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Structural Damage Detection using ARIMA Model

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ABSTRACT: Structural health monitoring (SHM) is related to the ability of monitoring the state and deciding the level of damage or deterioration within aerospace, civil and mechanical systems. Recently, the advancements in sensor technology have encouraged the use of low-cost smart sensors with on-board computation and wireless communication capabilities, making deployment of a dense array of sensors on large civil structures both feasible and economical. At the same time, the challenge lies in the development of the robust damage detection algorithms, which use the minimum computation and communication on any wireless smart sensor network (WSSN) for SHM. In this paper, an efficient algorithm based on the Autoregressive Integrated Moving Average model (ARIMA), employable on WSSN to detect and locate the damage during continuous real time health monitoring of civil engineering structures is devised. The efficiency of the algorithm is illustrated using a numerical example of a simply supported concrete beam girder.

KEYWORDS: Structural Health monitoring, damage detection, Time series models, measurement noise.

I. INTRODUCTION

Structural health monitoring (SHM), provides an increased level of safety for everyone and is motivated by the potential of economical and life safety benefits. Due to the dramatic decrease in the cost of engineering instrumentation used to measure dynamic signals, in conjunction with the availability of affordable computational power, SHM has begun to receive increased attention. The applications for SHM can be grouped into three general categories, Civil Infrastructure, Air/Space Structures, and Automotive/Industrial applications. Each of these categories forces the area of SHM to expand and concentrate on different groups of problems. In addition to the classification of the areas of SHM, further classification is possible in order to describe the level of information provided by the monitoring scheme. This classification identifies 5 levels of SHM detail, namely I) identification of the presence of damage, II) localization, III) diagnosis of damage type, IV) quantification of severity, V) prognosis of remaining life [1]. Inman [2] proposes that, when dealing with smart materials, 3 other sublevels should be added to the previous ones. Worden et al. [3] mention that the detection of whether damage is present or not is the most fundamental issue. Unfortunately, the Level 1 is still a daunting problem for practical applications, mainly in complex system, due to the significant uncertainties caused by modeling errors, unknown load data, etc, [4].

The challenge of SHM gets bigger when it is not possible to excite the structure with active sources due to weight or power constraints and also when the operational condition is not known. In these cases, the SHM must be carried out using only the vibration responses. On the other hand, when some knowledge about the physics of the system is available, its behavior can be simulated theoretically or numerically. However, physics-based assessment approaches are usually computationally intensive. In order to overcome this difficulty, data-based techniques can be used. They rely only on previous measurements performed on the healthy system and should be able to indicate changes in the material and/or geometric properties, boundary conditions, and system connectivity. Some methodologies combine

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these two approaches (physics-based and data-based) to reach a better confidence level in SHM processes. Due to the drawbacks of the physics-based techniques, the present work deals with the use of data-based assessment procedure.

There are several data-based techniques that have been recently investigated. Carden and Fanning[5] describe different common methodologies for SHM. Among those, the authors suggest that one of the most promising methodologies is the model construction based on time-series signature, called “black box” model. In this approach, large prediction errors comparing to the actual measurement will occur if the system presents accumulated damage. Fugate et al[6] conducted SHM in an unsupervised learning mode which is a very important feature once data from damaged structure are usually not available for most real-world engineering system. For instance, for very expensive structures like aircrafts, this is simply not possible. The use of a neural network, perceptron or any other supervised learning process, is difficult for practical applications due to the necessity of training damage pattern data. In this case, training data could be obtained from accurate models or by a previous knowledge of the history of damage signals. Sohn and Farrar[7] pose the SHM problem in statistical pattern recognition and time series analysis paradigm. The approach proposed by Sohn and Farrar [7] is composed of a two-stage prediction model, combining an auto-regressive (AR) and an auto-regressive with exogenous inputs (ARX) model. The model was constructed with selected and normalized acceleration signals obtained from the undamaged structure. The one-step-ahead error prediction was defined as a damage sensitive index. Carden and Brownjohn [8] classified different states of several structures using autoregressive moving average (ARMA) models. In this paper, Autoregressive Integrated Moving Average model (ARIMA) is used to determine the damage from the signal generated by a random load with operational variability and measurement noise.

II. TIME SERIES MODELS

A time series is a collection of quantitative observations that are evenly spaced in time and measured successively. Time series are analyzed in order to understand the underlying structure and function that produce the observations. Understanding the mechanisms of a time series allows a mathematical model to be developed that explains the data in such a way that prediction, monitoring, or control can occur. Observations made over time can be either discrete or continuous. Both types of observations can be equally spaced, unequally spaced, or have missing data. Discrete measurements can be recorded at any time interval, but are most often taken at evenly spaced intervals. Continuous measurements can be spaced randomly in time, such as measuring earthquakes as they occur because an instrument is constantly recording, or can entail constant measurement of a natural phenomenon such as air temperature, or a process such as velocity of an airplane. Time series are very complex because each observation is somewhat dependent upon the previous observation, and often is influenced by more than one previous observation. The challenge of time series analysis is to model the underlying mechanisms.

Time series analysis in SHM

SHM methods based on Time series, exclusively use the output only vibration time history data which are continuous and stochastic, collected from various sensors on the structure of interest and represent it as outputs of a selected time series model. Time series models rely on the fact that the value of the measured response of the linear system at any time can be predicted based on a linear combination of its values at a previous time and some random errors. The analogy behind using time series models for vibration-based damage identification of structures is that if a time series model is fitted to the vibration responses of the bridge, the obtained coefficients and properties of the model can capture the dynamic characteristics of the structure. Then, any deviation from the obtained model can be a sign of change or damage in the structure. Time series analysis in SHM offer unique advantages[9] such as

- (i) No need for physics based or analytical, such as Finite Element (FE) models.
- (ii) No need for complete structural models. In fact models describing only part of the dynamics and based on a limited number (even a single pair) of excitation and/or vibration response signals are sometimes adequate.
- (iii) Inherent accounting for uncertainties (measurement, environmental, operational and so on) through statistical tools.
- (iv) Statistical decision making with specified performance characteristics.
- (v) Effective operation even in the “low” frequency range.

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- (vi) Effective use of naturally obtained random vibration signals. This is very important as it implies that there is no need for interrupting the normal operation of the structure.

Inspired by the ease and advantages of the technique, time series based SHM is being employed in numerous applications by deriving meaningful damage features extracted from appropriately selected time series model. In the search for more sensitive damage features that can capture more information from the measured vibration time history responses of structures, researchers propose to use different types of time series models. Many existing SHM feature extraction methodologies are based on fitting linear models (e.g. a modal model) to measured system response data before and after damage. Changes in the parameters of these models are then used as indicators of damage. This physics-based modeling approach has been extended to data-based time-series models where in addition to model parameters, residual errors between measured and predicted responses are used as damage-sensitive features. There are three basic types of linear models: autoregressive (AR), moving-average (MA), and ARMA models. The formulations of the ARIMA model and the applications of this model in the field of SHM for damage detection are discussed in the following sections.

III. ARIMA MODEL

ARIMA models, also called Box-Jenkins models, are models that may possibly include autoregressive terms, moving average terms, and differencing operations. ARIMA modeling can take into account trends, seasonality, cycles, errors and non-stationary aspects of a data set when making forecasts. It alters the time series to make it stationary by using the differences between data points. This allows the model to pick out trends, typically using autoregressive moving averages and seasonal differencing in the calculations. In contrast to the ARMA model, which is adequate only for stationary time series, ARIMA model may be an adequate model for non-stationary time series.

The ARIMA model of parameters(p,d,q) is described by equation(8)

$$\begin{aligned}\phi(B)w_t &= \theta(B)\varepsilon_t \\ \phi(B) &\equiv 1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p \\ \theta(B) &\equiv 1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q \\ w_t &\equiv \nabla^d Z_t \quad (d \geq 0)\end{aligned}\tag{1}$$

Where the difference operator, ∇ is defined as follows

$$\begin{aligned}\nabla Z_t &\equiv Z_t - Z_{t-1} \\ \nabla^2 Z_t &\equiv \nabla(\nabla Z_t) \dots\end{aligned}\tag{2}$$

And the backshift operator B is defined by Eqn.(10)

$$\begin{aligned}BZ_t &\equiv Z_{t-1} \\ B^2 Z_t &\equiv B(BZ_t) = Z_{t-2} \dots\end{aligned}\tag{3}$$

Z_t is the original reading collected at time t, W_t is the respective differentiated signal and ε_t is the residual.

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Initially, the acceleration time histories are generated under the healthy condition of the structure and the data are standardized. These vibration time histories in the undamaged condition are named as healthy data sets. Similarly, damage data sets are the time histories obtained by simulating the damage(reduction of stiffness of the selected elements) in the structure. The data in all data sets were divided to smaller data samples. Segmenting the vibration responses is beneficial in representing different portions of the responses obtained under a varying loading condition as well as including the effect of uncertainty in data prediction using time series models. Then, ARIMA models were fitted to all the segmented data samples in healthy and current data sets.

Varying environmental and operational (loading) conditions can significantly affect the vibration responses of structures. Although the effect of varying environmental conditions was not considered in this study, the normalization procedure is performed to match the data samples in different data sets that correspond to similar operational conditions and measurement noise. For this purpose, the number of data samples that are segmented in the healthy data set, is much larger than the number of data samples in the current data sets. Therefore, the data samples in the healthy data set represent the vibration response of the beam collected under a variety of loading conditions and measurement noise. For each data sample in current dataset a data sample is matched from the healthy data set. The AR coefficients of the ARIMA model are used to match any two data subsets on the basis of their correlation value. After normalisation, damage features were extracted from the matched healthy and current data subsets by using the prediction errors of ARIMA models of those data subsets.

The damage index, calculated for data samples in the healthy and current data subsets is as follows:

$$D_{f=\frac{\sigma_y}{\sigma_x}} \quad (4)$$

Where σ_x^2 and σ_y^2 represent the variances of prediction errors from Healthy/Damage and Reference data sets, respectively. If the damage features calculated for healthy and damage conditions are shown as D_{fh} and D_{fd} respectively, it can expected that values of $D_{f=}$ will be close to 1. On the other hand, values are expected to be much higher since the calculated prediction errors are larger than $e_x(t)$. Finding the damage location was based on the assumption that the damage features calculated for a sensor close to the physical damage location will have the largest values.

IV. NUMERICAL STUDIES

The proposed damage diagnostic algorithm is illustrated by using two case studies of a simply supported beam girder. A simply supported concrete beam girder of 6m length shown in Figure 1, instrumented with 12 sensors is considered as the numerical example to demonstrate the proposed algorithm. The cross section of the beam chosen is 0.3 x 0.45 m. The density of concrete is 2400 Kg/m³, Young's modulus is 2.5e10 N/mm² and the poisson's ratio is 0.3. Single damage cases, namely case A and case B, are investigated using this example. Table 1. shows the details of the damage patterns used in the numerical studies performed using this combined AR algorithm.

Table 1: Details of the damage patterns

S.No	Damage Case	Details
1	CASE A- Stiffness reduction of 10% in element 5	Without measurement noise
2	CASE B- Stiffness reduction of 20% in element 5	With measurement noise

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In this case study, the damage is induced in the element no. 5 of the beam by reducing a percentage of stiffness of that element. Two damage patterns depending upon the percentage of stiffness reduction are considered as shown in the Table 1 are used in the study. The random vibration responses are generated for all the sensors. Healthy and current data sets were formed from 10s long vibration time histories collected at different sensor locations and from varied measurement noise and damage conditions of the beam. The measurement noise is added to the acceleration data in the form of Signal to Noise Ratio(SNR) varying from 40 to 60. These data sets were further divided into smaller data samples.

ARIMA models are fitted to the segmented data samples in the Healthy and Damage data sets in order to perform the data normalization step. A data sample in the Healthy data set was matched to each data sample in the current data subsets by finding the highest correlation between the coefficients of the fitted AR models. The matched datasets are considered to construct the damage index. The residuals from the matched data sets are used in Eqn.4, where the variance of prediction errors from the current data samples and Healthy data samples are needed. The damage indices obtained when the normalisation procedure is not employed is shown in Figure 2.

The damage indices obtained using the normalisation procedure for the two cases of the study are shown in Figure 3 and 4. From the figures, it can be seen that, the proposed technique is robust in identifying the presence and location of damage effectively by handling the operational variability and measurement noise .

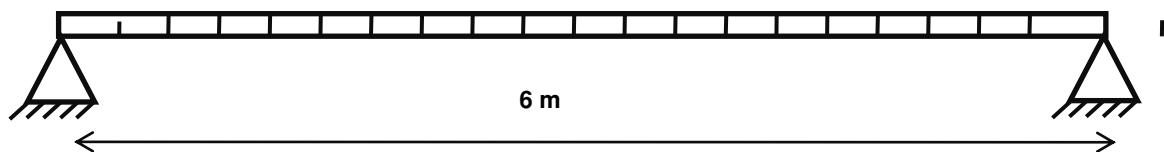


Fig. 1. Simply supported beam

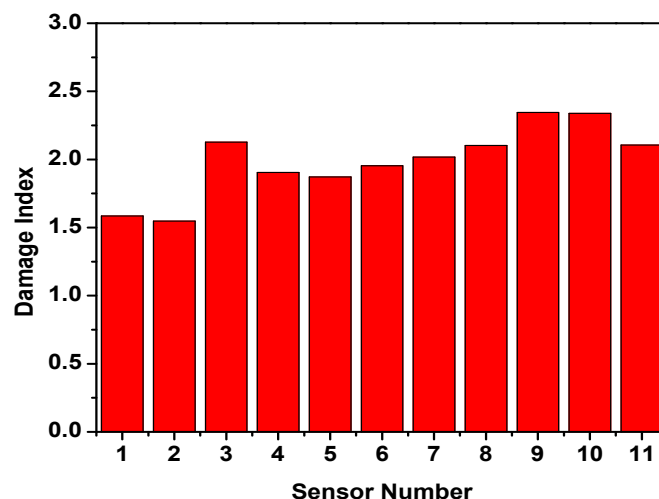


Fig. 2. Damage Index of Case A scenario using ARIMA without normalisation

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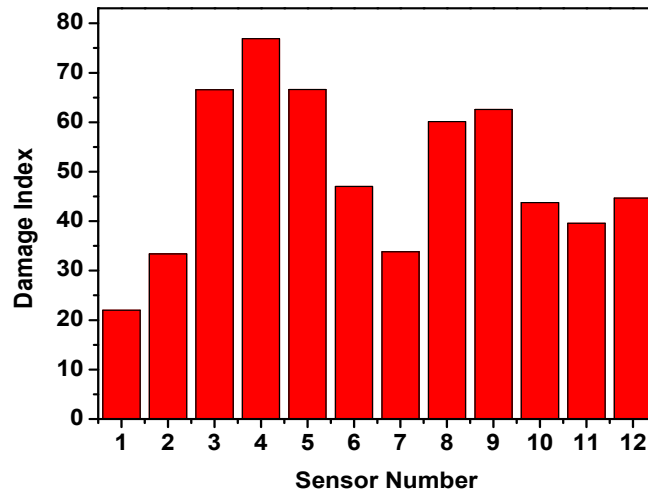


Fig. 3. Damage Index of Case A scenario using ARIMA with normalisation

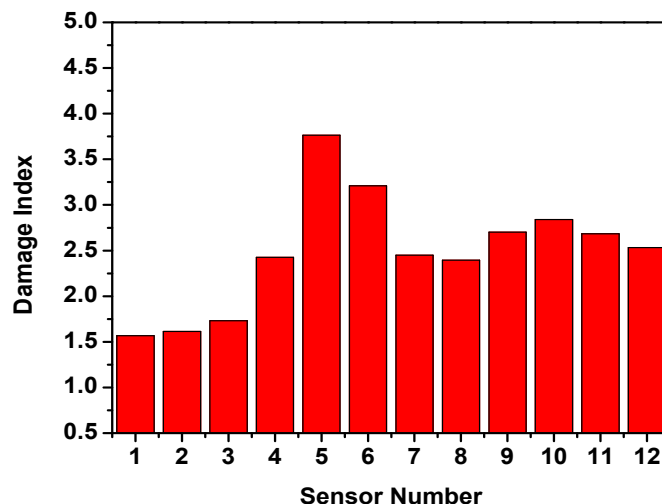


Fig. 4. Damage Index of Case B scenario using ARIMA with normalisation

V. CONCLUSION

In this paper, a novel damage diagnostic technique is presented. The proposed technique uses the prediction errors from ARIMA models to identify the damage and locate the damage precisely. A numerical example is employed to show the efficiency of the proposed approach. The results of the numerical studies carried out on a simply supported beam clearly show that the proposed algorithm is able to identify damage under the varied damage patterns successfully. Moreover, the algorithm is proved to be robust even in the presence of noise, when studied with different Signal to Noise Ratio(SNR) levels.

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