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Improved Image Classification with Neural Networks by Fusing Multispectral Signatures with Topological Data[1]

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ABSTRACT

Automated schemes are needed to classify multi-spectral remotely sensed data. Human intelligence is often required to correctly interpret images from satellites and aircraft. Humans succeed because they use various types of cues about a scene to accurately define the contents of the image. Consequently, it follows that computer techniques that integrate and use different types of information would perform better than single source approaches.

This research illustrated that multispectral signatures and topographical information could be used in concert. Significantly, this dual source tactic classified a remotely sensed image better than the multispectral classification alone. These classifications were accomplished by fusing spectral signatures with topographical information using neural network technology.

A neural network was trained to classify Landsat multi-spectral images of the Black Hills. Bands 4, 5, 6 and 7 were used to generate four classifications based on the spectral signatures. A file of georeferenced ground truth classifications were used as the training criterion. The network was trained to classify urban, agriculture, range and forest with 65.7% correct. Another neural network was programmed and trained to fuse these multispectral signature results with a file of georeferenced altitude data. This topological file contained 10 levels of elevations. When this non-spectral elevation information was fused with the spectral signatures the classifications were improved to 73.7% and 75.7%.

INTRODUCTION

Automated schemes are needed to classify multi-spectral remotely sensed data. For example, the upcoming Earth Observing System (EOS) will generate massive quantities of data that must be managed quickly (Dorfman, 1991; Short, 1991). Access to the resulting data and information should be quick and user friendly. Campbell and Cromp (1990) call for a user friendly system that is based on user domain-specific knowledge and goals. This concept requires that the data system be based on object-oriented storage and retrieval procedures that incorporate information about the image (Dorfman, 1991). Fekete has recommended a sphere quadtree technique for subdividing and relating spherical

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data into a data base. This technique relies on the identification of image contents such as coast lines.

If these recommended data base-information systems are to be based on content and knowledge about the data, then real time classification algorithms will be required. Data storage techniques, such as the sphere quadtree (Fekekte) or object oriented information, are based on the contents of the image/data. Data storage will depend on access codes, indexes, or keys specific to the content of data. These codes and indexes would be determined as the data arrives and prior to storage into the data base. An accurate and automated classification technique would be the basis for determining these indexes that will be used for cataloging and filing data. Due to the large quantity of data coming from the EOS, this classification-indexing and storage process should occur in real time or near real time to avoid building a backlog. Not only will it be necessary to transmit and store EOS data efficiently, but also EOS data should be categorized somehow during the transmit or storage process.

While EOS data management will be important, rapid or near real time multispectral remotely sensed data classification is important in its own right. There are potential satellite image applications that depend on rapid access to classification results. Images should be classified without the delay associated with most processing techniques. The results would be transmitted to the user in a timely fashion. This rapid classification and delivery would support the feasibility of many new applications. For example, fishermen could respond quickly to recent current shifts. Short term illegal wild cat mining or deforestation could be identified and arrested. Natural disasters such as oil spills could be monitored as they progress.

Real time classification techniques do not exist; however, neural network technology promises to allow us to automatically classify images in real time. The technique is simple yet can be deployed with parallel neural processing integrated circuits. These processors are relatively cheap and available for multispectral analysis (Harston, Zhant & Stewart, 1991; Kagel, 1991).

The neural network approach has classified various remotely sensed multispectral images (Campbell, Hill & Cromp, 1989; Benediktsson, Swain & Ersoy, 1990; Cromp, 1991; Harston & Schumacher, 1991; Kulkarni, 1990; Eberlein & Yates, 1991; Decatur, 1989). Decatur's work was with the synthetic aperture radar (SAR) HH, HV, and VV components of the return at the L band (1.225 GHz) and the others were with visual and infrared bands. Some of their results can be seen in Table III. While the results compare well with statistical classification techniques, better performance is desirable. It was hypothesized that fusion of spectral signatures with additional information might improve performance.

Human intelligence is often required to correctly interpret images from satellites and aircraft. Humans succeed because they use various types of cues about a scene to accurately define the contents of the image. Consequently, it follows that computer techniques that integrate and use different types of information would perform better than single source approaches. Work to date in our laboratory supports this supposition (Harston, 1991 a, b & c).

This research illustrated that multispectral signatures and topographical information could be used in concert. Significantly, this dual source tactic classified a remotely sensed image better than the multispectral information alone. These classifications were accomplished by fusing spectral signatures with topographical information using neural network technology.

METHOD

The data came from a Landsat Multispectral Scanner (MSS) image of the Black Hills. Thematic mapper (TM) spectral bands 4, 5, 6 and 7 were represented as intensity values from 0 to 255 in 512 by 512 byte image files. Additionally, files of elevation and ground truth data were available. The ground truth showed that broad contiguous areas were assigned to single classifications. There were 22 potential classifications, which covered urban, farm, range, forest, and water as major groupings. The four classes of data used in this study were urban, farm, range, and forest. These and the other data files were georeferenced.

The type of neural network used was the three layer feedforward networks with one layer as the hidden layer. The delta rule was used to train the output layer and backpropagation was used to train the hidden layer. All work was done on MS-DOS 386/486 VGA microcomputers and the code was written in C.

One neural network was trained to classify Landsat multi-spectral images of the Black Hills. Bands 4, 5, 6, and 7 were used to generate four classifications based on the spectral signatures. These classes included or collapsed several of the classifications found in the ground truth into urban, farm, range, and forest categories. The file of condensed georeferenced ground truth classifications was used as the training criterion. This network was called the spectral signature network.

Another neural network was trained with the four bands of TM data and a topography file of altitude or elevation data. This topological file contained 10 levels of elevations. These images/files were georeferenced to each other, and the ground truth file was used for training. This network was referred to as the fusion network.

Training for both networks consisted of hand picked samples from the larger image. The experiment was conducted twice, resulting in two spectral signature networks and two fusion networks. The second set of networks was tested with additional samples taken from the same image. These samples were taken from intersection points of a grid taken at 50 pixel (horizontal) and 25 pixel (vertical) locations on the upper part of the image. There were 25 test points taken from urban, farm, range, and forest areas that resulted in only one range and one urban testing sample. This kind of grid sampling and random sampling may be roughly representative of the types of data in the image but does not obtain equal numbers of cases for each category.

RESULTS

Both spectral signature networks learned 65.7% of the training sets (60,021 training trials for the second network). The first fusion network learned 73.7% of the training set, and the second fusion network learned 75.8% at 63,035 training trails. Further training resulted in decreased levels of performance.

The second set of networks, both spectral and fusion, were tested with other data taken from the multispectral image. The spectral signature network generalized to these novel data points at 52%, and the fusion network correctly classified 60% of these test cases.

These results (see Table I for results) were carefully reviewed with the image in view. Sixteen percent of the errors appeared to be correctly classified. That is, the ground truth did not appear to be correct from the visual examination of the image. Additionally, 4% of the errors were not clear from the visual image, and the ground truth classification could be debated. The results improved 16% for both the signature and fusion network test results when the scores were corrected for the obvious (not the 4% border line) ground truth errors.

Regardless of the corrections, it is clear that the fusion of altitude information with spectral signatures improved the learning. This improvement was 8% in the first set of networks and 10% in the second set of networks. Even the testing results improved by 8% with the second set of networks.

A detailed analysis of the errors indicated that the greatest number of errors came from misclassified farm data. Keep in mind that there were more test samples from farm areas than from other areas. The performance in each class can be seen in Table II. There was only one range test sample and that one was misclassified. This resulted in a 100% error rate for the range class.

The fusion with elevation data improved the farm scores from 60% to 80%. Unfortunately the forest performance was decreased from 87.5% to 75%. The test sample size was small at 25 cases so interpretation of the results may be limited. The misclassified range sample was one of the debatable or border line cases. These results are also found in Table II.

CONCLUSIONS

The use of altitude data with the spectral signatures improved the performance. This fusion of image and topographic data was simple to do with the neural networks. The elevation data improved the farm land classification but degraded the forest classification to a lesser extent. However, the results were positive overall and suggest that classification performance could be further improved if other types of data were included in the neural classification process.

The initial impression that the learning and test results were low should be interpreted in relationship to the results from similar classifications. For example, as seen in Table III, other types of statistical classification are also low (Benediktsson, Swain & Ersoy, 1990; Duda & Hart, 1973). In general, the neural techniques performed better, except with the multisource technique that used information in addition to the spectral data (Benediktsson, Swain & Ersoy, 1990). This multisource statistical technique included Landsat MSS, elevation, slope, and aspect data. This additional data improved the classification technique to 61%. Clearly, this result argues for the fusion with, or inclusion of, additional cues, regardless of the classification technique used.

Classification of raw spectral data without any clean up is also poor as seen in Table I with 55% (Campbell, Hill & Cromp, 1989) and 52% or 60% in this study. Neural studies often correct or select the data in some way. Campbell, Hill, & Cromp (1989) used only non-boundary pixels for training. Homogeneous fields were developed for training and testing by Benediktsson, Swain, & Ersoy, 1990. In the present case, the classification was corrected by visual inspection of the test cases. Some of these selection or correction procedures resulted in respectable test scored at 70% (Campbell, Hill & Cromp, 1990) and 76% in this study.

Given the improved classifications by fusing non spectral data with the spectral signature, possibly other supplementary information can be used by the neural network system to improve performance. A shadow file might be used to improve the classification of forests on both sides of the mountain. In another study, pixel patterns based on brightness and texture were classified within each MSS TM band (Harston, 1991d). These classifications were fused with an additional neural network that resulted in improved performance. Possibly, the texture, signature, altitude, and other data can be fused with neural technology to obtain even higher test performance.

The potential for classifying incoming Earth Observing System (EOS) data in real time is genuine. See papers authored by Short, Campbell, Fekete, Dorfman, and Cromp at the GSFC for a description of the importance of this problem. As indicated in our multi-spectral work to date, meaningful results are possible; however, higher levels of performance may be possible. It seems reasonable that more can be done with multi-spectral data when additional non-spectral information is integrated with the spectral results. Further work with seasonal, urban, hazy, and cloudy images is needed. Ultimately, a system that could classify regardless of variations or conditions could categorize incoming data in real time. Such categorizations would be useful for the Intelligent Data Management (IDM) project as a basis for defining, cataloging, and referencing images for a data base.

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TABLE I

NEURAL NETWORK TRAINING AND TESTING RESULTS

	TRIALS	TRAIN	TEST	CORRECT
EXPERIMENT I.				
SPECTRAL NN		65.7%		
FUSION NN		73.7%		
EXPERIMENT II.				
SPECTRAL NN	60,021	65.7%	52%	68%
FUSION NN	63,035	75.8%	60%	76%

TABLE II

CORRECTED PERFORMANCE FOR EACH CLASS

SPECTRAL SIGNATURE NEURAL NETWORK

CORRECTED GROUND TRUTH	NEURAL NETWORK CLASSIFICATION			
	URBAN	FARM	RANGE	FOREST
URBAN	100%	-	-	-
FARM	26.8%	60%	6.7%	6.7%
RANGE	-	100%	0%	-
FOREST	-	-	12.5%	87.5%

ELEVATION FUSION NEURAL NETWORK

CORRECTED GROUND TRUTH	NEURAL NETWORK CLASSIFICATION			
	URBAN	FARM	RANGE	FOREST
URBAN	100%	-	-	-
FARM	20%	80%	-	-
RANGE	-	100%	0%	-
FOREST	-	12.5%	12.5%	75%

TABLE III

MULTISPECTRAL IMAGE CLASSIFICATION PERFORMANCES

		NEURAL NETWORKS TRAINING	NEURAL NETWORKS TESTING	STATISTICAL CLASSIFICATION * ED	ML	MD	MULTI-SOURCE
CAMPBELL, HILL & CROMP, 1989 WASHINGTON, DC W/ GROUND TRUTH	ANY PIXEL	48%	55%				
	NON-BOUNDRY PIXELS	66%	70%				
BENEDIKTSSON, SWAIN & ERSOY, 1990 COLORADO MOUNTAINS	HOMOGENEOUS FIELDS	95%	52.5%	47%	49%	50%	61%
CROMP, 1991 BLACK HILLS LANDSAT MSS			60%				
HARSTON, 1991 MURFREESBORO LANDSAT MSS MULTISPECTRAL FUSION SYSTEM	MLC W/ NN	100%	61%				
	1 SAMPLE /CLASS SET	100%					
	BRIGHTNESS	85%	43%				
	BRIGHTNESS & TEXTURE	75%					
HARSTON & SCHUMACHER, 1991 TIMS IMAGES	SPECTRAL SIGNATURE W/ ROAD DETECTOR NN SYSTEM	95%	63%				
HARSTON & SCHUMACHER, 1991 BLACK HILLS LANDSAT MSS		W/ GROUND TRUTH		CORRECTED FOR VISUAL INTERPRETATION			
	SPECTRAL SIGNATURE	65.7%	52%	68%			
	SPECTRAL SIGNATURE W/ALTITUDE	75.8%	60%	76%			

* ED: MINIMUM EUCLIDEAN DISTANCE
ML: MAXIMUM LIKELIHOOD METHOD
MD: MINIMUM MAHALANOBIS DISTANCE
MULTISOURCE: STATISTICAL MULTISOURCE ANALYSIS