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Benefits of Dual Tree Complex Wavelet Transform over Discrete Wavelet Transform for Image Fusion

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Abstract

In various real life applications such as medical image diagnosis, image fusion plays important role. Because of undefined nature of practical imaging systems the capture images or acquired images are corrupted from different types of noises hence fusion of image is an integrated approach where reduction of noise and retaining the original features of image is essential. Here the input to fusion involves set of images taken from different modalities of the same scene; Output is a better quality image. Discrete Wavelet Transform (DWT) has a wide range of application in fusion of noise images. Although this technique has provided substantial development over more inhabitant methods, this transform faces two major drawbacks, the shift variance and lack of directionality associated with its wavelet bases. These drawbacks have been overcome by the application of a reversible and discrete complex wavelet transform (the Dual Tree Complex Wavelet Transform DT-CWT). This paper is therefore based on the disadvantages of DWT in the field of Image Fusion and overcoming those disadvantages using a modern Image Fusion technique DT-CWT.

Keywords: Wavelet Transform, Discrete Wavelet Transform (DWT), Dual-Tree Complex Wavelet Transform (DT-CWT), Image Fusion

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I. INTRODUCTION

Image fusion is a process which combines two or more images obtained by sensors of different wavelengths simultaneously viewing of the same scene, to form one composite image. The composite image is formed to improve image content and to make it easier to discover, identify targets and increase his situational awareness. The successful fusion of images acquired from diverse instruments is of great importance in many applications, such as medical imaging, microscopic imaging, robotics and many more other fields. The research activities are mainly in the area of developing fusion algorithms that improves the information content of the composite imagery, and for making the system durable to the changes in the scene, such as smoke and environmental conditions, i.e. day or night. Four different levels can be distinguished according to signal, pixel, feature and symbolic levels. When fusion is done at pixel level the input images are combined without any pre-processing. DWT has some limitation such as less directional selectivity, shift-invariance which has been overcome by Dual Tree Complex Wavelet Transform (DT-CWT) up to the great extent. Here in this paper an advanced approach of DT-CWT based image fusion method helping in overcoming the drawbacks of Discrete Wavelet Transform is been discussed. Even though it has complexity to implement but it gives better outputs than the Discrete Wavelet Transform based image fusion technique. Section 2 gives the brief idea about wavelet transform fusion, Section 3 involves the study of Discrete Wavelet Transform its drawbacks and limitations. Section 4 comprises detail study of Dual Tree Complex Wavelet Transform and elimination of shortcoming by Discrete Wavelet transform by this novel technique. Section 5 Conclude the whole paper.

II. WAVELET TRANSFORM FUSION

The basic idea of all multi-resolution fusion schemes is motivated by the human visual system being primarily sensitive to local contrast changes, e.g. the edges or corners. In the case of wavelet transform fusion all respective wavelet coefficients from the input images are combined using the fusion criteria. Since wavelet coefficients having large absolute values contain the information about the salient feature of the images such as edges and lines. In all wavelet based image fusion schemes the wavelet transforms W of the two registered input images I1(x,y) and I2 (x,y) are calculated and these transforms are combined using some kind of fusion rule Φ. Then, the inverse wavelet transform W1 is computed and the fused image I(x,y) is redesigned:

$$I(x,y) = W1\ (\Phi(W(I1(x,y)),W(I2(x,y)))$$

III. DISCRETE WAVELET TRANSFORM

In a separable implementation, each level of the quad-tree comprises of two stages of filtering. The first stage filters and sub-samples the rows of the image, initializing a pair of horizontal low pass and high pass sub-images. The second stage of the transform filters and sub-samples the columns of the filtered row signal to produce four sub-images, denoted B0, B1, B2 and B3. This separable filtering implementation is the most efficient way to perform the 2D DWT. Fig. 1 shows a two-level DWT decomposition of an image The sub-band images B1, B2 and B3 represent the detailed wavelet coefficients representing the horizontal, diagonal and vertical elements of the input signal. For m dimensional signals 2m sub-band images are produced at each level.

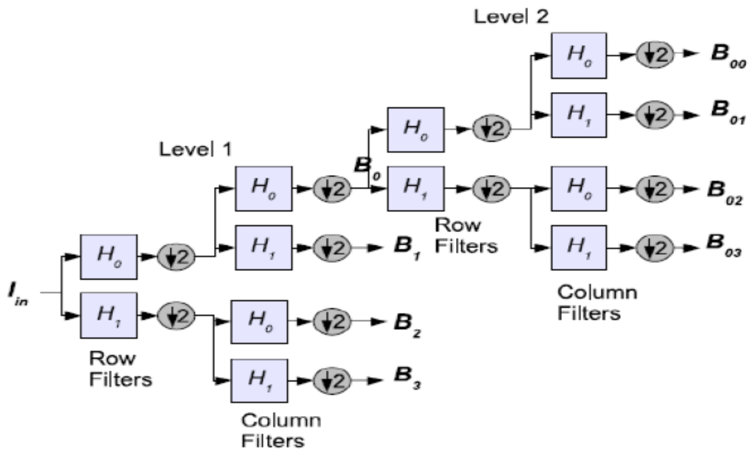

Fig. 1: Two-level DWT for a 2D signal

Although the DWT is widely used in image fusion and de-noising, its application to other image processing problems has been hampered by two drawbacks. These are:

A. Lack of Shift Invariance:

This means that small shifts in the input signal can cause major variations in the distribution of energy between DWT coefficients at different scales. A process is shift invariant if its output is independent of the absolute location of the data within the input to the process. The shift dependency occurs as a result of the aliasing that is introduced by the down-sampling that follows each filtering operation. Fig.3 illustrates the shift dependence of the DWT. The input signal is a 1 dimensional step response which is shifted 16 times. Four levels of DWT are taken and the sub-band signals related with each is shown below the input signal. Level four scaling functions are shown at the bottom of the image. The shift dependence of the transform is evident from the varying energy in each of the sub-band signals. In image processing applications, the shift dependence of the DWT has restricted its acceptability for texture analysis. This is because in any given input image, texture may show itself under any shift. If texture is to be specified by its sub-band decomposition, then this decomposition is required to remain constant irrespective of the location of the texture within the image. As a result, any transform used for examining the texture should be as close to shift invariant as possible.

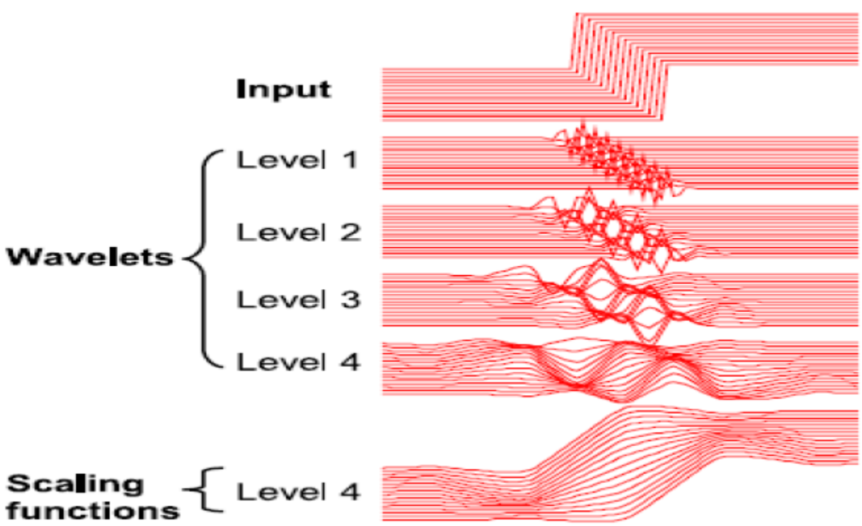

Fig. 2: Shift dependence of the DWT

B. Poor Directional Selectivity:

Separable filtering of the image rows and columns produces four sub-images at each level. These sub-band images are obtained using real filters which cannot distinguish between positive and negative frequency components. Therefore, each sub-band contains both positive and negative frequency components resulting in poor directional selectively of the DWT. Since it is unable to differentiate between positive and negative edge orientations, which results in increased unsuitability for texture analysis in DWT, given that textures are usually denoted by their frequency components [1]. Figure 4 illustrate inefficient directional selectivity of the DWT. In this figure level one sub-band images are placed on the boundary while the corresponding level two sub-band images are enclosed inside them. The final level scaling functions are shown at the top left hand corner of (ii). The intensity value in each sub-band images corresponds to the magnitude of the wavelet coefficient at that particular site. Each sub-band focuses either the horizontal, vertical or diagonal edge components of the input „circle‟ image. The poor directional selectivity of the DWT is especially evident in the sub-band that contains the diagonal components of the circle. All the sub-bands contain both the diagonal edges of the circle making it quite impractical to differentiate between them.

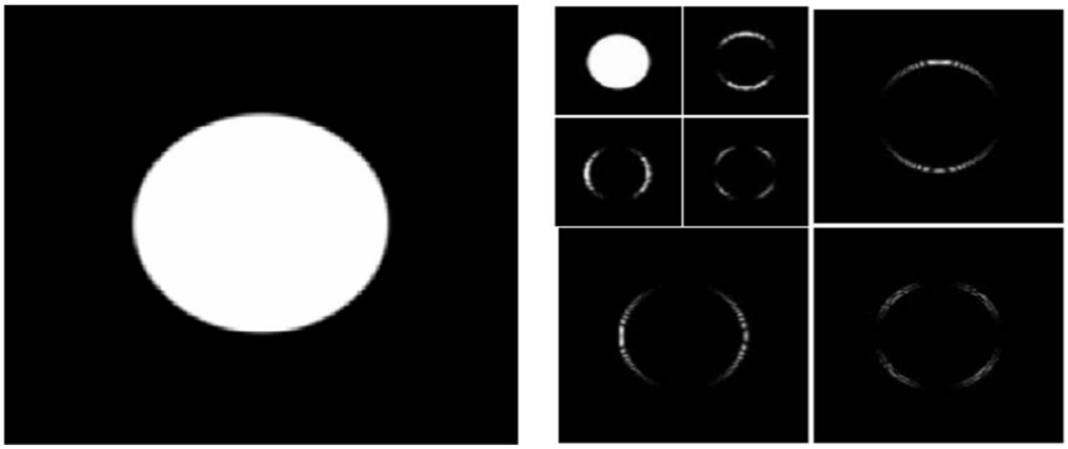

Fig. 3: The poor direction selectivity of the DWT

IV. DUAL-TREE COMPLEX WAVELET TRANSFORM

DT-CWT replaces single tree DWT structure with a dual tree real valued filters. The two parallel trees filters and down-sample the incoming input signal in the same way as DWT, but since there are two rather than one filtering tree, the aliasing effect that causes shift dependency in DWT get eliminated in DT-CWT. Discrete wavelet transform has been widely used in multi sensor image fusion, but it suffers from few major drawbacks such as poor directional selectivity and shift variance as discussed earlier in this paper. These mentioned problems were rectified by DT-CWT. At each level DT-CWT one of the trees produces the "real" part while the other tree produces the "imaginary" part of the complex wavelet coefficients. Filters in each tree are real-valued and the concept of complex coefficients only appears when outputs from the two trees are merged [11]. The inclusion of the second filter bank increases the redundancy of the transform to 2:1 for a 1D signal. A 2D dual-tree complex wavelet can be defined as $\psi(\mathrm{x}, \mathrm{y}) = \psi(\mathrm{x})\psi(\mathrm{y})$, where $\psi(\mathrm{x})$ and $\psi(\mathrm{y})$ are two complex wavelets, $\psi(\mathrm{x}) = \psi_h(x) + j\psi_g(x)$ and $\psi(\mathrm{y}) = \psi_h(y) + j\psi_g(y)$, $\psi_h(x)$ and $\psi_h(y)$ are real wavelet transforms of upper filter bank and lower filter bank, respectively. Then we get the following equations:

$$\psi(x,y) = [\psi_h(x) + j\psi_g(x)][\psi_h(y) + j\psi_g(y)] = \psi_h(x)\psi_h(y) - \psi_g(x)\psi_g(y) + j[\psi_g(x)\psi_h(y) + \psi_h(x)\psi_g(y)] \quad (1)$$

The real parts of six oriented complex wavelets of DT-CWT are as follows:

$$\psi i(x,y) = \frac{1}{\sqrt{2}}(\psi 1, i(x,y) - \psi 2, i(x,y)) \quad (2)$$

$$\psi i + 3(x,y) = \frac{1}{\sqrt{2}}(\psi 1, i(x,y) + \psi 2, i(x,y)) \quad (3)$$

For i=1, 2 and 3 we have:

$$\psi 1,1(x,y) = \phi_h(x)\psi_h(y), \psi 2,1(x,y) = \phi_g(x)\psi_g(y) \quad (4)$$

$$\psi 1,2(x,y) = \psi_h(x)\phi_h(y), \psi 2,2(x,y) = \psi_g(x)\phi_g(y) \quad (5)$$

$$\psi 1,3(x,y) = \psi_h(x)\psi_h(y), \psi 2,3(x,y) = \psi_g(x)\psi_g(y) \quad (6)$$

Where the imaginary parts of six oriented complex wavelets of DT-CWT are as follows:

$$\psi i(x,y)=\frac{1}{\sqrt{2}}(\psi 3,i(x,y)+\psi 4,i(x,y)) \qquad (7)$$

$$\psi i+3(x,y)=\frac{1}{\sqrt{2}}(\psi 3,i(x,y)-\psi 4,i(x,y)) \qquad (8)$$

For i=1, 2 and 3 we have:

$$\psi 3,1(x,y)=\phi_g(x)\psi_h(y),\psi 2,1(x,y)=\phi_h(x)\psi_g(y) \qquad (9)$$

$$\psi 1,2(x,y)=\psi_g(x)\phi_h(y),\psi 2,2(x,y)=\psi_h(x)\phi_g(y) \qquad (10)$$

$$\psi 1,3(x,y)=\psi_g(x)\psi_h(y),\psi 2,3(x,y)=\psi_h(x)\psi_g(y) \qquad (11)$$

In the above equations $\psi_h(x)$ and $\psi_g(x)$ denote the low pass filters of the upper filter bank and lower filter bank while, $\psi_h(y)$ and $\psi_g(y)$ represents the high pass filter of the upper filter bank and lower filter bank respectively. Each of the sub-band images contains the wavelet coefficients for both imaginary and real parts in the ±15degree, ±45degree and ±75degree directional edges in the original image [7].

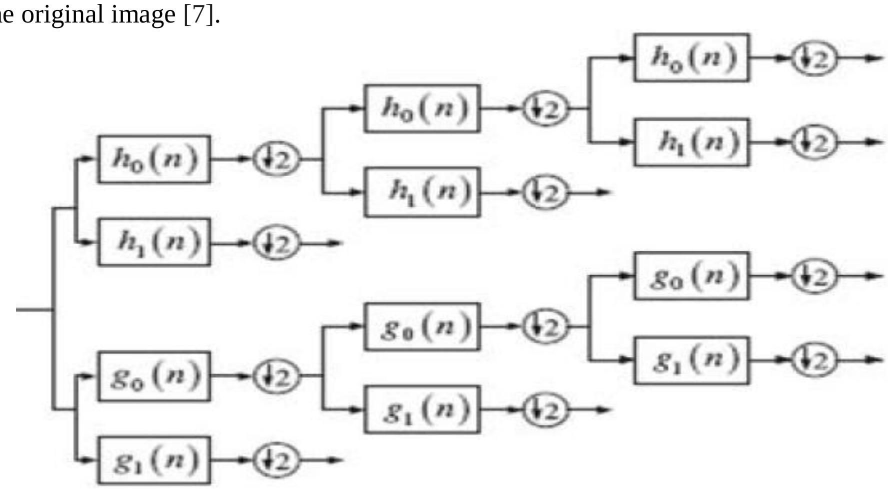

Fig. 4: Three-level DT-CWT Analysis Filter bank for decomposition of a 1D signal

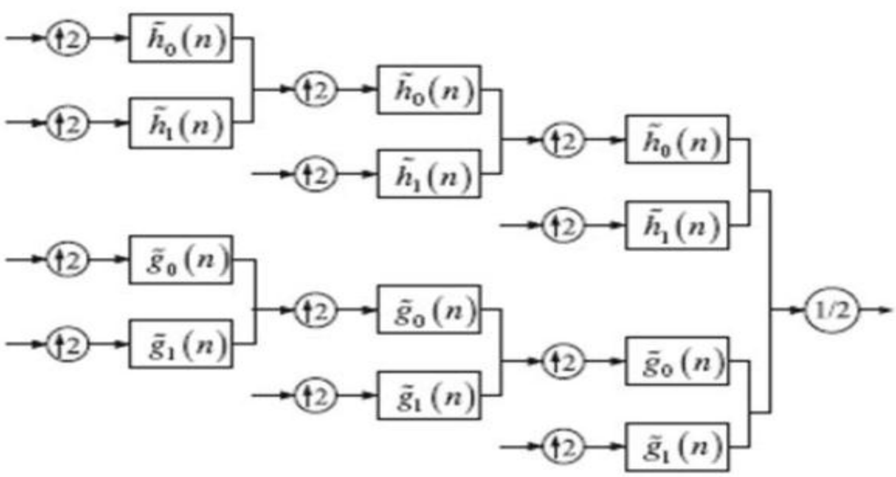

Fig. 5: Three-level DT-CWT Synthesis filter bank for reconstruction of 1D signal

Fig. 6 shows the sub-band signals associated with the DT-CWT. Since the energy with each sub-band signal at any given level remains constant despite of shift, the DT-CWT is therefore shift invariant. The good directional properties of the DT-CWT are shown in Fig.7. The "circle" image shown is the time decomposed using the DT-CWT. Unlike the DWT which combines positive and negative frequencies and produces three sub-band images at each level, the DT-CWT treats positive and negative frequencies separately and produces six sub-band images at each level. Each sub-band contains wavelet coefficients whose magnitudes are proportional to one of the ±15degree, ±45degree, ±75degree directional orientations of the input signal. Because positive and negative orientations are taken into account individually, the DT-CWT provides greater directional selectivity than the DWT [11].

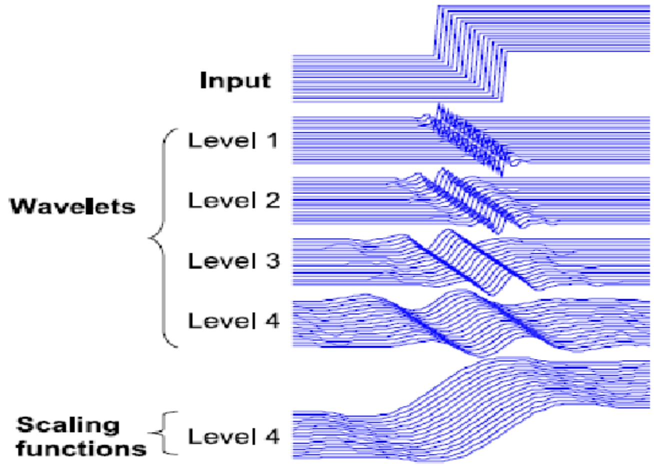

Fig. 6: Shift invariance of the DT-CWT

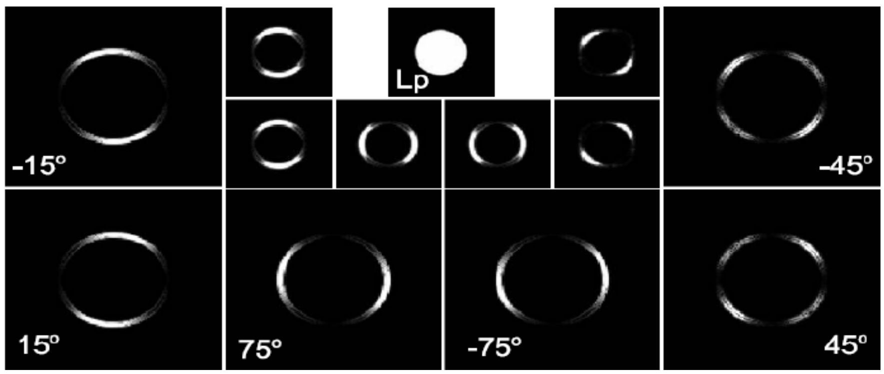

Fig. 7: The good directional properties of the DT-CWT are shown in the two-level DT-CWT decomposition of the „circle" image

V. CONCLUSION

The objective of this work is to propose a comparative analysis between newly designed wavelet transform fusion techniques with the existing fusion techniques. For an effective fusion of images a method should aim to retain essential features from all input images. These characteristics quite often appear at different positions and scales. Multi resolution testing methods such as the complex wavelet transform are ideally suited for image fusion. Simple DWT method for image fusion provides limited results and suffers from poor directional ability and shift variant property. Whereas DT-CWT based fusion techniques produces good quality fused images than DWT based techniques.

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