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EMPIRICAL MODELING FOR INTELLIGENT, REAL-TIME MANUFACTURE CONTROL

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ABSTRACT

Artificial neural systems (ANS), also known as neural networks, are an attempt to develop computer systems that emulate the neural reasoning behavior of biological neural systems (e.g. the human brain). As such, they are loosely based on biological neural networks. The ANS consists of a series of nodes (neurons) and weighted connections (axons) that, when presented with a specific input pattern, can associate specific output patterns. It is essentially a highly complex, non-linear, mathematical relationship or transform. These constructs have two significant properties that have proven useful to the authors in signal processing and process modeling: noise tolerance and complex pattern recognition. Specifically, the authors have developed a new network learning algorithm that has resulted in the successful application of ANS's to high speed signal processing and to developing models of highly complex processes. Two of the applications, the Weld Bead Geometry Control System, and Welding Penetration Monitoring System is discussed in the body of this paper.

INTRODUCTION: ARTIFICIAL NEURAL SYSTEMS

Artificial Neural Systems (ANS) are loosely based on biological neural networks offer a computer technology that is a useful tool in process modeling and signal processing. The ANS consists of a series of nodes (neurons) and weighted connections (axons). As with a biological neural network, the assignment of the values of the weights and the size and configuration of the network is the key to a successful net. Unfortunately, we have only begun to understand the inner workings of these constructs. Consequently, relatively crude tools are currently employed to develop working networks.

Typically, the approach to model development is to develop a thorough understanding of the underlying basic scientific or engineering principles of the process. Then, a model is developed that is based on mathematical relationships inherent in the process parameters. The principal drawback with this approach is the time and effort required to develop an understanding of these basic scientific or engineering relationships. Depending on the complexity of the problem, it can take many years and an extensive research program to develop the relationships. Often, instead, a number of simplifying assumptions are made and an approximate model is developed. That approach, while being an expedient method for developing an approximate model that could be useful, provides only a theoretical approximation that may not be valid for the actual problem application.

The artificial neural system, when a network can be found to solve the problem, provides an accurate model of the process or signal. Neural networks are empirical bases systems that, when presented with a specific input pattern, can associate specific output patterns. It is, essentially, a highly complex, non-linear, mathematical relationship or transform. However; it is not necessary for the developer of such a system to understand the basic underlying principles of a process in order to develop a highly accurate ANS based model of the process. Thus, in this way it is quite different from other mathematical modeling approaches.

Basic Principles

CONCLUSIONS

A fuzzy-neural network was successfully implemented for automatic camera platform positioning, eliminating the need to manually adjust FLC parameters for optimum performance. The simulations conducted in this study demonstrated that when structured knowledge and learning ability are combined, the result is robust performance that improves over time. The fusion of these two types of machine intelligence represents an important step in the evolution of intelligent control systems.

The FNN may be applied to a wide range of non-linear control systems, particularly where fuzzy control has already proven successful. In any system whose desired behavior can be described through a series of fuzzy rules, those rules can be translated into a network and thereby achieve the ability to adapt. The learning algorithm does not add an excessive amount of computation to an existing FLC, and thus it should be feasible for real-time applications where the system can learn "on the fly". Such experiments are planned for this system in upcoming research.

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The problem of ANS's is to decide how many nodes and connections are needed to model a specific problem, to decide how to configure them, and to decide the specific values of the connection weights and the transfer functions that exist within the network. Figure 1 shows a schematic diagram of a neural network and Figure 2 is a simple representation of the weights, transfer functions, and the mechanisms of network operation. There is no direct known correspondence between the network parameters and it's operation and the problem to be modeled by the network. As a consequence, there is currently a lack of good mechanisms which can be used to assign the weights and transfer functions in the network so that it can solve a problem. The methodology of finding a proper net configuration and weights to model a given problem is called the "Learning Algorithm". There are many learning algorithms that have been developed. They all have some advantages and restrictions. In the modeling area, the back-propagation method is the most popular one.

The back propagation method assumes that the search in weight space for an optimum, or near optimum, network configuration can be accomplished as an iterative search using the error gradient, (i.e. slope of the error surface) in L_2 space. That is, a series of moves are accomplished on the multi-dimensional error surface using approximately, the maximum mean squared error gradient direction as the move direction at each iteration. The error, also called the delta, in the network is defined as the mean squared error between the desired output representation and the actual output given the current weight matrix values. By calculating the maximum gradient of the delta for any given training example (set of input and corresponding output patterns), the weights are adjusted so that the net moves along that gradient direction in each presentation of the training example to the network. Using this procedure, the network slowly "learns" to associate all of the training example input patterns with the correct corresponding output patterns by finding a global minimum on the error surface. Since the primary driving force in back-propagation method is the mean squared error - delta, it also called the "delta rule."

This "basic" back propagation learning process has several significant drawbacks. First, the optimum configuration (i.e. number and relative location of hidden representation units or nodes) cannot be pre-determined and, yet, needs to be pre-assigned by using an "educated guess" in order to use this procedure. Since the node configuration can significantly affect the operation of the network, this will at best lead to a long series of re-trys and, at worse, to no useful network at all. Second, this process is very slow and the rate of learning (convergence to near zero error) is set arbitrarily -- traditionally at a value between zero and one. Even though several researches are going on, no currently known method for predetermining the learning rate (gain term) will consistently choose an optimum value, and the optimum value is significantly influenced by the specific problem being presented to the network. Third, it has been shown, that it generally, requires a larger network to "learn" a problem than is required to solve the problem. Based on many study, people generally know that the net could be trim to smaller size. However, there is no known method of reducing the size of the network optimally after training to optimize the net performance. Finally, learning instabilities exist in nearly every problem which will cause the network to stop learning (converging). One of these instability types is known as a local minimum. A local minimum is a depression in the error surface, but one which is not the best minimum or lowest error position. In its search routine, the network algorithm may fall into a local minimum and since the error gradient is toward the local minimum from all directions, may not be able to exit from it.

The Delta Activity Network

A new method was developed by the authors for training neural networks that has been shown to overcome all of the known problems with the back-propagation method, while maintaining the inherent stability and known network development capabilities of that method. This network was developed through the use of a thermodynamic model of the network operation which included both the delta energy and the activity or kinetics of the network. The technique, known as the Delta-Activity Network (D-A Net), has been used on several applications ranging from high speed signal processing to vision systems.

The authors have been studied the learning behaviors of artificial neural networks for years. Based on the thermodynamic and kinetic model of the learning, we discovered that the learning is not only driven by the delta, but also by another important factor - the activity. The activity is a kinetic measurement about how good the neural networks is willing to learn at certain stage of the learning. Sometimes, even the delta is large, but if the system has low activity, it won't learn. This is the case that local minimum or other kinds of learning instabilities accrues. Thus the delta-activity algorithm will watch the activity closely during the learning, maintain a reasonable activity while push the learning rate as high as possible.

The D-A Net has achieved learning rates as high as 1000 times that of the back propagation method while also preventing the network from falling into learning instabilities. Research conducted on this technique has confirmed the existence of at least three types of learning instabilities (local minimum being one of them) and the algorithm can avoid all three instabilities. In addition, using activity as the critical, the system configures itself dynamically during the learning process and so it can produce a near optimum network size for operation, often much smaller than the network needed to "learn" the problem.

This network has been successfully applied to model many real manufacture application problems. These applications are:

- ANS models of weld bead geometry in several different welding processes and joint types
- ANS model to predict weldment mechanical properties for SAW welding
- ANS model of weld metal hot cracking
- ANS model of heat flow for arc weld
- ANS based weld seam tracking system
- ANS based welding penetration monitoring system
- ANS based acoustic emission signal analysis to detect the welding failures
- ANS based underwater acoustical signal detection and classification
- ANS based ultrasonic signal process to detect helicopter tail rotor gearbox fault

In this paper, we will select few examples from above and given more detail discussions.

An ANS Model of Weld Bead Geometry

Background

The mechanical properties, geometry, and appearance of the weld bead are the three major characteristics of the final quality of a weld. They are interactive with each other. The weld bead geometry directly effects the mechanical properties of the weldment. A good weld bead geometry is necessary to insure a good quality weld. The weld bead geometry can be effected by various welding variables. These variables are:

- The process variable, such as the type of welding process, the welding current, voltage, travel speed and wire feed speed.
- The material variables, such as the type and size of base metal and fill metal.
- The joint configuration, such as the type and geometry of welding joint, and the welding position.

To model the bead geometry, an ANS has to perform the transformation from these variables to the bead geometry.

Approach

Four neural networks have been developed to model Gas Tungsten Arc Welding (GTAW), Gas Metal Arc Welding (GMAW), Flux Cored Arc Welding (FCAW), and Submerged Arc Welding (SAW). To simplify the problems, some variables are fixed. The GTAW net is developed based on a stainless steel butt joint weld. The input variables are current, voltage, wire feed speed, travel speed, plate thickness, and joint gap. The FCAW and GMAW nets are based on a plain carbon steel fillet weld.

Several experiments were done to generate the training and test samples. The following table lists the number of training samples used by each net:

Table I
The Number Of Training Samples Used By Each Net.

Net	Number Of Training Samples
GTAW	28
FCAW	34
GMAW	14
SAW	38

Each sample was sectioned and the cross section of the weld bead was measured following the definition to generate the training and test examples.

We have to point out here how few samples the ANS needed to develop a complete model of the weld bead geometry. For instance, in the GTAW case, if we used the Taguchi method, which is known as the best statistical method, we needed at least 150 samples to develop a complete model. Using ANS approach, only 28 samples were needed.

Another important function of the shell is its ability to give the user a suggestion about further experimental points. This function can insure the generation of a complete model with minimum amount of samples.

Results and Discussions

Figure 1 is the configuration of the GTAW net. The net takes 6 inputs and generates 4 outputs. It finally configured itself to have three hidden layers with 7 nodes in each layer.

Figure 2 shows the interface shell of GTAW net. There are two rows of mouse sensitive slide bars on the screen that can be set by the user or observed by the user. These bars can be moved to new values by using the mouse to "slide" the bar. The first row of the slide bars are the outputs of the net, which are the bead width, height, penetration, and the bottom bead width. The second row of slide bars are the input variables, they are the current, voltage, travel speed, wire feed speed, gap, and the plate thickness. At the top left corner is a graphical simulation of the bead cross section. When the net is running in the forward model, the user can slide the input bars, the output bars will change correspondingly and the graphical simulation will animate the bead cross section simultaneously. When the net is running in the inverse model, the user can set the bead geometry by sliding the top row bars and the gap and thickness by sliding the right two bars on the bottom row. The net will find the closest match bead and give the welding parameters which can be read from the bottom row of bars. The whole system runs in real time on a personal computer. Thus, this represents a very powerful planning tool for a welding engineering workstation as well as a complete model for real-time intelligent control.

Figure 2 and 3 show the performance of the GTAW model. In these two figures, the test sample, which the net has not been trained with, is compared with the prediction of the net. A very close match between the predictions of the net model and the actual welds is shown.

Figure 4 shows the GTAW net running in the inverse model. There are two graphical representations of bead cross section on screen. The user specified bead geometry is displayed as the top one. The bottom one is the closes match that the net found.

The GMAW network has similar interface as the GTAW system. However, it also takes two discrete inputs: type of electrode and type of shielding gas. And it also generate two additional discrete outputs: the spade and the silicon slag appearance. FCAW and SAW nets also have a similar interface.

These model networks are the heart of an intelligent control system for welding applications. The objective of an intelligent control system is not to control the primary independent welding parameters (e.g. voltage, current, travel speed, etc.) but to control the final weld quality. That is, control of weld quality parameters such as bead appearance, penetration, amount of spatter, etc. is the goal of an intelligent control system. Sensor data is not particularly useful unless it can be both analyzed and used to control the weld quality parameters. These model networks provide that capability.

The results of these models are being used to develop fuzzy logic based control systems on two projects including development of an intelligent automated welding system for the United States Navy Manufacturing Technology Program called WELDEXCELL.

An ANS Based Welding Penetration Monitoring System

Background

The development of real-time sensing and control techniques for weld penetration has been an active area of research for a number of years. A wide range of techniques have been employed, including pool oscillation measurements, surface infra-red measurements, determinations of the light emitted on the back side of a weld, spectroscopic determination of the presence of tracer elements, and the use of vision techniques to measure weld pool geometry, with the objective of relating to weld penetration.

The success of each of these methods has been limited, and all require the use of specialized transducers. The most successful technology to date appears to be the use of photo detectors to measure the amount of light produced at the back side of the weld, which is then correlated with penetration. Unfortunately, back side access is required, limiting suitability for many applications. Back side monitoring is difficult to make and it is costly.

Approach

Recently, several research works (see ref. [1-3]) have been done to study the weld pool oscillation. The researches show that a full-penetrated weld pool can be modeled as "rubber band" (no rigid base to support it) while a partially penetrated weld pool can be modeled as a half sphere. As a consequence, the pool oscillation pattern will be different in two models. Several methods have been applied to sensor the pool oscillation pattern in real-time, such as the lasers, and trying to relate them with the weld penetration. Unfortunately, the sensors are usually too expensive, and the data from those sensors are too "noisy" to process. These barriers limit the success of those approach.

The authors developed a new approach to detect the pool oscillation pattern and related it to the penetration in real-time. This uses a very in-expensive sensor, the voltage sensor, and the Delta-Activity ANS to process the sensor data. The theory behind this is that when the weld pool oscillates, the voltage between the base metal and welding torch tip will changed accordingly. By monitoring the voltage data in a continues time sequence, the pool oscillation pattern could be detect. However, the voltage data obtained are usually very noisy and contained much more information than just the pool oscillation parterre. Delta-Activity ANS is played a important role here to successfully filter out the pool oscillation pattern information from the rest.

The voltage signal is collected at a 1000 Hz sampling rate. A neural network was developed off-line. This neural network takes 100 data points as the inputs. The output of the ANS will indicate that either a full penetration (0) or a lack of penetration (1) is been detected. The experimental work used GTAW process for carbon and stainless steel butt joint welding on various plate thickness. Total 25 welding samples were used to train the net.

Result

After training finished, the ANS is installed on a 486 based PC. A GUI is developed to run the penetration monitoring system. If a lack of penetration is detected, the system will turn on a warning light and/or shutdown the welding process. Eventually, combining with the weld bead geometry model, the control loop could be closed and a corresponding welding parameter could be adjust automatically to insure a full penetration welding. This system is installed in AWI's workshop. Figure 5 is the computer GUI and Figure 6 shows that the system is monitoring a welding.

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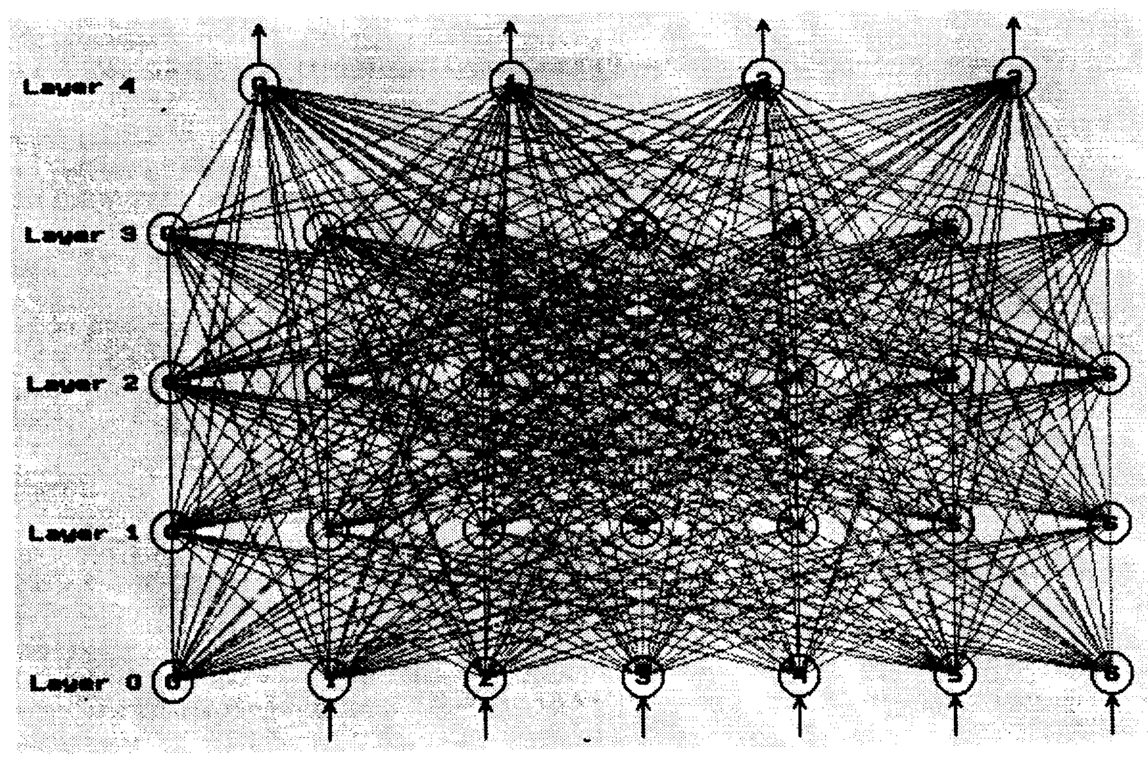

Figure 1. The Configuration of neural network for GTAW modeling

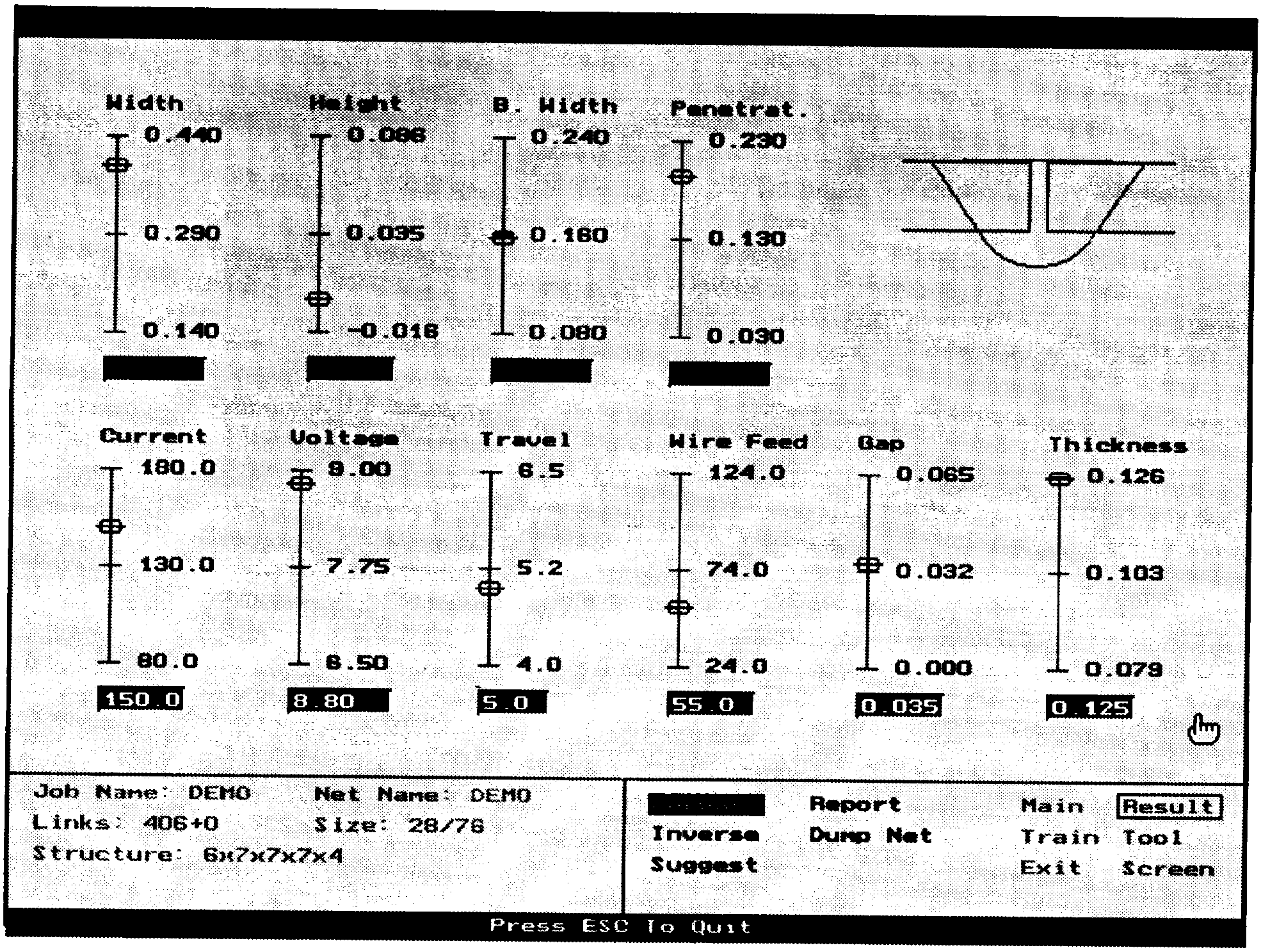

Figure 2. Neural network solution for the GTAW butt weld. Selected parameters of: voltage = 8.8 volts, current = 150.0 amperes, travel speed = 5.0 inches per minute, and wire feed rate = 55 inches per minute. In addition, the weld is being made in material of thickness = 0.125 inches and with a gap of 0.035 inches. The resultant shape parameters and bead graphic are shown in the interface.

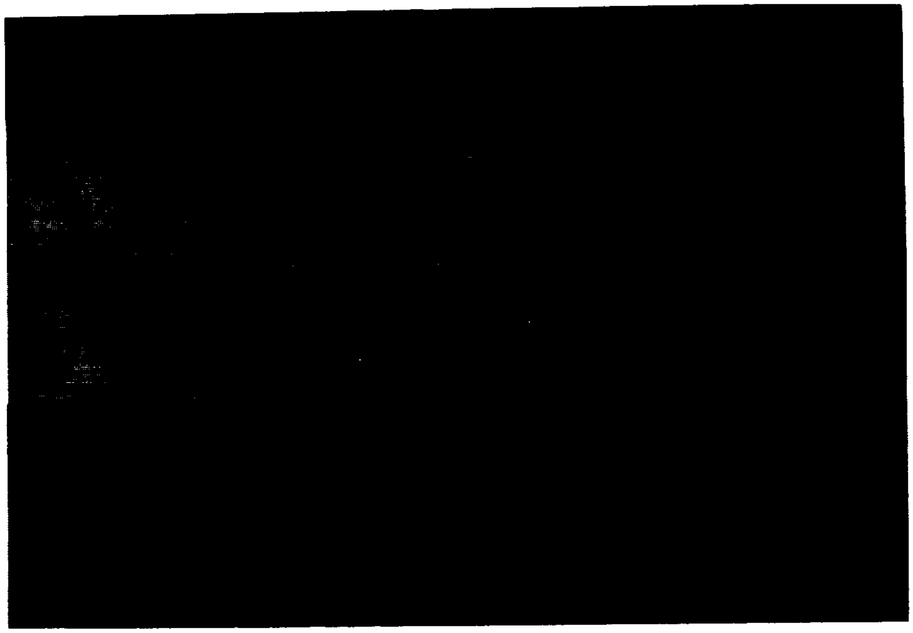

Figure 3. The actual weld bead cross section which was welded using the welding parameters described in the Figure 2.

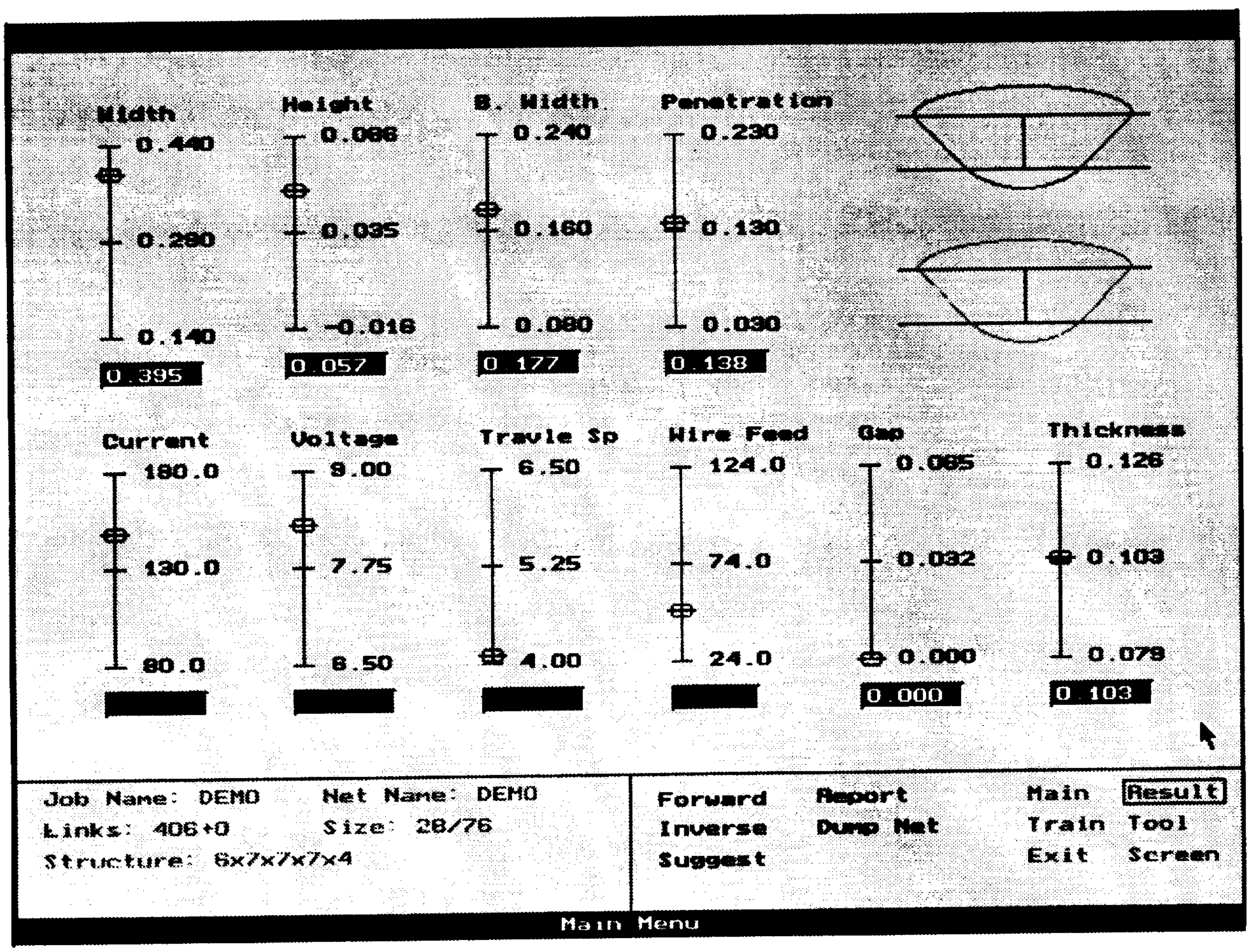

Figure 4. The GTAW network running in inverse model

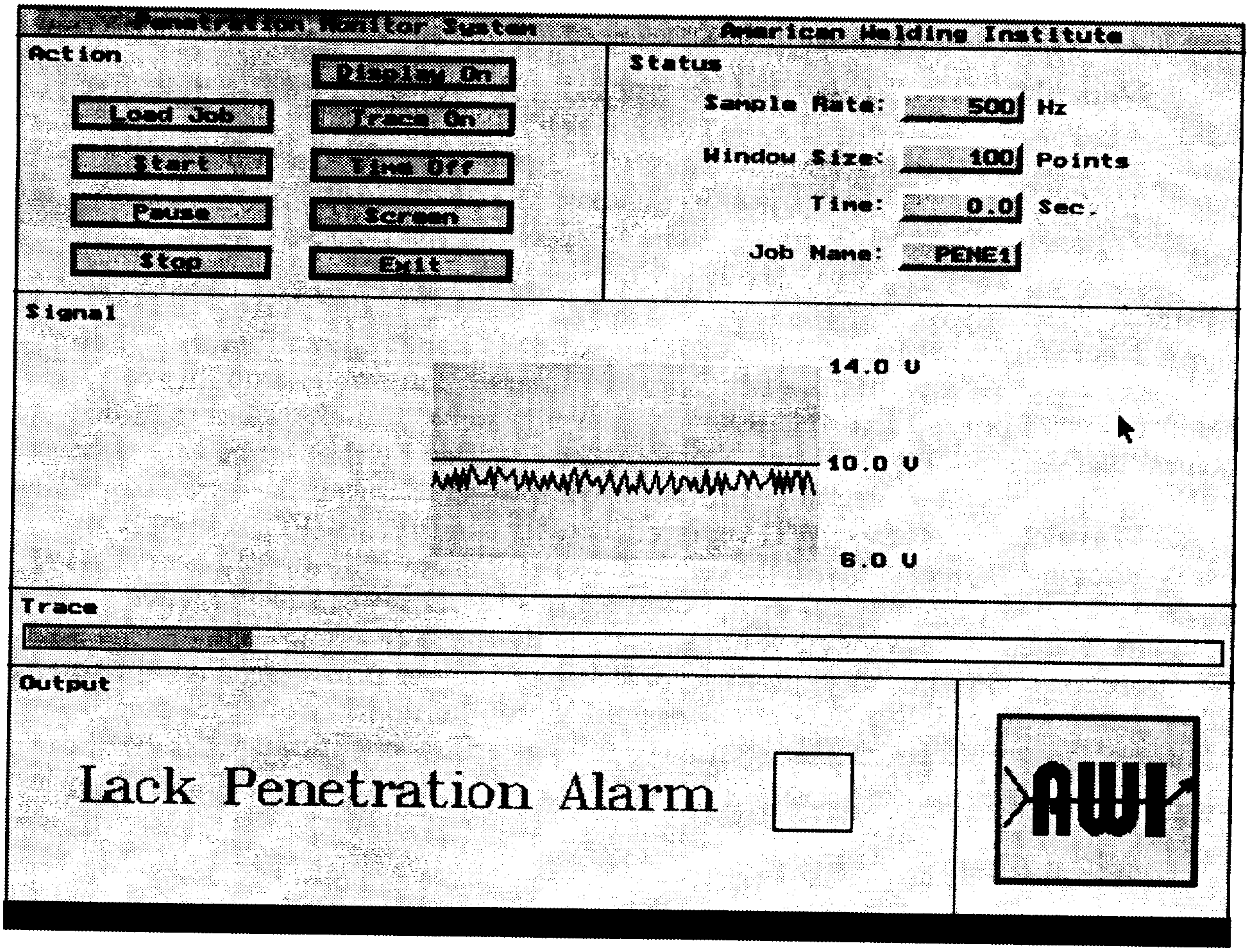

Figure 5. The GUI of real-time welding penetration monitoring system

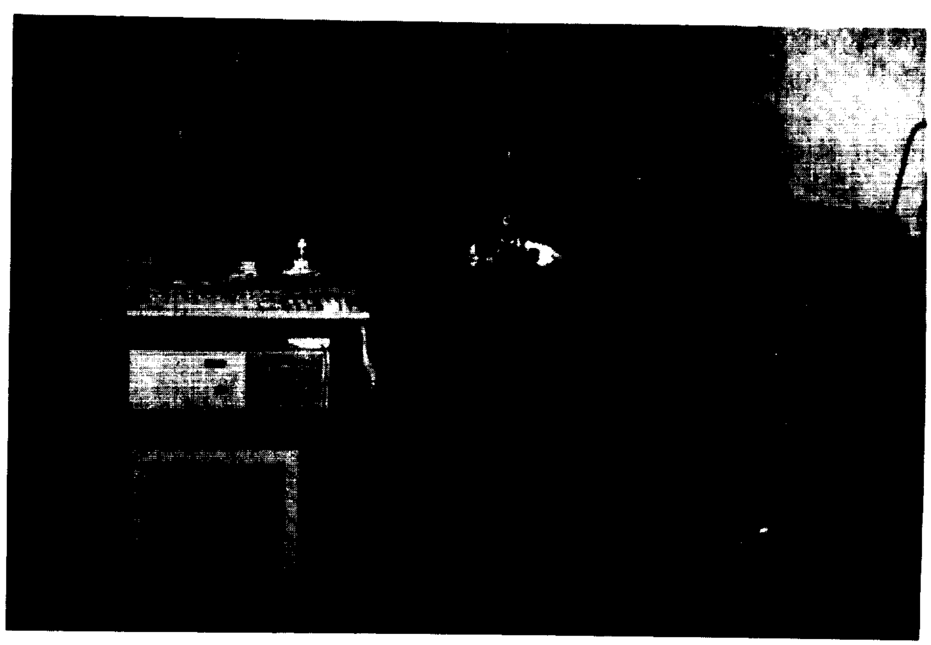

Figure 6. The GTAW Welding Penetration Monitoring System

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Neural Network Wavelet Technology, A Frontier of Automation

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Abstract:

Neural networks are interdisciplinary studies about animal brains. These have improved AI towards the 6th Gen Computers. Enormous amounts of resources were poured into this R/D awaiting for breakthroughs. International Neural Network Society held two Conferences attended by thousands each year, pushing the ultimate & exciting frontier of computing & info-tech.----our bio-brains,

Wavelet Transforms (WT) replaced Fourier Transforms (FT) favorably in every known Wideband Transient (WT) cases that began with the discovery of WT in 1985--the French geological exploration for oils by means of seismic wave imaging. The list of successful applications has the earth quake prediction, the Radar ID, speech recognitions, stock market forecasts, FBI finger print image compressions, telecommunication ISDN-data compression. More, the billion dollar medical-industrial has applications that still await the perfection--the intelligent heart beat pace-maker, the echoless hearing aids, in vivo constant level drug-dispensor, etc.

1. Introduction

A surging interest in neural nets began in 1980, when J. Hopfield wrote articles in Proc. Nat. Acad. Sci. p.2554 (1992) & p.3088 (1994), although pioneers such as Grossberg, Amari, Widrow, Kohonen, Fukushima, Anderson, Freeman, von der Malsburg, Rumelhart, Werbos, Carpenter, Cooper, have made significant contributions earlier. His model is simple for engineering because of interacting magnets (i.e. neuron points to the north for yes-vote, the south for no-vote) having simple matrix interconnects. Neurons are of McCulloch-Pitts (M-P) threshold logic.

2. Mathematical Foundation of Artificial Neural Networks

M-P Model of the ith neuron (in alphabetic order: u-input & v-output):

$$v_i = \sigma(u_i) = 1/(1+\exp(-u_i)); \qquad \text{Grossberg's: } (d/dt)v_i = c\,(v_i - \sigma(u_i)) \qquad (1)$$

where each voting v_j is weighted by previous memory W_{ij} as the net input u_i:

$$u_i = \Sigma_j W_{ij} v_j + \theta; \qquad \text{Hopfield's: } (d/dt)u_i = b\,(u_i - \Sigma_j W_{ij} v_j - \theta); \qquad (2)$$

$$W_{ij} = v_i v_j; \qquad \text{Hebb's: } (d/dt) W_{ij} = a\,(W_{ij} - v_i v_j) \qquad (3)$$