

# Comparative Analysis of Image Fusion in Satellite Images Using Various Transform's

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**ABSTRACT:** The project presents different methods to improve the quality of images obtained from earth observation satellite systems. It involves different approaches that are, NSCT with different levels of decomposition next NSCT with upsampling based pixel level fusion and last one is based on Curvelet based image fusion. NSCT is very efficient in representing the directional information and capturing intrinsic geometrical structures of the objects. It has characteristics of high resolution, shift-invariance, and high directionality. An integration of high spatial resolution extracted from PAN images into the high spectral resolution of MS images generates both high spatial and spectral resolution [1] pan sharpened image. Here, a given number of decomposition levels are used for multispectral images while a higher number of decomposition levels are used for Pan Images relatively to the ratio of the Pan Pixel size to the MS pixel size. This preserves both spectral and spatial qualities while decreasing computation time. By applying up sampling after NSCT, structures and detail information of the MS images are more likely to be preserved. Hence, pan-sharpening is done by fusing it with detail information provided by the Pan image at the same fine level. The system simulated result shows that used method provides better resolution in these images rather than prior approaches and it also measured the performance parameters such as correlation, PSNR and standard deviation.

**KEYWORDS:** Pre-processing, Sub-band decomposition using different transforms, Parameter analysis (PNSR, MSE and all).

## I. INTRODUCTION

REMOTE sensing images have either a high spatial resolution or low spectral resolution or vice versa [4]. The high spatial resolution can accurately describe small or narrow features like roads, cars, etc., while the high spectral resolution allows the detection and/or identification of vegetation stress or some other anomaly [5]. The multispectral (MS) bands of most sensors have higher spectral resolution, but lower spatial resolution compared to the associated panchromatic (PAN) band, while the PAN band has higher spatial resolution, but lower spectral resolution. A lot of research has been directed toward the fusion of high spatial low spectral resolution imagery with high spectral low spatial resolution imagery in order to get high spatial high spectral resolution imagery. The fused imagery provides better visual analysis and leads to a detailed and accurate classification. These techniques are known as “data fusion” techniques or “image fusion” techniques. The latter term seems more appropriate since we specifically fuse images. However, the term “pan sharpening” seems the most popular term in remote sensing since the PAN band of a sensor is often used to enhance the details in the MS bands of a sensor.

## II. LITERATURE SURVEY

Some of the popular pan-sharpening techniques are the intensity, hue, and saturation (IHS) [3], principal component analysis (PCA) [4], and the Brovey transform. These techniques are easy to understand and implement. However, they do not always provide a pan-sharpened image, which is spectrally similar to the original MS imagery. Thus, they only provide a better visual analysis and they are often not useful in cases where the pan-sharpened images are to be used for automated classification. Therefore, the focus of the pan-sharpening research is on preserving the spectral signature of the MS imagery. It has been found that the wavelet-based pan-sharpening technique preserves the spectral characteristics of the MS imagery. However, one of the drawbacks of the wavelet-based fusion scheme is its high computational complexity compared to other statistical algorithms (e.g., IHS, PCA, and Brovey).

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In this paper, we will briefly describe the NSCT-based pan sharpening algorithms in the standard form and then more efficient schemes improving the former [1]. The first method is similar to the standard method; however, the number of decomposition levels used for MS bands is lower than the number of decomposition levels for the Pan image. The second method represents an improvement of the first one by using a more efficient up sampling algorithm and applying some rules to fuse the NSCT coefficients. It is shown that upsampling is very important in preserving edges in the pan-sharpened images [7]. The upsampling step is accomplished using an interpolation algorithm based on NSCT [9]. The second method uses NSCT with an optimized number of decomposition levels and an efficient interpolation method. The last method or third method is based on Curvelet transform [2]. Also we had done comparative analysis of all three methods with different PAN and MS images. Graph and comparative table is shown in Results.

### III. SYSTEM METHODOLOGY

The Fusion of panchromatic and multispectral images for PAN sharpening based on,

- Non subsampled Contourlet transform and Pixel level Fusion
- Fast Discrete Curvelet Transforms and Local Magnitude Ratio (LMR) based fusion

#### IMPLEMENTATION FLOW USING NSCT:

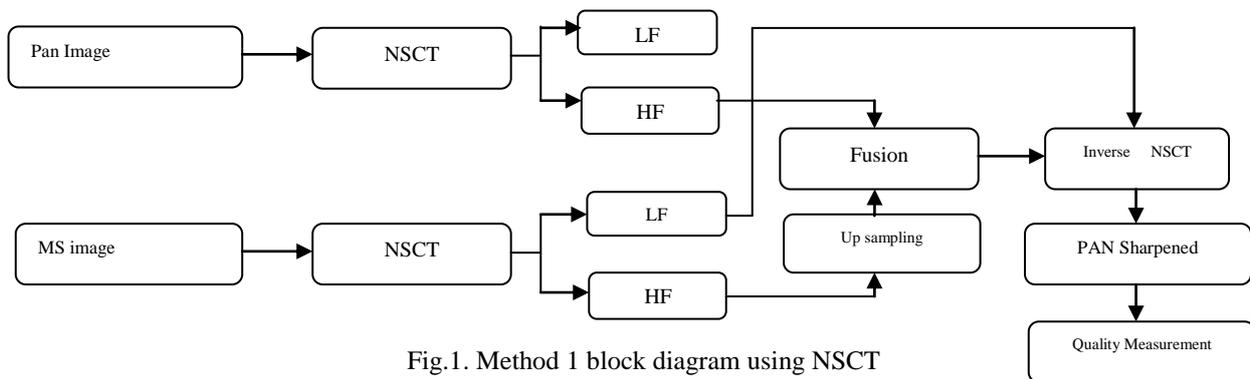


Fig.1. Method 1 block diagram using NSCT

#### IMPLEMENTATION FLOW USING CURVELET:

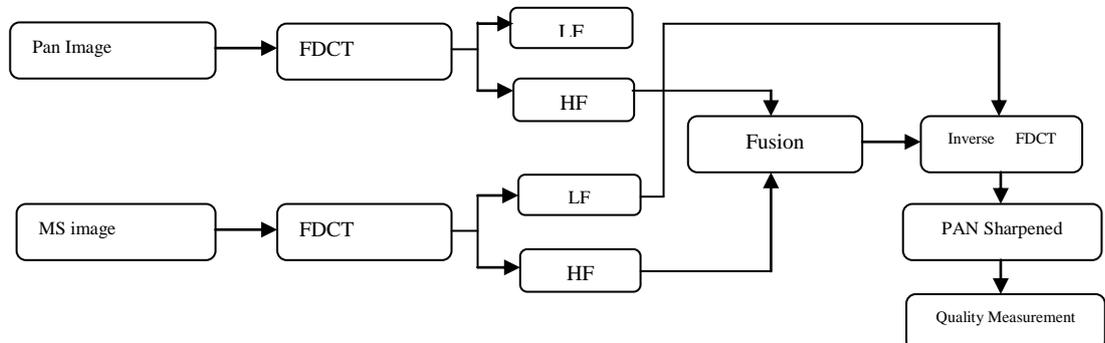


Fig.2. Method 2 block diagram using FDCT

### 3.1 Nonsubsampled Contourlet Transform

The non-subsampled Contourlet transform is a new kind of multi-scale and multi-directional transform that is recently developed on the base of Contourlet transform. It is absolutely shift invariance makes up the insufficiency of the subsampled Contourlet transformation proposed by Do and Vetterli. NSCT needs to be realized by the Pyramid scale

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decomposition and directional decomposition based on non-subsampled directional filter banks. Fig.1 shows the diagram of the NSCT and its band classification.

Shift-invariant version of CT having some excellent properties including both multilevel and multidirectional properties is NSCT [8]. NSCT able to design better representation of contours. Laplacian pyramid for multiscale decomposition and the DFB for directional decomposition is employed by CT. Reduction in the frequency aliasing of CT and to reach the shift invariance, downsamplers and the upsamplers are eliminated by NSCT during decomposition and reconstruction of image; that is designed on non-subsampled pyramid filter banks (NSPFBs) and the non-subsampled DFBs (NSDFBs).

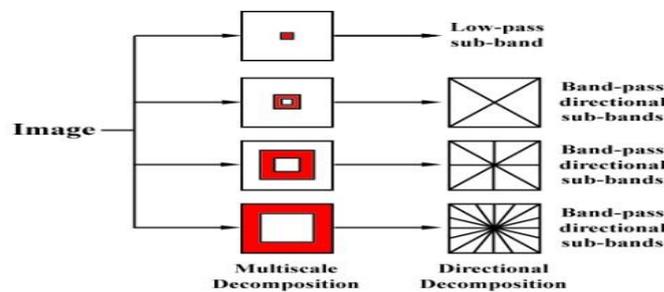


Fig.3. Non subsampled Contourlet Transform

Firstly, each level gets the low pass and band pass parts by steerable pyramid decomposition, then the band-pass part get the orientation information by directional filter banks, and the low-pass part works as the input of the next decomposition level. NSCT is a kind of multi-scale geometric analysis method with high redundancy. The NSCT coefficients correlated with useful information are represented as sparse distribution in each subband. Meanwhile, NSCT employs the anisotropic Contourlet-base as the basic decomposition unit of image, so it is multi-direction selectively, and each subband gives the detail information of image in one direction. Generally speaking, utilizing the anisotropic contourlet basis, the NSCT has the advantage of representing the singularity information of the image. In this aspect, it is better than NSWT with wavelet basis. And also, NSCT is of shift invariance, so it gives better performance than the down-sampled contourlet transformation.

### 3.2 Curvelet Transform

The Curvelet transform [11] has evolved as a tool for the representation of curved shapes in graphical applications. Then, it was extended to the fields of edge detection and image denoising. Recently, some authors have proposed the application of the curvelet transform in image fusion. The algorithm of the curvelet transform of an image  $P$  can be summarized in the following steps:

- The image  $P$  is split up into three subbands  $\Delta_1$ ,  $\Delta_2$  and  $P_3$  using the additive wavelet transform
- Tiling is performed on the subbands  $\Delta_1$  and  $\Delta_2$ .
- The discrete ridgelet transform is performed on each tile of the subbands  $\Delta_1$  and  $\Delta_2$ . A schematic diagram of the curvelet transform is depicted in Fig. 5.

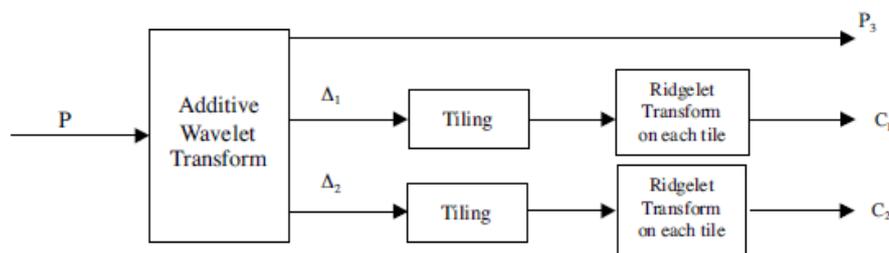


Fig.4. Curvelet transform schematic diagram [11]

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### 3.2.1 Subband Filtering [10]

The purpose of this step is to decompose the image into additive components; each of which is a subband of that image. This step isolates the different frequency components of the image into different planes without down sampling as in the traditional wavelet transform. The “*a trous*” algorithm given below is used for this purpose [2, 3]. Given an image  $P$ , it is possible to construct the sequence of approximations:

$$f_1(P) = P_1, f_2(P_1) = P_2, \quad f_3(P_2) = P_3, \dots, f_n(P_{n-1}) = P_n \quad (2)$$

Where  $n$  is an integer which is preferred to be equal to 3. To construct this sequence, successive convolutions with a certain low pass kernel are performed. The functions  $f_1, f_2, f_3,$  and  $f_n$  mean convolutions with this kernel which is given by [3]:

$$H = \frac{1}{256} \begin{pmatrix} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & 36 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & 1 \end{pmatrix} \quad (3)$$

The wavelet planes are computed as the differences between two consecutive approximations  $P_{l-1}$  and  $P_l$ , i.e.,

$$\Delta_l = P_{l-1} - P_l \quad (4)$$

Thus, the curvelet reconstruction formula is given by:

$$P = \sum_{i=1}^{n-1} (\Delta_i + P_n) \quad (5)$$

### 3.2.2 Tiling

Tiling [10] is the process by which the image is divided into overlapping tiles. These tiles are small in dimensions to transform curved lines into small straight lines in the subbands  $\Delta_1$  and  $\Delta_2$ . The tiling improves the ability of the curvelet transform to handle curved edges.

## VI. PAN-SHARPENING METHODS

### Method 1: NSCT-Based Pan-Sharpening With Different Numbers of Decomposition Levels [1]

In this method we use the NSCT based pan-sharpening with a different number of decomposition levels, where the number of decomposition levels for MS bands is lower than the number of decomposition levels for Pan Images.

### Method 2: NSCT-Based Upsampling and Pan-Sharpening With Different Numbers of Decomposition Levels [1]

Upsampling is an important and necessary step in a pan-sharpening process. The interpolation performed during upsampling can improve the quality of the pan-sharpened images [8]. At first, an MS image is decomposed using NSCT, then the interpolation is conducted on the resulting NSCT coefficients. Finally, the upsampled image is generated through inverse NSCT, applied to the interpolated coefficients.

#### Energy:

Find the energy of high frequency component for both MS and Pan Image using the below formula

$$LE(x, y) = \sum_{i=-M}^M \sum_{j=-N}^N (\text{Fine\_level\_coeff}(x+i, y+j))^2 \quad (6)$$

Once energy is calculated then apply the pixel level fusion by using this formula

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$$\text{Fused\_fine\_level\_coeff}(x, y) = \begin{cases} \text{MS\_fine\_level\_coeff}(x, y), & \text{if } \text{LE}_{\text{MS}}(x, y) \geq \text{LE}_{\text{pan}}(x, y) \\ \text{Pan\_fine\_level\_coeff}(x, y), & \text{otherwise} \end{cases} \quad (7)$$

### Method 3: Fast Discrete Curvelet Transforms and Local Magnitude Ratio (LMR) based fusion [2]

In this method we had applied Curvelet transform to find the low and high frequency component then find the LMR for high frequency component of both MS and Pan images then we had fused the images.

$$\text{LMR}_{j,l}(x, y) = \frac{|c_{j,l}(M(x, y))|}{|c_{j,l}(P(x, y))|} \quad (8)$$

## V. QUALITY INDICES

The quality assessment of the pan-sharpened MS images presents a problem since no reference image exists at the pan sharpened resolution. In this paper, we have selected the following widely used indices for assessing the quality of the obtained results [12].

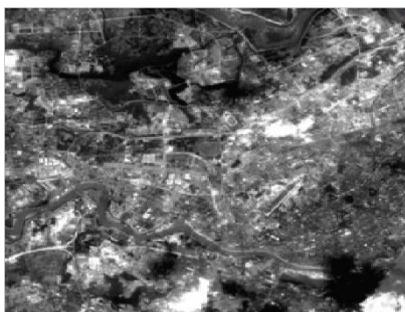
- 1) The correlation coefficient (CC): It is the most popular. It measures the similarity between the fused and original images. A CC value of indicates that the two images are highly correlated or similar.
- 2) The relative bias (BIAS): It is the difference between the mean of the original image and that of the fused one, divided by the mean of the original image
- 3) The relative variance (VAR): It represents the difference in variance between the original and fused images, divided by the variance of the original image
- 4) The standard deviation (SD) of the difference image in relation with the mean of the original image: It indicates the level of the error at any pixel .
- 5) The root-mean-square error (RMSE) .
- 6) The Peak-Signal-to-Noise-Ratio (PSNR): The ratio between the maximum possible power of a signal and power of corrupting noise that affects the fidelity of its representation.
- 7) The Percentage Residual Difference (PRD).

The best value for indices CC is 1, whereas it is 0 for indices BIAS, VAR, SD, and RMSE

## VI. EXPERIMENTAL RESULTS

In this section, the three methods are evaluated to obtain pan-sharpened image. Fig 6 illustrate the example of Pan-sharpened image based on methods described above. Quality indices vary for every set of input image (Pan Image and MS image).Visually, the resulting images appear similar. We can notice that there are no major differences noticeable from the naked eye. From table 1 we can concluded that:

- The method 1 is achieving good results for different images in terms of quality indices CC, RB, SD.
- The method 2 is achieving good results for different images in terms of quality indices RMSE, PRD.
- The method 3 is achieving good results for different images in terms of quality indices RV, PSNR.



a) Pan image



b) MS image



c) Method 1 Resulting Image

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d) Method 2 Resulting Image



e) Method 3 Resulting Image

Fig.5.Resulting Pan-Sharpended images (c, d, and e) evaluated from three different methods from input images (a, b)

## VII. CONCLUSION

In this paper we have provide detail information of image fusion using various transform like NSCT and Curvelet. For NSCT we had used energy based fusion and for Curvelet we have used LMR technique. We had implemented both algorithm and compare the result in the form of different quality indices. We conclude that NSCT is giving better accuracy then Curvelet transform.

The method 1 & 2 provides better pan-sharpened image in all aspects (Quality indices, Spectral and Spatial resolution) as compared to method 3. To obtain resulting images with good spectral quality and to inherit existing basic features in the MS image we put emphasis on upsampling. Upsampling is performed after NSCT. Thus we perform interpolation in second method after NSCT in addition to different decomposition levels for both pan and MS images. The obtained fine levels from MS and Pan Images are fused using the LE (Local Energy) as the fusion rule. Quality indices and pan-sharpened images obtained from the 1 & 2 methods are satisfactory with improved quality as compare to third method.

TABLE I

Pan-Sharpening Methods		CC	RB	RV	RMSE	PSNR	PRD	SD
Image 1	Method I	<b>0.8603</b>	<b>0.3106</b>	0.1572	13.7202	36.7572	0.1211	<b>7.4916</b>
	Method II	0.8602	0.1307	0.1582	<b>13.7240</b>	36.7560	<b>0.1212</b>	7.4904
	Method III	0.8215	0.3066	<b>0.2113</b>	13.6195	<b>36.7892</b>	0.1202	7.3923
Image 2	Method I	<b>0.9769</b>	<b>0.1288</b>	<b>0.0442</b>	10.4750	37.8187	0.0998	<b>8.1738</b>
	Method II	0.9711	0.1277	0.0420	<b>10.7487</b>	37.8172	<b>0.0999</b>	8.1696
	Method III	0.9616	0.1096	0.007	10.6697	<b>37.8493</b>	0.0991	8.0637
Image 3	Method I	<b>0.9854</b>	0.0627	0.0051	2.9393	<b>43.4484</b>	0.0260	<b>7.2803</b>
	Method II	0.9851	0.0627	0.0025	2.9803	0.0260	0.0264	7.2755
	Method III	0.9529	<b>0.0796</b>	<b>0.0088</b>	<b>5.7462</b>	40.537	<b>0.0508</b>	7.2709

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QUANTITATIVE ASSESSMENT OF 3 PAN- SHARPENED IMAGES USING 3 DIFFERENT METHODS.

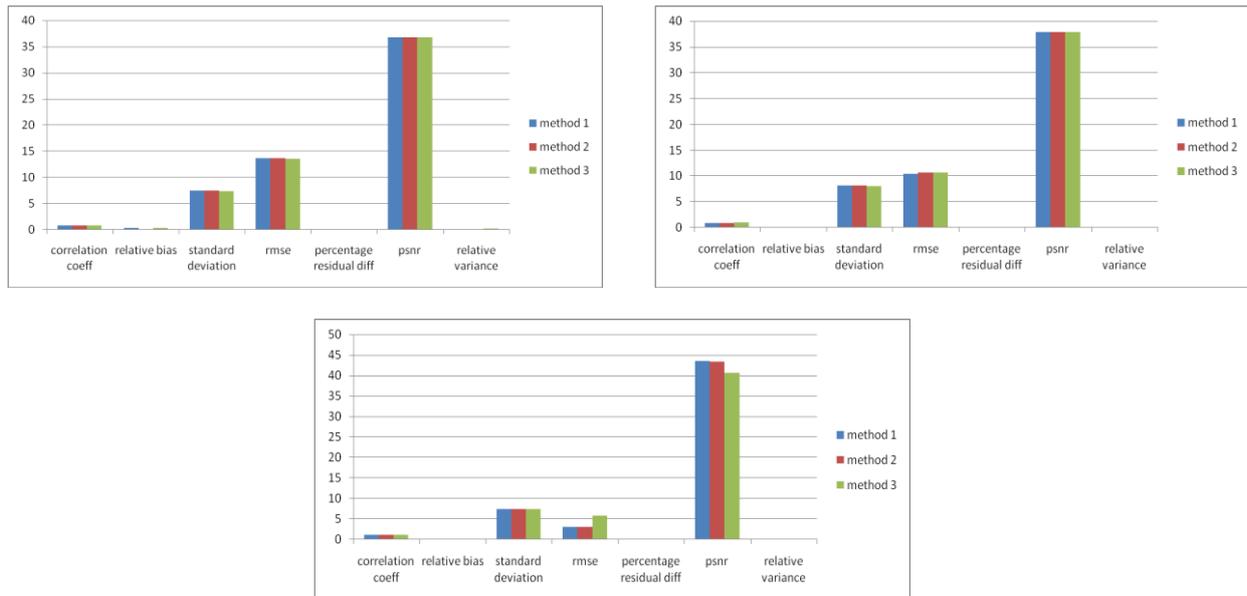


Fig.6.Quality Indices of 3 different Pan-Sharpended Images

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