Health Monitoring of Structures Using Statistical Pattern Recognition Techniques

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Abstract: The primary objective of structural health monitoring (SHM) is to determine whether a structure is performing as expected or if there is any anomaly in its behavior compared with the normal condition. It is also useful in detecting the existence, location, and severity of damage. Vibration-based damage detection methods are very frequently used in SHM. However, because of complicated features of real-life structures, there are uncertainties involved in the key input parameters (e.g., measured frequencies and mode shape data), which affect the performance of these methods. If vibration-based methods are incorporated with semianalytical methods, such as statistical pattern recognition techniques, better accuracy can result in structural health assessment. This paper explores the statistical pattern recognition techniques for damage detection and/or degradation in structures. A case study, the Portage Creek Bridge in Victoria, British Columbia, Canada, has been used. The following two approaches of the statistical pattern recognition techniques have been used: statistical pattern comparison and statistical model development. After filtering and normalizing the data obtained from the SHM system installed in the bridge, damage sensitive features have been extracted by autoregressive modeling of the time series data. Both idle and excited states of the bridge are considered in this case. From the statistical analysis of the strain and acceleration data, although the bridge is in a good condition, there is a small but steady deterioration in its performance. The study also demonstrates the feasibility of the statistical pattern recognition techniques in assessing the structural condition of a practical structure. **DOI: 10.1061/(ASCE)CF.1943-5509.0000346.**

CE Database subject headings: Structural health monitoring; Bridges; Statistics; Damage; Automatic identification systems.

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Introduction

In general, structural health monitoring (SHM) is concerned with performance monitoring of structures using various sensors and devices to ascertain the strength of critical members of the structure and find the presence of any damage or anomaly. SHM is also intended to evaluate the degradation rate and predict the remaining service life of a structure. An appropriate SHM system can help reduce the chance of catastrophic failure, maintenance cost, and down time for rehabilitation. According to Mirza and Haider (2003), more than 40% of the bridges in service in Canada are over 30 years old. Although many of them need minor repair and functional improvements, a significant number are structurally deficient and are in urgent need of rehabilitation or partial reconstruction. Chase and Washer (1997) conducted a similar survey for the bridges in the United States and found that about 187,000 bridges, representing more than 25% of all bridges, were deficient at that time and about 5,000 bridges were becoming deficient every year. This estimate was an improvement over previous years as a result of an increase in federal bridge funding for building and rehabilitation of bridges. More current statistics put the number of deficient bridges to about 12% of the total national and state bridges (Research and Innovative Technology Administration 2010). Most of these bridges were built before 1970, and their health condition is yet to be determined by any instrumental and scientific approach. The reduction from 25% in 1997 to 12% in 2007 is perhaps because of the continued reconstruction and rehabilitation efforts, as previously mentioned.

In the context of structural safety, maintenance, and rehabilitation purposes, the need for SHM has increased recently. Traditionally, visual inspection is utilized as the primary means of monitoring structural health conditions. Because of the drawbacks of visual inspection, other methods, such as nondestructive testing/nondestructive evaluation (NDT/NDE), are being increasingly used. However, NDT/NDE techniques are available for only periodic testing and monitoring local defects. By remotely monitoring a structure continuously or periodically, SHM offers to complement the information on the structural condition provided by visual inspection and NDE techniques. Structural model-based methods, such as vibration-based damage detection techniques, commonly used in SHM, are very sensitive to the noise in the data from the sensors (Bagchi et al. 2010). Data-driven techniques do not require a structural model, and they provide attractive alternatives to structural model-based techniques for damage detection. Statistical pattern recognition techniques provide opportunities for developing data-driven models for structural damage detection and condition assessment.

According to Sohn et al. (2000), sensors measuring strains and vibration of a structure produce signals that always respond to the

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change of environmental and operational conditions. Each group of signals can be considered a pattern (a definable entity) that has some relationship to the structural and ambient conditions. If the effect of the ambient condition to the patterns is normalized, they should be nearly identical or close to one another for similar load or vibration effect, as long as structural vibration properties remain unaltered. However, it can be assumed that the change in physical properties, mainly stiffness, should be reflected on the processed signal blocks or patterns. Farrar et al. (1999, 2001) proposed a generalized integrated approach for SHM by statistical pattern.

Statistical pattern recognition is relatively new in SHM applications where the data from sensors are collected and processed to remove the environmental (e.g., temperature) effects, and filtered or denoised. In this context, statistical pattern comparison and statistical model development approaches have been utilized recently (Sohn et al. 2001; Nair and Kiremidjian 2005) for assessing the condition structural elements. The statistical algorithms available for diagnosis based on SHM data are the following: outlier analysis, autoregressive exogenous (ARX) model, and autoregression moving average (ARMA) (Noman et al. 2009). Outlier detection is used when data are available only for the undamaged state of a structure. In the statistical pattern comparison approach, the damage detection algorithm attempts to identify damage states by observing significant change in features that cannot be explained by extrapolation of previously observed features when the structure was at a normal state. On the other hand, the statistical model development approach can detect trends in the data that are useful to predict when particular features fail to follow the established trends or become outliers. Statistical process control techniques can be used to identify trends using outlier analysis. If a structure is damaged, most values of extracted features should fall outside some threshold value determined by a specific algorithm. The main objective of this paper is to study the application of data-driven techniques and develop methodologies utilizing statistical pattern recognition schemes, such as statistical pattern comparison and statistical model development approaches, for interpreting SHM data, including damage detection and structural condition assessment.

Fig. 1. Portage Creek Bridge, Victoria, British Columbia, Canada

Damage Assessment by Statistical Methods

Time series analysis techniques are often utilized to extract the damage sensitive features of the vibration and strains data. Mathematical modeling of time series data is covered in relevant textbooks (Montgomery et al. 2008). Statistical pattern comparison and model development are commonly used techniques for statistical pattern recognition, which are used for evaluating the changes in time series patterns and features. They are briefly subsequently discussed in the context of structural condition assessment and damage detection.

Statistical Pattern Comparison Approach

The basic concept of this approach can be found in Sohn et al. (2001). It is logical to assume that the patterns in the data in the same state of the condition, either a steady or agitated state of a structure, taken at various points of time, will not vary much if the structure

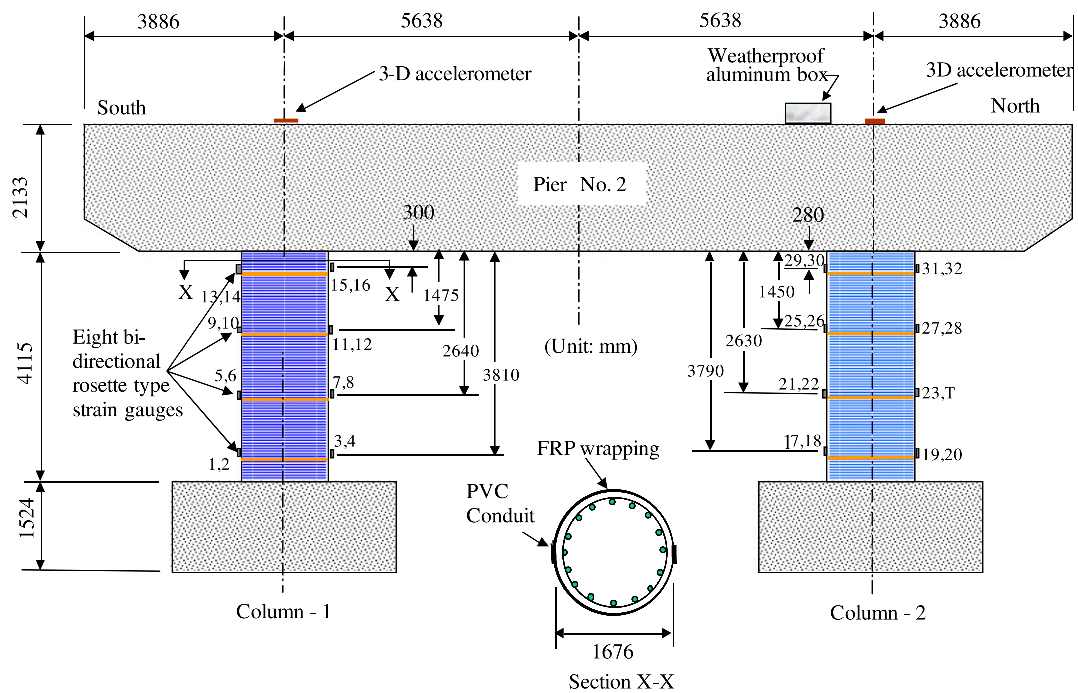

Fig. 2. Elevation of Pier 2 (short columns) with sensor locations

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does not change significantly. Conversely, if the structure has undergone a significant change, it should reflect in the patterns of both states of the condition.

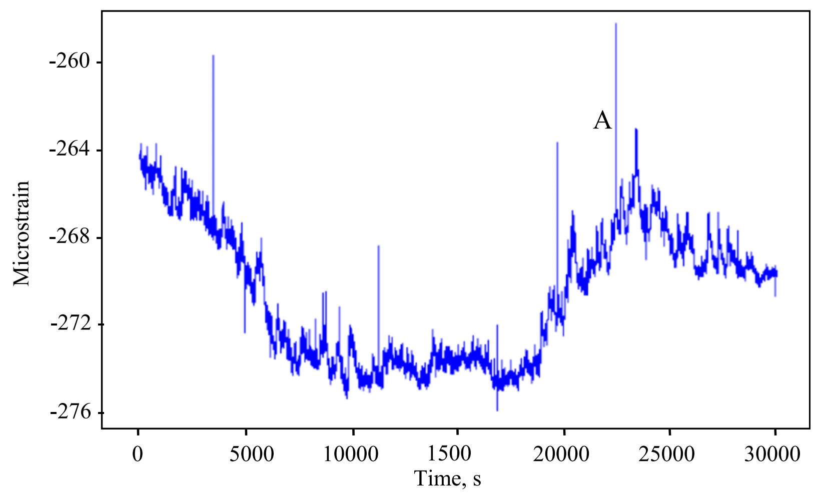
To observe the variation in a structure's response by studying the patterns of signals from the sensors or data blocks, it is necessary to nominate a certain block as a reference data block, with which patterns of the other data series or blocks are compared. Usually, the reference data blocks for a particular condition are taken from an earlier time of the observation of the structure, and other data blocks are called test blocks. The time series model, such as the AR model, used in this study, particularly developed for the reference block, is defined as a reference model. As a structure undergoes gradual changes because of degradation, the data pattern changes accordingly. Therefore, the pattern of other data blocks deviates from that of the reference block. If the reference model is fit to the test blocks, the residual errors should reflect the extent of variation of the signals. It is expected that if a structure undergoes significant changes, the residual error, compared with the reference model, will be significantly high.

After calculating all coefficients of a time series model and fitting it to the data, it is possible to get the residuals for all points. An average residual can be defined as $\varepsilon = (\text{residual } SS)/N$, where SS is the sum of the squares of the residuals of the model with respect to the actual data, N is the observation number, and ε is the key parameter that can be used to see how good a reference model fits to the pattern of test data blocks. A degree of match or closeness between r, the reference model, and a test block, as defined by $R = \varepsilon t/\varepsilon r$, is called the residual error index. Here, t and r are the test and reference blocks, respectively. If the value of R shows a clear increasing trend over a long time, the structure is degrading.

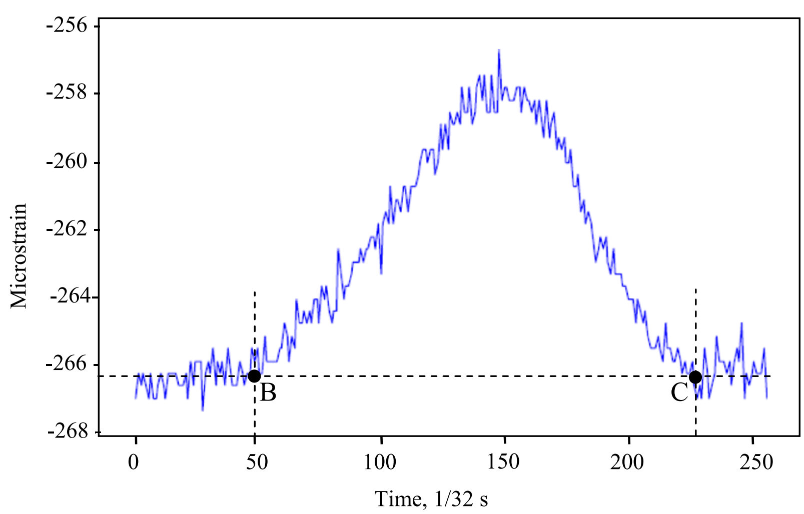
Statistical Model Development Approach

A statistical model can be utilized to analyze the distribution of extracted features to determine the damage state of a structure. Because there is no damaged case known for the bridge in the current study, an unsupervised learning technique has been used for developing and training a statistical model. Here, control chart analysis, a commonly used statistical process control technique for outlier analysis, has been used. It is applied to the calculated and selected damage sensitive features. When a structure undergoes damage or deterioration, the mean and/or variance of the extracted features should change accordingly (Nair and Kiremidjian 2005).

Extraction of statistical features in a time series data block corresponding to a sensor signal is an important step in statistical model development. All data are analyzed with an AR process. The variation of an AR process is mainly dependent on AR coefficients $\varnothing xj$.



(a)



(b)

Fig. 3. Typical time series of the strain from strain Gauge 1: (a) sampled at 1 Hz; (b) under vehicle load, sampled at 32 Hz

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Hence, $\varnothing xj$ is considered a structural degradation feature or damage sensitive feature. For the calculation of the AR coefficients, Yule-Walker methods have been applied (Brockwell and Davis 2002). Because a AR process is a zero mean method, the data blocks are mean corrected (i.e., the mean value is subtracted from the series).

Description of the Monitored Structure

The approach of damage detection methodologies developed herein has been demonstrated using a case study example, namely the Portage Creek Bridge (Fig. 1), located in Victoria, British Columbia (BC), Canada. The information on the sensing system can be found in Huffman et al. (2006). The Portage Creek Bridge is a 124-m-long, three-span structure with a RC deck supported on two RC piers, and abutments on H-piles. The bridge was designed prior to the introduction of current bridge seismic design codes and construction practices. Therefore, it was not designed to resist the earthquake forces, as required by recent standards. Later, seismic assessment performed on the piers, as reported in Mufti et al. (2004), showed that strength of the columns of Pier 2 was found to be insufficient according to the seismic provisions of bridge design standards at that time [Canadian Standards Association 1988, 2000; Federal Highway Administration (FHWA) 1995]. Because the bridge is classified as a municipal disaster route bridge, the BC Ministry of Transportation decided to retrofit the bridge pier to prevent collapse during a design seismic event, with a return period of 475 years. The innovative solution of fiber-reinforced polymer (FRP) wraps was chosen to strengthen the short columns to conform to the seismic provisions of the Canadian Standards Association (1988, 2000) and the AASHTO (1996). The strengthened columns of the bridge pier were instrumented by Intelligent Sensing for Innovative Structures (ISIS) Canada, a federally funded Network of Centers of Excellence, to assess the performance of a FRP strengthening system and the use of fiber-optic sensors. SHM was installed on the columns for that purpose. The strengthened columns were instrumented with eight bidirectional rosette-type strain gauges and four long-gauge fiber-optic sensors attached to the outer layer of the wraps (Fig. 2). In addition, two three-dimensional (3D) Crossbow accelerometers were installed on the pier cap above the columns, and a traffic web cam was mounted above the deck at the pier location (Bagchi et al. 2007).

Data Analysis Methodologies

Data Collection

For the current study, a set of data covering a period of 3 years between April 2003, and August 2006, available from the ISIS Canada Research Network, has been used. However, there are some time segments for which data are not available. These off-time segments are distributed through the whole period of the study. Of eight strain gauges on each column, one is possibly damaged (SG8). Thirty strain signals from 15 two-dimensional (2D) strain gauges, six accelerometer readings from two 3D accelerometers, and one temperature data series are available. The original sampling rate is 32 Hz with a Nyquist frequency of 16 Hz, which is deemed adequate, given that the fundamental frequency of the structure is about 2 Hz and first five modes contribute more than 95% of the mass. The fifth mode frequency is below 4 Hz, for which a sampling rate of 32 Hz is adequate.

In the beginning, the data sets were rendered graphically for various sampling rates and time segments to examine the overall nature and trend of the data. For example, the data series shown in Fig. 3 for Strain Gauge 1 (according to Fig. 2), or SG1 in short, was sampled at 1 Hz for a period of 8 h 20 min in April 2006. Careful inspection shows that the strain is oscillatory in time. There are also some random vertical straight lines. Those random lines resulted from some sudden impacts. Further analysis revealed that the oscillation was mostly because of the effect of temperature changes, and the random vertical lines were the results of live loads, possibly heavy vehicles.

The rightmost and longest vertical straight line in Fig. 3(a) (indicated by Line A) now looks like a spike. If the sampling rate is increased to 32 Hz for the data around the spike at Line A, Fig. 3(b) shows that the change of strain over a short period of time is the result of a gradually changing load, not an impact, as appeared in Fig. 3(a). This is the characteristic of a load applied on a pier by a vehicle moving on a bridge. As shown in Fig. 3(b), the interval between Points B and C indicates the duration of the load experienced by the pier while a truck passes over it. In this case, the duration is estimated to be 5.5 s.

Based on the observations similar to the one previously mentioned, to study the structural behavior of the bridge, it is necessary to analyze it under the following two conditions: (1) a steady-state condition where only small oscillations are observed, and (2) an agitated or live-loaded condition in addition to small oscillations.

Data Block Sampling and Analysis Schemes

The data or, in other words, signal blocks are collected for four types of analysis: (1) steady-state strain, (2) live-load strain, (3) accelerometer reading under a live load, and (4) temperature effect on the

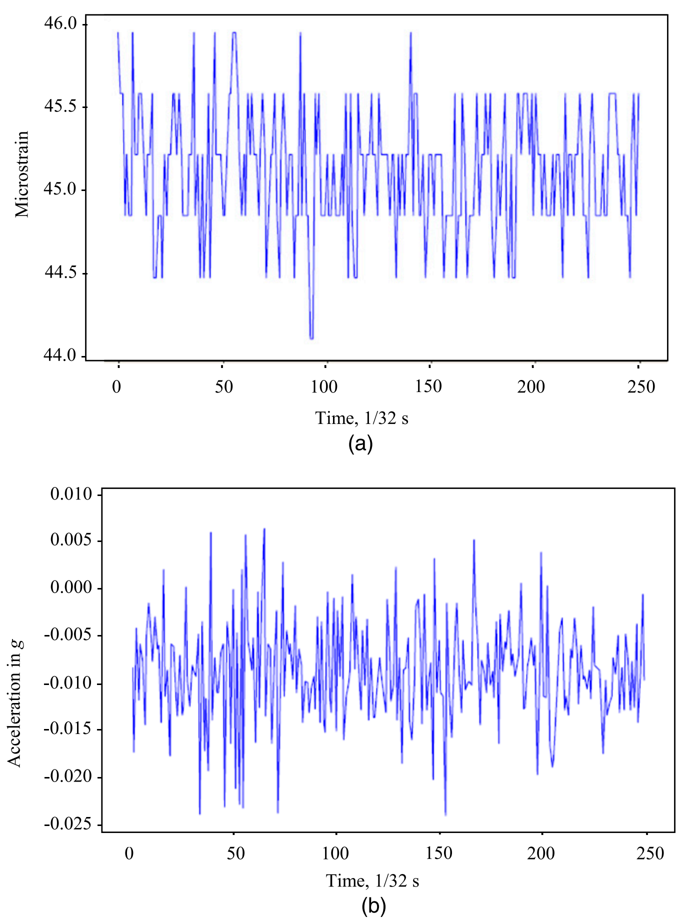

Fig. 4. Typical signals from sensors at a steady state: (a) strain signal from strain Gauge 1; (b) accelerometer signal from A1 in the *x*-direction

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strain. Details on data collection for all cases are subsequently described.

1. Steady-state strain: Fig. 4(a) shows typical steady-state condition plotting. It represents the condition when there is no live load, such as a vehicle on the bridge. Steady-state strain from SG1 was taken for the study in this case. For steady-state strain, the data blocks are taken for 8-s long (256 points at 32-Hz sampling rate). A total number of 27 data blocks covering the monitoring period is considered here.
2. Live-load strain: Fig. 4(b) shows a typical acceleration time history at a live-loaded condition. A typical strain history at such a condition is similar to the one shown in Fig. 4(b). The cases where the data values exceed those at steady-state conditions are considered to represent the live-load events. Correspondingly, nine random data blocks were taken that include heavy vehicle loads for each of the seven strain readings of Column 1 and eight strain readings of Column 2. Each block has a sampling frequency of 32 Hz and a duration of 8 s. The strain gauges are: SG1 (horizontal direction of SG1 in Column 1, as shown in Fig. 2), SG2, SG3, SG5, SG6, SG17, SG18, SG19, SG20, SG21, and SG22. The length of each block is chosen to be 8 s, because a truck typically does not take more than that time to pass over the pier [e.g., in the case shown in Fig. 3(b)].

Analysis of these signal blocks will not only provide information on the structural behavior of the bridge over time under live loads, but will also determine if all the gauges are working properly and find out the faulty one, if there is one. The change of behavioral patterns is expected to be similar for all gauges if they are all functioning properly. The magnitude and signs may vary among the data series, but relative values in the test blocks compared with the reference blocks of a particular strain channel should not differ significantly from the corresponding values of strains from other channels, particularly those in the same orientation. The data from the accelerometers and thermocouples are analyzed in the following ways:

1. Accelerometer reading under a live load: the data blocks of the accelerometer were taken at the same time, sampling frequency, and duration as the blocks of the live-load condition. An example of the time series is shown in Fig. 4(b).
2. Temperature effect on the strain: the strain values and temperature at time 00:00 of the first day of each month are taken for analysis. Care was taken that data thereby obtained are of strictly steady-state conditions. Then, linear regression is applied to the data of several months to determine the temperature strain relationship over those months.

Results of the Case Study

Pattern Comparison

To apply this method, several sample data blocks for selected strains and accelerometer readings have been used. The first block of each series of a particular strain or accelerometer is considered to be the reference block, and the rest of the data blocks from the set are called test data blocks. Some typical results of the analysis are presented in Figs. 5–7.

The residual error index value indicates the closeness with the AR model, which can also be a good indicator of structural condition

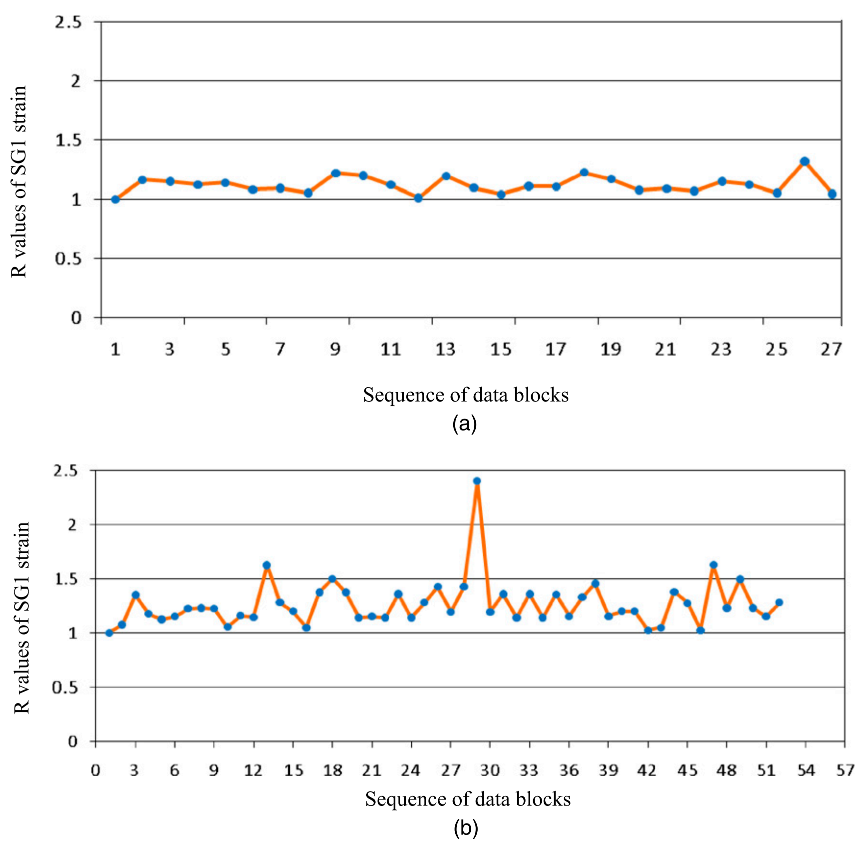

Fig. 5. *R*-values of the strain from strain Gauge 1: (a) 27 data blocks at a steady-state condition; (b) 55 data blocks in live-loaded occurrences on continuous scanning

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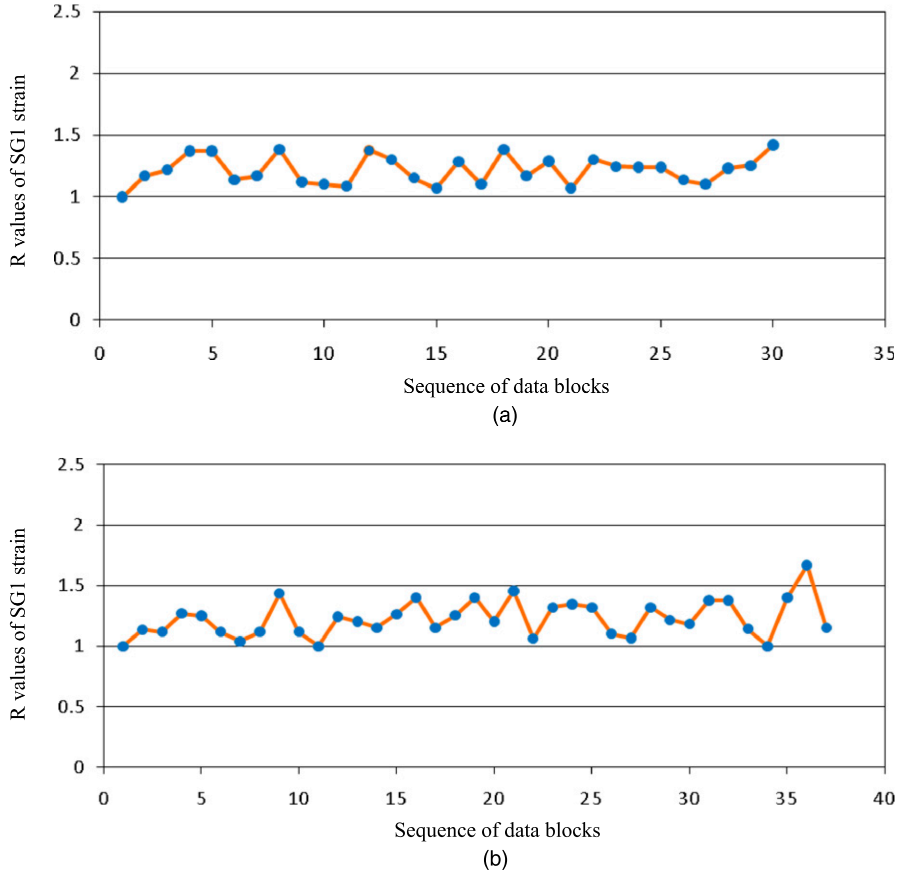

Fig. 6. *R*-values of the strain from strain Gauge 1 in live-loaded conditions: (a) 31 cases at one data block per day; (b) 39 cases at 5-day intervals

over time. It is logical that *R*-values of a particular strain acceleration signal should be steady and stay close to the baseline of 1 over time. Upward trend or deviation from the horizontal line at the *R*-value of 1 over time indicates degradation. Fig. 5(a) shows that the *R*-values for 27 blocks (monthly) of SG1 at a steady state do not have any particular trend. A similar characteristic is observed for the live-loaded conditions. Fig. 5(b) shows the *R*-values for 55 successive occurrences of live loads. On the other hand, Figs. 6(a and b) show the *R*-value for 31 blocks (one per day) and 39 blocks (one per 5 days), respectively, of the live-loaded condition of SG1. There is a noticeable peak value corresponding to the block Sequence 30 in Fig. 5(b). There could be two possible reasons for this:

1. The vehicle passing over Column 1 was such that it produced higher stress on the location of SG1 and its pattern deviated from the normal state; and
2. There was another vehicle nearby, and the combined effect produced an irregular pattern.

The *R*-values of 9 blocks of 7 strains in Column 1, and 8 blocks of 8 strains in Column 2, at 1 block per four-month interval over the entire period of monitoring, have been observed. All strain gauge data have been analyzed at the same time segments. From the analysis, almost all the strain signals produced similar patterns with *R*-values not deviating from each other significantly. This also indicates that all strain gauges are working properly. Fig. 7 shows the results of the analysis for Accelerometer A1, which also do not indicate a visible trend. The results of the pattern comparison method show that there is no indication that the structure is damaged or undergoing strength degradation.

Statistical Model Development

The signal blocks of data from strain Gauges SG1, SG2, and SG3 and Accelerometer A1 have been used for creating the pool of features, which are AR coefficients. Care has been taken not to mix up the strain with acceleration data for feature extraction; they are analyzed and presented separately. For the process control analysis according to Nair and Kiremidjian (2005), the first three AR coefficients give the most robust damage indication. Therefore, the first three coefficients of the AR analysis of strain blocks are taken. The mean and SD of the first quarter of the arranged features are taken as a reference. Here, X-bar control charts are used to monitor the changes of the selected feature over time. A subgroup of four features is considered. The subgroup size is taken as four, according to the suggestion of Montgomery (1997). The results for three AR coefficients of strain readings from SG1 and SG2 are shown in Figs. 8 and 9.

In examining the control charts in Figs. 8 and 9, only one outlier of a total of 132 (0.75%) subgroups of the first three AR coefficients of data from SG1 is detected, and no outlier is found for SG2. However, a slight downward tendency of the features is noticeable. Of a total of 124 subgroups of the first three AR coefficients for each of the *x*- and *y*-channels of Accelerometer A1, only one (0.81%) and zero outlier, respectively, have been detected. Three outliers of a total of 108 (2.78%) subgroups of the first three AR coefficients for the *z*-channel of Accelerometer A1 have been found.

Sohn et al. (2000) conducted a laboratory test on a set of concrete columns. At a very mild damaged state, statistical modeling showed 6.25% outliers, whereas at a significant damage it showed 29.17% outliers of all the subgroups. It is difficult to make a judgment based on a single study such as this and extend it to the bridge pier in the

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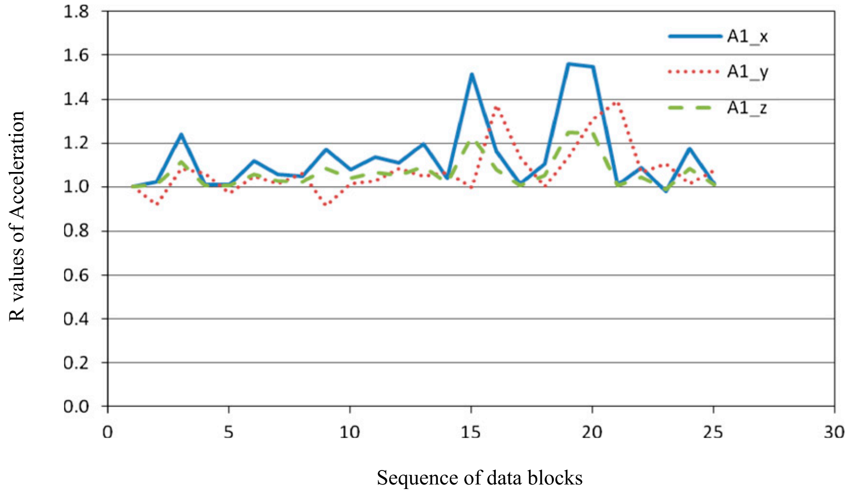
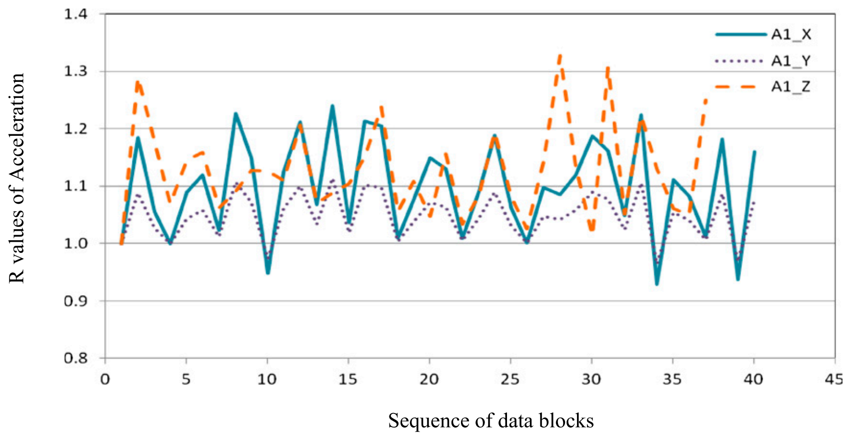


(a)



(b)

Fig. 7. *R*-values of *x*-, *y*- and *z*-acceleration from Accelerometer A1 in live-loaded conditions: (a) 24 cases with one data block per 5 days; (b) 37 cases with one data block per month

current study. However, it can be safely assumed that a small percentage of outliers ($< 3\%$) is indicative of virtually no change in the behavior of a system. Because the percentage of outliers in strain and acceleration data from the bridge columns in the current study is quite low, they are assumed to sustain no damage. This is, of course, expected for a bridge of this age. However, the tendency of the features getting closer to the limits toward the end of the monitoring period under consideration indicates that the structure is undergoing small degree degradation toward the end of that period.

From the data blocks for each sensor, there was an increment in the average strain readings in each year compared with the previous year. Here, only the data blocks for SG2 are discussed with respect to a finite-element (FE) model and the AR coefficients. The average strain values of SG2 for different summer periods in 2003, 2004, and 2006 are found to be 401,521, and $651\,\mu\varepsilon$, respectively.

A 2D FE model, as shown in Fig. 10, has been developed to perform a simple static analysis to show the structural changes over time. In this model, the weight of half of the deck system and the pier self-weight have been applied as a uniformly distributed load on the pier, which is estimated to be $370\,\mathrm{kN/m}$, and concentrated loads because of self-weight of the columns of 1,300 kN. For vehicle loading, CL1-W truck loading, as defined is the Canadian Standards Association (2006), has been applied as two concentrated loads on either side of the axle, and this loading has been applied on both lanes. The wheel load is 312.5 kN per wheel, but the load is increased to 500 kN, applying an impact factor of 1.6 to take the dynamic impact into consideration. An estimated lateral load of 2,000 kN was applied to represent the earthquake (EQ) and/or the wind load using the provisions of the Canadian Standards Association. In the finite-element analysis and the analysis of the monitored data, it is assumed that there is no change in traffic load or pattern during the monitoring period considered, and the measured strain data are filtered properly to remove the environmental effects on the strain. Considering the time window for a passing vehicle, the increase in strain because of vehicle load can be considered to be free from environmental effect, such as temperature change.

In the FE model, the loading condition and structural stiffness have been adjusted to obtain a strain value of 400 microstrain, which is the average strain value for summer 2003. The strain gauges installed on the column would not capture the strain because of the dead load, because the gauges are installed and calibrated when the bridge superstructure already existed. This has been considered in the adjustment of the model by removing the initial strain because of dead load from the strain values obtained from the finite-element analysis. Assuming no increment in traffic for the years and taking the temperature corrections into consideration, the stiffness of the structures has been updated to correspond with the strains for the subsequent years. The model adjustment yields are a gradual

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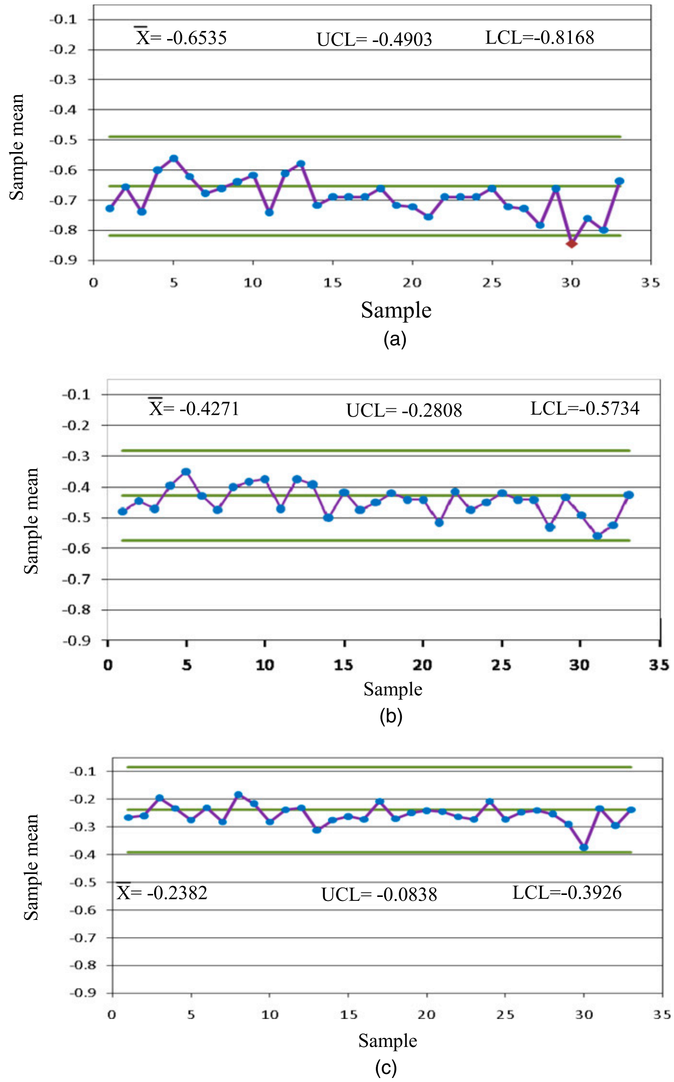

Fig. 8. Outlier analysis of the autoregressive coefficients of strain readings from strain Gauge 1 with a pool size of 132 and a subgroup size of four: (a) first autoregressive coefficients; (b) second autoregressive coefficients; (c) third autoregressive coefficients

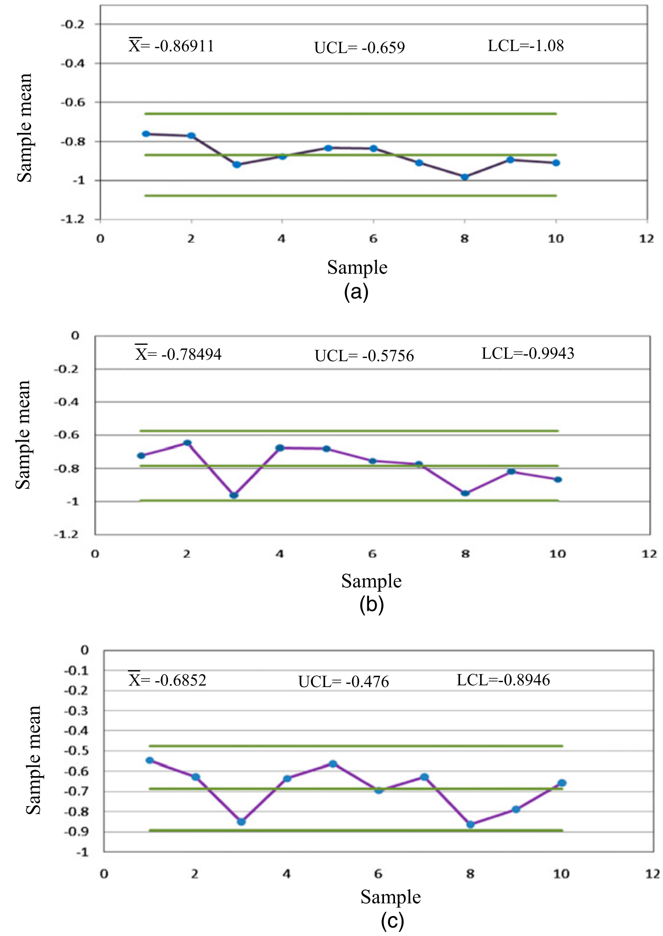

Fig. 9. Outlier analysis of the autoregressive coefficients of strain readings from strain Gauge 2 with a pool size of 40 and a subgroup size of four: (a) first autoregressive coefficients; (b) second autoregressive coefficients; (c) third autoregressive coefficients

decrease in stiffness of 20 to 30% to reflect the strain levels of 521 $\mu\varepsilon$ in summer 2004 and 651 $\mu\varepsilon$ in summer 2006, respectively. Although the strain component, as a result of environmental effects, is difficult to properly filter from the data, qualitatively, the reduction in stiffness indicates a gradual degradation of the bridge.

The first three AR coefficients are plotted for the data blocks of SG2 (Fig. 9). The curves are showing a slight downward tendency, which is indicative of a reduction of stiffness, as found with the FE model correlation. In reality, this stiffness degradation is expected to be quite low in the initial years after the rehabilitation of the bridge.

Temperature Effect on Strains

Temperature has a significant effect on the values of the strains. Data blocks taken at different temperatures with similar working conditions should show different values. The AR process, as applied in the previous section to analyze blocks of time series data, is a zero mean process. Occurrence of such data in real-life conditions is very rare. Removing the mean from the original values not only normalizes the data but also reduces the sample mean to zero. The temperature is almost constant for a time window of 8 s for data blocks that are considered in time series analysis in this work. Usually, the temperature component is automatically removed by the removal of the mean from all observations (for a small time window), and the transformed values represent mostly the structural response. However, for other types of analytical processes on the strain data where the zero mean process or any kind of normalization are not applied, temperature correction is needed to be applied explicitly to get the actual values of structural components of the data.

To evaluate the effect of temperature on the strain, Strain SG1 is selected. Fig. 11(a) shows a typical strain history for SG1 at a 1-s interval for a period of 8 h and 20 min, starting at midnight on a March day in 2006. As previously discussed, the big spikes in the graph are because of the effect of live loads from heavy vehicles passing over the pier to which the corresponding gauge is attached. The continuous small oscillations represent the steady state. The general upward trend of the graph toward the end is accounted for temperature effect.

Fig. 11(b) shows the relationship between strain and temperature considering 27 monthly readings of temperature and strain at Column 1, taken at time 0:0:0 on the first available day of each month. Linear relationships have been calculated by considering the following: (1) all 27 readings, (2) the first 10 readings, (3) the next 10 readings, and (4) the last seven monthly readings. Because of space limitation, only the first two cases are shown here [Figs. 11(a and b)].

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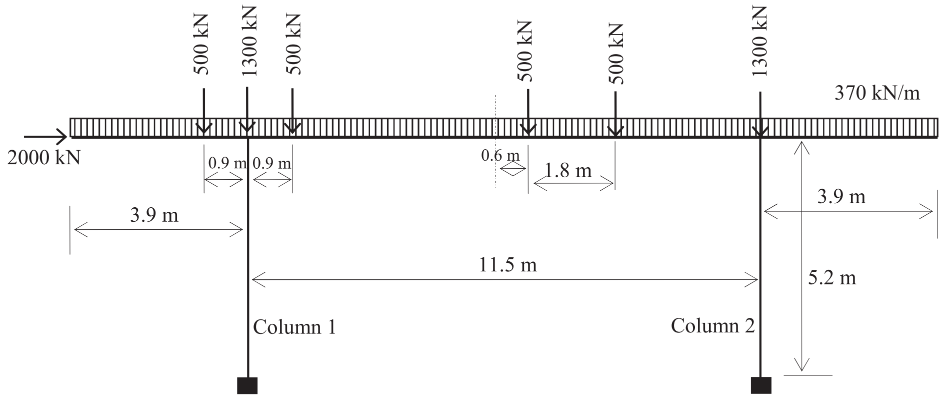

Fig. 10. A 2D model for Pier 2 of Portage Creek Bridge

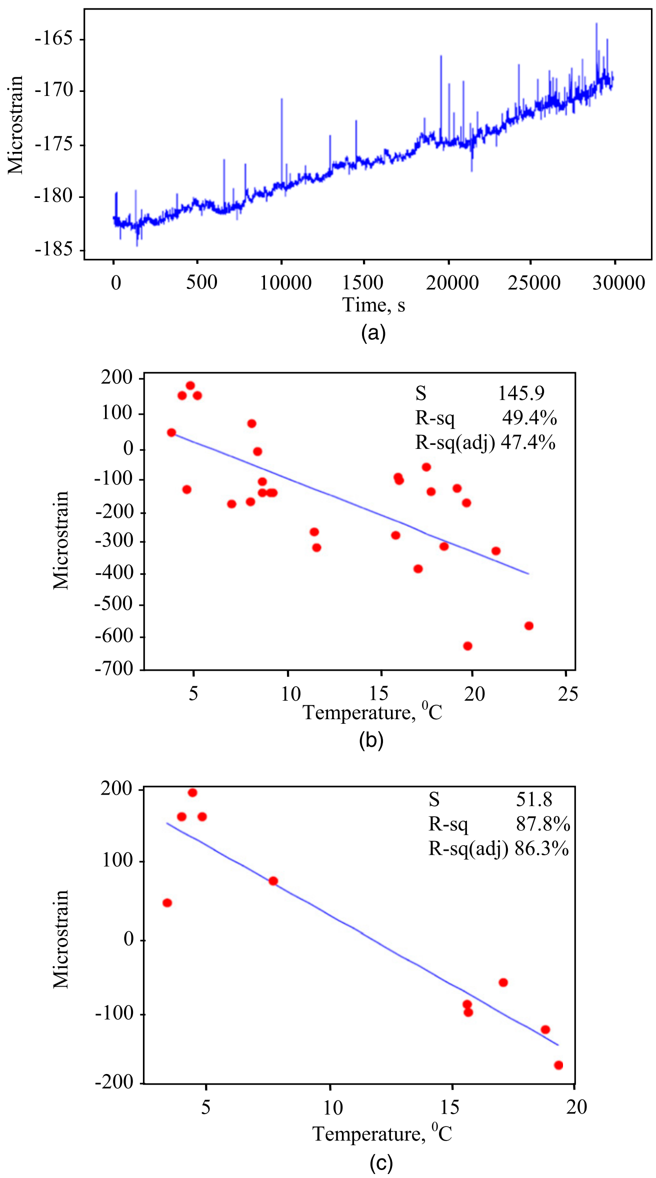

Fig. 11. Temperature effect: (a) strain values from strain Gauge 1 at 1 Hz for 8 h and 20 min at 0:0:0 time on March 1, 2006; (b) temperature and strain from strain Gauge 1 for 27 monthly readings; (c) temperature and strain from strain Gauge 1 for the first 10 monthly readings

Every strain gauge has its unique temperature-strain relationship. Though a liner relationship is ideally expected between temperature and strain, Figs. 11(a and b) show that linear regression does not always represent the accurate trend of the data. The linear relationship between the strain data and temperature is most likely altered because of the presence of significant live loads.

Discussion and Conclusions

Portage Creek Bridge (Victoria, BC, Canada) is one of the disaster route bridges in BC. In this case study, statistical modeling and pattern comparison techniques have been utilized for developing a methodology for structural damage detection and condition assessment. One of the unique advantages of statistical pattern recognition techniques is that the sensor data need not be completely noise free. However, for other procedures, for example vibration-based damage detection, it is necessary that the filtered data are noise free or have very low level of noise (Humar et al. 2006). The important observations from the study are summarized as follows:

- The AR process has been applied here from the derived data blocks of strain measurements to extract the AR coefficients, which are then statistically modeled for damage classification by X-bars. From the X-bars of strain and vibration data, the percentages of outliers are found to be quite small, which indicates that there is no damage in the structure or prominent structural degradation. However, a few cases suggest that the structure may be getting slightly degraded toward the end of the period considered, though it is still adequately safe.
- As an alternative approach to pattern comparison, statistical modeling and comparison of the reference models with blocks have been performed to determine the change in data pattern. Computed residuals, as represented in the *R*-values that represent the degree of closeness to the reference models, do not show any deviation or discrepancies to indicate any damage in the structure. The data patterns also indicate that the sensors are functioning properly.
- Temperature has a significant effect on the values of strains. The strain data generally show a linear relationship with temperature, as expected. No linearity between strain data and temperature is indicative of significant live loads on the structure.

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