AREA LEVEL FUSION OF MULTI-FOCUSED IMAGES USING DUAL TREE DISCRETE WAVELET PACKET TRANSFORM

K. Kannan[1], S. Arumuga Perumal[2] , K. Arulmozhi[3],

[1]Department of Electronics and Communication Engineering,

[2]Department of Computer Science, St. Hindu College, Nagarcoil, INDIA

[3]Kamaraj College of Engineering and Technology, Virudhunagar, INDIA

Email: [1]kannan_kcet@yahoo.co.in

Abstract

The fast development of digital image processing leads to the growth of feature extraction of images which leads to the development of Image fusion. Image fusion is defined as the process of combining two or more different images into a new single image retaining important features from each image with extended information content. There are two approaches to image fusion, namely spatial fusion and multi scale transform fusion. In spatial fusion, the pixel values from the source images are directly summed up and taken average to form the pixel of the composite image at that location. Multi scale transform fusion uses transform for representing the source image at multi scale. The most common widely used transform for image fusion at multi scale is Discrete Wavelet Transform (DWT) since it minimizes structural distortions. But, wavelet transform suffers due to poor directionality and does not provide a geometrically oriented decomposition in multiple directions. One way to generalize the discrete wavelet transform so as to generate a structured dictionary of base is given by the Discrete Wavelet Packet Transform (DWPT). This benefit comes from the ability of the wavelet packets to better represent high frequency content and high frequency oscillating signals in particular. However, it is well known that both DWT and DWPT are shift varying. The Dual Tree Discrete Wavelet Transform (DTDWT) introduced by Kingsbury, is approximately shift -invariant and provides directional analysis. And there are three levels for image fusion namely pixel level, area level and region level. In this paper, it is proposed to implement area level fusion of multi focused images using Dual Tree Discrete Wavelet Packet Transform (DTDWPT), extending the DTDWT as the DWPT extends the DWT and the performance is measured in terms of various performance measures like root mean square error, peak signal to noise ratio, quality index and normalized weighted performance metric.

Keywords: Image fusion, Dual Tree Discrete Wavelet Packet Transform, Root Mean Square Error, Peak Signal to Noise Ratio, Quality Index and Normalized Weighted Performance Metric.

I. INTRODUCTION

Image fusion is defined as the process of combining two or more different images into a new single image retaining important features from each image with extended information content. For example, IR and visible images may be fused as an aid to pilots landing in poor weather or CT and MRI images may be fused as an aid to medical diagnosis or millimeter wave and visual images may be fused for concealed weapon detection or thermal and visual images may be fused for night vision applications [4]. The fusion process must satisfy the following requirements such as it should preserve all relevant information in the fused image, should suppress noise and should minimize any artifacts in the fused image. There are two approaches to image fusion, namely Spatial Fusion (SF) and Multi Scale Transform (MST) fusion. In Spatial fusion, the pixel values from the source images are summed up and taken average to form the pixel of the composite image at that location [2]. Image fusion methods based on Multiscale Transforms are a popular choice in recent research[12] . MST fusion uses pyramid or wavelet transform for representing the source image at multi scale. Pyramid decomposition methods construct a fused pyramid representation from the pyramid representations of the original images. The fused image is then obtained by taking an inverse pyramid transform [1]. Due to the disadvantages of pyramid based techniques, which include blocking effects and lack of flexibility, approaches based on wavelet transform have begun [2], since it minimizes structural distortions. But, wavelet transform suffers due to poor directionality and does not provide a geometrically oriented decomposition in multiple directions. One way to generalize the discrete wavelet transform so as to generate a structured dictionary of base is given by the Discrete Wavelet Packet Transform (DWPT). This benefit comes from the ability of the wavelet packets to better represent high frequency content and high frequency oscillating signals in particular. However, it is well known that both DWT and DWPT are shift varying. The Dual Tree Discrete Wavelet Transform (DTDWT) introduced by Kingsbury [8, 9, 10], is approximately shift - invariant and provides directional analysis. There are three levels in multi resolution fusion scheme namely Pixel level fusion, feature level fusion and decision level fusion. The performance measures which can be computed independently of the subsequent tasks express the successfulness of an image fusion technique by the extent that it creates a composite image that retains salient information from the source images while minimizing the number of artifacts or the amount of distortion that could interfere with interpretation. In this paper, it is proposed to implement area level fusion of multi focused images using Dual Tree Discrete wavelet Packet transform extending the Dual Tree Discrete Wavelet Transform as the Discrete Wavelet Packet Transform extends the Discrete wavelet Transform and the performance is measured in terms of various performance measures like root mean square error, peak signal to noise ratio, quality index and normalized weighted performance metric.

II. DUAL TREE WAVELET TRANSFORM

The Dual Tree Wavelet Transform (DTWT) overcomes the limitations of DWT like poor directionality and shift invariance. It can be used to implement 2D wavelet transforms that are more selective with respect to orientation than the separable 2D DWT. For example, the 2D DTWT transform produces six subbands at each scale, each of which is strongly oriented at distinct angles. There are two versions of the 2D DTWT transform namely Dual Tree Discrete Wavelet Transform (DTDWT) which is 2-times expansive, and Dual Tree Complex Wavelet Transform (DTCWT) which is 4-times expansive.

A. Dual Tree Discrete Wavelet Transform

The DTDWT of an image is implemented using two critically sampled separable DWT in parallel. Then for each pair of subbands, the sum and difference are taken. The six wavelets associated with DTDWT are illustrated in figure 1 as gray scale images. Note that each of the six wavelet are oriented in a distinct direction. Unlike the critically-sampled separable DWT, all of the wavelets are free of checker board artifact. Each subband of the 2-D dual-tree transform corresponds to a specific orientation.

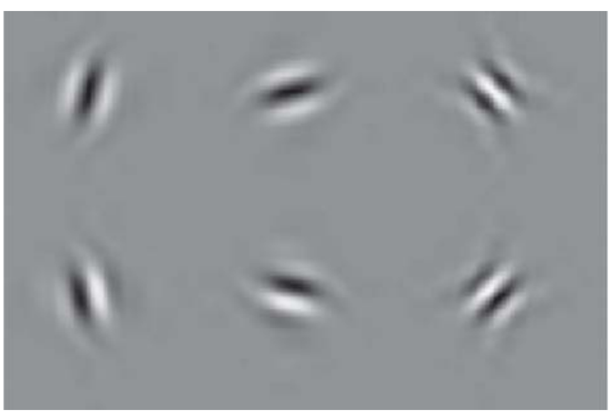


Fig. 1. Directionality of DTDWT

B. Dual Tree Complex Wavelet Transform

The DTCWT also gives rise to wavelets in six distinct directions and two wavelets in each direction. In each direction, one of the two wavelets can be interpreted as the real part of a complex valued wavelet, while the other wavelet can be interpreted as the imaginary part of a complex-valued wavelet. Because the complex version has twice as many wavelets as the real version of the transform, the complex version is 4-times expansive. The DTCWT transform is implemented as four critically sampled separable DWTs operating in parallel. However, different filter sets are used along the rows and columns. As in the real case, the sum and difference of subband images is performed to obtain the oriented wavelets. The twelve wavelets associated with the real 2D dual-tree DWT are illustrated in the following figure as gray scale images. The wavelets are oriented in the same six directions as those of DTDWT. However, there are two in each direction. If the six wavelets displayed on the first row are interpreted as the real part of complex wavelets, then the six wavelets displayed on the second row can be interpreted as the complex part of complex wavelets.

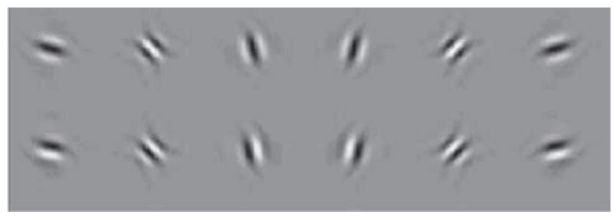


Fig. 2. Directionality of DTCWT

III. AREA LEVEL IMAGE FUSION

This section describes six methods of area level image fusion based on multi scale representation of source images using wavelets. Since the useful features in the image usually are larger than one pixel, the pixel by pixel selection rule of pixel level fusion may not be the most appropriate method. In feature level of fusion algorithm, an area based selection rule is used. The images are first decomposed into sub bands using wavelet transform. Then the feature of each image patch over 3X3 or 5X5 window is computed as an activity measure associated with the pixel centered in the window. To simplify the description of different feature level image fusion methods, the source images are assumed as A & B and the fused image as F. All the methods described in this paper can be used in the case of more than two source images.

Method1:

In this method, the maximum value of coefficients of sub-bands of wavelet transformed image over 3X3 or 5X5 window is computed as an activity measure of pixel centered in the window. The coefficient whose activity measure is larger in chosen to form the fused coefficients map. A binary decision map of same size as the wavelet transform is then created to record the selection results. This binary map is subject to consistency verification. Specifically in wavelet domain, if the centre pixel value comes from image A while the majority of the surrounding pixel values comes from image B, the centre pixel value should be switched to that image B. This method is called consistency verification method.

Method 2:

In this method, the maximum absolute value over 3X3 or 5X5 window is computed as an activity measure of pixel centered in the window. The coefficient whose activity measure is larger in chosen to form the binary decision map and the consistency verification is applied to form the fused coefficients map.

Method3:

This fusion scheme is the weighted average scheme suggested by Burt and Kolezynski (1993). This salient features are first identified in each source image. This salience of a feature is computed as a local energy in the neighborhood of a coefficient.

$$E(A,p) = \sum_{\varphi=Q} W(q)C_j^{\,2}(A,q) \tag{1}$$

where w(q) is a weight and $\sum_{\varphi=Q}$ w(q)=1. In practice, the neighborhood Q is small (typically 5X5 or 3X3) window centered at the current coefficient position. The closer the point q is near the point P, the greater w(q) is E(B,p) can also be obtained by this rule. The selection mode is implemented as:

$$Cj\,(F,p) = \begin{cases} Cj\,(A,p),\ E(A,p) \geq E\,(B,p) \\ Cj\,(B,p),\ E(B,p) > E\,(A,p) \end{cases} \tag{2}$$

This selection scheme helps to ensure that most of the dominant features are incorporated into the fused image.

Method 4:

In this fusion method, the salience measure of each source image is computed using Equation1. At a given resolution level j, this fusion scheme uses two distinct modes of combination namely Selection and Averaging. In order to determine whether the selection or averaging will be used, the match measure M(p) is calculated as

$$M(p) = \frac{2\sum_{\varphi=Q} W(q)C_j\ (A,q)C_j(B,q)}{E(A,p)+E(B,p)} \tag{3}$$

If M(p) is smaller than a threshold T, then the coefficient with the largest local energy is placed in the composite transform while the coefficient with less local energy is discarded. The selection mode is implemented as

$$Cj\,(F,p) = \begin{cases} Cj\,(A,p),\ E(A,p) \geq E\,(B,p) \\ Cj\,(B,p),\ E(B,p) > E\,(A,p) \end{cases} \tag{4}$$

Else if M(p) T, then in the averaging mode, the combined transform coefficient is implemented as

$$Cj\,(F,p) = \begin{cases} W_{max}Cj\,(A,p) + W_{min}Cj\,(B,p),\ E(A,p) \geq E(B,p) \\ W_{max}Cj\,(B,p) + W_{min}Cj\,(A,p),\ E(B,p) > E\,(A,p) \end{cases} \tag{5}$$

where

$$W_{min} = 0.5 - 0.5\left(\frac{1 - M(p)}{1 - T}\right) \text{and } W_{max} = 1 - W_{min})$$

In this study, the fusion methods are implemented using the parameters such as a window size 3*3 and a T-value of 0.75.

Method 5:

For a function f (x,y) it is common practice to approximate the magnitude of the gradient by using absolute values instead of squares and square roots:

$$\nabla f = |Gx| + |Gy| = |f(x,y) - f(x+1,y)| + |f(x,y) - f(x,y+1)| \tag{6}$$

This equation is simpler to compute and it still preserves relative changes in grey levels. In image processing, the difference between pixel and its neighbors reflect the edges of the image. Firstly compute the difference between the low frequency coefficient at the point p and its eight neighbors, respectively. The value E is acquired by summing squares of all the differences. At last, choose the low frequency coefficient with the greater value E as the corresponding coefficient of the fused image. This method can maintain the information of edges. So it can improve the quality of the fused image. The algorithm is as follows.

$$E(A,p) = \sum_{\varphi=Q} |C_j(A,q) - C_j(A,q)|^2$$

$$E(B,p) = \sum_{\varphi=Q} |C_j(B,q) - C_j(B,q)|^2$$

Finally, select the corresponding high frequency coefficient of the fused image.

$$Cj\,(F,p) = \begin{cases} Cj\,(A,p),\ E(A,p) \geq E\,(B,p) \\ Cj\,(B,p),\ E(B,p) > E\,(A,p) \end{cases} \tag{7}$$

Method 6: In this method, the gradient over 3X3 or 5X5 window is computed as an activity measure of pixel centered in the window. The coefficient whose activity measure is larger in chosen to form the fused coefficients map.

IV. EVALUATION CRITERIA

There are four evaluation measures are used in this paper, namely Root Mean Square Error (RMSE), Peak Signal to Noise Ratio (PSNR), Quality Index (QI)[3] and Normalized Weighted Performance Metric (NWPM)[4] which are given in the equations 8, 9, 10 & 11 respectively.

$$\text{RMSE}= \sqrt{\frac{\sum_{i=1}^{N}\sum_{j=1}^{N}[R(i,j)-F(i,j)]^2}{N^2}} \tag{8}$$

$$\text{PSNR}= 10\log_{10}(255)^2/(\text{RMSE})^2 \text{ (db)} \tag{9}$$

$$\text{QI}= \frac{4\sigma_{ab}ab}{(a^2+b^2)(\sigma_a{}^2+\sigma_b{}^2)} \tag{10}$$

$$NWPM = \frac{\sum \forall_{i,j} Q_{ij}^{AF}W_{ij}^{A} + Q_{ij}^{AF}W_{ij}^{B}}{\sum \forall_{i,j} W_{ij}^{A} + W_{ij}^{B}} \tag{11}$$

where A and B are the input images, R is the reference image, F is the fused image, a is the average value of A, b is the average value of B, $Q^{AF}(i,j)$ and $Q^{BF}(i,j)$ are the edge preservation values.

V. EXPERIMENTAL WORK

A pair of source images namely Pepsi of size 512x512 is taken. The pair of source images to be fused is assumed to be registered spatially. The images are wavelet transformed using the same wavelet, and transformed to the same number of levels. For taking the wavelet transform of the two images, readily available MATLAB routines are taken. In each sub-band, individual pixels of the two images are compared based on the fusion rule that serves as a measure of activity at that particular scale and space. A fused wavelet transform is created by taking pixels from that wavelet transform that shows greater activity at the level. The inverse wavelet transform is the fused image with clear focus on the whole image.

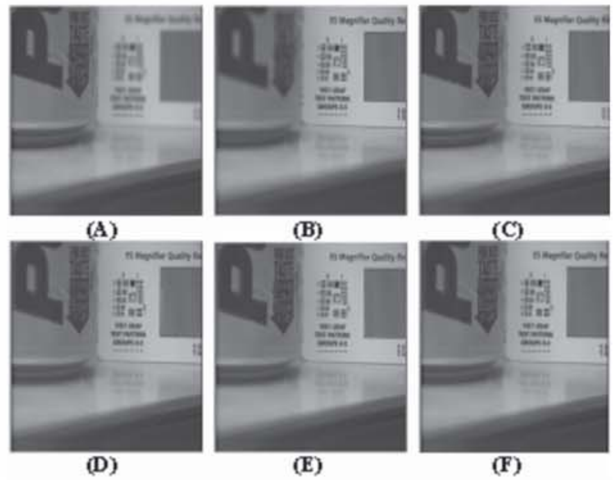
VI. RESULTS

For the above mentioned method, image fusion is performed using DWT, DWPT, DTDWT & DTDWPT and their performance is measured in terms of Root Mean Square Errors, Peak Signal to Noise Ratio, Quality Index & Normalized Weighted Performance Metric and the results are shown in figure 3 and tabulated in table1.

Table 1. Results of Area level Fusion

		Method1	Method2	Method3	Method4	Method5	Method6
RMSE	DWT	3.8485	3.773	3.7551	3.7309	3.7446	3.7446
	DWPT	3.8023	3.7697	3.7443	3.7304	3.7439	3.7355
	DTDWT	3.7079	3.7029	3.7063	3.6927	3.6997	3.6989
	DTDWPT	**3.5794**	**3.5645**	**3.5678**	**3.5626**	**3.5581**	**3.5646**
PSNR	DWT	36.4249	36.5972	36.6383	36.6945	36.6626	36.6627
	DWPT	36.5298	36.6048	36.6635	36.6957	36.6642	36.6838
	DTDWT	36.7481	36.7599	36.7519	36.784	36.7675	36.7695
	DTDWPT	**37.0546**	**37.0907**	**37.0829**	**37.0954**	**37.1064**	**37.0906**
QI	DWT	0.9965	0.9967	0.9967	0.9967	0.9967	0.9967
	DWPT	0.9966	0.9967	0.9967	0.9967	0.9967	0.9967
	DTDWT	0.9968	0.9968	0.9968	0.9968	0.9968	0.9968
	DTDWPT	**0.997**	**0.997**	**0.997**	**0.997**	**0.997**	**0.997**
NWPM	DWT	0.7287	0.7346	0.7327	0.737	0.7335	0.7338
	DWPT	0.7324	0.7357	0.7349	0.7378	0.7344	0.7345
	DTDWT	0.752	0.754	0.7525	0.7551	0.7523	0.7524
	DTDWPT	**0.7588**	**0.7622**	**0.7616**	**0.7624**	**0.7605**	**0.7604**

Fig. 3. Results of Area Level Image Fusion



(A) Input Image 1 (B) Input Image 2 (C) Reference Image (D) Fused Image using DWPT (E) Fused Image using DTDWT (F) Fused Image using DTDWPT.

VII. CONCLUSION

This paper presents the comparison of area level of fusion of multi focused images using DWT, DWPT, DTDWT and DTDWPT in terms of various performance measures. DTCWPT provides very good results both quantitatively and qualitatively for area level fusion. Hence using these fusion methods, one can enhance the image with high geometric resolution.

REFERENCES

[1] P. J. Burt and R. J. Kolczynski, "Enhanced image capture through image fusion", proceedings of the 4th International Conference on Computer Vision, pp. 173-182, 1993.

[2] H. Li, B.S. Manjunath, and S.K. Mitra, "Multi-sensor image fusion using the wavelet transform", Proceedings of the conference on '*Graphical Models and Image Processing*', pp. 235–245, 1995.

[3] Zhou Wang and Alan C. Bovik, "A Universal Image Quality Index", IEEE Signal Processing Letters, Vol. 9, No.3, pp. 81-84, March,2002.

[4] C.S. Xydeas and V. Petrovic, 2000," Objective Image Fusion Performance Measure", Electronics Letter, Vol.36, N0.4, pp. 308-309.

[5] I. W. Selesnick. Hilbert transform pairs of wavelet bases. IEEE Signal Processing Letters, 8(6):170–173, June 2001.

[6] I. W. Selesnick. The design of approximate Hilbert transform pairs of wavelet bases. IEEE Trans. Signal

Processing, 50(5):1144–1152, May 2002.

[7] I. W. Selesnick, R. G. Baraniuk, and N. G. Kingsbury. The dual-tree complex wavelet transform - A coherent framework for multiscale signal and image processing. IEEE Signal Processing Magazine, 22(6):123–151, November 2005

[8] N. G. Kingsbury. The dual-tree complex wavelet transform: A new efficient tool for image restoration and enhancement. In Proceedings of European Signal Processing Conference (EUSIPCO), 1998.

[9] N. G. Kingsbury. Image processing with complex wavelets. Philos. Trans. R. Soc. London A, Math. Phys. Sci., 357(1760):2543–2560, September 1999.

[10] N. G. Kingsbury. A dual-tree complex wavelet transform with improved orthogonality and symmetry properties. In Proceedings of IEEE International Conference on Image Processing (ICIP), 2000.

[11] N. G. Kingsbury. Complex wavelets for shift invariant analysis and filtering of signals. Journal of Appl. and Comp. Harmonic Analysis, 10(3):234– 253, May 2001.

[12] Rick S. Blum and Yang Jinzhong, 2006, Image Fusion Methods and Apparatus, US Patent, WO/2006/017233.

[13] Zhu Shu-long, 2004, “Image Fusion using Wavelet Transform”, Symposium on Geospatial Theory, Processing and Applications, pp. 5-9.

K. Kannan received his UG and PG degree in Engineering from Madurai Kamaraj University and Anna University through National Engineering College and Thiagarajar College of Engineering in the year 1992 and 2004 respectively and currently doing his Ph.D in the area of image processing. He has more than ten years of experience in teaching and currently working as Assistant Professor and Head in department of Electronics and Communication Engineering of Kamaraj College of Engineering and Technology, Virudhunagar. His area of interest includes Signal Processing, Image Processing, Embedded System and RTOS. So far he published more than fifty technical papers in national and international journals and conferences.