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Performance Appraisal of Q-Shift Complex Wavelet Transform for Image Fusion

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ABSTRACT *In this paper, we proposed a novel approach of Q-shift Dual Tree Complex Wavelet Transform(QDTCWT) for image fusion . The DTCWT is an over complete wavelet transform with limited redundancy and generates complex coefficients in parallel using a dual tree of wavelet filter bank structure. But, low pass delay produces a Hilbert pair relationship between two trees. This is well addressed by Q-shift filter bank structures for improving orthogonality and symmetry properties in level 2 and below. QDTCWT have feature like linear phase, tight frame, compact spatial support, good frequency domain selectivity with low side lobe levels, approximate shift invariance and good directional selectivity in two or more dimensions. This provides the QDTCWT basis mainly useful for image fusion purpose with high degree of shift-invariance and better directionality compared to the other traditional methods. The proposed algorithm has been demonstrated in the MATLAB 2010a environment and tested for different gray and colour images obtained from the different sensors for image fusion . The performance and efficiency of the algorithm are tested on the basis of various parameters such as Peak Signal–to-Noise Ratio(PSNR) and image quality index(IQI) as compared with the advanced methods already proposed by the previous authors. The results of this study revealed that the QDTCWT algorithm is capable of producing high quality image with greater fidelity, high robustness and accuracy over the other traditional image fusion methods.*

INTRODUCTION

Image fusion is the process by which two or more images are combined into a single image retaining the important features from each of the original images. The fusion of images is often required for images acquired from different instrument modalities or capture techniques of the same scene or objects. Important applications of the fusion of images include medical imaging, microscopic imaging, remote sensing, computer vision, and robotics. Image fusion provides an effective way of reducing this increasing

volume of information while at the same time extracting all the useful information from the source

images. Multi-sensor data often presents complementary information about the region surveyed, so image fusion provides an effective method to enable comparison and analysis of such data. The aim of image fusion, apart from reducing the amount of data, is to create new images that are more suitable for the purposes of human/machine perception, and for further image-processing tasks such as segmentation, object detection or target recognition in applications such as remote sensing and medical imaging. For example, visible-band and infrared images may be fused to aid pilots landing aircraft in poor visibility. Multi-sensor images often have different geometric representations, which have to be transformed to a common representation for fusion. 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. However, image fusion does not necessarily imply multi-sensor sources, there are interesting applications for both single-sensor and multi-sensor image fusion.

Fusion techniques include the simplest method of pixel averaging to more complicated methods such as principal component analysis and wavelet transform fusion. Several approaches to image fusion can be distinguished, depending on whether the images are fused in the spatial domain or they are transformed into another domain, and their transforms fused. Here in this paper we proposed the Q-shift complex wavelet transform for image fusion and de-noising application. The inherent properties of Q-shift complex wavelet transform[16,17] will outperform the fusion method suggested by the previous authors.

DUAL TREE COMPLEX WAVELET TRANSFORM

Kingsbury's complex wavelets [13, 14] have similar shapes to Gabor wavelets. The frequency responses for the 2D transform are shown in figure (1). As for the Gabor wavelets, there are 6 orientations at each of 4 scales (any number of scales can be used, but the number of orientations is built into the method).

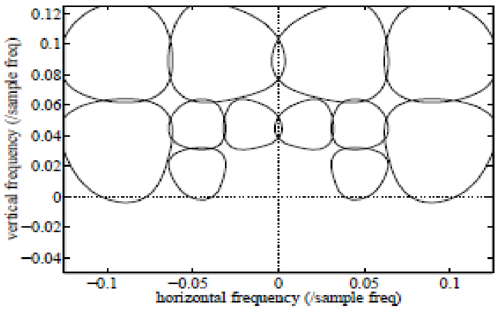

Figure 1: Contours of 70% peak magnitude of filters at scales 3 and 4

The main advantages as compared to the DWT are that the complex wavelets are approximately shift invariant and that the complex wavelets have separate subbands for positive and negative orientations. Conventional separable real wavelets only have subbands for three different orientations at each level and cannot distinguish lines near 45° from those near −45°. The complex wavelet transform attains these properties by replacing the tree structure of the conventional wavelet transform with a dual tree shown in figure (2). At each

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scale one tree produces the real part of the complex wavelet coefficients, while the other produces the imaginary parts. Note that all the filters in the dual tree are real. Complex coefficients only appear when the two trees are combined. The extra redundancy allows a significant reduction of aliasing terms and the complex wavelets are approximately shift invariant [15]; translations cause large changes to the phase of the wavelet coefficients, but the magnitude, and hence the energy, is much more stable. By using even and odd filters alternately in the trees it is possible to achieve overall complex impulse responses with symmetric real parts and antisymmetric imaginary parts.

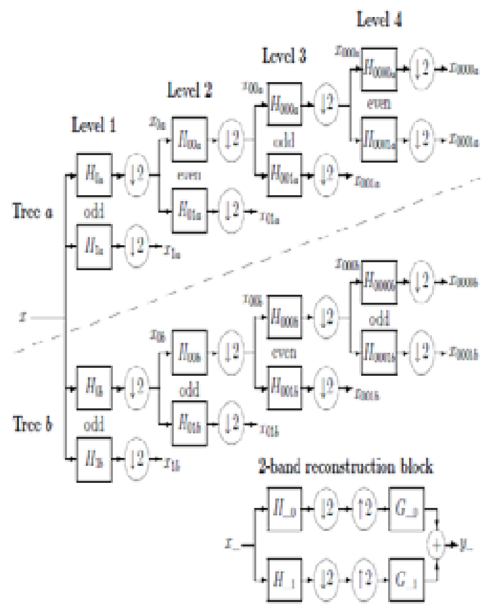

Figure 2: The complex wavelet dual tree Filter structure

The filters are designed to give a number of desired properties including strong discrimination between positive and negative frequencies. Note that it is impossible to discriminate positive and negative frequencies when using conventional real wavelets. This important property means that in a 2D version of the dual tree separable filters can be used to filter

an image and still distinguish the information in the first and second quadrants of the two-dimensional frequency response - information that allows us to distinguish features at angles near 45° from those near −45°. The filters are near-balanced and permit perfect reconstruction from either tree. The results of inverting both trees are averaged as this achieves approximate shift invariance. In d dimensions with N samples, the transform has a computational order of N2d. For comparison the fully decimated transform has order N and the non-decimated wavelet transform has order N((2d − 1)k + 1) where k is the number of scales.

Q- SHIFT DUAL TREE COMPLEX WAVELET TRANSFORM (PRPOSED METHOD)

The Q-shift dual tree complex wavelet transform based filter structure is shown in figure (3). The filter structure as shown in figure (2) has some drawback. In each subband one tree produces the real part and the other the imaginary part of the complex wavelet coefficient and so the filters in the two trees cannot be identical but must be designed to produce responses that are out of phase. More precisely, a delay difference of 1/2 sample is required between the outputs of the two trees. The main problems with the odd/even filter approach to achieving this delay are that [16,17]:

1. The sub-sampling structure is not very symmetrical.
2. The two trees have slightly different frequency responses.
3. The filter sets must be biorthogonal because they are linear phase.

These drawbacks have been overcome with a more recent form of the dual tree known as a Q-shift dual tree complex wavelet transform[16,17]. This tree is shown in figure (3). There are two sets of filters used, the filters at level 1, and the filters at all higher levels. The filters beyond level 1 have even length but are no longer strictly linear phase. Instead they are designed to have a group delay of approximately 1/4 . The required delay difference of 1/2 sample is achieved by using the time reverse of the tree a filters in tree b. The PR filters used are chosen to be orthonormal, so that the reconstruction filters are just the time reverse of the equivalent analysis filters. There are a number of choices of possible filter combinations. We have chosen to use the (13-19)-tap near-orthogonal filters at level 1 together with the 14-tap Q-shift filters at levels ≥ 2 [16,17]. The Q-shift transform retains the good shift invariance and directionality properties of the original while also improving the sampling structure.

When we talk about the complex wavelet transform we shall always be referring to this Q-shift version unless explicitly stated otherwise.

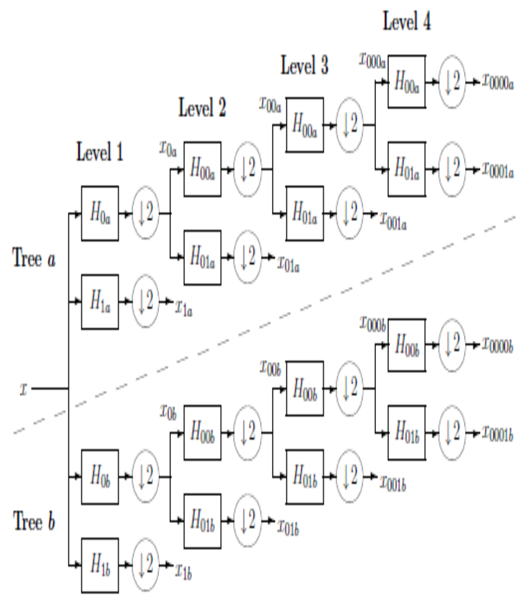

Figure 3: The Q-shift dual tree Filter structure.

Below Level 1 Half-sample delay difference is obtained with filter delays of 1/4 and 3/4 of a sample period (instead of 0 and 1/2 a sample for our original DT CWT). This is achieved with an asymmetric even-length filter H(z) and its time reverse H(z1). Due to the asymmetry (like Daubechies filters), these may be designed to give an orthonormal perfect reconstruction wavelet transform. Tree b filters are the reverse of tree a filters, and reconstruction filters

are the reverse of analysis filters, so all filters are from the same orthonormal set. Both trees have the same frequency responses. The combined complex impulse responses are conjugate symmetric about their mid points, even though the separate responses are asymmetric. Hence symmetric extension still works at image edges.

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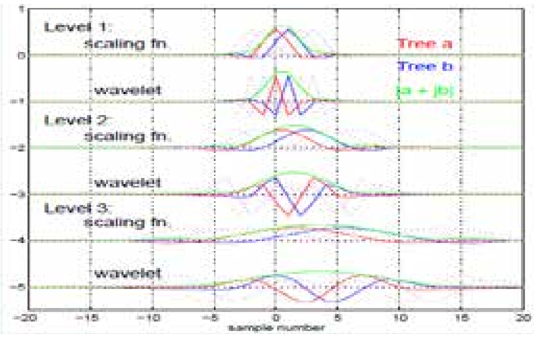

Figure 4: Q-shift DT CWT basis functions – Levels 1 to 3

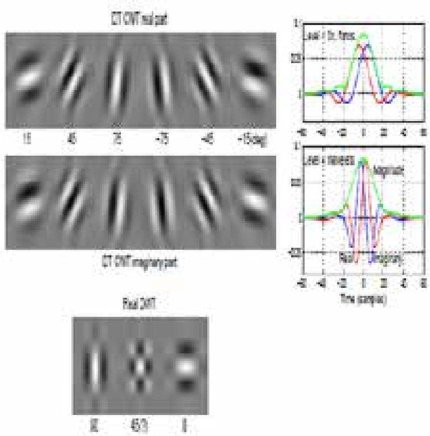

Figure5: Basis functions of 2-D Q-shift complex wavelets (top), and of 2-D real wavelet filters (bottom), all illustrated at level 4 of the transforms. The complex wavelets provide 6 directionally selective filters, while real wavelets provide 3 filters, only two of which have a dominant direction. The 1-D bases, from which the 2-D complex bases are derived, are shown to the right.

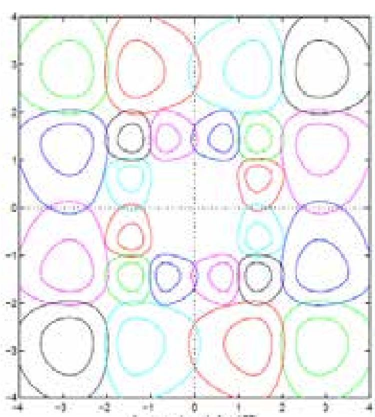

Figure6: Frequency Responses of 2-D Q-shift filters at levels 3 and 4

WAVELET TRANSFORM FUSION

The fusion process of two images using the DWT is shown in figure (4). Here in this process the two images such as mask and bust are taken from two different sources which is decomposed first and then fused to convert it in synthesized image with help of DWT. In figure(5) the two images were taken from a multi-focus set, i.e. two registered images of same scene each with a different camera focus. This figure shows that the coefficients of each transform have significantly different magnitudes within the regions of different focus. A simple "maximum selection" was used to generate the combined coefficient map. This effectively retains the coefficients of "in focus" regions within the image. This inverse wavelet transform is then applied to the combined coefficient map to produce the fused image which in this case shown an image retaining the focus from the two input images. Wavelet transform fusion is more formally defined by considering the wavelet transform ω of the two registered input images I1(x,y) and I2(x,y) is reconstructed.

$$I(x,y) = \omega^{-1}(\Phi(\omega(I_1(x,y)),\omega(I_2(x,y)))). \quad (1)$$

Figure 7: Image fusion process using the DWT and two registered Mask and Bust images.

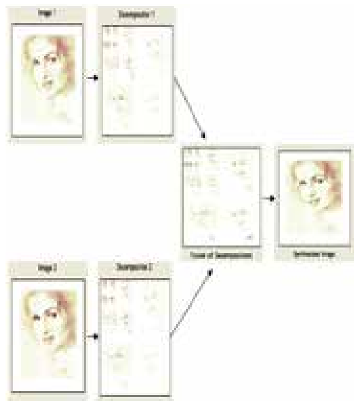

Figure 8: Image fusion process using the DWT and two registered multi-focus Katrina Kaif images

Figure(9) demonstrates the fusion of two images using the complex wavelet transform[11],[12]. The areas of the images more in focus give rise to larger magnitude coefficients within that region. A simple maximum selection scheme is used to produce the combined coefficient map. The resulting fused image is then produced by transforming the combined coefficient map using the inverse complex wavelet transform. The wavelet coefficient images show the orientation selectivity of the complex wavelet sub bands. Each of the clock hands which are pointing in different directions are picked out by differently oriented sub bands. We have implemented the same three fusion rules with the complex wavelet transform A complex wavelet transform was used with the filters given in [Kingusbury,2000] designed for improved shift invariance.

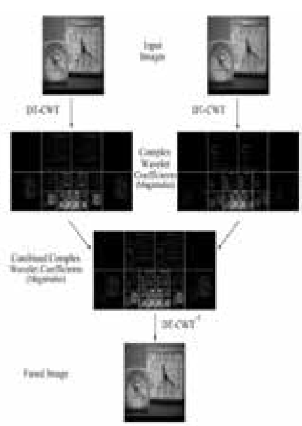

Figure 9: The image fusion process using the DT-CWT and two registered multi-focus clock images.

IMPLEMENTATION OF FUSION RULES

Three previously developed fusion rule[7],[8] schemes were implemented using discrete wavelet transform based image fusion:

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Maximum Selection (MS) Scheme: This MS scheme picks the coefficient in each sub-band with the largest magnitude.
Weighted Average (WA) Scheme: In this scheme a normalized correlation between the two images sub-bands over a small local area. The resultant coefficient for reconstruction is calculated from this measure via a weighted average of the two images coefficients.

Window based Verification (WBV) Scheme: It creates a binary decision map to choose between each pair of coefficients using a majority filter[1].

RESULT
The performance of DTCWT fusion method and QDTCWT fusion methods are compared by considering two different color images of Catherine 1(Left corrupted) and Catherine 2 (Right Corrupted) . The Synthesized image after DTCWT fusion method and QDTCWT based fusion methods are a shown in figures (13) and (14) respectively. It has been observed from figure(14) that the QDTCWT fusion techniques provide better quantitative and qualitative results than the DTCWT at the expense of increased computation. The QDTCWT method is able to retain edge information without significant ringing artifacts. It is also good at faithfully retaining textures from the input images. All of these features can be attributed to the increased shift invariance and orientation selectivity of the QDTCWT when compared to the DTCWT. Hence it has been demonstrated with the help of results that QDTCWT is an essential tool for image fusion and de-noising. Due to improved directive and shift invariant properties of QDTCWT fusion method outperforms the DTCWT fusion method.

Figure 10: Image 1Catherine Left Corrupted

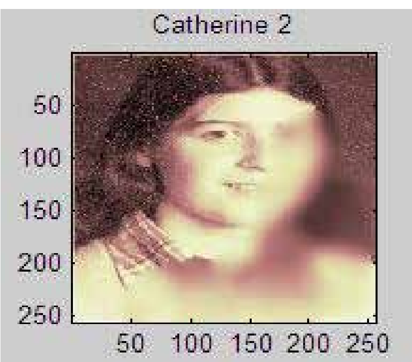

Figure 11: Image 2 Catherine Right Courrupted

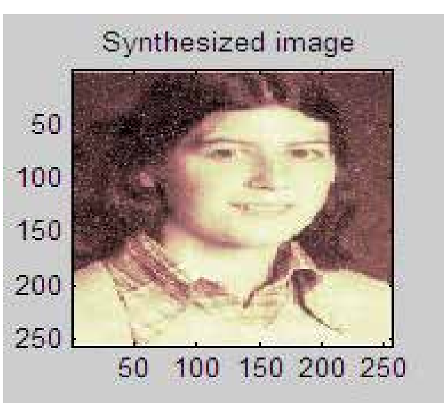

Figure 12: Image Fusion and Synthesized image of two image 1 and image 2 using DTCWT

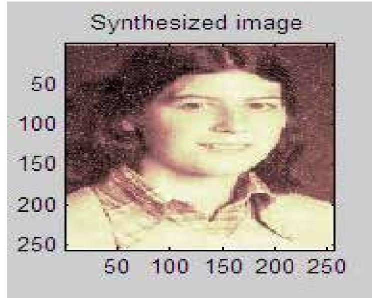

Figure 13: Image Fusion and Synthesized image of two image1 and image 2 using QDTCWT

Figure 14: Text Image 1

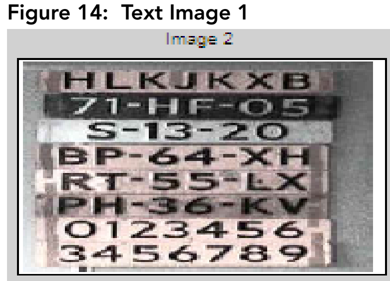

Figure 15: Text Image 2

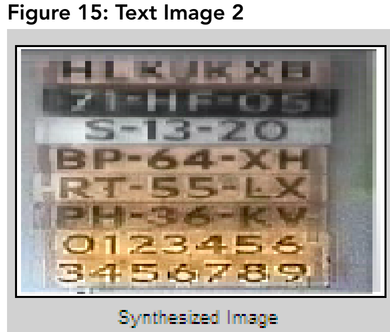

Figure 16: Image Fusion and Synthesized image of image 1 and image 2 using DTCWT

Figure 17: Image Fusion and Synthesized image of image 1 and image 2 using QDTCWT

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Figure 18: Tree Image 1

Figure 19: Tree Image 2

Figure 20: Image Fusion and Synthesized image of image 1 and image 2 using DTCWT

Figure 21: Image Fusion and Synthesized image of image 1 and image 2 using QDTCWT

TABLE 1: Comparison evaluation between DWT and DT-CWT for three different images.

Images	Text Image		Catherine Image		Tree Image	
	PSNR	NCC	PSNR	NCC	PSNR	NCC
DTCWT	27.63	0.81	18.54	0.81	20.39	0.88
QDTCWT	32.54	0.96	30.46	0.97	31.18	0.96

Figure 22: Comparative analysis of DTCWT and QDTCWT of three different images Text, Catherine and Tree

CONCLUSION

The objective of this work has been to proposed the comparative analysis between newly developed wavelet transform fusion methods QDTCWT with the existing fusion techniques. For an effective fusion of images a technique should aim to retain important features from all input images. These features often appear at different positions and scales. Multi resolution analysis tools such as the complex wavelet transform are ideally suited for image fusion. Simple DTCWT method for image fusion have produced limited results. The sub-sampling structure is not very symmetrical. The two trees have slightly different frequency responses. The filter sets must be biorthogonal because they are linear phase. The QDTCWT fusion technique of noisy Catherine 1 and Catherine 2 provides better results than the DTCWT fusion technique as depicted in figure(12) and figure (13). The QDTCWT based fusion method is able to retain important edge information without significant humming artifacts. QDTCWT provides increased shift-invariance and orientation selectivity when compared to the DTCWT. This is demonstrated and furnished in table1 shown above. The above figure (22) shows the analysis and performance of DTCWT and QDTCWT for three test images of Text, Catherine and Tree image.

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