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INTEGRATED STRUCTURAL HEALTH MONITORING SYSTEM FOR SEISMIC HAZARD MITIGATION APPLICATION

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ABSTRACT

This paper presents a new concept for integrated structural health monitoring (SHM) system and its potential use in seismic hazard mitigation application. In this integrated SHM system, dataflow is used as a unifying thread to integrate different components of a large scale on-line SHM system. Newly developed sensor data compression, interactive data retrieval and output-only structural parameter identification methods are adopted, which have a potential to address the challenging issues arising from current SHM practice. The proposed concept for integrated SHM system provides a framework for seismic monitoring systems, for which rapid data retrieval and analysis is highly desired during or immediately after strong earthquakes to enable rapid emergency relief and disaster assistance efforts. For performance evaluation, real sensor data d from a prototype integrated SHM system which is comprised of a model steel bridge, a real-time data acquisition system with remote access, were used in this study. The performance of the integrated SHM system with lossy data compression is also discussed in this paper.

Keywords: Damage detection, Data transmission, Earthquake, Sensor, Structural health monitoring

INTRODUCTION

In seismically active regions such as the west coast of the United States and Japan, the problem of gradual deterioration of the infrastructure over time is compounded by the sudden damage events due to the occurrence of earthquakes (Conte et al. 2003). Structural health monitoring (SHM) systems installed to these structures provide seismic response data which is essential to the quantitative study of structural behaviors during seismic events. By deploying an array of sensors distributed at key locations throughout the structure, damages suffered by the structure might be quickly diagnosed from measured seismic response data. For example, a real-time structural monitoring system installed in the 23-story Transamerica building in San Francisco is comprised of 30 sensors, with which engineers anywhere can assess the performance and safety of the structure immediately after an earthquake (Celebi et al. 2004). The development of reliable and cost-effective SHM system for civil structures is thus of importance to the society by cutting the retrofit cost and facilitating emergency relief and disaster assistance efforts after strong earthquakes.

Real-time monitoring requires not only reliable damage detection method but also efficient data transmission from remote site. In a strong earthquake event, real-time retrieving structural response data and analysis is important to emergency relief and disaster assistance efforts. For example, after a

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devastating earthquake, knowing which bridge is still operable will help decision maker to arrange a route for transporting rescue personnel and goods to disaster area.

Due to the large scale and complexity of civil infrastructure, current trend in on-line SHM system is towards the use of a large number of sensors (on the order of several hundreds of sensors) and future SHM systems may be comprised of even lager scale sensor networks. For example, the Wind and Structural Health Monitoring System (WASHMS) installed on the Tsing Ma Bridge in Hong Kong, China, is currently comprised of over 800 sensors (Ko 2003). For large scale sensor networks, efficient data transmission and data management become an increasingly important issue that deserves special attention. The WASHMS system is currently generating 140 Mbytes-per-hour sensor data which has posed challenges to data transmission and data mining. This problem becomes even more severe for wireless sensor networks which have limited communication bandwidth. Transmitting this huge amount of monitoring data to central data processing station via communication network with limited bandwidth might cause considerable time delay, especially during or immediately after strong earthquakes when communication bandwidth may become scarcely available because of possible damages to communication networks and a rise in emergency communication use.

Innovative sensor data compression methods are thus needed to facilitate fast and efficient transmission of seismic data. Data compression methods can be broadly classified into two categories (Nelson and Gailly 1995): lossless and lossy data compression. Lossless compression of seismic waveform data have been studied by a few researchers over the past two decades. Both linear predictor- and transform-based data compression methods have been used by Stearns and his collaborators (Stearns 1995) for compressing seismic waveform data. However, very little research has been reported on the effect of seismic data compression on the accuracy of structural health monitoring methods. From a SHM point of view, lossy compression is acceptable as long as signal distortion is kept within a reasonable level to which the damage index is insensitive, while achieving high compression rates. In the meanwhile, the huge amount of sensor data from large scale monitoring system also increases the burden on data analysis which may be necessary only for selected sensor data. Data users such as engineers or decision makers might want to retrieve sensor data at multi-resolution levels over different time periods. Very little if there's any research has been done on interactive data retrieval of seismic data which can be enabled by combining progressive data transmission and feature monitoring. With progressive transmission, one can transmit the coarser version of the sensor data first, followed by successive transmissions of the refined details. By doing so transmission bandwidth and time can be saved by retrieving fine waveforms only if deemed necessary after examining the coarse waveform first. Progressive compression is thus a highly desirable feature for interactive, multi-resolution retrieval and display of large volumes of seismic data, from remote sites. This paper presents the concept for an integrated SHM system which has a few important functionalities such as sensor data compression, interactive data retrieval and management. Such an integrated SHM system might alleviate the limited communication bandwidth problem and provide data users the flexibility to retrieve selected sensor data.

INTEGRATED STRUCTURAL HEALTH MONITORING SYSTEM

An on-line SHM system generally consists of three subsystems: data acquisition subsystem, data management subsystem and data retrieval subsystem, as shown in Fig. 1.

Aiming at a real-time SHM system with enhanced reliability and efficient data flow, the proposed integrated SHM system will combine the technological advances in sensor network, wireless communication, and information technology which provide the physical basis of its different functional modules. More specifically, the integrated SHM system has the following functional features:

- Wireless communication: Although currently having limitations such as limited bandwidth, wireless transmission of sensor data has several major advantages over conventional wired communications such as ease of deployment and location change, elimination of wiring damages likely to occur during strong earthquakes. Furthermore, the on-board computing capability of wireless sensor nodes allows for local signal processing such as data compression and feature extraction.

- Sensor data compression: the limited communication bandwidth and limited power are the two major issues that impede the broad application of wireless sensors. Innovative sensor data compression methods custom designed for wireless sensor network in SHM system can alleviate the above-mentioned problems associated with wireless sensors if not completely eliminated. Sensor data compression provides a potential solution to realizing rapid data access by engineers and decision makers immediately after a strong earthquake.
- Interactive data retrieval: large-scale on-line SHM system will generate a huge amount of sensor data. The huge data size also increases the burden on data analysis which may be necessary only for selected sensor data. Data users such as engineers or decision makers might have different interests in retrieving sensor data with varying resolutions during different time periods. Interactive data retrieval and management method provides data users the flexibility to select the time window and retrieve the selected sensor data with progressively increased resolution by first observing the changes in system features before downloading the data.
- Continuous knowledge updating: besides real-time damage detection, civil engineering structures can be considered as continually being tested under ambient vibration. The measurements from such ambient vibration test can be periodically analyzed to update the knowledge base for this structure. Knowledge extraction through data mining can be performed periodically for such purpose. A simple example would be to use strain measurements (i.e., how many strain cycles a hot spot has been loaded) for predicting the fatigue life the structure.

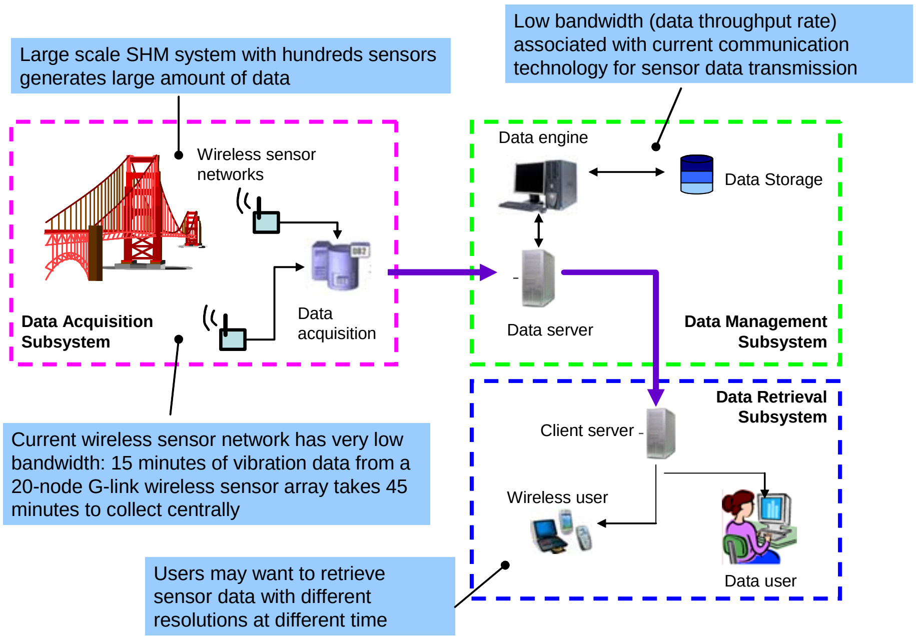


Figure 1. Schematic of a modern structural health monitoring system with wireless communication

The proposed integrated SHM system utilizes different algorithms in its different functional modules including sensor data compression for efficient data transmission, interactive data retrieval and structural system identification. For the data acquisition subsystem, linear predictor-based lossless data compression algorithm will be embedded on wireless sensor board to accelerate the data transmission; in the local data relay and central data processing station where sensor network data are available, AR model-based sensor network data compression method will be used to further reduce data size; then PCA-based data retrieval and management method will be used to interactively retrieve data from the sever by end users. In this way, data users will have the flexibility of interactively retrieving data based on the observed data features, for example, by selecting which data window and what data resolution to view. After receiving the progressively downloaded data, a second order structural system identification method will be used to locate and quantify structural damages, and predict the remaining structural capacity if possible.

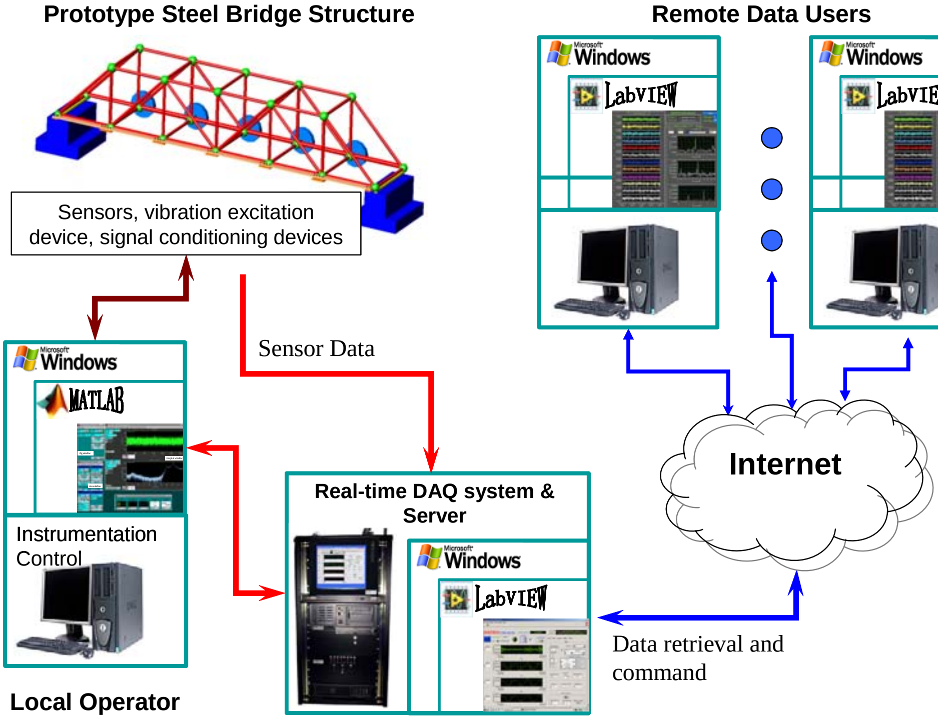
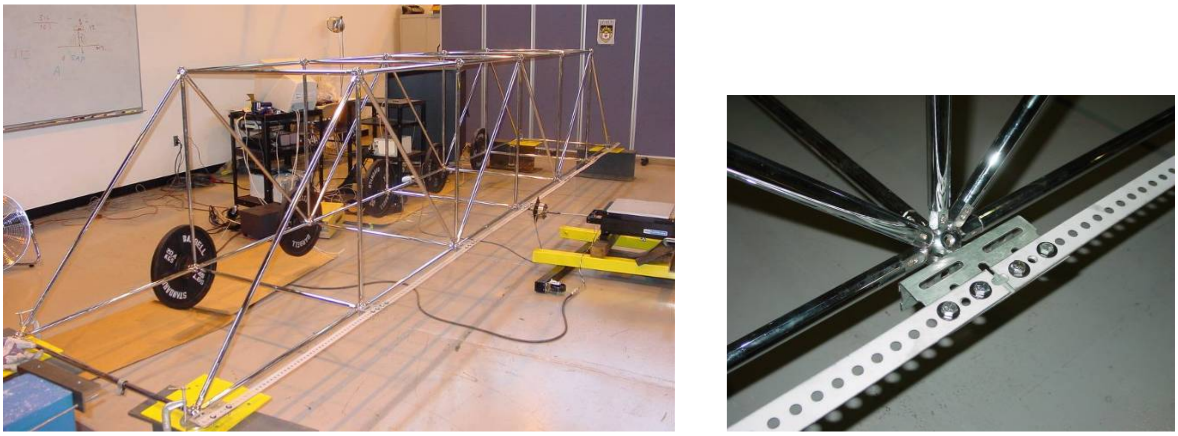


Figure 2. Schematics of the prototype integrated SHM system at Lehigh University

Under special situations where rapid data access is desired and some distortion to the sensor data can be tolerated, wavelet-based lossy data compression method (Zhang and Li 2006b) can be used at sensor node to achieve higher compression ratio at the cost of signal distortion. However, the wavelet-based lossy data compression method is not recommended for use in long-term monitoring applications requiring data integrity. Major advantages of such an integrated SHM system include: (1) sensor data size is reduced before sending the data to communication channel which will reduce the time latency and power consumption due to wireless transmission; (2) changes in system features can be observed before downloading data and used as an aid for determining what data to download; (3) The interactive data retrieval method provides the data user flexibilities on selecting data set and data resolutions. (4) The second order structural system identification method can be used to identify locations and severities of structural damages. For details of the respective technology, interested readers are referred to articles by Li and Zhang (2006a,b), Zhang and Li (2006a,b).

CASE STUDY: A PROTOTYPE INTEGRATED SHM SYSTEM

To demonstrate the concept for such an integrated SHM system, a vibration-based SHM system with remote access has been set up by the writers at Lehigh University. The schematics of this on-line SHM system are shown in Fig. 2. The structure being monitored (see Fig. 3-a) is a model steel bridge that measures 5-m x 1-m x 1-m. The four support nodes of the steel bridge structure are restrained from translational motion but allow rotation to some extent. Five steel weight blocks weighing 20.4 kg each (45 lbs) are attached to the 5 lower nodes on one side of the bridge structure each. Additional steel stripes (see Fig. 3-b) were bolted to all 7 lower nodes along one side of the bridge structure to provide additional stiffness in the transverse direction of the lower plane. Structural damages can be simulated by loosening the bolts at these connections.



(a) (b)

Figure 3. Pictures of the steel bridge structure in the prototype integrated SHM system: (a) overall view; (b) close-up view of the node with steel stripes

A schematics of this prototype integrated SHM system is shown in Fig. 2. A long stroke shaker with a 100-lbs maximum output force from the APS Dynamics, Inc., is used to excite the bridge structure at the middle node in the lower plane. The excitation force was measured with a 2-kips fatigue-rated load cell from Sensotec. The excitation force measurement was only used for system parameter identification in pre-test stage. For structural health monitoring in later stages, the excitation force (even it was measured) was not used since the system identification methods used in this stage do not require input information (i.e., output-only system ID methods). Five accelerometers (Model 393B04 from PCB Piezotronics) were used to measure the acceleration response of the steel bridge structure in this experimental study. The accelerometers were attached to the nodes along one side of the lower plane of the bridge structure. The RTMS-2001 real-time data acquisition system from Digitexx Data Systems was used for force and acceleration data recording and broadcasting the sensor data to Internet for remote data access. This 32-channel RTMS-2001 system offers an extensive set of remote tools for real-time monitoring, broadcasting streaming data (Internet, TCP, FTP), data retrieval, remote telecontrol, and event driven notification. Standard features of the system include delta-sigma A/D, pre-event, post-event, and signal filtering.

The following discussions are focused on two aspects of the proposed integrated SHM system: (i) the demonstration of the features of the integrated SHM system using this prototype system; (ii) Effects of the lifting scheme wavelet-based lossy data compression method (Zhang and Li 2006b) on system identification.

Features of the Prototype Integrated SHM System

The proposed SHM system has a capability of on-line structural health monitoring. Sensor data compression can also be executed on a real-time basis. Since the PCA transform-based interactice data retrieval method and the system identification method for damage detection have to be performed on a packet of data, time window was adopted to divide the continuously measured data into individual packets. Each measured data packet is denoted as one test data. One test data thus defined includes 1,024 data samples from each of the 5 accelerometers and therefore the data set contains a total of 5,120 samples. Since the sampling rate used by the data acquisition system was 200 Hz, the time window for dividing the measured data was therefore equal to 5.12 seconds. The following considerations were taken into account when selecting the time window: (i) the time window has to be sufficiently long to include the lower frequency contents of the original data to ensure the accuracy of system identification; (ii) the wavelet-based lossy data compression method requires the number of data samples to be the multiples of two.

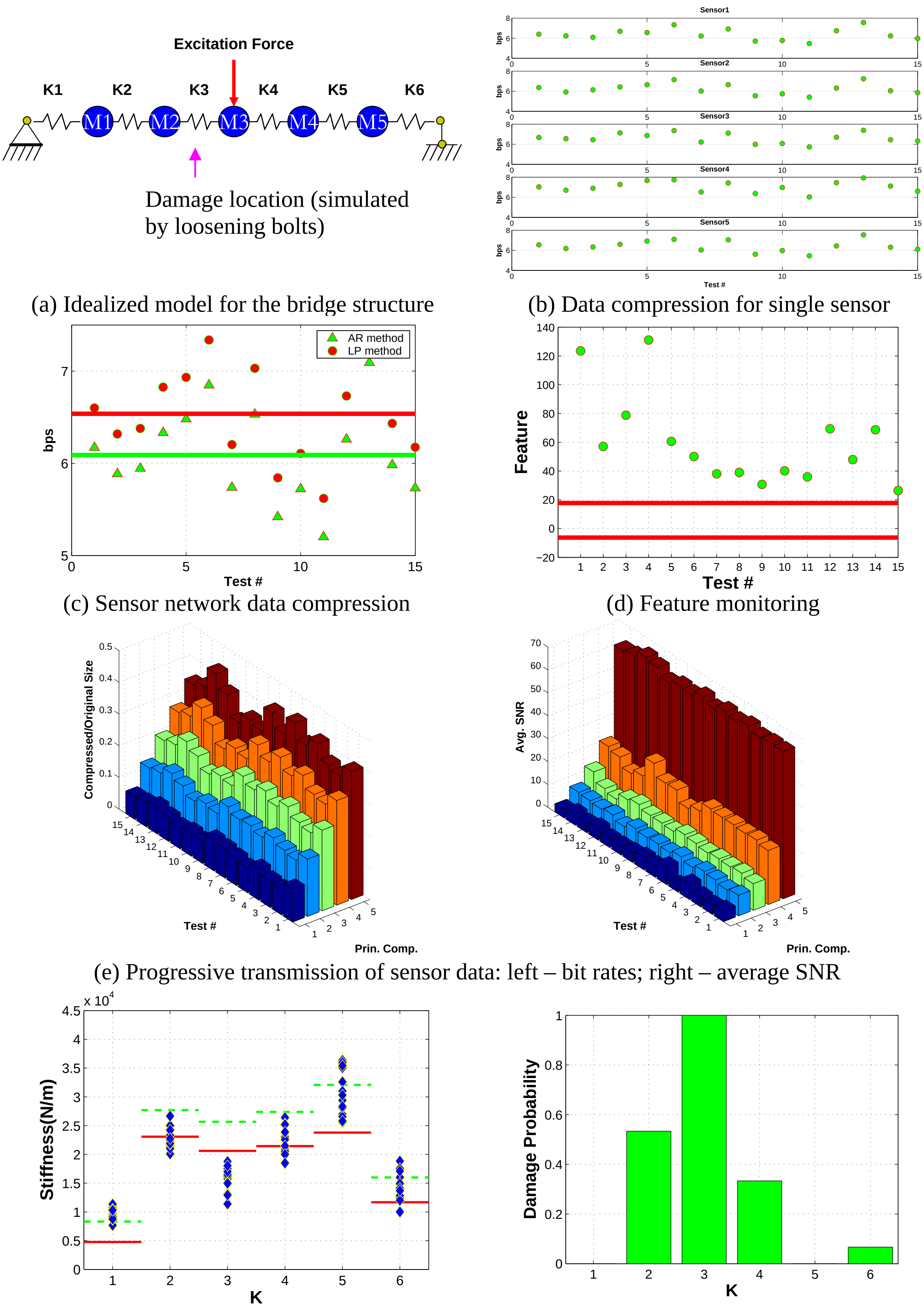
This study will focus on a vibration-based SHM method which uses the vibration responses of the structure for condition monitoring. In the vibration test of the bridge structure, random excitation with a bandwidth of 0 – 5 Hz was used to excite the structure. The 5 Hz bandwidth was chosen to excite the first several modes of the bridge structure. The first 5 modal frequencies of the bridge structure are: 1.64 Hz, 3.96 Hz, 6.24 Hz, 9.00 Hz and 11.09 Hz, respectively. A lumped-mass model for the bridge structure is shown in Fig. 4-a.

In the pre-test to establish a baseline, the following parameters need to be determined: predictor parameters for the linear predictor-based lossless compression method, distribution pattern for the quantizer in the wavelet-based lossy data compression method, upper and lower confidence control limits of the monitoring features for the interactive data retrieval method, lower limit of the structural stiffness identified by using the PEM-based second order system identification method. These parameters were determined using regression from a statistical analysis of 150 tests performed on the original structure. Details of this regression procedure are not presented here due to space limits.

Fig. 4 shows some the results from integrated monitoring of the bridge structure with a simulated damage scenario. The damage was simulated by fully loosening the steel strip connection as shown in the Fig. 3-b. The damage location is indicated in Fig. 4-a by a stiffness reduction in K3. Due to the configuration of this bridge, loosening a connection will affect the stiffness in neighboring spans. Therefore, the stiffness reduction was also observed in other spans. For this damage scenario, 15 tests were repeated in which a total of 15,360 (= 15 x 1,024) samples were collected from each sensor. It is assumed that before transmitting data from the sensor to the data acquisition system, the sensor data would be compressed using the linear predictor (LP)-based lossless data compression method at each sensor node. Fig. 4-b presents the average bits per sample (bps) of the sensor data after LP-based compression for each of the 5 accelerometers in these 15 tests. It is seen that the compressed data size is less than 8 bits/sample, and thus the data size was reduced by over 50% since the original data size is 16 bits for each sample.

On the local data relay or central data processing station where measurements from several or all sensors become available, the LP-based (using AR model) data compression method for sensor network data can be applied. By removing the spatial correlation between the measurements from different sensors, the AR model based data compression method can achieve higher compression ratios than the LP-based compression method for single sensor. Fig. 4-c shows the comparison of the compression results using the LP-based compression method for single sensor (denoted as LP method) and the AR model based compression method for sensor network data (denoted as AR method). The bit rate shown in this figure is the average bit rate of all five data sequences in each test. The solid lines in Fig. 4-c denotes the average value of the bit rates for the LP method and AR method respectively. It is seen that the AR method can further reduce the bits rates by about 0.6 bits per sample. This reduction in bit rates will translate into a higher compression ratio which will further reduce the time required for data transmission. When data is received at the data management station, an interactive data retrieval and management method (Li and Zhang 2006a) based on principal component analysis (PCA) will be applied. This method integrates feature monitoring, progressive data transmission with nearly lossless data compression.

Using the interactive data retrieval and management method, raw sensor data are preprocessed and stored as principal components on the data server in the data management station. Pre-defined features are first transmitted to data users to assist with data retrieval decision before sending them the actual data. Monitoring this feature can help data users make decisions on which data to retrieve at certain resolution level. As shown in Fig. 4-d, the solid line is the upper and lower bounds of the defined feature determined for the undamaged structure in the pre-test. If the feature goes outside the region between these two limits, it indicates the occurrence of major events such as changes in system properties, changes in excitation input (e.g., amplitude increase) or even changes in sensor itself (e.g., a bad sensor). The results shown in Fig. 4-d clearly shows that the features calculated from these 15 tests (with damage simulated by loosening the bolts at a connection) fall out of range between the pre-determined limits although it did not tell what type of changes have occurred in the system. Major changes in the feature being monitored certainly warrant the need for downloading the data with increased resolution levels. To find out what changes occur in the system, advanced information processing such as the PEM-based second order system identification method described below will be used.



(a) Idealized model for the bridge structure

(b) Data compression for single sensor

(c) Sensor network data compression

(d) Feature monitoring

(e) Progressive transmission of sensor data: left – bit rates; right – average SNR

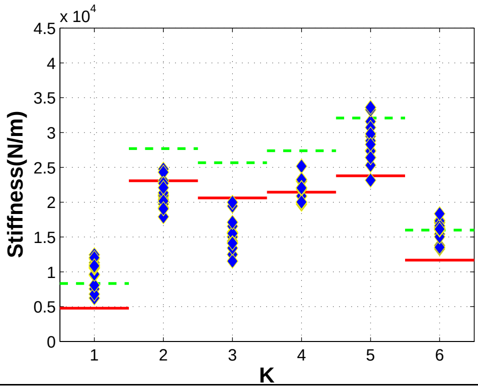
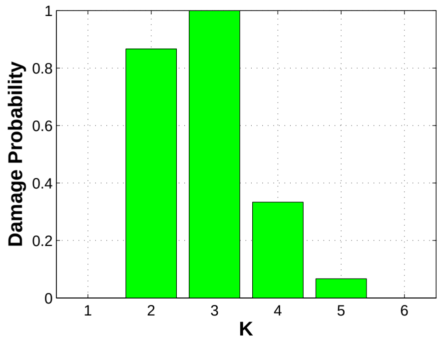
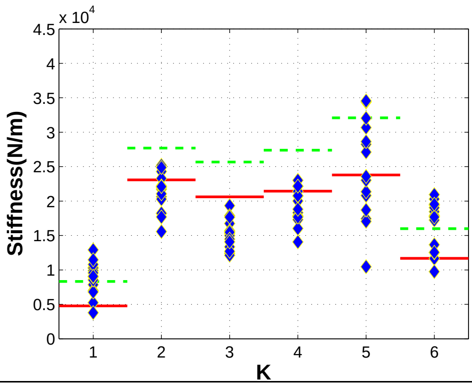
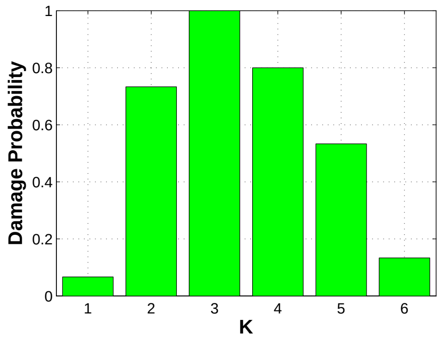
(f) Identified stiffness

(g) Statistical results for damage detection

Figure 4. Some results from the research on the integrated SHM system

Since the principal components contain different amount of information, the PCA-based interactive data retrieval method allows data users to download sensor network data progressively starting with the most important principal components. These principal components will also be compressed by LP-based compression method before transmission. By doing so, data can be downloaded and reconstructed progressively in a coarse to fine manner (i.e., with increased resolution). Therefore, before downloading all principal components is completed, only the key information is received by the data user. To measure the signal distortion associated with the received signals, signal-to-noise ratio (SNR) is used as a metric in this study. Fig. 4-e shows the progressively increased data size and the corresponding gradual increase of the SNR values during progressively downloading the principle components. If all 5 principle components (corresponding to the five accelerometers) were downloaded, the data size would be about 35% of the uncompressed data size with a SNR value near 60, which indicates very minor signal distortion for the transmitted data.

Table 1. Effect of wavelet-based lossy data compression on system identification results

	Identified Stiffness	Statistical Analysis
Wavelet-based lossy compression method with a 4-bit quantizer		
Wavelet-based lossy compression method with a 3-bit quantizer		

Finally, the downloaded data corresponding to the major events (as determined from the observed feature changes) will be analyzed using a PEM-based second-order structural system identification method (Li and Zhang 2006b). This system identification method directly identifies structural stiffness from ambient vibration data without the need for excitation input measurement. The statistical analysis of the identified stiffness during the pre-test stage provides the confidence limits for the structural stiffness. A stiffness value lower than the confidence limits will be classified as damage with 90% confidence. Fig. 4-f shows the identified stiffness for the six spans of the bridge structure from all 15 test data set for which further analysis is considered necessary due to the change in the monitored feature. Fig. 4-g shows the normalized occurrence frequency for the individual stiffness that is classified as being damaged in these 15 tests. Combining these results shown in these two figures, conclusion can be drawn to some confidence level that K3 was damaged. In the meanwhile, K6 may not have damage since only one identified results falls outside the pre-defined limits. Therefore, the finally acquired knowledge is that K3 was severely damaged and K2, K4 had some damage, and K6 most likely was not damaged. Since the identified features were structure stiffness, the remaining load capacity of the damaged structure can be predicted using these results in conjunction with a reliability analysis.

Effect of Lossy Data Compression on System Identification

Rapid data access and decision making are important to emergency relief and disaster assistance efforts during or immediately after extreme events. To achieve higher compression ratio, the wavelet-based lossy data compression method (Zhang and Li 2006b) can be used for the integrated SHM system if deemed necessary by engineering analysis. For lossy data compression, a critical step is to decide on the trade-off between higher compression ratio and signal distortion level. The lifting scheme wavelet-based lossy data compression method has the feature to limit the signal distortions to less important frequency band; therefore it can achieve a high compression ratio while retaining key information without much distortion. The key parameter which controls the performance of this method is the average quantizer bits. To demonstrate the concept, the measured data described in the preceding section were compressed using the wavelet-based compression method with an average quantizer bits number equal to 3 and 4 respectively.

Table 1 shows the damage detection results using the same system ID method with the reconstructed data after lossy compression. Compared with Figs. 4-f and 4-g, it is seen in Table 1 that the 4-bit wavelet method does not introduce much distortion to the identified stiffness and the same conclusion on damage scenario can be drawn from these slightly distorted identification results. However, significant distortions can be observed in the results corresponding to the 3-bit quantizer. The distortion affects the extraction of damage related knowledge from these parameters. Therefore, only well designed lossy compression method is acceptable that has a high compression ratio with reasonable signal distortions.

CONCLUSIONS

This paper presents a new concept for an integrated structural health monitoring (SHM) system and its potential application to seismic hazard mitigation. Features of the integrated SHM include: sensor data compression, interactive data retrieval based on feature monitoring, and statistical damage detection based on a PEM-based second order structural parameter identification method. These features are highly desirable to enhance the reliability, efficiency, and robustness of on-line SHM systems during earthquakes. To demonstrate the concept for such an integrated SHM system, a vibration-based SHM system with remote access has been set up at Lehigh University. The test results performed on this prototype integrated SHM system demonstrate the unique features and potential applications of the different functional modules in this integrated structural health monitoring system. The results also suggest that the lifting scheme wavelet-based lossy data compression has a potential to achieve a high compression ratio with controllable distortion effect on system identification and damage detection.

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