Intelligent Fault Diagnosis for Bridge via Modal Analysis

Wenjun Zhuang, Yunnan Communications Vocational and Technical College, China*

ABSTRACT

Due to natural disasters and man-made reasons, bridges are prone to structural damage during long-term usage, which reduces the associated carrying capacity, increases natural aging, and reduces safety. It is urgent to monitor the health status of bridge structure via intelligent technology. This paper proposes a bridge fault recognition structure. First, the signals of bridge parameter are collected by using distributed sensors. Then, the collected signals are processed by signal processing to extract the features in time and frequency domain. Lastly, the extracted features are used to learn an intelligent classifier. The large margin distribution machine is adopted as a classification model. The experimental results have proven the feasibility of the proposed bridge fault recognition structure.

KEYWORDS

Fault Diagnosis, Feature Representation, Hilbert Transform, Modal Analysis, Wavelet Transform

1. INTRODUCTION

As an important part of the transportation system, bridges play an important role in national transportation and economic development (Lertpaitoonpan et al. 2000, Chen et al. 2016). However, with the growth of bridge service time, the continuous erosion under the natural environment, and the rapid growth of traffic volume and load, the local structure of the bridge appears natural accumulation or accidental damage. Once the bridge structure is damaged (Kameshwar et al. 2021, Obrien et al. 2021) and cannot be maintained in time, it will not only shorten the service life of the bridge, but will also affect the safety of driving, and even may cause bridge safety accidents when the situation is serious. It is significantly important to maintain the health of the bridges in transportation system.

In recent years, by integrating science and technology (Celik et al. 2020), sensor technology (Ristic et al. 1994, Ali et al. 2014), signal processing & analysis technology (O’Neal et al. 2018, Nagarajaiah et al. 2010), and structural analysis (Domede et al. 2013, Wen et al. 2021) into bridge health detection, the bridge health detection can include more contents and the detection accuracy is improved. In the bridge health detection, the vibration detection (Chang et al. 2016, Wickramasinghe et al. 2016) can effectively reveal the overall dynamic characteristics of the bridge which belongs to the overall bridge structure detection method. Through vibration detection to find out the reasons of vibration changes inside the bridge, it can grasp the safety status of the bridge structure in real time.
In this paper, the actual vibration signal of the bridge is sampled by the acceleration sensor, and then the obtained signal is processed and analyzed, finally, the state characteristics of the measured object are distinguished by combining with the results of time-frequency analysis. When vehicles pass through the bridge, the vibration of bridge structure will be produced, which often presents non-stationary characteristics. The traditional stationary signal analysis method is either time domain analysis or frequency domain analysis. They cannot obtain the local information of time domain and frequency domain at the same time. Thus, these methods cannot deal with the response of non-stationary and nonlinear system. The time-frequency combined analysis can deal with non-stationary signals by observing the law of signal changing in time and frequency domain at the same time. Wavelet analysis (Ding et al. 2008) and Wigner Ville distribution (Liao et al. 2018) have been proved to have obvious advantages in processing non-stationary signals, and are widely used in vibration signal, image processing and other engineering fields.

The rest of this paper is organized as follows: the achievements and existing issues in bridge health detection is reviewed in Section 2; the architecture of proposed bridge health detection system is provided in Section 3; the flowchart and implementation are introduced in Section 4; the experiment and simulation are reported in Section 5; the last section is conclusions.

2. ACHIEVEMENTS AND ISSUES IN BRIDGE HEALTH DETECTION

Modares and Waksmanski (Modares & Waksmanski 2013) reviewed the parameters in bridge structural health monitoring sensing system and summarized the sensor types, accuracy, range and operating temperature. The parameters include cracking, corrosion, displacement, fatigue, force, temperature, strain, vibration, wind etc. Another review on sensors in bridge structural health monitoring system was provided by Taheri (Taheri 2019). The bridge health monitoring researches include: stiffness loss (Yang et al. 2016), time and temperature-dependent factors, fatigue evaluation, corrosion evaluation, and scour. The stiffness loss is a reliable indicator of bridge damage, which can be determined by bridge characteristic of structure (Prendergast 2017). The characteristic can be obtained by using high spatial resolution or and reliable signal processing technology. The vibration-based damage identification is one of possible bridge damage detection method, which can be used to estimate the stiffness loss (Limongelli 2019). The time and temperature may cause the deformation of bridges, which has been researched for several decades (Glisic et al. 2018; Bažant et al. 2012). Fatigue reliability is related to the age of infrastructures. An initial fatigue crack in bridge may cause serious results (Farreras et al. 2017; Guo et al. 2012). Corrosion refers to metallic parts in bridge and may degrade the bridge performance. It is necessary to monitor corrosion for detecting bridge degradation (Betti et al. 2016). Scour refers to the erosion of stream bed and bank around bridge foundations caused by flowing water (Chen et al. 2014).

In order to overcome the drawbacks of traditional wired bridge structural health monitoring sensing system, the wireless sensors and wireless communication are introduced into bridge structural health monitoring system (Noel et al. 2017). Wireless smart sensing in bridge structural health monitoring sensing system refers to a unit that has the capabilities of sensing, computation, data transmission and storage through sensor, microprocessor, radio frequency transceiver, memory and power source (Abdulkarem et al. 2020). Wireless smart sensing shows attraction and convenience due to the absence of long cables (Li et al. 2019).

By reviewing the famous bridge health detection system in the world, the bridge health detection has been successfully used in real applications. From the aspects of content, function, target, scale and system operation, the characteristics of current systems are summarized as follows:

- The detection information is comprehensive. Through the cooperation of various detection instruments (Yu et al. 2016), the systems can provide real-time feedback of various information
to reflect bridge conditions while the systems can continuously work and the vehicles still pass through the bridge intermittently.

- The detection content is abundant. In addition to the various structural characteristics of the bridge itself (Kim et al. 2011), such as stress, displacement, acceleration characteristics, it also includes many external environmental factors such as temperature, vehicle load, and traffic load.
- The testing instruments are diverse and advanced, which integrates a lot of subject knowledge (Lin et al. 2015). The system’s performance is also constantly upgrading and improving. Some detection systems do not only have the ability of big information data collection and communication, but also have the ability of large capacity storage and sharing through the remote network.

However, due to the high requirements of modern bridge health detection system, it includes multi-disciplinary and must face complex situation (Wong 2007). The current research progress is still in the basic stage, and there are many deficiencies, which need to be further explored, studied and improved in the field of bridge health detection. Two challenging issues are listed as follows:

- The uncertainty factors of bridge structure and different working environment destroy the sensitivity of structural response (Oh & Yang 2020), which may induce many errors and difficulties during the process of bridge health detection.
- There lacks comprehensive and in-depth research on the changes of working characteristics of bridges in service life. It is difficult to establish a unified bridge health assessment standard (Wan et al. 2019).

This paper mainly studies the application of time-frequency domain analysis in bridge health detection by using Fourier transform, wavelet packet analysis, and Wigner Ville distribution to establish intelligent bridge health detection system. First, the signals of bridge are denoised by wavelet packet analysis, then the denoised signals are processed by Hilbert transform to obtain the analytical signals, lastly, the Fourier transform and Wigner Ville distribution is performed on processed signals to obtain the spectrum and time-frequency distribution. The features of spectrum and time-frequency distribution are used to learn a classifier to identify the health status of bridge.

3. THE ARCHITECTURE OF BRIDGE HEALTH DETECTION SYSTEM

The vibration signal of bridge often presents non-stationary characteristics. The traditional stationary signal analysis method cannot pursue high resolution in both time domain and frequency domain, simultaneously. Thus, the associated performance is poor to process non-stationary signals. This paper adopts time-frequency domain analysis to monitor the status of bridges and establishes a bridge health detection system, which can utilize both time domain and frequency domain information. The bridge health system consists of four parts: sensor sub-system, data acquisition and transmit sub-system, data analysis and processing sub-system, and background information processing sub-system. The architecture of proposed bridge health detection system is reported in Figure 1.

As an important part of bridge health detection system, sensor sub-system is the information collector. The sensor sub-system includes a variety of sensors, such as acceleration sensor, displacement sensor, strain gauge, wind speed and direction sensor, and temperature sensor. The sensors are used to collect important parameters of the bridge, such as acceleration sensor, displacement sensor, strain gauge, wind speed and direction sensor, and temperature sensor. The sensors are used to collect important parameters of the bridge, such as acceleration sensor, deflection, main component stress. The acceleration sensor is used to measure acceleration in fault diagnosis and vibration test. The strain gauge refers to the measurement of internal stress and strain in a bridge. The displacement meter is used to measure the displacement of objects, such as distance, size, vibration, and deflection. The anemometer is used to measure wind speed and direction, which is often used to monitor the environment. The layout of sensors is particularly important to ensure the validity and
authenticity of data. Meanwhile, it is difficult to understand the real state of the bridge if there are not enough sensors to collect parameters of the bridge. On the other hand, too many sensors may cause information redundancy and increase the cost. The optimal placement of sensors is a hot topic in bridge health monitoring system.

As the standard protocol of Internet, TCP/IP defines the rule and convention in the communication between devices. The TCP/IP does not depend on the hardware platform or operating system. In data acquisition and transmission sub-system, TCP/IP is used to realize network transmission and sharing.

The data acquisition and transmit sub-system is used to process the original signals from sensor sub-system, such as removing noises, extracting meaningful features. The processed data is then transmitted to data analysis and processing sub-system for further processing. The background information processing sub-system includes information processing and database service. The data is transmitted between server and background control computer.

The bridge health detection system should automatically and real-timely carry out under various weather conditions and bridge operation conditions, have large capacity storage for collected information to communicate in real time and share with the network. According to the collected information, the bridge health detection system makes scientific evaluation and diagnosis for the status of bridge.

4. THE FLOWCHART AND IMPLEMENTATION OF BRIDGE HEALTH DETECTION

This section will adopt Fourier transform, wavelet analysis, Wigner Ville distribution to analyze the parameters of bridges which are collected by sensor sub-system. For the vibration signal of the bridge, first waveform analysis is used to remove the noises, then the denoised signals are processed by Hilbert transform to obtain associated analytical signal, finally Fourier transform and Wigner-Ville distribution are adopted to analyze spectrum and time-frequency distribution diagram. The spectrum and time-frequency information are input into a feature extraction method to remove the redundant features. The extracted features are used to learn an intelligent classifier which is used to determine the status of the bridge. The flowchart of the bridge health detection and diagnosis is shown in Figure 2.

According to the layout and design of the bridge, acceleration sensors are installed in different sections of the bridge pavement. The acceleration sensors sample the actual vibration signals of the bridge. The vibration signal in time domain is transformed into frequency domain by Fourier transform, which greatly simplifies the study of the problem. The frequency components and its
distribution are intuitive and convenient to be observed. In general, the vibration signal of healthy bridge pavement is low frequency signal. If there is abnormal high frequency signal, the structure of bridge pavement has a fault.

When the bridge is healthy, its vibration signal meets the mechanical structure, which is a low frequency signal. When there exists fault in bridge pavement, the vibration signal is mixed with high frequency information and there are many small defects in the time domain. For the vibration signal spectrum of healthy bridge, the amplitude at the fundamental frequency should be the largest, while the amplitude at the multiple frequency decays slowly. However, the spectrum with fault signal is irregular and may occur large amplitude in the non-doubling frequency.

The Fourier transform is one of the most basic methods to deal with bridge structure fault signals. It can only handle stable signal. However, most of the structural fault vibration signals of bridge pavement are complex non-stationary signals. The Fourier transform cannot achieve expected result to handle these signals.

Wigner Ville distribution combines the information in time domain and frequency domain to analyze the signal, which can intuitively observe the time-frequency characteristic information of the signal and obtain the law of frequency and amplitude changing with time. The vibration signals obtained from the bridge sensors are analyzed by time-frequency method to obtain the time-frequency information under different conditions to complete the health detection of the bridge.

The Wigner Ville distribution analyzes the signal from time and frequency domain. The Wigner Ville distribution divides the time and frequency domain into several small areas, and then does double integration along the time and frequency axis in each small area. The double integration is the energy of each small area, which is used to diagnose the status of bridge pavement. The vibration signal energy of healthy bridge is mainly in the low frequency band. When the bridge structure is unhealthy, the vibration signal energy is mainly in the high frequency band. It is reasonable to adopt the energy to detect the health of bridge structure.

Signal de-noising has always been a hot topic in bridge health diagnosis. The wavelet analysis has good time and frequency characteristics and multi-resolution analysis ability. It is suitable for removing noises in signals. Traditional wavelet analysis decomposes the signal into low-frequency part and high-frequency part, then continues to decompose the low-frequency part. The decomposition ignores the information of high-frequency part. Wavelet packet analysis decomposes the low-frequency and high-frequency parts of the signal simultaneously, and extracts different frequency components of the signal.
An original signal contaminated by noise can be expressed as follows:

\[ f(n) = x(n) + e(n) \]  

(1)

In equation (1), \( x(n) \) is the original signal, \( e(n) \) is the noisy signal, and \( f(n) \) is the mixed signal. The wavelet packet can analyze and denoise the mixed signal \( f(n) \) to weaken or eliminate noisy signal \( e(n) \).

For wavelet packet analysis, let \( d_{jp}(k) \) be the wavelet packet coefficient at position \((j, p)\). The wavelet packet analysis coefficient at \((j+1)^{th}\) layer is represented as following equation:

\[
\begin{align*}
    d_{j+1}^p(k) &= \sum_m d_j^p(m) h(m - 2k) \\
    d_{j+1}^p(k) &= \sum_m d_j^p(m) g(m - 2k)
\end{align*}
\]  

(2)

In equation (2), \( h(k) \) represents low-pass filter, while \( g(k) \) represents high-pass filter. The wavelet packet coefficient \( d_j^p(k) \) at position \((j, p)\) can be reconstructed by the following equation:

\[
d_j^p(k) = \sum_m \left[ d_{j+1}^p(m) h(k - 2m) + d_{j+1}^{p+1}(m) g(k - 2m) \right]
\]  

(3)

The energy distribution characteristics of original signal are different from that of noise. The energy distribution of the original signal is concentrated, which is mainly manifested in the wavelet packet coefficients with large amplitude. The energy distribution of noise is messy, especially for the wavelet packet which only contains noise. According to the difference, a proper threshold processing function is performed on wavelet packet coefficients for further optimizing the coefficients. Finally, the original signal is inversely transformed and reconstructed according to the optimized correlation coefficients. Thus, the wavelet packet analysis can remove the noise in mixed signal. The flowchart of denoising is illustrated in Figure 3.

In Figure 3, the first step decomposes the collected signal by using wavelet packet analysis. In this step, it requires to select a proper number of levels, \( N \), in wavelet packet analysis. In the second step, the wavelet packet decomposition coefficients are quantification by a threshold. By combining with an appropriate threshold function, each wavelet packet coefficients are quantification. In the

Figure 3. The flowchart of denoising process for vibration signal
third step, the signal is reconstructed by inverse wavelet transform. The wavelet packet reconstruction is performed according to the lowest-level wavelet packet decomposition coefficients. In this paper, the wavelet packet analysis adopts db5 as wavelet function. The Stein’s unbiased risk estimate is used as threshold selection criterion. The features for denoised signal are used to train a classifier to identify health status of the bridge, such as linear discriminant analysis (LDA) (Xanthopoulos et al 2013; Zhu et al. 2022), support vector machine (SVM) (Zhu et al. 2016; Zhu et al. 2021), decision tree (Mu et al. 2018), metric learning (Gao et al. 2022) or neural network (NN) (Wang et al. 03). In this paper, we adopt large margin distribution machine (Zhang et al. 2014) as the classifier in the proposed system. In order to ensure the integrity, the large margin distribution machine is recapped.

Let $X = [x_1, x_2, \ldots, x_n]$ be the training set, $Y = \{y_i\}_{i=1}^{n}$ be the associated label set. Here, $x_i \in \mathbb{R}^d$ and $y_i \in \{+1, -1\}$. The aim of large margin distribution machine (LDM) is to find a hyperplane which can separate two classes with optimal margin distribution in a kernel reproducing Hilbert space. The margin distribution is depicted as margin mean $\bar{\gamma}$ and margin variance $\hat{\gamma}$ as follows:

$$\bar{\gamma} = \frac{1}{n} \sum_{i=1}^{n} y_i w^T \varphi(x_i) = \frac{1}{n} (\bar{X}Y)^T w$$  \hspace{1cm} (4)

$$\hat{\gamma} = \frac{1}{n^2} \sum_{i=1}^{n} \sum_{j=1}^{n} \left( y_i w^T \varphi(x_i) - y_j w^T \varphi(x_j) \right)^2$$

$$= \frac{2}{n^2} \left( nw^T \bar{X}^T w - w^T \bar{X}YY^T \bar{X}^T w \right)$$  \hspace{1cm} (5)

LDM can be formulated as Eq. (6):

$$\begin{align*}
\min_{w, \xi} & \quad \frac{1}{2} w^T w + \lambda \hat{\gamma} - \lambda \bar{\gamma} + C \sum_{i=1}^{n} \xi_i \\
\text{s.t.} & \quad y_i w^T \varphi(x_i) \geq 1 - \xi_i, \\
& \quad \xi_i \geq 0, \quad i = 1, \ldots, n
\end{align*}$$  \hspace{1cm} (6)

Substituting Eq. (4) and (5) into Eq. (6), we can obtain the following optimal programming:

$$\begin{align*}
\min_{w, \xi} & \quad \frac{1}{2} w^T w + \frac{2\lambda}{n^2} \left( nw^T \bar{X}^T w - w^T \bar{X}YY^T \bar{X}^T w \right) - \frac{\lambda}{n} (\bar{X}Y)^T w + C \sum_{i=1}^{n} \xi_i \\
\text{s.t.} & \quad y_i w^T \varphi(x_i) \geq 1 - \xi_i, \\
& \quad \xi_i \geq 0, \quad i = 1, \ldots, n
\end{align*}$$  \hspace{1cm} (7)

Let the solution of Eq. (7) be $w = \bar{X} \alpha$. Then, Eq. (7) can be written as an optimal programming with variable $\alpha$ as follows:
\[ \begin{align*}
\min_{\alpha, \xi} & \quad \frac{1}{2} \alpha^T M \alpha - \frac{\lambda}{n} K Y w + C \sum_{i=1}^{n} \xi_i \\
\text{s.t.} & \quad y_i \alpha^T K_{x,i} \geq 1 - \xi_i, \\
& \quad \xi_i \geq 0, \quad i = 1, \ldots, n
\end{align*} \] (8)

Here, \( K = \tilde{X}^T \tilde{X} \) is the kernel matrix, \( M = 4\lambda \frac{nK^T K - (KY)^T (KY)}{n^2} + K \). By introducing Lagrange multipliers \( \beta_i \) for the constraint \( y_i \alpha^T K_{x,i} \geq 1 - \xi_i \), the dual form of Eq. (8) is written as follows:

\[ \begin{align*}
\min_{\beta} & \quad \frac{1}{2} \beta^T H \beta + \left( \frac{\lambda}{n} H e - e \right)^T \beta \\
\text{s.t.} & \quad 0 \leq \beta \leq 1
\end{align*} \] (9)

Eq. (9) can be solved by a quadratic programming (QP) solver. After obtaining \( \beta \), the solution of Eq. (8) is written as follows:

\[ \alpha = M^{-1} \left( KY \beta - \frac{\lambda}{n} \left( \tilde{X} Y \right) \right) = M^{-1} KY \left( \frac{\lambda}{n} e + \beta \right) \] (10)

For a test sample, its label is determined by using following function:

\[ f(x) = \text{sgn} \left( \sum_{i=1}^{n} \alpha_i k(x, x_i) \right) \] (11)

For multi-class classification, this paper adopts one-versus-one strategy.

5. EXPERIMENTS AND SIMULATIONS

In this section, we collect the typical data of bridge pavement and bridge vibration signals. There are 3,037 bridge pavement signals and 2,079 bridge vibration signals. The collected signals can be divided into three types: health, weak disease, and disease. There are 2,698 signals under health status, 1,818 signals under weak disease, and 600 signals under disease, respectively. The sampling frequency is denoted as \( F_s \). The acceleration sensors are set in different important parts of the bridge by engineers. The bridge vibration signal \( x(t) \) samples \( N \) points to obtain \( x(n) \). The sampling frequency is set as \( F_s = 100Hz \). The sampling period is set as \( T = \frac{1}{F_s} = 0.01s \). The frequency domain interval is set as \( \frac{F_s}{N} \).

The collected signals are denoised through wavelet packet analysis. The db5 wavelet is adopted in wavelet packet analysis. The number of levels in wavelet packet analysis is set as 4. The Stein’s unbiased risk is used as threshold selection method in wavelet packet analysis. The decomposition graph is illustrated in Figure 4.
The denoised signals $x(n)$ are input into Hilbert transform to obtain the corresponding analytical signal, where $z(n) = x(n) + jH[x(n)]$. The analytical signal can eliminate the negative frequency and suppress the cross term which is generated by Wigner distribution.

The vibration signal of the bridge satisfies the mechanical structure. From the principle of mechanics, a healthy vibration signal is a low-frequency signal. When the bridge occurs fault, the vibration becomes a signal which is mixed with high frequencies and the time domain occurs many small flaws. The high frequency component may be the fault signal, while the frequency spectrum of the vibration signal would change at this time. Under health state, the frequency spectrum of the vibration signal has the largest amplitude and the amplitude gradually attenuates at the double frequency. The frequency spectrum behaves irregular when it is mixed with fault signal. Sometimes, a large amplitude occurs at the non-octave frequency. The Fourier transform cannot keep high resolution in the time domain and frequency domain, simultaneously. The details in Fourier transform is not intuitive. The Wigner-Ville distribution can combine the time domain and the frequency domain information. It can visually observe the time-frequency characteristic information of the signal. By executing time-frequency analysis on the vibration signals which are obtained from the bridge sensors, the time-frequency information under three conditions: health, weak disease, disease, is available. In the time-frequency diagram, the energy accumulation area is at low frequency if the bridge is under healthy state; otherwise, the bridge may be under unhealthy state. From the perspective of intensity, if the intensity of the energy concentration area is abnormally high, it means that the bridge has been damaged. This situation is further analyzed by combining with the spectrogram. Through the combination of the position and intensity of the energy accumulation area in the time-frequency diagram, and the Fourier transform frequency, it can finally judge whether the bridge has disease or the degree of disease when the bridge has fault.

The experimental results of bridge health state recognition are reported in Table 1. In the experiment, we compare original signal, denoised signal after wavelet transform, and Fourier transform & Wigner Ville distribution processing. The classifier is compared with Linear Discriminant Analysis (LDA), k-nearest neighbor (NN), support vector machine (SVM), and neural network (NN) to recognize the health state of bridge. The experimental results are reported in terms of accuracy and recall.

When using LDA as classifier to recognize health state of bridge, the accuracy achieves 81.21%, 89.52%, and 93.68% for original signal, denoised signal, and FT & WVD, while the recall achieves 79.12%, 87.69%, and 92.03% for original signal, denoised signal, and FT & WVD. When using KNN as classifier to recognize health state of bridge, the accuracy achieves 79.87%, 88.46%, and 92.34% for original signal, denoised signal, and FT & WVD, while the recall achieves 77.73%, 86.91%, and 91.59% for original signal, denoised signal, and FT & WVD. When using SVM as classifier to recognize health state of bridge, the accuracy achieves 82.36%, 89.21%, and 93.72% for original signal, denoised signal, and FT & WVD, while the recall achieves 80.29%, 87.03%, and 92.34% for original signal, denoised signal, and FT & WVD. When using NN as classifier to recognize health
state of bridge, the accuracy achieves 81.65%, 89.13%, and 92.78% for original signal, denoised signal, and FT & WVD, while the recall achieves 79.38%, 86.96%, and 91.54% for original signal, denoised signal, and FT & WVD. When using LMD as classifier to recognize health state of bridge, the accuracy achieves 83.67%, 90.54%, and 94.32% for original signal, denoised signal, and FT & WVD, while the recall achieves 82.71%, 89.19%, and 92.85% for original signal, denoised signal, and FT & WVD. Our strategy FT & WVD plus LDM achieves the best results (94.32% for accuracy and 92.85% for recall).

From the results in Table 1, it can be found that both denoising processing and Fourier transform & Wigner Ville distribution can increase the accuracy and recall for all classifiers and LDM performs better than other classifiers. Our strategy is superior to previous ones.

6. CONCLUSION

The status of a bridge is influenced by natural aging, invasion of natural disasters, man-made reasons. If the bridge is under unhealthy status, the carrying capacity of bridge will reduce and there will exist potential incidents. In order to address this issue, this paper proposed a framework to recognize the health status of bridge to eliminate potential accidents. First, several sensors are set on the bridge, including acceleration sensor, displacement sensor, strain gauge, wind speed and direction sensor, and temperature sensor etc. Second, the parameters of bridge are collected by sensors. Third, the collected parameter signals are denoised by wavelet packet analysis. Fourth, the denoised signals are input into Hilbert transform to obtain analytical signals. Fifth, the analytical signals are processed by Fourier transform and Wigner Ville distribution. The processed signals are used to train a LMD model for recognize the health status of the bridge. The framework can recognize more than 92% status of the bridge.

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