

Image Quality Improvement By Using NSCT

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Abstract- The project presents that pan-sharpening based Non-subsampled contourlet transformation for satellite panchromatic and multi spectral images. It involves two different approaches that are, NSCT with different levels of decomposition and NSCT with up sampling based pixel level 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 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, SSIM and standard deviation

I.INTRODUCTION

The quality of images, provided by earth observation satellites systems, is directly linked to their spatial and spectral resolutions. Due to physical and technological constraints, satellite sensors cannot provide images with both high spatial and high spectral resolutions; the spectral and spatial resolutions have inverse relationship. Consequently, these systems produce, on the one hand, panchromatic images (Pan) with high spatial resolution and low spectral resolution. On the other hand, they produce multispectral (MS) images with high spectral resolution and low spatial resolution.

The integration of spatial information, extracted from the Pan image, into the MS image, provides an image with both high spatial resolution and high spectral resolution. This is known as pan-sharpening. Nowadays, the application of MS image pan-sharpening algorithms in remote sensing has become numerous due mainly to the growing number of satellite sensors. Up to now, a large collection of pan-sharpening methods have been proposed to improve MS images to higher resolutions using spatial information of the Pan images. Among them, algorithms based on the widely used Intensity-Hue-Saturation (IHS) transform, they produce high spatial resolution MS images but with color distortion, especially in vegetation areas. The proposed method in uses the Normalized Difference Vegetation Index (NDVI) to correct pan-sharpened images.

In the authors have introduced a new high-resolution NDVI index based on which they proposed a method to reduce color distortion and to enhance the vegetation. The principal component analysis (PCA) is also used for pan-sharpening. However, like IHS, its main drawback is the distortion of the spectral information. Recently, several pan-sharpening methods were proposed and are based on multi resolution approaches of the Laplacian pyramid, the wavelet transform, and the contourlet transforms (CTs). The wavelet transform is widely used in pan-sharpening due to its properties such as multi

resolution, localization, critical sampling and limited directionality (horizontal, vertical, and diagonal directions). However, it fails to capture the smoothness along the contours. CT seems to overcome this drawback.

In fact, CT is a multi resolution transform that provides an efficient directional representation and takes into consideration wavelet properties. Thus, CT has been used for image fusion and pan-sharpening. The non-subsampled Contourlet transform (NSCT) is a shift-invariant version of CT. In this paper, we will briefly describe the NSCT-based pan-sharpening algorithms in the standard form and then propose more efficient schemes improving the former. The first proposed 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 proposed 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 up sampling is very important in preserving edges in the pan-sharpened images. The up sampling step is using an interpolation algorithm based on NSCT. The second proposed method uses NSCT with an optimized number of decomposition levels and an efficient interpolation method.

II.PROPOSED SYSTEM

Various image fusion techniques have been proposed to meet the requirements of different applications, such as concealed weapon detection, remote sensing, and medical imaging. Combining two or more images of the same scene usually produces a better application-wise visible image. The fusion of different images can reduce the uncertainty related to a single image. Furthermore, image fusion should include techniques that can implement the geometric alignment of several images acquired by different sensors. Such techniques are called a multi-sensor image fusion. The output fused images are usually efficiently used in many military and security applications, such as target detection,

object tracking, weapon detection, night vision, etc. The Brovey Transform (BT), Intensity Hue Saturation (IHS) transforms, and Principal Component Analysis (PCA) [1] provides the basis for many commonly used image fusion techniques. Some of these techniques improve the spatial resolution while distorting the original chromaticity of the input images, which is a major drawback. Recently, great interest has arisen on the new transform techniques that utilize the multi-resolution analysis, such as Wavelet Transform [12] (WT).

The multi-resolution decomposition schemes decompose the input image into different scales or levels of frequencies. Wavelet based image fusion techniques are implemented by replacing the detail components (high frequency coefficients) from a colored input image with the details components from another gray-scale input image. However, the Wavelet based fusion techniques are not optimal in capturing two-dimensional singularities from the input images. The two-dimensional wavelets, which are obtained by a tensor-product of one-dimensional wavelets, are good in detecting the discontinuities at edge points.

However, the 2-D Wavelets exhibit limited capabilities in detecting the smoothness along the contours. Moreover, the singularity in some objects is due to the discontinuity points located at the edges. These points are located along smooth curves rendering smooth boundaries of objects. Do and Vetterli introduced the new two-dimensional Contourlet transform. This transform is more suitable for constructing a multi-resolution and multi-directional expansions using non-separable Pyramid Directional Filter Banks (PDFB) with small redundancy factor. Image fusion is the combination of two or more different images to form a new image by using a certain algorithm. The combination of sensory data from multiple sensors can provide more reliable and accurate information. It forms a rapidly developing area of research in remote sensing and computer vision. Most of fusion approaches were based on combining the multi scale decompositions (MSD's) of the source images. MSD-based fusion schemes provide much better performance than the simple methods studied previously.

Due to joint information representation at the spatial-spectral domain, the wavelet transform becomes the most popular approximation in image fusion. However, wavelet will not "see" the smoothness along the contours and separable wavelets can capture only limited directional information. Contourlet transform [1] was recently pioneered by Minh N. Do and Martin Vetterli .It is a "true" two-dimensional transform that can capture the intrinsic geometrical structure, which is key in visual information. Compared with wavelet, Contourlet provides different and flexible number of directions at each scale. It has been successfully employed in image enhancement, denoising and fusion.

Unfortunately, due to down samplers and up samplers presented in both the Laplacian pyramid and the directional filter banks (DFB), the foremost Contourlet transform is not shift-invariant, which causes pseudo-Gibbs phenomena around singularities

NSCT decomposition [7] is to compute the multi scale and different direction components of the discrete

images. It involves the two stages such as non sub sampled pyramid(NSP) and non sub sampled directional filter bank(NSDFB) to extract the texture, contours and detailed coefficients. NSP decomposes the image into low and high frequency sub bands at each decomposition level And It Produces N+1 Sub Images If Decomposition Level.

2.1 Block Diagram

The block diagram shows the two inputs in which NSCT decomposition is applied and up sampling is done. Finally output has some performance measures which are given in the output results.

2.1.1 Standard Nsct –Based Pan-Sharpening

Forward transform the pan and multispectral images using a sub-band and a directional decomposition such as the non-sampled contourlet transform. Generate the pan-sharpened image by performing the inverse transform.

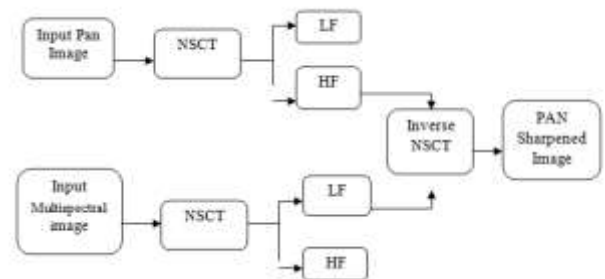


Fig.1. Standard NSCT based Pan-Sharpening

III. WAVELET TRANSFORM

Wavelets are mathematical functions defined over a finite interval and having an average value of zero that transform data into different frequency components, representing each component with a resolution matched to its scale.

3.1 1-D Continuous Wavelet Transform

The 1-D continuous wavelet transform is given by:

$$W_f(a, b) = \int_{-\infty}^{\infty} x(t)\psi_{a,b}(t)dt$$

The inverse 1-D wavelet transform is given by:

$$X(t) = \frac{1}{C} \int_{b=0}^{\infty} \int_{a=-\infty}^{\infty} \frac{1}{a^2} W_f(a,b)\psi_{a,b}(t)dbda$$

Where a - scaling parameter

b - Shifting parameter

$\psi_{a,b}(t)$ - Mother wavelet

$$\text{and } C = \int_{-\infty}^{\infty} \frac{|\psi(\omega)|^2}{\omega} d\omega < \infty$$

$\psi(\omega)$ is the Fourier transform of the mother wavelet $\psi(t)$. C is required to be finite, which leads to one of the required properties of a mother wavelet. Since C must be finite, then $\psi(0) = 0$ to avoid a singularity in the integral, and thus the $\psi(t)$ must have zero mean.

3.2 1-D WAVELET TRANSFORM

The stationary wavelets transform (SWT), which transforms a discrete time signal to a discrete wavelet representation. The first step is to discrete the wavelet parameters, which reduce the previously continuous basis set of wavelets to a discrete and orthogonal / orthonormal set of basis wavelets.

$$\psi_{m,n}(t) = 2^{m/2} \psi(2^m t - n); m, n \in \mathbb{Z} \text{ such that } -\infty < m, n < \infty$$

The 1-D DWT is given as the inner product of the signal $x(t)$ being transformed with each of the discrete basis functions.

$$W_{m,n} = \langle x(t), \psi_{m,n}(t) \rangle; m, n \in \mathbb{Z}$$

The 1-D inverse DWT is given as:

$$X(t) = \sum_m \sum_n W_{m,n} \psi_{m,n}(t); m, n \in \mathbb{Z}$$

3.3 2-D WAVELET TRANSFORM

The 1-D SWT can be extended to 2-D transform using separable wavelet filters. With separable filters, applying a 1-D transform [12] to all the rows of the input and then repeating on all of the columns can compute the 2-D transform. When one-level 2-D SWT is applied to an image, four transform coefficient sets are created. As depicted in Figure, the four sets are LL, HL, LH, and HH, where the first letter corresponds to applying either a low pass or high pass filter to the rows, and the second letter refers to the filter applied to the columns.

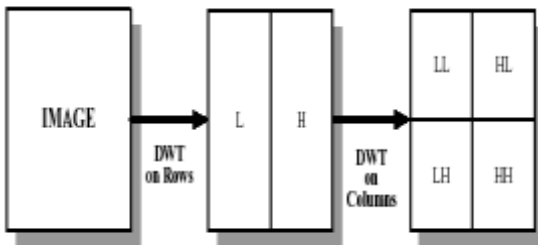


Fig.2. Block Diagram of DWT

One-level of wavelet decomposition produces four filtered and sub sampled images, referred to as sub bands. The upper and lower areas of respectively, represent the low pass and high pass coefficients after vertical 1D-DWT and up sampling. The result of the horizontal 1D-DWT and up sampling to form a 2D-SWT output image. We can use multiple levels of wavelet transforms to concentrate the data energy in the lowest sampled bands. Specifically, the LL sub band can be transformed again to form LL2, HL2, LH2, and HH2 sub bands, producing a two-level wavelet transform. An (R-1) level wavelet decomposition is associated with R resolution levels numbered from zero to (R-1), with zero and (R-1) corresponding to the coarsest and finest resolutions.

3.4 WAVELET RECONSTRUCTION

The reconstruction of the image is achieved by the inverse discrete wavelet transform (IDWT). The values are first up sampled and then passed to the filters. This is represented as shown in Fig.3.12

Wavelet Computation

Step1: Row wise processing to get H and L
 $H = (Ro-Re)/2$ and $L = (Re + Ro)/2$

Where Ro and Re is the odd Row and even Row wise pixel values

Step 2: Column wise processing to get LL, LH, HL and HH,

Separate odd and even columns of H and L, Namely, Hodd – odd column of H, Lodd- odd column of L

H even- even column of H, Leven- even column of L

$$LH = (L \text{ odd-Leven})/2, LL = (Leven + Lodd)/2$$

$$HL = (Hodd - H \text{ even})/2, HH = (Heven + Hodd)/2$$

3.5 NSCT Decomposition

Various image fusion techniques have been proposed to meet the requirements of different applications, such as concealed weapon detection, remote sensing, and medical imaging. Combining two or more images of the same scene usually produces a better application-wise visible image. The fusion of different images can reduce the uncertainty related to a single image. Furthermore, image fusion should include techniques that can implement the geometric alignment of several images acquired by different sensors. Such techniques are called a multi-sensor image fusion. The output fused images are usually efficiently used in many military and security applications, such as target detection, object tracking, weapon detection, night vision, etc. The Brovey Transform (BT), Intensity Hue Saturation (IHS) transforms, and Principal Component Analysis (PCA) [6] provides the basis for many commonly used image fusion techniques. Some of these techniques improve the spatial resolution while distorting the original chromaticity of the input images, which is a major drawback. Recently, great interest has arisen on the new transform techniques that utilize the multi-resolution analysis, such as Wavelet Transform (WT). The multi-resolution decomposition schemes decompose the input image into different scales or levels of frequencies.

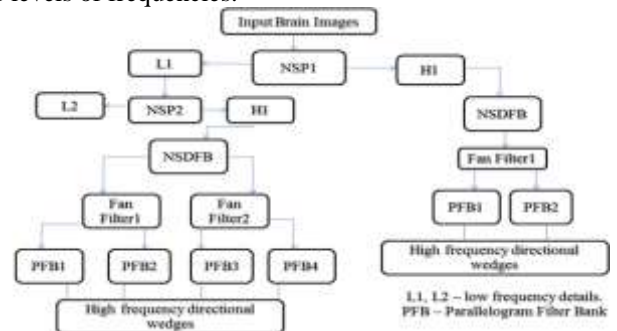


Fig.3. Decomposition Flow

IV.PARAMETER EVALUATION

Some of the performance parameters are explained below and obtained pan-sharpened image

images can be evaluated for peak-signal-to-noise ratio, mean square error and correlation coefficient.

4.1. Peak-Signal-To Noise Ratio And Mean Square Error

How do we determine the quality of a digital image? Human eyes perception is the fastest approach. However, although this criterion is effective in general, the results may differ from person to person. To establish an objective criterion for digital image quality, a parameter named PSNR (Peak Signal to Noise Ratio) is defined in equation as follows:

$$\text{PSNR} = 10 \cdot \log_{10} (255^2 / \text{MSE}) \quad (5.1)$$

Where MSE (Mean Square Error) stands for the mean-squared difference between the cover-image and the stego-image. The mathematical definition for MSE is defined in equation as follows:

$$\text{MSE} = \frac{1}{M \cdot N} \sum_{i=1}^M \sum_{j=1}^N (a_{ij} - b_{ij})^2 \quad (5.2)$$

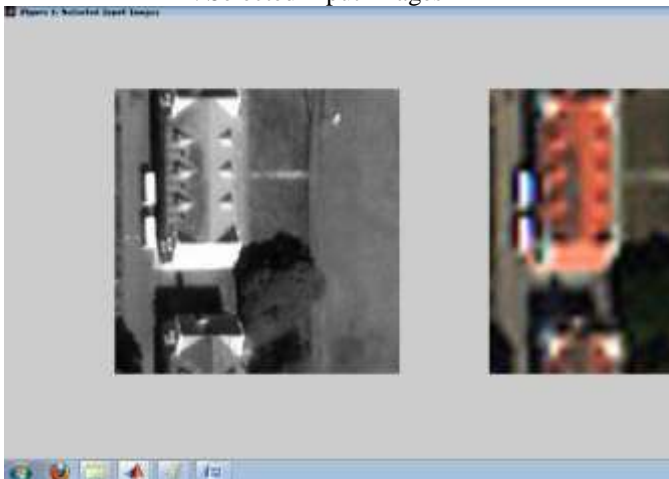
In this above equation a_{ij} means the pixel value at position (i, j) in the input image and b_{ij} is the pixel value at the same position in the output image. The calculated PSNR usually adopts dB value for quality judgment. The larger PSNR is, the higher the image quality is (which means there is only little difference between the input-image and the fused-image). On the contrary, a small dB value of PSNR means there is great distortion between the input-image and the fused-image.

Input: low visible satellite image

Output: Enhanced image with performance measures.

Standard Method

I. Selected Input Images



- It provides high spatial and spectral resolution MS images.

CONCLUSION

In this paper, the NSCT-based pan-sharpening method in its standard forms is considered. The improvement of the NSCT based image pan-sharpening is assured by using a low number of decomposition levels for MS images and a higher number of decomposition levels for the Pan image. This strategy allows getting simultaneously satisfying results and reducing computation time. The first proposed method exploits the discussed idea for providing pan-sharpened images with a

good spectral quality. Moreover, the up sampling process is considered and proposed to use up sampling after applying NSCT in order to preserve the detail information existing in the MS images.

Thus, a second method is proposed, where in addition to different numbers of decomposition levels, the interpolation is conducted after NSCT. The obtained fine levels from MS and Pan Images are fused using the LE as the fusion rule. Performances of the proposed strategies are tested on the WorldView-2 dataset. The obtained results confirm the added-value of using an adequate number of decomposition levels and up sampling after the NSCT decomposition. Both visual and quantitative qualities achieved by the proposed methods are satisfactory and the improvement of quality, compared to the standard NSCT-based method, is assured.

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