Binary Segmentation for Structural Condition Classification Using Structural Health Monitoring Data

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Abstract: Structural health monitoring (SHM) is the process of conducting structural condition diagnosis and prognosis based on appropriate analyses of in situ measurement data. Direct assessment of structural condition using time series response measurements can be classified as a type of statistical pattern recognition, in which structural condition is evaluated by comparing the statistical features of current data with those of baseline data. The philosophy behind this approach is that the time series response acquired under different structural conditions presents different statistical characteristics. As a consequence, the key step in structural condition classification is to detect the points at which the statistical properties of a time series response change; this is referred to as change-point analysis. The present study proposes the use of a computationally efficient binary segmentation (BS) approach for change-point detection in order to classify and assess structural health condition. The proposed approach, which falls into the category of data-driven diagnosis, does not require knowledge about the structure and is appealing for attaining an automated SHM system. The practicality and effectiveness are illustrated through real-world monitoring data acquired from a cable-stayed bridge and a high-speed train, both of which experienced structural damage/degradation over their service lives.
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Introduction

Maintaining the efficient, reliable, and safe operation of vital infrastructure systems such as tunnels, pipelines, railways, buildings, and bridges is critical for securing the well-being of people, protecting significant capital investments, and sustaining the vitality of regional economy. During their in-service period, infrastructure systems are inevitably subjected to material deterioration, structural damage, and natural hazards. All these factors, which affect the nature and rate of degradation of in-service infrastructure, can ultimately bring about the unserviceability of the structures. To ensure the safety of these public assets and conduct efficient maintenance practices, it is essential to assess the health condition of in-service structures in real time during their operation (Aktan et al. 1996; Yanev 2003; Brownjohn 2007). Visual inspections have long been the primary practice for detecting potential damage. However, for large-scale, complex infrastructure systems, visual inspections are time-consuming and expensive; they are not automated, they are subjective, and they vary with the knowledge and experience of the inspectors. In recognition of these shortcomings, structural health monitoring (SHM) has gained increasing attention in the last few decades, mainly due to its high capability and the automated nature of its implementation. With significant developments in sensing technologies (including innovative sensors and advanced data acquisition and transmission units), SHM systems have enabled continuous collection of field monitoring data, which is promising for automated condition assessment.

SHM involves the proper analysis of the data stream collected by an array of sensors in order to detect changes in features that may indicate the existence of structural damage or degradation. One goal of SHM is to enable structural operators and asset managers to assess the health status of target structures and support decision making with respect to maintenance, rehabilitation, and risk management. SHM technology has been applied to a wide range of infrastructure systems, such as bridges (Pines and Aktan 2002; Wong 2004; Chan et al. 2006; Peeters et al. 2009; Ou and Li 2010; Ni et al. 2011; Li et al. 2014), buildings (Lin et al. 2005; Kijewski-Correa et al. 2006; Brownjohn and Pan 2008; Ni et al. 2009, 2017) and tunnels (Glisic et al. 2000; Mohamad et al. 2012; Ye et al. 2013; Zheng and Lei 2017; Zhou et al. 2018). The philosophy behind vibration-based SHM methods is that changes in structural properties caused by damage, such as reductions in stiffness, lead to changes in structural dynamic characteristics and modal-relevant features. Depending on whether they rely on a physical model or not, vibration-based SHM methods can be categorized into two classes, model-based and data-driven techniques (Farrar and Worden 2007). The model-based (parametric) approach refers to the evaluation of health condition or damage via change ratios of structural parameters (e.g., stiffness or elastic moduli) determined by solving an inverse problem. Determination of the structural parameters can be made by formulating the problem as a constrained optimization problem, in which the objective is to minimize an error function that expresses the discrepancy between the model-derived and the measured dynamic properties (Hua et al. 2008, 2009; Moaveni et al. 2009; Khodaparast et al. 2011; Wan and Ren 2015, 2016). However, the data-driven (nonparametric) approach refers to the assessment of structural condition through statistical analysis of damage-sensitive features extracted from time series response measurements of the structure. The data-driven approach also formulates a model, but it is a statistical model of a time

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series aiming to root out characteristic quantities that represent the structural health state.

In general, the model-based approach involves three stages: modal identification, finite-element analysis, and solution of the optimization problem. Each of the three stages has its own limitations that have not yet been fully overcome, such as difficulty in accurately extracting high-order modal information, precise finite-element modeling, and nonconvex optimization with multiple local minima. These drawbacks tend to be more tedious when the target physical system is more complex and larger in scale. In contrast, the data-driven method avoids such weaknesses, because it applies signal-processing techniques to the measurements in order to monitor the condition of a structure and requires less prior engineering knowledge. This admirable feature—that the data-driven approach solely depends on signal processing of the measured data—makes it very attractive for the development of automated SHM systems. The execution of the data-driven SHM approach is usually posed in the context of statistical pattern recognition (SPR) (Sohn et al. 2001; Sohn and Farrar 2001; Gul and Catbas 2009). The principle of SPR for SHM is simple. A statistical model is set up to describe a sequence of time-ordered measurements under different conditions, one of which is the reference/baseline (undamaged) state; structural condition diagnosis is then conducted via statistical decision making in accordance with the extracted features associated with different conditions. A variety of time series modeling techniques have been proposed, including the state-space model (Liu et al. 2014; Nichols et al. 2003), the autoregressive model (Sohn et al. 2003; Lynch et al. 2004; Nair et al. 2006; Gul and Catbas 2010; Kopsaftopoulos and Fassois 2010; Saito and Beck 2010; Yao and Pakzad 2012), neural networks (Wu et al. 2002; Yan et al. 2011; Zhou et al. 2011), and the Bayesian model (Wan and Ni 2018a, b), among others.

In this study, we present a novel structural condition classification approach making use of change-point analysis (CPA) within the time series modeling context. CPA, as its name suggests, is intended to estimate the points at which the statistical properties of a sequence of observations change. It aims to divide the time-ordered dynamic data into distinct, homogeneous segments such that data within a segment follow an identical structure, whereas data from different segments are heterogeneous. The CPA has been applied in a variety of fields, such as bioinformatics (Lio and Vannucci 2000), econometrics (Zhou et al. 2010), climatology (Reeves et al. 2007), and oceanography (Killick et al. 2010), to name a few. For example, in bioinformatics, CPA has been used for the identification of genes with abnormal expression changes; in climatology, it has been utilized to detect climate changes such as temperature volatility and ozone concentration over a certain period of time. Although CPA has gained wide application in different areas, to the best of the authors' knowledge, it has rarely been explored for structural condition classification in the field of SHM. In this study, we propose the use of CPA for distinguishing the damaged state from the undamaged state, thereby conducting structural condition diagnosis. In addition, because of its ease of implementation and high computational efficiency (Killick et al. 2012), a binary segmentation (BS) algorithm is preferred here to search for change points at which structural condition varies. The performance of the proposed BS-based CPA approach for structural condition classification is demonstrated through two industrial examples, a cable-stayed bridge and a high-speed train.

Structural Condition Classification by Binary Segmentation

Consider a time series sequence consisting of multiple data sets ordered as $1, 2, \ldots, m$. Different data sets are collected under different structural condition states. Our task is to search for the change points that serve as condition change indicators. Fig. 1 illustrates the idea behind change-point analysis for structural condition classification. The key to structural condition classification is to detect the change points. The shift from one structural condition state to another inevitably leads to a change in structural responses. Structural responses measured under different structural condition states are likely to present distinctive statistical properties, e.g., mean and variance. Based on this premise, one possible way of identifying a set of change points is to detect the points between which the statistical properties of the time series segments remain unchanged. The specification of test statistics used to identify change in mean and variance is

$$\mu_t = \begin{cases} \mu_1 & t \le \tau \\ \mu_n & t > \tau \end{cases} \tag{1}$$

$$\sigma_t^2 = \begin{cases} \sigma_1^2 & t \le \tau \\ \sigma_n^2 & t > \tau \end{cases} \tag{2}$$

where μ_t and σ_t^2 = statistics of time series data; $\mu_1 \neq \mu_n$; and $\sigma_1^2 \neq \sigma_n^2$.

Change-point detection can be thought of as the identification of points within a data set where the statistical properties alter. A collection of change-point identification methods have been proposed in the last decades to detect changes in the statistical properties of time series. Among them, binary segmentation, proposed by Scott and Knott (1974), is perhaps the most popular search algorithm, because it is computationally efficient—with a computational cost of $\mathcal{O}(n \log n)$, where n is the length of the data sequence (Killick et al. 2012). Assume a set of time-ordered observations $\mathbf{y}_{1:n} = \{y_1, y_2, \ldots, y_n\}$ containing m change points with their location indices $\boldsymbol{\tau}_{1:m} = \{\tau_1, \tau_2, \ldots, \tau_m\}$. Additionally, we define $\tau_0 = 0$ and $\tau_{m+1} = n$. Each change-point index is an integer between 1 and $n - 1$ inclusive, and change points are ordered such that $\tau_i < \tau_j$ if and only if $i < j$. Consequently, the m change points will split the data into $m + 1$ segments, with the ith segment being $\mathbf{y}_{(\tau_{i-1}+1):\tau_i}$. A widely used approach to identify multiple change points is to solve a penalized minimization problem defined as

$$\boldsymbol{\tau}_{1:m} = \min\left\{\sum_{i=1}^{m+1} \mathcal{C}(\mathbf{y}_{(\tau_{i-1}+1):\tau_i}) + f(m)\right\} \tag{3}$$

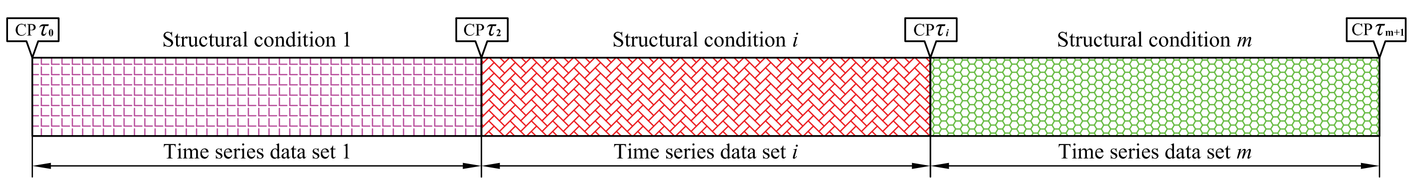

Fig. 1. Structural condition states separated by change points.

where $\mathcal{C}(\cdot)$ is the segment cost function; $f(\cdot)$ is the assigned model selection penalty function, which aims to avoid overfitting; and τ = change-point index. The choice of the segment cost function as twice the negative log likelihood has been commonly adopted in the change-point detection literature (Chen and Gupta 2011). In practice, the penalty term is considered as a linear function with respect to the number of change points (Killick et al. 2012), that is, $f(m) = \beta m$, where the penalty coefficient $\beta = 3\log(n)$ is determined according to the Bayes information criterion (BIC) (Zhang and Siegmund 2007).

A multiple change-point detection problem can be converted to the solution of a single change point in an iterative manner. To detect a single change point in the BS context, the optimization problem defined in Eq. (3) turns into a test as to whether there exists an integral $\tau \in \{1, 2, \ldots, n-1\}$ that satisfies

$$\mathcal{C}(\mathbf{y}_{1:\tau}) + \mathcal{C}(\mathbf{y}_{\tau:n}) + \beta < \mathcal{C}(\mathbf{y}_{1:n}) \tag{4}$$

The data within a segment is commonly modeled as being independent and identically distributed, drawn from a Gaussian distribution. As such, the log likelihood of data $\mathbf{y}_{\tau_{i-1}+1:\tau}$ with mean μ and variance σ^2 can be expressed as

$$\ell(\mathbf{y}_{\tau_{i-1}+1:\tau_i}; \mu, \sigma^2) = -\frac{\tau_i - \tau_{i-1}}{2}\log(\sigma^2) - \frac{1}{2\sigma^2}\sum_{j=\tau_{i-1}+1}^{\tau_i}\log\,(y_j - \mu)^2 \tag{5}$$

Thus, for detecting changes in both mean and variance, the associated segment cost function equal to minus twice the log likelihood is

$$\mathcal{C}(\mathbf{y}_{(\tau_{i-1}+1):\tau_i}) = (\tau_i - \tau_{i-1})\left\{\log\left[\frac{1}{\tau_i - \tau_{i-1}}\sum_{j=\tau_{i-1}+1}^{\tau_i}\left(y_j - \frac{1}{\tau_i - \tau_{i-1}}\sum_{i=\tau_{i-1}+1}^{\tau_i} y_i\right)^2\right] + 1\right\} \tag{6}$$

Note that for computational convenience, the constant item involved in the log likelihood is omitted.

In summary, BS starts by applying the aforementioned detection method to the whole data set. If no change point is found, the detection procedure is stopped; otherwise, the data is separated into two segments based on the identified change point in order to detect whether change point(s) exist in each segment. If a change point is detected in either or both segments, we split these segments into further segments and carry out the detection procedure for each new segment. The detection procedure is repeated until no further change points are identified. The primary steps in implementing the BS algorithm for multiple change-point detection can be summarized as follows:

1. Prepare data sequence $\mathbf{y}_{1:n} = \{y_1, y_2, \ldots, y_n\}$, segment cost function $\mathcal{C}(\cdot)$, and penalty constant β; initialize change-point set $\boldsymbol{\tau} \leftarrow \emptyset$, in which the left arrow stands for the assignment operator;
2. Select an element y_τ of the data sequence $\mathbf{y}_{1:n}$ and calculate the segment costs based on the following expressions:

$$\mathcal{C}(\mathbf{y}_{1:\tau}) = \tau\left\{\log\left[\frac{1}{\tau}\sum_{j=1}^{\tau}\left(y_i - \frac{1}{\tau}\sum_{j=1}^{\tau} y_i\right)^2\right] + 1\right\}$$

$$\mathcal{C}(\mathbf{y}_{\tau:n}) = (n-\tau+1) \times \left\{\log\left[\frac{1}{n-\tau+1}\sum_{j=\tau+1}^{n}\left(y_i - \frac{1}{n-\tau+1}\sum_{j=\tau+1}^{n} y_i\right)^2\right] + 1\right\}$$

$$\mathcal{C}(\mathbf{y}_{1:n}) = n\left\{\log\left[\frac{1}{n}\sum_{j=1}^{n}\left(y_i - \frac{1}{n}\sum_{j=1}^{n} y_i\right)^2\right] + 1\right\}$$

3. Evaluate $\lambda(y_\tau) = \mathcal{C}(\mathbf{y}_{1:n}) - \mathcal{C}(\mathbf{y}_{1:\tau}) - \mathcal{C}(\mathbf{y}_{\tau:n}), \tau \in [1, n]$;
4. If $\lambda(y_\tau) \le \beta$, no change point is found and the detection process is terminated; otherwise, the selected element y_τ is identified as a change point and is then merged to form a new change-point set such that $\boldsymbol{\tau} \leftarrow [\boldsymbol{\tau}, \tau]$;
5. Split the data sequence $\mathbf{y}_{1:n}$ into two subsets, $\mathbf{y}_{1:\tau}$ and $\mathbf{y}_{\tau:n}$; and
6. Execute the change-point identification procedure (Steps 2–5) for different subsets of the sequence iteratively until no further change points are found.

Application I: Cable-Stayed Bridge

Description of Bridge and SHM System

The Tianjin Yonghe Bridge, which has been considered as the test bed for a benchmark study initiated by Li et al. (2010, 2014), is a double-tower cable-stayed highway bridge with a total length of 510 m. The main span of the bridge is 260 m, and the side spans are 99.85 and 25.15 m, respectively. The bridge is 11 m wide, with a 9-m wide vehicle lane and two 1-m wide pedestrian lanes. The two towers are 60.5 m high and composed of concrete, each comprising two transverse beams. The towers and the bridge deck are connected by a total of 176 stay cables, each being composed of a series of parallel galvanized steel wires with a diameter of 5 mm each. This cable-stayed bridge was opened to public traffic in December 1987. After 19 years of operation, several cracks as much as 2 cm wide were found at the bottom of the segment over the mid span, and the stay cables close to the anchors were seriously corroded. In recognition of this, significant repair and maintenance work was conducted between 2005 and 2007; the bridge was reopened to the public in late 2007 (Kaloop 2010).

During the repair and rehabilitation period, a sophisticated SHM system was devised, installed, and operated by the Center of Structural Monitoring and Control (SMC) at Harbin Institute of Technology, China. More than 150 sensors were deployed on the main girders, towers, and stay cables. Among these, 14 uniaxial accelerometers were installed on both downstream and upstream sides of the bridge deck, and a biaxial accelerometer was fixed on the top of the south tower to monitor horizontal oscillation. In addition, an anemometer and a temperature sensor were attached on the top of the south tower to measure wind velocity in three directions and the ambient temperature, respectively. The deployment of sensors is shown in Fig. 2. More details about this bridge and the instrumentation system can be found in Li et al. (2010, 2014).

Classification of Structural Condition States

As reported in Li et al. (2014), two types of damage inflicted on the bridge, namely, auxiliary pier detachment and wide concrete

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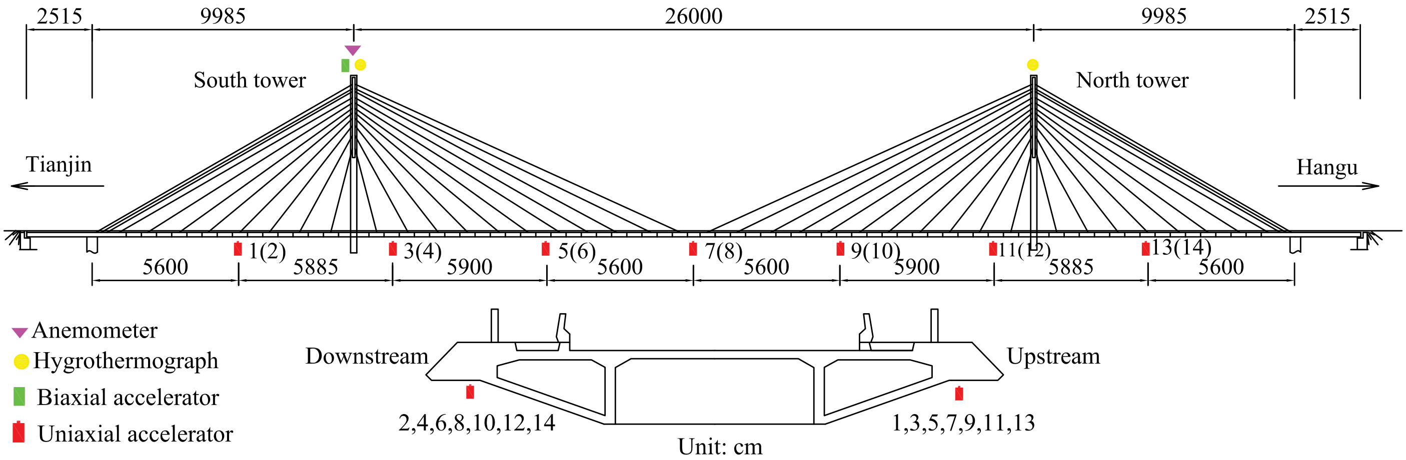

Fig. 2. Deployment of sensors on Tianjin Yonghe Bridge.

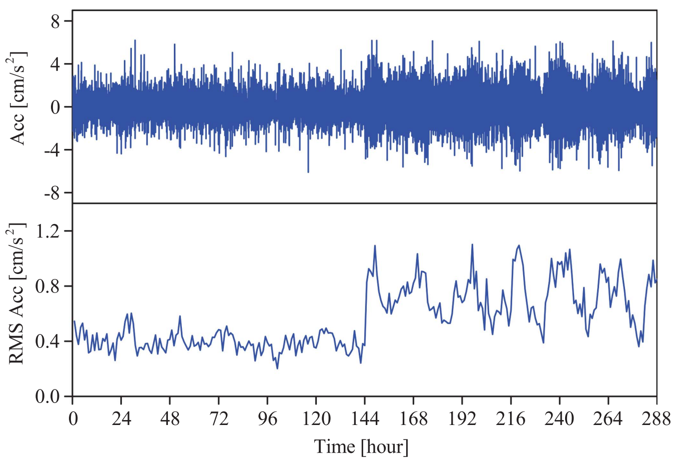

Fig. 3. Acceleration time series response measured by accelerometer deployed at side span.

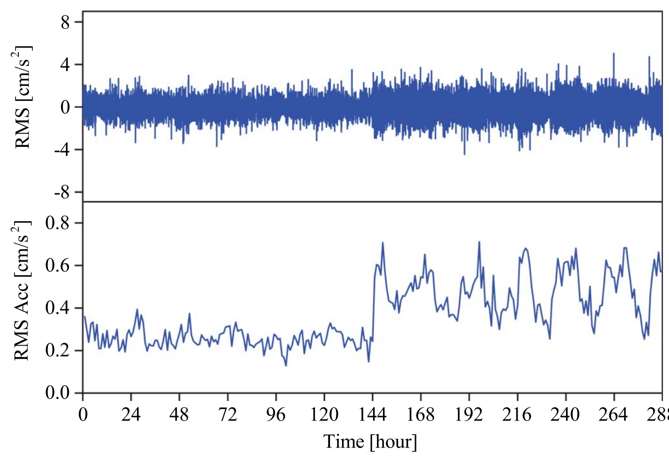

Fig. 4. Acceleration time series response measured by accelerometer deployed at main span.

cracks, were detected by inspection techniques in August 2008. The SHM system has been continuously acquiring in-service monitoring data for the bridge since 2007, and thus the instrumentation system has witnessed the shift from an undamaged state to a damaged state. The data regarding both the undamaged and damaged condition states of the bridge was recorded naturally. Without loss of generality, data acquired by two accelerometers (one located at a side span and the other positioned at the main span) were used to verify the proposed BS-based condition classification approach. Real-time monitoring data collected over a total of 8 days were tested. Specifically, the data from the first 4 days were associated with undamaged condition, while the data from the latter 4 days corresponded to the damaged condition. The acceleration time history and its root mean square, representing a shift from an undamaged state to a damaged state, are shown in Figs. 3 and 4. As seen from the time series data—especially the RMS—there were two patterns with different response magnitudes, which reflect the undamaged and damaged states.

By executing the implementation procedures described in the section "Structural Condition Classification by Binary Segmentation," a change point with time index 144 was detected by the BS-based CPA method. Inclusive of the starting and ending time indices, the detected change points partitioned the time series data into segments representing two distinct structural condition states. The structural conditions classified by the BS method are shown in Fig. 5, in which the dashed lines indicate the change points. The fact that the classification results agreed well with the true results validates that the BS method is feasible and effective for the classification of structural conditions.

Application II: High-Speed Train

Description of Onboard Monitoring System

An onboard monitoring system was installed on an in-service high-speed train to collect monitoring data during routine operation. The train consisted of 5 motor cars and 3 trailer cars; the 1st, 2nd, 4th, 7th, and 8th cars were motor cars and the rest were trailer cars. The 3rd trailer car and the 4th motor car were instrumented for onboard monitoring. The tasks of this onboard monitoring were twofold: (1) online monitoring of the vibration of structural components (namely, the axle box, bumper, bogie frame, and coach) of the in-service train before and after wheel lathing, aiming to understand how an out-of-round (OOR) defect (e.g., irregularity, wheel flat, or polygonization) of wheels affects the vibration of vehicle components and passenger ride comfort; and (2) online monitoring of stresses of the bogie frame, which is prone to fatigue cracking, in order to obtain authentic stress spectra for fatigue life evaluation. The safety of the bogie frame was of the most concern, since it plays an important role in bearing static and dynamic loads from the car body, controlling wheelsets on straight and curved tracks and connecting the wheels, axles, brakes, and suspensions. It is worth pointing out that the lathing process is an operation in which wheels with an OOR defect are reshaped with a lathe in order to restore a smooth rolling profile.

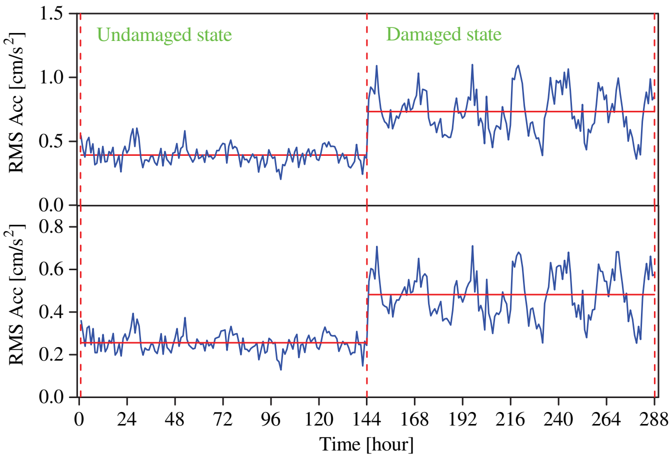

Fig. 5. Classification of undamaged and damaged condition states by binary segmentation.

As illustrated in Fig. 6, a total of 72 sensors were mounted on the high-speed train, consisting of 12 triaxial accelerometers, 52 fiber Bragg grating (FBG) strain sensors (including triaxial and uniaxial sensor types), 4 FBG temperature sensors, 2 global positioning system (GPS) sensors, 1 microphone, and 1 video sensor. For the 3rd trailer car, accelerometers were deployed on the axle box, bumper, and bogie frame of its 7th and 6th axles and on the axle box and bumper of its 5th axle; one accelerometer was also positioned on the floor of the carriage. For the 4th motor car, one accelerometer was deployed on each axle box, bumper, and bogie frame of its 6th axle. Among the installed accelerometers, the one inside the carriage was a triaxial FBG accelerometer and the rest were all piezoelectric accelerometers. The arrangement of the 12 accelerometers is illustrated in Fig. 7, and their installation locations are shown in Fig. 8.

Classification of Wheel Conditions

With the extension of the in-service period, rail wheels suffer from OOR defects. Improperly shaped wheels increase rolling

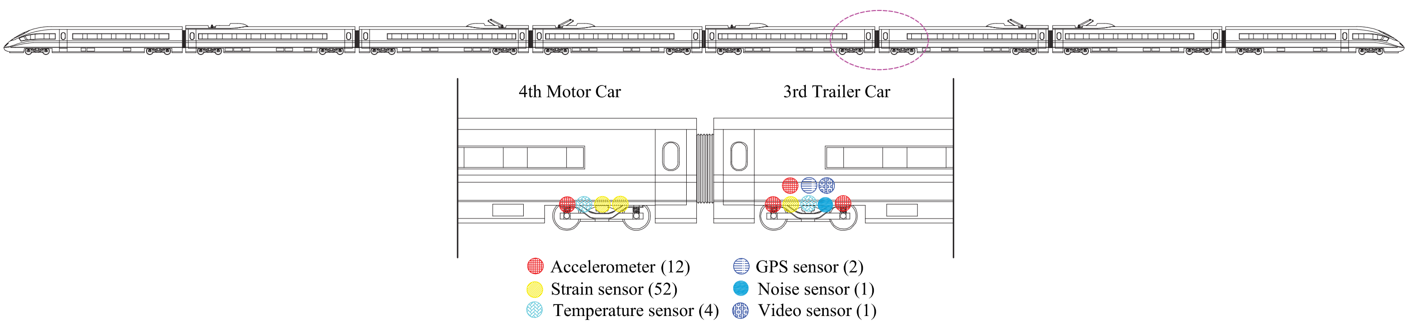

Fig. 6. Onboard monitoring system installed on an in-service high-speed train.

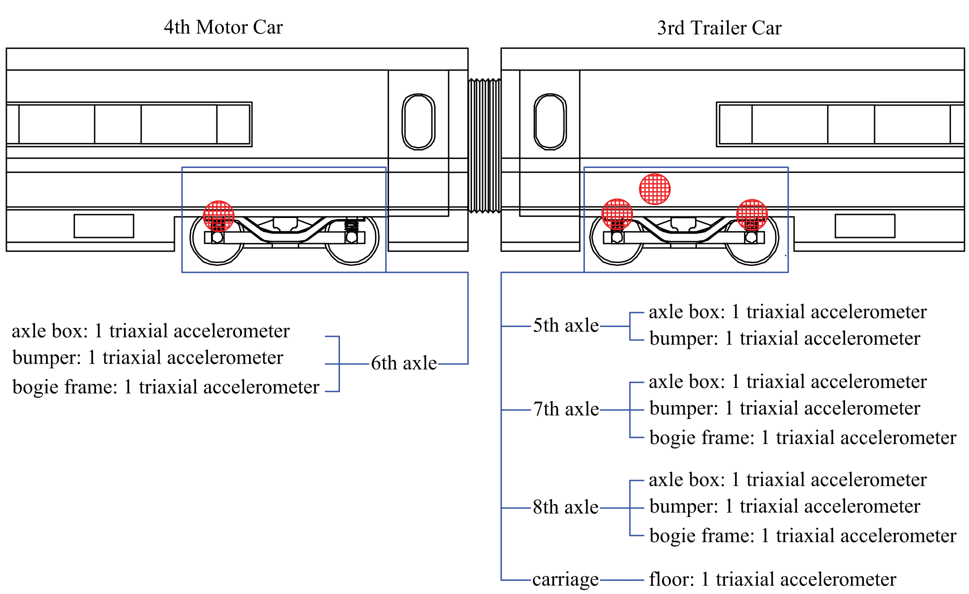

Fig. 7. Deployment of accelerometers on the 3rd and 4th cars.

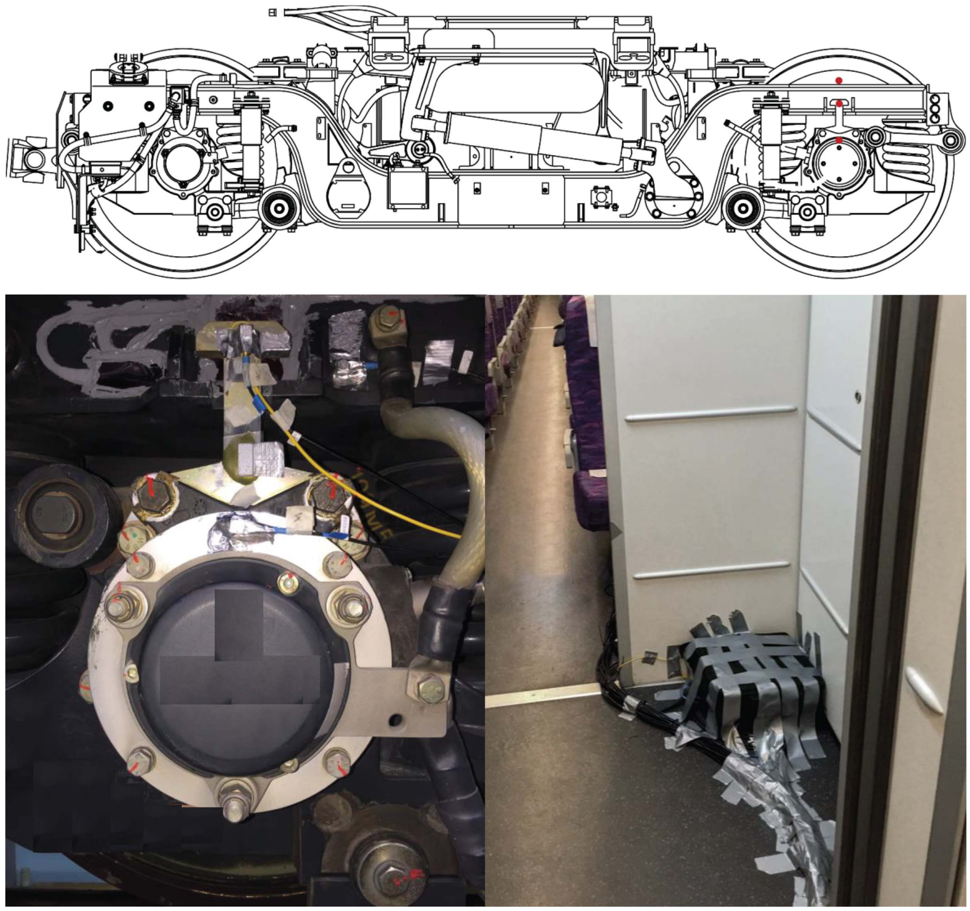

Fig. 8. Accelerometers installed at bogie and coach. (Images by Yi-Qing Ni.)

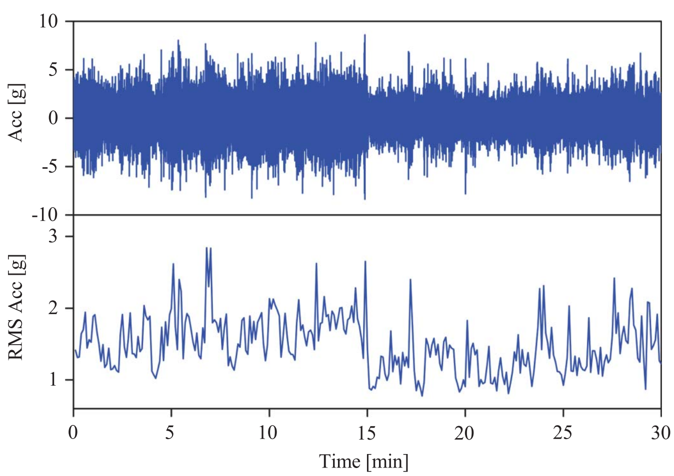

Fig. 9. Acceleration time series response measured by accelerometer positioned at the 3rd trailer car ($g = 9.81\ \mathrm{m/s^2}$).

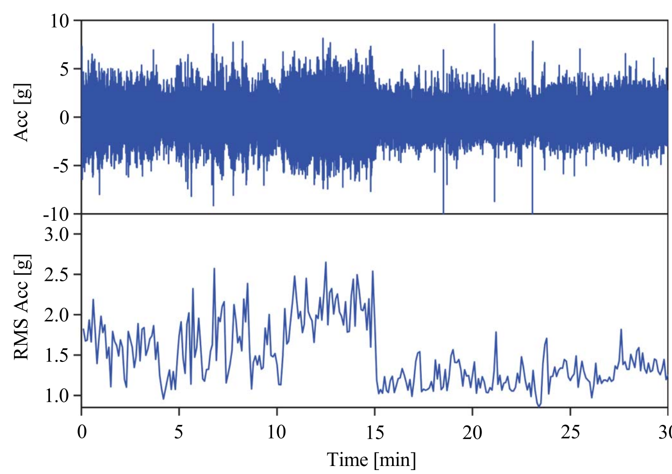

Fig. 10. Acceleration time series response measured by accelerometer positioned at the 4th motor car ($g = 9.81\ \mathrm{m/s^2}$).

resistance, reduce energy efficiency, and may create unsafe operation, such as catastrophic derailment. For this reason, the wheel profiles should be periodically monitored to ensure a proper wheel–rail interface. The onboard monitoring system was installed on the high-speed train before wheel lathing. After a certain period, the wheels were refined by the lathing process to maintain their roundness and smoothness. The onboard monitoring system collected response data for the train for a long period before and after the wheel lathing. Without loss of generality, the acceleration data recorded by two accelerometers from different axle boxes were used to verify the BS-based condition classification approach. In particular, for illustration purposes, we utilized 30 min of accelerometer data; the first half and the latter half were measured before and after wheel lathing, respectively. Figs. 9 and 10 show the acceleration time histories together with RMS. The original data and the RMS data display both magnitude difference and mean shift.

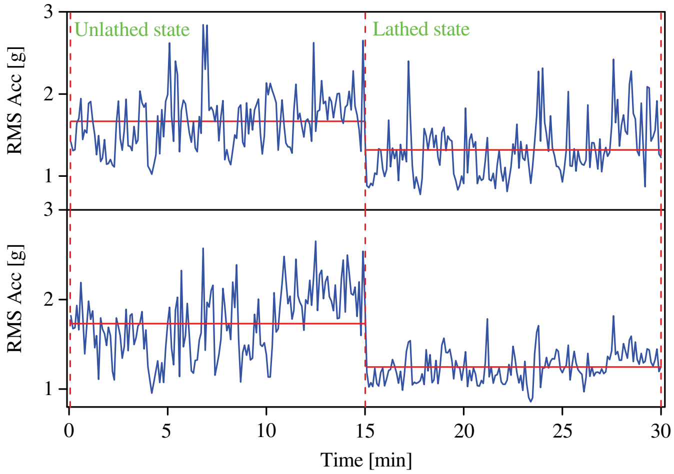

Fig. 11. Classification of unlathed and lathed states by binary segmentation.

These two patterns encode two distinct conditions—unlathed and lathed wheels.

Now we move on to the classification of the condition of the wheels in unlathed and lathed condition. The BS-based CPA method described in the section "Structural Condition Classification by Binary Segmentation" detected two states divided by an identified change point with time index 15 min. The wheel conditions classified by the BS method are shown in Fig. 11, in which the dashed lines represent the change points. Once again, it is confirmed that the proposed BS method is effective and reliable for the classification of structural conditions.

Conclusions

This study casts SHM into a statistical pattern recognition paradigm to detect abnormal changes (damage) in structures. Time series of response measurements obtained under distinct structural conditions are heterogeneous and manifest different statistical properties in terms of, for example, mean and variance. Based on this premise, a health-condition classifier was constructed using a BS technique that allowed for the reliable detection of multiple change points, points at which the time series data shift from one specific structure to another structure. The BS procedure formulates the classification of structural condition states as a problem of detecting change points, in which the identified change points are the boundaries of different health states. As a time series analysis technique, the BS-based condition classification method, which does not rely on a physical model and is solely implemented in a statistical manner, shows great potential for automated structural condition diagnosis. The proposed approach was first applied to monitoring data from a cable-stayed bridge before and after it experienced damage. Specifically, the damaged status was determined by an inspection of auxiliary pier detachment and wide concrete cracks. The results showed that the conditions of undamaged and damaged scenarios existing in the bridge were accurately detected by the proposed BS-based method. Next, time series data collected from a high-speed train before and after wheel lathing were used to further explore the effectiveness and feasibility of the proposed method. The results verified that the BS-based approach is effective for classification of lathed and unlathed states. In summary, real-world data collected from two full-scale, complex engineering systems validated that the proposed approach is an effective and efficient structural condition classification scheme.

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