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STRUCTURAL PERFORMANCE ANALYSIS AND PREDICTION FOR IN-SERVICE BRIDGE WITH SHM DATA MINING

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Abstract: Structural performance analysis and prediction for the in-service bridge is complicated and challenging, influenced by many unknown and uncertain factors. Many structural health monitoring (SHM) systems have been installed in the large span, dominant, and even small or medium-span bridges recently. A lot of SHM data of structural dynamic and physical response can be collected, and thus the structural performance analysis and prediction can be further improved. This paper firstly analyzes the essential issue of traffic load, bridge structure, and structural response in SHM, such as the two inverse problems. The characters of the bridge SHM data are also pointed out, including the mass data, the variation with different traffic loads and time periods. Then, the distribution function analysis, association analysis, and time series analysis methods are employed to analyze the SHM data, aiming to reflect the structural distribution function, the lateral distribution performance, and the deterioration extent, so as to provide a reference for traffic load management. One case study is also carried out to verify the three methods. The result shows that the SHM data mining methods can be used to analyze the structural distribution function and reflect the lateral distribution performance as well as the deterioration extent to a certain extent.

1 Introduction

In the past few years, there have been many bridge safety accidents, due to the lack of resistance capacity after a long time of service, such as the overturn instability and fracture accidents of some small- or medium-span bridges. Some large span bridges' components will have to be replaced due to the damage accumulation of different degrees. SHM aims to realize the structural online monitoring, early warning, and even diagnosis, etc., which provides a good prospect for the engineer. So far, many SHM has been widely used in some large span and controlling bridges, some small- or medium-span bridges have also been installed and named as the cluster SHM system.

The traditional structural performance analysis and prediction can be traced back to 1980s, which were always based on the structural dynamic response and focused on the monitoring of large structures, offshore platforms, etc., along with modal analysis (Richardson 1980). Several methods were also provided for structural deterioration analysis, damage detection, and assessment, e.g., vibrational signature analysis, dynamic finite element model updating, as well as the analysis of frequency variations and mode shapes (Mazurek and DeWolf 1990, Hearn and Testa 1991, Mottershead and Friswell 1993, Stubbs et al. 2000). A detailed review of the damage identification and SHM based on vibration character was also performed, including the study of several damage identification methods (mode shape variation, measured flexibility, etc.) and applications (beam, truss, bridge, etc.) (Doebling et al. 1996).

Compared with the traditional method, structural performance analysis and prediction based on the physical response (displacement, microstrain, etc.) are typically performed with mathematics statistics and data mining (Hill et al. 2006). Data mining, also known as the Knowledge Discovery in Databases (KDD), first appeared at the 11th international conference on artificial intelligence held in Detroit, Michigan, in 1989, and the first international conference on KDD and data mining was held in Montreal, Canada, in 1995; so far, several methods have also been put forward, such as the association rule, classified analysis, etc. (Cheng 2006, Fang 2007). A support vector machine was also used to formulate the regression models, so as to quantify the effect of temperature on modal frequencies (Ni et al. 2005). The cluster model, association model, and time series analysis model were also established for a long time SHM data analysis (Dong 2006, Sun 2014). Several statistical classification methods and models were selected to classify the damage and predict the lateral spread displacement of concrete buildings, such as the naive Bayes, k-nearest-neighbor, random forest, etc. (Liu and Tesfamariam 2012). One compressive sensing-based method for SHM data analysis was also proposed (Li et al. 2015).

In conclusion, there has been a relatively long history and more achievements for traditional structural performance analysis and prediction based on the dynamic response, while the structural performance analysis and prediction based on the dynamic response still needs further improvement. Additionally, the dynamic response is a structural inherent character, while the physical response always changes both with the structure itself and the variation of external load effects. What is more, the limit value can also be clearly founded out in most of the current codes and specifications on the bridge structure. Therefore, it is more direct and easier for the structural performance analysis and prediction.

This article will first analyze the essential issue of traffic load, bridge structure, and structural response in SHM, and then the character of bridge SHM data will be summarized. The distribution function analysis, correlation and time series analysis methods will be employed for the analysis and prediction of structural response, structural lateral distribution performance and deterioration extent. One case study will also be performed to verify the data mining methods.

2 Methodology

2.1 Essential Issue in Bridge SHM

Bridge structural dynamic and physical response is essentially a structural dynamic problem, of which the traffic load is the external excitation, and the bridge structure is usually characterized with different physical and vibration parameters, then different kinds of structural response can be generated. The relationships can be shown as follows (Figure 1):

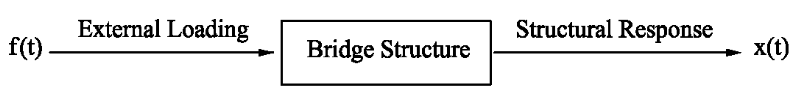

Figure 1: The diagram of bridge structure, external load, and structural response

According to Figure 1, supposing the external traffic load and the bridge structure are known, the different structural response can then be calculated. This is very common and relatively perfect in the design stage of the new bridge structure, aiming to test whether the bridge structure can meet the design requirement.

While, the analysis and prediction of structural performance and even the external traffic load can be named as the two inverse problems, of which the former one usually supposes the external traffic load and the structural response are known, or at least, the structural response is known, the latter one usually supposes the bridge structure and the structural response are known, or at least, the structural response is known.

Additionally, the former one is typically used in the carrying capacity analysis of some old or damaged bridge structures, as well as the on-line analysis and prediction based on the SHM data mining, while the latter one can also be realized with the consideration of the SHM data mining and some assumptions of the bridge structure, as to provide some references for the traffic management department.

2.2 Character of Bridge SHM Data

According to section 2.1, the bridge SHM data, in essence, is the different structural responses with the different external traffic load effects and time periods, which can be typically characterized with the mass data, the variation with the traffic load and time period, the variation with the measurement position, and the variation with the measurement physical attribute.

Taking a simply supported girder bridge with five small T-type beams as an example, the SHM system has five strain sensors and five deflection sensors. Supposing the data collection frequency is one minute, and if a single sensor will need the storage space about 4MB per day, then it will be about 120MB one month, 1400MB one year, and thus the SHM data of the whole bridge will be about 14000MB. What's more, there will be many different bridge SHM systems in one management center. Therefore, a huge high-performance computer and space will be needed to store and view the data.

Additionally, the SHM data always changes with the variation of traffic load and different time periods. For the highway bridge, there is more traffic during the daytime (mainly passenger cars, buses, trucks, and pickup trucks) and less traffic in the nighttime (mainly trucks and pickup trucks). The SHM data of daytime is relatively intensive with high values, while the SHM data of nighttime is relatively discrete and larger variation can only be observed with the traveling of truck or pickup truck. For the urban bridge, there is more traffic during the daytime (mainly the passenger cars, buses, some trucks) and almost no traffic in the nighttime, then the SHM data is relatively concentrated in the daytime.

What is more, most of the highway and urban bridges have two or three or even more lanes and consist of different small beams with a wide lateral cross section. Usually, the outside lane is for the trucks, the inside lane is for the passenger cars, and the middle lane is usually for the buses and pick trucks. Thus, the different beams will carry different traffic loads, and at any instant time, the SHM data of different beams will vary greatly, and then reflect the structural lateral distribution performance of the whole bridge. So far, several bridge accidents have occurred because of the weak lateral distribution performance, such as the single beam or slab fracture.

For an intact bridge structure, the different structural parameters (microstrain, displacement, and even acceleration, etc.) are always based on the structural mechanics and material mechanics, which has a good mapping relationship. However, there will be a different degree of deterioration after a long time of service, and the mapping relationship of the structural stress and displacement effect will be gradually weakened, which can be properly analyzed and predicted with SHM data mining.

2.3 Data Mining Methods

Data mining is based on and derived from the basic statistical method, aiming to discover new meaningful associations, patterns, and trends from a large number of data. Data mining has some significant advantages, such as the applicability of mass actual data, convenient for enterprise users without the professional statistical background (Fang 2007). Data mining now has more than ten calculation methods, such as the distribution function analysis, the association analysis, time series analysis, etc.

2.3.1 Distribution Function Analysis

The basic statistical method is usually based on the overall or part of the samples, aiming to describe the distribution status of the overall data, such as the normal distribution, multimodal distribution, etc. E.g., supposing p_i, μ_i, and σ_i are respectively the probability, mean, and standard deviation of the i th normal distribution, $\sum_{i=1}^{n} p_i = 1$. The bimodal probability distribution can then be described as the weighted sum of two normal distribution curves (Figure 2), the expression formula is $F(x)=\sum_{i=1}^{n} p_i \phi(\frac{x-\mu_i}{\sigma_i})$. (Hu and Zhou 2011):

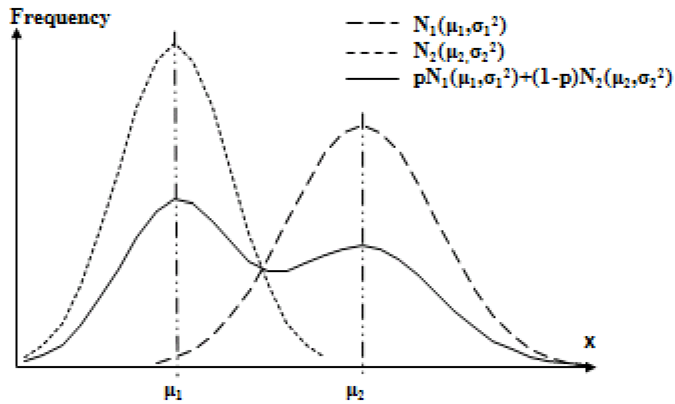

Figure 2: The diagram of the bimodal normal distribution

With the basic distribution analysis of bridge SHM data, the response distribution function and time effect can be grasped at a macro level, which can provide a basic reference for the overall safety, and even help to further improve and develop the SHM system.

2.3.2 Association Analysis

Association analysis aims to discover the valuable relationship information from a mass data, based on the support and confidence of association rule. The association rule that satisfies minimum support and confidence is named as the strong rule, and the item set that meets minimum support is named as the frequent item set. During the detailed analysis, all the frequent item sets should be found out firstly, and the frequency of these item sets should be at least equal to the minimum support frequency set up in advance. Secondly, according to the frequent item sets obtained, generating the corresponding strong association rule, which must satisfy the minimum support (Cheng 2006).

Taking the typical Apriori analysis method as an example, which is based on the sequential discovery and loop method. Firstly, discovering the first frequent item set L_1 from the whole data set, and then discover the second frequent item set L_2 from the whole data set with L_1, repeating this process until no more frequent item sets are found out.

The join operation and delete operation are the main two steps of discovering the frequent item set L_k with L_{k-1}. Firstly, the candidate item set C_k can be generated with the join of two item sets of L_{k-1} so as to discover the frequent item set L_k. Supposing l_1 and l_2 are the item sets of L_{k-1}, $l_i[j]$ is the j term of l_i and $l_i[k-2]$ is the second last term of l_i. Supposing the join operation of L_{k-1} is $L_{k-1} \oplus L_{k-1}$, which means the first (k-2) item sets of l_1 and l_2 are similar $(l_1[1]=l_2[1]) \wedge L \wedge (l_1[k\text{-}2]=l_2[k\text{-}2]) \wedge (l_1[k\text{-}1]<l_2[k\text{-}1])$, then l_1 and l_2 of L_{k-1} can be connected, $(l_1[k\text{-}1]<l_2[k\text{-}1])$ can also avoid the duplicate item sets' generated. Secondly, $L_k \subseteq C_k$, while not all the item sets of C_k are the frequent item sets. To reduce the workload of C_k, one property that one infrequent item set (k-1) can not be a subset of frequent item set (k).

With the association analysis of bridge SHM data, the structural lateral distribution performance of different small beams and the deterioration extent of one beam can be reflected to a certain extent.

2.3.3 Time Series Analysis

The bridge SHM data is a typical time series, variating from 00:00 to 24:00 in one day, and keeps repeating one week, one month, and even one year. With the time series analysis method, one model will be set up to predict the structural response, the structural lateral distribution performance and deterioration extent, which can even predict the traffic load with some assumptions of the bridge structure.

Taking the Holt-Winters method as an example, which does not have to store a lot of historical data and usually consists of single exponential smoothing prediction, quadratic exponential smoothing prediction, three exponential smoothing prediction or even higher (Yan et al. 2015). The Holt-Winters method is often used for nonlinear short-term prediction, which only needs the current actual value y_t and the single smoothing exponent value $s_t^{(1)}$, then the simple predictions of the time period T can be realized with a reasonable smoothing coefficient a. The prediction model is shown as follow:

[1] $\hat{y}_{t+T} = a_t + b_t \times T + c_t \times T^2$

In equation (1), $\hat{y}_{t+T}$ is the prediction value of period $(t+T)$; a_t, b_t c_t are the different model parameters, of which $a_t = 3s_t^{(1)} - 3s_t^{(2)} + s_t^{(3)}$, $b_t = \frac{a}{2(1-a)^2} \times \left[(6-5a)s_t^{(1)} - 2(5-4a)s_t^{(2)} + (4-3a)s_t^{(3)}\right]$, $c_t = \frac{a^2}{2(1-a)^2}(s_t^{(1)} - 2s_t^{(2)} + s_t^{(3)})$.

$s_t^{(1)}$, $s_t^{(2)}$, $s_t^{(3)}$ are the single, quadratic, and three smoothing exponent, of which $s_t^{(1)} = a \times y_t + (1-a)s_{t-1}^{(1)}$,

$s_t^{(2)} = a \times s_t^{(1)} + (1-a)s_{t-1}^{(2)}$, $s_t^{(3)} = a \times s_t^{(2)} + (1-a)s_{t-1}^{(3)}$.

3 One Case Study

Taking a simply supported girder bridge as an example, which belongs to the G30 state highway, located in the central part of China and opened to the traffic in 2011. The overall length is 40m and the bridge deck width is 12m. The superstructure consists of five small concrete T-type beams, and the substructure is designed with three-pillar type abutment and double-column type pier. Both the microstrain and displacement sensors are arranged in the mid-span cross-section of different beams (Figure 3, Figure 4).

Selecting part of the SHM data as the analysis object, preprocessing and excluding the data according to the value of load test and design. Supposing the traffic load is still in normal range and consistency, and then analyze the structural response distribution, the lateral distribution performance, and deterioration extent.

Figure 3: The lateral diagram of the bridge

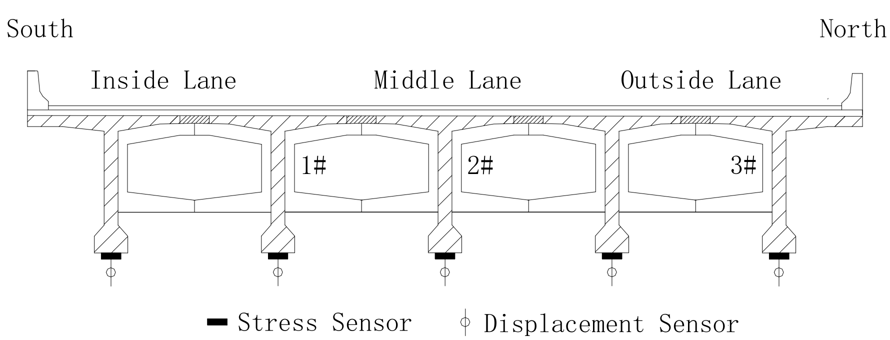

Figure 4: The cross section and measurement point diagram of the bridge

3.1 Distribution Analysis of Structural Response

Taking the SHM data of beam 1, beam 2, and beam 3 in one day as an example. The microstrain of beam 1, beam 2, and beam 3 respectively follow the trimodal distribution, bimodal distribution, and unimodal distribution. Their different distribution function expressions can also be fitted and shown in equation [2]-[4]. The microstrain distribution diagram of different beams is shown in Figure 5 (the imaginary line represents the mixing of the unimodal or multimodal normal distribution), and the microstrain of different beams over different hours can also be shown in Figure 6.

[2] $$F^{beam1}(x) = 0.036\Phi\left(\frac{x-0.900}{0.342}\right) + 0.348\Phi\left(\frac{x-5.163}{2.077}\right) + 0.616\Phi\left(\frac{x-10.401}{2.242}\right)$$

[3] $$F^{beam2}(x) = 0.980\Phi\left(\frac{x-8.445}{2.722}\right) + 0.020\Phi\left(\frac{x-16.924}{1.783}\right)$$

[4] $$F^{beam3}(x) = \Phi\left(\frac{x-15.016}{12.716}\right)$$

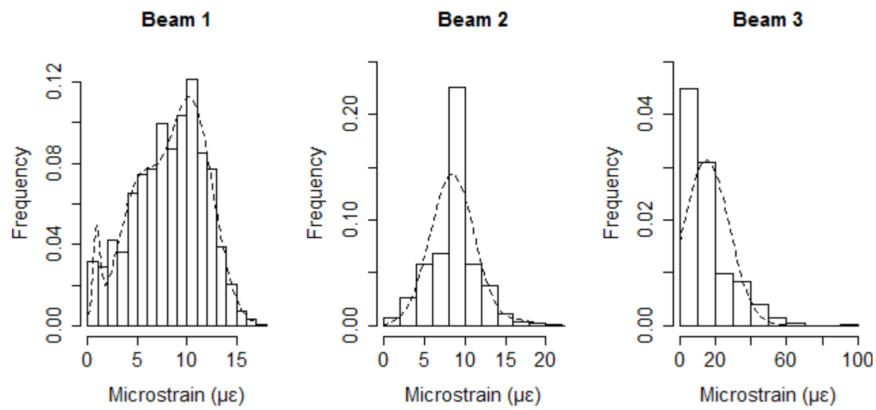

Figure 5: The microstrain distribution diagram of different beams

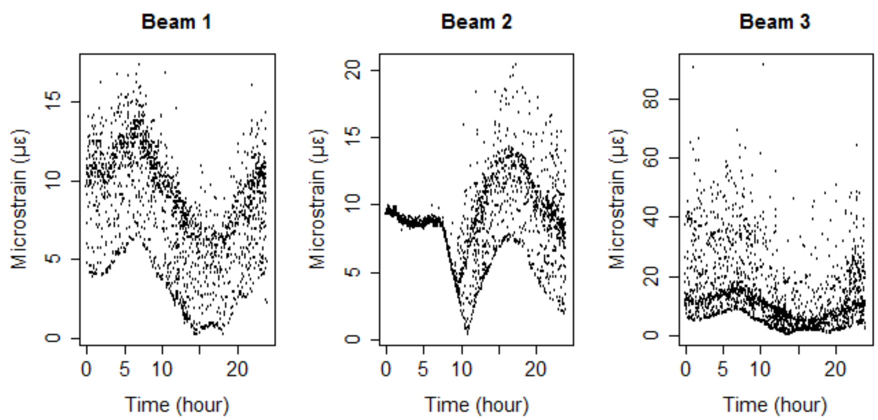

Figure 6: The microstrain of different beams over different hours in one day

According to Figure 5, the microstrain of beam 1, beam 2, and beam 3 respectively follow the trimodal distribution, bimodal distribution, and unimodal distribution. Most of the SHM data is relatively small, some large data may be caused by the individual vehicles or trucks, which have little effect on the overall structural overall safety. The maximum microstrain values of beam 1, beam 2, and beam 3 are 17.3με, 20.4με, and 91.6με respectively, which are also less than the allowable value of the load test and design.

According to Figure 6, the microstrain of beam 1 and beam 3 almost follow the sinusoidal and cosinusoidal fluctuation, while the microstrain of beam 2 is more complex, maybe this is due to the mixed load from beam 1 and beam 3. The microstrain values rise gradually from 0 o'clock, and the crests appear at around 8 o'clock in the morning. Afterward, the microstrain values decline gradually, and the troughs appear at around 18 o'clock in the afternoon. The maximum value of microstrain of beam 1 is almost equal to that of beam 2 and significantly less than that of beam 3.

Therefore, the driver can try to drive from 13 o'clock to 18 o'clock in the afternoon and avoid driving around 8 o'clock and even 24 o'clock. Perhaps some restrictions measures can be implemented around 8 o'clock, especially for beam 3.

3.2 Structural Lateral Distribution Performance and Deterioration Extent Analysis

The microstrain correlation diagram, as well as the deflection and microstrain correlation diagram of different beams, are shown in Figure 7 and Figure 8 (M.b.1, M.b.2, M.b.3 represent the microstrain of beam 1, beam 2, and beam 3).

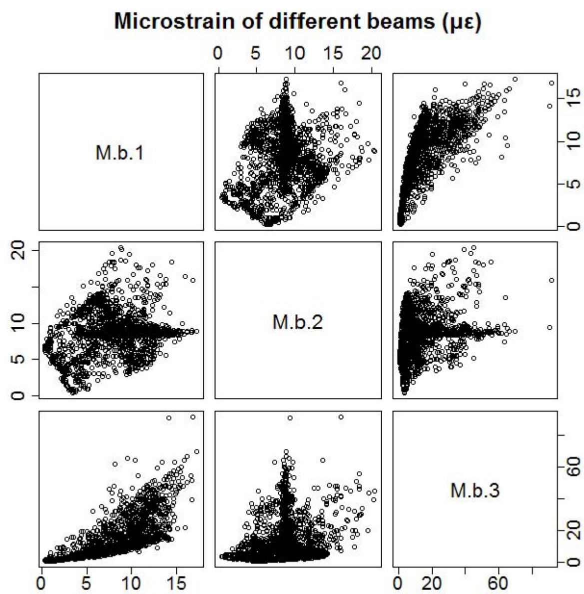

Figure 7: The microstrain correlation diagram of different beams

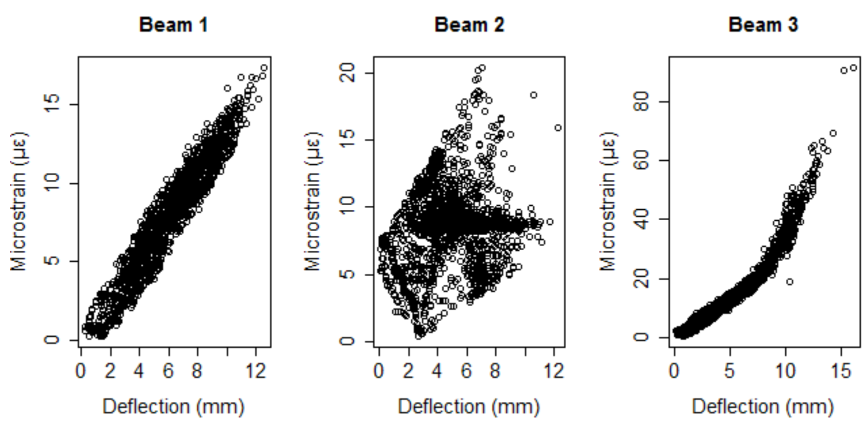

Figure 8: The deflection and microstrain correlation diagram of different beams

According to Figure 7 and Figure 8, the correlation of beam 1 and beam 2 is better than that of beam 2 and beam 3, and the correlation of beam 1 and beam 3 is relatively poor. The deflection and microstrain correlation of different beams are also significant, of which beam 1 has the strongest correlation, the next is beam 2, while beam 3 has a weak correlation.

Thus, to a certain extent, the lateral distribution performance of beam 1 and beam 2 is better than that of beam 2 and beam 3; beam 1 almost still follows the good mapping relationship and shows little deterioration, the next is beam 3, and the worst is beam 2 (maybe this is due to the mixed load from beam 1 and beam 3). As it is known that beam 1 is the inside lane for car driving, while beam 3 is the outside lane for truck driving, and beam 2 is close to beam 1 and beam 3.

Therefore, as a maintenance manager, more attention should be paid on beam 3, perhaps some maintenance and restrictions measures can be implemented when there is a sudden variation of the correlation.

3.3 Structural Response, Lateral Distribution and Deterioration Performance Prediction

3.3.1 Structural Response Prediction

Taking the SHM data of beam 2 as an example. The microstrain diagram of beam 2 from 0 o'clock, and 7 in the morning to 24 o'clock, and 10 in the evening is selected, the period effect, filtering, and forecast of the microstrain of beam 2 is shown in Figure 9 (the credibility is represented by the shaded area).

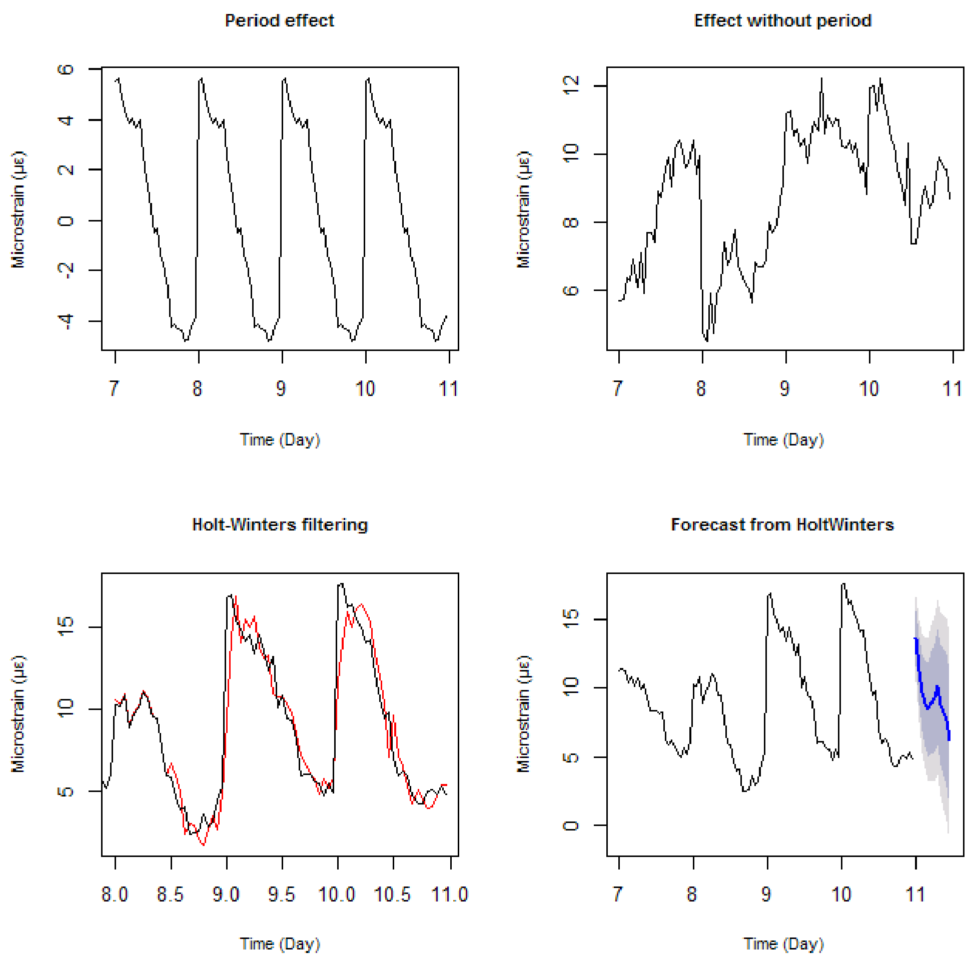

Figure 9: The period effect, filtering, and forecast of microstrain of beam 2 from 7 to 10

According to Figure 9, the microstrain of beam 2 has a significant period variation and less than the random variation. The microstrain has a significant decrease in the afternoon of different days and also has a significant increase in the morning of different days. Perhaps this is due to the different traffic volume of different time periods, which can also be verified by the comparison of period effect and nonperiodic effect of different days. The Holt-Winters filtering method can match the variation tendency to a certain extent, and then the microstrain prediction of 11 can be realized.

3.3.2 Structural Lateral Distribution and Deterioration Performance Prediction

Taking the microstrain correlation of beam 2 and beam 3 as an example, so as to predict the structural lateral distribution performance; taking the deflection and microstrain correlation of beam 3 as another example, so as to predict the structural deterioration extent. Both examples are from 0 o'clock, and 7 in the morning to 24 o'clock, and 10 in the evening, the period effect, filtering, and forecast of the microstrain correlation, as well as the deflection and microstrain correlation, are shown in Figure 10 (the credibility is represented by the shaded area).

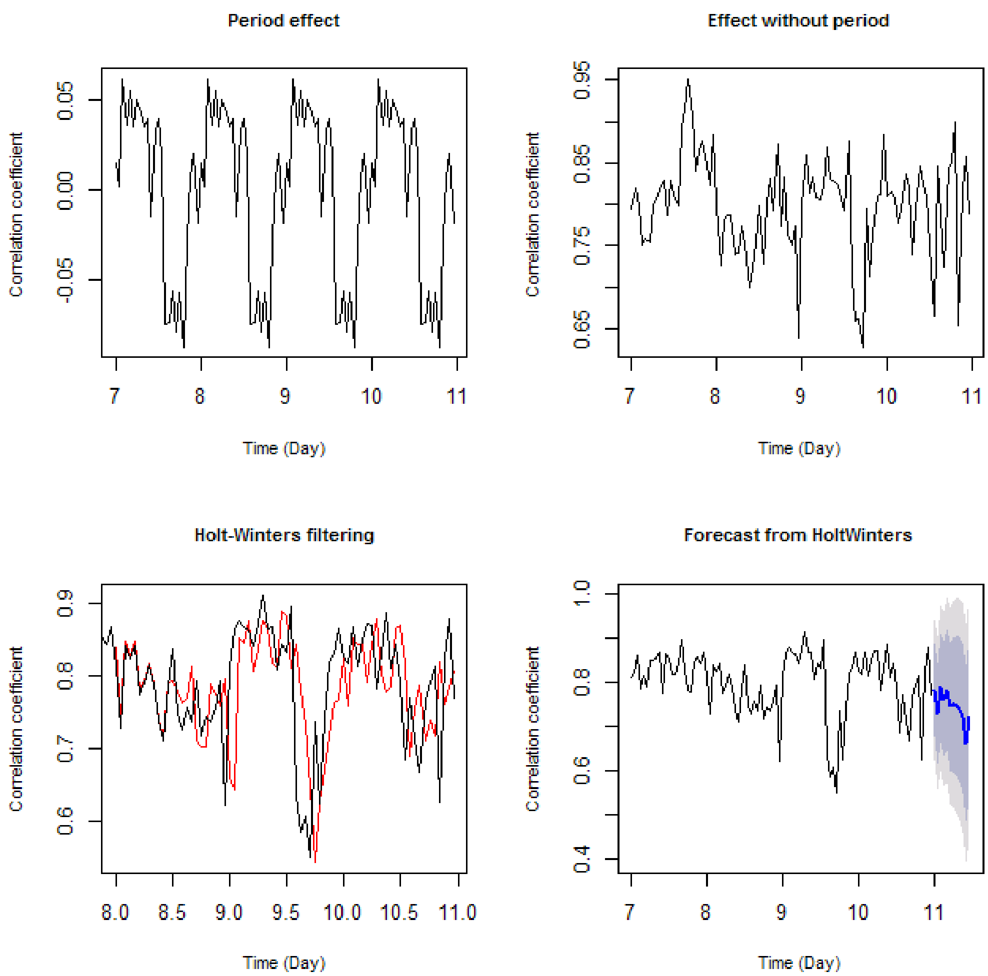

Figure 10: The period effect, filtering, and forecast of microstrain correlation for beam 2 and beam 3

According to Figure 10, the microstrain correlation of beam 2 and beam 3 has a significant period variation, even it is significantly less than the random variation. The microstrain correlation has a significant decrease in the evening of 9, and in the afternoon of 10 and 11, maybe it is due to the different traffic volume of beam 2 and beam 3 in the afternoon, which can also be verified by the comparison of period effect and nonperiodic effect of different days. The Holt-Winters filtering method can track the variation tendency of the microstrain correlation to a certain extent, and then the microstrain correlation prediction of 11 can be realized.

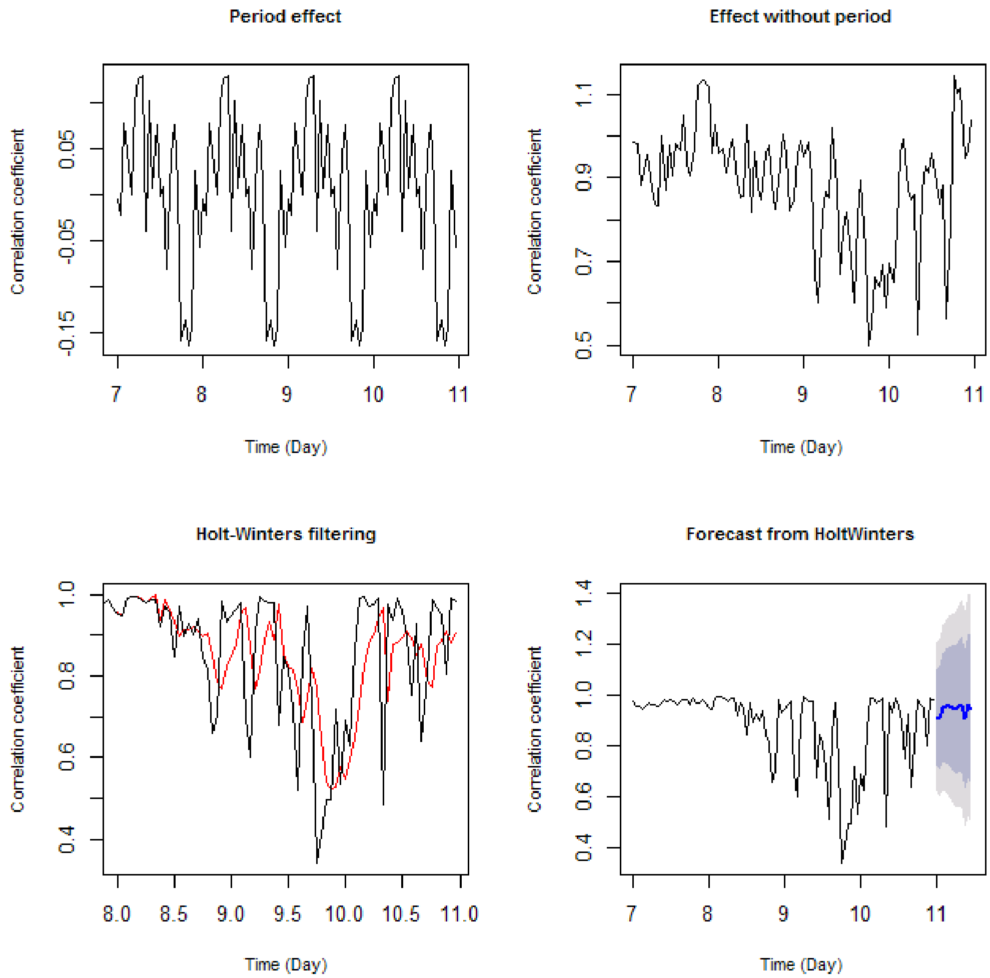

Figure 11: The period effect, filtering, and forecast of deflection and microstrain correlation of beam 3

According to Figure 11, the deflection and microstrain correlation of beam 3 has a significant period variation, which is significantly less than the random variation. The deflection and microstrain correlation has a significant decrease in the afternoon of 9, 10, and 11. Perhaps it is due to the different traffic volume in the afternoon, which can also be verified by the comparison of period effect and nonperiodic effect of different days. The Holt-Winters filtering method can match the variation tendency to a certain extent, and then the deflection and microstrain correlation prediction of 11 can be realized.

4 Conclusion

This study investigates the essential issue of traffic load, bridge structure, and structural response in SHM, a detailed analysis of the bridge SHM data character is also performed. The distribution function, association analysis, and time series analysis methods were selected and verified in one case study. The following conclusions can be drawn:

Structural performance analysis and prediction based on SHM data mining is essentially an inverse problem of structural dynamics. The bridge SHM data can be typically characterized with the mass data, the variation with the traffic load and time effect, the variation with the measurement position, and the variation with the measurement physical attribute, of which the second one can be analyzed by the distribution function method, the third one and the fourth one can be reflected to a certain extent by the association analysis.

The case study bridge still has good overall service performance. The driver can try to drive from 13 o'clock to 18 o'clock in the afternoon and avoid driving around 8 o'clock and even 24 o’clock. Perhaps some restrictions measures can be implemented around 8 o'clock, and more attention should be paid on the outside lane. With the consideration of Holt-Winters method in time series analysis, the prediction of the structural response, the lateral distribution performance, and the deterioration extent can be realized to a certain extent.

Acknowledgements

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