ISSN: 0975-766X
CODEN: IJPTFI
Available Online through
Research Article
www.ijptonline.com

PERFORMANCE EVALUATION OF NSCT AND SWT TECHNIQUES IN FUSION OF PET AND CT IMAGES FOR MEDICAL APPLICATIONS

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Received on 26-10-2015 *Accepted on 22-11-2015*

Abstract

Multi-modal medical image fusion is emerging as a powerful tool in medical diagnosis due to the advent of different imaging modalities in medical applications. In this paper a novel fusion framework based on Non Subsampled Contourlet Transform (NSCT) has been proposed. Initially the images are decomposed into low and high frequency coefficients employing NSCT fusion technique. After decomposition, the low frequency coefficients are fused using average rule and the high frequency coefficients by gradient rule. For experimental analysis, eight sets of PET and CT images are considered and the results are compared with Stationary Wavelet Transform (SWT). The performance of the proposed method is analyzed by considering different quality metrics like Entropy, PSNR, CC, RMSE, SD, SC, MI and MD. Experimental results demonstrate that Non-Sub sampled Contourlet Transform (NSCT) is superior to Stationary Wavelet Transform (SWT) in terms of visual inspection and objective analysis.

Keywords: Non-Sub sampled Contourlet Transform (NSCT), Stationary Wavelet Transform (SWT), and Quality metrics.

I. Introduction

In recent years, medical image fusion plays a vital role due to its critical role in health care. The main objective of image fusion is to convey all the meaningful information from the input sensors into a single composite image which appears to be an essential pre-processing step in medical diagnosis. Different types of imaging modalities such as X-ray, Computed Tomography (CT), Positron Emission Tomography (PET), and Magnetic Resonance Imaging (MRI) etc provide limited information in which some information is unique and some are common [1]. Computed Tomography (CT) provides information regarding the dense structures like bones with less distortion [2]. Magnetic Resonance Imaging (MRI) provides information regarding the soft tissues whereas Positron Emission Tomography (PET) provides information regarding blood flow activity in the body.

Combined Positron Emission Tomography (PET) and Computed Tomography (CT) are very useful in diagnosis where tumor is difficult for analysis.

Image fusion is widely used in areas like aerial and satellite imaging, medical imaging, robot vision and vehicle or robot guidance. The rapid development in technology enables us to obtain high quality fused output with both spectral and spatial information [3]. Image fusion is broadly classified into three classes- Feature based, Pixel based and Decision making based image fusion**.** So far many image fusion techniques like Neuro fuzzy [4], wavelet transform [5-7], bandlet transform [8], curvelet transform [9], contourlet transform [10], Undecimated Wavelet Transform [11], Pulse Coupled Neural Network [12] etc. have been developed.

So far only extensive work has been carried out on image fusion techniques. Gaurav Bhatnagar et al have proposed a new fusion framework based on Non-Sub sampled Contourlet Transform (NSCT) [13]. Pixel level fusion has been used to fuse high and low frequency coefficients. Initially the images are decomposed adapting NSCT technique. After decomposition the high frequency components are fused adapting directive contrast technique. The directive contrast method determines the difference of intensity value at a particular region with the neighbourhood pixels. The phase congruency method measures the feature perception of the images and thus produces a brightness invariant representation of the low frequency components. Experimental results have proved that the proposed algorithm is more efficient than existing multi-scale wavelet techniques.

Yudong Zhang et al have proposed a new technique called Stationary Wavelet Transform (SWT) for extracting features from brain images. [14]. Traditional Discrete Wavelet Transform (DWT) suffers from a translation variant property. Hence the output produced will have slight movement when compared to the input MRI image. To overcome the above drawback, Stationary Wavelet Transform (SWT) has been proposed. Haar wavelet transform has been employed and the decomposition level is set as 3. Experimental results show that Stationary Wavelet Transform (SWT) is superior to Discrete Wavelet Transform (DWT) while concerning with the shift-invariance property.

Andreas Ellmathaler et al presents a different scheme to improve the performance of multi-scale image fusion (i.e) undecimated wavelet transform based fusion scheme [15]. In this technique, the image decomposition technique is split into two successive filtering operations. Normally the fusion takes place after convolution with the first filter pair. This leads to minimization of coefficients values which causes errors in the fused image. But non-sub sampled nature of UWT allows touse non-orthogonal filter banks which are more robust to artifacts during fusion. This technique provides various advantages than traditional methods. UWT techniques reduce ringing artifacts in the fused image. Here source images are initially filtered using first spectral factor, followed by normal fusion. The obtained output is again filtered using remaining spectral factors. Finally the fused image is obtained by taking inverse transform. The obtained output will be free from ringing artifacts and also from coefficient spreading problems. Moreover, UWT techniques are invariant to shifts that occur in input images. The fusion rule employed in this paper is “select max” rule.

The remaining part of the paper is organized as follows: Section II describes about proposed work. Section III briefly describes the image fusion algorithm. Section IV provides results for different fusion rules. Section V furnishes performance measures and section VI gives plot for various performance measures. In Section VII results and discussions are provided and finally conclusion is given in Section VIII.

II. Proposed Work

Wavelet transform has been considered as an ideal method for image fusion. Discrete Wavelet Transform (DWT) is a most commonly used wavelet transform technique. Though DWT is most commonly used, it suffers from shift variance problem. To overcome the above problem, Stationary Wavelet Transform (SWT) was introduced. Though, Stationary Wavelet Transform **is** shift invariant, wavelet transform performs better at isolated discontinuities but not at edges and textured regions. Wavelet transform captures only limited information along the three directions viz. Vertical, horizontal and diagonal. To retain the directional and multiscale properties of the transform, laplacian pyramid was replaced by non-sub sampled pyramid structure to retain the multiscale property and a non-sub sampled filter bank for directionality in a Contourlet Transform. When processing the coarser levels of pyramid there is a potential aliasing and loss in resolution.

The above issue is avoided by up sampling the Directional Filter Bank (DFB) in Non-Sub sampled Contourlet Transform (NSCT). Non-Sub sampled Contourlet Transform (NSCT) is a combination of both non subsampled pyramid and non sub sampled directional filter bank.

NSCT represents images in the form of contour segments. As a result, it captures two dimensional geometrical structures in a more effective manner than traditional image fusion methods.

NSCT is a geometric analysis technique that utilizes the geometric regularity present in the individual images and provides an output image with better localization, multi-direction and shift invariance.

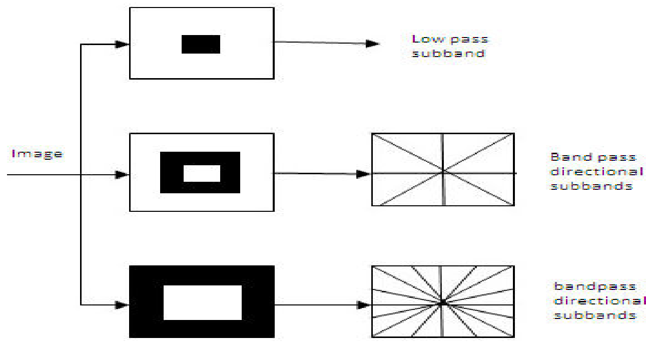


Fig. 1: Structure of Non-Subsampled Filter Bank (NSFB) that implements NSCT

III. Image Fusion Algorithm

The image fusion steps followed in contourlet transform are as follows:

1. The input images are initially registered an it is an essential preprocessing step in image fusion algorithm.
2. The images are decomposed into low and high frequency components by using Non-Sub sampled Contourlet Transform technique.
3. The low frequency components are fused using average rule

z(i,j) = (m(i,j) + m1(i,j))./2

4. The high frequency components are fused using gradient rule.

dx = 1;

dy = 1;

[dzdx1,dzdy1] = gradient(Mh1,dx,dy);

gm1 = sqrt((dzdx1 .^ 2 + dzdy1 .^2));

5. Finally Inverse Non-Sub sampled Contourlet Transform (INSCT) is done to reconstruct the image.
6. The quality of fused image is analyzed both visually and quantitatively.

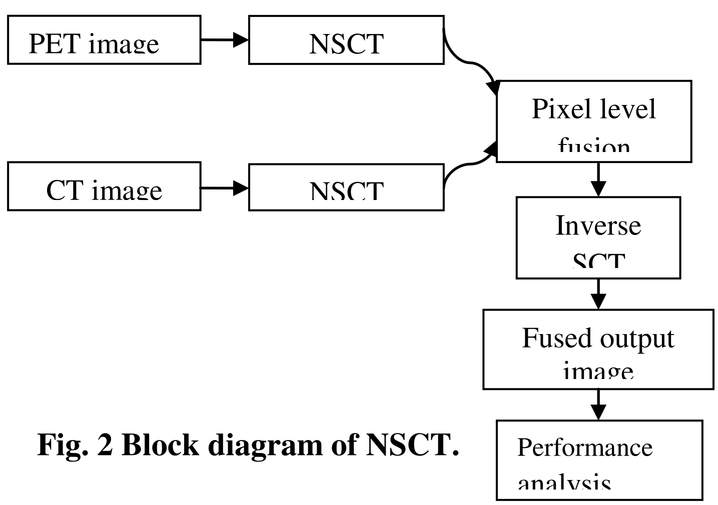


Fig. 2 Block diagram of NSCT.

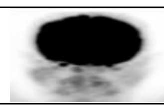
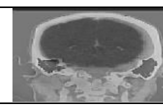
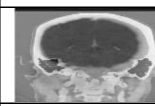
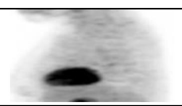
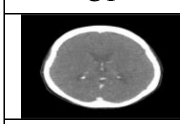
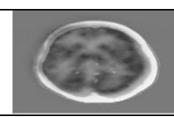
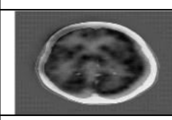
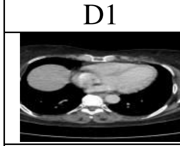
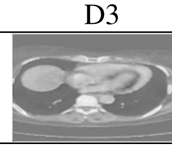
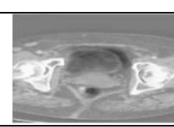
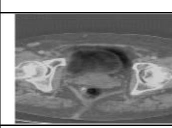
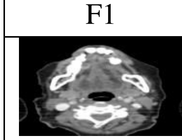
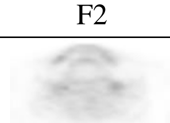
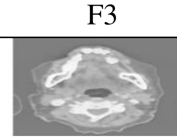
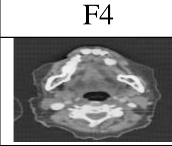
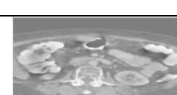
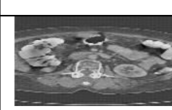
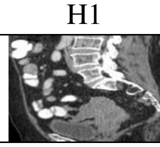
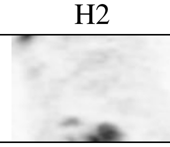
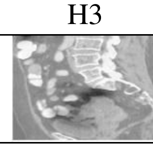
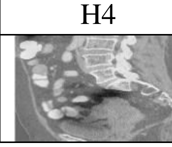
IV. Objective Evaluation Metrics

Several objective evaluation metrics have been proposed in the recent years which are required for analysis of the quality of an image. There are also several performance metrics employed to assess the quality of an image. In this paper Entropy, Peak Signal to Noise Ratio, Root Mean Square Error, Correlation Coefficient, Standard Deviation, Structural Content, Mutual Information and Maximum Difference have been used to analyze the quality of the output images. The fusion results for individual CT and PET images are tabulated in Section V and the performance measures are tabulated in Section VI.

Results for different fusion rules are given in section V where..

A1-H1	CT input images.
A2-H2	PET input images.
A3-H3….A4-H4	Fused output images.

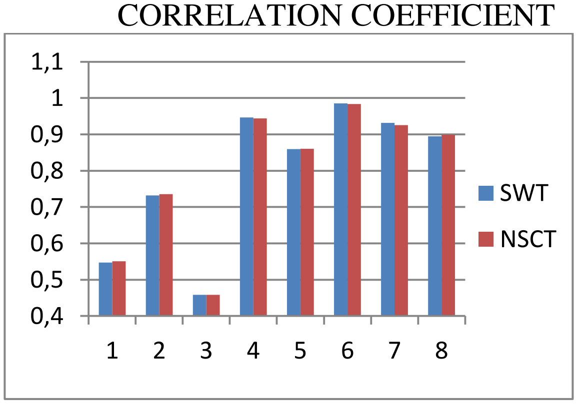
V. FUSION RESULTS OF CT AND PET IMAGES

Input Image1	Input Image2	SWT	NSCT
A1	A2	A3	A4
			
B1	B2	B3	B4
			
C1	C2	C3	C4
			
D1	D2	D3	D4
			
E1	E2	E3	E4
			
F1	F2	F3	F4
			
G1	G2	G3	G4
			
H1	H2	H3	H4
			

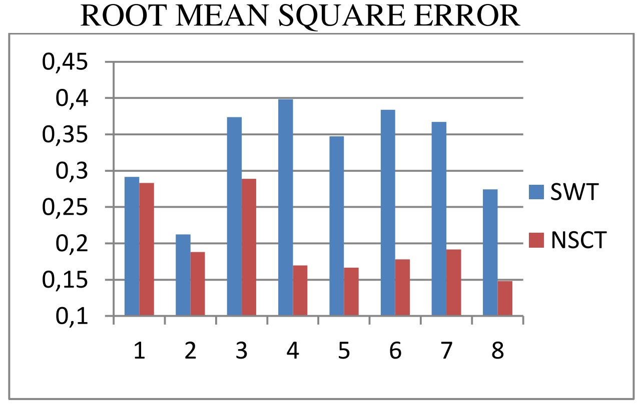
VI. PERFORMANCE MEASURES									
Input images	**Transform**	**Correlation Coefficient**	**Root Mean Square Error**	**Peak Signal to Noise Ratio**	**Entropy**	**Standard Deviation**	**Structural Content**	**Mutual Information**	**Maximum Difference**
A1, A2	SWT	0.5472	0.2917	53.4810	3.2234	14.3613	0.9730	5.8163	156.4827
	NSCT	**0.5505**	**0.2831**	**53.6111**	**3.2960**	**14.1417**	**1.9588**	**6.5438**	**143.0234**
B1, B2	SWT	0.7317	0.2123	54.8622	3.3064	8.1243	0.8514	4.5401	137.3602
	NSCT	**0.7355**	**0.1883**	**55.3832**	**4.2960**	**8.0371**	**2.9311**	**4.6104**	**129.0000**
C1, C2	SWT	0.4580	0.3737	52.4050	2.4096	18.2610	0.6420	3.7584	192.8445
	NSCT	**0.4586**	**0.2889**	**53.5230**	**3.2960**	**17.5257**	**5.2238**	**4.0308**	**128.7266**
D1, D2	SWT	0.9470	0.3982	52.1301	2.6537	4.5349	0.3719	5.6520	170.1405
	NSCT	**0.9440**	**0.1698**	**55.8317**	**3.1960**	**4.4995**	**4.9194**	**5.9530**	**96.0156**
E1, E2	SWT	0.8596	0.3472	52.7247	2.9944	8.4198	0.4225	6.5516	183.0968
	NSCT	**0.8605**	**0.1664**	**55.9201**	**3.2960**	**8.3470**	**3.8095**	**7.1363**	**171.0000**
F1, F2	SWT	0.9849	0.3840	52.2872	2.6142	14.4165	0.4313	6.3683	121.2899
	NSCT	**0.9833**	**0.1780**	**55.6263**	**3.0960**	**13.8911**	**5.2340**	**6.3822**	**41.6797**
G1, G2	SWT	0.9319	0.3671	52.4828	2.7392	4.4205	0.4624	5.9253	171.1216
	NSCT	**0.9254**	**0.1915**	**55.3101**	**3.2960**	**4.2749**	**5.9453**	**6.3668**	**89.5234**
H1, H2	SWT	0.8950	0.2744	53.7469	3.1806	8.5995	0.5582	6.2828	131.3679
	NSCT	**0.8994**	**0.1481**	**56.4247**	**3.5960**	**8.6127**	**3.3991**	**6.3530**	**78.0000**

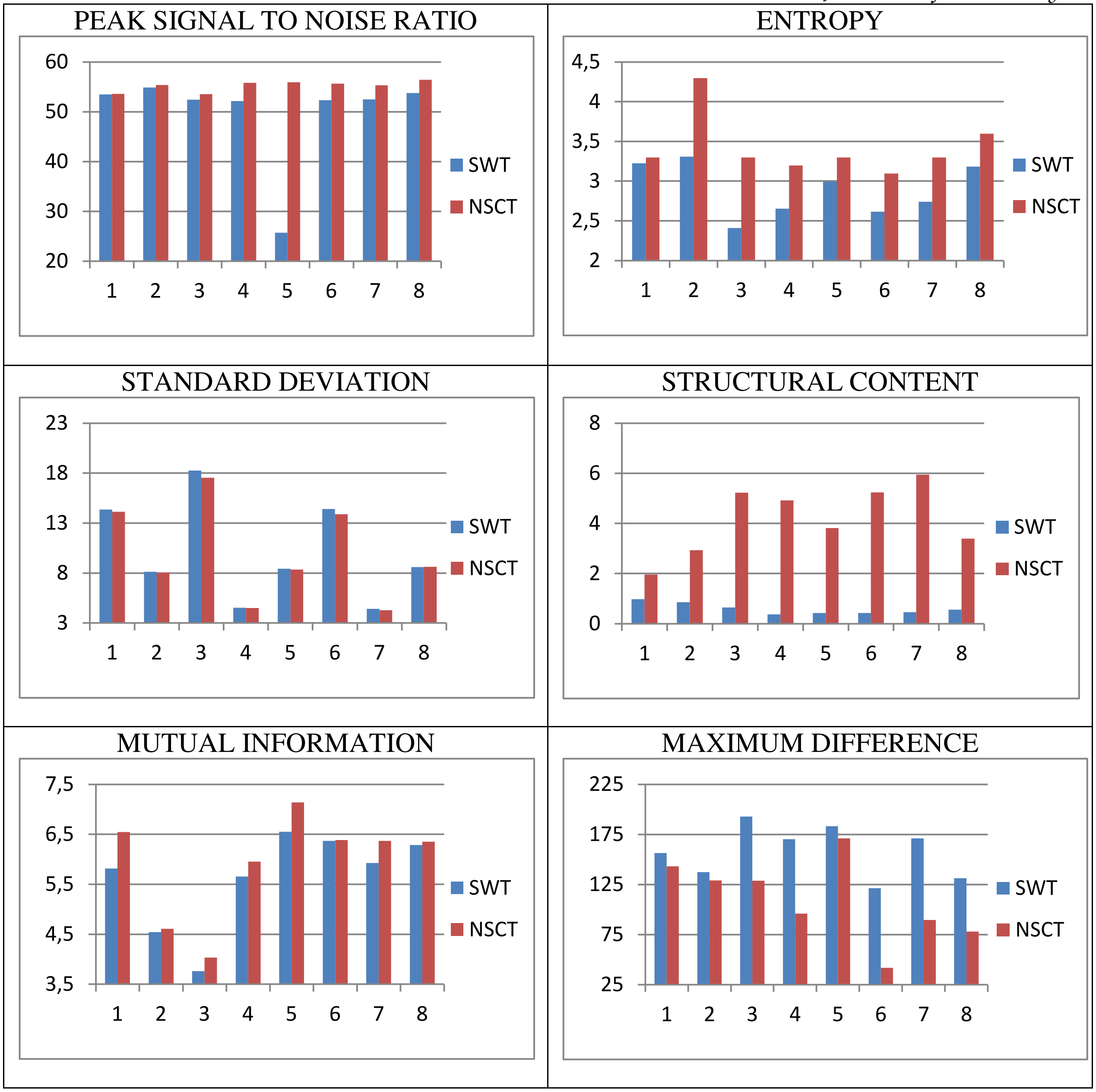
VII. PLOT FOR PERFORMANCE MEASURES

CORRELATION COEFFICIENT



ROOT MEAN SQUARE ERROR





VIII. Results and Discussion

Experiments were conducted on eight pairs of CT and PET images collected from Bharath Scans. Figures A1-H1 represents the CT images, Figures A2-H2 represents the PET images and the figures A3-H3 represent the fused images. The low frequency coefficients are fused using average rule and the high frequency coefficients are fused using gradient rule. The fused image is obtained by taking inverse Non-Sub sampled Contour let Transform. To analyze the quality of the image, performance measures such as Entropy, RMSE, CC, PSNR, SD, MD, MI and SC have been used. From visual and quantitative analysis, it is clear that Non-Sub sampled Contour let Transform produces better results than Stationary Wavelet Transform.

IX. Conclusion

In this paper, a novel multimodal image fusion based on Non-Subsampled Contourlet Transform has been proposed and the results are compared with the Stationary Wavelet Transform. To validate the effectiveness of the proposed method performance measures such as RMSE, PSNR, SD, CC, MD, MI, SC and Entropy have been used. Experimental results illustrate that the proposed method is superior than Stationary Wavelet Transform (SWT) in terms of visual and quantitative analysis. The parameters such as Entropy, CC, PSNR, MI and SC have increased while RMSE and MD have considerably decreased. Therefore NSCT method preserves more information than SWT which plays a vital role in medical diagnosis.

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