

Low-Cost Damage Detection of Cable-Stayed Bridges Using Signal Processing and Machine Learning

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ABSTRACT: Today, it is possible to detect damage in the early stages with the aim of structural health monitoring (SHM) techniques and prevent financial losses and loss of lives. However, high prices of SHM systems has caused that such systems do not gain popularity in our country. The aim of this study is providing a low-cost damage detection technique for bridges based on signal processing and machine learning. In order to reduce expenses, the number of sensors to monitor the vibration of the structure was decreased. Since sensor number reduction can lead to a drop in damage detection accuracy, most up to date signal processing methods were used. In the first step of the paper, several time-frequency signal processing techniques were compared and EWT was selected as the best method. In the next step, after decomposition of signals by time-frequency techniques, a new damage index was introduced base on cross wavelet transform (CWT) and then calculated damaged indices were classified using support vector machine (SVM) to be able to distinguish healthy and damage states. Results showed that the proposed method can detect damage with high accuracy.

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1. INTRODUCTION

Today, structural health monitoring (SHM) systems are very common in advanced countries. However, due to the large expenses of such systems, they have not gained popularity in our country. The first problem is the high prices of sensing systems. These systems need advanced technology and therefore are not produced in our country. The second problem is that SHM systems consist of numerous sensors which adds the expenses. Low-cost SHM methods introduced so far have mainly focused on low-cost sensors. However, such methods still use a large number of sensors [1]. Although using low-cost sensors have decreased the final prices of SHM systems in many countries, they are not applicable to our country due to the high prices of these sensors.

The aim of this study is to propose a low-cost bridge health monitoring method. For this reason, only one sensor was used to detect damage. Since the reduction of a number of sensors can adversely affect the accuracy of the system, in the first part of the study, most up to date signal processing procedures were investigated and their accuracy to extract signals was compared. In the second stage, a damage detection algorithm was proposed based on signal processing and machine learning.

2. BENCHMARK PROBLEMS

In this paper, a bridge benchmark problem was utilized to detect damage. The problem is the SMC project conducted by

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Harbin institute of technology which includes Yonghe bridge health monitoring. Yonghe bridge is among the first cable-stayed structures constructed in mainland China. It connects to major cities. The structure had 510 m bay length and 11 m width. The towers included two vertical beams with a height of 60.5. After 19 years of operation, the structure experienced serious damaged in the deck and an auxiliary pier. After repair, a health monitoring system was mounted on the structure to continuously monitor the vibration of the bridge. The system included 14 uniaxial accelerometers mounted on the bridge deck and a biaxial sensor on the southern tower. The data for Jan 2008 was considered as the data of damaged state and data for July 2008 was considered as the healthy state of the bridge [2]. In this paper, the records of sensor 7 on the deck were employed for analysis.

3. SIGNAL PROCESSING

Vibration signals of real structures may be nonlinear and non-stationary in nature. Therefore, time-frequency signal processing methods are the best choice to analyze such signals. Among the time-frequency methods, the instantaneous ones are most suitable since they provide a high-frequency resolution which helps to distinguish signals of damage states with higher accuracy. On this basis, in the first step of the paper, a comparison was carried out to evaluate the accuracy of four signal processing procedures including empirical mode decomposition (EMD) [3], empirical mode decomposition by optimization on splines (EMDOS) [4],



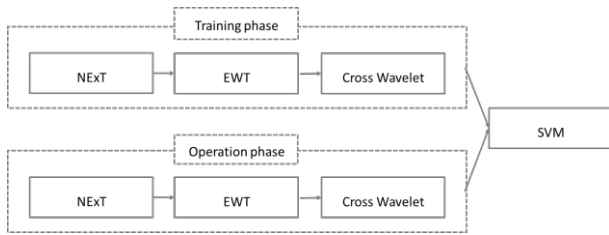


Fig. 1. Summary of the damage detection method

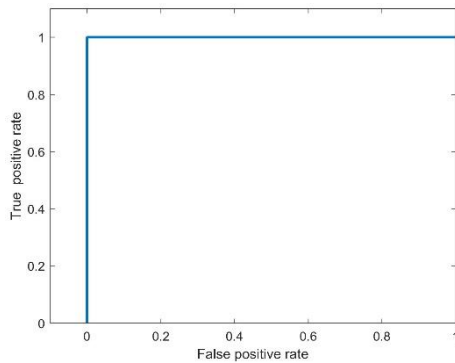


Fig. 3. ROC curve of training data

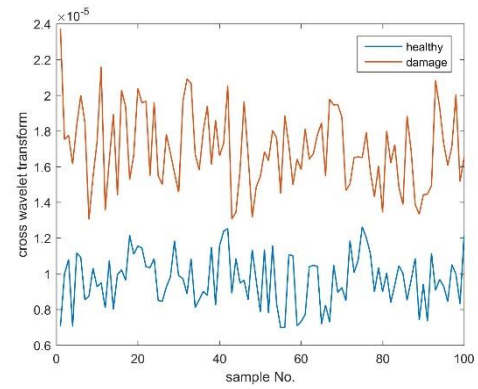


Fig. 2. Damage index for 100 blocks

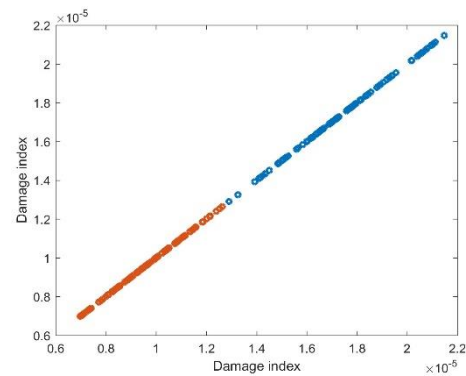


Fig. 4. Classification results

empirical mode decomposition by time-varying filter (TVF-EMD) [5], and empirical wavelet transform (EWT) [6]. Among these methods, EMD is the most well-known method and is successfully utilized in many engineering problems. EMDOS and EWT are more recent and are claimed to outperform EMD in the decomposition of signals.

The comparison results indicated that although these methods showed a better frequency resolution, their instantaneous nature led to more dispersion in the extraction of frequencies. Frequencies obtained by these methods showed large fluctuations which make the processing of signals more complicated. Instead, wavelet analysis showed a lower frequency resolution but it yields more stable frequencies. On this basis, instead of using Hilbert transform to obtain frequencies from the extracted IMFs, Cross Wavelet (XWT) [7] analysis was used in the next step to compare signals of healthy and damaged states.

4. DAMAGE DETECTION PROCEDURE

In the previous step, an efficient signal processing procedure was selected. In this section, a new damage detection procedure is introduced. Figure 1 shows a summary of the proposed procedure.

1- First, continuous vibration signals of the structure were divided into several blocks. These blocks include 15 sec of vibration signals. Therefore, they consist of 1500 sampling points.

2- NExT [8] algorithm was applied to the signals to extract free vibration from the original signal. The aim is to improve the accuracy of frequency demodulation.

3- Modes of vibration were decomposed by EWT to obtain simpler vibrations of the structure.

4- The first mode of vibration for the desired state and

the base healthy states were analyzed by XWT to calculate wavelet coefficients. The average of the wavelet coefficients was considered as a damage index. Figure 2 shows the damage index values for healthy and damaged states for 100 blocks. According to Figure 2, the healthy and damage states can be easily distinguished. However, damage indices showed large fluctuations.

5- Although damage can be identified from the last step, to build an automated procedure, post-processing is needed. Here, support vector machine (SVM) [9] was employed to classify healthy and damaged states. Since SVM is a supervised classification technique, it must be trained first. 100 blocks were used to train SVM. Figure 3 shows the accuracy and results of the training phase. It is clear that training was carried out with 100% accuracy.

To validate the SVM efficiency, 100 blocks from the rest of the data was used for validation. According to Figure 4, the SVM had correctly classified all the data.

5. CONCLUSION

In this study, a low-cost health monitoring method was proposed to detect damage in bridges. To increase the accuracy of the procedure, the first four signal processing methods were investigated and the most efficient one was selected. Next, a damage index was proposed using machine learning to classify healthy and damage states. Based on the results, the following conclusions can be drawn:

1- Among the signal processing procedures, two more

recent ones (i.e. EMDOS and EWT) were more efficient than EMD to extract vibration modes. EWT was the best procedure for this structure since it benefits from both wavelet and EMD strongpoints

2- Although the reduction in sensor number can decrease the reliability of the SHM method, using a hybrid method that employs signal processing and machine learning can sufficiently improve the ability of the system to accurately detect damage.

REFERENCES

- [1] Lynch, J. P., & Loh, K. J. (2006). A summary review of wireless sensors and sensor networks for structural health monitoring. *Shock and Vibration Digest*, 38(2), 91-130.
- [2] Kaloop, M. R., & Hu, J. W. (2015). Stayed-cable bridge damage detection and localization based on accelerometer health monitoring measurements. *Shock and Vibration*, Article ID 102680
- [3] N.E. Huang, Z. Shen, S.R. Long, M.C. Wu, H.H. Shih, Q. Zheng, N.C. Yen, C.C. Tung and H.H. Liu, (1998), The Empirical Mode Decomposition and the Hilbert Spectrum for Nonlinear and Nonstationary Time Series Analysis, *Proceeding of the Royal Society London*, A: 454
- [4] Oberlin, T., Meignen, S., & Perrier, V. (2012). An alternative formulation for the empirical mode decomposition. *IEEE Transactions on Signal Processing*, 60(5), 2236-2246.
- [5] Li, H., Li, Z., & Mo, W. (2017). A time varying filter approach for empirical mode decomposition. *Signal Processing*, 138, 146-158.
- [6] Gilles, J. (2013). Empirical wavelet transform. *IEEE transactions on signal processing*, 61(16), 3999-4010.
- [7] Prokoph, A., & El Bilali, H. (2008). Cross-wavelet analysis: a tool for detection of relationships between paleoclimate proxy records. *Mathematical Geosciences*, 40(5), 575-586.
- [8] James, G. H., Carne, T. G., & Lauffer, J. P. (1995). The natural excitation technique (NExT) for modal parameter extraction from operating structures. *Modal Analysis-the International Journal of Analytical and Experimental Modal Analysis*, 10(4), 260.
- [9] Hearst, M. A., Dumais, S. T., Osuna, E., Platt, J., & Scholkopf, B. (1998). Support vector machines. *IEEE Intelligent Systems and their applications*, 13(4), 18-28.

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