On the Implementation of a Land Cover Classification System for SAR Images using Khoros*

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Abstract

The Synthetic Aperture Radar (SAR) sensor is widely used to record data about the ground under all atmospheric conditions. The SAR acquired images have very good resolution which necessitates the development of a classification system that process the SAR images to extract useful information for different applications. In this work, a complete system for the land cover classification was designed and programmed using the Khoros, a data flow visual language environment, taking full advantages of the polymorphic data services that it provides. Image analysis was applied to SAR images to improve and automate the processes of recognition and classification of the different regions like mountains and lakes. Both unsupervised and supervised classification utilities were used. The unsupervised classification routines included the use of several Classification/Clustering algorithms like the K-means, ISO2, Weighted Minimum Distance, and the Localized Receptive Field (LRF) training/classifier. Different texture analysis approaches such as Invariant Moments, Fractal Dimension and Second Order statistics were implemented for supervised classification of the images. The results and conclusions for SAR image classification using the various unsupervised and supervised procedures are presented based on their accuracy and performance,

1. Introduction

Traditionally, the source of region distribution information has been maps created by ground survey, An alternative approach could be the use of remote sensing and image processing techniques. In numerous studies such remotely sensed data has been used to accurately map vegetation, crop and other land-cover types. Most of these studies have been performed using LANDSAT, SPOT and AVHRR data, and in other cases using SAR data.

But, visible spectrum images of the ground depend on the atmospheric conditions of the area under analysis. Then, important information about the ground can not be taken all the time. A possible solution is the use of an active microwave sensor such as the Synthetic Aperture Radar (SAR).

In this paper, a land cover classification system designed for SAR images is presented. This system is built under the Khoros environment. The classification system was designed, and analyzed based on supervised and unsupervised classification approaches. The knowledge obtained with this work could highlight fundamental computational issues like memory size and CPU execution time. In addition, important parameters related to the implementation structure of some algorithms can be analyzed and possible relations can be established between them and the response of the land cover classification system.

2. Data Acquisition

The data used in this project was obtained from the Jet Propulsion Laboratory homepage. The image was created using data from the Spaceborne Imaging Radar C/X-Band Synthetic Aperture Radar (SIR-C/X-SAR) [1]. The image is a false-color composite of the Mammoth Mountain area in California's Sierra Nevada Mountains centered at 37.6 degrees north, 119.0 degrees west, (see Fig 1). It was acquired onboard space shuttle Endeavour on its 67th orbit on

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April 13, 1994. In the image, red is C-band HV-polarization, green is C- band HH-polarization and blue is the ratio of C-band VV- polarization to C-band HV-polarization.
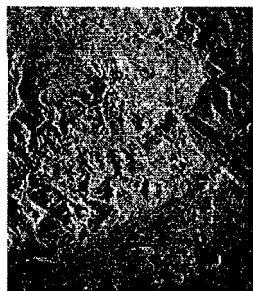

Figure 1: Original SAR image.

3. Supervised Classification System

Image classification systems are basically divided into two categories: supervised and unsupervised classification systems [2]. In the supervised systems, there is a supervisor to teach the system first, how to classify known set of images, and then the system goes ahead freely classifying other images, Usually it needs a *priori* information derived from field survey, photo interpretation and other sources about regions of the image. The supervised classification system is composed of two stages: the training and the classification stages. In the training stage, the user teaches the system how to classify the different regions of the image. This process is based on the proper selection of features and the fine tuning of several parameters of the system. The main function of the training stage is the selection of the objects which will determine the composition of the classes. First, the input SAR image is partitioned using a simple segmentation algorithm called labeling [3], The labeling algorithm performs segmentation based on the 4 (or 8) connectivity of a given pixel with its neighbors. Second, each region of the segmented image is analyzed to extract features using a texture analysis method.

The texture analysis was performed using invariant moment, fractal dimension and Gray level cooccurrence matrix (GLCM) texture features based methods. Lets take an overview of the different techniques.

3.1 Invariant Moments

The two dimensional (p+q)th order moments are defined as

$$m_{pq} = \sum_i \sum_j i^p j^q I(i,j) \quad \text{p, q} = 0, \ 1, 2 \ldots \tag{1}$$

where $I(i,j)$ is the image of the object. The center of gravity or mean can be calculated from

$$\bar{x} = \frac{m_{10}}{m_{00}} \qquad \bar{y} = \frac{m_{01}}{m_{00}}. \tag{2}$$

The central moments are defined as

$$\mu_{pq} = \sum_i \sum_j (i - \bar{x})^p \ (j - \bar{y})^q I(i, j) \tag{3}$$

which are invariant under translation,

Similarly, a more general set of invariant moments can be obtained. These are the seven low-order central invariant moments Ml , ... M_7[4] and they are independent of size, orientation and position. The first six

502

moments are invariant under rotation and reflection, However, the last one, M_7 , is sensitive to reflection, its value changes sign for a reflected image of the object, but its magnitude remains unaltered.

3.2 Fractals

One important parameter used to characterize a surface is the fractal dimension. The concept of fractals is based on the continuous repetition of a mathematical pattern on a given random selected location of a space, Classical geometry is based on integer dimensions; fractal geometry, instead, deals with non-integer dimensions. That is, while a line has one dimension and a plane has two dimensions, a fractal curve will have a dimension between one and two depending on the intricacy of it, It has been proved that nature exhibits some structures similar to fractal objects and fractal models are used to synthesize and analyze different textures with good results [5], It has been proved that there is a correlation between the roughness of the surface and the value of the fractal dimension, As the fractal dimension increases more complex is the fractal and in the same way the roughness of the texture. The fractal dimension can be obtained using the following relation,

$$D = \frac{\ln(N_r)}{\ln \frac{1}{(\frac{1}{r})}}$$

(4)

where r is the reduction ratio, N_r is the number of copies and D is the fractal dimension.

The estimation of the fractal dimension of an image is based on the probability that there are m pixels within a window of size L centered on a pixel from a particular class. For a selected range of window sizes (L), the window is centered on the first occurrence of the pixel belonging to a particular class. The number of pixels within a window of size L, belonging to a specific class are counted (including the center pixel of the window), and a histogram is formed as the window is moved over the image. This histogram produced as part of **the** method represents the total number of occurrences, m, of a class of pixels in a window of size L.

3.3 Gray-level cooccurrence matrix

The second order statistics provide a simple approach to capture the spatial relationship in a texture pattern. The GLCM considers the distribution of the intensities as well as the positions of pixels with equal or nearly equal intensity values. The GLCM is calculated as the number of times a given pair of pixels separated by a distance d are found in the image according to its corresponding locations[6]. The GLCM can be computed independently for each one of the nearest neighbors based on the angles 0°, 45°, 90° or 135°. Once the cooccurrence matrix is generated the Haralick texture features can be measured. The complete list of Haralick's features can be seen in reference [7].

4. Unsupervised Classification System

The unsupervised classification system does not require a supervisor to teach the system. It is based on clustering algorithms which determine the composition of the classes. Initially, C points are selected to serve as candidate cluster centers. Each pixel is examined and they are assigned to the nearest candidate cluster. This assignment would be made on the basis of the Euclidean or City distance measure. A new set of means are computed from the previous grouping produced. If the new means converge with the previous ones the procedure terminates. Otherwise, the procedure returns to second step with the current mean set. The next step after the clustering process is the classification of the clusters in a particular class.

One of the most popular classification algorithms is the Weighted Minimum Distance. It can distinguish a single class from the rest of the data or multiple classes from each other. Each pixel is assigned to the nearest candidate class

based on the minimum Euclidean Distance or minimum Euclidean Squared Distance. Another unsupervised Khoros classification algorithm is based on the Localized Receptive Field (LRF) Training/ Classifier.

Localized Receptive Field is a two layer topology units which consists of a single layer of self organizing, " localized receptive field" units and a single layer of perception. The single layer of perception units use the Least Mean Square or the Adaline learning rule to adjust weights. The weights are trained and then similar images may be quickly classified based on the training data set.

5. Methodology

In the supervised classification, the SAR image was segmented in 28 different regions using the labeling algorithm based on 4-connectivity neighbors. Then, the texture analysis techniques were applied to the segmented image and a matrix of features was produced for each method. The feature under analysis had to be extracted from its corresponding matrix and a histogram of the feature through the different regions of the image was displayed, The features were the seven invariant moments, the fractal dimension, the second angular moment and contrast with horizontal neighbors. The histogram is analyzed and 4 objects were selected based on the statistical frequency of the features, see Table 1 and Table 2.

class	Object	Object Number	Feature Value
0	snow	5	0.2373
1	bare ground	7	0.2798
2	open water	21	05195
3	unknown	23	0.6672

Table 1: Prototyping table for Invariant Moments

Class	Object	Object Number	Feature Value
o	snow	11	1.5483
1	unknown	12	1.6508
2	bare ground	14	1.7666
3	open water	24	1.3765

Table 2: Prototyping table for Fractal Dimension

Features with higher frequencies are selected as the prototype classes or training data. After the training, classification stage follows the same steps as the training stage. The SAR image is segmented in 28 regions and then the texture analysis algorithm is applied for each region of the image. The vector produced in the training and classification stages are compared using the minimum distance classifier and the different regions were classified, (see Fig. 2).

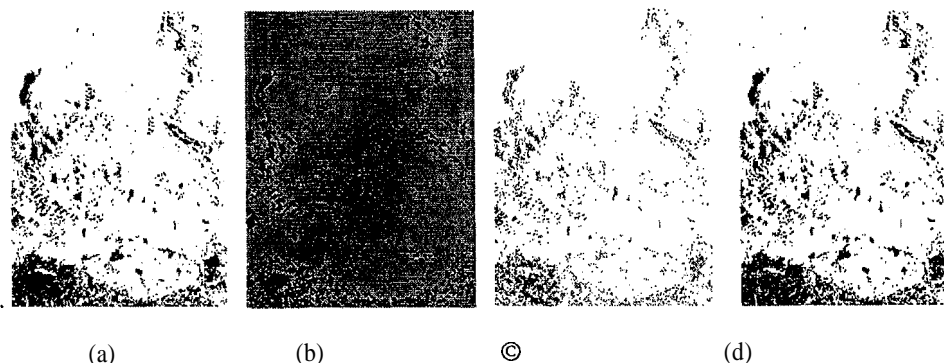(a)   (b)   ©   (d)

Figure 2: Classified images using (a) invariant moments, (b) fractal dimension, (c) second angular moment and (d) contrast.

In the unsupervised classification, the K-means and the Isodata 2 algorithms were applied to the SAR image [81 [9]. Then, the cluster centers were labeled and combined with the original image to produce a multiband image. This image was used on the Weighted Minimum distance and the Localized Receptive Field classifiers, (see Fig. 3).
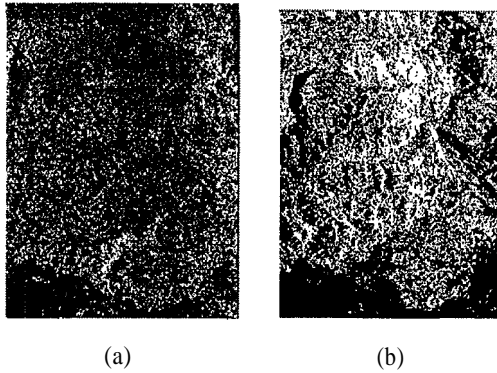

(a)   (b)

Figure 3: Classified images using (a) K-means/ LRF classifier and (b) ISO2/Weighted minimum distance classifier.

Conclusions

The Invariant moments approach is the simplest one and could not correctly classify the open water region, It could discriminate between snow and bare ground very well, that is, it can discriminate between well defined regions.

Fractal dimension proved to be better than the invariant moment approach to classify a region. It produced good enough results in the classification of the open water region and the time to analyze the image was comparable with the invariant moments and less than the concurrence matrix method. The fractal dimension measures quantitatively the roughness of a surface in a way similar to human perception of the texture. Unfortunately, the roughness is not the only important texture feature, because there are quite different textures with the same fractal dimension. Fractals do not take into account the distribution of pixels; so its ability to discriminate different textures is not efficient. Another important issue to keep in mind is that the range in which we plot the log Nr vs log (I/r) is linear. Real objects has a range limited by lower and upper bounds.

The matrix obtained from the cooccurrence matrix approach is a square matrix with more elements than the original image. Note, that the number of operations required to process an image is directly proportional to the size of the original image. The computational dynamic storage cost of this process depends on keeping two consecutive lines of the image data in main memory, so storage constrains are determined only by the width of the image data.

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