Sensor Network for Structural Health Monitoring of a Highway Bridge

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Abstract: A bridge monitoring TestBed is developed as a research environment for sensor networks and related decision-support technologies. A continuous monitoring system, capable of handling a large number of sensor data channels and three video signals, is deployed on a four-span, 90-m long, reinforced concrete highway bridge. Of interest is the integration of the image and sensor data acquisition into a single computer, thereby providing accurate time synchronization between the response and corresponding traffic loads. Currently, video and acceleration records corresponding to traffic induced vibration are being recorded. All systems operate online via a high-speed wireless Internet network, allowing real-time data transmission. Elements of the above health monitoring framework are presented herein. Integration of these elements into an automated functional system is emphasized. The recorded data are currently being employed for structural system identification via a model-free technique. Effort is also underway to correlate the moving traffic loads with the recorded accelerations. Finally, the TestBed is available as a resource for verification of new sensor technologies, data acquisition/ transmission algorithms, data mining strategies, and for decision-support applications.

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Introduction

The interest in structural health monitoring (SHM) for bridges and civil infrastructure remains strong in view of the worldwide demand and the advances in enabling information technologies (Mufti 2002; Pines and Aktan 2002; Casciati 2003; Chang et al. 2003; Sohn 2003; Chong et al. 2003; Carden and Fanning 2004; Tomizuka et al. 2006). Numerous structures and bridges worldwide are currently instrumented with sensor arrays to monitor ambient vibration, strain, and displacement (e.g., Bolton et al. 2002; Masri et al. 2004; Wahbeh et al. 2005; Ko and Ni 2005; Guan et al. 2006). Machine learning and system identification techniques are used for analysis of the recorded system response (Proc., 5th and 6th Int. Workshop on Structural Health Monitoring 2005, 2007, Nayeri et al. 2008).

Recently, efforts have been underway to include traffic load as the source of dynamic excitation with the aid of video imaging (Elgamal et al. 2003, 2004; Chen et al. 2004, 2006; Catbas et al. 2004; Chen and Feng 2006; Fraser 2006). Generally, image tracking for traffic applications is an area of increasing interest with a large scope of potential applications (e.g., Beymer et al. 1997; Collins et al. 2001; Kogut and Trivedi 2001; Morris and Trivedi 2006). A summary of video traffic monitoring systems and associated functionalities may be found in Kastrinaki et al. (2003).

Aligned with the efforts above, this paper presents developments to deploy operational sensor/video monitoring TestBeds. In the following sections, a pilot system-integration bridge-deck monitoring effort is briefly described. On this basis, a highway bridge TestBed sensor network is configured and deployed. Using the recorded data, a system identification procedure is presented and employed to extract and monitor the bridge's dynamic characteristics. Techniques for use of the recorded video are highlighted for extracting locations, velocities, and categories of vehicles. Finally, conclusions are drawn along with recommendations for further research.

Pilot Technology Integration TestBed

Initially, a demonstration TestBed serving as a development and verification environment for the integrated structural monitoring framework (Fig. 1) was established on a series of bridge-deck panels (Fraser 2006) located on campus at the University of California, San Diego (UCSD). This TestBed served a crucial role in developing, troubleshooting, and evaluating the reliability of all aspects related to structural monitoring. A PC-based data acquisition system with live Internet connectivity was deployed along with a network camera for continuous monitoring of the bridge decks.

Over a 3-year period, video and strain data, synchronized separately by a network time protocol (NTP) Internet time server, were recorded and archived in a series of databases, and made

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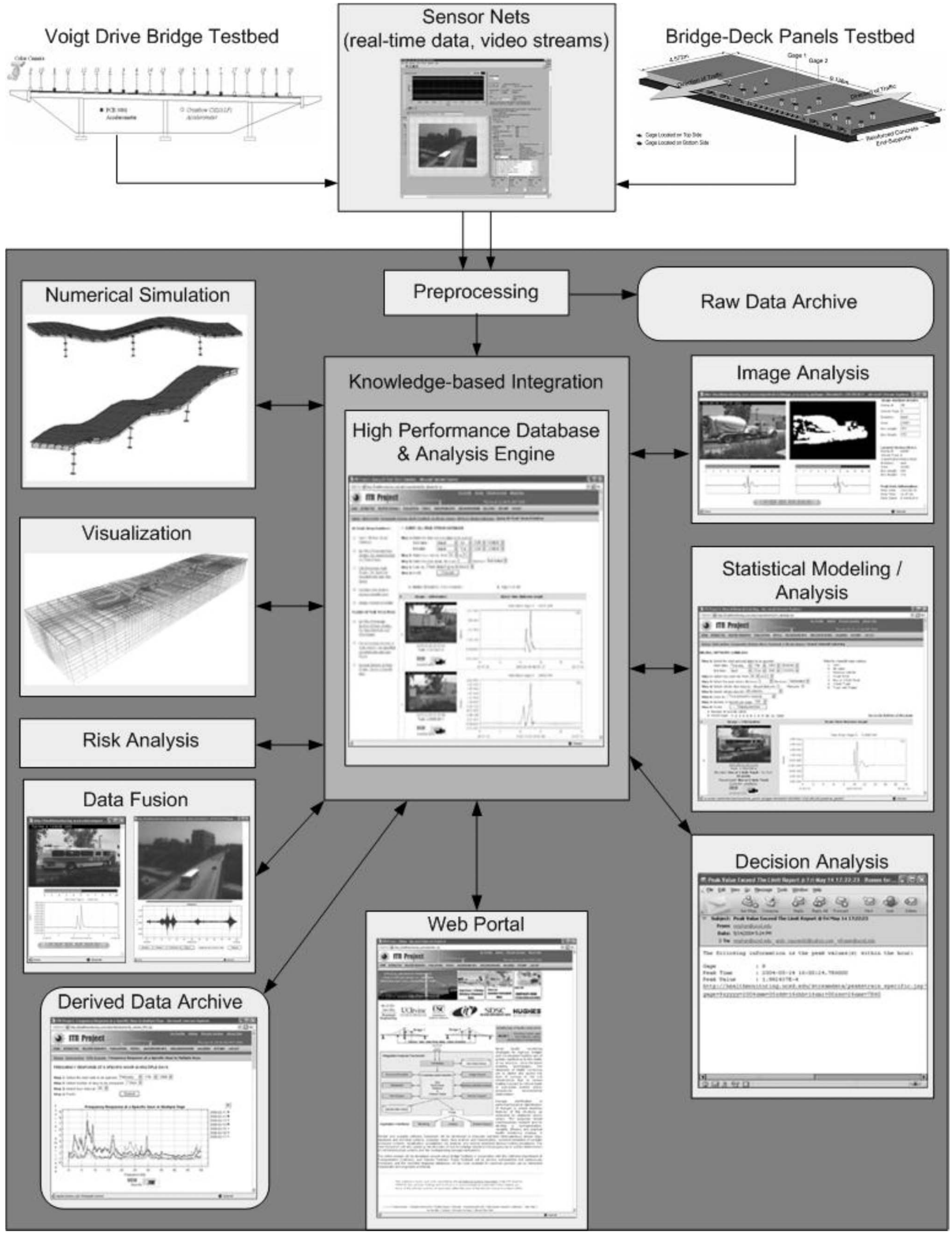


Fig. 1. Integrated research framework based on project TestBeds (adapted from http://healthmonitoring.ucsd.edu)

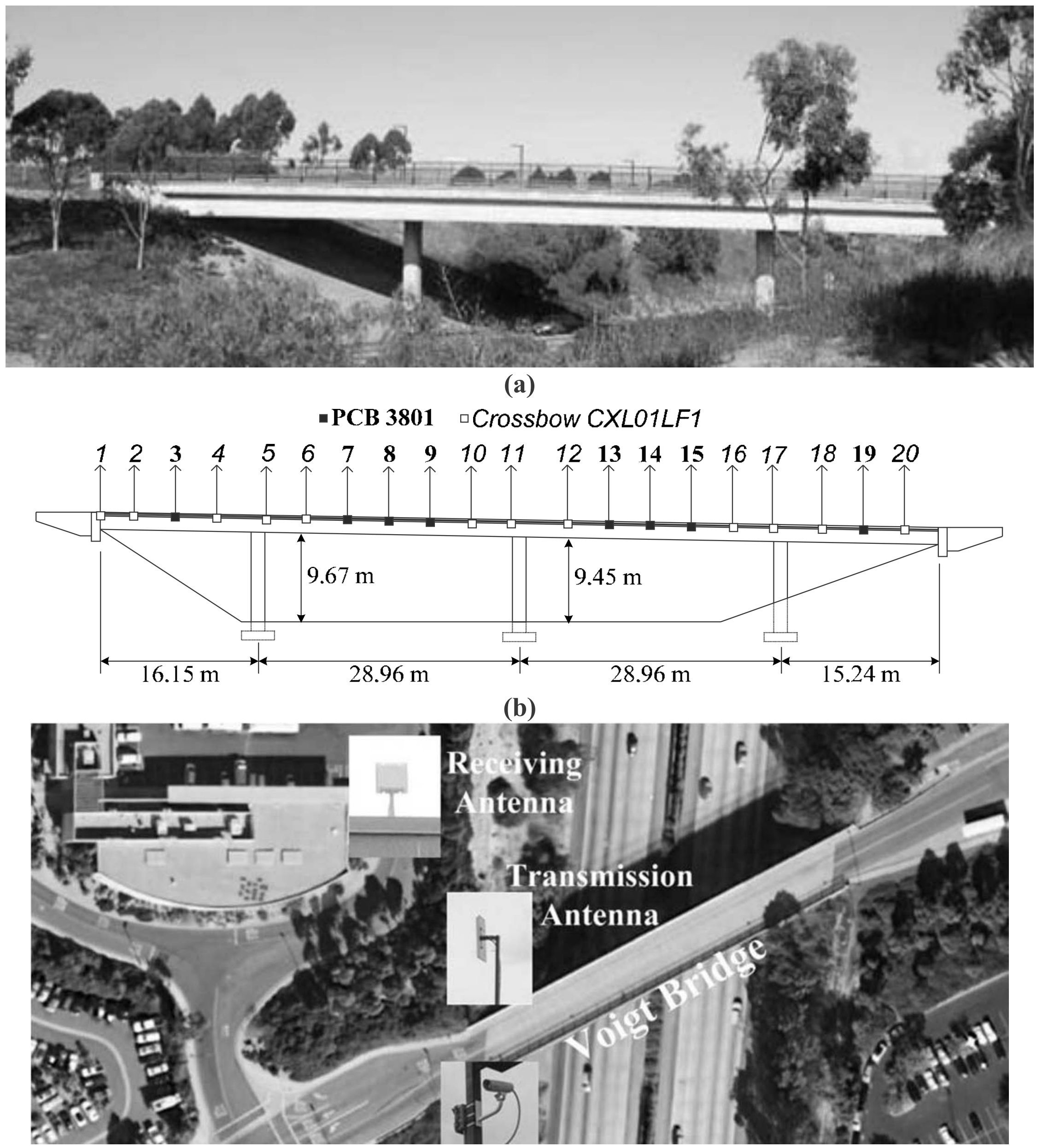


Fig. 2. (a) Voigt Drive/I-5 Bridge TestBed; (b) elevation view of TestBed with locations of accelerometers; and (c) locations of camera and wireless transmission antennas deployed on monitoring system (original map courtesy of http://maps.google.com)

available for online querying. The continuously recorded data was post processed and separated into over 400,000 discrete events, each composed of a 10-s strain time history and a 40 image video of the vehicle crossing the bridge decks. Local processing potential for data reduction and event detection was demonstrated within an hourly peak-strain database established using two of the strain gages (Fraser 2006). Captured by the records in these databases are a diverse variety of vehicle types ranging from golf carts to five-axle semitrucks. The entire video and sensor data set is publicly available for query searching and downloading through the Web portal (http://healthmonitoring.ucsd.edu).

Recently, the recorded data set was used to develop a strain-based vehicle classification approach, as a machine learning application (Yan 2006). To achieve this goal, the principal components analysis technique was applied to extract essential features from the strain time histories. Using these features as input, a two-layered back-propagation neural network was built and trained to sort vehicles into five classes. In this regard, availability of the video images provided essential information for developing the needed labeled data sets. The trained network was tested, and satisfactory results were achieved, showing viability of the classification approach for this bridge deck system (Yan et al. 2008).

Highway Bridge TestBed

Following the above pilot effort, a monitoring system was recently deployed on the Voigt Drive/Interstate-5 bridge (Fig. 2), located on the Eastern edge of the UCSD main campus (32°52′53″N, 117°13′43″W). The system incorporates an accelerometer sensor array and an integrated camera monitoring framework (Fraser 2006). Built in 1964, this two-lane, two-way

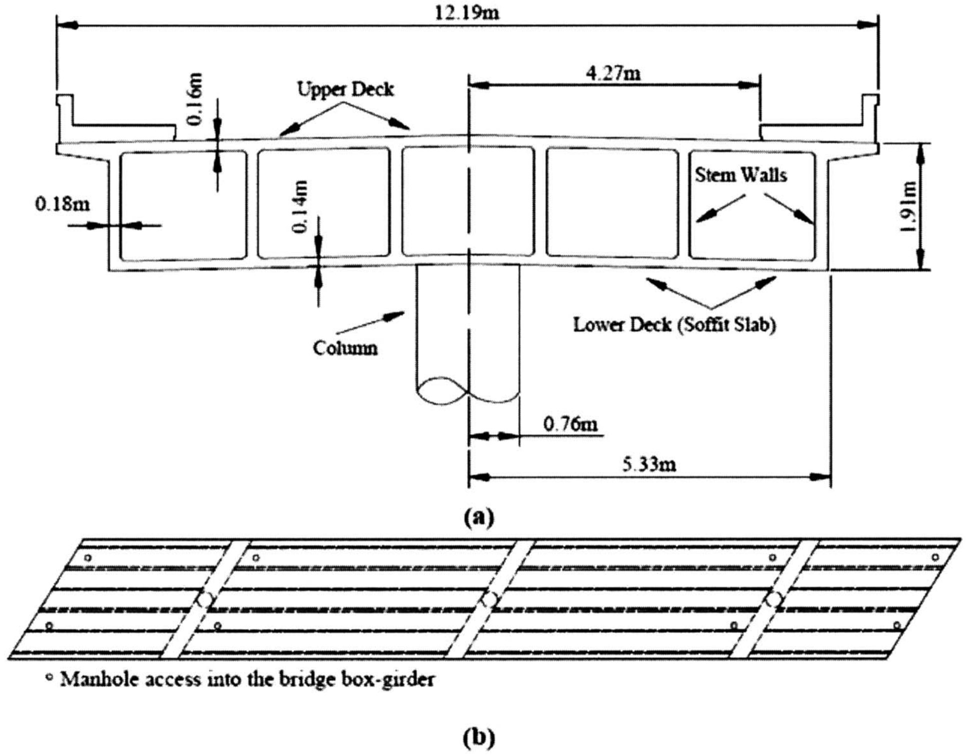


Fig. 3. (a) Representative cross section of Voigt Drive/I-5 Bridge; (b) top view of bridge deck

bridge is about 90 m in length, and carries traffic over Interstate-5 (I-5). The single-column bent, four-span, reinforced concrete box girder structure has a skew angle of approximately 32º (Fig. 2) and a construction style typical of a large number of highway overpasses in California. Cap beams (lateral diaphragms) 1.8 m in thickness, are situated over each of the columns, thus providing additional stiffness to the bridge girders.

Secure access into the bridge-deck cells is provided through manhole conduits (Fig. 3). This access into the interior of the bridge makes it possible to place all of the sensors and data acquisition hardware inside the bridge box girder deck structure, thereby: (1) simplifying the installation process as the sensor network deployment causes no interference with traffic on or below the bridge and (2) providing security and protection from the ambient weather conditions. In its current instrumented configuration, the Voigt Bridge TestBed has already served as a live laboratory for verification of wireless SHM networks (Wang et al. 2006, 2007; Loh et al. 2007).

Sensor Array Instrumentation

Data will be presented and analyzed from the initial sensor deployment effort which consisted of a configuration involving a total of 20 accelerometers, spaced approximately 15 ft apart (Fig. 2). The accelerometers were oriented to measure vibration in the vertical direction due to the moving traffic loads. In this initial phase of sensor deployment, it was decided to focus on a single bridge cell, traversing the northern boundary of the bridge (Fig. 3). This cell was chosen for its convenient accessibility through manholes located in the sidewalk on the north side of the bridge (Fig. 3).

The overall monitoring system architecture is presented in Fig. 4. Cut-outs in the base of each of the cap-beam lateral diaphragms (for high power electrical lines that are no longer in service) allowed for running the sensor cables throughout the 4 bridge spans (Fraser 2006).

Video Camera

A Sony XCD-X710CR digital camera (30 frames per second maximum sampling rate) was installed up a light post on the South-Western end of the bridge (Figs. 2 and 4). This camera is positioned to monitor traffic crossing over the bridge, in order to correlate each vehicle with the corresponding dynamic response. Using National Instruments (NI) LabVIEW software, images are acquired from the camera at a programmable sampling rate and time stamped using the system clock on the data/image acquisition computer. As such, highly accurate synchronization between the accelerometer data and the camera images was achieved (Fraser 2006).

Synchronized Data Acquisition System

Data from the sensors was collected on the bridge using a local computer (Fig. 4), housed within the northwest corner of the instrumented bridge-deck cell. The data acquisition, processing, and data transmission codes were embedded on this computer (NI PXI controller) and all start automatically when the system boots up (controlled remotely, thereby requiring no human interaction). With the current 16-bit NI PXI-6031E data and NI PXI-8252 image acquisition boards (Fig. 4), this system can be expanded to support three cameras, and over 300 analog inputs (for sensors not requiring signal conditioning or those where conditioning is handled by additional hardware—such as the employed accelerometers). Further, this system can accommodate high sampling

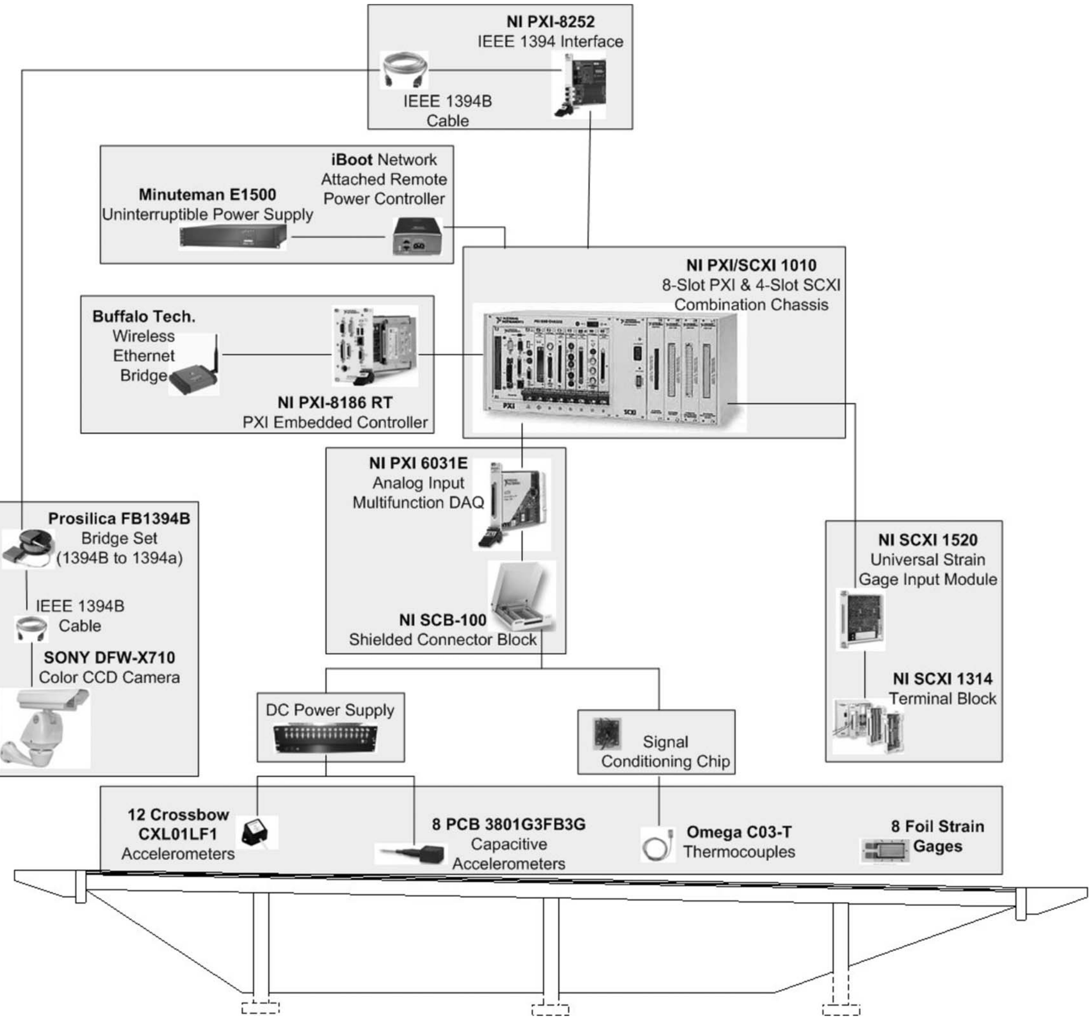


Fig. 4. Schematic of hardware architecture

rates and other sensor types with special requirements [e.g., integrated electronics piezoelectric (IEPE) sensor signal conditioning].

The firewire output from the Sony camera was connected to the data acquisition computer through an IEEE 1394 firewire interface board. A "while loop" was embedded within the LabVIEW data acquisition code which configures the camera (image resolution and size), controls the acquisition sampling rate, decodes the acquired Bayer image, and saves the picture in a compressed color jpeg format. In its current state, the camera and image acquisition code are configured to sample and archive 640×480 pixel color images at 3 frames per second (FPS). Within LabVIEW, a compression ratio of 70% was used. While higher sampling rates and image sizes with no compression are feasible, these were deemed unnecessary in accurately identifying and tracking traffic on the bridge.

Internet Connectivity

For controlling the data acquisition system, and for streaming data from the bridge, a wireless cloud was created to access the wired UCSD Internet network located in a nearby building (Fig. 2). A high bandwidth Internet connection was established on the bridge by installing a wireless router on the Southeast corner of this building (approximately 60 m from the bridge). Using a wireless Ethernet bridge with an external antenna mounted on the bridge guard rail (Fig. 2), the wireless stream is converted to a standard wired Internet signal, connected to the data acquisition system by an Ethernet cable.

Remote access to the data acquisition computer is allowed using the Windows remote desktop connection and the NI LabVIEW webserver. Through the webserver, changes can be made to the data acquisition parameters (e.g., sampling rates, sensor calibration constants, buffer size, etc.). To make changes to the data acquisition program, including overwriting the current version, the Windows remote desktop connection can be also used. Should the acquisition computer freeze and access becomes unavailable, a network-attached remote power controller was installed along with the PXI controller (Fig. 4). This device allows authorized users to cycle power to the controller thereby rebooting and restoring the system. To ensure proper authorization, access is restricted to users with registered IP addresses.

Data Archiving

A data acquisition program was developed to digitize the analog response from each accelerometers at a rate of 1,000 samples per second. Once digitized, the data are placed into a ring buffer. After a predetermined number of samples are collected in the buffer, the data are written to disk as a text file in ASCII format

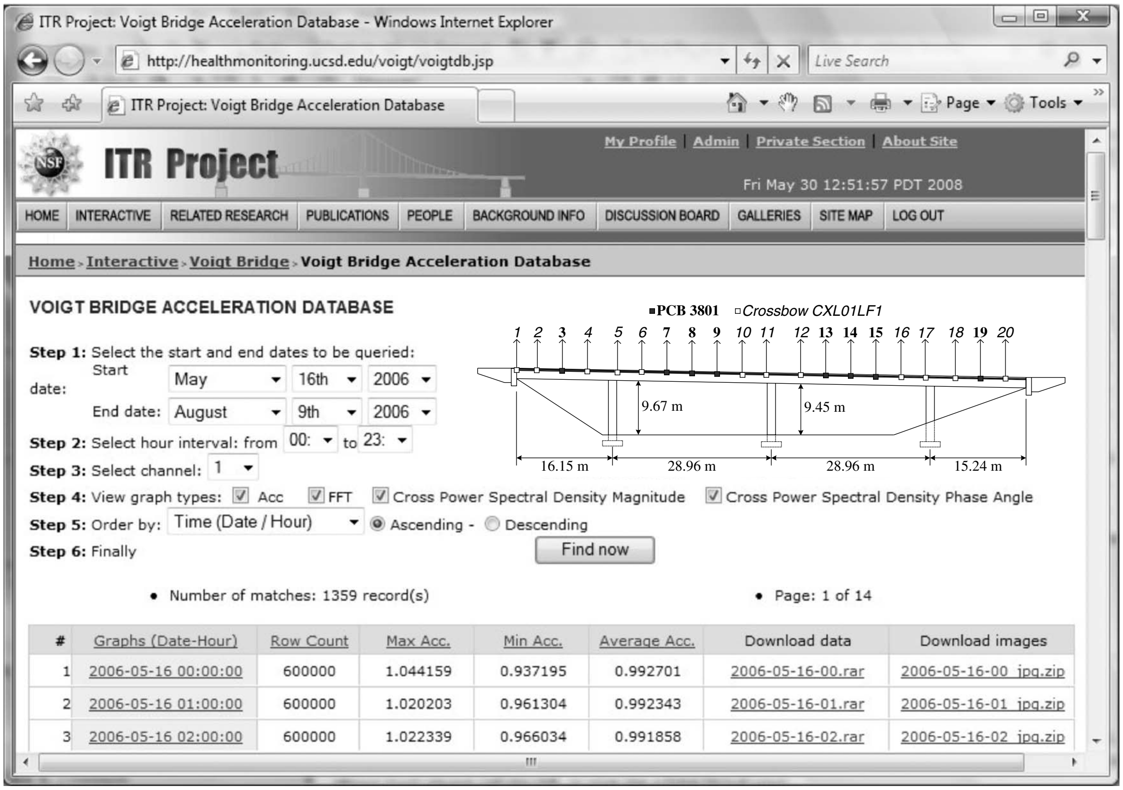


Fig. 5. Web page for querying, browsing, and downloading the recorded acceleration and video data

and the buffer is cleared. A java-based data transmission program (Fraser 2006) opens these files, compresses the data, and streams the zipped data using File Transfer Protocols (FTP) to the archiving server on the campus network. For this purpose, a practical extraction and report language (PERL)-based loader program was developed to read the streamed data, perform basic signal processing, and archive the data within an IBM DB2 database.

Upon confirmation of successful transmission, the data are deleted from the acquisition computer. Should the Internet connection temporarily go down, no information is lost as the system continues to acquire data and write to disk on the local hard drive. Once the connection is restored, the streaming program automatically resumes operation. On this basis, adequate network bandwidth is available for continuous 24/7 data transmission from the deployed sensor/video array.

Web Portal for Data Retrieval and Dissemination

Work was undertaken concurrently in different areas in order to build the necessary integrated software and hardware system infrastructure (Elgamal et al. 2003; Elgamal et al. 2004). A Web portal was established (http://healthmonitoring.ucsd.edu) to provide secure access to the data being collected on the bridge and automatically archived in the IBM DB2 database. Over 1,000 10-min records are currently archived in this database (one record at the beginning of each hour).

After secure login, online capabilities (Fig. 5) include: (1) direct access to the database via the portal; (2) queries for issues such as data recorded during selected times of the day/month; (3) sorting of the data by date and/or by peak acceleration; and (4) convenient download of the sensor and video data (zipped). Via the portal, any record may be viewed (Fig. 6) using a display and zoom graphical interface (http://ptolemy.berkeley.edu/). Using MATLAB, frequency domain displays of the recorded time histories may be generated and viewed, in order to monitor the salient system resonant characteristics (Fig. 7). As shown in Fig. 6, an option to view (zoom in) any 1-min segment of this record along with the corresponding video is also available (Fig. 8). Within the above portal framework, other query and functionalities of interest may be conveniently added, particularly for the purpose of image-sensor data correlations as shown schematically in Fig. 9. The Web portal configuration details are more comprehensively described in Fraser (2006).

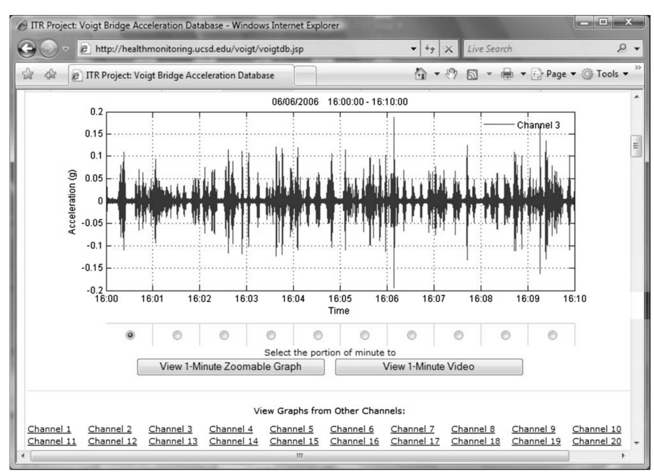


Fig. 6. Ten-minute vertical acceleration record for any of the 20 accelerometer channels

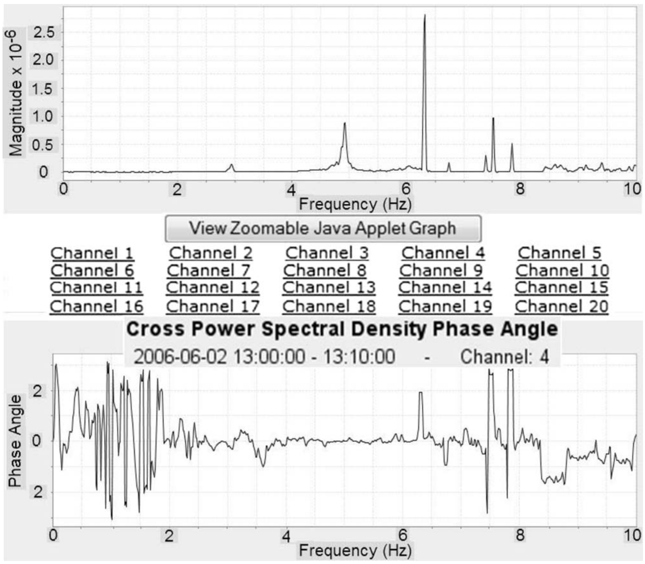


Fig. 7. Frequency domain displays of the recorded time histories

Data and Analysis

Dynamic Response of the Voigt Bridge

Systematically combining the input traffic excitation with the output sensor data remains an area of further research. In this regard, the bridge vibration is not only due to crossing traffic on the bridge deck, but also due to the major traffic crossing I-5 below. For such challenging input definition situations, an output-only system identification approach is warranted. Herein, the data-driven stochastic subspace identification (SSI-DATA) method (Van Overschee and De Moor 1996) is used to identify the bridge modal parameters from the recorded accelerometer data.

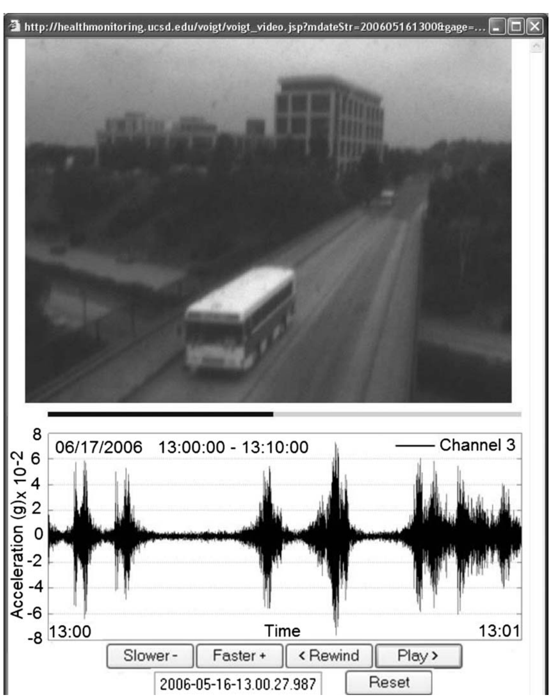


Fig. 8. Web page for displaying the recorded acceleration time history along with time-synchronized video

Data collected and archived over a duration of 45 days (first 10 min. of every hour, for a total of 1,080 records) was used in the identification process. The SSI-DATA algorithm extracts a system model in state-space using output-only measurement data as described briefly below.

Identification Approach

A discrete time state-space representation of order n for a linear time-invariant system is given by

$$\mathbf{z}(k+1) = \mathbf{A}\mathbf{z}(k) + \mathbf{B}\mathbf{u}(k) \tag{1a}$$

$$\mathbf{x}(k+1) = \mathbf{C}\mathbf{z}(k) + \mathbf{D}\mathbf{u}(k) \tag{1b}$$

where $n/2$=number of the system degrees of freedom $\mathbf{A} \in \Re^{n\times n}, \mathbf{B} \in \Re^{n\times l}, \mathbf{C} \in \Re^{m\times n}, \mathbf{D} \in \Re^{m\times l}$=state space matrices in discrete-time; $\mathbf{z}(k) \in \Re^{n}$=state vector; $\mathbf{u}(k) \in \Re^{l}$=load vector function (input excitation of size l); and $\mathbf{x}(k) \in \Re^{m} = [x_1(k), x_2(k), \ldots, x_m(k)]^T$, a column vector of size m (=number of measured output channels) which represents the system response at discrete time $t=k(\Delta t)$ along the m measured degrees of freedom (Δt is time step). In practice, the input excitation $\mathbf{u}$ is often unknown/unmeasured and only the response of the structure is recorded. Thus, the discrete time state-space model in Eq. (1) is extended to the following stochastic version (Van Overschee and De Moor 1996, Peeters and De Roeck 2001a):

$$\mathbf{z}(k+1) = \mathbf{A}\mathbf{z}(k) + \mathbf{w}(k) \tag{2a}$$

$$\mathbf{x}(k+1) = \mathbf{C}\mathbf{z}(k) + \mathbf{v}(k) \tag{2b}$$

where state matrices $\mathbf{A}$ and $\mathbf{C}$=same as in Eq. (1): $\mathbf{A}$=state transition matrix, which completely characterizes the dynamics of the system, and $\mathbf{C}$=output matrix that specifies how the system state $\mathbf{z}(k)$ is transformed into the measured system response/output; $\mathbf{w}(k) \in \Re^{n}$=process noise due to external disturbances and modeling inaccuracies; and $\mathbf{v}(k) \in \Re^{m}$=measurement noise due to sensor inaccuracies. Since the input excitation $\mathbf{u}(k)$ of Eq. (1) is unknown and impossible to distinguish from the noise terms $\mathbf{w}(k)$ and $\mathbf{v}(k)$, it is now implicitly included in these noise terms. Both noise terms $\mathbf{w}(k)$ and $\mathbf{v}(k)$ are assumed to be zero mean, white vector sequences.

The system state-space matrices $\mathbf{A}$ and $\mathbf{C}$ are estimated from the recorded accelerometer data using the SSI-DATA procedure. In this procedure, the output Hankel matrix is used to estimate the Kalman filter state. The matrices $\mathbf{A}$ and $\mathbf{C}$ are then identified from this Kalman state via a least-squares approach (Van Overschee and De Moor 1996, He 2008). Once $\mathbf{A}$ and $\mathbf{C}$ are determined, the modal parameters (natural frequencies ω_i, damping ratios ζ_i, and mode shapes ϕ_i) of the $N=n/2$ vibration modes can be obtained from (Juang and Pappa 1985, Lus et al. 2002)

$$\omega_i = |\ln(\lambda_{2i})/\Delta t|, \quad i = 1,2, \ldots, N \tag{3a}$$

$$\zeta_i = -\cos\{\text{angle}[\ln(\lambda_{2i})]\}, \quad i = 1,2, \ldots, N \tag{3b}$$

where λ_i=ith eigenvalue of matrix $\mathbf{A}$. In view of the state-space representation [Eq. (2)], it should be noted that λ_{2i-1} and λ_{2i} are complex conjugate pairs of eigenvalues, which correspond to the same vibration mode. The vibration mode shapes are obtained from

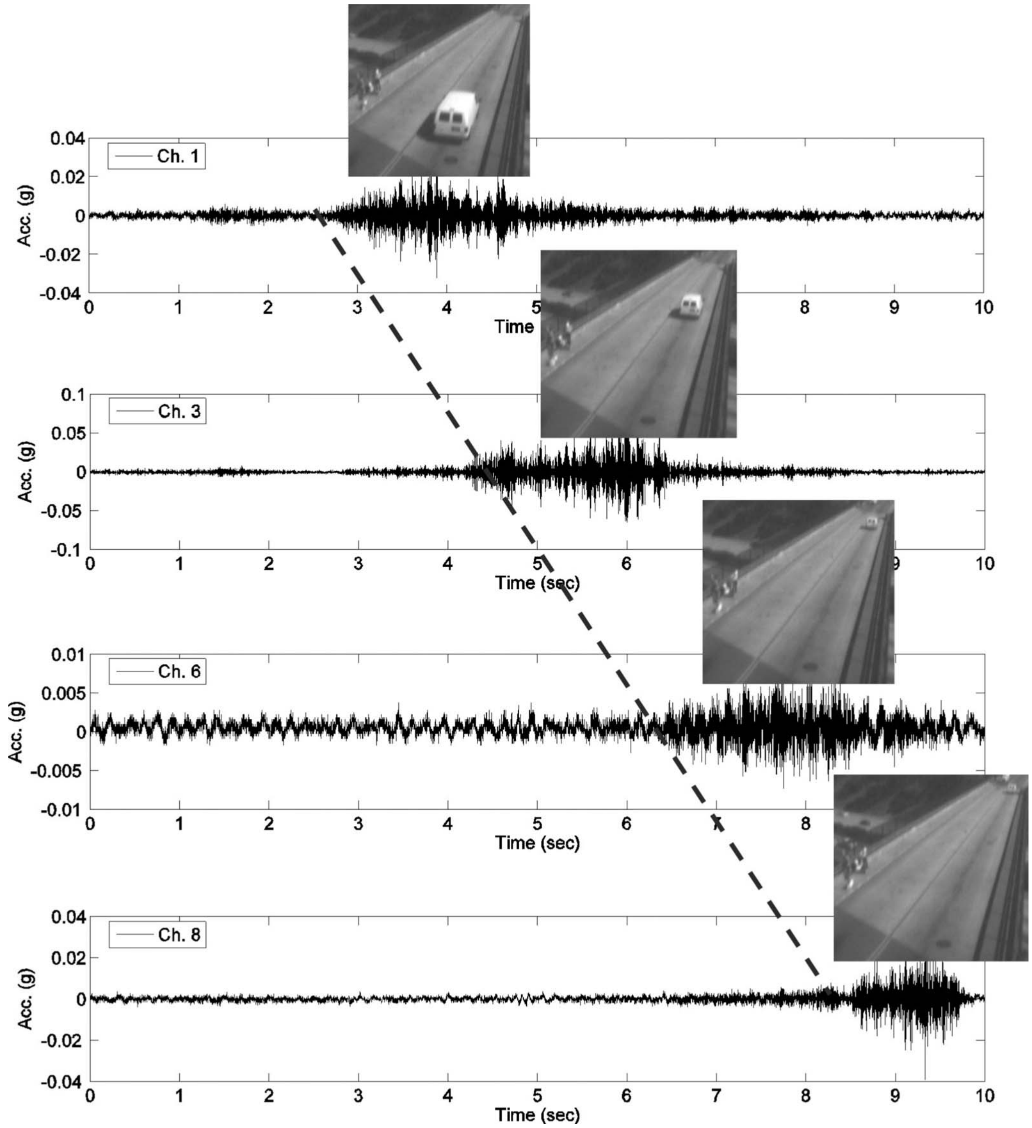


Fig. 9. Schematic display of time-synchronized acceleration and video (vertical response at the middle of each span; Sensors 3, 8, 14, and 19 of Fig. 2)

$$\phi_i = \mathbf{C} \bullet \mathbf{T}_{2i} \tag{4}$$

where $\mathbf{T}_i$=ith eigenvector of matrix $\mathbf{A}$ (similarly, $\mathbf{T}_{2i-1}$ and $\mathbf{T}_{2i}$ are complex conjugate pairs of eigenvectors, which correspond to the same vibration mode).

An automated modal analysis procedure has been developed (He 2008) to apply SSI-DATA for continuous health monitoring of the Voigt Bridge. In this implementation of SSI-DATA, first a stabilization diagram (Peeters and De Roeck 2001a) is constructed for system order $n=2,4,\ldots,50$ (Fig. 10). According to the stabilization diagram logic, for a realized state-space model of a given order n, an identified mode is considered as a physical vibration mode of the bridge if its modal parameters satisfy each of the following four conditions: (1) The deviation of its natural frequency from the average value obtained from models of order less than n is less than 1%; (2) the modal assurance criterion (MAC) value (Allemang and Brown 1982) between the mode shape and the average thereof identified from models of order less than n is higher than 95%; (3) the corresponding identified damping ratio is nonnegative and less than 20% (the relative change of damping ratio with respect to the average value from models of

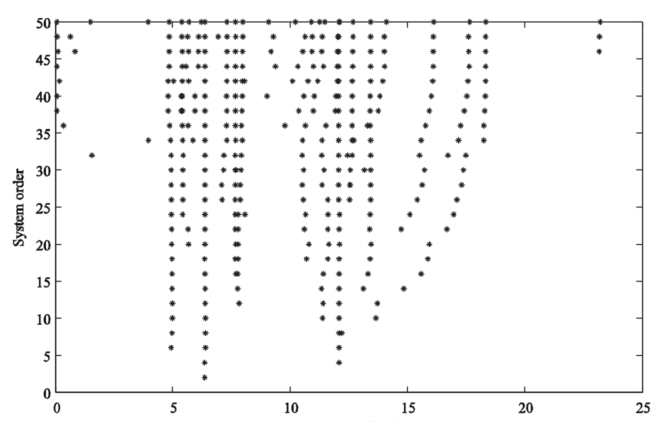


Fig. 10. Sample stabilization diagram obtained using SSI-DATA (one diagram is derived for each10 min data set)

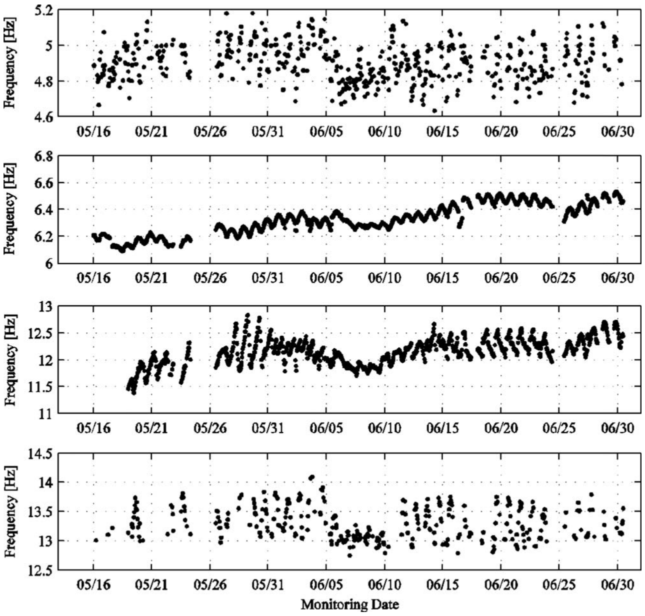


Fig. 11. Variation in four identified natural frequencies during the 45-day monitoring period in 2006 (May 16–June 30)

order less than n is not considered herein due to the relatively high estimation uncertainty characterizing this parameter); and (4) by increasing progressively the model order n (starting from $n=2$), the identified modal parameters satisfy the first three conditions defined above at least 10 times. The system order is then determined by the minimum order which contains all the physical modes identified using the above Criteria 1 through 4. Finally, the bridge modal parameters are extracted from the realized state space model with the determined minimum order.

Characteristics of Dynamic Response

As mentioned earlier, the bridge acceleration responses were digitized at the rate of 1,000 samples/sec resulting in a Nyquist frequency of 500 Hz, which is much higher than the bridge's natural frequencies of interest (<20 Hz in this study). In the aforementioned implementation of SSI-DATA, the data were first low-pass filtered below 25 Hz using a high order (1,024) finite impulse response (FIR) filter and then down-sampled to 100 samples/s in order to improve the computational efficiency of the system identification procedure. After this resampling, the Nyquist frequency (50 Hz) remains significantly higher than the natural frequencies of interest.

In each of the investigated 1,080 records, the corresponding traffic pattern will more clearly excite certain resonant frequencies. Light-traffic data sets (e.g., some midnight—3 a.m. records) would be less likely to meet the above described identification criteria. Over the 45-day data set, the variation in identified natural frequency for four selected vertical modes is shown in Fig. 11. Using a fixed "reference" and three roving accelerometers, the corresponding mode shapes were sampled at 34 spatial locations along the bridge deck as shown in Fig. 12(a). The corresponding modes, obtained from a wireless accelerometer network (Loh et al. 2007) display much similarity [Fig. 12(b)].

Overall, Table 1 summarizes the natural frequencies, as obtained from the above automated system identification procedure during the monitoring period of 45 days. For each identified mode, the frequency change is defined as $\Delta f=(f_{\max}-f_{\min})/f_{\min}$. It is seen that the relative changes in the bridge identified natural frequencies are of the order of 7–13% for the four modes of Fig. 11. These changes are primarily caused by the varying environmental conditions such as temperature, since the bridge did not undergo any structural change (damage/deterioration) during the monitoring period.

From Fig. 11, it is observed that the temporal variation pattern of the identified natural frequencies for the first and fourth modes is less consistent than that of Modes 2 and 3. In order to more clearly visualize these daily variation patterns, the identified frequencies of Modes 2 and 3 are shown (Fig. 13) over a shorter monitoring period for clarity (from May 27 through June 2). During this time frame, it is seen that the daily variation pattern of these two identified natural frequencies also exhibits a change over time. In this regard, additional data are currently being recorded, and research is directed to further clarify the variation of dynamic response characteristics with the ambient environmental conditions (Farrar et al. 1997; Farrar and James 1997; Sohn et al. 1999; Alampalli 1998, 2000; Peeters and De Roeck 2001b; Teughels and De Roeck 2004; Balmès et al. 2008). Depending on the type of structure, the monitoring period, and the extent of ambient temperature variation, natural frequencies were observed to vary in the ranges of 4–7% (Farrar et al. 1997) and 14–18% (Peeters and De Roeck 2001b).

Image Processing and Vehicle Classification

The image sequences captured using the video camera, provide a large amount of data (each picture frame is defined by an array or grid of 640×480 pixels). Using this video data, information such as location, velocity, and size of vehicle, can be extracted [e.g., Gonzalez et al. (2004), Chen et al. (2006), and Fraser (2006)] by computational image processing techniques in the following fashion:

1. Definition of background scene: To determine change within a series of images due to a passing vehicle, a background model must first be developed. Options include the Gaussian mixture model for high variance scenes (Stauffer and Grimson 1999), the simpler frame averaging technique for static scenes (Cucchiara et al. 2000), and the robust median (Gaussian) background estimation method employed herein (Baldini et al. 2002). This method applies a temporal median filter to each pixel over N previous frames (Gonzalez et al. 2004), with $N=20$ herein to keep stagnant objects from dominating the median.
2. Vehicle detection: In order to determine the characteristics of traffic on the bridge, the moving vehicles must be separated from the background image. For that purpose, the "background subtraction method" may be used (Ridder et al. 2000; Friedman and Russell 1997). This method compares each new frame to the updated background scene, and separates the pixels that have different properties.

   On this basis, the absolute difference $D(x,y,t)$ between the background and target images (Fig. 14) can be computed. Before subtraction, the standard MATLAB functions *imadjust* and *stretchlim* were employed so as to increase image contrast (Gonzalez et al. 2004). Using the MATLAB function *IM2BW*, $D(x,y,t)$ is converted to a binary image $M(x,y,t)$, where pixel values of one denote motion (white zones in Fig. 14).

   A filter is then tailored and applied to eliminate superfluous pixel zones that are below a specified size threshold

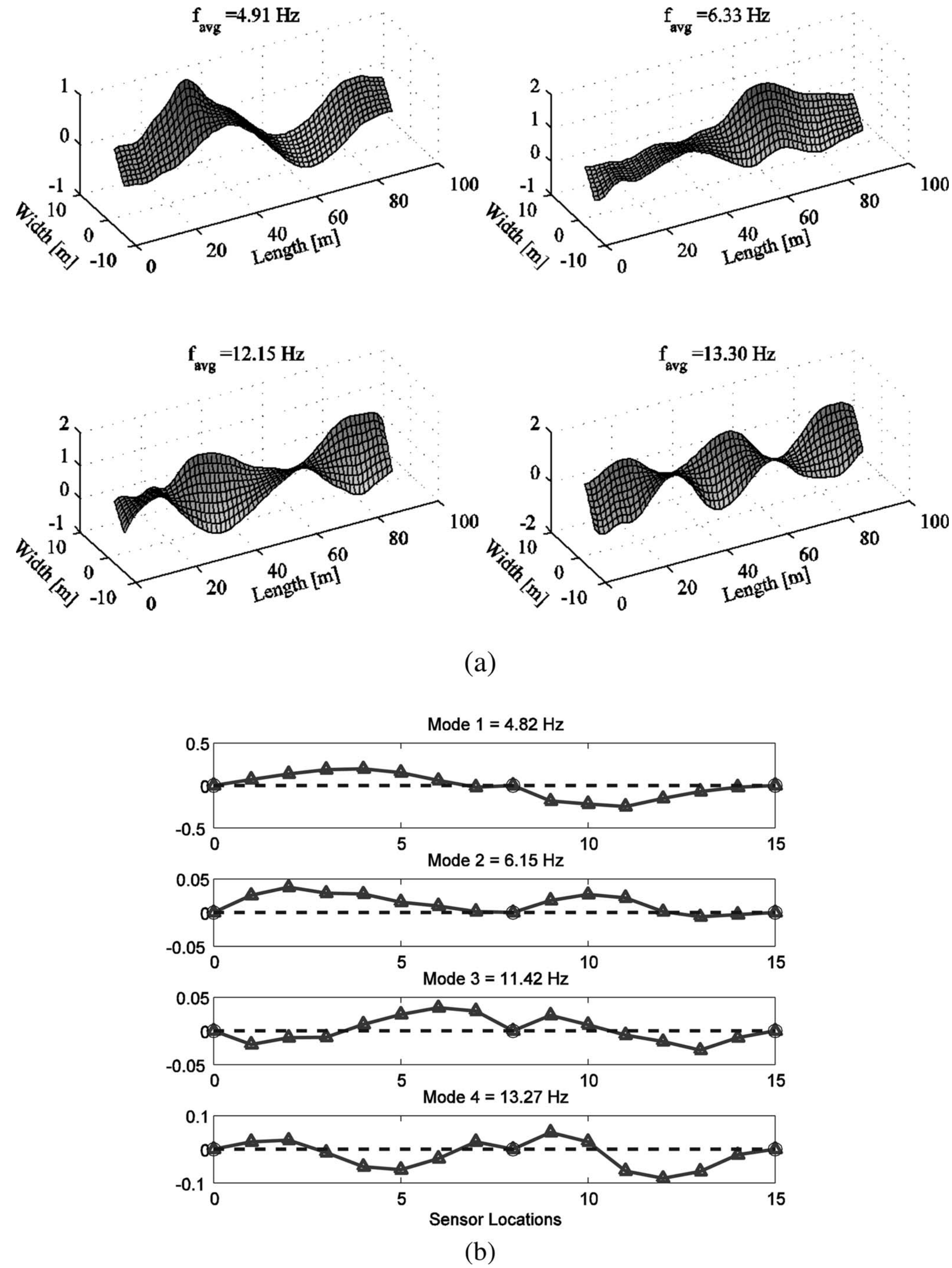


Fig. 12. (a) 3D representation of identified mode shapes (34 stations of measurement along the bridge); (b) mode shapes from wireless network (after Loh et al. 2007)

Table 1. Summary of Natural Frequency Identification Results during the Monitoring Period of 45 Days

Mode number	Minimum f_{min} (Hz)	Average (Hz)	Maximum f_{max} (Hz)	Frequency change $(f_{max}-f_{min})/f_{min}$ (%)
1	4.63	4.91	5.18	12
2	6.09	6.33	6.53	7
3	11.38	12.15	12.84	13
4	12.75	13.30	14.10	11

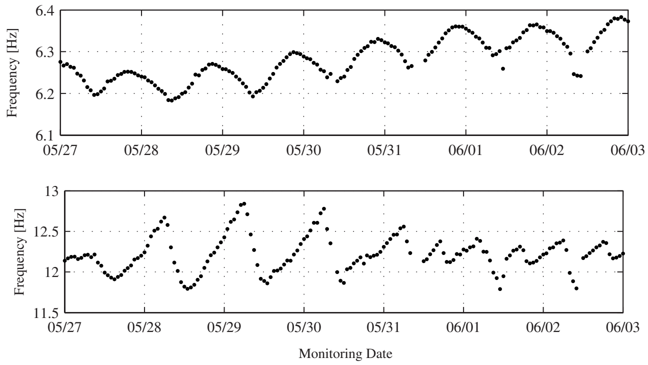


Fig. 13. Hourly identified natural frequencies of the second and third modes of Fig. 11 during the period of May 27–June 2, 2006

Fig. 15. Mapping of spatial configuration used for determining vehicle position on the bridge

(Gonzalez et al. 2004). In addition, certain regions of $M(x,y,t)$ outside of the bridge (spatial domain in the picture) contain objects of no interest (e.g., vehicles passing under the bridge). Objects detected in these external regions (Fig. 14) were simply eliminated (pixels are blacked out by setting their values to 0).

3. Vehicle tracking for location and speed estimation: Analysis in this section is conducted on $M(x,y,t)$, the binary map of moving pixels in which values of 1 correspond to motion (denoted in white in Fig. 14). A region finding algorithm (*regionprops* function in MATLAB) is applied to find groups of white pixels and their areas and centroids (Gonzalez et al. 2004). Tracking an object from frame-to-frame is accomplished by defining a characteristic vector $p(n,t)$ composed of the nth region centroid coordinates and bounding box dimensions at time t.

   To determine which detected object in the previous frame is most closely correlated with detected object n in the current frame, it is necessary to find k such that the vector norm

$$F(n,k) = \|p(n,t) - p(k,t-1)\| \qquad (5)$$

   is minimized for each n. If $F(n,k)$ exceeds a limiting threshold, no correlation is assumed.

To identify the actual vehicle location on the bridge, it is necessary to determine the "world" coordinates of the vehicle, i.e., transform the "screen plane" coordinates to the "world plane" spatial geometry (Fu and Moosa 2002; Hutchinson et al. 2006). For this purpose, markers on both sidewalks along the bridge were placed at a known distance from the camera and pixel values at these points were identified (a one-time effort).

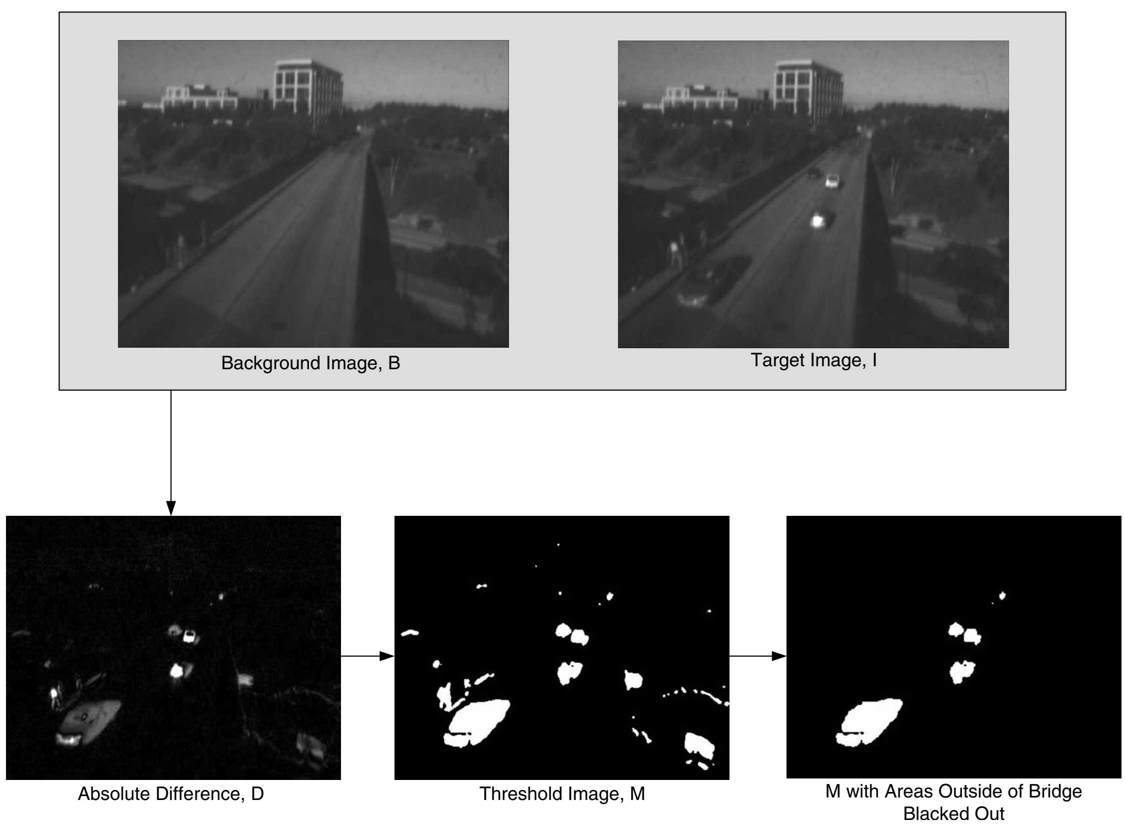
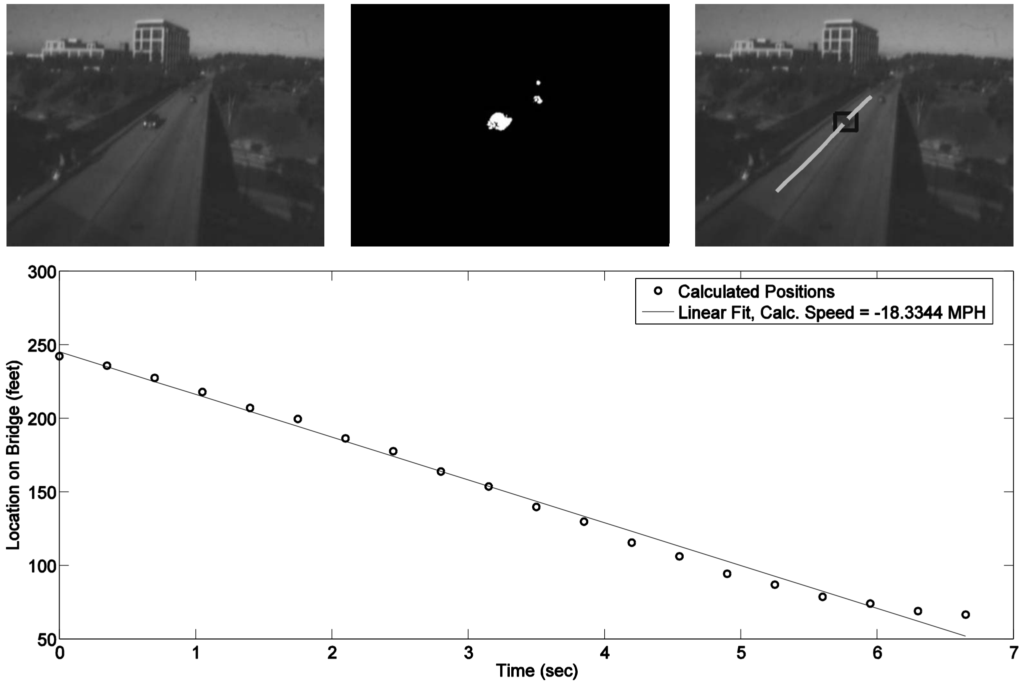
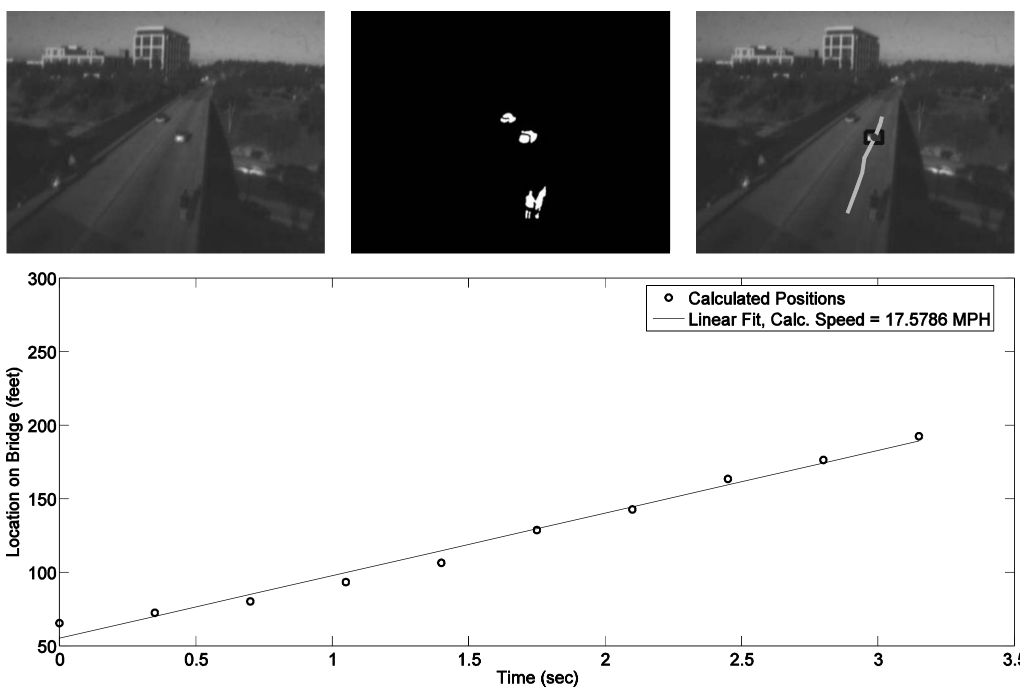


Fig. 14. Image processing sequence



(a)



(b)

Fig. 16. Original recorded picture, processed image, and image with extracted features (top, left to right) and vehicle location on bridge time (a) for westbound car; (b) for eastbound car

Using this information, the bridge deck was then discretized into a mesh of known locations (Fig. 15). Next, a least-squares model was used to locate and track the temporal location of a vehicle as it crosses the bridge.

The recorded images with extracted features along with plots of the position versus time are shown for typical westbound and eastbound cars (Fig. 16). Representing these locations by a straight line approximation average (Fig. 16) allows the slope thereof to represent the vehicle velocity. Building on the above, further research is progressing in the following two main directions:

1. Vehicle-identification enhancements which include handling of merging objects and implementation of shadow suppression algorithms for increased accuracy (Prati et al. 2003). More robust tracking methods, capable of dealing with ob-

jects hidden during certain frames, may be also implemented as discussed in (Baldini et al. 2002).

2. Vehicle size and speed output from the video processing algorithm can be used to generate load time histories for finite element modeling applications. Machine learning techniques can be employed to correlate the input traffic excitation to the output bridge response (output from the FE model compared to that measured on the bridge). Anomalies in this correlation may be used as a basis for SHM and related decision-support applications.

Summary and Conclusions

Building on a recently developed integrated structural monitoring framework, a highway bridge TestBed has been established on the Voigt Drive/Interstate-5 overcrossing, located on the UCSD campus. A continuous monitoring framework was built around a robust expandable system that is capable of supporting over 300 sensor channels and three cameras. Time-synchronized video and acceleration data are continuously recorded, archived, and made available online for browsing and downloading through a secure Web portal.

Over a 45-day period, over 1,000 acceleration records were studied to identify changes in the bridge dynamic response. Variation in natural frequencies in the range of 7–13% was observed. Video signal processing was used to identify vehicle location and speed. Finally, future research is being directed toward: (1) long-term assessment of the resonant bridge characteristics and changes due to the ambient environmental conditions and (2) correlation of the vehicle loads with the recorded dynamic bridge response.

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References

Alampalli, S. (1998). "Influence of in-service environment on modal parameters." *Proc., IMAC 16*, Academic Press, Santa Barbara, Calif., 111–116.

Alampalli, S. (2000). "Effects of testing, analysis, damage, and environment on modal parameters." *Mech. Syst. Signal Process.*, 14(1), 63–74.

Allemang, R. J., and Brown, D. L. (1982). "A correlation coefficient for modal vector analysis." *Proc., 1st Int. Modal Analysis Conf., Society for Experimental Mechanics*, Orlando, Fla., Society of Experimental Mechanics, Bethel, Conn., 110–116.

Baldini, G., Campadelli, P., Cozzi, D., and Lanzarotti, R. (2002). "A simple and robust method for moving target tracking." *Proc., IASTED Int. Conf. Signal Processing, Pattern Recognition and Applications (SPPRA2002)*, ACTA Press, Crete, Greece, 108–112.

Balmès, É., Basseville, M., Bourquin, F., Mevel, L., Nasser, H., and Treyssède, F. (2008). "Merging sensor data from multiple temperature scenarios for vibration monitoring of civil structures." *Structural health monitoring*, Vol. 7, SAGE, 129–142.

Beymer, D., McLauchlan, P., Coifman, B., and Malik, J. (1997). "A real-time computer vision system for measuring traffic parameters." *Proc., IEEE Conf. on Computer Vision and Pattern Recognition*, San Juan, Puerto Rico, IEEE Computer Society, Washington, D.C.

Bolton, R., Stubbs, N., and Sikorsky, C. (2002). "Automation of modal property extraction for a permanently instrumented highway bridge." *Proc., 20th Int. Modal Analysis Conf. (IMAC 20)*, Los Angeles, Calif., Society of Experimental Mechanics, Bethel, Conn., 1217–1223.

Carden, E. P., and Fanning, P. (2004). "Vibration based condition monitoring: A review." *Struct. Health Monit.*, 3(4), 355–377.

Casciati, F. (2003). "An overview of structural health monitoring expertise within the European union." *Structural health monitoring and intelligent infrastructure*, Z. S. Wu and M. Abe, eds., Swets and Zeitlinger, Lisse, 31–37.

Catbas, F. N., Brown, D. L., and Aktan, A. E. (2004). "Parameter estimation for multiple-input multiple-output modal analysis of large structures." *J. Eng. Mech.*, 130(8), 921–930.

Chang, P. C., Flatau, A., and Liu, S. C. (2003). "Review paper: Health monitoring of civil infrastructure." *Struct. Health Monit.*, 2(3), 257–267.

Chen, Y., and Feng, M. Q. (2006). "Modeling of traffic excitation for system identification of bridge structures." *Comput. Aided Civ. Infrastruct. Eng.*, 21(1), 57–66.

Chen, Y., Tan, C.-A., and Feng, M. Q. (2004). "Physics-based traffic excitation for highway bridges." *Proc., SPIE Conf. Smart Structures and Materials 2004: Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems*, San Diego, Calif., SPIE, Bellingham, Wash.

Chen, Y., Tan, C.-A., Feng, M. Q., and Fukuda, Y. (2006). "A video-assisted approach for structural health monitoring of highway bridges under normal traffic." *Proc., SPIE Conf. Smart Structures and Materials 2006: Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems*, San Diego, Calif.

Chong, K. P., Carino, N. J., and Washer, G. (2003). "Health monitoring of civil infrastructures." *Smart Mater. Struct.*, 12, 483–493.

Collins, R. T., Lipton, A. J., Fujiyoshi, H., and Kanade, T. (2001). "A system for video surveillance and monitoring." *Proc. IEEE*, 89(10), 1456–1477.

Cucchiara, R., Grana, C., Piccardi, M., and Prati, A. (2000). "Statistical and knowledge-based moving object detection in traffic scene." *Proc., IEEE Int. Conf. on Intelligent Transportation Systems*, IEEE Computer Society, Washington, D.C.

Elgamal, A., et al. (2003). "Health monitoring framework for bridges and civil infrastructure." *Proc., 4th Int. Workshop on Structural Health Monitoring*, Stanford, Calif., DEStech Publications, Inc., Lancaster, Penn.

Elgamal, A., et al. (2004). "A framework for monitoring bridges and civil infrastructure." *Proc. of the 3rd China-Japan-US Symposium on Structural Health Monitoring and Control*, Dalian, China, Oct. 14–16 (Invited Paper).

Farrar, C. R., Doebling, S. W., Cornwell, P. J., and Straser, E. G. (1997). "Variability of modal parameters measured on the Alamosa Canyon Bridge." *Proc., IMAC 15*, Orlando, Fla., Society of Experimental Mechanics, Bethel, Conn., 257–203.

Farrar, C. R., and James, G. H., III. (1997). "System identification from ambient vibration measurements on a bridge." *J. Sound Vib.*, 205(1), 1–18.

Fraser, M. (2006). "Development and implementation of an integrated framework for structural health monitoring." Ph.D. dissertation, Dept. of Structural Engineering, Univ. of California at San Diego, La Jolla, Calif.

Friedman, N., and Russell, S. (1997). "Image segmentation in image

Sequences: A probabilistic approach." *Proc., 13th Conf. on Uncertainty of Artificial Intelligence*, Aug. 1–3, Morgan Kaufmann, San Francisco, Calif.
Fu, G., and Moosa, A. G. (2002). "An optical approach to structural displacement measurement and its application." *J. Eng. Mech.*, 128(5), 511–520.
Gonzalez, R. C., Woods, R. E., and Eddins, S. L. (2004). *Digital image processing using MATLAB*, Prentice-Hall, Upper Saddle River, N.J.
Guan, H., Karbhari, V. M., and Sikorsky, C. S. (2006). "Web-based structural health monitoring of an FRP composite bridge." *Comput. Aided Civ. Infrastruct. Eng.*, 21(1), 39–56.
He, X. (2008). "Vibration-based damage identification and health monitoring of civil structures." Ph.D. thesis, Dept. of Structural Engineering, Univ. of California at San Diego, La Jolla, Calif.
Hutchinson, T. C., Kuester, F., Doerr, K.-U., and Lim, D. H. (2006). "Optimal hardware and software design of an image-based system for capturing dynamic movements." *IEEE Trans. Instrum. Meas.*, 55(1), 164–175.
Juang, J. N., and Pappa, R. S. (1985). "An eigensystem realization algorithm for modal parameter identification and model reduction." *J. Guid. Control Dyn.*, 8(5), 620–627.
Kastrinaki, V., Zervakis, M., and Kalaitzakis, K. (2003). "A survey of video processing techniques for traffic applications." *Image Vis. Comput.*, 21(4), 359–381.
Ko, J. M., and Ni, Y. Q. (2005). "Technology developments in structural health monitoring of large-scale bridges." *Eng. Struct.*, 27, 1715–1725.
Kogut, G. T., and Trivedi, M. M. (2001). "Maintaining the identity of multiple vehicles as they travel through a video network." *Proc., IEEE Conference on Intelligent*, Transportation Systems, Oakland, Calif., 756–761.
Loh, K. J., Lynch, J. P., Wang, Y., Law, K. H., Fraser, M., and Elgamal, A. (2007). "Validation of a wireless traffic vibration monitoring system for the Voigt Bridge." *Proc., World Forum on Smart Materials and Smart Structures Technology*, Chongqing and Nanjing, China, CRC Press, Boca Raton, Fla.
Lus, H., Betti, R., and Longman, R. W. (2002). "Obtaining refined first order predictive models of linear structural systems." *Earthquake Eng. Struct. Dyn.*, 31, 1413–1440.
Masri, S. F., Sheng, L.-H., Caffrey, J. P., Nigbor, R. L., Wahbeh, M., and Abdel-Ghaffar, A. M. (2004). "Application of a web-enabled real-time structural health monitoring system for civil infrastructure systems." *Smart Mater. Struct.*, 13, 1269–1283.
Morris, B., and Trivedi, M. M. (2006). "Robust classification and tracking of vehicles in traffic video streams." *Proc., IEEE Int. Intelligent Transportation Systems Conf.*, Toronto, Canada, IEEE Computer Society, Washington, D.C.
Mufti, A. A. (2002). "Structural health monitoring of innovative Canadian civil engineering structures." *Struct. Health Monit.*, 1(1), 89–103.
Nayeri, R. D., Masri, S. F., Ghanem, R. G., and Nigbor, R. L. (2008). "A novel approach for the structural identification and monitoring of a full-scale 17-story building based on ambient vibration measurements." *Smart Mater. Struct.*, 17, 2.
Peeters, B., and De Roeck, G. (2001a). "Stochastic system identification for operational modal analysis: A review." *J. Dyn. Syst., Meas., Control*, 123(4), 659–667.
Peeters, B., and De Roeck, G. (2001b). "One-year monitoring of the Z24-Bridge: Environmental effects versus damage events." *Earthquake Eng. Struct. Dyn.*, 30(2), 149–171.
Pines, D. J., and Aktan, A. E. (2002). "Status of structural health monitoring of longspan bridges in the United States." *Prog. Struct. Eng. Mater.*, 4(4), 372–380.
Prati, A., Mikic, I., Trivedi, M. M., and Cucchiara, R. (2003). "Detecting moving shadows: Algorithms and evaluation." *IEEE Trans. Pattern Anal. Mach. Intell.*, 25(7), 918–923.
Proc., 5th Int. Workshop on Structural Health Monitoring. (2005). "Structural health monitoring 2005: Advancements and challenges for implementation." F.-K. Chang, ed., Stanford, Calif., DEStech Publications, Inc., Lancaster, Penn.
Proc., 6th Int. Workshop on Structural Health Monitoring, Stanford 2007: Quantification, Validation, and Implementation. (2007). F.-K. Chang, ed., Stanford, Calif., DEStech Publications, Inc., Lancaster, Penn.
Ridder, C., Munkelt, O., and Kirchner, H. (2000). "Adaptive background estimation and foreground detection using Kalman filtering." *Proc., Int. Conf. on Recent Advances in Mechatronics*, UNESCO Chair on Mechatronics, Istanbul, Turkey, 193–199.
Sohn, H. (2003). "A review of structural health monitoring literature 1996-2001." *Proc., Third World Conf. on Structural Control*, Vol. 2, John Wiley, Como, Italy, 9–15.
Sohn, S., Dzonczyk, M., Straser, E. G., Kiremidjian, A. S., Law, K. H., and Meng, T. (1999). "An experimental study of temperature effect on modal parameters of the Alamosa Canyon Bridge." *Earthquake Eng. Struct. Dyn.*, 28, 879–897.
Stauffer, C., and Grimson, W. E. L. (1999) "Adaptive background mixture models for real-time tracking." *Proc., IEEE Conf. on Computer Vision and Pattern Recognition*, Ft. Collins, Colo., IEEE Computer Society, Washington, D.C., 246–252.
Teughels, A., and De Roeck, G. (2004). "Structural damage identification of the Highway Bridge Z24 by FE model updating." *J. Sound Vib.*, 278(3), 589–610.
Tomizuka, M., Yun, C.-B., and Giurgiutiu, V., Eds. (2006). "Smart Structures and materials 2006: Sensors and smart structures technologies for civil, mechanical, and aerospace systems." *Proc., SPIE Conf. Smart Structures and Materials 2006: Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems*, San Diego, Calif., SPIE, Bellingham, Wash.
Van Overschee, P., and De Moor, B. (1996). *Subspace identification for linear systems*, Kluwer Academic, AA Dordrecht, The Netherlands.
Wahbeh, M., Tasbihgoo, F., Yun, H., Masri, S. F., Caffery, J. P., and Chassiakos, A. G. (2005). "Real-time earthquake monitoring of large-scale bridge structures." *Proc., 5th Int. Workshop on Structural Health Monitoring*, Stanford University, Stanford Calif., 190–197.
Wang, Y., Loh, K. J., Lynch, J. P., Fraser, M., Law, K. H., and Elgamal, A. (2006). "Vibration monitoring of the voigt bridge using wired and wireless monitoring systems." *Proc., 4th China-Japan-US Symp. on Structural Control and Monitoring*, Hangzhou, China.
Wang, Y., Lynch, J. P., Law, K. H., Loh, C.-H., and Elgamal, A. (2007). "Reliable information management in a low-cost wireless structural monitoring and control network." *Proc., SPIE 14th Int. Symp. on Smart Structures and Materials & Nondestructive Evaluation and Health Monitoring*, San Diego, Calif., SPIE, Bellingham, Wash.
Yan, L. (2006). "Statistical inference approaches for structural damage detection." Ph.D. dissertation, Dept. of Structural Engineering, Univ. of California, San Diego, La Jolla, Calif.
Yan, L., Fraser, M., Elgamal, A., Fountain, T., and Oliver, K. (2008). "Neural networks and principal components analysis for strain-based vehicle classification." *J. Comput. Civ. Eng.*, 22(2), 123–132.