Multifocus and multispectral image fusion based on pixel features using discrete cosine harmonic wavelet transformed and morphological filter

Shikha Dhyani[1], R P Singh[2]

[1]*M-tech scholar, Department of ECE,BTKIT Dwarahat,Almora-263653,Uttrakhand,India*
[2]*Assistant Professor, Department of ECE, BTKIT Dwarahat,Almora-263653,Uttrakhand,India*

---***---

Abstract - *The energy compaction and multi-resolution properties of wavelets have made the image fusion successful in combining important features such as edges and textures from source images without introducing any artifacts for context enhancement and situational awareness. The wavelet transform is visualized as a convolution of wavelet filter coefficients with the image under consideration and is computationally intensive. The advent of lifting-based wavelets has reduced the computations but at the cost of visual quality and performance of the fused image. To retain the visual quality and performance of the fused image with reduced computations, a discrete cosine harmonic wavelet (DCHWT) based image fusion followed by morphological filter using top hat transform is proposed.. The performance of Enhanced DCHWT is compared with DCHWT image give remarkable differences.*

***Key Words*: Image Fusion, Pixel Significance, Multifocus, Multisensor, Discrete Wavelet Transform, Harmonic Wavelet Transform, Discrete Cosine Harmonic Wavelet Transform.**

1. INTRODUCTION

The concept of data fusion goes back to the 1950's and 1960's, with the search for practical methods of merging images from various sensors to provide a composite image which could be used to better identify natural and manmade objects . Fusion is a process which can be used to improve excellence of information from a set of images. By the process of image fusion the good information from each of the given images is fused together to form resultant image whose quality is superior to any of input images [1]. There are important requirements for image fusion process[4]. The fused image should reserve all relevant information from the input images. -Image fusion should not introduce relics which can lead to wrong diagnosis. Image fusion techniques have been used in various application areas including remote sensing, biomedical imaging, and multi-exposure multi-focus image integration and advance in large number of sophisticated medical imaging modalities like: Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Positron Emission Tomography (PET), Ultrasound, X-ray, Single Positron Emission Computed Tomography (SPECT), Electrocardiography (ECG) etc. have added to the visual response from these devices in terms of interpretation and diagnostic analysis [6],[7]. In the field of remote sensing, medical imaging and machine vision the multi-sensor data may have multiple images of the same scene providing different information. As optical lenses in charged coupled devices have limited depth of focus, it is not possible to have a single image that contains all the information of objects in the image, so image fusion is required. There are two groups into which image fusion methods are divided, namely spatial domain fusion method and Transform domain fusion method. Spatial domain fusion method will directly deal with pixels of input images. In Transform domain fusion method image is first transformed into frequency domain. Use of the Simple primitive technique will not improve good fused image in terms of performance parameter like peak signal to noise ratio (PSNR), Normalized correlation (NC), and Mean square error (MSE). Recently, Discrete Wavelet Transform (DWT) and Principal Component Analysis, Morphological processing and Combination of DWT with PCA and Morphological techniques have been prevalent fusion of image[2][3][5].

1.1 Discrete Cosine transform based Image Fusion

DCT is a process to modify a signal into elementary frequency components. DCT is a closely related to discrete Fourier transform (DFT), using the DCT a signal is categorized into its basic frequency components. When we use DCT on X*Y sized matrix, the 2D-DCT extract the energy information of the image and then it will focus on some specific features located in the upper left Corner of the outcome real-valued X*Y DCT matrix The workings of DCT coefficients return the average energy of pixel blocks whereas the AC components return the intensity of image. As DCT separates an image hooked on discrete blocks of pixels of differing significance or weight age in an image so we can say that DCT is a flossy technique [9].

Discrete cosine transform is defined [9] as equation (7).

$$F(i,j) = \alpha(i)\alpha(j)\sum_{x=0}^{A-1}\sum_{y=0}^{B-1} f(x,y)\cos[\frac{\pi(2x+1)i}{2A}]cos\left[\frac{\pi(2y+1)j}{2B}\right] \quad (7)$$

$$where\ i = 0,1,2,\dots M-1\ and\ j\ = 0,1,2,\dots B-1$$

$$\alpha(u) and\ \alpha(v) = \begin{Bmatrix} \sqrt{\frac{1}{M}} & for\ u,v = 0 \\ \sqrt{\frac{2}{M}} & for\ u,v \neq 0 \end{Bmatrix}$$

1.2 Discrete Wavelet Transform based Image Fusion

We can calculate Wavelet coefficients by a wavelet transform which shows changes according to time interval at a specific resolution. Taking the time interval makes it easy to calculate and remove the noise from image. The term wavelet transform is explained as decomposition of the data or the image into wavelet coefficients, comparing the detail coefficients with a given threshold value, and shrinking these coefficients close to zero to take away the effect of noise in the data. The image is reconstructed from the modified coefficients which are known as the inverse discrete wavelet transforms [10]. DWT transformations convert the image into four different frequency sub band as LL, LH , HL and HH as figure 1. Where range of frequency is represented as LL<LH<HL< HH. The feature or characteristics of image is represented by low frequency coefficients or LL sub band so LL frequency sub band is used for image fusion [11].

2. Discrete cosine harmonic wavelet transform based Image Fusion

In DCT, the generation of an even symmetric periodic sequence removes the discontinuity as the symmetric signal moves from one period to the next period smoothly. As a result, like the DFT, the DCT does not suffer from leakage effects or Gibbs ripple.

For a real symmetric signal xs(t) and a real symmetric wavelet function ψs(t), Eq. can be written as

$$W_c(a,b) = \frac{|a|^{\frac{1}{2}}}{2\pi}\int_{-\infty}^{\infty} X_s(\omega)\Psi_s(a\omega)\cos(\omega b)d\omega,$$

where Xs(ω) ands(ω) are the cosine transforms of xs(t) and wavelet function ψs(t), respectively. Wc(a, b) is the wavelet transform in the cosine domain rather than the Fourier domain.

$$\Psi_s(\omega) = \begin{cases} 1, & \omega_c - \omega_0 < \omega < \omega_c + \omega_0, \\ & -\omega_c - \omega_0 < \omega < -\omega_c + \omega_0, \\ 0, & \text{elsewhere.} \end{cases}$$

The corresponding wavelet ψs(t)in time domain becomes

$$\begin{aligned} \psi_s(t) &= \frac{\omega_0}{\pi} \frac{\sin \omega_0 t}{\omega_0 t} \cos(\omega_c t) \\ &= \frac{\omega_0}{\pi} \operatorname{sinc}(\omega_0 t) \cos(\omega_c t). \end{aligned}$$

In DCHWT, the signal is decomposed by grouping the DCT coefficients in a way similar to that of DFT coefficients except for the conjugate operation in placing the coefficients symmetrically (as DCT is rea)l. Further, symmetric placement is also not necessary due to the very definition of DCT. The inverse DCT (IDCT) of these groups results in discrete cosine harmonic wavelet coefficients (DCHWCs). The DCT of these processed sub-bands (groups of DCHWCs) results in sub-band DCT coefficients, which are repositioned in their corresponding positions to recover the overall DCT spectrum at the original sampling rate. Akin to Fourier-based HWT, DCHWT also has similar advantages like (a) flexibility of built-in decimation and interpolation operations, (b) no band-limiting and image-rejection filters are necessary, (c) availability of fast algorithms based on the DCT. In addition, DCHWT is computationally simpler than the Fourier-based HWT as it involves only real operations and hence it is even more computationally simpler than convolution.

Gray-scale morphological filter

basic operations of dilation, erosion, opening, and closing to gray-scale images. *f*(*x, y*) is a grey-scale image and *b*(*x, y*) is a structuring element and both functions are discrete. The structuring elements are used to examine a given image for specific properties. The **dilation** of *f* by a ***flat*** structuring element *b* at any location (*x, y*) is defined as the ***maximum*** value of the image in the window outlined by *b* ˆ when the origin of *b* ˆ is at f(x,y)

$$[f \oplus b](x, y) = \max_{(s,t) \in b} \{ f(x - s, y - t) \}$$

where we used that

$$\hat{b} = b(-x, -y)$$

The **erosion** of *f* by a ***flat*** structuring element *b* at any location (*x, y*) is defined as the ***minimum*** value of the image in the region coincident with *b* when the origin of *b* is at (*x, y*). Therefore, the erosion at (*x, y*) of an image *f* by a structuring element *b* is given by:

$$[f \ominus b](x, y) = \min_{(s,t) \in b} \{ f(x + s, y + t) \}$$

the **opening** of the image *f* by structuring element *b* is defined as the erosion of *f* by *b* followed by a illation of the result with *b*:

$$f \circ b = (f \ominus b) \oplus b$$

Similarly, the closing of *f* by *b* is

$$f \bullet b = (f \oplus b) \ominus b$$

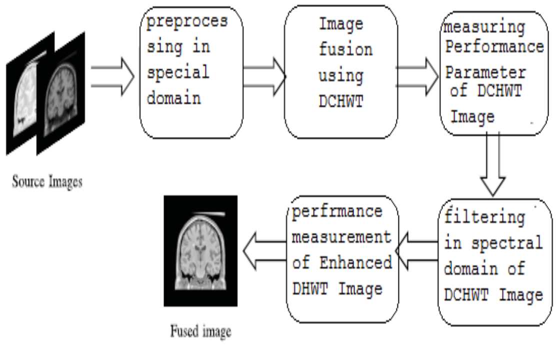
top-hat and bottom-hat transformations One principal application of these transforms is in removing objects from an image by using an SE in the opening and closing that does not fit the objects to be removed. The difference then yields image with only the removed objects. The **top-hat** is used for light objects on a dark background and the **bottom-hat** for dark objects on a light background. An important use of top-hat transformation is in correcting the effects of non-uniform illumination. Let $f : E \mapsto R$ be a grayscale image, mapping points from a Euclidean space *E* (such as R^2 or Z^2) into the real line. Let $b(x)$ be a grayscale structuring element. Then, the white top-hat transform of *f* is given by:

$$T_w(f) = f - f \circ b,$$

The black top-hat transform of *f* (sometimes called the *bottom-hat* transform [1]) is given by:

$$T_b(f) = f \bullet b - f$$

Algorithm:



In proposed method after preprocessing of images ,images are fused using DCHWT where the signal is decomposed by grouping the DCT coefficients in a way similar to that of DFT coefficients except for the conjugate operation in placing the coefficients symmetrically (as DCT is real).along with performance evaluation of the fused image .after fusion image post processing has to be done in spectral domain using top hat transform for better performance parameter of images.

3. RESULT

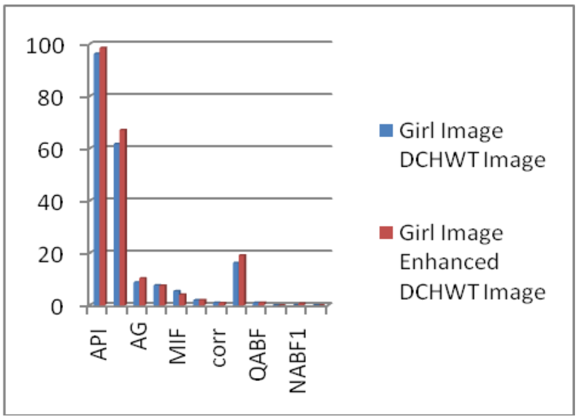
Test Image1: Girl Image

Image to be Fused

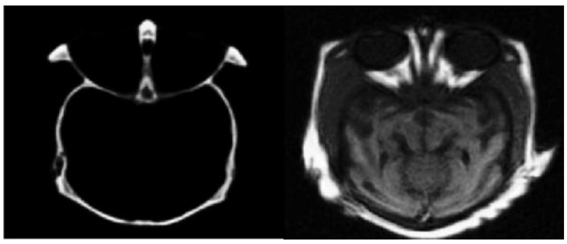
DCHWT Image Enhance DCHWT Image

Difference in performance parameters:

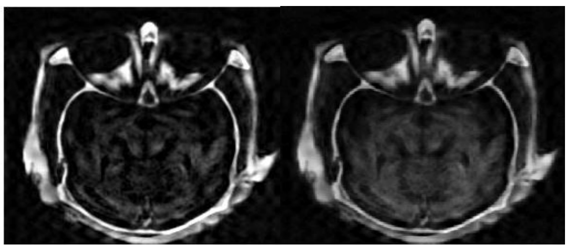
Performance Parameter	Girl Image	
	DCHWT Image	Enhanced DCHWT Image
API	96.2801	98.4702
SD	61.749	67.0458
AG	8.817	10.3543
entropyF	7.6591	7.5048
MIF	5.4019	4.0715
FS1	1.9719	1.9807
corr	0.9677	0.9277
SF	16.2488	19.117
QABF	0.9624	0.9621
LABF	0.0347	0.0216
NABF1	0.0492	0.67
NABF	0.0029	0.0163



Test Image 2: Medical Image



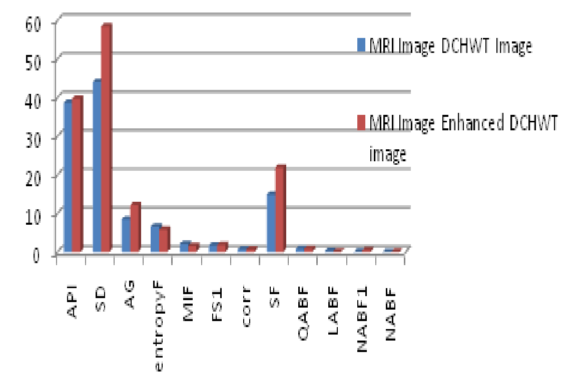
Images to be fused



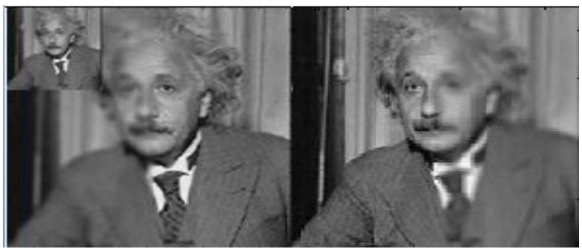
DCHWT Image Enhanced DCHWT Image

Difference in performance parameters:

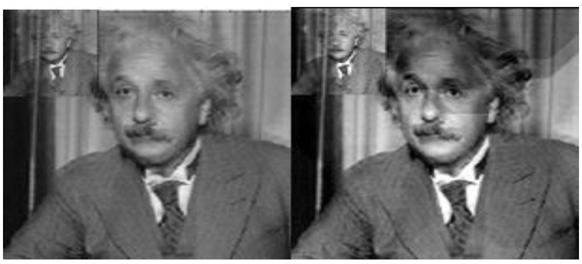
Performance parameters	MRI Image	
	DCHWT Image	Enhanced DCHWT image
API	38.6518	39.6547
SD	44.0615	58.4216
AG	8.4393	12.1293
entropyF	6.5875	5.8497
MIF	2.1038	1.5365
FS1	1.7258	1.7883
corr	0.6746	0.632
SF	14.8591	21.8363
QABF	0.8258	0.8713
LABF	0.1704	0.1034
NABF1	0.0297	0.4748
NABF	0.0037	0.0253



Test Image3: Doctor image



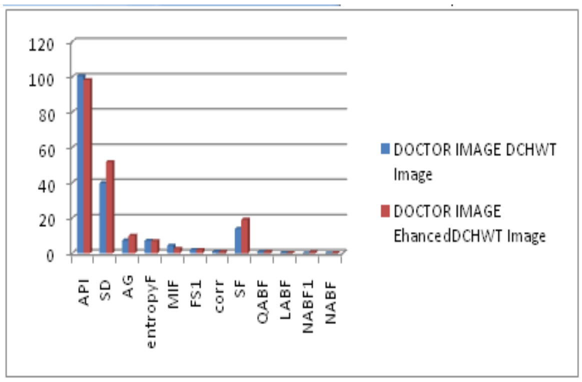
Images to be Fused



DCHWT Image Enhanced DCHWT Image

Difference in performance parameters:

Performance parameters	DOCTOR IMAGE	
	DCHWT Image	EhancedDCHWT Image
API	100.545	98.3019
SD	39.8567	51.7203
AG	7.2581	10.0259
entropyF	7.1731	6.9846
MIF	4.3042	2.5591
FS1	1.9785	1.9654
corr	0.9496	0.764
SF	13.9344	19.0657
QABF	0.8723	0.8667
LABF	0.1194	0.0699
NABF1	0.0439	0.6499
NABF	0.0083	0.0633



Test Image4: Disk image

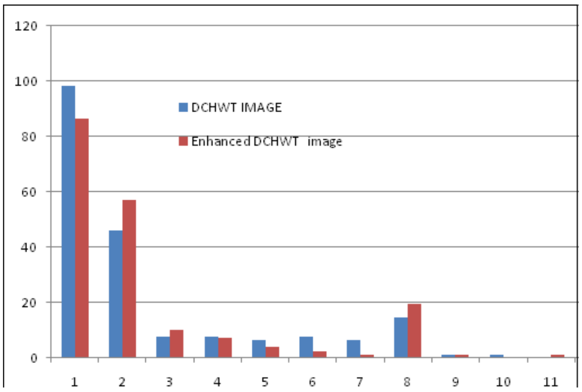
Image to be Fused

DCHWT Image Enhanced DCHWT Image

International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395 -0056
Volume: 03 Issue: 06 | June-2016 www.irjet.net p-ISSN: 2395-0072

Difference in performance parameters:

Performance parameters	DCHWT IMAGE	DISC Image Enhanced DCHWT image
API	98.0119	86.3175
SD	45.8656	56.5659
AG	7.4589	9.9324
entropyF	7.2799	7.0822
MIF	6.093	3.5549
FS1	7.2799	1.9462
corr	6.093	0.929
SF	14.2413	19.0648
QABF	0.9799	0.8849
LABF	0.8915	0.0528
NABF1	0.106	0.7088
NABF	0.0173	0.0623



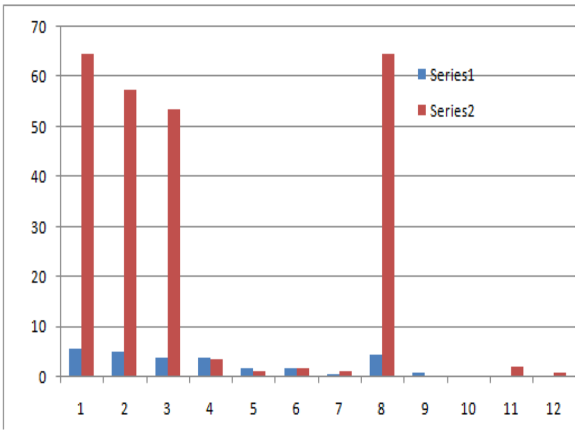
Test Image 5: Gun Image

Images to be fused

DCHWT Image Enhanced DCHWT Image

Difference in performance parameters:

GU N Image		
Performance parameters	DCHWT	Enhanced DCHWT
API	5.5832	64.5084
SD	5.0729	57.3759
AG	3.8231	53.5011
entropyF	3.9264	3.6463
MIF	1.758	1.226
FS1	1.9294	1.8962
corr	0.6751	1.1042
SF	4.6309	64.656
QABF	0.889	0.0338
LABF	0.1107	0.0025
NABF1	0.0229	1.9504
NABF	3.11E-04	0.9636



3. CONCLUSIONS

For better result of performance parameter of fused image tophat transform followed by DCHWT is good as compare to DCHWT only.

REFERENCES

[1] Sweta K. Shah, Prof. D.U. Shah "Comparative Study of Image Fusion Techniques based on Spatial and Transform Domain," in International Journal of Innovative Research in Science, Engineering and Technology , Vol. 3, Issue 3, March 2014.

[2] Yufeng Zheng, Edward A. Essock and Bruce C. Hansen, "An Advanced Image Fusion Algorithm Based on Wavelet

Transform – Incorporation with PCA and Morphological Processing"

[3] Shrivsubramani Krishnamoorthy, K P Soman," Implementation and Comparative Study of Image Fusion Algorithms" .International Journal of Computer Applications (0975 – 8887) Volume 9– No.2, November 2010.

[4] A.Ufade, M.Kawade, "Comparision of spatial domain and transform domain image fusion technique for restoration of blur images", International Conference on Recent Trends in engineering & Technology, 2013.

[5] Jonathon Shlens, "A Tutorial on Principal Component Analysis". Center for Neural Science, New York University New York City, NY 10003-6603 and Systems Neurobiology Laboratory, Salk Insitute for Biological Studies La Jolla, CA 92037.

[6] Rania Hassen, Zhou Wang, and Magdy M. A. Salama, "Objective Quality Assessment for Multiexposure Multifocus Image Fusion." IEEE transactions on image processing, vol. 24, no. 9, september 2015.

[7] Vikrant Bhateja, Member, Himanshi Patel, Abhinav Krishn, Akanksha Sahu, and Aimé Lay-Ekuakille, "Multimodal Medical Image Sensor Fusion Framework Using Cascade of Wavelet and Contourlet Transform Domains."ieee sensors journal, vol. 15, no. 12, december 2015.

[8] Lewis, John J., Robert J. O'Callaghan, Stavri G. Nikolov, David R. Bull, and Nishan Canagarajah. "Pixel-and region-based image fusion with complex wavelet" Information fusion, Vol.8, No. 2, pp:119-130, 2007.

[9]Kusum Rani1, Reecha Sharma2, "Study of Different Image fusion Algorithm." International Journal of Emerging Technology and Advanced Engineering, Volume 3, Issue 5, May 2013.

[10]Yong Yang, Member, Song Tong, Shuying Huang, and Pan Lin, "Multifocus Image Fusion Based on NSCT and Focused Area Detection" IEEE Sensors Journal, Vol. 15, No. 5, May 2015.

[11]Dosodia, Priya, Amarjeet Poonia, Sandeep K. Gupta, and Shubh Lakshmi Agrwal. "New Gabor-DCT Feature Extraction Technique for Facial Expression Recognition."In Fifth International Conference on Communication Systems and Network Technologies *(CSNT)*, pp. 546-549. IEEE, 2015.