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WATER REGIONS EXTRACTION FROM RADAR IMAGERY
USING A NEURAL NETWORK

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ABSTRACT

An artificial neural network concept is explored and developed for detecting and extracting water regions from radar imagery. A backpropagation neural network consisting of three layers of processing elements (PEs) is selected for this application. The input layer is composed of nine PEs that are arranged to process a single pixel at the same time. Two PEs in a hidden layer are sufficient for delineating water from other terrain categories. A single output PE with a thresholding function classify effectively all test images into two terrain categories: water and non-water. Large-scale Synthetic Aperture Radar (SAR) images, containing 512 by 512 pixels, were used as the test images for this experiment. Two blocks of water regions totalling 2,048 pixels were extracted for training the network. All the water pixels were classified correctly, while more than 99 percent of the non-water pixels were correctly classified.

INTRODUCTION

The automatic detection and extraction of water regions from radar imagery have been a subject of research for some time. Various pattern classification methods dealing with segmentation, classification, and extraction of terrain categories such as water, forests, fields, and built-up areas have been reported [1]. Statistical pattern recognition, image processing, and computer vision algorithms were exclusively used in a conventional computer system to solve the above problem. Because of their single-channel data processing capability, most conventinonal computers are inherently slow. In addition, the majority of terrain classification software routines are very complicated and require an excessively long time to implement and run.

In this paper, an alternate technique is described for processing and classifying SAR imagery using an artificial neural network. Artificial neural networks, which attempt to model the functions and architectures of the human brain, are massively parallel and highly adaptive or trainable. This implies that they can be operated at a high speed and they are fault-tolerant. Thus, the selection of a neural network for processing and classifying large scale SAR imagery seems reasonable and justifiable. The following sections discuss in detail the implementation of a backpropagation neural network, the training processes and testing results for the network, and the conclusions for this research.

IMPLEMENTATION OF THE NEURAL NETWORK

The water finding task described above is a pattern classification problem. It can be solved by using many neural network architectures such as backpropagation, ADALINE (Adaptive Linear Neuron), ART (Adaptive Resonance Theory), Boltzman machine, feature map, Hamming net, etc. However, a backpropagation neural network was chosen to solve our problem because it is most suitable for the pattern recognition application. It is also the simplest in architecture and implementation. It requires supervised training, which is relatively easy to implement.

Network Topology: The neural network was implemented on an HNC neurocomputing

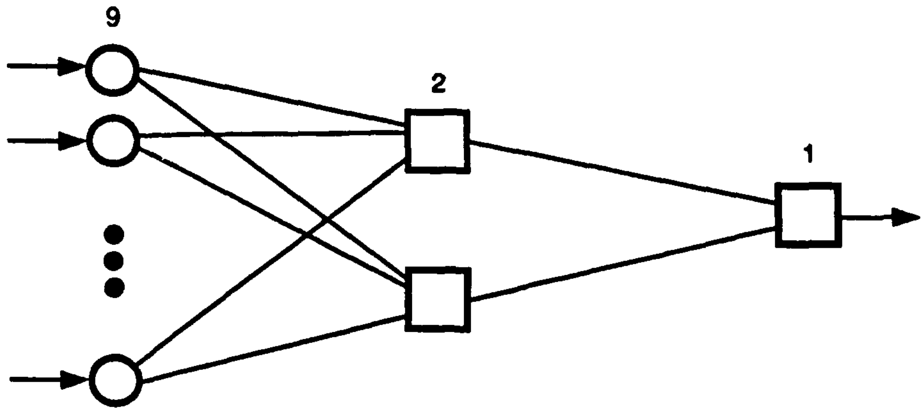

Figure 1. Network Configuration

coprocessor [2] interfaced with a SUN4 computer. It is a fully interconnected linkage of three layers as shown in Figure 1. The input layer consists of 9 PEs which are arranged to process a single pixel value simultaneously. Two PEs in a hidden layer are sufficient for delineating water from other terrain categories. A single PE with a thresholding function classified effectively all test images into two terrain categories: water and non-water.

Besides the input, hidden, and output layers, there are three auxiliary layers of PEs associated with this network. These auxiliary layers of PEs are automatically provided by the neurocomputer for the purposes of facilitating network training and performance once the main topology is determined. These auxiliary layers are not shown in Figure 1 for simplicity, however, they are briefly introduced below. A training layer is connected to the output layer in a one-to-one manner. This necessitates that the number of PEs in both the training and output layers be the same. A bias layer containing a single PE with a constant state of 1.0 is connected to each hidden and output PE. There is also a layer which computes statistics on the network's performance. The PEs in the input layer serve only to distribute the inputs; they perform no computation. For this reason, they are shown as circles to distinguish them from the computing PEs, which are shown as squares in Figure 1. Each computing PE in both hidden and output layers performs two tasks: summing and activation. The first task computes a summation for all input signals feeding into the PE. Each input signal represents a product of the output signal from the previous layer PE multiplied by its corresponding weight. A sigmoid activation function is applied to this summed signal to produce an output signal for this computing PE, thus completing the second task.

Network Implementation: The software for this backpropagation neural network was written by using the C language and the vendor supplied User Interface Subroutine Library (UISL), and was successfully implemented onto the neurocomputer described earlier. A switch was provided so that the network can be operated either in a training mode or in a classification mode. In the training mode, all 20 weights (18 weights between the input and hidden layers, and 2 weights between the hidden and output layers) are displayed on the screen of the SUN4 computer, and their changes can be observed and examined in real time. Two indicators were also provided to show the instantaneous changes of Mean Squared Error (MSE) and Mean Absolute Error (MAE) for the network during training. Memory is assigned to save the learned weights once the network training is successfully completed, and the satisfactory MSE and MAE are obtained. In the classification mode, a block diagram illustrating the fully connected three-layered backpropagation neural network configuration (see Figure 1) is displayed. The input pixel value feeding an input PE is shown to the left side of each input PE, while the corresponding classified output value (either water:183 or non-water:0) is displayed on the right side of the output PE.

NETWORK TRAINING AND CLASSIFICATION RESULTS

Network Training: The training of the neural network was accomplished by using a block of 1,024 water pixels extracted from a water region of the first test image (Figure 2a). Each training pixel was sequentially fed into the network, and the MSE and MAE were automatically adjusted until the network converged. For our case, the MSE decreased very rapidly from approximately 0.5 to 0.00007 in less than 5 minutes. Originally, it was planned to use the same training set for classifying all test SAR images. However, it was discovered that the network poorly classified another SAR image (Figure 3a) having much brighter water regions (higher pixel values). This problem was solved by extracting another training set, having 1,024 pixels, from a water region of the second image and retrained the neural network.

Network Classification and Results: Two large-scale SAR images taken from the Elizabeth City, North Carolina area were used as test images for evaluating the classification accuracy of this backpropagation neural network. Each image consists of 512 by 512 pixels, and each pixel was digitized into 8 bits. These test images are shown in Figures 2a and 3a. A gray value of 183 was assigned as a water pixel, while a 0 gray value a non-water pixel. The first original SAR image, shown in Figure 2a, contains a large water body on its right side. The left side of the image consists mainly of fields, forests, and a built-up area. The classification results for this image are illustrated in Figure 2b. As seen in Figure 2b all water pixels were correctly classified. More than 99 percent of the non-water pixels were classified correctly. The misclassified non-water pixels belong to forest shadow regions which have pixel values similar to that of water pixels (in between 40 and 60). The second original image, shown in Figure 3a, consists of two large water bodies which are divided by a peninsula, and several small lakes located on the lower right part of the image. The land part of the image consists mainly of fields and forests. Similar classification results were obtained for this SAR image as shown in Figure 3b. Except for several water pixels on the top middle part of the image, all water pixels were correctly classified. The non-water pixels were again classified more than 99 percent correct. For the second image, the misclassified non-water pixels mainly belong to forest shadows and a small section of a road which is adjacent to the bottom of the image.

CONCLUSIONS

1. The classification of water pixels from SAR imagery using a backpropagation neural network appears to be quite interesting and useful.

2. A high classification accuracy can be obtained with a backpropagation neural network using only three computing PEs.

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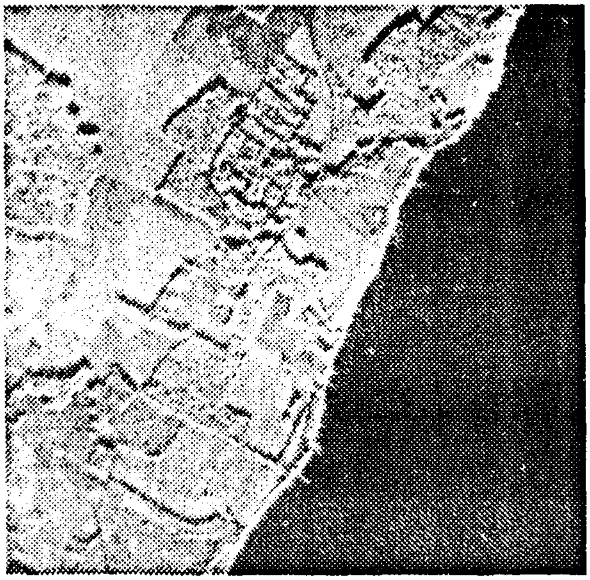

Figure 2a. First SAR Test Image

Figure 2b. Classified Results for The First SAR Test Image

Figure 3a. Second SAR Test Image

Figure 3b. Classified Results for The Second SAR Test Image