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Fusion of Multi-band SAR Images Based on Directionlet Transform

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Abstract

A novel image fusion scheme for multi-band SAR images based on Directionlet transform is proposed. Firstly, multi-band images are decomposed into low-frequency coefficients and high-frequency coefficients with multi-scales and multi-directions using the Directionlet transform. For the low-frequency coefficients, the average fusion method is used. For the high frequency sub-band coefficients of each direction, the directive edge information measurement and the larger value of region variance information measurement are used to select better coefficients for fusion. Finally the fused image can be obtained by applying inverse transform on the fused Directionlet coefficients. Experimental results show that comparing with traditional algorithms, the proposed algorithm can get better visual effect and the salient information of the original image as texture and contour details is well maintained.

Keywords*: Fusion, SAR Image, Directionlet Transform*

1. Introduction

Data fusion is an effective technique for various target oriented classification of remote sensing data and plays a key role in many remote sensing areas. Synthetic aperture radar (SAR) remote sensing images can provide multi-resolution and multi-frequency image data. It is well known that different kinds of SAR image sensors provide different image information. For example, fusion of high spatial resolution data and multispectral data gives a hybrid image, which has good terrain details, and useful spectral information, which in turn can discriminate small objects or land cover types. Single SAR image can not provide all important information necessary for detecting an object by human or computer vision. Therefore multi-sensor SAR images fusion can carry much more information than a single SAR image for the feature extraction, classification, detection, segmentation, and object recognition in SAR images [1].

The aim of image fusion is to integrate complementary and redundant information from multiple images with a certain algorithm, to create a single image better than any of the individual source images. Fusion of SAR images for land cover application is performed in three different processing levels according to the stage at which the fusion takes place: pixel level, feature level and decision level [2].

Currently, most image fusion applications employ pixel-based methods. Pixel level image fusion algorithms are important in image fusion processing. The advantage of pixel fusion is that the images used contain the original information. Furthermore, the algorithms are rather easy to implement and time-efficient [3].

Geometrical features in images, like edges and contours, play the most important role in many image processing areas, such as image compression, image denoising and image fusion. Image decomposition is an important link of image fusion and affects the information extraction quality, even the whole fusion quality [4]. Many researchers recognized that multi-scale transforms are very useful for analyzing the information of images processing. Multisource image fusion methods as statistical methods, Bayesian methods, evidence theory, neural networks, support vector machines, regional features methods, Principal Component Analysis (PCA),and Brovey Transform have been tested mostly with optical image data [5].

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Over the last decade, the standard separable two-dimensional wavelet transform has been widely applied in the field of image processing and provided good processing effect for its sparse representation of smooth images [6]. However, the wavelet transform fails to efficiently capture one-dimensional discontinuities, such as edges and contours. While the image contours, edges and texture have the geometric features of the high dimensional singularity. These features contain much information, thus the wavelet transform is not the optimal choice for describing images. Since contours are very important elements in visual perception of images, to provide a good visual quality of fused images, it is fundamental to preserve good reconstruction of these directional features. It is limited by the spatial isotropy of the wavelet basis functions as well as the lack of directionality [7].

In order to design anisotropic basis functions that can capture anisotropic sparse representation of geometrical information in images, many new anisotropic image decomposition methods have already been considered and exploited by adaptive or non-adaptive processing, such as Bandetlets, Curvelets and Contourlets. These transform can be designed to satisfy the anisotropy scaling relation for curves, and it can exactly capture the image edges to different frequency coefficients [8].

Minh N. Do and Martin Vetterli pioneered a new system of representations named contourlets which is a "true" two dimensional transform that can capture the intrinsic geometrical structures that are key features in visual information [9]. The contourlet transform can be designed to satisfy the anisotropy scaling relation for curves, it can exactly capture the image edges to different frequency coefficients.

In this paper, we investigate a multiresolution image fusion through a multiresolution Directionlet transform, which decomposes data into a coarser resolution representation for the approximation of low frequency information, and a finer representation for detailed high frequency information. This transform is a new truly separable discrete multi-directional transform with a subsampling method based on lattice theory. Directionlet transform keeps simplicity in design and computation based on a separable construction, lines and columns in an image are treated independently and the basis functions are simply products of the corresponding one dimensional function [10]. We present a new algorithm for multi-band SAR image fusion processing using Directionlet transform. We also compare this method with other traditional fusion methods.

2. Theory of Directionlet Transform

In spite of the success of the standard wavelet transform (WT) in image processing in recent years, the efficiency of its representation is limited by the spatial isotropy of its basis functions built in the horizontal and vertical directions. the standard WT produces isotropic basis functions, which fail to provide a sparse representation of edges and contours. Our goal is to construct an anisotropic perfect reconstruction and critically sampled transform with high-pass filters having directional vanishing moments, while retaining the simplicity of 1-D processing and filter design from the standard separable 2-D WT.

Directionlet transform is a new lattice-based multi-scale analysis anisotropic multi-directional wavelet transform. The Directionlet transform based on integer lattices allow iterating 1-D filters efficiently across different directions. Anisotropic basis functions have directional vanishing moments along different directions, while retaining the simplicity of 1-D processing and filter design from the standard separable 2-D wavelet transform.

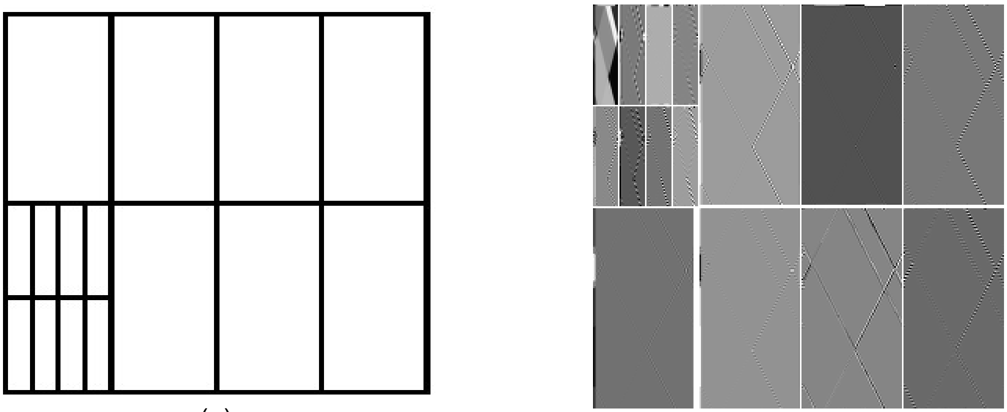
2.1. Anisotropic Wavelet Decomposition

In the standard 2-D wavelet transform, the 2-D wavelet filter banks are separable. The wavelet basis functions are obtained as the direct product of two independent 1-D basis functions in the horizontal and vertical directions. The filtering and sub-sampling operations in the transform are iterated with an equal number of steps along both the horizontal and vertical directions at each scale. In the standard 2-D WT, the number of 1-D transforms along the horizontal and vertical directions is the same at each scale, that is, the standard 2-D WT is isotropic.

In the anisotropic wavelet transform (AWT), the transform is anisotropic because the transform steps along one direction are applied more times than the ones along the other direction, that is, the number of transforms applied along the horizontal and vertical directions is unequal. There are n_1 horizontal and n_2 vertical transform at each scale, where n_1 is not necessarily equal to n_2. We defined such an anisotropic wavelet transform as $AWT(n_1, n_2)$ [10].

The AWT allows for anisotropic iteration of the filtering and sub-sampling applied on the Low-Pass, similar to in the standard Wavelet transform. An example of the construction and basis functions is shown in Figure 1, where the AWT (2, 1) is used. Figure 1(a) shows the result of the AWT (2, 1) with two steps of iteration. The result of the AWT (2, 1) of an image with two steps of iteration is shown in Figure 1(b).

In the above example we have shown that AWT retains the simplicity of separable filtering and sub-sampling comparing with the standard 2-D WT and provides anisotropic basis functions that can capture more efficiently anisotropic features in image. However, anisotropic wavelet transforms use only the horizontal and vertical directions and the high pass filters in the transform have vanishing moments only along these two directions. We need more than these two standard directions in image transform. Multi-directionality and directional vanishing moments are also need in achieving sparse representation.



(a) (b)

Figure 1. An example of the construction and basis functions for AWT. (a) The filtering scheme for the AWT (2, 1), where two step of iteration is shown. (b) The example of decomposition in frequency for the AWT (2, 1), where two step of iteration

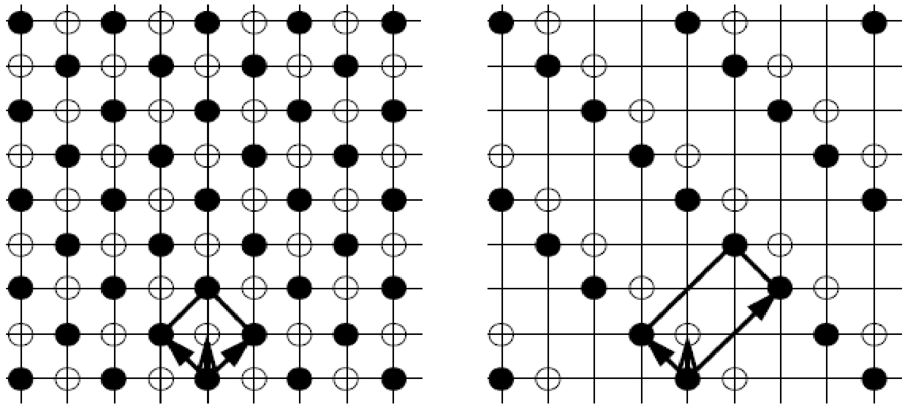
2.2. Lattice-Based Multi-Directional Frame

To obtain multi-directional basis functions, integer lattices are used to realize the combination of rational slopes. The class S-Mondrian consists of the skewed Mondrian-like image along two directions with the rational slope $r_1 = b_1 / a_1$ and $r_2 = b_2 / a_2$, where a_1, a_2, b_1 and b_2 are integers. A novel method based on integer lattices transforms can avoid directional interaction. Any integer lattice Λ can be represented by a non-unique generator matrix:

$$M_\Lambda = \begin{bmatrix} a_1 & b_1 \\ a_2 & b_2 \end{bmatrix} = \begin{bmatrix} d_1 \\ d_2 \end{bmatrix}, a_1, a_2, b_1, b_2 \subset Z \quad (1)$$

We call the direction along the first vector d_1 with the slope r1=b1/a1 as the transform direction. Similarly, the direction along the second vector d_2 with the slope r_2 is named as the alignment direction. This will overcome the directional interaction.

Figure 2 shows the lattice Λ is determined by the generator matrix M_{Λ}; 1-D filtering is applied along 45^o, where the slope r_1 corresponds to the vector [1, 1]. The generator matrix is $M_{\Lambda'}$ after the sub-sampling, and the shift vectors is s_0 and s_1.



$$M_{\Lambda} = \begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix} \quad \begin{matrix} \bullet & s_0 = [0 \quad 0] \\ \circ & s_1 = [0 \quad 1] \end{matrix} \quad M_{\Lambda'} = \begin{bmatrix} 2 & 2 \\ -1 & 1 \end{bmatrix}$$

Figure 2: The lattice Λ is determined by the generator matrix M_{Λ}, 1-D filtering is applied along 45^o. The generator matrix is $M_{\Lambda'}$ after the sub-sampling, and the shift vectors is s_0 and s_1

2.3. Directionlet Transform

In Directionlet transform, firstly, given an integer lattice Λ transforms, which are skewed transform [11]. Then the skewed anisotropic wavelet transform built on the lattice Λ has n_1 and n_2 transforms in one iteration step along the transform and alignment directions, respectively. The basis functions of the skewed anisotropic wavelet transform have anisotropic and multi-directional [12].

Directionlet transform is a new lattice-based perfect reconstruction and critically sampled anisotropic multi-directional wavelet transform. The transform retains the separable filtering, subsampling and simplicity of computations and filter design from the standard two-dimensional wavelet transform, unlike the case of other existing directional transform constructions (e.g. curvelets, contourlets or edgelets). The corresponding anisotropic basis functions, which are called directionlets, have directional vanishing moments along any two directions with rational slopes.

3. Directionlet Based Image Fusion

The source images are obtained from different sensors, which can present different resolutions, sizes and spectral characteristics. We apply the Directionlet transform to image fusion to create new fused images that have more important information than the source images. Before image fusion, the source images have to be correctly aligned on a pixel by pixel basis. We assume here that the images to be combined are already perfectly registered, so that corresponding features coincide.

3.1. The Fusion Steps are as Following

Step 1: Decompositions of the input source images are computed at different levels using Directionlet transform. The source images are decomposed into sub-bands which can be treated as sub-images. The pixels of the sub-images consist of corresponding decomposition coefficients.

Step2: Fusion rule to combine source subimages for the decomposition image. We select coefficients between two source images corresponding subbands to form the coefficients of composite subbands. The selected coefficients must represent the salient features in the subbands of the source image.

Step3: The fused image is constructed by successively performing reconstruction. The inverse Directionlet transform is applied to the chosen coefficients to get the the ultimate fused image.

3.2. Fusion Method

In the source images Directionlet decomposition, the low frequency sub-band image coefficients show the image approximate characteristic. Therefore the low frequency image fusion generally adopts the average method as the following equation shows:

$$C_F(i,j) = \frac{C_A(i,j) + C_B(i,j)}{2} \quad (2)$$

where $C_A(i,j)$ and $C_B(i,j)$ is low coefficients of image A and image B respectively. $C_F(i,j)$ is low coefficients of fused image.

For the coefficients of the high frequency, larger absolute values of multi-scale decomposition coefficients correspond to sharper brightness changes such as edges, lines and region boundaries. Therefore a general fusion rule is to select the larger absolute value of the two coefficients at each pixel. In this way the fusion takes place in all the resolution levels and the more dominant features at each scale are preserved in the new multi-resolution representation. But the pixel by pixel maximum selection rule may not be the most appropriate method, because this method does not consider the directional characteristic. Here, an area-based image fusion rule is used. The fact that a given pixel is highly correlated with those of neighboring is considered in this method.

The purpose of image fusion requires that the fused image must effectively preserve the details of the input images. For the coefficients of the high frequency, an edge-based image fusion method is used by selecting the corresponding sub-band signals of each input image according to the directive edge values.

For the coefficients of the highest frequency, fusions by the rule of choosing the greater of the Edge Information Measurement with the region consistency check. For example, in the case of the fusion of two input images A and B, let F represent the fused image, we have:

$$M(i,j) = \sum_{n=-1}^{1} \sum_{m=-1}^{1} W(m,n) D(i+m, j+n) \quad (3)$$

where D(i, j) is high frequency coefficients with region center (i, j); M(i, j) is fused image high frequency coefficients; W(i, j) were the Laplacian edge detection mask, defined as:

$$W(m,n) = \begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix} \quad (4)$$

The fused high frequency coefficients can be selected with following definition:

$$D_{l,F}^{k}(i,j) = \begin{cases} D_{l,A}^{k}(i,j) & |M_{l,A}^{k}| > |M_{l,B}^{k}| \\ D_{l,B}^{k}(i,j) & |M_{l,A}^{k}| \le |M_{l,B}^{k}| \end{cases} \quad (5)$$

where, $D_{l,T}^{k}\ (k=1,2,...M;T=A,B,F)$ denote the sub-band signals of input images A and B and fused image F, respectively, and $M_{l,T}^{k}\ (k=1,2,...M;T=A,B,F)$ represent the Edge Information Measurement of A and B:

For the coefficients of the other high frequency, fusion with the following rule. We can get high-frequency coefficients by choosing the weighted variance as the fusion coefficient which is calculated according to the local variance fusion rule.

The variance of image reflects the dispersion degree between the gray value and the gray mean value. The standard deviation is the square root of the variance. The larger the standard deviation is the more disperse the gray level. Suppose the size of the image is M by N, and that $D(i,j)$ is the pixel in the image. The definition of the standard deviation is:

$$MeanC=\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}C(i,j) \tag{6}$$

$$\delta(i,j)=\sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(C(i,j)-MeanC)^{2}} \tag{7}$$

where MeanC is mean value of region window coefficients. $\delta(i,j)$ is the standard deviation.

Fused Directionlet coefficients can be selected with following definition:

$$C_F(i,j)=\frac{\delta_A}{\delta_A+\delta_B}C_A(i,j)+\frac{\delta_B}{\delta_A+\delta_B}C_B(i,j) \tag{8}$$

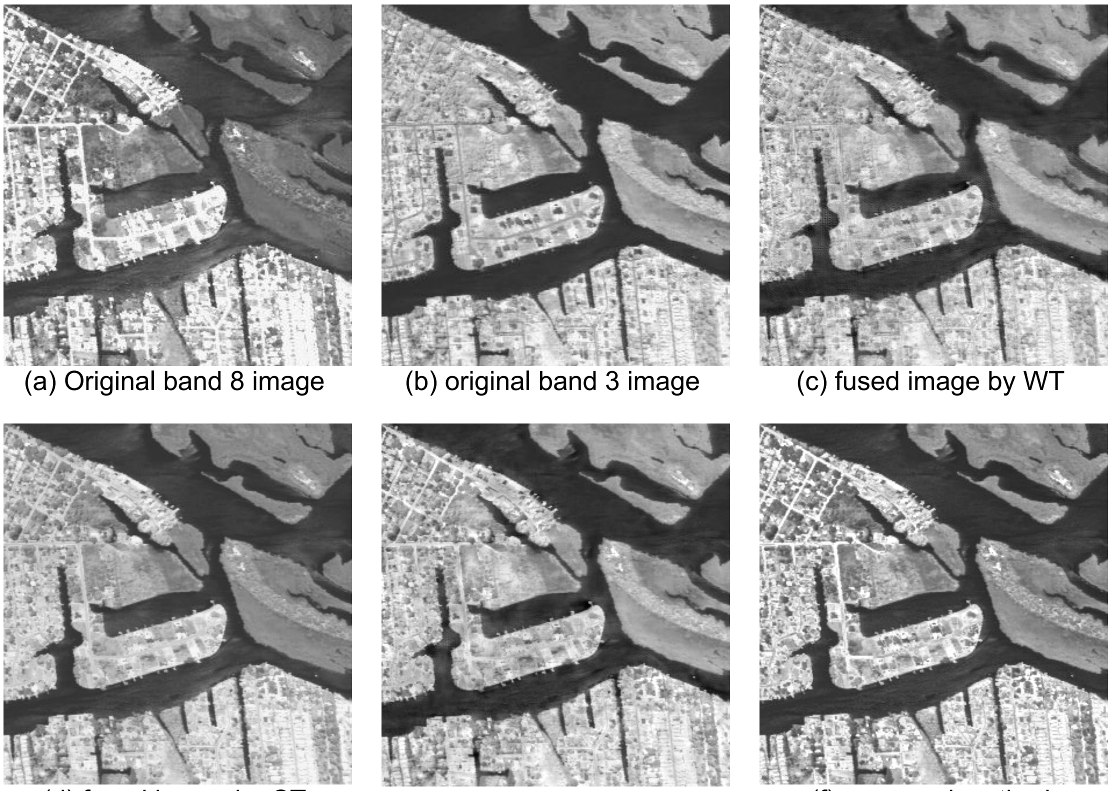
4. Experiment of Image Fusion and Result

In order to test our image fusion algorithm, in this section, the methods proposed above were tested for image fusion of the multi-band SAR image, the experimental results of the original multi-band image (cropped to 256×256 for visibility of the speckle) and fused image by different methods are shown in Figure 3.

Figure 3 (a) and (b) are two remote images with different band respectively. Figure 3 (c)-(e) show fused images with Wavelet transform (WT), Contourlet transform (CT), and shift-invariable Contourlet transform (NSCT) method, respectively. Figure 3 (f) shows that the fused image is a clear image with rich features, such as smooth contours and geometric structures using Directionlet transform. These fused images are better than any one of the source images and all contain much obvious characteristic information of the different band remote images.

To enable an objective comparison with other methods, the performance of the proposed fusion technique is compared with that of the WT method, the CT method and the NSCT method [13]. Criteria values of fused images by different methods are shown in Table 1

Table 1 presents a comparison of the experimental results of image fusion using the different methods of combination the average value, the standard deviation, the entropy, the mean cross entropy (MCE) and the root cross entropy (RCE). From the results given in table 1 we can see that the entropy is the greatest value with Directionlet-based method. The MCE and RCE with the proposed method are the smallest in the four methods. In a word, the fused result based on Directionlet transform is the best in the given methods.



(a) Original band 8 image (b) original band 3 image (c) fused image by WT

(d) fused image by CT (e) fused image by NSCT (f) proposed method

Figure 3. Fused image with the different methods. (a) Original band 8 image, (b) Original band 3 images, (c) fused image by WT, (d) fused image by CT, (e) fused image by NSCT, (f) Fused image with proposed method.

Table 1. Criteria value of fused images by different methods

Criteria / method	average value	Standard deviation	entropy	the mean cross entropy	the root cross entropy
WT	141.901	59.390	7.4274	0.6940	0.7046
CT	142.899	64.526	7.5274	0.5030	0.6465
NSCT	143.024	63.721	7.5326	0.5020	0.6439
DT	140.716	65.931	7.4903	0.3644	0.3786

5. Conclusion

A novel fusion method based on Directionlet transform has been proposed for performing the pixel-level fusion of spatially registered images. Thus, the proposed fusion system significantly reduces reconstruction artifacts and the loss of contrast information, conditions which a commonly observed in conventional DWT-based fusion.Experimental results show that the proposed fusion algorithm based on Directionlet transform is able to achieve an excellent balance between improve contrast effectively and preserve more target characteristics of original image comparing to other algorithms.

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