A Neural Network Approach to Sensitivity Analysis of AVIRIS Spectral Bands

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Abstract

The purpose of the project described in this paper was to perform sensitivity analysis on the 224 bands collected by the Advanced Very High Resolution Imaging Spectrometer (AVIRIS) sensor. The sensitivity analysis was conducted utilizing artificial neural network technology. A baseline was established by performing partial training of a neural network using the equivalent six non-thermal TM bands as input. The remaining AVIRIS data was divided into nine groups of contiguous bands. The first, last and middle bands of each group were added to the baseline inputs and used to partially train a separate neural network using parameters identical to the baseline network. While several of the groups demonstrated a small (or even negative) impact on pixel classification, the presence of other groups improved the performance of the neural network. The results obtained support the viability of the neural network approach in ascertaining the sensitivity of band groups within the AVIRIS data.

Introduction

The advent of the hyper-spectral sensor has enabled the collection of data associated with spectral bands that have never before been analyzed with respect to ground cover classification. This new technology raises questions concerning the contribution of these new bands with respect to the classification of ground cover. Traditionally, the data available from the LandSat or the Spot series of satellites have bandwidths that are not sufficiently narrow to provide highly discrete information concerning the scene contents. Hyper-spectral data offers the potential to utilize narrow band passes that could potentially reveal much greater separability of landcover classes. The commercial potential for this capability is considerable. The forest industry represents a large market that would benefit greatly from processed data that could accurately separate species of trees.

This paper is organized as follows. First, the task to be accomplished is described. This is followed by a discussion of the approach used in accomplishing the task along with details of the design, data representation and testing methods used. Finally, the results obtained and conclusions drawn from the results are presented.

Task

The purpose of the project is to perform basic sensitivity analysis on the 224 bands comprising an AVIRIS remote sensor image. Sensitivity is defined to be the ability of a band to make a significant positive contribution to the correct classification of a pixel in an AVIRIS image. Due to the large number of bands included in the data and the contiguous nature of the bands sampled, the decision was made to divide the bands into nine groups and perform the analysis based on these groups instead of individual bands.

Approach

The approach used employs neural networks to determine the sensitivity of selected groups of AVIRIS bands relative to the classification of pixels in a sample AVIRIS image. The neural network paradigm was chosen because of its ability to discover patterns inherent in data and to use those patterns to generalize essential features of the data.

The AVIRIS Remote Sensor

The Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) is a 224 band multispectral scanner. It is flown on board a NASA ER-2s. The system was developed by JPL and was designed as one of the prototypes to the High Resolution Imaging Spectrometer (HIRIS) proposed for orbit on the future Earth Observing System (EOS).

The sensor instrument consists of 4 spectrometers that output 224 spectral bands. The data from the sensor is generally distributed in image frames of 512 lines (rows), 614 samples (columns) and 224 bands. The frequency of the 224 bands covers the spectrum from 390 to 2498 nanometers. Each band has a range of 9.6 to 10 nanometers. The data is distributed in the form of 16 bit integer values.

Additional information concerning AVIRIS can be found in the work of Macenka and Chrisp (1987), Porter and Enmark(1987), and Vane, Chrisp, Enmark, Macenka and Solomon(1984)

The data set acquired for the project is an area around Moffett Field near San Francisco, California. The flight occurred on February 17, 1993. This area contains vegetation, wetland and urban features.

The Backpropagation Network Paradigm

While there are many neural network paradigms, backpropagation is probably the most widely used model for pattern recognition and classification applications. The reader is assumed to be familiar with this paradigm. If not, a detailed discussion of backpropagation neural networks can be found in in many texts including Knight (1990) and Wasserman (1989).

Network Design and Data Representation

A public domain backpropagation neural network package called NETS Version 3.0 (Baffes, Shelton and Phillips 1991) developed by the Software Technology Branch of the Lyndon B. Johnson Space Center was chosen to create the necessary neural networks for the project. This software was selected for its portability and ease of use.

After some experimentation, the following network configuration was chosen.

Input layer	9 neurons
Hidden layers	1 with 35 neurons
Output layer	60 neurons

Of the nine input layer neurons, six are used for the average of each of the non-thermal TM bands. The remaining three neurons are used for the first, middle and last band of each of the groups to be tested. For the baseline network, these three inputs were set to zero.

The number of neurons in the hidden layer was chosen because it seemed to provide the best convergence of the several variations that were tested.

Each pixel of the AVIRIS image was classified into one of sixty training classes. These training classes serve as the expected output of the neural network.

One of the challenges with the hyper-spectral data is associating a classified data value with the spectral signature generated by the 224 bands. Many available classification routines allow a limited number of input bands to be used in the classification. The pixels in the test image were classified using the average of the AVIRIS bands corresponding to the non-thermal TM bands. The six non-thermal TM bands spectrum and their corresponding AVIRIS bands are shown in Table 1. Band six is 10,400 to 12,500 nanometers which is outside the AVIRIS range.

TM Band	Nanometer Range	AVIRIS Bands
1	450 - 520	6 - 13
2	520 - 600	14 - 21
3	630 - 690	25 - 33
4	760 - 900	41 - 54
5	1550 - 1750	125 - 145
7	2080 - 2350	181 - 208

Table1: TM and AVIRIS band correspondence

The AVIRIS bands that correspond to these ranges were averaged to create a six band image file. This file was run through a "isodata" classification program to generate an image file with sixty classes. This file was then merged with the original AVIRIS data to create a file that had the 224 spectral bands for each location (pixel) associated with one of the sixty training classes.

Next, each training class was associated with an output neuron value. The sixty output neurons represent a 1-of-n classifier scheme. In generating the training pairs, the integer group number classification is converted into a binary representation in which a pixel in group *n* produces an expected output where the *n*th element is set to one and all other elements are set to zero.

It should be noted that the selection of an appropriate network configuration is generally a heuristic endeavor guided mostly by experience coupled with experimentation. However, the determination of an optimal network configuration was not an objective of the project. Also, since the network configuration and training parameters were held constant for all the test groups they should have no impact on the sensitivity analysis.

Results

In all, there were ten neural networks generated for the project. One network was created for the baseline data consisting of the averages of the six non-thermal TM bands. This network served as the baseline against which the other networks were compared.

Another neural net was created for each of the groups shown in Table 2. These networks contained the first, middle and last spectral band values for the group in addition to the TM band averages of the baseline network. A training set and a test set of 200 randomly selected input/output pairs were created. The same random number sequence was used for all training sets so that all ten training sets would contain the same pixels in the same order. The same method was used for the test sets except that a different random number sequence was used.

Therefore, all the training sets were identical except for the three test group inputs. Likewise, all the test sets were identical (but different from the training sets) except for the three test group inputs.

Group Name	Range (nanometers)
Blue	400 - 498
Green	508 - 597
Red	607 - 696
Near IR	706 - 994
Unknown #1	1004 - 1541
Mid IR	1551 - 1749
Unknown #2	1759 - 2073
Far IR	2082 - 2350
Unknown #3	2360 - 2498

Table 2. Test group wavelength ranges

Each neural net was trained using the same network configuration and training parameters. The training time was limited to 500 cycles (one cycle presents all of the pairs in a training set to the neural net). The 500 cycle limit provided baseline classification performance in the 70% range. This allowed some margin for improvement in the test groups.

Figure 1 shows the minimum RMS (root mean squared) error obtained for each network. After training, the performance of each neural network was tested by determining how well it was able to classify pixels appearing in the sample image. Each network was tested using both its training set (Training IOP), that it had seen often, and a test set that it had never seen (Test IOP). The results of the performance tests are presented in Figure 2.

Conclusions

The paragraphs that follow discuss the results relative to each of the band groups tested. Since the results obtained represent the entire test population, it was not possible to draw any statistical conclusions concerning the significance of the differences between the test groups.

The results obtained for the nine groups fell into one of three categories. Some of the groups provided better performance and faster convergence (lower RMS for the same training period). Other groups demonstrated worse performance and slower convergence. The last category contained those groups that had mixed results. Exact values obtained for both classification performance and convergence toward low RMS are shown in Table 3.

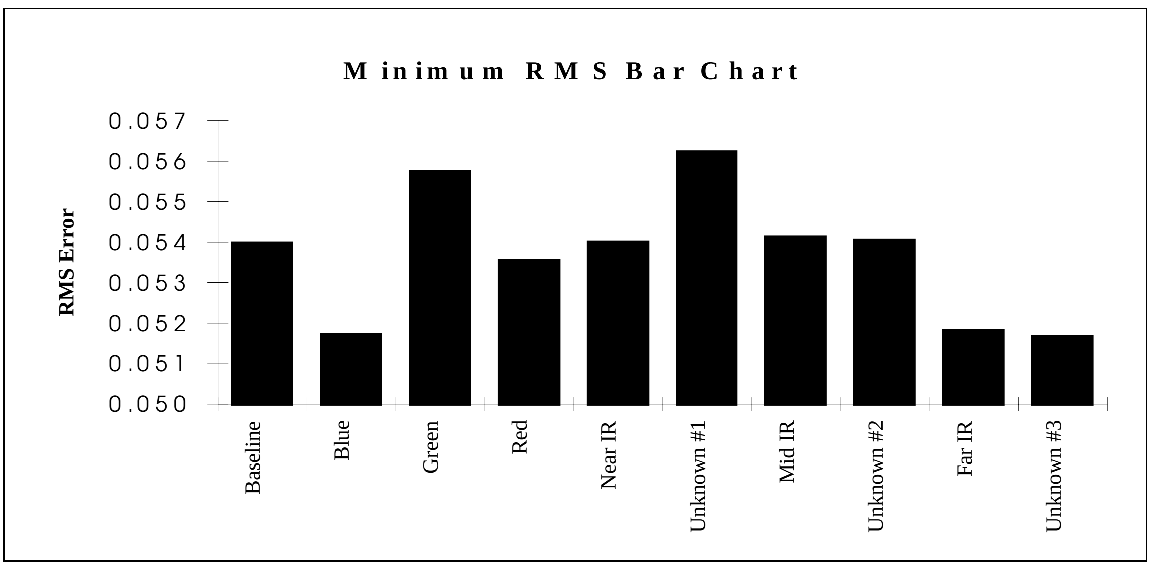

Figure 1. Minimum RMS values obtained for each group

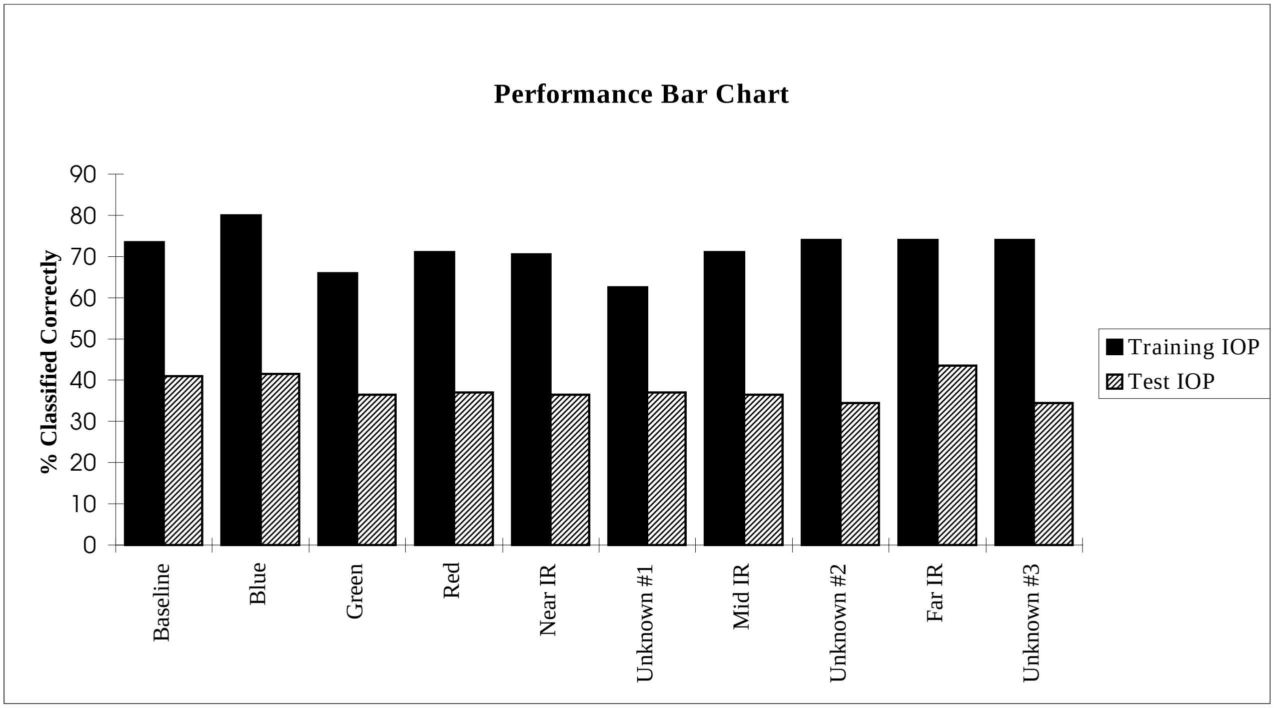

Figure 2. Performance data for training and test sets

The BLUE and FAR IR groups performed better than the baseline in classifying both the training set and the test set. They also provided better convergence than the baseline. On the basis of the tests performed, these groups represent a significant contribution to the classification capability of the AVIRIS data.

The GREEN, NEAR IR, UNKNOWN #1 and MID IR groups performed worse than the baseline in both performance tests and the convergence rate. It is possible that the poorer performance is the result of introducing extraneous "noise" into the training set. The use of these groups may actually hinder the classification capability of the AVIRIS data.

CATEGORY	**GROUP**	**Training %**	**Test %**	**RMS**
BASELINE	Baseline	73.5	41	0.053967
GOOD	Blue	80	41.5	0.051723
	Far IR	74	43.5	0.051812
POOR	Green	66	36.5	0.055743
	Near IR	70.5	36.5	0.054001
	Unknown #1	62.5	37	0.056221
	Mid IR	71	36.5	0.054124
MIXED	Red	71	37	0.053551
	Unknown #2	74	34.5	0.054049
	Unknown #3	74	34.5	0.051672

Table 3: Test group performance data

The RED, UNKNOWN #2 and UNKNOWN #3 groups performed worse on the classification tests but produced a slightly better convergence rate. These conflicting results make it impossible to draw viable conclusions concerning these groups.

While there is obviously more work to be done, preliminary results indicate that a substantial number of the AVIRIS bands may contribute to the accurate classification of ground cover types in AVIRIS images.

As a final note, the results obtained serve to support the viability of the application of neural network technology to make maximum use of the information inherent in the AVIRIS data. Also, there are several applications of neural network technology to the AVIRIS data that show promise but were not within the scope of this project. Among these are the investigation the sensitivity of individual AVIRIS bands, the possibility of utilizing other neural network paradigms (such as ART) in generating the original classification groups for the pixels and the maximization of neural network classification accuracy. There appears to be great potential in the continued investigation of the synergy between these two technologies.

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