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Terrain and Land Classification of Polsar Data

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ABSTRACT:
Synthetic Aperture Radar is a form of two dimensional or three dimensional data which plays an important role in remote sensing. The Synthetic Aperture Radar operates in all weather conditions and generate high resolution images. The Polarimetric Synthetic Aperture Radar (PolSAR) is a four or fully polarimetric radar which can provide scattering information under different combinations of wave polarizations. SAR and PolSAR are widely used for observation of natural scenes.
This paper describes the PolSAR classification which involves two steps. They are pre processing and post processing. In the pre processing, the input can be taken from the SENTINEL 1 data of Visakhapatnam. The classification algorithms of Polarimetric Synthetic Aperture Radar (PolSAR) images are generally composed of the feature extractors that transform the raw data into discriminative representations, followed by trainable classifiers. Traditional approaches always suffer from the hand-designed features and misclassification of boundary pixels. Following the great success of K-MEANS and minimum distance algorithm is presented in this project.
This paper proposes a new network based on K-MEANS for PolSAR image classification. The patch images extracted from raw coherency matrix are fed to the input layer. Then, the proposed network extracts nonlinear relationship between the input samples automatically. Finally, the original label map and contour information are combined to make the decision of each pixel, outputting the final label map. Experimental results on public datasets illustrate that the proposed method can automatically learn the intrinsic features from the PolSAR image for classification purpose.

KEYWORDS: PolSAR, K-MEANS,SENTINEL
SOFTWARE: SNAP, ArcGIS, ENVI

I. INTRODUCTION:

The fully polarimetric synthetic aperture radar (PolSAR) is used for active remote sensing since it can provide scattering information under different combinations of wave polarizations. PolSAR systems measures the properties of distant targets by detecting the change of the polarization state, the target induces to the incident wave. PolSAR data can be used to acquire more information. In most SAR, PolSAR systems, the size of the resolution cell is much larger than the wavelength. The synthetic aperture radar (SAR) can operate in all weather conditions and generate high resolution images. The PolSAR plays a very important role in many fields like geology, military, topography, glaciology etc. The terrain and land classification PolSAR data is one of the most difficult tasks in remote sensing image field. In order to improve the classification accuracy of PolSAR image, many researchers have forward the application of spatial information into PolSAR image classification. The classification methods of PolSAR data which includes spatial information can be mainly divided into three categories. They are pre-processing, post-processing and the third method is using the spatial information directly for classification. Here the input data is taken from the Visakhapatnam zone through a sensor named as SENTINEL-1. In general the polarimetric scattering information available from PolSAR image can be effected by the speckle noise which effects the ouput results. The pre-processing step involves three stages. They are speckle filtering, radiometric correction and geometric correction. The post-processing includes the classification algorithms.

II. OBJECTIVE:

The objective of this paper is classifying the remotely sensed PolSAR data using the classification algorithms. Speckle (granular noise) is formed during back scattering. It is more difficult to classify if the image contain noisy content. Image classification includes few steps to get a high resolution image. Before classifying the SAR data, it has to be pre-processed and then speckle noise is to be removed by using filtering techniques. The SAR data image has to be decomposed and then it can be classified into required features. Image classification is extracting information classes from multiband raster image. Classification is the process of assigning land cover classes to pixels. Here the pixel or pel or picture element is the smallest unit in the image and the land cover classes includes vegetation, water, buildings etc. There are two main image classification techniques in remote sensing.

1. Unsupervised image classification
2. Supervised image classification

Unsupervised image classification:

- A classification procedure is unsupervised if no training data is required and the user only needs to specify the information that does not describe individual class characteristics. It is mainly used for understanding the data.

Supervised image classification:

- Supervised classification uses the spectral signature defined in the training set .The training data can come from an imported ROI file or the regions created on the image. The common supervised classification algorithms are maximum likelihood and minimum distance classification. In this supervised classification technique the number of classes should known priorly.

PROPOSED METHOD:

Unsupervised Classification :

Clustering: Pattern classification by distance functions .

Premise:

Pixels which are close to each other in feature space are likely to belong to the same class.

• The "distance" between pixels in feature space is the measure of similarity.

• Distance may be scaled in pixels, radiance, reflectance

• Most effective if the clusters are disjoint.

• Requires the least amount of prior information to operate.

Distance in feature space is the primary measure of similarity

in all clustering algorithms.

Two "patterns" in a two-dimensional measurement space are illustrated in the figure. The patterns are identifiable because the points group or cluster in this measurement space.

Pixels that are "close" in feature space will be grouped in the same class.

a) The relative distances may change when data are calibrated (digital counts ==> radiance) or atmospherically corrected or rescaled in ways that treat different spectral bands differently..

b) If two features have two different units, they must be scaled to provide comparable variance. Otherwise the "distance" will be biased toward the feature with the smallest absolute range.

PROPOSED ALGORITHM:

K-means Algorithm - adaptive cluster centers

• In the previous clustering examples, once a point has been selected as a clustering center, it remains a clustering center, even if it is a relatively poor representative of its cluster.

• The K-means algorithm allows the cluster centers to shift in order to optimize a performance index.

• Many variations of the K-means algorithm have been developed, but the steps of a basic procedure will be shown here.

$$d = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

Where d is the distance between the clusters

Algorithm for K-means:

Step 1: Initialize number of clusters, k and center.

Step 2:For each pixel of an image, calculate the Euclidean distance d, between the center and each pixel of an image.

Step 3:Assign all the pixels to the nearest center based on distance d.

Step 4:After all pixels have been assigned, recalculate new position of the center

Step 5:Repeat the process until it satisfies and reshape the cluster pixels into image.

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Minimum distance:

$$T = \sum_{i=0}^{n}\sum_{j=0}^{n}(Z_i - Z_j) \Big/ \sum_{k=1}^{n-1}\frac{k(k+1)}{2}$$

Where
$\mathbf{Z}_1$ and $\mathbf{Z}_2$ are 1st and 2nd cluster values
T is the Euclidean distance

Algorithm for minimum distance:

Step 1: Initially the mean value for all class image is calculated in each band of data. The minimum distance is initialized to be high value.
Step 2: The Euclidian distance (T) from each unknown pixel to the each vector for each classified is calculated.
Step 3: All pixels are classified to the closest region of interest.

III. RESULTS AND ANALYSIS:

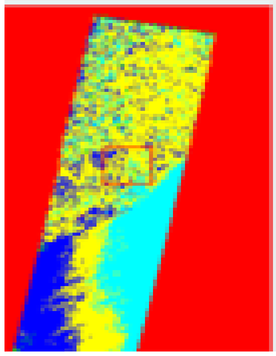

Figure 1: Classified image of K- MEANS Clustering

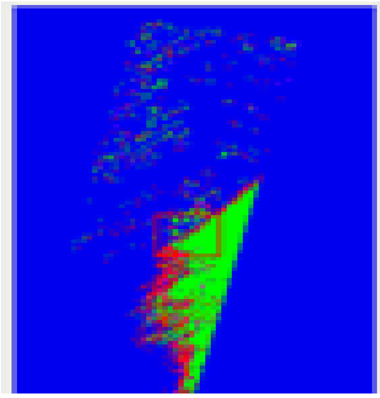

Figure 2: Classified image of Minimum distance.

K –MEANS VV confusion matrix

Overall accuracy = (121/369) = 32.7913%
Kappa co-efficient= 0.1345

Ground Truth (pixels)

CLASSES	Vegetation	Urban	Soil	Water	Total
Class 1	9	0	0	0	9
Class 2	4	1	2	0	7
Class 3	22	32	75	24	153
Class 4	67	64	33	36	200
Total	102	97	110	60	369

Ground Truth(percent)

CLASSES	Vegetation	Urban	Soil	Water	Total
Class 1	0.02	0.00	0.00	0.00	2.44
Class 2	3.92	1.03	1.82	0.00	1.90
Class 3	21.57	32.99	68.18	40.00	41.46
Class 4	65.69	65.98	30.00	60.00	54.20
Total	100.00	100.00	100.00	100.00	100.00

Class	Commission (Percent)	Omission (Pixels)	Commission (Pixels)	Omission (Pixels)
Class 1	0.00	91.18	0/9	93/102
Class 2	85.71	98.97	6/7	96/97
Class 3	50.98	31.02	78/153	35/110
Class 4	82.00	40.00	164/200	24/60

Class	Prod. Acc. (Percent)	User. Acc. (Percent)	Prod. Acc. (Pixels)	User Acc. (Pixels)
Class 1	8.82	100.00	9/102	9/9
Class 2	1.03	14.29	1/97	1/7
Class 3	68.18	49.02	75/110	75/153
Class 4	60.00	10.00	36/60	36/200

MINIMUM DISTANCE VV confusion matrix
Overall accuracy = (96/250) = 38.4000%
Kappa co-efficient= 0.0747

Ground Truth (pixels)

CLASSES	Vegetation	Urban	Soil	Water	Total
Vegetation	10	19	7	4	40
Urban	2	1	2	1	6
Soil	40	46	82	25	193
Water	2	4	2	3	11
Total	54	70	93	33	250

Ground Truth(percent)

CLASSES	Vegetation	Urban	Soil	Water	Total
Vegetation	18.52	27.14	7.53	12.12	16.00
Urban	3.70	1.43	2.15	3.03	2.40
Soil	74.07	65.71	88.17	75.76	77.20
Water	3.70	5.71	2.15	9.09	4.40
Total	100.00	100.00	100.00	100.00	100.00

Class	Commission (Percent)	Omission (Pixels)	Commission (Pixels)	Omission (Pixels)
Vegetation	75.00	81.48	30/40	44/54
Urban	83.33	98.57	5/6	69/70
Soil	57.51	11.83	111/193	11/93
Water	72.73	90.91	8/11	30/33

Class	Prod. Acc. (Percent)	User. Acc. (Percent)	Prod. Acc. (Pixels)	User Acc. (Pixels)
Vegetation	18.52	25.00	10/54	10/40
Urban	1.43	16.67	1/70	1/6
Soil	88.17	42.49	82/93	82/193
Water	9.09	27.27	3/33	3/11

IV. CONCLUSION

By all counts and with proven results, classification analysis of PolSAR data has been done with the help different classification techniques. Initially the data has to be filtered by using lee filter in order to remove the speckle noise. This paper proposes K-MEANS clustering and minimum distance algorithms and these techniques are used to segment the interested area from the background. Image segmentation is the classification image into different groups. Among those two classification methods minimum distance VV has given the better accuracy results (Overall Accuracy-38.4000%, Kappa Co-efficient- 0.0747) compared to K-MEANS clustering algorithm.

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