Multicomputer-based Neural Networks for Imaging in Random Media

F.H. Schlereth, J.M. Fossaceca, A.D. Keckler, Department of Electrical and Computer Engineering, 2-189 CST, Syracuse University, Syracuse, NY

R. L. Barbour, Department of Pathology and Biophysics, SUNY Health Science Center, Brooklyn, NY

Abstract

In this paper we describe a new technique for imaging in random media using a neural network approach based on a modified backpropagation algorithm. Simulation results indicate that we are able to produce images of simple structures in 2-D media with a reasonable computation time. Our approach is computation intensive and for this reason we have developed a machine architecture and machine, Kilonode, which is well suited to this class of computing problems, and which can ultimately be produced at a cost which is suitable for commercial application of the neural network algorithms.

I. INTRODUCTION

Attempts to recover images from objects which diffuse radiation pose an especially challenging problem both in terms of defining a suitable reconstruction algorithm and with regard to identifying an appropriate computing environment for efficient processing. In this paper we describe results of an algebraic technique for imaging the interior of objects which diffuse penetrating radiation using a novel multicomputer environment. Our interest in this problem concerns the possibility of obtaining 3-D optical images of tissue which could identify the availability of oxygen by evaluating oxygen-dependent changes in the near infrared spectrum of hemoglobin. These studies were motivated by recent reports from our group [1-3] and others, [4-6]which showed promising results for imaging in dense scattering media given only diffusely scattered signals.

In our model we assume the use of an NIR laser to provide the input radiation and suitable detectors to measure both transmission and backscatter. In our present work we assume a simple Markov process model for the way in which the energy travels in the medium, but it should be noted that the reconstruction technique we propose can use any model, including nonlinear as well as linear effects, and higher order processes. Current simulations are in 2-D but the methods are easily extended to 3-D.

The algorithms we propose are more closely related to algebraic reconstruction algorithms such as ART, SIRT and SART [7] than to algorithms based on the Born and Rytov approximations such as used for tomographic imaging with diffracting sources. Our algorithms are a significant departure from those based on these standard algebraic methods. We assume only a probabilistic knowledge of the path of the radiation, and minimal knowledge of the absorption profile of the medium.

In more traditional algebraic methods a matrix, w, is assumed, where $w_{i,j}$ represents the fractional area of the jth image cell intercepted by the ith ray. The equation which is solved is

$$[w]*f] = p]$$

where f] represents the absorption of each of the cells and p] the detector readings. It is assumed that [w] is known. Typically the dimension of p] is M and the dimension of f] is N, where M<N in most cases of practical interest. Standard methods are available for the solution of such equations such as least squares, linear programming or the Kaczmarz method. [7]

We propose a different model of the physical problem. We assume that the radiation entering the medium travels through the medium according to some well defined probabilistic model which can be simulated using relaxation techniques. An example of a relaxation technique is the solution of Laplace's equation using the standard five point grid template. That computational model is based on a simple discrete approximation to the partial differential equation.

$$4f_{i,j}(n+1) = f_{i-1,j}(n) + f_{i,j+1}(n) + f_{i,j-1}(n) + f_{i+1,j}(n).$$

(n) refers to the iteration number.

For the case of a 2-D approximation we assume that each cell loses all of its energy to its eight nearest neighbors at each step of the relaxation iteration, and the portion it loses is modified by an absorption coefficient. For the homogeneous case, the absorption is uniform throughout the medium. The relaxation equation governing this case is as follows:
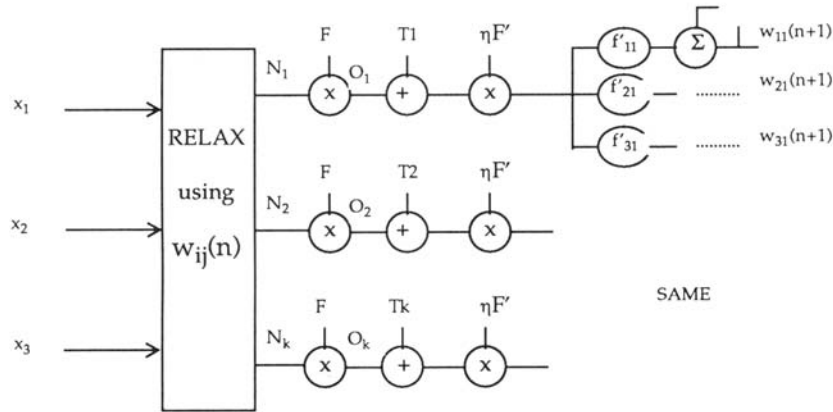
Figure 1 Neural Network Block Diagram

$$8f'_{i,j}(n+1) = f_{i-1,j+1}(n) + f_{i,j+1}(n) + f_{i+1,j+1}(n) +$$
$$f_{i-1,j}(n) + f_{i+1,j}(n) +$$
$$f_{i-1,j-1}(n) + f_{i,j-1}(n) + f_{i+1,j-1}(n),$$

and

$$f_{i,j}(n+1) = w_{ij} \, f'_{i,j}(n+1)$$

where w_{ij} is the absorption coefficient for the i,j^{th} cell.

Thus we propose a discrete model for the transmission of radiation, not necessarily based on a differential equation, but rather based directly on a discrete physical model of the medium. The complexity of this model has an effect on computation time, but not on the basic methodology. In generating this model we follow a suggestion in [4,5].

Energy is introduced into the medium by proper selection of the boundary conditions. We assume that energy can be introduced on all six faces of a rectangular body, or a suitable set of faces on an irregular body. These relaxation iterations become a basic part of the image estimation method, so it is a requirement that suitable computational facilities be available.

In the following we describe a neural network formulation of our image estimation algorithm, and the computing system we have designed to meet the computational demands. The algorithm we propose is closely related to the system identification problem, which is commonly used in the design of control systems. We believe our algorithm is a novel application of the combination of several well-known and accepted computing techniques.
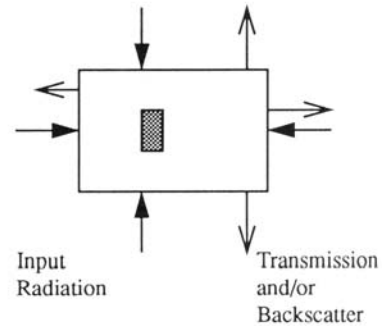

Input Radiation

Transmission and/or Backscatter

Figure 2 Physical Model

II. NEURAL NET FORMULATION

In the following some knowledge of neural networks is assumed. Two references are cited which present an excellent introduction. [8] is the simpler, and [9] goes into the mathematical details. We also rely heavily on the LMS algorithm of Widrow. [10].

In the case of the physical model we assume that it is possible to introduce radiation from all sides of an object. It seems clear, at this stage of our work, that it will be very difficult to locate an object, such as the one shown, on the basis of backscatter or transmission from a single surface alone, although it is by no means impossible as shown by the work of Barbour, et al [1-3] and Aronson et al[2]. We believe that by locating various sources as shown, we can obtain a better reconstructed image.

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SBC - Single Board Computer
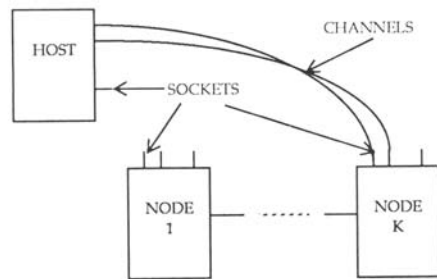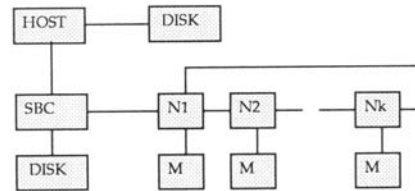M - Memory; Nk - CSPI Supercard

Figure 3 Kilonode Block Diagram

Figure 1 shows a block diagram of the neural network we have constructed to perform the image estimation algorithm. Figure 2 shows the physical model. In Figure 1 the inputs x, represent input energy into the medium. The $w_{i,j}$'s represent the absorption of each of the cells. Using these values for absorption we compute the flux, $f'_{i,j}$ in each cell, and in particular the cells at the surface which produce the observables, O_k. These are then fed through the activation function, F, a gain constant η, and the derivative of the activation function F'.

The output of this part of the circuit is fed into a set of loops which update the values for the $w_{i,j}$. The multiplications prior to the summation in the update loop are equal to the flux in the cell, $f'_{i,j}$, prior to multiplication by the absorption coefficient. T_k are the training vectors, which would represent measurements in an actual application, but in our case represent simulated test cases. The challenge is to derive an estimate for the $w_{i,j}$'s, which is, in fact, an estimate of the true image.

This computing strategy requires that the relaxation operation be performed as part of an inner loop which is repeatedly executed. The number of computations required is estimated as follows. Assume 3-D, for which there are N^3 cells. In our proposed model each cell has 26 neighbors. One relaxation operation requires $O(26 N^3)$ floating point operations for a single pass or iteration. Our experience has been that we can achieve a reasonable degree of convergence in about 40 relaxation iterations. Thus, for the case of a 100x100x100 cells, a single relaxation requires $O(10^9)$ operations for a single update. $(26x40x10^6)$ Neural networks are known to be slow to converge, and we are estimating $O(100)$ neural network iterations to achieve convergence. Currently, however, convergence of the neural network is requiring $O(1000)$ operations.

Using Kilonode we can perform operations required for the 3-D relaxation operation in about 100 seconds on a single node. We propose the use of a 100 node machine which, in our case, has an efficiency of about 90%. This means that we should be able to achieve convergence to an image in about

100 seconds, assuming that the neural net given a reasonable starting point, converges in 100 iterations.

One important improvement will result from the use of a good estimate for the starting values for $w_{i,j}$, such as might be obtained from the methods proposed by Barbour et al [1,3]. Another improvement in the cost/performance of computing will be obtained by the use of special processors to perform the relaxation operation. This is a very real possibility since the operations involved are very simple (adds and shifts) and the communication requirements are minimal. However for the present it is important to use parallel machines such a Kilonode because we are still in the stages of exploring various algorithmic possibilities and studying the numerical effects associated with many new neural algorithms.

Our computing methods represent a significant departure from the norm for several reasons. First, we attempt to estimate the weight matrix directly, making only probabilistic assumption about the path of the rays. Second, rather than use a matrix multiplication as part of the neural network model, we use a relaxation solver to form intermediate estimates of the image. Our third departure from the conventional is the computing machine we have designed which is equal to the task of the increased complexity. Our computer is described next.

III. KILONODE

Kilonode is a computing machine with a scalable parallel architecture capable of supporting thousands of powerful computing nodes. The hardware used for realizing this machine is based on the Intel i860 microprocessor as embodied in board level products generally available from a number of vendors. Currently we are using the CSPI Supercard with excellent results. As mentioned above, future versions might utilize a simpler processor for performing the relaxation operations.

A block diagram for Kilonode is shown in Figure 3. The host is connected to Kilonode via Ethernet, VME bus, FDDI or other. The host and each of the nodes have 16 channels used to communicate among the host and nodes. This permits the con-

## Figure 4 ESTIMATED ABSORPTION MATRIX FOR 1000 ITERATIONS

ABSORPTION MATRIX

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ESTIMATED MATRIX

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The numbers in this Table are absorption coefficients. 1.0 is no absorption. 0.0 is full absorption
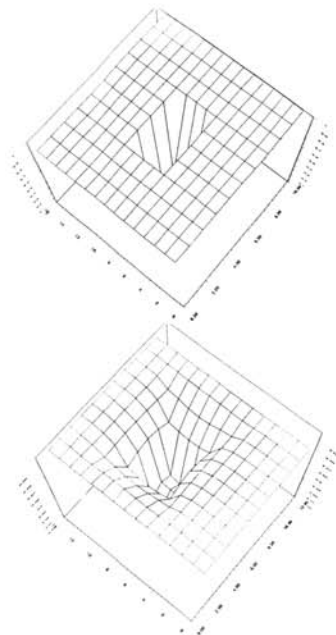
struction of many topologies. For most applications a simple ring is preferable, as shown in Figure 3.

Scalability derives from the simplicity of the architecture and the node manager. This, in turn, derives from the concentration on algorithm design for ultra-large computing, and on the idea of sending only the numerically intensive parts of a computation to the Kilonode server. Growing a system from 4 to 40 nodes involves little more than installing the additional hardware.

The performance of Kilonode on a standard benchmark program (1000x1000 matrix inverse) indicates that we achieve an efficiency of almost 50% for a 1000 node machine. The relaxation problem is much simpler, requiring much less communication and should have even better performance.

Without a machine such as Kilonode it is not possible to entertain work of this kind. The development of neural network algorithms is an art, requiring much experimentation. We measure our computing times in term of minutes rather than hours, and that makes this work feasible.

IV. RESULTS and CONCLUSIONS

In our present work we have used a linear activation function in order to gain a better understanding of the stability of the basic neural network control loop. The stability is a function of η. With a suitable choice of η stable operation of the net is assured.

The results of image estimation with the use of backscatter alone indicates that while we are able to discern the presence of an absorber, the degree to which we can localize the absorber is very poor. From this we have concluded that it is necessary to introduce additional information, such as data from other sources, either on the same face or other faces of the object, or from a priori knowledge such as might be obtained form techniques such as those proposed by Barbour.

The ability to discern the presence of an absorber based on surface measurements depends on the signal to noise ratio and on the sensitivity of the surface data to the position of the absorbing object. At present we have not performed measurements to determine the noise levels, although the experimental setup is in place.

We have however run many 2-D simulations with absorbers at different depths, and results are encouraging. As a typical

example, an absorber at a depth of 10 cells, with a length of 5 cells in a medium whose width is 31 cells will produce differences in reading, as compared with the homogeneous case, of about 5%. These we feel is very respectable and should produce real data with adequate signal to noise ratio.

The introduction of data based on information derived form other sources requires the use of data preprocessing or, in neural network terminology, functional links. [9]. For example when we introduce radiation on opposites sides of an object it is natural to use the difference of the backscatter response form each of the faces as primary input to the neural network. In principal the neural network should eventually learn this transformation, but we feel this is an unnecessary computational burden. Similar considerations apply to the use of data introduced into other faces of the object.

Figure 4 shows the results of a 2-D image obtained from backscatter using a single source entering from the top, bottom and each of the sides. In performing the iterations we take advantage of a priori knowledge of the location of the absorber by desensitizing the layers near the surface during the initial learning phases. In this way the network attempts a correction at internal layers first. After this initial phase we allow all of the layers to take part in the learning process.

In Figure 4, the first 1000 iterations were performed with the outer layers desensitized. After that 500 additional iterations were performed allowing all of the cells to adapt. It is important to note that early learning was not "unlearned", although there was some blurring of the edges.

V. FURTHER WORK

Transform methods are an important extension of this work. There is no reason why the relaxation part of the solution cannot converge to a transform of the image, rather than the image itself. However the choice of a suitable transform is not clear at the present time.

Another area of activity is in the stability of the neural network solution. We have seen oscillatory behavior which impedes convergence to a final solution, although the solution in the presence of instabilities is actually better. It is clear that we must develop an adaptive learning procedure wherein we change the gain of the neural network as a function of the iteration number, using the error measure as control.

We intend to explore the possibilities of a two layer network with a suitable activation function between the layers. One purpose of the second layer will be to compensate for the fact that the "gain" between an interior cell and the surface is very small. The function of the second transformation is to compensate for this effect in an adaptive manner.

To be sure, these results are preliminary, but it is clear to us that as we explore larger models, which we are only able to consider because of the availability of a computing platform such as Kilonode, the results will be sharpened. In particular we must consider the effects of noise on the performance of these neural network algorithms.

VI. REFERENCES

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