A,F}(a, f)}{p_A(a) p_F(f)} \quad (11)$$

$$MI_{BF} = \sum_b \sum_f p_{B,F}(b, f) \log_2 \frac{p_{B,F}(b, f)}{p_B(b) p_F(f)} \quad (12)$$

$$MI_{AB}^F = MI_{AF} + MI_{BF} \quad (13)$$

MI_{AF} and MI_{BF} quantify mutual information between source image A and fused image F and, source image B and fused image F respectively. MI_{AB}^F is measure of overall mutual information between source images and fused image.

$$FS = 2 - |MI_{AF} / (MI_{AF} + MI_{BF}) - 0.5| \quad (14)$$

$$r_{AF} = \frac{\sum_i \sum_j (a_{(i,j)} - \bar{A})(f_{(i,j)} - \bar{F})}{\sqrt{((\sum_i \sum_j (a_{(i,j)} - \bar{A})^2) (\sum_i \sum_j (f_{(i,j)} - \bar{F})^2))}} \quad (15)$$

$$r_{BF} = \frac{\sum_i \sum_j (b_{(i,j)} - \bar{B})(f_{(i,j)} - \bar{F})}{\sqrt{((\sum_i \sum_j (b_{(i,j)} - \bar{B})^2) (\sum_i \sum_j (f_{(i,j)} - \bar{F})^2))}} \quad (16)$$

Here r_{AF} and r_{BF} represents normalized correlation between source image and fused image, and *CORR* stands for overall average normalized correlation.

$$CORR = (r_{AF} + r_{BF})/2 \quad (17)$$

As the ground truth is not available; it is difficult to get exact measure of how close the fused image is to an optimum solution. So to be sure of performance of our method, along with fusing some standard real life multifocus image pairs, we have also fused some simulated multifocus image pairs. For generating these simulated multifocus images, we first took a well focused image which can be used as the 'ground truth' (*GT*) and created two masks, one for the foreground and one for the background. Then to generate first simulated multifocus

source image, we blurred the background using Gaussian blur keeping foreground in focus and for second source image we kept original background in focus and blurred the foreground. As these pairs were generated using a well focused image, the original image can now be used as ground truth and so for these images we could also compute *Mean Square Error* (*MSE*) using equation 18, where error between fused image *F* and original image is computed.

$$MSE = \left(\frac{\sum_{i=1}^m \sum_{j=1}^n (f_{i,j} - Original_{i,j})^2}{m \times n} \right) \quad (18)$$

Theoretically, for parameters 1 to 9: higher the value, better is the quality of fused image; whereas for remaining parameters (L_{ABF} , N_{ABF}): lower the value, better is the quality.

V. EXPERIMENTAL RESULTS AND ANALYSIS



Fig. 2. Multifocus 'book' Source Images (a) image1 (b) image2



Fig. 3. Simulated Multifocus 'lena' Source Images (a) image1 (b) image2

Results of fusion using the proposed method with different window size w are compared with eleven existing techniques. First method is a simple spatial domain average, where fused pixel is average of source pixels. Wavelet (*DWT*) [3] and Curvelet-Wavelet (*CVT - DWT*) [2] are two of the best recent methods of multifocus image fusion. *DWT* [31] and Wavelet Packet (*DWPT*) [32] are methods used for medical image fusion, whereas *DWPT* [14] and Contourlet (*CNT*) [33] are methods for fusing multispectral surveillance images. Besides these, we have also compared the results with fusion using *DWT*, *DWPT*, curvelet (*CVT*) and *CNT* with '*mean-max*' fusion rule where for low frequency coefficients



Fig. 4. Fused 'lena' Image using Proposed Method for Different Window Size

average, and for high frequency coefficient maximum of the source coefficients is taken as the fused coefficient [14].

We have experimented with several standard test pairs of multifocus images provided by online resource for research in image fusion (ImageFusion.org). However, as the results were consistent with all test images, in this paper, results of only one of the pairs namely 'book' shown in Fig. 2, are discussed and tabulated (Table II). We have also generated our own database of ten simulated multifocus image pairs by processing well focused images, so that for these pairs ground truth can be made available and performance evaluation can be complete in true sense. One of such pair generated from well-known 'lena' image (size 512×512), is shown in Fig. 3. After fusing all ten pairs, average of all evaluating parameters were computed for comparison which is given in Table I. Resultant fused image of the proposed methods, with different window size, are as shown in Fig. 4 and 5. Quantitative results for all window size between 3 to 9, are given in Table I and II. We have also computed evaluation parameters assuming ground truth as the fused image, listed in the first row of Table I. This can be used as the reference for comparison for results obtained with simulated multifocus image pairs.

Existing Contourlet based fusion methods, has the highest value for *Gradient* indicating the sharpest fused image, but both the methods also have the highest *MSE* value as can be seen in the Fig. 6. This clearly shows that the *Gradient* can not be a good measure of performance always, as its value

TABLE I
PERFORMANCE COMPARISON FOR SIMULATED MULTIFOCUS IMAGE PAIRS

	<i>API</i>	<i>SD</i>	\bar{G}	<i>H</i>	<i>MI</i>	<i>FS</i>	<i>CORR</i>	Q_{ABF}	L_{ABF}	N_{ABF}
<i>Ground – truth</i>	124.109	47.94	8.93	7.45	6.17	1.844	0.979	0.77	–	–
<i>Average</i>	124.111	45.41	5.26	7.36	5.24	1.88	0.988	0.575	0.422	0.0003
<i>DWT</i> _(mean-max) [14]	124.115	47.01	9.25	7.44	5.21	1.924	0.979	0.66	0.256	0.18
<i>DWT</i> [3]	124.204	47.48	9.06	7.44	5.89	1.915	0.979	0.68	0.193	0.053
<i>DWT</i> [31]	124.084	45.21	5.23	7.38	4.13	1.492	0.982	0.426	0.522	0.205
<i>DWPT</i> _(mean-max) [14]	124.124	45.72	7.45	7.38	4.37	1.809	0.982	0.476	0.48	0.06
<i>DWPT</i> [32]	124.742	46.92	9.12	7.43	5.34	1.929	0.978	0.654	0.216	0.056
<i>DWPT</i> [14]	124.155	46.03	8.12	7.38	5.23	1.909	0.985	0.646	0.317	0.025
<i>CVT</i> _(mean-max) [14]	124.687	45.59	5.99	7.38	4.66	1.867	0.986	0.496	0.448	0.049
<i>CVT – DWT</i> [2]	124.352	47.949	9.06	7.45	4.19	1.594	0.979	0.706	0.209	0.399
<i>CNT</i> _(mean-max)	124.094	46.41	10.63	7.49	3.77	1.89	0.967	0.365	0.422	0.043
<i>CNT</i> [33]	125.157	46.48	10.66	7.49	3.69	1.878	0.967	0.309	0.423	0.046
<i>WDF</i> _{w = 3}	124.116	46.62	8.44	7.39	5.72	1.949	0.983	0.734	0.258	0.012
<i>WDF</i> _{w = 5}	124.123	46.48	8.3	7.39	5.85	1.967	0.983	0.729	0.266	0.018
<i>WDF</i> _{w = 7}	124.119	46.39	8.19	7.39	5.81	1.965	0.983	0.724	0.271	0.026
<i>WDF</i> _{w = 9}	124.121	46.36	8.12	7.39	5.77	1.961	0.984	0.719	0.276	0.039

TABLE II
PERFORMANCE COMPARISON FOR FUSED *book* IMAGE

	<i>API</i>	<i>SD</i>	\bar{G}	<i>H</i>	<i>MI</i>	<i>FS</i>	<i>CORR</i>	Q_{ABF}	L_{ABF}	N_{ABF}
<i>Average</i>	85.15	59.85	5.06	7.29	5.72	1.8471	0.985	0.484	0.494	0.0002
<i>DWT</i> _(mean-max) [14]	84.927	62.44	9.11	7.33	6.95	1.988	0.973	0.638	0.233	0.105
<i>DWT</i> [3]	84.213	62.17	8.63	7.24	7.88	1.981	0.972	0.638	0.239	0.065
<i>DWT</i> [31]	84.957	59.87	5.74	7.30	4.38	1.49	0.977	0.425	0.49	0.256
<i>DWPT</i> [14]	84.925	60.33	7.56	7.29	5.47	1.878	0.977	0.377	0.509	0.053
<i>DWPT</i> [32]	84.924	60.04	5.54	7.32	4.59	1.496	0.973	0.455	0.439	0.498
<i>DWPT</i> [14]	84.952	61.08	7.73	7.31	5.78	1.879	0.979	0.605	0.352	0.027
<i>CVT</i> [14]	85.952	60.03	6.89	7.49	4.91	1.908	0.982	0.409	0.497	0.033
<i>CVT – DWT</i> [2]	85.582	63.19	8.69	7.36	7.11	1.976	0.974	0.666	0.242	0.134
<i>CNT</i> _(mean-max)	85.067	61.17	12.98	7.55	4.8	1.997	0.96	0.282	0.463	0.048
<i>CNT</i> [33]	86.246	61.31	12.71	7.56	4.76	1.999	0.959	0.283	0.463	0.048
<i>WDF</i> _{w = 3}	84.838	61.79	8.01	7.28	7.63	1.975	0.976	0.675	0.301	0.018
<i>WDF</i> _{w = 5}	84.875	61.68	7.82	7.28	7.49	1.985	0.977	0.676	0.307	0.016
<i>WDF</i> _{w = 7}	84.889	61.63	7.76	7.28	8.52	1.929	0.977	0.679	0.309	0.014
<i>WDF</i> _{w = 9}	84.899	61.59	7.72	7.27	9.92	1.869	0.977	0.676	0.31	0.014

can be higher due to artifacts also, which can be disastrous.

The proposed fusion has the second highest *Gradient* value (very close to the *Gradient* of the ground truth for 'Lena') and also has minimum value for *MSE* (refer to Fig. 6), indicating minimum artifacts introduced compared to all other methods. The proposed method also gave one of the highest value for Q_{ABF} indicating that edge information is preserved very well. It can be clearly seen that most of the time when *MSE* is reducing, Q_{ABF} is improving unlike all other parameters, indicating that Q_{ABF} is more relevant measure of fusion quality. This inference can be useful for performance analysis of fusion when ground truth is not available and so *MSE* computation is not possible, like in Table II. Table II also shows that the proposed methods have highest value of Q_{ABF} , lowest value of L_{ABF} and very low value for N_{ABF} indicating best quality with minimum loss and very low noise.

The existing multifocus fusion [2] gives one of the lowest *MSE*, but it has almost double loss (L_{ABF}) and much higher noise (N_{ABF}) and lower fusion quality Q_{ABF} compared to the proposed method.

The proposed techniques also have high values for *Entropy*, *Mutual Information*, *Fusion Symmetry* and *Correlation*, indicating increase in relevant information. Visual quality of proposed fusion is also clearly superior as seen in Fig. 4 and 5. We observed empirically that the result is best with a window size between 3 to 9, but selection of optimal window size will depend on the image into consideration.

VI. CONCLUSION

In short, proposed fusion rule using statistical properties of neighborhood and adaptive weights is well suited for fusion of multifocus images in wavelet as well as spatial domain. The method shows significant improvement over other methods,

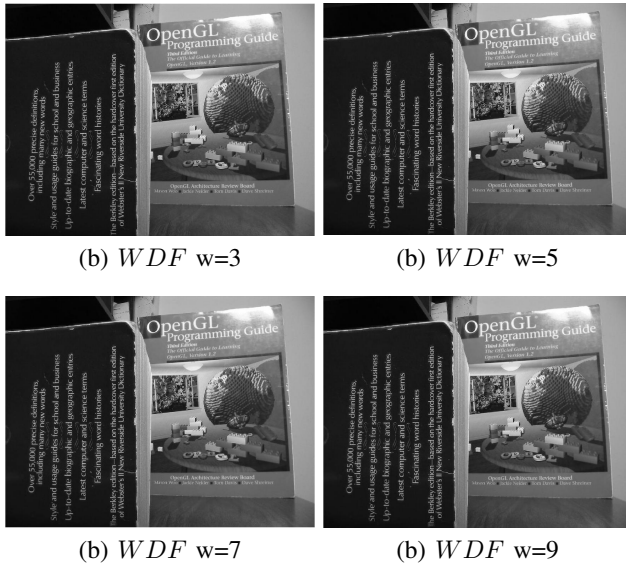


Fig. 5. Fused 'book' Image using Proposed Method for Different Window Size

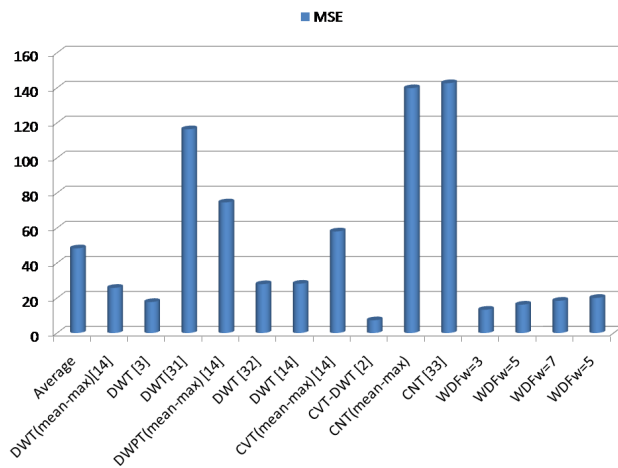


Fig. 6. MSE in fused 'lena' Image using Different Methods

outperforming in all the evaluation indices, as can be seen from the results given in Table I and II.

The major achievements of proposed methods is minimum artifacts and maximum edge preservation. The claim is well justified from the results where ground truth was made available. This clearly indicates that the proposed methods introduces minimum artifacts compared to existing techniques and this is a significant achievement, as artifacts may lead to wrong interpretations which can be catastrophic. Especially in applications like surveillance and medical images, this can be vital as artifacts can result into false alarms. In addition, the proposed methods also yield excellent sharpness, clarity and edge preservation along with increase in information, mutual information, information symmetry and high correlation. The authors are also working on fusion of infrared and visible

band surveillance images in order to verify the quality of performance.

VII. ACKNOWLEDGEMENTS

This work was supported by Microsoft Research India under the MSRI PhD Fellowship Award 2008. The authors would also like to acknowledge Dr Ardy Goshtasby and his company Image Fusion systems Research for providing the test images used in the simulations.

REFERENCES

- [1] R. Blum, Z. Liu, Multi-sensor Image Fusion and Its Applications, CRC Press, London, United Kingdom, 2005.
- [2] Shutao Li, Bin Yang, Multifocus Image Fusion by Combining Curvelet and Wavelet Transform, Pattern Recognition Letters, vol.29, pp.1295–1301 (2008).
- [3] S. Arivazhagan, L. Ganesan, T. G. Subash Kumar, A modified statistical approach for image fusion using wavelet transform, Springer Journal SIVIP, Vol.3, pp. 137–144 (2009)
- [4] I. De, B. Chanda, A Simple and Efficient Algorithm for Multifocus Image Fusion using Morphological Wavelets, Signal Processing 86(5), pp. 924–936 (2006).
- [5] S. Li, J.T. Kwok, I.W. Tsang, Y. Wang, Fusing images with different focuses using support vector machines, IEEE Transactions on Neural Networks 15 (6), pp. 1555–1561 (2004).
- [6] Yingjie Zhang, Liling Ge, Efficient fusion scheme for multi-focus images by using blurring measure, Elsevier Digital Signal Processing (19), pp 186–193 (2009).
- [7] Qiang Zhang, Bao-long Guo, Multifocus image fusion using the nonsub-sampled contourlet transform, Elsevier Signal Processing Journal (2009).
- [8] R. Redondo, F. Sroubek, S. Fischer, G. Cristóbal, Multifocus image fusion using the log-Gabor transform and a Multisize Windows technique, Elsevier Information Fusion (10), pp 163–171 (2009).
- [9] M. Choi, R.Y. Kim, M.G. Kim, The curvelet transform for image fusion, Society for Photogrammetry and Remote Sens., B8, pp. 59–64 (2004).
- [10] Sheng Zheng, Wen-zhong Shi, Jian Liu, and Jinwen Tian, Remote Sensing Image Fusion Using Multiscale Mapped LS-SVM, IEEE Trans. Geosci. Remote Sens., VOL. 46, NO. 5, May 2008.
- [11] TAO Guan-qun, LI Da-peng and LU Guang-hua., Application of wavelet analysis in medical image fusion, Journal of Xidian University, vol. 31, pp. 82–86 (2004).
- [12] Yong Chai, You He, C. Ying, CT and MRI Image Fusion Based on Contourlet Using Novel Rule, 2nd International Conference on Bioinformatics and Biomedical Engineering, ICBBE 2008, pp. 2064–2067 (2008).
- [13] Yang Licai, L. Xin, Y Yucui, Medical Image Fusion Based on Wavelet Packet Transform and Self-adaptive Operator, 2nd International Conference on Bioinformatics and Biomedical Engineering, ICBBE 2008, pp. 2647–2650 (2008).
- [14] Parul Shah, S. N. Merchant, U. B. Desai, Fusion of Surveillance Images in Infrared and Visible Band using Curvelet, Wavelet and Wavelet Packet Transform, will be published in International Journal of Wavelets, Multiresolution and Information Processing (IJWMIP), vol. 8, issue 2, pp. 271–292 (2010).
- [15] S. Gabarda, G. Cristóbal, Cloud covering denoising through image fusion, Image and Vision Computing 25 (5), pp. 523–530 (2007).
- [16] P.J. Burt, A gradient pyramid basis for pattern selective image fusion, Proceedings of the Society for Information Display Conference, pp. 467–470 (1992).
- [17] A. Toet, Image fusion by a ratio of low-pass pyramid, Pattern Recognition 9 (4), pp. 245–253 (1989).
- [18] H. Li, B.S. Manjunath, S.K. Mitra, Multisensor image fusion using the wavelet transform, Graphical Models and Image Processing 57 (3), pp. 235–245 (1995).
- [19] G. Pajares, J. Cruz, A wavelet-based image fusion tutorial, Pattern Recognition 37 (9), pp. 1855–1872 (2004).
- [20] I. De, B. Chanda, B. Chattopadhyay, Enhancing effective depth-offield by image fusion using mathematical morphology, Image and Vision Computing 24 (12), pp. 1278–1287 (2006).
- [21] A. Goshtasby, Fusion of multi-exposure images, Image and Vision Computing 23 (6), pp. 611–618 (2005).

- [22] X. Yang, W. Yang, J. Pei, Different focus points images fusion based on wavelet decomposition, in: Proceedings of Third International Conference on Information Fusion, vol. 1, pp. 3–8 (2000).
- [23] Tao Li, Jian Liu, Zhicheng wang and Yan Tian, A novel image fusion approach based on wavelet transform and fuzzy logic, International journal of wavelets, multiresolution and information processing (IJWMIP), vol. 4, issue 4, pp. 617–626 (2006).
- [24] H. Wang, J. Peng, W. Wu, Fusion algorithm for multisensor images based on discrete multiwavelet transform, IEEE Proceedings of Vision, Image, and Signal Processing 149(5), pp. 283–289 (2002).
- [25] S. Li and Y. Wang, Multisensor image fusion using discrete multiwavelet transform, in: Proceedings of the 3rd International Conference on Visual Computing, pp. 93–103 (2000).
- [26] Shutao Li, Multisensor remote sensing image fusion using stationary wavelet transform: effects of basis and decomposition level, International Journal of Wavelets, Multiresolution and Information Processing (IJWMIP), vol. 6, issue 1, pp. 37–50 (2008).
- [27] Liu Bin and Jiexiong peng, Image fusion method based on short support symmetric non-separable wavelet, International Journal of Wavelets, Multiresolution and Information Processing (IJWMIP), vol. 2, issue 1, pp. 87–98 (2004).
- [28] G. Piella, A general framework for multiresolution image fusion: from pixels to regions, Information Fusion 4 (4), pp. 259–280 (2003).
- [29] J. J. Lewis, R. J. O’Callaghan, S. G. Nikolov, D. R. Bull, C. N. Canagarajah, Region-based image fusion using complex wavelets, in: Proceedings of 7th International Conference on Information Fusion, Stockholm, Sweden, pp. 555–562, June 2004.
- [30] Susan J. Devlin, R. Gnanadesikan, J. R. Kettenring, Robust Estimation and Outlier Detection with Correlation Coefficients, Biometrika, Vol. 62, No. 3, pp. 531–545 (1975).
- [31] CHENG Shangli, H. Junmin, L. Zhongwei, Medical Image of PET/CT Weighted Fusion Based on Wavelet Transform, Intl. Conf. on Bioinformatics and Biomedical Engineering (ICBBE), pp. 2523–2525 (2008).
- [32] Yang Licai, L. Xin, Y. Yucui, Medical Image Fusion Based on Wavelet Packet Transform and Self-adaptive Operator, Intl. Conf. on Bioinformatics and Biomedical Engineering (ICBBE), pp. 2647–2650 (2008).
- [33] Soad Ibrahim, Michael Wirth, Visible and IR Data Fusion Technique Using the Contourlet Transform, IEEE Intl. Conf. on Computational Science and Engineering, pp. 42–47 (2009).
- [34] V Petrovic, C Xydeas, Objective Image Fusion Performance Characterisation, Proceedings of ICCV’05, Volume 2, pp 1866–1871 (2005).
- [35] G Qu, D Zhang, P Yan, Information measure for performance of image fusion, Electronics Letters, Vol. 38(7), pp 313–315 (2002).
- [36] A. Toet, J. K. Ijspeert, A. M. Waxman and M. Aguilar, Perceptual evaluation of different image fusion schemes, Displays, Vol. 24, pp. 25–37 (2003).