An Object Oriented Approach for Multi-Channel and Multi-Polarization NASA/JPL POLSAR Image Classification

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Abstract: This paper presents an object oriented approach (OOA) for classification of multi-channel and multi-polariz ation NASA/JPL POLSAR images. Some test results in Taiwan are also given and analyzed. It is concluded that this approach can utilize as more information of both lo w- and high-levels involved in all images as possible for image classification and thus provides a better classificatio n accuracy. For instance, the OOA has a better overall cla ssification accuracy(98.27%) than the nearest-neighbor clas sifier(91.31%) and minimum-distance classifier(80.52%).
Keywords: Polarimetric SAR (POLSAR), object oriented image classification.

1. Introduction

Basically, classification techniques for polarimetric SAR images can be currently categorized into three types of algorithms based on: (1) image processing techniques, (2) statistical models, and (3) electromagnetic wave scattering mechanisms, respectively [1,2]. More details please refer to [1]. This paper only analyzes the proposed object-oriented fuzzy approach for classifying multi-channel and multi-polarization SAR images.

2. OOA for POLSAR Image Classification

In this approach, the commercial software package "eCognition" is used as a basic tool. More details on eCognition's concepts and methods please refer to [3]. Fig. 1 shows the data processing flowchart of the proposed OOA, which involves two classification steps: (1) supervised fuzzy image classification (SFIC), and (2) object oriented image classification (OOIC). The OOIC adopts different kinds of knowledge features [4], e.g. object features (such as layer value, shape, texture, hierarchy, thematic attributes) and class-related features (such as relations to neighbor objects, to sub-objects, to super-objects)[3].

The multiresolution segmentation (MRS) used in eCognition is a bottom-up region-merging technique [5]. It allows the largely knowledge-free extraction of homogeneous image object primitives in any chosen resolution, especially taking into consideration local contrasts. Given a certain definition of heterogeneity for image objects and a certain average size of image objects, the criteria of region-merging are: (1) average heterogeneity of image objects should be minimized; or (2) average heterogeneity of image objects weighted by their size should be minimized. The heterogeneity criterion consists of (1) color (or spectral) heterogeneity, and (2) shape heterogeneity. The latter includes two subcriteria for smoothness and compactness. The details please see [3].

1. Input polarimetric SAR images
2. Automatically determine a suitable threshold value
3. Multiresolution image segmentation
4. Edit knowledge base system
5. Select training areas
6. Supervised fuzzy image classification (SFIC)
7. Edit knowledge base system
8. Object oriented image classification (OOIC)
9. Accuracy assessment and output results

Fig. 1. Flowchart of OOA for POLSAR Image Classification.

A so-called scale parameter is a measure for the maximum change in heterogeneity that may occur when merging two image objects such as the two small image objects shown in Fig. 2 into a large one of image size of 3x3 pixels. This value is squared and serves as the threshold, which terminates the segmentation algorithm. A statistic method is developed for automatically determining a suitable threshold of the scale parameter adopted in the OOA. In our approach shown in Fig. 1, this value is defined as the sum of average heterogeneity values of all images in a object area of interest. One never needs to input the threshold, since it can be automatically determined by this statistic figure.

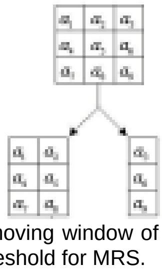

Fig. 2. A horizontally moving window of 3x3 pixels for determining a suitable scale threshold for MRS.

The first step in image classification operations is the supervised fuzzy realization of the nearest neighbor approach. It needs samples, typical representatives for each class and creates conditions in multidimensional feature space. Fuzzy classification basically translates feature values of arbitrary range into fuzzy values between 0 and 1, indicating the degree of membership to a specific class. After a representative set of sample objects has been declared for each class, the nearest neighbor classification searches for the closest sample object in the feature space for each image object. If the closest sample object belongs to Class A, the object will be assigned to Class A.

The second step is OOIC operations. Firstly, the class hierarchy formulates the knowledge base for classifying image objects and contains all classes in a hierarchically structured form. It includes (1) inheritance hierarchy, (2) groups hierarchy, and (3) structure hierarchy. Inheritance hierarchy reduces the redundancy and complexity in the class description. Groups hierarchy combines the classes previously separated by the classification in a common semantic meaning. Structure hierarchy fuses previously heterogeneous regions to single objects. Moreover, classes can be differentiated by using contextual information (class-related features).

3. Test Results and Analysis

The test data (NASA/JPL POLSAR) was collected during the PacRim 2000 Mission on 27 Sep. 2000[6]. It contains linearly-polarimetric (HH, HV, VV) power images of both C-, L-, and P-band and covers a farm area in the southern Taiwan, where P-band data are not used in all tests, since their quality is very bad. The ground truth data of land use in the same area as shown in Fig. 1 was generated by integrating and editing both large scale aerial photos taken on 28 Aug. and 19 Sep. 2000, field survey data, and interview results with inhabitants there in Feb. 2003.

The scale threshold 6 is determined by the above-mentioned statistic figure. Fig. 4 shows the selected training areas, where each is located inside a region of the same land use. Fig. 5 shows the distribution of different land use samples in the six-dimensional feature space. In general, the separability between road type and dry cropland is the worst. Fuzzification assigns a membership degree (membership value) between 0 and 1 to each feature value. The membership degree in the test area is shown in Fig. 6. Most membership degree is larger than 80%. Building areas have a lower membership value of less than 50%. The classification results of the minimum-distance classification (MD), SFIC and OOIC methods are shown in Fig. 7 and 8, respectively. Apparently, the first one contains image objects with a most fractally borderline. This effect is even stronger in highly textured areas. Compared to it, the OOIC results provide image objects of a most compact form and show much smoother edges. The overall accuracy of OOA is better than that of MD and SFIC, please refer to Table 1.

The classification results using different scale thresholds are compared with each other, please refer to Fig. 9. It shows clearly that the producer's accuracy on classifying utility pole is the best, if the threshold determined by our approach is adopted. Besides, the overall accuracy of OOIC is better than that of SFIC in all cases with scale thresholds of 3, 5, 6, 10, and 13. In general, the overall accuracy of both OOIC and SFIC becomes better, if a larger scale threshold is used. Also, Fig. 10 shows that the number of falsely classified pixels is reduced, if a larger threshold is utilized.

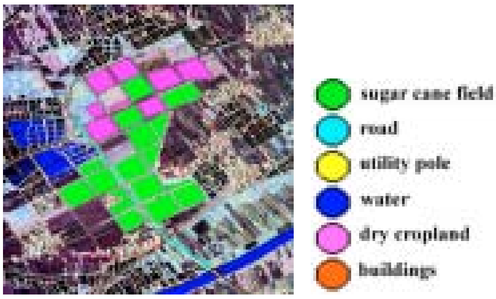

Fig. 3. Ground truth data of land use in test area of 4.6×3.3km.

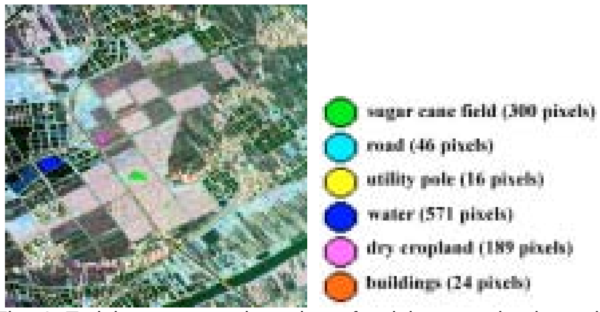

Fig. 4. Training areas and number of training samples in each type of land use.

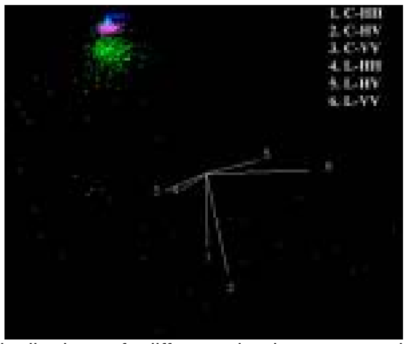

Fig. 5. Distribution of different land use samples in six-dimensional feature space.

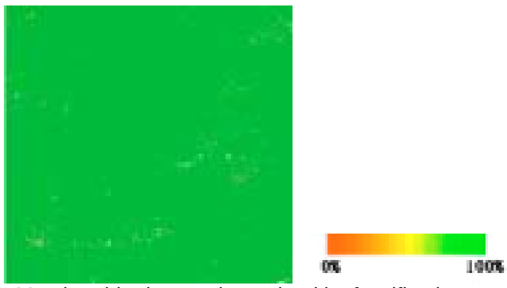

Fig. 6. Membership degree determined by fuzzification.

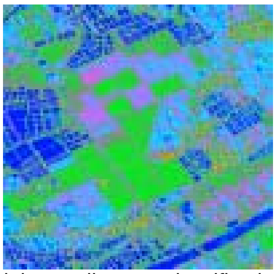

Fig. 7. Result of minimum-distance classification.

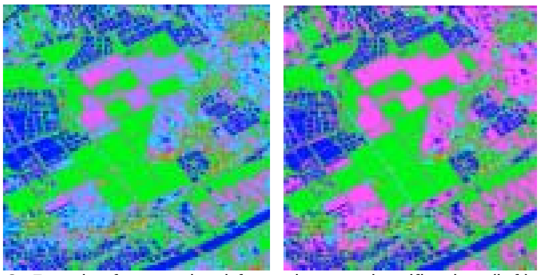

Fig. 8. Result of supervised fuzzy image classification (left) and object oriented image classification (right).

Table 1. Overall accuracy with/without adding an histogram-equalized C_HH image denoted as CHH_e (total number of reference pixels = 36528)

MD with CHH_e	SFIC method		OOIC method	
	no CHH_ e	With CHH_e	no CHH_e	With CHH_e
0.8052	0.9067	0.9131	0.9776	0.9827

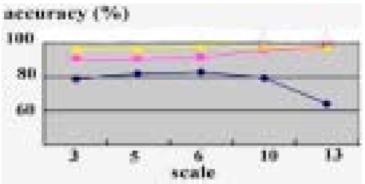

Fig. 9. Classification accuracy by using different scale values, where denotes producer's accuracy of utility pole, denotes overall accuracy of supervised fuzzy classification, and denotes overall accuracy of object oriented classification.

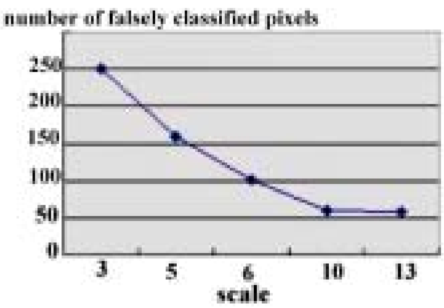

Fig. 10. Number of falsely classified pixels in sugar cane filed.

4. Conclusions

Contributions of this paper to multi-channel and multi-polarization NASA/JPL POLSAR image classification are as follows: (1) to propose a statistic approach for automatically determining a suitable threshold of the scale parameter adopted in the OOA. (2) to adopt additionally a class-dependently contrast-enhanced image, e.g. a histogram-equalized C_HH image in our tests, to multiresolution image segmentation operations and thus to provide better area-features. (3) to utilize the object oriented model for exploiting as many kinds of features and relationships as possible included in POLSAR data sets such as area features, intrinsic features (e.g. color, shape, texture) of a object, topological features between objects, context features (semantic relationship) between objects, class relationship, and class inheritance relationship as well, and thus to improve the classification accuracy.

Since a pixel, also called a mix-pixel, often contains radar scattering information from different types of land covers, fuzzy approach is adopted to do an image classification taking mix-pixels into account. Comparing to pixel-based classification, area-based classification not only reduces the data volume used but also can take both noise and mix-areas into account, where mix-areas are ones containing small portion of other land covers. Thus, area-based classification is adopted in this paper.

Test results show that the fuzzy realization of nearest neighbor classification gives an overall classification accuracy of 91.31% and kappa coefficient of 86.44%, whereas the object-oriented classification has a better overall accuracy of 98.27% and kappa coefficient of 97.23%.

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