Acuracy and Quality Assesment of Image Using CURVELET Transform And Minimum Distance Classification Method

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ABSTRACT - With the availability of multisensor, multitemporal, multiresolution and multifrequency image data from operational Earth observation satellites the fusion of digital image data has become a valuable tool in remote sensing image evaluation. Digital image fusion is a relatively new research field at the leading edge of available technology. It forms a rapidly developing area of research in remote sensing. Earth observation satellites provide data covering different portions of the electromagnetic spectrum at different spatial, temporal and spectral resolutions. For the full exploitation of increasingly sophisticated multisource data, advanced analytical or numerical data fusion techniques are being developed.

Fused images may provide increased interpretation capabilities and more reliable results since data with different characteristics are combined. The images vary in spectral, spatial and temporal resolution and therefore give a more complete view of the observed objects. It is the aim of image fusion to integrate different data in order to obtain more information than can be derived from each of the single sensor data alone.

It is a current need of research to extensively use the freely available satellite images. The most commonly available satellite images are Moderate Resolution Imaging Spectroradiometer (MODIS) and The Advanced Very High Resolution Radiometer (AVHRR). The problems with these images are their poor spatial resolution that restricts their use in various applications. This restriction may be minimized by application of the fusion techniques where high resolution image will be used to fuse with low resolution images. Another important aspect of fusion of different sensors data as optical and radar images (where both can provide the complimentary information), and the resultant fused image after fusion may give enhanced and useful information that may be beneficial for various application. Therefore, in this paper an attempt has been made to fuse the full polarimetric Phased Array type L-band SAR (PALSAR) image with MODIS image and assess the quality of fused image. PALSAR image has a advantage of availability of data in four different channels. These four channels are HH (Transmitted horizontal polarization and received also in horizontal polarization), HV (Transmitted horizontal polarization and received vertical polarization), VH (Transmitted vertical polarization and received horizontal polarization) and VV (Transmitted vertical polarization and received vertical polarization), which provides various landcover information. The three major land covers agriculture, urban and water are considered for evaluation of fusion of these images for the Roorkee area of India. The results are quite encouraging, and in near future it may provide a better platform to maximize the use of MODIS images.

Keyword : CURVELET TRANSFORM, MINIMUM DISTANCE CLASSIFICATION METHOD

II. LITERATURE REVIEW

A lot of literature says that image fusion have produced a variety of approaches like image overlay, image sharpening, and image cueing through pixel, feature, or region/shape combinations. The applicability of these approaches and techniques differ on the image content, contextual information, and generalized metrics of image fusion gain. An image fusion gain can be assessed relative to information gain or entropy reduction.

Myungjin Choi, Rae Young Kim, Myeong-Ryong Nam, and Hong Oh Kim describes the image fusion using the curvelet transform. A useful technique in various applications of remote sensing involves the fusion of different types of satellite images, namely multispectral (MS) satellite images with a high spectral and low spatial resolution and panchromatic (Pan) satellite image with a low spectral and high spatial resolution. The results of most wavelet-based methods of image fusion have a spatial resolution that is less than that obtained via the Brovey,
intensity–hue–saturation, and principal components analysis methods of image fusion. Concept of using the curvelet transform, because the curvelet transform represents edges better than wavelets. Because edges are fundamental in image representation, enhancing the edges is an effective means of enhancing spatial resolution. Image fusion is and will be an integral part of many existing and future surveillance systems. However, little or no systematic attempt has been made up to now on studying the relative merits of various fusion techniques and their effectiveness on real multi-sensor imagery. It is a current need of research to extensively use the freely available satellite images. The most commonly available satellite images are Moderate Resolution Imaging Spectroradiometer (MODIS) and Advanced Very High Resolution Radiometer (AVHRR). The problems with these images are their poor spatial resolution that restricts their use in various applications. This restriction may be minimized by application of the fusion techniques where high resolution image will be used to fuse with low resolution images.

A. MODIS AND PALSAR IMAGES

The functional design of satellite data production systems is based upon the processing of raw instrument data into a hierarchy of increasingly refined data products. These production processes discard large amounts of data throughout the processing chain. This forces the user community to use data that may be inappropriate for their application requirements, precludes opportunities for sophisticated users to take advantage of the entire sensed data set, and makes data reprocessing and on-demand data processing resource intensive. As new remote-sensing systems with improved geometric and radiometric quality and improved calibration stability become available, the requirement for data storage structures that will support flexible application-specific uses of the sensed data will increase.

MODIS (or Moderate Resolution Imaging Spectroradiometer) is planned for launch onboard the morning (AM1) and afternoon (PM1) Earth Observing System (EOS) platforms in 1998 and 2000, respectively. MODIS will sense all of the earth’s surface in 36 spectral bands spanning the visible (0.415 m) to infrared (14.235 m) spectrum at nadir spatial resolutions of 1 km, 500, and 250 m. MODIS will provide both day and night full earth coverage every two days and full coverage every day for latitudes above approximately 30. MODIS will be the primary EOS sensor for providing data on global biospheric dynamics and will reduce reliance upon data sensed by instruments such as the Advanced Very High Resolution Radiometer (AVHRR). The MODIS land science team is currently developing remote-sensing algorithms for deriving global time-series data products on various terrestrial geophysical parameters that will be used by the earth science community. The products include land surface reflectance, land surface temperature, spectral vegetation indexes, snow and sea ice cover, fire detection, land cover and land cover change, spectral albedo, bidirectional reflectance characterization, and a number of biophysical variables that will contribute to an improved understanding of global carbon cycles, hydrologic balances, and biogeochemical cycles.

PALSAR cannot observe the areas beyond 87.8 deg. north latitude and 75.9 deg. south latitude when the off-nadir angle is 41.5 deg.

- Valid for off-nadir angle 34.3 deg. (Fine mode), 34.1 deg. (ScanSAR mode), 21.5 deg. (Polarimetric mode)
- S/A level may deteriorate due to engineering changes in PALSAR

B. CURVELET TRANSFORM

Image Fusion produces a single image by combining information from a set of source images together, using pixel, feature or decision level techniques. The fused image contains greater information content for the scene than any one of the individual image sources alone. The reliability and overall detail of the image is increased,
because of the addition of analogous and complementary information. Image fusion requires that images be registered first before they are fused.

We introduce a new image fusion method based on a curvelet transform. The fused image using the curvelet-based image fusion method yields almost the same detail as the original panchromatic image, because curvelets represent edges better than wavelets. It also gives the same colour as the original multispectral images, because we use the wavelet-based image fusion method in our algorithm. As such, this new method is an optimum method for image fusion.

The main feature of the curvelet transform is that it is sensitive to directional boundaries and capable of representing the highpass details of object contours at different scales through few sparse nonzero coefficients. The different steps which is used for Curvelet fusion

Step 1: ATrous Wavelet Transform
Step 2: Ridgelet Transform
Step 3: Curvelet Transform

C. ATrous WAVELET TRANSFORM

The ATrous wavelet transform (ATWT) is a nonorthogonal, multiresolution decomposition defined by a filter bank \( h_n \) and \( \{ g_n = d_n - h_n \} \), with the Kronecker operator \( d_n \) denoting an all pass filter. The filter bank does not allow perfect reconstruction to be achieved if the output is decimated. In the absence of decimation, the low pass filter is up sampled by \( 2^J \), before processing the jth level; hence the name “ATrous” which means “with holes”. In two dimensions, the filter bank becomes \( h_{full}, h_{low} \) and \( \{ d_{full}, d_{low} = h_{full}, h_{low} \} \) which means that the 2-D detail signals is given by the pixel difference between two successive approximations. For \( J \)-level decomposition, the ATWT accommodates a number of coefficients \( J + 1 \) times greater than the number of pixels. Due to the absence of decimation, the synthesis is simply obtained by summing details levels to the approximation, thereby the ATWT for the \( f(m,n) \) is given by

\[
f(m,n) = c_j(m,n) + \sum_{j=1}^{J} d_j(m,n)
\]

D. RIDGELET AND CURVELET TRANSFORMS

Curvelets are a non-adaptive technique for multi-scale object representation. Being an extension of the wavelet concept, they are becoming popular in similar fields, namely in image processing and scientific computing.

Wavelets generalize the Fourier transform by using a basis that represents both location and spatial frequency. For 2D or 3D signals, directional wavelet transforms go further, by using basis functions that are also localized in orientation. A curvelet transform differs from other directional wavelet transforms in that the degree of localisation in orientation varies with scale. Curvelets are an appropriate basis for representing images (or other functions) which are smooth apart from singularities along smooth curves, where the curves have bounded curvature, i.e. where objects in the image have a minimum length scale. This property holds for cartoons, geometrical diagrams, and text. As one zooms in on such images, the edges they contain appear increasingly straight. Curvelets take advantage of this property, by defining the higher resolution curvelets to be skinnier the lower resolution curvelets. However, natural images (photographs) do not have this property; they have detail at every scale. Therefore, for natural images, it is preferable to use some sort of directional wavelet transform whose wavelets have the same aspect ratio at every scale. The theory of ridgelet and curvelet transforms, presented are used in image fusion technique

E. CONTINUOUS RIDGELET TRANSFORM

Let \( \psi \) be in \( L^2(\mathbb{R}) \) with sufficient decay and satisfying the admissibility condition,

\[
K \frac{\int |\psi(e)|^2 e^{-|e|} \, de}{|c|^2} < \infty
\]
In this process, we adopt Meyer wavelet $\psi$ which has high smoothness and a compact support in the frequency domain. Suppose that $\psi$ is normalized so that

$$K_\psi = \text{1}$$

For each $a > 0$, $b \in \mathbb{R}$, and $\theta \in [0; 2\pi]$: ridgelet basis functions are defined by

$$\psi_{a,b,\theta}(x) = a^{-\frac{1}{2}} \varphi\left(\frac{x_1 \cos \theta + x_2 \sin \theta - b}{a}\right)$$

The Radon transform

$$f \in L^2(\mathbb{R}^2)$$

is given by the following equation

$$Rf(\theta, \epsilon) = \int \int f(x_1, x_2) \delta(x_1 \cos \theta + x_2 \sin \theta - \epsilon) dx_1 dx_2$$

where $\delta$ is the Dirac distribution. For $f \in L^2(\mathbb{R}^2)$ the continuous ridgelet coefficient is given by

$$R_f(a, b, \theta) = \int f(x) \overline{\psi_{a,b,\theta}(x)} dx$$

(1)

Then any function $f \in L^1(\mathbb{R}^2) \cap L^2(\mathbb{R}^2)$ is represented as a continuous superposition of ridgelet functions

$$f(x) = \int \int \int R_f(a, b, \theta) \psi_{a,b,\theta}(x) d\alpha/\alpha^2 db d\theta/4\pi$$

Notice that (1) is also given by the wavelet transform of the Radon transform $f$:

$$R_F(a, b, \theta) = \int Rf(\theta, \epsilon) a^{-\frac{1}{2}} \varphi\left(\frac{\epsilon - b}{a}\right) d\epsilon$$

Deans found that the two-dimensional Fourier transform of $f$ is equal to the one-dimensional Fourier transform of the Radon transform of $f$

$$f(e^{i\cos \theta} e^{i \sin \theta}) = \int Rf(\theta, \epsilon) e^{-i \epsilon t} d\epsilon$$

Hence the Radon transform of $f$ is obtained by the one dimensional inverse Fourier transform of $f(e^{i\cos \theta} e^{i \sin \theta})$ as a function of $\epsilon$.

**F. CURVETLET TRANSFORM**

Let $Q$ denote a dyadic square

$$Q_s = \left[\left[\frac{K_1}{2^s}, \frac{K_1+1}{2^s}\right] \times \left[\frac{K_2}{2^s}, \frac{K_2+1}{2^s}\right]\right]; K_1, K_2 \in \mathbb{Z}$$

let $Q_s$ be the collection of all dyadic squares of scale $s$. We also let $w_Q$ be a window near $Q$ obtained by dilation and translation of a single $w_1$, satisfying

$$\sum_{Q \subseteq Q_s} w_Q^2 = 1$$

We define multiscalce ridgelets where

$$w_{Q_s} \psi_{a,b,\theta}; s \geq 0, \theta \in \Theta, a > 0, b \in K, \theta \in [0, 2\pi]; \psi_{Q_s f}(x_1, x_2) = 2^s f(2^s x_1 - K_1, 2^s x_2 - K_2)$$

Then we have the reconstruction formula

$$f = \sum_{Q \subseteq Q_s} f w_{Q_s}$$
The curvelet transform is given by filtering and applying multiscale ridgelet transform on each bandpass filters as follows

1) **Subband Decomposition.** The image is filtered into subbands:

\[ f \rightarrow (P_0 f, \Delta_1 f, \Delta_2 f, \ldots) \]

where a filter \( P_0 \) deals with frequencies \( |\sigma| \leq 1 \) and the bandpass filter \( \Delta \) is concentrated near the frequencies \([2^S, 2^{2S+2}]\) for example,

\[ \Delta = \phi_{2S} \ast f, \phi_{2S} (\sigma) = \phi (2^{-2S} \sigma) \]

2) **Smooth Partitioning.** Each subband is smoothly windowed into “squares” of an appropriate scale

\[ \Delta f \rightarrow (w_0 \Delta f)_{Q \in \mathcal{Q}} \]

3) **Renormalization.** Each resulting square is renormalized to unit scale

\[ g_{Q} = \left(T_{Q}\right)^{-1} (w_0 \Delta f), Q \in Q \]

4) **Ridgelet Analysis.** Each square is analysed via the discrete ridgelet transform. For improved visual and numerical results of the digital curvelet transform, Starck et al. presented the following discrete curvelet transform algorithm

1) apply the ‘a trous algorithm with \( J \) scales

\[ I(x, y) = C_j(x, y) + \sum_{j=1}^{J} W_j(x, y) \]

where \( C_j \) is a coarse or smooth version of original image \( I \) and \( W_j \) represents “the details of \( I \)” at scale \( 2^{-j} \);

2) set \( B_1 = B_{\text{min}} \)
3) for \( j = 1, \ldots, J \) do
a) partition the subband \( W_j \) with a block size \( B_j \) and apply the digital ridgelet transform to each block;

b) else \( B_{j+1} = B_j \)
III. STUDY AREA AND DATA USED

In this research, study areas have been selected for the application of various tasks undertaken. Roorkee region of India is chosen for landcover classification Roorkee Region state of Uttaranchal, India, depicted in Figure 1, and it lies between latitudes $29^\circ 77'\ N$ and is located in the Haridwar district of the $30^\circ 00'\ N$ and longitudes $77^\circ 33'\ E$ and $78^\circ 01'\ E$. The Roorkee Region has a blend of urban, water and agriculture bodies with a flat region.

![Map of Roorkee Region](image)

Figure 1: Location of the study area (Roorkee region) for fusion techniques, in the Haridwar district, India

Solani river catchment around Roorkee town in the state of Uttarakhand, India has been selected as the test site for landcover classification (figure 1.6). The area is relatively flat with a maximum slope of $4\%$ (elevations ranging from 245.5 m to 289.9 m above the sea level). The region extends from $29^\circ 77'\ N$ and $30^\circ 00'\ N$, and its longitude ranges from $77^\circ 33'\ E$ and $78^\circ 01'\ E$. The study area basically consists of agricultural, water and urban classes. The central region of the test site is covered by Upper Ganga canal which is the main source of water in the area. Urban class is mostly comprised of residential areas.

IV. EXPERIMENTAL STUDY AND ANALYSIS

Several diverse image fusion schemes exist. Our goal in image fusion is to preserve maximum perceptually important information from the source images while not adding distracting artifacts and keeping the scheme robust.
to imperfections such as poor registration of the source images. In order for image fusion to be used optimally, the sensors must be perfectly co-aligned so as to produce original images that are in spatial registration. Since perfect alignment of the sensors is extremely difficult, image fusion methods try to compensate for poor registration whenever possible. The below figures shows the original images of PALSAR in different operating modes like HH, HV, VV, and the NDVI image, and bands of MODIS i.e BAND1, BAND2 is also present. The used method for the classification is supervised classification in which we use minimum distance classification method and the classified and fused images are of April 2011.

Figure 2: Absolute value raw image of PALSAR HH mode

Figure 3: Absolute value raw image of PALSAR HV mode
Figure 4: Absolute value raw image of PALSAR VV mode

Figure 5: NDVI Image

Figure 6: Image of MODIS Band 1
ACURACY AND QUALITY ASSESSMENT OF IMAGE USING CURVELET TRANSFORM AND MINIMUM DISTANCE CLASSIFICATION METHOD

Figure 7: Image of MODIS Band 2

Figure 8: Fused and classified image BAND1_HH

Figure 9: Fused and classified image BAND2_HH
Figure 10: NDVI_HH

Figure 8, 9, and 10 shows the resultant images of image fusion using curvelet transform. The polarized band of PALSAR HH is fused with MODIS BAND1, BAND2, and NDVI. The fusion of BAND1_HH gives the overall 47.11% accuracy and kappa coefficient is 0.2268. Whereas in BAND2_HH the quality of fused image is improved and the measured accuracy is 50.22% and kappa coefficient is 0.2704. From the figure, it is clear that all the regions can be classified easily. But the fusion of HH with NDVI doesn’t give any valuable information and the accuracy is also very low.
Figure 11, 12 and 13 shows the resultant images of image fusion using curvelet transform. The polarized band of PALSAR HV is fused with MODIS BAND1, BAND2 and NDVI. The fusion of BAND1_HV gives the overall 53.33% accuracy and kappa coefficient is 0.3162. But from the figures it is not possible to say anything about the region and classes. All the classes are merged with each other, we can only do some perception about the region. Similarly the fusion of NDVI_HV is also not very clear.
Figure 14, 15 and 16 shows the resultant images of image fusion using curvelet transform. The polarized band of PALSAR VV is fused with MODIS BAND1, BAND2 and NDVI. The fusion of BAND1_VV gives the overall 45.08% accuracy and kappa coefficient is 0.2023. But from the figures it is not possible to say anything about the region and classes. All the classes are merged with each other. The region of solani river and urban are mixing we can only do some perception about the regions. Whereas in fusion of BAND2_VV the accuracy is improved and side by side we can differentiate between water, urban and vegetation. The estimated accuracy and kappa coefficient are respectively 56.38% and 0.35. Similarly the fusion of NDVI_VV is not very clear.

Table 1: Supervised Classification of urban using minimum distance classification

<table>
<thead>
<tr>
<th></th>
<th>PRODUCER ACCURACY</th>
<th>USER ACCURACY</th>
<th>PRODUCER ACCURACY (PIXEL)</th>
<th>USER ACCURACY (PIXEL)</th>
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<td>59/100</td>
<td>59/63</td>
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<tr>
<td>VV</td>
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<td>-</td>
<td>-</td>
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<td>70.00</td>
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<td>87.72</td>
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Table 2: Supervised Classification of vegetation using minimum distance classification

<table>
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<th></th>
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<th>USER ACCURACY (PIXEL)</th>
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<td>27.07</td>
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<td>50.00</td>
<td>30.38</td>
<td>24/48</td>
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</table>

Table 1 represents the supervised classification of images using minimum distance classification method. From the table it is clear that the producer accuracy of raw images of HH, HV and VV are respectively 44.59 and 39 whereas user accuracy are 77.19, 93.65 and 65. When the images are fused with NDVI only the accuracy of VV band increases for the urban region for HH and HV it decreases means it is difficult to find the urban region in these bands. When the fusion of raw images is done with band 1 and band 2 both the user and producer accuracy decreases but in the case of BAND2_VV it increases which represents that urban region is classified with higher accuracy.

Table 2 shows the classification of vegetation using minimum distance classification. The producer and user accuracy of HH, HV and VV modes are represented in the table. When the raw images are fused with NDVI the producer accuracy of NDVI_HH and NDVI_VV increases from 32 to 40 and 44 to 54 respectively whereas user accuracy goes from 14.81 to 16.26 and 20.56 to 34.62. These data refers that the vegetation is occurred in these regions. The fusion with band 1 and band 2 also refers the increase in values in all three modes i.e HH, HV, VV. Form the table it is clear that the maximum value of vegetation is received by using NDVI.

By comparing both the table we can conclude that by using NDVI index the maximum number of vegetation region can be classified as compare to urban region. The fusion process gives the result that the accuracy of fused images are more than the unfused images and the accuracy of image is also increases. So it will be helpful for us to determine the regions.

Data fusion is useful for several purposes such as land surface objects and phenomena detection, recognition, identification, tracking, classification and many other applications. These objectives maybe encountered in many fields of study like remote sensing, defense systems, robotics, medicine, space, environmental, urban,
agricultural studies. Data fusion has been used in many aspects of satellite image analysis: multi sensor fusion, image processing and analysis, classification, image sharpen, improve geometric corrections provide stereo-viewing capabilities for stereophotogrammetry land mapping applications enhance certain features not visible in either of the single data alone complement datasets for improving classification accuracy etc. Single data sources usually offer limited information due to their limited maneuver abilities in the data collection. The ideal of data fusion is getting the highest potential of the fused images the highest potential can be defined as any properties of dataset.

V. Acknowledgment
The authors would like to thank Dr. Dharamendra Singh and Dr. Sandip Vijay for supervising this work. The authors would like to thank IIT, Roorkee and D.I.T, Dehradun for providing the supporting atmosphere and labs.

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