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FUSION OF MULTISPECTRAL AND PANCHROMATIC IMAGES AND ITS QUALITY ASSESSMENT

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ABSTRACT

Image fusion is the process of merging two or more images obtained from the same sensor at different times or from two or more sensors at the same instant. The objective is to obtain more information from the fused image than from the individual images. In satellite images, the lower spatial resolution multispectral images are fused with higher spatial resolution panchromatic images. The fusion should result in the transfer of spectral and spatial information without introducing any artifacts. The goal is to combine the spectral and spatial resolutions of the multispectral and the panchromatic images respectively to obtain a high-resolution multispectral image. Most of the fusion techniques that have been proposed are based on the compromise between the desired spatial enhancement and the spectral consistency. This paper provides an overview of the techniques available in the literature for the fusion of multispectral and panchromatic images. The evaluation of the fusion technique employed is also an important step in the fusion process. Various quality metrics have been used in the literature to study, compare and assess the fusion technique employed. This paper provides a brief study on such quality metrics employed in the literature.

Keywords: fusion, pan sharpening, wavelet, contourlet, noiselet, shearlet, quality assessment metrics.

1. INTRODUCTION

Different types of sensors are used in the satellites for capturing different images of the same area. The most commonly recorded image types in a satellite are typically multispectral images panchromatic images. While the panchromatic images record the total intensity of the radiation falling on each pixel, the multispectral images record the intensity of radiation in small band of visible spectra, including the RGB and the infrared region [4]. The electromagnetic bandwidth captured by the sensor is referred to as the spectral resolution [26]. Satellite sensors can detect wavelengths in three or more bands. The size of the smallest object that can be resolved on the ground is called as the spatial resolution. It can also be defined as the size described by one pixel [26]. High spatial resolution is provided by panchromatic images and high spectral resolution is provided by multispectral images. While the multispectral image can be considered as having low spatial resolution but accurate color data the panchromatic image can be considered as having higher spatial resolution but a gray scale image. Both high spectral and high spatial information are needed for obtaining more information. The fused image should provide more information on the scene than the individual MS and PAN images separately. Image fusion can in general be done at different levels namely pixel level, feature level, object level and decision levels. The level of fusion to be used depends on the intended application of the fused image [1], [2]. Many fusion techniques have been proposed for the fusion of multispectral and panchromatic images. The most widely used fusion techniques were intensity-hue-saturation (IHS), high pass filtering, principal component analysis (PCA), multi-resolution analysis-based methods etc.., and [1].

2. IHS FUSION

The fusion of MS and Panchromatic images using IHS transform ,see figure 1, is based on the ability of the IHS method to separate the spectral information present in the RGB components from the spatial information present in the intensity component [5]. Dong Jiang *et al* [1] have defined the IHS components as follows:

I = (R+ G+ B)/3
H= (B-R)/3(I-R), S=1-R/I, when R= Minimum (R, G, B)
H= (R-G)/3(I-G), S=1-G/I, when G= Minimum (R, G,

The intensity band or component is replaced by the high resolution panchromatic image in the fusion. The fused image can then be obtained by proceeding with the reverse IHS method using the panchromatic component along with the H and S components. The fused image thus obtained will also be an RGB image but would also have the spatial detail of the panchromatic image incorporated into it [5].

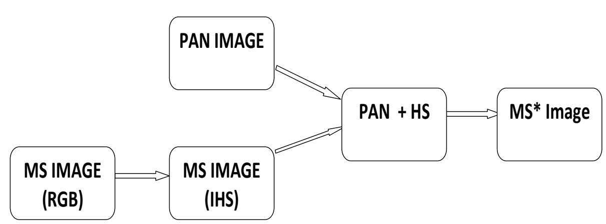

Figure-1. IHS fusion principle.

The advantage of the IHS is that large volumes of data can be processed quickly and sharp images are

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generated. The disadvantage is that it might result in spectral distortion from the original multispectral image. Many modifications have been proposed to overcome this disadvantage. The fast IHS introduced by Tu et al in 2001 the fused image resulted in higher resolution and sharper edges without any additional changes to the spectral data [6]. The disadvantage observed in this method is the color distortion when compared with the original multispectral image. Several modifications have been proposed to overcome this difficulty. One such method proposed by Tu et al in 2005 proposes to use four bands with the fourth band being an infrared component. This resulted in lesser color distortion since it allowed the calculated intensity of the multispectral image to better match the panchromatic image [6]. Another modification to the IHS method, called the IHS-SA, proposed the incorporation of weighted coefficients on the green and blue bands so as to reduce the difference between the intensity and the panchromatic bands [Tu et al., 2005] [6]. Melissa Strait et al 2008 have proposed a method called Adaptive IHS, in which the calculation of the intensity band depends on the multispectral and panchromatic images [6]. Here the intensity band is approximated as close as possible to the panchromatic image and thereby the spectral distortion is minimized.

3. PCA FUSION

In PCA the original bands of MS images are to be synthesized and thereby create new bands which are called the principal components [1]. In other words the PCA converts the intercorrelated multispectral bands into a set of unrelated components called the principal components [6]. Among the principal components thus synthesized, while the first principal component PC1 contains the spatial information that is common to all the bands used as input data in the PCA, the other components have the spectral information corresponding to each band [5] [14]. The PAN image is histogram matched with the first principal component. Then the first component which has the highest variance is replaced by the PAN image, while the remaining components are left unaltered. Now the inverse PCA is applied to the dataset consisting of the modified first principal component and the unaltered remaining principal components to get the new RGB bands.

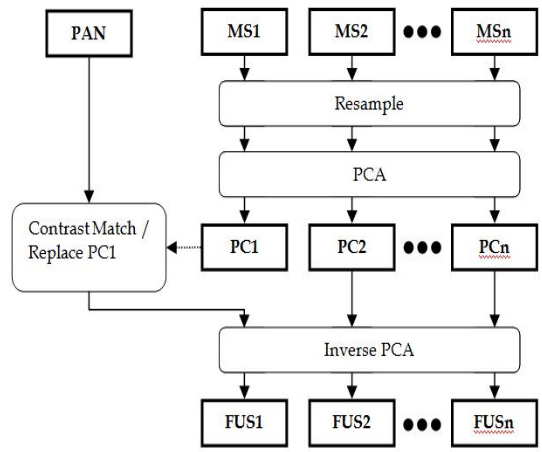

Figure-2. PCA based fusion.

4. WAVELETS

In wavelet based fusion of MS and PAN images, the MS and PAN images are decomposed using wavelet transform. The coefficients are then fused based on fusion rules and the IDWT is applied to the fused coefficient map. The figure 2 [32] shows a typical wavelet based fusion scheme. With the advent of multiresolution anlaysis, wavelets became an important tool in image processing more so in image fusion.

Wavelet based fusion techniques have been found to give better results when compared with the standard fusion techniques considering the spatial and spectral qualities [15, 16, 17]. Schemes combining the wavelets with standard fusion methods have also been proposed. Among the various multiscale transforms available the simplest one is

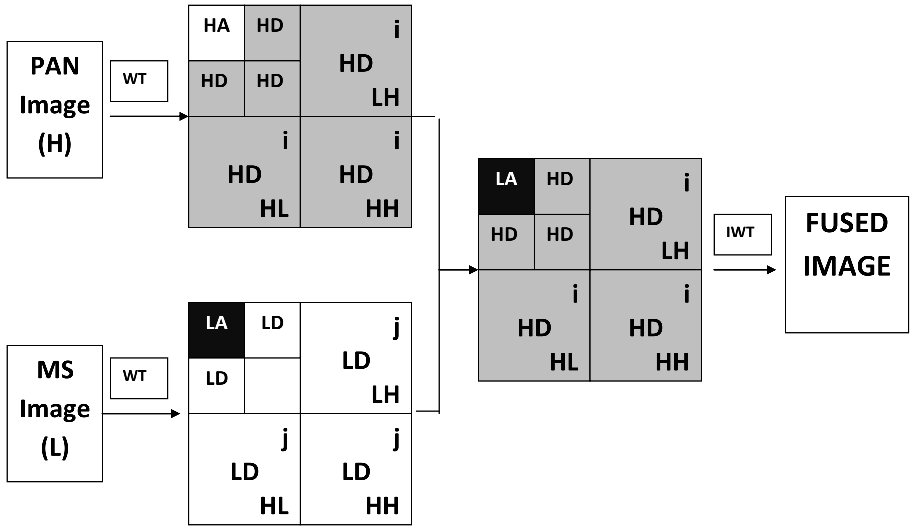

Figure-3. Wavelet based fusion.

the Discrete Wavelet Transform. In the 2D-DWT the image data are discrete. Also the spatial spectral resolution is dependent on the frequency in the DWT. DWT can be combined with the IHS and PCA methods to give better results.

Different fusion rules like max, min, weighted average etc., can be used. Biorthogonal filters are used in DWT to avoid phase distortion and achieve perfect reconstruction. The Dual Tree Complex Wavelet Transform (DTCWT) has been used to achieve shift invariance and has yielded better results.

5. CURVELETS

Though the wavelet based fusion results in high spectral quality, they have less spatial information when compared with methods like IHS and PCA. Applications require the fused image to have the spectral resolution of the MS image as well as the spatial resolution of the PAN image [7]. The basis elements of curvelets exhibit high directional sensitivity. Curvelets are transforms that are highly anisotropic. Hence the curvelets are better than wavelets in representing edges and are therefore well suited in the extraction of the detailed spatial information from an image [7]. In curvelet transform, the frame elements are indexed by scale and location parameters. When compared with the wavelet transform, the curvelet transform exhibits directional parameters. Also elements with high directional specificity are present in the curvelet pyramid. While wavelets are based on isotropic scaling principles the curvelets are based on anisotropic scaling principle. The scaling law that governs the elements is given by width $\approx$ length^2. Thus the curvelets are better than the wavelets in representing edges [7]. A drawback of the curvelet is that it is not singly generated. In other words it is not derived from operators applied to a single or finite set of generating functions [24]. Another drawback of curvelet is that the construction of curvelets involves rotations and the digital lattice is not preserved. This results in the absence of a direct transition from the continuum to digital setting [24].

6. CONTOURLETS

Wavelets lack directionality and are not good in capturing the geometrical smoothness of the contours [30]. Contourlet is an extension of the wavelet and uses multiscale and directional filter banks [30]. The basis images of the Contourlet transform are oriented at various directions with multiple scales and also have flexible aspect ratios [30]. Contourlets exhibit directionality and anisotropy. Contourlets need fewer coefficients for representing a smooth contour in comparison with wavelets. As explained in by Minh N Do et al [18] the wavelets have

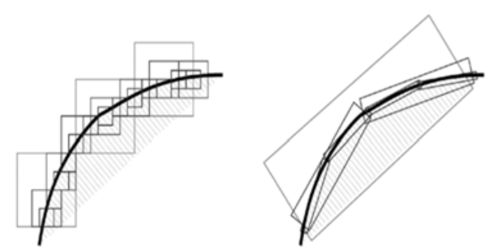

Figure-4. Wavelets and Contourlets in representing a smooth contour.

square report only and require more number while the Contourlets can have elongated supports thereby requiring less number of coefficients for efficient representation of a smooth contour, as illustrated in Figure-4 [30] [18] [31]. Contourlets are also computationally efficient due to the iterated filter banks. Contourlets have the ability of capturing and linking the point of discontinuities in forming a linear structure i.e. contours.

The derivation of contourlets transform coefficients is a two stage process. In the first stage a

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multiscale transform is applied and in the second stage a local direction transform is applied [9]. While the Laplacian pyramid is used to obtain the point of discontinuities and multiscale transformation the local directional filter bank is used to obtain a smooth contour from these wavelet like coefficients. Contourlets have the flexibility of having different numbers of direction at each scale [9]. This makes contourlets better than the other representations [18, 19, 20, 21]. Contourlets have been applied for fusion of MS and panchromatic images. The Non Subsampled Contourlet Transform (NSCT) proposed by Minh N Do et al [19] is a fully shift invariant version of the Contourlet transform. Vijay P Shah et al [9] have proposed a method based on adaptive PCA and Contourlet transform. The results obtained by Vijay P Shah et al using nonsubsampled Contourlet transform provided better results than the subsampled approach [9].

7. NOISELETS

Noiselet basis functions are constructed by twisting the translates and dilates of the mother function [11]. The signal is totally spread out in scale and in time by the noiselet transforms coefficients. Hence information pertaining to the original signal is available in each subset of the noiselet transformation at all the scales and times [11]. This can be used in the reconstruction of the signal at a lower resolution. The wavelets and curvelets show a below par performance in the case of satellite images with bends, curves, curls. The noiselets perform well under the rough curved surfaces.

8. SHEARLETS

The multiscale transforms like wavelets, curvelets, contourlets, redgelets, bandlets etc. have the limitation of not being able to capture edges and other anisotropic features satisfactorily. Compared to other multiscale transforms, representation of multidimensional data is efficient in the case of shearlets. Shearlet transform has a single or finite set of generating functions and provides almost optimal representations for a large class of multidimensional data [4]. Shearlet also allows the continuum and digital realms to be treated as unified and has fast algorithmic implementations [4]. Wavelets are good in handling pointwise singularities alone and are not equally good in handling well distributed singularities like the singularities along curves [4]. The implementation of shearlets can be categrised as frequency domain based and spatial domain based [4]. While good frequency localization can be achieved by the former better spatial localization can be achieved by the latter. Variations in the application of shearlets for fusion of multispectral and panchromatic images can be seen in the literature. Different schemes like Compactly Supported Shearlet Transform (CSST), Dual Tree Compactly Supported Shearlet Transform (DTCSST), Non Subsampled Shearlet Transform (NSST) have been proposed in the literature. Miao Qiguang et al. [24] have proposed a fusion scheme based on shearlets and PCNN. In the method proposed by Miao Qiguang et al. [24], fusion of shearlet coefficients is governed by the PCNN.

9. QUALITY ASSESSMENT

The evaluation of the fusion technique employed is also an important step in the fusion process. Various quality metrics have been used in the literature to study, compare and assess the fusion technique employed. The commonly used traditional metrics include Correlation Coefficient (CC), Correlation Coefficient is a similarity metric wherein a value closer to one represents good similarity between the compared images [35]. Erreur relative globale adimensionnelle de synthése (ERGAS) [37], Spectral Angle Mapper (SAM) [38] and Q4 index [39]. ERGAS is a global quality index. It is sensitive to mean shifting and dynamic range change [40] [41]. A lower value for ERGAS denotes good spectral quality. Typically it is less than the number of spectral bands in the MS image. SAM represents the similarity between the fused and the fused image [34]. The lower the value of SAM, the better is the fused quality [34]. The quality measure Q4 proposed by Alparone et al [42] is dependent on the individual UIQI of each band and the SAM [8]. Root Mean Square Error (RMSE) and Structural Similarity Index (SSIM) are also popularly used for quality assessment of the fused image. RMSE should be as close as possible to zero and SSIM should be near to +1 for good quality fusion [8].

10. CONCLUSIONS

The fusion of multispectral and panchromatic images has been in vogue for last many years with methods ranging from IHS to shearlets. Wavelets fare better than the standard methods in that the spectral information distortion is minimized [33]. Wavelet based methods are associated with two computation algorithms namely the Mallot algorithm and *atrous* algorithm of which the second one fares better [29]. Curvelets have been found to fare better in spatial representation and in representing edges than the wavelets. Contourlets are efficient in representing the intrinsic geometrical structures. The noiselets perform better in the case of rough curved surfaces and the shearlets are good in representing multidimensional data. There exists a tradeoff between the spatial and spectral resolutions that can be obtained [27]. The quality assessment of the fusion technique using different metrics including RMSE, CC, ERGAS, SSIM has been studied. The visual quality inspection methods are also to be considered based on the applications. The image quality index used should take into account both the global features and the local features of the image at information and data levels [34].

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