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OPTIMIZATION OF NEURAL NETWORK PATTERN RECOGNITION SYSTEMS FOR GUIDED WAVES DAMAGE IDENTIFICATION IN BEAMS

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ABSTRACT. Neural network pattern recognition is an advanced regression technique that can be applied to identify guided wave response signals for quantifying damages in structures. This paper describes a procedure to optimize the design of a multi-layer perceptron backpropagation neural network with signals preprocessed by the wavelet transform. The performance can be further improved using a weight-range selection technique in a series network since there is increased sensitivity of the neural network to experimental damage patterns if the training range is reduced. Damage identification in beams with longitudinal guided waves is used in this study.

Keywords: Guided Wave, Pattern Recognition, Wavelet Transform, Neural Networks, Signal Processing
PACS: 43.20.Gp, 43.60.Lq, 43.60.Hj, 87.18.Sn

INTRODUCTION

Ultrasonic guided waves have gained much interest in the evaluation of damages in structural health monitoring. Although guided waves are physically sensitive to discontinuities in a structure, the transient wave response measured is susceptible to noise, dispersive changes, pulse overlapping, and unwanted wave modes [1]. Consequently, observing the raw signal alone to quantitatively identify damages can prove difficult especially when there are many possible damage cases to consider.

The pattern recognition concept in neural networks fits well to cope with this problem by learning patterns of randomly selected damage cases and then generalizing these cases to an approximate function. A neural network that has generalized the given patterns can identify a new damage case that has not been seen before provided that it lies within the learning range. Neural network pattern recognition is thus generally an advanced regression technique and has been recently implemented in processing guided waves, e.g. [2].

Neural networks offer a wide range of customization options [3] that can lead to the difficulty of selecting a design with optimal damage identification performance. A systematic design procedure for a multi-layer perceptron backpropagation neural network is presented here. The computation time in training the neural network is also significantly reduced by decomposing the signals with the wavelet transform in a preprocessing stage.

The cost of implementing neural networks is low when simulated patterns are used in training the network. However, large uncertainties in damage prediction generally exist in this procedure when an experimental damage pattern is presented to the trained network. The performance of the optimized neural network can thus be further improved using a weight-range selection technique in a series network.

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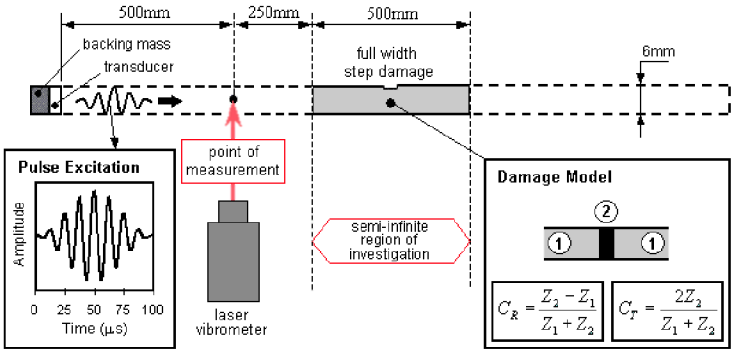


FIGURE 1. Point of measurement and semi-infinite region in the beam with a full width step damage. Pulse Excitation inset shows the 8-cycle 80kHz Hanning windowed tone burst pulse while the Damage Model inset shows the inhomogeneity model for generating simulated patterns.

EXPERIMENTAL AND SIMULATED PATTERNS

To study the neural network pattern recognition system, a 2-metre long 12mm × 6mm aluminum beam is considered. A 40mm × 1mm full width step damage is located at the center of the beam, as shown in Figure 1. An 8-cycle 80kHz Hanning windowed tone burst pulse (see the Pulse Excitation inset in Figure 1) is excited by a longitudinal Pz27 piezoceramic transducer attached by epoxy adhesive at one end of the beam. A brass backing mass is bonded to the transducer to increase the signal-to-noise ratio [1]. Out-of-plane displacements are measured at the center of the 6mm thickness of the beam with a Polytec OFV 303/OFV 3001 laser vibrometer system. All measurements are collected at 500mm from the transducer end. Considering this measurement location and a 500mm semi-infinite region of investigation at the center of the beam helps to prevent severe pulse overlapping in the measurement, which is not included in the current study concept.

The damage region is modeled as an inhomogeneity [4] with average material properties (see the Damage Model inset in Figure 1). The location and length of the inhomogeneity are exactly that of the damage. The acoustic wave impedance, Z, is defined as the product of the material density, wave velocity and the cross-sectional area. Since the cross-sectional area is a function of the thickness, Z at the damage region is different from the original beam. Therefore, reflection and transmission coefficients at the boundaries, C_R and C_T respectively, can then be found from Z, as in Equation (1). Together with the group velocity of the pulse, the signal patterns can then be easily simulated.

$$C_R = \frac{Z_2 - Z_1}{Z_1 + Z_2}, \quad C_T = \frac{2Z_2}{Z_1 + Z_2} \tag{1}$$

PREPROCESSING: DISCRETE WAVELET TRANSFORM

Sampling at 1MHz, the average wave response captured on an oscilloscope can be seen in Figure 2(a). The equivalent simulated signal based on the inhomogeneity model is also shown. Both signals span from the start of the incident pulse at 100μs to just before the onset of the free end reflection of the first transmitted pulse at 940μs. This gives in total 841 sampling points for each signal and since the same number of hidden neurons is

(a)

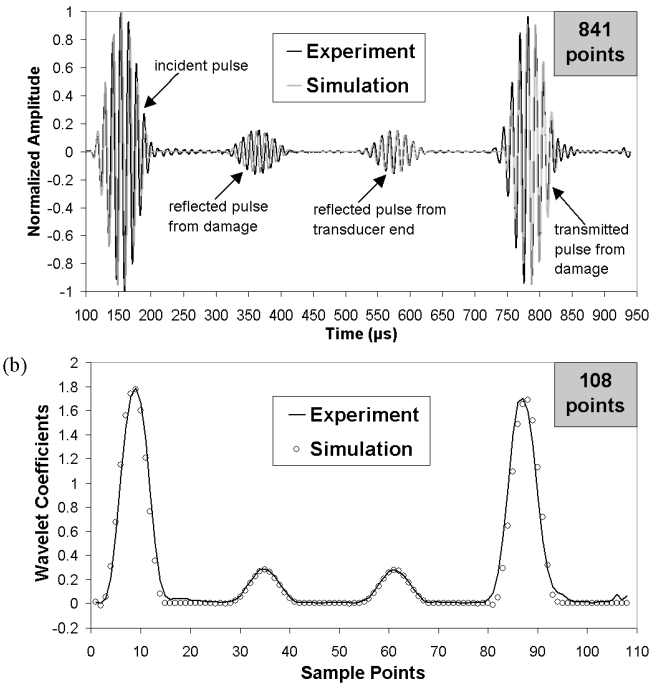


FIGURE 2. (a) Experimental and simulated signals in the 100-940μs range. (b) The discrete wavelet transform of the absolute experimental and simulated signals at the 3rd level of decomposition for the 8th order Daubechies wavelet.

required in a multi-layer perceptron neural network, learning patterns of this length can consume a large amount of computation time. Although the arrival times match reasonably accurately between the signals, there are substantial amplitude and phase differences that can lead to large errors in pattern recognition. The cause of these differences is rather complicated and difficult to ascertain but is expected to be the result of numerous effects including but not limited to, noise, pulse rotation, mode coupling, and dispersion [1].

The discrete wavelet transform can decompose the signal by reducing the number of sampling points through a wavelet derived filter bank in dyadic scales [5]. Performing the discrete wavelet transform on the absolute signals produces wavelet transforms as illustrated in Figure 2(b). The wavelet coefficients shown are the result of 3 levels of decomposition with the 8th order Daubechies wavelet. The discrete wavelet transform has reduced the number of points to 108, i.e. approximately 12% of the original number, while preserving all essential features that describe the damage, viz. arrival times, pulse magnitudes and lengths.

NEURAL NETWORK DESIGN

The multi-layer perceptron neural network containing a single hidden layer of neurons, M, with a hyperbolic tangent sigmoid activation function, F, can generalize patterns arbitrarily well for wavelet coefficients obtained from the guided wave response signals. This architecture gives a function:

$$O_v = \sum_{m=1}^{M} W_{v,m} \mathrm{F}\left(\sum_{u=1}^{U} W_{m,u} I_u + B_m \right) + B_v \tag{2}$$

where I is the input, O is the output, U is the number of inputs in a pattern (U = 108 from Figure 2(b)), subscript v is the output number, W is the weight, and B is the bias.

This neural network applies supervised learning where input-target pairs are required for training and the objective is to reduce the error between computed outputs and supplied targets for a given corresponding input. Weights and biases are firstly initialized randomly, then adjusted iteratively during training so that at the end, the inputs can map correctly to the targets. Backpropagation with the mean square error (*MSE*) function in Equation (3) and the resilient backpropagation (RP) algorithm is used to adjust these weights and biases. The *MSE* function evaluates the error between outputs and targets while the RP algorithm adjusts the weights and biases based on the sign change of the derivative of the *MSE* function with respect to the corresponding weights and biases [3].

$$MSE = \frac{1}{PV} \sum_{v=1}^{V} \sum_{p=1}^{P} \left(O_v - T_v \right)_p^2 \tag{3}$$

where O is the output, T is the target, V is the number of outputs and P is the number of training patterns. Three parameters (V = 3) are selected to identify the damage, namely the damage center position (DCP), the damage depth (DD), and the damage length (DL). DCP is determined by the pulse arrival time while DD and DL are determined by the pulse magnitude and length respectively. Since the three damage parameters are relatively different in orders of magnitude, they are scaled in the range [-1,1]. Half the training patterns are added with small amplitudes of random Gaussian noise to give some sensitivity to the function approximated to small amounts of noise [6], observed in the transient response signals (see Figure 2(a)). The rest of the clean patterns are necessary to capture the correct mapping of the inputs to the targets without the influence of noise.

M in Equation (2) and P in Equation (3) are unknowns that can be optimized for training. The total weights and biases in the network, N_w, and the total functions evaluated during training, N_f, can be found from Equation (4). According to [7], good generalization can be achieved in a single hidden layer network when there are at least twice as many functions compared to the total weights and biases. Evaluating this criterion together with Equation (4) allows M to be estimated, as in Equation (5). Although good generalization can be achieved, this estimate does not constitute the optimum M. However, it can provide an idea of the range of number of neurons that can be tested to find the optimum M.

$$N_w = (U+1)M + (M+1)V \quad , \quad N_f = PV \tag{4}$$

$$M \approx \frac{V(P-2)}{2(U+V+1)} \tag{5}$$

A neural network with no hidden layer, thus no hidden neurons, typically requires 10 times as many training patterns as U for noisy inputs and only twice as many training patterns as U for clean inputs for generalization [8]. Since the averaged guided wave response contains only noise of around 1% the amplitude or less (see Figure 2(a)), even with the additional layer of neurons in the network considered, Equation (6) is assumed as a sufficient guideline to predict the minimum number of patterns required for good generalization. That number of training patterns, P, can then be generated from simulation

based on the damage model. Also with P known, a neuron range can be selected for testing to find the optimum M based on the result from Equation (5). The neural network is trained to the number of iterations specified and if the *MSE* function does not converge, the network is reinitialized and retrained again but at a higher number of iterations. Convergence of the *MSE* function is necessary to ensure that the error in training has reached a minimum.

$$P = 10U \tag{6}$$

The random initial weights and biases provide a broad variation in generalization. Even when minimum error is achieved after training for a particular set of initial weights and biases, the trained network might not necessarily give the best generalization for new input patterns. Therefore, it is essential to conduct a reasonable number of trials for training different random initial weights and biases to obtain a broader spectrum of generalization. Identifying new input patterns can then be based on outputs averaged over all the trained neural networks from the trials. 100 trials are used in this study.

The quality of generalization of the trained neural network can be measured by means of a test set. The test set contains Q randomly simulated patterns and corresponding expected damage parameters, E, that lie within the training range. Q is arbitrary as long as it is representative of the training range. Here Q is taken to be 540 patterns, which is equivalent to half the number of training patterns. The trained neural network performance is then measured by evaluating the generalization error, G, that is defined as:

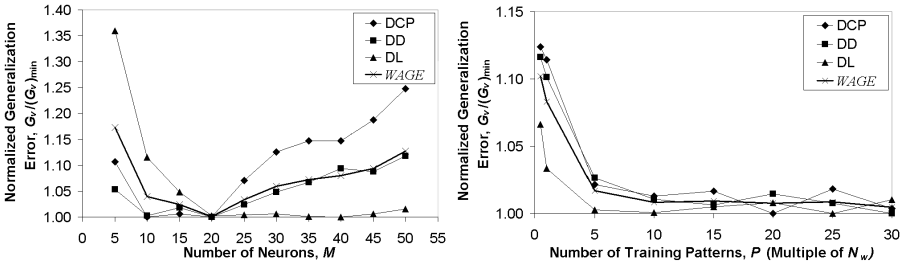
$$G_v = \frac{1}{K}\sum_{k=1}^{K}\left[\frac{1}{Q}\sum_{q=1}^{Q}\left(O_v - E_v\right)_q^2\right]_k \tag{7}$$

where K is the number of trials and v is the output number and since three damage parameters are evaluated here, v = 1,2,3. G is calculated based on the *MSE* like the error function in training because it statistically measures the bias and variance, which are ways of gauging generalization [6]. When more than one damage parameter (i.e. $V > 1$) is considered like in the present study, the weighted average generalization error, *WAGE*, is calculated to measure the overall generalization. In *WAGE*, given in Equation (8), the normalized generalization errors are weighted by assigning each damage parameter with a weight factor, *WF*, depending on its criticality in a particular application. The damage parameters are weighted equally in the present study. The number of neurons with the lowest *WAGE* value is selected as the optimum M required in the network.

$$WAGE = \frac{WF_1\ G_1/(G_1)_{\min} + WF_2\ G_2/(G_2)_{\min} + \ldots + WF_V\ G_V/(G_V)_{\min}}{V} \tag{8}$$

The next step is to optimize P. A recommendation given in [8] suggests that for noisy patterns, $30N_w$ is required for good generalization and since the guided wave response signals contain low noise levels, this criterion is taken to be the upper limit of P of the test range while the lower limit is simply given by Equation (6). The same procedure is repeated to find the optimum P.

The results of finding the optimum M and P are plotted in Figure 3. Based on *WAGE*, Figure 3(a) clearly shows that for the present network, the optimum M is 20. In Figure 3(b), the *WAGE* values converge after $5N_w$ with no significant improvement in the generalization. Therefore, to minimize the computation time, the optimum P is taken to be



(a) (b)

FIGURE 3. The plots for measuring generalization from neural network tests by considering *WAGE* for finding (a) the optimum number of neurons, M, and (b) the optimum number of training patterns, P.

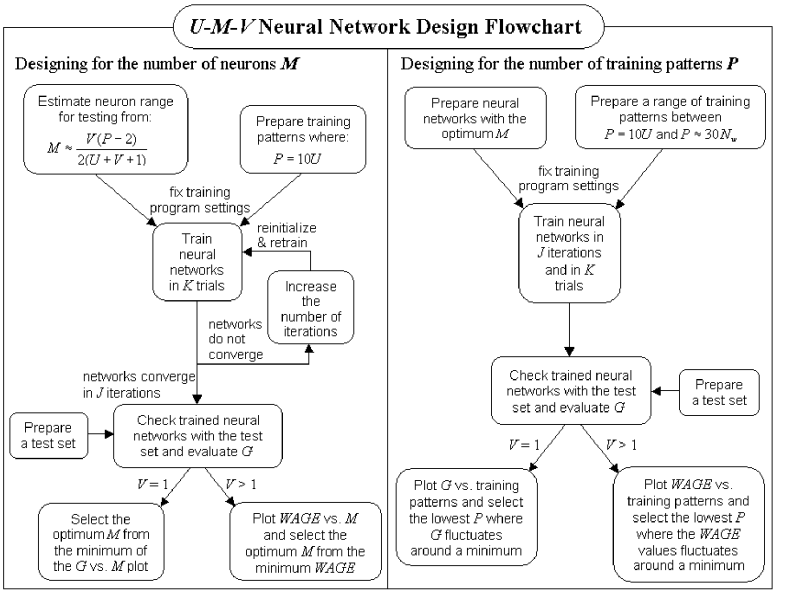


FIGURE 4. Design flowchart to determine the optimum M and P for a single hidden layer neural network.

$5N_w$. The procedure to design for the optimum M and P in a multi-layer perceptron backpropagation neural network with a single hidden layer of neurons is summarized in the flowchart in Figure 4.

TEST RESULTS: EXPERIMENT VS. SIMULATION

The designed neural network is trained and then used to test the experimental pattern for the real damage described in Figure 1. Previously during the design stage, the training iterations are fixed so that the different networks with varying M and P can be compared equally. But now to ensure convergence of the *MSE* function without overfitting [8] the mapping of the simulated patterns, early stopping using a validation set is applied [3,6]. Here the validation set contains randomly generated patterns that fall in the training range with a size that is half the number of training patterns. The test, as in the design stage, is conducted in 100 trials for broader generalization. The errors in identifying the DCP in the 100 trials are shown in Figure 5 for both the tests with experimental and simulated patterns

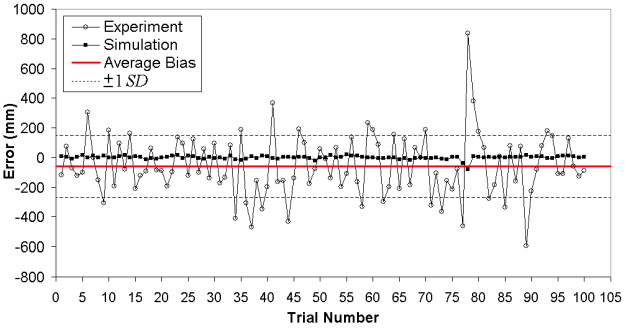


FIGURE 5. Pattern recognition DCP prediction errors in 100 trials for experimental and simulated test patterns of the same damage (DCP = 1000mm, DD = 1.0mm, DL = 40mm).

for the same damage parameters. Similar trends for tests between experimental and simulated patterns are observed for DD and DL.

The consistent and low errors (average bias = 0.3mm, *SD* = 0.1mm) for tests with the simulated pattern prove that the neural network design procedure has produced optimized generalization with respect to the training patterns. However, it is also clear from the results that there is significant increase in the uncertainty of identifying the DCP for the experimental pattern with *SD* of 209.3mm. The average bias of 58.4mm is still acceptable, yielding less than 12% error when compared with the 500mm range of investigation. The large *SD* can be attributed to features in the experimental pattern not being captured in the corresponding simulated pattern and the influence of the random selection of initial weights and biases, which may result in large errors as illustrated for example in trials 6, 34, 37, 41, 44, 77-79, and 89. Thus, the necessity to take a reasonable number of trials to obtain an average bias that gives an acceptable prediction of the damage parameters is obvious.

SERIES NETWORK

The ±1 standard deviation, *SD*, for the experimental patterns in Figure 5 is a statistical parameter that can be used to improve the quality and to lower the uncertainty of prediction. A new set but same number of training patterns is simulated within ±1 *SD* and a second cycle of neural network training and testing is performed. In this cycle, only test results that are within the ±1 *SD* range are accepted. This filters off poor initial weights and biases during training that can give poor generalization with respect to experimental patterns. In the new test results, a new ±1 *SD* range is defined for the subsequent cycle and the process repeats for a specified number of cycles. This procedure is called the weight-range selection technique in a series network.

The results in a series network with three cycles are shown in Figure 6 for the three damage parameters of the present damage studied. Good improvement in the damage identification is observed in DCP with the number of cycles while DD and DL achieve the best predictions in the 2nd and 1st cycle respectively. Since the number of training patterns is kept constant throughout the series network, a smaller range with the same amount of training information is likely to improve generalization due to a more accurate function approximated by the network. However, as seen in the average biases in DD and DL, this is not always the case and it depends on the new mapping between the inputs and targets during training in the smaller range, and how sensitive that mapping is related to the experimental patterns. In contrast, the *SD* decrements with cycles for all three damage

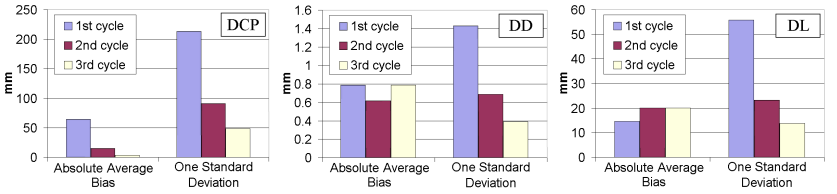


FIGURE 6. Experimental pattern test results for the weight-range selection technique in a series network.

parameters, mainly because of the removal of predictions that are out of the training range after the 1st cycle. Furthermore, as the training range reduces, the neural network can predict with lower uncertainties since there are less damage cases to consider.

CONCLUSION

The application of neural network pattern recognition to identify damage in beams has shown that:

- discrete wavelet transform is a useful preprocessing tool to prepare neural network input data to reduce computational costs.
- a systematic procedure of testing and evaluating the quality of generalization via *G* and *WAGE* enables the design of a network with optimum network parameters.
- the determination of very accurate experimental damage parameters is possible provided a reasonable number of trials is used to obtain reliable average biases.
- the weight-range selection technique in a series network can improve the quality of damage predictions.

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