Unsupervised Classification of Land-Coverage Using Polarimetric SAR images

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***Abstract*— Widely used unsupervised classification method H/A/alpha classification, explores the scattering information of land-coverage data, but performs poorly on the decision boundary. Maximum Likelihood Supervised Classification using Wishart distribution, based on the statistic properties requiring picking up training set manually from large SAR image, can't be automated. In this project, I propose a hybrid classification scheme combining both methods, exploit the scattering mechanism of targets and is also automated.**

Keywords-component: hybrid; automated; K-means; ML supervised classification; Unsupervised H-A-α classification

I. Introduction

Fully polarimetric synthetic aperture radars are devices used to transmit and receive both the orthogonal components of an electromagnetic wave. The vector information, compared with just magnitude information recorded by traditional radar device, ensures that the complete scattering information carried by returning waves can be used for later application. Using the appreciably more information observed by fully polarimetric SAR, the images can be widely used in classification, target detection and so on. Classification of ground cover, such as forest, vegetation, sea-ice types, ocean and urban areas, has been an important application of Polarimetric images. It is also a crucial step in SAR Automatic Target Recognition (ATR) System.
Canonically, classification methods for SAR images can be divided into two categories, supervised and unsupervised methods. Two methods from different categories, are widely used. Cloude and Pottier [1] proposed H-A-α classification and J.-S.Lee [2] proposed supervised ML classification. However,both methods have their pros and cons. In this project, I combine these two method to develop a new hybrid unsupervised classification scheme and examine the performance with ALOS Polarimetric SAR data.

II. Fundamental Properties of PoLSAR Image

A. Polarimetric SAR Image Data

First, a polarimetric radar measures the complete scattering matrix S of a medium at a given incidence angle. The scattering matrix is given by

$$S = \begin{bmatrix} S_{HH} & S_{HV} \\ S_{HV} & S_{VV} \end{bmatrix} \qquad (1)$$

The first H denotes the horizontal antenna and V denotes vertical antenna. The second H means horizontally polarized while V means vertically polarized signal. Thus, S_{HH} represents horizontally received horizontally polarized signal while S_{HV} represents the horizontally received vertically polarized signal. Since most of the targets presents symmetric property, S_{HV} is almost the same with S_{VH} , instead of using scattering matrix, scattering vector is used for computation convenience.

$$K = [S_{HH} \quad \sqrt{2}S_{HV} \quad S_{VV}]^T \qquad (2)$$

Besides the scattering vector, another widely used signal is coherence matrix T. Coherence matrix T is defined as

$$T = K^T K \qquad (3)$$

Coherence matrix T and scattering vector K both are sufficient statistics for Polarimetric information. In this project, I use T matrix to derive the algorithm and process the data.

B. SAR Image Speckle Filtering

Unlike optical remote sensing image, which is very neat , SAR image are affected by speckle. Speckle confers to SAR images a granular aspect with spatial variations.

To remove the speck effect, the efficient and convenient method is just taking average over a rectangular window. In SAR image processing, the number of pixels averaged is called looks, usually called L. Then the T matrix would become

$$<T>=\frac{1}{L}\sum_{i=1}^{L}T_i \qquad (4)$$

The filtering procedure will reduce the noise for the following classification scheme.

C. Supervised ML classification

Research has shown that covariance matrix of SAR image follows a complex Wishart distribution,given by

$$p([T]) = \frac{n^{qn}\,|[T]|^{n-q}\,\exp(-tr(n[\Sigma]^{-1}[T]))}{K(n,q)\,|[\Sigma]|^{n}} \qquad (5)$$

$$\text{with} \quad K(n,q) = \pi^{q(q-1)/2}\prod_{i=1}^{q}\Gamma(n-i+1)$$

Where $\Gamma(.)$ represents the Gamma distribution. After the training data, we get the covariance matrix of specific class, written as Σ. In Bayes framework, to define a pixel to one class is to fine the maximum probability of P(T|Σ). Then this decision rule problem can be expressed as

$$i = \arg\min d(T \mid \Sigma_i)$$
$$d(T \mid \Sigma_i) = \ln|\Sigma| + tr(\Sigma^{-1} T) \tag{6}$$

This method use the statistic properties and region information of SAR image, however, doesn't fully exploit the SAR polarimetric information.

D. H-A-Alpha Decomposition

H-A-Alpha decomposition theorem is the basis for the classification algorithm below. This theorem exploit the algebraic structure of the coherency matrix T. The parameters extracted using H-A-Alpha method represent the scattering mechanism of the targets, which gives a good feature for classification. The coherency matrix T, can be written as :

$$T = \begin{bmatrix} |S_{HH}+S_{VV}|^2 & (S_{HH}+S_{VV})(S_{HH}+S_{VV})^* & 2S^*_{HV}(S_{HH}+S_{VV}) \\ * & |S_{HH}-S_{VV}|^2 & 2S_{HV}(S_{HH}+S_{VV}) \\ * & * & 4|S_{HV}|^2 \end{bmatrix} \tag{7}$$
$$= \sum_{i=1}^{3} \lambda_i e_i e_i^*$$

Where λ are the eigenvalues and e are the corresponding eigenvectors, which elements are defined as:

$$e_i = [\cos(\alpha_i) \quad \sin(\alpha_i)\cos(\beta_i)e^{j\delta_i} \quad \sin(\alpha_i)\cos(\beta_i)e^{j\gamma_i}]^T \tag{8}$$

Then derived from the eigenvalues and eigenvectors, three parameters are used to describe the polarimetric properties: the entropy H, the angle α and the anisotropy A, defined respectively as :

$$H = -\sum_{i=1}^{3} P_i \log P_i, \qquad P_i = \lambda_i / (\lambda_1 + \lambda_2 + \lambda_3)$$
$$\alpha = \sum_{i=1}^{3} P_i \alpha_i \tag{9}$$
$$A = (\lambda_2 - \lambda_3)/(\lambda_2 + \lambda_3)$$

The H A α parameters can represent different scattering mechanisms of the target. Cloude and Pottier proposed an algorithm to identify in an unsupervised way polarimetric scattering mechanisms in the H-α plane, since H (entropy) is a measure of the inherent reversibility of the scattering data and the α is used to identify the underlying average scattering mechanism.

The H-α classification plane is divided into 8 basic zones, characterizing 8 different scattering behavior. The plane is shown below

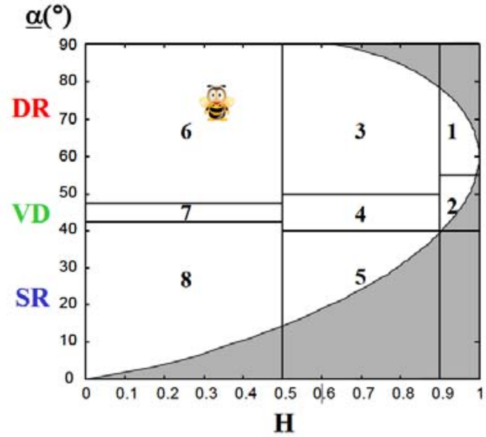


Figure 1 :H-alpha plane classification

The vertical axis α discriminate surface reflection (SR), volume diffusion (VD) and double bounce reflection (DB) and horizontal axis H represents low, medium and high degree of randomness. H-A-alpha decomposition gives the initial value for the classification, but since the threshold of H-A-alpha classification is rigid, the method doesn't work well when the pixels fall near the classification boundary.

III. ALGORITHM PROCEDURE AND TEST RESULT

Since the limitation of wishart classification and H-A-α classification, a hybrid classification method, combining the advantage of both methods, are explored in this project. The flow of the method is illustrated as

a) ***Read the SAR image raw data and contrust the T matrix for each pixel .***

b) ***Take 4*4 window of the T matrix image(equavalent to 16 looks) to get the new image.***

c) ***Decompose every T matrix to get the H A a values of the SAR image.***

d) ***Mapping each pixel into H-α plane according to their H-α values derived from the decomposition.***

e) ***According to the position in the H-α plane, label pixels into 8 classes.***

f) ***For each class, find the class center T_m matrix.***

g) ***Compute every pixel's distance with 8 centers and relable the pixels into the nearest center class.***

h) ***Recompute the class center and the pixel distance , repeat g the new class center until convergence.***

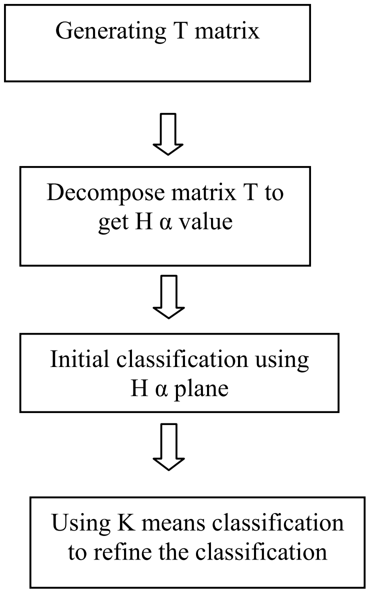


Figure 2 : algorithm flow chart

IV. EXPERIMENT AND RESULT

In this project, I use ALOS Polarimetric SAR image of Hawaii area to test the result.

ALOS (Advanced Land Observation Satellite) , is a Japanese satellite launch in 2006. The satellite is used to map terrain in Asia and Pacific. Hawaii area from google map, is like

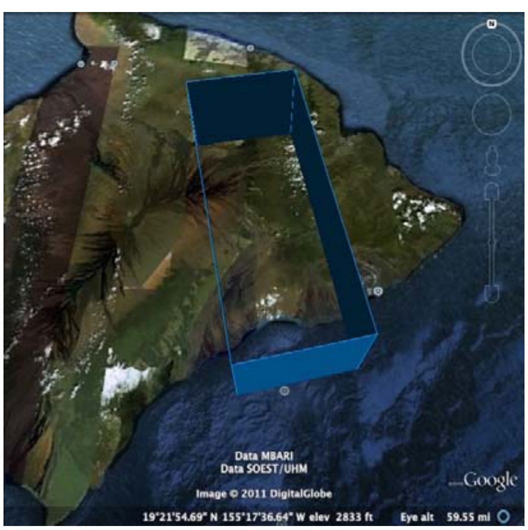
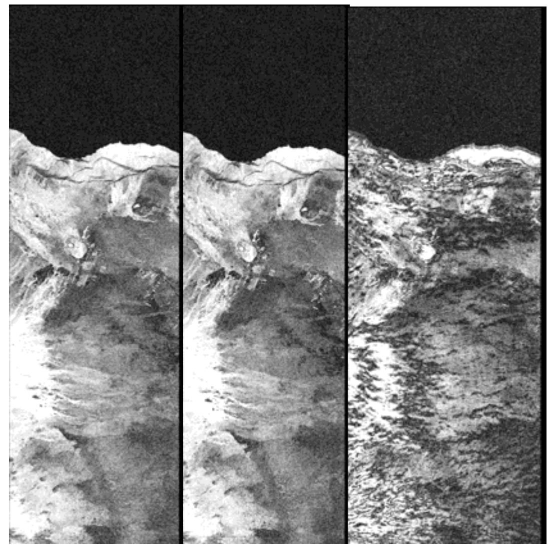


Figure 3: google map image of experiment data area

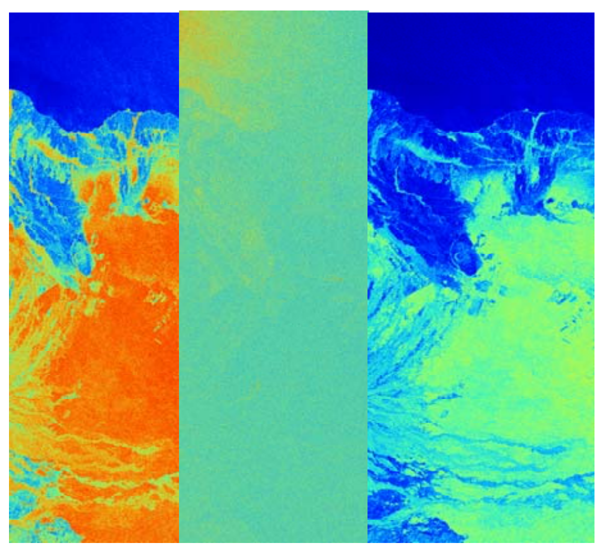
The SAR image data is like below



S_{HH} S_{VV} S_{HV}

Figure 4: magnitude of three channels

After H-A-α decomposition, plot the H A α value



H A α

Figure 4 : H A α value of the image

Plot the data into H/α plane, the result is

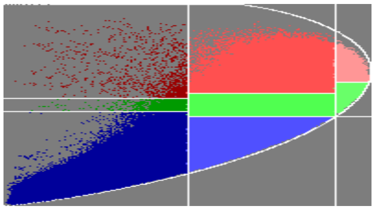


Figure 6: H-alpha plane of SAR image

The classification result for the image

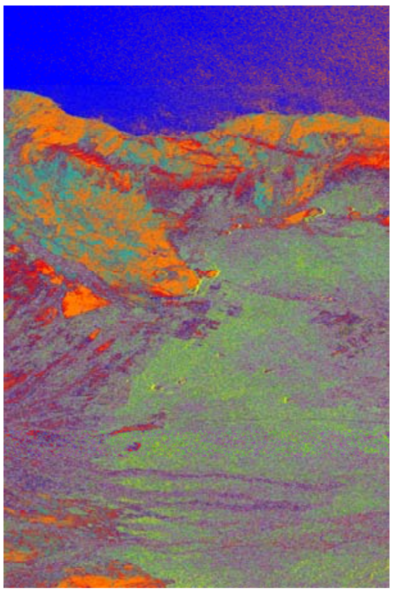


Figure 7: classification result

(color represents different class)

CONCLUSION AND FUTURE WORK

Since the large size of SAR image (18432*1248 pixels) and lack of exact information of ground, the classification result is hard to evaluate for the whole image. However, from the image, we can see this method can mostly separate the sea area (blue), mountain area (orange), forest area (green) and ground area (red).

Besides, the algorithm is automated, so every to implemented.

However, we can see that especially in the sea area, a lot of pixels are mislabeled.

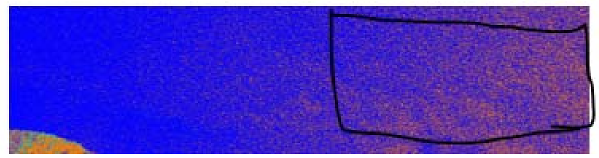


Figure 8: Mislabeled Sea pixels

I suspect the reason for this error might be

1) from the data set. The pixels on the right side are far range field (the distance to the radar sensor is further compared with left side pixels). Image correction with respect to range is needed to remove this effect

2) lack of context information. After mapping the pixels in H-α plane, the original context information is lost. So considering the context information in the algorithm will help.

SAR image classification is a big and hot area in Remote Sensing. This project is just a preliminary work. Because of the limited time, the paper is just a first stage of this work. I will explore further on this topic in the future.

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