SEISMIC DAMAGE IDENTIFICATION BASED ON INTEGRATED ARTIFICIAL NEURAL NETWORKS AND WAVELET TRANSFORMS

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ABSTRACT

In recent years, Structural Health Monitoring (SHM) has been proposed and practiced for condition assessment of structures. SHM covers shortcomings of non-destructive tests and is comprised of a sensory system, data acquisition system, and damage identification system. In this study, numerical and experimental investigations are concentrated on the application of Artificial Neural Networks (ANNs) and Wavelet Transforms (WTs) for damage identification of civil engineering structures. As a major outcome of this research, three novel damage identification methods are developed. The first damage identification method enables the SHM systems to identify damage to cantilever structures through decomposition of mode shapes by integrating WTs and ANNs. The second damage identification method enables SHM systems to identify damage to cantilever structures via decomposition of response accelerations by means of WTs and ANNs. The third damage identification method takes advantage of only ANNs and enables the SHM systems to identify seismic-induced damage to concrete shear walls in real-time by measuring inter-storey drifts. In addition, a novel optimal strain gauge placement method for seismic health monitoring of structures is proposed. This method considers the seismicity of construction site and the importance level of structures. Results from the first method showed that when the imposed damage levels were severe, medium, and light, the proposed method could quantify them with less than 5%, 12%, and 16% errors, respectively. In addition, the second method quantified seismic-induced damage to the studied structure with an averaged error of 8%. Moreover, the third method classified damage levels of the studied concrete shear walls with a success rate of 91%. The proposed optimal strain gauge placement method reduced the number of required sensors for the studied structure from 206 sensors to 73 sensors. The obtained results demonstrated the feasibility, robustness, and efficiency of the proposed methods for damage identification of civil engineering structures.

ABSTRAK

Kebelakangan ini, sistem *Structural Health Monitoring* (SHM) telah dicadang dan diamalkan untuk penilaian keadaan struktur. SHM ini boleh mengatasi kelemahan ujian tanpa musnah dan melingkungi sistem deria, sistem perolehan data, dan sistem penentuan kerosakan. Dalam kajian ini, pelbagai siasatan berangka dan eksperimen telah ditumpukan atas aplikasi *Artifical Neural Networks* (ANN) dan *Wavelet Transform* (WT) untuk menentukan kerosakan struktur kejuruteraan awam. Hasil utama penyelidikan ini adalah tiga kaedah baru penentuan kerosakan. Kaedah penentuan kerosakan pertama membolehkan sistem SHM untuk menentukan kerosakan struktur julur melalui penguraian bentuk mod dengan mengintegrasikan WT dan ANN. Kaedah kedua boleh membantu sistem SHM untuk menentukan kerosakan atas struktur julur melalui penguraian pecutan balas dengan cara WT dan ANN. Kaedah ketiga menggunakan ANN sahaja untuk menentukan kerosakan seismik pada dinding ricih konkrit dengan mengukur hanyutan di antara pelbagai tingkat. Di samping itu, suatu kaedah penempatan tolok tekanan yang baru juga telah dicadangkan untuk pemantauan kesihatan seismik struktur. Kaedah ini mengambil kira seismik tapak pembinaan dan tahap kepentingan struktur. Hasil daripada kaedah pertama menunjukkan bahawa apabila tahap kerosakan adalah teruk, sederhana, dan ringan, kaedah ini boleh mengukurnya dengan masing-masing kurang daripada 5%, 12%, dan 16% kesilapan. Lebih daripada itu, kaedah kedua telah mengukur kerosakan seismik atas struktur yang dikaji dengan ralat purata sebanyak 8%. Selain itu, kaedah ketiga telah mengklasifikasikan tahap kerosakan atas dinding ricih konkrit dengan kadar kejayaan setinggi 91%. Kaedah penempatan tolok tekanan yang dicadangkan juga telah mengurangkan bilangan sensor yang diperlukan daripada 206 sensor (pengagihan seragam) kepada 73 sensor. Keputusan yang diperolehi telah menunjukkan feasibiliti, keteguhan, dan kecekapan kaedah-kaedah yang dicadangkan untuk mengesan kerosakan struktur.

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LIST OF ABBRIVATIONS

APS_i	-	Input auto power spectrum
APS_O	-	Output auto power spectrum
ATC	-	Airport traffic control
COMAC	-	Coordinate modal assurance criteria
CPC	-	Cross power spectrum
CQC	-	Complete quadratic combination
CWT	-	Continuous wavelet transform
DWT	-	Discrete wavelet transform
FE	-	Finite Element
FFT	-	Fast Fourier transform
FRF	-	Frequency response function
KLIA	-	Kuala Lumpur International airport
MAC	-	Modal assurance criterion
MSE	-	Mean squared error
NTH	-	Nonlinear time history
PCA	-	Principal component analysis
PCs	-	Principal components
PGA	-	Peak Ground acceleration
PGV	-	Peak Ground Velocity

LIST OF SYMBOLS

ψ^{a}	-	Mode shape vector of mode a
ψ^{b}	-	Mode shape vector of mode b
λ''	-	Mode shape curvature
λ	-	Displacement of mode shapes
U_i	-	Strain energy of Bernoulli-Euler beam
EI	-	Flexural stiffness
$[V]$	-	Flexibility matrix
$[\psi]$	-	Matrix of mode shape
$[\Pi]$	-	Diagonal matrix of modal frequency squared
x_i	-	Input signal of neurons
u_i	-	Weight of neurons
s_i	-	Desired output of neurons
α	-	Learning rate
s_j	-	Standard deviation
$\overline{m}$	-	Mean value of data sets
$\hat{X}$	-	Normalized data set matrix
[C]	-	Covariance matrix
μ_i	-	Eigenvalues
ν_i	-	Eigenvectors
φ_t	-	Wavelet function
A_j	-	Approximate coefficients of DWT
D_j	-	Detail coefficients of DWT
M	-	Mass matrix

C	-	Damping matrix
K	-	Stiffness matrix
O_w	-	FFT of output signal
I_w	-	FFT of input signal
ξ	-	Modal damping
D_u	-	Modal damping of undamaged states
D_d	-	Modal damping of damages states
f_u	-	Natural frequency of undamaged states
f_d	-	Natural frequency of damaged states
f_e	-	Natural frequency of experimental testing
f_f	-	Natural frequency of FE models
DI	-	Damage indicator
V	-	Base shear
C_s	-	Seismic response coefficients
R	-	Response modification factor
S_{DS}	-	Design spectral acceleration in short period
I_e	-	Importance factor
W	-	Effective seismic mass
F_i	-	Seismic loads at storey levels
w_i	-	Total effective seismic load at level (i)
h_i	-	The height from the base to level (i)
Γ	-	Modal participating factor
$\mathbf{m}$	-	Mass matrix
Φ_n	-	Mass-normalized mode shape
T_n	-	Period of nth mode shape
C_d	-	Deflection amplification factor
Ω_0	-	Overstrength factor
DI_i	-	Damage index
θ_{ui}	-	Ultimate curvature capacity
θ_i	-	Curvature demand
X_t	-	Target values
X_P	-	Predicted values

LIST OF APPENDICS

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CHAPTER 1

INTRODUCTION

1.1 Background

During the past centuries, the demand of societies for new structures like bridges, tunnels, and high-rise buildings had been increasing. On the one hand, people reliance on the public structures has reached to a level that picturing a world without such structures is not feasible. On the other hand, owing to aging, corrosion, overloading, etc. the integrity of in service structures is decreasing such that may result in unpredictable disasters. Examples of such disastrous incidences can be found worldwide. Collapse of Kaoshiung-Pingtung Bridge in Taiwan in year 2000 (Figure 1.1), collapse of Mianus River Bridge in Connecticut in year 1983 (Figure 1.2) and collapse of an eight-lane highway bridge in Minneapolis into the Mississippi River in year 2007 are some examples. These incidents indicate that a health monitoring and integrity assessment system is required to ensure the reliability and safety of in service structures. For decades, engineers have relied on Non-destructive Tests (NDT) for condition assessment of in service structures. NDT can be carried out by visual inspection, acoustic emission, X-ray, radiography, ultrasonic waves, etc. Despite wide application in civil engineering practice, most of NDT techniques suffer from major shortcomings.

NDT presume that damage locates in the inspected area. However, owing to anti-fire coverage or ceilings, damaged areas may remain hidden. NDT is a local damage detection method, thereby when it is applied to large structures becomes costly and time-consuming. In addition, results of NDT often depend on the experience and proficiency of test takers.

Figure 1.1 Collapse of Kaoshiung-Pingtung Bridge in Taiwan in year 2000(BBC NEWS, 2000).

Figure 1.2 Collapse of Mianus River Bridge in Connecticut in year 1983(Morgan, 1983).

Over past three decades, extensive researches have been carried out to overcome the problems of NDTs. Some researches proposed global damage identification techniques that were capable of assessing the condition of the entire structure at once. These techniques formed Structural Health Monitoring (SHM) systems as a new generation of methods for integrity assessment and health monitoring of structures. SHM is defined as "a process of implementing a damage detection strategy within a system to enable autonomous state awareness for structural integrity" (Sohn *et al.* 2004). SHM reduces inspection costs, minimizes preventative maintenance, and extends remaining useful life of structures. Moreover, SHM data can be used for designing lighter-weight structures and conformity assessment of dynamic behaviour for the newly designed structures. SHM consists of sensory system, data acquisition system and damage detection system. Along with ongoing advances in the sensory and data acquisition systems, many efforts have been made to improve the performance of damage detection techniques. Damage identification methods can be categorized into two groups that include Time-domain, and Frequency-domain approaches. The concept behind Frequency-domain methods lies in the fact that, damage alters the stiffness of structures and leads to a change in natural frequencies, mode shapes, and modal damping. Therefore, by measuring the modal parameters before and after damage, useful information regarding the damage presence, location, and severity is obtained. Time-domain damage identification techniques make use of dynamic responses in order to identify imposed damage. Dynamic responses include structural displacement, accelerations, strains, etc.

Despite variety in the damage identification algorithms, practical applications of SHMs have been associated with significant problems. For example, change in the temperature and humidity can alter measured modal parameters (Xia *et al.*, 2006) consequently may result in false damage prediction. Such uncertainties in the captured data and material properties, has encouraged researcher to focus on the new techniques that are less sensitive to the change in the environmental condition and noisy data. In this study, numerical and experimental investigations were concentrated on the application of Artificial Neural Networks (ANNs), Wavelet Transforms (WTs) and Principal Component Analysis (PCA) for damage identification of civil engineering structures. ANNs are robust tools for pattern recognition and classification. Even in the presence of noise, they provide acceptable performance. WTs are a time-frequency analysis based on a windowing technique with variable-sized regions. Wavelets are capable of describing a signal in a localized time and frequency domain (Chui, 1997; Walter, 1994). PCA is a powerful multivariate statistical technique capable of reducing the dimensionality of data and reducing noise effects on the measured dynamic responses (Jolliffe, 1986).

As major outcomes of this research, three different damage identification methods were developed. These methods cover both Time-domain and Frequency-domain damage identification approaches. In addition, a novel method for optimal strain gage placement for seismic health monitoring of structures was proposed.

1.2 Problem Statement and Motivation for the Research

As stated in the introduction, increasingly demands for health monitoring and integrity assessment of structures, pushed conventional non-destructive tests toward global damage identification techniques that were capable of covering drawbacks of NDTs. Although at the beginning, these techniques were only employed to monitor damage to structures due to ageing, corrosion, and overloading, soon they were adopted for the health monitoring of seismic-induced damaged structures.

Earthquakes frequently strike areas that are close to active faults. Because of ground motion, so many structures that have not been designed for seismic loads collapse immediately. However, there are structures that resist against seismic actions while having minor to medium damage. For such damaged structures, integrity assessment soon after the earthquake is a vital task. The main reason is that aftershocks can demolish damaged structures while they are occupied by people. In year 2011, a 5.7 magnitude earthquake hit the Turkey’s eastern province of Van almost a month after the strong earthquake that had occurred at the same area. Although, many of the city's buildings had already been evacuated, the second earthquake levelled two hotels that were still occupied and so many people died. Events like this emphasis on the urgent need for reliable tools that can assess the condition of damaged structures soon after earthquakes.

Seismic-induced damage significantly differs from damage caused by actions like corrosion, fatigue, settlement, etc. Earthquake loads are inherently transient and this transient nature of seismic excitations weaken the performance of the damage detection methods that are based on stationary stochastic-excitation assumption (Sohen *et al.*, 2001). In seismic damage identification techniques, seismic actions are only considered as the cause for damage. In addition, seismic damage identification of structures should be accomplished in real-time or soon after the extreme event; otherwise, they cannot effectively incorporate in deciding on evacuation or occupation of structures.

Efforts have been made to create practical seismic damage identification algorithms. Some of the proposed algorithms estimated the overall damage to different types of structures using measured earthquake ground motion indices (Lautour and Omenzetter, 2009; Yamazaki *et al.* 1993; Molas and Yamazaki, 1995).These algorithms determine the vulnerability of existing structures to seismic loads after a seismic event. Other studies have focused on identifying seismic damage to structures using their dynamic characteristics (Zhu and Law, 2007; Law *et al.* 2010). These algorithms monitor the seismic health of structures during, or soon, after ground motion to detect, localize and estimate the severity of damage.

Over the past decades, ANNs have been employed for damage identification with a certain degree of success (Faravelli and Pisano, 1997; Zapico *et al.*, 2007; Bakhary *et al.*, 2010). ANNs are robust and promising tools for pattern recognition and classification; even in the presence of noise, they provide acceptable performance. The ANN-based damage identification approaches mostly take advantage of modal parameter to detect the presence of damage, locate it, or estimate its severity. There are several drawbacks for practical implementation of such techniques when they are used for seismic damage identification. For example, it is not always feasible to measure all required mode shapes. This is because sometimes, changes in the stiffness of certain elements only alter higher mode shapes (Mangal et al, 1996), which often cannot be measured. Moreover, a full-scale structure test by Ji *et al.* (2011) revealed that when damage was distributed over the height of structure rather than being concentrated on a floor, changes in the mode shapes were infinitesimal. This meant that mode shapes might not be sufficient for seismic-induced damage localization. To effectively detect seismic damage, it is essential to identify the damage in real-time, or soon after, the ground motions. However, measurement of modal parameters takes time and cannot be done during a seismic event.

The above-mentioned facts and findings indicate that for seismic damage identification, modal parameters are not appropriate input parameters for neural networks. As an alternative approach, several researchers (Cattarius and Inman, 1997; Zhu and Law, 2007; Law *et al.* 2010) proposed response-based damage identification methods. These techniques make use of dynamic responses in order to identify imposed damage. One of the significant advantages of response-based techniques is their ability to measure dynamic responses with ease. Moreover, dynamic responses can be measured in real-time, meaning that damage identification can be carried out during seismic events. Furthermore, dynamic responses can be measured for all degrees of freedom at each time interval simultaneously, providing significant real-time information about the behaviour of a structure. Despite aforementioned advantages, only a few response-based methods have been proposed by researcher for seismic-induced damage identification (Celebi *et al.*, 2004, Reda Taha, 2006). These techniques have been incapable of damage localization and quantification.

In recent years, in addition to ANNs, Wavelet Transforms (WTs) have attracted attention of researchers for damage identification. WTs are a time-frequency analysis based on a windowing technique with variable-sized regions. Wavelet transforms are capable of describing a signal in a localized time and frequency domain (Chui, 1997; Walter, 1994). When change in the structural stiffness occurs, a sharp transition is created in its dynamic responses. This sharp transition amplifies wavelet coefficients of the transformed signal. This property is used for damage identification (Gogging et al, 2007; Fan and Qiao, 2009; Hester and Gonzalez, 2012). Wavelet transforms have been successfully employed for damage identification of structures both numerically and experimentally. The main useful characteristic of Wavelet transforms is that for damage identification they can be applied to both time and frequency domain data (Todorovska and Trifunac, 2010; Wu and Wang, 2011). Moreover, it has been shown that WTs are robust and promising tools even when dealing with noisy data. Despite benefits that arise from application of WTs, wavelet based methods have some inherent problems. When they are applied to the time-domain data only the presence of damage and the time of damage occurrence can be detected from the decomposed signals (Todorovska and Trifunac, 2010). Moreover, when they are applied to frequency domain data (e.g. Mode shapes) damage quantification remains problematic.

Considering aforementioned facts, this study is intended to investigate application of ANNs and WTs for damage identification using time domain and frequency domain data. Although this research mostly emphasises on the time domain data for seismic-induced damage identification, it also proposes a damage identification techniques that takes advantage of frequency domain data. The obtained results of this study also brightness limitation and capabilities of WTs, for seismic-induced damage identification of structures. In addition, it demonstrates that when WTs are combined with ANNs, damage localization, and quantification are achievable.

1.3 Objectives of the study

The main aim of this research is to develop novel methods for damage identification using ANNs and WTs. This research also investigates capabilities and limitations of WTs for damage detection of civil engineering structures by means of numerical and experimental approaches. The specific objectives of this research are as follow:

1. To develop a vibration-based damage identification method using ANNs and WTs. This method employs mode shapes as damage fingerprint.

2. To develop a Response-based seismic-induced damage identification method using ANNs and WTs. This method employs response accelerations as damage fingerprint.

3. To develop a Response-based seismic-induced damage identification method using ANNs alone. This method employs inter-story drifts as damage fingerprint.

4. To develop an optimal strain gage placement method for seismic health monitoring of structures.

1.4 Research Scope

This research is intended to propose novel response-based and vibration-based damage identification methods using ANNs and WTs. The scope of this study is limited to the following areas:

1- The development of a Vibration-based damage identification method using ANNs and WTs suitable for cantilever type structure including following subjects:

a) To determine a suitable dynamic-based damage fingerprint to be used as input patterns for ANNs.
b) To develop finite element models and verify them through experimental test.
c) To investigate the capabilities and limitations of DWT and CWT for vibration-based damage identification methods.
d) To design an ANN system, based on Network Ensembles for optimized network training.

2- The development of Response-based seismic-induced damage identification methods using ANNs and WTs suitable for cantilever type structures including the following subjects:

a) To determine a suitable response-based damage fingerprint to be used by WTs.
b) To investigate capabilities and limitations of Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT) for seismic-induced damage identification.
c) To investigate capabilities and limitations of Principal Component Analysis (PCA) for dimensionality and noise reduction.
d) To develop suitable nonlinear finite element models for the selected case study structure.
e) To investigate seismic behaviour of the selected case study structure by linear and nonlinear analysis.
f) To design an ANN system, based on Network Ensembles for optimized network training.

3- The development of Response-based seismic-induced damage identification methods using ANNs suitable for low and mid-rise concrete shear wall buildings including the following subjects:

a) To determine a suitable response-based damage fingerprint to be used as input patterns for ANNs.
b) To determine suitable nonlinear analyses capable of generating well-distributed training data sets for ANNs.
c) To design an appropriate architecture for the ANNs considering the determined damage fingerprint.

4- The development of an optimal strain gage placement method suitable for seismic health monitoring of civil engineering structures including the following subject:

a) To investigate the application of performance-based seismic design of structures for sensor installation in SHM systems.

1.5 Significance of research

Recent advances in electronic devices as well as unpredictable failure of in service structures have encouraged authorities to install structural health monitoring systems on important structures. Installation of structural health monitoring systems can result in the following advantages (Ansari , 2005):

1- Monitoring and evaluating of structures in Real-time under service condition.
2- Reducing downtime of structures.
3- Improving safety and reliability of structures.
4- Reducing maintenance cost.
5- In-service structures can be used more productively.

Abovementioned advantages are general benefits that arise from application of structural health monitoring systems. Since this study is intended to work on seismic-induced damage identification, it also addresses issues related to integrity of structures during or soon after earthquakes. After a strong ground motion, it is crucial to estimate the severity of imposed damage on important structures. Because based on the estimated severities, people can be asked to evacuate risky buildings and reduce the aftershocks hazard. Moreover, by returning low damaged structures to operation statues, post-earthquake problems can be significantly decreased.

Furthermore, damage localization by SHM reduces required time for visual inspections and results in less repairing time and cost.

1.6 Outline of Thesis

This thesis consists of nine chapters. The organization of this thesis is as below:

Chapter 1 presents an introduction to the work, describes research objectives and scope, and explains significance and motivation of this research.

Chapter 2 presents a literature review of existing Time-domain and Frequency-domain damage identification methods with more emphasis on ANN-based and WT-based methods. Theoretical backgrounds of artificial neural networks, wavelet transforms, and principal component analysis are also presented in this chapter.

Chapter 3 presents the modal testing and experimental modal analysis of the selected structures. Theoretical backgrounds of signal processing, frequency response function, and modal parameter estimation are presented in this chapter. The created finite element models and their verification method are also described.

Chapter 4 describes the methodology of the proposed methods for damage identification and optimal sensor placement. Theses methodologies include the proposed vibration-based damage identification method using ANNs and WTs and the two Response-based damage identification methods using ANNs and WTs. Moreover, the methodology of the proposed method for optimal strain gage placement is also described.

Chapter 5 presents the obtained results of the proposed vibration-based damage identification method using ANNs and WTs. Numerical and Experimental demonstrations of the applied method to the selected structure are presented in this chapter.

Chapter 6 presents the obtained results of the proposed response-based seismic-induced damage identification method that makes use of ANNs and WTs. Numerical demonstration of the applied method to Kuala Lumpur International Airport (KLIA) tower is presented in this chapter. This chapter is divided into three phases. The first phase describes the selected case study structure and illustrates the created finite element models and verification method. The second phase studies application of CWT and DWT for seismic-induced damage detection. The last phase presents the proposed damage identification technique.

Chapter 7 presents the obtained results of the proposed response-based seismic-induced damage identification method that makes use of ANNs. Numerical demonstration of the applied method on a 5-story concrete shear wall building is presented in this chapter.

Chapter 8 presents the proposed method for optimal strain gage installation for seismic health monitoring of structures. Numerical demonstration of the applied method to Kerman Air Traffic Control (ATC) tower, Iran, is presented in this chapter.

Chapter 9 summarizes the work of this thesis. Recommendations for future work are also presented in this chapter.

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