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Research Article

Stayed-Cable Bridge Damage Detection and Localization Based on Accelerometer Health Monitoring Measurements

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In situ damage detection and localization using real acceleration structural health monitoring technique are the main idea of this study. The statistical and model identification time series, the response spectra, and the power density of the frequency domain are used to detect the behavior of Yonghe cable-stayed bridge during the healthy and damage states. The benchmark problem is used to detect the damage localization of the bridge during its working time. The assessment of the structural health monitoring and damage analysis concluded that (1) the kurtosis statistical moment can be used as an indicator for damage especially with increasing its percentage of change as the damage should occur; (2) the percentage of change of the Kernel density probability for the model identification error estimation can detect and localize the damage; (3) the simplified spectrum of the acceleration-displacement responses and frequencies probability changes are good tools for detection and localization of the one-line bridge damage.

1. Introduction

Structural health monitoring (SHM) systems are important in assessing various forms of bridges, especially long-span bridges damage detection and safety evaluation. Detecting bridges damage existence and localization, identifying damages, and quantifying their severity are necessary to assess and know previous stages of bridges state. Long-span bridges, like cable-stayed, are often affected by different types of loads [1–3]. The assessment of long-span bridges during working process is a main advantage of SHM, while studying the effect of environmental and traffic loads cannot be controlled or measured easily [3, 4]. Li et al. [3] noted that the vibration application damage detection for engineering structures is strongly affected by some factors, namely, variations in material properties, environmental variability (such as temperature, wind velocity, and humidity), variability in operational conditions (such as traffic flow) during measurement, and errors associated with measured datasets and processing techniques. However, SHM of bridges with monitoring loads effects is a good tool to measure and assess the behavior of bridges. The early damage detection is one of the advantages of SHM, while the vibration acceleration measurements are sufficient to detect damage and localization [4].

The basic theory for damage detection and localization depends on the vibration or oscillation performance response measured of structures. For instance, frequencies changes, damping rates geometric changes, and mode shapes which represent the changes of the dynamic properties occurred with damage effects [5–7]. Extensive research work was carried out on the development of nondestructive damage assessment methods and on the translation of changes in the modal characteristics with damage in a structure [4, 5, 8]. Review techniques for the damage detection using model properties changes can be found in [5]. The output only and input-output techniques are almost used to detect the damage of long-span bridges [4]. For continuous health monitoring study, the output technique is more suitable [4].

The stochastic structural response analysis is one of random nature structural parameters analysis [9], which can classify global response properties. This type of analysis is depending mainly on the SHM techniques and concerns studying the performance of structures based on output or measurements responses in both static and dynamic states. It is necessary to employ signal processing and statistical classification to convert sensor data on the bridge health status into damage info for assessment.

The time and frequency domains statistical and identification approaches are widely used to evaluate the stochastic structures response [9–11]. For example, Catbas and Aktan [12] proposed the global and local conditions damage indices for the assessment of highway bridge. Furthermore, they presented the linear and nonlinear conditions and damage indices for the global condition assessment of structures. In addition, they recommended that the structures monitoring continuously can identify the damage and movement assessment. Li and Chen [9] introduced and applied the probability density evaluation method to the dynamic analysis of nonlinear behavior of structures with simulation response of tall buildings, and they found that the probability density functions for the dynamic response were irregular and far from normal distribution. In addition, Kaloop [13] used the probability density function to evaluate long-span bridges based on global positioning monitoring system and he found that this method can be used to investigate the static and dynamic performance of bridges. Follen et al. [11] proposed nonparametric and parametric statistical conditions to evaluate bridges in long-term monitoring system. They used the probability density function of absolute maximum strain of heavy truck events to evaluate bridges status and concluded that damage can be predicted by using the nonparametric probability prediction method. Moreover, many studies used probability to assess the time domain behavior of structures (e.g., [14–16]).

Moreover, the artificial neural networks are seen as a good tool that can be used for model identification and damage detection of different types of structures [1, 3, 4, 14]. Neural networks for pattern recognition and dynamic response from finite element simulated data were used for the identification of damage in suspension bridges [14]. In addition, adaptive neural networks based on local response of structure were applied to detect bridges damage [17]. Arangio and Bontempi [4] combined probability with neural networks to assess the damage behavior of cable-stayed bridge and used this method to study the behavior of Yonghe bridge due to damage effects. Furthermore, they found that this method can be applied to detect bridge behavior under damage effects. Lee et al. [18] used a neural networks-based damage detection method; two numerical example analyses on a simple beam and a multigirder bridge are presented to demonstrate the effectiveness of the used method. The results of their study confirmed the applicability of neural networks method. From the previous studies, it can be seen that the main basic of damage detection and localization is structures parameters change. Moreover, the nonlinearity soft computing model identification techniques have proved to be very efficient.

Novel applications of time series and frequency domains are presented in this paper for structural health monitoring and in situ damage detection particularly for problems with large measurements data. The objective of the paper is to apply simple techniques that can be used to detect online structural damage. The statistical moments and model identification are used as a simple method to detect in situ damage and localization of structures. In addition, the spectrum response and power for the acceleration time series measurements are suggested methods to investigate the damage based on real SHM data. The probability of the time series model errors and frequency is used as new application in this study to detect the damage.

2. Yonghe Bridge Description, Previous Studies, and Structural Health Monitoring

The Yonghe bridge is one of the earliest cable-stayed bridges constructed in Mainland China (Figure 1). It connects Tianjin and Hangu cities. The total length of bridge is 510 m that consists of 260 m main span and two side spans of 25.15 and 99.85 m each and 11 m width. The towers heights are 60.5 m. More details of bridge construction materials and properties can be found in [2, 7]. The bridge is opened to traffic at the end of 1987 and after 19 working years, cracks are observed at the bottom of the midspan girder. The bridge was repaired between 2005 and 2007 and reopened for traffic at the end of 2007 [7]. Moreover, to monitor and collect time series data, a SHM system has been established and implemented by the Harbin Institute of Technology Research Center. The acceleration monitoring system contains fourteen uniaxial accelerometers permanently installed on the deck of the main span and the two side spans and one biaxial accelerometer installed on the top of one tower (Figure 1); more details about the bridge SHM design and observations can be found in [2, 3, 7]. In August 2008, two different kinds of damage were detected during the bridge inspection where the closure segment at both side spans was seriously cracked. Meanwhile the piers were damaged by overloading and the bridge experienced partial loss of the vertical supports [3, 4], as shown in Figure 2. Li et al. [19] presented the history and reliability indices for the damage. In addition, the results of their study confirmed that the first failure mode has little influence on the total bridge length reliability indices, while the reliability indices of segments near midspan point are increased [19]. Furthermore, they found that the detachment of the supports changed the structural system, so the reliability indices of segments near the side span decrease dramatically. These segments will be seriously damaged in this failure mode, and the analysis results agreed well with the practical situation [19]. Figure 2 illustrates the practical auxiliary pier detachment and the damage situation of side span damage. Kaloop and Li [1] studied the effect of environmental and traffic load on the tower static and dynamic movements using global position monitoring system measurements. Li et al. [3] presented the temperature and wind effects on the bridge in both time and frequency domains for the acceleration measurements.

The data for the reopening condition for the accelerations were observed on September, 1, 2007. The data for the health condition include time histories of the accelerations recorded

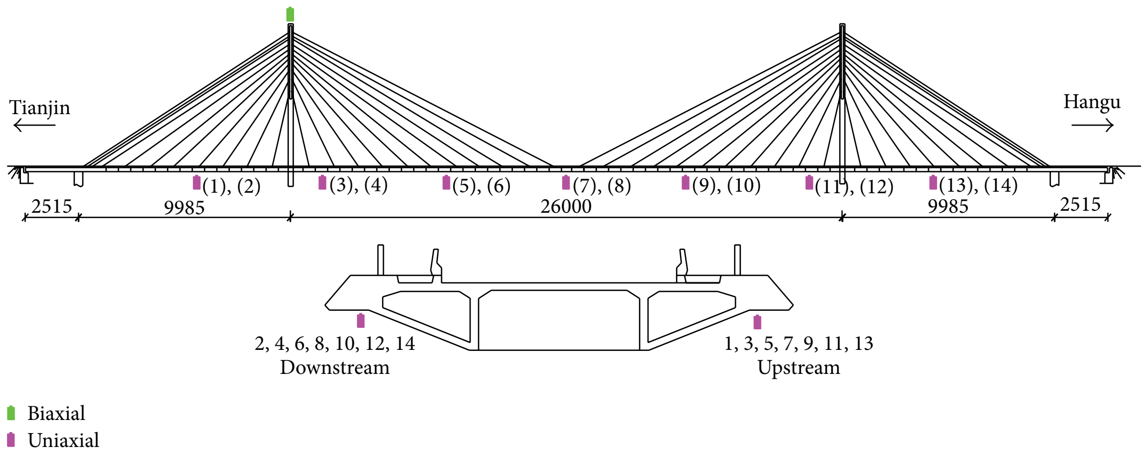
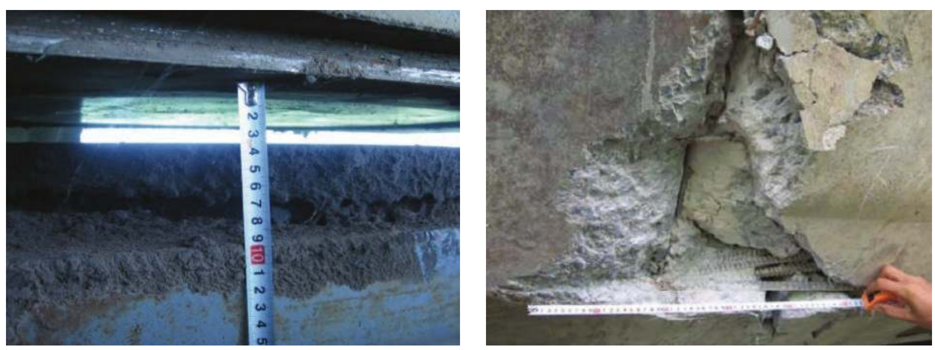


FIGURE 1: Yonghe bridge elevation and accelerations health monitoring system.



(a) (b)

FIGURE 2: (a) Auxiliary pier detachment and (b) damage situation of segment Tianjin direction.

by the 14 deck sensors that were repeated for 24 hours on January 17, 2008. The sampling frequency of the accelerations is 100 Hz and the accelerometer properties can be found in [2]. The damage condition includes other measurements recorded at the same locations shown on July 31, 2008. Meantime, as has already been stated, some damages have been observed. However, the 9th of April and the 7th of June, 2008, are the selected dates to estimate the exact time at which damage occurred. The dataset again includes registrations of 1 hour of the accelerations repeated for the 24 hours at the same sampling frequency (100 Hz). Because the observation numbers and based on previous studies [1–4, 7], it can be seen that the maximum affected traffic loads are during 9.00 to 18.00. However, we selected one hour (11.00-12.00) for three positions (1, 2; 7, 8; and 13, 14) to compare the result and assess acceleration monitoring time in this study.

Figure 3 shows the (11.00-12.00) September 2007 (as a base data), January 2008 (as a healthy state) for both sides of the bridge, and one day (00.00–24.00) monitoring data for the July 31st, 2008 to show clearly the damage behavior. The prestatistical acceleration time series monitoring data show that the amplitude of acceleration is seen smaller at the base time and increased seriously to damage state. Moreover, the difference between upstream and downstream acceleration amplitude is shown; it means that the movement, torsion, and damage occurred. Figure 3(c) shows that the amplitude of acceleration for points 1, 2, 13, and 14 decreased by 80%, while the amplitude acceleration for points 7 and 8 decreased by 60%. Fortunately, load limit measures were taken promptly after the failure occurred [19]. Furthermore, a dramatically acceleration amplitude decreased near 18.00 on the 31st of July because the traffic load limit measures are taken at that time to avoid the collapse of the bridge, and the cracks show not propagate any more [2]. In addition, it can be seen that the acceleration at the midspan point is approximately equal to the side spans acceleration amplitude for the upstream during the selected base and healthy states. Also, it can be seen that the midspan acceleration is approximately equal to the downstream acceleration amplitude during the selected base and healthy states. Thus, it means that either the bridge behavior from its reopening time is not stable or there are some loads changes that occurred. Moreover, it can be seen

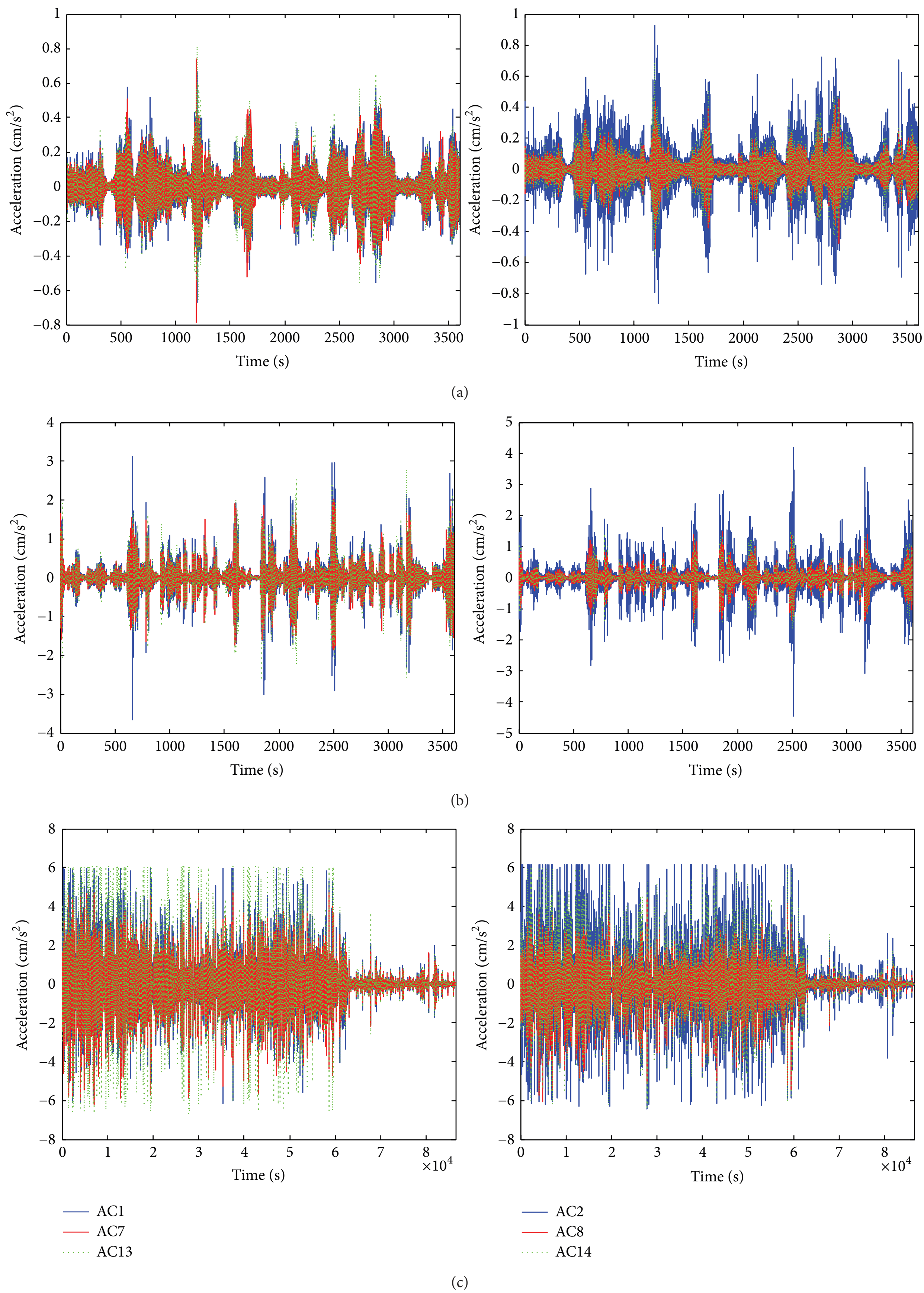


Figure 3: Acceleration monitoring for selection points at (a) Sept, 2007, (b) Jan, 2008, and (c) Jul, 2008.

Table 1: Mean and standard deviation of monitoring selection points (cm/sec^2).

Mon. point	Sep, 2007		Jan, 2008		Apr, 2008		Jun, 2008		Jul, 2008	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
AC1	0.019	0.495	0.015	0.3145	0.018	0.405	0.021	0.799	0.019	0.625
AC7	0.074	0.248	0.062	0.143	0.064	0.184	0.067	0.363	0.074	0.313
AC13	0.088	0.323	0.086	0.1438	0.078	0.240	0.083	0.516	0.087	0.412
AC2	0.127	0.372	0.142	0.249	0.135	0.304	0.134	0.586	0.127	0.469
AC8	−0.005	0.353	0.017	0.204	0.007	0.262	−0.0002	0.518	−0.005	0.439
AC14	0.072	0.375	0.090	0.231	0.078	0.292	0.074	0.580	0.072	0.472

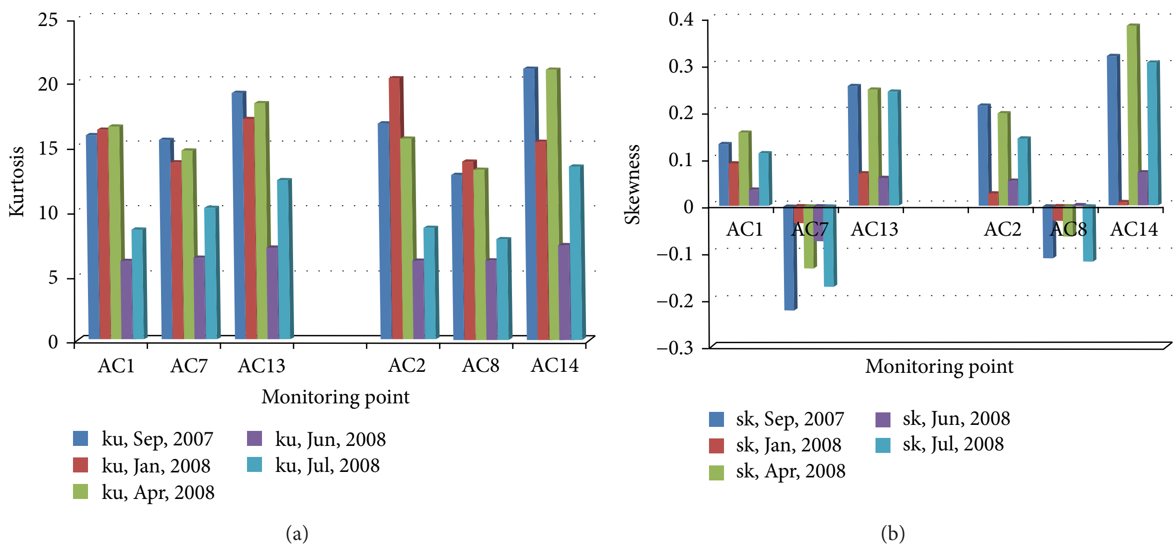


Figure 4: Monitoring acceleration (a) kurtosis and (b) skewness for selection points.

that the amplitude of the midspan acceleration is lower than side spans amplitude observation during damage state. However, the suitable benchmark that can be used to detect the behavior of the bridge is the midspan point. In addition, next part will include more discussion for the monitoring points.

3. Methodology Results and Discussions

3.1. Time Series Acceleration Analysis

3.1.1. Statistical Moments Analysis. The first four statistical moments (mean, standard deviation, skewness, and kurtosis) are used to define the probability density function motion change and interface between two surfaces in motion begin damaged [20]. A brief review of the first four moments is shown in the following references [20, 21].

The statistical moments for the acceleration monitoring time selection (Sept, 2007; Jan, Apr, Jun, and Jul, 2008) at time (11.00-12.00) for the upstream and downstream are shown in Table 1 and Figure 4. From this table, it can be seen that the mean and standard deviation for the monitoring points with selection time show little changes, while, the standard deviation is changed with damage\effects. However, the acceleration measurements standard deviation can be used to detect bridge behavior.

From Figure 4, it can be concluded that the relative change of kurtosis between monitoring times for the monitoring points AC1, AC7, and AC13 is 2.5, 12.6, and 11.6% and that for points AC2, AC8, and AC14 is 17.2, 7.5, and 36.8% between base and healthy state times, respectively. In addition, the change between healthy and damage states is 62.7, 56.2, and 60.7% for the AC1, AC7, and AC13, while for points AC2, AC8, and AC14 it is 60.7, 52.9, and 64.6%, respectively. However, the two monitoring areas for points (1, 2) and (13, 14) are showing high relative change for the kurtosis. Moreover, the changes values of skewness are shown randomly and the maximum changes can be seen at points 13 and 14. However, from the statistical moment results, it can be concluded that the standard deviation can refer to the damage effect and kurtosis can be used to detect the damage and localization based on relative monitoring data with previous monitoring time. In addition, it can be seen that the statistical moment method is easy in site or online damage detection and localization.

3.1.2. Model Identification Analysis. The simple general regression neural network (GRNN) is used in this study. This method is presented in [22]. Figure 5 shows the diagram of identification model damage detection. The monitoring time

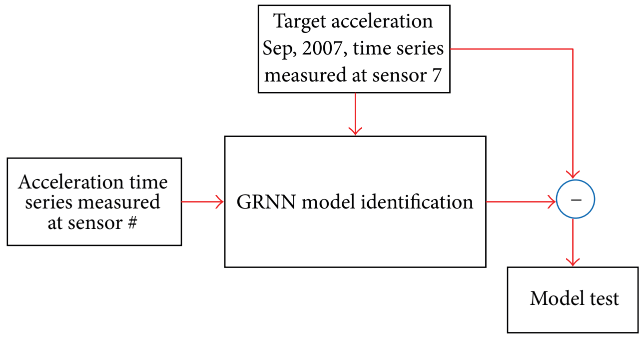


Figure 5: Damage detection GRNN model diagram.

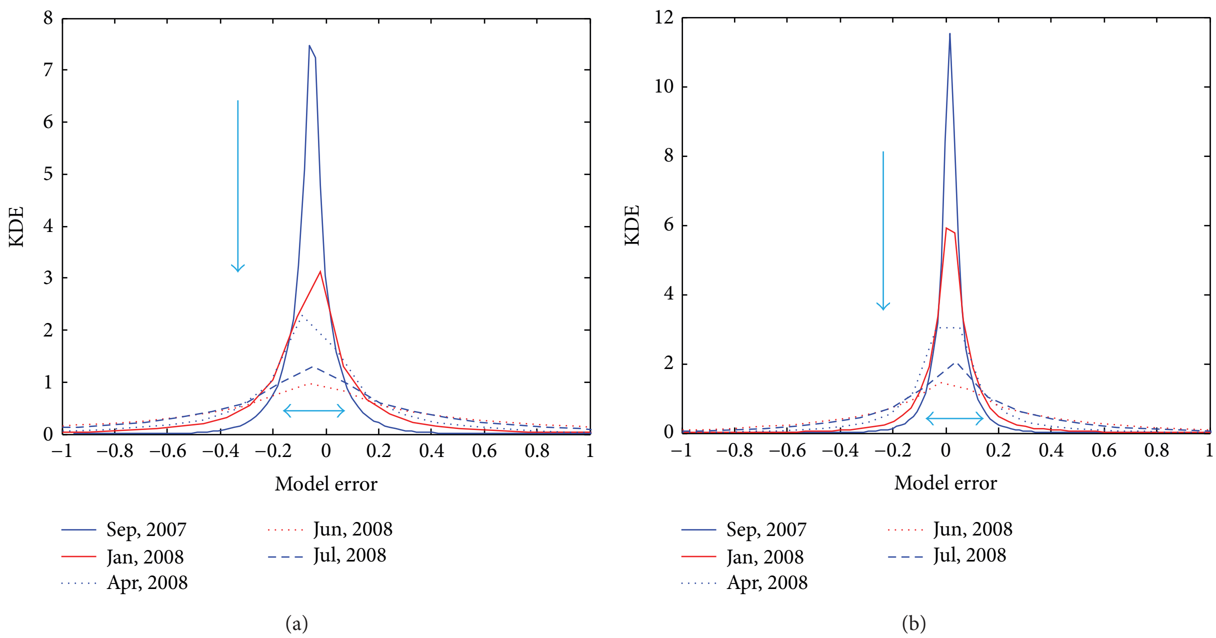


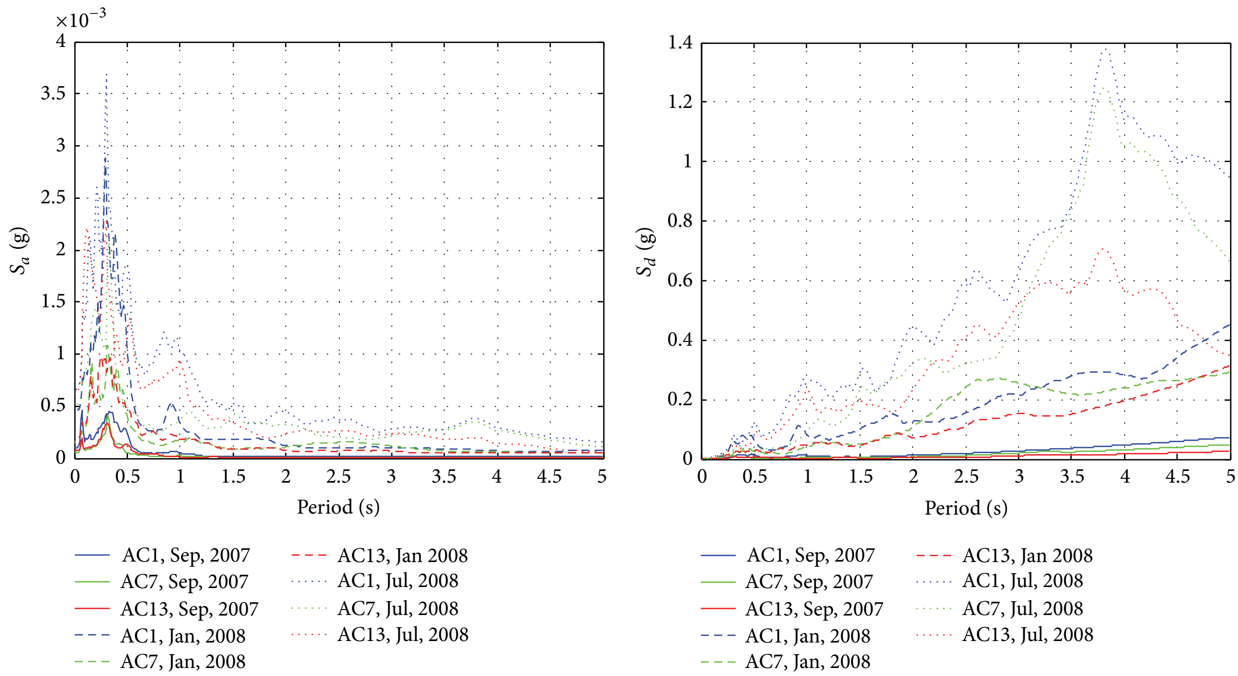
Figure 6: Model error test for the points (a) 1 and (b) 13.

(Sep, 2007) at point 7 is used as a benchmark point to assess the monitoring points (1 and 13) with time selection. The Kernel density estimation (KDE) for the model error is used to detect the bridge behavior from healthy to damage states for the monitoring dates of Sep, 2007; Jan, Apr, Jun, and Jul 2008.

Figure 6 shows the KDE for points 1 and 13 model errors estimation. From this figure, it can be seen that the probability of the model identification error curve is flatting with bridge working and the flatting increases with the damage effects. In addition, it can be seen that the KDE values decreased at two monitoring points from Sept, 2007, to Jun, 2008, and then increased. It means that the damage occurred about Jun 2008. In addition, it can be seen that the KDE values at point 13 are greater than the values at point 1 by about 50% from the beginning to the bridge damage. It means that the damage occurred due to the unsymmetrical behavior of the bridge during working status while the bridge is symmetrical, as shown in Figure 1; moreover, it refers that damage behavior effect at point 1 is more than for that at point 13. With these results, it is clear that the percentage changes of KDE for point 13 to point 7 are 30, 26, and 21% at Jan, Apr, and Jun, Jul, respectively. While, it can be seen that the percentage changes of KDE for point 1 are 45 at Jan, Apr, Jul, and 52% at Jun, respectively. This indicator can be used as a damage index for the bridge. Accordingly, it can be concluded that the healthy and damaged status of model identification results of the proposed approach suggests the presence of an anomaly of the bridge behavior; furthermore, the probability error estimation is a simple method that can be used to detect the damage.

3.2. Frequency Spectrum Analysis

3.2.1. Response Spectrum Analysis. The response spectrum is used mainly on the design of structures in the seismic areas effects. The response spectrum is not used much for the structures damage detection and localization. The theory of spectrum is discussed in [23]. The structures response spectrum



(a) Acceleration spectrum

(b) Displacement spectrum

FIGURE 7: Spectrum response for the bridge monitoring points selection at base, healthy, and damage cases.

is a peak or steady-state response (acceleration, velocity, and displacement) of a time series dynamic monitoring data of varying natural frequency.

This section contains the acceleration Yonghe bridge health monitoring spectrum response. The monitoring acceleration measurements in different cases are used with natural design damping (5%) to calculate the bridge acceleration and displacement responses. It should be noted that the maximum response will change when the design damping used changes, but the damage indicator calculated will not change. The damage indicator or index of acceleration response at time i ($\mathrm{DI}_{\mathrm{ACC}}(i)$) can be calculated as follows:

$$\mathrm{DI}_{\mathrm{ACC}}(i) = \frac{S_a(i) - S_a(b)}{S_a(b)}, \tag{1}$$

where S_a is the maximum acceleration response at monitoring times i and b refers to benchmark (base point) monitoring time.

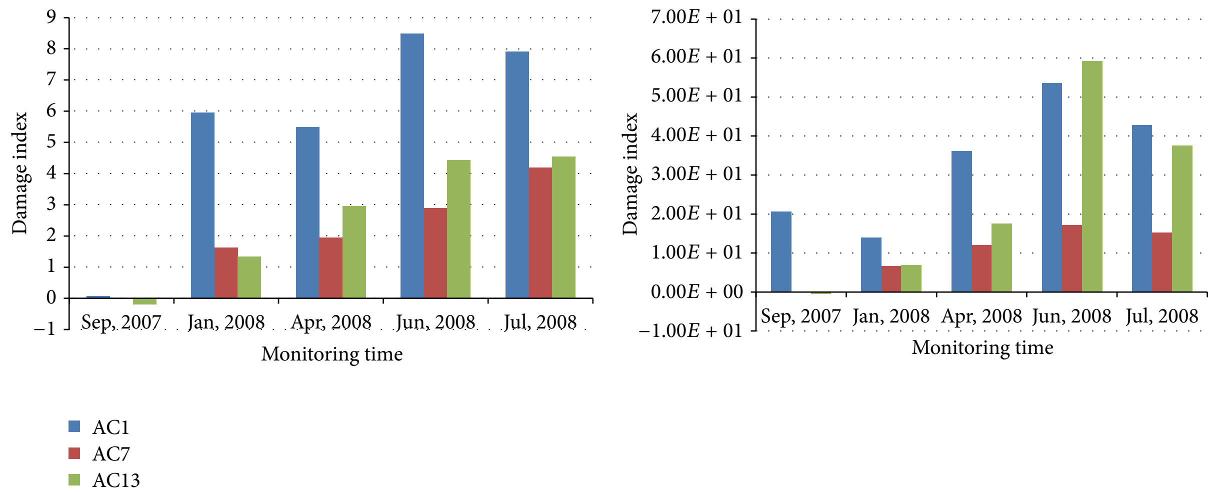
The displacement response is calculated in this study to compare the bridge behavior during monitoring time and to assess the damage and detect it with location at period 1 sec, which refers to the elastic displacement response of the bridge. The damage index for the displacement response at time i ($\mathrm{DI}_{\mathrm{DIS}}(i)$) can be calculated as follows:

$$\mathrm{DI}_{\mathrm{DIS}}(i) = \frac{S_d(i) - S_d(b)}{S_d(b)}, \tag{2}$$

where S_d is the displacement response at monitoring times i and b refers to benchmark monitoring time at period 1 sec.

The monitoring point AC7 at September 1, 2007, is used as a base or benchmark time monitoring and damage detection for other monitoring points. The acceleration and displacement responses of the bridge base for both the healthy and damaged states are presented in Figures 7(a) and 7(b), respectively. From Figure 7(a), it can be seen that the acceleration response is increased with bridge working and is increased more with bridge cracks and damages. Moreover, it can be seen that the three selected positions acceleration response are approximately equal, at the monitoring base time. While the AC1 acceleration response can be seen higher than AC7 and AC13 responses at monitoring healthy state. Furthermore, the difference in acceleration response between monitoring points is increased with bridge working and damage cases and decreased with fully damage state. In addition, it can be shown that the damping of the acceleration response is decreased from base to damage cases, and the AC13 acceleration response has shown greater values than the AC7 acceleration response at damage case. From Figure 7(b), it can be seen that the displacement response for the bridge behavior at the selected monitoring times is the same for the acceleration response results. Furthermore, it can be seen that the maximum displacement response for the AC1 point is 0.55, 0.81, and 1.38 mm at times April, June, and July, 2008, with periods 3.27, 3.39, and 3.83 sec, respectively.

The bridge damage index calculation is presented in Figure 8. It shows the acceleration response damage index (1). From this figure, it can be seen that the bridge behavior around AC1 is not normal from January 2008. Moreover, the damage index shows that the damage occurred around



(a) Acceleration response damage index

(b) Displacement response damage index

FIGURE 8: Damage index for the monitoring points at base, healthy, and damage cases.

the monitoring point AC1, which coincides with the visual inspection of the bridge state. In addition, it can be seen that the damage index of both AC1 and AC13 is greater than the AC7 damage index; it means that the bridge deck cracks can be detected at points 1 and 13 during June 2008 monitoring time. Furthermore, it can be shown that the damage index is decreased at July, 2008, that occurred due to fully damage effects. The displacement response damage index (2) is shown in Figure 8(b). From this figure, it can be concluded that the displacement response damage index is more accurate than that calculated from acceleration response. Also, the displacement response damage index refers that the damage occurred around points 1 and 13 and these results are confirmed from the visual inspection. From these results, it can be concluded that the acceleration and displacement response can be used to detect the damage and localization based on selected benchmark time. In addition, the displacement response can be used to detect the bridge girder cracks. Finally, the damage occurred around points 1 and 13 and these results are concluded in [1, 2, 4].

3.2.2. Frequency Probability Analysis. The frequency domain change is one of the methods that can be used to detect damage and localization [5–7]. In this section, the probability and significant level power spectrum density calculation are used to detect the bridge damage and localization. The power spectrum methods are introduced in [21]. The time series acceleration of SHM data are often evenly spaced; however, there is no problem to use the Lomb-Scargle algorithm in this study to calculate the significant and probability of the frequency of the monitored points.

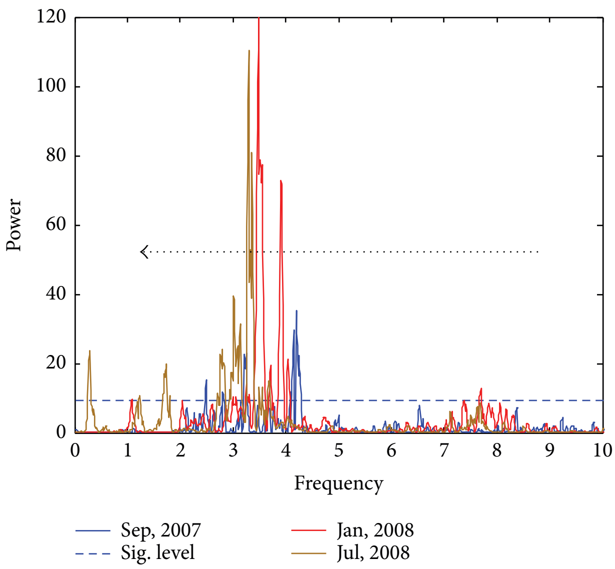
The algorithm evaluates the actual acceleration time series data measured at monitoring time (t). Assuming an acceleration time series measurements $y(t)$ of N data points, the Lomb-Scargle normalized periodogram P_x as a function of angular frequency $\omega = 2\pi f > 0$ is given by [21]

$$P_x(\omega) = \frac{1}{2S^2}\left(\frac{\left(\sum_j \left(y_j - \overline{y}\right)\cos\omega(t_j - \tau)\right)^2}{\sum_j \cos^2\omega\left(t_j - \tau\right)} + \frac{\left(\sum_j \left(y_j - \overline{y}\right)\sin\omega(t_j - \tau)\right)^2}{\sum_j \sin^2\omega\left(t_j - \tau\right)}\right), \quad (3)$$

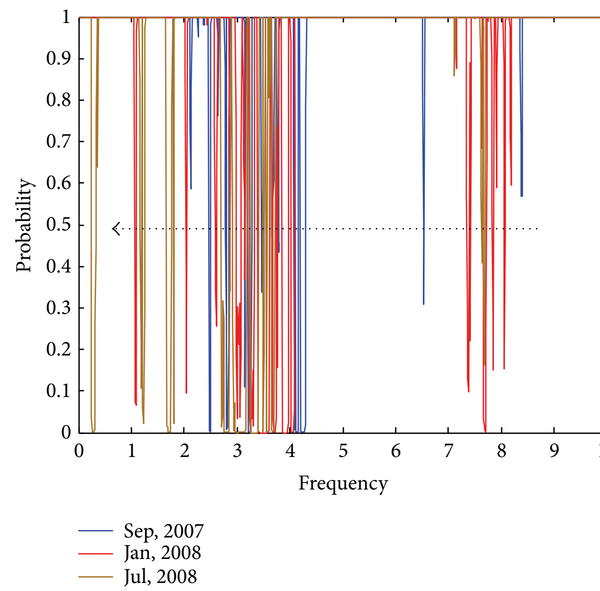
where $\overline{y}$ and S^2 are the arithmetic mean and the variance of the acceleration measurement data. The constant τ is an offset that makes $P_x(\omega)$ independent of shifting the ti's by any constant amount. Scargle [24] showed that this particular choice of the offset τ has the consequence that the solution for $P_x(\omega)$ is identical to least-squares fit of sine and cosine functions to the data series $y(t)$. The least-squares fit of harmonic functions to data series in conjunction with spectral analysis had previously been investigated by Lomb [25]. Scargle [24] showed that the Lomb-Scargle periodogram has an exponential probability distribution with unit mean. The probability that $P_x(\omega)$ will be between some positive quantity z and $z + dz$ is $\exp(-z)dz$. If we scan M independent frequencies, the probability of none of them having a larger value than z is $(1 - \exp(-z))M$. We can therefore compute the false alarm probability of the null hypothesis, for example, the probability that a given peak in the periodogram is not significant by

$$P(> Z) \equiv 1 - \left(1 - e^{-Z}\right)^M. \quad (4)$$

Press et al. [26] suggested using the Nyquist criterion to determine the number of independent frequencies M assuming that the data were evenly spaced. In this case, the appropriate



(a) Significant frequency



(b) Probability frequency

Figure 9: Significant and probability frequency changes.

Table 2: Lomb-Scargle frequencies and power spectrum.

Monitoring time	AC1		AC7		AC13	
	Freq. (Hz)	Max. PSD	Freq. (Hz)	Max. PSD	Freq. (Hz)	Max. PSD
Sep, 2007	4.2	35.14	3.16	39.35	4.2	39.65
Jan, 2008	3.49	119.7	3.49	47.43	3.92	55.3
Apr, 2008	4.19	117.3	3.1	84.07	4.18	88.27
Jun, 2008	2.8	181.9	2.4	154.3	3.05	84.57
Jul, 2008	3.3	110.3	3.09	101.4	3.29	40.25

value for the number of independent frequencies is $M = 2N$, where N is the length of the time series. More detailed discussions of the Lomb-Scargle method can be found in [24, 26].

Figure 9 shows the significant and probability of the bridge frequency calculation based on Lomb-Scargle method for point AC1. Figure 9(a) shows the power spectrum frequency distribution and 95% significant frequencies at monitoring times. From this figure, it can be seen that the bridge first frequency mode is significant at 1.09 Hz and 0.29 Hz with the bridge working and damage times, respectively. The first mode bridge frequency is decreased by 56% and 88% due to working and damage affects. Figure 9(b) shows the probability frequencies of point AC1. From this figure, it can be seen that the frequencies probability decreased also with monitoring time. Table 2 presents the calculated maximum power spectrum density (PSD) and the high PSD frequency.

From Table 2, it can be seen that the maximum power spectrums and frequencies for the monitored points at the beginning of the working of the bridge are highly correlated. But with working and healthy status, it shows that the increased rate for AC1 maximum PSD is higher than AC7 and AC13. In addition, it can be seen that the PSD is increased with traffic loads effect and it can be noticed that the PSDs for point AC1 are still different for the AC7 and AC13 points from the bridge working state, while, with bridge cracks and damages, no correlation can be seen between the frequencies and PSDs value. From the results, it can be concluded that this method can be used to detect the bridge damage and localization based on significant and probability frequencies shift and different correlation PSD and frequencies between monitoring points.

4. Conclusions

This study demonstrates that simple and effective damage detection and localization algorithms based on a pattern classification framework can detect structural changes using the data that was collected from a real structure. The acceleration observation of the Yonghe bridge health monitoring system is used in this study to represent four methods that can be used to detect and localize the damage, which are the statistical moment, the model identification in time domain, the power spectrum, and the response spectra in frequency domain. The conclusions drawn from this study are as follows.

The prestatistical acceleration time series monitoring data show that the amplitude of acceleration is seen smaller at base time selection and increases seriously to damage state. Moreover, the difference between upstream and downstream acceleration amplitude is shown; it means that the movement, torsion, and damage occurred. In addition, the standard deviation can refer to the damage effect and kurtosis can detect and localize the damage based on relative monitoring data with benchmark monitoring time. Moreover, this method is easy in site or online damage detection and localization. The indicator of Kernel density error changes can be used as a damage index for the bridge damage. Moreover, it can be concluded that the health and damage status of model identification results proposed approach suggests the presence of an anomaly in the bridge behavior and the probability error estimation is a simple method can be used to detect the damage.

The acceleration and displacement response spectra are used to detect and localize the damage based on benchmark time selection. In addition, the displacement response can detect the cracks behavior for the bridge's girder. Moreover, the simplified acceleration and displacement damage indicators are good tools to estimate and localize the damage. The probability Lomb-Scargle algorithm frequency time series can detect and localize the damage based on the shift of significant frequencies and maximum PSD with different correlations between monitoring points.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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