DYNAMIC STRUCTURAL HEALTH MONITORING OF CONFEDERATION BRIDGE: LESSONS LEARNED, CHALLENGES AND FUTURE DIRECTIONS

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Abstract

The 12.9km long Confederation Bridge connecting Prince Edward Island and New Brunswick in eastern Atlantic Canada is the world's longest bridge built over ice covered sear water. With 45 main spans of 250m each and a 100-year design life, the design criteria of the Confederation Bridge are not covered by any code or standard in the world. Since the bridge opening in 1997, a comprehensive structural health monitoring system has been collecting data on the response behaviour and performance of the bridge under ambient traffic, wind and earthquake load actions. This paper summarizes the lessons learned, challenges identified and the future directions of the vibration structural health monitoring program. In the early phase of the project, dynamic response data have been used to verify the dynamic properties and design assumptions of the bridge. Subsequently, vibration data are used to provide support for decision making on the efficient operational management and maintenance of the bridge and to help with structural condition assessment. Ambient and strong wind event and traffic induced vibration monitoring data have been used to calibrate and improve the accuracy of the bridge computer models. The variability characteristics of uncertainties in the monitoring data crucial for realistic structural health and condition assessment application of bridges using field monitoring data are evaluated and a first ever data variability or uncertainty model based on actual field data has been developed. Implications of data noise and variability on structural condition assessment of bridges are discussed. An application platform developed for the Confederation Bridge monitoring project for real-time data processing, analysis and visualization is described. Future directions of vibration based structural health monitoring of critical bridges and bridge infrastructure networks are presented.

Keywords: bridge dynamics; structural health monitoring; system identification; pattern recognition; damage detection

1. Introduction

The Confederation Bridge is a 12.9 km long pre-stressed concrete bridge over the Northumberland Strait that provides the only fixed link between New Brunswick on mainland Canada and Prince Edward Island. It is one of the world's longest bridges operating in water with winter sea ice cover. The bridge is divided into 21 approach spans, two transition spans of 165 m each and 43 main spans of 250 m each at a typical height of 40 m above the mean sea level. The main-span portion of the bridge comprises 22 repetitive structural frame modules of 500 m length each. Each frame module is a 440 m portal frame made up of a 250 m centre span and two 95 m overhangs, one on each side of the centre span, plus a 60 m simply supported drop-in expansion span, as shown in Figure 1a. Because it operates under very severe and harsh environment conditions over a period significantly longer than the normal design service life of typical bridges, a comprehensive and detailed understanding of the behavior of the Confederation Bridge is essential in order to accurately predict and evaluate its performance in the future. A comprehensive long-term monitoring system on the Confederation Bridge has been in operation since the bridge opening in 1997 to collect data and information about its behaviour and performance. The monitoring system records both environmental and bridge response data including vibration responses, concrete temperature, short and long term deformations and material properties, ice cover conditions and interactions of ice features with the bridge piers, and weather data. Details of the Confederation Bridge monitoring instrumentations and research programs have been presented in a separate publication [1]. The dynamic monitoring system is dedicated to the measurement of the vibration responses of the bridge caused by significant sources of dynamic excitations, including wind, heavy traffic, ice loads and earthquakes. The vibration instrumentation comprises a total of 76 accelerometers of both piezoelectric and servo types distributed between Piers 30 to 33 of the bridge, as shown in Figure 1b.

The monitoring project of the Confederation Bridge represents a unique and ideal opportunity for research to advance the state-of-the-art and practices of vibration based structural health monitoring (VBSHM) technology because of the availability of comprehensive long-term monitoring data and information covering not only the dynamic responses of the structure but also other important structural behaviour and performance aspects, such as concrete temperature, material properties and wind speed, etc. The basic theoretical premise of VBSHM is that any changes in the vibration properties of a structure can be attributable to damage or deterioration of the structure. However, practical applications of VBSHM techniques to bridges in the field often encounter difficulties because of noises or uncertainties in the data affected by fluctuations in the environmental conditions and loading actions masking the changes due to structural damage. The data from the

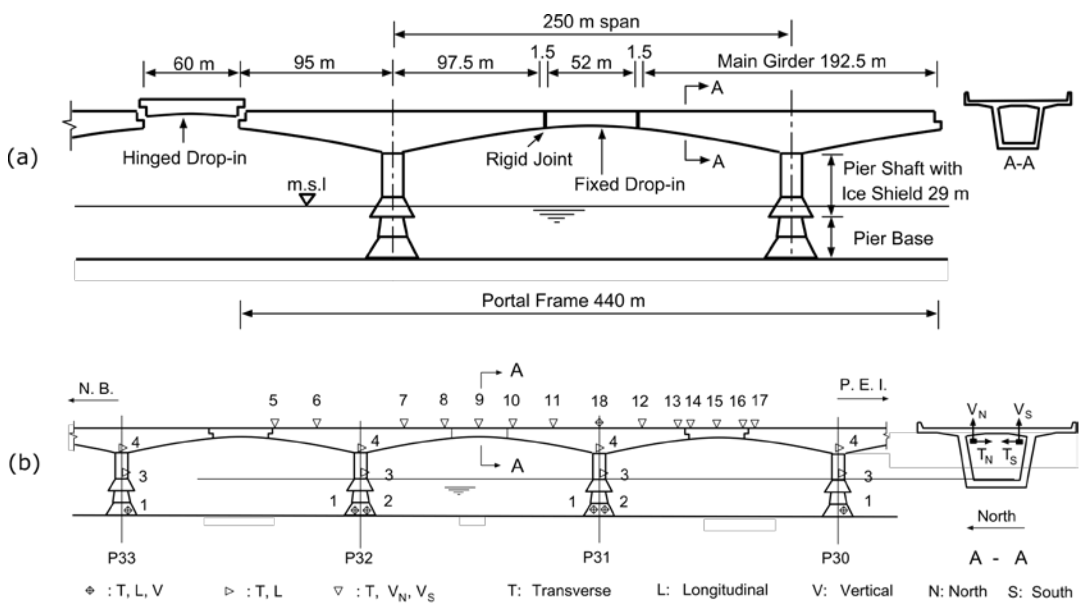


Fig. 1 – (a) Dimensions, main components; (b) Accelerometer locations in Confederation Bridge

monitoring project of the Confederation Bridge are used not only to better understand the behaviour of the bridge but also to characterize the variability of the monitoring data that will facilitate advances in the practical use of monitoring data for structural assessment and damage detection. The data is also especially relevant to the study of the influences of environmental factors on the variability of monitoring data and results. The weather condition at the Confederation Bridge site ranges (-20^{o}C to +25^{o}C) from hot summer to very cold and windy winter season (>100km/hr) and has exposure to significant loading from seasonal ice floes in the strait.

This paper presents an overview of the lessons learned, challenges identified, and future directions of the vibration structural health monitoring program. Dynamic response and monitoring data have been used to verify the dynamic properties and design assumptions of the bridge. Ambient and strong wind event and traffic induced vibration monitoring data have been used to calibrate and improve the accuracy of bridge computer models. The variability characteristics and uncertainties in the monitoring data crucial to successful realistic structural health and condition assessment application of bridges using field monitoring data have been investigated. To interpret the large amount of data, an application platform (SPPLASH) developed for the Confederation Bridge monitoring project for real-time data processing, analysis, and visualization is described. Four system identification algorithms applied to real vibration monitoring data in the presence of high level uncertainty and noise related to field measurement data are discussed. Another approach in tackling the challenges of practical structural health monitoring and condition assessment using a data driven approach is described. Data driven models are based on "features" with no physical meaning, for example, the pattern recognition technique. This is also linked to big data and data analytics and is discussed for applications in structural health monitoring herein. Finally, some conclusions and future directions of vibration based structural health monitoring of critical bridges and bridge infrastructure networks are presented.

2. Dynamic Response Monitoring and Measurements

Vibration responses of the bridge girders are measured in the vertical and lateral horizontal directions, as shown in the accelerometer layout in Figure 1b. This setup facilitates the recovery of vertical bending, lateral bending and torsional vibration modes of the bridge superstructure. The response behaviour observed in the instrumented segment of the bridge is considered representative of the behaviour of the main-span portion of the structure.

The vibration sensors used in the monitoring system include both piezo-electric accelerometers and servo accelerometers. Signals are sampled using a strict sample and hold analog to digital conversion by a network of high-speed data loggers before being sent to on-site computers and transmitted back to Carleton University in Ottawa for data processing and analysis. Typical data sampling rates vary between 100 Hz and 167 Hz. Dedicated communication lines between the different data loggers ensure simultaneous triggering and recording. The data loggers operate in continuous buffered data collection mode, which upon triggering by detection of specific dynamic events, such as heavy traffic signals or high winds, or simply upon user request, store time history response data in hard disk for detailed analysis and research. Otherwise, only statistic information determined from the time history data, such as mean, maximum, minimum and standard deviation, are stored.

The structural monitoring framework encompasses not only the monitoring instrumentation and data collection systems at the bridge site, but extends to also include the computer infrastructure for the distribution, processing and utilization of the monitoring data. Details of the monitoring system setup have been described in previous publications [1, 2], while the development of the associated computer tools have been discussed by [3].

Figure 2 shows typical time domain plots of bridge acceleration responses at mid-span of the portal frame for sensor location 9. The datasets were collected from November 2000 to May 2002. The figures illustrate the typical distinctive characteristics of data under different loading scenarios. Frequency content collected under high-wind scenarios are characterized in the low-frequency range, mostly below 1.0 Hz. Alternatively, the frequency content of the responses under traffic is markedly different from those associated with the high wind scenarios and are concentrated mainly in the 2.5 Hz to 3.5 Hz range. In the ambient responses, which represent typical operating conditions where the bridge is subjected to random combinations of wind and traffic loading the bridge responses essentially exhibit a combination of the characteristics of the wind-driven and traffic-driven responses described above. Under the presence of ice floes, the responses of the bridge are not too dissimilar to the response under the ambient scenarios without ice. The characteristic frequency content including dominant

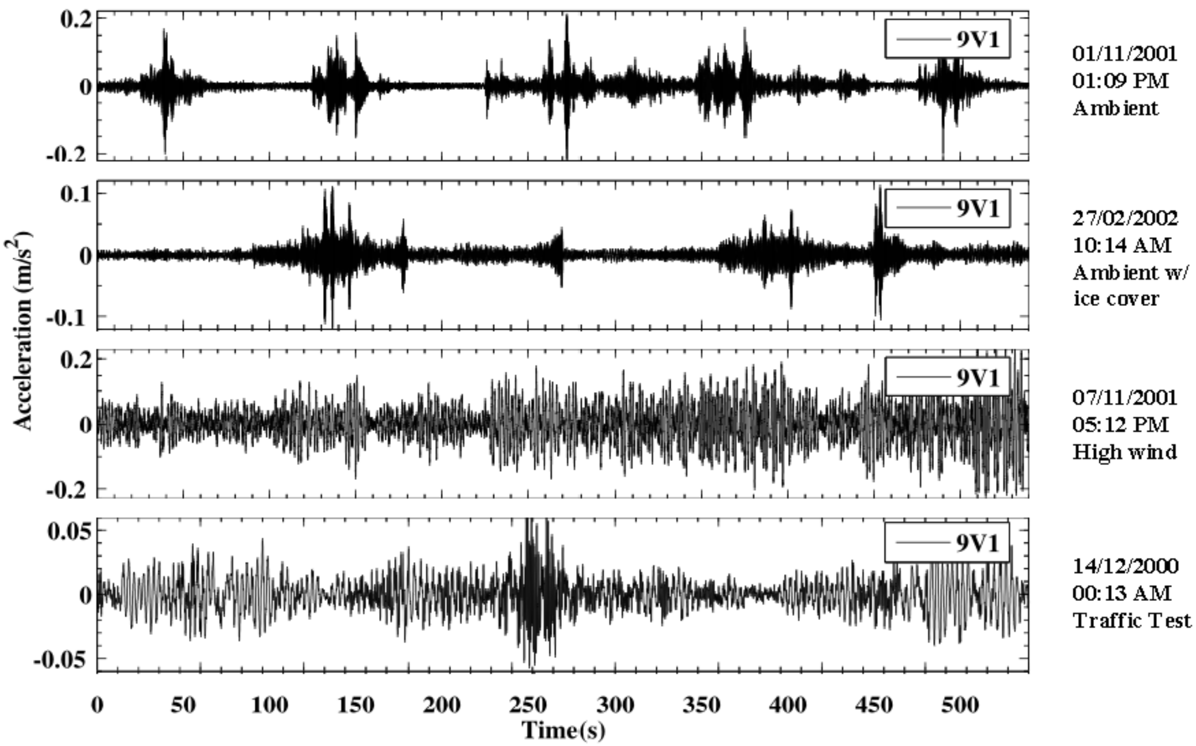


Fig. 2. – Typical vertical acceleration time histories under different loading scenarios

frequencies in the dynamic behaviour under each of these loading scenarios has been established and is essential for use of the monitoring data for structural assessment and health monitoring of the bridge in the future.

From the system identification analysis of the monitoring data, twenty-five vibration modes are identified in the 0 – 5.2 Hz range. The extracted vibration modes are compared to the expected design values based on finite element models of the bridge constructed from design drawings and material specifications of the structure with the aim of verifying that the bridge behaves as expected from design. Taking into consideration the time varying properties of the structure, such as the concrete modulus of elasticity, the identified modal frequencies differ only by -3% to 4% on average from expected design values (the slight difference depends on the type of finite element model used to obtain the expected design values). The extracted mode shapes are reasonably close to those expected from the design with the exception of some localized discrepancies. In addition, damping ratio design assumptions, which vary according to the type of loading have also been verified against modal damping ratios extracted from the monitoring data. The damping ratios assumed at the design stage for bridge response under wind seem to be reasonably conservative compared to the extracted values. Damping ratios of 2% and 5% assumed in the earthquake design are slightly higher than the extracted values, but also seem to be reasonable since significant additional damping can be expected in the large amplitude responses to strong ground motion. Additional details on the dynamic characteristics and finite element modelling of the Confederation Bridge are available in references [4, 5].

The variability observed in the dynamic properties extracted by system identification of the field monitoring data is highlighted because it represents a major challenge for the use of the monitoring data for structural condition assessment given that the typically small changes in the extracted properties caused by damage or deterioration of the structure could easily be masked by the normal variability of the data. On average, identified modal frequencies exhibit a standard deviation of 1.8% from mean values while damping ratios exhibit significantly higher variability. The higher uncertainty of the damping ratios stems from the complexity of the damping phenomena. Identified mode shapes also show some variability. Understanding the causes of the variability, together with the development of improved system identification and damage detection algorithms, is essential for the field application of vibration based health monitoring in the future.

3. Real-time Structural Health Monitoring Application Platform

The processing and analysis of large datasets collected from continuous monitoring systems often require a significant amount of time and effort. In order to accelerate the processing of these continuous monitoring data and to facilitate more rapid data analysis, and more timely interpretation and use of the results; a real-time data processing and analysis application platform SPPLASH has been developed which encompasses all aspects of data manipulation. This application platform consists of data processing, analysis and visualization modules, all integrated through graphical user interfaces (GUIs). The applications are designed and adapted to run in a real-time mode by automatically sorting incoming data and re-directing it to the processing and animation modules for graphic display of bridge displacements and motion in near real-time, as limited by the network speed. With this capability, after the occurrence of extreme events such as windstorms, earthquakes or ship impacts, bridge responses and condition of the facility can be assessed in a timely manner for decision support of its operation.

The design of such a tool helps to overcome the numerous challenges on the development of intelligent automatic data processing and analysis, reliable condition assessment algorithms that take into account the stochastic variations in data behaviour, and the development of graphical user interfaces (GUIs) and visualization tools to facilitate engineering interpretation of the monitoring information. The developed application platform has a modular design in which each module has its own GUI for configuration of the processing of data and is designed to interface seamlessly with other appropriate modules in the application platform. Modules for data processing, data display and plotting, system identification, and visualization of bridge responses have been developed. With the modular design, additional application modules can be developed and added to the platform to perform new tasks in the future. Another advantage of the modular design is that the application architecture can easily be adapted to take advantage of the rapidly increasing computing power by parallel processing. For example, modules performing CPU intensive tasks, such as data processing, system identification and 3D visualization can be handled by separate dedicated processors or computers in a distributed network computing environment. The processing and visualization modules are designed to have the capability to operate in real-time mode enabling the animation of bridge responses, such as the displacements, in near real-time as limited by the network speed.

3.1 Data Processing

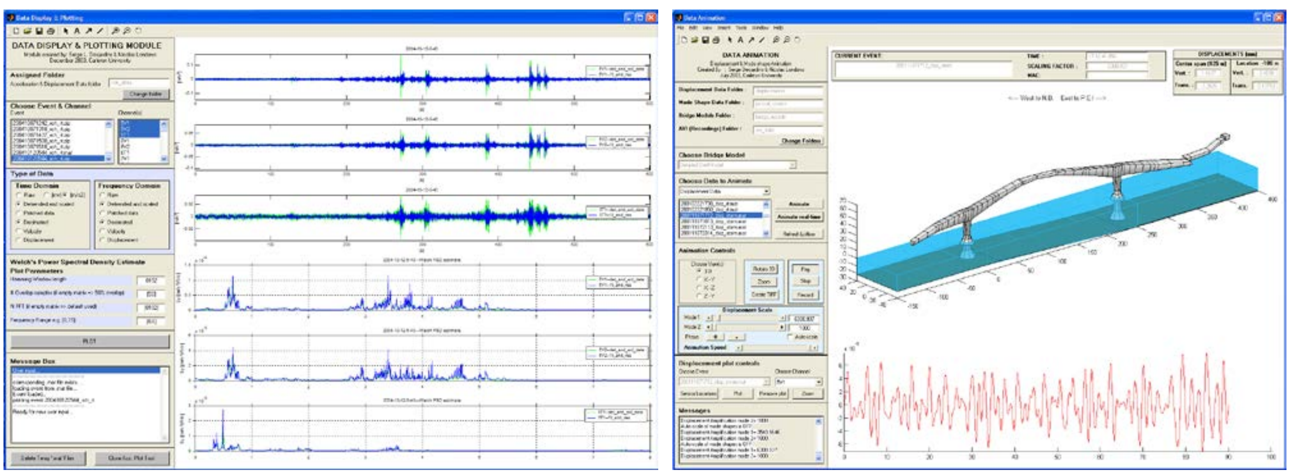
File sorting and processing of the raw monitoring data is performed in order to correct the above listed problems and to produce suitable outputs for data analysis and visualization. The file sorting operation organizes the data files into appropriate input files for the processing engine. File sorting tasks include organization of the data files, identification and separation of different data events, and the assembling of matching data event segments to form a complete data event of proper duration.

The data processing operations and procedures carried out by the processing engine includes a number of steps. Data assimilation or synchronization of data events from different loggers into full datasets corresponding to the same dynamic event are carried out first. Any small gaps where data samples are found to be missing are patched and any duplicate records are purged from the dataset. A baseline adjustment of the accelerometer time-history signals and conversion of the data to engineering units is then carried out. The data then undergoes resampling to a common sampling rate and is decimated to within the typical frequency content of interest for the structure, typically below 15 Hz. Finally, the data signals are integrated to obtain displacement and acceleration time histories for the response of the structure.

3.2 Data Display and Visualization

The primary purpose of this platform from the user perspective is to simplify the process of extracting meaningful engineering information from the monitoring data. To facilitate this process, a visualization module including a data plotting tool with extensive plotting capabilities provides a convenient environment for the analysis of large datasets within a reasonable time frame. Using the developed GUI, displacement and acceleration time histories and spectral plots can be easily manipulated to obtain the desired information on the behaviour of the structural system, as shown in Figure 3a. Data may be viewed at any intermediate stage of processing to qualitatively evaluate the processing results. Different channels may be plotted simultaneously in the same figure providing easy comparison. A second visualization module includes a 3D bridge model for animation of bridge displacement responses and mode shapes, shown in Figure 3b. Bridge responses during a dynamic event such as a windstorm, an earthquake or simply during normal operational conditions can be animated for more effective visualization and interpretation of the results, which provides valuable insight into the bridge behaviour. The animation module permits flexible user interaction. Parameters of the animations include scaling factor, view angle and playback speed. The animation and plotting capabilities are seamlessly integrated. There is also an option to record animation sequences for playback on common media players.

In the future, given that important challenges currently existing in vibration based health monitoring can be overcome, it should be possible to integrate the real-time data processing modules with data analysis tools and damage detection algorithms to facilitate timely condition assessment of the monitored facilities based on evaluation of continuous dynamic monitoring data. The data visualization modules facilitate the extraction of engineering information from large datasets collected by a continuous monitoring system. Timely extraction of engineering information from the bridge response monitoring data is also very important for the operation of bridge facilities. For example, a warning system has been implemented using the extracted information to give early warning to facility operators if it is detected that certain response value exceeds a specified safety or threshold limit during normal operation or after the occurrence of an extreme event, such as an earthquake.



(a) (b)

Fig. 3 – Graphical user interfaces (a) data display module; (b) animation module

3.3 Spectral Analysis

As a preliminary analysis of the bridge monitoring response signals, power spectral density (PSD) analysis of the monitoring data can be conducted to identify the dominant structural vibration frequencies and distribution of the energy of the signals in the frequency domain. In the developed computer application platform, PSD functions of the monitoring responses can be visualized through the data display module, as shown in Figure 3. The PSD function module can be applied to the analysis of the data signals at any intermediate or processing stage.

3.4 System Identification

Determination of the structural vibration frequencies, mode shapes and damping ratios of the structural system from the monitoring data are important aspects of structural health monitoring as they are the fundamental parameters of vibration based structural condition assessment techniques. To obtain more accurate values for structural frequencies, mode shapes and damping ratios of the structural system, a number of different system identification techniques have been implemented in the modular application platform discussed in the following section, including Stochastic Subspace Identification (SSI), PolyMAX, Eigensystem Realization Algorithm

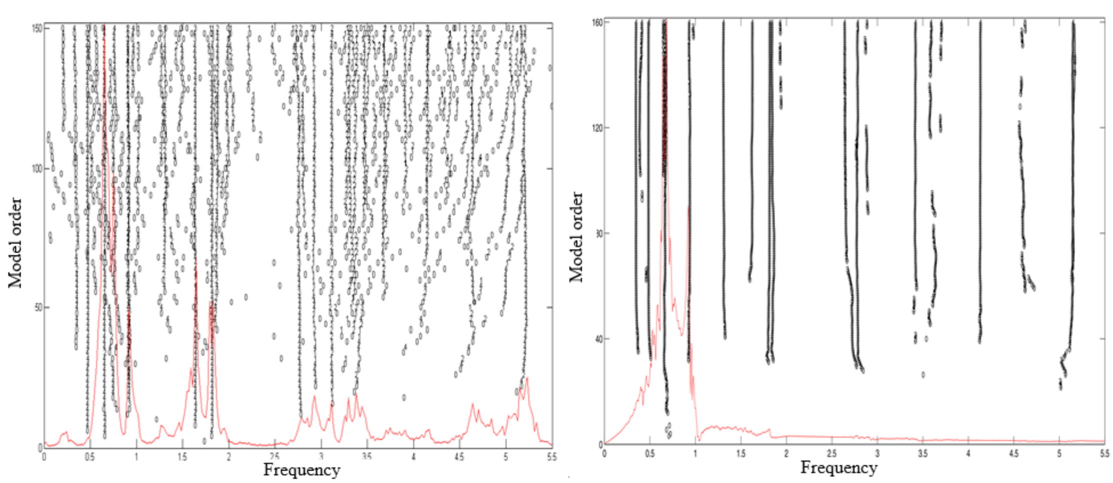
(ERA) and Frequency Domain Decomposition method (FDD). Additional details on the development of the real-time analysis application platform are available in a separate publication [3].

4. Comparison of System Identification Techniques

The Confederation Bridge is exposed to harsh environmental conditions including high wind and moving ice floes as well as a wide range of seasonal environmental fluctuations, which make it an ideal setting for studying the practical applicability of VBSHM due to the high level of uncertainties present in the environmental and loading conditions. The latest development of promising output-only modal identification technique, PolyMAX allows new capabilities in automatic data processing for the estimation of modal parameters due to its ability in providing a clear stabilization diagram of the system poles of the monitored structure. The accuracy and efficiency of four different identification methods: (1) Stochastic Subspace Identification (SSI), (2) PolyMAX, (3) Eigensystem Realization Algorithm (ERA) and (4) Frequency Domain Decomposition (FDD) method are compared using a total of 14 data sets selected from the confederation bridge monitoring database for analysis. The range of average concrete temperature in the dataset is -2.7°C to -1.4°C, while the average wind speed range is 7.2 m/s to 14.8 m/s. The ranges of these values, 1.3°C and 7.6 m/s are reasonable when compared to the yearly variations of 45°C and 30 m/s for the typical annual average environmental conditions at the bridge site. As described earlier the FDD, ERA and PolyMAX methods have been added to the existing Confederation Bridge monitoring software platform (SPPLASH) and the results obtained by these four identification algorithms are compared with finite element models of the bridge.

4.1 Stochastic Subspace Identification

Four vertical and two lateral sensors at monitoring locations 7 and 9 are used as reference sensors for cross-correlation computation. These sensors are suitable references because of their relatively high response amplitudes and because their locations do not simultaneously coincide with modal nodes of any of the important vibration modes of the bridge. In the present study, proper models are identified by the SSI method with a model order of 150 i.e. models containing 75 modes. Even though the actual model order of the data analyzed here is typically around 40, a relatively high maximum model is used in the construction of the stabilization diagrams to allow for a clear visualization of stabilized trends. In the assessment of the stabilized modal parameters, a stabilization limit of 0.5% is chosen for frequency identification, whereas for mode shape and damping the limits are 1% and 15% respectively. Figure 4a shows the stabilization diagram for dataset 1 obtained by SSI method.



(a) (b)

Fig. 4. – Stabilization diagram: (a) SSI method; (b) PolyMAX method

4.2 PolyMAX Method

Here, the primary identification data, positive power spectrum is estimated via the correlogram approach with 2048 correlation lag time. The same 6 sensors (4 vertical and 2 lateral) at monitoring locations 7 and 9, selected in the SSI method are used as reference sensors here. To reduce the error due to leakage, a 1% exponential window is applied prior to correlogram spectrum estimation. To generate the stabilization diagram by the PolyMAX method, the model order between 150 and 200 is selected and the same stabilization criteria as in the SSI method for frequency, mode shape and damping are employed. Figure 4b shows a typical stabilization diagram for one of the dataset obtained by the PolyMAX method.

4.3 Eigensystem Realization Algorithm (ERA)

For the ERA method, the correlations calculated with respect to the same 6 sensors at monitoring locations 7 and 9 (4 vertical and 2 lateral sensors) are used as identification data. A Hankel matrix of the dimension 8750x600 corresponding to 9.3s of "free response" data is evaluated. Because there is no "gap" in the singular value i.e. it is very difficult to determine the number of modes being excited by just examining the singular value plot. In most of the datasets, the truncation of block Hankel matrix is carried out with the model order of 50 to 60 so that approximately 25-30 modes are identified. As the frequency range of interest is 0-5.5 Hz, only the frequencies below 5.5 Hz are considered in the system identification analysis. Modes with high damping ratio are discarded. A threshold of 5% damping ratio is established. Repeated modes are eliminated based on the lowest energy content given by the singular values.

4.4 Frequency Domain Decomposition (FDD) Method

The spectra are estimated via Welch periodogram method using 2048 points FFT with a Hamming window of 50% segment overlap. This results in a frequency resolution of 0.0122 Hz for singular value plot. For each dataset, two spectral matrices were calculated, one for vertical and another one for lateral accelerations. Then, a singular value decomposition of the spectral matrices was performed to evaluate the corresponding non-zero singular values. Figure 5 shows the average singular values of all datasets for both directions. Damping estimate is performed in time domain assuming a SDOF around a peak via enhanced FDD.

4.5 Comparison of System Identification Results

Modal vibration frequencies, mode shapes and damping ratios obtained by four system identification methods are compared to the theoretical values based on the calculated finite element model to examine the correlation between extracted and analytical modal properties. Both SSI and PolyMAX algorithms are able to identify 21 modes below 5.5 Hz. The ERA method fails to detect a mode at 0.55 Hz whereas in case of FDD method; two modes namely at 0.55 Hz and 0.84 Hz are not identified. The finite element modal frequencies based on the field measurement of concrete modulus are in close agreement to the measured values with an overall observation of

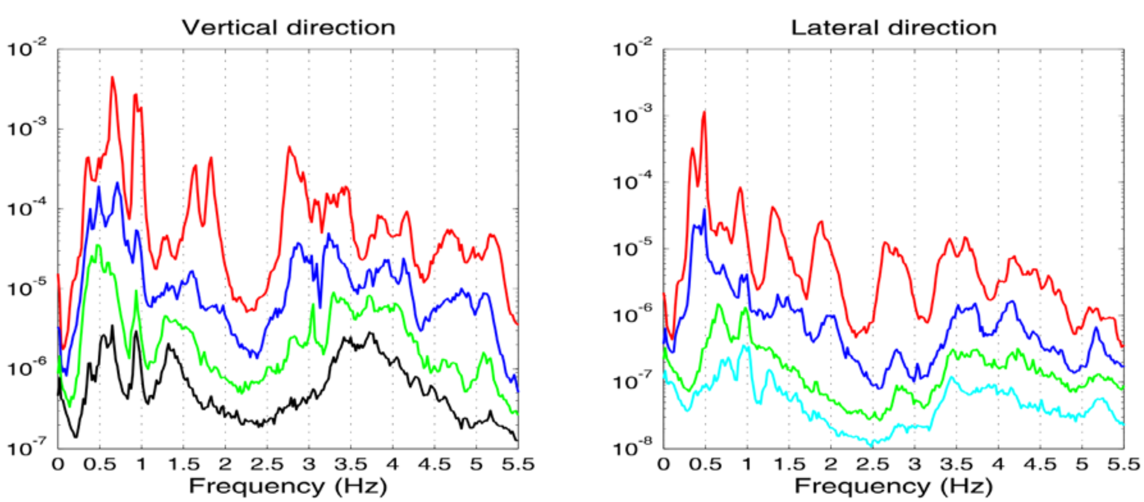


Fig. 5 – Average singular values of spectra matrix

estimated frequencies being slightly lower than the theoretical frequencies. Furthermore, the good agreement between the measured modal frequencies and the updated finite element model values show that the field observed structural dynamic properties as related to stiffness and mass are reasonably close to the design values.

In particular, the SSI method offers a more consistent frequency estimate compared to other algorithms. The variation in the identified frequencies relative to the mean appears to be higher for the lower frequency vibration modes and shows a decreasing trend for higher frequency modes. This observation has very important significance since the lower vibration modes often represent the dominant vibration behaviour of most structures under typical dynamic loading conditions, and thus can have an impact on the proper selection of vibration based algorithms for health monitoring purposes.

In general, the standard deviations obtained for the damping ratios are much higher than those obtained for the modal frequencies especially for ERA and FDD methods; the high variance on damping estimate is quite noticeable. In case of FDD method, damping estimate for low frequency modes are unrealistically high, an indication of high leakage bias in spectra computation. In fact, the closeness of the modes and the relatively low frequency resolution adapted to guarantee significant number of averages which is essential for good performance of FDD technique, leads to an unaccepted biased spectra estimation. On the other hand, both SSI and PolyMAX methods provide comparable damping estimate. The average modal damping ratio by SSI method is 1.62% corresponding to 53% standard deviation of the mean while for PolyMAX; these values are 1.67% and 62% respectively. It is worth noting that the mean extracted modal damping ratios show a slight decreasing trend with increasing frequency. Additional details on the comparison of different system identification techniques are available in a separate publication [6].

Among all the methods, SSI algorithm seems to be more consistent in frequency, damping and mode shape estimate. The application of PolyMAX and SSI methods to the ambient vibration data results in a very similar estimates for natural frequencies and damping ratios while for mode shape estimation; SSI outperforms PolyMAX method. The more traditional identification algorithm, ERA method provides comparable results at least in terms of frequency and mode shape estimation. Furthermore, all four algorithms exhibit higher variance in damping estimate especially for ERA and FDD method, it is quite noticeable.

5. Pattern Recognition by Time Series Analysis

In recent years, another approach in tackling the challenges of practical VBSHM and condition assessment of large structures in the field is the development of a data driven approach. A common challenge of vibration-based structural condition assessment algorithms is how to account for the uncertainties in the monitored bridge responses due to noise from the sensors, variability of the environmental conditions, assumptions in the structural models and processing and analysis algorithms. Alternatively, data driven models are techniques that eliminate the constraints of a physical theoretical model, and thus in theory may be better suited for accounting for the influence of uncertainty in the monitoring of data or signals. The basic premise of structural health monitoring (SHM) is that any change in the dynamic properties of a system is directly correspondent to change in the condition or state of health of the overall system. Field measurement output-only acceleration data from the Confederation Bridge monitoring project has been used to investigate changes in vibration response characteristics of the bridge structure in the past [1]. To improve the accuracy and reliability of vibration-based structural health monitoring and assessment techniques, monitoring vibration responses of bridges have been analyzed by pattern recognition by time series analysis. This technique is a unique combination of random decrement averaging method, autoregressive modelling, and Mahalanobis squared distance measure for outlier detection, proposed by Gul et al. [7]. The techniques has been applied to the Confederation Bridge structure structure to study changes in dynamic response behaviour under ambient load conditions. The objective of using these techniques is to quantify the variability characteristics of the measured vibration responses to different loading scenarios for excitations due to traffic, wind, ice, and earthquake.

5.1 Random Decrement Method

The Random Decrement (RD) technique is a time domain procedure, where the structural responses to operational loads are transformed into random decrement functions. Following the RD technique, it is assumed that the response of a system to random input loads, at time instant, *t*, is the summation of the response to an initial displacement, the response to an initial velocity, and the response to the random input loads between the initial state and the time instant *t*. By averaging a large number of time segments of the response with the same initial condition, the random part of the response will vanish, and what remains is the response of the system to the initial conditions. Therefore, measured acceleration time histories can be transformed into pseudo-free vibration response by RD method. Noise reduction is another important advantage of RD averaging method especially for the experimentally measured structural responses. More details and applications of the RD technique to the Confederation Bridge project can be found in the reference [8].

5.2 Time Series Analysis

One approach to extract characteristic information from time series data is by autoregressive modelling. An autoregressive (AR) model of order *r* is employed to fit a curve to a signal, such that the value of the estimated function at time *t* is a linear combination of *r* consecutive values prior to time *t*. For each time series $X(t)$ previously obtained by RD averaging of the standardized signal, an AR model is constructed. The coefficients of the AR models are reported as features of the original signal. These features which contain characteristics of the measured acceleration response are then passed to a pattern recognition method for outlier detection.

5.3 Pattern Recognition

Pattern recognition techniques can be employed to detect changes in dynamic characteristics of structures under various loading and structural conditions. One of the most common pattern recognition techniques among those applied to SHM problems is outlier detection. Mahalanobis squared distance measure [9] is one of the outlier detection techniques, which is capable of detecting deviation of an observation cluster from a reference cluster or a series of clusters. Extracted features of the measured acceleration response from the Confederation Bridge monitoring project are analyzed by a Mahalanobis distance-based outlier detection method. A “pool” of reference datasets from the Confederation Bridge structural health monitoring project has been considered and

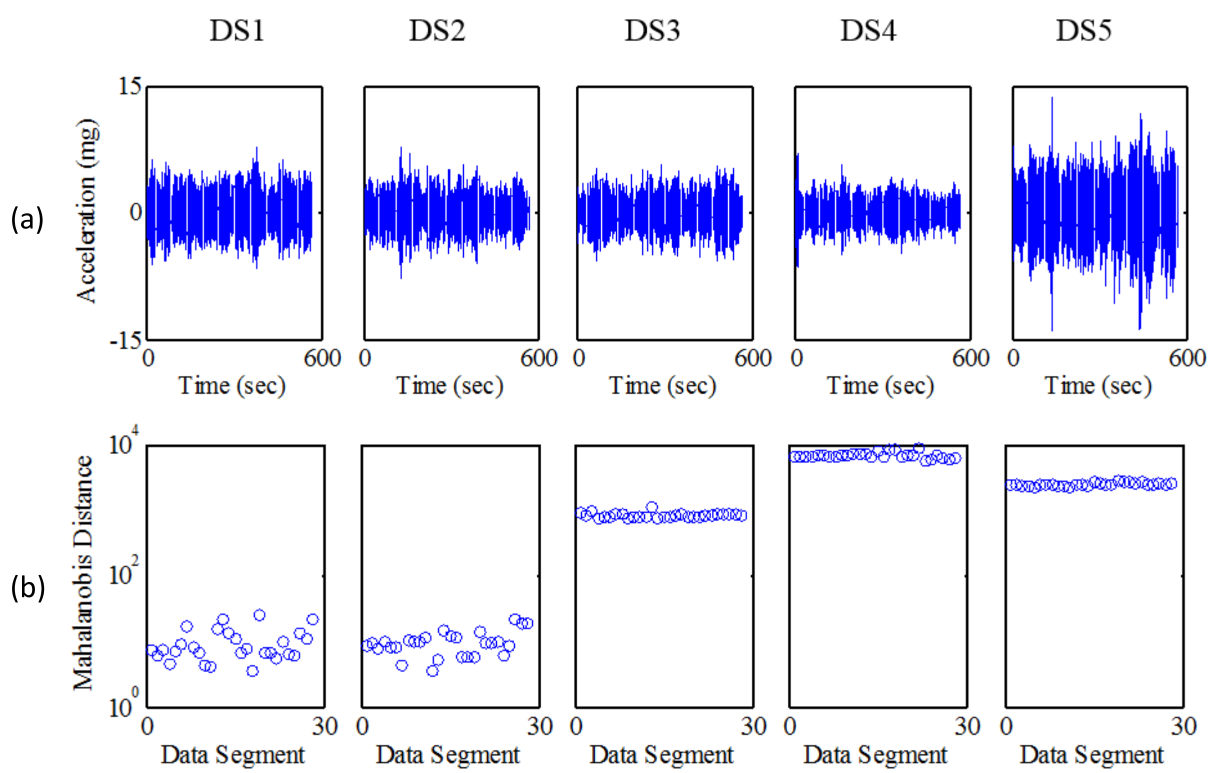


Fig. 6 – (a) Acceleration time-histories of the selected datasets from the Confederation Bridge; (b) Mahalanobis distance between extracted features (DS1/DS2: reference datasets)

the Mahalanobis distances of the extracted features of this pool from the extracted features of different observation datasets are computed. As shown in Figure 6a, five vertical acceleration time-history datasets (DS1-DS5) under ambient loading condition with a sampling frequency of 125 Hz and duration of 570 seconds for each signal have been used (sensor location 9). The datasets then undergo the process of random decrement averaging and autoagressive modelling to compute the Mahalanobis distance, which is shown in Figure 6b.

The steps of the pattern recognition algorithm is shown in Figure 7. Each signal is first standardized by subtracting the signal mean and then dividing by standard deviation of the signal. The standardized signals are then processed by the random decrement (RD) averaging method to obtain pseudo-free vibration response. After averaging the standardized signals using auto RD, an auto-regressive (AR) model is fitted to the averaged signals. For each averaged signal, the ratio of the standard deviation of the AR model estimation residuals to the standard deviation of the averaged signal is kept as small as 1% to ensure a confidence level of 99% in the AR modelling. Enforcing this selected confidence level helps to substantially reduce the effect of time series modelling parameters such as AR model order on the extracted features. The coefficients of the AR model are then reported as features of the original signal. These extracted features are assumed to carry dynamic characteristics of the bridge structure and they can be used for pattern recognition.

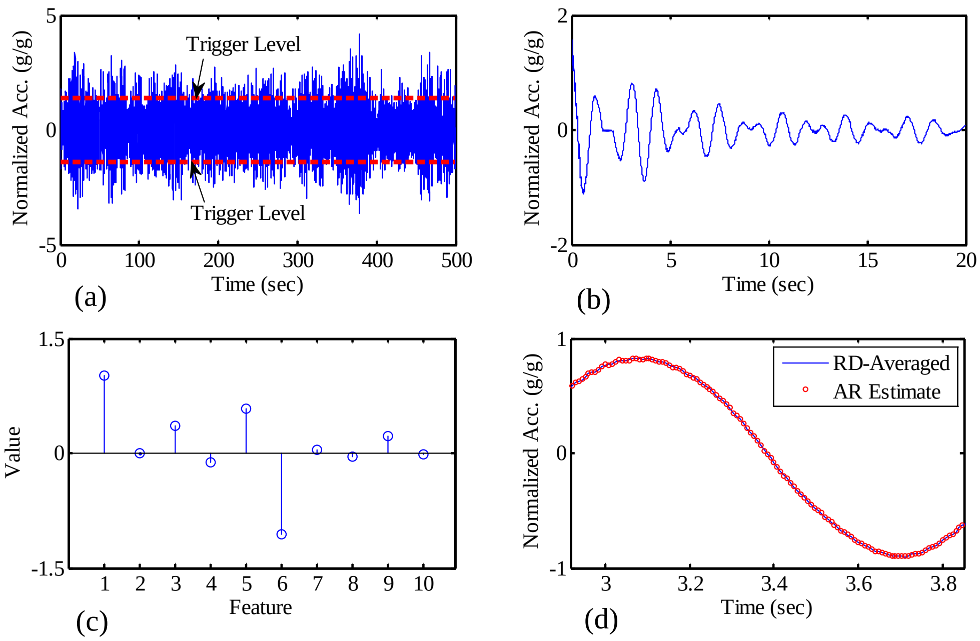


Fig. 7 – Autoregressive model applied to dataset DS1 with RD averaging: (a) standardized acceleration time-history; (b) RD-averaged signal; (c) extracted features; (d) comparison of AR estimate and RD-averaged signal.

To examine the variability of the extracted features between different datasets, the methodology of feature extracting described in this section is applied to all other datasets, and Mahalanobis distance-based outlier detection method is used to detect deviation of an observation set of features from a reference set of features. For this purpose, preceding datasets DS1 and DS2 are chosen as reference to represent healthy states, and other datasets are considered as observation. In addition to the condition of minimum 99% confidence level for the AR model, a minimum RD length of 500 seconds is used as another condition to increase the accuracy of the extracted features before passing to next step for pattern recognition. Figure 6b shows the Mahalanobis distance from reference datasets to observation datasets for all data segments satisfying these two conditions (i.e. minimum 99% confidence level for the AR model, and a minimum RD length of 500 seconds). For the observations, it is evident from the figure that different events are clearly separated by using this methodology. However, this cannot be simply interpreted as a change in structural properties because there exists traces of external loading in the extracted features, and further study is required to quantify these effects before detecting damage. This presents a challenge moving forward to distinguish the effects of changes in external loading from those of structural changes in the response of the bridge.

6. Conclusions and Future Directions

Vibration based health monitoring of civil engineering structures has the potential to provide timely essential information about the state of structural integrity of important civil engineering structures, either on a routine basis or after extreme unexpected loading. The technology and developments presented herein could be used in conjunction with the current structural assessment techniques to provide a more informative and accurate global assessment of the structural health. To facilitate the timely processing of continuous monitoring data, a near real-time structural health monitoring platform (SPPLASH) has been developed to extract engineering information from large data sets of continuous monitoring data for both research and operation of the bridge in a timely manner. Four different system identification techniques have been implemented into the modular design of the monitoring platform and have been shown to be a reliable tool for extracting modal properties of a structure. However, in many cases the condition assessment of large structures in the field is limited by uncertainty and noise in the continuous monitoring data. To overcome the limitations and constraints of a physical theoretical model, a unique data driven pattern recognition by time series analysis has been applied to selected acceleration datasets from the Confederation Bridge structural health monitoring project. It is observed that the methodology is capable of recognizing patterns in the bridge response and quantify deviation of the response characteristics from a certain reference. However, to perform damage detection, further study is needed to distinguish effects of external loading from those of structural changes in the bridge response. Using the monitoring data collected from the long-term structural health monitoring system of the Confederation Bridge, a comprehensive database of the ambient vibration response of the instrumented bridge under different environmental and loading scenarios, such as summer (without ice cover) and winter (without ice cover) season ambient conditions, traffic and strong wind triggered events. The statistical characteristics of the uncertainties associated with different loading and environmental conditions have been quantified. These together with the vibration response database will serve as the crucial baseline reference for future evaluation and detection of any change in the structural condition, deterioration or damage of the bridge. Experiences and lessons learned from the long-term vibration monitoring project also show that continuous monitoring is essential for updating the vibration response database in order to be able to continuously refine the uncertainty models and to minimize the sensitivity of monitoring data due to noises and uncertainties in structural health monitoring evaluation application.

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