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Structural health monitoring data reconstruction of a concrete cable-stayed bridge based on wavelet multi-resolution analysis and support vector machine

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Abstract. The accuracy and integrity of stress data acquired by bridge heath monitoring system is of significant importance for bridge safety assessment. However, the missing and abnormal data are inevitably existed in a realistic monitoring system. This paper presents a data reconstruction approach for bridge heath monitoring based on the wavelet multi-resolution analysis and support vector machine (SVM). The proposed method has been applied for data imputation based on the recorded data by the structural health monitoring (SHM) system instrumented on a prestressed concrete cable-stayed bridge. The effectiveness and accuracy of the proposed wavelet-based SVM prediction method is examined by comparing with the traditional autoregression moving average (ARMA) method and SVM prediction method without wavelet multi-resolution analysis in accordance with the prediction errors. The data reconstruction analysis based on 5-day and 1-day continuous stress history data with obvious preternatural signals is performed to examine the effect of sample size on the accuracy of data reconstruction. The results indicate that the proposed data reconstruction approach based on wavelet multi-resolution analysis and SVM is an effective tool for missing data imputation or preternatural signal replacement, which can serve as a solid foundation for the purpose of accurately evaluating the safety of bridge structures.

Keywords: structural health monitoring; data reconstruction; wavelet multi-resolution analysis; support vector machine

1. Introduction

As the key components of transportation systems, bridges play a vital role in the social and economic developments. However, they are always exposed to harsh environments and suffered from complex external loadings (e.g., highway traffic, railway traffic, wind, wave, earthquake, ship collision, etc.). This will induce the structural elements of bridges to be damaged and cause their mechanical performances to be degraded. As a result, structural failures or catastrophic accidents may happen when structural damage reaches a critical state. To assure the safety of bridge structures, long-term continuous monitoring of environmental factors and operational loadings is essential to promptly grasp the realistic structural conditions and to proactively formulate the early-warning strategies.

Recently, long-term structural health monitoring (SHM) of bridges has been one of the major attentions for researchers and engineers in civil, mechanical, material, and computer science fields (Ye *et al.* 2012, Ye *et al.* 2013, Yi *et al.* 2013a, b, Li *et al.* 2014, Ye *et al.* 2014, Li *et al.* 2015, Ye *et al.* 2015, Yi *et al.* 2015, Ye *et al.* 2016a, b, c, d). Design and implementation of such a system is an integration of the instrumentation and information technologies with the knowledge and experience of bridge design, construction, management, assessment and maintenance. An on-line SHM system is able to provide reliable information pertaining to the integrity, durability and reliability of bridges. The information can then be incorporated into bridge maintenance and management system for optimizing the maintenance actions and improving the design standards, specifications, codes and guidelines.

It has been a hot research issue to assess safety condition of bridges based on massive long-term and real-time monitoring data, while the prerequisite for fulfilling this task is that the monitoring data are complete and precise enough to represent the real condition characteristics of the bridge (Chen 2007). In other words, the accuracy and integrity of different types of data acquired from the bridge heath monitoring system is of significant importance for bridge safety assessment. However, a bridge health monitoring system under long-term harsh environment tends to include a large number of missing data or obvious preternatural signals due to aging, damage and replacement of sensors and monitoring instruments. In some cases, these missing data will easily lead to false alarming because the data are very similar to those when the bridge is in danger. Therefore, it is of great importance to find an effective data reconstruction approach for bridge heath monitoring system.

The most simple and practical missing data process approach for bridge health monitoring system is an

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elimination method, but it is well known that the elimination method will inevitably eliminate some valid data. Researchers also have proposed several alternative data imputation methods such as single imputation, multiple imputation, liner regression-based data reconstruction method (Thissen *et al*. 2003, Soares *et al*. 2004, Wu *et al*. 2004, Wu *et al*. 2008), while these methods have been proven to be relative impractical in some cases. As the rapid development of machine learning, more attentions have been paid to neural networks-based data reconstruction method due to the powerful computation capacity via advanced computers. However, it is reported by researchers that this method has some inherent drawbacks such as slow learning speed, difficulty in model structure selection, over-fitting and under-fitting (Dong *et al*. 2005, Fan *et al*. 2016). To solve this problem, some investigators have proposed a data forecasting method by use of support vector machine (SVM) because of its unique characteristic of small sample and nonlinear, which has been applied to missing data prediction in several areas (Song *et al*. 2002, Smola and Scholkopf 2004, Lin *et al*. 2006, Chen 2007, Lu *et al*. 2009, Qiu and Lane, 2009, Salcedo-Sanz *et al*. 2011, Kazem *et al*. 2013, Zhang *et al*. 2013, Chen and Yu 2014, Cheng *et al*. 2017). For the data prediction of bridge health monitoring system, the properties of the monitoring data should be taken into account. For instance, the stress time histories acquired from bridge heath monitoring system usually have a periodic variation characteristic with a period of one day. These multi-component stress time histories are composed by low-frequency signals and high-frequency signals which may be caused by different kinds of factors. Therefore, it is necessary to find an effective solution in data imputation of bridge health monitoring system by considering the characteristic of each data component.

This paper presents a data reconstruction approach for bridge heath monitoring system based on wavelet multi-resolution analysis and SVM. The proposed method has been applied to reconstruct the abnormal data recorded by the SHM system instrumented on a prestressed concrete cable-stayed bridge. The accuracy of the proposed method is first examined by comparing the predicted data with the raw data in accordance with prediction errors. Then, the continuous stress data with obvious preternatural signals are divided into two parts (temperature-induced stresses and traffic-induced stresses) according to wavelet multi-resolution analysis. The preternatural signals are replaced by the predicted values obtained by SVM regression prediction models. Finally, the reconstructed temperature-induced stresses and traffic-induced stresses are combined into an entire stress history. The results indicate that the proposed data reconstruction approach for bridge heath monitoring system based on wavelet multi-resolution analysis and SVM is an effective tool in missing data imputation or preternatural signal replacement. The data reconstruction approach can serve as a solid foundation for the purpose of accurately evaluating the structural safety of bridges.

2. Wavelet multi-resolution analysis and support vector machine

2.1 Wavelet multi-resolution analysis

In a bridge health monitoring system, the recorded structural responses are caused by multiple external excitation sources. For instance, the in-service strain monitoring data acquired from the sensors deployed on key structural components are mainly induced from three effects: highway and/or railway traffic, wind and temperature. Strain components due to different effects play different roles in shaping strain quantities. There are trend ingredients (low-frequency components) in all the strain time histories which can be attributed to be the daily cycle effect of temperature variation (Ni *et al*. 2012). Under the temperature effect, the bridge girder mainly behaves by expanding or contracting along the longitudinal direction. In contrast, under highway/railway traffic load, the bridge deck undergoes flexural bending. These two types of distinct responses are mixed in the strain monitoring data. This mixture phenomenon implies that one of the effects may be contaminated or distorted by the others. It is desirable to characterize them separately when each effect on the structural behavior is required to be quantified. The extraction of a specific effect is not easy when the measured signals are non-stationary and non-Gaussian in nature. In this connection, a wavelet-based nonparametric approach is proposed to decompose the strain ingredients by multi-resolution analysis.

Transform-domain processing of a signal involves mapping it from the signal space to the transform space using a set of basis functions. For a wavelet transform, a particular function is chosen as the mother wavelet and a family of daughter wavelets is defined by scaling and shifting, serving as a complete set of basis functions. In wavelet-based multi-resolution analysis, the same function can be adopted and repeated with different scale and shift parameters. Multi-resolution analysis is a process of choosing a set of basis functions originated from the same mother wavelet. From a practical point of view, wavelet multi-resolution analysis allows a decomposition of the signal into various resolution scales: the data with coarse resolution contain the information about low-frequency components, and the data with fine resolution contain the information about high-frequency components (Ni *et al*. 2012).

Using a selected mother wavelet function, $\Psi(t)$, the continuous wavelet transform of a signal is defined as

$$W_\Psi f(a,b)=\left\langle f,\Psi_{a,b}\right\rangle=\frac{1}{|a|^{1/2}}\int_{-\infty}^{\infty} f(t)\overline{\Psi}\left(\frac{t-b}{a}\right)dt,\quad a>0 \tag{1}$$

where $\Psi(t)$ is the mother wavelet, a is a scale parameter, and b is a time parameter. The overbar represents complex conjugation. It is known that the function $f(t)$ can be reconstructed from $W_\Psi f(a,b)$ by the double-integral representation as represented by

$$f(t)=\frac{1}{C_\Psi}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} W_\Psi f(a,b)\Psi\left(\frac{t-b}{a}\right)\frac{1}{a^2}dadb \tag{2}$$

In practical signal processing, a discrete version of the wavelet transform is often employed by discretizing the scale parameter, a and the time parameter, b. In general, the procedure becomes much more efficient if dyadic values of a and b are used. That is

$$a = 2^j, b = 2^j k, \; j, k \in Z \tag{3}$$

where Z is a set of positive integers. With some special choices of $\Psi(t)$, the corresponding discretized wavelets, $\{\Psi_{j,k}\}$ are expressed by

$$\Psi_{j,k}(t) = 2^{j/2}\Psi\left(2^j t - k\right) \tag{4}$$

It constitutes an orthonormal basis. With this orthonormal basis, the wavelet expansion of a function $f(t)$ can be obtained as

$$f(t) = \sum_j \sum_k \alpha_{j,k} \Psi_{j,k}(t) \tag{5}$$

where

$$\alpha_{j,k} = \int_{-\infty}^{\infty} f(t) \Psi_{j,k} dt \tag{6}$$

In the discrete wavelet analysis, a signal can be represented by its approximations and details. The detail at level j is defined as

$$D_j = \sum_{k \in Z} \alpha_{j,k} \Psi_{j,k}(t) \tag{7}$$

and the approximation at level J is defined as

$$A_J = \sum_{j > J} D_j \tag{8}$$

It follows that

$$f(t) = A_J + \sum_{j \le J} D_j \tag{9}$$

Eq. (9) provides a tree-structure decomposition of a signal and a reconstruction procedure as well. By selecting different dyadic scales, a signal can be broken down into numerous low-resolution components.

2.2 Support vector machine

Based on the SVM theory, a support vector regression is to approximate the given observations in an m-dimensional space by a linear function in another feature space (Collobert and Bengio 2001, Clarke *et al*. 2005, Sapankvych and Sankar 2009). Firstly, SVMs estimate the regression using a set of linear functions defined in a high dimensional space. Secondly, SVMs carry out the regression estimation by risk minimization where the risk is measured using Vapnik's ε-insensitive loss function (Drucher *et al*. 1997). Thirdly, SVMs use a risk function consisting of the empirical error and a regularization term which is derived from the structural risk minimization principle. Given a set of data points $G=\{(x_i, d_i)\}^n{}_i$. x_i is the input vector, d_i is the desired value, and n is the total number of data patterns, SVMs approximate the function by

$$y = f(x) = \sum_{i=1}^{D} w_i \phi_i(x) + b \tag{10}$$

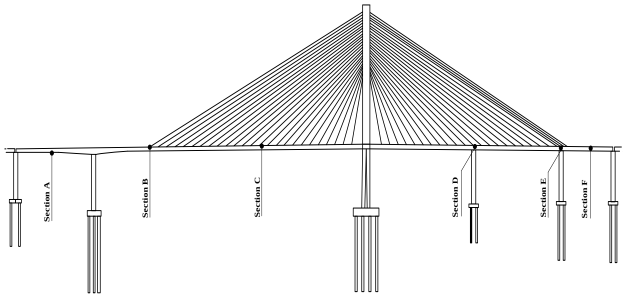


Fig. 1 Deployment sections of FBG-based strain sensors

where $\{\phi_i(x)\}$ is called features, b and $\{w_i\}$ are the coefficients to be estimated from the data. Thus, a nonlinear regression in the low dimensional input space is transferred to a linear regression in a high dimensional (feature) space. The coefficients $\{w_i\}$ can be determined from the data by minimizing the function

$$R[w] = \frac{1}{N} \sum_{i=1}^{N} \left| f(x_i) - y_i \right|_{\varepsilon} + \lambda \| w \|^2 \tag{11}$$

where λ is a regularization constant and the cost function is defined as

$$\left| f(x_i) - y_i \right|_{\varepsilon} = \begin{cases} \left| f(x) - y \right| - \varepsilon & \text{for} \left| f(x_i) - y_i \right| \ge \varepsilon \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

which is called Vapnik's ε-insensitive loss function. It is shown that the minimizing function has the following form

$$f(x, \alpha, \alpha^*) = \sum_{i=1}^{N} (\alpha_i - \alpha_i^*) k(x_i, x) + b \tag{13}$$

With $\alpha_i \alpha_i^*=0$, $\alpha_i, \alpha_i^* \ge 0$ $i=1,\ldots,N$ and the kernel function $k(x_i, x)$ describes the inner product in the D-dimensional feature space.

$$k(x, y) = \sum_{j=1}^{D} \phi_j(x) \phi_j(y) \tag{14}$$

It is important to note that the features ϕ_j need not be computed; rather what is needed is the kernel function that is very simple and has a known analytical form (Shin *et al*. 2005). The only condition required is that the kernel function has to satisfy Mercer's condition. Some of the mostly used kernels include polynomial, Gaussian and sigmoidal. Note also that for Vapnik's ε-insensitive loss function, the Lagrange multipliers are sparse, i.e., they result in nonzero values after the optimization only if they are on the boundary, which means that they satisfy the Karush-Kuhn-Tucker conditions. The coefficients are obtained by maximizing the following form

$$\begin{aligned} \mathrm{R}(\alpha^*, \alpha) = & -\varepsilon \sum_{i=1}^{N} (\alpha_i^* + \alpha_i) + \sum y_i (\alpha_i^* - \alpha_i) \\ & - \frac{1}{2} \sum_{i,j=1}^{N} (\alpha_i^* + \alpha_i) \times (\alpha_i^* - \alpha_i) k(x_i, x_j) \end{aligned} \tag{15}$$

subject to

$$\alpha_{j,k} = \int_{-\infty}^{\infty} f(t)\Psi_{j,k}dt \tag{16}$$

Only a number of coefficients α_i, α_i^*will be different from zero, and the data points associated to them are called support vectors (Muller *et al.* 1999, Dibike *et al*. 2001, das Chagas Moura *et al*. 2011, De Brabanter *et al*. 2011).

Parameters C and ε are free and have to be decided by the user. Computing b requires a more direct use of the Karush-Kuhn-Tucker conditions that lead to the quadratic programming problems stated above. The key idea is to pick those values α_k, α_k^* for a point x_k on the margin, i.e., α_k or α_k^* in the open interval (0, C). One x_k would be sufficient but for stability purposes it is recommended that one take the average over all points on the margin.

3. Data reconstruction of a concrete cable-stayed bridge

3.1 Introduction of investigated concrete cable-stayed bridge

In the past two decades, China has experienced splendid developments in the area of prestressed concrete cable-stayed bridges. Great achievements have been made in terms of design levels and construction technologies. More than 50 prestressed concrete cable-stayed bridges with main span exceeding 200 m have been built in different regions. In this study, the investigated bridge consists of main bridge, eastern approach bridge, western approach bridge, mountain tunnel, traffic safety facilities and other ancillary works, of which the main bridge is a double-cable-plane, prestressed concrete and single-tower cable-stayed bridge. The full length is 2482 m and the main span is 258 m. The span arrangement between two mountains is 74.5 m+258 m+102 m+83 m+49.5 m with a total length of 567m. There are 102 stay cables at the upstream and downstream sections with four cable planes at east and west sides. The bridge deck is 29.5 m in width. The designed speed is 60 km/h on the main bridge with six lanes. The navigation clear height of the bridge is 32 m.

After the completion of its construction, the investigated bridge has been instrumented with a long-term SHM system comprising a strain monitoring subsystem. The real-time monitoring data are acquired through fiber Bragg grating (FBG) sensors to measure the structural strain, structural temperature, and cable force. The huge amounts of field monitoring data are collected by data acquisition stations and then transferred to the bridge monitoring center for further analysis. In the monitoring center, the tasks of data storage and analysis are performed by means of specific hardware and software. As one of the most important parameters, the strain data are measured by the FBG sensors deployed on six different sections of the bridge as illustrated in Fig. 1.

3.2 Wavelet-based SVM prediction method

Based on the wavelet multi-resolution analysis and SVM regression approach mentioned in the previous section, a data reconstruction method is proposed in this study as illustrated in Fig. 2. The stress time history data with preternatural signals obtained from the SHM system of the investigated bridge are first divided into two parts (temperature-induced stress time history and live load-induced stress time history) according to the wavelet multi-resolution analysis. The preternatural signals are then replaced by the predicted values derived by the SVM regression model. Finally, the reconstructed temperature-induced stresses and live load-induced stresses are combined into an entire stress time history.

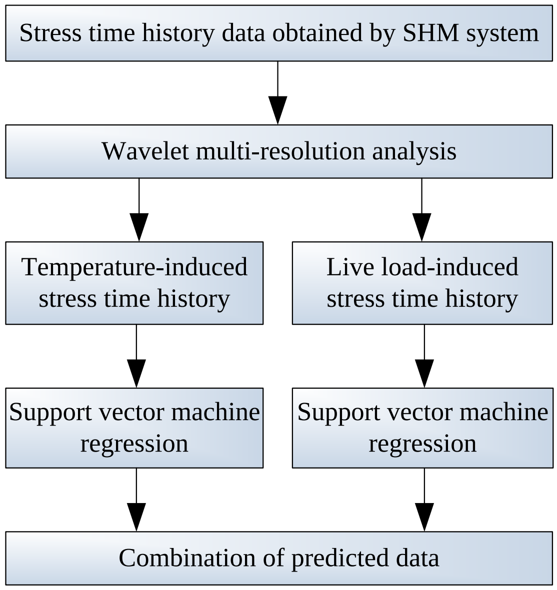


Fig. 2 Flowchart of proposed method

The effectiveness and accuracy of the proposed wavelet-based SVM prediction method is examined by comparing the predicted data with the traditional autoregression moving average (ARMA) method and the SVM prediction method without wavelet multi-resolution analysis in accordance with the prediction errors (Dong *et al*. 2005, Fan *et al*. 2016). The stress data of the investigated bridge from 1 October 2015 to 7 October 2015 are selected to conduct the comparative study and check the results predicted by different prediction methods. Based on the 144 hourly strain data of six days (1 October 2015 to 6 October 2015), the 24 data in one day at each hour is predicted by the ARMA prediction method, SVM regression prediction method, and wavelet-based SVM prediction method, as illustrated in Fig. 3. The prediction error of the wavelet-based SVM prediction method is obviously smaller than those of the ARMA prediction method and SVM regression prediction method, as shown in Fig. 4. Therefore, it can be concluded that the proposed wavelet-based SVM prediction method has a better performance for monitoring data reconstruction.

3.3 Reconstruction of abnormal strain monitoring data

In the analysis process of strain monitoring data of the investigated bridge, a few obvious preternatural signals are found as shown in Fig. 5(a). A complete set of stress data is

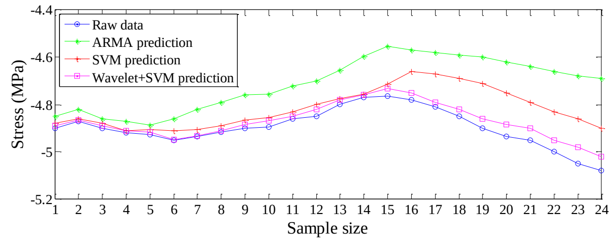


Fig. 3 Comparison of prediction results of three different methods

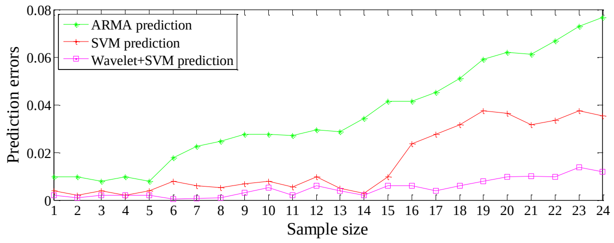
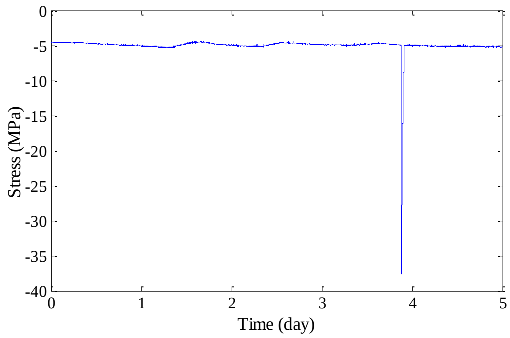
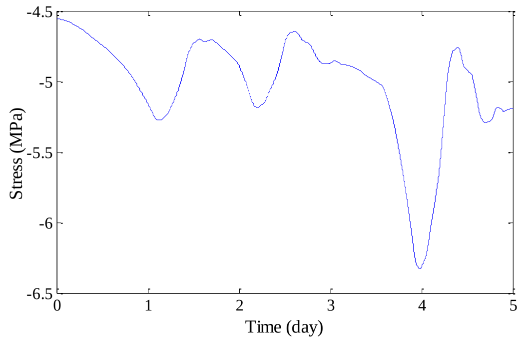


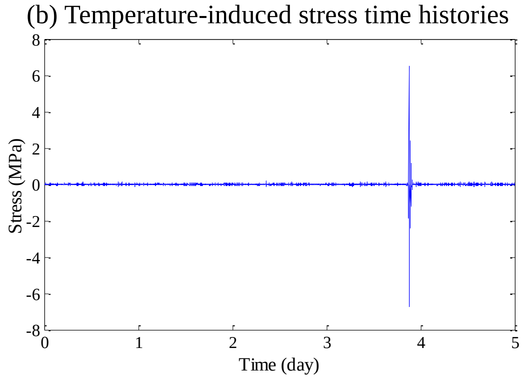
Fig. 4 Comparison of prediction errors of three different methods



(a) 5-day stress time histories

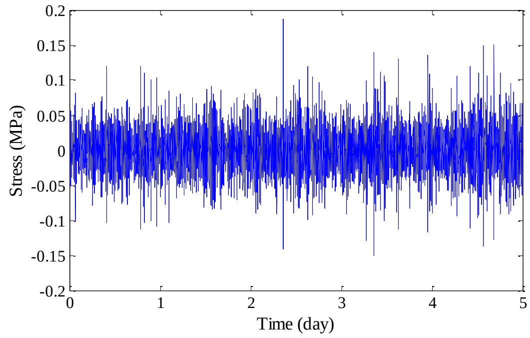


(b) Temperature-induced stress time histories

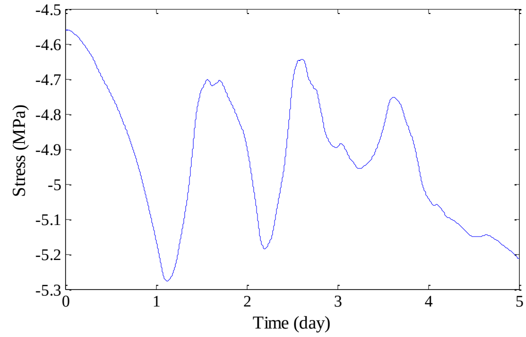


(c) Live load-induced stress time histories

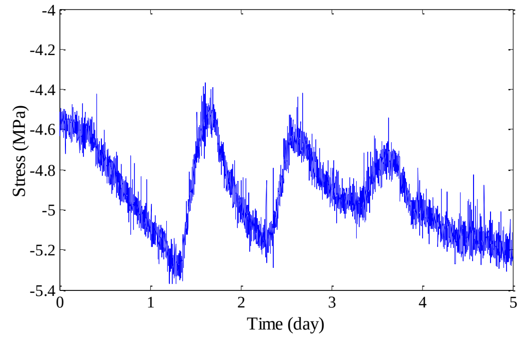
Fig. 5 5-day stress time histories with preternatural signals



(a) Live load-induced stress time histories



(b) Temperature-induced stress time histories

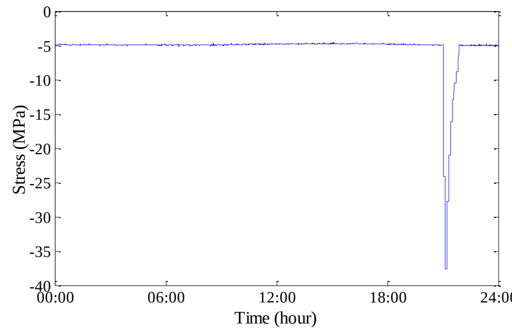


(c) 5-day stress time histories

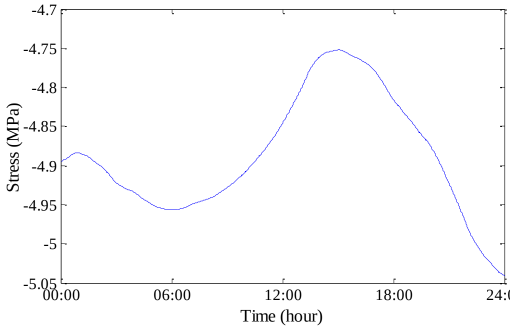
Fig. 6 Data reconstruction based on 5-day stress time histories

of great importance for bridge safety assessment, and thus it is a necessity to carry out the data reconstruction. The wavelet multi-resolution analysis is used to distinguish temperature-induced stresses and live load-induced stresses for SVM-based machine learning because these two parts in a total stress history have their own characteristics. In a wavelet multi-resolution analysis, the measured strain signals are decomposed into two parts including high-frequency and low-frequency components. For each wavelet level, the high-frequency part (details) is separated, and the remaining low-frequency part (approximations) is transferred into the next level of decomposition. Through wavelet-based multi-resolution analyses, the strain component attributable to the temperature effect is obtained from the lowest-frequency part in the wavelet transform domain.

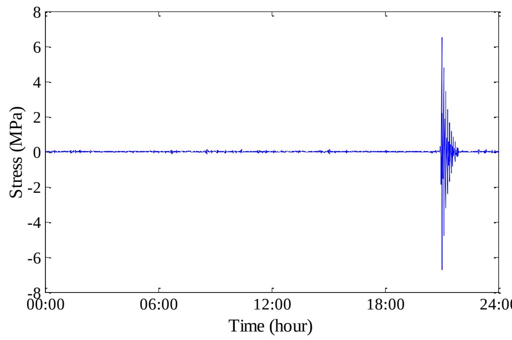
Fig. 5 illustrates the wavelet-based decomposed stress time histories for an FBG-based strain sensor deployed on the investigated bridge. In these stress time histories, the low-frequency parts of 9-level decomposition of stress data



(a) 1-day stress time history

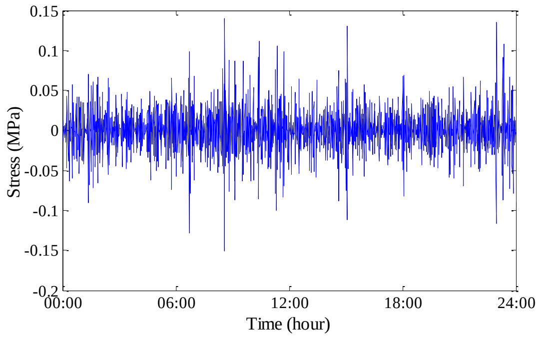


(b) Temperature-induced stress time history

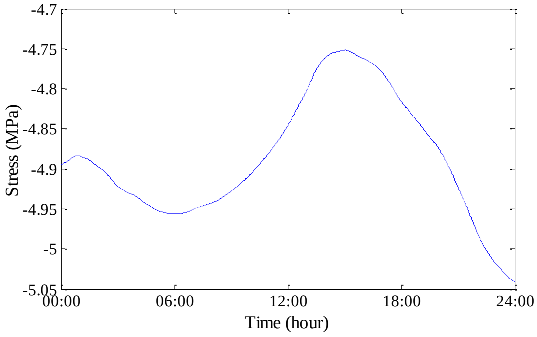


(c) Live load-induced stress time history

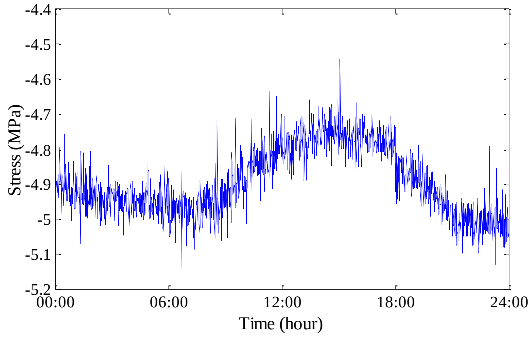
Fig. 7 1-day stress time history with preternatural signals



(a) Live load-induced stress time history



(b) Temperature-induced stress time history



(c) 1-day stress time history

Fig. 8 Data reconstruction based on 1-day stress time history

represent the reconstructed temperature-induced stresses, as illustrated in Fig. 5(b). A comparative analysis between the initial stress and the temperature-induced stress indicates that the temperature-induced stress time history has the same variation tendency and periodic characteristic in one day. The temperature-induced stress takes a major part of the total stress which means that the main stress changes during the bridge operational status are caused by the temperature effect. Also, Fig. 5(c) shows the high-frequency parts of 9-level decomposition of stress data which consist of live load (highway traffic and wind) induced stresses. The purpose of data reconstruction is to replace the abnormal signals with the prediction data. The preternatural signals are eliminated before the prediction analysis of each part. Fig. 6 shows the stress data prediction process by wavelet-based multi-resolution analysis and SVM regression. The stress history is processed by each part (temperature-induced stress and live load-induced stress) and then combined into a complete stress time history.

The data reconstruction of two parts of obvious preternatural signals, as illustrated in Figs. 5(a) and 5(b), is conducted with the aid of SVM. For details, the 5-day stress data are trained and tested with a parameter optimization process, and the regression model is determined by optimal parameters, which is employed to output the predicted data. Then the two parts of imputation data are combined to restore or model a realistic stress history, as shown in Fig. 6(c). All the parameter optimization, regression and prediction process is accomplished by software Matlab2014a with the toolbox Libsvm-3.1 (Chang and Lin 2011).

One of the advantages of SVM data prediction is its accuracy and effectiveness when the sample is relatively small. In this study, in addition to the data prediction results through 5-day data as shown in Fig. 6, the prediction results are obtained by the proposed method to verify the applicability by use of relatively small sample of 1-day data as shown in Figs. 7-8. In each case, as mentioned earlier in this paper, the stress time history with abnormal signals is first divided into two parts, the temperature-induced stress time history and live load-induced stress time history by wavelet-based multi-resolution analysis. Then, the abnormal signals are eliminated for further analysis, and the missing data of each part is predicted based on different time durations by SVM regression. Each parameter of SVM regression model is evaluated by the optimization analysis of grid search method in the Matlab toolbox Libsvm-3.1. Finally, a complete stress time history is obtained by combining the two parts of the stress time history with prediction data. That is, the abnormal signals are replaced by the predicted data. In order to verify the effectiveness of the predicted results obtained by 1-day data, the prediction error is calculated on the basis of results achieved by 5-day data. The prediction error of 1-day is calculated as 0.0533, which means that the prediction results by the proposed method based on 5-day data and 1-day data are almost the same. This is meaningful and significant when the sample of measured data is relatively small to achieve acceptable results for further analysis in case the continuous stress data are required.

4. Conclusions

This paper presents a data reconstruction approach for bridge heath monitoring system based on wavelet multi-resolution analysis and SVM. The proposed method has been applied for data imputation in accordance with the recorded data by the SHM system instrumented on a prestressed concrete cable-stayed bridge. The effectiveness and accuracy of the proposed method is examined by comparing the predicted results with the raw data according to the prediction errors. The continuous stress data with obvious preternatural signals are divided into two parts (temperature-induced stresses and live load-induced stresses) by wavelet-based multi-resolution analysis. The preternatural signals are replaced by the predicted values obtained by SVM regression prediction model. The reconstructed temperature-induced stress and live load-induced stress are combined into an entire stress history.

The obtained results demonstrate that: (i) the prediction error of wavelet-based SVM prediction method is smaller than that obtained by the ARMA prediction method; (ii) the wavelet-based multi-resolution analysis can reduce the prediction error of data reconstruction in combination with SVM regression; and (iii) the predicted results by the proposed method based on 1-day data and 5-day data are almost the same which is meaningful and significant when the sample of measured data is relatively small. The proposed data reconstruction approach for bridge heath monitoring system is an effective tool in missing data imputation or preternatural signal replacement, and can serve as a solid foundation for the purpose of accurately evaluating the structural safety of bridges.

Acknowledgments

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