A Bridge Structural Health Monitoring and Data Mining System

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ABSTRACT

Structural health monitoring (SHM) is becoming a more widely accepted way to improve bridge management. In 2005, a fiber optic SHM system was developed and deployed by the Iowa State University Bridge Engineering Center to continuously monitor bridge performance under ambient traffic loads and to detect potential gradual deterioration or sudden damage, specifically for Iowa's fracture-critical bridges. Strain time history data collected by this system were utilized to construct a baseline model that is based upon extreme-matching distribution. Structural responses deviating from the baseline distribution are considered as indication of damage or degradation.

As a means to improve the damage/deterioration prediction capabilities of the above mentioned system, it is postulated that the dispersion of the extreme-matching data could be minimized using truck (position, type, etc.) information. Thus, techniques for the determination of detailed truck information are being investigated. Finite element analysis was carried out to verify the proposed truck detection and damage detection algorithms.

In this paper, the SHM system, relevant autonomous data mining results, and numerical verification are presented. Moreover, ongoing efforts in estimating the truck geometry/type, weight, and velocity are described.

Key words: fiber Bragg grating—strain—structural damage identification—structural health monitoring—truck identification

INTRODUCTION

Bridge aging and deterioration are impacting the nation's transportation safety and efficiency. In the United States, more than 50% of all bridges were constructed before 1950, and as of the year of 2003 27.1% of them (160,570) were rated as structurally deficient or functionally obsolete. It will cost $9.4 billion a year for 20 years to eliminate these bridge deficiencies (U.S. DOT 2003). To optimize the maintenance funding allocation and improve bridge management, it is essential to understand the real performance. Further, detecting damage/deterioration as early as possible will help owners get out in front of the deterioration curve and stay there. However, current predominant visual inspections have been shown by the Federal Highway Administration to be inefficient and unreliable at detecting localized damage (FHWA 2001). Other discrete short-term performance assessment approaches (e.g., traditional nondestructive testing techniques) only provide snapshots of structural conditions. They are inadequate for long-term structural integrity evaluation, especially for problems like fatigue damage detection. All these underline the importance of developing reliable and cost-effective tools for long-term structural health status evaluation.

Technological advancements in sensing, computing, and networking within the last decade have facilitated the exploration of long-term structural health monitoring (SHM) techniques, which conceptually allow for noninterruptive remote monitoring and evaluation of bridges or bridge components for extended periods of time. These approaches have been more and more widely accepted as a potential tool to prevent catastrophic failures and to improve bridge management.

On the other hand, dependent upon the number of deployed sensors and data acquisition frequency, the volumes of the data that are typically collected by long-term SHM systems are unmanageably large. Therefore, data mining, which addresses the problem of how to extract useful information from the data sets, is crucial for a successful SHM system deployment. Reliable damage identification is the objective of an SHM data mining procedure. In the literature, various damage detection algorithms have been proposed based on different mechanical principles. In general, they can be classified into two categories: dynamic-based or non-dynamic-based (Sohn et al. 2003). Dynamic-based damage detection algorithms use dynamic response parameters, such as natural frequencies, modal shapes, and damping, as the damage indicator. One attractive feature of dynamic-based monitoring that has contributed to its popularity is that the dynamic properties of a bridge are generally not impacted by the loading conditions. This eliminates unknowns involved in the monitoring that utilizes ambient traffic loads. However, application has shown that these dynamic-based methods have their own limitations when applied to complicated structures. First, variation in excitation or environmental conditions can cause changes in the dynamic properties that are large enough to mask changes due to damage formation. Secondly, the global dynamic parameters are not sensitive to certain types of local damages that are located in small structural response regions (such as joint details). Moreover, the multidegree of redundancies associated with highway bridges may also reduce the sensitivity of dynamic-based damage detection approaches. Due to these factors, a strain-based method is considered to potentially be more appropriate for fatigue formation detection. In addition, compared to dynamic parameters, strain is easier to monitor and better understood by bridge engineers.

In 2005, upon the request of Iowa Department of Transportation (Iowa DOT), the Bridge Engineering Center at Iowa State University began to develop and deploy a remote strain-based SHM system, which continuously monitors the performance of a fracture-critical steel girder bridge under ambient traffic loads. These fracture critical bridges were found to be fatigue damage–prone in the unstiffened web gap region due to out-of-plane bending. As a retrofit, the floor beam connection plates in the negative moment regions were cut back to reduce stress levels. However, fatigue crack formation at cut-back areas has not been fully eliminated. Therefore, having the ability to continuously monitor for fatigue damage at the retrofit cut-back areas was considered to be necessary. The developed SHM system was installed on the

US-30 South Skunk Bridge near Ames, IA. It autonomously collects, reduces, and analyzes strain data and generates periodic structural performance reports that may be used to support maintenance decision making. Although the system was developed for fracture-critical bridges, it could be easily extended to other steel girder bridges.

The hardware of the US-30 bridge SHM system consists of three components: a data acquisition component, a data processing and management component, and a data communication component. For data acquisition, 40 fiber Brag grating (FBG) strain sensors were strategically deployed throughout the bridge. They are classified as either target sensors (TSs) or non-target sensors (NTSs) according to their location. Specifically, TSs were installed at the retrofit cut-back areas to sense the local strain response, while the NTSs were installed at non-damage-prone areas to capture the global structural response. Obviously, TSs are more sensitive to the interested fatigue damage than NTSs due to their vicinity to the potential damage locations. Details of the system hardware components will be discussed later.

The software for the US-30 SHM system has two modules: a user friendly graphic user interface (GUI) and an autonomous data mining kernel. The data mining procedure developed for this system includes three major steps. First, a data cleansing step is designed to remove unwanted temperature and dynamic effects; then, the cleaned strain data are reduced to a series of TS-NTS extreme-matchings for each truck event; finally, a unique unsupervised damage detection method is carried out that is loosely based upon the control chart concept. In the initial training period, an adequate number of event samples are collected to construct baseline extreme-matching distributions. A structural response that deviates from the baseline distribution is considered to be an indication of structural damage or degradation.

Recently completed finite element analysis verified the effectiveness of the data mining approach. However, the numerical analysis results also indicated that truck parameters, including truck geometry configuration, truck weight, and transverse position can contribute to the deviation of the baseline extreme-matching distributions. Therefore, including a truck detection function, which determines these factors, into the existing system is postulated to improve damage detection ability. This function has been conceptually developed and implemented at the synthetic data level. Field testing and field data debugging will be performed in the near future. After field verification, the new module will be integrated into the existing SHM data mining system.

HARDWARE SYSTEM

The SHM system developed for and installed on the US-30 bridge is schematically depicted in Figure 1. As shown in the figure, according to the physical location of the equipment, the components can be classified into two portions: the bridge site portion and an office site portion. The bridge site component is composed of 40 strategically deployed FBGs, a Micron Optical Si425 interrogator, a Linksys router, and a desktop computer. The data collected by sensors and the interrogator are relayed through the router to the bridge site computer, where they are temporarily stored and immediately processed. After the data have been processed, extracted information and a periodic structure performance evaluation report are sent to the remote office computer for permanent storage.

Data Acquisition Component

The SHM system utilizes strategically deployed FBG sensors and a si425-500 interrogator to collect the strain data. Sensor installation location and orientation must be carefully designed to capture the global structural response, as well as the localized strain response at damage-prone areas. Figure 2a depicts the six instrumented cross sections for a demonstration application on a bridge located on US-30 near Ames, IA. Details of typical TSs and NTSs installed at Section C are shown in Figure 2b.

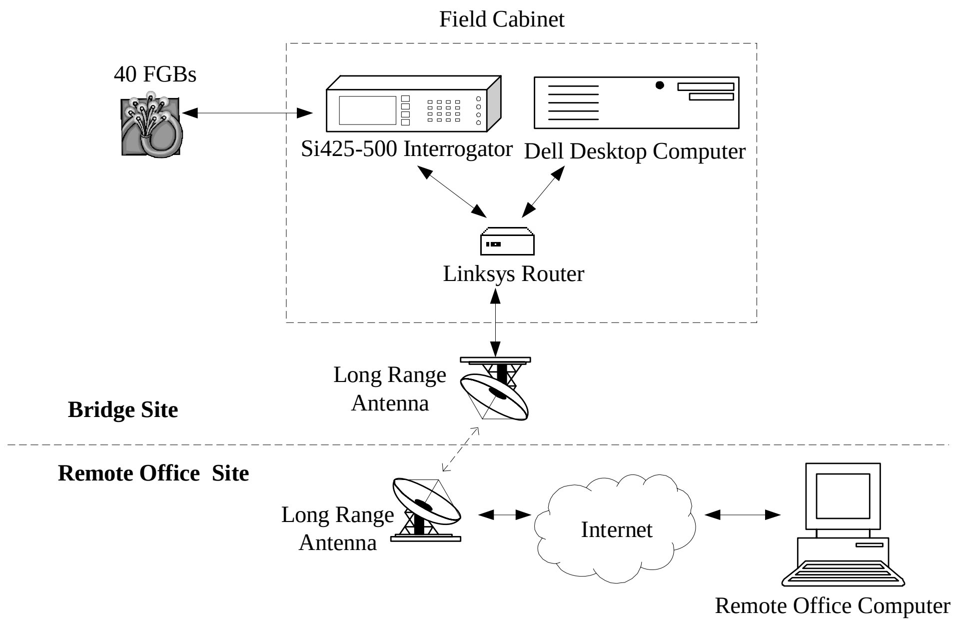
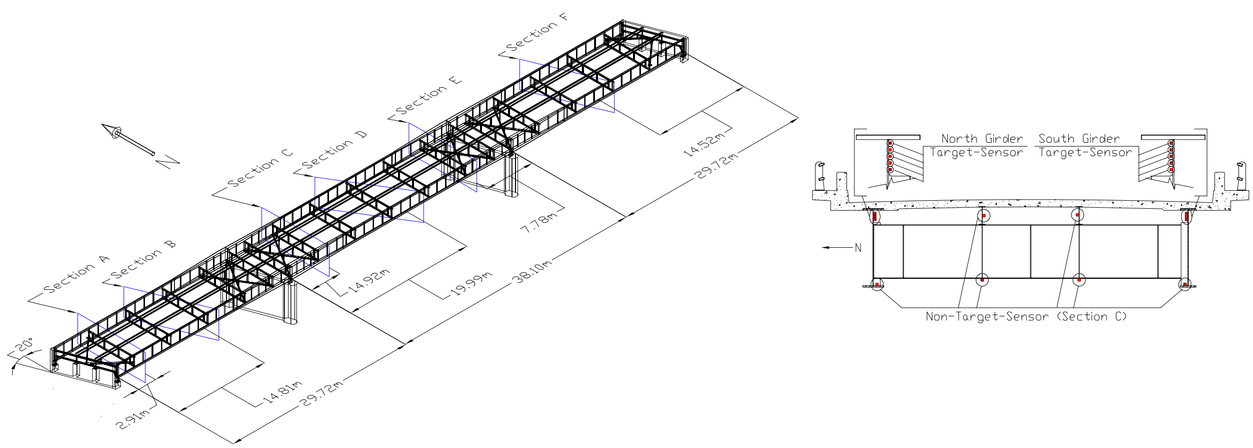


Figure 1. Schematic of the SHM hardware system



a. Instrumented sections **b. TSs and NTSs at Section C**

Figure 2. Sensor deployment

Considering the gradient of the strain field in some of the sensing areas, three different types of FBG strain sensors were used in this system. A 10mm FBG is suitable for global sensing, since the strain fields at these areas are relatively uniform and the strain averaged over the sensor length can accurately represent the strain at a desired point. The 10mm FBG is embedded in a 210 x 20 x 1 mm CFRP packaging, which protects the sensor and provides more surface bonding area to ensure a robust and easy installation. The fiber pigtails exiting from each side of the packaging (entry fiber and exit fiber) consist of SMF simplex cable (3 mm jacketing) and FC/APC mechanical connectors. Due to the complex nonuniform strain field, the 10 mm sensor is not suitable for the strain sensing at cut-back regions. To measure strains in these regions, two different 5 mm FBGs were studied and designed: (1) single 5 mm FBG in a small form factor CFRP packaging and (2) an array of five 5 mm FBGs embedded in a single CFRP package.

The 40 FBGs on the US-30 bridge are distributed among three individual fiber optic leads, and each fiber was connected to one channel of the si425-500 interrogator. The FBGs within any one fiber were designed with approximately 5 nm of separation between adjacent center wavelengths. Several procedures were performed to ensure longevity of the system. The optical fibers were intermittently secured with cable ties to mounting bases that were bonded to the bridge. In addition, all FBGs, fusion splices, and mechanical connectors were covered with a layer of silicone sealant to protect them from moisture. Finally, after the fiber optic network was installed, an optical time domain reflectometer was used to scan the network and check for regions with large optical attenuation. Examples of such optical loss include sharp bends or pinches in the fiber that could lead to extremely low optical levels or even fiber breakage. This would result in the inability to interrogate the FBGs.

Data Processing and Management and Data communication Component

The data processing and management equipment consists of two computers, which are located at the bridge site and office site, respectively. The bridge site computer is responsible for temporary data storage and real-time data processing. The information extracted from the raw data was sent to the remote office computer through a wireless internet connection. The si425-500 interrogator and bridge site computer operate within a private subnet that is managed by the router through wired connections. Data streams are transferred from the interrogator to the computer through a TCP/IP socket. The private network is then connected to internet.

SOFTWARE SYSTEM

The software for the developed system has two modules: a user friendly GUI and an autonomous data processing kernel. Both modules are implemented with LabView, which is a development environment for visual programming. As presented in Figure 3, the GUI allows the user to configure the system operation parameters and easily switch between training and monitoring modes. The kernel is designed to perform automatic data collection and data mining. More than three gigabytes of data are collected by the US-30 SHM system every day. Analyzing such large data sets requires the development of an efficient data mining solution that is well founded in structural performance and feature identification. The designed data mining algorithm analyzes the relationships and patterns of the raw data and evaluates the structural health status using the statistical method known as control chart analysis. Steps of the data mining procedure, including data cleansing, data reduction, and data interpretation, will be described in the following.

Data Cleansing

Static ambient traffic–induced strain was decided to be the desired measurement metric for the damage detection algorithm. However, in normal operation, strains caused by other uncertain factors, such as temperature and dynamic effect, are unavoidable and are recorded together with the desired signal. Fortunately, these types of signals are typically pattern-based and can be removed after the recognition of the pattern. In this system, a zeroing function and a low-pass Chebyshev filter are developed to remove the temperature and dynamic effect, respectively. As can be seen from Figure4a, the temperature-induced strain is constant for a sufficiently short monitoring period, and it can be removed by simple subtraction.

An iterative method is involved to determine the temperature-induced strain. The configuration of the Chebyshev filer for each sensor is determined using Fast Fourier Transform (FFT) and Power Spectra Density (PSD) forms of analysis. Figure4b is an example that shows the effectiveness of the selected Chebyshev filter.

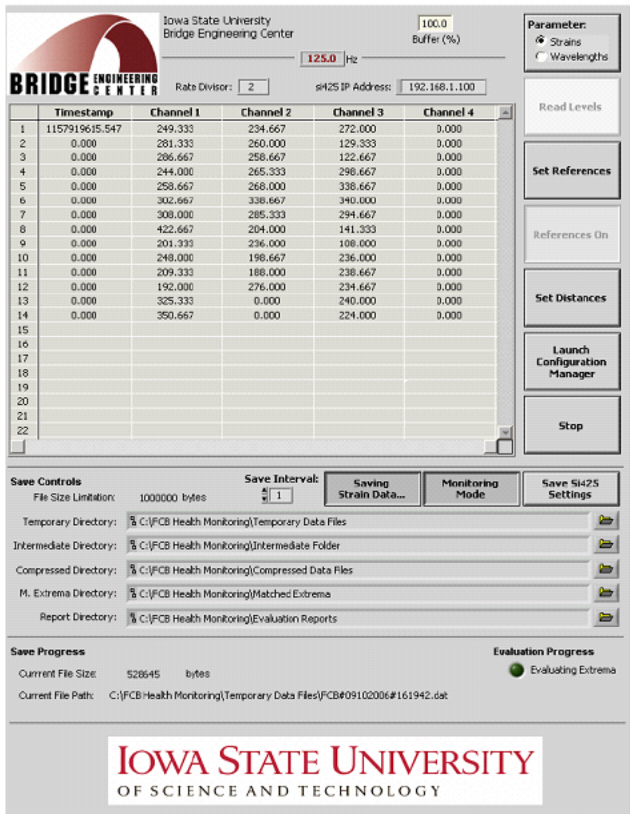
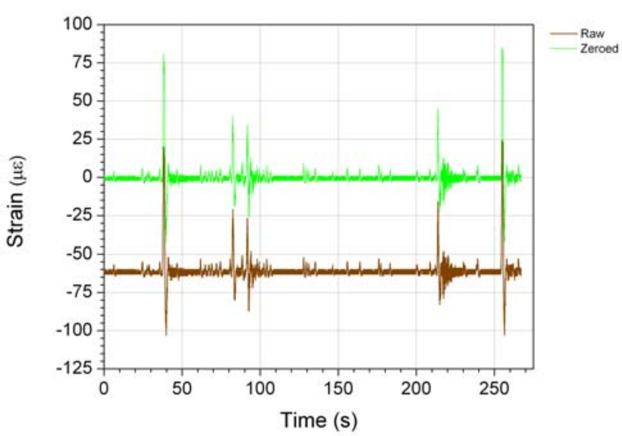
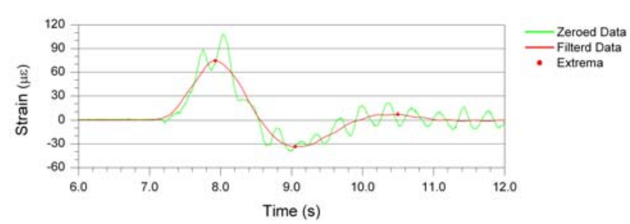


Figure 3. GUI of the SHM software





a. Data zeroing **b. Data filtering**

Figure 4. Data cleansing

Data Reduction

The data acquisition equipments of the US-30 system record strains at 40 points with the frequency of 125Hz. To extract the useful information, the event extremes (both maximum and minimum) were first identified and then matched to create the TS-NTS extreme-matchings. Using the extreme-matchings instead of the entire strain time history increases the data processing speed and reduces the required data storage space dramatically. An example of the extreme-matching distribution is presented in Figure 5.

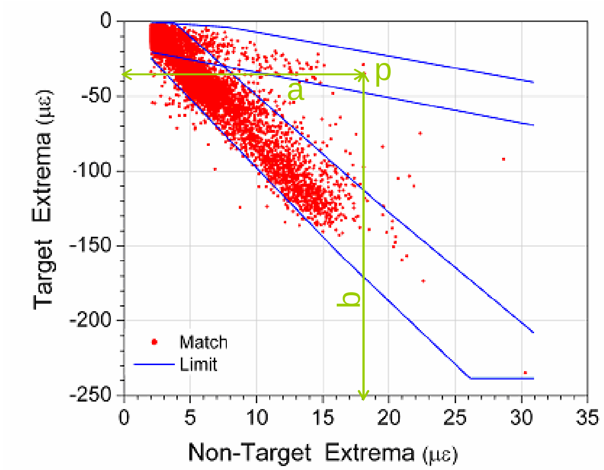


Figure 5. Example of the TS-NTS extreme-matching distribution

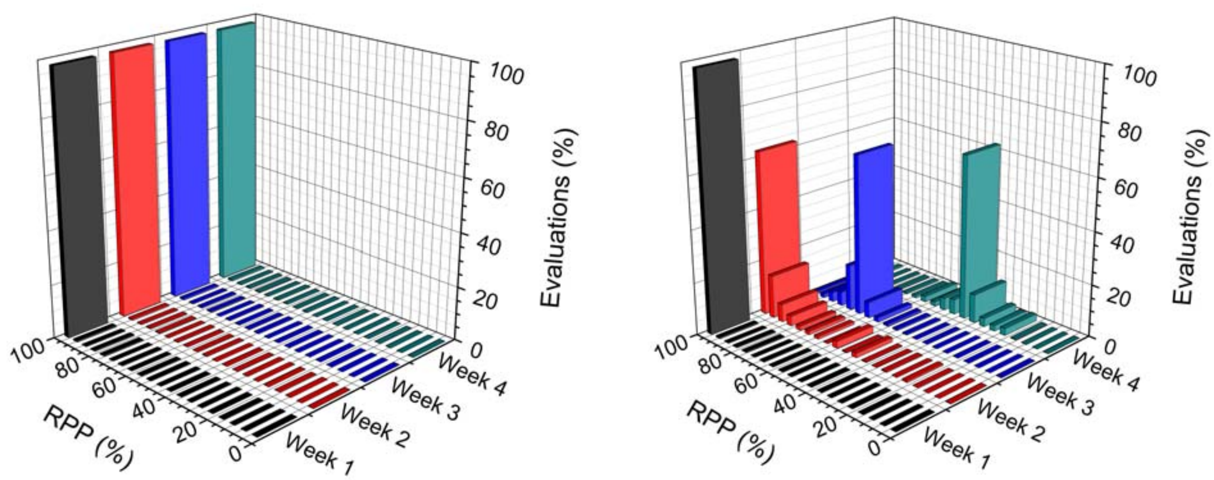
Data Interpretation

Interpretation of the monitoring data in terms of the integrity of the structure is the key function of the SHM system. For this approach, a unique unsupervised learning algorithm was designed based on the concept of control chart analysis. Unsupervised learning means that the data from the damaged structure are not required for system training. Control chart analysis is a statistical data analysis technique that has been widely used in process control in the chemical industry, in manufacturing, and in nuclear power plants. Using this technique, measured quantities are continuously monitored for anomalies. The analysis procedure typically involves two stages. First, the control limits are established based on the distribution of the observations, which are obtained from the normal condition. Then, new data for an unknown condition of the system are compared against the control limits. The system alarm is activated when the new observations fluctuate outside the control limits.

The data interpretation approach designed for this system involves two stages as well. In the initial training stage, the system was exposed to the response pattern of the undamaged structure. After sufficient learning time, the baseline distributions for the TS-NTS extreme-matchings are constructed as shown in Figure 5. In this case, the upper and lower limits used in control chart analysis were set manually. Points outside the limits indicate unusual events and are termed a fail assessment; points within the limits are termed a pass assessment. With this approach, one single fail assessment cannot be used as damage indication, since it could be caused by atypical vehicles or vehicle combinations. However, if the number of fail assessments increases significantly or shows an increasing trend, it is believed that this is a sign of the formation of damage or deterioration. To quantitatively evaluate the pass and fail assessment, a relationship pass percentage (RPP) is computed with Equation (1), and it is used as the structural damage indicator.

$$\text{RPP (\%)} = \frac{\text{Number of "Pass" Assessments}}{\text{Total Number of Assessments}}(100) \tag{1}$$

During autonomous monitoring, weekly RPP histograms are generated automatically. Figure 6a presents a typical one month of weekly RPP histogram for an undamaged structure. The RPP is not expected to be 100% and will fluctuate slightly from week to week due to the existence of atypical events. However, when structural damage or deterioration starts to form, the RPP histogram should show notable changes. As shown in Figure6b, it is predicted that the mean of the weekly RPP will slowly decrease for deteriorated structures. For damaged structures, the changes would be much faster.



a. Undamaged structure b. Prediction for damaged structure

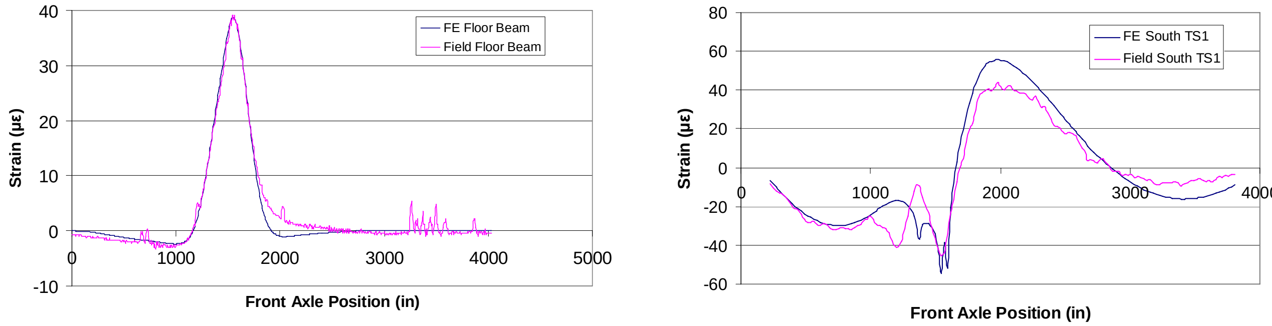
Figure 6. One month of weekly evaluation reports

NUMERICAL STUDY

To understand the performance of the damaged bridge and to verify the effectiveness of the developed system, a finite element analysis (FEA) was carried out with a commercially available software package. In this analytical study, the distributions of TS-NTS extreme-matching for damaged and undamaged structures were compared to see if they were statistically different (i.e., that damage could be detected) and to determine the minimum detectable crack size.

Finite Element Model Description

A 3D finite element (FE) model was constructed for the numerical study. In this model, shell elements were used to create the deck, stringers, floor beams, and girders. Composite action between the deck and girders/stringers was modeled with rigid links. The FE model was verified and tuned using controlled field testing data, and the final model represents the global response of the structure well (see Figure 7a) with only satisfactory representation at the local level (see Figure 7b).

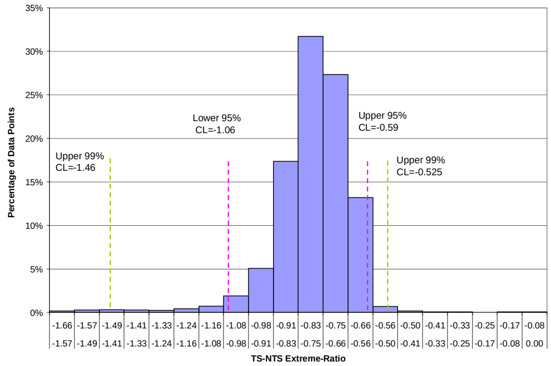


a. Example for NTS **b. Example for TS**

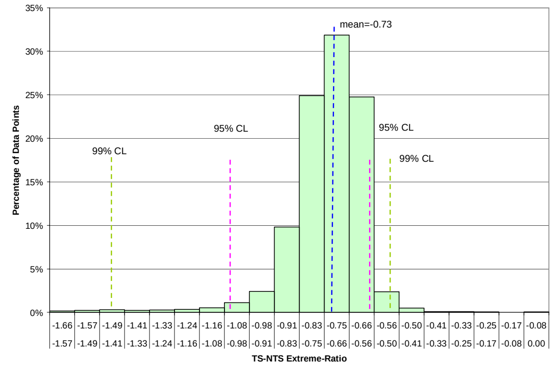
Figure 7. Comparison FEA results to field data

Conceptual Verification of the Implemented Crack Detection Algorithm

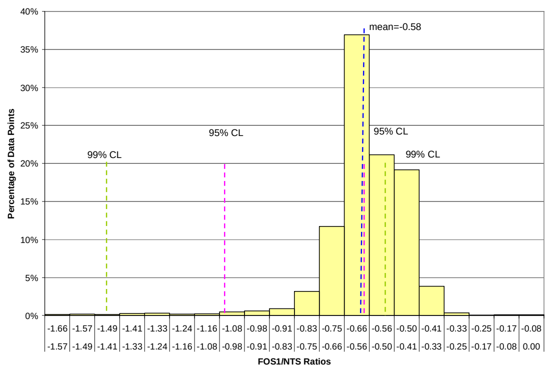
To determine the strain response effects caused by structural damage, a crack with the size of 0.5 in., 0.75 in., and 1in. was introduced to the FE model right above the web of the floor beam and two in. below the top flange of the girder. A histogram of extreme-ratios was constructed for both the damaged and undamaged structure. The extreme-ratio could be calculated easily from predefined extreme-matching. For example, in Figure 5, the extreme-ratio for the selected point *p* is simply the ratio of *a*/*b*. Figure8a presents the histogram of the extreme-ratio for the undamaged structure. This histogram was constructed from actual field monitoring data. The 95% and 99% confidence limits (CLs) for the histogram distribution were created and are also shown in the plot. A histogram for the damaged structure was constructed in the following way. The mean of the distribution was obtained from the FEA results, while the variance and the sample size were assumed to be the same as those used in the undamaged structure distribution. For a particular structural condition, if the mean of the associated extreme-ratio is out of the defined CLs, the damage of the structure is considered to be statistically significant. Figures 8a through 8d suggest that the implemented damage detection algorithm can detect a crack with a size between 0.75 and 1 in. with a confidence level of 99%. It should be noted that the analysis approach is not exactly the same as that used in the monitoring system and that the assumption about variance may not be realistically a good assumption. Nonetheless, the analysis results conceptually verified the correctness of the damage detection method.



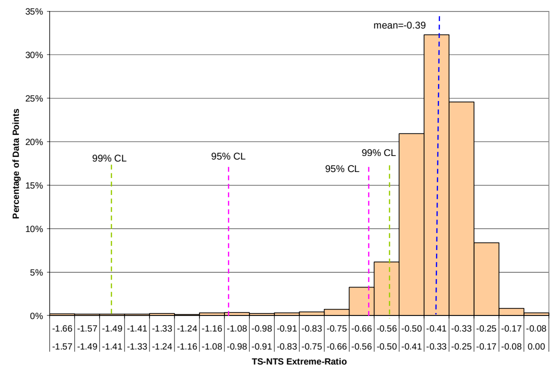
a. No crack



b. 0.5 in. crack



c. 0.75 in. crack

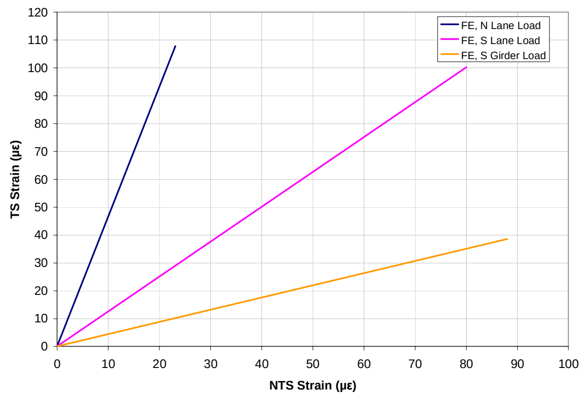


d. 1 in. crack

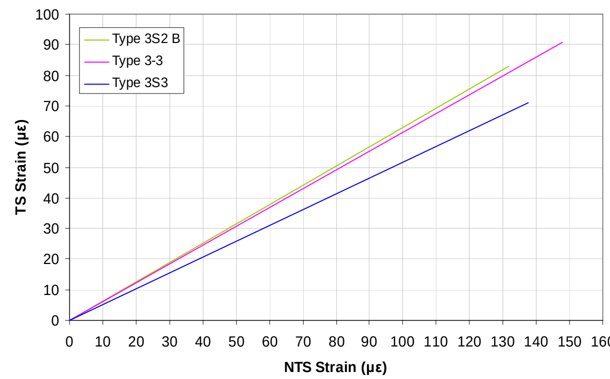
Figure 8. Histogram of the extreme-ratio for damaged and undamaged structures

Identification of other Relevant Parameters

In the early stage of development, it was thought that the TS-NTS extreme-ratio would not be affected by strain variance caused by truck parameters due to the linearity of the structure. However, the analytical results indicated the relevance of these parameters. It can be seen from Figure9a that identical trucks acting at three different locations produced three different extreme-ratio values. Similarly, Figure9b indicates that trucks with the same total weight but different geometry configurations produced different extreme-ratio values too. Ignoring these parameters in the baseline distribution, which represents the undamaged structure, may result in a decrease in the damage detection ability of the system.



a. Effect of truck transverse position



b. Effect of truck geometry

Figure 9. Factors that affect the extreme ratio

PROPOSED DATA MINING IMPROVEMENTS

As discussed previously, the existing damage detection approach may be improved by including more relevant factors into the baseline evaluation model. Further, constructing the limits used in the control chart analysis through an advanced statistical approach instead of the currently used subjective/manual method may also improve the damage detection capabilities.

A unique truck detection function has been designed to quantitatively evaluate truck parameters for this monitoring. A multiple bottom-of-the-deck sensor deployment strategy similar to the one shown in Figure10 allows for the detection of the number of axles, transverse position, speed, and axle spacing. For a particular deck bottom sensor, each truck axle produces a unique peak point in the strain time history data when it is in the vicinity of the sensor. Figure 11 presents synthetic strain time histories for six selected sensors produced by a three-axle vehicular event. The locations of the sensors are shown in Figure10. The three peaks in each sensor data instance (Figure 11) represent the three vehicle axles. As the coordinates of the sensors and the timestamp for each peak are known, computing of the truck speed and truck axle spacings is straightforward. The relative magnitudes of the strain peaks for sensors within the same group can also be used to infer the truck transverse position. For example, as shown in Figure10, S11, S12, and S13 belong to one sensor group (SA1), while S21, S22, and S23 belong to the other sensor group (SA2). In Figure11, the peak value for S11 is greater than that for S12 and S13. This shows that the transverse position of the truck is nearer to S11 than to the other two sensors.

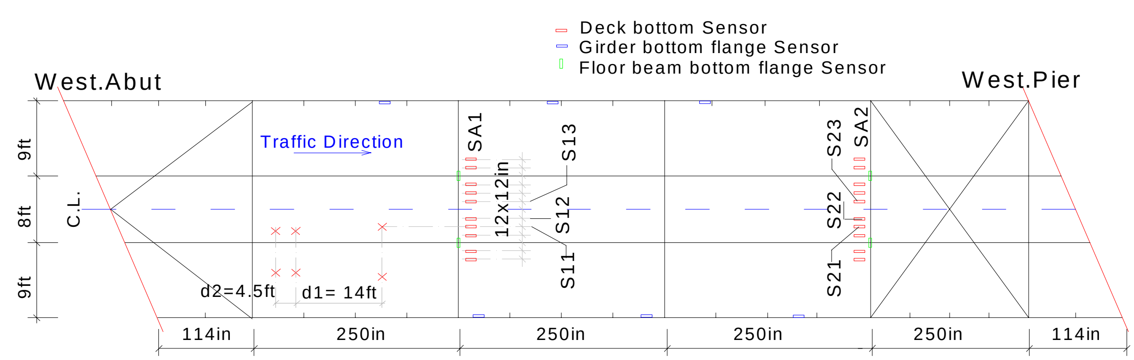


Figure 10. Sensor deployment for truck detection

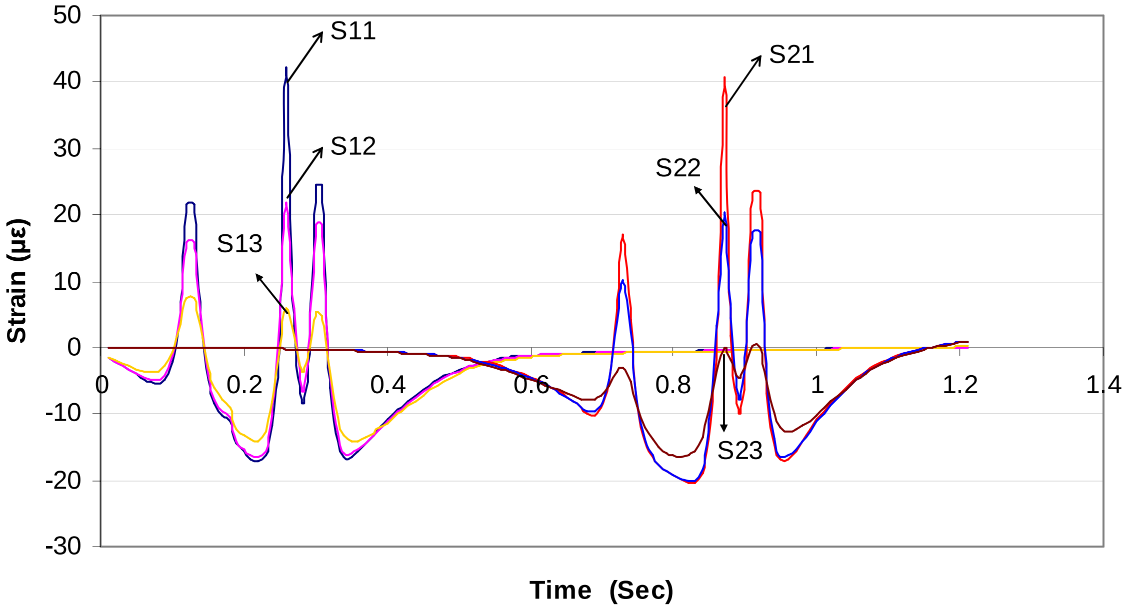


Figure 11. Synthetic strain time history plot for six selected deck bottom sensors

The truck axle weights and total weight can be calculated with a novel concept. Specifically, an axle-based influence line/surface for the girder bottom flange sensor can be constructed by running a control truck on the bridge multiple times and then solving the simultaneous equations shown in (2):

$$\begin{vmatrix} W_{11} & W_{12} & W_{13} \\ W_{21} & W_{22} & W_{23} \\ W_{31} & W_{32} & W_{33} \end{vmatrix} \begin{vmatrix} I(P) \\ I(P-D_1) \\ I(P-D_2) \end{vmatrix} = \begin{vmatrix} R_1(P) \\ R_2(P) \\ R_3(P) \end{vmatrix} \tag{2}$$

where,

$W_{11}, W_{12} \cdots W_{33}$ are axle weights for control trucks

I( ) are values in the influence line for specified locations

$R_1(P)$, $R_2(P)$, and $R_3(P)$ are strain response at the sensing points

P is the longitudinal coordinate for the girder bottom flange sensor

D_1 and D_2 are truck axle spacings

Typically, $W_{12} = W_{13}$ & $W_{22} = W_{23}$, so $I(P) = \dfrac{W_{22}R_1(P) - W_{12}R_2(P)}{W_{22}W_{11} - W_{12}W_{21}}$

Figure12 shows the good agreement between the influence line constructed from synthetic data using the described approach and the theoretical solution. To make the synthetic data more realistic, each value has been randomly deviated up to 2% to simulate random noise.

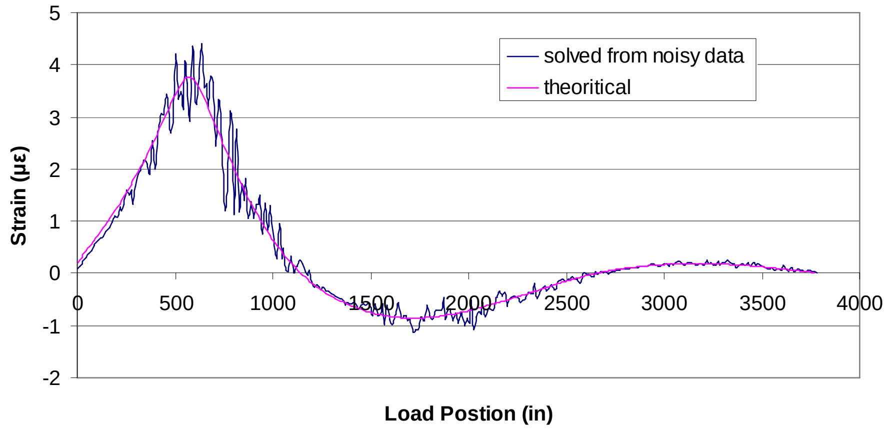


Figure 12. Influence lines for the sensing position

Knowing the influence line/surface, truck speed, and strain time history data, axle weights of trucks could be estimated through a linear least squares optimization. Equation (3) is the objective function of the optimization, in which, R_reconstruct (P,D,W) is a function of the truck first axle position (P), axle spacings (D), and axle weights (W). P and D are known from the monitoring data, and W is the optimization variable. After determining the weight of each axle, the total gross weight is then calculated as the summation of axle weight. As it turns out, the influence line/surface constructed from the control truck can be utilized in the axle weight estimation for any type of truck. Therefore, during the training stage, the system does not have to be exposed to all type of trucks. Table 1 summarizes the weight estimation results for a semi truck using the influence line, which was constructed from a three-axle dump truck.

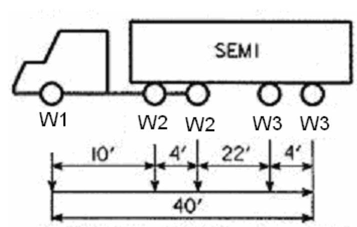
$$SumSquareErr = \sum_{P} (R\_reconstruct(P,D,W) - R\_monitor(P))^2 \qquad (3)$$

where,

P is the positions of first axle of the truck
D represents the truck axle spacings
W represents the axle weights of the truck

Table 1. Axle weight and total weight estimation for a semi truck

	Target (k)	Predicted (k)	Error
W1	6	5.38	-1.03%
W2	6.5	6.74	3.7%
W3	7.75	7.61	-1.7%
W Total	34.5	34.09	-1.19%



Following further verification of this approach, statistical data analysis approaches will be developed to set the control chart limits and set up alarming thresholds for the RPP histogram. It is thought that these analysis approaches will in some way incorporate the vehicle configuration information.

CONCLUSIONS AND FUTURE WORK

The SHM system described herein enables bridge owners to remotely monitor bridges for gradual deterioration or sudden damage formation. The system is trained with performance data to identify the typical bridge response when subjected to ambient traffic loads. During monitoring, strain records in data files are zeroed and filtered, and event extremes are extracted automatically. After the TS-NTS extreme-matching searching is completed, RPPs are calculated using the knowledge learned during the training stage. From generated RPP histograms, bridge owners can evaluate the structure's health without needing to fully understand the data mining procedure. The effectiveness of the system was studied through a numerical analysis. Improvements have been proposed and partially implemented with the simulation data.

In the future, efforts will be made toward improving the damage detection capabilities and reducing the possibility of false positive alarms. As discussed before, the uncertainty with the system may be reduced by incorporating more variables into the baseline model. More sophisticated statistical pattern recognition approaches are also being developed to improve the damage detection ability of the system.

REFERENCES

FHWA. 2001. *Reliability of Visual Inspection for Highway Bridges*. Washington, DC: Federal Highway Administration.

Sohn, H., C.R. Farrar, F.M. Hemez, D.D. Shunk, D.W. Stinemates, and B.R. Nadler. 2003. *A Review of Structural Health Monitoring Literature:1996-2001*. LANL Report, LA-13976-MS. Los Alamos, NM: Los Alamos National Laboratory.

U.S. DOT. 2003. *Transportation Statistics Annual Report.* Washington, DC: Bureau of Transportation Statistics, U.S. Department of Transportation.