Satellite Image Fusion using Fast Discrete Curvelet Transforms

C.V.Rao, J.Malleswara Rao, A.Senthil Kumar, D.S.Jain, V.K.Dadhwal
National Remote Sensing Centre, Indian Space Research Organization, Hyderabad-500037, India
Email: rao_cv@nrsc.gov.in

Abstract—Image fusion based on the Fourier and wavelet transform methods retain rich multispectral details but less spatial details from source images. Wavelets perform well only at linear features but not at nonlinear discontinuities because they do not use the geometric properties of structures. Curvelet transforms overcome such difficulties in feature representation. In this paper, we define a novel fusion rule via high pass modulation using Local Magnitude Ratio (LMR) in Fast Discrete Curvelet Transforms (FDCT) domain. For experimental study of this method Indian Remote Sensing (IRS) Resourcesat-1 LISS IV satellite sensor image of spatial resolution of 5.8m is used as low resolution (LR) multispectral and Cartosat-1 Panchromatic (Pan) image. This fusion rule generates HR multispectral image at 2.5m spatial resolution. This method is quantitatively compared with Wavelet, Principal component analysis (PCA), High pass filtering (HPF), Modified Intensity-Hue-Saturation (M.IHS) and Grams-Schmidt fusion methods. Proposed method spatially outperform the other methods and retains rich multispectral details.

Keywords—Image Fusion, Fast Discrete Curvelet Transforms, Local Magnitude Ratio (LMR).

I. INTRODUCTION

Image fusion integrates the multisensor data to create a fused image containing high spatial, spectral and radiometric resolutions. In remote sensing, image fusion is most valuable technique for utilization of multisensor, multispectral at various resolutions of earth observation satellites [10]. Spatial resolution plays a vital role to delineate the objects in the remote sensing image. It is easy to interpret the features with high spatial resolution [20] image with multispectral information than the single high resolution Pan image. Image fusion enhance the spatial, spectral and radiometric [11] resolutions of images.

There are several satellite image fusion techniques but spatial and spectral details retention simultaneously is a trade off. F.Nencini et al. [5] proposed a fusion method based on interband structure model (IBSM) in first generation curvelet transform domain. The method uses Quick-bird and Ikonos multispectral and Pan images. The experimental results shown that the method slightly better than the Atrous Wavelet Transform (AWT) and outperform Grams-Schmidt spectral sharpening method. Ying Li et al. [6] proposed a Fast Discrete Curvelet Transform (FDCT) based remote sensing image fusion. The method uses Synthetic Aperture Radar (SAR) and Thematic Mapper(TM) images for fusion. This work concluded that FDCT based fusion method retain good spatial details and simultaneously preserve the rich spectral content compared with Discrete Wavelet Transform (DWT) and Intensity-Hue-saturation (IHS). Arash Golibag et al. [7] focuses on region based image fusion using linear dependency decision rule based on Wronskian determinant. The method uses multispectral Landsat and IRS Pan images for fusion. Shutao Li et al. [8] have done multifocus image fusion by combining curvelet and wavelet transform. Cai Xi [9] proposed FDCT based image fusion by using Support Vector Machines (SVM) and Pulse Coupled Neural Network (PCNN) to narrate the good sensitivity to boundaries of objects, concluded that the method has better performance than FDCT.

Fast Fourier and wavelet transform based image fusion methods retain better spectral characteristics but represent poor spatial details in fused images. Objective of this paper is to develop a method, which retains better characteristics of both spatial and spectral qualities of source images. Wavelet transforms do not represent the curved objects as in HR Pan image. Curvelet transforms overcome such difficulties of wavelet. Over a period, curvelet transforms are evolved in two generations, such as first generation curvelet transforms and second generation curvelet transforms named as Fast Discrete Curvelet Transforms (FDCT). First generation curvelet transforms computational complexity is more to compute the curvelet coefficients [5]. To overcome these difficulties Emmanuel J.Candes [1] developed FDCT. FDCT represents linear-edges and curves accurately than any other mathematical transforms.

II. FAST DISCRETE CURVELET TRANSFORMS (FDCT)

Multi resolution ideas like wavelet [1] and related ideas led to convenient tools to navigate through large datasets, to transmit compressed data rapidly, to remove noise from signals and images, and to identify crucial transient features in such datasets. Wavelets perform well only at representing point singularities, since they ignore the geometric properties of structures and do not exploit the regularity of edges. Curvelet transform was proposed [1] in order to overcome the drawbacks of conventional two-dimensional discrete wavelet transform. In the two-dimensional (2D) case, the curvelet transform allows almost optimal sparse representation of objects with $C^2$ singularities. Emmanuel J.Candes et al.[1] developed and described the continuous curvelet transform as follows. Let $a_j = 2^{-j}$, $j \geq 0$ be the scale, $\theta_{j,l} = \frac{\pi j}{2}$ with $l = 0, 1, ..., 4.2^{j/2} - 1$ be the equidistant sequence of rotation angles. Here $\lfloor x \rfloor$ denotes the smallest integer being greater than or equal to $x$. 

$$b_{k_1,k_2} = R_{\theta_{j,l}}^T(k_{1}, k_{2})$$

$k_1, k_2 \in Z$ and where $R_{\theta_{j,l}}$ denotes the rotation matrix with angle $\theta_{j,l}$.

This choice lead
to a discrete curvelet system that forms a tight frame, i.e., every function \( f \in L^2(\mathbb{R}^2) \) is represented by a curvelet series and hence discrete curvelet transform is invertible. The scaled windows are defined by using the Meyer windows [14] in polar coordinates of frequency domain as

\[
U_j(r, w) = 2^{-3j/4}W(2^{-j}r)V\left(\frac{w}{\theta_{j,l}}\right), j \in N
\]

Where \( W(r) \) and \( V(t) \) are radial and angular windows respectively. The basic curvelet is defined by the Fourier transform of \( U_j(r, w) \).

\[
\hat{\phi}_{j,0,0}(\xi) = U_j(\xi)
\]

and the family of curvelet functions is given by translation and rotation of \( \phi_{j,0,0} \in L^2(\mathbb{R}^2) \).

\[
\phi_{j,k,l}(x) = \phi_{j,0,0}(R_{\theta_{j,l}}(x - b_{j,l}^l))
\]

The family of curvelets is obtained by the Fourier transform of \( \phi_{j,k,l}(x) \) and it is denoted by \( \phi_{j,k,l}(\xi) = e^{-i(b_{j,l}^l,\xi)}U_j(R_{\theta_{j,l}}\xi) \)

\[
e^{-i(b_{j,l}^l,\xi)}2^{-3j/4}W(2^{-j}r)V\left(\frac{w + \theta_{j,l}}{\theta_{j,l}}\right)
\]

They are supported inside the polar wedge with radius \( 2^{j-1} \leq r \leq 2^{j+1} \) and angle \( 2^{-j/2}(\pi - 1 - \theta) \leq \theta \leq 2^{-j/2}(\pi + 1 - \theta) \) for each scale \( j \) and orientation \( l \).

Finally some coarser scale curvelet elements for low frequencies is given by \( \phi_{-1,k,0} = \phi_{-1}(x - k), k \in \mathbb{Z}^2 \) where \( \phi_{-1}(\xi) = W_0(|\xi|) \) with \( W_0(r)^2 = 1 - \sum_{j \geq 0}W(2^{-j}r)^2 \).

The system of curvelets \( \{\phi_{-1,k,0} : k \in \mathbb{Z}^2\} \cup \{\phi_{j,k,l} : j \in N, l = 0,1,\ldots,2^{j/2} - 1, k \in \mathbb{Z}^2\} \) satisfies a tight frame property. Every function \( f \in L^2(\mathbb{R}^2) \) is represented by a curvelet series and hence discrete curvelet transform is invertible \( f = \sum_{j,k,l}f(\phi_{j,k,l})\phi_{j,k,l} \) and the Parseval identity \( \sum_{j,k,l}|f(\phi_{j,k,l})|^2 = \|f\|^2_{L^2(\mathbb{R}^2)} \) holds for all \( f \in L^2(\mathbb{R}^2) \).

The curvelet coefficients are obtained by using the Plancherel’s theorem for \( j \geq 0 \).

\[
c_{j,k,l} = \int_{\mathbb{R}^2} f(x)\overline{\phi_{j,k,l}(x)}dx = \int_{\mathbb{R}^2} f(\xi)\overline{\phi_{j,k,l}(\xi)}d\xi
\]

Where \( c_{j,k,l} \) is the curvelet coefficients at scale \( j \) and in the direction \( l \) at location \( k \).

The low frequency (coarse scale) coefficients are shown at the center of the display in Fig. 1. The cartesian concentric corona show the coefficients at different scales. The outer corona corresponds to high frequencies. There are four strips associated to each corona in north, south, east and west direction, these are further subdivided in angular panels. Each panel represents coefficients at a specified scale and orientation suggested by the position of the panel.

III. PROPOSED APPROACH

In a directional sub-band, bigger curvelet coefficients of HR Pan image and LR multispectral image represent sharp local feature [19]. In this paper, we define a Local Magnitude Ratio (LMR) to inject high frequency details of the local image feature into the fused image. LMR is defined as follows.

Let us suppose that \( c_{j,l}(M) \), \( c_{j,l}(P) \) are the sub-band curvelet coefficients at scale \( j \) in a direction \( l \) of the multispectral band \( M \) and panchromatic image \( P \) at higher frequencies respectively.

\[
LMR_{j,l}(x,y) = \frac{|c_{j,l}(M(x,y))|}{|c_{j,l}(P(x,y))|}
\]

Where \( LMR_{j,l}(x,y) \) is the sub-band curvelet coefficients at scale \( j \) in direction \( l \) at location (x,y).

If \( LMR_{j,l}(x,y) \leq 1 \) then \( c_{j,l}(P(x,y)) \) represents good local feature. If \( LMR_{j,l}(x,y) > 1 \) then \( c_{j,l}(M(x,y)) \) represents good local feature. Fusion rule to inject high spatial details from HR panchromatic image into LR multispectral image bands is defined using LMR of curvelet coefficients in the directional high frequency sub-bands.

IV. IMAGE FUSION ALGORITHM USING FDCT

Spatial resolution ratio between HR Pan image and LR multispectral image is 2. Input images size must be power of 2 for coherent multi resolution decomposition in FDCT domain. To obtain HR multispectral image, high frequency details are injected into each LR multispectral band in FDCT domain. The fusion rule based on the LMR in FDCT domain is defined as follows.

1) LR multispectral image is resampled to the scale of HR Pan image in image coregistration. i.e., both the images must be at identical geometry and of same size.
\[ c_{j,l}(F(x,y)) = \begin{cases} 
    c_{j,l}(P(x,y)) \cdot \text{LMR}_{j,l}(x,y) & \text{if } \text{LMR}_{j,l}(x,y) > 1; \\
    c_{j,l}(P(x,y)) & \text{if } \text{LMR}_{j,l}(x,y) \leq 1; 
\end{cases} \]  
(7)

2) The multispectral data in Green, Red and near-infrared bands are extracted band wise.

3) Apply fast discrete curvelet transform (FDCT) to multispectral band M and Panchromatic image P. The input images are decomposed into four levels in multiple directions. Number of directions depends on the image size and decomposition levels.

\[ L_{MS} = \{ c_{3,l}(M), c_{2,l}(M), c_{1,l}(M), a_0(M) \} \]
\[ H_{Pan} = \{ c_{3,l}(P), c_{2,l}(P), c_{1,l}(P), a_0(P) \} \]

where \( L_{MS} \) is the set of curvelet coefficients for low resolution multispectral band, where \( H_{Pan} \) is the set of curvelet coefficients for high resolution panchromatic image and \( a_0(M) \) is the coarser scale coefficients of the multispectral band M, similarly \( a_0(P) \) for the panchromatic image P.

4) Fusion rule 1 is defined for the curvelet coefficients at lower frequencies (coarser scale coefficients). Construct coarser scale coefficients for fused image F from LR multispectral band M such that \( a_0(F) = a_0(M) \).

5) Fusion rule 2 is defined for the curvelet coefficients at higher frequencies based on high pass modulation. Construct the multidirectional multiresolution curvelet coefficients \( c_{j,l}(F) \) by using Equation (7) for fused image.

6) Construct the set of curvelet planes for fused image as

\[ H_{Fus} = \{ c_{3,l}(F), c_{2,l}(F), c_{1,l}(F), a_0(F) \} \]

and apply the Inverse Fast Discrete Curvelet Transforms (IFDCT).

7) Apply steps (3) to (6) for each multispectral band.

8) Combination of three resultant fused bands provide the HR multispectral fused image.

V. EXPERIMENTAL RESULTS AND COMPARISONS

Resourcesat -1 LISS IV image is taken as LR multispectral image which is ortho rectified and resampled to 5m spatial resolution. Cartosat-1 data taken as an HR Pan image of resolution 2.5m and these images are in 1:2 scale ratio. HR Pan image size is \(2048 \times 2048\) and LR multispectral image size is \(1024 \times 1024\). For clear visualization, subset images of the fused images of different techniques are shown in Fig. 3. Fig. 3(a) is the original HR Pan Cartosat-1 image and Fig. 3(b) is the resampled LR multispectral image. Fig. 3(c) is the HR multispectral image obtained by new fusion rule based on FDCT. Fig. 3(d) - 3(h) are obtained by the wavelet transform, PCA, HPF, Modified IHS and Grams-Schmidt fusion techniques respectively implemented in Earth Resources Data Analysis System (ERDAS 2013) satellite image processing software. Quality of the fused images is evaluated with both spatial and spectral quality measures.

A. Spatial Quality Evaluation

Each MS band in a fused image is compared to the HR Pan image for spatial quality evaluation.

1) Entropy: Entropy is a measure to directly conclude the performance of image fusion. The Entropy can show the average information included in the image and reflect the detail information of the fused image. Commonly, the greater the entropy of the fused image is, the more abundant information included in it, and the greater the quality of the fusion. According to the information theory of Shannon, the entropy
Fig. 3. Color compositions of full-scale fusion results for the reported detail (NIR, Red, and Green bands as R, G, and B channels)

The entropy of an image is defined as

\[ E = - \sum_{i=0}^{n} p_i \log_2 p_i \]

Where \( E \) is the entropy of the image and \( p_i \) is the probability of \( i \) in the image. Here \( p_i \) is the frequency of pixel values from 0 to \( n \) in the image. We normalized the HR Pan data and LR MS data radiometric resolutions. Entropy values are shown in Table I.

<table>
<thead>
<tr>
<th>Band</th>
<th>FDCT</th>
<th>Wavelet</th>
<th>PCA</th>
<th>HPF</th>
<th>M.IHS</th>
<th>GS</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6.22</td>
<td>5.91</td>
<td>5.66</td>
<td>5.89</td>
<td>6.09</td>
<td>5.85</td>
</tr>
<tr>
<td>2</td>
<td>6.78</td>
<td>6.55</td>
<td>6.81</td>
<td>6.68</td>
<td>6.70</td>
<td>6.79</td>
</tr>
<tr>
<td>3</td>
<td>6.29</td>
<td>6.15</td>
<td>6.20</td>
<td>6.12</td>
<td>6.12</td>
<td>6.11</td>
</tr>
<tr>
<td>Average</td>
<td>6.43</td>
<td>6.23</td>
<td>6.23</td>
<td>6.23</td>
<td>6.30</td>
<td>6.25</td>
</tr>
</tbody>
</table>

2) Correlation coefficient of high pass filtered images:

High frequency details from the Pan image are compared to the high frequency details from each band of the fused images using a method proposed by Zhou et al. [16]. To extract the high frequency data, apply the following convolution kernel to the images:

\[
mask = \begin{bmatrix}
-1 & -1 & -1 \\
-1 & 8 & -1 \\
-1 & -1 & -1
\end{bmatrix}
\]

The correlation coefficients between the high-pass filtered fused bands and the high-pass filtered Pan image is used as an index of the spatial quality [17]. The principle is that the spatial information unique in Pan image is mostly concentrated in the high frequency component of Pan image has been injected into the fusion. Correlation coefficient of high pass filtered images band-wise are shown in Table II.
TABLE II. CORRELATION COEFFICIENT OF HIGH PASS FILTERED IMAGES

<table>
<thead>
<tr>
<th>Band</th>
<th>FDCT</th>
<th>Wavelet</th>
<th>PCA</th>
<th>HPF</th>
<th>MIHS</th>
<th>GS</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>0.97</td>
<td>0.14</td>
<td>0.99</td>
<td>0.82</td>
<td>0.90</td>
<td>0.90</td>
</tr>
<tr>
<td>2</td>
<td>0.98</td>
<td>0.18</td>
<td>0.93</td>
<td>0.92</td>
<td>0.92</td>
<td>0.96</td>
</tr>
<tr>
<td>3</td>
<td>0.97</td>
<td>0.19</td>
<td>0.39</td>
<td>0.83</td>
<td>0.87</td>
<td>0.94</td>
</tr>
<tr>
<td>Average</td>
<td>0.97</td>
<td>0.18</td>
<td>0.71</td>
<td>0.86</td>
<td>0.90</td>
<td>0.64</td>
</tr>
</tbody>
</table>

3) Average gradient: Spatial quality of fused image \( f \) by average gradient can be calculated by using the equation

\[
ag = \frac{1}{(M-1)(N-1)} \sum_{x=1}^{M-1} \sum_{y=1}^{N-1} \sqrt{\left( \frac{\partial f(x,y)}{\partial x} \right)^2 + \left( \frac{\partial f(x,y)}{\partial y} \right)^2}
\]

Where \( f(x, y) \) is the pixel value of the fused image at position \((x, y)\). The average gradient reflects the clarity of the fused image. It can be used to measure the spatial resolution of the fused image, i.e., a larger average gradient indicates higher spatial resolution. Average gradient values band-wise are shown in Table III.

TABLE III. AVERAGE GRADIENT

<table>
<thead>
<tr>
<th>Band</th>
<th>FDCT</th>
<th>Wavelet</th>
<th>PCA</th>
<th>HPF</th>
<th>MIHS</th>
<th>GS</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4.41</td>
<td>3.96</td>
<td>4.25</td>
<td>4.21</td>
<td>4.10</td>
<td>4.08</td>
</tr>
<tr>
<td>2</td>
<td>4.63</td>
<td>4.05</td>
<td>5.44</td>
<td>4.28</td>
<td>4.38</td>
<td>5.21</td>
</tr>
<tr>
<td>3</td>
<td>4.43</td>
<td>3.93</td>
<td>4.52</td>
<td>3.65</td>
<td>3.54</td>
<td>4.28</td>
</tr>
<tr>
<td>Average</td>
<td>4.49</td>
<td>3.98</td>
<td>4.40</td>
<td>3.71</td>
<td>4.01</td>
<td>4.13</td>
</tr>
</tbody>
</table>

B. Spectral Quality Evaluation

Resampled multispectral bands of LISS-IV sensor image and corresponding bands in the fused image are compared for spectral quality evaluation.

1) Spectral Angle Mapper (SAM): Let \( v \) and \( \hat{v} \) be two vectors having \( l \) components of resampled multispectral LISS IV sensor band and the corresponding band in the fused image respectively. Spectral angle mapper (SAM) is the absolute value of the angle between the two vectors [5].

\[
SAM(v, \hat{v}) = \cos^{-1}\left( \frac{\langle v, \hat{v} \rangle}{||v||_2||\hat{v}||_2} \right)
\]

SAM is measured in either degrees or radians and is usually averaged over the whole image to yield a global measurement of spectral distortion. SAM values equal to zero denotes the absence of spectral distortion. Table IV shows the SAM values for each fused band.

TABLE IV. SPATIAL ANGLE MAPPER (IN DEGREES)

<table>
<thead>
<tr>
<th>Band</th>
<th>FDCT</th>
<th>Wavelet</th>
<th>PCA</th>
<th>HPF</th>
<th>MIHS</th>
<th>GS</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.04</td>
<td>0.07</td>
<td>0.06</td>
<td>0.03</td>
<td>0.08</td>
<td>0.02</td>
</tr>
<tr>
<td>2</td>
<td>0.05</td>
<td>0.07</td>
<td>0.21</td>
<td>0.05</td>
<td>0.11</td>
<td>0.17</td>
</tr>
<tr>
<td>3</td>
<td>0.03</td>
<td>0.06</td>
<td>0.11</td>
<td>0.04</td>
<td>0.06</td>
<td>0.09</td>
</tr>
<tr>
<td>Average</td>
<td>0.04</td>
<td>0.07</td>
<td>0.13</td>
<td>0.04</td>
<td>0.08</td>
<td>0.09</td>
</tr>
</tbody>
</table>

2) Universal Image Quality Index (UIQI): Let A and B be the resampled MS LISS IV sensor band and the corresponding band in the fused image respectively. The Universal Image Quality Index [18] is defined by Wang and Bovik (2002) as

\[
Q = \frac{\sigma_{AB}}{\sigma_A^2 + \sigma_B^2 + 2\sigma_{AB}} \left( \frac{2m_A m_B}{(m_A)^2 + (m_B)^2} \right)^2 \left( \frac{2\sigma_A \sigma_B}{(\sigma_A)^2 + (\sigma_B)^2} \right)^2
\]

Where \( \sigma_A^2, \sigma_B^2 \) are the variances of images A and B respectively, \( \sigma_{AB} \) is the covariance of the images A and B, \( m_A, m_B \) are mean of the images A and B respectively. Higher value of UIQI indicates the better fusion method. UIQI values for each band are shown in Table V. FDCT has better score than other methods.

TABLE V. UNIVERSAL IMAGE QUALITY INDEX

<table>
<thead>
<tr>
<th>Band</th>
<th>FDCT</th>
<th>Wavelet</th>
<th>PCA</th>
<th>HPF</th>
<th>MIHS</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>0.18</td>
<td>0.10</td>
<td>0.07</td>
<td>0.12</td>
<td>0.08</td>
<td>0.12</td>
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<tr>
<td>2</td>
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<td>3</td>
<td>0.14</td>
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<td>0.09</td>
</tr>
<tr>
<td>Average</td>
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<td>0.08</td>
<td>0.10</td>
<td>0.11</td>
<td>0.09</td>
</tr>
</tbody>
</table>

VI. CONCLUSION

We have described new fusion method based on fast discrete curvelet transforms (FDCT). Two fusion rules are defined, fusion rule 1 is for curvelet coefficients at lower frequencies and fusion rule 2 is for the curvelet coefficients at higher frequencies. Fusion rule 1 substitute the coarser scale coefficients of LR multispectral bands into the coarser scale coefficients of HR Pan image. Fusion rule 2 is based on the high pass modulation using Local Magnitude Ratio (LMR) of the curvelet coefficients in each orientation and scale. Bigger curvelet coefficients of HR Pan image and LR multispectral image represent sharp local feature. LMR directs the injection of high frequency details of the local image feature in HR Pan image into fused image. For experimental study of this method Indian Remote Sensing (IRS) Resourcesat-1 LISS IV satellite sensor image of spatial resolution of 5.8m is used as low resolution (LR) multispectral image and Cartosat-1 Panchromatic (Pan) of spatial resolution 2.5m is used as high resolution (HR) Pan image. This fusion rule generates HR multispectral image at 2.5m spatial resolution. This method is quantitatively compared with Wavelet, Principal component analysis (PCA), High pass filtering (HPF), Modified Intensity-Hue-Saturation (MIHS), and Grams-Schmidt fusion methods. Proposed method spatially outperforms the other methods and retains rich multispectral details.

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