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The Bridge Maintenance Management in the Context of Big Data

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Abstract. The maintenance and management of bridge is crucial to their normal operation. The application of big data technology makes the processing of massive data in the process of bridge maintenance and management more timely and accurate. In order to evaluate the status of suspension bridge in operation period more accurately and timely, on the basis of summarizing the big data sources of bridge, wavelet separation method is used to separate the waveform of displacement data at the support of suspension bridge. Considering the influence of temperature on displacement data, the sections with inconsistent temperature and displacement curves were eliminated, and the data were divided into three continuous time periods for fitting analysis. The analysis results show that the fitting and analysis of the temperature - beam end longitudinal displacement data in each continuous period can more accurately and timely evaluate the status of the key constraint devices of the bridge, and then provide data support for the bridge maintenance management.

1 Introduction

The With the construction and operation of large number of Bridges, maintenance management is inevitable, but the management and maintenance of bridges rely on data reflecting the status quo of Bridges. Big data, cloud computing and other technologies have been widely used in fatigue life analysis of bridges [1], establishment of degradation models [2], deformation of Bridges [3], cost optimization [4] and other aspects. For bridge management and maintenance data volume, quantity type complex and diverse characteristics, based on manual processing of massive data has been unrealistic, with the help of cloud computing [5], deep learning [6] and other big data processing methods, data storage, cleaning, analysis, and then obtain real and reliable actual measurement data, accurately reflect the real comprehensive state of the bridge, to provide data support for the realization of intelligent bridge management and maintenance [7].

However, Structural health monitoring (SHM) techniques have been widely used in long-span bridges[8].The condition assessment as well as damage detection could be done based on the big data collected by this real-time dynamic health monitoring system[9].Taking the data of domestic large bridge health monitoring systems as an example: the daily data volume of the Su-tong Bridge is about 10 GB, and the annual data volume is about 3TB; the daily data volume generated by the Xi hou-men Bridge is about 3GB, and the annual data volume generated is about 1TB[10]. With the need for later maintenance and management, new sensors are constantly installed and the data volume will further increase. How to store, extract, analyze and utilize such a huge amount of data [11], and evaluate and control the safety and durability of bridges, and provide data support for bridge management and maintenance in a timely and effective.

2 Main sources of bridge maintenance management data

Bridge health and environmental monitoring data. Bridge health and environmental monitoring data are the sum of data on the structural response and mechanical state of the bridge and the additional environment under operational conditions. It generally includes: load data obtained by load detection sensors, internal force response data obtained by structural static and dynamic response monitoring sensors, surface morphology data obtained by geometric monitoring sensors, physicochemical environmental data obtained by environmental monitoring sensors [10], and signal density data obtained by signal detection sensors.

Numerical model and simulation data. The numerical model of a bridge is the computer data file about the bridge created during the design, construction, and operation phases, including drawings and models related to the bridge structure, as well as numerical models of ship collision, explosion, earthquake, heavy vehicle, and environment required for bridge risk assessment.

Data of Manual collection and performance evaluation. Data from manual collection and performance evaluation is an understanding of the bridge operating conditions obtained through human experience and subjective analysis. According to the specifications, bridge inspections are divided into regular, periodic, and special inspections, with special inspections divided into specialized inspections and emergency inspections.

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Specification and maintenance reinforcement data. Various materials, components, diseases, evaluations, as well as spatial attributes, material attributes, geometric attributes and other information of the bridge are quantified based on the parameters set by the specification, which is manifested in the coding and definition of the information classification and clustering process.

3 Application case of big data in bridge condition assessment

Expansion joints and bearings are important components to meet the deformation needs of bridges and to transfer load deformation. For large span suspension bridges, accurate assessment of the bridge expansion and contraction function can detect the disease in time. The longitudinal displacement sensors are installed upstream and downstream of towers A and B respectively, with one end of the sensor fixed to the upper part of the lower crossbeam of the main tower and the other end fixed to the end of the main beam across the expansion joint.

The girder end longitudinal displacement data with a sampling frequency of 1Hz for 1 month (30 days) of the bridge was selected, and the initial value was subtracted from the real-time measurement value to arrive at the valid girder end longitudinal displacement data, which was used as the source data for subsequent analysis.

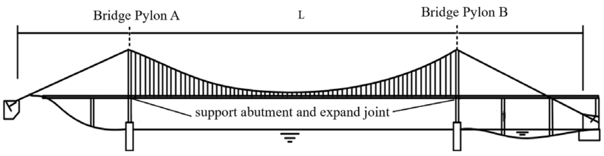


Fig. 1. Schematic diagram of background bridge(self-drawn)

Wavelet separation method is used to separate the waveform of the longitudinal displacement source data of the upstream and downstream side beam ends of the background bridge A and B towers respectively. Wavelet transform is based on Fourier transform and uses finite-length or fast decay waves (i.e. wavelet basis functions) to reconstruct the signal, which has the characteristics of multi-resolution analysis and can characterize the local features of the signal in both time and frequency domains.

By stretching and shifting the parent wavelet y(t), a wavelet sequence is obtained. For the continuous case:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\,\psi\left(\frac{t-a}{a}\right), a, b \epsilon R; a \neq 0 \tag{1}$$

Where: a—factor of stretch: b—factor of translation. Then the continuous wavelet transform of any function f(t) is:

$$W_f^{\psi}(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} f(t)\psi^*\left(\frac{t-a}{a}\right)dt \tag{2}$$

This method converts the studied signal into approximate and detail terms through multi-resolution analysis. The coarse resolution subspace (i.e., approximate subspace) contains the information of low-frequency decomposition and retains the main features of the original signal; the fine resolution subspace (i.e., detail subspace) retains the information of high-frequency components and reflects the detail features of the original signal.

According to the above method, multiple waveforms such as long-period and short-period fluctuations can be separated. Fig. 2 takes the waveform separation diagram of the downstream side of tower A for 1 day as an example, and Fig. 2 and Fig. 3 show the short-period fluctuations caused by noise and vehicle load, respectively (at 0:00-6:00, the waveform in Fig. 3 has a smaller amplitude than other moments, and the waveform in Fig. 3 is significantly smaller, which is consistent with the little human activity in the early morning hours). As can be seen from the figure, the latter two fluctuation frequencies are significantly higher than the temperature-induced waveform frequencies, so the source data can be averaged at lower frequencies to eliminate the effects of short-period factors such as wind and vehicle impact, while maximizing the retention of the effects caused by anomalous factors. Based on the magnitude of the high frequency fluctuation at the details of the daily fluctuation curve, we can determine whether the key restraint device of the large span suspension bridge is continuously subject to the effect of abnormal factors, and propose the content of the key inspection in the face of such problems, so as to provide data support for the subsequent maintenance management.

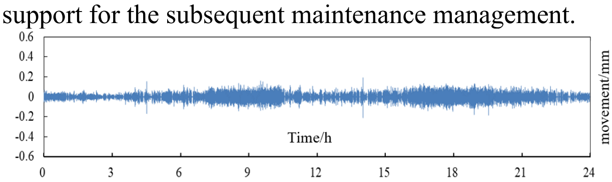


Fig. 2. Displacement waveforms affected by noise(self-drawn)

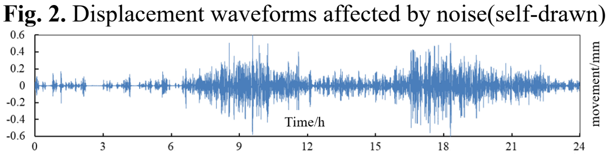
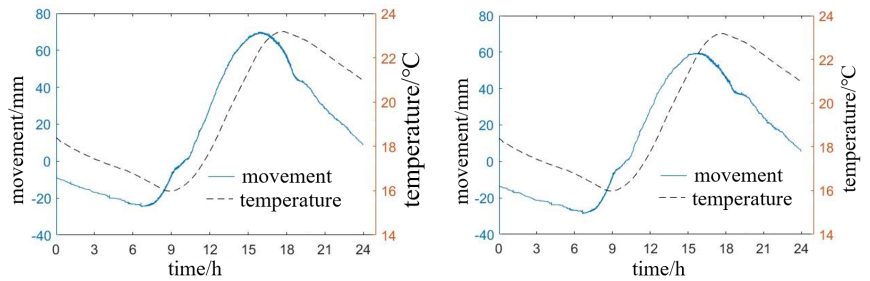


Fig. 3. Displacement waveforms affected by vehicle load(self-drawn)

3.1 Analysis of daily fluctuation curves of temperature and displacement data

Using the 1Hz longitudinal displacement source data of the beam end and the temperature source data of the beam body at every 0.003Hz, the daily fluctuations of the beam body temperature and the longitudinal displacement of the beam end along the two longitudinal axes were plotted over time. Fig. 4 is the data graph of one day.



(a) upstream of pylon A(self-drawn) (b) downstream of pylon A(self-drawn)

Fig. 4. Diurnal fluctuation trend of temperature and longitudinal displacement of beam

According to Fig.4, the overall trend of long-period fluctuation of temperature - displacement is analyzed. After the time lag effect is removed, the temperature of each side of the background bridge and the displacement of beam end have a good consistency over time. It is concluded that the key constraint devices of the bridge do not have serious problems such as complete jam. However, the displacement fluctuation curve is obviously not smooth, and it is considered that the longitudinal displacement of the background bridge end has a relatively frequent transient stagnation and stuck condition.

3.2 Correlation analysis between temperature and longitudinal displacement of beam end in specific time period

Due to external factors such as sunrise and sunset or the inevitable difference in response speed and time lag effect between temperature sensor and displacement sensor, invalid data (box selected area) are generated. In this regard, through the analysis and processing of displacement waveform and temperature change curve after averaging, the sections with inconsistent overall trend of temperature and displacement curve are accurately eliminated for sunrise and sunset periods. Then, considering sunshine and other factors, the remaining time is divided into three continuous periods, as show in Fig.5.

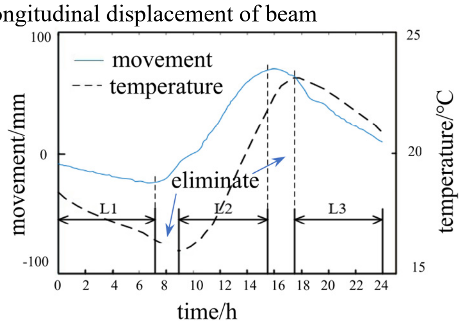
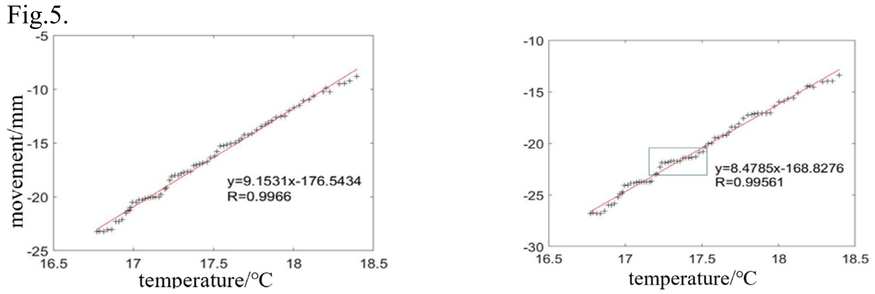


Fig. 5. temperature displacement scatter diagram (self-drawn)

For fitting the data analysis of a month, and the correlation coefficient of correlation strength standard, with 0 < | R | 0.3 as weak or less relevant, 0.3 < | R | 0.5 or less for low-alcohol, 0.5 < | R | 0.8 or less significant correlation, 0.8 < | R | < 1 is highly related to 0.80. The result of one day of pylon A were presented in Fig.6.

The data of one month were similarly processed, and the results showed that the correlation coefficients were all greater than 0.80 in each period, whilst there was no sharp mutation in the graph, indicating that the displacement of the expansion joint was linearly correlated with the height of the temperature trend of the beam body. It was preliminarily determined that the key constraint device did not have serious blockage and jam in each period.



(a) upstream of pylon A (b) downstream of pylon A

Fig. 6. Fitting of L1temperature displac ement scatter of one day(self-drawn)

4 Conclusion

Big data has been widely used in the fields of damage analysis, condition assessment and intelligent management and maintenance of bridges. However, in general, the application of big data in bridge engineering is still in the development stage. Due to the many kinds of data on bridges, large volume, complex sources, and different data structures and formats, how to establish a multi-source heterogeneous big data fusion platform and realize low-cost, highly fault-tolerant and portable data storage are the primary requirements for the implementation of big data applications in bridge engineering. Deep learning research in the context of big data is flourishing, which can help unify the inspection and monitoring condition assessment and contribute to the intelligent maintenance management of bridges.

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References

1. Ma Ru-jin, Xu Shi-qiao, etc. Big Data-Based Fatigue Life Analysis of Steel Box Girder in Large-Span Suspension Bridge[J]. Journal of South China University of Technology, 2017, 45 (06):66-73.
2. Zhang Yang, Huang Yi-ya, etc. Multi-stage degradation model of bridge technical condition based on inspection and evaluation big data[J]. Highway, 2018, 63(2):5
3. Wang Y , Wang P , Tang H, et al. Assessment and prediction of high speed railway bridge long-term deformation based on track geometry inspection big data[J]. Mechanical Systems and Signal Processing, 2021, 158(4):107749.
4. Wang Shu-tao. Optimization Design of Big Data Calculation Model for Railway Bridge Concrete Engineering cost[J]. concrete, 2020, (2):4.
5. Yang Xing-wang, Tang Cheng, et al. State-of the art review of cloud computing for bridge engineering in 2020[J]. Journal of Civil and Environmental Engineering, 2021, 43(S01):261-267
6. Fu-Tao Ni, Jian Zhang, etc. Deep learning for data anomaly detection and data compression of a long-span suspension bridge[J]. Computer-Aided Civil and Infrastructure Engineering, 2020, 35(7), 685–700.
7. Christian Cremona, Joao Santos. Structural health monitoring as a big-data problem[J]. Structural Engineering International, 2018, 28(3), 243–254
8. Sun Li-min, Shang Zhi-qiang, Xia Ye. Research status and prospect of bridge structure health monitoring under the background of big data[J]. China Journal of Highway and Transport, 2019, 32(11):20.
9. Sun L, Shang Z, Xia Y, et al. Review of Bridge Structural Health Monitoring Aided by Big Data and Artificial Intelligence: From Condition Assessment to Damage Detection[J]. Journal of Structural Engineering, 2020, 146(5):04020073.
10. Chen Ai-rong, Pan Ming, Wang Da-lei, et al. Bridge Maintenance and Safety in the era of Big Data [J]. Shanghai Highway, 2014, (1):7.
11. Ren Pu, Ding You-liang, etc. Data Storage and Early-warning Methods of Bridge Health Monitoring System Based on Big-data[J]. Science Technology and Engineering, 2019, 19(12), 266–270.