TEXTURE BASED CLASSIFICATION OF REMOTELY SENSED IMAGES USING MULTIRESOLUTION METHODS

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ABSTRACT

Multi-resolution analysis (MRA) has been successfully used in image processing with the recent emergence of applications to texture classification and segmentation. Several studies have explored the utility of wavelet-based MRA features in various applications of image compression, image denoising and classification of natural textures. Recently, the curvelet and contourlet transforms have emerged as new multi-resolution analysis tools to deal with non-linear singularities present in the image. This paper explores and proposes a texture based classification of remotely sensed images using features derived from the curvelet and contourlet transforms. These features characterize the textural properties of the image and are used in a classifier to recognize different texture classes. Using these MRA based feature descriptors class separability is defined in feature space. The results are compared with wavelet based statistical features.

1. INTRODUCTION

Texture analysis is often discussed in image processing domain, however most methods do not exploit the fact that texture occurs at various spatial scales. Often used technique such as the gray level co-occurrence statistics is limited to altering inter-neighbor spacing and to four directions of neighbors and hence does not capture the texture very well. This is particularly true in case of remotely sensed images and therefore it is necessary to adopt a proper model that can overcome the above limitation in order to segment remotely sensed images.

Multi-resolution analysis allows for the preservation of an image according to certain levels of resolution or degree of blurring. MRA allows for the zooming in and out on the underlying texture structure. Therefore, the texture extraction is not affected by the size of the pixel neighborhood. This multi-resolution quality is one of the reasons why wavelets have been useful in textural analysis (Jain and Farrokhnia 1991; Unser 1991; Laine and Fan 1993).

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 classification scheme using moment based features derived from 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.

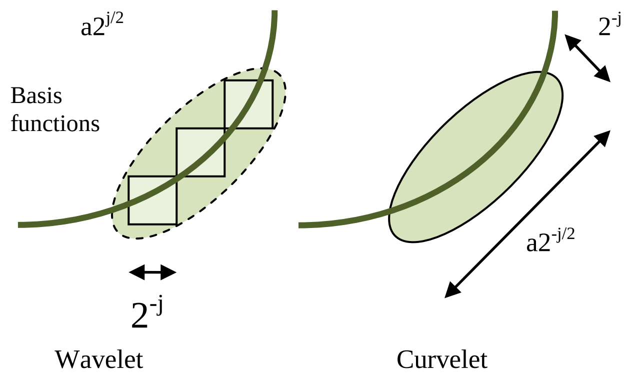


Fig. 1. Non-linear approximation of a 2-D piecewise smooth signals using wavelets and curvelets (Do and Vetterli, 2002)

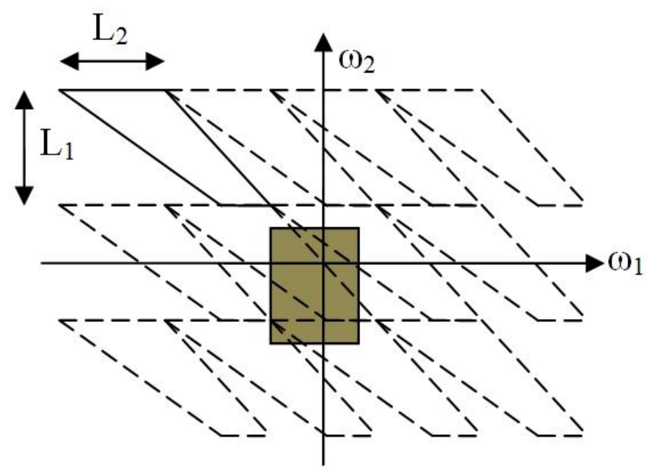


Fig. 2. Multiplication of FFT data with curvelet window, the data on a wedge shaped support is mapped into a rectangle (Nguyen and Chauris, 2010)

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 (Cand`es et al., 2006) is used.

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

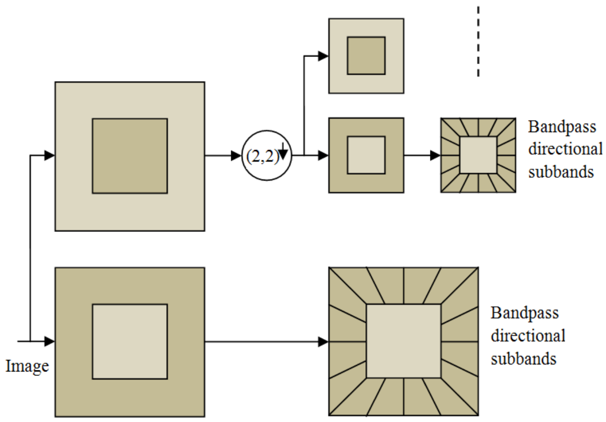


Fig. 3. Contourlet filter bank (Do and Vetterli, 2005)

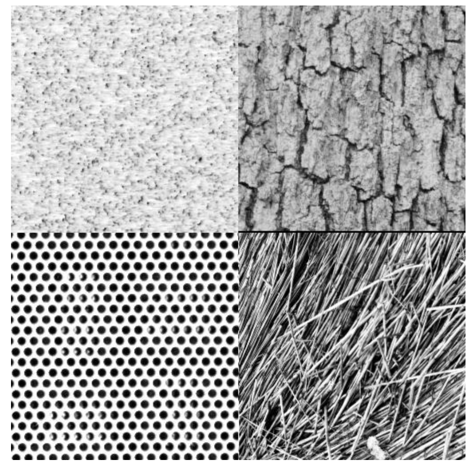
Bandpass images from the LP are given to a DFB so that directional information can be captured. The scheme can be iterated on the coarse image. The combined result is a double-iterated filter bank that decomposes images into directional sub-bands at multiple scales.
Since the multi-scale and directional 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 texture classification algorithm consists of three main steps: segmentation of pure regions, extraction of the most discriminative moment based statistical texture features, and creation of classifier that will identify the various regions. The regions are initially cropped manually to obtain pure samples of each texture, then wavelet, curvelet and contourlet transforms are applied and a set of moment and energy based texture descriptors are extracted from the transformed coefficients. These features characterized the textural properties of the images and classification is done using minimum distance to mean classifier.

4. RESULTS AND ANALYSIS

To evaluate the performance, a simulated image using Brodatz textures (Fig. 4) and an IRS-1C panchromatic (spatial resolution of 5.8m) image of Mumbai city (Fig. 5) are utilized. This is suitable for texture analysis since its resolution is not adequate to extract individual roads or narrow roads but groups of them render a visible checked pattern in dense urban areas.
Total five classes (water, shallow water, high build-up area, low or partially build-up area and open area) are considered for feature extraction. Next, Euclidean distance between normalized feature vectors for each pair of classes for wavelet, curvelet and contourlet methods are computed. These distances are represented as class separability measures. Table 1 indicates the relative separation between classes in the texture feature space.


(a) Original image compiled from Brodatz samples (Brodatz, 1966)

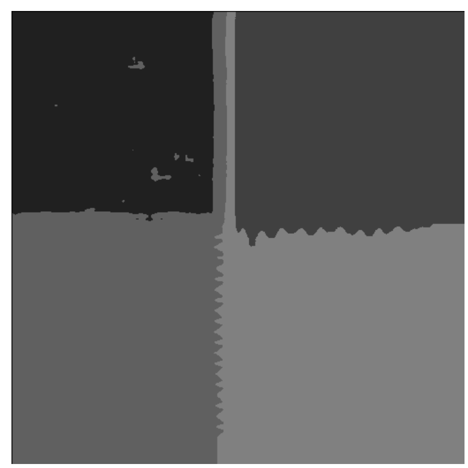
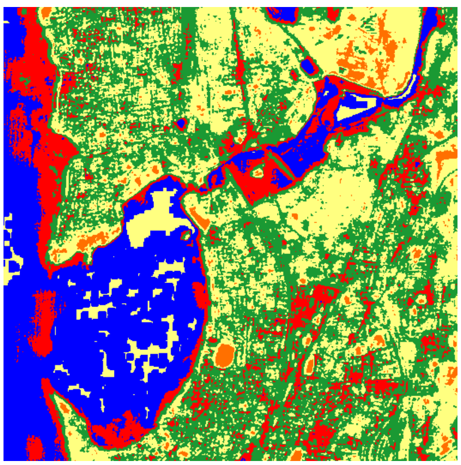
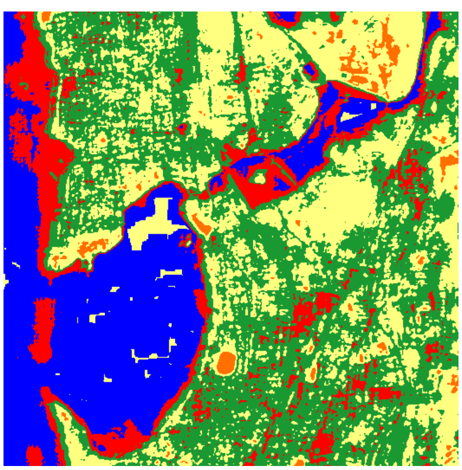

(b) Segmented image using curvelet method

Fig. 4. Segmentation of synthetic image

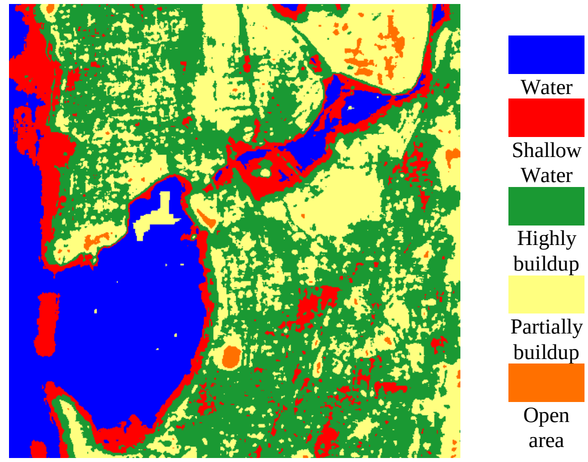
(a) Original image



(b) Segmented image using wavelet method



(c) Segmented image using contourlet method



(d) Segmented image using curvelet method

Fig. 5. Segmentation on IRS 1C image

Table 1: Performance in terms of class separability

Class pairs	Distance between feature descriptors		
	Wavelet	Curvelet	Contourlet
Water-Shallow Water	4.1	8.6	7.5
Water-High Buildup area	5.2	8.8	7.6
Water-Low Buildup area	3.2	7.3	6.1
Water-Open area	4.8	9.1	7.8
Shallow Water-High Buildup	4.8	9.4	8.1
Shallow Water-Low Buildup	6.2	13.5	10.5
Shallow Water-Open Area	2.2	8.4	8.4
High Buildup–Low Buildup	5.4	8.2	7.8
High Buildup-Open Area	5.1	11.9	9.5
Low Buildup-Open Area	5.9	7.4	6.3

5. CONCLUSIONS

In this paper, the application of wavelet, contourlet and curvelet based MRA is presented for textural segmentation. The idea behind proposed method is to effectively represent curvilinear discontinuities in satellite images using curvelet and contourlet based MRA techniques. Textural information in terms of statistical moments and energy are extracted at various scales and in different directions with the help of curvelet and contourlet coefficients. The multi-scale curvilinear approach yielded better class discrimination for all the class pairs. It is observed that curvelet and contourlet based features are more powerful than wavelet based features for all the class pairs. The classes are properly segmented with sharper boundaries. The results are very encouraging and suggest that proposed method can be pursued further for SVM based classification.

6. REFERENCES

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