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System identification-based frequency domain feature extraction for defect detection and characterization

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ABSTRACT

Feature extraction is the key step for defect detection in Non-Destructive Evaluation (NDE) techniques. Conventionally, feature extraction is performed using only the response or output signals from a monitoring device. In the approach proposed in this paper, the NDE device together with the material or structure under investigation are viewed as a dynamic system and the system identification techniques are used to build a parametric dynamic model for the system using the measured system input and output data. The features for defect detection and characterization are then selected and extracted from the frequency response function (FRF) derived from the identified dynamic model of the system. The new approach is validated by experimental studies with two different types of NDE techniques and the results demonstrate the advantage and potential of using control engineering-based approach for feature extraction and quantitative NDE. The proposed approach offers a general framework for selection and extraction of the dynamic property-related features of structures for defect detection and characterization, and provides a useful alternative to the existing methods with a potential of improving NDE performance.

1. Introduction

Active sensing-based non-destructive testing and evaluation (NDT&E) techniques using acoustic (e.g. ultrasonic) and electromagnetic (e.g. eddy current) effects have been widely used for structure health monitoring (SHM) to detect defects inside a structure [1] [2], and different methods have been proposed and studied as can be seen from literature published [3] [4] [5] [6]. A common point in the aforementioned NDT&E techniques is that they all use an output-only approach to perform defect detection where the measured response from a NDT transducer, such as piezoelectric wafer made of Lead Zirconate Titanate (PZT) or pulsed eddy-current (PEC) probe, is analyzed and the features reflecting the health status of the structure/or material under investigation are extracted for defect determination. The general procedure can be summarized as follows: (1) record a baseline/or reference response under a specified excitation, this is normally obtained under defect free condition; (2) measure the response from the transducer installed on the structure/or material to be monitored under the same excitation as used for generating the baseline/or reference response; (3) compare the measured response with the baseline/or reference response for health monitoring and defect detection. The comparison is usually performed by first selecting and extracting some features from both the measured response and the reference response, and then compare these features to determine the health status of the structure under investigation.

A key step for defect detection and characterization using the above approach is the selection and extraction of features from measurements. As can be seen, with the aforementioned procedure, the inspection device was treated as a signal generator where only the response from non-destructive transducer is utilized for feature extraction and it is implicitly assumed that the excitation used in the active sensing inspection is the same as that used for obtaining baseline/or reference response when we perform comparison. Hence any discrepancy between the excitation used for generating baseline response and that used for inspection will affect the accuracy of detection. Also, the features extracted for defect detection will be input-dependent and the different methods have to be employed to select and extract features from the measured response for different types of NDT technique used.

The problem is revisited in this paper and we aim at developing a

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general framework for feature selection and extraction that can be used with different types of active sensing-based NDT techniques. To this end, the problem is considered from a system perspective and the transducer, such as PZT sensor/or PEC probe, together with the structure under inspection will be viewed as a system (hereafter refer to as an NDT system) where the input to the system is the excitation signal of the NDT device and the output of the system is the corresponding non-destructive transducer's response. Instead of analyzing transducer response alone, we propose to use both input (excitation) and output (response) signals from the system for feature extraction. The proposed method is based on the well-recognized fact that the defects (such as cracks, corrosion) in a structure can change its mechanical/electrical properties, hence the dynamic behavior of the NDT system. Consequently, the basic idea with the new NDE data analysis is to identify such changes in the system's dynamic behaviors with respect to defect-free situations in order to more effectively achieve the objectives of NDT&E.

Based on above discussion, the dynamic property-related features are proposed to be used for defect detection. Specifically, the frequency response function (FRF) of the NDT system derived from input-output measurements is used for feature extraction in this paper because the FRF is less contaminated and can provide more information on defects to be detected. The remainder of the paper is organized as follows. Section 2 discusses the idea behind the new method proposed and present the development of the methodology. This is followed by two experimental studies with different types of NDT techniques in, where a PEC-based system for crack detection and an ultrasonic inspection-based SHM system for corrosion detection using the new method developed are presented. The conclusions and some ideas for future research are presented in Section 5.

2. Methodology

In an active sensing-based NDT system, the system output, or more specifically, the response of the NDT transducer to the excitation (input) depends on both the input signal and the dynamic characteristics of the NDT system itself. As discussed in last section, the basic idea behind the defect detection method proposed in this paper is to detect the changes in dynamic behavior of the NDT system due to a defect. The dynamic behavior of a system is usually described by a parameterized mathematical model. Therefore, in order to capture the dynamic behavior of an NDT system, the system identification technique needs to be applied to identify a model from the measured input-output data for representing the dynamic characteristics of the NDT system under investigation. Once the model is obtained, the defect detection can then be achieved by monitoring the change in the features extracted from the identified model. The general procedure of the proposed method for defect detection is therefore as follows: (1) identify a dynamic model using input-output data obtained from the NDT system; (2) select and extract dynamic behavior-related features of the system derived from the identified model; (3) compare these features of the identified model with those extracted from a reference model representing defect-free conditions. Because there is no requirement for using the same inspecting signal as in the case with traditional NDT&E techniques, and the dynamic behavior-related features can reflect the inherent characteristics of the NDT system, the new method has potential to overcome disadvantages with traditional output only based data analyses and provides more effective solutions to the NDT&E problems in engineering practice.

To facilitate reader and communicate the idea as clearly as possible, the system identification technique used in this paper will be briefly explained before describing the new frequency domain feature extraction method for defect detection and characterization in this section.

2.1. System identification

System identification is a technique dealing with the problems of constructing mathematical models of dynamic systems from test data. There are in general two types of approaches that can be used to solve this problem and they are referred to as the "Grey-box" modelling approach and the "Black-box" modelling approach. The "Grey-box" modelling approach attempts to combine physical modelling with parameter estimation techniques where the model is constructed from the first-principles up to some unknown parameters and model identification then amounts to the estimation of these unknown parameters using the measurements. The "Black-box" modelling approach, on the other hand, does not assume any prior physical knowledge on the model and the model is identified from input-output measurements only. In this paper, as we aim at developing a general method for feature selection and extraction that can be used with different types of NDT systems based on different physical principles, the "Black-box" identification approach needs to be used. The identification can be performed either in the time domain or in the frequency domain, but for the active sensing-based NDT systems studied in this paper, the measurements are sampled time-domain data, and therefore our attention will focus on the time-domain identification method.

Choosing a model structure is usually the first step in system identification. Clearly, models may come in various forms and complexity. As the identified model in this paper is intended to be used for defect detection, our attention will not focus on the model itself, but rather we are interested in the changes in some features extracted from the identified model which are caused by the defects to be detected. To this end, the ARX (Auto-Regression with eXogeneous input) model structure will be chosen for model identification in this paper, because ARX model is not difficult to be identified, well-suited for modelling the sampled data and can approximate any linear system arbitrarily well if the model order is high enough (see e.g. [7, p.336]). Let $y(t)$ denote the output (response) of the system at the time instant t, $u(t)$ denote the input (excitation) of the system, the ARX model that describes the relationship between the input $u(t)$ and the output $y(t)$ is a linear difference equation of the following form:

$$y(t) + a_1 y(t-1) + \cdots + a_n y(t-n) = b_1 u(t-1) + \cdots + b_m u(t-m) \tag{1}$$

where $a_1, \cdots, a_n$ and $b_1, \cdots, b_m$ are the model parameters to be estimated. By introducing vectors:

$$\boldsymbol{\theta} = [a_1 \cdots a_n \; b_1 \cdots b_m]^T \tag{2}$$

$$\boldsymbol{p}(t) = [-y(t-1) \cdots -y(t-n) \;\; u(t-1) \cdots u(t-m)]^T \tag{3}$$

Model (1) can be rewritten in a more compact form:

$$y(t) = \boldsymbol{p}^T(t)\theta \tag{4}$$

Model (2) can be viewed as a way to determine the current output value given previous input and output observations. Such a model structure which is linear in parameter $\boldsymbol{\theta}$ is known in statistics as linear regression. The vector $\boldsymbol{p}(t)$ is called the regression vector and its components are the regressors. Note that, $\boldsymbol{p}(t)$ in (2) contains previous values of the output variable $y(t)$, model (2) is then partly auto-regression and this is where the name of the structure stems from. Given $N+l$, *where* $l = \max(n, m)$, pairs of input-output observations, the model parameter $\boldsymbol{\theta}$ can be estimated with the least squares (LS) method:

$$\widehat{\boldsymbol{\theta}} = [\boldsymbol{P}^T\boldsymbol{P}]^{-1}\boldsymbol{P}^T\boldsymbol{y} \tag{5}$$

where

$$\boldsymbol{y} = \begin{bmatrix} y(1+l) \\ \vdots \\ y(N+l) \end{bmatrix} \quad and \quad \boldsymbol{P} = \begin{bmatrix} \boldsymbol{p}^T(1+l) \\ \vdots \\ \boldsymbol{p}^T(N+l) \end{bmatrix} \tag{6}$$

Once the vector $\boldsymbol{y}$ and regression matrix $\boldsymbol{P}$ are defined with input and output measurements, the solution can readily be found by modern numerical software, such as widespread MATLAB. It needs to be pointed out