NONLINEAR AUTOREGRESSIVE WITH EXOGENOUS INPUT NEURAL NETWORK FOR STRUCTURAL DAMAGE DETECTION UNDER AMBIENT VIBRATION

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DEDICATION

This thesis is dedicated to my husband, parents, and siblings for their love, encouragement, and prayers.

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ABSTRACT

Time-series method has become of interest in damage detection, particularly for automated and continuous structural health monitoring. In comparison to the commonly used method based on modal data, time-series method offers a straightforward application due to having no requirement for modal analysis. Sensor clustering has been proven effective in improving the ability of time-series method to detect, locate and quantify damage. However, most of the applications rely on free vibration response that can be obtained directly by impact testing, which is difficult to practice for in-service structures, or indirectly by transforming the ambient vibration response. Therefore, a reliable method that allows direct utilisation of ambient vibration response for damage detection in structures without any data transformation is proposed in this study. The implementation of the proposed response-only method involves a three-stage procedure; (i) sensor clustering, (ii) time-series modelling and (iii) damage detection. Each sensor cluster is represented by a time-series model called nonlinear autoregressive with exogenous inputs (NARX) model, which is developed via artificial neural network (ANN) using undamaged acceleration data. The model is then utilised for predicting the damaged response and the difference between prediction errors is used to extract damage sensitive feature (DSF). The existence of uncertainties is addressed through setting up a damage threshold using several sets of undamaged data. The effectiveness of the method is demonstrated through a numerical slab model and experimental structures of reinforced concrete slabs and steel arches. It is found that the proposed structural damage detection approach based on NARX neural network is superior to linear ARX model as the approach is able to detect damage under ambient vibration. The results show that the highest predicted DSF corresponds to the location of damage and its value increases relatively with the severity of damage. Better damage detection is obtained when damage threshold is integrated into the proposed approach where the precision is increased by more than 24%. Overall, the proposed method is proven applicable to identify the existence, location and relative severity of structural damage under ambient vibration.

ABSTRAK

Pengesanan kerosakan pada struktur berasaskan kaedah siri masa telah menjadi tarikan terutamanya bagi pengawasan kesihatan struktur secara automatik dan berterusan. Berbanding kaedah yang biasa digunakan iaitu berdasarkan data modal, kaedah siri masa lebih mudah digunakan kerana tidak memerlukan analisis modal. Konsep penggugusan penderia telah terbukti berkesan dalam menambah baik kebolehan kaedah siri masa bagi mengesan kewujudan, lokasi dan tahap kerosakan struktur. Walau bagimanapun, penggunaannya bergantung kepada getaran bebas yang boleh diperolehi sama ada secara langsung melalui ujian hentaman yang sukar dilaksanakan pada struktur yang sedang beroperasi, atau secara tidak langsung melalui pengubahan data getaran ambien. Oleh itu, satu kaedah yang membolehkan penggunaan terus data getaran ambien untuk pengesanan kerosakan tanpa melibatkan pengubahan data telah dicadangkan dalam kajian ini. Perlaksanaan kaedah yang dicadangkan melibatkan tiga peringkat iaitu (i) penggugusan penderia, (ii) permodelan siri masa dan (iii) pengesanan kerosakan. Setiap gugusan penderia diwakili oleh satu model siri masa iaitu model tak lelurus auto mundur dengan input luar kawalan (NARX) yang dibina melalui rangkaian neural tiruan (ANN) menggunakan data pecutan struktur tidak rosak. Model ini kemudiannya digunakan untuk meramal data struktur yang telah rosak dan perbezaaan antara ralat ramalan digunakan untuk mengekstrak ciri sensitif kerosakan (DSF). Kewujudan ketidaktepatan diambil kira melalui penetapan satu ambang kerosakan menggunakan beberapa set data struktur tidak rosak. Keberkesanan kaedah pengesanan kerosakan ditunjukkan melalui satu model berangka bagi papak dan dua struktur ujikaji iaitu papak konkrit bertetulang dan gerbang keluli. Didapati bahawa kaedah pengesanan kerosakan yang dicadangkan iaitu berdasarkan rangkaian neural NARX adalah lebih baik berbanding model lelurus ARX kerana ia dapat mengesan kerosakan di bawah getaran ambien. Hasil kajian menunjukkan bahawa DSF yang paling tinggi sepadan dengan lokasi kerosakan dan nilainya bertambah secara relatif dengan tahap kerosakan struktur. Pengesanan kerosakan yang lebih baik diperolehi apabila ambang kerosakan digabung dengan kaedah yang dicadangkan dengan ketepatannya meningkat lebih daripada 24%. Secara keseluruhannya, kaedah yang dicadangkan terbukti dapat digunakan untuk mengenal pasti kewujudan, lokasi dan tahap relatif kerosakan struktur di bawah getaran ambien.

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LIST OF ABBREVIATIONS

A/D	-	Analogue-to-digital
ACF	-	Autocorrelation function
ANN	-	Artificial neural network
AR	-	Autoregressive
ARIMA	-	Autoregressive with integrated moving average
ARMA	-	Autoregressive moving average
ARMAX	-	Autoregressive moving average with exogenous input
ARX	-	Autoregressive with exogenous input
CMSE	-	Cross modal strain energy
COMAC	-	Co-ordinate Modal Assurance Criterion
DIM	-	Damage index method
DLAC	-	Damage Location Assurance Criterion
DOF	-	Degree of freedom
DSF	-	Damage sensitive features
EMD	-	Empirical mode decomposition
FE	-	Finite element
FFT	-	Fast Fourier Transform
FR	-	Fit ratio
FRF	-	Frequency response function
GA	-	Genetic algorithm
MAC	-	Modal Assurance Criterion
MI	-	Mutual information
MISO	-	Multi input single output
MSE	-	Mean square error
MSEC	-	Modal strain energy change
NARX	-	Nonlinear autoregressive with exogenous input
NDT	-	Non-destructive test
NNE	-	Neural network emulator
NSIN	-	Neural system identification networks
PACF	-	Partial autocorrelation function

PCA	-	Principle component analysis
PENN	-	Parametric evaluation neural network
POMs	-	Proper orthogonal modes
PSD	-	Power spectral density
RMS	-	Root mean square
RMSPDDV	-	Root mean square of prediction displacement difference vector
SD	-	Standard deviation
SHM	-	Structural health monitoring
SNR	-	Signal-to-noise ratio
SSA	-	Singular spectrum analysis
SSE	-	Spectral strain energy

LIST OF SYMBOLS

M	-	Mass
C	-	Damping
K	-	Stiffness
F	-	Flexibility
$\ddot{x}(t)$	-	Acceleration
$\dot{x}(t)$	-	Velocity
$x(t)$	-	Displacement
ω_i	-	Modal natural angular frequency
$\emptyset_i$	-	Mode shapes
E	-	Young's modulus
ρ	-	Mass density
μ	-	Poisson's ratio
σ	-	Standard deviation
$t0$	-	Start time
td	-	Load duration
A	-	Load amplitude
n_u	-	Input order
n_y	-	Output order

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Civil engineering infrastructures such as bridges, buildings and many others play important roles in providing essential welfare for society. However, the resistance of the in-service infrastructures deteriorates with time, owing to many factors such as exposure to harsh environment, long-term fatigue and natural hazard i.e. earthquakes and storms. These factors accumulate local and global damage such as crack, corrosion, material disintegration and many others that will cost more for repair works or at worst, can cause catastrophic structural failure that involves severe economic and human life losses. Incidences due to loss of structural integrity can be found worldwide. For example, the collapse of the I-35W bridge over the Mississippi River in Minneapolis, Minnesota, on 01 August 2007, in which the National Transportation Safety Board reported that failure of gusset plates U10W initiated the collapse (Liao and Okazaki, 2009). Warning signs in the form of out-of-plane displacements went undetected (Li and Hao, 2016), causing injury to 145 people and the death of 13 others. The incident exposes the weakness of visual inspection and indicates that a more sophisticated early detection of damage through a Structural Health Monitoring (SHM) system is important for ensuring the reliability and safety of infrastructure.

1.2 Background of study

For decades, structural integrity has been maintained by means of manual visual inspection and non-destructive test (NDT) such as ultrasonic waves, magnetic field, radio-frequency, eddy-current, thermal field etc. Although NDTs have been applied widely, such methods are regarded as local method as the vicinity of the damage is generally required. These local assessments are usually performed periodically and therefore, structural conditions in between the inspection intervals cannot be obtained. In addition, the results of these techniques are dependent on human expertise, hence prone to human error and lead to subjective conclusion.

Researchers have long sought for a better solution to the problems concerned and proposed a method to assess structural condition as a whole with no requirement for prior information of the suspected damaged region. The method is referred to as global method, called SHM system. The system is formed by a sophisticated technology, incorporating sensing devices with advanced data collection and processing as well as damage detection algorithm. With SHM system, structural monitoring and evaluation can be performed in real-time under regular operation, hence improving structural safety and reliability, prolonging the life of structure, reducing downtime and reducing maintenance cost (Mufti *et al.*, 2005).

Damage is defined as changes of physical properties of a structural system, including material property, geometry and boundary conditions (Farrar *et al.*, 2001). A key element in SHM is damage detection which usually makes use of vibration properties to identify damage. Damage identification can be further classified into four levels: (I) detection of damage presence, (II) damage localisation, (III) damage quantification, and (IV) estimation of remaining service life. In recent years, vibration-based damage detection has been intensively developed by researchers and practitioner in the SHM field to identify damage presence, location and severity. The theory behind vibration-based damage detection is that vibration parameters are the functions of the physical properties of structures such as mass and stiffness. Therefore, the presence of damage will change the behaviour of structural vibration properties and by examining the change, damage information can be obtained.

The methods of vibration-based damage detection can be divided into three categories depending on the type of vibration parameters, which are modal-based, frequency-based and time-series based damage detection methods. As for the first category, damage detection is made based on modal parameters such as natural frequencies and mode shapes which require extraction from measured vibration data. Therefore, the reliability of damage identification is likely dependent on the accuracy of the extracted parameters. Furthermore, there are some arguments on the suitability of modal data in damage detection. For instance, modal data is not sensitive to local damage and minor damage because damage is a local phenomenon, while modal data is a structural global feature (Alvandi and Cremona, 2006; Worden *et al.*, 2008). This limitation can be overcome by using higher modes where the modes correspond more to local changes, but measuring high vibration modes is more difficult in real practice, especially for large and heavy structures under ambient excitation, which are usually low in frequency (Mei and Gül, 2015). In contrast, frequency response function (FRF) which falls in the frequency-based method provides more information as compared to modal domain, but its prime drawback is the requirement for the accurate known input (Deraemaeker and Preumont, 2006), hence limiting its practicability for the in-service structures as the excitation under operation conditions is generally difficult to measure. Moreover, the conversion from time-domain to frequency-domain data discards some information contained in the measured response (Lei *et al.*, 2019). On the other hand, the method based on time-domain performs damage detection through direct analysis of the measured time-series response. Therefore, the implementation of this category of method is relatively more feasible for automation of the SHM system since it is simpler, faster and can avoid the innate errors of modal extraction. As a result, it seems to be very beneficial to apply the time-series approach for damage detection in this study.

1.3 Research problem statement

As mentioned earlier, the common method used in vibration-based damage detection is based on modal-domain data that is insensitive to minor damage and time-consuming due to dependency on the modal feature extraction. An alternative has been initiated to avoid the modal extraction via time-series analysis. Although the applications of time-series approaches have revealed great potential at damage detection due to its simplicity (no requirement of finite element (FE) model) and straightforward properties (without modal extraction), most of them are up to Level II damage identification only. In this regard, the concept of sensor clustering introduced by Gul and Catbas (2011b) seems promising as the method resulted in good sensitivity

baseline condition is referred to the initially undamaged structure, thus the method will be able to identify all the future damages after the construction. When the data of the newly constructed structure is not available, the existing structure can also be taken as the baseline, provided it is assured that the structure is damage-free. The baseline condition used in this study is referred to the healthy structure which is in its undamaged state. To show the superiority of the proposed approach based on NARX neural network, the applicability of linear ARX model is investigated numerically to detect damage under both impact excitation and ambient vibration. Then, the feasibility of the proposed approach based on NARX neural network is further demonstrated through numerical and experimental examples. Due to the large scope of the research, field work is not conducted in this study.

In the development of NARX neural network, series-parallel NARX neural network with one hidden layer architecture is utilised. The structure of the NARX network is comprised of tan-sigmoid transfer functions in the hidden layer and a linear transfer function in the output layer (Rai and Upadhyay, 2017). The number of hidden neurons as well as the orders of input and output are selected through trial and error approach. For network training process, backpropagation learning algorithm with Levenberg–Marquardt learning function is used (Sheremetov *et al.*, 2014). These network configurations are used throughout the numerical study as well as experimental study.

In numerical study, a continuous two-span concrete slab is employed in Chapter 4. The slab is modelled using the Structural Dynamics Toolbox (SDT) (Balmes *et al.*, 2009) which is run on the Matlab platform with presumed physical and material properties. Damage in many studies (Roy *et al.*, 2015; Abdeljaber and Avci, 2016; Rahami *et al.*, 2018; Azim and Gul, 2019) has been represented as a stiffness reduction, particularly Young's modulus (E) value (Wickramasinghe *et al.*, 2016; Clementi *et al.*, 2017; Umar *et al.*, 2018; Hellgren *et al.*, 2020). Although stiffness reduction may not represent precisely all damage types in civil engineering, it is applicable to damage due to bolt loosening, corrosion and cracking (Sun and Büyüköztürk, 2015). Therefore, damage in the numerical example is modelled by reducing the E value of selected segments. In the consideration of noise as presented in section 4.6, the original simulated acceleration responses are contaminated with white gaussian noise in the form of signal-to-noise ratio (SNR) (Krishnasamy *et al.*, 2018). The effects of sampling frequency, sampling duration, reduced number of sensors and measurement noise on the ability of the proposed approach to detect damage in the numerical slab model are investigated.

In experimental study, ambient vibration test is conducted on two types of experimental structures, which are reinforced concrete slab and semi-circular steel arch. The purpose of having two different experimental models is to examine the effectiveness of the proposed method to detect damage in different types of structure. To create damage cases, notch-type damage and saw cut damage are simulated for slab and arch structures, respectively. The recorded uniaxial acceleration responses are used for the verification of the proposed approach for damage detection.

1.7 Thesis outline

This thesis consists of six chapters and has been organised as follows:

Chapter 1 presents the background of the study area, the problem statements, the research objectives, the significance of study, the research scope and limitations, the outline of the thesis.

Chapter 2 presents the review of existing literature related to SHM, the basic theory of vibration-based damage detection as well as various damage detection methods which are further categorised according to the type of vibration parameters. The advantages and disadvantages of each method are discussed in the chapter. The applications of ANN for vibration-based damage detection are also reviewed.

Chapter 3 describes the research methodology and theoretical background of this study. The proposed time-series approach is explained in this chapter through a three-stage procedure: sensor clustering, time-series modelling and damage detection. The design of linear ARX model and NARX neural network are further detailed in the stage of time-series modelling. The process to determine damage threshold is also included in the chapter.

Chapter 4 demonstrates the application of the NARX neural network with sensor clustering in damage detection under ambient vibration using a numerical model. To show the superiority of the NARX neural network, the performance of linear ARX model in identifying damage under impact excitation and ambient vibration are also presented. Sensitivity studies on the effect of sampling frequency, sampling duration and a smaller number of sensors to the damage detectability of the proposed method are conducted. Besides, this chapter also addresses the effect of uncertainties in the vibration data, in which damage threshold is determined and then incorporated with the proposed NARX neural network.

Chapter 5 provides the details of experimental models, vibration testing procedures and damage scenarios. The implementation of the proposed NARX neural network is demonstrated using the measured experimental data. Also, the final damage detection results by incorporating damage threshold for each experimental structure are presented.

Chapter 6 concludes the study by highlighting the foremost findings of the study according to the research objectives and suggests some recommendations for future work related to the subject of this study.

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