MULTIRESOLUTION BASED TEXTURAL ANALYSIS OF REMOTELY SENSED IMAGES FOR CHANGE DETECTION

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ABSTRACT

This paper presents a multiresolution textural approach to change detection in multi-temporal synthetic aperture radar (SAR) images. Texture analysis is often discussed in image processing domain, but most methods do not exploit the fact that texture occurs at various spatial scales. Often used techniques such as the gray level co-occurrence statistics is limited to altering inter-neighbor spacing and hence does not capture the texture very well. The proposed approach exploits curvelet and contourlet based multi-scale decomposition of Pauli RGB decomposed images from SAR data where textural information is extracted at various scales and in different directions in terms of statistical moments and energy to generate the feature map. The L1-norm is used in the proposed method to generate the difference image, which is thresholded using the maximum entropy principle to obtain final change detection map. The results are compared with the changes detected by wavelet based textural features. Accuracy assessment is performed for change maps and comparative analysis is carried out in terms of missed changes, false-alarms and overall accuracies. It is found that the proposed method exhibits high change detection accuracy with better edge continuity.

1. INTRODUCTION

The detection of changes occurring on the earth surface through the use of multi-temporal remote sensing images is one of the most important applications of remote sensing technology. It serves wide range of applications related to environmental monitoring (Chavez and Mackinnon, 1994), agricultural surveys, urban studies (Merril and Jiajun, 1998), and forest monitoring (Hame et al., 1998).

Change detection (CD) involves the analysis of two co-registered remote sensing images of the same area at different times. In the analysis of multi-temporal remote sensing data acquired by multispectral sensors, various methods have been developed and described in the literature. Most are based on the change vector analysis (Singh, 1989). This technique exploits a simple vector subtraction operator to compare pixel-by-pixel the two multispectral images. The separation between changed and unchanged classes is done on the magnitude of the resulting spectral change vectors by means of various thresholding methods (Singh, 1989). A simple thresholding on cumulative histogram of difference image and logarithmic ratio image is used for change detection (Dekker, 1998).

Dierking and Skriver (2002) found that intensity images are better suited for change-detection purposes than correlation coefficient and phase difference between the co-polarized channels. They used the ratio operator to compare the temporal images and a decision mechanism based on a desired value of the probability of false alarms.

By contrast, some other methods include a feature selection process and apply classification on the features instead of on the original difference image. Bovolo and Bruzzone (2005) used a wavelet-based decomposition of the log-ratio image for change detection. The principal component analysis (PCA) technique has been used in Celik (2009) to extract the features from the overlapping patches of the difference image, and then *k*-means is used to clustering the features into two classes. In Celik and Ma (2010), wavelet transform is applied to get the difference image, and binary change detection has been conducted on each sub-band and then they are fused as the final change map.

Most of the feature space based methods in literature use wavelet based features for change detection. Wavelet based MRA showed great effect when dealing with 1D and 2D signals with point singularity features. Wavelets can only capture limited directional information due to its poor orientation selectivity (Welland, 2003) and might not capture enough directional information in remotely sensed images. In order to avoid this shortcoming and process images of high dimension more effectively, curvelet (Candes and Donoho, 2000) and contourlet transforms (Do and Vetterli, 2002) are used. This paper explores and proposes a texture based change detection scheme using moment based features derived from the wavelet, curvelet and contourlet transforms.

2. MRA FOR IMAGE ANALYSIS

2.1 Curvelet Transform

Wavelet transform decomposes the image into a series of high-pass and low-pass filter bands, and extracts directional information that captures horizontal, vertical, and diagonal details. However, these three linear directions are limiting and might not capture enough directional information in remotely sensed images.

Curvelet transform is a multi-scale and multi-directional transform with wedge shaped basis functions. Basis functions of wavelets are isotropic and thus they require large number of coefficients to represent the curve singularities. Curvelet basis functions are wedge shaped and have high directional sensitivity and anisotropy (Candes and Donoho 2000). The curvelets at different scales and directions span the entire frequency space and their basis functions are considered as grouping of wavelet basis functions locally into linear structures so that they can capture the curvilinear discontinuity more efficiently. Curvelet basis functions can be viewed as a local grouping of wavelet basis functions into linear structures so that they can capture the smooth discontinuity curve more efficiently as demonstrated in Fig. 1.

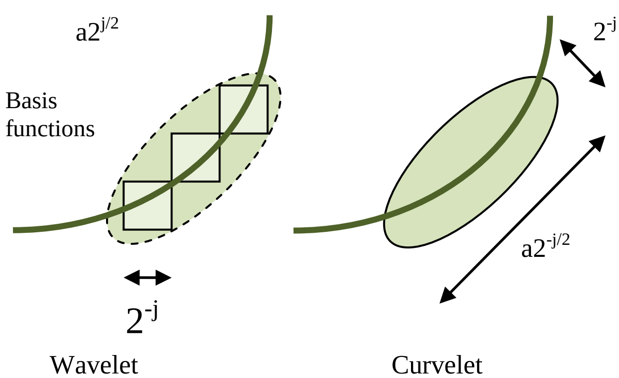


Fig. 1. Non-linear approximation of a 2-D piecewise smooth signals using wavelets and curvelets (Do and Vetterli 2002)

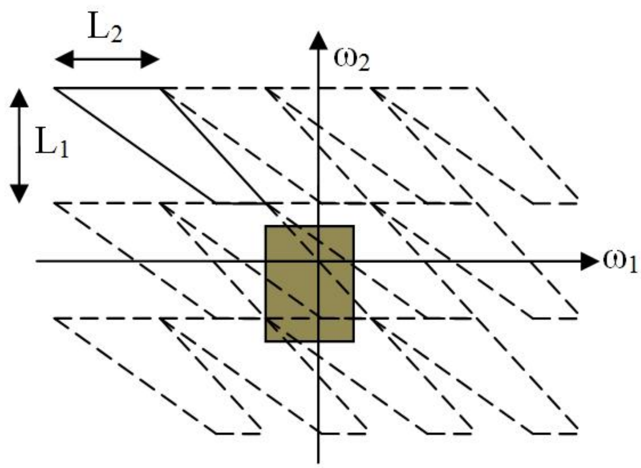


Fig. 2. Multiplication of FFT data with curvelet window, the data on a wedge shaped support is mapped into a rectangle (Nguyen and Chauris, 2010)

According to Gibb's phenomenon discontinuities destroy the sparsity of a Fourier series (Mallat, 1989). Therefore more number of coefficients is required to reconstruct a discontinuity within good accuracy. As wavelets are localized and multi-scale, they perform much better in one dimension, but because of their poor orientation selectivity, they do not represent higher dimensional singularities effectively. The curvelet transform is organized in such a way that most of the energy of the object is localized in just a few coefficients, but there is no basis in which coefficients of an object with an arbitrary singularity curve would decay faster than in a curvelet frame. This rate of decay is much faster than that of any other known system, including wavelets (Cand`es and Demanet, 2003). This faster decay gives optimally sparse representations which in turn is suitable for image reconstructions. Curvelets partition the frequency plane into dyadic sub-bands and (unlike wavelets) sub-partition those into angular wedges which again display the parabolic aspect ratio. Hence, the curvelet transform refines the scale-space viewpoint by adding an extra parameter; orientation, and operates by measuring information about an object at specified scales and locations.

The curvelet transform has gone through two major revisions. First generation (Cand´es and Donoho, 2000) used a complex series of steps involving the ridgelet analysis of the radon transform of an image. Their performance was very slow; therefore, an improved version was developed which is known as Fast Discrete Curvelet Transform (FDCT). In this paper, wrapping based fast discrete curvelet transform is used.

The wrapping based FDCT takes a 2D image as an input in the form of a Cartesian array $f[m, n]$, where $0 \le m<M, 0 \le n<N$ where M and N are the dimensions of the array. The

following are the steps of applying wrapping based FDCT algorithm (Cand`es et al., 2006);

1) Apply the 2D FFT to an image to obtain Fourier samples F[m, n]
2) For each scale j and angle l, form the product $U_{j,l}$ [m, n] F[m, n] (Fig. 2).
3) Wrap this product around the origin and obtain coefficients in frequency domain.
4) Apply IFFT to get the curvelet coefficients in spatial domain.

2.2 Contourlet Transform

The contourlet transform is a new extension to wavelet filters in two dimensions and is constructed using non-separable and directional filter banks (DFB). Its expansion is composed of basis images oriented at varying directions in multiple scales, with flexible aspect ratios. With this set of basis images, it effectively captures the smooth edges that are the dominant features in natural images with only a small number of coefficients. First, a wavelet-like transform for edge detection and then a local directional transform for smooth segment detection are used to implement the contourlet filter (Do and Vetterli, 2005). With this insight, a Pyramidal DFB structure is constructed, in which the Laplacian Pyramid (LP) is used to capture the point discontinuities, followed by a DFB to link point discontinuities into linear structures.
Fig. 3 describes a multi-scale and directional decomposition, where band-pass images from LP are input to directional filter banks to extract the directional information. This is iterated on the coarser image for further decomposition into sub-bands. By combining these two steps, the support size of the PDFB basis functions is changed from one level to the next according to the curve scaling relation as demonstrated in Fig. 4.

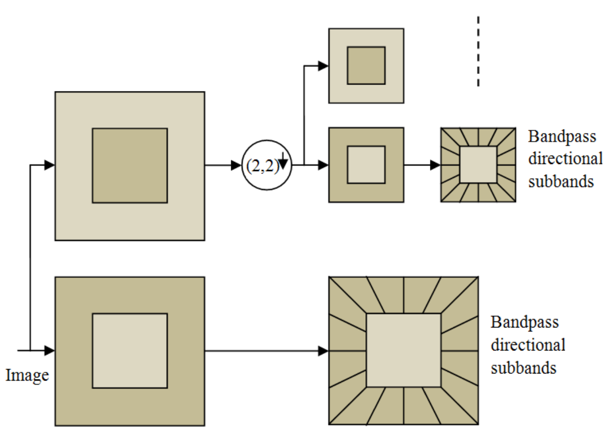


Fig. 3. Contourlet filter bank (Do and Vetterli, 2005)

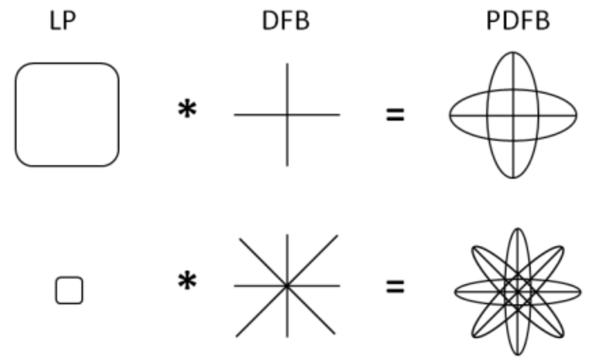


Fig. 4. Support of basis by PDFB (Do and Vetterli, 2002)

Bandpass images from the LP are given to a DFB so that directional information can be captured. The scheme can be iterated on the coarse image. The combined result is a double-iterated filter bank that decomposes images into directional sub-bands at multiple scales.
Since the multi-scale and directional decomposition stages are decoupled in the discrete contourlet transform, we can have a different number of directions at different scales, thus providing a flexible multi-scale and directional expansion of remotely sensed images.
In this paper, the algorithm depicted in Fig. 3 is implemented using orthogonal and bi-orthogonal filter banks of wavelet and contourlet tools in MATLAB.

3. METHODOLOGY

In this study change detection algorithm consists of four main steps:

1) Three level MRA decomposition,
2) Extraction of the moment based statistical texture features,
3) Computing L1 norm between features derived from two multi-temporal images and
4) Applying entropy based thresholding to get final change map.

The moment based features characterize the textural properties of the changed and unchanged areas of the image here.

4. RESULTS AND ANALYSIS

To illustrate the advantage of proposed method, we display Pauli RGB decomposition and reference image for selected SAR data of the areas near to San Francisco in Fig. 5(a-c).
Fig. 6 and Table 1 show the change detection results and performance measures respectively. Fig. 6(a) shows that wavelet based features are unable to detect the change properly in the top-right corner of the image, whereas same change is detected with better accuracy using contourlet and curvelet based features (Fig. 6(b-c)). Fig. 6(c) shows the change detected by curvelet, it is observed the change

detected areas have better edge regularity as compared to that of wavelets. The result of the proposed curvelet method seems better than others since the unchanged background areas are very clean without any spots and the changed areas are better detected. In particular, the edge continuity of the changed areas and curve-shaped changed areas are better preserved by the proposed method than others. Wavelet based change performs worst which has largest number of misclassification pixels; False Positive + False Negative (8.04%) and lowest Percentage Correct Classification (90).


(a) Pauli RGB 2009


(b) Pauli RGB 2015

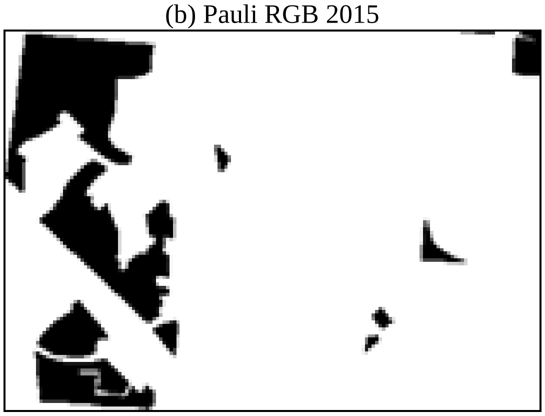
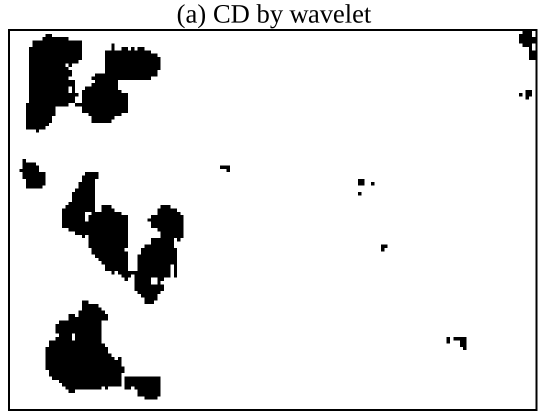

(c) Reference image

Fig. 5. Original Pauli RGB SAR image


(a) CD by wavelet


(b) CD by contourlet

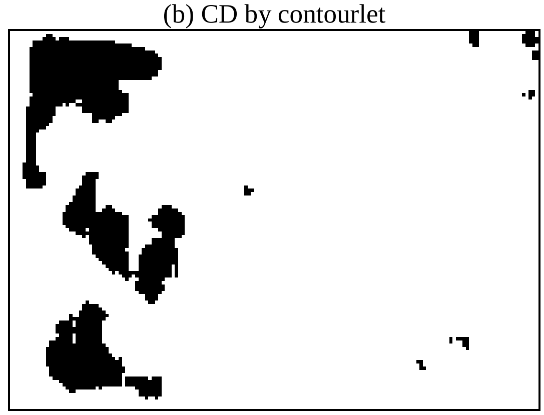

(c) CD by curvelet

Fig. 6. Change detection using MRA

Table 1: Change detection performance

Parameters	MRA method		
	Wavelet	Curvelet	Contourlet
False Positive (%)	0.76	1.2	1.1
False Negative (%)	7.28	4.79	5.34
True Positive (%)	5.47	7.96	7.41
True Negative (%)	86.5	86.06	86.13
Correct Classification (%)	90	94	94

5. CONCLUSIONS

In this paper, we have presented an MRA based change detection method for Pauli RGB SAR image based on textural features at different scales of MRA. Since curvelet and contourlet filters are good at representing images with both homogenous region and areas with textural details containing curvilinear edges, the proposed methodsperform well at preserving edge continuity and detecting curve-shaped structures. On observing the final change map it can be concluded that the spatial fidelity obtained with the proposed method of curvelet and contourlet is more than that obtained with the wavelet based approach. The experimental results and quantitative analysis show that the proposed method performs better than the existing method of wavelet and is promising in change detection.

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