HARDWARE BASED NEURAL NETWORK DATA FUSION FOR
CLASSIFICATION OF EARTH SURFACE CONDITIONS

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ABSTRACT

Hardware based neural network data fusion system is used for fast and accurate classification of surface conditions, based on SSMI satellite measurements. The system processes sensory data in three consecutive phases: (1) pre-processing to extract feature vectors and enhance separability among detected classes; (2) preliminary classification of Earth surface patterns at two, separate and parallelly acting classifiers: back propagation neural network (BP ANN) and binary decision tree (BDT) classifiers; and (3) data fusion of results from preliminary classifiers to obtain the optimal performance in overall classification. Both BDT classifier and fusion centers are implemented by neural networks. This system is implemented in a prototype of a massively parallel and dynamically reconfigurable Modular Neural Ring (MNR) co-processor. It brings up the detection accuracy to 94% compared with 88% for BP ANN and 80% for BDT classifiers.

1. INTRODUCTION

Artificial neural networks (ANN), have demonstrated capabilities for robust pattern classification in the presence of noise and object-to-background sensory uncertainty, such as environmental monitoring applications including land cover determination, vegetable mapping, soil survey, etc. This paper presents a neural network data fusion system (in Fig. 1) which will utilize multichannel SSMI satellite imagery, to combine supervised trainable and self-organized neural network architectures with specific knowledge-based classification techniques, with reference to fast and accurate classification of earth surface. This neural approach is intended to compensate different classification techniques by using data fusion method and to reduce the lengthy training time required in supervised learning network. Hardware implementation in a Modular Neural Ring (MNR) co-processor is able to further increase the computation speed to obtain a fast real-time performance. The overall neural network data fusion system, can also be seen as a four-layered supervised network which is composed of several modular and hierarchical networks. In this paper, we will discuss the description of the neural network data fusion system and hardware implementation. Some experimental results will be presented and summary will be given.

2. NEURAL NETWORK DATA FUSION SYSTEM

![Figure 1. Neural Network Data Fusion System for SSMI Measurements](image)

Although existing neural network paradigms have demonstrated excellent capabilities in learning and generalization, efficient training and determination of its...
internal topology (such as number of hidden neurons) still remain challenging tasks. This neural network data fusion system provides an alternative approach to attack these problems and can be easily implemented in a hardware. Basically, this system treats each classifier as different sensor and fuse each (sub-optimal) classification results to obtain the optimal results. The sizes and connections of intermediate layers (or hidden layers) can be determined based upon the desired data flow.

This data fusion system processes sensory data in three consecutive phases, as follows: (1) pre-processing, aimed at extracting feature vectors and in enhancing separability among detected classes; (2) preliminary classification of Earth surface patterns at two, separate and parallely acting, classifiers back-propagation ANN (AP ANN) and binary decision tree (BDT); and (3) fusion of classification results performed at global fusion center (GFC) from different classifiers and imagery to obtain the optimal decision. The configuration is a hierarchical neural network architecture, in which each functional neural net will handle different processing phases in a pipelined fashion.

2.1 Pre-processing

Pre-processing for SSMi imagery includes mainly the generation of \((7 \times 7)\) covariance matrices from measured brightness temperatures at each pixel. Information about pixel brightness temperatures, covariance matrix elements, and desired surface class definitions, is collected in a feature vector for the supervised training of a neural network classifier. It has been demonstrated that increasing the elements of the feature vector by adding more relevant parameters, derived nonlinearly from original features, can reduce the number and size of hidden layers, and can also reduce the training time [4].

![Diagram of BDT Classifier and its Neural Implementation](image-url)
2.2 Preliminary Classification

a. BP ANN Classifier

A two-layered (one hidden layer) supervised back propagation algorithm is used to train the network to become a feed forward pattern recognition engine [3] to learn the input feature vectors corresponding to different output classes. There are 14 input neurons corresponding to SSMI measurements as well as their covariance matrix, 60 hidden neurons, and 5 output neurons representing 5 surface conditions. It takes around 40 and 160 iterations of presenting training set to train the BP ANN classifier up to 90% and 100% of accuracy, respectively.

b. BDT Classifier

The BDT classifier is constructed to implement Grody's global classification algorithms as in Figure 2 [1]. They are designed to analyze global coverage of satellite data sets and to classify based on the physical characteristics of measurements and on surface types. This technique performs a hierarchical tree-structured decision procedure through the evaluation of polynomial functions of input feature elements and through thresholding. The special topology of BDT classifiers, used for surface condition classification based on SSMI measurements is drawn from the so-called Entropy Net architecture [4]. This architecture includes a two-layered topology, of which the lower layer performs arbitrary mapping of thresholding operations while the upper layer performs logical operations (e.g. AND, OR) which allow us to convert the hierarchical decision procedure into a fully parallel process. The weight vectors between the layers are determined from the coefficients of polynomial functions. A striking advantage of the neural implementation architecture is that it allows us to specific the number of neurons needed in each layer, along with the desired output. This, in turn, leads to an accelerated progressive training procedure, that also allows each layer to be trained separately.

There are 5 neurons corresponding to 4 SSMI measurements as well as one element of covariance matrix and 5 output neurons for each surface class. The individual decision from both BP ANN and BDT modules are sent to the global fusion center (GFC) for final decision.

2.3 Fusion Processing

The fusion processing involves global fusion center (GFC) operations, which integrates results from both BP ANN and BDT classifiers. The GFC is composed of several different data fusion center (DFC), each of which corresponds to different types of output classes.

3. HARDWARE IMPLEMENTATION

The neural network data fusion system for real time processing is implemented in a prototype of a massively parallel and dynamically reconfigurable Modular Neural Ring (MNR) architecture [6] which is capable of maintaining a high performance for digital and neural applications. The MNR architecture is composed of multiple primitive processing ring (pRing) embedded in a global communication structure and is interfaced to a...
host workstation as in Fig. 4. It is a multiple-SIMD (single instruction multiple data) architecture. Each of the pRings consists of 40 processing elements (PE) that are capable of mapping any number of neurons. It has been shown that the MNR provides very high efficient hardware utilization and very low communication delay overhead. The achieved speed/capacity performance is increased linearly with the number of processing elements, without upper limit.

Covariance matrix evaluation, involving the manipulation of two matrices, by merely assigning two manipulated matrices to the weights and input vectors of the feed forward neural architecture. Two pRings are used to implement the BP ANN module: first one for handling the 16x64 weight matrix of input-hidden connection and second one for 64x16 weight matrix of hidden-output connection. The third pRing is used for the parallel implementation of the BDT which handles a 16x16 weight matrix. Since some weights are not utilized (for example, the input-hidden connection in BP ANN only requires 14x61 weight matrix), they are filled with zero weights to satisfy hardware implementation requirements. The operation and performance of the hardware-based networks remain almost unchanged. Once the training is finished, the weights and bias are then stored in the memory of each PE for future processing. Both BP ANN and DBT operations are performed at the MNR architecture simultaneously. The individual decision from each operation is then fed to the data fusion center (DFC) for final optimum decision performed at host computer.

4. CLASSIFICATION RESULTS

This study uses SSMI microwave satellite measurements. The more detailed description of the SSMI measurements and pre-processing can be found in literatures [1]. The SSMI instrument, flown on board the Defense Meteorological Satellite Program (DMSP) polar orbiting satellites, is a seven-channel conically-scanning microwave radiometer, measuring brightness temperatures at 19, 22, 37, and 85 GHz. All measurements are obtained with dual polarizations (H and V) except for 22 GHz channel. It provides unique signatures for identifying surface features and obtaining the temperature and condition of the Earth's atmosphere. The measurements (brightness temperature or sometimes called antenna temperatures) used in this study were made between November 1988 and January 1989 and covers over the northern hemisphere. The data was identified and confirmed by "ground truth" as five different data sets corresponding to five different surface classes: non-scattering medium (Non-Sm), precipitation over the ocean (R-Ocean), snow cover land (Snow), precipitation over the land (R-Land), and the desert (Desert). Each class has different samples ranging from 500 to 5000 and there are totally over 13,500 samples. Table 1 illustrates some SSMI measurement classification characteristics including SSMI measurements and surface features [2].

There are totally 13,787 samples of data used in this study. Each of five different classes contains from 500 to 5,000 different samples. We used 500 samples of data as training sets which represent 3.6% of the total samples. Each training set, obtained randomly from the total data set, consists of equal amount of samples from five different classes. Rest of the samples (over 96%) are used for testing the network. Once the BP ANN is trained either fully or partially, it is used to perform the classification. The classification accuracies, by using the fully-trained BP ANN classifier (i.e., all training patterns are recognized by this BP ANN), are 82%, 98%, 97%, 78%, and 79% for non-scattering medium, precipitation over ocean, snow, desert, and precipitation over land, respectively (Lure, et al., 1992). The classification accuracies from BDT are 99%, 56%, 81%, 57%, and 70% for each surface class. Note that the class of non-scattering medium represents the surface which can not be easily, specifically identified as any other four surfaces. The overall accuracy for BP ANN approach is around 88% whereas it is around 80% for BDT classifier. The preliminary results show that the neural network data fusion system improve the classification accuracy for all classes by around 4% from BP ANN's results. The overall accuracy of neural network data fusion is improved to 94%. Even without fully-trained (e.g., 90% of training set are learned correctly by BP ANN) the overall classification accuracy can still maintain similar classification accuracies. From the coefficients of data fusion center, it is also found that BP ANN plays more important role in classifying the non-scattering medium, snow, and desert; whereas the BDT are more dominant in classifying the other two surfaces. The significance of each SSMI measurement to classification of each of five surface types can also be obtained through the linearization procedure of the weights described in the previous study [2].

5. SUMMARY

In this study, neural network data fusion system is presented to classify surface types based on the SSMI measurements. Both back propagation ANN (BP ANN) and binary decision tree (BDT) classifier are used for
this study. Seven SSMI measurements (brightness temperature at 19, 22, 37, and 85 GHz for H and V polarizations, except H for 37 GHz) at each image pixel are extracted as an input feature vector. Five surface types including non-scattering medium, precipitation over the ocean, snow cover land, precipitation over the land, and the desert are used as target patterns. After trained by using less than 4% of the samples, both BP ANN and BDT are able to perform the classification over 13,500 samples. The overall accuracy for BP ANN and BDT approaches are 88% and 80%, respectively. The neural network data fusion system which fused the individual decision from BP ANN and BDT improved the overall accuracy to 94%. The significance of contribution from either approach is determined based on the coefficients of data fusion center. The fusion system is currently implemented in a massively parallel and dynamically reconfigurable neural network hardware (Modular Neural Ring) for real time parallel processing and integrated in an image processing system at NOAA/NESDIS. The data fusion system not only preserves the advantages of both BP ANN and BDT classifiers (for example, the capability of physical interpretation of input feature space from the BDT classifier and robust classification from the BP ANN) but reduce the pitfall of individual classifier (for example, brute-force training of the BP ANN module and sensitive to noise for the BDT module).

<table>
<thead>
<tr>
<th>Channel Frequencies and Polarization</th>
<th>T1(H)</th>
<th>T1(V)</th>
<th>T2(H)</th>
<th>T2(V)</th>
<th>T3(H)</th>
<th>T3(V)</th>
<th>T4(H)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Surface Conditions</td>
<td>Non-SM</td>
<td>R-Ocean</td>
<td>Snow</td>
<td>R-Land</td>
<td>Desert</td>
<td></td>
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Table 1. SSMI classification characteristics

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