

# Sorting of PoLSAR image by using SNAP software in context based Max Margin

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**Abstract:** Synthetic aperture Radar is a two- dimensional radar or three-dimensional radar that plays a prominent role in remote sensing. After many researchers have been done the advanced radar is polar metric synthetic aperture radar. PolSAR radar is fully polar metric radar it provides valuable data on relating experimental target than conventional artificial aperture radar. Therefore, it plays a significant job in numerous grounds like agriculture, military and geology. Based on this classification, ISODATA and minimum distance classification are utilized to explain the spatial and spectral data of polarimetric synthetic aperture radar. The initial step is to create the spatial data utilized for pre- processing stage. The PolSAR image is produced by decomposition and super pixels and then the date is estimated. The next method is to utilize spatial data for post-processing it sustains the minimum distance classification .The result is obtained by minimum distance categorization. The third method utilizes spatial data openly for categorization. In this method, SENTINEL data is applied to classify the PolSAR image. This SENTINEL data is classified by using SNAP software Based on Max-Margin the trademark work is structured and restrictive arbitrary field is utilized to proliferate the logical data in both naming field and perception field. Otherworldly term and spatial term are two significant pieces of the representation  
**Keyword:** POLSAR, ISODATA, SENTINEL data, SNAP, ArcGIS, ENVI

## 1. Introduction

The polSAR is a superior radar structure, it plays a significant role in radar remote sensing. polSAR can obtain the more information than the SAR data. Therefore, polSAR plays a very important role and it contains the information of various scattering mechanisms. Therefore, POLSAR is used in numerous fields like agriculture, military. For improving the categorization, we use different types of classification. the classification method of POLSAR can involves three stages such as preprocessing, post processing and spatial information directly given to classification.

In pre processing stage first collecting the SAR data from both sentinel1 and sentinel2sensor. In the second step it involves two stages radiometric correction and geometric alteration. Radiometric amendment is utilized to lessen the mistakes in computerized number of pictures. Mathematical adjustment is to dodge mathematical contortions from misshaped pictures and is accomplished by building up connection between the picture arrange framework and the mathematical organize framework Depending on types on clamor. The third step is to decrease the spot separating clamor; dot decrease by spatial sifting is acted in computerized picture investigation condition. It is due to the variation in the back scattering of the image, it has various filters like mean filter, median filter and lee sigma filter. The target decomposition it considers matrices as a linear combination of several other scatterers. In classification stage the process of assigning pixels into groups. Classification of different types of objects as well as different characteristics with single channel

polarization and Classification involves 2 steps supervised classification and unsupervised classification. In post processing stage, a confusion matrix by using ground truth ROI and merge all the region of interests in order to find the accuracy. The third stage uses spatial information directly for classification.

## 1.1 Objective

The main objective of this polSAR classification by using contextual based max margin method is to provide the scattering information is contributed by different scattered and Speckle (granular noise) is formed during back scattering. It is more difficult to classify if the image contains 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 categorization is hauling out data classes by multiband raster image. Categorization is the procedure of conveying land cover programs to pixels.

Here the pixel element is the smallest unit in the image and the land cover classes includes vegetation, water, buildings etc.

Unaided order:

The separation between pixels in include space is the proportion of likeness.

Distance might be scaled in pixels, brilliance, and reflectance

Most compelling if the groups are disjoint.

Requires minimal measure of earlier data to work unsupervised arrangement, it initial gathering of pixels into groups dependent on the bunching properties and no preparation information is required and the client just needs to determine the data that doesn't depict singular class attributes. It is fundamentally utilized for understanding the information. So as to make bunches investigator utilize the picture grouping calculations, for example, K means and ISO Data.

Regulated picture arrangement

Regulated arrangement utilizes the phantom mark characterized in the preparation set. The preparation information can emerge out of an imported ROI document or the districts made on the picture. The basic managed characterization calculations are greatest probability and least separation order. In this managed order method, the quantity of classes should know priority

## 2. Proposed System

Unaided Classification

Bunching: Pattern grouping by separation works

Reason: Pixels which are near one another in highlight space are probably going to be long to a similar class

Distance in include space is the essential proportion of similitude in all bunching calculations.

### 2.1 Algorithm

Algorithm of ISO DATA:

1. Select an initial set of clustering centers

2. Specify process parameters
3. Compute the cluster size parameter,  $D_i$

$$D_i(x) = |x - z_i| = [(x - z_i)'(x - z_i)]^{1/2}$$

Where

$(x - z_i)$  indicates a column vector

$(x - z_i)'$  indicates the transpose, a row vector

### 3. Minimum Distance:

Where  $Z_1$  and  $Z_2$  are 1<sup>st</sup> and 2<sup>nd</sup> cluster values  $T$  is the Euclidean distance

Algorithm

Step 1: Initially the mean value for all class image is designed in every band of data. The minimum distance is initialized to be high value.

Step 2: The Euclidean distance ( $T$ ) from each unknown pixel to each vector for each classified is calculated.

Step 3: All pixels are classified to the closest region of interest.

### 4. Result & Analysis

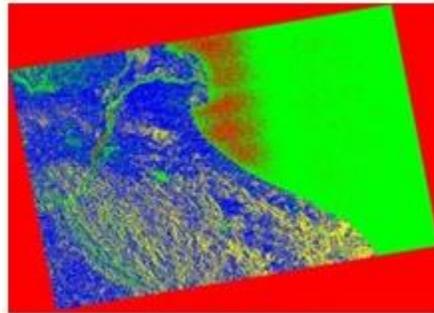


Fig 1: Classified ISO Data VH Image

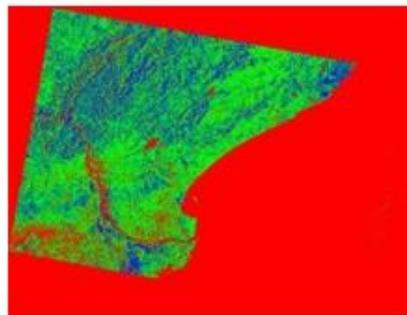


Fig 2: Classified ISOData VVImage

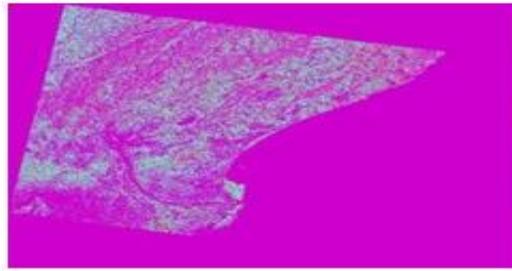


Fig 3: Classified Minimum Distance VH Image



Fig 4: Classified Minimum Distance VV Image

**ISODATA VH CONFUSION MATRIX**

Overall Accuracy = (58/145) 40.000% Kappa coefficient =0.1315

CLASS	ROI:Vegetation	ROI: Urban	ROI: Bare Soil	TOTAL
CLASS 1	0	0	0	0
CLASS 2	22	12	0	34
CLASS 3	36	29	46	111
TOTAL	58	41	46	145

Ground Truth (percent)

CLASS	ROI:Vegetation	ROI: Urban	ROI: Bare Soil	TOTAL
CLASS 1	0.00	0.00	0.00	0.00
CLASS 2	0.00	29.27	0.00	23.45
CLASS 3	37.93	70.73	100.00	76.55
TOTAL	62.07	100.00	100.00	100.00

CLASS	Commission (%)	Omission (%)	Commission (pixels)	Omission (pixels)
CLASS 1	0.00	100.00	0/0	58/58
CLASS 2	64.71	70.73	22/34	29/41
CLASS 3	58.56	0.00	65/111	0/46

CLASS	Prod. Accuracy (%)	User Accuracy (%)	Prod. Accuracy (pixels)	User Accuracy (pixels)
CLASS 1	0.00	0.00	0/58	0/0
CLASS 2	29.27	35.29	12/41	12/34
CLASS 3	100.00	41.44	46/46	46/111

Table1: ISODATA VH Accuracy Values

CLASS	ROI:Vegetation	ROI: Bare Soil	ROI: Urban	TOTAL
CLASS 1	11	0	0	11
CLASS 2	36	79	32	147
CLASS 3	35	11	49	95
TOTAL	82	90	81	253

Ground Truth (percent)

CLASS	ROI:Vegetation	ROI: Bare Soil	ROI: Urban	TOTAL
CLASS 1	13.41	0.00	0.00	4.35
CLASS 2	43.90	87.78	39.51	58.10
CLASS 3	42.68	12.22	60.49	37.55
TOTAL	100.00	100.00	100.00	100.00

CLASS	Commission (%)	Omission (%)	Commission (pixels)	Omission (pixels)
CLASS 1	0.00	86.59	0/11	71/82
CLASS 2	46.26	12.22	68/147	11/90
CLASS 3	48.42	39.51	46/95	32/81

CLASS	Prod. Accuracy (%)	User Accuracy (%)	Prod. Accuracy (pixels)	User Accuracy (pixels)
CLASS 1	13.41	100.00	11/82	11/11
CLASS 2	87.78	53.74	79/90	79/147
CLASS 3	60.49	51.58	49/81	49/95

Table.2: ISO DATA VV Accuracy Values

**ISO DATA VV CONFUSION MATRIX:**

Overall Accuracy=(139/253)54.9407% Kappa coefficient=0.3162

Minimum Distance Confusion Matrix

Overall Accuracy = (104/253) 41.1067%

Kappa coefficient =0.1047

Kappa coefficient =0.1931

**MINIMUM DISTANCE VV CONFUSION MATRIX**

Overall Accuracy=(119/253) 47.0356%

**ACCURACY ASSESMENT TABLE**

Classification	Classifier	Overall Accuracy	Kappa coefficient
Unsupervised classification technique	ISODATA (VH)	40.0000%	0.1315
	ISODATA (VV)	54.9407%	0.3162
Supervised classification technique	Minimum distance (VH)	41.1067%	0.1047
	Minimum distance (VV)	47.0356%	0.1931

Table 3: Accuracy Assessment

## 5. CONCLUSION

Classification analysis of POLSAR image has been done with the help of different classifiers. Initially data has to be filtered by using Lee Sigma filter in order to remove the speckle noise content. The different classification algorithms have been including both supervised (Minimum Distance) and unsupervised (ISODATA) techniques. Among these two-classification method Isodata VV has given the better accuracy results (Overall Accuracy – 54.9407% and Kappa coefficient– 0.3162) compared to other classification algorithms.

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