A novel Image Fusion Technique using Dual Tree Complex Wavelet Transform

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Abstract— Fusion is basically extraction of best of inputs and transferring it to the output. Image fusion is the process of combining the relevant information from a set of images into a single image, where the resultant image will be more informative and complete than any of the input images. A novel image fusion technique based on Dual-Tree Complex Wavelet Transform (DT-CWT) is presented in this paper. Fusion rule based on magnitude of analytic wavelets is used to extract information from the source images decomposed using Oriented 2D DT-CWT. The fused image is obtained through inverse 2D DT-CWT reconstruction process. Experimental results show that the proposed fusion method based on Oriented 2D DT-CWT is remarkably better than the fusion methods based on real oriented 2D Dual Tree transform, Stationary Wavelet Transform and classical Discrete Wavelet Transform. This paper is organized as follows: (i)introduction ((ii) design overview and algorithm (iv) results and discussions (v) conclusion.

Keywords— Wavelets, 2D-DTCWT,Fusion,Hilbert Transform,Directionality,Shift invariantce,PSNR,MSE.

INTRODUCTION

Data fusion is a process dealing with data and information from multiple sources to achieve refined and improved information for decision making[4].Image and video fusion is a specialization of the more general topic of data fusion, dealing with image and video data. Image fusion can be defined as the process by which multiple images, or some of their attributes are combined together to form a single image. Image fusion provides an effective way for the reduction of increased volume of information by extracting all the useful information from the source images. With rapid developments in the domain of imaging technologies, image fusion has become inevitable in wide fields such as medical imaging, remote sensing, robotics and military applications[3].

Fourier Transform approach for image fusion does not provide simultaneous localization in both space and frequency. Thus Fourier transform is not suitable for multiresolution based image processing. Another Fourier based approach called Short Time Fourier Transform (STFT) which is considered as an improved version of Fourier transform uses narrow windows so that part of non-stationary signal appears to be stationary. This approach provided good spatial resolution but poor frequency resolution. Discrete Wavelet Transform (DWT) provides simultaneous localization in both frequency and space and found to be an efficient tool for image processing applications [12].

The wavelet transform suffers from four fundamental, intertwined shortcomings. The first problem is that wavelet coefficients tend to oscillate positive and negative around singularities as wavelets are band pass functions. This complicates wavelet-based processing, specifically making singularity extraction and signal modeling very difficult [6].Moreover, since an oscillating function passes often through zero, the conventional wisdom that singularities yield large wavelet coefficients is exaggerated. Certainly, it is possible for a wavelet overlapping a singularity to have a small or even zero wavelet coefficient. The second problem is Shift variance, ie, a small shift of the signal greatly disturbs the wavelet coefficient oscillation pattern around singularities. Lack of Shift invariance also complicates wavelet-domain processing; algorithms must be made capable of coping with the wide range of possible wavelet coefficient patterns caused by shifted singularities [9][5]. Aliasing is another problem. Wavelet coefficients are computed via iterated discrete-time decimations interspersed with non ideal low-pass and high-pass filtering resulting in substantial aliasing,ie,wide spacing of wavelet coefficients occurs. Certainly if the wavelet and scaling coefficients are not changed then the inverse DWT cancels this aliasing. Any wavelet coefficient processing such as filtering,thresholding and quantization upsets the delicate balance between the forward and inverse transforms and this leads to artifacts in the reconstructed signal.Stationary wavelet Transform (SWT) does not have shift sensitivity as the downsampling operations are eliminated. But this results in very high redundancy [11].Finally, multi dimensional real wavelets are simultaneously oriented along several directions resulting in checker board appearance.Modeling and processing of geometric image features like ridges and edges becomes complicated due to lack of directional selectivity [2].The main reason for the short comings of DWT is that it is based on real valued oscillating wavelets.

Fourier transform does not suffer from these problems. The magnitude of the Fourier transform does not oscillate positive and negative but rather provides a smooth positive envelope in the Fourier domain.Second,the magnitude of the Fourier transform is perfectly shift invariant, with a simple linear phase offset encoding the shift. Third, the Fourier coefficients are not aliased and do not rely on a complicated aliasing cancellation property to reconstruct the signal; and fourth, the sinusoids of the M-D Fourier basis are highly directional plane waves. This is because Fourier transform is based on complex-valued oscillating sinusoids.

$$e^{j\Omega t} = \cos(\Omega t) + j \sin(\Omega t) \text{ ,with } j = \sqrt{-1}. \quad (1)$$

The oscillating cosine and sine components are the real and imaginary parts respectively and they are 90◦ out of phase with each other.So they forms a Hilbert transform pair and together they constitute an analytic signal $e^{j\Omega t}$ that is supported on only one-half of the frequency axis[7].

DESIGN OVERVIEW AND ALGORITHM

Nick Kingsbury proposed two versions of 2D Dual Tree transform. The first one is Real Oriented 2D Dual Tree Transform with orientations in six distinct directions and approximate shift invariance. The second one is Oriented 2D Dual Tree Complex Wavelet Transform which is fully shift invariant with orientations same as that of Real Oriented 2D Dual Tree Transform[10].Dual tree wavelets are not only approximately analytic but also oriented and thus more suitable for analyzing and processing oriented singularities like edges in images and surfaces in 3-D data sets. Although wavelet bases are optimal for 1-D signals, the 2-D wavelet transform does not possess these optimality properties for natural images[1][8]This is because the separable 2-D wavelet transform is less efficient for line and curve singularities(edges) even though it represents point singularities efficiently.The 2D Dual Tree Transform represents edges more efficiently than separable DWT by isolating edges with different orientations in different subbbands,and they frequently give superior results in image processing applications compared to the separable DWT.

By considering a 2D wavelet $\psi(x, y) = \psi(x)\, \psi(y)$ associated with row-column implementation of wavelet transform, where $\psi(x)$ is a complex wavelet given by $\psi(x) = \psi_h(x) + j\psi_g(x)$,the expression for $\psi(x, y)$ obtained is given as

$$\begin{aligned}
\psi(x, y) &= [\psi_h(x) + j\psi_g(x)]\,[\psi_h(y) + j\psi_g(y)] \\
&= \psi_h(x)\, \psi_h(y) - \psi_g(x)\, \psi_g(y) \\
&\quad + j[\psi_g(x)\, \psi_h(y) + \psi_h(x)\, \psi_g(y)] \\
\text{Real Part } \{\psi(x, y)\} &= \psi_h(x)\, \psi_h(y) - \psi_g(x)\, \psi_g(y) \quad (2) \\
\text{Imaginary Part } \{\psi(x, y)\} &= \psi_g(x)\, \psi_h(y) + \psi_h(x)\, \psi_g(y) \quad (3)
\end{aligned}$$

The real part of this complex wavelet is obtained as the difference of two separable wavelets and is oriented in -45^0.The spectrum of real part of complex wavelet does not possess checker board artifact as the complex wavelet $\psi(x)$ is approximately analytic,ie, $\psi_g(x)$ is the Hilbert transform of $\psi_h(x)$. Real 2D wavelet oriented at $+45^0$ can be obtained by making $\psi(x, y) = \psi(x)\, \psi(y)^*$,where $\psi(y)^*$is the complex conjugate of $\psi(y)$.Four more oriented real wavelets in the direction of $+75^0$,-75^0 $+15^0$ and -15^0 can be obtained by repeating the above procedure on $\Phi(x)\psi(y)$, $\Phi(x)\psi(y)^*$, $\psi(x)\Phi(y)$, $\psi(x)\,\Phi(y)^*$.The real part of the complex Dual Tree wavelet Transform alone constitutes the Real Oriented 2D Dual Tree Transform.

Oriented 2D Dual Tree Complex Wavelet Transform was developed by considering the imaginary part in equation(3) along with the real part in equation(2).The spectrum of Imaginary part of complex 2D wavelet in 2D frequency plane is same as its real part oriented at -45^0.This transform give rise to six distinct directions and there are two wavelets in each direction as shown in Figure1.One of the wavelet can be interpreted as the real part of a complex valued 2D wavelet and the other wavelet is interpreted as the imaginary part of a complex 2D wavelet. The magnitude of each complex wavelet is an approximately circular bell-shaped function. Real version of Dual tree transform is two times expansive whereas the complex version of Dual Tree transform is four times expansive.

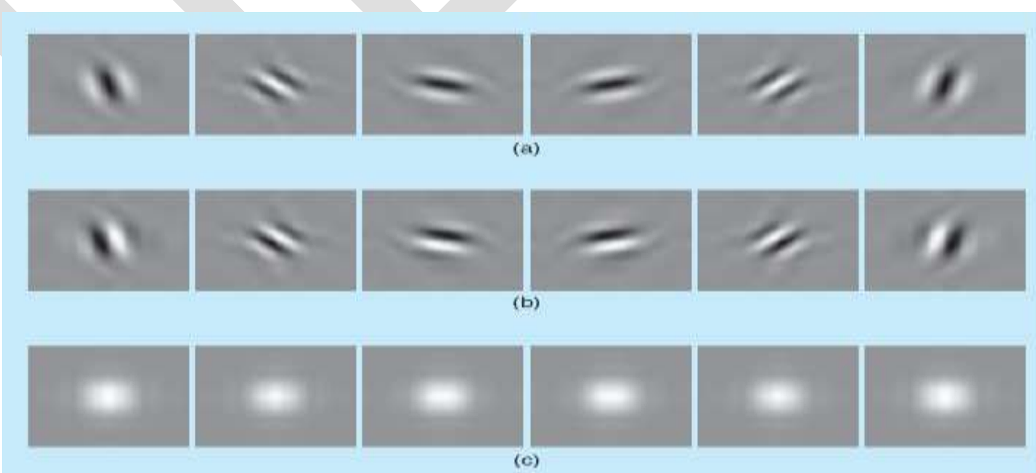

Figure 1:Wavelets associated with the oriented 2D-dual tree CWT.(a)real part of complex wavelet;(b)imaginary part;and (c)illustrates the magnitude

As shown in figure (2) image fusion is performed by decomposing the input images into approximation and detail images using Dual Tree Complex Wavelet Transform.The fusion rule is then applied on the sub images and inverse Dual Tree Wavelet Transform is applied on fused subimages to obtain the fused image.

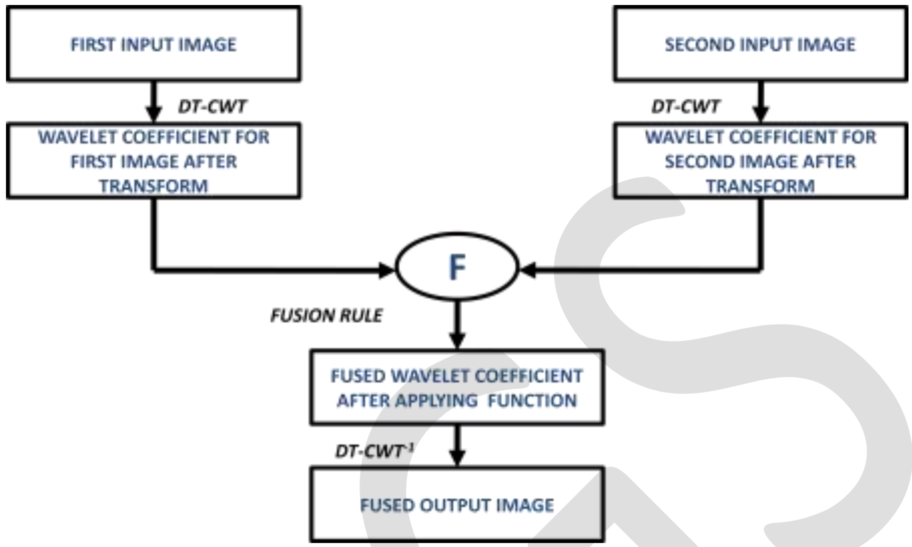

Figure 2:Image fusion methodology

The block diagram in figure(3) explains how image decomposition can be achieved using 2D Dual Tree complex wavelet Transforms. The scaling functions Φ(x)and Φ(y) are implemented using low pass filters and the wavelet functions ψ(x) and ψ(y) are implemented using high pass filters ,which forms Hilbert Transform Pairs.

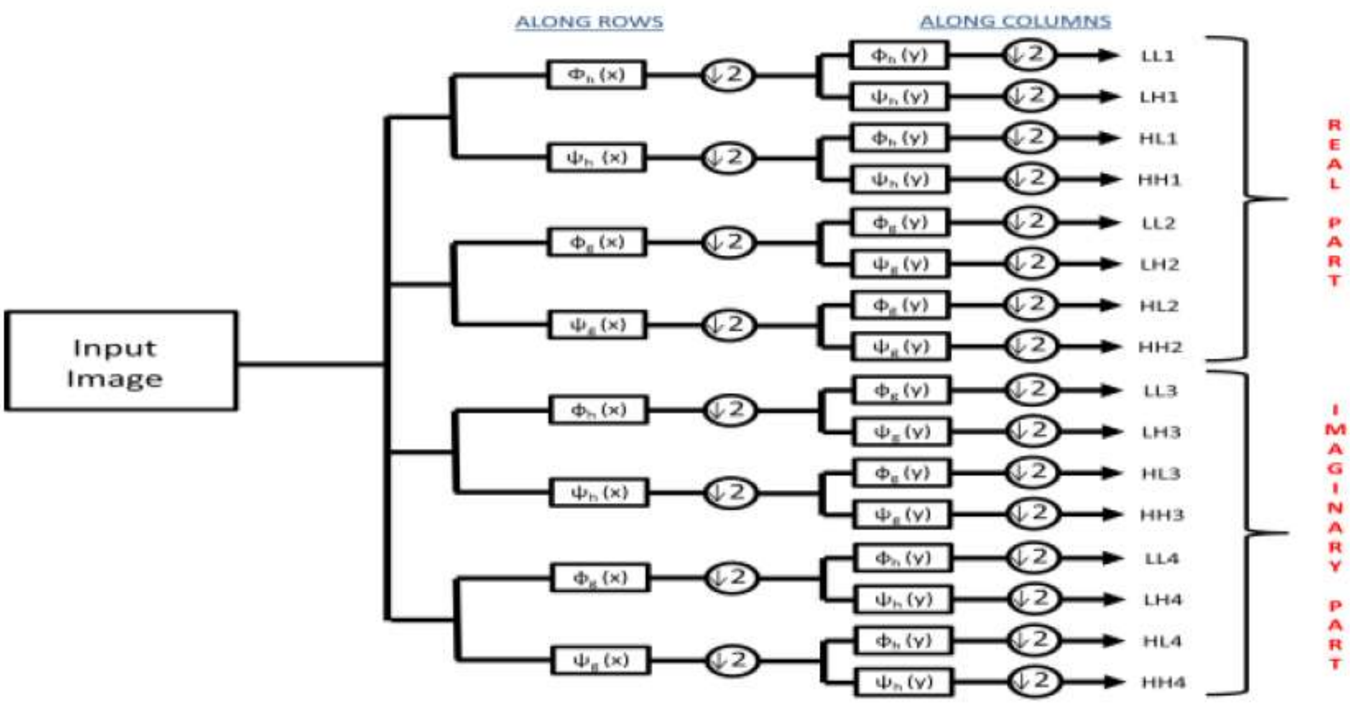

Figure 3:Image decomposition using DT-CWT

The oriented 2-D dual-tree CWT requires four separable wavelet transforms in parallel, and so it is no longer strictly a Dual-Tree Wavelet Transform. However, it is referred as such for convenience and because it is derived from the 1-D dual-tree CWT. Similarly, while the wavelets are approximately analytic, non-separable and oriented, the implementation is still very efficient, requiring only the addition and subtraction of respective subbands of four 2-D separable wavelet transforms.

Pixel based fusion algorithm applied for DWT,SWT and Real Oriented 2D Dual Tree Transform involves selecting the maximum valued pixels from the subbands of the source images. In the case of oriented 2D Dual Tree Complex Wavelet Transform fusion process involves the calculation of magnitude of complex wavelets using its real and imaginary parts. Then the pixel values from the real and imaginary subimages of source images corresponding to maximum magnitude are selected to create fused subimages. Inverse Dual Tree Transform is applied on the fused subimages to obtain the resultant fused image.

RESULTS AND DISCUSSIONS

To make an objective evaluation of the fused image quality metrics were used. The performance comparison of the proposed methods with DWT and SWT is accomplished in terms of non-referential image quality measures such as PSNR and MSE.
PSNR is defined as the ratio between the maximum possible value (power) of a signal and the power of distorting noise that affects the quality of its representation. It is expressed in terms of the logarithmic decibel scale.

$$\mathrm{PSNR} = 20\log_{10}\left(\frac{\mathrm{MAX_f}}{\sqrt{\mathrm{MSE}}}\right), \quad (4)$$

where MSE is Mean Squared Error and MAX f is the maximum signal value that exist in the original image
MSE is the average of the squares of the "errors" between actual image and fused image. It is the amount by which the values of the original image differ from the degraded image.

$$\mathrm{MSE}= \frac{1}{mn}\sum_0^{m-1}\sum_0^{n-1}\|f(i,j)-g(i,j)\|^2 \quad , \quad (5)$$

where f(i,j) represents original image,g(i,j) represents degraded image,m and n corresponds to the numbers of rows and columns of the image.

Figure4:Pair of Input images

Both the input images in figure(4) are registered and the first input image has a PSNR of 34.52 while second input image has a PSNR of 21.52.The fused resultant images using various techniques are shown in figure (6)


(1)


(2)


(3)


(4)

Figure 5: Fused image based on algorithms (1) to (4) are DWT,SWT, Real oriented 2D Dual Tree Transform and Oriented 2D DT-CWT .

Table 1 shows the evaluation of image fusion using various methods. Image decomposition using oriented 2D DT-CWT and fusion based on selecting the pixel values from the source images corresponding to maximum magnitude of a complex wavelet provides the best result.

Transform	PSNR	MSE
DWT	42.8705	26.296
SWT	44.9671	24.4015
Real Oriented 2D Dual Tree Transform	48.3963	20.9755
Oriented 2D DT-CWT	53.0757	17.4400

Table 1:Qualitative analysis of image fusion

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CONCLUSION

In this project work, attention was drawn towards the current trend of the use of multiresolution image fusion techniques, especially approaches based on Complex Wavelet transforms. A novel image fusion architecture based on Oriented 2D DT-CWT has been proposed, which is capable of achieving improved directionality. Qualitative analysis presented in Table 1 shows that Image fusion based on Oriented 2D DT-CWT has improved PSNR and lowest MSE values. The experimental results shows image quality mainly depends on fusion rules and directionality property of mutliresolution techniques when the input images are registered.

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