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Smart electromagnetic structures (SEMS) are defined as structures capable of interacting with their surrounding electromagnetic fields and either influencing the field or sensing and adapting to its presence. A structure is smart when it integrates sensing elements (e.g., antennas), processing elements (neural networks) and control elements (diodes) autonomously. SEMS provide an adaptive electromagnetic (EM) environment for the structure on which they are mounted. The ability to adapt derives from the closed loop nature of the SEMS. The speed of adaptation is determined by the speed of the loop. Which is set by the computational elements. Our experiments have shown the time required for a response is about fifteen gate delays.  
The integration of artificial neural processors with tuneable antennas was proposed several years ago by our group. We have studied this synergy over the past three years. The control of the operating frequency of a microstrip patch antenna has been demonstrated. We believe that ours is a unique program offering great potential for payoff in the area of electromagnetic smart skins.  
Our main goal in this program was to "...determine the feasibility of a neural network controlled antenna and to quantify the ability of the antenna and the NN to learn to tune automatically to the center frequency of a received signal." We have achieved these goals and spun off neural networks that have application of radar and communications systems.  
Because of its self adaptability the closed loop neural control of an antenna element, provides the potential for design of an easily manufacturable antenna which is immune to typical siting problems, and is tolerant to moderate external damage.

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# Smart Electromagnetic Structures: The Neural Antenna

Final Technical Report

By  
Michael H. Thursby Ph. D.

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## Introduction

Smart electromagnetic structures (SEMS) can be defined as structures capable of interacting with their surrounding electromagnetic fields and either influencing the field or at least sensing and adapting to its presence. We will define a structure as being "smart" when it integrates sensing elements (e.g., antennas), processing elements (neural networks) and control elements (diodes) in an autonomous manner. SEMS have the potential to provide an adaptive electromagnetic (EM) environment for the structure on which they are mounted. The adaptive nature of such a structure may allow the structure to modify its far field image. The ability to adapt derives from the closed loop nature of the SEMS, hence the speed of adaptation is determined by the speed of the loop. The speed of the closed loop system is governed by the computational elements. We consider an Artificial Neural Network (ANN) as the processor. The architecture described requires three gate delays for each iteration, and three to five iterations to complete the desired task. Early experiments have shown the time required for a response is about fifteen gate delays. In silicon technology this would result in a response time of approximately 750 nsecs [11]. With GaAs technology the response time would be reduced to 15 nsecs. Even a digital implementation of a neural network with a response time of 450 microseconds would be possible. Even the response time in silicon technology would be suitable for many applications.

The integration of artificial neural processors with tuneable antennas was proposed several years ago by our group, funding provided by the ARO URI has allowed us to explore this synergy over the past three years. The control of the operating frequency of a microstrip patch antenna has been demonstrated. We have established the baseline for research in this area. At present we are the only university who is publishing work in this area in the U.S.. We believe that ours is a unique program offering great potential for payoff in the area of electromagnetic smart skins.

Our progress involved understanding the analysis techniques of both neural networks and micropatch antennas. Our main goal in this URI program was to "...determine the feasibility of a neural network controlled antenna and to quantify the ability of the antenna and the NN to learn to tune automatically to the center frequency of a received signal." We have achieved these goals and have in addition had several spin-offs in the area of neural networks that have direct application to the area of radar and communications systems.

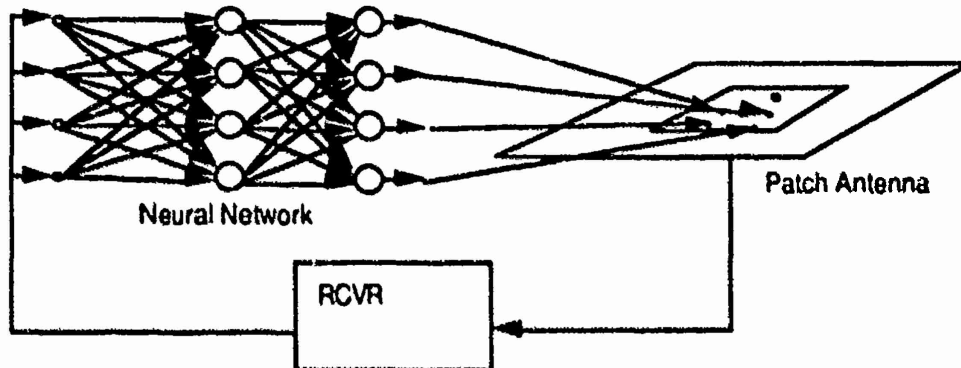
We plan to extend the research that was carried out previously in our lab to further investigate the application of neural processors to the closed loop control of antenna elements. We will extend the technique to several other antenna systems, including a Vivaldi notch antenna and a wire antenna.

Because of its self adaptability the closed loop neural control of an antenna element, provides the potential for design of an easily manufacturable antenna which is immune to typical siting problems, and is tolerant to moderate external damage. The use of a neural processor in such a system will provide very fast response times, especially when the system is implemented in its native parallel architecture.

## 1.0 Statement of the Problem Studied

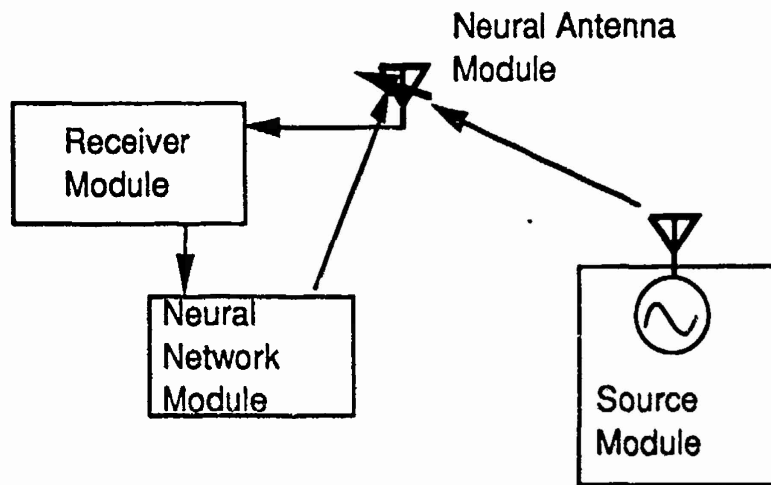
The micropatch antenna has been the mainstay of conformal antennas for many years<sup>5</sup>. The antenna has many advantages including simplicity and size, and a few drawbacks, e.g., narrow bandwidth. The electrical characteristics of the antenna can be adjusted using control elements embedded in the patch itself<sup>6</sup>. We will describe research carried out in the Autonomous Systems Laboratory(ASL) of Florida Institute of Technology(Florida Tech.) on the control of microstrip patch antenna elements using a neural network (NN) in the feed back loop to automatically adjust the operating characteristics of the patch. The advantages of a neural net over a classical processor and algorithmic control scheme are that the net has the potential to be taught by example, rather than requiring the calculation of new control points for each new condition. The neural net has the advantage of being able to make the required determinations in near real time. The additional ability of the net to adapt to previously unknown inputs (generalization) and its fault tolerance makes the neural antenna an ideal candidate for flexible tactical antennas for the future. In addition, the antenna could be manufactured with a set of control devices placed at convenient points on the patch surface. The network could then determine the configuration of these points necessary to achieve the desired tuning effect after manufacture thus reducing the effect of manufacturing tolerance on the performance of the antenna.

The combination of a simple neural network with a microstrip patch antenna shown in Figure 1 has the potential to enhance the characteristics of the patch antenna. An example of this is center frequency tuning which will be described below.



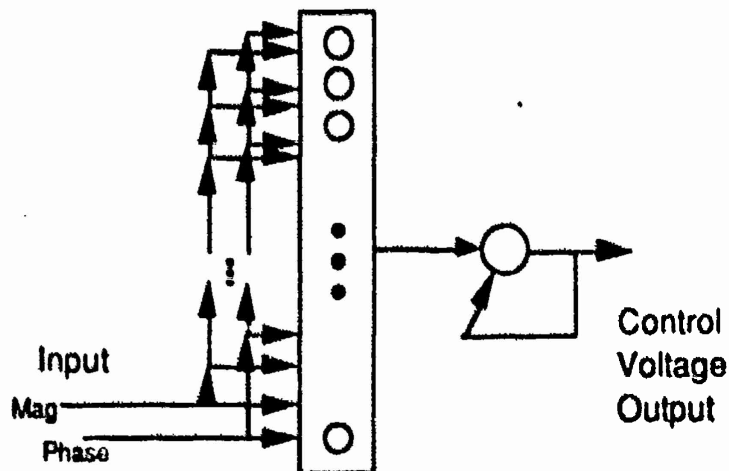
**Figure 1.** The microwave patch antenna with tuning points and a neural network to drive the points can be considered a smart antenna structure.

With a combined NN and antenna it becomes possible to "retrain" the antenna when and if performance requirements change. The trained network will respond rapidly to changing electromagnetic conditions. Typically one gate delay per layer of the network is required for the system to adapt to new conditions. The number of layers may vary, but two or three layers is sufficient for all problems<sup>7</sup>. The network will therefore be able to adapt in near real time (ca. 30-70 nsec) to a changing environment. The training of the antenna during the fabrication phase can take place on deliverable equipment so that the antenna can further be adapted to the specific environment in which it will operate (e.g. VSWR, signal level, frequency, boresight angle, etc.) This allows the NN antenna system to adapt to changes in environment. Training time depends on the type of network and training algorithm chosen but can be achieved "off line."



**Figure 2** Block diagram of the software simulation of a single patch with a single tuning varactor installed.

The fundamental power of the neural net antenna resides in the ability of the neural processor to learn to control the antenna and in the case of frequency control to move the antenna center frequency (bias voltage) to coincide with the frequency of the stimulating source. A model of the neural antenna system has been implemented using the C language on a Macintosh Iix. The block diagram of the simulation system is shown in Figure 2. The receiver module is a simple I and Q channel coherent receiver. The neural network is a Jordan type network with memory. Figure 3 shows the diagram of the network.



**Figure 3** The Jordan like network used for the neural antenna control processor.

### 1.1 Neural Network Model

Our goal in training the smart antenna structure is to provide high-speed frequency tracking of an unknown incoming signal. The system which is composed of tunable antenna, a neural network controller and receiver performs this function. The closed loop antenna element is trained to optimize the antenna function within the system.

The network described consists of two layers, fourteen neurons in the input layer and twenty neurons in the hidden layer. One neuron is in the penultimate layer. Each neurons uses a sigmoidal squashing function allowing an numerical output ranging from +1 and -1. One linear neuron with fixed weights and an integrating connection is used for the output of the network.

Conventional neurons with a sigmoid squashing function, configured in a Jordan multi-layer neural network are used. Two neurons in the input layer receive sensor information from the receiver, the rest of the input layer neurons receive delayed values in a shift register fashion from their neighbor. There are a total of seven pairs of neurons in the input layer.

For training a conventional back-propagation algorithm was used to adapt the weights. Since the input layer has time-delayed input values, we wait to change the weights until all input neurons have received an actual input from a given test pattern. The strategy for training will be described in more detail below.

## 1.2 The Smart Antenna Operation

The neural network must determine the proper bias voltage for the tuning element embedded in the antenna to tune the antenna center frequency to coincide with the unknown incoming signal frequency. Figure 4 shows the change in center frequency due to change in input voltage for the tunable patch antenna.

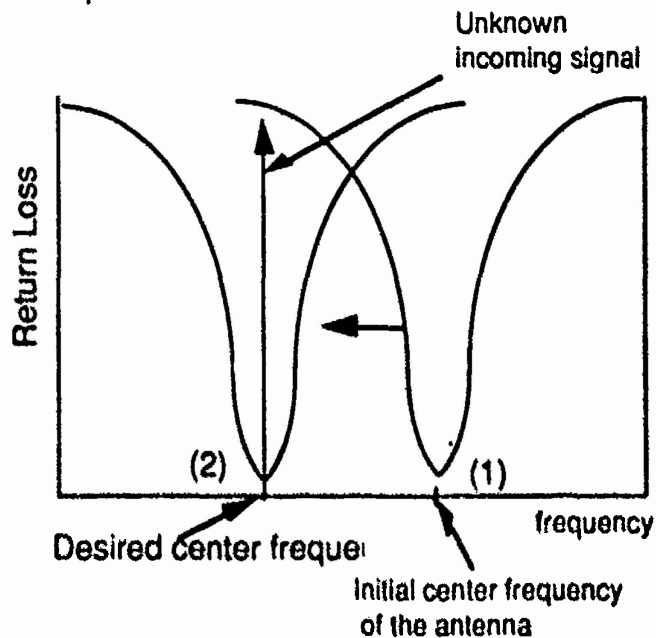


Figure 4. Relationship between the center frequency and unknown incoming signal frequency.

An antenna whose center frequency can be varied by changing the bias voltage on a device embedded in the antenna was first described by Schaubert<sup>6</sup>. We applied this concept to move the center frequency of the antenna from position (1) to position (2) by applying the proper bias voltage which is determined by the neural network.

First we must develop an algorithm to train the sequential neural network to do this.

## 1.3 Training Algorithm

The neural network was trained with a conventional back-propagation (BP) algorithm. The basic BP algorithm was modified to include a strategy for choosing the input training patterns and for calculating the error terms. Input values for the neural network came from the receiver. The target values were determined at the output of the neural network. Target values were determined by subtracting accumulated voltage from the desired target voltage.

We initially chose four different pairs of diode voltages as training patterns initial bias values, desired bias values; (5v,25v), (10v,20v), (20v,10v), and (25v,5v).

A step by step description of the training process is given below;

**Step 1. Initialize all Input neurons, weights, and offsets.**

Set all Input neurons, weights, and node offsets to small random values.

**Step 2. Choose an Input pattern at random.**

Set the receiver output to an initial bias voltage randomly chosen from the training set.

**Step 3. Apply the Input and propagate it forwards through the network,**

The output of the individual neurons within the network are calculated as shown below;

$$o_i(t) = f(\text{net}_i(t))$$

Where  $\text{net}_i$  is define as;

$$\text{net}_i \begin{cases} = \sum_j I_j \cdot W_{ij} & \text{for hidden neurons} \\ = \sum_k O_k \cdot W_{ik} & \text{for output neurons} \end{cases}$$

and  $f$  describes the squashing function.

**Step 4. Determine the desired output**

For our network the time course of the system results in the bias voltage that corresponds to the final tuning frequency of the antenna being presented at the output of the network. The constraint that this time function must be well behave is implied. The input and desired pattern will be changed at every iteration of the network. We choose a desired output as a value which make the difference between accumulated voltage and a target voltage zero.

$$\begin{aligned} T_i(t) &= AV(t) - TV \\ &= (O_i(t) + AV(t-1)) - TV \end{aligned}$$

where,  $AV(t)$  = accumulated voltage at time  $t$

$TV$  = target voltage used for a given initial starting voltage.

For a better understanding how to decide the desired output, we show a graph of accumulated voltage vs. time. Figure 5. shows the untrained network response for a starting input diode voltage of 20v and target voltage of 10v, the graph shows 30 iterations of the network (epoches).

Accumulated voltage vs. time

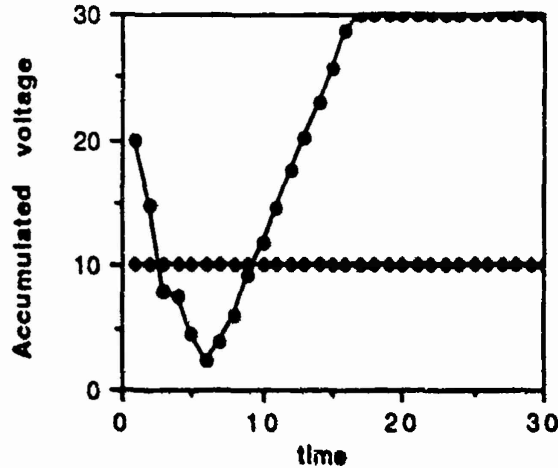


Figure 5. Plot of accumulated voltage and target voltage(10v) vs. time without training.

With a starting voltage of 20V. and the target of 10 volts the untrained network was well behaved for only eighteen epoches. The error can be seen as the difference between the desired value(a constant 10 volts) and the actual net output(e.g. a t=9 the error is approximately zero.) After 18 epoches the output saturates and no further change information is available. The desired response of the system would be for the output to go directly from 20 volts to 10 volts in one step. This would provide an ideal step response with no overshoot or ringing. For the epoches before the system saturates the error values can be measured and used for back propagation. Figure 6 show the output of the penultimate neuron for the above session. Since there has been no training, the output value looks like a random walk until the system saturates.

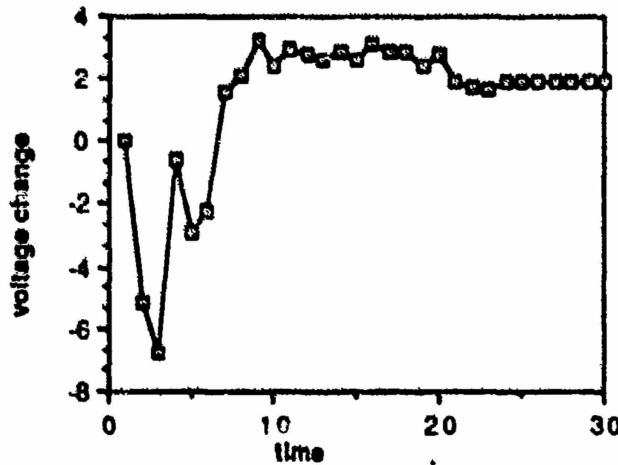


Figure 6. Plot of voltage variation on the penultimate neuron.

Step 5. Compute the change of the weights using back-propagation rule.

Weight changes are computed by the relation:

$$\Delta W_{j,i}(t+1) = \eta \delta_j O_i + \alpha \Delta W_{j,i}(t)$$

Where  $\eta$  is the learning rate of the network and  $\alpha$  is given by :

$$\delta_{pj} = \frac{\partial E_p}{\partial net_{pj}}$$

and  $\alpha$  is the momentum.  $E_p$  is the error function for the network. For further discussion of the learning algorithm see Rumelhart <sup>8</sup>.

**Step 6. Calculate the new Input**

Based on the tuning voltage determined by the network the receiver and antenna system output is determined. For a detailed description of the model see Thursby, et al <sup>9</sup>, Drici, et al <sup>10</sup>.

**Step 7. Repeat step 3 through 6 during response time.**

The response time is defined as the time from the start of the stimulus until the system has reached steady state or has caused the system to saturate.

**Step 8. Update all weights**

The weight change is computed after a complete response has been obtained. The weights are calculated as follows. For each epoch  $l$  the difference between the desired output and the actual output is used to determine the weight change for each epoch. After the weight changes for all epoches have been accumulated, the average weight change for each weight is calculated;

the average weight change for the weight between neuron  $l$  and  $k$  for pattern  $l$  given by,

$$[\Delta W_{lk}^l] = \frac{1}{N} \sum_{l=1}^N \Delta W_{lk}^l$$

Change the weights with averaged weight changes using

$$W_{lk}^{new} = W_{lk}^{old} + [\Delta W_{lk}]$$

Repeat steps 2 through 8 until the error is reduced to an acceptable level.

The error is defined as:

$$E = \sum_j (T_j - O_j)$$

**2.0 Summary of Important Results**

We have developed a unique research emphasis that has direct application to DoD needs and interests. The ability of a structure to adapt to its environment, and in this case to its electromagnetic environment intimates of the potential to build a skin or structure capable of modifying its electromagnetic environment in real time. The combination of antennas with a rapid and robust processing technology such as neural nets has the potential to fulfill this goal.

A multi-disciplinary program always has the problem of finding a home in between two established disciplines with the hope that someday the multi-disciplinary area will carve out its own niche for acceptance. The concept of smart skins in which the smart electromagnetic structures is embodied has indeed begun the process of self government. The area has several yearly conferences its own journal and a following of several thousand practitioners. with this start it is quite likely that the area will continue to grow. As witnessed at several national conferences the concept of neural networks and their application to the control of structures both mechanical and electromagnetic has received quite a bit of attention, and has achieved some success. Florida Tech. and the Autonomous systems lab have been able to play a significant part in this growth as a direct result of the URI funding.

## 2.1 Modelling A Neural Antenna

The model used to date for the neural antenna and the impedance modifying elements has been based on the University of Colorado code written by Gupta, Chang and Benalla, and the Transmission Line Code developed at Auburn University. The latter has been made available through a cooperative effort between Florida Tech. and the Harris Corporation. Our efforts have been directed towards the establishment of a baseline for these codes to verify their accuracy and our measurement methods with respect to micropatch antennas and the embedded control devices used in the neural antenna.

In addition to the electromagnetic model for the antenna alone there is a model for the entire system. This model is made up of several different components some are embodied in software and others in hardware. Figure 1 shows the sketch of the model. The status of this model is that the software model for the system is running and giving good results. The second phase of the modeling and prototype development has begun and parts of the model are being externalized in hardware. The antenna and controlling voltage supply have been removed from the software and are being tested as hardware elements coupled to the software model. The HP8510B network analyzer is being used to simulate a receiver. The model is running on a Apple Macintosh II controlling a set of transputers as the computational devices.

### 2.1.1 Results Of Training

The system was trained to respond to four different starting and target frequencies. The final error in training was less than 0.05%. The network converged to similar error values for several different initial weight sets. Thus the configuration seems to be stable. Figure 9 shows the results of training the network to produce the desired response.

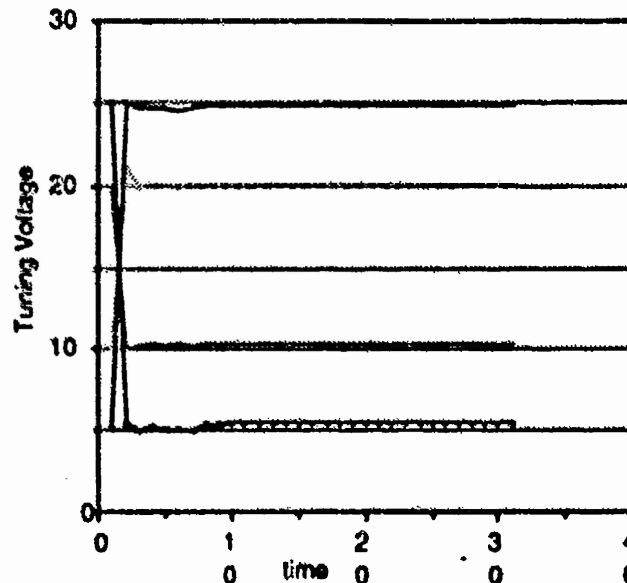


Figure 9 Results of training network to tune the antenna.

Figure 10 shows the results of several tests of initial and final values that were not used for training. The ability of the antenna system to tune to the desired center frequency is demonstrated by the rapid movement from the starting voltage to the desired final voltage.

### 2.1.2 Further Test Results

Because of the inherent non linear nature of the system we have investigated the response of the trained network from several points of view. First the network response to different initial conditions for a fixed target should not change significantly over the operating

range of the system. To test this we presented the system with several different initial conditions for a given target value.

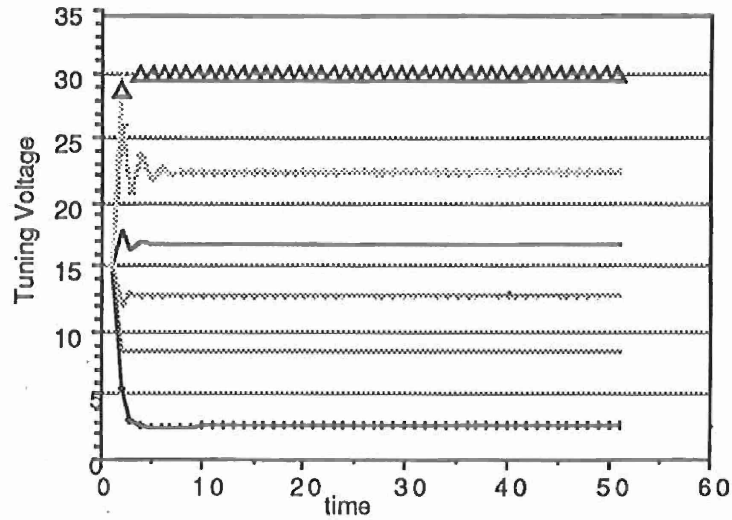


Figure 10 Results of testing the trained neural antenna with previously untested conditions.

The response of the system to these conditions is shown in figure 11. Four different target voltages 5v, 10v, 20v, and 25v, were chosen for this set of tests. Regardless of which starting voltage we choose, the system converge to the desired target voltage in four or fewer iterations.

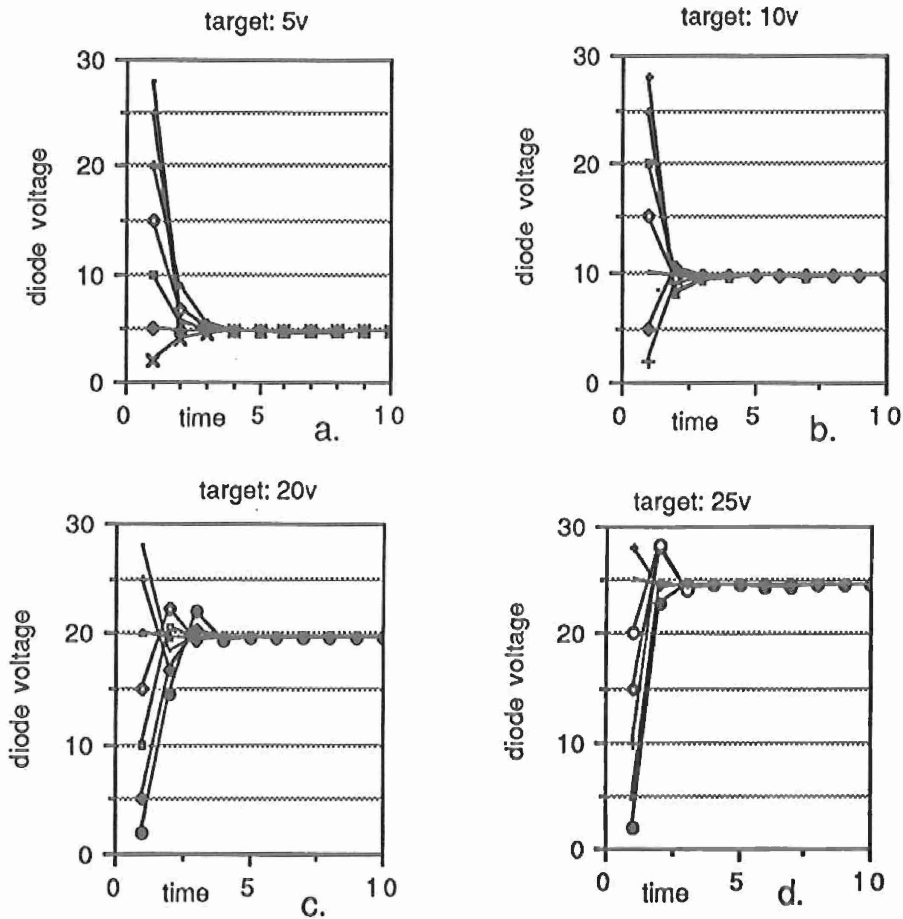


Figure 11. Response of the network with training patterns.

The second case of interest is one where the input condition is held constant and the desired output is varied over the range of operation of the system. This corresponds to the actual operating range of the embedded control device. Figure 12 shows results of test cases where different target voltages were used to test the network with the same starting voltage (15v).

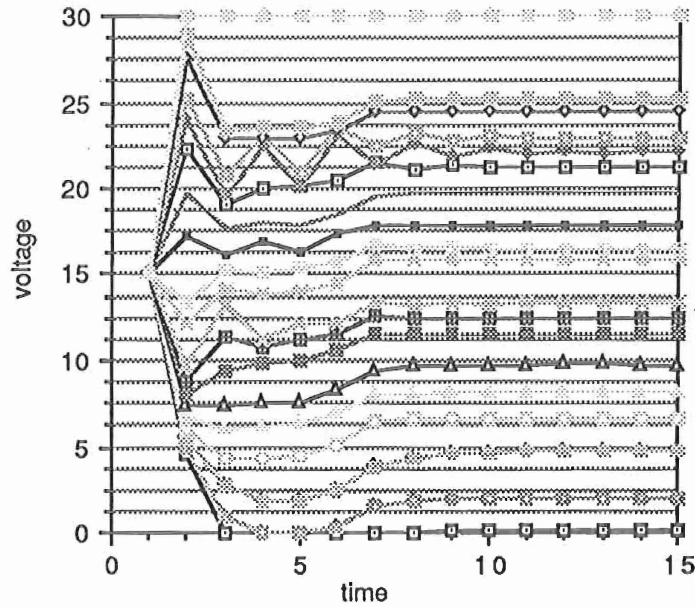


Figure 12. Test result for non-trained target voltage. .

The steady state error of the network when compared with the desired tuning voltage is shown in Figure 13

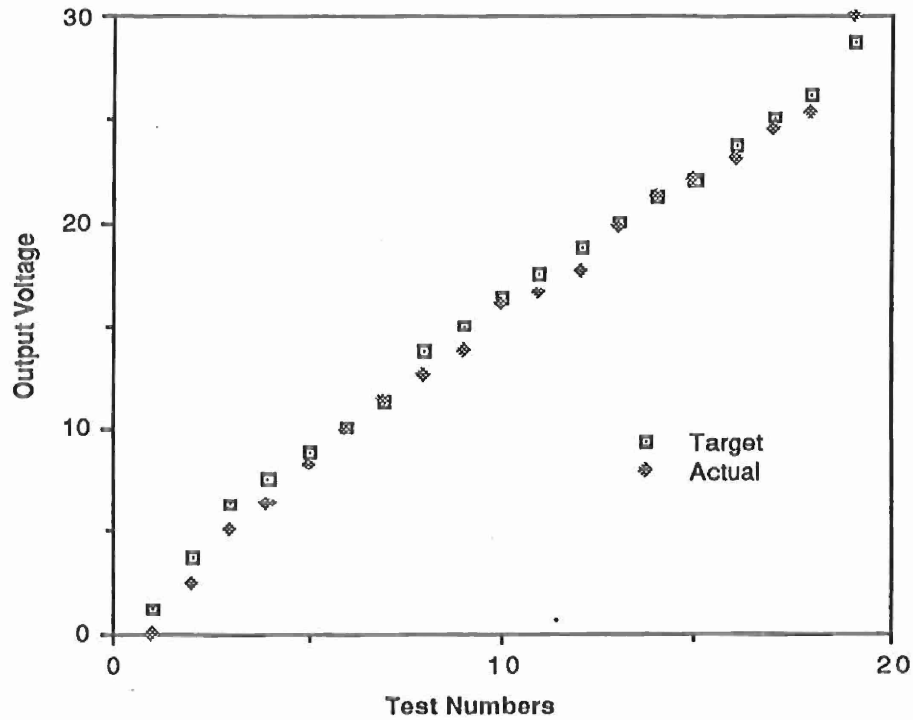


Figure 13. The error produced by the neural antenna system over the set of test cases shown in Figure 12.

Figure 13 shows that the error from the desired response of the system is well contained and centers around the desired response.

We have also tested the system against a linearly changing input frequency for the unknown input signal. Both positive and negative sloped frequency characteristics have been tested. The response of the system to a positively increasing frequency signal is shown in Figure 14.

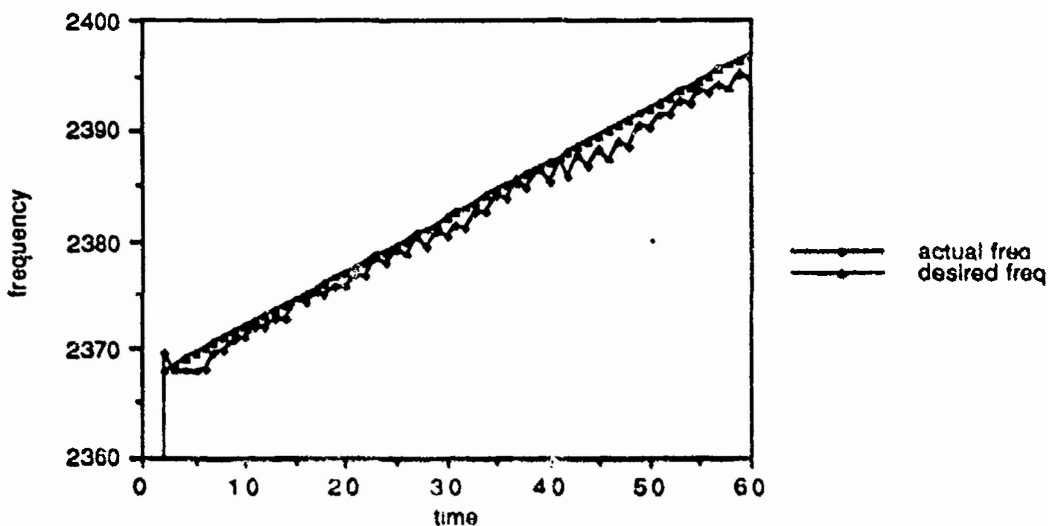


Figure 14. System response for linearly sweeping target frequency.

For slower sweep rates the response of the network is seen to be step like in response, with the network waiting for a threshold to be crossed before compensating further for the change of frequency. As the slope increases the step sizes decrease and the graph shown in Figure 14 demonstrates an almost continuous updating of the output in response to the input signal. The greater the slope the better the network is able to track the input.

## 2.2 Prototype System

The antenna system which exists in software is being transferred from software to hardware one component at a time. The first element to be externalized is the antenna system itself. The antenna and control diode have been constructed. This has been used to generate the data used in the software model for the initial training of the antenna system. The second element to be externalized is the control element driver. An IEEE 488 bus controlled power supply has been added to the system HP model 6633A. The system is now being trained using the antenna rather than a model. The time required to train has increased due to the use of different interfaces however the antenna is training with the actual antenna inserted in the system.

## 2.3 Use of Transputers in the Training and Operation of Artificial Neural Networks

The learning algorithm for the neural network is implemented with a set of four transputers with a Mac II as the host. The Mac II is used as the system controller for the antenna system. The inherent speed of the transputer is required for the training to be accomplished in a reasonable time. Once the network weights have been determined the network can be implemented using dedicated neural network hardware.

### **3.0 Related Spin-off Topics**

#### **3.1 Application of Microstrip Patch Antennas to Ground Penetrating Radar(GPR)**

The ability of antennas to operate underground is of interest in the area of mining, geological exploration and environmental monitoring. The use of such antennas is in the area of ground penetrating radar. The use of radar for the identification of underground structures has been active for many years. Remote operations of this type using unmanned vehicles is of interest in the mining industry. The design of an antenna for such an application can benefit from an automatically tuned antenna, as the electromagnetic environment around the antenna is continually changing and not easily observable. Thus, the neural antenna could optimize the response without intervention from man. We are pursuing the use of neural antennas in the GPR area. The neural antenna and its capability to change operating characteristics autonomously is also appealing in such a remote operating scenario such as a remotely operated GPR.

#### **3.2 Neural Interpretation of Radar Signals**

As part of our investigation of neural networks and their capabilities we have been looking at their use in signal processing. The use of compression codes in radar signal processing is wide spread and provides significant resolution improvement. We have been investigating the use of artificial neural networks for the correlation function of the received radar pulse. In a masters thesis from our lab<sup>12</sup> we have described a technique for correlation which results in a significant decrease of the time sidelobes from the correlator, and a decrease in the main pulse spreading with doppler shift. We are currently studying the effects of system noise on this system. The implications are that the neural correlator is better than the conventional Fourier correlator and at least as fast.

### **4.0 Potential for Contribution to Defense Missions of the Army**

The mission of the army requires operation in all areas of the world under all conditions and on land, in the air and at sea. The realm of space has also become the venue of the U.S. Army. To operate in such a diverse set of location requires extremely flexible equipment. The element of communications as a vital element of the battle field commanders tools and the integral role of antennas play in communications make their study of significance to the army. The use of conformal antennas is desirable under all circumstances. Not only is it desirable to have conformal antennas in the air but on land a conformal antenna will present less of a hazard and be less prone to damage. The use of controllable conformal antennas is also appealing because of the antennas ability to adapt to damage and to continue to operate in spite of physical damage to the antenna and supporting structures. The siting of antennas on the surface of vehicles is always a critical consideration from both the electrical and mechanical standpoint.

### **5 List of All Publications and Technical Reports**

- Aghili, S. M., Thursby, M. H., and Marpaka, D. R., "Artificial Neural Network Based Stability Testing of Two-Dimensional Infinite Impulse Response Digital Filters", IEEE 1992 International Conference on Acoustics Speech and Signal Processing, San Francisco, California, March 23-26, 1992.
- Aghili, S. M., Marpaka, R., and Thursby, M. H., "Neural Net Based Recognition of Stability Regions of Recursive Filters," Proceedings of IEEE Southcon 90, Orlando, FL, pp. 326-331, March 21-24, 1990.
- Alavia, A. Tino, Grossman, Barry G. and Thursby, Michael H., "Processing Of One-Fiber Interferometric Fiber-Optic Sensor Signals", Proceedings of SPIE OE/FIBERS 89, September 1989.
- Drici, Z., Grossman, B., and Thursby, M., "Layered Tapc Dielectrics for Microstrip Patch Antennas," IEEE, AP-S International Symposium/URSI Radio Science Meeting, May 1990.

- Grossman, Barry, Xing Gao, and Michael Thursby, "Composite Damage Assessment Employing an Optical Neural Network Processor and an Embedded Fiberoptic Sensor Array", Proceedings of SPIE OE/Fibers '91, September 1991.
- Grossman, Barry, Howard Hou, Ramzi Nassar, Anbang Ren, and Michael Thursby, "Neural Network Processing of Fiberoptic Sensors and Arrays", Proceedings of SPIE OE/Fibers '90, September 1990.
- Grossman, Barry, Frank Calmi, Tino Alavie, Jorge Franke, Xing Gao, Howard Hou, Ramzi Nassar, Walid Costandi, Anbang Ren, and Michael Thursby, "Smart Structures and Fiberoptic Sensor Research at Florida Institute of Technology-1990", Proceedings of SPIE OE/Fibers '90, September 1990.
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### 6.1 Faculty

- M. Thursby Ph.D. -Principal Investigator  
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 W. Shelton Ph.D. -Co-Principal Investigator  
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#### Doctoral Students

- Yoo, Ki-Suck  
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 Aguilar, Joe  
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