

Unsupervised Classification of Radar Imagery of Wetlands Using the Soft Competition Scheme

S. L. Durden and Z. S. Haddad

Jet Propulsion Laboratory

California Institute of Technology, Pasadena, CA 91109 USA

(818)354-4719/(818)393-5285/sdurden@jpl.nasa.gov

ABSTRACT

We apply a technique developed in the field of vector quantization to the problem of unsupervised classification of radar imagery of wetlands. The method can perform better than traditional unsupervised methods, such as k-means, because it performs soft classification at each step. The method is applied to Alaska data and shown to give results that are similar to previous results using supervised classification. Results are also shown for data from Belize.

INTRODUCTION

Synthetic aperture radar (SAR) has been shown to be sensitive to vegetation type and to presence or absence of surface water [1]-[3]. Such information is useful in understanding the ecology of wetland areas and the impact of seasonal flooding. Because of the high correlation of vegetation type and presence of standing water with the methane exchange rate in boreal wetlands [4], SAR may also be useful in distinguishing between land cover classes of differing methane exchange rates. This application is examined in [3] using supervised classification methods. In general, good results have been obtained in applying supervised methods to classification of radar data. Unfortunately, in practice it is often difficult to obtain suitable training data. This leads us to explore the use of unsupervised methods. Work in this area has already been done using a variety of methods [5], [6]. The method presented here is based on a method used in vector quantization, in which one looks for optimal codebooks to represent data. Specifically, one wishes to find a set of code vectors which can adequately represent the data. The problem is essentially that of finding clusters whose mean best represents the input data. This problem is identical to unsupervised radar classification and the methods from vector quantization can be applied directly. We first review the method and discuss its implementation for SAR imagery. We then demonstrate the results on data published in [3], which were classified using supervised methods. We also show application of the unsupervised approach to data acquired in Belize, Central America.

SEGMENTATION METHOD

One of the simplest methods for segmentation of data into classes or clusters is the k-means algorithm. This al-

gorithm assumes some initial class parameters and then classifies the data accordingly. Given the classes, the class parameters are re-computed. These two steps are repeated until convergence. A related algorithm is the self-organizing feature map (SOFM), which is a type of neural network [7]. In the general unsupervised classification problem, we are presented with data samples $x(n)$, where x is a vector representing the radar measurements at each pixel. In the SOFM technique the class mean vectors w_j are initialized to random values; j is the class index and ranges over the expected number of classes. At each step we determine the distance $|x(n) - w_j(n)|$ for all j . The w_j with the minimum distance wins. The winning w and those in its neighborhood Λ are updated according to

$$w_j(n+1) = w_j(n) + \eta(x(n) - w_j(n)) \quad j \in \Lambda \quad (1)$$

where η is a learning rate parameter. When the neighborhood size is reduced to 1, only the winning vector is updated. In this case SOFM reduces to the k-means algorithm [7].

Both the k-means algorithm and the SOFM perform a hard classification at each iteration, meaning that each sample is classed as one and only one of the classes existing at that step. Better results may be obtainable by using so-called soft classification, in which each sample can have more than one class or a combination of class characteristics associated with it. In the Soft Competition Scheme (SCS) [8] the SOFM is modified in that a winner is not chosen. Rather, the class vectors w for all j are updated according to

$$w_j(n+1) = w_j(n) + \eta_j(n) P_n(j) (x(n) - w_j(n)) \quad (2)$$

where $P_n(j)$ is the probability that $x(n)$ belongs to class j . This probability is estimated from $|x(n) - w_j(n)|$ as also used in the SOFM:

$$P_n(j) = \frac{\exp(-\beta(n)|x(n) - w_j(n)|^2)}{\sum_k \exp(-\beta(n)|x(n) - w_k(n)|^2)} \quad (3)$$

where the index of the sum k runs from 1 to the number of classes. Equation (3) is a Gibbs distribution where $\beta(n)$ is a parameter analogous to the inverse temperature. As the algorithm is applied, β is gradually raised, lowering the temperature. In (2) the learning rate parameter is no longer a constant but varies with both the

class and the time step. Details of the implementation of this method are given in [8]. The primary advantage of the method is that all class vectors w are updated for each x rather than only the winner. Those x that are closer to a particular w have a larger effect on it during the update through the probability $P_n(j)$. Early in the procedure when β is small, the probabilities weak functions of the class j . This keeps the method from getting stuck in a local minimum. As β increases, the probabilities become stronger functions of the class j , and as β becomes very large the method approaches hard classifications.

Following the completion of the SCS, we have clusters of radar data. The mean and variances are computed for each cluster, or class. At this point we have information equivalent to that at the start of a supervised classification; that is, we have the characteristics of the classes present in the image. The only difference is that we do not have a name to go with each class. Since the class name is needed only for interpretation, we proceed with a supervised classification using the results of SCS. In our case we use the same supervised classifier as used in [3]. This classifier uses the Maximum *a Posteriori* (MAP) statistical classifier, which maximizes the probability density function (PDF) $p(L|X)$ of the pixel labels L conditioned on the radar observations X . In [3] simulated annealing was used for the solution. Here, we have used the iterated conditional modes (ICM) [9]. The final result of the method is a set of classes with known mean and variance and an image classified according to these class characteristics. We can then use external information, such as maps, to apply names to the classes. It might also be possible to use experimental or modeling data to determine the type of terrain, given the class scattering characteristics.

DATA DESCRIPTION

The northern wetlands data used in this study were acquired over Minto Flats, Alaska, on 18 July 1993, using the NASA/JPL DC-8 AIRSAR polarimetric SAR. Because of severe interference at P-band, only L-band and C-band data were used in this study. The data have been averaged to 64 looks, to reduce speckle noise, resulting in a spatial resolution of approximately 50 m. The time of the data acquisition was near the peak, mid-summer growing season. Land cover within the study area can be divided into four classes: forest, bog, water, fen. The methane rate varies substantially with the class, with the highest methane emissions from inundated fens and lowest from forests, which are actually weak methane sinks [3]. The classification is based on both the like and cross-polarized data (LHH, LHV, CHH, and CHV). A second AIRSAR data acquisition over Belize, Central America is also classified here. These data were acquired in March 1990 and include rainforest and

some wetlands. These data have undergone averaging like the Alaska data. The data classified here were acquired in an area adjacent to data presented in [10]. The classification uses the HH polarized data at P-, L-, and C-bands.

CLASSIFICATION RESULTS

The method was applied to the Alaska data using the same number of classes as used in the supervised case in [3]. The classification results are shown in Fig. 1 and are quite similar to those in [3]. As noted above, the unsupervised method does not provide a name for the class, only its characteristics, along with the classified image. By comparing Fig. 1 with the results in [3], it was obvious which classes in Fig. 1 corresponded to those in [3]. The labels for Fig. 1 use the results of this comparison. In examining Fig. 1, the white areas are of particular interest since they correspond to the high methane producing fen areas. These are shown in white. The open water areas are also well separated. The bog and forest areas, are less well separated; however, these were difficult to separate in [3] using supervised methods. Table 1 shows the backscatter σ^0 characteristics of the classes found by the unsupervised method. They compare quite well with the radar characteristics used in training for the supervised methods in [3].

For the Belize data the number of classes was not known *a priori*, and so results were obtained for several numbers (3-5). Results appeared best using 4 classes and are shown in Fig. 2. The classification results were compared with maps of the area to determine the type of vegetation corresponding to the class. The light gray area in Fig. 2 is likely flooded reeds. These areas had very low P-band return (-22 dB σ^0) and very high C-band return (σ^0 of -2 dB). Apparently the reeds were substantially shorter than the P-band wavelength of 68 cm. Hence, at P-band the area looks like open water and has low backscatter. At C-band the reeds must have length at least that of the C-band signal (5 cm). Interaction between the reeds and water surface provides a large backscatter, such as seen in flooded rice fields [11]. The other areas in Fig. 2 are similar to each other in terms backscatter characteristics and probably correspond to forest with varying degrees of surface water.

CONCLUSIONS

We have applied a vector quantization method to unsupervised classification of radar imagery. The method uses soft classification at each step and is less likely to get stuck in local minima during the classification process than methods using hard classification. We found results similar to supervised methods for imagery containing Alaskan wetlands. The method also pro-

vided useful classification for data acquired over Central America.

ACKNOWLEDGMENTS

This work was performed by the Jet Propulsion Laboratory, California Institute of Technology, under contract with the National Aeronautics and Space Administration (NASA). The authors would like to thank Drs. L. Morrissey and G. Livingstone for helpful discussions on radar sensing of wetlands and methane production.

REFERENCES

- [1] K. O. Pope, J. M. Reybenayas, and J. F. Paris "Radar remote sensing of forest and wetland ecosystems in the Central American tropics," *Remote Sensing of Environment*, vol. 48, pp. 205-219, 1994.
- [2] L. L. Hess, J. M. Melack, S. Filoso, and Y. Wang, "Delineation of inundated area and vegetation along the Amazon floodplain with the SIR-C synthetic aperture radar," *IEEE Trans. Geosci. Remote Sensing*, vol. 33, pp. 896-904, 1995.
- [3] S. L. Durden, Z. S. Haddad, L. A. Morrissey, and G. P. Livingstone, "Radar classification of boreal communities for methane exchange studies," *Int. J. Remote Sens.*, vol. 17, pp. 1267-1273, 1996.
- [4] L. A. Morrissey and G. P. Livingstone, "Methane flux from tundra ecosystems in arctic Alaska," *Journal of Geophysical Research*, vol. 97, pp. 16661-16670, 1992.
- [5] E. Rignot, R. Chellappa, and P. Dubois, "Unsupervised segmentation of polarimetric SAR data using the covariance matrix," *IEEE Trans. Geosci. Remote Sensing*, vol. 30, pp. 697-705, 1992.
- [6] L. K. Soh and C. Tsatsoulis, "Segmentation of satellite imagery of natural scenes using data mining," *IEEE Trans. Geosci. Remote Sensing*, vol. 37, pp. 1086-1099, 1999.
- [7] S. Haykin, *Neural Networks*. New Jersey: Prentice Hall, 1994, pp. 408-427.
- [8] E. Yair, K. Zeger, and A. Gersho, "Competitive learning and soft competition for vector quantizer design," *IEEE Trans. Signal Proc.*, vol. 40, pp. 294-309, 1992.
- [9] C. Stiller and J. Konrad, "Estimating motion in image sequences," *IEEE Signal Proc. Magazine*, pp. 70-91, July 1999.
- [10] A. Freeman and S. L. Durden, "A three-component scattering model for polarimetric SAR data," *IEEE Trans. Geosci. Remote Sensing*, vol. 36, pp. 963-973, 1998.
- [11] S. L. Durden, L. A. Morrissey, and G. P. Livingstone, "Microwave backscatter and attenuation dependence on leaf area index for flooded rice fields,"

IEEE Trans. Geosci. Remote Sensing, vol. 33, pp. 807-810, 1995.

Table 1. Alaska Class Characteristics (σ^0 in dB)

Class	LHH	LHV	CHH	CHV
Forest	-8	-15	-6	-12
Bog	-10	-17	-6	-13
Water	-25	-35	-21	-30
Fen	-15	-23	-7	-15

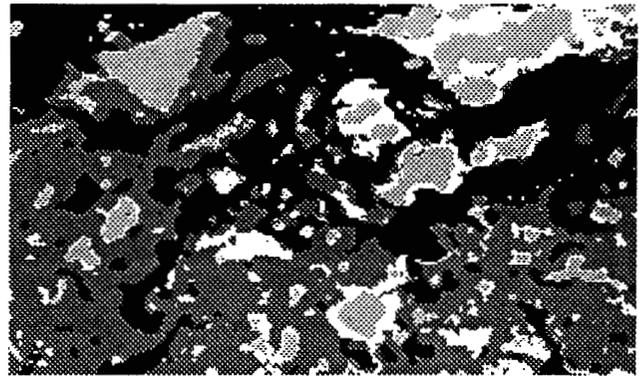


Figure 1. Unsupervised classification of LHH, LHV, CHH, CHV imagery over Alaska. Black is forest and tall shrub. Dark gray is bog. Light gray is open water, and white is fen. Image dimension is 8.4 km by 4.9 km.

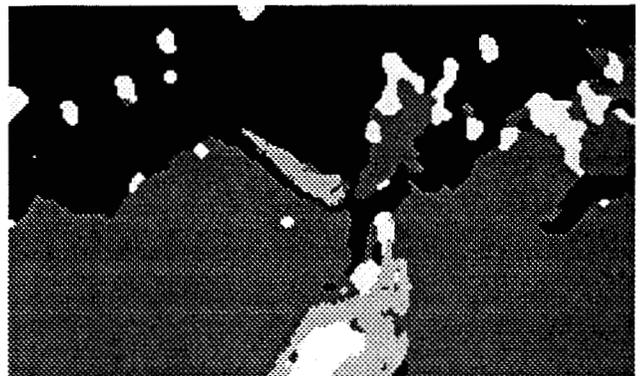


Figure 2. Classification of PHH, LHH, and CHH cross section measurements in Belize, Central America. Image dimension is 8.4 km by 5.4 km.