Innovative Multilevel Image Fusion Algorithm using Combination of Transform Domain and Spatial Domain Methods with Comparative Analysis of Wavelet and Curvelet Transform

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ABSTRACT
Image fusion is widely used term in different applications namely satellite imaging, remote sensing, multifocus imaging and medical imaging. In this paper, we have implemented multi level image fusion in which fusion is carried out in two stages. Firstly, Discrete wavelet or Fast Discrete Curvelet transform is applied on both source images and secondly image fusion is carried out with either spatial domain methods like Averaging, Minimum selection, maximum selection and PCA or with Pyramid transform methods like Laplacian Pyramid transform. Further, comparative analysis of fused image obtained from both Discrete Wavelet and Fast Discrete Curvelet transform is done which proves effective image fusion using proposed Curvelet transform than Wavelet transform through enhanced visual quality of fused image and by analysis of 7 quality metrics parameters. The proposed method is very innovative which can be applied to medical and multifocus imaging applications in real time. These analyses can be useful for further research work in image fusion and also the fused image obtained using Curvelet transform can be helpful for better medical diagnosis.

Keywords
Averaging, AG, Cc, CT, Discrete Wavelet Transform, E, Fast Discrete Curvelet Transform, Image fusion, Image Quality Metrics, Laplacian Pyramid, Maximum Selection, Minimum Selection, MRI, PCA , PSNR, RMSE, SD.

1. INTRODUCTION
With rapid advancement in technology, different sensors are available in market which provides multimodal images with different physical characteristics, geometry, time and frequency domain characteristics. It is difficult for sensor to acquire all these characteristics into a single image. Hence the technical method to combine all these characteristics into a single image with rich information content is image fusion. Image fusion is commonly used term which includes different applications namely satellite imaging, remote sensing, multifocus imaging and medical imaging. More research work is done for satellite imaging and remote sensing applications. Few attempts are made in the field of medical imaging. Image fusion methods are broadly classified into two domains namely spatial domain and Transform domain methods. The spatial domain methods include fusion methods such as averaging, Brovey method, principal component analysis (PCA) and IHS. The disadvantage of spatial domain methods is that they produce spatial distortion in the fused image. Spatial distortion can be handled precisely by frequency domain approaches on image fusion. Transform domain methods include Multiresolution Analysis (MRA, such as Pyramid transforms (Laplacian pyramid, gradient pyramid, etc.), Wavelet transforms (Discrete wavelet transform, Multiwavelet transform, Complex wavelet transform, etc.)) and Multiscale transforms such as Ridgelet [8], Curvelet and Contourlet). These methods show a better performance in spatial and spectral quality of the fused image compared to other spatial methods of fusion.

Most of research work for Medical image fusion is done using spatial domain methods like Averaging, PCA, etc., multiresolution transforms like Laplacian pyramid transform, Discrete Wavelet transform and multiscale transforms like Curvelet transform are most commonly used for image fusion. The Laplacian pyramid method is used for fusion which causes blocking effects in fused image and also fails for spatial orientation during decomposition process [4, 5].The Discrete Wavelet transform proves to be better than pyramid transform due to better signal to noise ratio and straight edges are detected well as it operates on point singularity. But the discrete Wavelet transform has poor directionality and also fails to represent curvilinear structures [6]. Curvelet transform has advantages over wavelet transform in terms of high directionality, representing curve-like edges efficiently and reduces noise effect [7].

Literature survey of image fusion reveals, mostly image fusion is carried out only at single level but in this paper we have implemented multi level image fusion in which fusion undergoes through two levels. Also until now only one of fusion method, either transform domain methods or spatial domain methods are used in research work [3]. Recently, image fusion with single transform and spatial domain are used to improve fusion result [1, 2]. So here in this paper two transform domain methods like Wavelet and Curvelet transform are used along with five spatial domain methods. None of the research paper covers such broad implementation of two different domain methods with comparative performance analysis. Further, comparative analysis of fused image obtained from both Discrete Wavelet and Fast Discrete Curvelet transform is done which proves effective image fusion using proposed Curvelet transform than Wavelet transform through enhanced visual quality of fused image and by analysis of 7 quality metrics parameters. The method is innovative which carries out complex fusion algorithms at 2-levels which can be used for medical and multi-focus image fusion. As we have implemented firstly, transform domain methods which gives high quality spectral contents in fused image as well as high spatial resolution is also obtained due to spatial domain methods applied at second level. So, the proposed multi level image fusion method is very innovative which can be applied to medical and multifocus imaging applications in real time.

The rest of the paper is organized as follows: Section 2 presents the proposed image fusion algorithm. Section 3 gives the experimental results and comparison of different fusion rules. Finally, section 4 gives the concluding remarks.

2. THE PROPOSED MULTI LEVEL IMAGE FUSION METHOD

2.1 Block Diagram

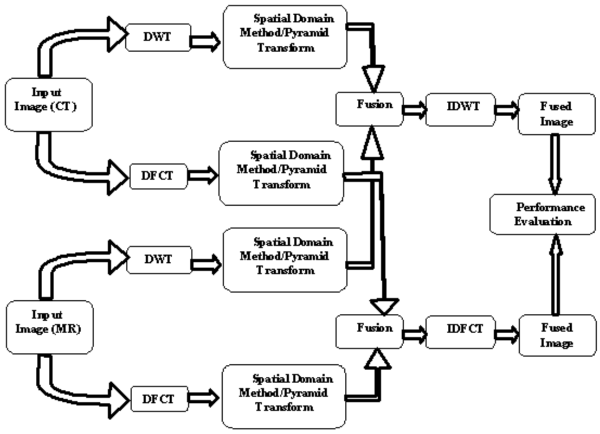


Figure 1: Block diagram of Proposed Method

The Figure 1 represents the block diagram of multi level image fusion which is carried out in two stages. Firstly, 2D - Discrete Wavelet transform is applied on both the source images which gives decomposed wavelet coefficients at level 1 which preserves better information content from source images and then at second level any of the spatial domain methods like Averaging, Minimum selection, maximum selection and PCA or Pyramid transform methods like Laplacian Pyramid transform is applied on wavelet coefficients to get new coefficients. The new coefficients obtained of both the source images after level 2 are combined together to get fused coefficients which gives high spatial resolution and high spectral quality contents. The final fused image is obtained by applying Inverse Discrete Wavelet transform on fused coefficients. Similarly, by applying Fast Discrete Curvelet transform on both the source images, curvelet coefficients by calculating image orientation from different angles are obtained at level 1 and then at second level any of the spatial domain methods like Averaging, Minimum selection, maximum selection and PCA or Pyramid transform methods like Laplacian Pyramid transform is applied on curvelet coefficients to get new coefficients. The new coefficients obtained of both the source images after level 2 are combined together to get fused coefficients which gives higher spatial resolution and higher spectral quality contents than those obtained from wavelet transform as curvelet transform has high directionality. The final fused image is obtained by applying Inverse Fast Discrete Curvelet transform on fused coefficients. Comparative analysis of fused image obtained from both Discrete Wavelet and Fast Discrete Curvelet transform is done which proves effective image fusion using Curvelet transform than Wavelet transform through enhanced visual quality of fused image and by analysis of 7 quality metrics parameters. The curvelet fused image has better PSNR as compared to wavelet fused image as curvelet transform reduces noise and due to this reason it is mainly applicable for image denoising application. Also it preserves better curved edges from both the source images. Entropy which represents richness of information content in an image is high for DFCT than DWT. Thus fused image obtained by DFCT gives effective image fusion result than DWT. More details about rest of quality metrics parameters are discussed in section 3.

2.2 Multilevel Image Fusion Algorithm

The proposed algorithm is implemented for fusion of Medical imaging and Multifocus imaging applications. Usually, medical images namely CT and MR are of main concern for medical diagnosis of brain, spine, and chest etc related diseases. They help physicians for better diagnosis and based on it further planning of treatment is decided. The CT image contains only bone details where as MR image contains soft tissue details and both contain complementary information. Thus, the role of fusion comes into picture which combines both CT and MR images into a single fused image which contains bone as well as soft tissue details with accurate information. The obtained fused image must not contain any artifacts or noise effects as it may mislead the diagnosis of disease.

The same proposed algorithm can be applied for multifocus images in which, both the images from same scene are captured with different focus namely left and right focus. The multifocus image fusion is mostly used in satellite imaging applications and digital camera applications etc. The section 3 shows experimental results obtained by applying proposed algorithm for medical imaging and multifocus imaging applications.

The steps involved in proposed algorithm can be summarized as follows:

(1) The two source images CT, image1 $[m1, n1]$ and MR, image2 $[m2, n2]$ to be fused are applied as input to system.

(2) Both the source images are registered and are made of same dimension, 256 x 256.The images of file format namely, .bmp, .jpg, .tif, .gif, .png etc can be read.

(3) In the proposed multilevel image fusion algorithm the fusion of two source images undergoes into two stages which works as follows.

Stage 1.

a) The 2D Discrete Wavelet Transform is applied on both the source images using haar transform which undergoes column filtering and then row filtering at 2 levels.

b) The wavelet coefficients from both the source images are obtained which preserves original contents from source images.

c) Similarly, Fast Discrete Curvelet transform with wrapping method is applied to both source images.

d) The FDCT algorithm steps is explained as follows-

- Apply 2D FFT transform to both source image and obtain fourier samples of both images as $A[i1, i2]$ and $B[i1, i2]$ where $-i/2 \le i1, i2 < i/2$.The obtained frequency samples of both images are periodized.

- The periodization of widowed data is done for each scale s and angle a, form the product for source image $A[i1,i2]$ as

$$d_1[i1,i2] = U_{s,a}[i1,i2]A[i1,i2] \quad (1)$$

And source image $B[i1,i2]$ as

$$d_2[i1,i2] = U_{s,a}[i1,i2]B[i1,i2] \quad (2)$$

- The obtained window data $d_1[i1,i2]$ and $d_2[i1,i2]$ are wrapped around the origin to restrict the rectangular window length $L1,a \times L2,a$ near the origin. The product obtained is

- $A_{s,a}[i1,i2] = W(U_{s,a}A)[i1,i2]$ (3)

- $B_{s,a}[i1,i2] = W(U_{s,a}B)[i1,i2]$ (4)

Where dimensions must be in range $0 \le i1 < L1,a,$ $0 \le i2 < L2,a$

- Hence, the wrapping transformation is a simple reindexing of the data.

- Apply the inverse 2D FFT to each $A_{s,a}$ and $B_{s,a}$

- The curvelet coefficients, $A_{s,a}$ and $B_{s,a}$ of both the source images which are obtained contains high directionality.

Stage 2.

a) The different image fusion methods based on spatial and pyramid transform are applied on obtained wavelet and curvelet coefficients from stage 1.

b) The spatial and Laplacian pyramid transform methods used are discussed as follows

i. For Minimum selection rule, fusion is done by taking the minimum valued pixels from $A(i1,i2)$ and $B(i1,i2)$ sub images.

$$F_{\min} = \min imum(A(i1,i2), B(i1,i2)) \quad (5)$$

ii. In PCA rule, fusion is done with principal component analysis calculation for $A(i1,i2)$ and $B(i1,i2)$ sub images and then integrating product of principal components (P_I, P_{II}) with each source sub images into a single image.

$$F_{PCA} = P_I(A(i1,i2)) + P_{II}(B(i1,i2)) \quad (6)$$

iii. Averaging Rule, fusion is done by taking the average of pixels values from coefficients matrix obtained after DWT and DFCT applied on two source images, namely $A(i1,i2)$ and $B(i1,i2)$ sub images.

$$F_{Avg} = (A(i1,i2) + B(i1,i2))/2 \quad (7)$$

iv. For Laplacian pyramid rule, fusion is done by first filtering the $A(i1,i2)$ and $B(i1,i2)$ sub images and then difference is calculated by expansion or interpolation way and then discrete convolution is performed to reconstruct the fused image, F_{lap}.

v. For Maximum selection rule, fusion is done by taking the maximum valued pixels from $A(i1,i2)$ and $B(i1,i2)$ both sub images of source images.

$$F_{\max} = \max imum(A(i1,i2), B(i1,i2)) \quad (8)$$

Based on the maximum valued pixels between $A(i1,i2)$ and $B(i1,i2)$ sub images, a binary decision map is formulated. Eq. (9) gives the decision rule D_r for fusion of DWT and FDCT obtained coefficients of two source images.

$$D_r(i,j) = 1, A(i1,i2) > B(i1,i2)$$

$$=0, \text{ otherwise} \quad (9)$$

c) Either spatial or Laplacian pyramid transform method is applied separately to both wavelet coefficients and curvelet coefficients of both the source images which gives two separate new coefficients of wavelet and curvelet transform .

d) Fusion is applied separately on both wavelet and curvelet based new coefficients obtained at level 2.

e) The two concatenated images are obtained based on wavelet and curvelet transform whose coefficients contain both high spatial resolution as well as high spectral quality contents.

(4) Apply Inverse 2D Discrete Wavelet transform (IDWT) and Fast Discrete Curvelet Transform (IDFCT) on both the concatenated images based on DWT and FDCT to reconstruct the resultant fused images and display the result.

(5) Comparative statistical analysis of fused image obtained from multilevel fusion process based on DWT and DFCT is done with 7 quality metrics parameters such as Mean, Standard deviation, Entropy, Average Gradient, PSNR, RMSE and Corelation Coefficient.

3. EXPERIMENTAL RESULTS AND STATISTICAL ANALYSIS

The experimental results of proposed algorithm for medical image fusion are shown in Figure 2(a, b, c, d, and e) and for multifocus images are shown in Figure 3(a, b, c, d, and e) with different transforms at two stages. Also comparative analysis of multi level image fusion by DWT and FDCT is shown in Table 1 and Table 2.The different 7 statistical parameters are calculated for both fused images obtained by DWT and FDCT. The mean of an image represents the average of pixel values, thus its value must be high for better contrast in an image. The Standard deviation represents the deviation of pixel values from mean. Higher the SD higher is the contrast of an image. The Entropy is measure of information content in an image, so higher the E then better is the image information. Average gradient represents the clarity or contrast in an image, thus its value must also be high. The PSNR represents the peak signal to noise ratio, so it must be high for less noise in an image.

RMSE represents root mean square error, so to occur less error in fused image the RMSE must be small for better fused image. The Correlation Coefficient, C_C represents correlation of fused image with any of one source images, thus value must be near to one. The result of both DWT and FDCT with stage 2 fusion methods is compared by statistical analysis and it shows better result with laplacian pyramid method than the other methods in terms of increased visual quality of image and improved entropy, PSNR, RMSE and other parameters of fused image. Similarly, comparison of DWT and FDCT results shows efficient fusion result by FDCT with Laplacian pyramid method than any FDCT stage 2 methods as well as all DWT methods. Hence the experimented result by proposed algorithm shows better fusion by FDCT with laplacian method for both medical and multifocus imaging applications than any of other implemented multi level fusion methods. The all 7 quality metrics parameters shows improved values and visual quality is also increased for FDCT with Laplacian pyramid transform fusion algorithm in comparison with rest of implemented algorithms.

Figure 2(a): Result of Image 1 and Image 2 fused by proposed method with Minimum Selection Rule.

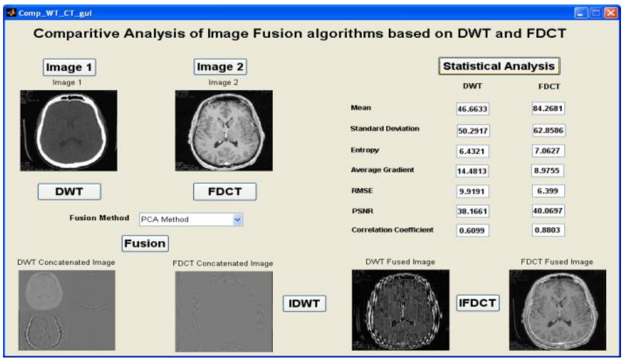


Figure 2(b): Result of Image 1 and Image 2 fused by proposed method with PCA Method.

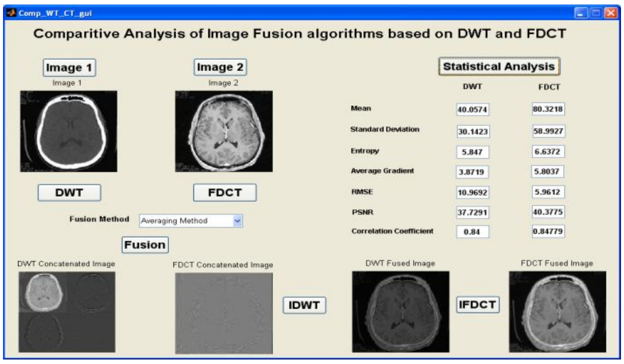


Figure 2(c): Result of Image 1 and Image 2 fused by proposed method with Averaging Method.

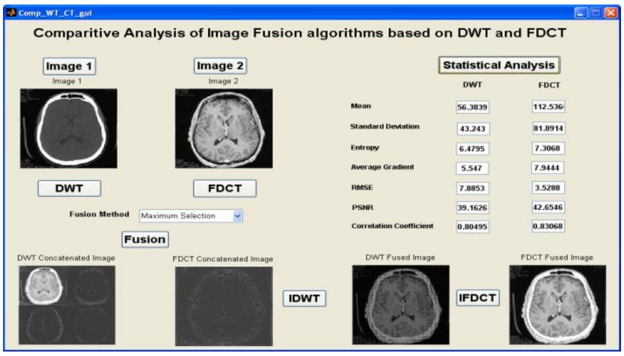


Figure 2(d): Result of Image 1 and Image 2 fused by proposed method with Maximum Selection.

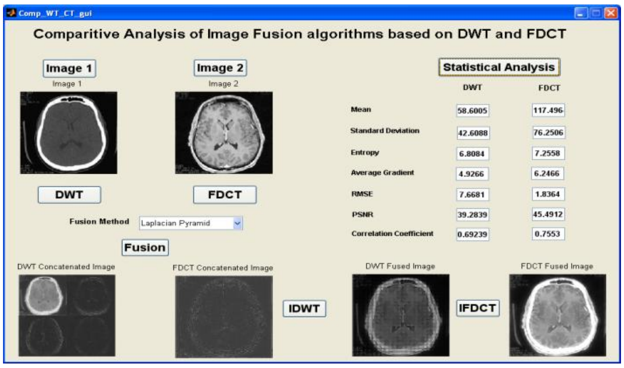


Figure 2(e): Result of Image 1 and Image 2 fused by proposed method with Laplacian Pyramid.

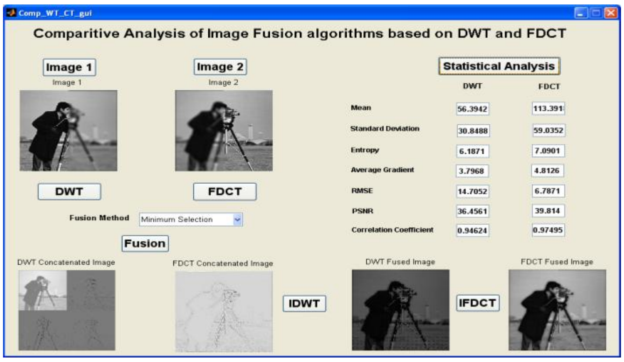


Figure 3(a): Result of Image 3 and Image 4 fused by proposed method with Minimum Selection.

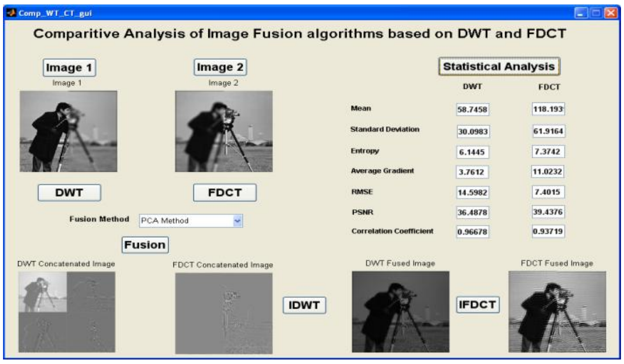


Figure 3(b): Result of Image 3 and Image 4 fused by proposed method with PCA Method.

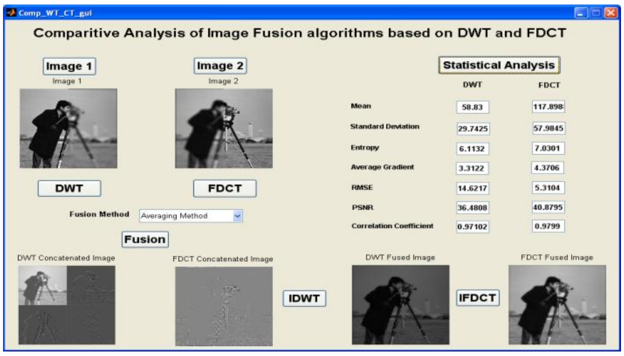


Figure 3(c): Result of Image 3 and Image 4 fused by proposed method with Averaging Method.

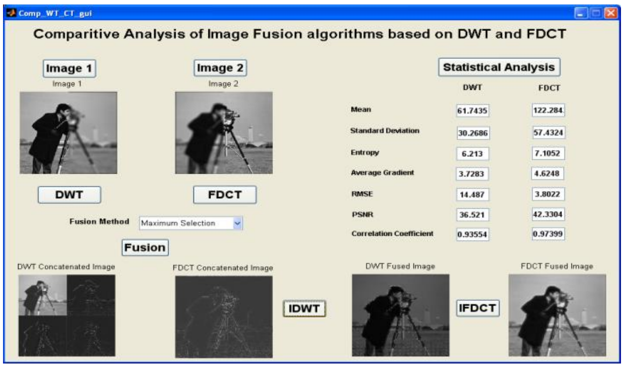


Figure 3(d): Result of Image 3 and Image 4 fused by proposed method with Maximum Selection.

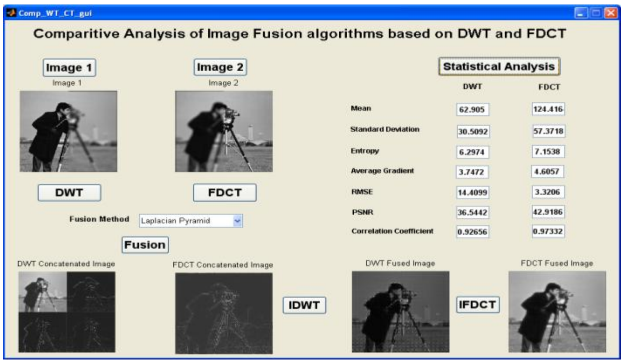


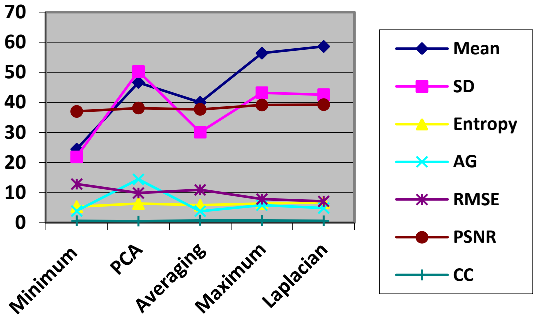
Figure 3(e): Result of Image 3 and Image 4 fused by proposed method with Laplacian Pyramid.

Table 2. EVALUATION OF FUSED IMAGES OBTAINED FROM Figure 2(a, b, c, d, e)

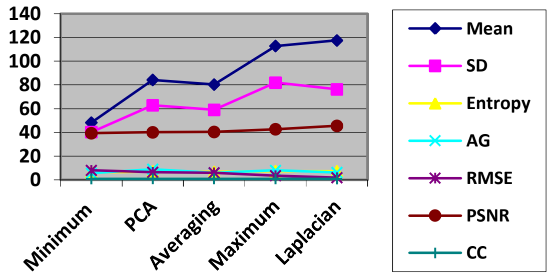
Level-2 Fusion Methods	Mean		SD		E		AG		RMSE		PSNR		C_C	
	WT	CT	WT	CT	WT	CT	WT	CT	WT	CT	WT	CT	WT	CT
Minimum Selection	24.47	48.24	21.90	40.26	5.4	6.26	3.93	5.53	12.89	7.99	37.02	39.31	0.71	0.77
PCA	46.66	84.26	50.29	62.85	6.43	7.06	14.48	8.97	9.91	6.39	38.16	40.06	0.60	0.88
Averaging	40.05	80.32	30.14	58.99	5.84	6.63	3.87	5.80	10.96	5.96	37.72	40.37	0.84	0.84
Maximum Selection	56.38	112.83	43.24	81.89	6.47	7.30	5.84	7.99	7.88	3.52	39.16	42.65	0.80	0.83
Laplacian Pyramid	58.60	117.49	42.60	76.25	6.80	7.25	4.92	6.24	7.16	1.83	39.28	45.49	0.69	0.75

Table 2. EVALUATION OF FUSED IMAGES OBTAINED FROM Figure 3(a, b, c, d, e)

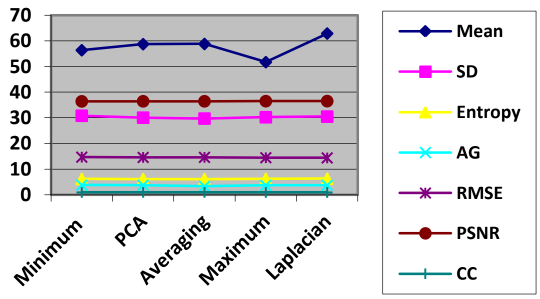
Level-2 Fusion Methods	Mean		SD		E		AG		RMSE		PSNR		C_C	
	WT	CT	WT	CT	WT	CT	WT	CT	WT	CT	WT	CT	WT	CT
Minimum Selection	56.39	113.39	30.84	59.03	6.18	7.09	3.79	4.81	14.70	6.78	36.45	34.81	0.94	0.97
PCA	58.74	118.19	30.09	61.91	6.14	7.37	3.76	11.02	14.59	7.40	36.48	39.43	0.96	0.93
Averaging	58.83	117.89	29.74	57.98	6.11	7.03	3.31	4.37	14.62	5.31	36.48	40.87	0.97	0.97
Maximum Selection	51.74	122.28	30.26	57.43	6.21	7.10	3.72	4.62	14.48	3.80	36.52	42.33	0.93	0.97
Laplacian Pyramid	62.90	124.41	30.50	57.37	6.29	7.15	3.74	4.60	14.40	3.32	36.54	42.91	0.92	0.97



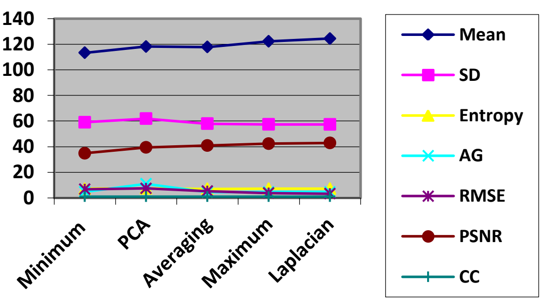
Graph 1. Statistical analysis of medical fused image with proposed DWT based multilevel algorithm



Graph 2. Statistical analysis of medical fused image with proposed FDCT based multilevel algorithm



Graph 3. Statistical analysis of multifocus fused image with proposed DWT based multilevel algorithm



Graph 4. Statistical analysis of multifocus fused image with proposed FDCT based multilevel algorithm

In all the graphs, the quality metrics namely mean SD, E, AG, CC and PSNR value either increases or remains constant starting from minimum fusion method to Laplacian fusion method. But the quality metric, RMSE value decreases from Minimum to Laplacian pyramid fusion method. So thus, the Laplacian pyramid fusion method at stage 2 gives best result than any other method at stage2. The Graph 2 shows enhanced fusion performance in comparison with Graph 1 in terms of statistical parameter analysis. Similarly, Graph 4 shows enhanced fusion performance in comparison with Graph 3 in terms of statistical parameter analysis.

4. CONCLUSION

The proposed multilevel image fusion algorithm based on DWT and FDCT works efficiently for fusion of medical and multifocus imaging applications. In this paper, the comparison of DWT and FDCT is done by tabular and graphical representation which shows improved fusion quality by statistical analysis of 7 quality metrics parameters. The FDCT based multilevel image fusion works better than DWT based multilevel image fusion. But of all the combinations of transforms implemented in this paper the FDCT with Laplacian pyramid transform gives the best fusion result for both medical and multifocus images in terms of enhanced visual quality, richness of information content in fused image, better PSNR and low RMSE value. The proposed algorithm and results obtained can be used by researchers or academicians for further research work on image fusion. The future work includes, implementing other fusion methods based on latest multiscale geometric analysis transform and some improvements in pre as well as post processing of image fusion.

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