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Cascaded Lifting Wavelet and Contourlet Framework Based Dual Stage Fusion Scheme for Multimodal Medical Images

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Abstract

A scheme for multi scale based feature level image fusion for Multimodal medical images has been proposed here. The scheme is based on joint cascaded framework of Lifting wavelet transform (LWT) with Non subsampled contourlet transform (NSCT). These multiscale decomposition (MSD) methods are used back to back to decompose the images of different medical modalities. The low and high frequency coefficients obtained from two stage decompositions are fused according to different fusion rules. At first stage high frequency components (detail information) are fused by Karhunen –Loeve (KL) transform while low frequency by weighted superposition. Later on at second stage the max rule fusion method has been employed for both. Image reconstruction at the intermediary level is obtained by applying Inverse LWT (ILWT) and at final stage Inverse NSCT has been employed. Haar wavelet function is chosen here for its less computational cost property. The effectiveness of the proposed method (LWT-NSCT) is observed by enhanced values of assessment parameters of evaluation indices metric as compared to contemporary and popular transform based fusion methods. Now the attractive features of both transforms i.e. lifting and NSCT like sparse data representation, integer to integer mapping, high vanishing moments and saving of auxiliary memory are attractable features of this method.

Keywords: Multi scale; Image fusion; Multimodal; Lifting wavelet; NSCT; KL transform

Introduction

Image fusion is an eminent technique used in modern medical diagnostic science [1]. It is a technique of adding complementary information from two or more images obtained from different modalities and obtaining the resultant image (fused image) enriched with information of both images [2,3]. For gray medical images this technique has certainly proved its importance. Analysis of edges, corners, boundaries and patches etc are most important, unavoidable and most desirable features of a medical image [4,5].

In the area of medical diagnosis the amount of information obtained from a scene of images by multi sensor environment is much more as compared to single sensor environment .Single sensor and single modality images are generally insufficient to deliver detail information of a scene. This occurs due to physical limitations and poor calibration of single sensor. Images acquired with a single sensor may be limited of information but certainly with some strong features contained in it. This problem of limited information can be easily handled through a multi sensor environment. The images from different sensors may be complementary to each other. These images from different sensors with complementary features are when combined together to produce an image with maximum information and details in it is called Image fusion [6,7] .

The fused image is now rich with maximum details in each individual image [8]. Medical Image modalities like Computed Tomography (CT), Ultrasound (US), Magnetic Resonance Imaging (MRI), X-ray etc. have become eminent and integral part in the area of medical diagnosis [1,3,4]. Different medical imaging modalities have different conclusive approaches regarding diagnosis of a diseased body part. For example CT scan provides information of dense tissues like bones while MRI provides information of soft tissues like nerves and tumors [1,4,5]. Medical specialists generally recommend both techniques for same body part to achieve high conclusive accuracy about a disease. Radiologist generally prefers to combine the results of both diagnosis techniques in a single image which is called multimodal image fusion. Now the single image has the combined features of both images. A good fusion scheme avoids redundancy and efficiently saves the memory of a digital machine or a computer system [4-8]. Image Fusion is basically done in two domain. One is in transform domain which is a better way for edge protection and removal of block effect. While other is spatial domain method which has many deficiencies like poor edge performance and un-consistent fusion results [2-6].

Based on different transform based methods with different fusion rules many multimodal image fusion schemes has been suggested in recent years [1-5]. In this paper a comparative study between proposed technique (LWT-NSCT) and different wavelet based fusion methods along with few other popular multi resolution transforms like curvelet and contourlet has been discussed [3,4,6,9]. In our proposed work (LWT-NSCT) we are performing back to back decomposition of images with further selectively fusion of coefficients with different fusion rules. The proposed method belongs to a category of multimodal medical image fusion which employs cascaded framework of different types of transforms as like Ripplet with Non-subsampled Shearlet domain (NSST) [1] and Static wavelet transform(SWT) with Non Subsampled Contourlet Transform (NSCT) [4]. The simulated results proves the proposed method as a state of art method in medical image fusion as per improved and satisfactory values of assessment parameters like Entropy (E), Average Gradient (AG), Peak signal to noise ratio(PSNR), Structural Similarity (SSIM), Fusion Factor (FF), Edge Strength, Measurement of

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Enhancement(ME) [1-5]. A comparative study based on the analysis of fusion quality matrics (FQM) is presented between proposed method and other contemporary popular transform domain fusion methods like Contourlet (CT) [9], Curvelet (CVT) [3,6], Cascaded Static wavelet transform and NSCT (SWT-NSCT), LWT method etc. [7,8,10]. Few more fusion method results are compared with proposed method (LWT-NSCT) like Quaternion wavelet transform (QWT) [2], Daubechies complex wavelet transform (D_xCWT)[5], single stage SWT and Discrete Wavelet Transform (DWT).

Background and Literature Survey

Image processing technique such as image fusion has become an important and unavoidable issue in the field of medical imaging and diagnosis [1]. Its role has become dominant especially when dealing with gray medical images which generally are low informative as compare to colour medical images. In such gray medical images it is highly difficult to identify the region of interest (ROI) like patches, boundaries, corners and edges. Several multiscale decomposition (MSD) based fusion schemes with different fusion rules has been proposed in recent years [2]. Mostly such popular MSD schemes are based on wavelet transforms and on other transforms like curvelet, beamlet and countourlet transform etc [1-4]. In all such fusion schemes the first process is image decomposition which is the primary step which generates the high and low frequency coefficients which are the main sources of information. The second part of such fusion schemes are the fusion algorithms which specifies how different coefficients from different images are to be fused or mingled [1-5]. Very recently in the work of Chai et al. [1], fusion scheme was employed using Quaternion wavelet and multiple features. The fusion rule opted for wavelet coefficients are weighted average and choose-max respectively for low and high frequency coefficients. Bhateja et al. [3] proposed multistage cascaded approach of stationary wavelet Transform (SWT) with Contourlet transform along with Principle Component Analysis (PCA) and maximum fusion rule. Singh and Khare [4] used Daubechies Complex Transform (DxCWT) for image decomposition and deploy fusion rule as per selection of higher magnitude of wavelet coefficients. Majumdar and Bhardwaj [6] and Kor et al. [7] proposed Lifting wavelet Transform (LWT) based image decomposition along with wavelet transform modulus maxima criteria as fusion rule. Bhardwaj and Nayak also proposed same scheme for highly noise sensitive images like ultrasound and dentistry [8,9].

Proposed Fusion Methodology

In this paper successive sub-band decomposition of images at two stages along with different fusion rules has been proposed as shown in Figure 1. In this cascaded framework both the images are first decomposed by Lifting wavelet transform (LWT) [7-10]. The LWT decomposition convert the image into four frequency sub bands called approximation(a), Vertical(v), Horizontal(h) and Diagonal(d) coefficients [9,10]. Despite approximation all three coefficients are rich in detail information of images. The low frequency components called approximation coefficients from both images are fused according to weighted superposition rule while the vertical, Horizontal, Diagonal coefficients of both images are fused according to KL transform [3,11]. Through inverse LWT the two fused images are obtained in spatial domain having combined feature of both multimodal images. One fused image has low details while other has good details .Both the images again separately decomposed by NSCT transform [3]. The low and high frequency coefficients of both images at decomposition stage two are fused by maximum fusion rule [4]. After using inverse NSCT we obtained the final fused image comprised of excellent information from both modalities [3,8]. The performance of final fused image is evaluated according to the higher values of elements of assessment metric table comprises of assessment parameters like Entropy, Average Gradient, Standard deviation, Fusion factor(FF), Structural Similarity (SSIM), Peak signal to noise ratio(PSNR) [12]. Figure 1 is explaining the proposed method of fusion.

Image decompositions at first stage by using LWT

With excellent property of multi resolution LWT is used here for image decomposition [13]. It is basically a discrete wavelet transform (DWT) which can be viewed as predictor-error decomposition. The "predictors" are the scaling coefficients at a given scale (*j*) are used for the analysis of data at the next higher resolution or scale (*j-1*). The wavelet coefficients thus generated are prediction errors [14,15]. LWT is factoring the wavelet transforms into some steps called Lifting [16,17]. The LWT process an image in the iteration of the three steps called lazy, predict and update. In Lazy wavelet transform step the image x[n] is explained in eq(1)

$$x[n] \in R, \ (n \in Z)$$

Divided into its even and odd polyphase components

$$x_e[n] \text{ and } x_o[n]$$

Respectively where

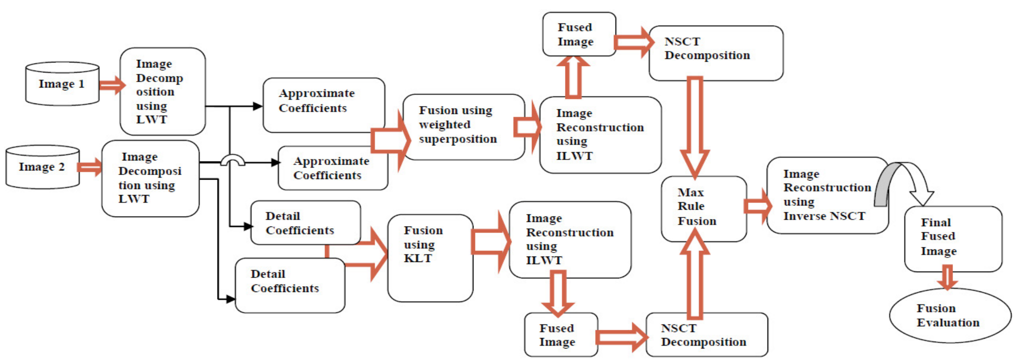

Figure 1: Block Diagram of Proposed Image Fusion Method.

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$$x_e[n] = x[2n]$$
$$x_o[n] = x[2n+1]$$

In the Predict step of LWT the neighbouring even coefficients as in eq(2) are used to predict odd poly phase Coefficient and the detail wavelet coefficients (high pass) are generated as an error generated in the process of

Predicting the odd samples from the even samples as in eq 3-5.

$$d = x_o - P(x_e)$$

Now the odd components can be calculated as

$$x_o = P(x_e) + d$$

In the last update step of LWT the even set is updated here using the wavelet coefficients to compute the scaling function coefficients (low pass) as in eq(6).An operator *U* called update operator is applied to detail Coefficients obtained in the predicting step as in given eq(7) .

$$S = x_e + U(d) \tag{7}$$

It reproduces x_e as in eq (8)

$$x_e = s - U(d)$$

LWT is a fast implementation of Wavelet Transform because of its almost similar nature of operation on low pass and high pass filtering. Perfect reconstruction of original image is it's another attracting property [17,18]. It also saves lots of auxiliary memory and have an advantage of simple inverse transform property [18]. It also reduces computational complexity by a factor of two. A separable wavelet transform is implemented on images by first applying 1-D wavelet transform along the columns and then along the rows of an image. This provides 1-level wavelet decomposition that consists of four components labeled as LL, LH, HL and HH, respectively [6,7,9,10].

Fusion rules at first stage

Low frequency coefficients called approximation coefficients obtained from decomposition of both modalities are fused by weighted superposition method. High frequency coefficients called detail coefficients obtained from decomposition of both modalities are fused by KL transform.

Image decompositions at second stage (By using NSCT)

The reconstructed images at first stages are again decomposed by contourlet transform .The special class of contourlet transform called Non sub sampled contourlet transform (NSCT) is used here. Being in shift invariant nature it removes the problem of shift variance in images. Both reconstructed images of first stage are subband decomposed into low and high frequency coefficients.

Fusion rule at second stage

At this second level of fusion simply maximum fusion rule is used for fusing the image coefficients obtained from contourlet transform based image decomposition as discussed above. In this the coefficients with maximum values from each multimodal image set are chosen and then fused. Finally inverse contourlet transform (INSCT) is used to reconstruct the final fused image.

Algorithm 1: Proposed Fusion Algorithm

Start

a: calculate LWT coefficients(of two different modalities).

Approximation(A_i)

Vertical(V_i)

Horizontal(H_i)

Diagonal(D_i)

b: Computation of column vectors from LWT coefficients.

c: Computation of Covariance matrix Cov_{xx} from these vectors.

d:obtain the diagonal elements of the Covariance vector.

e :Computation of Eigen values (Ω_1 and Ω_2) and Eigen vectors $£_1$ and $£_2$ of Covariance matrix Cov_{xx}.

$$£_1 = \begin{bmatrix} £_1 & (1) \\ £_1 & (2) \end{bmatrix} and \;\; £_2 = \begin{bmatrix} £_2 & (1) \\ £_2 & (2) \end{bmatrix}$$

f. Calculate mean of Eigen vector and divide each element with that

mean.we will find that column vector are corresponding to large Eigen value.

g: Multiply normalized Eigen vector by each term of Lifting wavelet coefficient matrix.

h: Computation of uncorrelated components KLT_1 and KLT_2 for the eigen values having max. values

i.e Ω_{max} =max(Ω_1, Ω_2)

so,

$$KLT_1 = \frac{£_{max(1)}}{\sum_i £_{\max(i)}}, KLT_2 = \frac{£_{max(2)}}{\sum_i £_{\max(i)}}$$

i:Compute Inverse LWT of two scaled matrices as obtained in step g.

j:Compute Non subsampled contourlet coefficients .

k:Compute maximum matrix as per following

$$n(x,y) = \{n_1(x,y), n_1(x,y) \geq n_1(x,y)\}$$
$$n(x,y) = \{n_2(x,y), n_2(x,y) \geq n_2(x,y)\}$$

l: Compute Inverse NSCT of matrix as obtained in step k

m: Obtain Fused image as output stop

Results and Discussion

Three Preregistered medical modality image data sets of a human brain are fused by proposed method (CLW-NSCT).The image data set used here is available at Johnson and Becker's whole brain atlas [15]. Simulations of result are done on a computer with 8 GB RAM and 2.27 GHZ CPU speed .The MATLAB (R2015a) is used as the main simulating software. The resultant fused image from all medical datasets are qualitatively and quantatively assessed according to values of evaluation indices mentioned and explained in fusion quality matrics table as shown in Table 1 and Figures 2, 3. Eight different fusion evaluation indices described here are Standard Deviation(SD), Entropy

S.NO	Assessment Parameter	Definition and Significance
1	Standard Deviation(SD)	$[\frac{1}{m\times n}\sum_1^m (f(n,m)-\mu)^2]^{\frac{1}{2}}$
2	Entropy(E)	$\sum_{L=0}^{L-1} P_i \log_2 P_i$
3	Edge strength(S_F^{AB})	$\frac{\sum_{n=1}^N\sum_{m=1}^M S^{AF}(n,m)W^A(n,m)+S^{BF}(n,m)W^B(n,m)}{\sum_{i=1}^N\sum_{j=1}^M (W^A(i,j)+W^B(i,j))}$
4	Structured similartity (SSIM)	$\left(\frac{\rho_{xy}}{\rho_x\rho_y}\right)\left(\frac{2\overline{xy}}{(\overline{x})^2+(\overline{y})^2+K_1}\right)\left(\frac{2\rho_x\rho_y}{(\rho x)^2+(\rho y)^2+K_2}\right)$
5	Measurement of Enhancement(ME)	$\frac{1}{K_1K_2}\sum_{m-1}^{K_1}\sum_{l-1}^{K_2} 20ln\left(\frac{I^{l,m}_{max}}{I^{l.m}_{min}}\right)$
6	PSNR	$10\log_{10}\frac{(2^r-1)^2}{MSE}$
7	Gradient	$\frac{1}{(m-1)(n-1)}\sum_{i=1}^{m-1}\sum_{j-1}^{n-1}\sqrt{\frac{\Delta I_x^2\Delta I_y^2}{2}}$ $\Delta I_x = f(i+1,j)-f(i,j)$ $\Delta I_y = f(i+1,j)-f(i,j)$
8	Fusion Factor	$FF = I_{AF}+I_{BF}$

Table 1: Assessment Parameters Used For Fused Image.

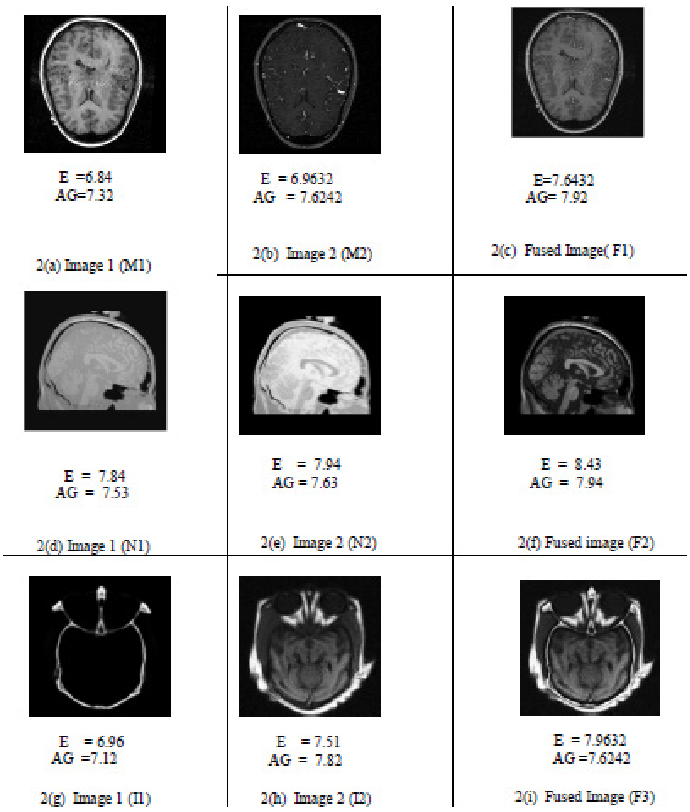

Figure 2: Three Multimodal Image Data Sets with Image Fusion by Proposed Method.

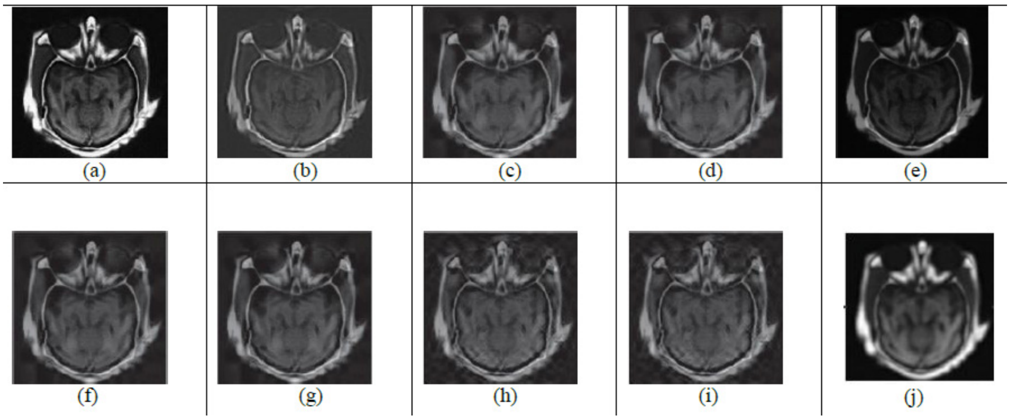

Figure 3: Comparison between Different Fusion Methods For Set 3 Fused Image. (a)Proposed method(LWT-NSCT) ,(b) QWT,(c) SWT-NSCT(d) LWT,(e) DxCWT,(f) NSCT,(g) CT,(h)CVT,(i)SWT,(j)DWT.

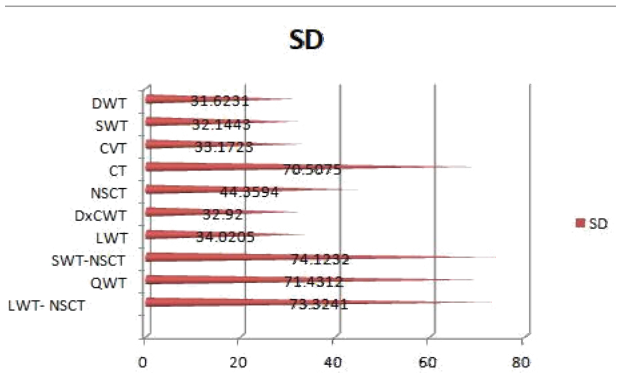

Figure 4: Comparison of standard deviation (SD) of fused image with different fusion methods.

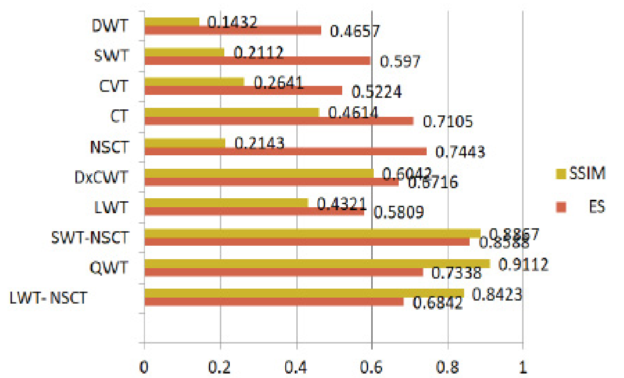

Figure 6: Comparison of SSIM and ES of fused image with different fusion methods.

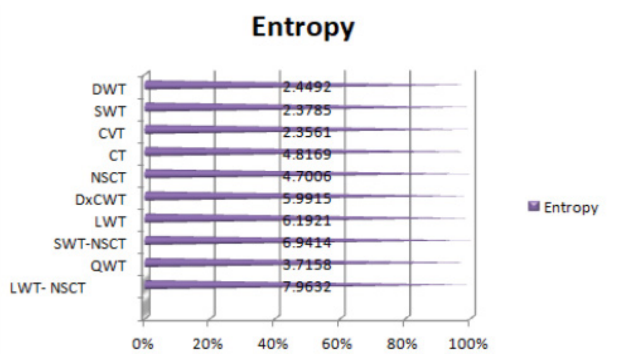

Figure 5: Comparison of Entropy of fused image with different fusion methods.

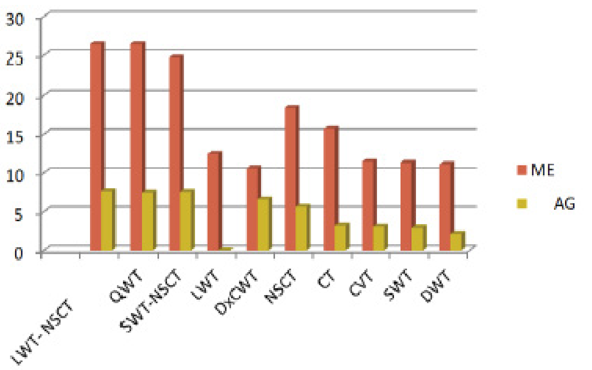

Figure 7: Comparison of ME and AG of fused image with different fusion methods.

(E), Edge Strength (S_F^{AB}), Structure Similarity (SSIM), Measurement of Enhancement(ME), Peak signal to noise ratio (PSNR), Average Gradient(AG), Fusion Factor (FF) [3,6,7,19,20]. A quantatively comparision between proposed method and few other bench mark multi resolution transform based single decomposition stage image fusion methods like DWT [6,10], DxCWT [4] SWT, Curvelet transform (CVT) [2], Contourlet transform (CT), LWT [6,7,9,10,13,17,18,20-22], Non subsampled contourlet transform (NSCT) and QWT [1] can be analysed through Figures 4-9 as shown. Further the proposed method is also compared with a double stage decomposition fusion method employing SWT –NSCT proposed by bheteja et al [3] as shown in Table 2 and Figure 3. It is found that the proposed method is even superior in many aspect of quantatively analysis.

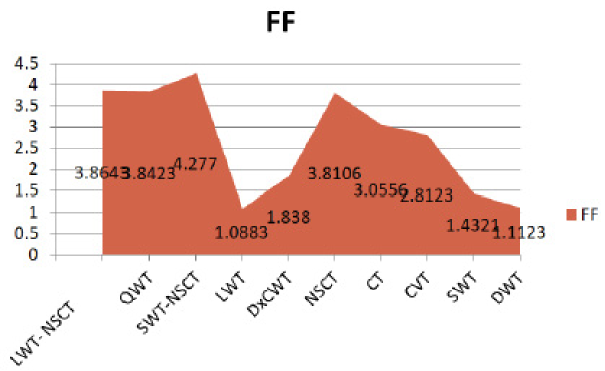

Figure 8: Fusion Factor mountain graph obtained with different fusion methods.

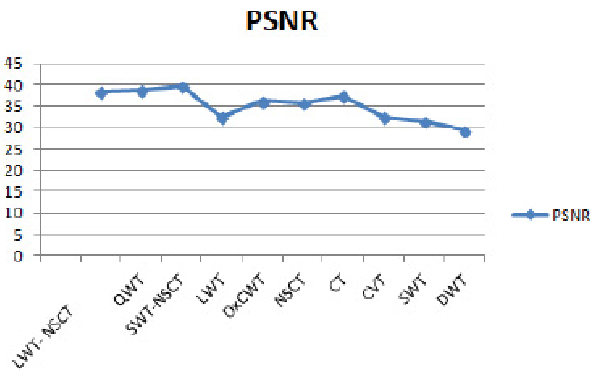

Figure 9: Graphical representation of PSNR for fused image with different fusion methods.

Methods	SD	Entropy	ES(S_F^{AB})	SSIM	ME	AG	FF	PSNR
Proposed(LWT-NSCT)	73.3241	7.9632	0.6842	0.8423	26.4313	7.6242	3.8643	38.4331
QWT	71.4312	3.7158	0.7338	0.9112	26.4301	7.4087	3.8423	78.7132
SWT-NSCT	74.1232	6.9414	0.8588	0.8867	24.7221	7.5142	4.2770	39.5643
LWT	34.0205	6.1921	0.5809	0.4321	12.4532	0.0264	1.0883	32.4213
DxCWT	32.9200	5.9915	0.6716	0.6042	10.5847	6.6152	1.8380	36.2758
NSCT	44.3594	4.7006	0.7443	0.2143	18.4062	5.6423	3.8106	35.7186
CT	70.5075	4.8169	0.7105	0.4614	15.7001	3.1562	3.0556	37.3535
CVT	33.1723	2.3561	0.5224	0.2641	11.4712	3.0234	2.8123	32.4332
SWT	32.1443	2.3785	0.5970	0.2112	11.3112	2.9123	1.4321	31.5324
DWT	31.6231	2.4492	0.4657	0.1432	11.1123	2.1224	1.1123	29.4312

Table 2: Evaluation Indices for Set 3 Fused Image.

References

1. Chai P, Luo X, Zhang Z (2017) Image Fusion Using Quaternion Wavelet Transform and Multiple Features. IEEE Access 5: 6724 - 6734
2. Srivastava R, Prakash O, Khare A (2016) Local energy-based multimodal medical image fusion in curvelet domain. IET Comput Vis 10: 513-527.
3. Bhateja V, Patel H, Krishn A, Sahu A, Ekuakille AL (2015) Multimodal medical image sensor fusion framework using cascade of wavelet and Contourlet transform domains. IEEE Sensors J 15: 6783-6790.
4. Singh R, Khare A (2012) Fusion of Multimodal Medical Images using Daubechies Complex Transform-A Multiresolution Approach. Inform Fusion 19: 49-60.
5. Starck JL, Candes EJ, Donoho DL (2002) The curvelet transform for image denoising. IEEE Trans Image Process 11: 670-684.
6. Majumdar S, Bhardwaj J (2014) Feature Level Fusion of Multimodal Images Using Haar Lifting Wavelet Transform. Int J Comp Inform Sys Control Eng 8: 947-951.
7. Kor S, Tiwary US (2004) Feature level fusion of multimodal medical images in lifting wavelet transform domain. IEMBS 1: 14790-1482.
8. Do MN, Vetterli M (2005) The Contourlet Transform: An Efficient Directional Multiresolution Image Representation. IEEE Trans Image Process 14: 2091-2106.
9. Sweldens W (1996) The lifting scheme: A custom-design construction of biorthogonal wavelets. Applied and computational harmonic analysis 3: 186-200.
10. Bavirisetti DP, Dhuli R (2016) Fusion of Infrared and Visible Sensor Images Based on Anisotropic Diffusion and Karhunen-Loeve Transform. IEEE Sensors J 16: 203-209.
11. Daubechies I, Swelden W (1998) Factoring Wavelet Transfroms into Lifting Steps. J Fourier Anal Appl 4: 247-269.

12. Li S, Yang B (2010) Hybrid multi resolution method for multisensory multimodal image fusion. IEEE Sensors Journal 10: 1519-1526.

13. Liang J, He Y, Liu D, Zeng X (2010) Image fusion using higher order singular value decomposition. IEEE Trans Image Process 21: 2898-2909.

14. http://www.med.harvard.edu/aanlib/home.html

15. Sweldens W (1997) The lifting scheme: construction of second generation wavelets. J SIAM J Math Ana1 29: 5l1-546.

16. Sweldens W (1995) The lifting scheme: A new philosophy in biorthogonal wavelet constructions: Proc. SPIE-Int Soc Opt Eng 69: 68-79.

17. Li H, Manjunath BS, Mitra SK (1995) Multisensor image fusion using the wavelet transform. Graphical Models and Image Process 57: 235-245.

18. Dixon TD, Canga EF (2007) Selection of image fusion quality measures:objective, subjective, and metric assessment. J Opt Soc Am A Opt Image Sci Vis vol: 24.

19. Venkatrao PH, Damodar SS (2018) Fusion: Holoentropy and SP-Whale optimisation-based fusion model for magnetic resonance imaging multimodal image fusion. IET Image Process 12: 572-581.

20. Jiang Q, Jin X, Lee SJ, Yao S (2017) A Novel Multi-Focus Image Fusion Method Based on Stationary Wavelet Transform and Local Features of Fuzzy Sets. IEEE Access 5: 20286-20302.

21. Chunha AL, Zhau J (2006) The Non-subsampled Contourlet Transform: Theory, Design and Applications. IEEE Trans on Img Proc 15: 3089-3101.

22. Li S, Yang B, Hu J (2011) Performance comparison of different multi resolution transforms for image fusion. Inf Fusion 12: 74-84.