Piece-Wise Linear Estimation of Mechanical Properties of Materials with Neural Networks

Inho Shin
Mando Machinery Co., Research and Development Center

ABSTRACT

Many real-world problems are concerned with estimation rather than classification. This paper presents an adaptive technique to estimate the mechanical properties of materials from acousto-ultrasonic waveforms. This is done by adapting a piece-wise linear approximation technique to a multi-layered neural network architecture.

The piece-wise linear approximation network (PWLAN) finds a set of connected hyperplanes that fit all input vectors as close as possible. A corresponding architecture requires only one hidden layer to estimate any curve as an output pattern. A learning rule for PWLAN is developed and applied to the acousto-ultrasonic data. The efficiency of the PWLAN is compared with that of classical back-propagation network which uses generalized delta rule as a learning algorithm.

OVERVIEW

PWLAN is used to enhance acousto-ultrasonic nondestructive evaluation method of the strength and elastic modulus of composite fiber materials. The work is performed in the frequency domain since the envelope of the acousto-ultrasonic waveform has complicated amplitude variations while the corresponding frequency spectrum exhibits numerous prominent frequency components.

The sample spectra are digital fast Fourier transforms of waves supplied by a digitizing oscillocope. The network using PWLAN utilizes 3 out of 9 acoustoultrasonic waveforms from 3 different positions repeated 3 times.

INTRODUCTION

The goal of nondestructive evaluation is to provide a basis for determining whether a structure will perform reliably or not. The acousto-ultrasonic method is one of several approaches for the characterization of the properties of materials. Acousto-ultrasonics, a relatively new technique, appears to have promise as a predictor of material strength and stiffness. Generally, stress wave factor (a measure of transmitted energy) was observed to increase with increasing strength and modulus of polymer matrix composite and ceramic matrix composite materials [1]. There are a number of numerical methods to estimate the correlation between a stress wave factor and the mechanical properties of a material. The main purpose of this work is to design a real-time adaptive neural network algorithm for the estimation of mechanical properties.

Many algorithms and network architectures have been developed for parallel machines for pattern classification tasks. The problem of finding the mechanical properties of materials from acousto-ultrasonic waveforms, however, is a problem of estimation rather than classification.

It has been shown [2] that the generalized delta rule network can learn a continuous function f(x) given the values of this function at a finite number of points. Such a network uses sigmoidal function at each node to threshold the node's output. Since the role of each node is to discriminate the input patterns they will lay on two sides of a dividing hyperplane. The use of analytical sigmoidal functions allows the network to be used as an estimator of class membership functions.

In essence, the PWLAN finds a set of connected hyperplanes which maps an input vector into an output vector in a feature space. For example, a segment of a line in a two dimensional space can map an input x to an output y, if the line is aligned to the data points properly. A connection of such lines along with the non-linearly distributed data points can make a good approximation of y for the given data points.

A corresponding network architecture requires only one hidden layer to estimate any curve as an output pattern. A learning rule for PWLANs is developed and explained in the following section. The performance of the PWLAN is compared with that of a backpropagation network on both artificially generated data and the real data.

METHODS

In this section, we describe the mathematics and modeling of PWLAN. Let t_m be a target value of input vectors x_m defined as $t_m = f(x_m)$. Let

$$O_j = \sum_{i=1}^{n} a_{ji}x_i + a_{j,n+1}, \qquad (1)$$

where O_j represents a hyperplane in an n+1 dimensional vector space and a_{ij} is i^{th} coefficient of j^{th} hyperplane. Note that any connected hyperplane in an n+1 dimensional space can be expressed as a linear combination of hyperplanes which have a bend on the edge of the connections. Therefore, p connected hyperplanes can be expressed as follows:

$$y = \sum_{j=1}^{p} b_j|O_j| + b_{p+1} \qquad (2)$$

where b_j is j^{th} coefficient of the linear sum of bent hyperplanes. For convenience, we will assume that $x_{n+1}=1$ and $O_{p+1}=1$. The equation (2) then becomes

$$y = \sum_{j=1}^{p+1} b_j\left|O_j\right| = \sum_{j=1}^{p+1} b_j\left|\sum_{i=1}^{n+1} a_{ji}x_i\right| \qquad (3)$$

Now, the task is to find the a_{ij}'s and the b_j's in an adaptive manner so that y will be a good approximation of the target value t, given a finite number of samples(pairs of x and t). A neural network implementation of the above equation is shown in Figure 1.

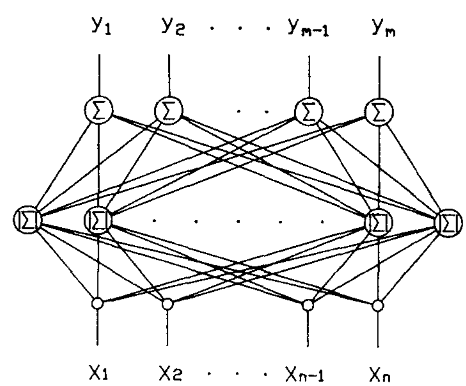

Figure 1. Architecture of a neural network.

During the training phase of the network, the pattern x_m is presented to the network's input. The weights are then adjusted so that the desired output t_m is obtained at the output node. For each pattern, the square of the error between the target value and the output value is $E_m = (t_m - y_m)^2$. The weights are adjusted to reduce the system error E_m. The system error changes with respect to the weights as follows:

$$\frac{\partial E_m}{\partial b_j} = -2(t_m - y_m)\left|O_j\right| \qquad (4)$$

$$\frac{\partial E_m}{\partial a_{ji}} = -2(t_m - y_m)b_j\frac{\partial}{\partial a_{ji}}\left|O_j\right| \qquad (5)$$

$$\hat{=} \begin{cases} -2(t_m - y_m)b_j x_i & \text{if } O_p > 0, \\ 2(t_m - y_m)b_j x_i & \text{if } O_p < 0, \\ 0 & \text{if } O_p = 0. \end{cases} \qquad (6)$$

By taking incremental changes of weights proportional to the negative direction of the system error, with properly chosen constant η, a local minimum of the system error can be achieved. The resulting learning rule are:

$$\Delta a_{ji} = \eta\,(t_m - y_m)\, b_j\, x_i\ \mathrm{sign}(O_i), \qquad (7)$$

$$\Delta b_j = \eta(t_m - y_m)\ |O_j\,| \qquad (8)$$

where sign() returns -1,1 or 0 depending on the sign of the argument.

RESULTS

a) Testing PWLAN on generated data sets.

Two single-valued functions of one variable, $y_1 = 3.2x(x-1) + 0.1$ and $y_2 = 0.8e^{-10x} + 0.1$, are used to generate 20 sample points and presented to PWLAN. The basic task is to have the network learn the input-output pairs and then generate an estimate of the original function by plotting the output with respect to x.

Thirty hidden nodes are used in the network and compared with the results of backpropagation network having the same architecture. Figure 2 shows the estimated functions after 0,4,100 and 400 iterations on both networks. A comparison of computational speed for both is shown in Figure 3.

b) Estimation of strength and elestic modulus of materials using PWLAN

Acousto-ultrasonic measurements were performed on bend test specimens using a sensor fixture with two transducers. The sender and receiver were both 2.25 MHz broad band transducers. Silicon rubber dry couplant pads were cemented to the 0.64 cm diameter wear plates of the transducers. The pads were used to demonstrate the utility in place of gel type couplants which are inconvenient. The specimens were clamped between the transducers and a jack with adjustable force set at 12 N. The fixture-specimen-jack arrangement is shown in figure 4.

Pulses arriving at the receiver were displayed and digitized on the oscilloscope. From there they were transmitted to the computer for processing. The signal energy was defined as the square of the amplified transducer output voltage integrated over the time of the sweep. This was used as stress wave factor. Data was taken at 1.9 cm intervals. The transducer spacing was 3.8 cm thus producing a 50 percent overlap between adjacent positions.

Eighteen digitized waveforms were collected from the acousto-ultrasonic stress wave factor measurement system[3,4,5,6]. Each waveform consisted of 512 real values of amplitudes. The digitized waveforms were transformed into the frequency domain using a fast Fourier transform algorithm. The sample spectra were partitioned into several, equally spaced, frequency intervals. The spectral energies were added together within a given interval to produce a stress wave factor defined as

$$SWF = S_{rms}^{\ 2} = \frac{1}{F}\int_{f_1}^{f_2} s^2 df. \qquad (9)$$

These stress wave factors are the input features to PWLAN. In this study, 1, 2, and 257 partitions were tried. The stress wave factors were normalized using the maximum asymptotic value found from the samples. The corresponding output features were mapped linearly onto the interval [0.1,0.9] so that they match the maximum and minimum values at 0.9 and 0.1, respectively.

This procedure was applied to each sample on all 9 acousto-ultrasonic waveforms and averaged with respect to three different positions of the transducers. As a result of applying this procedure, a complete set of 18 learning data sets with 1-, 2-, and 257-dimensional input and scalar output is produced. The training of PWLAN is straightforward, and the results for 1-dimensional case are shown in Figure 5.

DISCUSSION

It has been shown that, for estimation problems, there is a significant difference in the performance of the backpropagation neural network classifier and PWLAN. The mean square error in PWLAN approaches local minimum much faster than in the backpropagation network.

In order to implement higher order version of PWLAN, it will be necessary to extand the input features into higher order terms [2]. The advantage of the algorithm is that even for the higher order cases,the network would require only one hidden layer. This allows the use of the same architecture for any complexity of the input data.

Since a node in the hidden layer can produce a bend on the output estimation curve, the number of bends on the estimated hyper curve is less or equal to the number of nodes in hidden layer. Therefore, it will be possible to use available priori knowledge of sample distribution to decide the size of the hidden layer.

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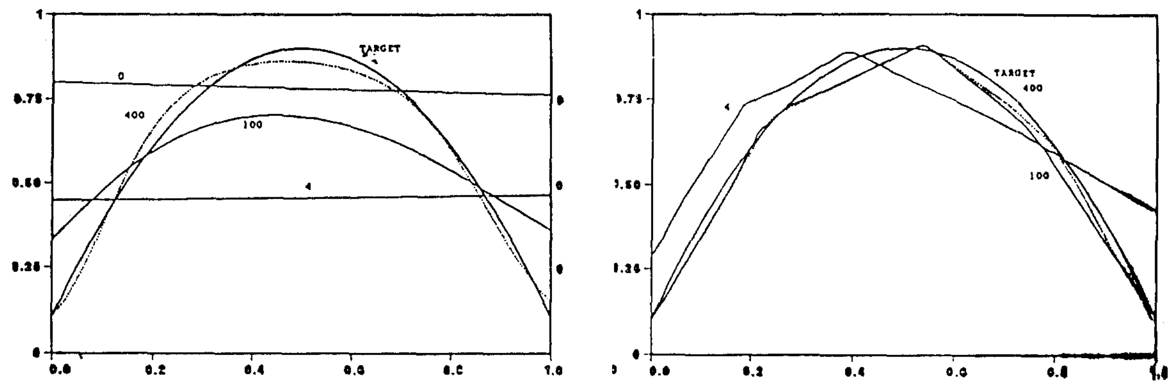
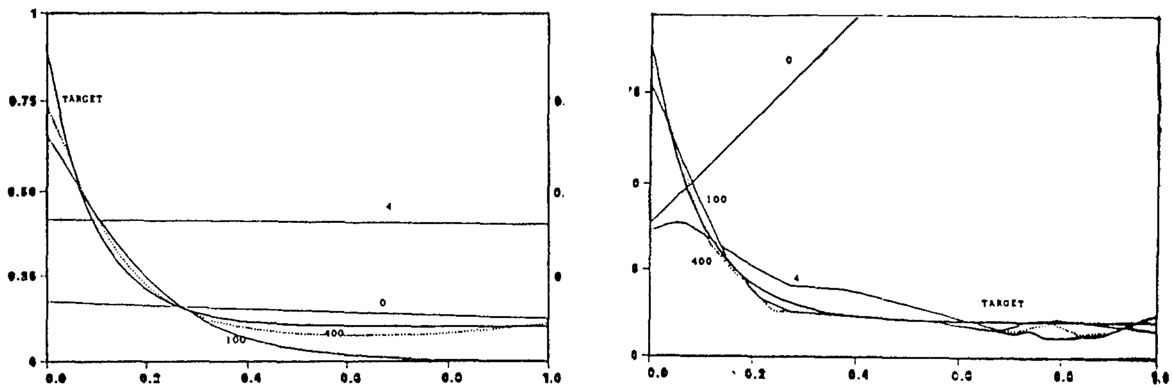


BPN PWLAN

Figure 2-a. Estimation of $y_1 = 3.2\,x(x-1) + 0.1$



BPN PWLAN

Figure 2-b. Estimation of $y_2 = 0.8\,e^{-10x} + 0.1$

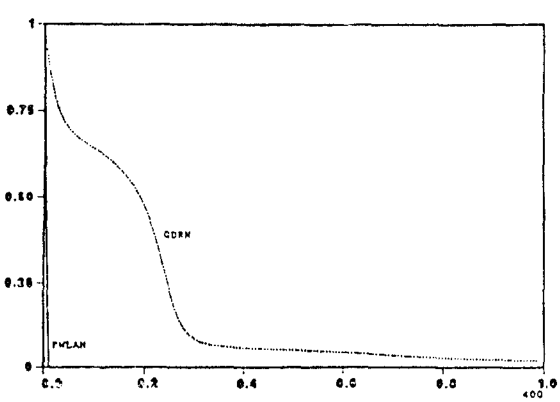


Figure 3. System error behavior on both networks when they estimate the above functions.

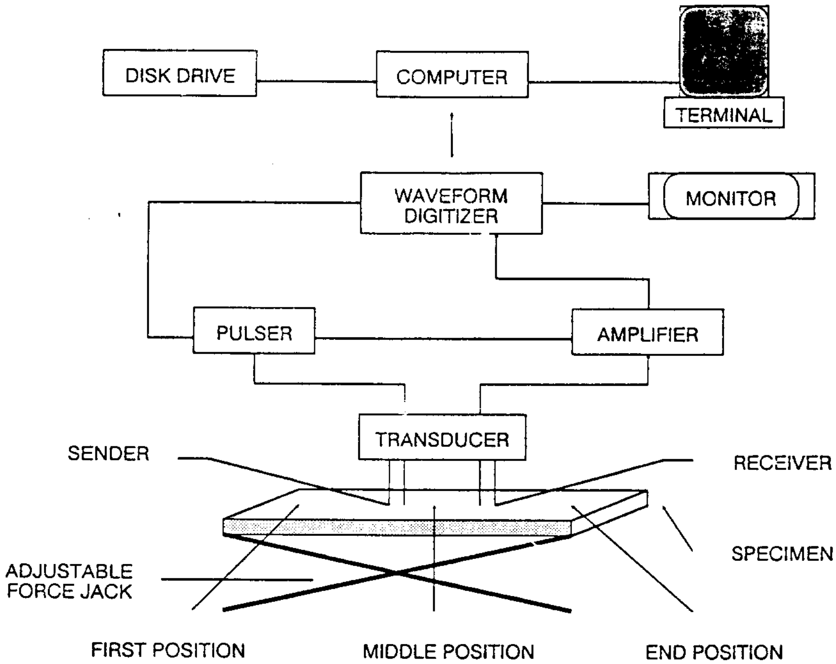


Figure 4. The fixture-specimen-jack arrangement.

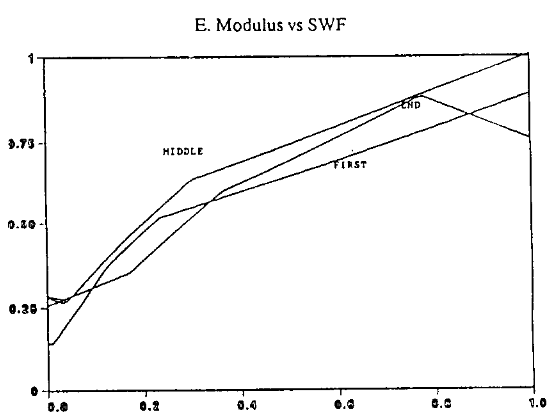


Figure 5-a. Elestic Modulus vs Stress Wave Factor.

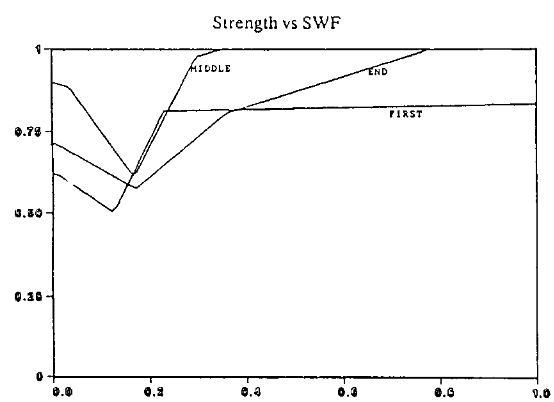


Figure 5-b. Strength vs Stress Wave Factor.