교량 건전성 모니터링을 위한 정보처리기법

An Overview of Information Processing Techniques for Structural Health Monitoring of Bridges

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요 지

교량 건전성 모니터링은 응답 데이터를 활용한 구조모델링기술, 신호분석, 정보처리 기술의 발전에 따라 손상추정 및 안전성평가와 함께 중요한 연구주제로 부각되었다. 교량 모니터링 시스템은 일반적으로 센서, 데이터 취득장비, 전송시스템 등과 같은 하드웨어와 신호처리, 손상추정, 전시 및 데이터 관리 등과 같은 소프트웨어로 구성된다. 본 논문에서는 교량의 건전도 모니터링을 위한 정보처리기술에 대한 연구 개발 활동을 정리하였다. 교량 건전성 모니터링의 과정에 대한 간단한 소개와 함께, 다양한 신호처리 및 손상추정 알고리즘을 포함한 정보처리기법에 대해서 소개하였다. 현 교량 건전성 모니터링 시스템에서의 주요 문제점과 향후 연구개발활동을 논의하였다.

핵심용어 : 구조 건전성 모니터링, 교량, 정보처리, 신호처리, 손상추정

Abstract

The bridge health monitoring has become an important research topic in conjunction with damage assessment and safety evaluation of structures owing to the improvement of structural modeling techniques incorporating response measurements and the advancements in signal analysis and information processing capabilities. The bridge monitoring systems are generally composed of hardwares such as sensors, data acquisition equipment, data transmission systems, etc, and softwares such as signal processing, damage assessment, display and management, etc. In this paper, the research and development(R&D) activities on the information processing for structural health monitoring of bridges are reviewed. After a brief introduction to the process of bridge health monitoring, various information processing techniques including various signal processing and damage detection algorithms are introduced in detail. Several challenges addressing critical issues in the current bridge health monitoring system and future R&D activities are discussed.

Keywords : *structural health monitoring, bridge, information processing, signal processing, damage detection*

1. Introduction

Bridge structures are exposed to various external loads such as traffic, earthquakes, gusts, and wave loads during their lifetime. The structures may get deteriorated and degraded with time in unexpected ways, which may lead to structural failures causing costly repair and/or heavy loss of human lives. Consequently, structural health monitoring(SHM) has become an important research topic in conjunction with damage assessment and safety evaluation of structures. The use of system identification approaches for damage detection has been expanded in recent years. This is due to the improvement of structural modeling techniques

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incorporating response measurements and the advancements in signal analysis and information processing capabilities.

Since the early 1990's developments and applications of bridge monitoring systems have become active in Korea. The number of the deteriorated infra-structures, mostly built in the rapidly industrialized period of 1970's, has increased rapidly. Also the recognition of the infrastructure system's potential devastating disruption of due to natural and man-made hazards has increased as well. Particularly after the tragic collapse of the Sungsu Bridge crossing the Han River in Seoul in 1994, the Korean governmental authorities have issued more stringent requirements on bridge management and operational programs. The programs include systematic visual inspection, instrumentation, load capacity tests, and field measurements for design and construction verification and long-term performance monitoring and assessment.

Recently a number of long-span bridges were built in Korea and most of those bridges are equipped with a large amount of sensors and modern monitoring systems. The SHM systems are generally composed of two major parts: (1) hardwares such as sensors, data acquisition equipment, data transmission systems, etc, and (2) softwares such as signal processing, damage assessment, information display and management, etc. The first part of the SHM system involves observation of the structure using periodically sampled response measurements from arrays of sensors, storage of the measured data, and transmission of data to the control center. In the second part, extraction of the damage-sensitive features from the measurements is performed using various signal/information processing techniques, and then damage assessment algorithms are applied to determine the current state of the structural integrity. Since the number of bridges with monitoring system has increased, it is still more necessary to develop an effective damage assessment algorithm based on the monitoring data.

Damage detection methods for SHM can be classified as global or local methods based on the type of information to be used. Local methods concentrate on a part of the structure and are based on various nondestructive tests such as: acoustics emission, hardness, magnetic fields, radiography, X-rays, and piezoelectric sensors. Global methods can be classified as dynamic monitoring and static monitoring methods based on the kind of the measured data. The dynamic monitoring method, which has been used broadly for the damage detection, is based on vibration measurements. Vibration-based damage detection relies on the fact that a local stiffness change affects the global dynamic characteristics of the structure. Various algorithms and techniques for damage estimation and SHM of structures have been presented by many researchers. Recently, several attempts have been executed to apply the developed techniques to real structures. However, the application of those techniques to large civil structures such as bridges is difficult and contains many problems to be resolved.

In this paper, the research and development(R&D) activities on the information processing for bridge health monitoring are reviewed. First, the process of SHM is introduced to point out when the information processing techniques are necessary. Details on information processing in bridge health monitoring including various kinds of signal processing and damage detection algorithms will be explained. Several challenges addressing critical issues in the current bridge health monitoring system are introduced. Finally, future R&D activities will be envisioned followed by concluding remarks.

2. Structural Health Monitoring for Bridges

The process of bridge health monitoring involves the definition of potential damage scenarios for the system, the observation of the system over a period of time using periodically spaced measurements, the extraction of features from these measurements, and the analysis of these features to determine the current state of health of the system. The output of this process is periodically updated information regarding the capability of the system to continue to perform its desired function in light of the inevitable aging and degradation

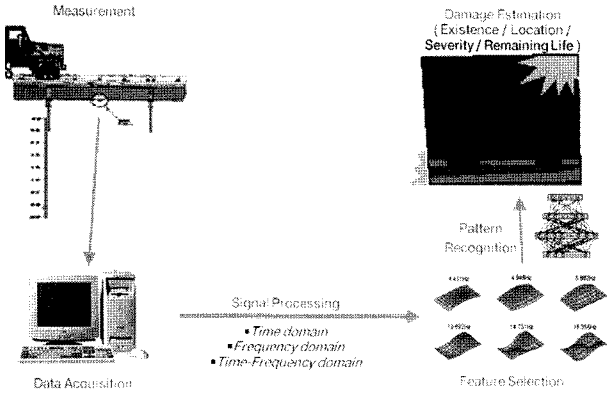


Figure 1 The process of bridge health monitoring

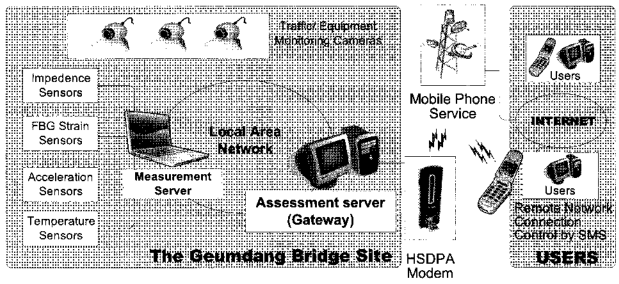


Figure 2 Remotely Controllable SHM System Using 3.5G Mobile Telecommunication Technology (Lee et al., 2008).

resulting from the operational environments. Figure 1 shows the procedure of bridge health monitoring. Damage detection methods in viewpoint of structural health monitoring for bridge structures need some special features such as (1) quick calculation suitable for continuous on-line monitoring, (2) low possibility of damage missing, and (3) handling a huge information applicable to a large civil-infra structures.

2.1 Measurement and Data Acquisition

Measurement and data acquisition portions of the SHM process involve selecting the types of sensors to be used, selecting the location where the sensors should be placed, determining the number of sensors to be used, and defining the data acquisition/storage/ transmittal hardware. This process is application specific. Economic considerations play a major role in these decisions. The primary sensors used for bridge health monitoring are strain gauges, displacement transducers, accelerometers, tiltmeters, etc. In addition to the structure's responses, environmental variability such as temperature, humidity and wind speed is of great concern. Long-span bridges have been instrumented with these conventional sensors. For example, 66 sensors for static and dynamic measurements were installed at Jindo Bridge; 74 channels are used to measure the static data such as bi-axial tiltmeters, submersible tiltmeters, and static strain gauges and 36 channels are used to measure the dynamic data such as dynamic strain gauges, accelerometers, and anemometers in Namhae Bridge; a total of 380 sensors were installed at Yongjong Bridge; 21 sensors for static and 99 for dynamic data were instrumented at Seohae Bridge(Yun et al. 2004a).

Not limited to these conventional sensors, the smart sensors, such as piezoelectric sensors, optical fiber sensors, optic sensors, MEMS and Wireless sensors, etc. enrich and complement a currently available list of sensors for monitoring the structural response of bridges. As to the data transmission and recording, the researches on wireless data acquisition systems for large civil engineering structures have been increased rapidly(Yi et al., 2006; Kim, 2008; Heo et al., 2007). 3.5 generation mobile telecommunication technology, HSDPA(High Speed Downlink Packet Access) was utilized to construct remotely controllable bridge monitoring system in rural areas where conventional internet services are not readily available as shown Figure 2(Lee et al., 2008).

2.2 Feature Selection

Feature selection is a very important process. Since the features are used to distinguish the damaged structures from undamaged ones, many researchers have paid a lot of attention to select proper features representing the structure's status. Usually, the condensation of the data is the first step in the feature selection process. Data condensation is advantageous and necessary, particularly in the on-line monitoring system where comparisons of many data sets over the lifetime of the structure are envisioned. Also, robust data reduction techniques must retain sensitivity of the chosen features to the structural changes of interest in the presence of environmental noise. The best features for damage detection are typically application specific. Numerous features are often chosen for a structure and assembled into a feature vector. In general, a low dimensional feature vector is desirable. Various signal processing techniques in frequency domain, in time domain, and in time-frequency domain can be employed to identify features for damage detection. Fitting linear or nonlinear, physical-based or non-physical-based models of the structural response to measured data can also help identify damage-sensitive features. Basic modal properties including natural frequencies, mode shapes and modal damping ratios, mode shape curvature changes, dynamic flexibility matrices and stiffness indices from updated finite element models are most commonly used for damage detection in bridges(Doebling et al., 1996).

2.3 Damage Estimation

Damage estimation process in the bridge health monitoring involves the pattern classification/ recognition process. Usually four levels of damage identification(detection, localization, quantification, and prediction) are discriminated(Rytter 1993). The damage detection methods for SHM techniques can be classified as global or local methods based on the type of information to be used. They can be also classified into two groups according to the dependence on the structural model: i.e. signal-based and model-based methods(Doebling et al., 1998; Zou 2000). Signal-based methods detect damages by comparing the structural responses before and after damages, not using the information on the structural model. Damages are defined by damage indices, which may be determined using the results of the experimental modal analysis(Abdel Wahab and De Roeck 1999; Pandey et al. 1991; Sampaio et al. 1999; Stubbs et al. 1995) or the time-frequency domain analysis(Hou and St. Amand 2000; Quek et al., 2001; Zou 2002). Signal-based damage estimation methods are generally appropriate to detect the damage existence and locations, but they are not effective for estimating damage severities. On the other hand, model-based methods can estimate the damage severities as well as locations by correcting the mathematical model of the structure based on the experimental data. This is possible since the structural damages result in changes of the dynamic characteristics(Brownjohn 2001; Shi et al., 1998; Stetson and Harrison 1981; Yun and Hong 1992). Using the measured data, various techniques have been developed for estimating the stiffness changes due to damage. Recently, soft computing techniques such as the neural networks and genetic algorithm and various pattern recognition algorithms such as probabilistic neural networks and support vector machine have been utilized increasingly, since the damage detection problem falls into pattern classification/recognition problem(Chou and Ghaboussi 2001; Lee and Yun 2007; Levin and Lieven 1998; Specht 1990; Vapnik 1995; Wu et al., 1992; Yun and Bahng 2000). In the following section, more details on various damage detection methodologies will be addressed.

3. Information Processing Techniques

Information processing in bridge health monitoring includes (1) signal processing for feature extraction from the continuously monitored data and (2) damage detection based on the damage-sensitive features or raw measurement signals using various pattern recognition and optimization techniques.

3.1 Signal Processing Techniques

3.1.1 Frequency domain methods

Filtering is the fundamental signal processing tool in frequency domain, which may be used for a range of applications such as rejecting unwanted signals, data smoothing, sample rate conversion(upward and downward decimation), etc. Three basic ideal filters are low-pass, high-pass and band-pass filters. To design a filter for a specific bridge monitoring system, engineers should use prior knowledge on the structure's expected responses and the sensors' performance, since filtered signals may lose significant information on the structure's status.

Experimental modal analysis(EMA) has drawn lots of attention from structural engineers for updating the analysis model and estimating the present state of structural integrity. EMA is the procedure to find the frequency, damping and mode shapes from experiment, and those modal parameters can describe the structure's physical model(mass, stiffness, and damping). Forced vibration tests such as impact tests can be carried out for this end, however, it may be restricted to small-scaled structures and/or it may be difficult and expensive for large structures such as dam, and long-span bridges. In those cases, ambient vibration tests under wind, wave, or traffic loadings may be more effective alternatives. In a continuous bridge monitoring system, the ambient vibration data will be the fundamental data to be processed.

Since the modal parameters are, in nature, the structure's frequency information, most of the experimental modal analyses are carried out in frequency domain. The peak picking(PP) method using power spectral density(PSD) functions is widely used in practice(Bendat and Piersol 1991). The frequency domain decomposition(FDD) method that utilizes the singular value decomposition of the PSD matrix may be used to separate close modes(Brincker et al., 2000). The method was originally used to extract the operational deflection shapes in mechanical vibrating systems(Otte et al., 1990). Enhanced Frequency Domain Decomposition(EFDD) method is newly devised to identify damping in a closely spaced mode, which combines FDD algorithm and time domain modal parameter identification algorithm for a single degree of freedom system(Brincker et al., 2001).

Recently, experimental modal analysis has been carried out in the long-span bridges to obtain the dynamic characteristics such as natural frequencies and mode shapes(Chang et al., 1994). Jung et al. (2002) carried out ambient vibration tests on Namhae suspension bridge and the effect of traffic and temperature on the measured natural frequencies was investigated. Kim and Park(2008) performed modal parameter identification based on the ambient vibration data of Seohae Cable-stayed Bridge. Cable tension is of great concern in the long-span cable bridges(Kim et al., 2006). Kim et al.(2007) developed back analysis technique for the estimation of cable tension force of Gwang-An suspension bridge based on the identified natural frequencies from acceleration data.

3.1.2 Time domain methods

There are several time-domain modal parameter identification methods, most of which use an assumption that the ambient loads are Gaussian white noise processes. Ibrahim time domain method was developed in late 1970s(Ibrahim 1977), which was formulated based on the condition with free vibration responses in continuous time domain. The eigensystem realization algorithm(Juang 1994) and the stochastic subspace identification method(Overschee and De Moor 1996) were developed based on the system theory in the discrete time domain. Yi and Yun(2003) carried out comparative studies on output-only modal identification algorithms by comparing the modal parameters obtained from various experimental data such as ASCE benchmark structure subjected to roof excitation, National Taiwan University(NTU) building frame model subjected to earthquake excitation, and a bridge model under traffic loadings. Before applying modal parameter identification algorithms to ambient vibration data, the random decrement(RD) technique can be employed to produce free-decay signals, from which the modal parameters can be easily extracted, by averaging the measured responses which are divided using several triggering scheme(Cole, 1968).

As one of the most popular time-domain method, the Autoregressive Moving-Average(AR-MA) algorithm can be used to describe the input-output relationship of a system. Since a few coefficients in ARMA model can represent the system's characteristics, the complexity dimension to be processed in a bridge health monitoring system will be affordable. Variations of the ARMA method to accommodate multi-point multi-output situations are the co-called Autoregressive Moving-Average with

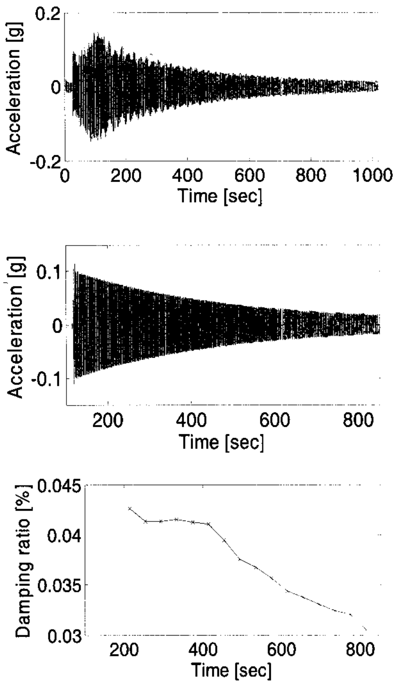


Figure 3 Estimation of a cable damping using Hilbert Transformation(Kim et al., 2008).

exogenous variables, ARMAX, and the Autoregressive Moving-Average Vector, ARMAV(Maia and Silva, 1997). Sohn et al.(2000) utilized an auto-regressive (AR) model fit to the measured time histories from an undamaged structure, and selected the coefficients of the AR model as the damage-sensitive features.

Hilbert transformation can be used to investigate the time varying modal parameters(Jang, 2005). Since it can be applicable to a single mode vibration data, filtering the raw signal is required to re-generate signals with specific frequency contents. Kim et al.(2008) identified the amplitude-dependent, time varying damping ratios of a stay cable using Hilbert transform.

3.1.3 Time-Frequency domain techniques

Fourier transform decomposes a signal into its various frequency components. As it uses the sinusoidal basis functions that are localized in frequency only, it loses the transient feature of signals. Therefore, it is necessary to implement the time-frequency analysis for diagnostics of transient signals. As one of the time-frequency domain transformation techniques, the short-time Fourier transform calculates the local spectral density using windowing techniques to analyze a small section of the signal at a time. However, it is impossible to simultaneously achieve high resolution in time and frequency.

In order to overcome the limitations of harmonic analysis, alternative families of orthogonal basis functions called wavelets have been used. The wavelet analysis was originated from 1909's by Haar, but it began to be widely used in the field of signal processing, such as image processing, pattern recognition, regression estimation, and other various applications since 1990 (Mallat, 1998). In recent years, wavelet transform has been also frequently used for damage detection. Zou et al.(2002) applied wavelet decomposition for identification of a cracked rotor, Newland(1999) used harmonic wavelets to identify ridge and phase in the frequency analysis of transient signals. Hou and St. Amand (2000) used a wavelet decomposition to damage detection for a single degrees of freedom system with multiple breakable springs, and Lu and Hsu(2002) used it for detection of mass concentration of an inhomogeneous string.

The Hilbet-Huang Transform(HHT) was developed for time-frequency analysis of dynamic signals by Huang et al.(1998). The HHT can be applied to many mathematical and engineering problems and is superior to the existing Fourier-based method in processing non-stationary data. Recently, its applications increase. In civil engineering, Zhang. and Ma.(2001) used the HHT to analyze near-source ground motion recordings. Another basic application of the HHT is the system identification of linear structures by Yang and Lei (2000) who presented the identification of the dynamic characteristics of linear multi-degrees of freedom(MDOF) systems using measured impulse response based on the HHT method. The HHT may be applied to analyze structural response and extract damping. Chen and Xu(2002) used empirical mode decomposition to identify modal damping ratios of structures with closely spaced modal frequencies.

Time-frequency domain methods such as Hilbert-Huang transform(HHT) and wavelet transform techniques have been applied to the detection of damage locations

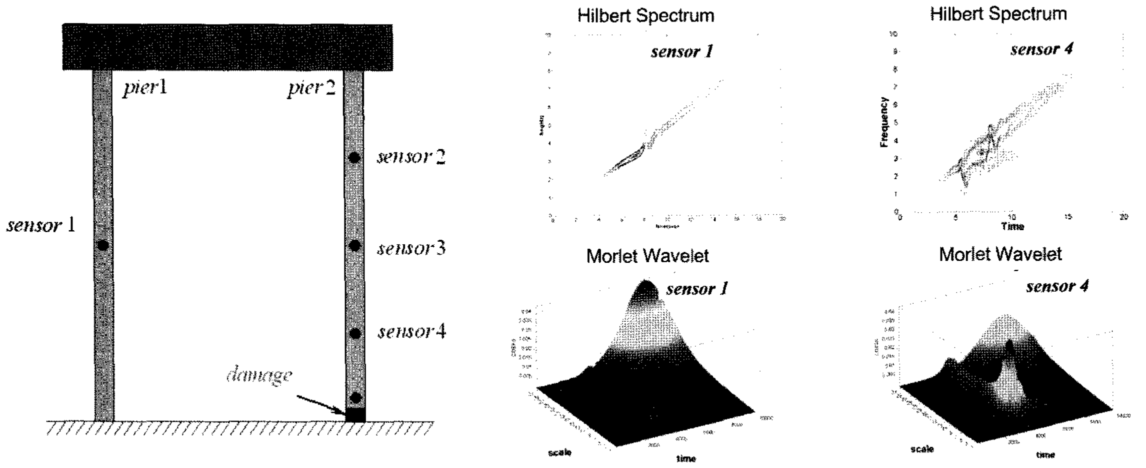


Figure 4 Damage Detection for Bridge-Pier System Using Time-frequency Domain Methods(Jang, 2003)

in several civil infrastructures(Jang, 2003). The HHT and wavelet methods may be used to identify the locations of damages which exhibit nonlinear and non-stationary behavior, since the instantaneous frequency characteristics of the measured signals can be analyzed by those methods. Various numerical simulations have been carried out on bridge structures with damages using controlled excitations with sweeping frequency as shown in Figure 4. Bilinear model using a gap element is employed to model the behavior of cracked elements in the numerical simulations. The results indicate that time-frequency domain methods can reasonably identify the damage locations based on a limited number of acceleration sensors.

3.1.4 Principal Component Analysis

Principal component analysis(PCA) is a statistical technique that linearly transforms an original set of variables into a substantially smaller set of uncorrelated variables that represents most of the information in the original set of variables(Jlooiffe, 1986). It can be viewed as a classical method of multivariate statistical analysis for achieving a dimensionality reduction, also known as Karhunen-Loeve(KL) transform(Krzanowski, 2000). Based on the fact that a small set of uncorrelated variables is much easier to understand and use in further analysis than a larger set of correlated variables, this data compression technique has been widely applied to virtually every substantive area including engineering, biology, medicine, chemistry, meteorology, geology, as well as the behavioral and social sciences.

Park et al.(2008) utilized the PCA algorithm for data compression and noise reduction of the electro-mechanical impedance signatures, since the size of the raw impedance data is prohibitive for a direct use and the raw impedance data are usually very sensitive to some ambient noise effects. The most significant principal components(PCs) obtained from the raw impedances contain dominant frequency responses. In order to determine an adequate number of the PCs which can represent the original impedances well, the reconstruction using a different number of the PCs was

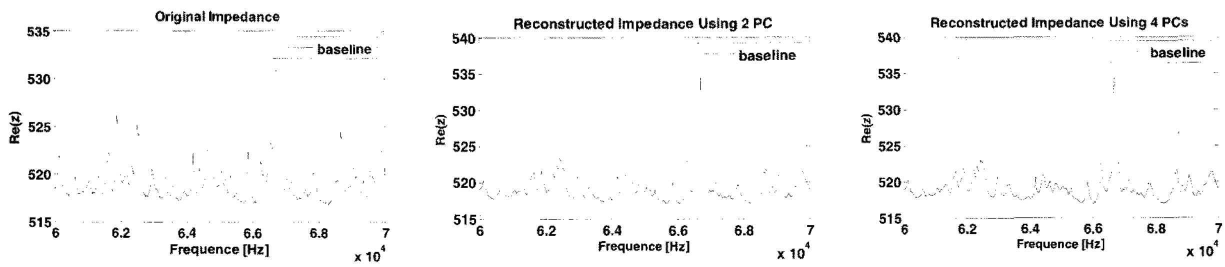


Figure 5 Reconstructed impedances using a different number of principal components(Park et al., 2008)

investigated as in Figure 5.

3.2 Damage Detection Methods

3.2.1 Signal-based damage detection

Various kinds of feature vectors have been utilized in the signal-based damage detection. Examples are raw strain or acceleration data, frequency response function, electro-mechanical impedance, modal quantities including natural frequencies, mode shapes and modal damping. Variations of modal quantities such as Modal Assurance Criterion(MAC), Coordinate Modal Assurance Criterion(Heo et al., 2003), mode shape curvature, and time varying dynamic characteristics such as wavelet coefficients have been widely utilized as damage-sensitive feature vectors.

Changes in modal parameters

Modal parameters are identified from the measured response time-histories, most often accelerations. The amount of literature that uses resonant frequency shifts as a feature for damage detection is quite large. Observing the change of structural properties that affects vibration frequency was the primary stimuli for developing signal-based damage identification technology. The natural frequencies can be measured more accurately than the mode shapes. However, it is well known that the natural frequencies are sensitive to the environmental effects such as temperature, humidity, etc.

In general, changes in frequencies cannot provide spatial information about structural changes. Mode shape vectors are spatially distributed quantities; therefore, they provide information that can be used to locate damage. Mode shape curvature can be computed by numerically differentiating the identified mode shape vectors twice to obtain an estimate of the curvature which is much sensitive to small perturbations in the system than the mode shape itself. Also, for beam- and plate-like structures changes in curvature can be related to changes in strain energy, which has been shown to be a sensitive indicator of damage(Abdel Wahab and De Roeck, 1999; Kim and Stubb, 1995; Li and Yam, 2001; Pandey et al., 1991; Yao, 1992).

Outlier analysis

An automated damage diagnostic system without requiring any *a priori* mathematical model of the structure may provide an efficient SHM tool for real structures. In order to satisfy this requirement, a so called "novelty detection" outlier analysis method has emerged as a robust unsupervised learning pattern recognition tool for damage detection of structures (Park, 2003a; Worden, 2000). The outlier analysis aims to establish simply whether or not a new pattern is significantly different from the previous patterns, at the same time automatically ignoring any negligible differences such as random fluctuations due to noise. That is, an outlier is an observation that is significantly different from the rest of the population and therefore the outlier is believed to be generated by an alternate mechanism. Researchers have paid attention to the extreme value distribution from a perspective of statistical damage assessment, since the response of a damaged structure will show significant abnormalities (Sohn, 2005).

3.2.2 Model-based damage detection

Least Square Error-Based Methods

The damage detection methods based on the minimization of the least-squared errors between the measured and the calculated responses by the finite element model have been studied. Several regularization techniques are introduced to alleviate the ill-posedness of the system identification problem. A geometric mean scheme is presented to determine an optimal regularization factor for Tikhonov regularization technique in the system identification problems of linear elastic continua. The characteristics of non-linear inverse problems and the role of the regularization are investigated by the singular value decomposition of a sensitivity matrix of responses(Park et al., 2001). Hjelmstad and Shin (1997) proposed an adaptive parameter grouping updating scheme to localize the damage zones in the structure and utilized a Monte Carlo method with a data perturbation scheme to provide a statistical basis for assessing damage. Lee et al.(1999) presented a system identification scheme to determine the geometric shape of an inclusion in a finite body. A variable regularization factor scheme is proposed for a consistent regularization effect. Numerical simulations and laboratory experiments have been performed on various kinds of model structures(Park, 2003b). Yi and Yun(2002) applied the inverse perturbation technique for FE model updating, in which Tikhonov regularization algorithm was employed to reduce the ill-posedness during the FE model updating.

Modal Strain Energy based-based Methods

Kim and Stubbs(2002) recently proposed an improved damage indication method to predict locations and severities of damage in structures using changes in modal strain energy. The damage prediction accuracy was numerically assessed for a two-span continuous beam using a few vibration modes. Kim et al.(2003a) presented a methodology to nondestructively locate and estimate the size of damage in structures for which a few natural frequencies or a few mode shapes are available. A frequency-based damage detection method and a mode-shape-based damage detection method were developed, and numerical simulations were performed on a prestressed concrete beam.

Kalman Filter

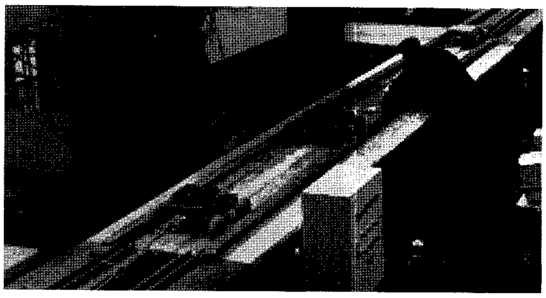
In 1960, R.E. Kalman published his famous paper describing a recursive solution to the discrete-data linear filtering problem. Yun and Shinozuka(1980) applied the extended Kalman filtering to the identification of a structural dynamic system with nonlinear damping terms by introducing the state vector augmented with the unknown parameters to be identified. Loh and Chung(1993) applied the extended Kalman filtering on identification hysteretic nonlinear systems. Recently the extended Kalman filtering technique is applied to identification of time-varying dynamic characteristics by Sato and Takei(1997) and Loh et al.(2000).

The extended Kalman filter has been widely used for detection of the parameter changes due to the structural degradation and damage because the technique can identify time-varying parameters including abrupt changes of parameters. However the extended Kalman filter has several drawbacks such as divergence phenomenon and biased estimation. Many adaptation algorithms and innovative filtering techniques such as sequential prediction error method, unscented Kalman filter and Gauss-Hermite filters have been studied to enhance the results of the parameter estimation for systems with MDOF based on a limited numbers of the measured components(Koo and Yun, 2002).

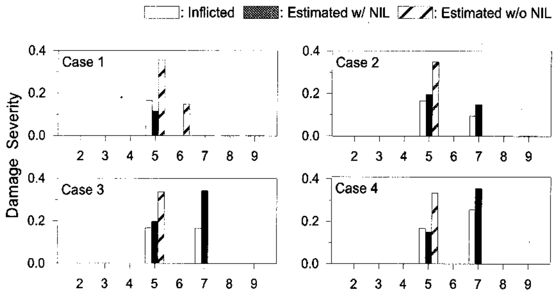
3.2.3 Soft computing techniques for pattern recognition

Soft computing techniques such as neural networks (NN) and genetic algorithms(GA) have been utilized increasingly for the damage estimation due to their excellent pattern recognition capability(Chou and Ghaboussi, 2001; Wu et al., 1992; Yun and Bahng, 2000). Basically, NN and GA can be utilized as an optimization tool in the least square error-based approach, in which those methods were found to have almost same performance. NN requires all training samples to be prepared *prior*, whereas GA calculates the cost(lost) function for several cases(training samples) at each step(generation). Therefore, NN is fit to the on-line health monitoring system and GA can be utilized for further investigations after damage alarming happens.

Probabilistic neural networks(PNN) and support vector machine(SVM) have been utilized for various pattern recognition problems. PNN differs from NN, since it requires only forward processing whereas NN needs to be trained by error back-propagation algorithms. SVM can provide an optimal decision boundary in classification problem, since it is based on the Structural Risk Minimization(SRM) principle and the optimal decision boundary maximizes the margin. To apply PNN and SVM techniques to damage detection of bridge structures, special concerns should be paid to reduce the number of input and output variables, since they can show excellent classification performance with small dimension of complexity.

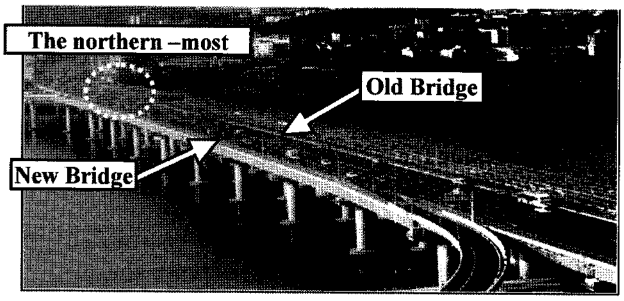


(a) Vehicle running tests

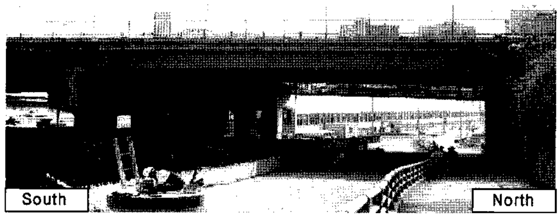


(b) Damage estimation results

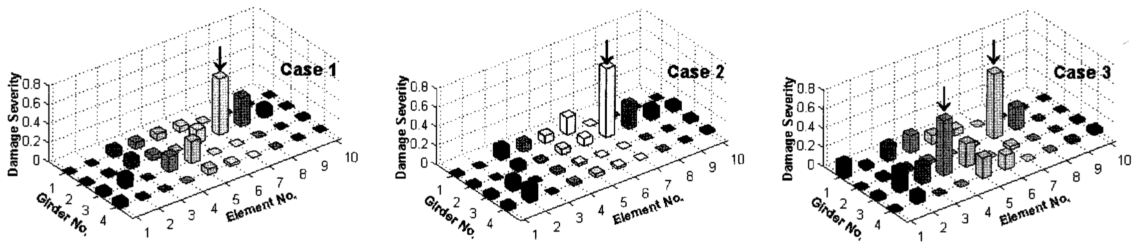
Figure 6 Laboratory Test(Lee et al., 2002)



(a) Hannam Grand Bridge



(b) Test Bridge : Northern-most span of old bridge



(c) Damage detection results

Figure 7 Field Test on Hannam Grand Bridge(Lee et al. 2005)

Neural Networks

Pattern-recognizing techniques using neural networks (NN) have been well utilized in the field of structural identification for complex structures. Using NN, structural identification can be carried out without the mathematical models and the inverse search procedure. For on-line health monitoring, the damage identification should be quickly carried out for adequate diagnosis on the structural integrity. Moreover, when the health monitoring system gives an indication of occurrence of damages, detailed analyses should immediately follow for verification. The NN-based identification approach has great advantage for on-line health monitoring, since it needs very short time to assess the structural integrity based on the measured data once the NN has been trained properly. Moreover, the NN can deal with various types of input data. Lee et al.(2002) presented a NN-based damage estimation of a bridge structure using ambient vibration data caused by the traffic loadings. An improved algorithm to consider the modeling errors in the baseline finite element model was also presented(Lee et al., 2005). Experimental studies were carried out on a bridge model subjected to vehicle loadings and on a span of Hannam Grand Bridge over Han River in Seoul to confirm the applicability of the NN-based approach.(Figures. 6-7).

Genetic Algorithms

The genetic algorithm is a random search algorithm based on the mechanics of natural selection and natural genetics. GA revolves around the genetic reproduction processes and survival of the fittest strategies. GA has many advantages such as (1) it can optimize with continuous or discrete parameters; (2) it can deal with a large number of parameters; (3) it has possibility of optimizing parameters with extremely complex objective function that has several local minima, and (4) it is well suited for parallel computing techniques.

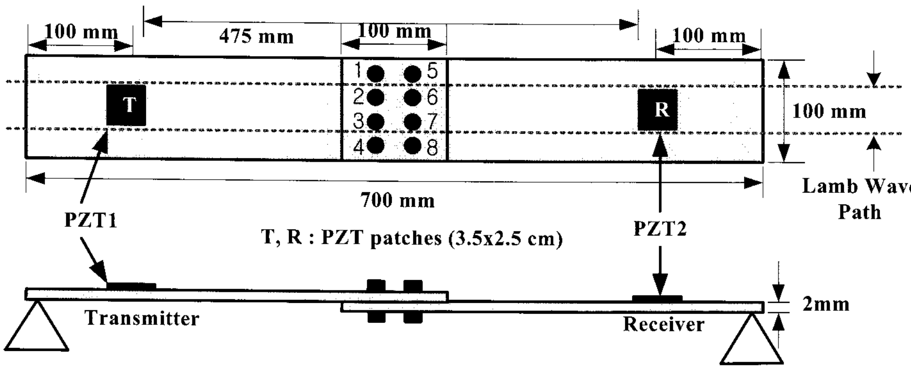
Yun et al.(2004b) applied the genetic algorithm to modify the structural model of two actual bridges based on the modal data such as natural frequencies and mode shapes. Jung and Kim(2006) suggested a model updating method based on a hybrid optimization technique using genetic algorithm and Nelder-Mead simplex method. Lee(2005) suggested a method to identify damages of free vibrating thin plate structures using the combined finite element method and the micro-genetic algorithm.

Support Vector Machine

Recently, the support vector machine(SVM) has been applied to various pattern recognition applications such as text classification and image recognition(Vapnik, 1995; Ye et al., 2005), and has been extended to regression analysis(Muller et al., 1997; Vapnik, 1999; Zhang et al., 2006). The support vector machine(SVM) is an automated learning system that uses a hypothesis space of linear functions in a high dimensional feature space. The formulation is based on the Structural Risk Minimization(SRM) principle. The simplest model is called as the linear SVM, and it works for data that are linearly separable in the original feature space only. In the early 1990s, nonlinear classification in the similar procedure as in the linear SVM became possible by introducing nonlinear functions called kernel functions without being conscious of actual mapping space.

Park et al.(2006) applied support vector machine to discriminate damages out of Lamb wave path and damages in Lamb wave path for the steel beam plate model. Wavelet coefficients and the time of flights of Lamb waves guided by two PZT patches were utilized as input feature vectors to support vector machine.

Probabilistic Neural Networks



(a) Experimental Configuration

Intact & out-of-path damages   Intact & in-path damages

(b) Feature Space Divided by SVM Classifiers

Figure 8 Loose bolt detection using support vector machine(Park et al., 2006)

Probabilistic neural networks(PNN) is basically a pattern classifier that combines the well-known Bayes decision strategy with the Parzen non-parametric estimator of the probability density functions of different classes(Specht, 1990). PNN has an advantage of quick calculation, since it is basically forward process. It does not need the training process as in the conventional neural networks. PNN uses supervised learning algorithms, and the training patterns are to be generated from the FE model. Training process in PNN is just to allocate some training samples to a certain class. The class to be identified can be defined according to the damage mechanism, the type and location of structural members, the individual structural members etc.

PNN has been used for damage detection of bridge structures. Ni et al.(2000) applied PNN to identify the damage type and location in the cable-stayed Ting Kau Bridge from the simulated noisy modal data. Cho et al.(2002) presented two-step approach using PNN to identify the damage location and the severity of damage using simulation data. Aoki et al.(2002) identified collapse mechanism of chemical plants using PNN for seismic vulnerability assessment. Lee and Yun(2007) identified the damage location of the old Hannam Grand Bridge using PNN based on the mode shape differences between before and after damage. To reduce the number of classes to be identified, some neighboring elements were grouped to the same class.

4. Challenges in information processing for structural health monitoring of bridges

Some issues remain to be resolved before the conventional information processing techniques become truly viable methods for structural identification and damage assessment such as

- Measurement noise,
- A limited number of sensors,
- A large number of structural members.
- Sensitivity to environmental conditions,
- A new paradigm of decentralized SHM

The effect of measurement noise can be relieved by the noise injection learning algorithm in the neural networks-based damage detection methods(Lee et al., 2002), and the regularization scheme in the least square error-based approach(Park et al., 2001). However, field engineers should pay careful attention to obtain data as clean as possible at site, since no sophisticated algorithm can produce valuable results from garbage.

The number of sensors is related to the damage to be monitored as well as the cost. The researches about optimum number and locations of sensors for health monitoring have been carried out.(Heo and Choi, 2002) studied an optimal sensor location(OSL) criterion suitable to the continuous health monitoring of a cable stayed bridge, in which a kinetic energy optimization technique and an effective independence method were analyzed. Park(2003c) utilized Shannon′s sampling theorem to reconstruct exact mode shapes of a structural system from a limited number of sensor points and localizing damage in that structure with reconstructed mode shapes. Kwon et al.(2004) proposed a new optimal sensor location(OSL) method for locating accelerometers for modal identification, which applies the maximum likelihood method to determine OSL and results in a fisher information matrix(FIM) based on the eigenvector sensitivity with respect to structural parameters.

For realistic bridge structures, the degree of freedom (DOF) could be very large. The more complex the structural system is, the more difficult the required numerical calculation is. In addition, for the large structures, measuring and identifying the whole structures are very difficult, and the accuracy of the estimate is rarely reliable. One resolution is to use the substructural identification technique(Yun and Bahng, 2000); the structure can be examined substructure by substructure. Some subsections of a structural system may be more important and/or critical for structural safety. Another resolution is to use a multi-stage approach for damage detection of large structures(Ko et al., 2002; Lee and Yun, 2006). This multi-stage diagnosis strategy aims at successive detection of the occurrence, location and extent of the structural damage. It has many advantages such as efficiency in computational time and better estimation accuracy, etc. Moreover, it is suitable for on-line monitoring scheme. In a multi-stage approach, the assessment of damage severities is performed on the potential damaged members, which are to be identified in the previous stage. Accordingly, the damage assessment is undertaken on the less number of members, which can make the estimate results more accurate.

The issues on a limited number of sensors but a large number of structural members can be relieved by using the smart sensor technologies such as optical-fiber sensors, MEMS sensors, etc. Optical-fiber sensors have an advantage of multiplexing which can increase the number of sensors for bridge monitoring(Kim, 2006). MEMS sensors have an advantage of very low cost(Kim, 2008). Therefore, as the technologies on smart sensors are rapidly developed, a number of sensors can be fully employed in a structural health monitoring system in a cost-effective manner.

In real structures, the temperature effects on the measured structural responses can be much larger than the effects of damages, which may make the damage detection for real structures difficult. The changes of the measured data due to the environmental effects should be studied and those due to the damage should be discerned. Many researchers have studied the temperature effect on the dynamic response of a structure. Kim et al.(2003b) studied the variability of modal properties caused by temperature effects in plate-girder bridges and utilized the frequency-correction formulas to get rid of the temperature effects. Giraldo et al.(2006) accommodated the influence of external conditions by means of a principal component analysis of the identified parameters. Koo(2008) investigated the variation of impedance signatures measured by PZT sensors due to temperature effects, and suggested a new algorithm using cross-correlation coefficient with an effective frequency shift.

Algorithms for SHM can be categorized as either centralized or decentralized. The centralized approach requires all measured data to be synchronized and sent to a single location. Decentralized SHM algorithms allow each sensor to work independently without communication with surrounding sensor nodes. However, such decentralized approaches cannot account for spatial information(e.g., gradients in the strain/displacement responses, changes in mode shapes, etc.). Gao(2005) has recently proposed one of the first SHM strategies that is hierarchical in nature, allowing communities of nodes to collaborate, and account for spatially measured, multi-scale information. As the wireless sensors technologies have been developed rapidly, the scheme of decentralized SHM draws lots of attention and the algorithms suitable for the decentralized wireless sensor system should be embedded at a local control station, which is equipped with data acquisition boards, on-board computing processors, and wireless telemetry.

5. Concluding Remarks

In this paper, the information processing techniques for bridge health monitoring including signal processing techniques and damage detection algorithms have been reviewed. The developments and applications of the SHM systems have been very active particularly on long span bridges in Korea. However, the current system is limited to the development and installation of the monitoring systems for collection of the bridge responses under various operational and environmental loadings. They utilized advanced technologies such as data transmission by optical cables and web-based data display and management. However, further improvements are needed for information processing for active use of current monitoring facilities. In this regard, several challenges in information processing for structural health monitoring of bridges have been suggested. Since no sophisticated algorithm can produce valuable results from garbage data, the R&D activities on hardware components including smart sensors should be preceded.

Recently, several mega-projects sponsored by Ministry of Land, Transport, and Maritime Affairs (MLTM) have been initiated and several more projects are scheduled to be launched soon. In those projects,

(1) smart sensors such as GPS, wireless sensors, optical fiber sensors, etc., to gather geological, geographical, material and structural information, (2) information processing and structural health monitoring based on the measured data, and (3) integrated and automated system harvesting multi-disciplinary techniques from information technology, material science, mechanical engineering, robotics, electric/electronic engineering, not limited to civil and architectural engineering, are being highlighted. It is highly expected for practical bridge monitoring system to be actively realized through those application projects several years later.

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