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An Efficient Image Fusion Method For Fusion of Low Resolution Infrared And Visual Image.

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Abstract

Due to the fast development of digital image processing the growth of feature extraction of images which leads to the development of image fusion. The process of combining two different images into a new single image by retaining salient features from each image with extended information content is known as image fusion, wherein the resultant fused image will be more informative and complete than any of the input images. Two approaches to image fusion are spatial fusion and transform fusion. In this paper I proposed an image fusion method for fusion of low resolution infrared camera image with visual image, the focus of this paper is to propose an efficient algorithm to fuse a visual image and a corresponding low resolution IR image such a concealed weapon detection application. Discrete wavelet transform plays a vital role in image fusion since it minimizes structural distortions among the various other transforms. Lack of shift invariance, poor directional selectivity and the absence of phase information are the drawbacks of discrete wavelet transform. These drawbacks are overcome by dual tree complex wavelet transform. The fused image obtained by the proposed algorithm will maintain the high resolution of the visual image incorporate any single image. The feasibility of the proposed fusion technique is tested and demonstrated by some experimental results in form of visual, mathematical output and various fusion assessment methods like signal to noise ratio (SNR), peak signal to noise ratio (PSNR), root mean square error (RMSE) and correlation coefficient. Those outputs are compared with various popular image fusion techniques.

Keywords—DT-CWT, filter bank, image fusion, infrared image, visual image

Introduction

Image fusion can be defined as the process of combining two or more different images into a new single image retaining salient features from each image with extended information content. For example Infrared and visible images are fused to help pilots landing in poor weather, visible and microwave images are used to detect weapons and Magnetic Resonance Imaging and Computed Tomography images are fused for medical diagnosis[1]. The fusion process should preserve all relevant information in the fused image, should reduce noise and should suppress any artifacts in the fused image. Image fusion is an important research topic in areas such as computer vision, automatic object detection, remote sensing, image processing, robotics, and medical imaging. The user can collect useful information without gazing at and comparing images from multiple sensors.

Multi-camera images often have different geometric representations, which have to be transformed to a common representation for fusion[2]. This representation should retain the best resolution of either sensor. A prerequisite for successful in image fusion is the alignment of multi-sensor images. Multi-sensor registration is also affected by the differences in the sensor images. Wavelet based fusion techniques have been reasonably effective in combining perceptually important image features. Shift invariance of the wavelet transform is important in ensuring robust sub band fusion. Therefore, the novel application of the shift invariant and directionally selective Dual Tree Complex Wavelet Transform (DT-CWT) to image fusion is now introduced. This novel technique provides improved qualitative and quantitative results compared to previous wavelet fusion methods.

The complex wavelet transform (CWT) is a complex-valued extension to the standard discrete wavelet transform (DWT)[3]. It is a two-dimensional wavelet transform which provides multi resolution, sparse representation, and useful characterization of the structure of an image. Further, it purveys a high degree of shift-invariance in its magnitude. However, a drawback to this transform is that it is exhibits 2d (where d is the dimension of the signal being transformed) redundancy compared to a separable (DWT).

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The use of complex wavelets in image processing was originally set up in 1995 by J.M. Lina and L. Gagnon [3] in the framework of the Daubechies orthogonal filters banks [4]. It was then generalized in 1997 by Prof. Nick Kingsbury [3][4][5][6].

Methodology

Dual Tree Complex Wavelet Transform

One major drawback of DWT[7] is its poor directional selectivity for diagonal features, because the wavelet features are separable and real. The way to increase the directionality is to use the complex extension of DWT, named as Dual Tree Complex Wavelet Transform (DTCWT). DTCWT gives better directional selectivity in 2-D with Gabor like filters. Standard DWT offers the feature selectivity in only 3 directions with poor selectivity for diagonal features, where as DT-CWT has 12 directional wavelets (6 for each of real and imaginary trees) oriented at angles of ±15°, ±45°, ±75° in 2-D as shown in following Fig. 3. The improved directionality with more orientations suggests the advantage of DT-CWT in a vide rage of directional image processing applications, e.g. texture analysis. Approximate Shift Invariance, Good Directional Selectivity in 2-Dimensions, Perfect Reconstruction, Limited Redundancy and Efficient order - *N* Computations are the major properties of DTCWT.

Figure 1(a): Directionality for DT-CWT

1(b): Directionality for DWT

The properties of the DT-CWT can be summarized as

- Approximate shift invariance;
- Good directional selectivity in 2 dimensions;
- Phase information;
- Perfect reconstruction using short linear phase filters;
- Limited redundancy, independent of the number of scales, 2 : 1 for 1D (2*m* : 1 for *m*D);
- Efficient order-N computation only twice the simple DWT for 1D (2m times for mD).

Filter Bank Structure of DT-CWT

As in the case of filter design[5][6] for real wavelet transforms, there are various approaches to the design of filters for the dual-tree CWT. In the following, i describe methods to construct filters satisfying the following desired properties:

- Approximate half-sample delay property
- PR (orthogonal or biorthogonal)
- Finite support (FIR filters)
- Vanishing moments/good stopband
- Linear-phase filters (desired, but not required of a wavelet transform for it to be approximately analytic).
- Moreover, only the complex filter responses need be linear phase;

Dual-tree complex wavelet transform (DT-CWT) which is an enhancement to the discrete wavelet transform (DWT), possesses two key properties, i.e., the transformation is nearly shift invariant and it has better directionality in higher- dimensional space.

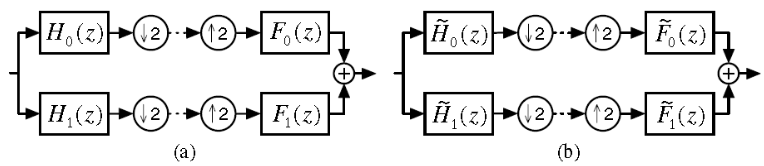

Figure 2: A typical two-channel analysis/synthesis dual-tree structure (a) primal filter bank; (b) dual filter bank.

In this section, a brief detail is given for DT-CWT only. Consider a two-channel dual-tree filter bank implementation of the complex wavelet transform. Shown in Figure 2(a), the primal filter bank P in each level defines the real part of the wavelet transform.

Fusion Assessment Methods

Since the emergence of image fusion techniques in various applications, methods that can assess or evaluate the performance of different fusion techniques objectively, systematically and quantitatively have been recognized as an important necessity. In this portion various fusion assessment techniques that have been proposed in the field of image fusion, is discussed.

Signal to Noise Ratio (SNR), Peak Signal to Noise Ratio (PSNR), Root Mean Square Error (RMSE) and Correlation Coefficient [10,11,12,13] are commonly used measures in assessing image fusion techniques, in case when the reference image is available, that consider an image as a special type of signal. The quality of a signal is often expressed quantitatively with the signal to noise ratio defined as

$$SNR = 10\log_{10}\left(\frac{\sum_{m=1}^{M}\sum_{n=1}^{N} z(m,n)^2}{\sum_{m=1}^{M}\sum_{n=1}^{N}[z(m,n)-s(m,n)]^2}\right) \quad \text{.................................(1)}$$

The PSNR, RMSE and Correlation Coefficient are measures similar to the SNR and defied as

$$PSNR = 10\log_{10}\left(\frac{Peak^2}{\sum_{m=1}^{M}\sum_{n=1}^{N}[z(m,n)-s(m,n)]^2}\right) \quad \text{.................................(2)}$$

For 8-bit image peak 11111111 is equal to 255.

$$RMSE = \left(\frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}[z(m,n)-s(m,n)]^2\right)^{1/2} \quad \text{............................(3)}$$

$$CORCO = \left(\frac{\sum_{m=1}^{M}\sum_{n=1}^{N}(z(m,n)-\bar{z})(s(m,n)-\bar{s})}{\sum_{m=1}^{M}\sum_{n=1}^{N}[z(m,n)-\bar{z}]^2 \sum_{m=1}^{M}\sum_{n=1}^{N}[s(m,n)-\bar{s}]^2}\right) \quad \text{....................(4)}$$

Fusion Method

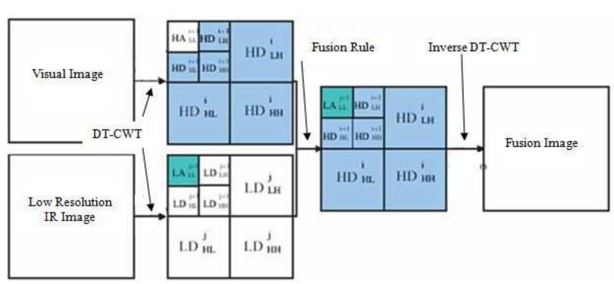

Figure 3: Fusion method

In above image fusion first apply DT-CWT to both images so it decomposed into detail coefficients. Each image divided into 16 sub images with different detailed parameter per level decomposition. After that I used image fusion rule either maximum selection or averaging for fusing the wavelet coefficients. After that apply the inverse DT-CWT to reconstruct the image.

Result

By applying various common methods and proposed DT-CWT methods the output shown below. SNR, PSNR, RMSE, and COR CO. are found and compare for each methods[14,15].

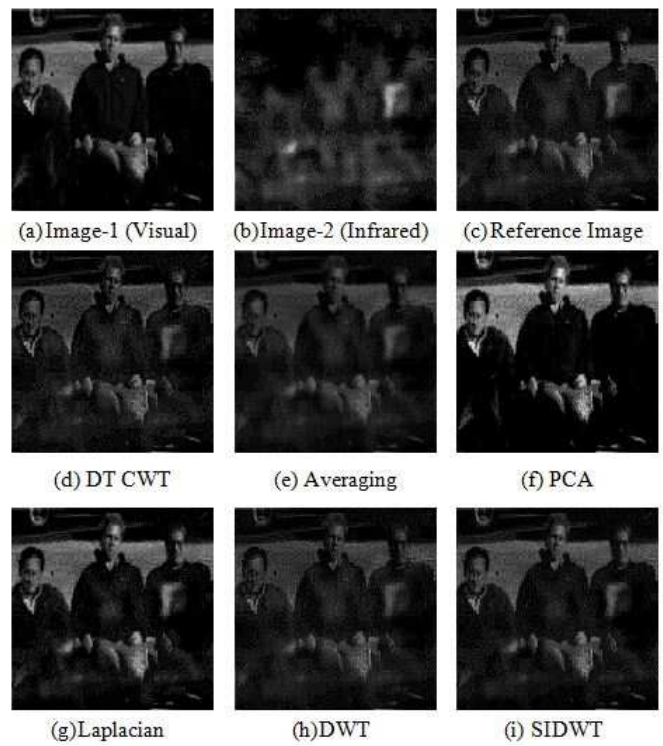

Figure 4 : (a) First image to fuse (Visual Image) (b)Second image to fuse (Low Resolution IR Image) (c)Reference Image (d) Image Fusion using DT-CWT (e) Image Fusion using Averaging (f) Image Fusion using PCA (g) Image Fusion using Laplacian Pyramid (h) Image Fusion using DWT (i) Image Fusion using SIDWT

TABLE I
Comparison Table for various methods for Image

Image to Fuse	Method	DT-CWT	AVERAGE	PCA	LAPLACIAN	DWT	SIDWT
Visual	**SNR**	37.731	31.683	10.8289	22.1735	33.0704	34.1091

Image and Low Resolution IR Image	**PSNR**	77.8261	72.8316	41.6536	56.4482	73.9599	72.8912
	RMSE	5.2068	6.6838	31.772	15.1629	6.3171	6.6639
	COR CO	0.9774	0.97	0.7976	0.9557	0.9708	0.9684

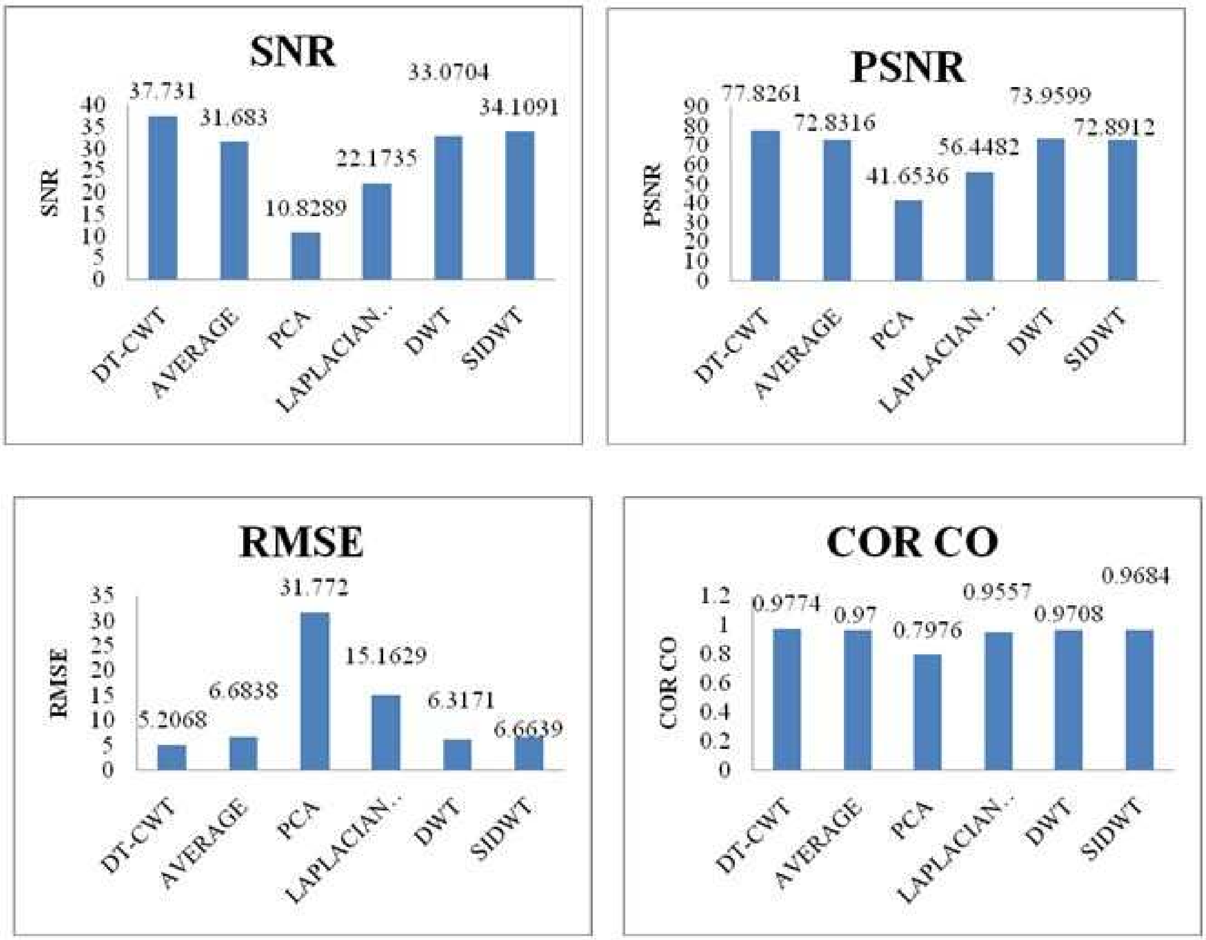

Figure 5: SNR, PSNR, RMSE, COR CO. vs Various Methods

As shown in figure 4 Image (a) and Image (b) are fused using six various famous methods. From visual quality of fused image we can see that quality of fused image (d) which is fused using DT-CWT fusion methods have more information as compared to all other images. That is mathematically tested using various Fusion assessment methods. Various parameters like SNR (Signal to Noise Ratio), PSNR (Peak Signal to Noise Ratio), RMSE (Root Mean Square Error) and COR CO (Correlation Coefficients) are calculated for all six methods using reference image and putted into table 1 as well as plotted on above Figure 5. From table and graph we can see that PSNR, SNR and COR CO are highest for proposed method while RMSE is lowest for proposed methods which is desirable. From all above thing it is concluded that proposed DT-CWT based image fusion method is batter than all other methods. It is worth noting that, in the fused image, the cold regions inside the area of human body will have different from the same place in the visual image. That's why the concealed weapon is shown in different from the surrounding human body part. However, some parts of clothing near the weapon may not have contact with the human body and thus they may have a similar gray-level as the concealed weapon. However, we can still identify the location of the weapon. It should be pointed out that, one advantage of the proposed fusion method is that for the whole procedure, no parameter tuning or training is needed which means we don't need to pre-use some images to find a good set of parameters that would perform well first.

Conclusion

In this paper, I proposed an image fusion method for concealed weapon detection application where i fuse visual and low resolution IR images to provide a fused image that provides a detailed description of the people in the scene and any hidden weapons detected by the IR image. The proposed method is very useful in security system to find the complete view of human being with concealed weapon which is not possible by only visual camera or any low resolution IR image.

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References

[1] M. Waxman, M. Aguilar, R. A. Baxter, D.A. Fay, D. B. Ireland, J. P. Racamato, W. D. Ross, Opponent-color fusion of multi-sensor imagery: visible, IR and SAR, Proceedings of IRIS Passive Sensors, vol.1, pp. 43-61, 1998.

[2] Xiao Gang, Yang Bo, Jing Zhongliang. “Infrared and Visible Dynamic Image Sequence Fusion Based on Region Target Detection”, The 10th International Conference on Information Fusion. July 2007.

[3] N.G. Kingsbury. The dual-tree complex wavelet transform with improved orthogonality and symmetry properties. IEEE International Conference on Image Processing, pages 375–378, September 2000.

[4] Kingsbury, N G (May 2001). "Complex wavelets for shift invariant analysis and filtering of signals" (PDF). Journal of Applied and Computational Harmonic Analysis 10 (3): 234–253.

[5] Selesnick, Ivan W.; Baraniuk, Richard G. and Kingsbury, Nick G. (November 2005). "The Dual-Tree Complex Wavelet Transform" (PDF). IEEE Signal Processing Magazine 22 (6): 123–151.

[6] N. G. Kingsbury. “Complex wavelets for shift invariant analysis and filtering of signals”, Journal of Applied and Computational Harmonic Analysis, Vol 10, No 3, pp 234-253, 2001.

[7] I. W. Selesnick. “The design of approximate hilbert transform pairs of wavelet bases”, IEEE Trans. on Signal Process, 50(5): pp 1144-1152, 2002.

[8] M. Aguilar, and J. R. New, Fusion of multi-modality volumetric medical imagery, ISIF 2002, pp. 1206-1212.

[9] R. C. Gonzalez, R. E. Woods, Digital Image Processing, Second Edition, Prentice Hall, New Jersey 2002.

[10] Shivsubramani Krishnamoorthy, K P Soman, “Implementation and Comparative Study of Image Fusion Algorithms”, International Journal of Computer Applications, Vol. 9, No. 2, pp. 25-35, Nov. 2010.

[11] T.A. Wilson, S.K. Rogers and M. Kabrisky, “Perceptual-based image fusion for hyperspectral data”, IEEE Transactions on Geoscience and Remote Sensing, Vol. 35, No. 4, 1997, pp. 1007–1017

[12] J.-H. Park, K.-O. Kim and Y.-K. Yang, “Image fusion using multiresolution analysis”, in Proc. of the International Geoscience and Remote Sensing Symposium, Vol. 2, 2001, pp. 864–866

[13] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: From error visibility to structural similarity“, IEEE Transactions on Image Processing, vol. 13, no. 4, pp.600-612, Apr. 2004

[14] O. Rockinger. Image fusion toolbox for Matlab. Technical report, Metapix, 1999. http://www.metapix.de/toolbox.htm. 2, 3.2

[15] The Online Resource for Research in Image Fusion www.imagefusion.org