International Journal of Science and Research (IJSR)
ISSN (Online): 2319-7064
Index Copernicus Value (2013): 6.14 | Impact Factor (2013): 4.438

Remote Sensing Satellite Image Fusion Using Fast Curvelet Transforms

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Abstract: ***This paper presents a novel fusion rule via high pass modulation using Local Magnitude Ratio (LMR) in Fast Discrete Curvelet Transforms (FDCT) domain. It is based on the Fourier and wavelet transform methods , which retain rich multispectral details but less spatial details from source images. Wavelets perform well only at linear features but not at non linear discontinuities because they do not use the geometric properties of structures. Curvelet transforms overcome such difficulties in feature representation. In 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. The method has been compared with values obtained from different techniques such as Wavelet, Principal component analysis (PCA), High pass filtering(HPF), Modified Intensity-Hue-Saturation (M.IHS) and Grams-Schmidth fusion methods. Some experimental results and conclusions about the performance of the method are presented.***

Keywords: Image fusion, Interband structure modeling (IBSM), Spatial Resolution, Ridgelet transform, Fast Discrete Curvelet Transforms, Local Magnitude Ratio (LMR).

1. Introduction

The image should focus everywhere to obtain more information, instead of focusing on just one object. This kind of images is useful in many fields such as digital imaging, microscopic imaging, remote sensing, computer vision and robotics. The problem is with the optical lenses, particularly those with long focal lengths, suffer from the problem of limited depth of field [1]. A popular way to solve this problem is image fusion, in which one can acquire a series of pictures with different focus settings and fuse them to produce an image with extended depth of field [2].

Remote sensing image fusion aims at integrating the information conveyed by data, acquired with different spatial and spectral resolutions, for purposes of photoanalysis, feature extraction, modeling, and classification [6]. A notable application is the fusion of multispectral (MS) and panchromatic (Pan) images collected from space. Image fusion techniques take advantage of the complementary spatial/spectral resolution characteristics for producing spatially enhanced MS observations. This specific aspect of fusion is often referred to as band-sharpening [7].

Image fusion methods based on injecting high frequency components taken from the Pan image into resampled versions of the MS data have demonstrated a superior capability of translating the spectral information of the coarse scale MS data to the finer scale of the Pan image with minimal introduction of spectral distortions [8]. The curvelet transform is obtained by applying the ridgelet transform [10] to square blocks of detail frames of an undecimated wavelet decomposition. Since the ridgelet transform possesses basis functions matching directional straight lines, the curvelet transform is capable of representing piecewise linear contours on multiple scales through few significant coefficients. This property leads to a better separation between geometric details and background noise, which may be easily reduced by thresholding curvelet coefficients before they are used for fusion [9].

Image fusion requires the definition of a model establishing how the missing high pass information to be injected into the resampled MS bands is extracted from the Pan image. The goal is to make the fused bands as similar as possible to what the narrow-band MS sensor would image if it had the same spatial resolution as the broad-band one, by which the Pan band is captured. This model is referred to in the literature [11–13] as an interband structure model(IBSM). It deals with the radiometric transformation (gain and offset) of spatial structures (edges and textures) when they are passed from Pan to MS images. The model is usually space varying; it is calculated at a coarser resolution and inferred to the finer resolution. To increase its specificity, it would be desirable to calculate such a model in a different domain, in which linear structures that are injected are represented by few sparse coefficients [14–16].

In this work, we propose an image fusion method which operates in the nonseparable transformed domain of the curvelet transform. The algorithm is defined for either Resourcesat-1 LISS IV or Cartosat-1 imagery, having scale ratio between Pan and MS equal to 4, but may be easily extended to other scale ratios that are powers of two. A thorough performance comparison on both Resourcesat-1 LISS IV and Cartosat-1 datasets is carried out among a number of advanced methods described in the literature. Results highlight the benefits of the proposed method for achieving high resolution of satellite remote sensing imagery.

2. Literature Survey

2.1 Curvelet Transform

The main feature of the curvelet transform is that it is sensitive to directional edges and capable of representing the highpass details of object contours at different scales through few sparse nonzero coefficients. curvelet transform [3] proposed the idea of which is to represent a curve as superposition of functions of various lengths and widths obeying the scaling law width _ length2.

Curvelets differ from wavelet and related systems, and it takes the form of basis elements, which exhibit a very high directional sensitivity and are highly anisotropic. In two dimensions, for instance, curvelets are more suitable for the analysis of image edges such as curve and line characteristics than wavelet. The implementation of curvelet transform has been studied by many researchers. In this section, we introduce the implementation of the second generation curvelet which is simpler, faster, and less redundant [4].

The main benefit of curvelets is their capability of representing a curve as a set of superimposed functions of various lengths and widths. The curvelet transform is a multiscale transform but, unlike the wavelet transform, contains directional elements. Curvelets are based on multiscale ridgelets with a bandpass filtering to separate an image into disjoint scales.

The new fast discrete curvelet transform (FDCT) which implements via wrapping is simpler and faster . Here, we only briefly list the steps of the implement of the FDCT, and interested readers may consult the literature [4] for more details. The corresponding software package CurveLab is available at [5].

2.2. Ridgelet Transform

The next step is finding a transformation capable of representing straight edges with different slopes and orientations. A possible solution is the ridgelet transform [10], which may be interpreted as the 1-D wavelet transform of the Radon transform of f. This is the basic idea behind the digital implementation of the ridgelet transform. An inconvenience with the ridgelet transform is that it is not capable of representing curves. To overcome this drawback, the input image is partitioned into square blocks and the ridgelet transform is applied to each block. Assuming a piecewise linear model for the contour, each block will contain straight edges only, that may be analyzed by the ridgelet transform.

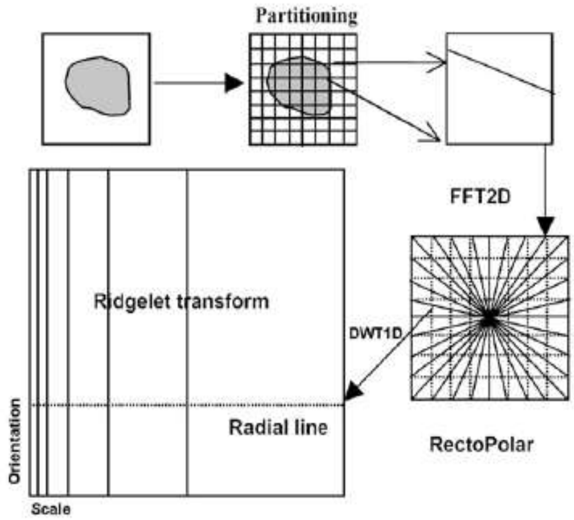


Figure 1: Flowchart of discrete ridgelet transform applied to square blocks of a bitmap image.

The operation of a block ridgelet transform is potrayed in the Fig.1. It highlights that the discrete Radom transform is obtained with a recto-polar resampling of the 2D-FFT of the image block.

2.3. Injection Model

The definition of an IBSM suitable for ruling the transformation of highpass details before they are injected into the resampled MS bands, is a crucial point. In this work, the model has been stated as an adaptive cross-gain. Such a gain weights CT coefficients, after they have been possibly soft thresholded to reduce the background noise. In fact, the spatially uncorrelated noise is uniformly spread onto the CT coefficients; instead, correlated spatial details are concentrated in few sparse coefficients.

The approximations c2 of the MS bands and Pan image are further analyzed with a block ridgelet transform, as shown in Fig.1. A simple IBSM is given by the ratio of local standard deviations of ridgelet coefficients calculated from the approximations (c2) of an MS band and of the Pan image, respectively.

A simple IBSM is given by the ratio of local standard deviations of ridgelet coefficients calculated from the approximations (c2) of an MS band and of the Pan image, respectively. Fig.2 summarizes the calculation the cross-gain map at the finer resolution level s1. Analogously, the map of s2 is calculated with a coarser partition.

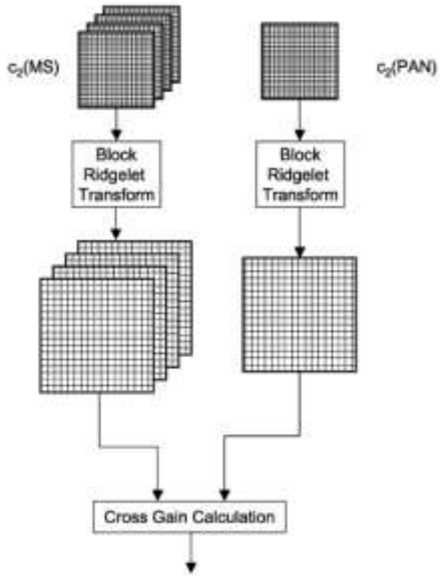


Figure 2: Flowchart of cross-gain calculation in a block-wise directional domain.

Problem Definition

Multisensor data fusion has become a discipline which demands more general formal solutions to a number of application cases. Several situations in image processing require both high spatial and high spectral information in a single image. This is important in remote sensing.

However, the instruments are not capable of providing such information either by design or because of observational constraints. One possible solution for this is data fusion using FDCT(Fast Discrete Curvelet Transforms) technique.

3. Methodology

Above analysis indicates that although the fused results obtained by wavelet or curvelet transform individually are encouraging, there certainly is room for further improvement. Each transform has its own area of expertise and this complementary characteristic may be useful for fusion. So we proposed a combined method considering both the advantages of the wavelet transform and the curvelet transform.

Source images are transformed into curvelet coefficients which contain more edge information of the source images. The coefficient values will be larger if it is corresponded to an edge, but for small details, such as texture or angle points, the coefficients are still small. Instead of fusing the curvelet coefficients directly, we further fuse the coefficients using the wavelet transform-based method. Thus the decomposed coefficients not only contain edge information but also contain small details information.

To obtain HR multispectral image, high frequency details are injected into each LR multispectral band in FDCT domain. Input images size must be power of 2 for coherent multi resolution decomposition in FDCT domain. Fusion process shown in Fig.3 is carried out by the following steps:

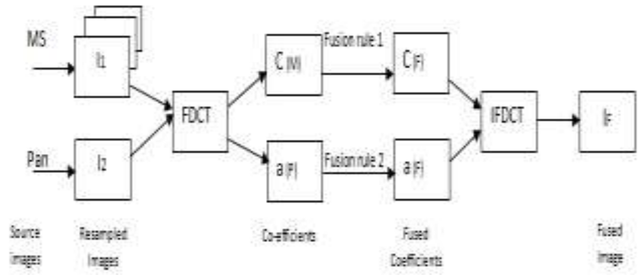


Figure 3: Fusion Process using FDCT on MS and Pan Images

Step.1: LR multispectral image is resampled to the scale of HR Pan image. Both images I1 and I2 must be at identical geometry and of same sizes.
Step.2: Extract band wise the multispectral data in Green, Red and near infra-red bands.
Step.3: Apply FDCT to multispectral band M and Panchromatic image P. Input images are decomposed into four levels in multiple directions.
Step.4: Fusion rule 2 is defined for the curvelet coefficients at lower frequencies a(p) of LR multispectral image and the fused image.
Step.5: Fusion rule 1 is defined for the multidirectional multi resolution curvelet coefficients at higher frequencies C(M) based on high pass modulation.
Step.6: A set of curvelet planes C(F) and a(F)is constructed for the fused image and IFDCT is applied.
Step.7: Combination of three resultant fused bands provide the HR multispectral fused image IF.

In a directional sub-band, bigger curvelet coefficients of HR Pan image and LR multispectral image represent sharp local feature [13]. 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 $cj,l(M)$, $cj,l(P)$ 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.

$$LMRj,l(x, y) = |cj,l(M(x, y))||cj,l(P(x, y))|$$

Where $LMRj,l(x, y)$ is the sub-band curvelet coefficients at scale j in direction l at location (x,y).

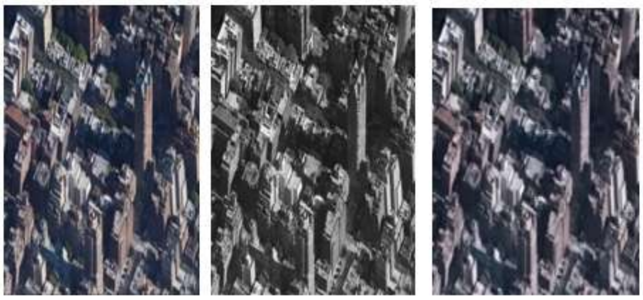
If $LMRj,l(x, y) \leq 1$ then $cj,l(P(x, y))$ represents good local feature. If $LMRj,l(x, y) > 1$ then $cj,l(M(x, y))$ represents good local feature. Fusion rule to inject high spatial details from HR panchromatic image into LR multispectral image bands is defined using LMR of curvelet coefficients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

4. Results and Discussions

For the FDCT-based fusion method, Resourcesat -1 LISS IV image is taken as LR multispectral image which is ortho rectified and resampled to 5m spatial resolution and Cartosat-1 data is taken as an HR Pan image of resolution 2.5m . Both of these images are in 1:2 scale ratio. HR Pan image size is 2048×2048 and LR multispectral image size is

1024 × 1024. For clear visualization, subset images of the fused image of FDCT technique is shown in Fig. 4.

Fig. 4(b) is the original HR Pan Cartosat-1 image and Fig. 4(a) is the resampled LR multispectral image. Fig. 4(c) is the HR multispectral image obtained by new fusion rule based on FDCT. The values obtained by the wavelet transform, PCA, HPF, Modified IHS and Grams-Schmidth fusion techniques respectively implemented in Earth Resources Data Analysis System (ERDAS 2013) satellite image processing software are taken for comparison.



a)LISS IV b)Cartosat-1 c)FDCT

Figure 4: Color compositions of full-scale fusion results for the reported detail (NIR, Red, and Green bands as R, G, and B channels)

Quality of the fused images is evaluated with both spatial and spectral quality measures.

4.1 Spatial Quality Evaluation

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

1) Entropy: The Entropy can show the average information included in the image and reflect the detail information of the fused image. According to the information theory of Shannon, the entropy of image is defined as

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

Where *E* is the entropy of image and *pi* is the probability of *i* in the image , here *pi* is the frequency of pixel values from 0 to n in the image. Entropy values band wise are shown in Table 1.

Table 1: Entropy

FDCT	Wavelet	PCA	HPF	MIHS	GS
7.3971	6.21	6.23	6.23	6.30	6.25

2) Correlation coefficient of high pass filtered images:

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]. 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. [18]. Correlation coefficient of high pass filtered images band-wise are shown in Table 2.

Table 2: Correlation Coefficient Of High Pass Filtered Images

FDCT	Wavelet	PCA	HPF	MIHS	GS
0.99502	0.18	0.77	0.86	0.90	0.64

3) Average gradient: Average gradient reflects the clarity of the fused image. Spatial quality of fused image *f* by average gradient can be calculated by using the equation

$$ag = \frac{1}{(M-1)(N-1)} \sum_{x=1}^{M-1} \sum_{y=1}^{N-1} \sqrt{\frac{|\frac{\partial f(x,y)}{\partial x}|^2 + |\frac{\partial f(x,y)}{\partial y}|^2}{2}}$$

Where $f(x, y)$ is the pixel value of the fused image at position (x, y). Average gradient values band-wise are shown in Table 3.

Table 3: Average Gradient

FDCT	Wavelet	PCA	HPF	MIHS	GS
4.072	3.98	4.40	3.71	4.01	4.13

4.2. Spectral Quality Evaluation

For evaluating Spectral quality of images, resampled multispectral bands of LISS-IV sensor image and corresponding bands in the fused image are compared.

1) Spectral Angle Mapper(SAM):
Spectral angle mapper (SAM) is the absolute value of the angle between the two vectors [19]. SAM is measured in either degrees or radians and is usually averaged over the whole image to yield a global measurement of spectral distortion. Table.4 shows the SAM values for each fused band.

Table 4: Spectral Angle Mapper (In Degrees)

FDCT	Wavelet	PCA	HPF	MIHS	GS
0.06	0.07	0.13	0.04	0.08	0.10

2) Universal Image Quality Index (UIQI):

Universal objective image quality index, is easy to calculate and applicable to various image processing applications. Instead of using traditional error summation methods, the proposed index is designed by modeling any image distortion as a combination of three factors: loss of correlation, luminance distortion, and contrast distortion. Higher value of UIQI indicates the better fusion method. Table.5 shows the UIQI values for each band.

Table 5: UNIVERSAL IMAGE QUALITY INDEX

FDCT	Wavelet	PCA	HPF	MIHS	GS
0.99	0.08	0.08	0.10	0.11	0.09

5. Conclusion

The application on Remote sensing satellite images puts forward an image fusion algorithm based on the Second Generation Fast Discrete curvelet Transform. In this paper, we firstly analyze the results of the fusion method using FDCT-based method. Then a comparison on performance values of different image fusion methods will give the better conclusion on the proposed FDCT based fusion method. In our algorithm, firstly, each of the registered images are decomposed using curvelet, then the coefficients are fused using the fusion rules. 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. Fused coefficients are reconstructed by performing the inverse curvelet transform. 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. The experimental results on given images showed that the proposed method has better performance than Wavelet, Principal component analysis (PCA), High pass filtering (HPF), Modified Intensity- Hue Saturation (M.IHS), and Grams-Schmidt fusion methods. Proposed method spatially outperforms the other methods and retains both spatial and rich multispectral details.

6. Future Scope

In the future enhancement work, we propose a method to interpret the features more efficiently, having high resolution by using Contourlet Transforms. 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. In the proposed methods, a given number of decomposition levels are used for multispectral (MS) 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.

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