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Damage Detection of Cable-Stayed Bridges Using Frequency Domain Analysis and Clustering

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ABSTRACT: Cable-stayed bridges are vital structures which need significant maintenance and repair costs every year. Therefore, health monitoring of such structures can mitigate human and financial losses. In this paper, a damage detection method for cable-stayed bridges was proposed using signal processing and clustering. Since the accuracy of signal processing can considerably affect the accuracy of damage detection results, in the first part of the paper, a comparison was carried out between the popular FDD method and two newer AFDD and TDD methods, which were improved some of the FDD drawbacks. Then, the most effective method was selected. Among these procedures, FDD was successfully implemented in signal-based procedures. However, the two newer ones had not adequately investigated in comparison to FDD. In the second part, by using competitive neural network for clustering, a new damage index was introduced by calculation of the Euclidian distances of cluster centers. Results showed that the proposed damage detection algorithm can differentiate healthy and damage states with acceptable accuracy.

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1- Introduction

Signal-based health monitoring approaches are effective methods for detection of damage in large and complex structures [1,2]. Among these methods, Frequency Domain Decomposition (FDD) is one of the most reliable tools and has attracted many researches for damage detection purpose [3,4].

Although FDD has been successfully utilized in many structural health monitoring algorithms, it has several drawbacks. First, selection of peaks in PSD spectrum is not automated. Second, it does not have a procedure to calculate structural damping. By using TDD or AFDD methods such drawbacks can be covered.

2- Benchmark problems

In this paper two benchmark problems were utilized. The first one was a SHM benchmark problem developed by ASCE/IASC [5]. The structure was a 4-story braced frame adopted from ¼ scale experimental UBC university problem. The whole model was numerical, modeled in MATLAB environment. The second benchmark problem was SMC project [6]. This was included Yonghe bridge health monitoring data. Yonghe bridge was among the first cable-stayed structures constructed in mainland china. It was connected to major cities. The structure has 510 m bay length and 11 m width. The towers were included two vertical beams with the height of 60.5. After 19 years of operation, the structure experienced serious were damaged in deck and an auxiliary pier. After repair, a health monitoring system was mounted on the structure to continuously monitor vibration of the bridge. In this paper the records of 14 sensors on the deck were employed for analysis.

3- Signal processing

First, a comparison was carried out to evaluate accuracy of AFDD [7] and TDD [8] methods. Mode shapes were calculated to find the best procedure. Results showed that mode shapes obtained by both procedures were similar from mode 1 to 4 for both procedures. However, they were differed in higher modes. To better understand the accuracy of the procedures, MAC [9] values were also calculated. Results showed that TDD procedure cannot accurately extract the modal parameters. In the next step, damping ratios for different modes were compared. 8 modes were considered to calculate damping. Results showed that damping coefficients for damaged case were lower. Also, in healthy case, larger fluctuations of damping coefficient were observed in different modes. In damage case, damping was increased by increase in mode numbers.

4- Damage detection algorithm

Although in the last step damages could be found due to frequency changes, post-processing was needed to build an automated damage detection technique. First,

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signals were divided to 1-hour sections. Signal sections were analyzed by AFDD and frequencies are extracted. This was repeated for 24 sections of signals (i.e. every day). By doing so, environmental effects such as day-night temperature changes, vehicle load, and wind speed effects were considered. In the next step, frequencies were clustered by competitive neural network. Since the first 8 modes of vibration are extracted, frequencies were categorized to 8 clusters. Next, center of each cluster was determined. Finally, damage index was calculated using Euclidean distance of cluster centers. The difference in Euclidean distances between a base case and the desired one was a measure of damage. If in any case distance exceeded a pre-defined value, the case was considered as damage case.

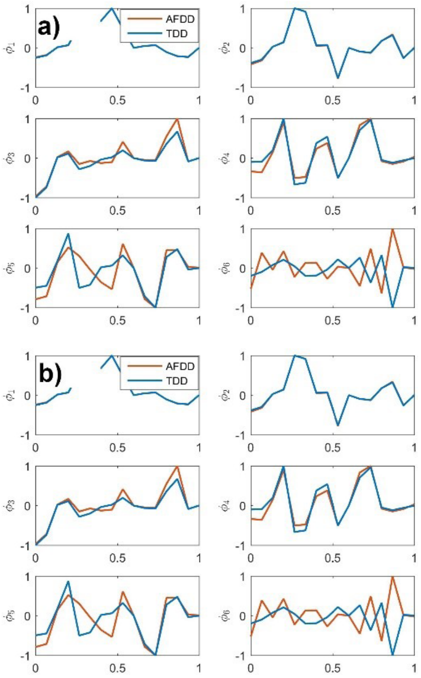

Figure 1. Mode shapes a) AFDD b) TDD

Figure 2 shows the frequency variations for 24 hours. It is obvious that large fluctuations are observed in frequencies due to environmental effects. However, frequency shifts due to damage were clear. Shifts in higher modes were larger, which show higher sensitivity of higher modes to damage. In health case, first mode was spread between 0.33 to 0.41 Hz. But, in damage case frequencies were between 0.26 to 0.27 Hz. In general, frequency variations were less in damage case. To be able to quantify the extent of damage, damage measures were calculated. Table 1 lists the damage indexes for several damage cases. According to the Table, it is clear that damage indexes for damage case showed much larger values. Therefore, it can be concluded that the introduced procedure was able to successfully detect damage. Also results showed that environmental effects had not a considerable effect on the damage index values.

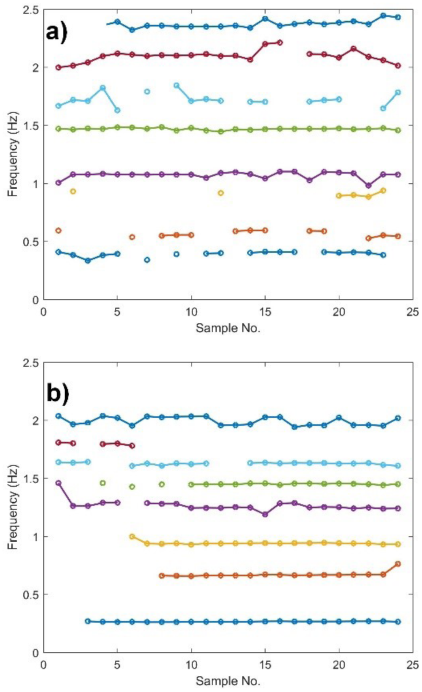

Figure 2. Day-night frequency changes a) healthy state b) damaged state

Table 1. Damage index for different damage cases

Data name	17 Jan.	9 Apr.	7 Jun
Data type	healthy	damage	damage
Damage index	0.05	0.38	0.31

5- Conclusions

In this paper a damage detection method based on signal processing and artificial neural networks was presented. First, efficiency of two signal processing methods was investigated and the best procedure was selected. Second, a new damage index was introduced by implementation of competitive neural networks. Based on the results the following conclusions can be drawn:

1. Although the mode shapes obtained from both AFDD and TDD were similar, MAC analysis revealed that TDD yields were correlated modes. Therefore, it was not a suitable procedure for this case.
2. Comparison of AFDD and TDD showed that TDD was yielded lower damping coefficients in healthy state. Also, in TDD, variations of damping coefficients in different modes was lower
3. Variation in environmental parameters can affect the extracted frequencies up to 10%.
4. Damage caused frequency shifts. However, this was more tangible for higher modes of vibration.
5. In general, incorporation of signal proceeding and data mining was an effective way to detect damage. However, in this study, 4 cases of structural state were investigated.

For a definitive comment about the reliability of the proposed method, more structural cases were needed.

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