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Performance Evolution of Block Based Shift Invariant Wavelet Transforms for Multimodal Medical Image Fusion

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Abstract: *There are many applications for multimodal image fusion such as remote sensing, multi-spectral imaging and medical imaging. Medical images are obtained from multiple sensors. Image fusion has appeared as a new research area because of the availability of multisensory data in the medical field. Several images of the same scene provide different information although the scene is the same. The Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) are the two images which are captured with two different biomedical sensors. In general, the discrete wavelet transform is used effectively to decompose an image. But conventional wavelet transform suffers from Shift sensitivity, poor directionality and lack of phase information. Therefore, complex wavelet transforms like Dual tree complex wavelet transform (DT-CWT) and Double Density Dual Tree Complex Wavelet Transform (DD-DT-CWT) would be preferred in order to overcome the difficulties of wavelet transform. In this paper, fusing process is implemented based on statistical properties of the two fused wavelet coefficients. The performance of the fusion result is evaluated by entropy, overall pixel intensity, AC power measure and standard deviation.*

Keywords: *Dual tree complex wavelet transform, Double density dual tree complex wavelet transform, Block based statistical properties, medical image fusion*

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I. Introduction

Computer aided diagnoses (CAD) and medical treatments strongly depend on image processing methods and are of increasing importance in modern day to day life. Over the past decade, sophisticated imaging techniques such as Magnetic resonance imaging (MRI) and Computed Tomography (CT) scanning provide abundant information that is useful for diagnosis. Multimodal medical image fusion [1] has emerged as a challenging and promising area of research. . Image fusion [2] is combining multiple source images into a single one which ideally contains all desired features of the source images. Image fusion is widely used to extract the attributes or better features by retaining common features of both the multimodal medical images. Complementary information will be obtained from medical images of different modalities which will be useful in analysis and diagnosis purposes. Discrete Wavelet transform (DWT) [3] is used in multimodal image fusion in combination with various algorithms because wavelet transform provides both good time and frequency resolutions. However, DWT has several drawbacks Though, DWT has established an impressive tool for medical signal and image processing and it suffers from three major drawbacks namely shift sensitivity, poor directionality, and lack of phase information. So, complex wavelet transform (CWT) [4] are considered preserving all these features and it plays a vital role for analysing of non stationary signals. It is to note that the Fourier transform does not suffer from these problems [5]. Inspired by the Fourier representation, CWT can be implemented. Dual tree complex wavelet transform (DT-CWT) [6] another variant of wavelet transform, is used to overcome the shift variance problem of DWT. DT-CWT can be considered as an approximation to DWT that removes the down-sampling operation from traditional critically sampled DWT, produces an over-complete representation. DT-CWT is shift invariant because the spatial sampling rate is fixed across scale. A distinguished member of the family of the discrete wavelet transforms is the double density dual tree wavelet transform (DD-DT-DWT) [7]. The DD-DT-DWT is expansive with a factor of two, compared to the critically sampled DWT.

The main objective of this paper is to investigate the application of DT-CWT and DD-DT-DWT in medical image fusion and also focus on how to fuse properties of medical images of different modalities like MRI and CT using block based statistical properties of wavelet coefficients.

DUAL TREE COMPLEX WAVELET TRANSFORM:

The conventional wavelet transform suffers from four fundamental shortcomings namely shift variance, oscillations, aliasing and lack of directionality. The DT-CWT is a recent enhancement to the DWT with complex valued scaling function $\phi_c(t)$ and complex valued wavelet function $\psi_c(t)$ which can be represented as

$$\phi_c(t) = \phi_r(t) + j\phi_i(t) \tag{1}$$

$$\psi_c(t) = \psi_r(t) + j\psi_i(t) \tag{2}$$

Where, $\psi_r(t)$ and $\phi_r(t)$ are real and even function of t and $\psi_i(t)$ and $\phi_i(t)$ are imaginary and odd function of t. However, $\psi_r(t)$ and $\psi_i(t)$ form a Hilbert transform pair for wavelet function and similarly $\phi_r(t)$ and $\phi_i(t)$ form Hilbert transform for scaling function. Hence, $\phi_c(t)$ and $\psi_c(t)$ are both analytic signal and supported on only one half of the frequency axis. The DT-CWT was introduces by Kingsbury, it consists of two real discrete wavelet transforms. The first DWT gives the real part of the transform while the second DWT gives the imaginary part. The two real DWTs use two different sets of perfect reconstruction (PR) filter which are jointly designed so that the overall transform is approximately analytic. The analysis filter banks used to implement DT-CWT of a signal x(n) and is shown in Fig. 1. The two real wavelet transforms use two different sets of filters, with each satisfying the PR conditions. The two sets of filters are jointly designed so that the overall transform is approximately analytic. The filters $h_0(n), h_1(n)$ denote the low-pass and high-pass conjugate quadrature filter (CQF) pair for the upper bank. The autocorrelation of the filter can be expressed as

$$\sum_n h_0(n)h_0(n+2k) = \delta(k) = \begin{cases} 1 & for \quad k = 0 \\ 0 & for \quad k \neq 0 \end{cases} \tag{3}$$

and

$$h_1(n) = (-1)^{(1-n)} h_0(n-1) \tag{4}$$

Similarly, the filters $g_0(n), g_1(n)$ forms another CQF pair denotes the low-pass and high –pass filters respectively for the lower filter bank. The DT-CWT of an input real vector X can be represented by the rectangular matrix given below

$$F = \begin{bmatrix} F_h \\ F_g \end{bmatrix} \tag{5}$$

Let $w_h = F_h X$ and $w_g = F_g X$ represents real part and imaginary part of the dual tree CWT then $w_h + jw_g$ represents complex dual tree wavelet coefficients.

A distinguished member of the family of discrete wavelet transforms (DWT) is the double density dual tree complex wavelet transform (DD-DT-CWT). The input signal is split in three channels, each decimated by a factor of two. The DD-DT-CWT possesses the properties of DD-DWT and DT-DWT. DD-DT-CWT consists of two oversampled iterated filter banks operating in parallel. The oversampled filter bank is shown in Fig. 2.The signal on the first channel is processed by an identical filter bank. The DD-DT-DWT is expansive with a factor of two, compared to the critically sampled DWT. A dual tree is formed by two wavelet transforms processing the same input signal and satisfying a certain relationship: one of the wavelets is an approximate Hilbert transform of the other.

II. The Proposed Method

Experiments performed on multimodal images MRI and CT. Both the images modalities are complement in nature. CT images are sensitive to bone and hard tissues while MR images are more informative about soft tissues. In this simulation two images of size 256x256 are considered. Fusion of the resultant of these two images will be more useful for diagnosis purpose in case of diseases like tumours. The procedure to obtain fused image is shown below.

Step 1: Source images $f1(x,y)$ and $f2(x,y)$ are decomposed to two level using DT-CWT to obtain approximate and detail wavelet coefficients $W1(u,v)$ and $W2(u,v)$ respectively.

Step 2: Maximum selection [8][9] fusion rule is performed to select horizontal, vertical and diagonal detail wavelet coefficients of $W1(u,v)$ and $W2(u,v)$.

$$W(u,v)=\begin{cases}W1(u,v), if\left|W1(u,v)\right|\geq\left|W2(u,v)\right|\\ W2(u,v), if\left|W2(u,v)\right|\geq\left|W1(u,v)\right|\end{cases} \tag{6}$$

Step 3: Average value of approximate coefficients of both the images $W1(u,v)$ and $W2(u,v)$ is obtained.
Step 4: The updated coefficients obtained in step 2 & 3 are used to obtain Inverse DT-CWT to obtain fused image.
Step 5: Above steps 2-4 are repeated for DD-DT-CWT.
Step 6: The results obtained using DT-CWT and DD-DT-CWT are given in Fig. 4.

Proposed method:
The proposed method to obtain the fused image is shown in Fig.3 and the algorithm can be summarized as follows:
Step 1: Source images $f1(x,y)$ and $f2(x,y)$ are decomposed to two level using DT-CWT to obtain approximate and detail wavelet coefficients $W1(u,v)$ and $W2(u,v)$ respectively.
Step 2: The decomposed detail wavelet coefficients of both the images are divided into overlapping blocks of size 3x3.
Step 3: The mask of size 3x3 shown in Table-2 (a) is applied on detailed coefficients $W1(u,v)$ and $W2(u,v)$ obtained in step-2 to calculate the response of the filter $R1(u,v)$ and $R2(u,v)$ respectively.
Step 4: Maximum selection fusion rule is performed to select coefficients whose filter response is maximum..

$$W(u,v)=\begin{cases}W1(u,v),\ if\ \left|R1(u,v)\right|\geq\left|R2(u,v)\right|\\ W2(u,v),\ if\ \left|R2(u,v)\right|\geq\left|R1(u,v)\right|\end{cases}$$

Step 5: Average value of approximate coefficients of images $W1(u,v)$ and $W2(u,v)$ is obtained.
Step 6: The updated coefficients obtained in step 4 & 5 are used to obtain Inverse DT-CWT to obtain fused image.
Step 7: Above steps 3-6 are repeated using masks shown in Table-2 (b) to (d).
Step 8: Above steps 3-6 are repeated by calculating variance, skew and kurtosis of the 3x3 blocks to find the response. The performance measures of the above procedure are tabulated in Table. 3.
Step 9: Above steps 1-8 are repeated using DD-DT-CWT and the performance measures are tabulated in Table. 4.
Step 10: Above steps 1-9 are repeated for block size of 5x5 in step-2 by using the masks in the Table. 5 and finding block based statistical properties like variance, skew and kurtosis [10]. The performance measures are tabulated in Table.6 and Table.7 for DT-CWT & DD-DT-CWT respectively.

III. Evaluation Parameter For Image Fusion

i. Average Gradient
An Edge content of an image is also known as average gradient of an image which measures sharpness of an image.

$$EC=\frac{1}{MN}\sum_{x}\sum_{y}\left|\nabla f(x,y)\right|^{2} \tag{7}$$

Where, $\nabla f(x,y)$ is the gradient of fused image $f(x,y)$, x,y are known as the spatial co-ordinates and M,N are number of pixels in a row and column respectively.

ii. Overall Pixel Intensity
Overall pixel intensity is also known as average value of an image under consideration. The value should be higher when the image is enhanced comparatively with the degraded image.

$$\overline{F}=\frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}f(x,y) \tag{8}$$

iii. Standard Deviation

Standard deviation is also known as spread of gray levels of an image from its mean. Higher the value of standard deviation indicates improvement in the enhancement of an image.

$$SD = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N}(f(x,y)-\overline{F})^2}{MN-1} \tag{9}$$

.

iv. AC Power Measure

AC power measure can be obtained as the difference between average squared magnitude of an image and square of the average value of the image.

$$F_{ac} = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N} f(x,y)^2 - \overline{F}^2 \tag{10}$$

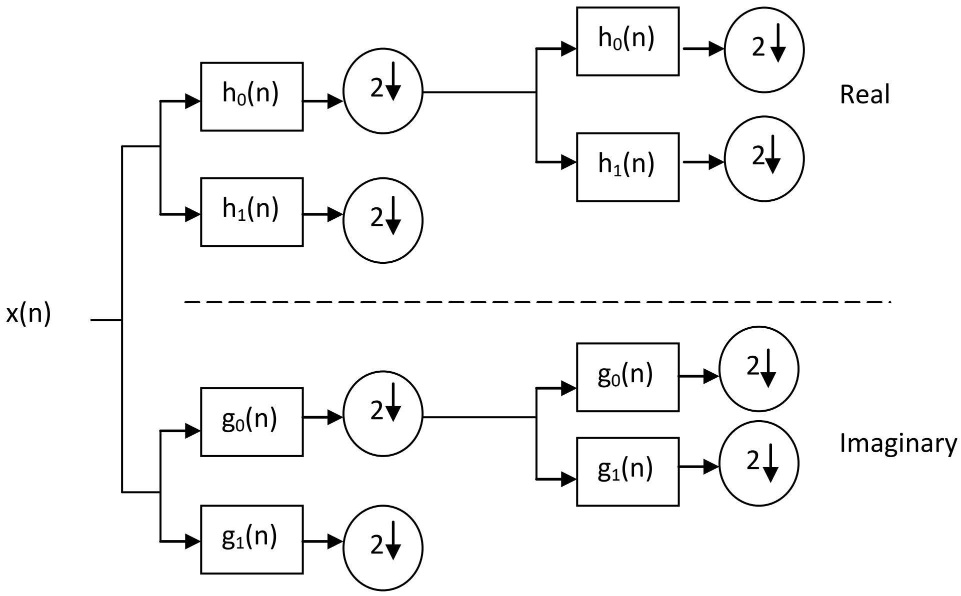

Fig. 1 Filter bank of Two Level DT-CWT

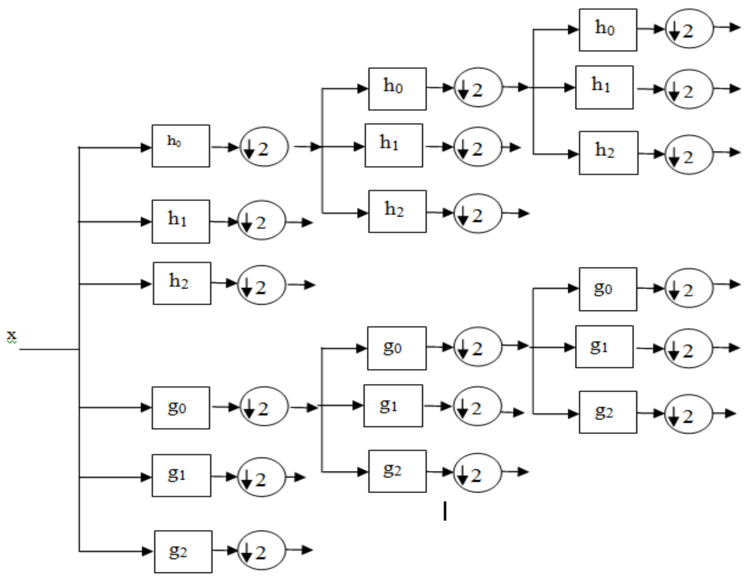

Fig. 2 Iterated filter bank for the DD-DT-DWT

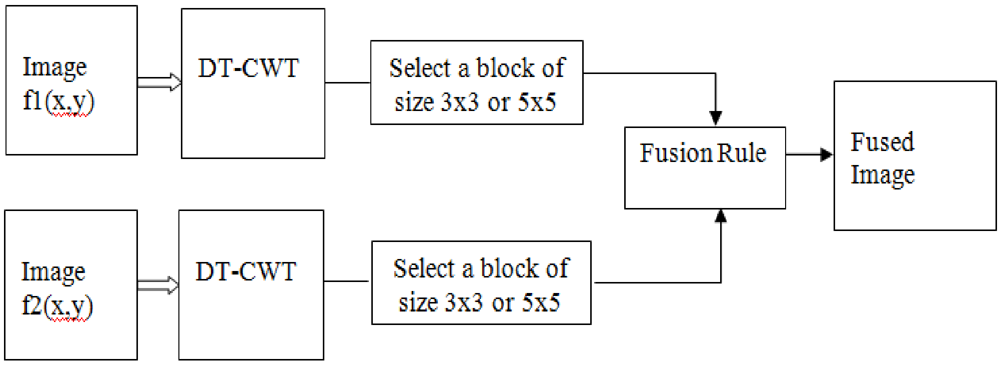

Fig. 3 Image fusion block diagram

Table 1: Performance analysis of fused images obtained using DT-CWT and DD-DT-CWT

S..No	Performance Measure	DT-CWT	DD-DT-CWT
1	Entropy	6.092	6.134
2	SDME	25.760	24.165
3	AC Power	1305.434	1456.366
4	Average Gradient	0.054	0.062
5	Standard Deviation	36.131	38.162
6	Average Intensity	32.675	32.708

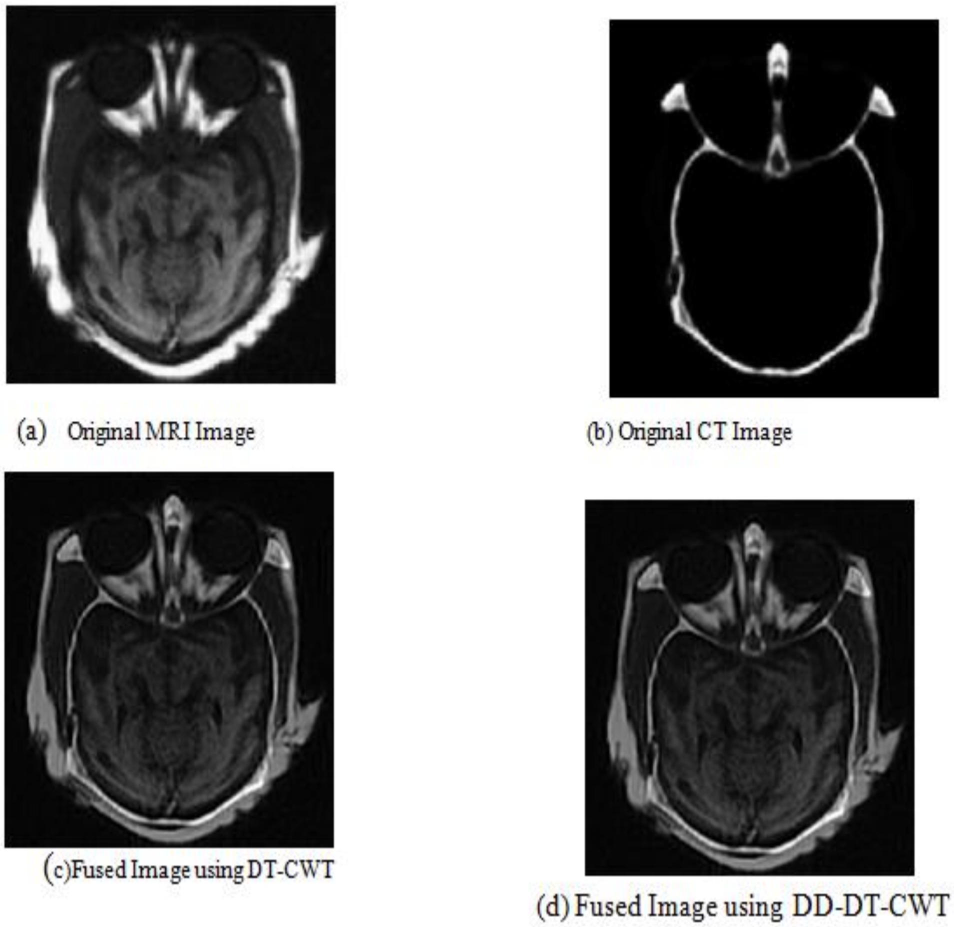

Fig. 4 Fusion of images using DT-CWT and DD-DT-CWT

IV. Simulation Results

Table 2: Masks used to obtain the response when the wavelet coefficients are decomposed using block size of 3x3

0	0	0		0	-1	0		0	0	-1		-1	-1	-1
-1	2	-1		0	2	0		0	2	0		-1	8	-1
0	0	0		0	-1	0		-1	0	0		-1	-1	-1

(a) (b) (c) (d)

Table 3: Performance measures of 3x3 block based fused images obtained using DT-CWT

Performance Measure	DT-CWT	DT-CWT with Horizontal mask	DT-CWT with Vertical mask	DT-CWT with diagonal mask	DT-CWT with sharpening filter mask	DT-CWT with variance	DT-CWT with Skewness	DT-CWT with Kurtosis
Entropy	6.092	6.092	6.090	6.090	6.091	6.092	5.880	5.882
SDME	25.760	25.650	26.040	25.498	25.820	25.843	25.145	25.891
AC Power	1305.434	1298.737	1294.458	1299.255	1304.480	1300.862	1224.280	1214.534
Average Gradient	0.054	0.053	0.0531	0.053	0.054	0.0536	0.0422	0.0402
Standard Deviation	36.131	36.038	35.978	36.045	36.117	36.067	34.989	34.850
Average Intensity	32.675	32.674	32.675	32.676	32.676	32.674	32.673	32.674

Table 4: Performance measures of 3x3 block based fused images obtained using DD-DT-CWT

Performance Measure	DD-DT-CWT	DD-DT-CWT with Horizontal mask	DD-DT-CWT with Vertical mask	DD-DT-CWT with diagonal mask	DD-DT-CWT with sharpening filter mask	DD-DT-CWT with variance	DD-DT-CWT with Skewness	DD-DT-CWT with Kurtosis
Entropy	6.134	6.163	6.160	6.164	6.164	6.165	5.910	5.887
SDME	24.165	24.047	24.027	24.420	22.477	24.863	24.680	26.036
AC Power	1456.366	1400.383	1395.977	1405.288	1417.218	1408.918	1199.164	1167.519
Average Gradient	0.062	0.060	0.060	0.060	0.061	0.060	0.044	0.040
Standard Deviation	38.162	37.421	37.363	37.487	37.646	37.535	34.629	34.169
Average Intensity	32.708	32.706	32.711	32.710	32.711	32.711	32.682	32.676

Table 5: Masks used to obtain the response when the wavelet coefficients are decomposed using block size of 5x5

0	0	0	0	0		0	0	-1	0	0		0	0	0	0	-1		-1	-1	-1	-1	-1
0	0	0	0	0		0	0	-1	0	0		0	0	0	-1	0		-1	-1	-1	-1	-1
-1	-1	4	-1	-1		0	0	4	0	0		0	0	4	0	0		-1	-1	24	-1	-1
0	0	0	0	0		0	0	-1	0	0		0	-1	0	0	0		-1	-1	-1	-1	-1
0	0	0	0	0		0	0	-1	0	0		-1	0	0	0	0		-1	-1	-1	-1	-1

Table 6: Performance measures of 5x5 block based fused images obtained using DT-CWT

Performance Measure	DT-CWT	DT-CWT with Horizontal mask	DT-CWT with Vertical mask	DT-CWT with diagonal mask	DT-CWT with sharpening filter mask	DT-CWT with variance	DT-CWT with Skewness	DT-CWT with Kurtosis
Entropy	6.092	6.156	6.154	6.1542	6.156	6.156	5.950	5.939
SDME	25.760	26.820	26.275	26.660	27.075	26.343	24.088	27.777
AC Power	1305.434	1204.634	1204.524	1204.710	1204.228	1212.855	1193.218	1198.897
Average Gradient	0.054	0.0433	0.0432	0.043	0.043	0.044	0.038	0.039
Standard Deviation	36.131	34.708	34.706	34.709	34.702	34.826	34.543	34.625
Average Intensity	32.675	32.742	32.742	32.741	32.742	32.746	32.694	32.699

Table 7: Performance measures of 5x5 block based fused images obtained using DD-DT-CWT

Performance Measure	DD-DT-CWT	DD-DT-CWT with Horizontal mask	DD-DT-CWT with Vertical mask	DD-DT-CWT with diagonal mask	DD-DT-CWT with sharpening filter mask	DD-DT-CWT with variance	DD-DT-CWT with Skewness	DD-DT-CWT with Kurtosis
Entropy	6.134	6.196	6.193	6.194	6.191	6.195	5.939	5.924
SDME	24.165	31.823	29.611	30.333	29.542	29.366	26.144	26.489
AC Power	1456.366	1178.027	1186.470	1184.668	1181.765	1203.410	1155.239	1148.357
Average Gradient	0.062	0.045	0.047	0.046	0.046	0.046	0.0424	0.040
Standard Deviation	38.162	34.322	34.445	34.419	34.377	34.690	33.989	33.887
Average Intensity	32.708	32.819	32.814	32.818	32.812	32.829	32.707	32.701

V. Conclusion

In this paper, Image fusion of MRI and CT images is obtained. The fusion procedure is implemented using DT-CWT and DD-DT-CWT. The DD-DT-CWT has given over all the best performance over DT-CWT. The proposed scheme to find the responses is implemented by dividing wavelet coefficients into block of sizes 3x3 and 5x5. The 5x5 block decomposition of DD-DT-CWT gives better entropy and overall intensity values comparatively with all the other methods when horizontal mask is used to select wavelet coefficients. This method can preserve all useful information from primitive images and the clarity of fused image has been improved. The fused image obtained will be more useful for diagnosis.

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