SEGMENTATION OF POLARIMETRIC SAR IMAGES USIG WAVELET TRANSFORMATION AND TEXTURE FEATURES

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ABSTRACTS:

Polarimetric Synthetic Aperture Radar (PolSAR) sensors can collect useful observations from earth's surfaces and phenomena for various remote sensing applications, such as land cover mapping, change and target detection. These data can be acquired without the limitations of weather conditions, sun illumination and dust particles. As result, SAR images, and in particular Polarimetric SAR (PolSAR) are powerful tools for various environmental applications. Unlike the optical images, SAR images suffer from the unavoidable speckle, which causes the segmentation of this data difficult. In this paper, we use the wavelet transformation for segmentation of PolSAR images. Our proposed method is based on the multi-resolution analysis of texture features is based on wavelet transformation. Here, we use the information of gray level value and the information of texture. First, we produce coherency or covariance matrices and then generate span image from them. In the next step of proposed method is texture feature extraction from sub-bands is generated from discrete wavelet transform (DWT). Finally, PolSAR image are segmented using clustering methods as fuzzy c-means (FCM) and k-means clustering. We have applied the proposed methodology to full polarimetric SAR images acquired by the Uninhabited Aerial Vehicle Synthetic Aperture Radar (UAVSAR) L-band system, during July, in 2012 over an agricultural area in Winnipeg, Canada.

1. INTRODUCTION

PolSAR image segmentation can be used for both detecting of land cover types, and improving of classification results. Image segmentation, in general, is defined as the process of partitioning an image into homogenous areas. This process is a critical stage for the success of further analysis. This is the first step of automatic image processing, such as feature extraction, classification, object detection and recognition (Wang et al., 2004). Unlike the optical images, SAR images suffer from the unavoidable speckle, which causes the segmentation of this data difficult. Speckle is caused by the random interactions (constructive and destructive) of the reflections from the scatterers on the imaged surface (Venkatachalam et al., 2000). Hence, segmentation techniques that work successfully on optical images do not produce desired results on segmentation of SAR images. Speckle in SAR images complicates the image interpretation and image analyses, and reduces the effectiveness of image segmentation and feature classification (Lee et al., 2009).

For segmentation of PolSAR images, many approaches have been proposed. Among these approaches, the multiresolution technique is one of the best methods, which is based on multiresolution analysis (MRA), provided by Mallat (Mallat et al., 1989). During multiresolution segmentation methods, wavelet transformation is widely used to express the multiresolution representation of images (Zheng et al., 2013). Since it is happen that different ground-objects have same or similar backscattering coefficient, as a result they will express the same or similar gray level value. In addition, the existence of speckle aggravates confusion furthermore (Xue, et al, 2012). So use only the information of gray level value is not sufficient and effective for segmentation of PolSAR images. Because the equal fields affected by speckle in PolSAR images are generally corresponding to the same field of gray level in the texture measure image, better result of PolSAR image segmentation will be gotten when texture information is used (Wang et al., 2004). An image texture is defined as a function of spatial variation in pixel intensities (gray level values). There are different ways for texture analysis such as statistical approaches and structural approaches. Statistical approaches use statistical properties for characterise textures. But structural approaches use the mathematical rules underlying their appearance for characterise textures and use the principle 'texture primitives'. Statistical approaches when used that Microtextures are dominate. Microtextures refer to textures which are localised and contain rapid variations in image intensity (gray levels), as opposed to macrotextures which refer to textures with large patterns or have great regularity in their composition. Therefore we apply statistical approaches in this paper for texture analysis and texture extraction. Statistical methods include first-order statistics and second-order statistics, especially the grey-level co-occurrence matrix (GLCM) (Ng, Brian Walter., 2013).
Efforts and researches of (Du et al., 1992), (Venkatachalam et al., 2000) and (Li et al., 2009) are example of using wavelet for segmentation of SAR images.
The rest of this paper is outlined as follows: In section 2 the theory of discrete wavelet transforms (DWT) is briefly discussed. In section 3, proposed methodology of segmentation is explained. Segmentation results and details of implementation of proposed method are the subject of section 4. Finally, in the last section, conclusions of the work are drown.

2. DISCRETE WAVELET TRANSFORM

Among different methods of multiresolution analysis (MRA), this paper is used time-frequency analysis with wavelet. Wavelet transformation has become popular method in signal and image processing. According to Mallat's pyramid algorithm (Mallat et al., 1989) wavelet transformation is used for representation of an image in multiresolution. One the important features of wavelet when used in image analysis is processed in both space domain and frequency domain, In contrast, when use the Fourier transformation, it is only a time domain transformation, which has no time-frequency localization features. The discrete wavelet transform (DWT) is an implementation of the wavelet transform using a discrete set of wavelet scales and translations, thereby separating the data into different frequency components with each component resolution matched to its scale (Dutta et al., 2014).
The 2-D discrete wavelet transform (DWT) hierarchically decompose the original image into sub bands where the sub bands are high and low frequency component of the initial image. By once applying DWT, the original image is decomposed to four sub bands as follows HH1, HL1, LH1 and LL1. For the next coarse level of decomposition, LL1 sub-band only selected for further decomposition. Again, obtain four other sub bands as follows HH1, HL1, LH1 and LL1. DWT decomposition for 2 level of decomposition shown in Figure 1. Sub-band HH represent the horizontal and vertical high frequency component, sub-band HL represent the horizontal high and vertical low frequency component, sub-band LH represent the horizontal low and vertical high frequency component and sub-band LL represent the horizontal and vertical low frequency component of image. The low frequency contents (LL sub-band) contain much of information and are called the approximation coefficients. While high frequency content (LH, HL, HH sub-bands) which contain noise and edges are called the detailed coefficients.

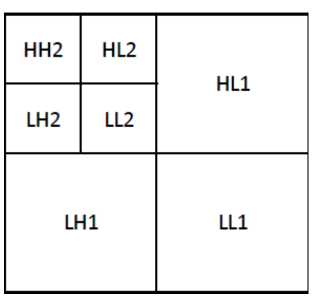


Figure 1. 2 level DWT decomposition

Using the coefficients of approximation and detailed sub-band images, can be demonstrate the texture discrimination and use for PolSAR image segmentation.

3. METHODOLOGY

In this paper, we use the wavelet transformation and texture features for segmentation of PolSAR images. The summery of steps of proposed method is shown in Figure 2 and completely is described in the rest of this section.

3.1 Preprocessing

In proposed method, initial input image is span of PolSAR image. To generate the span image from PolSAR image, first, produce the coherency matrix [T] or covariance matrix [C]. Then, according to equation (1), make up span image. T_{ii} and C_{ii} in equation (1) are diagonal elements of [T] and [C] matrices.

$$\begin{aligned} span &= T_{11}^{2} + T_{22}^{2} + T_{33}^{2} \\ span &= C_{11}^{2} + C_{22}^{2} + C_{33}^{2} \end{aligned} \tag{1}$$

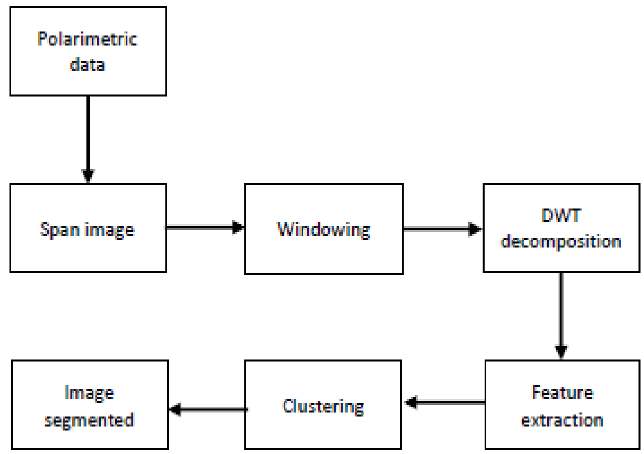


Figure 2. Flowchart of segmentation of PolSAR image

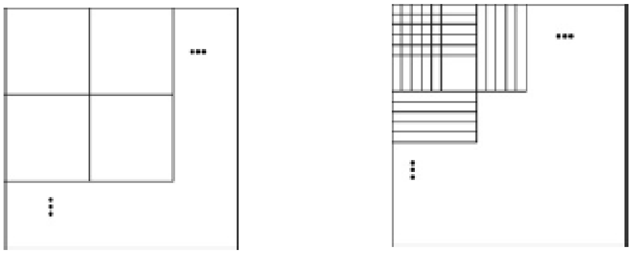
3.2 Feature extraction

The topic of texture analysis can be divided into two main problems: classification and segmentation. Texture classification problems deal with the ability of an artificial system to effectively discriminate between different textures. Texture segmentation studies algorithms which divide a given image into distinct regions based on textural information (Ng, Brian Walter., 2013). In this paper we apply statistical approaches for texture analysis and texture extraction. Statistical methods use the grey-level co-occurrence matrix (GLCM) for feature textures. The features are used in this paper are energy and contrast which are expressed in equation (2) and (3). For computing the energy and contrast features, using overlapping windows is suggested. The window in the classical multiscale segmentation methods is not overlapping as shown in Figure (3.a). So for more efficient segmentation, new method of windowing is presented by (Li and et al., 2009) that using the overlapping window as shown in Figure (3.b).

$$Energy = \sum_{i,j=1}^{N} \mathrm{W(i, j)}^2 \tag{2}$$

$$Contrast = \sum_{i,j=1}^{N} (i-j)^2\, \mathrm{W}(i,j) \tag{3}$$

Where $w(i,j)$ in above equations are wavelet coefficients and i and j are position of pixel in overlapping windows.
Then DWT is performed for each window and extract energy and contrast from window and belong values to the central pixel.



(a) (b)

Figure 3. Windows. (a) Multiscale segmentation without overlapping window. (b) Multiscale segmentation with overlapping window

For d-level DWT decomposition, produce 3d+1 DWT sub-bands. It is clear that whatever level of decomposition is increased, the length of feature vectors are increased as well as. It is very well-known that long feature vectors may reduce the efficiency of a classifier, therefore level of decomposition in multiresolution analysis, should not be very low that details is removed and should not be very high that reduce the efficiently of classifier.
Dimension of feature vector is 3d+4. For example, if level of decomposition is 2 (d=2), feature vector as follows:

$$FV = [s_0 \quad e_0 \quad c_0 \quad e_{HH-1} \quad e_{HL-1} \quad e_{LH-1} \quad e_{HH-2} \quad e_{HL-2} \quad e_{LH-2} \quad e_{HH-2}] \tag{4}$$

In above equation, *s* correspond to *span*, *e* correspond to *energy* and *c* correspond to contrast measures.

3.3 Clustering

In clustering step, we use the two popular clustering algorithm, as follows: fuzzy c-means (FCM) clustering and k-means clustering. The both implementation of algorithms, produced relatively similar results.
Summary of the proposed of segmentation of PolSAR images is as follows:
Step 1: Produce the coherency matrix [T] or covariance matrix [C] from polarimetric data and then generate span image from them.
Step 2: The window of size $n \times n$ is considered. For each center pixel in a region of an overlapping window, the 2-level discrete wavelet decomposition is applied and the energy and contrast measures of channels are made up of the feature vector for each pixel.
Step3: Again, step 2 is repeated for all pixels in span image and complete the feature vectors for all pixels.
Step 4: Two method of clustering are used for image segmentation. Fuzzy c-mean clustering (FCM) and k-means clustering.

4. POLARIMETRIC SAR DATA

We have applied the proposed methodology to full polarimetric SAR images acquired by the Uninhabited Aerial Vehicle Synthetic Aperture Radar (UAVSAR) L-band system, during July, in 2012 over an agricultural area in Winnipeg, Canada. The radar will be fully polarimetric, whit a range bandwidth of 80 MHz (2m range resolution), and will support a 16 km range swath (Rosen et al., 2006). This area consists of a rich variety of annual crops including cereals, wheat, oilseeds, soybeans, corn, and pasture/forage. Figure 4, shows the color composite of Pauli decomposition and span image is shown in figure 5. Size of image is 512×512 and size of overlapping window is considered 7×7 , 9×9 and 11×11. Each overlapping window, taken from top left corner of the span image is decomposed using DWT decomposition. Here, the mother wavelet is haar, and the number of decomposition is two.

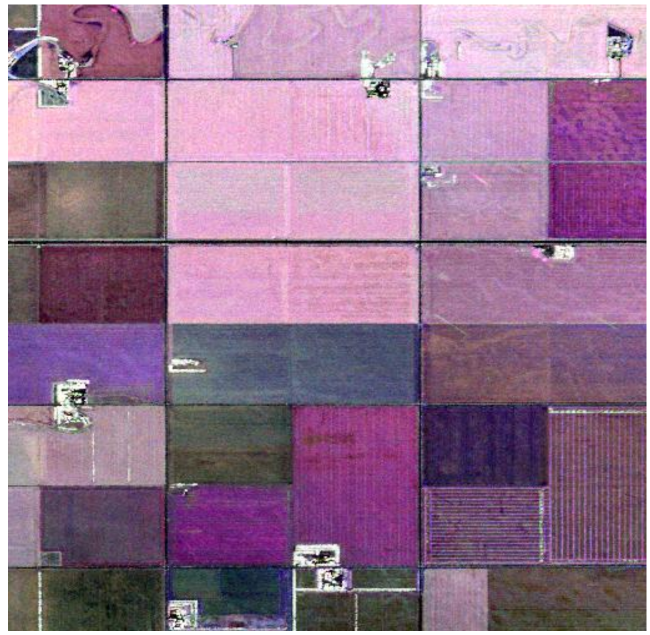


Figure 4. Color composite of Pauli decomposition

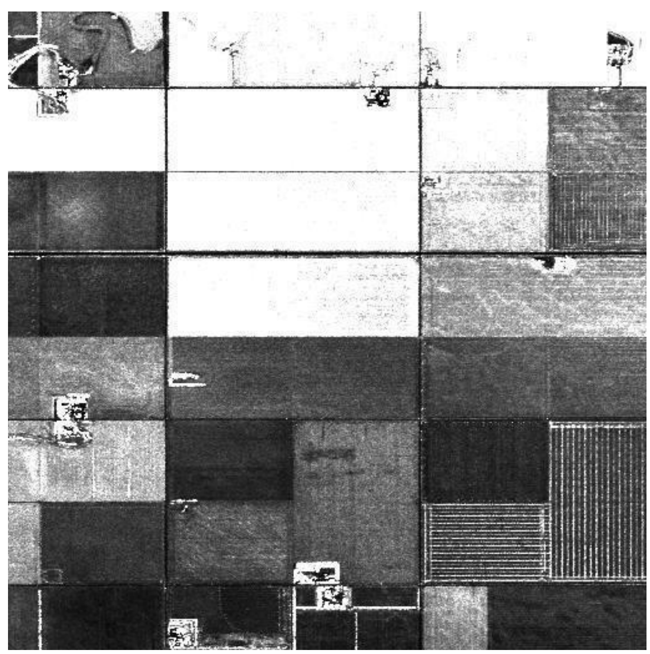
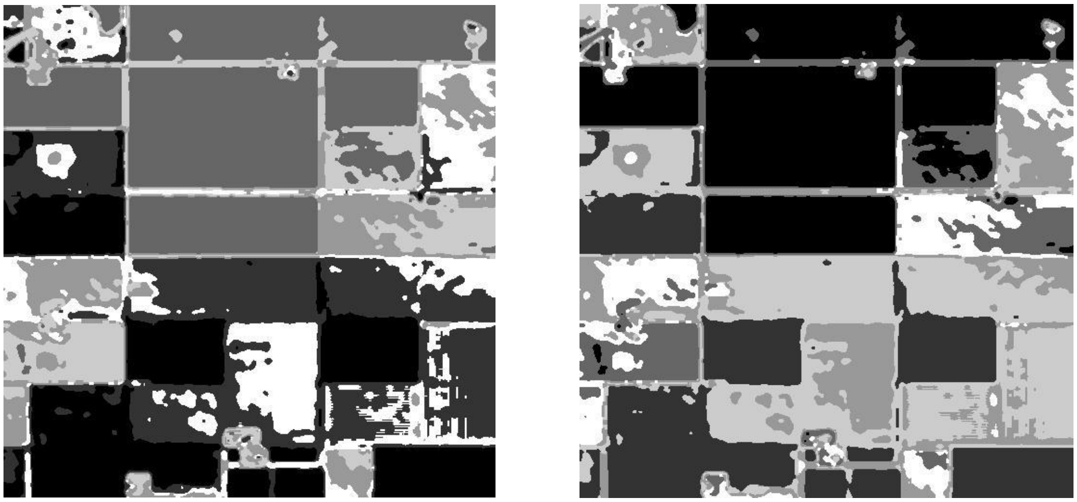


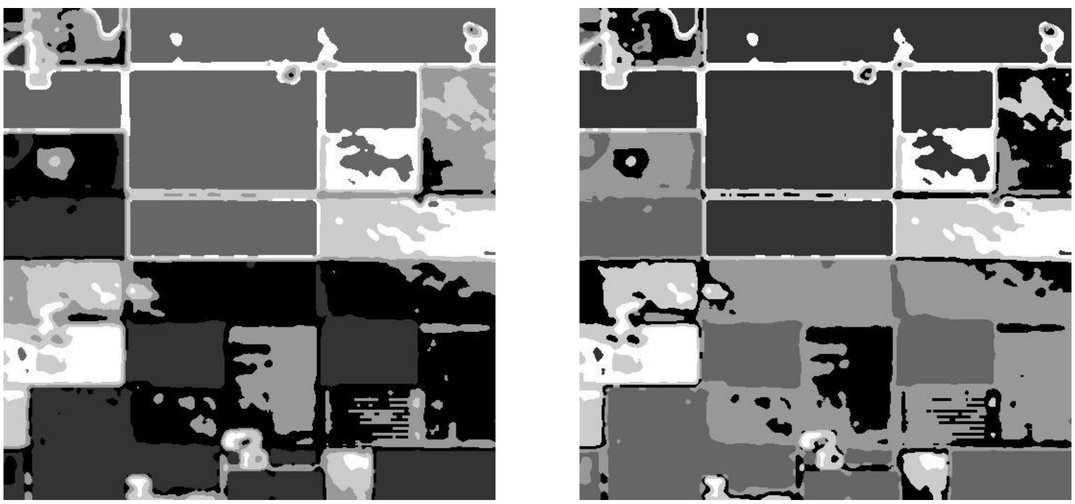
Figure 5. Span image of polarimetric data

Segmentation of PolSAR images is shown in Figure 6, Figure 7 and Figure 8 for different sizes of windows.



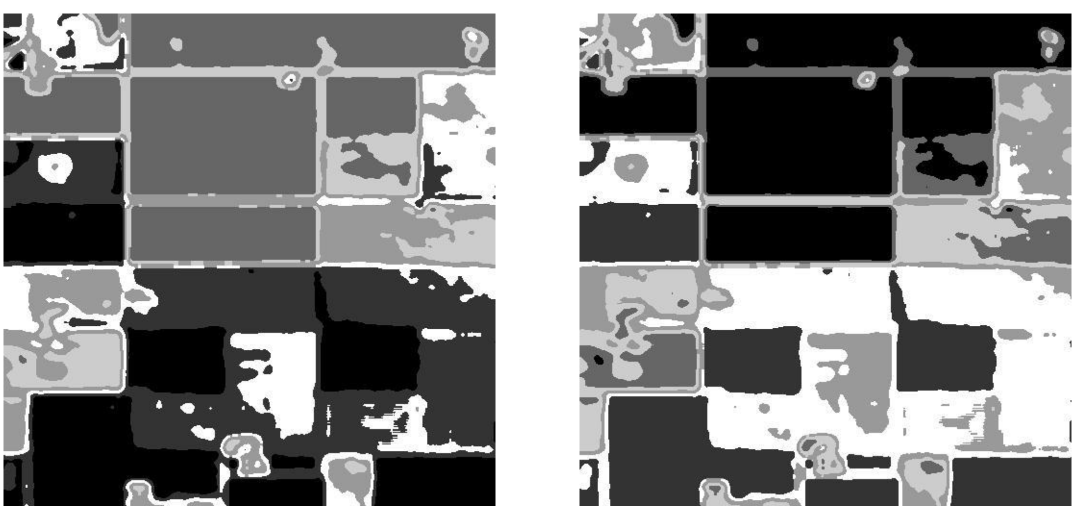
(a) (b)

Figure 6. Result of segmentation. (a) FCM clustering with 7×7 windowsize (b) k-means clustering 7×7 windowsize



(a) (b)

Figure 6. Result of segmentation. (a) FCM clustering with 9×9 windowsize (b) k-means clustering 9×9 windowsize



(a) (b)

Figure 6. Result of segmentation. (a) FCM clustering with 11×11 windowsize (b) k-means clustering 11×11 windowsize

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5. CONCLUSION

This paper presented a segmentation method for full polarimetric SAR data based on wavelet transformation and texture features. The final results showed that use the information of texture features along with other features increases the overall accuracy than the use only one of the texture features or intensity features. In this paper uses the new windowing method. Using overlapping windows leads to better results than using sliding windows. As well as use the larger windowsize, lead to better results.

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