

10.13 SPECT Reconstruction Using a Backpropagation Neural Network Implemented on a Massively Parallel SIMD Computer

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SPECT RECONSTRUCTION USING A BACKPROPAGATION NEURAL NETWORK IMPLEMENTED ON A MASSIVELY PARALLEL SIMD COMPUTER

John P. Kerr and Eric B. Bartlett
Biomedical Engineering Program
Iowa State University
Ames, IA 50011

Abstract

In this paper, the feasibility of reconstructing a single photon emission computed tomography (SPECT) image via the parallel implementation of a backpropagation neural network is shown. The MasPar, MP-1 is a single instruction multiple data (SIMD) massively parallel machine. It is composed of a 128x128 array of 4-bit processors. The neural network is distributed on the array by dedicating a processor to each node and each interconnection of the network. An 8x8 SPECT image slice section is projected into eight planes. It is shown that based on the projections, the neural network can produce the original SPECT slice image exactly. Likewise, when trained on two parallel slices, separated by one slice, the neural network is able to reproduce the center, untrained image to an RMS error of 0.001928.

Introduction

In recent years, artificial neural networks (ANNs) have been the subject of extensive theory, implementation and applications research. Spawned by the ever-increasing processing power of computers, ANNs have proven to be useful in applications for which conventional techniques have had difficulty. Such applications include pattern and speech recognition, and image enhancement.

One area in which the image enhancement capabilities of neural networks may be applied is nuclear medical emission computed tomography (ECT). ECT utilizes the radiation emitted by a medical radionuclide to produce a three-dimensional image. This image is reconstructed from a series of two-dimensional projections. Reconstruction is typically achieved through a computationally expensive filtered backprojection algorithm [1]. Although this method provides useful diagnostic information, it does have several limitations that create high statistical uncertainty in the reconstructed image [2,3]. Neural networks on the other hand, have the capability of handling many of the causes of these uncertainties, including attenuation and scatter effects. However, the training time required to simulate a

reconstruction ANN large enough to handle useful images (i.e., 64x64) may not be practical. Training a network fully, often requires presenting the entire training set several thousands of times. Therefore, the time in which the ANN can be trained is an important consideration in ECT reconstruction.

Although much success has been achieved with neural networks, the applicability of ANN's to large-scale problems has been limited. Implemented primarily through simulation on digital serial computers, the size of the neural network and hence, the size of the problem that can be evaluated is limited by the processing speed of the implementing computer. The architecture of a multi-layer neural network has a natural parallel structure. One way to utilize this architecture and improve processing time is to simulate the ANN on a parallel machine.

The objective of this paper is to demonstrate the feasibility of single photon emission computed tomography (SPECT) image reconstruction via a backpropagation neural network [4], implemented on the MasPar MP-1 parallel computer.

SPECT Data Set

Small sections of conventionally reconstructed SPECT images were used as the training set for demonstrating neural network reconstruction capabilities. Each 8x8 section used for training the ANN was taken from a clinical 64x64 SPECT image slice. The planar inputs were generated by projecting each image slice into eight 8-quadrant planes. Each plane was rotated 22.5° from the previous plane around the image, giving eight incremental views covering 180° around the image. Each of the eight quadrants of each planar view is a summation of the intensity values projected from the 8x8 section.

Two sets of training data were used to demonstrate SPECT reconstruction. The first set consisted of a single datum. The objective of training a single image was to demonstrate the neural networks ability to memorize a SPECT image. The second data set consisted of two parallel sections separated by one slice, taken from a clinical SPECT image. The objective here was not only to show the ANN's ability to recall more than one image, but also to determine its ability to generalize the relationship between the planar and reconstructed data. This was achieved by testing the networks ability to reconstruct an image slice not used in the training set.

Multi-layer Neural Network on a Distributed Array of Processors

The MasPar MP-1 is a single instruction multiple data (SIMD), massively parallel machine. Composed of a 128x128 interconnected array of 4-bit processors, the performance of the MP-1 is dependant on how readily the problem at hand can be distributed among the 16,384 processors. The backpropagation architecture can utilize this parallel processing power, by executing the functions of all processing elements (PEs) in each layer simultaneously.

The architecture implemented for determining the feasibility of SPECT reconstruction by an ANN, required 64 inputs, for the eight planar projections, and 64 outputs, to produce the 8x8 reconstructed image slice. The optimal number of PEs in the hidden layer was determined by training a number of networks with various hidden layer sizes. The neural network was distributed on the processor array by dedicating a processor to each node and each interconnection in the network, figure 1. These processors are aligned on the array so as to best utilize the high speed north-south, east-west communication pathways. This distribution of the network allows data to propagate from layer to layer more efficiently than less direct pathways. The training time required for large architectures was significantly less on the MP-1 than on the VAXStation 3520 serial computer, to which serial and parallel training rate comparisons were made, Table I.

I_1	w_{111}	w_{112}	w_{113}	...	w_{11j}			
I_2	w_{121}	w_{122}	w_{123}	...	w_{12j}			
I_3	w_{131}	w_{132}	w_{133}	...	w_{13j}			
.			
.			
.			
I_{64}	H_1/w_1	H_2/w_2	H_3/w_3	...	H_j/w_j			
	w_{211}	w_{221}	w_{231}		w_{2j1}	O_1		
		
		
		
	w_{2163}	w_{2263}	w_{2363}	...	w_{2j63}	O_{63}		
	w_{2164}	w_{2264}	w_{2364}	...	w_{2j64}	O_{64}		

Figure 1 ANN Distribution on 128x128 PE Array.

Table I Serial Vs. Parallel Processing Rates

ANN Architecture					
1000 iterations of a single datum training set (time)					
	64x8x64	64x16x64	64x24x64	64x32x64	64x40x64
VAXStation 3520 (serial)	62 s	135 s	176 s	225 s	277 s
MasPar MP-1 (parallel)	62 s	66 s	72 s	75 s	77 s

Single Image Memorization

A number of different neural network architectures were trained on a single SPECT image. Each network architecture trained to an RMS error of zero (single-precision), except for an architecture with only two hidden nodes. All other architectures reproduced the SPECT images exactly. This precise recall accuracy was achieved in less than 100 training iterations, except for 1-, 3-, 4-, and 5- hidden node architectures which required as many as 200 iterations to reach an RMS error of zero. Overall memorization of a single SPECT image was not a problem for the backpropagation neural networks.

ANN Generalization of Multiple SPECT images

The next task was to determine the neural networks ability to generalize the training set in order to accurately produce novel images. This was addressed by training an ANN on two 8x8 parallel image slice sections which were separated by one slice. The network was trained on these two images and achieved an RMS error of 0.001928. Then the untrained middle image slice was fed forward through the neural network. The output image generated had an RMS error of 0.001231. The full 64x64 reconstructed SPECT image from which the untrained 8x8 section was taken, is shown in figure 2. The actual SPECT image section and the ANN generated SPECT image section are shown in figures 3 and 4. The network that produced the image in figure 4, had a 64x8x64 architecture and was trained for 6000 iterations on the two image training set.

Discussion and Concluding Remarks

The neural networks ability to memorize a SPECT image and to generalize between two slice images to reconstruct the center, untrained image shows that full SPECT image reconstruction via an ANN is feasible. Although a statistical comparison of the reconstructed image to the original image was made, the most important measure of the ANN's image reconstruction ability is a visual one. This is particularly true of SPECT information collection which is through visual interpretation. It can be seen in figures 3 and 4 that the anatomical features of the original SPECT section are present in the image reconstructed by the ANN.

The next step in developing SPECT reconstruction with an ANN will be to train the network on multiple slices, every other one, from all the slices of a SPECT brain image. This will be important in determining if the ANN can generalize over a large range of images and accurately reproduce the untrained slices.

From that point the same approach taken for 8x8 image reconstruction will be applied to full 64x64 SPECT images. This will require a modification to the parallel implementation of the ANN. Although the processing times achieved with the MP-1 are encouraging, many high-speed serial machines could more efficiently train the architectures used in this paper. Superior training rates are attainable through better utilization of the PE array. An improved parallel backpropagation implementation algorithm has been proposed [5]. A new algorithm will be necessary for full SPECT image reconstruction, and for what may eventually be a more efficient SPECT reconstruction technique.

The primary constraint to accurate ECT image reconstruction involves the presence of noise, systematic errors, artifacts, and physical photon transport effects such as scatter and attenuation [2, 3]. Improved SPECT reconstruction via an ANN may be achieved by compensating for these problems in the training set. One way in which the accuracy of reconstruction can be improved is by modeling the physics of these problems in conjunction with the reconstruction algorithm used to produce the ANN training set. The Monte Carlo method can be used to simulate attenuation, scatter, and other effects so that the ANN can be trained to correct for these undesired artifacts [6, 7]. ANN SPECT reconstruction would then offer the advantages associated with the Monte Carlo method, but without the inherent computational cost.

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Figure 2 Reconstructed 64x64 SPECT image from which the 8x8 untrained section was taken (denoted by arrow).

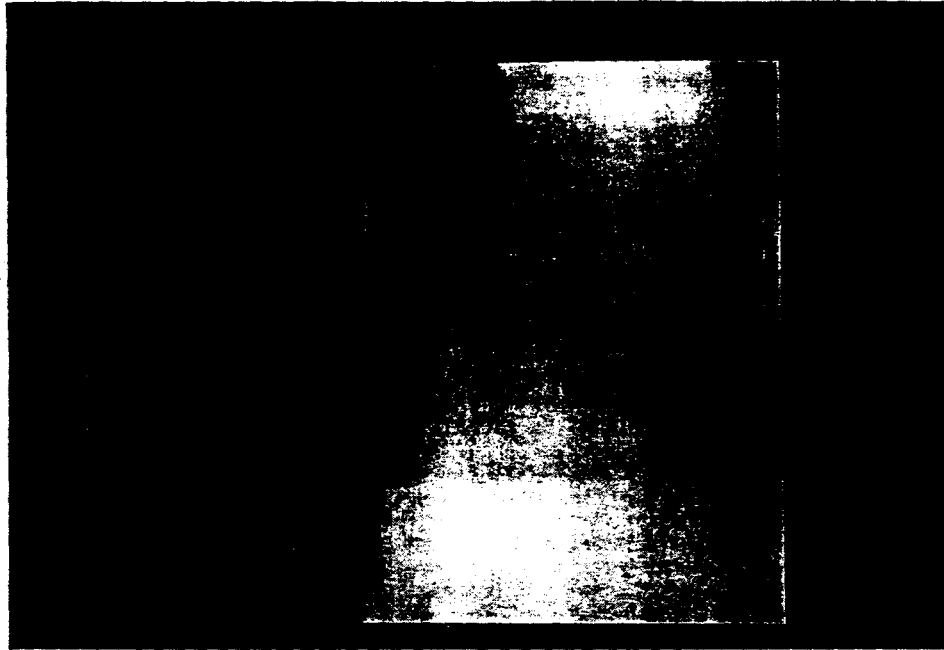


Figure 3 Conventionally reconstructed 8x8 SPECT section.

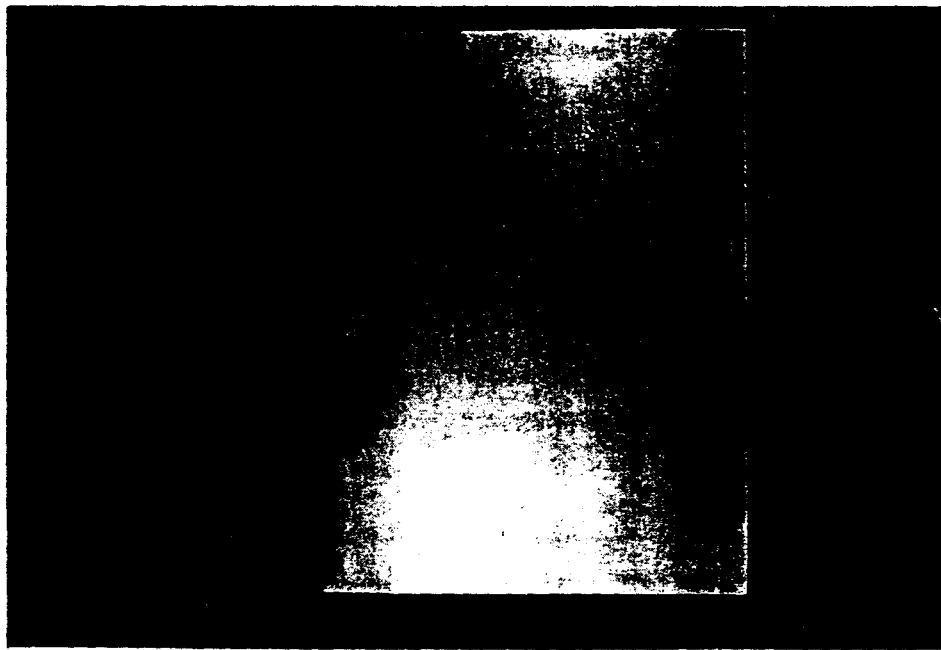


Figure 4 ANN reconstructed 8x8 SPECT section.