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Hierarchical development of training database for artificial neural network-based damage identification

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Abstract

Though serving as an effective means for damage identification, the capability of an artificial neural network (ANN) for quantitative prediction is substantially dependent on the amount of training data. In virtue of a concept of "*Digital Damage Fingerprints*" (DDF), a hierarchical approach for the development of training databases was proposed for ANN-based damage identification. With the object of exploiting the capability of ANN to address the key questions: "*Is there damage?*" and "*Where is the damage?*", the amount of training data (damage cases) was increased progressively. Mutuality was established between the quantity of training data and the accuracy of answers to the two questions of interest, and was experimentally validated by identifying the position of actual damage in carbon fibre-reinforced composite laminates. The results demonstrate that such a hierarchical approach is capable of offering prediction as to the presence and location of damage individually, with substantially reduced computational cost and effort in the development of the ANN training database.

Keywords: Artificial neural network; Training database; Composite structure; Damage identification

1. Introduction

The conceptual basis of an artificial neural network (ANN) is a computational model of a neural construction involving highly interconnected processing units in parallel, termed *neurons* [1]. Appropriate training of these neurons, i.e. a procedure to seek the best numerical association among neurons in terms of the input information, can provide a prediction with regard to an unknown input. The ANN technique has found recent applications in structural damage evaluation [2–6], which is known as a typical inverse pattern recognition problem. In these applications, damage parameters (e.g. position and size) are correlated with changes in the captured structural signatures through proper training of ANN.

However, as a high order non-linear approach, ANN-based damage identification is considerably subject to several factors, including network architecture, neuron number, learning/training algorithm, etc. In particular, the quality and quantity of training data play crucial roles in mastering ANN performance. For training data quality, a diversity of structural features, such as modal data, dynamic response, and static characteristics, have been adopted, as summarised elsewhere [7]. For training data quantity, a basic consideration is that the number of training cases must be sufficient to cover the entire area of interest in the structure. Although constructing the identification theoretically requires an infinite number of training cases, it can be argued that superfluous training can lead to misleading and even erroneous predictions as insufficient training does [8]. Moreover, surplus training comes at the cost of demanding computational requirements and excessive effort in database development. For this

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reason, studies [9–13] have been dedicated to reduction of the amount of training data. Levin and Lieven [9] proposed a two-part approach for the selection of training data, where the dynamic vibrational parameters of the structure, e.g. natural frequency, were chosen from a low level to a high level to construct different sets of training data at variable capacities. An advantage of this updating method is the ability to work with a limited number of degrees of freedom and modes. Ni et al. [10] separated location prediction of damage from severity prediction, using two independent ANNs trained by measured structural modal data. Mohamed et al. [12] proposed a fault diagnosis scheme for a power transformer, consisting of several parallel ANNs, to detect damage location and define its classification. All these efforts were aimed at reducing the volume of training data for ANNs and making the approach more cost-efficient, to negotiate the desired prediction precision with the amount of training data.

However, judicious and appropriate determination of the amount of training data required for a specific application is one of those extremely intractable issues that is beyond the current capability of mathematical evaluation. In this study, the dependence of ANN prediction on the amount of training data for the purpose of damage identification was examined, by addressing the key questions: "*Is there damage?*" and "*Where is the damage?*". A hierarchical approach was developed to construct ANN training databases hosting different training cases. A signal processing technique integrated with a concept of "*Digital Damage Fingerprints*" (DDF) was applied to extract the essential features in captured structural dynamic signatures. A laminated carbon-fibre/epoxy (CF/EP) composite plate containing a cylindrical through-thickness hole from a previous study [8] was used in validation. To implement a progressive increase in training data, the structure was imaginarily partitioned hierarchically, and the DDF under each partition were collected to construct the training databases. The overall capability of ANNs, trained by different databases, to predict the occurrence and presence of the through-thickness hole in the composite laminate was considered, with reference to both precision and computational efficiency.

2. Finite-element analysis

2.1. Problem description

Consider a square plate with quasi-isotropic or homogeneous properties and all clamped edges, as shown in Fig. 1. Nine circular piezoelectric lead zirconate titanate (PZT) disks are surface-bonded either at the centre of the plate or at a distance of d away from the plate edges, numbered clockwise by Si ($i = 1, 2, \ldots, 9$). With dual functionality for actuation and sensing, each PZT disk acts as both an actuator and a sensor, giving a total of 36 actuator–sensor pairs, viz. 72 actuator–sensor paths.

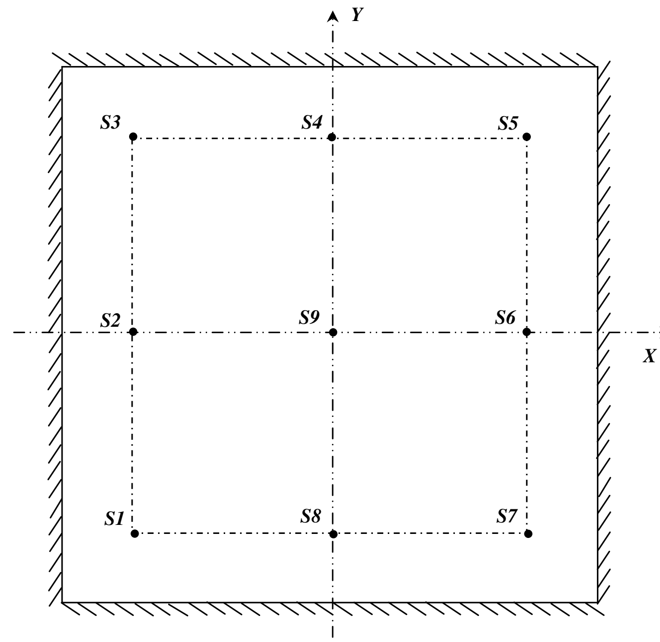

Fig. 1. A plate-like structure with nine surface-bonded PZT sensors.

Focusing on the inner region enclosed by sensor S1–S8, the plate was hierarchically quartered into 1^2 (level I), 2^2 (level II), 4^2 (level III) and 8^2 (level IV) sub-regions (grid), as schematically elucidated in Fig. 2(a)–(d), respectively. For each partition condition, one cylindrical through-thickness hole with a diameter of Φ was presumed to be located at the centre of each grid, contributing 1^2, 2^2, 4^2 and 8^2 damage cases, respectively, plus one benchmark case (no damage). Note that there is only one through-thickness hole of the same size in each case. For convenience of discussion, these cases are denoted by C-I$_i$ ($i = 1$), C-II$_i$ ($i = 1$, 2, 3 and 4), C-III$_i$ ($i = 1, 2, \ldots, 16$), and C-IV$_i$ ($i = 1, 2, \ldots, 64$), respectively, for the four levels of hierarchy, and C-0 for the benchmark. Three indices, presence (0 or 1) and location (x, y), were introduced for each case to define the damage.

Allowing for the homogeneity of the material and the geometric symmetry of the structure, only those cases where damage was centred in the shadowed grids (see Fig. 2) were analysed, while cases in other grids were evaluated through proper signal mapping technique (detailed later).

2.2. FEM modelling and simulation

For illustration, one damage case, C-II$_2$ in Fig. 2(b), is analysed. Consider that the plate is an 8-ply $[45/-45/0/90]_s$ CF/EP composite laminate, measuring 475 mm × 475 mm × 1.275 mm. Being transversely isotropic, the effective material properties of such a laminate were obtained in terms of classic laminate theory, as detailed in Table 1. Three-dimensional solid brick elements were employed in modelling. To ensure precision of simula-