Statistical Bridge Signatures

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Abstract: Instrumentation of bridge structures provides a stream of data representing operational structural response under loading. The authors define the term *bridge signature* as the expected response of a particular bridge under loading, as measured by different instruments. In this research, the authors propose a new method to develop and evaluate a bridge signature. The signature can be monitored over time and statistically evaluated to detect potential structural deterioration and damage. An instrumentation system was implemented on the Powder Mill Bridge in Barre, Massachusetts, as a research prototype for the development of a structural health monitoring (SHM) system. Heavy truck events due to daily traffic were collected using an automatic measurement system, which triggers above a given threshold of recorded strains. Using the measured strain data due to daily traffic, a bridge signature was created using nonparametric statistical techniques. Maximum experimental strain values from heavy truck events were used to establish a nonparametric probability distribution that describes the behavior of the undamaged bridge under normal operating conditions. Nonparametric prediction intervals were added to the bridge signature, which define where future distributions of strain data from the undamaged bridge should fall. To study the robustness of this method for use in damage detection, three damage scenarios were simulated using a calibrated finite-element model. Comparison of the prediction intervals of the undamaged bridge signature to the analytical damaged distributions showed that, for all three damage scenarios, the damaged distributions fell outside of those intervals, which indicates that this method can potentially identify the presence of structural damage. This study shows that the proposed method is robust and computationally efficient for operational bridge damage detection using only measured strain data from truck loadings. **DOI:** 10.1061/(ASCE)BE.1943-5592.0000596.

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Introduction

Traffic volumes in the United States have increased from 1.81 trillion miles traveled annually in 1986 to 2.98 trillion miles in 2011 [Federal Highway Administration (FHWA) 2011]. The FHWA estimates that, by the year 2050, Americans will travel approximately 5 trillion vehicle miles annually (FHWA 2010). This increase in traffic volume has taken a toll on our nation's infrastructure. Of the 605,000 bridges in the United States, some 67,000 are classified as structurally deficient and more than 76,000 are labeled functionally obsolete (FHWA 2012). The increase in American dependence on infrastructure and the deteriorating state of the nation's bridges, coupled with high construction costs and limited funding, illustrate the need to improve efficiency and reduce costs associated with bridge management and maintenance.

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Currently in the United States, bridges are inspected at least once every 2 years (FHWA 2004). Bridge inspections are performed using methods that haven't changed much in decades. Bridges are inspected manually, mostly relying on visual observations. In some cases, additional nondestructive tests may be specified, but the majority of the work is by visual inspection. After inspection, the engineer prepares a report on the bridge's condition. This process is, to an extent, subjective, and different engineers may rate the same bridge differently. Given that these bridge reports help guide maintenance decisions of the bridge owners, a more objective inspection system is desirable.

Developing technology offers new opportunities for bridge inspection and resulting decisions for maintenance. Finite-element modeling and structural health monitoring (SHM) of bridges can provide bridge owners with a more objective evaluation of a bridge's performance and structural health, and can potentially reduce maintenance costs and increase public safety.

Doebling et al. (1996) provided a literature review of SHM and vibration-based, damage-detection techniques, and Farrar and Worden (2007) offered an introduction to SHM that included a discussion of the history of SHM techniques, motivation for systems, and system implementation considerations. Sartor et al. (1999) discussed the economic advantage of SHM systems, noting that short-term monitoring of structures can provide significant insight into structural behavior and help bridge owners determine whether structural rehabilitation is necessary.

Ni et al. (2008) presented a system for identifying structural damage on a cable-stayed bridge using mode shapes, but noted that, in some cases, structural damage can be masked by ambient factors such as temperature change or traffic pattern variations. Scianna and Christenson (2009) proposed a method in which random traffic excitation data were used to excite the bridge health–monitoring benchmark problem. Their method used change in natural frequencies to identify structural damage, and included a probabilistic framework for dealing with the variation in excitation due to traffic variability. The method did not, however, account for changing environmental conditions, such as temperature variation or wind loading.

Catbas et al. (2012) presented the possibility of using video imaging to record vehicles crossing a bridge and to classify the vehicles using a database of known vehicles types for comparison. Such a system could help estimate the axle spacing of vehicles, and even provide approximate weight distributions. However, this method needs refinement, and may not be able to predict weight distributions accurately enough to identify damage based on changes in strain readings.

Olund and DeWolf (2007) described a long-term SHM project in which a combination of strain measurements, rotations, accelerations, and temperatures were taken on three bridges in Connecticut over the course of several years. Cardini and DeWolf (2009) installed a system to collect truck-event strain data from a steel-girder highway bridge over time. The authors discussed the possibilities of using a change in load distribution factors for each girder, peak strain range, or neutral axis location as a sign of structural damage. Alampalli and Lund (2006) presented a methodology for estimating fatigue life of certain bridge components through collection and processing of strain data. Orcesi and Frangopol (2010) presented a methodology for including long-term, truck-event strain measurements in bridge serviceability analysis by calculation and use of moment distribution factors for bridge girders. Lu (2008) developed a system for bridge SHM with truck events, statistical damage detection, and determinations of weight in motion.

While it is relatively straightforward to predict bridge outputs (e.g., static strains or dynamic accelerations) given bridge inputs (e.g., truck size, load path, and weight distribution, or dynamic excitation locations and frequency range), the loading inputs are not always easily obtained. In some cases, load tests have been performed with a truck of known size and weight, and strain output data has been collected and correlated. At best, load tests only can be performed occasionally, and, for many highway bridges, closing the structure for testing, even occasionally, is unrealistic because of impacts on traffic. These constraints make it desirable to develop an automated system of SHM and damage identification that is based on bridge data collected under operational conditions.

Thus, a new method of structural damage identification for bridges, through the establishment of a bridge signature and the addition of prediction intervals, is proposed. The signature is defined as an expected response of a bridge structural system to daily traffic as measured by an instrumentation system. This response can be evaluated by nonparametric statistical methods that employ a very limited number of assumptions and enable the development of prediction intervals associated with the signature. The approach documents how the bridge signature can be defined over a period of time. Variations from the baseline prediction intervals associated with the bridge signature may indicate structural damage.

The authors have collected truck loading events (that is, when a truck crosses the bridge) for approximately 6 months. The strain data from these events was used to estimate a nonparametric cumulative probability distribution of maximum strain outputs that were used to define the bridge signature. Any change in this signature over time may be indicative of changes in structural element properties here referred to as structural damage. The authors show that, given certain damage scenarios, the proposed nonparametric statistical approach can identify the presence of structural damage, using only strain outputs from future truck event monitoring and without any information about the loading inputs. This approach for bridge SHM is unique because it decouples the measured structural response from detailed finite-element analysis.

Powder Mill Bridge

The new Powder Mill Bridge carries Vernon Avenue over the Ware River (Fig. 1). It replaced an older, deteriorated structure and was opened for traffic in September 2009. The bridge is located in Barre, Massachusetts, and is owned by the town of Barre. It is a three-span, continuous-steel-girder, composite-concrete-deck slab bridge with two lanes running north and south across the river. This bridge was selected because it is a typical bridge that is used frequently in the U.S. highway system.

Fig. 1. Powder Mill Bridge (Sanayei et al. 2012, ©ASCE)

The main span is 23.5 m (77.1 ft) while the first and third spans are 11.75 m (38.6 ft). The bridge was instrumented with a variety of sensors, including 100 strain gauges (Fig. 2).

The Powder Mill Bridge is near the town of Barre's waste management station. Although the site is rural, large trucks frequently cross the bridge traveling to and from Massachusetts Route 122. This ideal location provides a steady stream of loading events on the bridge, which in turn have helped supply the data for this research.

Instrumentation was completed in October 2009. Sanayei et al. (2012) provided a complete description of the Powder Mill Bridge and its instrumentation. Fig. 3 shows the bridge instrumentation layout. For this study, the authors focused on outputs from two strain gauges: SG-34 and SG-42. SG-34 is located on Girder 3 near the South Pier measuring strains due to negative moments; SG-42 is located on Girder 3 near the center of the main span measuring strains due to positive moments. These specific gauges were chosen as they are near the center of the roadway on the lower flange of the steel girder, and SG-34 is located roughly in the location that receives the maximum negative bending stress, while SG-42 is located in the area that receives the maximum positive bending stress. From this point forward, for the sake of readability, SG-34 and SG-42 are referred to as SG$-$ and SG$+$, respectively.

Fig. 2. On-site data acquisition system (Sanayei et al. 2012, ©ASCE)

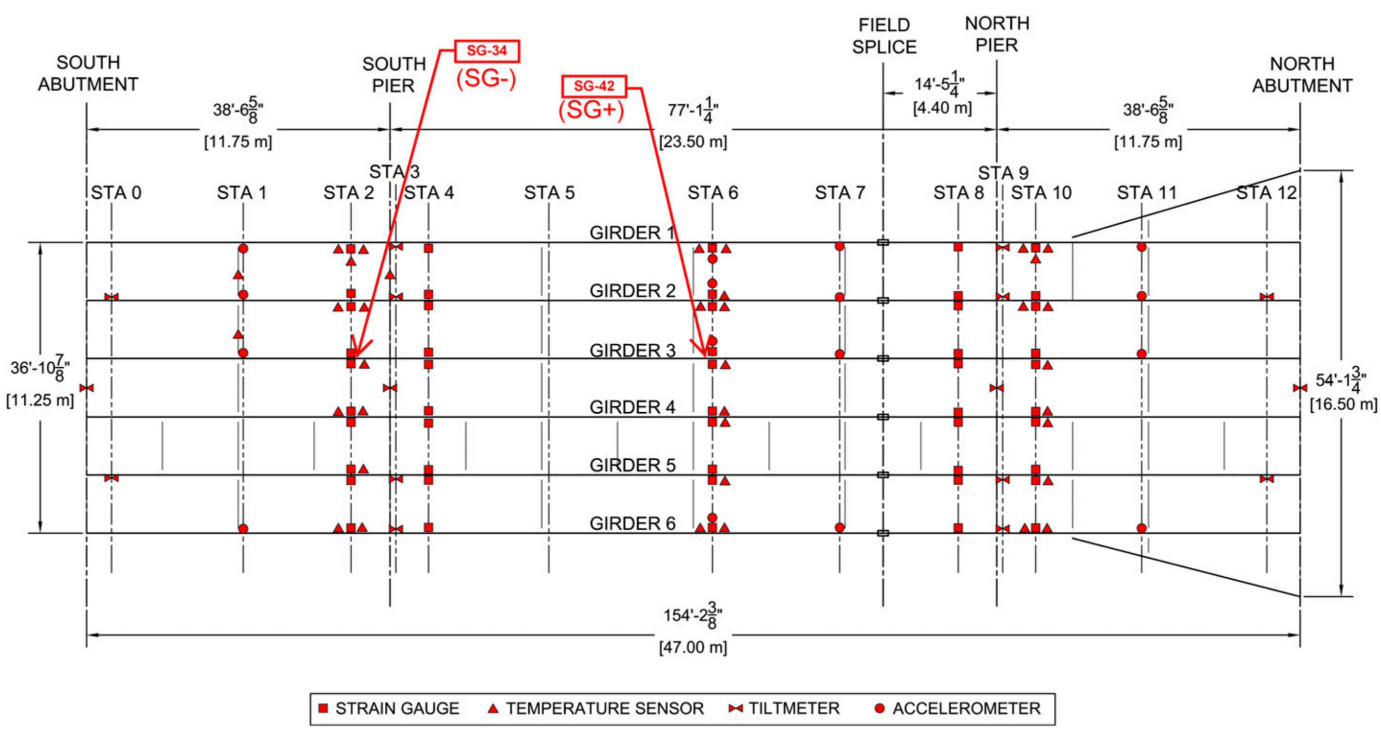

Fig. 3. Powder Mill Bridge sensor layout

Long-Term Monitoring System

For bridge monitoring, data may be recorded intermittently or continuously for long-term SHM. In this research, intermittent truck-event measurements were recorded. For intermittent measurements, all strain measurements were collected for trucks going over the bridge with a normal speed. As a result, trucks were on the bridge for a short period of time. Then the recorded data for each truck was zeroed out at the beginning of the measurements. Thus, the zeroed-out response record of the bridge was only due to the truck live load during a short period of time. Because the environmental conditions and specifically temperature do not change significantly over the few seconds that a truck event is being recorded, and the bridge is operating in the linear elastic range, the temperature effects are minimal or none. When data are monitored continuously, however, evaluation must consider the effects of different seasons during day and night with large temperature fluctuations. In such cases, environmental and temperature conditions must be included in the analysis of continuous measurement on highway bridges for SHM.

The authors developed an intermittent, long-term monitoring program to collect measured strain data from truck events. This system was deployed on site in July 2012. Since July 2012, the authors have collected strain data from truck events at a sampling rate of 50 Hz (0.02-s intervals). Our program currently is set up to collect strain data for vehicles weighing more than approximately 36 kN (8.1 kips). The program identifies a truck event, and then zeroes out the strain readings based on the ambient strain in each sensor prior to the event. Strain readings are zeroed out at the beginning of each truck event by recording only the changes in strain owing to the truck event. Absolute strain values due to temperature changes or residual strains due to construction included in the event data are removed. The processing and saving of the truck events are done by an on-site computer, which can be accessed remotely to allow for downloading of the truck-event data. Fig. 4 shows strain outputs from a typical truck event on the Powder Mill Bridge. Note that, in Fig. 4, for clarity, a moving average filter was used in plotting the strain outputs to eliminate the small dynamic effects.

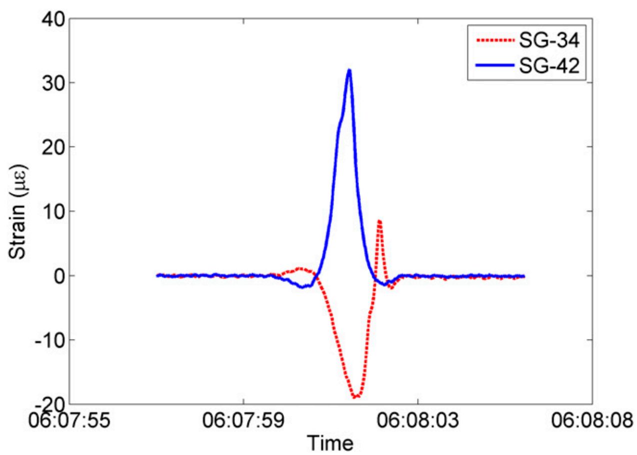

Fig. 4. Strain outputs from a typical truck event on Powder Mill Bridge

To address the issue of measured signal quality, there is always a small amount of noise present in any measurement. Because the maximum strain measurement in each sensor is used for each truck event, the signal-to-noise ratio is high. As long as there is similar noise present in the measurements that make up the signature distribution and in the measurements that make up the current distribution, measurement noise is a nonissue.

Strain data were collected for 88 days, spaced intermittently between July 2012 and January 2013, from 5,135 truck events. Fig. 5 shows the histograms of the absolute maximum strain output per event. These histograms illustrate the bimodal nature of the probability distribution of the truck-event strain output.

Based on the histogram of SG+ maximum strain values in Fig. 5, a heavy truck event was defined as an event from which the maximum strain output from SG+ was greater than 39 $\mu\varepsilon$, which is equivalent to a live load stress level of 7.79 MPa (1.13 ksi). On the upper end, these strains were as large as approximately 110 $\mu\varepsilon$, which is equivalent to a live load stress level of 22.0 MPa (3.19 ksi). This strain value was selected for this bridge and data set owing to its bimodal histogram. This was done to simplify the histogram for modeling of heavier trucks that potentially can observe changes in the bridge superstructure. This strain threshold resulted in a total of 1,670 measured heavy truck events. Fig. 6 shows the histograms of the absolute maximum strain values from SG+ and SG− from the same heavy truck events.

Definition and Development of a Bridge Signature

The histograms illustrated in Fig. 6 represent the probability density function (PDF) of absolute maximum strain output of heavy truck

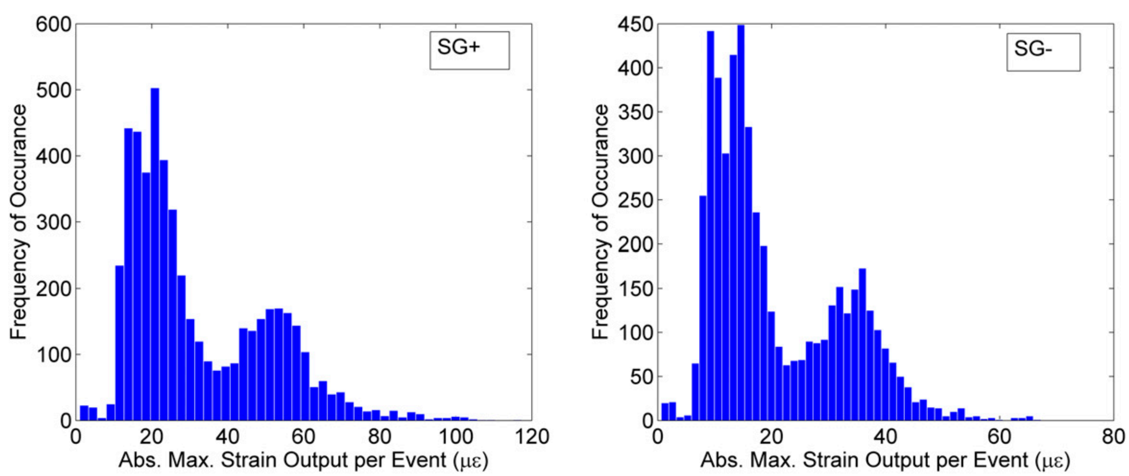

Fig. 5. Histograms of maximum strain outputs from all captured truck events

events, normally defined using the function $f(\varepsilon)$, where ε is the strain. The characteristic shape of each PDF defines the bridge signature. Comparisons among probability distributions using various goodness-of-fit statistics and hypothesis tests are usually performed using the cumulative distribution function (CDF), $F(\varepsilon)$, or its complement $[1 - F(\varepsilon)]$, which is termed the survival distribution function (SDF). For example, standard hypothesis tests (e.g., chi-Square test and Kolmogorov-Smirnov test), which are used to distinguish between PDFs or CDFs (or equivalently between SDFs), are normally based on the CDF or its inverse quantile function (NIST 2012). All such distributional goodness-of-fit approaches involve comparisons between theoretical probability distribution functions and data such as shown in Fig. 6. The proposed approach here is nonparametric, avoiding the need to identify a theoretical PDF or CDF. For a more complete review of nonparametric approaches to the estimation of CDFs and SDFs, refer to (Vogel and Fennessey 1994).

For each of our two critical strain gauges, for n heavy truck events and $i = 1, \ldots, n$, the absolute maximum strain values per event, $\varepsilon_{(i)}$, were ranked such that $\varepsilon_{(1)}$ is the largest observed value and $\varepsilon_{(n)}$ is the smallest. The proposed signature SDFs were defined as the ordered values of the absolute maximum strain output per heavy truck events plotted against their probability of exceedance, p_i, using a Weibull plotting position $p_i = i/(n+1)$, where i is the rank of the observation and n is the sample size. A plotting position is simply an estimate of the exceedance or nonexceedance probability of the observation of rank i. The Weibull plotting position is attractive because it provides an unbiased estimate of the exceedance probability, regardless of the PDF or CDF, from which the strain measurements originate (David 1981). Alternatively, and equivalently, the SDF curves can be estimated using

$$E_p = \varepsilon_{(i)} \quad \text{if } i = [(n+1)p]$$
$$E_p = \varepsilon_{(i+1)} \quad \text{if } i < [(n+1)p]$$

where the quantity in brackets $[(n+1)p]$ = the integer component of the quantity $(n+1)p$ that will always be less than or equal to $(n+1)p$. Note that more complex and accurate nonparametric estimators of the SDF are possible, as given by Vogel and Fennessey (1994); however, such estimators only are needed when sample sizes are generally quite small (i.e., $n < 50$). The simple estimator uses the rank associated with each observation to obtain its exceedance probability. More advanced estimators outlined in Vogel and Fennessey (1994) involve two or more ranks, along with their associated observations, to obtain resulting SDF curves for each value of exceedance probability p. E_p is then plotted versus p to create the SDFs, or bridge signatures, of maximum strain outputs from heavy

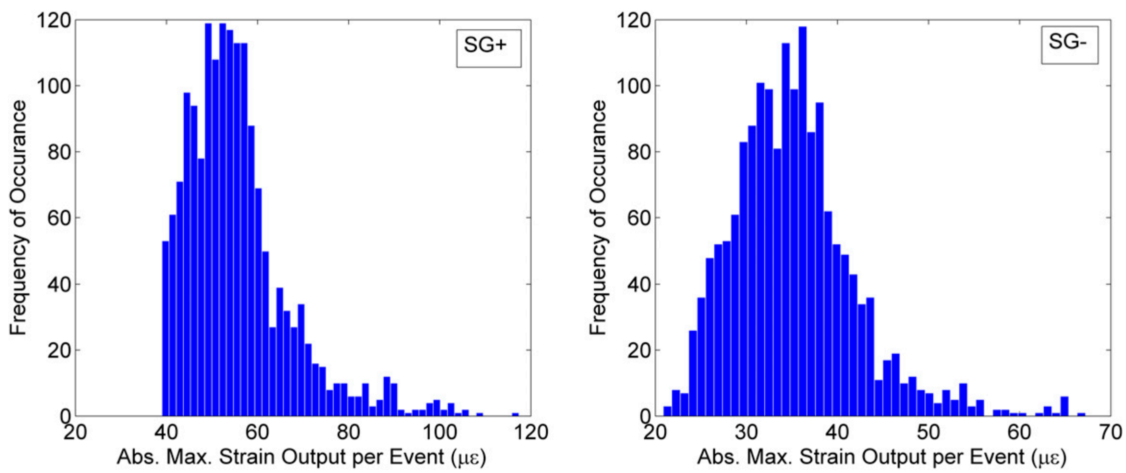

Fig. 6. Histograms of maximum strain outputs from only heavy truck events

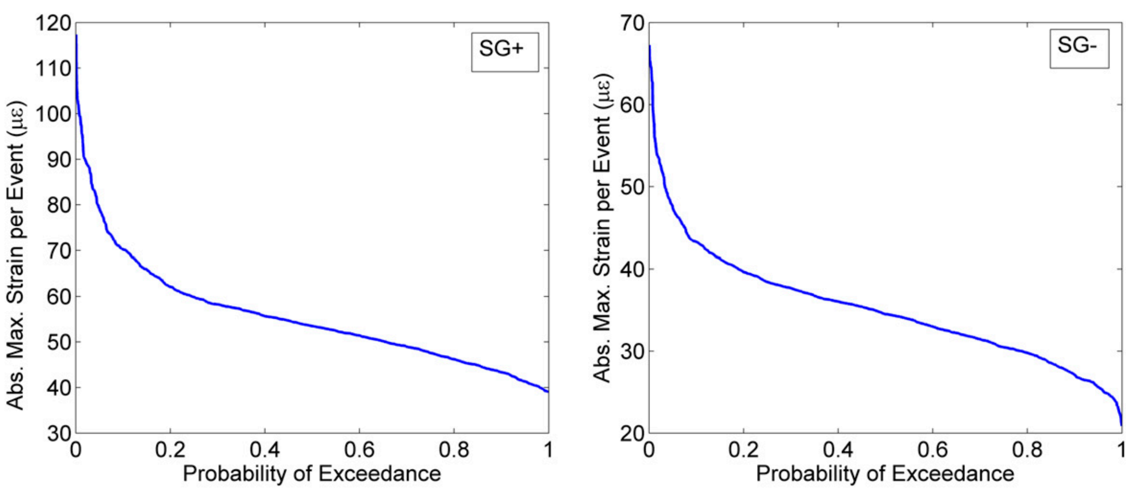

Fig. 7. Bridge signatures from heavy truck events on Powder Mill Bridge

truck events for SG+ and SG− on Powder Mill Bridge, as shown in Fig. 7.

Sample Size Needed for Stable Statistical Bridge Signatures

There is the question of how many heavy truck events are needed to provide a stable and reproducible statistical bridge signature or SDF. A small collection (on the order of 5 to 50) of heavy truck events is not enough to capture the variability in traffic loading, or to give a good sense of the distribution of maximum strain outputs over the long term. A stable SDF would be a curve in which the strain value at a certain probability of exceedance does not change significantly when more data from the same distribution (i.e., that of the undamaged bridge) are added. Fig. 8 illustrates the signature SDF value from SG + at different percentiles versus the number of heavy events used to develop the signature. It shows that a stable estimate of the SDF is obtained when the number of events exceeds roughly $n = 1{,}000$. This result may be unique to this bridge, and future research is needed to ensure that this minimum sample size results in stable SDFs for other bridges.

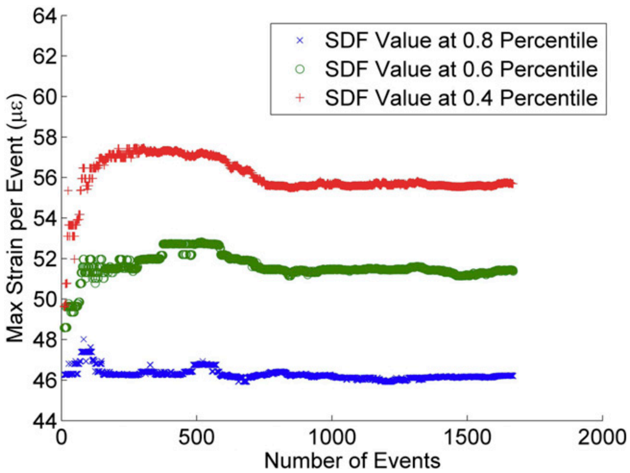

Fig. 8. SDF values versus number of events included for SG+

Nonparametric Prediction Intervals for Bridge Signatures

A goal is to develop an approach that can reliably distinguish between a bridge signature for a damaged bridge and an undamaged bridge. To distinguish between bridge signatures, it is necessary to understand the variability of estimates of individual bridge signatures or SDFs. Parametric confidence intervals for CDFs or SDFs require assumptions for the distribution of data. However, our approach is nonparametric. Therefore, a nonparametric approach also is needed for deriving confidence intervals that do not depend on any statistical assumptions regarding the underlying probability distribution of the measured strain data. Bootstrapping is a nonparametric statistical resampling method that can be used to evaluate the sampling properties of any statistic including a SDF or CDF. A thorough

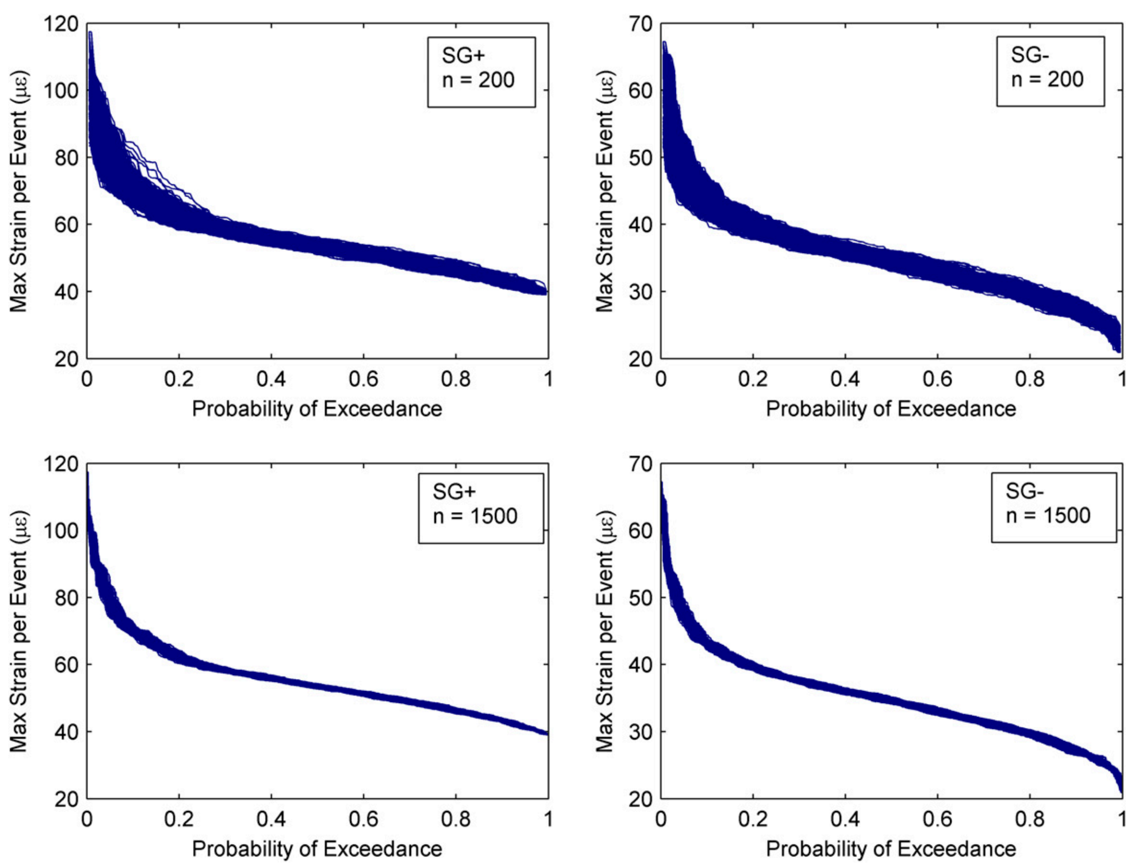

Fig. 9. Bootstrapped SDF data sets

introduction to bootstrapping can be found in Efron and Tibshirani (1993). The bootstrap method is a computational approach that replaces complex statistical theory with computer-intensive resampling of the available data. The bootstrap method can be used to solve nearly any traditional statistical problem.

Bootstrapping is implemented by sampling randomly with replacement from the observed data set to create additional data sets that can be used in further statistical analysis. The theory of the bootstrap has shown that, for independent and identically distributed random variables, such resampling with replacement preserves all the statistical properties of the data, including its SDF and CDF. In our case, the observed data sets were the absolute maximum strain values from the 1,670 heavy truck events from SG− and SG+. For each of the two critical strain gauges, the bootstrap method was used to develop two new sets of resampled data. Each new resampled data set then was used to develop 1,000 new resampled SDF curves. Fig. 9 shows the first resampled data sets obtained via bootstrapping, resulting in $n = 200$ events per SDF. The second data sets were constructed via bootstrapping, resulting in $n = 1{,}500$ events per SDF in Fig. 9.

These SDFs or bridge signatures, derived from bootstrapped data sets, show that, as the number of heavy truck events per SDF increases, the variability among the curves decreases. Assuming no damage to the bridge, no significant traffic pattern changes, and no issues with the data acquisition system, the data sets with $n = 200$ can be interpreted as reflecting the behavior of the SDFs or bridge signature that 1,000 sets of 200 heavy trucks crossing the bridge could produce in the future. The data sets with $n = 1{,}500$ can be interpreted as the bridge signature or SDFs that 1,000 sets of 1,500 heavy trucks crossing the bridge could produce in the future.

Nonparametric prediction intervals can be added to the SDFs in Fig. 9, as was suggested originally by Vogel and Fennessey (1994), for hydrologic applications. Each of the 1,000 SDFs, or bridge signature curves, or 1,000 sets of E_p, is made up of the ordered values $\varepsilon_{(i,j)}$ for $i = 1, \ldots, n$, as previously defined, and $j = 1, \ldots, 1{,}000$. For each i, $\varepsilon_{(i,j)}$ can be ranked such that $\varepsilon_{(i,1)}$ is the largest and $\varepsilon_{(i,1{,}000)}$ is the smallest observation. For 95% prediction intervals with 1,000 curves, 5% of the events at each i value should fall outside the intervals; that is, the 95% prediction interval values at each i value are

$$PI_{\text{HIGHER BOUND}(i)} = \varepsilon_{(i,25)}$$
$$PI_{\text{LOWER BOUND}(i)} = \varepsilon_{(i,975)}$$

The 95% prediction intervals for each of the four sets of bootstrapped SDF curves are shown in Fig. 9 along with the 1,000 SDFs used for their creation. The interpretation of the prediction intervals in these figures is critical to determine the number of loading events that provides sufficient basis for a reliable and reproducible definition of the bridge signature.

Use of data sets with more truck events should lead to prediction intervals closer to one another. More importantly, Fig. 10 suggests that excluding significant traffic pattern changes, data acquisition system damage, or structural damage to the bridge, 95% of all future bridge signatures (made up of either 200 or 1,500 heavy truck events, as appropriate) should fall within the given prediction intervals. If a future bridge signature collected from the Powder Mill Bridge falls outside the established prediction intervals, that would suggest that traffic patterns changed significantly, the data acquisition system malfunctioned, or that structural damage occurred.

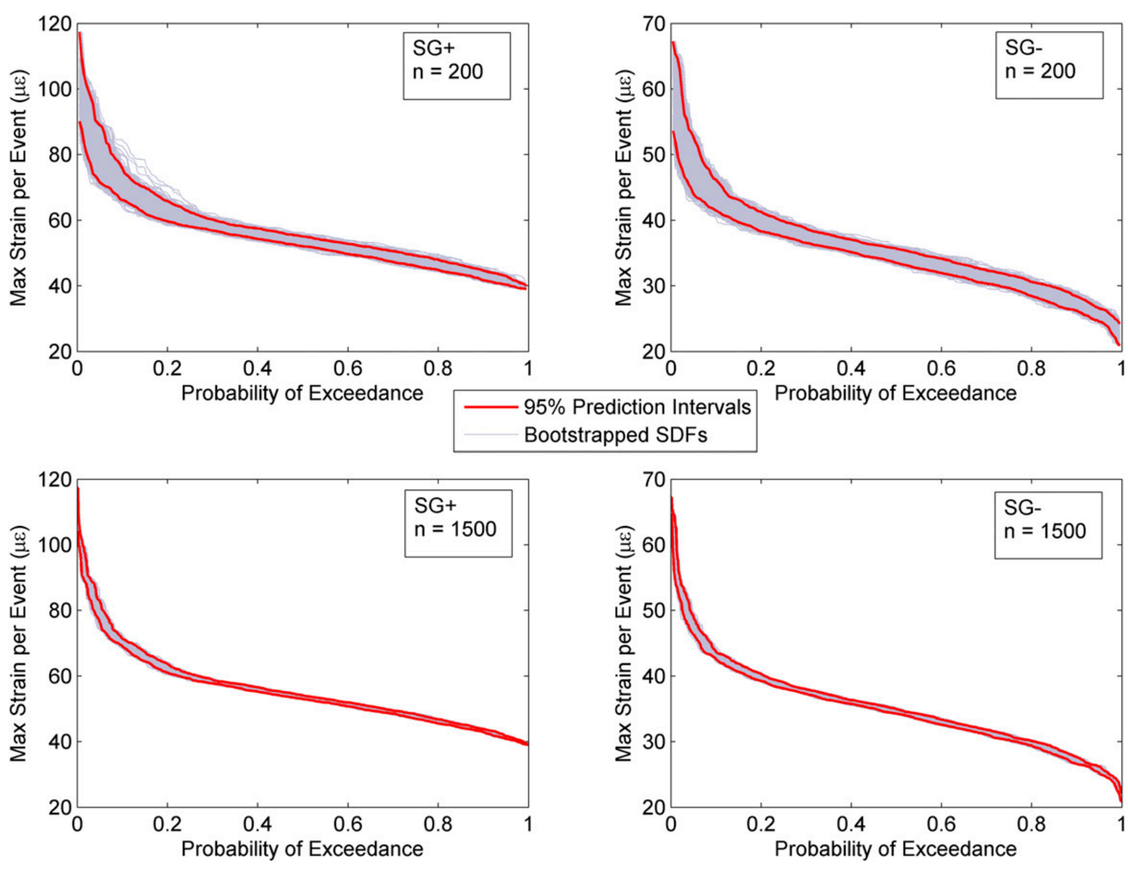

Fig. 10. Prediction intervals overlaid on bootstrapped data sets

Of these three possibilities, the data acquisition system malfunction in which only the strain values from the sensors increase by moderate amounts is highly unlikely. If significant traffic pattern changes were to occur, it is likely that the shape of a future SDF would change, rather than the entire SDF shifting up or down. This is due to the change in frequency of the different vehicles. For example, an increase in the amount of heavier truck traffic over time would show on the left ends of the curves. Therefore, if the shape of a future SDF curve is consistent with the signature SDF, but the future curve lies wholly or in part outside of the established prediction intervals, it is likely that structural damage has occurred.

Use of a Bridge Signature for Damage Detection

In the proposed method, the authors are searching for a change, here called damage or some form of structural change that is observable using the statistical-based bridge signature. In this approach the bridge can be new or old. The approach of looking for changes in response will work well with bridges that already have experienced deterioration (an old bridge) or have inherent flaws (a new bridge). The bridge signature would be treated as the baseline condition, to which future response could be compared to observe new changes. The method of collecting truck event data on an existing structure is the same for new and old bridges. First, a period of time is required to establish a statistical bridge signature; then, new truck event data is accumulated and processed in the same way.

Various bridge damage scenarios were simulated for comparison with the measured strain statistical signatures of the undamaged Powder Mill Bridge. This was done to evaluate the capabilities of the proposed method, if there is any damage. In using statistical signatures for damage identification in real bridges in service, there is no need to have a finite-element model at any stage of the bridge life. However, if a major change is identified, after visual inspections and verification, a finite-element model can be constructed for bridge evaluation.

For creating simulated damage scenarios, the authors used a calibrated finite-element model of the Powder Mill Bridge. For more information on the model and model calibration, refer to Sanayei et al. (2012).

Deck repairs cost bridge owners more than all other maintenance activities combined (Lee 2012). There are many causes of concrete deck damage that include alkali-silica reaction, reinforcement corrosion, and freezing and thawing. Some damage scenarios would result in a large section of the deck being compromised, while other scenarios, such as rebar delamination or potholes, might be more localized. For any type of deck deterioration scenario, the bending stiffness of the deck is reduced.

To examine the capacity of the proposed method for identification of structural damage, a signature distribution of a damaged bridge must be created for comparison. Given that damaging the actual structure is not feasible, the authors chose to model damage scenarios using a calibrated finite-element model.

Three different damage scenarios on the Powder Mill Bridge were simulated. Damage Case 1 was a 20% reduction in the bending stiffness of the concrete deck over the entire positive bending region of span 2. Damage Case 2 was a 50% reduction in the bending stiffness of the concrete deck over the entire positive bending region of span 2. Damage Case 3 was a 50% reduction in the bending

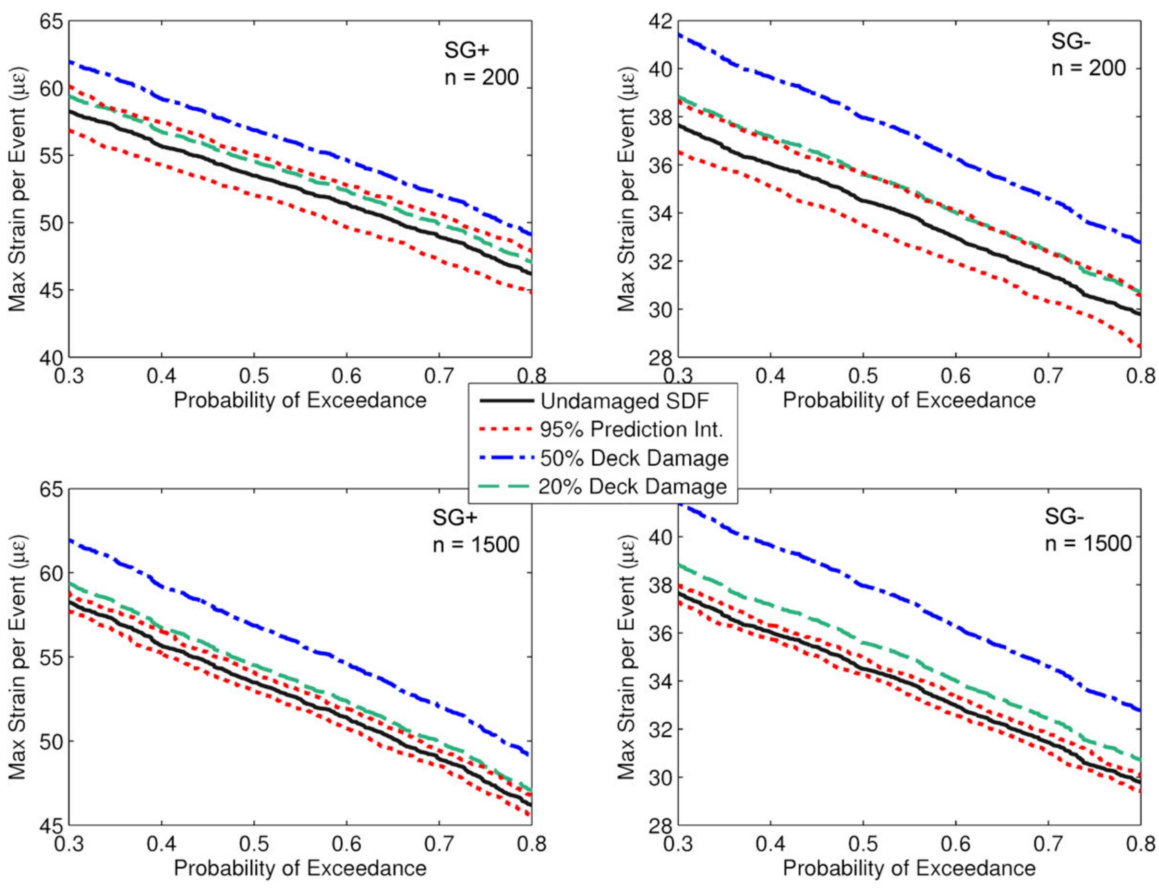

Fig. 11. Damage Cases 1 and 2: analytical SDFs due to large-scale deck damage

stiffness of a 2 × 2-m area in the center of the southbound lane at the midpoint of span 2, representing localized damage.

The Powder Mill Bridge model was calibrated using strain data from a load test, which was performed using a 3-axle dump truck. Therefore, it can be assumed that, using the 3-axle dump truck statistics for which the model was calibrated, the model simulates reasonably accurate strain values for linear elastic events.

First, the 3-axle dump truck was run over the entire length of the undamaged bridge finite-element model twice: (1) once on the northbound lane, and (2) once on the southbound lane. The maximum strain values at the locations of SG− and SG+ from each truck run were saved. Next, for each of the three aforementioned damage scenarios, the 3-axle dump truck was simulated over the model in the same fashion. For each damage scenario, the percentage change in maximum strain values from the undamaged runs were calculated, and the percentage change values from the northbound run and the southbound run were averaged in each damage case. This process resulted in estimates of the percentage differences between the maximum strain values (due to the dump truck) of the undamaged case and the three damaged cases. Given linear elastic behavior of the structure, one may assume that a damaged bridge signature would be the measured undamaged bridge signature shifted by the percentage change for the appropriate damage scenario.

Figs. 11 and 12 show the damaged analytical SDFs plotted with the experimental SDFs and the previously established prediction intervals. Fig. 11 indicates that 20% deck damage in Damage Case 1 on the main span positive bending region could be detected because the bridge signature for the damaged signature of SG− lies outside the 95% prediction intervals for the undamaged bridge signature using 200 new heavy truck events. However, for the same damage scenario, more trucks would be needed for the change to be detectable using only SG+ data. Interestingly, this damage scenario would be detectable using SG+ after collecting about 1,500 new heavy truck events. Note that, in Figs. 11 and 12, the probability of exceedance on the horizontal axis ranges from 0.3 to 0.8; this was done solely for the purposes of plot readability.

Fig. 11 also indicates that 50% deck damage in Damage Case 2 on the main span positive bending region could be detected readily by using data from either SG− or SG+, and would require fewer than 200 new heavy truck events.

Fig. 12 suggests that the 20% localized deck damage in Damage Case 3 would not be detectable using SG− data, even with 1,500 new heavy truck events. This damage scenario could, however, be detected using SG+ data by collecting approximately 1,500 new heavy truck events and comparing the new SDF to the undamaged signature SDF.

The number of new heavy truck events required to detect a given damage scenario is based on how much of a change the given damage scenario would cause in the maximum strain outputs at SG− or SG+. As more heavy truck events are collected and compared to the signature SDFs, the prediction intervals become smaller. Therefore, the number of new heavy events required to detect a certain damage scenario would be simply a number large enough such that the prediction intervals fall inside of the damaged SDF.

The proposed damage-detection method could be implemented as an early warning system for some types of structural bridge damage. Bridge owners could begin measuring strain data (or other types of data) just after the bridge opening, and could establish the signature

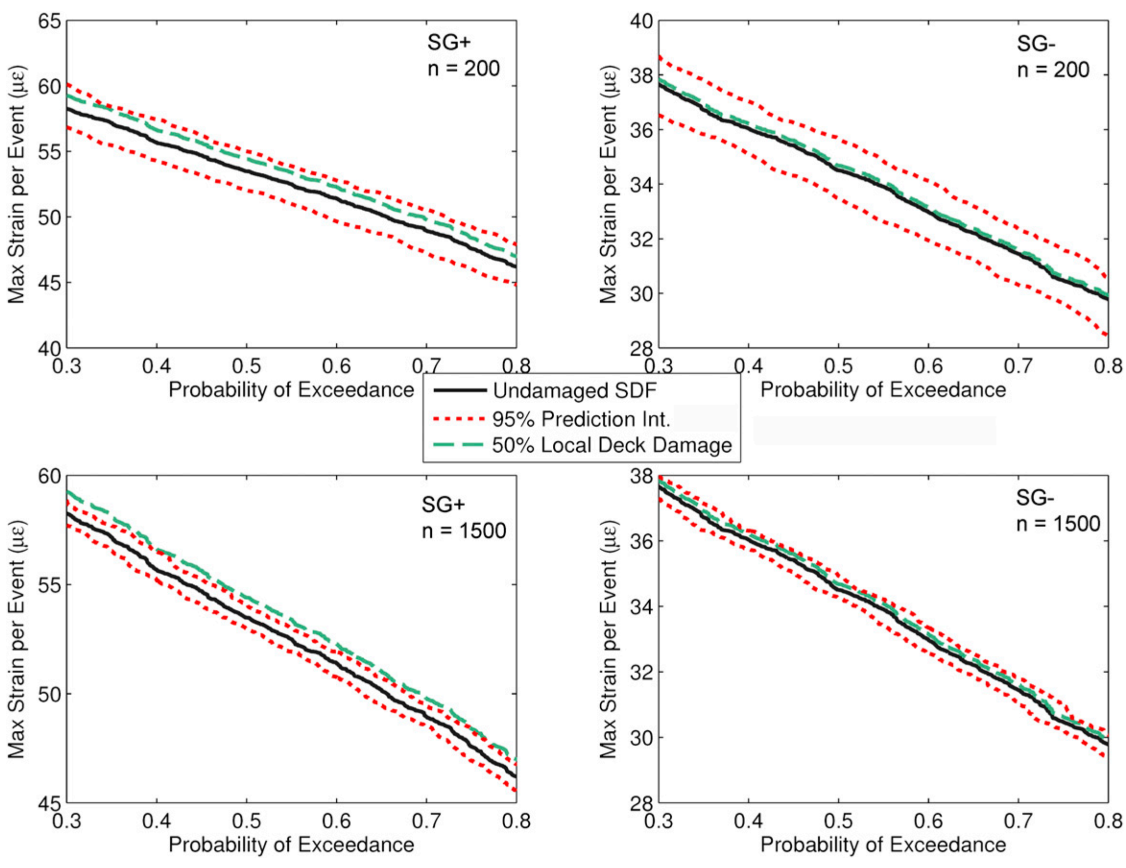

Fig. 12. Damage Case 3: analytical SDFs due to localized deck damage

J. Bridge Eng.

distribution. Over the life of the bridge, new distributions could be plotted daily (using perhaps a moving window of, perhaps 1,500 heavy truck events). Each day, the current distributions could be checked against the signature distribution. More prediction intervals could be added to the signature distribution. Perhaps, both 75 and 95% prediction intervals could be established, and each day the automated system could check to see where the current distribution falls. A new distribution inside the 75% prediction intervals could yield a green light, between the 75 and 95% prediction intervals could yield a yellow light, and outside of the 95% prediction intervals could yield a red light. Bridge owners could greatly benefit from such a simplified and automated system. Note that a green light would simply mean that the system has not found any structural changes, and it could not be interpreted as no structural damage is present. The green light/yellow light/red light system could be implemented alongside, not in place of, typical visual bridge inspections.

On the Powder Mill Bridge, for this study, the authors collected strain data for 1,670 heavy truck events over 88 days, which is equivalent to approximately 130 heavy events per week.

Implementation of Proposed Damage-Detection System

The authors did not have access to a damaged bridge, and, therefore, simulated damage on the newly constructed Powder Mill Bridge using a calibrated finite-element model. Implementation of this system for damage detection would not require a calibrated finite-element model. Thus, the success of the approach does not depend on resolution of errors associated with finite-element modeling and matching corresponding bridge response. The proposed system uses only in situ bridge traffic loading and statistical manipulation of strain outputs to identify damage. The proposed method is an operational damage-detection system, rather than an input-output-based system.

This study was focused on strain outputs from two critical strain gauges. For a full-scale implementation of this system, more strain gauges could be monitored and included. Analysis could be performed on the outputs of each strain gauge, and findings of each gauge could be synthesized using statistical techniques.

Conclusions

A new method was proposed and implemented for a long-term SHM and damage-detection system. The proposed method involves creation of a cumulative probability distribution of maximum strain values, which provides a representation of the bridge signature. The authors captured truck events due to daily traffic strain measurements from the Powder Mill Bridge in Barre, Massachusetts. The absolute maximum strain values from each (heavy) truck event were then used to develop a bridge signature defined on the basis of the shape of the cumulative PDF of the strain data. Nonparametric statistical methods were introduced for defining the bridge signature and for developing prediction intervals of the signature, which can be used to evaluate whether significant changes in the bridge signature have occurred. The bootstrap method, a nonparametric statistical method based on intensive computer-based resampling of the observed data, enabled the development of a methodology that does not depend on complex statistical theoretical assumptions regarding the sampling properties of cumulative density estimates (which would be needed if a parametric statistical approach were employed).

Three damage scenarios were modeled using a calibrated finite-element model of the bridge studied, and, in all three cases, the analytical distribution of the damaged structure fell outside of the established prediction intervals for at least one strain gauge, using 1,500 truck events. This allows us to conclude that structural damage detection using the new method is possible.

In the future, the proposed system could be implemented on newly constructed bridges to assist in bridge inspections, and to provide continuous and operational, long-term monitoring of a bridge's structural health. Future work on this method should include studies of other bridges and creations of bridge signatures using data from a variety of measured operational responses.

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