CRACK PARAMETER CHARACTERIZATION BY A NEURAL NETWORK

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INTRODUCTION

A neural network with binary outputs is presented to determine the angle and the depth of a surface-breaking crack from ultrasonic backscattering data. The estimation procedure is divided into two steps:

1. The angle of the crack is estimated in the range from 10 to 70 degrees with a precision of 5 degrees. To improve the accuracy of estimation, information on the integral of the backscattered signal is utilized.
2. When the angle of the crack has been estimated, the depth of the crack is determined with a precision of 0.5mm in the range from 2.0mm to 4.0mm. This determination is achieved by employing sets of neural networks corresponding to various angles of the crack.

Experimental data has been obtained for a stainless steel plate with a surface-breaking crack, immersed in water. The crack is insonified from the opposite side of the plate. The angle of incidence with the normal to the insonified face of the plate is taken to be 18.9°. The neural networks are feed-forward layered networks. The training algorithm is an error back-propagation algorithm. Numerical solutions obtained by the boundary element method have been used for training. The performance of the trained network has been tested by unlearned numerical data and by experimental data.

PROBLEM CONFIGURATION

An experimental configuration of an inclined surface-breaking crack of depth a in a stainless steel plate of thickness h (20mm) is considered. The problem is to determine the depth a and the inclined-angle ϕ of a crack by measuring the back-scattered waveforms. The plate is immersed in a water bath as shown in Fig.1. Ultrasound is generated by an immersed piezoelectric transducer. The angle of incidence with the normal to the insonified top face of the plate is taken as 18.9°. This angle of incidence exceeds the critical angle, and the incident ultrasonic beam is therefore primarily converted into a beam of transversely polarized ultrasound in the plate, which propagates under an angle of 45° with the vertical.

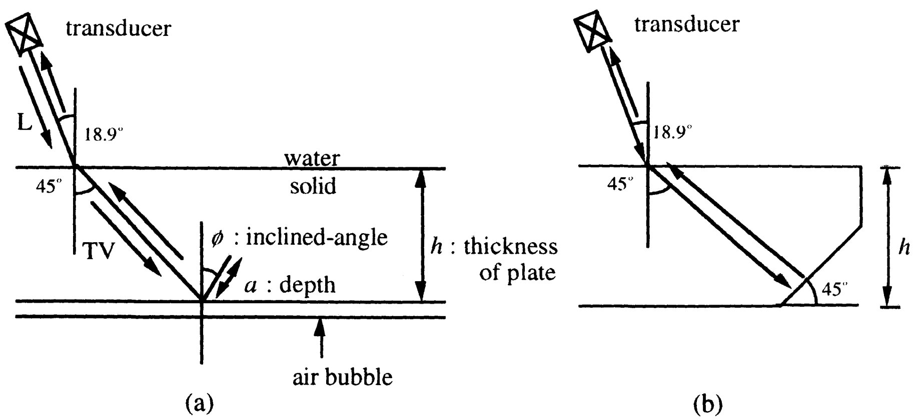

Figure 1. Inclined surface-breaking crack in a stainless steel plate (a), and inclined-corner reflection of the reference signal.

Experimental back-scattered signals for some inclined cracks are used to verify the performance of the neural network which has been trained by the use of calculated theoretical signals. In order to compare the experimental signals with calculated theoretical ones, the experimental signals have to be pre-processed using a reference signal.

In the frequency domain, the experimentally obtained back-scattered signal may be expressed as

$$Y_{exp}(\omega) = T_0 H_w H_b H_{ws} H^{exp}_{crack} H_{sw} H_w T_r \ . \tag{1}$$

The response functions in this expression represent the effects of

$T_0(w)$: transducer output,	$H_w(w)$: water path,
$H_b(w)$: beam spreading,	$H_{ws}(w)$: water $\rightarrow$ solid interface,
$H_{sw}(w)$: solid $\rightarrow$ water interface,	$T_r(w)$: transducer reception,

and

$H^{exp}_{crack}(\omega)$: interaction with crack in solid.

For the corresponding theoretical results, the expression is exactly the same except for the response of the crack:

$$Y_{theory}(\omega) = T_0 H_w H_b H_{ws} H^{BEM}_{crack} H_{sw} H_w T_r \ . \tag{2}$$

In equation (2), $H^{BEM}_{crack}(\omega)$ represents the interaction with the crack of the incident wave as calculated by the boundary element method(BEM). The BEM calculation is based on two-dimensional elastodynamic theory for an elastic body with a inclined surface-breaking crack. The detailed treatment of this problem can be found in the paper by Zhang and Achenbach[1].

To cancel the response functions except the term $H^{BEM}_{crack}(\omega)$ in Eq.(1), the signal for a corner reflection is introduced as the reference signal, see Fig.1. For the same transducer angle and the same specimen but with an inclined corner whose face is perpendicular to the incident wave, this reference corner signal can be written as

$$X_{ref}(\omega) = T_0 H_w H_b H_{ws} H_{cor}(\omega) H_{sw} H_w T_r \ , \tag{3}$$

where $H_{cor}(\omega)$ represents the reflection from the inclined corner in the solid, and it has been assumed that the sound propagation paths for the two cases are approximately the same. The formal deconvolution of the experimental signal of Eq.(1) by the reference signal of Eq.(3) yields

$$\frac{Y_{exp}(\omega)}{X_{ref}(\omega)} = \frac{H^{exp}_{crack}(\omega)}{H_{cor}(\omega)} \tag{4}$$

Since the term $H_{cor}(\omega)$ can be calculated analytically, the left-hand side of Eq.(4) can be directly compared with the theoretically calculated interaction term.

The backscattered waveform data in the frequency domain have been obtained by the use of BEM analysis. The data were calculated for a total of twenty seven angles of inclination of the crack ranging from 7.5 degrees to 72.5 degrees with increments of 2.5 degree, for a total of five depths ranging from 2.0mm to 4.0mm with increments of 0.5mm. Some of these data have been used for the training of the neural network, and the others for the testing of its performance. Some of training data in the frequency domain are shown in Fig.2. The plotted amplitudes have been normalized by the amplitude of the incident wave.

BASIC STRATEGY

If either the angle or the depth of a crack is known, the other parameter can be estimated accurately [2-4]. On the other hand, it is a very difficult task to determine both the angle and the depth at the same time. For those reasons, the estimation procedure has been divided into four steps: First, the angle of the crack is estimated by a neural network that has been trained with data for various angles and various depths. This trained network usually works well, but sometimes its output is not reliable. When the crack angle is estimated inaccurately, its depth will also be wrong. As the next step, other possibilities for the angle of a crack are estimated by considering the integral of the backscatter data. Next, for all angles that are estimated in step1 and step2, the depth of the crack is determined by employing neural networks corresponding to the crack angles. The final step is to select the most appropriate parameters by comparing the results of step1, step2 and step3.
The estimation procedure is schematically shown in Fig. 3.

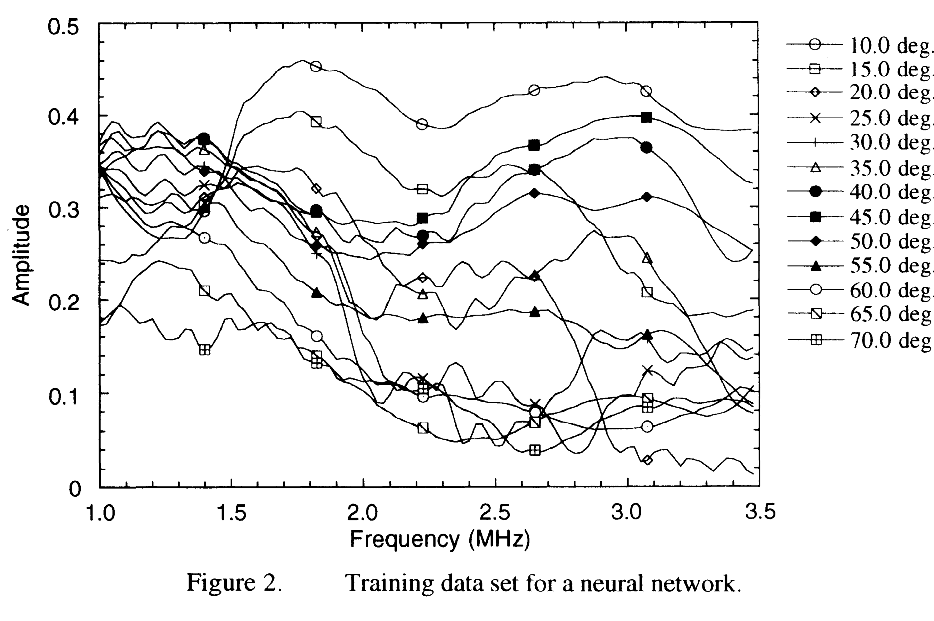

Figure 2. Training data set for a neural network.

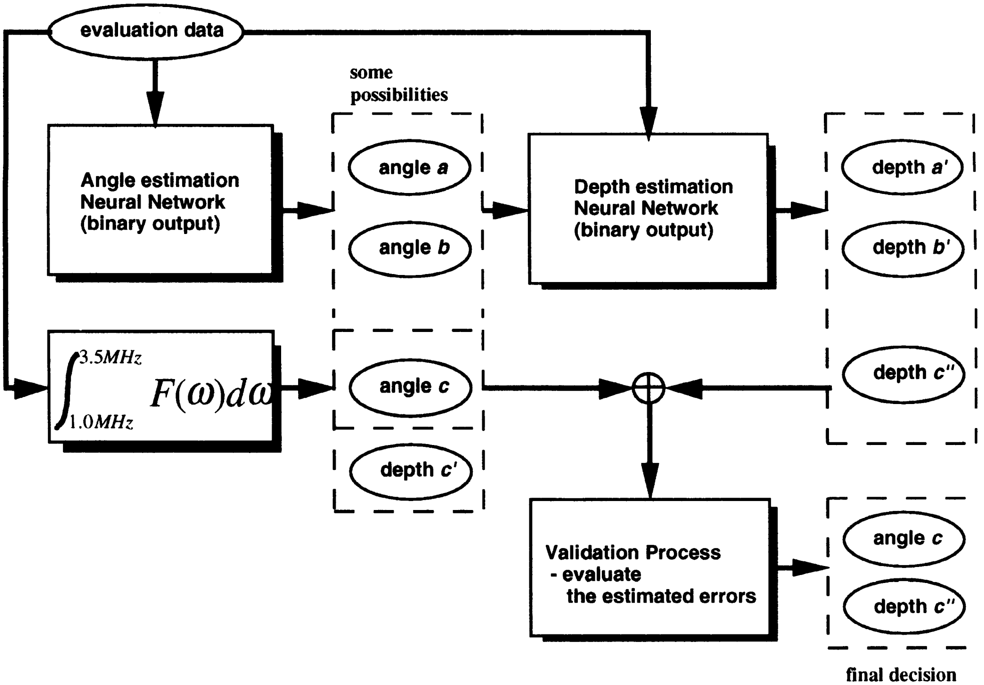

Figure 3. Schematic flow chart for the estimation procedure.

METHODS

Neural networks

The crack angle estimation neural network and the depth estimation neural network are set up separately. For input data, a hundred and one points from backscattered waveforms in the frequency domain are used.

The network specifications are almost the same for both networks: The network is a 3-layered or a 4-layered feed-forward type, the training algorithm is an error backpropagation algorithm, and the value of the output units is binary, which means that one output unit corresponds to a specific angle or depth of a crack. For the case of angle estimation, the network has thirteen output units which represent the crack angle from 10 degrees to 70 degrees with increments of 5 degrees. For the case of depth estimation, the networks have five output units which represent the crack depth from 2.0mm to 4.0mm with increments of 0.5mm.

As a training data set, data for a total of sixty five crack configurations whose crack angle varies from 10 degrees to 70 degrees with increments of 5 degrees and whose crack depth varies from 2.0mm to 4.0mm with increments of 0.5mm have been used for the angle estimation network. For the depth estimation network, data for a crack of specified angle but whose depth varies from 2.0mm to 4.0mm with increments of 0.5mm have been used, since this network has been applied after the angle of a crack is determined. The determined angle has a range of plus or minus 5 degrees, since the angle is reported as a discrete value with increments of 5 degrees. For example, if the output from the angle estimation network is 50 degree, the actual angle may range from 47.5 degrees to 52.5 degrees, since as a training data set for the case of 50 degrees, 47.5, 50.0, and 52.5 degrees have been used. Other cases are summarized in Table 1. A total of fifteen data have been used for each depth estimation network.

Table 1. Training data set for the depth estimation network.

angle (deg.)	angle for training data (deg.)
10	7.5, 10.0, 12.5
15	12.5, 15.0, 17.5
20	17.5, 20.0, 22.5
25	22.5, 25.0, 27.5
30	27.5, 30.0, 32.5
35	32.5, 35.0, 37.5
40	37.5, 40.0, 42.5
45	42.5, 45.0, 47.5
50	47.5, 50.0, 52.5
55	52.5, 55.0, 57.5
60	57.5, 60.0, 62.5
65	62.5, 65.0, 67.5
70	67.5, 70.0, 72.5

*crack depth for training data : 2.0, 2.5, 3.0, 3.5, 4.0mm

Integrated waveform considerations

In this paper, the integral of the signal in the frequency domain is also used. The integral depends on both the angle and the depth of a crack (Fig. 4). Generally, if the integral is known, a pair of angles and the depth of a crack can be estimated. Specifically, the sets of parameters can be determined by interpolating in this three-dimensional space.

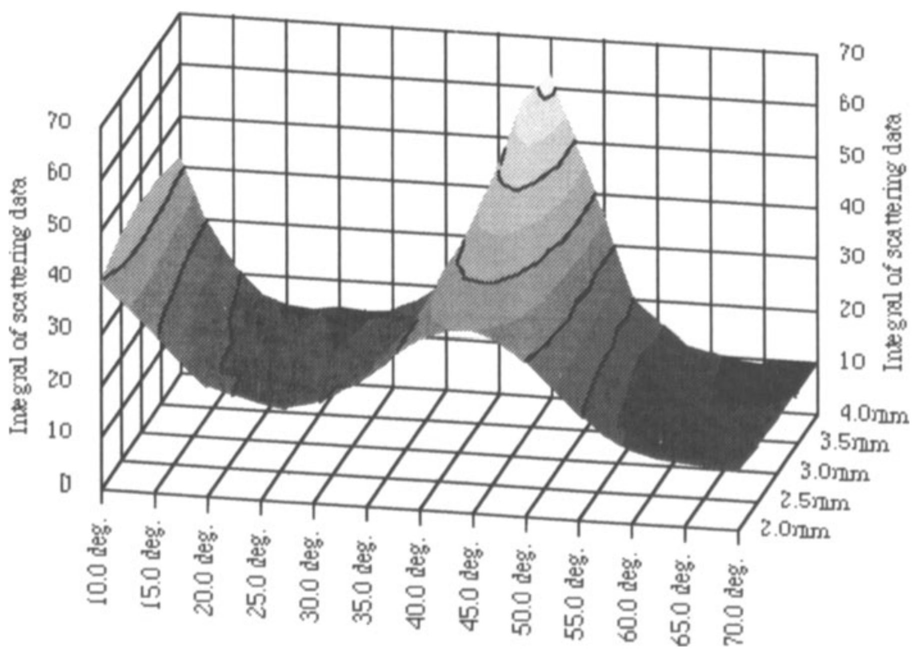

Figure 4. The integral of backscatter data.

RESULTS

Crack angle estimation by the neural network for numerical data

The numerical data for 2.25mm, 2.75mm, 3.25mm and 3.75mm crack depths have been used to test the neural network. Table 2 summarizes the network performance when the data for 3.75mm crack depth are entered into the network. The first row of the table lists the crack angles associated with the output units. The other rows list the response numbers when the indicated angle data are entered into the trained network. If the network works perfectly, the diagonal components of this table are 1.0's and the others are 0's. (In this table, blank spaces mean 0.0's.) Although this trained network works quite well, some angles are estimated incorrectly. Therefore, the information on the integral of the backscattered signal is utilized to improve the accuracy of estimation.

Crack depth estimation by neural networks for numerical data

Table 3 shows a summary of results for numerical data for a crack depth of 3.75mm. The numbers of the first column are angles for input data, the numbers of the second column are angles estimated by the trained neural network, corresponding to the results shown in Table 2. By considering the integral of the waveform, sets of parameters are obtained, which are listed in the third column. For all the angles in the third column, the depths of the cracks are determined by the neural network, and the results are listed in the fourth column. The question mark means that the neural network could not determine the depth. By comparing the results of the third and the fourth columns, the most appropriate parameters are selected as a final decision. If both the angle and the depth of a crack are determined correctly, a grade-A is given for the evaluation. For the case of the crack inclined under 25 degrees, two sets of parameters are selected as a final decision, because the estimated errors are the same for 25 and 30 degrees. Since these estimated values are not far from the actual ones, a grade-B is given.

A total of 52 cases has been evaluated. The depths of the cracks are 2.25mm, 2.75mm, 3.25mm, and 3.75mm, and the angles varied from 10 to 70 degrees with 5 degrees increments.

As a result, an A-grade was given for 45 cases, a B-grade for 6 cases, and only one case was wrongly estimated.

Table 2. Network performance for inputs of numerical data. (crack depth : 3.75mm)

	output units	10 deg.	15 deg.	20 deg.	25 deg.	30 deg.	35 deg.	40 deg.	45 deg.	50 deg.	55 deg.	60 deg.	65 deg.	70 deg.
	10deg.	0.98												
	15deg.		0.99											
	20deg.			0.22		0.90								
InputData	25deg.						0.97							
for	30deg.					1.00								
Neural	35deg.						1.00							
Network	40deg.							0.65						
	45deg.								1.00					
	50deg.							0.96		0.25				
	55deg.										0.99			
	60deg.											0.86		
	65deg.												0.53	0.99
	70deg.													0.97

Table 3. Summary of crack parameter estimation for numerical data.

actual angle (deg.)	estimated angle by NN (deg.)	estimation by integral	estimated crack depth by NN (mm)	final decision (deg. - mm)	evaluation
10	10	10deg. - 2.4mm or 10deg. - 3.7mm or 45deg. - 2.6mm	10deg. - 3.5mm 45deg. - 2.0mm	10deg. - 3.5mm	A
15	15	15deg. - 3.8mm or 30deg. - 2.5mm	15deg. - 3.5~4.0mm 30deg. - 2.0mm	15deg. - 3.5~4.0 mm	A
20	20 or 30	20deg. - 3.8mm or 25deg. - 3.7mm or 30deg. - 3.8mm	20deg. - 4.0mm 25deg. - ? 30deg. - 2.5mm	20deg. - 4.0mm	A
25	35	20deg. - 3.8mm or 25deg. - 3.7mm or 30deg. - 3.8mm or 35deg. - 3.9mm	20deg. - ? 25deg. - 4.0mm 30deg. - 3.5mm 35deg. - 3.0mm	25deg. - 4.0mm or 30deg. - 3.5mm	B
30	30	20deg. - 3.9mm or 25deg. - 3.8mm or 30deg. - 3.8mm	20deg. - 2.0mm 25deg. - ? 30deg. - 3.5~4.0mm	30deg. - 3.5~4.0mm	A
35	35	20deg. - 2.8mm or 35deg. - 3.4mm or 35deg. - 3.6mm or 55deg. - 2.3mm	20deg. - 2.0mm 35deg. - 4.0mm 55deg. - 3.5mm	35deg. - 4.0mm	A
40	40	10deg. - 2.1mm or 40deg. - 3.7mm or 45deg. - 2.4mm	10deg. - 2.5mm 40deg. - 3.5~4.0mm 45deg. - 2.0mm	40deg. - 3.5~4.0mm	A
45	45	45deg. - 3.7mm	45deg. - 3.5mm	45deg. - 3.5mm	A
50	40 or 50	40deg. - 2.6mm or 45deg. - 2.1mm or 50deg. - 3.6mm	40deg. - 3.5~4.0mm 45deg. - 2.0mm 50deg. - 3.5~4.0mm	50deg. - 3.5~4.0mm	A
55	55	20deg. - 3.6mm or 25deg. - 3.2mm or 30deg. - 3.6mm or 55deg. - 3.7mm	20deg. - 3.0mm 25deg. - 2.0mm 30deg. - 2.0mm 55deg. - 3.5mm	55deg. - 3.5mm	A
60	60	60deg. - 3.8mm or 65deg. - 3.0mm or 70deg. - 3.1mm	60deg. - 3.5mm 65deg. - 4.0mm 70deg. - 3.5mm	60deg. - 3.5mm	A
65	65 or 70	65deg. - 3.7mm	65deg. - 4.0mm	65deg. - 4.0mm	A
70	70	65deg. - 3.2mm or 70deg. - 3.8mm	65deg. - 3.5mm 70deg. - 3.5mm	70deg. - 3.5mm	A

*crack depth : 3.75mm

Crack angle and depth estimation for experimental data

Three specimens with artificial cracks were prepared to test the strategy developed in this paper. The angle/depth combinations are listed in the first column of Table 4. The experimental data obtained for these specimens were deconvolved with the reference signal to be evaluated by neural networks that are trained by numerical data. Since the original deconvolved data are noisy, smoothed data are used to determine the parameters of cracks according to the procedure of this paper. Figure 5 shows the smoothed deconvolved experimental signals.

Table 4 summarizes the results. Both the angle and the depth of the cracks were determined accurately for all three cases.

CONCLUSIONS

Neural networks have been developed to estimate crack angles and crack depths from the waveforms of ultrasonic measurements.

A data set computed from a measurement model has been used for network training to compose a sufficient large database.

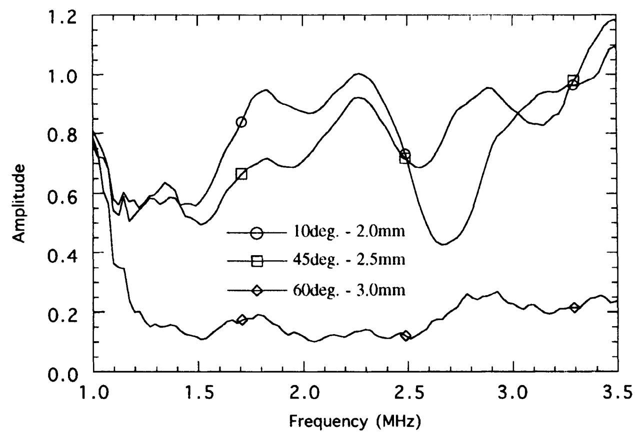

Figure 5. Deconvolved experimental data for the evaluation.

Table 4. Summary of crack parameter estimation for experimental data.

actual size (deg. mm)	estimated angle by NN (deg.)	estimation by integral	estimated crack depth by NN (mm)	final decision (deg. - mm)	evaluation
10 deg. 2.0mm	10	10deg. - 2.0mm or 40deg. - 3.7mm	10deg. - 2.0mm 40deg. - 4.0mm	10deg. - 2.0mm	A
45 deg. 2.5mm	45	10deg. - 2.1mm or 45deg. - 2.4mm	10deg. - 2.0mm 45deg. - 2.5mm	45deg. - 2.5mm	A
60 deg. 3.0mm	25 or 55	60deg. - 3.0mm	60deg. - 3.0~3.5mm	60deg. - 3.0~3.5mm	A

By using neural networks for angle estimation and for depth estimation separately, both the angle and the depth of a crack can be estimated.

To improve the accuracy of estimation, the integral of the backscatter data has been utilized.

The system has been tested with both numerical data and experimental data, and satisfactory results have been obtained.

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