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Entropy-based Classification Followed by Unsupervised and Supervised Wishart Classifications

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ABSTRACT

The aim of this study is to classify the Pi-SAR (polarimetric and interferometric synthetic aperture radar) data for urban land cover mapping using advanced polarimetric classification methods. For the actual classifications, entropy-based method followed by unsupervised and supervised Wishart maximum likelihood classification (MLC) are used. The performances of the unsupervised and supervised methods are compared in terms of discrimination of different urban land cover types.

INTRODUCTION

In recent years, with the development of radar polarimetry, different refined classification techniques for the classification of polarimetric SAR (POLSAR) data, based mainly on statistical methods, fuzzy (iterative) classifiers and neural networks have been developed. Lee *et al.* [1] introduced a new method for terrain classification by combining the unsupervised classification based on polarimetric target decomposition and the maximum likelihood classifier (MLC) based on the complex Wishart distribution. In this method, Cloude and Pottier's method [2] is used for the initial classification of the POLSAR image and then, the results are used as training sets for the Wishart classification. Ferro-Famil *et al.* [3] developed a new (unsupervised) classification scheme for dual frequency POLSAR data sets using a (6x6) polarimetric coherency matrix to simultaneously take into account the full polarimetric information from both images and proposed two approaches for the final classification. The first approach was based on an iterative algorithm that uses a maximum likelihood decision rule evaluated from the Wishart density function of the coherency matrix, while the second approach introduced the polarimetric cross-correlation information and refined the results by iteratively creating new classes during the classification process. Du and Lee [4] applied the fuzzy c-mean method for the classification of POLSAR data. The method used the full polarimetric information contained in the covariance matrix and a distance measure derived from the probability density of the polarimetric covariance matrix. Chen *et al.* [5] proposed a supervised neural method for classification of POLSAR data. The method integrates a fuzzy neural network as a classifier, a covariance matrix as a feature vector, and a distance measure based on the complex Wishart distribution. Some researchers have also investigated the possibilities of integrating both polarimetric and interferometric SAR data for land cover classification and judged that the results were promising [6].

The aim of this research is to classify the polarimetric Pi-SAR data for land cover mapping using advanced polarimetric classification methods such as the entropy-based method as well as unsupervised and supervised Wishart MLC methods. In order to evaluate the accuracies of the advanced methods, the performances of the selected methods have been compared with the performance of the traditional statistical MLC. The results indicated that the advanced methods perform better than the traditional method for the land cover mapping.

TEST SITE AND PI-SAR DATA SETS

Test Site

As a test site, the central part of Sendai city located in northern Japan has been selected. The area is about 4.1kmx3.5km and represents complex urban environment. The selected part of the city is characterized by such main classes as high density urban, low density urban, forest, extended vegetated surface, bare ground and water. The high density urban includes mainly tall buildings located in the downtown area, while low density urban includes more residential houses, though there are some tall buildings, too. The forest class consists of different types of deciduous and coniferous trees located in mountainous part of the Botanical Garden. The extended vegetated surface mainly includes grass, but there are also some trees of different types and size. The bare ground includes bare soil, tennis court and other open fields. The water refers to the Hirose River that flows through the Sendai city.

Pi-SAR Campaign in Sendai Area

Pi-SAR is an airborne high resolution imaging radar system with fully polarimetric and interferometric functions. It has a dual-frequency mode operating at X-band and L-band frequencies. The polarimetric functions and characteristics of the system are shown in Table I. In Sendai area, the Pi-SAR missions have been performed in August 2001, June 2002, June and August 2003 and February 2004, and the fully polarimetric, multifrequency data were acquired. In the Pi-SAR mission of August 2003, besides the polarimetric imaging, interferometric observation was performed. In this study, fully polarimetric and interferometric Pi-SAR data of 30 August 2003 have been used.

Table I
THE CHARACTERISTICS OF THE PI-SAR SYSTEM.

Parameter	X-band	L-band
Polarization	HH, HV, VH, VV	HH, HV, VH, VV
Frequency	9.55 GHz	1.27 GHz
Wavelength	31.4mm	236mm
Spatial resolution	1.5m	3.0m
Incident angle	10-75 degrees	20-60 degrees

GEOMETRIC REGISTRATION OF THE PI-SAR PRODUCTS

To conduct an integrated analysis, the primary polarimetric Pi-SAR images need to be coregistered. As the X-band and L-band data have different incident angles at near and far ranges, their integration requires a very accurate coregistration. In order to coregister the coordinates of the DEM and L-band image, on clearly delineated sites of both images,12 regularly distributed ground control points (GCP) have been selected and a linear transformation has been applied. As a resampling technique, nearest neighbour resampling approach was applied and the related rms error was 0.96 pixel. Similarly, the coordinates of the X-band image were transformed to the coordinates of the L-band image. To perform an accurate registration, 24 more regularly distributed GCPs were selected comparing the locations of the selected points on both images. For the transformation, a second order transformation and nearest neighbor resampling approach have been applied and the rms error was 0.98 pixel.

THE THEORETICAL REVIEW OF THE ENTROPY-BASED METHOD

Cloude and Pottier developed an unsupervised classification algorithm based on the target decomposition theory [2]. The method is based on the eigenvalue analysis of coherency (or covariance) matrix. For the polarimetric data, the whole information contained in the scattering matrix (*S*) can be written as a vector:

$$\overline{k_i} = 1/\sqrt{2}\left[S_{hh} + S_{vv} \;\; S_{hh} - S_{vv} \;\; 2S_{hv} \right] \qquad (1)$$

which leads to the definition of the Pauli coherency matrix (*T*) defined as

$$T = E\left(\overline{k_i}\,\overline{k_i}^{\dagger} \right) \qquad (2)$$

The advantage of the Pauli coherency matrix over the covariance matrix is that it leads to the direct interpretation to the underlying physical scattering mechanisms [3]. After applying eigenvalue analysis, the coherency matrix (*T*) can be decomposed into a weighted sum of three unitary matrices of rank one, each of which represents a pure scattering mechanism

$$\langle T \rangle = \sum_{i=1}^{3} \lambda_i e_i e_i^{\dagger} = \lambda_1 T_1 + \lambda_2 T_2 + \lambda_3 T_3 \qquad (3)$$

where λ_i and e_i are the eigenvalue and eigenvector of $\langle T \rangle$. From this decomposition two important parameters: entropy (*H*) that represents the random behavior of a scattering medium and angle alpha (*α*) that represents the mean scattering mechanisms are extracted. Furthermore, the unsupervised classification can be achieved by projecting the pixels of a POLSAR image into the *H-α* plane which is segmented into eight regions. The well described theoretical fundamentals and applications of the *H-α* method can be found in [1], [2].

THE THEORETICAL REVIEW OF THE WISHART MLC

The Wishart classification performs a statistical maximum likelihood classification based on the multivariate complex Wishart distribution for the polarimetric coherency (or covariance) matrix [1], [2]. The probability density function for the coherency matrix is written as

$$P\left(\langle T\rangle\right)=\frac{n^{qn}\left|\langle T\rangle\right|^{n-q}\exp\left[-nTr\left(\Sigma^{-1}\langle T\rangle\right)\right]}{\pi^{q(q-1)/2}\Gamma(n)\cdots\Gamma(n-q+1)\left|\Sigma\right|^{n}} \tag{4}$$

where n is the number of looks, q is the number of elements in the target vector (for the reciprocal case q=3 and for the bistatic case q=4), Tr is the trace of a matrix, $\Sigma=E\left[\langle T\rangle\right]$, $\Gamma()$ is the gamma function and | | represents the determinant.

Following the same procedures as in [1] and [7], and assuming that the classes have the equal prior probabilities, a distance measure between the sample coherency matrix $\langle T\rangle$ and a cluster mean of the class C_m is defined as

$$d\left(\langle T\rangle,C_m\right)=Ln\left|\Sigma_m\right|+Tr\left(\sum\nolimits_m^{-1}\langle T\rangle\right) \tag{5}$$

and the pixel is assigned to the class C_m, if

$$d\left(\langle T\rangle,C_m\right)\le d\left(\langle T\rangle,C_j\right) \text{ for all } C_j\neq C_m .$$

In case of the unsupervised Wishart classification, the clusters are defined from the H-α method. Using the H-α decomposition, the POLSAR image is segmented into eight regions which in turn are used to form the training sets to be used for the MLC. In case of the supervised Wishart classification, a user should select the pixels of the representative classes to form the training samples. Then, based on the defined training samples the POLSAR image is classified by assigning each pixel to the most likely class using the MLC.

THE CLASSIFICATION RESULTS

Initially, the original Pi-SAR X-band and L-band data have been converted to the polarimetric scattering matrices (*S*), which in turn were converted to the (3x3) Pauli coherency matrices (*T*). The conversion (i.e., from *S* to *T*) was performed without multilook averaging, because as the method decreases the size of the data and degrades the original spatial resolution, it was necessary to keep the spatial resolution as well as the details contained in the original data sets.

To perform the unsupervised classification, initially, the Pauli coherency matrices related to both X-band and L-band images were decomposed using the H-α method proposed in [2]. During the decomposition process, to reduce the speckle of the images, a 3x3 size boxcar filter [8] has been applied. As results of the H-α decomposition, 8 zones in which the pixels are distinguished from each other by the behavior of the scattering mechanisms, have been determined. Then, these 8 zones were used as input training sets to the Wishart classification and the classification continues until a certain termination criterion is met. As the termination criterion of the MLC, the percentage of pixels switching class (*Th*) and the maximum number of iterations (*Im*) have been used and the following values were selected: *Th*=5% and *Im*=6.

TABLE II
CONFUSION MATRIX PRODUCED FOR THE UNSUPERVISED CLASSIFICATION OF THE X-BAND IMAGE.

Classified data	**Reference data**				
	High density urban	**Low density urban**	**Forest**	**Vegetated surface**	**Bare ground**
High density urban	9159	2610	429	89	35
Low density urban	1182	3001	555	15	42
Forest	150	1651	4515	142	60
Vegetated surface	737	852	775	677	165
Bare ground	702	3132	3985	100	304
Total	11930	11246	10259	1023	606
Overall Accuracy = (17656/35064) 50.35%					

The iteration process ends, when the number of pixels switching classes becomes smaller than a predetermined number. As could be seen from the results, it is not easy to distinguish among the objects of classes. As the unsupervised classification automatically classifies the image into a number of classes, in most cases the final class identification has to be made with the help of human knowledge. In the classified images, we tried to define the available 6 classes, however, due to the scattering properties of the objects in the selected radar frequencies, on the classified X-band image 5 classes such as high density urban, low density urban, forest, extended vegetated surface and ground classes, whereas on the classified L-band image only 4 classes such as high density urban, low density urban, forest and ground classes, were distinguishable. In both classification results, the water appeared as the same as the ground class.

For the accuracy assessment of the classification results, the overall performance [9] has been used. As ground truth information, for each image, the regions containing the purest pixels have been selected. The confusion matrices indicated overall accuracies of 50.35% and 69.36% for classification results of the X-band and L-band images, respectively (Tables II and III).

TABLE III
CONFUSION MATRIX PRODUCED FOR THE UNSUPERVISED CLASSIFICATION OF THE L-BAND IMAGE.

Classified data	**Reference data**			
	High density urban	**Low density urban**	**Forest**	**Bare ground**
High density urban	9021	291	586	9
Low density urban	934	4096	928	38
Forest	589	3190	6874	46
Bare ground	321	591	1497	425
Total	10865	8168	9885	518
Overall Accuracy = (20416/29436) 69.36%				

To perform the supervised classification, initially, on each of the Pi-SAR images, training samples representing the selected classes have been selected through thorough analysis, using a polygon-based approach. Likewise the case of the unsupervised classification, on the X-band image 5 classes and on the L-band image 4 classes were defined. The final signatures included about 254-628 pixels depending on the size of the classes. Then, the images were classified using the Wishart classifier. During the classification, to reduce the speckle of the images and increase the spatial homogeneity of the classes, a 3x3 size boxcar filter has been applied. The confusion matrices indicating the overall accuracy of the Wishart classifier are shown in Tables IV and V. As seen from the results, the performance of the supervised classification is better than the performance of the unsupervised classification.

TABLE IV
CONFUSION MATRIX PRODUCED FOR THE SUPERVISED CLASSIFICATION OF THE X-BAND IMAGE.

Classified data	**Reference data**				
	High density urban	**Low density urban**	**Forest**	**Vegetated surface**	**Bare ground**
High density urban	9068	1792	319	16	0
Low density urban	1106	3878	1308	11	14
Forest	43	1563	3364	56	17
Vegetated surface	1404	2876	2156	892	46
Bare ground	309	1137	3112	48	529
Total	11930	11246	10259	1023	606
Overall Accuracy = (17731/35064) 50.57%					

TABLE V
CONFUSION MATRIX PRODUCED FOR THE SUPERVISED CLASSIFICATION OF THE L-BAND IMAGE.

Classified data	**Reference data**			
	High density urban	**Low density urban**	**Forest**	**Bare ground**
High density urban	9219	260	152	0
Low density urban	1028	4812	811	26
Forest	343	2458	7308	0
Bare ground	275	638	1614	492

Total	10865	8168	9885	518
Overall Accuracy = (21831/29436) 74.16%				

CONCLUSIONS

The aim of this research was to classify the Pi-SAR data for urban land cover discrimination using advanced polarimetric classification methods. For this purpose, the entropy-based method, followed by the unsupervised and supervised Wishart MLC were used. As could be seen from the results of the classifications, the supervised Wishart method as it is based on human knowledge and expertise for selecting reliable training samples demonstrated better performance than the unsupervised Wishart method.

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