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SPECTRAL CHARACTERIZATION OF PULSED ULTRASOUND USING NEURAL NETWORKS

MARK A. JOHNSON
MICHAEL A. CIPOLLO
R. D. SCANLON

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US ARMY ARMAMENT RESEARCH, DEVELOPMENT AND ENGINEERING CENTER
CLOSE COMBAT ARMAMENTS CENTER
BENÉT LABORATORIES
WATERVLIET, N.Y. 12189-4050

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Mark A. Johnson, Michael A. Cipollo, and R.D. Scanlon

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13. ABSTRACT *(Maximum 200 words)*

A novel nondestructive evaluation technique that uses the spectral signature of a pulsed ultrasound signal to identify metals had recently been abandoned because of the difficulty in interpreting the results. Traditional analysis is inconvenient to apply to this type of problem because of the complicated, noisy, and incomplete nature of the data. Neural networks provide a radically different approach to computation. These massively parallel systems provide a mechanism to extract pertinent information from input data while maintaining a high degree of fault tolerance. This report discusses design of a neural network system capable of accepting data from nondestructive test equipment and producing output relative to the quality of the sample being tested.

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BACKGROUND

Ultrasound

The use of pulsed ultrasound to identify metals with unacceptable concentrations of impurities is a novel nondestructive technique. Impurities in metal such as sulfur stringers may directly affect the frequency response of an ultrasonic signal as it travels through the material. The impact that the impurities have on the spectrum may not be known, only that certain frequency components may attenuate while others may resonate. However, the complex, noisy, and inconsistent nature of the signals obtained using this technique make interpretation of the results difficult.

Neural Networks

Traditional neural networks are inspired by biological models, but bear little resemblance to their biological counterparts. Recent advances in network design have made the neural network an attractive alternative to conventional pattern recognition techniques. A neural network is a collection of interconnected neuromimes. A neuromime (Figure 1) is an exemplification in electronic circuitry of an abstraction of a living neuron. The neuron is seen as an electronic device with all the communication between neurons via synapses. The synapse multiplies the information passing through it by a scalar (called a weight). The input to a neuromime is given as

$$x_j = \sum_i w_{ji} o_i \tag{1}$$

where

x_j = net input to current neuron

w_{ji} = weight from previous layer to current layer

o_i = output or activity of a neuron at previous layer or input to layer

The neuromime acts as an integrator with a nonlinear output. A neural network represents the flow of information from input to output. In biological neurons there is a flow of ionic currents, but in neuromimes (neurons, nodes) the activity is represented by a scalar, which is visualized as the instantaneous frequency of a pulse generator producing a pulse position modulated signal. This frequency is sigmoidal with a finite upper asymptote. Rumelhart et al. (ref 1) suggest the following logistic model for this activity:

$$o_j = \left(\frac{1}{1 + e^{-(x_j + \theta_j)}}\right) \tag{2}$$

where

o_j = output or activity of a neuron at current layer

x_j = net input to current layer

θ_j = bias

The bias provides a threshold for activation. These output scalars pass to other neurons in the network through the synapses (Equation 1). The positioning of the synapses determines the character of the network. The connections usually cause the neurons to fall into groups called slabs or layers. A typical network consists of a sequence of slabs either fully or randomly interconnected with no connections among neurons sharing a common slab (Figure 2).

Neural networks are dynamical systems governed by rules that transform the network from one state to another. They consist of a series of interconnected nodes, with activation values assigned to each node and weights assigned to the connections. Information is stored in these weights using a learning algorithm to modify the interconnects. The nature of the learning algorithm is such that information is distributed in parallel among all nodes in the network as the network converges to the desired response. Convergence implies that the network has found regularities and correlations in the input data. After proper training, the network responds only to these trends in the data, making it highly insensitive to noisy and incomplete data.

A popular training algorithm (ref 1) involves presenting feature vectors at the input nodes and target vectors at the output nodes of a multilayer network and modifying interconnects to implement a least squares gradient descent (Equation 2). True gradient descent requires the learning rate η to be infinitesimally small, however, practical applications require a finite value that can lead to oscillations in w_{ji}. A momentum term is often added to minimize these oscillations while increasing the learning rate.

$$\Delta w_{ji} = \eta(\delta_j o_i) + \alpha \Delta w_{ji} \tag{3}$$

where

Δw_{ji} = weight change

η = learn rate

δ_j = error contribution of current neuron

o_i = afferent

$\alpha\Delta w_{ji}$ = momentum

As might be expected, the error contribution δ_j for output units is proportional to the difference between the desired results (targets) and the current output (Equation 4). The computation of δ_j for hidden units is proportional to the contribution each unit makes to the errors in the next slab (Equation 5).

$$\delta_j = (t_j - o_j)o_j(1 - o_j) \tag{4}$$

where

δ_j = error term of hidden unit

t_j = target or desired output

o_j = current output

$$\delta_j = o_j(1 - o_j)\sum_k \delta_k w_{kj} \tag{5}$$

where

δ_j	=	error term of hidden unit
o_j	=	current output
$\sum_k \delta_k w_{kj}$	=	contribution of current unit to error in next layer

The number of units in each layer is most often empirically determined, and care must be taken to use a large enough training set to ensure patterns are not simply memorized. Training time can be prohibitive in many applications so special purpose neural network simulators are being developed to exploit the inherent parallelism of the networks.

A network's performance is often measured in connection updates per second (CUPS). This can be defined as the rate of synapse modifications during one forward and one backward propagation through the network. A typical 8 MHz PC-AT is capable of approximately 4K CUPS, while a 25 MHz 80386DX attains 30K CUPS. The network used for training in this experiment is executed on a parallel processing system comprised of 40 transputers exercising a suite of homogeneous processing functions running under an OCCAM harness (ref 2). OCCAM permits the decomposition of processes into parallel procedures that execute simultaneously on different transputers, or time shared on a single transputer. These parallel processes can only communicate via channels, cannot share memory, and only synchronize when communicating. This hierarchical decomposition into parallel processes allows a suite of neural processes to be executed on a single transputer, while information is routed between nodes in the network. The problem domain is partitioned into subdomains across the transputer network. The transputers are configured as a one-dimensional hardware mesh topology. More complicated array structures are possible that minimize communication traffic and introduce disjoint paths for fault tolerance. However, communication protocol is greatly simplified by using only two of the four available hardware links. In addition, the granularity of the network can easily be adjusted without reconfiguring these links in order to optimize the computation/communication tradeoffs and achieve a satisfactory load balance.

Two algorithms were studied to address the computation/communication problem. The first partitions the network among the transputers so that activation and synapse values are maintained at each node. On a forward or backward pass, values are computed using partial data as it becomes available. In this configuration, communication overhead is reduced, but transputers often sit idle waiting for data. In addition, the size of the network is restricted by the memory limitations at the nodes. Only 400K CUPS was attained using this technique because of practical limitations on the number of transputers used.

An alternative approach uses data partitioning (ref 3) to achieve faster throughput during training. It can be assumed for a small η, Δw_{ji} is small compared to w_{ji} and many iterations can be run before updating w_{ji}. Consequently, several simulations can be performed in parallel on different training patterns. Therefore, instead of distributing the network among the transputers, the same network is implemented on each transputer using a different set of training patterns. On a backward pass, each transputer computes Δw_{ji} for its training set and broadcasts it to the host where Δw_{ji} is accumulated and w_{ji} updated. The host processor transmits these new weights to each processor as the process repeats recursively until the desired error is achieved. 3.5M CUPS was achieved using this technique, however communication limits the practical use of this approach to large networks with a large training set. In addition, stability problems may arise if the learning rate is too high (> 0.5).

APPROACH

Metals with similar composition but different impurity concentrations were separated into two groups and machined from bar stock. Figure 3 shows typical impurity concentrations of the samples in each of the two groups. Since grain structure may affect the spectral signature, samples from each group were heat treated to erase coarse multiphase microstructure. Figure 4 shows the different grain structures in each of the groups prior to heat treatment. Figure 5 shows the grain structure resulting from heat treatment.

Figure 6 shows the laboratory setup that is used to collect ultrasonic signatures from the test samples. A Panametrics Pulser Receiver, Model 5052PR, transmits a series of 10 MHz ultrasonic pulses through a piezoelectric transducer coupled to the sample under test. The pulses travel through the metal and are reflected back to the transducer and received by the pulser. As the pulses travel through the sample, the nature of the metal determines which frequency components resonate or attenuate. A Panametrics Stepless Gate, Model 5052G, gates only the first echo received by the pulser to a Tektronix 497P spectrum analyzer. The spectrum analyzer extracts the frequency spectrum of the echoes and transmits this information through an IEEE-488 bus to the PC for analysis. A neural network is then employed to identify the salient features of these signals and produce output relating to the quality of the sample being tested.

RESULTS

Spectral data were collected at different locations on each specimen from a selection of samples for each metal group. Approximately 300 feature vectors comprised of 100 normalized spectral components were extracted from the data. A 100 x 20 x 2 network was trained on these data with activity of the two output neurons used to classify the metals into one of the two groups. The network converged to a solution using the salient features of the spectral signature to classify the samples from each group. The network was trained on the transputers and then ported to the PC where the input feature vectors can be obtained from the spectral components in real time. The system was tested on the training samples, as well as the remaining bar stock, and successfully classified the specimens from each group.

This technique may be expanded to identify a range of impurity concentrations (per ASTM E-45-87, "Standard Practice for Determining the Inclusion Content of Steel") by employing a different network architecture. Complex geometries found in practice will likely require larger networks. Self-organizing systems that model the probability distribution of the training data are being studied to reduce network size.

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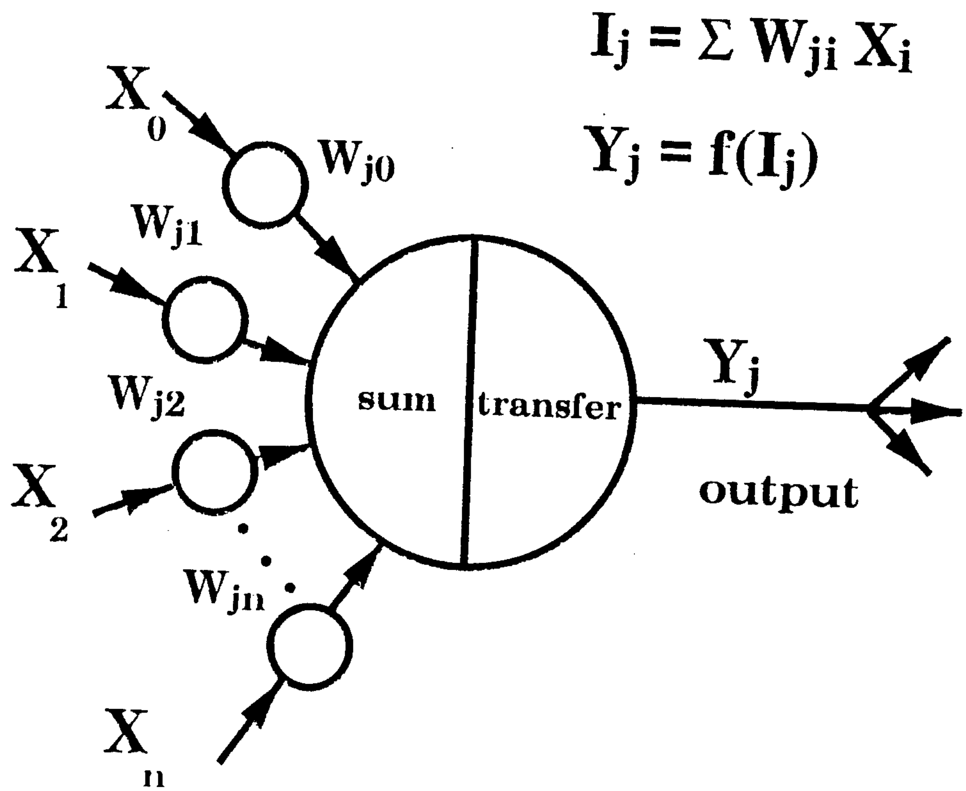

Figure 1. Typical Neuromime

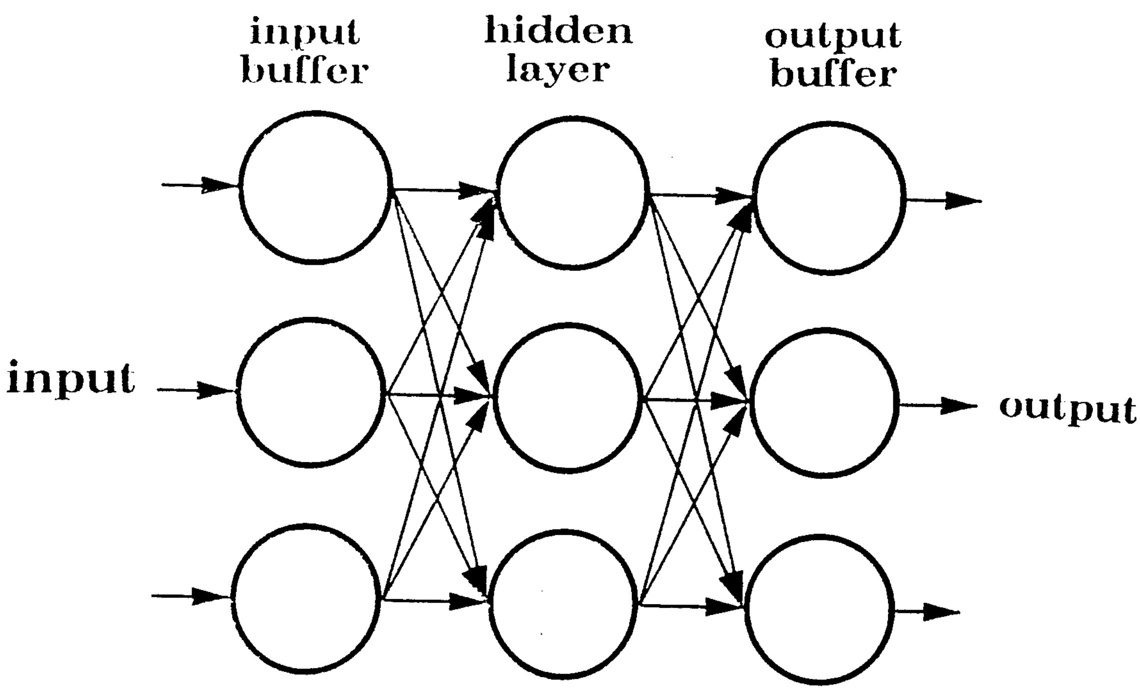

Figure 2. Three Layer Network

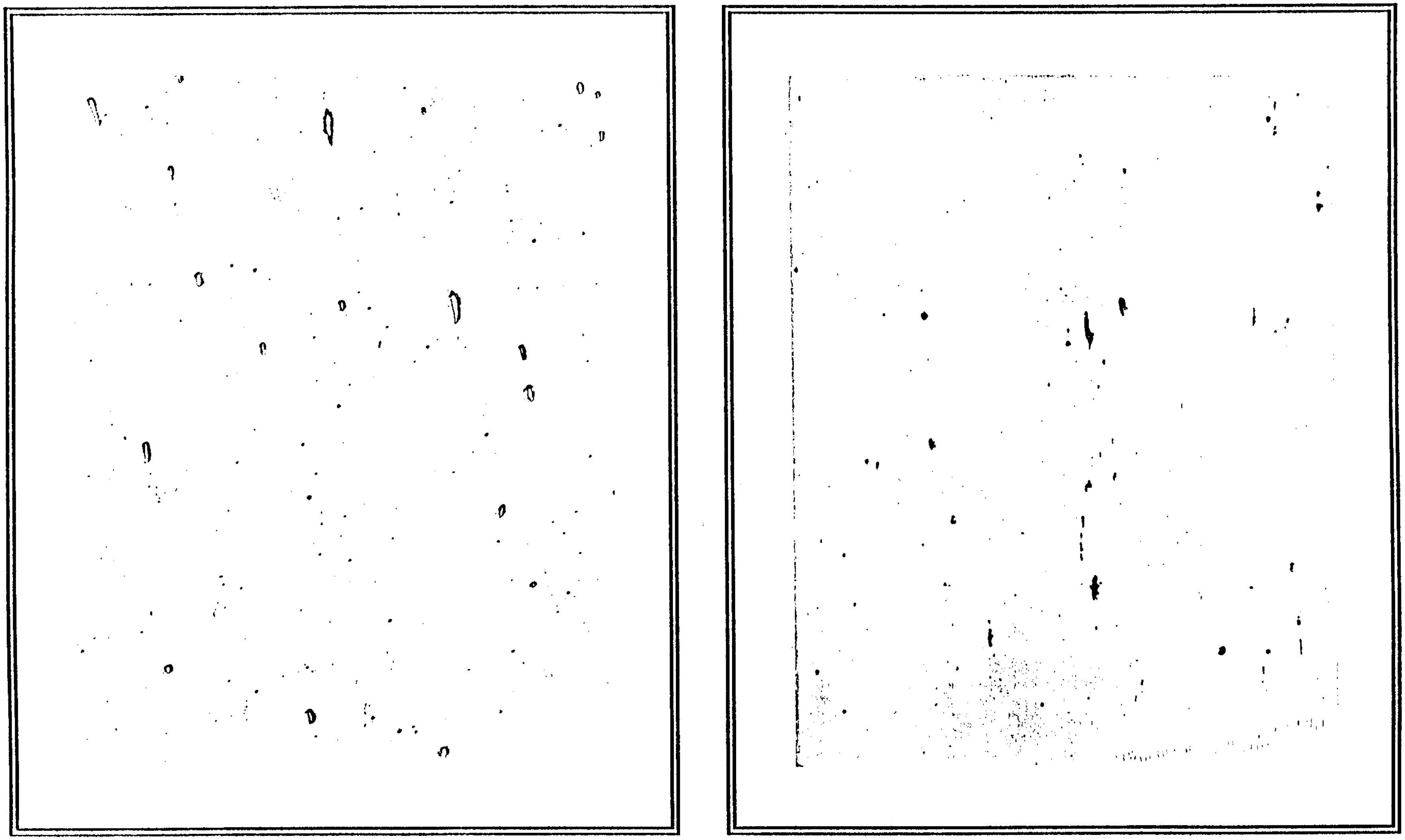

Figure 3. Typical impurity concentrations of the sample groups.

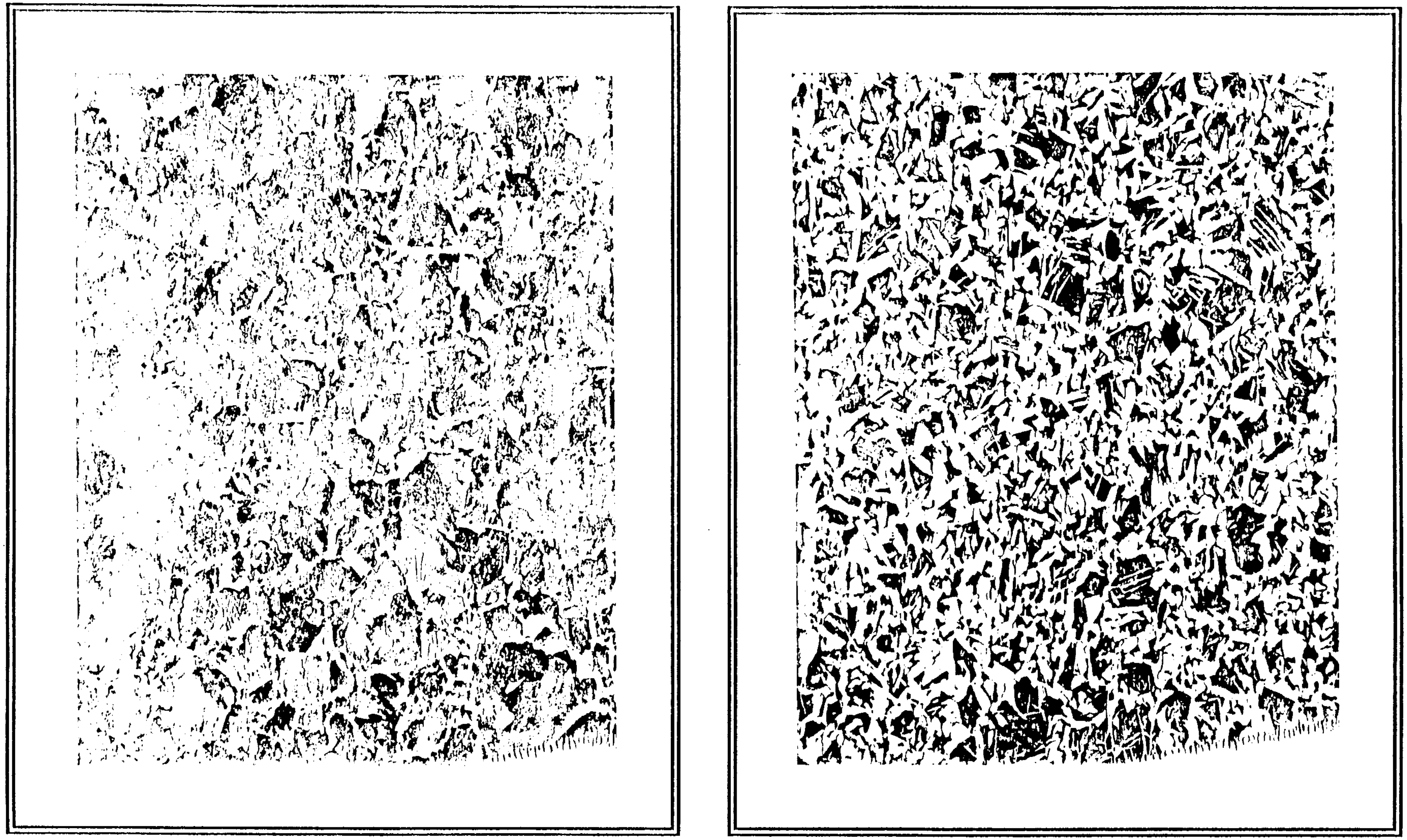

Figure 4. Different grain structures prior to heat treatment.

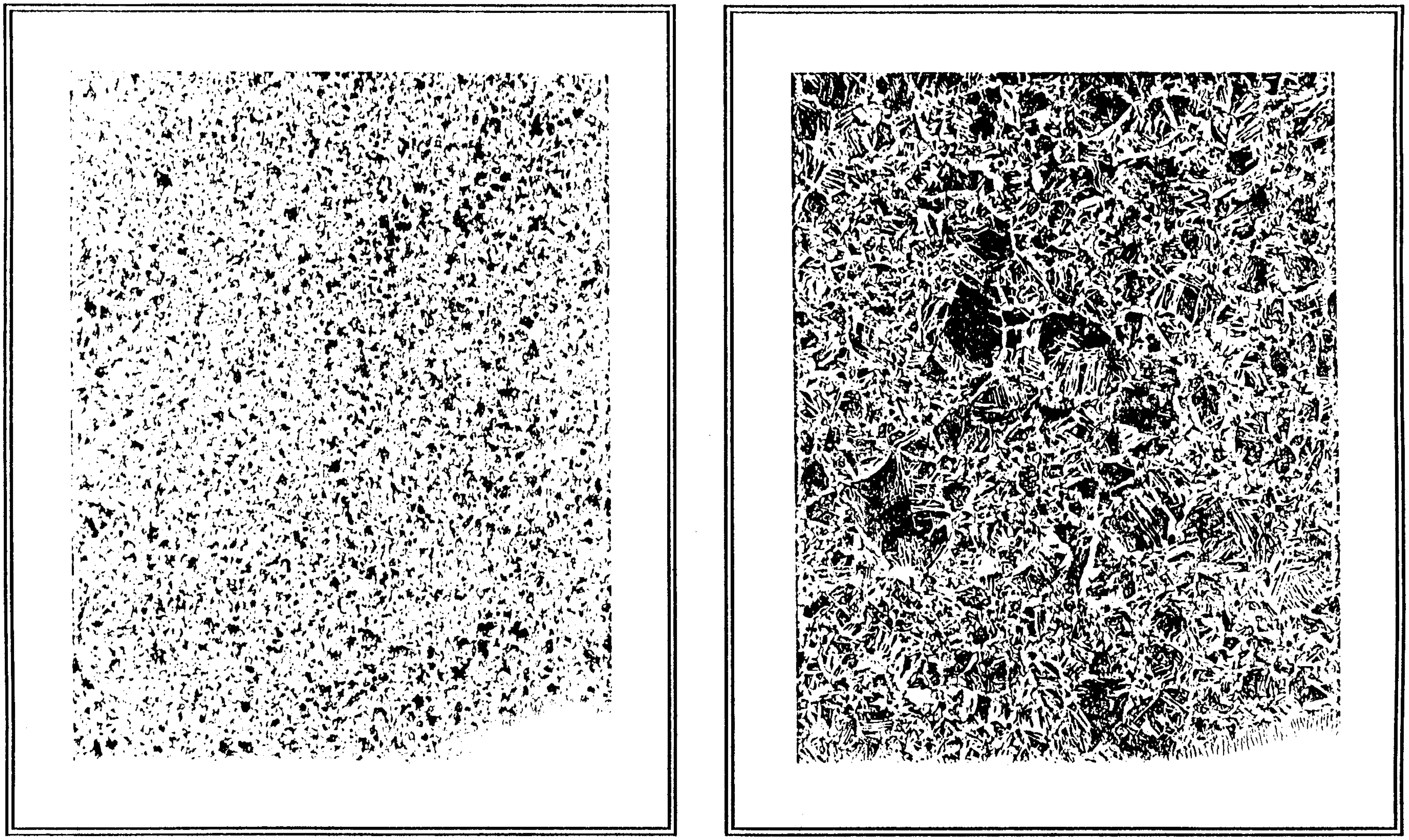

Figure 5. Resulting grain structure after heat treatment.

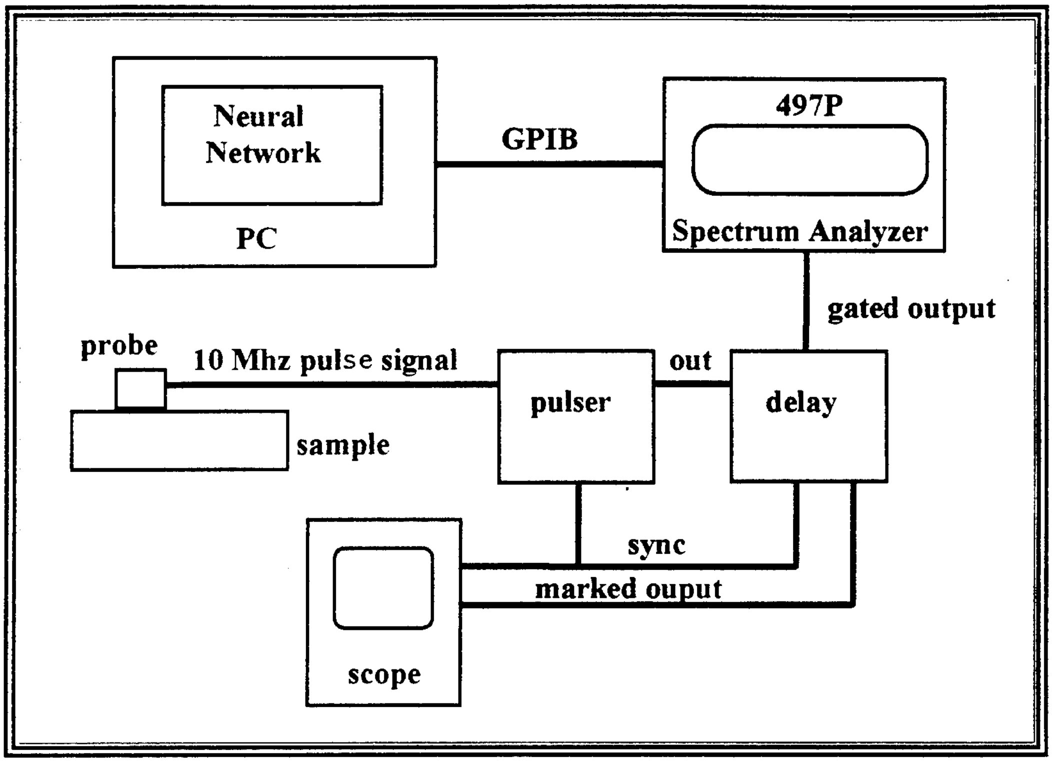

Figure 6. Laboratory setup.

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