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Optimal Decomposition Level of Discrete, Stationary and Dual Tree Complex Wavelet Transform for Pixel based Fusion of Multi-focused Images

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Abstract: The fast development of digital image processing leads to 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. Two approaches to image fusion are Spatial Fusion and Transform fusion. 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 Stationary Wavelet Transform and Dual Tree Complex Wavelet Transform. This paper describes the optimal decomposition level of Discrete, Stationary and Dual Tree Complex wavelet transform required for better pixel based fusion of multi focused images in terms of Root Mean Square Error, Peak Signal to Noise Ratio and Quality Index.

Keywords: Image Fusion, Discrete Wavelet Transform, Stationary Wavelet Transform and Dual Tree Complex Wavelet Transform.

1 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 fused to detect weapons and Magnetic Resonance and Computed

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Tomographic images are fused for medical diagnosis. The fusion process should preserve all relevant information in the fused image, should reduce noise and should suppress any artifacts in the fused image.

Two approaches to image fusion are Spatial Fusion and Transform fusion. In Spatial fusion, the pixel values from the source images are manipulated in spatial domain to calculate the activity measure to form the pixel of the composite image at that location [1]. Transform fusion uses transform for representing the source image suitable in a form to calculate the activity measure more accurately. Multi resolution transforms are used in image fusion to represent the source image at multi scale. The most widely used multi resolution transform for image fusion is Discrete Wavelet Transform (DWT) since it reduces structural distortions. But, wavelet transform suffers from lack of shift invariance, poor directional selectivity and absence of phase information. These disadvantages are overcome by Stationary Wavelet Transform (SWT) and Dual Tree Complex Wavelet Transform (DTCWT). And there are three levels in multi resolution fusion scheme namely Pixel level fusion, Feature level fusion and Region level fusion. In pixel level fusion, the activity measure to form the composite image is calculated using the pixel of interest only. In feature level fusion, an area based activity measure is calculated since useful features in the image usually are larger than one pixel. In region level fusion, the source images are segmented into different regions and the activity measure for each and every region is calculated to form the regions of composite image. Among these three levels, pixel based fusion provides best results and more research taken place in this level. In this paper, it is proposed to find the optimum level of decomposition of DWT, SWT and DTCWT required for better pixel level fusion of multi focused images taken by digital camera in terms of various performance measures.

2 Discrete Wavelet Transform

The Discrete Wavelet Transform (DWT) of image signals produces a non-redundant image representation, which provides better spatial and spectral localization of image formation, compared with other multi scale representations such as Gaussian and Laplacian pyramid [2]. Recently, Discrete Wavelet Transform has attracted more and more interest in image fusion. An image can be decomposed into a sequence of different spatial resolution images using DWT. In case of a 2D image, an N level decomposition can be performed resulting in $3N+1$ different frequency bands and it is shown in Fig. 1.

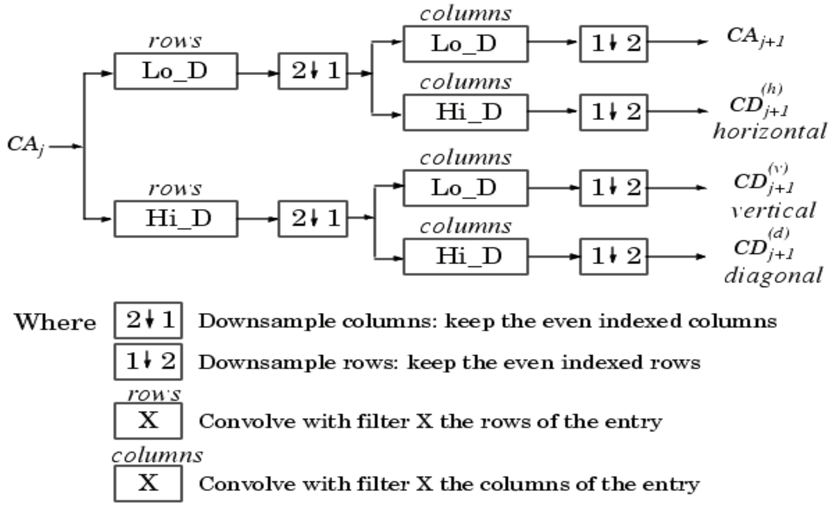


Fig. 1 – 2D - *Discrete Wavelet Transform.*

3 Stationary Wavelet Transform

The Discrete Wavelet Transform is not a time- invariant transform. The way to restore the translation invariance is to average some slightly different DWT, called decimated DWT, to define the stationary wavelet transform (SWT). Let us recall that the DWT basic computational step is a convolution followed by decimation. The decimation retains even indexed elements. But the decimation could be carried out by choosing odd indexed elements instead of even indexed elements. This choice concerns every step of the decomposition process, so at every level we chose odd or even. If we perform all the different possible decompositions of the original signal, we have $2J$ different decompositions, for a given maximum level J. Let us denote by j = 1 or 0 the choice of odd or even indexed elements at step j. Every decomposition is labeled by a sequence of 0's and 1's: = 1, J. This transform is called the decimated DWT. It is possible to calculate all the decimated DWT for a given signal of length N, by computing the approximation and detail coefficients for every possible sequence. The SWT algorithm is very simple and is close to the DWT one. More precisely, for level 1, all the decimated DWT for a given signal can be obtained by convolving the signal with the appropriate filters as in the DWT case but without down sampling. Then the approximation and detail coefficients at level 1 are both of size N, which is the signal length. The general step j convolves the approximation coefficients at level j–1, with up sampled versions of the appropriate original filters, to produce the approximation and detail coefficients at level j. This can be visualized in the following Fig. 2.

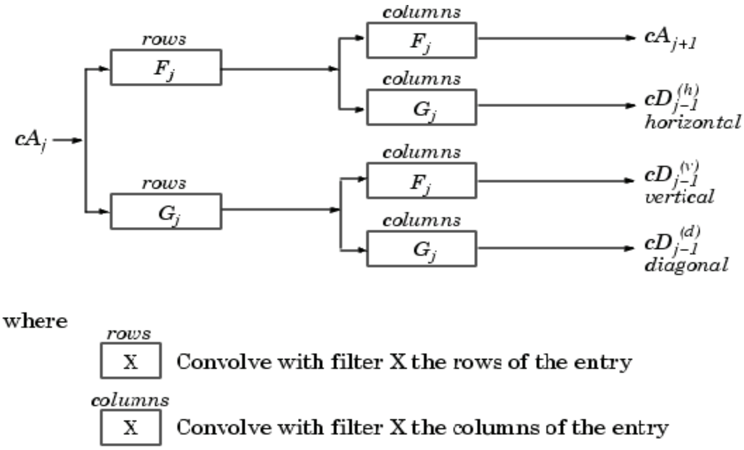


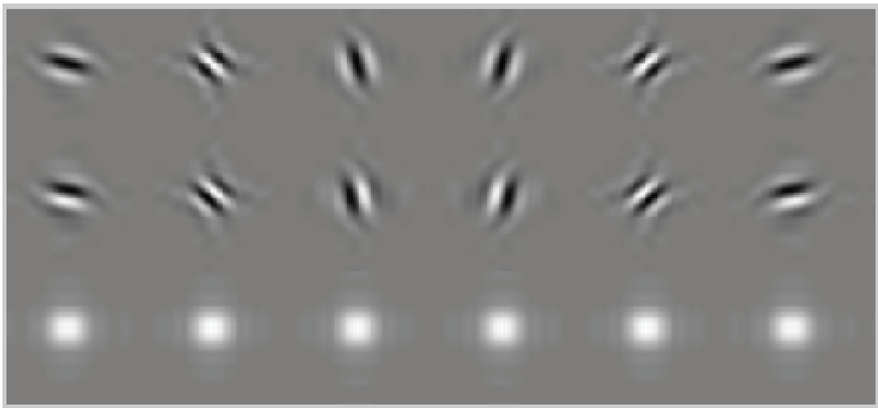
Fig. 2 – 2D - *Stationary Wavelet Transform.*

4 Dual Tree Complex Wavelet Transform

Another major drawback of DWT 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 [3].

The filter bank structure of the CWT has CWT filters which have complex coefficients and generate complex output samples. This is shown in Fig. 4, in which each block is a complex filter and includes down sampling by 2 (not shown) at its outputs. Since the output sampling rates are unchanged from the DWT, but each sample contains a real and imaginary part, a redundancy of 2:1 is introduced. The complex filters may be designed such that the magnitudes of their step responses vary slowly with input shift only the phases vary rapidly. The real part is an odd function while the imaginary part is even. The level 1 filters, Lop and Hip in Fig. 4, include an additional pre filter, which has a zero at $z = -j$, in order to simulate the effect of a filter tree extending further levels to the left of level 1.

a) DWT



b) DTCWT

Fig. 3 – *Directionality.*

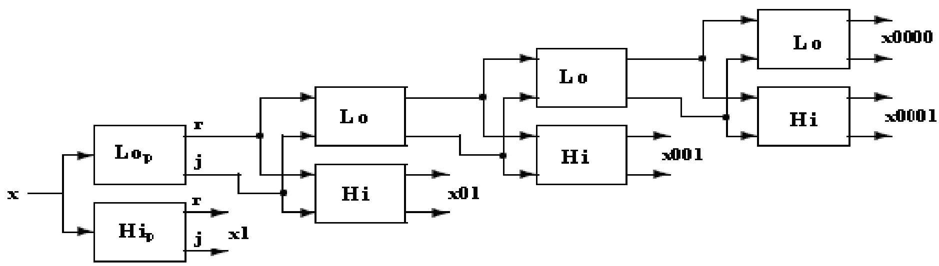


Fig. 4 – *Four levels of Complex Wavelet Tree for real* 1-D *input signal x.*

Extension of complex wavelets to 2-D is achieved by separable filtering along rows and then columns. However, if row and column filters both suppress negative frequencies, then only the first quadrant of the 2-D signal spectrum is retained. Two adjacent quadrants of the spectrum are required to represent fully a real 2-D signal, so we also need to filter with complex conjugates of either the row or column filters. This gives 4:1 redundancy in the transformed 2-D signal.

If the signal exists in $m - d$ ($m > 2$), then further conjugate pairs of filters are needed for each dimension leading to redundancy of 2^m:1. The most computationally efficient way to achieve the pairs of conjugate filters is to maintain separate imaginary operators, j_1 and j_2, for the row and column processing, as shown in Fig. 5. This produces 4-element `complex' vectors: $\{r, j_1, j_2, j_1 j_2\}$ (where r means 'real'). Each 4-vector can be converted into a pair of conventional complex 2-vectors, by letting $j_1 = j_2 = j$ in one case and $j_1 = -j_2 = -j$ in the other case. This corresponds to sum and difference operations on the $\{r, j_1 j_2\}$ and $\{j_1, j_2\}$ pairs in the summation blocks in Fig. 5 and produces two complex outputs, corresponding to first and second quadrant directional filters respectively. Complex filters in multiple dimensions provide true directional selectivity, despite being implemented separably, because they are still able to separate all parts of the $m - D$ frequency space. For example a 2-D CWT produces six band pass sub-images of complex coefficients at each level, which are strongly oriented at angles of ±15°, ±45°, ±75°, shown by the double-headed arrows in Fig. 5.

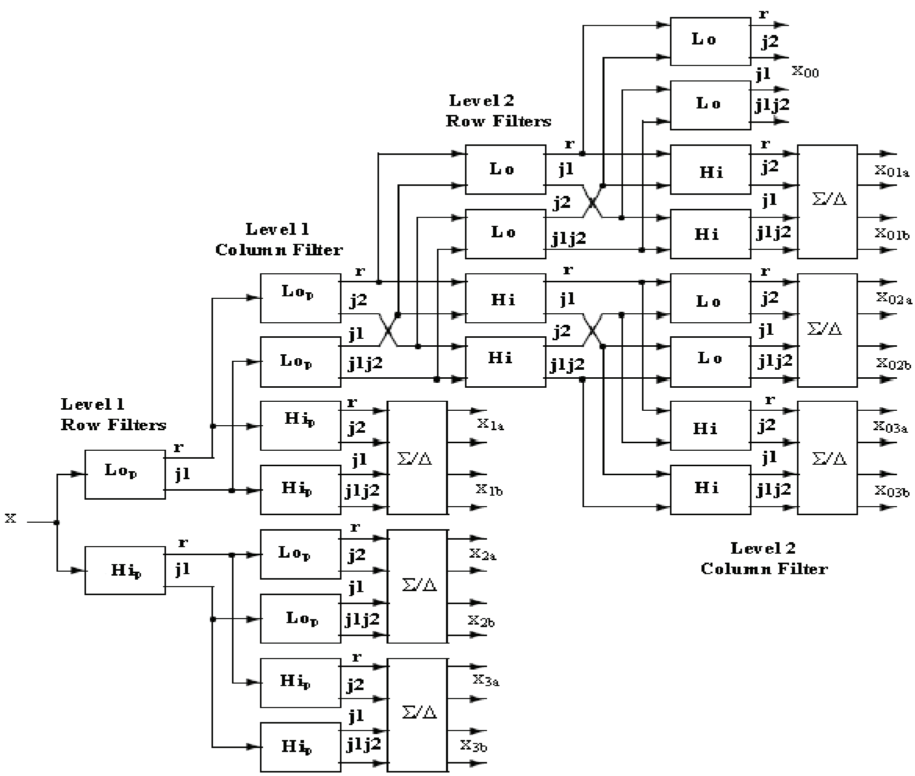


Fig. 5 – *Two levels of the Complex Wavelet tree for a real* 2-D *input image x giving* 6 *directional bands at each level.*

5 Wavelet Based Image Fusion

Wavelet transform is first performed on each source images, and then a fusion decision map is generated based on a set of fusion rules. The fused wavelet coefficient map can be constructed from the wavelet coefficients of the source images according to the fusion decision map. Finally the fused image is obtained by performing the inverse wavelet transform [4]. Let $A(x,y)$ and $B(x,y)$ are images to be fused, the decomposed low frequency sub images of $A(x,y)$ and $B(x,y)$ be respectively $lA_J(x,y)$ and $lB_J(x,y)$ (J is the parameter of resolution) and the decomposed high frequency sub images of $A(x,y)$ and $B(x,y)$ are $hA_j^k(x,y)$ and $hB_j^k(x,y)$ (j is the parameter of resolution and $j=1,2,3,\ldots,J$ for every j, $k=1,2,3,\ldots$). Then, the fused high and low frequency sub-images $F_j^k(x,y)$ are given as $F_j^k(x,y)=A_j^k(x,y)$ if $G(A_j^k(x,y))\geq G(B_j^k(x,y))$, else $F_j^k(x,y)=B_j^k(x,y)$ and $F_J(x,y)=lA_J(x,y)$ if $G(A_J(x,y))\geq G(B_J(x,y))$, else $F_J(x,y)=lB_J(x,y)$ where G is the fusion rule and $F_j^k(x,y)$ and $F_J(x,y)$ are used to reconstruct the fused image $F'(x,y)$ using the inverse wavelet transform. The block diagram representing the wavelet based image fusion is shown in Fig. 6.

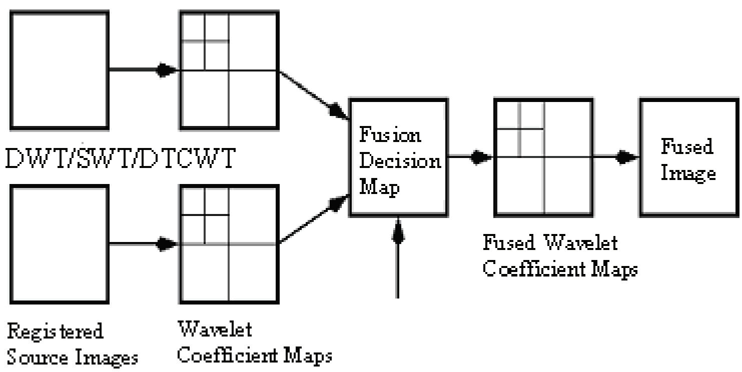


Fig. 6 – *DWT/SWT/DTCWT Based Image Fusion.*

6 Pixel Level Image Fusion

This section describes five methods of pixel level image fusion based on multi scale representation of source images using wavelets. To simplify the description of different pixel level image fusion methods, the source images are assumed as *A* and *B* and the fused image as *F*. All the methods described in this paper can be used in the case of more than two source images.

Method 1: All the four sub bands of the fused image *F* is simply acquired by averaging the wavelet coefficients of source images *A* and *B*. i.e. $F_j^k (A_j^k + B_j^k)/2$ and $F_J (lA_J + lB_J)/2$. However when this method is applied, there is chances of reduction of contrast of features uniquely presented in either of the images.

Method 2: All the four sub bands of the fused image *F* is simply formed by taking the wavelet coefficients from source images which is having the maximum value. i.e. $F_j^k = \max(A_j^k, B_j^k)$ and $F_J = \max(lA_J, lB_J)$. Limitation is in the fusion of patterns that have roughly equal salience but opposite contrast, which results pathological [1].

Method 3: Since larger absolute transform coefficients correspond to sharper brightness changes, the good integration rule is to select, at every point in the transform domain, the coefficients whose absolute values are higher [5]. i.e. $F_j^k = \max(\text{abs}(A_j^k), (B_j^k))$ and $F_J = \max(\text{abs}(A_j^k), \text{abs}(B_j^k))$.

Method 4: This method uses method1 for low frequency sub bands and uses method 3 for high frequency bands. i.e. $F_j^k = \max(\text{abs}(A_j^k), (B_j^k))$ and $F_J = (lA_J + lB_J)/2$.

Method 5: This method is slight modification of Method 4. It takes the average of approximation and diagonal details of source image to form the LL and HH sub band and uses absolute maximum criterion to form the LH and HL sub bands of fused image.

7 Evaluation Criteria

There are four evaluation measures are used in this paper, as follows.

- The root mean square error (RMSE) between the reference image *R* and fused image *F* is given by,

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}\sum_{j=1}^{N}[R(i,j) - F(i,j)]^2}{N^2}}. \tag{1}$$

- The signal to Noise ratio between the reference image *R* and fused image *F* is given by,

$$\text{PSNR}= 10\log_{10}(255)^2/\text{MSE (db)}. \tag{2}$$

- Quality index of the reference image (*R*) and fused image (*F*) is given by[6],

$$Q=\frac{4\sigma_{ab}ab}{(a^2+b^2)(\sigma_a{}^2+\sigma_b{}^2)}. \tag{3}$$

  The maximum value Q = 1 is achieved when two images are identical, where *a* and *b* are mean of images, σ_{ab} be covariance of *R* and *F*, $\sigma_a{}^2$, $\sigma_b{}^2$ be the variance of image *R*, *F*.

- The Normalized Weighted Performance Metric (NWPM) which is given in the equation (4) as [7],

$$\text{NWPM}=\frac{\sum\forall_{i,j}Q_{ij}^{AF}W_{ij}^{A}+Q_{ij}^{AF}W_{ij}^{B}}{\sum\forall_{i,j}W_{ij}^{A}+W_{ij}^{B}}. \tag{4}$$

8 Experiments

The methods proposed for implementing pixel level image fusion using wavelet transform take the following form in general. The two source images to be fused are assumed to be registered spatially. The images are wavelet transformed using the same wavelet, and transformed to the same number of levels. For taking the wavelet transform of the two images, readily available MATLAB routines are taken. In each sub-band, individual pixels of the two images are compared based on the fusion rule that serves as a measure of activity at that particular scale and space. A fused wavelet transform is created by taking pixels from that wavelet transform that shows greater activity at the pixel locations. The inverse wavelet transform is the fused image with clear focus on the whole image.

9 Results and Discussion

For the above mentioned five methods of pixel level fusion, image fusion is performed using discrete, stationary and dual tree complex wavelets from first level decomposition to seventh level decomposition for the Pepsi image of size 512×512, their performance is measured in terms of RMSE, PSNR, Q and NWPM. The results are shown in Fig. 7 and tabulated in **Tables 1**, **2**, **3** and **4**. From the above results, it is inferred that whatever be the type of wavelet and whatever may the level of decomposition, there is no change in the fused image for averaging method. For the second method, third level, seventh level and sixth level are the optimum level of decomposition for DWT, SWT and DTCWT respectively. Seventh level is better for DWT and SWT and sixth level is better for DTCWT in Method3. Method4 provides better result for all wavelet transform at fourth level. Level three is better for DWT and fourth level is better for SWT and DTCWT in Method5. But for the better results, Method4 is better among all the methods and DTCWT is better among this wavelet transform.

Table 1
PSNR *Values obtained through the five methods of Pixel level Fusion.*

	LEVEL	1	2	3	4	5	6	7
Methodl	DWT	32.3651	32.3651	32.3651	32.3651	32.3651	32.3651	32.3651
	SWT	32.3651	32.3651	32.3651	32.3651	32.3651	32.3651	32.3651
	DT-CWT	32.3651	32.3651	32.3651	32.3651	32.3651	32.3651	32.3651
Method2	DWT	28.8378	29.0843	**29.2332**	29.1092	28.9884	28.9997	28.9871
	SWT	29.2691	30.2319	30.9366	31.3439	31.5263	31.5905	**31.6164**
	DT-CWT	29.0893	30.1886	30.7292	31.0942	31.3585	**31.3879**	31.1706
Method3	DWT	29.4931	31.7586	33.5991	34.6046	34.8925	35.171	**35.2497**
	SWT	30.0491	32.7883	35.0278	36.4159	36.8993	37.0599	**37.1191**
	DT-CWT	29.3345	32.2002	34.6557	36.599	37.4088	**37.6497**	36.888
Method4	DWT	32.9964	34.8538	35.6098	**35.6535**	35.332	35.3124	35.3018
	SWT	33.6565	36.031	37.2864	**37.5866**	37.4063	37.279	37.1889
	DT-CWT	32.7934	35.3561	37.166	**38.1881**	38.0656	37.9324	36.7269
Method5	DWT	33.0138	34.8312	**35.4644**	35.4296	35.1293	35.1168	35.1091
	SWT	33.6553	35.9676	37.1164	**37.3766**	37.2313	37.13	37.0653
	DT-CWT	32.8102	35.3633	37.0576	**37.9704**	37.8381	37.7166	36.5782

Table 2
RMSE *Values obtained through the five methods of Pixel level Fusion.*

	LEVEL	1	2	3	4	5	6	7
Methodl	DWT	6.1416	6.1416	6.1416	6.1416	6.1416	6.1416	6.1416
	SWT	6.1416	6.1416	6.1416	6.1416	6.1416	6.1416	6.1416
	DT-CWT	6.1416	6.1416	6.1416	6.1416	6.1416	6.1416	6.1416
Method2	DWT	9.2183	8.9603	**8.8081**	8.9348	9.0599	9.048	9.0612
	SWT	8.7717	7.8513	7.2395	6.9079	6.7644	6.7145	**6.6946**
	DT-CWT	8.9552	7.8906	7.4144	7.1094	6.8963	**6.873**	7.0471
Method3	DWT	8.5484	6.5859	5.3283	4.7458	4.5911	4.4462	**4.4061**
	SWT	8.0183	5.8496	4.5201	3.8525	3.644	3.5772	**3.5529**
	DT-CWT	5.8462	4.3524	3.5338	3.1415	3.1861	**3.2353**	3.717
Method4	DWT	5.7111	4.6116	4.2272	**4.206**	4.3645	4.3744	4.3797
	SWT	5.2932	4.0271	3.4851	**3.3667**	3.4374	3.4881	3.5245
	DT-CWT	5.8462	4.3524	3.5338	**3.1415**	3.1861	3.2353	3.717
Method5	DWT	5.6997	4.6236	**4.2985**	4.3158	4.4676	4.4741	4.478
	SWT	5.2939	4.0566	3.554	**3.4491**	3.5073	3.5485	3.575
	DT-CWT	5.8348	4.3489	3.5781	**3.2212**	3.2706	3.3167	3.7812

Table 3

Q *Values obtained through the five methods of Pixel level Fusion.*

	LEVEL	1	2	3	4	5	6	7
Methodl	DWT	0.9906	0.9906	0.9906	0.9906	0.9906	0.9906	0.9906
	SWT	0.9906	0.9906	0.9906	0.9906	0.9906	0.9906	0.9906
	DT-CWT	6.1416	6.1416	6.1416	6.1416	6.1416	6.1416	6.1416
Method2	DWT	0.9808	0.9813	0.9815	0.9806	0.9799	0.9798	0.9797
	SWT	0.9828	0.9859	0.9877	0.9885	0.9888	0.9888	0.9889
	DT-CWT	0.9821	0.9856	0.987	0.9878	0.9881	0.9882	0.9876
Method3	DWT	0.9838	0.9905	0.9938	0.9949	0.9951	0.9953	0.9954
	SWT	0.986	0.9928	0.9957	0.9967	0.9969	0.997	0.997
	DT-CWT	0.9832	0.9915	0.9953	0.9969	0.9973	0.9974	0.9968
Method4	DWT	0.9919	0.9948	0.9956	0.9957	0.9954	0.9954	0.9954
	SWT	0.993	0.996	0.997	0.9972	0.9972	0.9971	0.997
	DT-CWT	0.9915	0.9953	0.9969	0.9976	0.9975	0.9975	0.9968
Method5	DWT	0.9919	0.9947	0.9955	0.9955	0.9952	0.9952	0.9952
	SWT	0.993	0.9959	0.9969	0.9971	0.997	0.997	0.9969
	DT-CWT	0.9915	0.9953	0.9969	0.9975	0.9974	0.9973	0.9967

Table 4

NWPM *Values obtained through the five methods of Pixel level Fusion.*

	LEVEL	1	2	3	4	5	6	7
Methodl	DWT	0.6338	0.6338	0.6338	0.6338	0.6338	0.6338	0.6338
	SWT	0.6338	0.6338	0.6338	0.6338	0.6338	0.6338	0.6338
	DT-CWT	0.6338	0.6338	0.6338	0.6338	0.6338	0.6338	0.6338
Method2	DWT	**0.5707**	0.5456	0.5392	0.534	0.5328	0.5325	0.5324
	SWT	0.5838	0.5828	**0.5853**	0.5847	0.5849	0.5851	0.5851
	DT-CWT	0.5819	**0.5894**	0.5858	0.5813	0.5796	0.5794	0.5791
Method3	DWT	0.6082	0.672	0.7012	0.7102	0.7116	0.713	**0.7132**
	SWT	0.652	0.7296	0.7494	0.756	0.7585	0.759	**0.759**
	DT-CWT	0.6071	0.7139	0.7461	0.7554	0.758	**0.7584**	0.758
Method4	DWT	0.6665	0.7008	0.7072	0.7107	0.7123	07132	**0.7134**
	SWT	0.7193	0.7502	0.7566	0.7576	0.7585	0.7588	**0.7589**
	DT-CWT	0.6644	0.7369	0.7514	0.7561	0.758	**0.7583**	0.758
Method5	DWT	0.6689	0.7024	0.7044	0.7058	0.7072	0.7079	**0.708**
	SWT	0.7206	0.7504	0.7548	0.7549	0.7558	0.7559	**0.7559**
	DT-CWT	0.6774	0.7453	0.7501	0.7481	0.7493	**0.7503**	0.7498

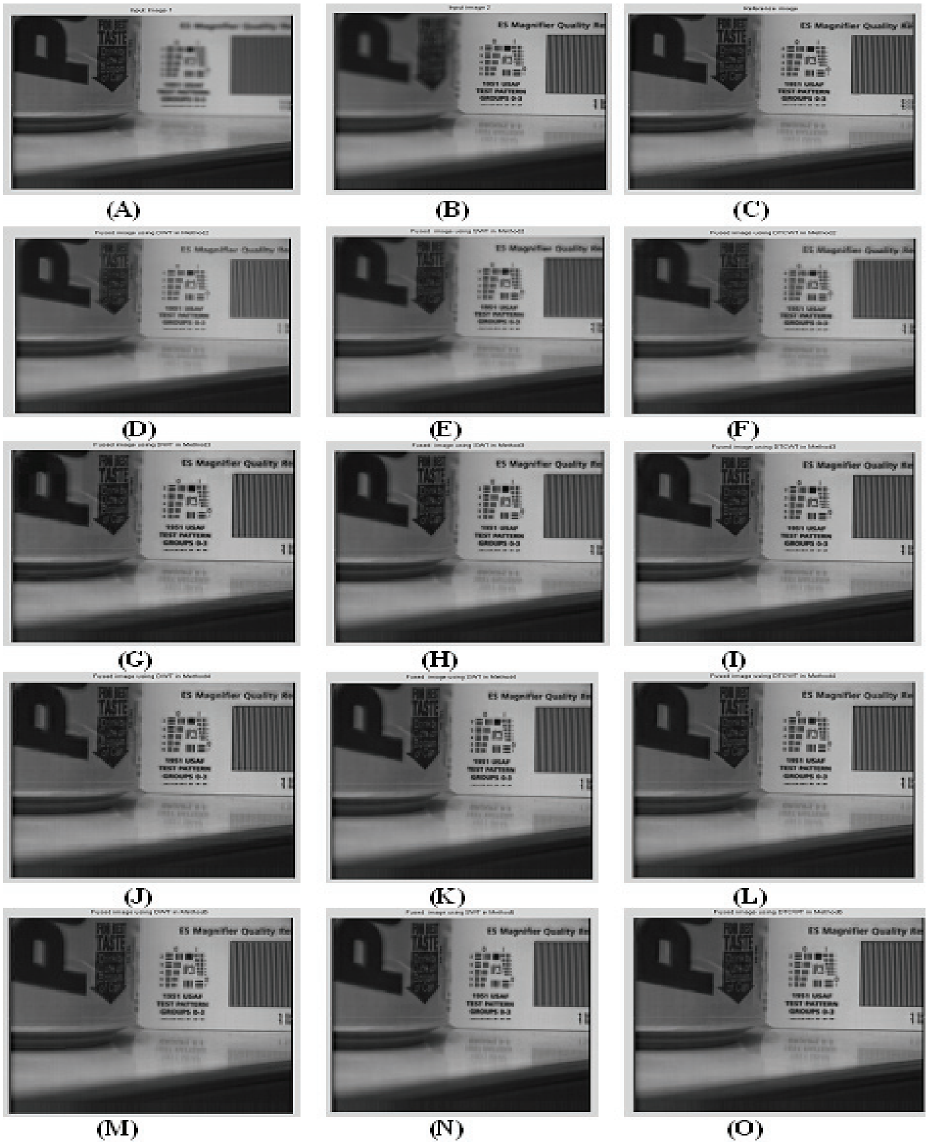


Fig. 7. – *Results of Pixel Level Image Fusion*:
(A) Input Image 1; (B) Input Image 2; (C) Reference Image;
(D),(E), (F) are Method2 Fusion Results using DWT,SWT & DTCWT;
(G),(H), (I) are Method3 Fusion Results using DWT,SWT & DTCWT;
(J),(K), (L) are Method4 Fusion Results using DWT,SWT & DTCWT;
(M),(N), (O) are Method5 Fusion Results using DWT,SWT & DTCWT.

10 Conclusion

This paper presents the optimal level of decomposition of Discrete, Stationary and Dual Tree Complex wavelet transform in pixel level fusion of multi focused images taken by a digital camera. The pixel level dual tree complex wavelet transform fusion in Method4 provides computationally efficient and better qualitative and quantitative results. Hence using these fusion method one can enhance the image with high geometric resolution.

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