Analysis of Traffic Effects on a Dutch Highway Bridge

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Summary

In this paper, we propose a method for reliably extracting modal parameters from concrete bridges, which depends on the proper identification of vehicles passing the bridge. We collect data from a sensor network installed on a large highway bridge in the Netherlands, called the Hollandse Brug. There are three sensor types involved in the network, sensing strain, vibration and temperature. Large traffic events, such as trucks crossing the bridge, can be recognized clearly in the strain signal, so we use it to identify the exact moments of vehicles passing. At the same time, the measured strain is also influenced by other factors, such as traffic jams and temperature changes. We remove these factors, which interfere with the proper identification of traffic events, with an improved threshold-based classification method, and obtain a number of peaks with the *zero-crossing* and *local maximum* method. We then divide these peaks into different categories with a supervised classification method. The signals produced by the vibration sensors when excited by passing trucks is a good source for analysing structural parameters of the bridge, so we extract the free vibration periods of the vibration signals associated with truck events in the strain signals, and subsequently conduct modal analysis.
Keywords: concrete bridge; ambient excitation; baseline drift; traffic identification; modal analysis

1. Introduction

To acquire data from physical structures such as bridges, there are two general excitation methods [10]: the forced and ambient excitation method. With the *forced excitation* method, the input forces are controllable and measurable (such as with an impact hammer or a shaker), so it is easy to obtain a clear and interpretable signal. This method is usually adopted in laboratory tests or to obtain short-term data from a real structure. With the *ambient excitation* method in contrast, it is hard to measure the input forces accurately, because these forces are usually various and uncertain. But this method is suitable for long-term data acquisition. In a real-time structural health monitoring system, catching long-term informative data helps to diagnose health problems under different conditions.

The data investigated in this paper is obtained from a sensor network installed on a Dutch highway bridge. The bridge is called the Hollandse Brug, shown in Fig. 1, which is located between the Flevoland and Noord-Holland provinces in the Netherlands [11, 12]. The sensor network was installed on this bridge during a renovation launched in 2007, to monitor the condition of the bridge. There are three kinds of sensors involved in the sensor network: strain, vibration and temperature. Each sensor type provides a specific perspective on the dynamics of the bridge. Furthermore, there is a weather station and a

Fig. 1: The Hollandse Brug

video-camera to measure the weather and the actual traffic on the bridge.

The sensor network collects data at a frequency of 100 Hz from the bridge, which not only contains vehicles with various weights, lengths, speeds, and directions, but also includes environmental factors such as wind, temperature, rain and so on. In most studies, laboratory tests of simple structural systems are considered, rather than real structures in their operating environment [10]. Although some studies work on real structures, they just consider a short period of data, and assume that various environmental conditions remain the same during this period [13].

In this work, we focus on extracting the *free vibration periods* of traffic events from our structural health monitoring system, which is a critical step to analyse the modal parameters of the bridge. The free vibration period means the period after a vehicle has passed, and before a next vehicle appears on the bridge. The reason for choosing this period is that the bridge is put in motion by the vehicle, but the actual weight does not actually influence the frequency of vibration after the vehicles has disappeared, nor do any other vehicles. To extract data that meet such requirements, we need to be able to effectively recognise traffic events first. We combine several signal processing and data mining techniques to pre-process the baseline drift and identify traffic events in the strain signal, and then continue to investigate modal parameters, mainly about the natural frequencies, with the corresponding free vibration periods in the vibration signal.

2. Methods

In the sensor network, both the strain and vibration signal respond to traffic events. The left two pictures of Fig. 2 illustrate one truck event in the time and frequency domain, for either sensor type. From this picture, it is easy to see that the truck event in the strain signal is represented as a peak, which occurs when the vehicle is actually on the measured span, and disappears rapidly when the vehicle passes. The truck event in the vibration signal produces oscillations, which will last for a long period after the truck has passed, if it is not disturbed by subsequent vehicles. Based on this observation, it is reasonable to select the strain signal to recognize traffic events [7, 8]. To monitor and evaluate the health of the bridge, spectral analysis is one of the widely used methods [9, 10]. The right two pictures of Fig. 2 (right) illustrate the spectrum of both the strain and vibration signal, which are produced by a discrete Fourier transform (DFT). It is clear that the spectrum of the vibration signal is more informative than that of the strain signal. So both the strain and vibration signals are employed in our experiments: first, we use the strain signal to detect traffic events; then conduct spectral analysis on the corresponding vibration signal.

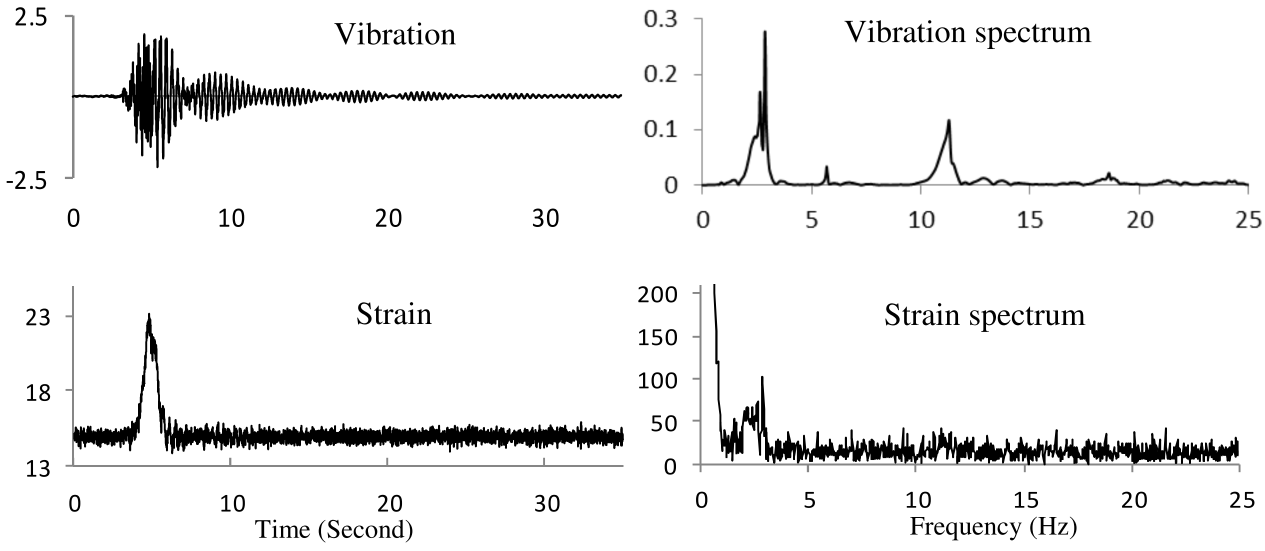

Fig. 2: The strain and vibration signal in the time and frequency domain

Since there are 91 strain sensors and 34 vibration sensors in our sensor network, which sensors are suitable? One simple standard of choosing the strain sensors is if it clearly represents traffic events. That is to say, the peak of the selected strain signal should have a strong amplitude. We chose one truck event on each side as excitation, looked into the response of all of the strain sensors, and finally chose one sensor on each side of the bridge as target. After choosing the strain sensors, the selection of vibration sensors becomes easier. We just take the vibration sensors near the selected strain sensors as our target vibration sensors.

The procedure of processing strain and vibration signal is illustrated as Fig. 3. Details of each step can be found below.

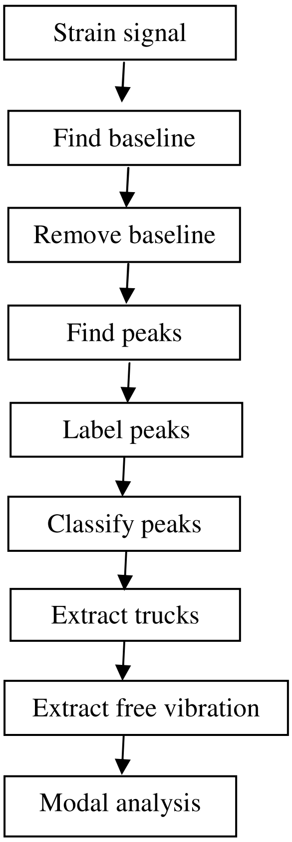

Fig. 3: process overview.

Step 1: Find baseline. The baseline of the strain signal is influenced a lot by temperature and traffic jams. To measure the amplitudes of peaks correctly, we must find the baseline first.

Step 2: Remove baseline. Baseline removal is quite straightforward. It is obtained by subtracting the baseline from the original strain signal.

Step 3: Find peaks. Using the *zero-crossing* and the *local maximum* methods, we succeed to detect a number of peaks, with *amplitude*, *duration* and *area under peak* as peak descriptive features.

Step 4: Label peaks. Based on the video stream, we hand-label each peak as either of *noise*, *car on lane 1*, *truck on lane 1*, *car on lane 4* or *truck on lane 4*. This will be our training data.

Step 5: Classify peaks. Based on the obtained peak features and labels, we try to find the boundaries between each class, by means of classification techniques from the Data Mining field [6].

Step 6: Extract single truck events. One whole traffic event is composed of the traffic-free period before the traffic peak, the actual peak and the traffic-free period after the traffic peak. We should look into the traffic events on both lanes to catch all traffic.

Step 7: Extract free vibration. Free vibration fragments are extracted from the vibration signal, which corresponds to the traffic-free period directly after a truck-related peak in the strain signal.

Step 8: Modal analysis. The Discrete Fourier Transform is employed to analyze the modes of the free vibration period of the vibration signal.

3. Finding the baseline

Both traffic jams and meteorological factors, notably temperature, can cause baseline drift in the strain signal, as shown in the left picture of Fig. 4. The baseline drift is a great obstacle to detect traffic peaks. To analyse traffic peaks extracted under varying circumstances, we must get rid of the influence of baseline drift first. There are several ways to find and remove a baseline. Schultz et al. [1] conducted an excellent literature review and comparison of various baseline-removal methods. Most of the methods can be divided into two classes: time-domain methods and frequency-domain methods. The noise median method [2], first-derivative method [3], polynomial method [4] and threshold-based classification method [5] are carried out in the time domain. In the frequency domain, the baseline is usually treated as a low frequency signal, the spectrum of the signal with traffic peaks belongs to the medium frequencies, and the spectrum of independent noise may be distributed among medium and high frequencies. Filtering out low frequency components in the signal spectrum helps to remove the baseline.

In our experiments, we adopt Dietrich's method [5]. We first smooth our target strain signal with a small moving average filter to get rid of high frequency noise, then calculate the first derivative of the smoothed signal. After the first-derivative operation [5], the smoothly varying baseline drift disappears, and the mean value $\bar{x}$ and sample standard deviation s of the obtained signal are then determined. By iteratively employing a threshold of $\bar{x}+3s$, we can classify each point into either of two groups: traffic peaks and baseline. Because broad peaks and overlaps exist in our signal, some points may be misclassified. To correct this problem, just looking into two neighbours of one target point, as Dietrich's method, is not enough. We select a length of 20 points based on the statistical results of broad peaks and overlaps in our strain signal. A natural cubic spline is then fitted to the elements in the original strain signal corresponding with that in the baseline group, and an approximation of the true baseline is then obtained, shown as the red line in the left picture of Fig. 4.

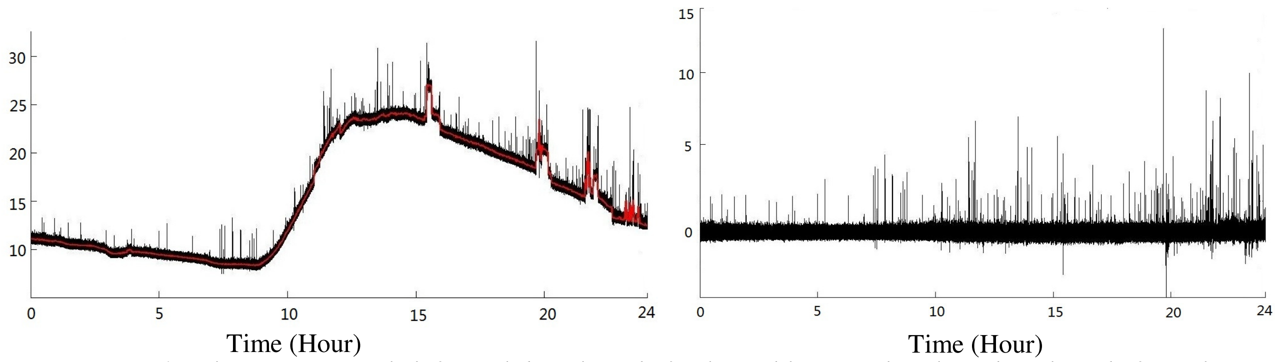

Fig. 4: The strain signal (left) with baseline drift (the red line) and without baseline drift (right).

Note how the baseline includes temperature related changes to the strain, as well as various levels of congestion. The baseline-removed signal is shown as the right picture of Fig. 4.

4. Finding trucks

To simplify the problem, we take a dataset of one hour at 3:00 am. The traffic during this time is not too heavy, and most of time there is just a single lane on either side in use. After processing the selected strain signal with zero crossing and local maximum methods, we obtained a number of peaks, with amplitude, duration and area under peak as peak features.

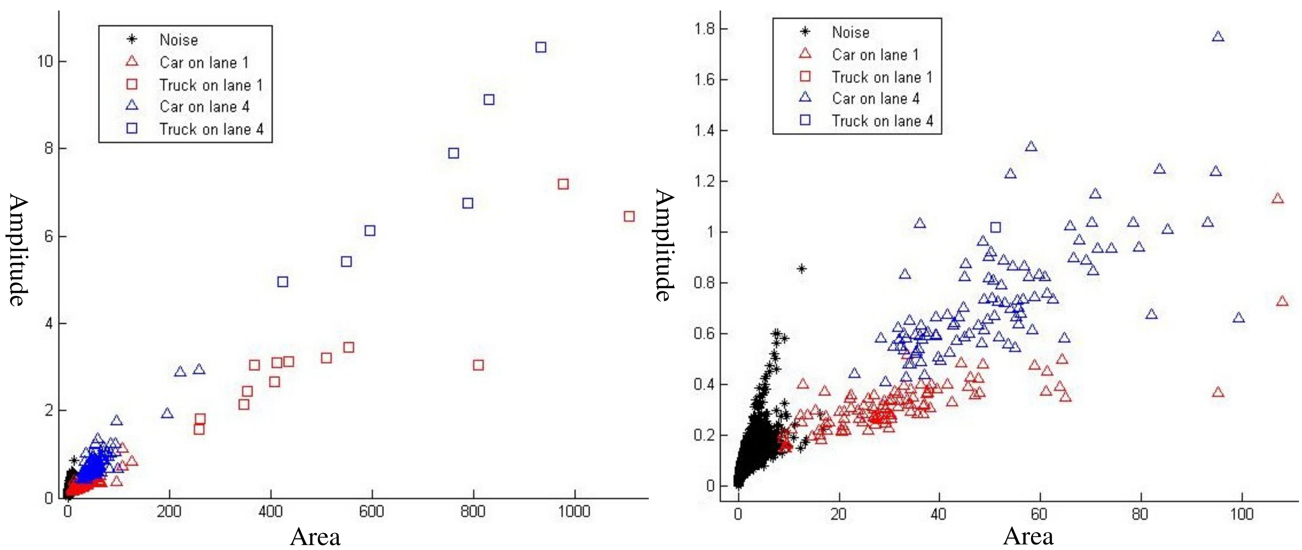

Fig. 5: All peak labels within one hour (left) and detail of the same graph (right).

We went on to hand-label these detected peaks according to the video taken during this period on the bridge. All the peaks were given one of five categories: *noise*, *car on lane 1*, *truck on lane 1*, *car on lane 4* and *truck on lane 4*. The scatter plot based on area and amplitude of the strain peaks on lane 4 are illustrated as Fig. 5.

From the labels in Fig. 5, we can see that truck events on either lane are easy to distinguish, but the boundaries between car events on opposite lanes and the boundaries between the noise and car events on opposite lanes are blurry. When cars on an opposite lane are not heavy enough, they are easily mistaken as noise in the strain signal of the current lane. But the vibration sensor is much more sensitive to traffic events than the strain sensor, which can catch a small car event on another lane. To detect the completely free vibration period according to the strain signal, we must make the boundaries as clear as possible.

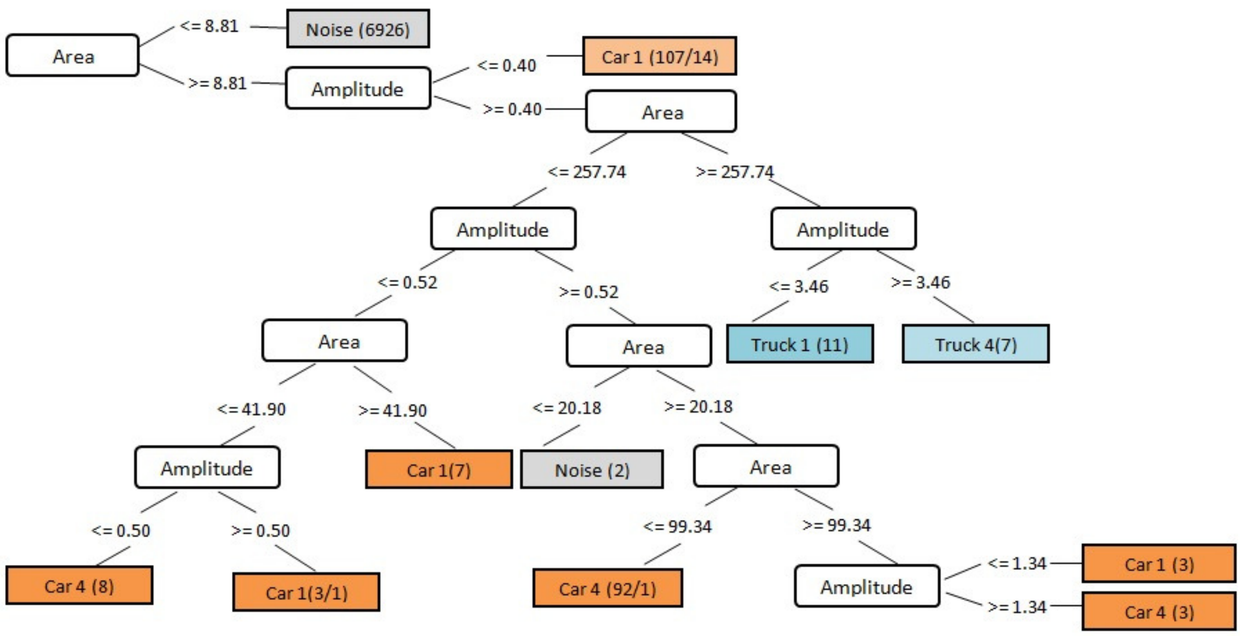

Fig. 6: Decision tree of strain peaks on lane 4

We processed our labelled peaks with Weka [6], a powerful Data Mining tool. A decision tree was produced using the C4.5 algorithm. The result of one decision tree based on the strain peaks on lane 4 is shown in Fig. 6, which takes *area on lane 4*, *amplitude* and *label* as attributes.

The training data (derived from the one hour of labelled data) is composed of 7169 instances, of which 7137 (99.55%) instances are correctly classified. The confusion matrix is shown as Table 1.

Table 1: The confusion matrix

predicted					
truck 4	truck 1	car 4	car 1	noise	actual
7	0	1	0	0	truck 4
1	10	0	0	0	truck 1
0	2	97	4	0	car 4
0	0	3	98	4	car 1
0	0	2	15	6925	noise

The result, with few minor mistakes, is already quite good, but can be further improved by combining the traffic events on the lane of opposite traffic direction.

We applied this model to a bigger data set (the *test set*), which was obtained by selecting one hour per day at 3:00 am for 45 days. We succeeded to catch 17,220 traffic events (of which 852 trucks) on lane 1 and 13,064 traffic events on lane 4 (of which 768 trucks).

5. Modal analysis of free vibration

We focus on truck events on the bridge, because they can cause obvious oscillations in vibration signal, which is useful to detect free vibration. By selecting truck events with at least 20 seconds of free vibration, we obtained 72 events on lane 1 and 77 events on lane 4.

5.1 Modes of the bridge

As shown in Fig. 2, a number of modes appear in the spectrum of each truck event. To obtain all the possible modes of the bridge, we looked into the spectrum of the free vibration period of each selected truck event. After normalizing the 149 spectra, we get the graph in Fig. 7. From this, we can easily detect several interesting modes. Table 2 provides statistics of these modes. The approximate location of each mode is defined according to Fig. 7, and the occurrence of a mode is counted if there is at least one peak, whose amplitude is bigger than the average amplitude. The third column in Table 2 is calculated by counting what fraction of the 149 spectra actually show a peak at the specified location in the spectrum.

As illustrated below, the amplitude indicates the strength of each mode. Mode 2 (2.69 Hz) and mode 3 (2.88 Hz) are the principal modes of the bridge, which occur in every event. Mode 4 and mode 5 are also important modes, which have strong amplitude and happen in most events. Mode 1 and mode 8 have modest occurrence, but their amplitudes are relatively weak. Mode 6 and mode 7 are so weak that they can be ignored in most cases.

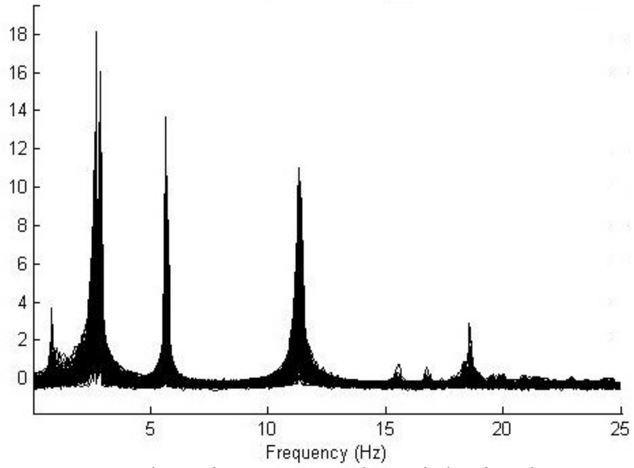

Fig. 7: The vibration modes of the bridge

Table 2: Statistics of modes

Mode	Frequency (Hz)	Occurrence
mode 1	0.73-0.93	71.8%
mode 2	2.69	100%
mode 3	2.88	100%
mode 4	5.61-5.77	97.3%
mode 5	11.22-11.43	98.7%
mode 6	15.35-15.55	12.1%
mode 7	16.55-16.90	10.7%
mode 8	18.30-18.70	48.3%

5.2 The vehicle mass influence

The main purpose of selecting the free vibration period of one traffic event is to get rid of the influence of vehicle mass. To verify the necessity of this operation, we selected one traffic event caused by a truck, and applied DFT to the period when the truck is on the bridge (T) and the period of free vibration (F) respectively. As illustrated in Fig. 8, the modes derived from these two periods are different.

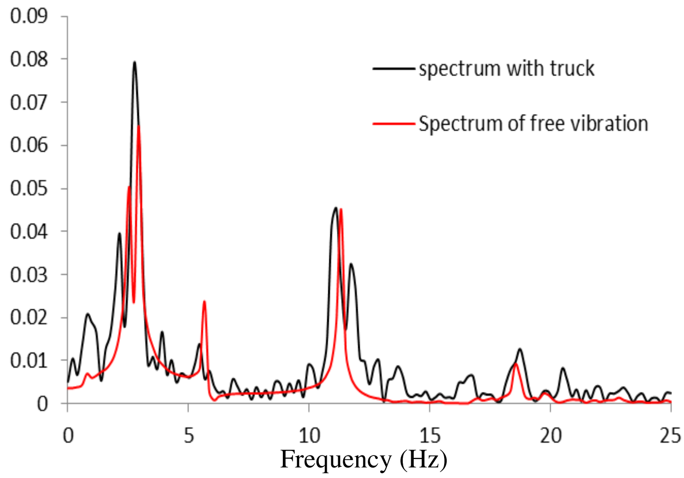

Fig. 8: The spectra with truck and free vibration

If we simply take the bridge as an Euler-Bernoulli beam, the vehicle and bridge interaction system [14] can be modelled as a damped parallel spring mass system, and the natural frequencies fn of the system can be represented as follows:

$$fn = \frac{1}{2\pi}\sqrt{\frac{k}{m}}$$

where k represents for the stiffness of the bridge, m represents the total mass on the bridge.

For a short period, we can assume the stiffness of the bridge as a constant. The only factor influencing the natural frequencies is the mass. When the truck is on the bridge, the mass of the bridge increases, and the natural frequencies should decrease. From Fig. 8, we can see that mode 2, mode 3, mode 4 and mode 5 indeed show a left shift of the peaks. Furthermore, the spectrum of T contains more peaks than that of F, and the low frequency mode 1 of T is stronger than that of F.

5.3 The evolution of modes over time

Through the studies in the previous two sections, we already obtain a general picture about the bridge modes, and realize that the mass of vehicles has influences on the natural frequencies of the bridge. In this section, we will look into the evolution of modes over time. Because of damping, the amplitude of oscillations will reduce during the free vibration period of one single traffic event.

In order to achieve the goal, we chose a specific traffic event with a long free vibration period, and employed a sliding window of 10 seconds moving along the free vibration period. In Fig. 9, we show four spectra selected at the beginning, in the middle and at the end of the free vibration period.

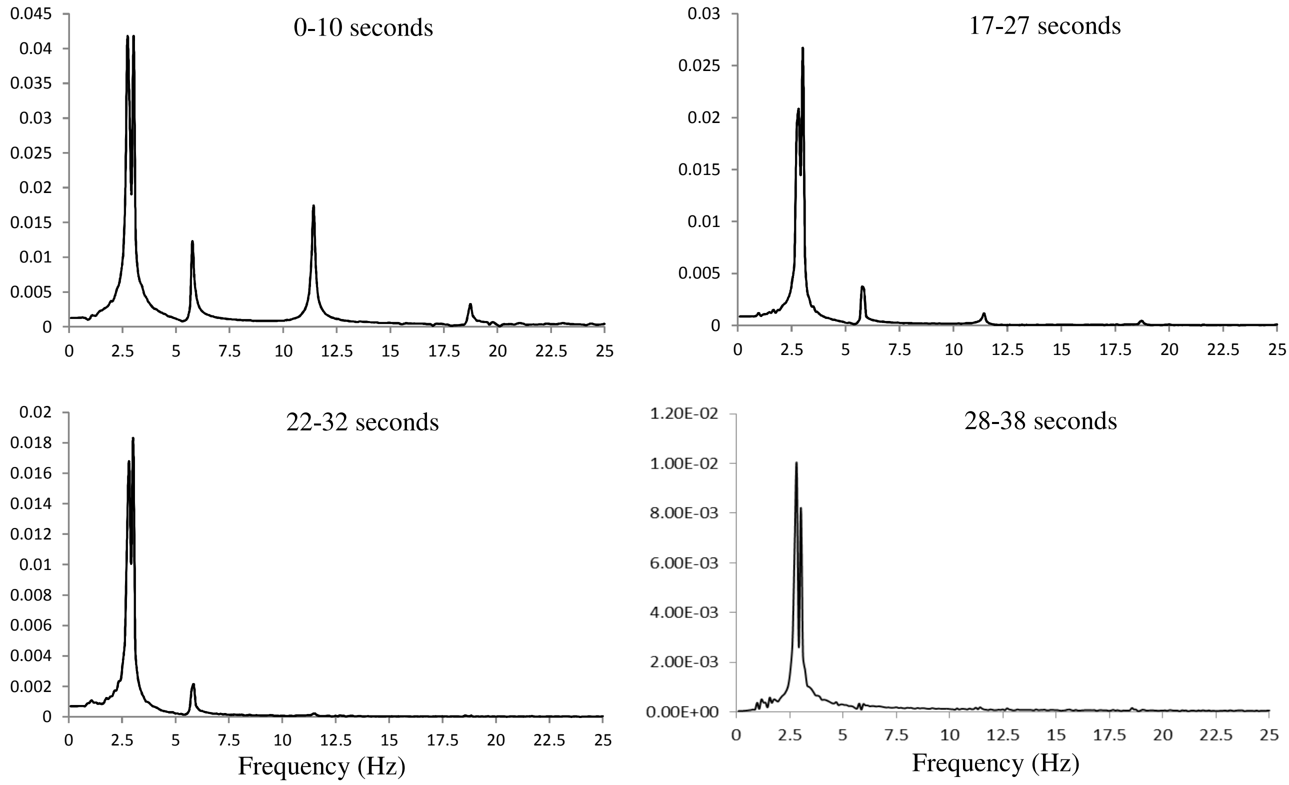

Fig. 9: The evolution of modes

Based on the observation above, we can draw a conclusion that with time passing by, the high frequency modes decay faster than the principal frequency modes (mode 2 and mode 3) , and at last, the bridge will vibrate mostly at its principal frequencies.

6. Outlook on other applications

The traffic identification method introduced in this paper supports the extraction of modal parameters. Because of its generality, this method can easily serve other purposes.

The method can be used to count traffic on the bridge, providing useful statistics to infrastructure managers. Based on these statistics, they can predict the service life of the bridge.

This method also provides us an accurate way to distinguish traffic types. As illustrated in the Table 1, among these traffic instances, there are just 19 trucks out of all 7169 instances within the investigated hour. For analysis purposes, just collecting truck events saves a huge amount of storing space.

The traffic identification method is also capable of collecting the amplitude and duration of each traffic event from the strain signal, which indicates the weight and speed of that vehicle. This information can be used to regulate the traffic and can also be used to investigate the influences of traffic weight and speed on the modes of the bridge by civil engineers.

This method can also be used to process signals obtained from other domains. For example, doctors can use it to deal with electrocardiogram (ECG) signals. The baseline noise in ECG may distort the s-t segment [15], which is a very important low frequency segment containing information related to heart attacks.

7. Conclusion

In this paper, we combined signal processing and data mining techniques to extract and classify traffic events in an ambient excitation setting. Based on the obtained signals about truck events, we succeeded in obtaining 8 modes about our target bridge, and then investigated further the influences of vehicle mass on the natural frequencies and the evolution of modes over time. Finally, we provide an outlook on other applications of our methods. We believe that our method is useful in the management of infrastructure.

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