Structural Damage Detection Using Active Members and Neural Networks

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Introduction

THE detection of damage in structures is a topic which has considerable interest in many fields. Detecting damage in space structures when subjected to the harsh environment of space could allow for the repair of the structure to occur before the damage threatens the mission objectives. Offshore oil platforms constantly have problems with potential member failure in the corrosive sea environment. Buildings and bridges, where structural failure proves catastrophic, would also benefit from a reliable method of detecting and pinpointing structural damage.

In the past, many methods for detecting damage in structures have relied on finite element model refinement methods.[1–4] Hajela and Soeiro[1] determined the damage present in a structure by updating the finite element model to match the static and dynamic characteristics of the damaged structure. Their method was an outgrowth of those presented in Refs. 2 and 3 where undamaged members' section properties changed during the model update process, thus smearing the damage over a wide portion of the structure and making specific damage difficult to locate. Hajela and Soeiro also extended their damage detection techniques to composite structures[4] where a gradient-based optimization scheme was used to update the finite element model.

Other methods of detecting damage in structures rely strictly on measured data. Cawley and Adams[5] used only natural frequency data, Pandey et al.[6] used mode shape curvature data, and Swamidas and Chen[7] used strain, displacement, and acceleration data to monitor and detect changes and damages in various structures. These methods require comparing measurements of the structure in the nominal (undamaged) state with those at a later date where some damage is potentially present in the structure. These methods have the drawback that they can only identify that the structure has changed; they cannot identify the location and extent of the damage.

Neural networks have the unique ability to be trained to recognize known patterns and classify data based on these patterns. Neural networks have been used with success for structural design tasks[8] and for classification of experimental data such as sonar target classification.[9] With proper training, neural networks should be able to process the dynamic response measurements taken from the structure, classify the data, and provide a tool for determining the location and level of damage present in a structure.

This Note presents a structural damage methodology in which only active member transfer function data are used in conjunction with an artificial neural network to detect damage in structures. Specifically, the method relies on training a neural network using active member transfer function pole/zero information to classify damaged structure measurements and to predict the degree of damage in a structure. The method differs from many of the past damage detection algorithms in that no attempt is made to update a finite element model or to match measured data with new finite element analyses of the structure in a damaged state.

Damage Detection Methodology Overview

Transfer functions taken between sensors and actuators located on a structure before and after some form of damage has been introduced show changes in the pole/zero spacing and, perhaps, pole/zero patterns. It is easy to see these changes when reviewing them, but it is difficult to classify them. For example, Fig. 1 shows two transfer functions taken of a structure with and without damage. The differences in pole/zero spacing are small, yet detectable, to the naked eye. However, there is no convenient way to correlate the pole/zero spacing and the location and amount of damage present in the structure. Furthermore, given the transfer function of the damaged structure, no adequate method exists for locating which structural members are damaged and how much damage is present.

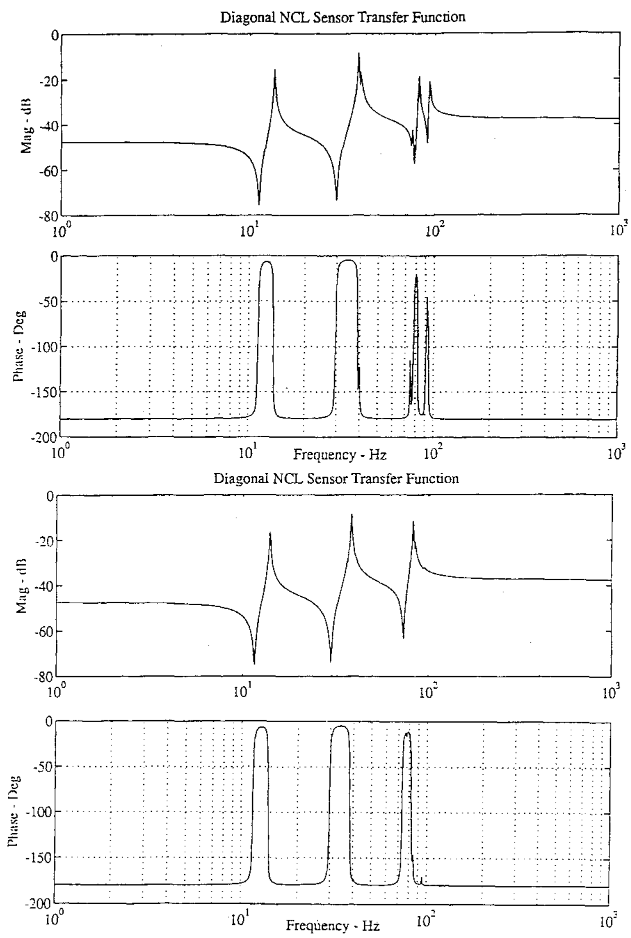

Fig. 1 Typical undamaged and damaged structure transfer functions.

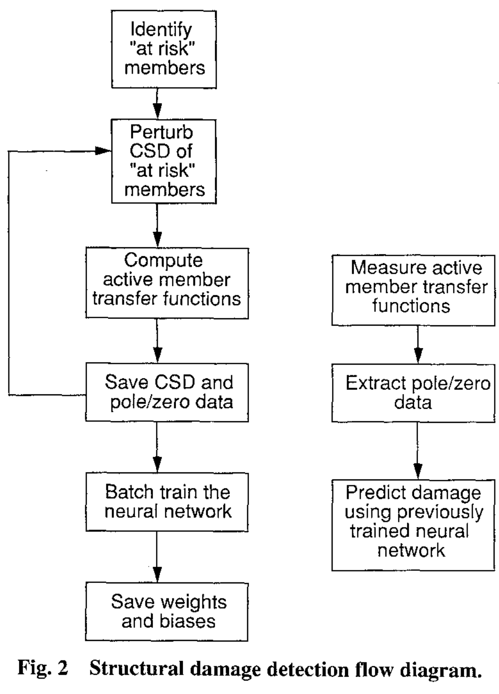

Fig. 2 Structural damage detection flow diagram.

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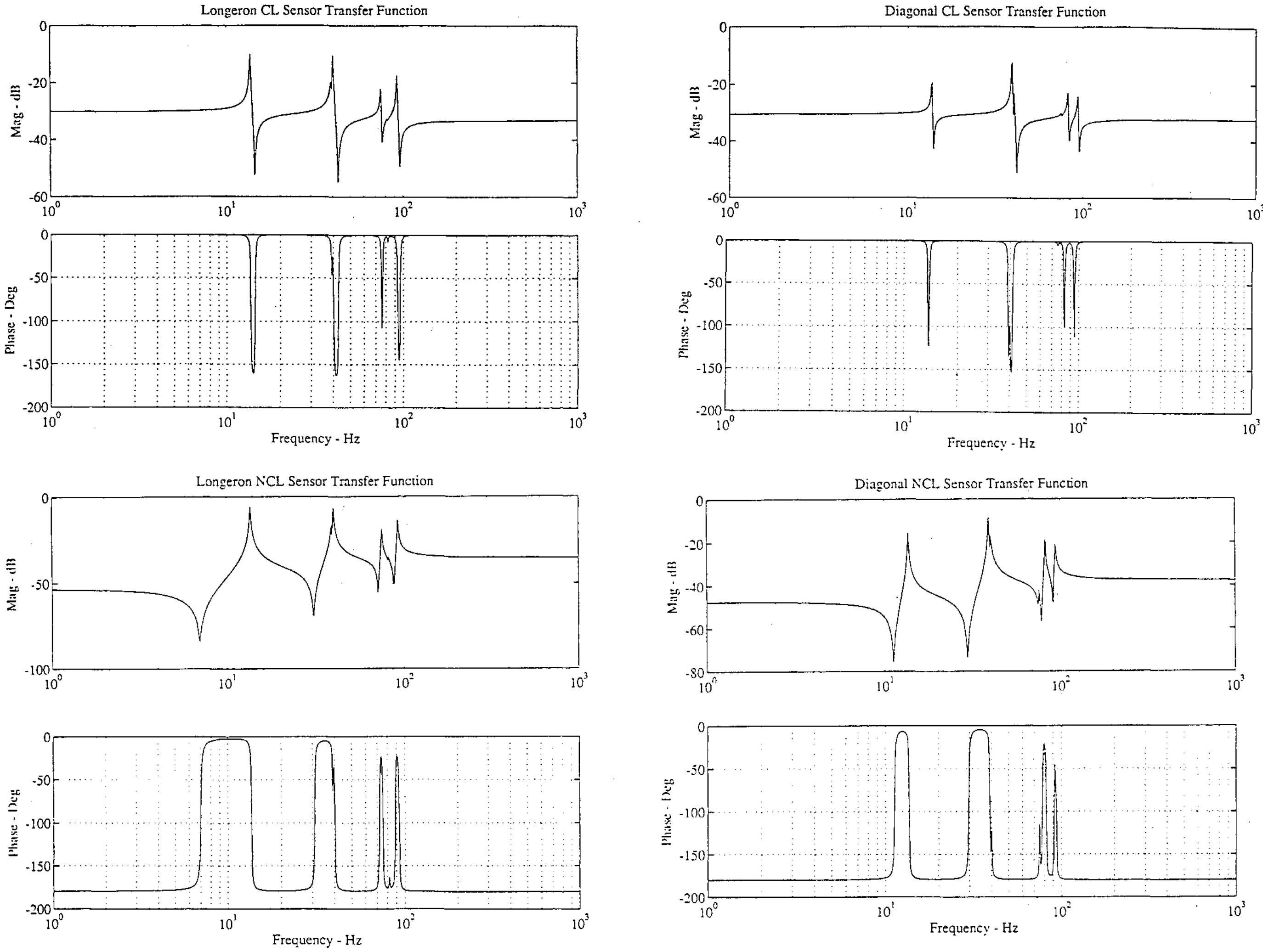

Fig. 3 Ten-bar truss active member transfer functions.

Table 1 Simulated damage test cases

Member no.	Test case 1 Actual area	Test case 1 NN[a] area	Test case 2 Actual area	Test case 2 NN area	Test case 3 Actual area	Test case 3 NN area
1	1.00	1.00	1.00	1.00	1.00	1.00
2	1.00	0.92	1.00	1.00	1.00	1.01
3	1.00	0.99	0.80	0.82	0.80	0.83
4	0.75	0.66	1.00	1.00	1.00	1.04
5	1.00	1.06	1.00	1.02	1.00	1.09
6	1.00	1.05	1.00	1.01	0.80	0.85
7	1.00	0.97	0.95	0.97	1.00	1.10
8	1.00	1.04	1.00	1.02	1.00	1.03
9	1.00	0.90	1.00	1.00	1.00	0.99
10	1.00	1.02	1.00	1.00	0.70	0.76

[a]NN = neural network.

The method described in this Note utilizes finite element data to simulate damage in a structure, with the resulting active member transfer functions used as input training data in an artificial neural network. The method assumes that a reasonable finite element model of the structure in the nominal configuration (i.e., without damage) is available and yields transfer functions that properly characterize the structure.

A flow diagram, outlining the details of the damage detection methodology, is shown in Fig. 2. A set of members which are assumed to be at most risk within the structure are identified. These members, which may be a subset or the complete set of members within the structure, will subsequently be used to generate training data for the neural network. Each of the selected "at risk" members' cross-sectional areas are varied and the resulting pole/zero information within the active member transfer functions saved. Using the pole/zero information as inputs to the neural network and the corresponding member cross-sectional areas as outputs, the neural network is batch trained until a suitable level of error bound is achieved. (Achieving this error bound is most likely an iterative process involving the number of neurons in the hidden layer, the learning rate, and the number of iterations used to train the network.) The resulting neural network weights and biases represent a mapping from pole/zero information to structural member cross-sectional areas. Given a measured set of pole/zero data on a potentially damaged structure, the neural network output provides the location of the damaged members and an estimate of the cross-sectional area of the damaged members.

For the work reported herein, active members similar to those described in Refs. 10 and 11 were used. Each active member consisted of a host material, either graphite composite or a metallic material, with piezoceramic sensors and actuators embedded in or bonded to the host material.

Various architectures of neural networks were tried during the development of the damage detection methodology. Both single- and double-hidden layer networks using tangent sigmoidal and log sigmoidal activation functions were considered. All neural networks were batch trained using the active member transfer function pole/zero information as inputs and the cross-sectional areas of the truss members as outputs.

Example Problem

The example structure on which the damage-detection methodology just outlined will be demonstrated is the ubiquitous 10-bar truss structure. This structure has been used for many structural optimization methodology demonstrations including one utilizing neural networks.[8] The nominal design for the structure without active members typically consists of all 10 aluminum members having a cross-sectional area of 1.0 in.[2] Active members were substituted for element number 1 (the bottom root longeron) and for element number 8 (the upwardly pointing root diagonal). This baseline design with active members has natural frequencies of 13.6, 39.0, 40.2, 75.6, 82.3, 93.0, and 94.0 Hz.

Transfer functions between the active member actuators and sensors were generated. A typical set of transfer functions for the two active members is shown in Fig. 3. The location of the poles and zeroes relative to their location for the undamaged structure gives an indication of the health of the remainder of the structure.

Input training data for the neural network consisted of the imaginary parts of the transfer function poles and zeroes. Output data from the neural network consisted of the cross-sectional areas of each of the 10 bars in the truss. A complete set of training data was obtained by sequentially decreasing the stiffness of each member of the truss by a known amount and presenting the resulting input and output training data just described to the neural network.

All results presented below were obtained using a neural network with a single-hidden layer of 14 tangent sigmoidal neurons. Additional configurations of neural networks were trained and used to locate and predict the damage in the 10-bar truss, but did not achieve better results than the single-layer, 14-neuron network. Two networks that achieved approximately equivalent results were a double-hidden layer network (with 5 and 4 tangent sigmoidal neurons) and a single-hidden layer network with 17 log sigmoidal neurons.

Table 1 contains a list of the simulated damage cases that were run on the 10-bar truss structure. The resulting neural network predictions of the member cross-sectional areas are also given in Table 1. Test case 1 represents a condition where a single member was damaged (i.e., member number 4). This type of damage is within the domain of the training data and gives an indication of the adequateness of the training of the neural network. The damage assessment from the neural network indicates that member 4 is damaged and the predicted level of damage, $A_4 = 0.66$, compares well with the actual level of damage used to generate the damaged structure transfer functions. The network also predicts slight damage to members 2 and 9, which is a result of the static indeterminancy in the 10-bar truss. Test cases 2 and 3 represent multiple member damage conditions where 2 and 3 members are damaged simultaneously, respectively. These types of damage are outside the domain of the training data of the neural network. Nonetheless, the neural network pinpoints the damage very well for both cases. Furthermore, the level of damage is predicted within a few percent for test case 2 and within approximately 10% for test case 3.

Conclusions

A methodology for detecting damage in structural systems has been described. The method utilizes the active members that are already present for a controlled structure in conjunction with a trained artificial neural network. A numerical example demonstrated the feasibility of the method which pinpoints the damaged members and which gives a very good estimate of the damage present in each member. The keys to making the problem tractable for larger problems are adequately identifying the members at high risk for potential damage and including enough pole/zero information in the training of the neural network.

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Optimal Fail-Safe Design of Elastoplastic Structures

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Introduction

THE objective of this work is to develop a consistent and broadly applicable model for elastoplastic fail-safe structural optimization. Toward this end, the multicriteria model for the optimal fail-safe design of structures presented in Ref. 1 (see also Ref. 2) is extended to treating elastoplastic design problems based on a new general elastoplastic analysis variational formulation as applied to two-dimensional truss structures (see Taylor[3]).

The new formulation is capable of covering the whole loading range of a structure, i.e., from zero load to limit load. The basis for the formulation is the assertion that the load factor for a proportional loading case assumes a maximum relative to all statically admissible stress states for a given bound on the complementary energy (i.e., it corresponds to the lower bound theorem of limit load analysis). The model for this formulation, expressed here for a two-dimensional truss composed of M bars, is given in terms of the vector $t \in R^M$ of normalized (with respect to the yield stress σ_Y) bar stresses, and the load factor λ as follows:

$$\min_{t_k} -\lambda \tag{1}$$

subject to

$$\begin{cases} \sum_{j=1}^{M} C_{ji} t_j - \lambda f_i = 0 & \\ t_k - 1 \le 0 & i = 1, \ldots, 2I \\ -t_k - 1 \le 0 & k = 1, \ldots, M \\ \dfrac{\sigma_Y^2}{2} \sum_{n=1}^{M} \sum_{m=1}^{M} t_n D_{nm} t_m - \varepsilon^2 \le 0 & \end{cases}$$

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