

Comparative Evaluation of Image Fusion Technique Using Shift Invariant Transforms

Tinku J. Mattappillil¹, P. Soundarya Mala², Dr. V. Sailaja³, Rajeswara Mahidar⁴

¹(M. Tech Student (DECS), Godavari Institute of Engineering & Technology, Rajahmundry)

²(Associate Professor, ECE Department, Godavari Institute of Engineering & Technology, Rajahmundry)

³(Professor, ECE Department, Godavari Institute of Engineering & Technology, Rajahmundry)

⁴(Asst. Professor, ECE Department, Sasi Institute of Tech & Engineering, Tadepalligudem)

Abstract

Image fusion is very popular for its application in various real life applications such as remote sensing applications, medical image diagnosis. The non-idle nature of practical imaging systems the capture images are corrupted by noise, hence Fusion of images is an integrated approach where the reduction of noise is essential. Discrete Wavelet Transform (DWT) has a wide range of application in fusion of noise images. However shift-invariance is important in ensuring robust subband fusion. To overcome this, Shift invariant Wavelet Transforms are becomes popular. In this paper proposed two shift invariant transforms for fusion of noise mages. They are Dual-Tree Complex wavelet transform (DT-CWT) and Non Sub sampled Contourlet Transform (NSCT). Experiments are carried out on a number of images like SAR images, MRI images, doll images and toy images to evaluate performance of the proposed method. Results are compared in terms of quality measures peak signal-to-noise ratio, cross correlation and image visual quality.

Keywords – Discrete Wavelet Transform, Dual Tree-Complex Wavelet Transform, Image Fusion, Non Sub sampled Contourlet Transform.

I. Introduction

Image fusion is a process of combing two or more images capturing by different imaging systems or multiple sensors of the same scene which produce a quality image when compared to the source images. Discrete Wavelet Transform (DWT) has a wide range of application in fusion of noise images. However DWT has some limitations such as aliasing, oscillation of wavelet coefficients at a singularity, shift-variance, and use short support wavelets (ie. Harr) only. This transform also uses very redundant representation, which translates into a higher computational cost. Most over this transform has a limitation of less directional selectivity. To overcome the shift variance limitation, Dual –Tree Complex Wavelet Transform (DT-CWT) and Non Sub sampled Contourlet Transform (NSCT) are introduced for fusion of noise images.

1.1 Wavelet Based Fusion

Generally most of fusion methods are base on wavelet transforms. The fusion methods are most commonly employed. In this two or more registered images say I_1 , I_2 all from the same scene are taken, then any one of the transform W can be applied to each image. Then the transformed images are fused using any one

of the proposed fusion rule \emptyset . Then inverse transform is applied to the fused image to reconstruct the Image which has better than the all registered images.

The registered images are taken as $I_1(x,y), I_2(x,y)$ the fused reconstructed image is $I(x,y)$ and W^{-1} is inverse transform then fusion is defined as :

$$I(x,y) = W^{-1}(\emptyset(W(I_1(x,y)), W(I_2(x,y)))) \quad (1)$$

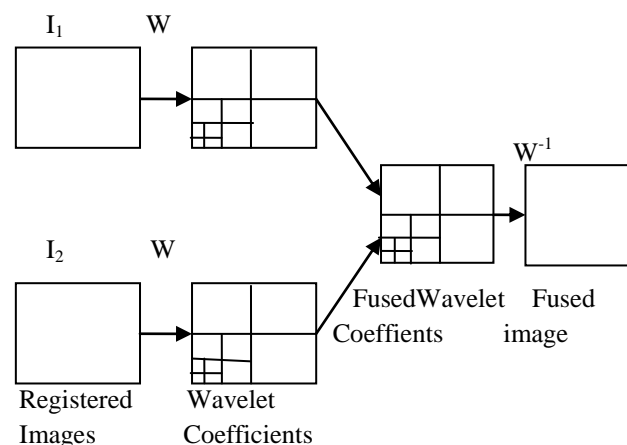


Figure 1: Fusion of two images using wavelet transforms

Wavelet based fusion provides more advantages over other pyramid based fusion schemes. The wavelet provides directional information. No blocking effect occurs in region where input images are

significantly different. Wavelet based fusion gives better signal-to-noise ratio.

II. Dual-Tree Complex Wavelet Transform (DT-CWT)

The Dual-tree Complex wavelet transform (DT-CWT) is complex valued extension of the standard wavelet. Complex Wavelet Transform uses complex valued filtering that decomposes the image into real and imaginary parts in transform domain. The real and imaginary coefficients are used to compute magnitude and phase information. The Dual-tree Complex wavelet transform uses separable spatial filters iteratively to produce frequency sub bands as in the Discrete Wavelet Transform [1]. The Dual-tree Complex wavelet transform produces shift-invariance [2]. Shift-invariance can also be achieved in DWT by doubling the sampling rate. This is effected in the DT-CWT by eliminating the down sampling by 2 after first level filter. Two fully decimated trees are then produced by down sampling, effected by taking first even and then odd samples after the first level of filters. To get uniform intervals between the two tree's samples, the subsequent filters need half a sample different delay in one tree. Application to image can be achieved by separable complex filtering in two dimensions.

The real 2-D dual-tree DWT of an image x is implemented using two critically-sampled separable 2-D DWTs in parallel. Then for each pair of subbands we take the sum and difference. The complex 2-D DT-DWT also gives rise to wavelets in six distinct directions. The complex 2-D dual-tree is implemented as four critically-sampled separable 2-D DWTs operating in parallel as shown in fig 2. 2-D structure needs four trees for analysis and for synthesis. The pairs of conjugate filters applied to two dimensional images (x, y) can be expressed as:

$$(h_x + jg_x)(h_y + jg_y) = (h_x h_y - g_x g_y) + j(h_x g_y + g_x h_y) \quad (2)$$

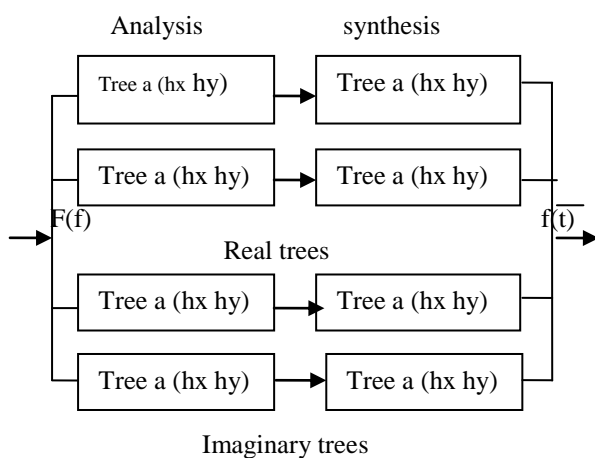


Figure 2: Filter bank structure for 2-D dual-tree DWT

The complex wavelets are able to distinguish

between positive and negative the diagonal subbands can be distinguished and horizontal and vertical subbands are divided giving six distinct subbands in each scale at orientations $\pm 15^\circ$, $\pm 45^\circ$, and $\pm 75^\circ$. The oriented and scale dependent subbands are visualized spatially in fig 3.

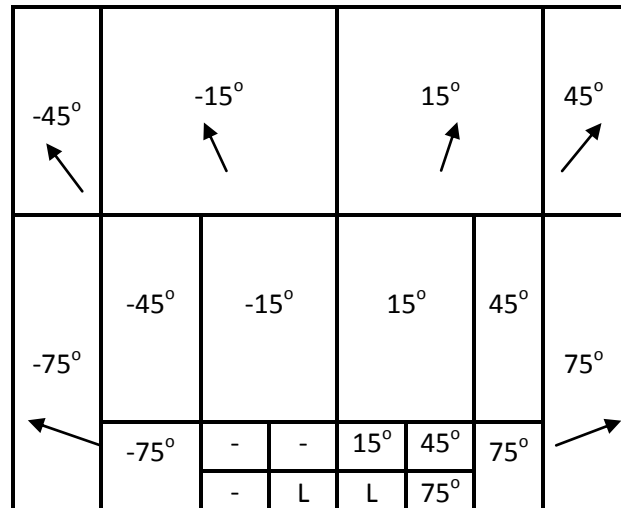


Figure 3: Complex Wavelet Transform Scale and orientation labeled subbands

The DWT have three subbands in 0° , 45° and 90° directions only but DT-CWT having six subbands in $\pm 15^\circ$, $\pm 45^\circ$, and $\pm 75^\circ$ thus DT-CWT improves the directional selectivity.

III. Non Sub sampled Contourlet Transform

The contourlet transform was proposed to address the lack of geometrical structure in the separable two dimensional wavelet transform. Because of its filter bank structure the contourlet transform is not shift-invariant. In this paper we propose the non sub sampled contourlet transform (NSCT) and study its application to image fusion. The construction proposed in this paper is based on a non sub sampled pyramid structure and non sub sampled directional filter banks. At the core of the proposed scheme is the non separable two-channel non sub sampled filter bank. We study the filter design problem and propose a design framework based on the mapping approach. We exploit the less stringent design condition of the non sub sampled filter bank to design filters that lead to a NSCT with better frequency selectivity and regularity when compared to the contourlet transform.

3.1 The Non sub sampled Pyramid

The shift sensitivity of the LP can be remedied by replacing it with a 2-channel non sub sampled 2-D filter bank structure. Such expansion is similar to the 1-D 'a trous' wavelet expansion [3] and has a

redundancy of $J + 1$ when J is the number of decomposition stages. The ideal frequency support of the low-pass filter at the j^{th} stage is the region $\left[-\frac{\pi}{2^j}, \frac{\pi}{2^j}\right] \times \left[-\frac{\pi}{2^j}, \frac{\pi}{2^j}\right]$. Accordingly, the support of the high-pass filter is the complement of the low-pass support region on the $\left[-\frac{\pi}{2^{j+1}}, \frac{\pi}{2^{j+1}}\right] \times \left[-\frac{\pi}{2^{j-1}}, \frac{\pi}{2^{j-1}}\right]$ square. The proposed structure is thus different from the tensor product *a trous* algorithm. It has $J + 1$ redundancy. By contrast, the 2-D *a trous* algorithm has $3J + 1$ redundancy.

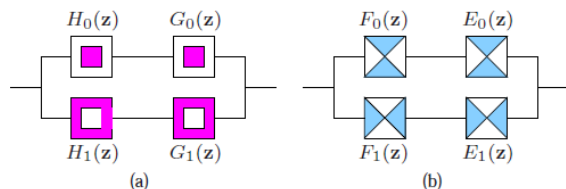


Figure 4: Two types of desired responses (a) The pyramid desired response. (b) The fan desired response.

The directional filter bank [3] is constructed by combining critically sampled fan filter banks and pre/post re-sampling operations. The result is a tree-structured filter bank which splits the frequency plane into directional wedges. A fully shift-invariant directional expansion is obtained by simply switching off the down samplers and up samplers in the DFB equivalent filter bank. Due to multi rate identities, this is equivalent to switching off each of the down samplers in the tree structure, while still keeping the re-sampling operations that can be absorbed by the filters. This results in a tree structure composed of two-channel non sub sampled filter banks. The NSCT is obtained by carefully combining the 2-D non sub sampled pyramid and the non sub sampled DFB (NSDFB) [4]. The resulting filtering structure approximates the ideal partition of the frequency plane displayed in fig 1. It must be noted that, different from the contourlet expansion, the NSCT has a redundancy given as:

$$R = \sum_{j=0}^J 2^{2j} \quad (3)$$

where 2^{2j} is the number of directions at scale j .

IV. Fusion of Images

About wavelet Fusion of two registered images already discussed in section 1.1. In wavelet based image fusion first any one of wavelet applied to the image, after that we used one of the fusion rule for fusing the wavelet coefficients. After that, apply the inverse wavelet to reconstruct the image. In this, For fusion uses any one of the fusion rule mention bellow. There are three fusion rules generally used to implement wavelet based image fusion.

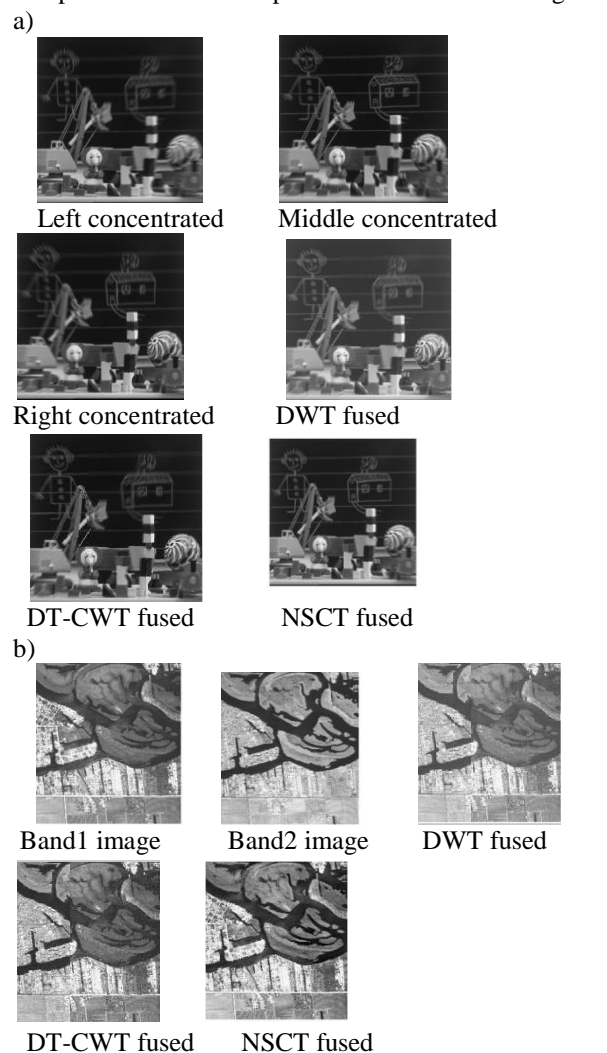
1. Maximum Selection (MS) scheme: This simple scheme just picks the coefficient in each subband with the largest magnitude
2. Weighted Average (WA) scheme: This scheme developed by Burt and Kolczynski [Burt and

Kolczynski, 1993] uses a normalized correlation between the two images' subbands over a small local area. The resultant coefficient for reconstruction is calculated from this measure via a weighted average of the two images coefficients.

3. Window Based Verification Scheme: This scheme developed by Li et al [Li et al, 1995] Creates a binary decision map to choose between each pair of coefficients using a majority filter.

V. Experimental Results

Experiments are carried out on number of grey scale and color images to compare the performances of NSCT, DT-CWT fusion method with DWT fusion method. The results concerning on the experiments that have been conducted on different images, viz. Lena, toy, MRI, SAR, clock and doll images. Here uses images of size 300X300. To evaluate comparison evaluation used two commonly used metrics Peak Signal-to-Noise Ratio (PSNR) and Normalized cross correlation (NCC). And also visual quality used for comparison. Visual comparison demonstrated in fig 3.



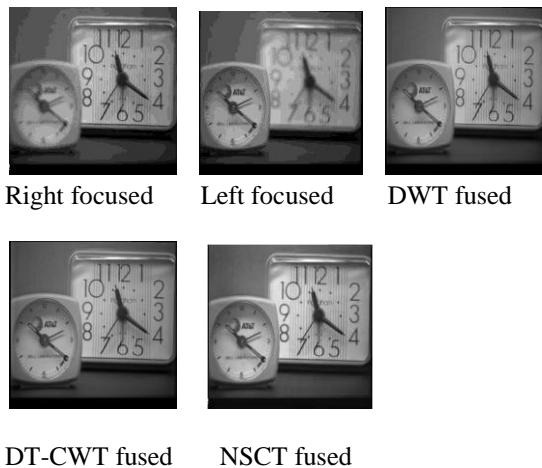


Figure 5: Visual comparison of some test images (a) toy image (b) SAR image (c) Clock image
 Comparison evaluation of different test image using DWT, DT-CWT and NSCT is tabulated below.

images	Toy Image		SAR Image		MRI image		Clock Image	
	PSNR	NCC	PSNR	NCC	PSNR	NCC	PSNR	NCC
DWT	20.49	0.89	18.14	0.88	16.83	0.87	19.89	0.89
DT-CWT	34.13	0.97	32.19	0.98	32.36	0.98	33.71	0.97
NSCT	34.98	0.93	34.96	0.92	34.52	0.99	37.50	0.879

Table 1: Comparison evaluation between DWT, DT-CWT and NSCT using different images

VI. Conclusion

The NSCT and DT-DWT fusion technique of noisy images provides better than DWT. But the NSCT provides almost same results as DT-CWT at the expense of increased computation time. The DT-DWT method is able to retain edge information without significant ringing artifacts. NSCT is best suitable for images with more curvatures like medical images. NSCT and DT-DWT provides increased shift-invariance and orientation selectivity when compared to the DWT.

VII. Acknowledgement

The Author would like to thank P.Soundarya mala, Associate Professor ECE Dept, Godavari Institute of Engineering and Technology, Rajahmundry, Dr. V. Sailaja, HOD ECE Dept, Godavari Institute of Engineering and Technology, Rajahmundry, Rajeswara Mahidar, Asst.Professor ECE Dept Sasi Institute of Tech And Engineering, Tadepalligudem for their great help for success completion and also grateful for the anonymous reviewers who made constructive comments. The author is very thankful to one and all who helped to complete this work successfully.

References

- [1] N.G.Kingbbury, The dual-tree complex wavelet transform with improved orthogonality and symmetry properties, *IEEE International Conference on Image processing*, pages 375-378, September 2000.
- [2] N.G.Kingbbury, The dual-tree complex wavelet transform: a new technique for shift invariance and directional filters, *IEEE Digital Signal Processing Workshop*, 1998.
- [3] M. J. Shensa, The discrete wavelet transform: Wedding the `a trous and Mallat algorithms. *IEEE Trans. Signal Proc.*, vol. 40, no. 10, pp. 2464–2482, October 1992.
- [4] A. L. Cunha, J. Zhou, and M. N. Do, The non sub sampled contourlet transform: Theory, design, and applications, *IEEE Trans. Img. Proc.*, submitted, 2005.
- [5] S.M. Mahbubur Rahman, M. Omair Ahmad and M.N.S. Swamy, Contrast-based fusion of noisy images using discrete wavelet transform, *IET Image Process.*, 2010, Vol. 4, Iss. 5, pp. 374–384 doi: 10.1049/iet-ipr.2009.0163.
- [6] O.Rockinger, Image sequence fusion using a shift invariant wavelet transform *IEEE Transaction on Image Processing*, volume 3, pages 288-291, 1997.
- [7] N.G.Kingbbury, Design of Q-Shift Complex Wavelets for Image Processing using frequency Domain Energy minimization Preprint, ICIP03.
- [8] PETROVIC´ V.S., XYDEAS C.S.: *Sensor noise effects on signal level image fusion performance*, Inf. Fusion, 2003, 4, (3), pp. 167–183
- [9] Resources for research in image fusion: [Online], <http://www.imagefusion.org/>
- [10] The Math works, ‘Wavelet Toolbox (ver 5) User’s guide’, 2007, [URL:www.mathworks.com](http://www.mathworks.com).
- [11] MRI database in the whole brain atlas:[online], <http://www.med.harvadr.edu/AANLIB/home.html>
- [12] Tania Stathaki, *Image Fusion Algorithms and applications* Academic Press is an imprint of Elsevier, ISBN: 978-0-12-372529-5
- [13] H.B. Mitchell, *Image Fusion theories, techniques, and applications* ISBN 978-3-642-11215-7, Springer-Verlag Berlin Heidelberg, 2010.