MULTI-TEMPORAL ERS-1 SAR AND LANDSAT TM DATA FOR AGRICULTURAL CROP CLASSIFICATION: AN ARTIFICIAL NEURAL NETWORK APPROACH

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ABSTRACT:

Multi-temporal ERS-1 synthetic aperture radar (SAR) and Landsat TM data were used to evaluate an artificial neural network approach for crop classification. Six major crops, i.e., winter wheat, corn (good growth & poor growth), soybeans (good growth & poor growth), barley/oats, alfalfa, and pasture/cut-hay-alfalfa, were classified into eight classes. The results show that both a single-date and multi-temporal SAR data yielded poor classification accuracies using a maximum likelihood classifier (MLC). With per-field approach using a feed forward artificial neural network (ANN), the overall classification accuracy of three-date SAR data improved almost 20%, and the best classification of a single-date (Aug. 5) SAR data improved the overall accuracy by about 26%. These accuracies (<60%), however, were not high enough for operational crop inventory and analysis. Using the combination of TM3,4,5 and Aug. 5 SAR data, the best per-field ANN classification of 96.8% was achieved. It represents a 8.5% improvement over a single TM3,4,5 classification alone. It also represents a 5% increase over the best per-pixel classification. This indicates that a combination of mid-season SAR and VIR data was best suited for crop classification. The results also show that the best ANN classification had a 5% higher accuracy than a minimum distance (MD) classification using the same dataset.

INTRODUCTION

Radar remote sensing has the potential to play an important role in agricultural crop monitoring due to its independence from solar illumination and cloud cover. With the launch of the European Remote Sensing Satellite (ERS-1), the first long-duration spaceborne imaging SAR system became available. This and other spaceborne SAR systems, such as JERS-1, ERS-2 and the Canadian RADARSAT, provide researchers with an excellent opportunity for developing multi-temporal SAR agricultural applications.

The synergistic effect of integrating SAR data and imagery acquired in the visible and infrared (VIR) portions of the spectrum has also been recognized as important for two main reasons. First, timeliness of SAR fills information gaps during overcast or hazy periods at the critical stages of the growing season, and second, the combination of data from different parts of the spectrum often leads to increased classification accuracy. Previous studies have shown that combining airborne SAR and satellite VIR data improves crop classification accuracies (Brown *et al.*, 1984; Guindon *et al.*, 1984; Hirose *et al.*, 1984; Brisco *et al.*, 1989; Fiumara and Pierdicca, 1989; Dixon and Mack, 1990; Brisco and Brown, 1995). Very little research, however, has been done to improve crop classification accuracies using data from two satellite sensors (Kohl *et al.*, 1993; Fog *et al.*, 1993). Thus, the potential of Satellite SAR and VIR synergism still needs further investigation.

Conventional statistical classifiers, such as MLC, make a number of untenable assumptions about the dataset to be classified (Foody *et al.*, 1995). For example, this parametric approach requires the data to have a Gaussian distribution. SAR data, however, are not normally distributed due to speckles. Therefore, the accuracies of SAR crop classification using conventional statistical classifiers are often not high enough for crop inventory and analysis. In order to improve classification accuracy, it is necessary to explore robust classifiers using non-parametric and non-statistical approaches.

ANN classifier presents a distribution-free approach to image classification. It also has the special advantages of simple local computations and parallel processing (Schalkoff, 1992). In the past few years, studies have shown that neural networks compared well to statistical classification methods in classification of multi-date, multi-source remote sensing/geographic data, very high dimensional data and classification with high number of classes (e.g., Benediktsson *et al.*, 1990a; Benediktsson *et al.*, 1990b; Kanellopoulos *et al*, 1991). Foody *et al.* have (1994; 1995) also found that ANN produced higher classification accuracies in general than those derived from statistical classifiers when they were applied to airborne SAR data for classifications of agricultural crops. Therefore, it is desirable to investigate the effectiveness of ANN for crop classifications using satellite SAR and VIR data.

The objective of this study was to evaluate the synergy of multi-temporal ERS-1 SAR and Landsat TM data for crop classification using an artificial neural network approach. The specific objectives were:

- to evaluate the crop classification accuracies using a single-date SAR data alone and multi-temporal SAR data,
- to evaluate the synergism of multi-temporal ERS-1 SAR and Landsat TM data for improving crop classification, and

- to evaluate ANN (non-statistical) as a post-segmentation classifier in comparison to a minimum distance (MD, non-parametric) classifier.

STUDY AREA AND DATA DESCRIPTION

The study area is situated in an agricultural area in Oxford County, southern Ontario, Canada. This site has been used previously for intensive study of the relationships between radar data and agricultural parameters. The major field crops include corn, soybeans, winter wheat, barley/oats, alfalfa and pasture.

Three dates of early- and mid-season ERS-1 C-VV SAR data were acquired during 1992 growing season (June 15, July 24 and August 5). July 24 SAR data were acquired in ascending mode, while others were acquired in descending mode. One date of Landsat TM data were also acquired on August 6, 1992. Detailed field information was collected at the time of the overpasses and was input to a geographic information system to aid in developing and understanding the classifications.

METHODOLOGY

In the analyses presented in this paper, single-date SAR data, multi-temporal SAR data, and combinations of SAR and TM data were classified. In all cases, a per-field classification approach is adopted since this conforms to conventional mapping strategies and has been widely used in radar remote sensing as a means of reducing the effect of speckle (Foody *et al.,* 1994; Ban *et al.,* 1995). ANN was used in post-segmentation classifications and was compared to a MD classifier. MLC was also performed for comparison purposes.

Pre-preparation

The raw signal SAR data were processed by Atlantis Processor at the Canadian Center for Remote Sensing and geometrically corrected to field boundaries (Universal Transverse Mercator -UTM projection). The geocoded field-boundary file for the study area was digitized from SPOT imagery in a GIS and then imported into an image processing system. To eliminate the effects of field-boundary pixels and minor image registration errors on crop discrimination, a 5-pixel buffer was applied to the field boundaries. This procedure is similar to that used by Ban *et al.* (1995).

Calibration and Validation Blocks Selection

The major crops classified in this study were winter wheat, corn, soybeans, barley/oats, alfalfa and pasture/cut-hay-alfalfa. Due to the differences in growing stages and ground cover density, corn and soybeans were further divided into two classes, good growth or poor growth. For each crop, pixel sample blocks were randomly extracted within representative fields in order to calibrate the minimum-distance-to-means classifier and to train the artificial neural network.

To assess the accuracy of the classifications, validation pixels, independent from the calibration pixels, were randomly selected for each crop. Fields that exhibited anomalies, such as spectral reflectance/backscatter that deviated significantly from the norm of a particular class, were excluded from both the calibration and validation samples. These anomalies usually resulted from weeds infection, crop management and/or soil drainage characteristics. The calibration and validation blocks selection were based on the crop information, i.e., crop growth stage, ground cover, height, row direction, etc. in a PAMAP GIS.

Calibration and validation pixels were extracted from different fields, a requirement for the field approach where a field was defined as a homogeneous area and all pixels were assigned the mean value of the field. This reduced the number of fields that could be used for calibration and validation, so calibration had to be restricted to fewer fields.

Per-pixel Classification

In order to assess the effectiveness of the non-parametric and non-statistical approaches, a comparison to a MLC was required. A number of classifications for SAR, TM and their combinations using MLC were performed.

Per-field Classification

Since a field only grows a single crop in Canada, it is desirable to use a per-field classification. Also a per-field approach reduces the SAR speckle effects, as discussed earlier.

Segmentation. A per-field classifier permits segmentation of the ERS-1 SAR data into homogeneous fields using field boundaries. A unique grey level was assigned as a label to each output polygon of the field-boundary file which was then input for the homogeneous classifier as a theme channel. The homogeneous classifier defined the homogeneous segments of interest. There were two values that could be assigned to segments, namely the mean and the mode. Only the mean was tested in this study. The pixel values in each field were replaced with the mean value for that field.

Post-segmentation Classification. Two post-segmentation classifiers, MD and ANN, were investigated. MD is the minimum Euclidean distance classifier. It assigns each pixel to the class which has the minimum distance between the pixel value and the class mean. In situations where MLC's multivariate normal distribution assumption does not hold, MD may perform better than MLC, because MD does not require making assumptions. In this study, EASI/PACE software, MINDIS was used (PCI, 1994).

ANN classifiers provide an emerging paradigm for pattern recognition implementation that involves large interconnected networks of relatively simple and typical non-linear units (i.e., neural nets) (Schalkoff, 1992; Foody *et al.,* 1995). A neural network consists of interconnected processing elements called units ("nodes" or "neurons"). These are organized in two or more layers. There is an input layer of units which are activated by the input image data. The output layer of units represents the output classes to train for. In between, there is usually one or more hidden layers of units. An Artificial Neuron Computational Structure is shown in Figure 1.

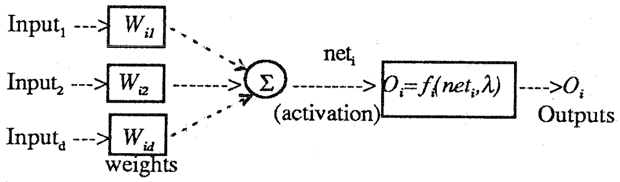

Figure 1. An Artificial Neuron Computational Structure. where $net_i=\sum_j W_{ij} O_{ij}$ (Schalkoff, 1992).

The programs use a back-propagation network that learns using the Generalized Delta Rule:

$$\Delta W_{jk} = \eta\ \delta_k\ o_j + \alpha\ \Delta\ W_{jk}$$

where η = learning rate, α = momentum, δ_k = error at the kth-layer, o_j is the output of layer j and W_{jk} is the connection weight between the jth-layer node and the kth-layer node (Li and Si, 1992).

The term "back-propagation" refers to the training method by which the connection weights of the network are adjusted. The training of the network is similar to any supervised classification procedure, i.e. calibration blocks have to be selected and used to adapt the classifier. In this case network weights were adapted. The back-propagation learning procedure is simple and will not be detailed here.

A multi-layer feed forward neural network using back-propagation was evaluated in this research. Specifically, EASI/PACE software NNCREAT, NNTRAIN and NNCLASS (PCI, 1994) were used.

RESULTS AND DISCUSSION

Per-pixel Classification

Although three-date SAR combination had an 4% improvement of classification accuracy over the best single date classification alone, the overall validation accuracies for both single-date SAR and multi-temporal SAR were very low (see Table 1). The first reason for the poor accuracies was that MLC was not an effective classifier for SAR data classifications due to speckle. The second reason for the poor performances was that ERS-1 SAR data do not provide enough differences for eight crop classes due to its high incidence angle. Satellite SAR systems with multi-incidence angle, multi-resolution, and multi-wavelength, such as the Canadian RADARSAT, are very desirable to improve the performance of satellite SAR data for crop classification. The third reason for the poor accuracies was that the calibration and validation blocks were selected based on the August 5 field data, but the change of the crops over the growing season could cause confusions. For example, a pasture/cut-hay class in August was an alfalfa class in June.

TM3,4,5 alone produced a 89.8% classification accuracy (Table 1). Combinations of SAR and TM data improved the classification accuracies in general. The best overall accuracy (91.85) was the combination of all three dates SAR and TM3,4,5. It represents a 2% increase over the TM3,4,5 classification alone.

Per-field Classification

Per-field classification with an ANN proved to be very effective. The crop classification accuracies improved by almost 20% using the combination of June, July and August SAR data. The best single-date (Aug.5) SAR classification with ANN improved the overall accuracy by about 26% (Table 2). The accuracies (<60%), however, were not high enough for operational crop inventory and analysis.

The best per-field classification of 96.8% with an ANN classifier was achieved using the combination of TM3,4,5 and Aug. 5 SAR data (Table 2). It represents a 8.5% improvement over a single TM3,4,5 classification alone. It also represents a 5% increase over the best per-pixel classification. This indicates that a combination of mid-season SAR and VIR data was best suited for crop classification. Another possible explanation is that the SAR data and TM data were acquired one day apart and the ground condition was the same. In this classification, all crops achieved 100% accuracies except alfalfa and pasture/cut-hay-alfalfa classes (Table 3). Alfalfa had 16.3% commission error to first corn class (i.e., good growth), and pasture/cut-hay-alfalfa had a 15.1% commission error with second class of soybeans (i.e., poor growth).

The second best classification accuracy was achieved using the combination of TM3,4,5 and July 24 SAR data (Table 2). The classification accuracy of TM3,4,5 using an ANN, however, is lower than that of a MLC. This is possibly due to the second corn class (i.e., poor growth) was not well trained. It resulted in poor accuracy of second corn class (only 25.9%) with a commission error to barley/oat class 62.1%, while all other classes were 100% correctly classified.

The best ANN classification improved 5% in accuracy than a MD classification using the same dataset. ANN produced better accuracies in general than those derived from a MD classifier (Tables 3&4). This is because the post-segmentation classifier based on the MD classification of field means used calibration data obtained as in a per-pixel classification. Such a procedure fails to exploit the full range of information that segmentation offers.

Table 1. MLC classifications for SAR, TM data and their combinations, 8 crop classes

SAR, June 15	SAR, July 24	SAR, Aug.5	TM345, Aug. 6	Overall Accuracy (%)
x				30.32
	x			28.75
		x		33.68
x	x	x		37.66
			x	89.81
x			x	90.30
	x		x	91.40
x	x	x	x	91.85

Table 2. ANN per-field classifications for SAR, TM data and their combinations, 8 crop classes

SAR, June 15 Mean	SAR, July 24 Mean	SAR, Aug.5 Mean	TM345, Aug. 6 Mean	Overall Accuracy (%)
		x		59.94
x	x	x		57.24
			x	88.48
x			x	88.08
	x		x	95.92
		x	x	96.81
x	x		x	93.62
x	x	x	x	93.89

Table 3. ANN per-field classification for the combination of TM3,4,5 and Aug. 5 SAR data, 8 crop classes

	Winter Wheat	Corn 1	Corn 2	Soybeans 1	soybeans 2	Alfalfa	Pasture/ cut-hay-alf	Barley/ Oats
Winter Wheat	100.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Corn 1	0.0	100.0	0.0	0.0	0.0	0.0	0.0	0.0
Corn 2	0.0	0.0	100.0	0.0	0.0	0.0	0.0	0.0
Soybeans 1	0.0	0.0	0.0	100.0	0.0	0.0	0.0	0.0
soybeans 2	0.0	0.0	0.0	0.0	100.0	0.0	0.0	0.0
Alfalfa	0.0	16.3	0.0	0.0	0.0	83.7	0.0	0.0
Pasture/ cut-hay-alf	0.0	0.0	0.0	0.0	15.1	0.0	84.9	0.0
Barley/Oats	0.0	0.0	0.0	0.0	0.0	0.0	0.0	100.0

Table 4. MD per-field classifications for SAR, TM data and their combinations, 8 crop classes

SAR, June 15 Mean	SAR, July 24 Mean	SAR, Aug. 5 Mean	TM345, Aug. 6 Mean	Overall Accuracy (%)
	x			36.86
			x	92.25
	x		x	91.94
x	x	x	x	91.94

CONCLUSIONS

Multi-temporal ERS-1 synthetic aperture radar (SAR) and Landsat TM data were used to evaluate an artificial neural network approach for crop classification. Six major crops, i.e., winter wheat, corn (good growth & poor growth), soybeans (good growth & poor growth), barley/oats, alfalfa, and pasture/cut-hay-alfalfa, were classified into eight classes. The results show that both a single-date and multi-temporal SAR data yielded poor classification accuracies using a maximum likelihood classifier (MLC). With per-field approach using a feed forward artificial neural network (ANN), the overall classification accuracy of three-date SAR data improved almost 20%, and the best classification of a single-date (Aug. 5) SAR data improved the overall accuracy by about 26%. These accuracies (<60%), however, were not high enough for operational crop inventory and analysis. Using the combination of TM3,4,5 and Aug. 5 SAR data, the best per-field ANN classification of 96.8% was achieved. It represents a 8.5% improvement over a single TM3,4,5 classification alone. It also represents a 5% increase over the best per-pixel classification. This indicates that a combination of mid-season SAR and VIR data was best suited for crop classification. The results also show that the best ANN classification had a 5% higher accuracy than a minimum distance (MD) classification using the same dataset.

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