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Correlating modal properties with temperature using long-term monitoring data and support vector machine technique

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Abstract

For reliable performance of vibration-based damage detection algorithms, it is of paramount importance to distinguish between abnormal changes in modal parameters caused by structural damage and normal changes due to environmental fluctuations. This paper addresses the modeling of temperature effects on modal frequencies for the cable-stayed Ting Kau Bridge (Hong Kong), which has been instrumented with a long-term structural health monitoring system. Based on one-year measurement data obtained from 45 accelerometers and 83 temperature sensors permanently installed on the bridge, modal frequencies of the first ten modes and temperatures at different locations of the bridge are obtained at one-hour intervals. Then the support vector machine (SVM) technique is applied to formulate regression models which quantify the effect of temperature on modal frequencies. In order to achieve a trade-off between simulation performance and generalization, the measurement data is separated into two subsets for the model development: one for training the models, and the other for validating the models. A squared correlation coefficient is defined for optimizing the SVM coefficients to obtain good generalization performance. The results obtained by the SVM models are compared with those produced by a multivariate linear regression model, and show that the SVM models exhibit good capabilities for mapping between the temperature and modal frequencies.

Keywords: Cable-stayed bridge; Long-term monitoring; Modal variability; Temperature effect; Correlation analysis; Support vector machine (SVM)

1. Introduction

Instrumentation-based monitoring has become an increasingly accepted technology in the civil engineering community, for diagnosing structural health and condition. In the past decades, a variety of structural health monitoring methods based on measurement data has been developed for the detection of damage, and among them, vibration-based damage identification methods have been most widely studied [1,2]. Vibration-based damage identification methods use measured changes in dynamic parameters (mainly modal parameters) to evaluate changes in physical properties that may indicate structural damage or degradation. In reality, however, civil engineering structures are subject to varying environmental and operational conditions such as traffic, wind, humidity, solar-radiation and, most importantly, temperature. These environmental effects also cause changes in modal parameters which may mask the changes caused by structural damage. For reliable performance of damage detection algorithms, it is of paramount importance to distinguish between abnormal changes in dynamic parameters resulting from structural damage and normal changes due to environmental fluctuations, so that neither the normal changes will raise a false-positive alarm nor the abnormal changes a false-negative alarm in structural health monitoring [3–7].

Considerable research efforts have been devoted to investigating the influence of environmental conditions on modal frequencies of bridges via field measurements and dynamic tests [8–16]. Most of these investigations have indicated that temperature is the most significant environmental effect affecting bridge modal properties. Roberts and Pearson [8] made a series of field measurements for a nine-span box girder bridge over a twelve-month

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period, aimed at understanding and hence isolating temperature effects on modal frequencies. Abdel Wahab and De Roeck [9] conducted dynamic tests for a prestressed concrete bridge in spring and in winter, and observed a change of 4% to 5% in the natural frequencies. Farrar et al. [10] and Cornwell et al. [11] studied the variability of modal properties of the Alamosa Canyon Bridge caused by different environmental factors. Based on the measurement data from the Alamosa Canyon Bridge, Sohn et al. [12] subsequently proposed a linear adaptive model (multiple linear regression model) to discriminate the changes of modal frequencies due to temperature from those caused by structural damage or other environmental effects. Alampalli [13] conducted several tests over nine months on a steel-stringer bridge with a concrete deck, to examine the sensitivity of measured modal parameters to variations resulting from test and in-service environmental conditions. Lloyd et al. [14] presented the correlation of modal frequencies with temperature variations during a seven-month period of observation for a prestressed segmental concrete bridge, and documented the temperature sensitivities for the first four vertical modes. Rohrmann et al. [15] studied the thermal effect on modal frequencies of an eight-span prestressed concrete bridge by using three-year continuous monitoring data in an attempt to establish functional proportionality between the temperature variations and changing natural frequencies. Peeters and De Roeck [16] reported one-year monitoring of a four-span post-tensioned concrete box girder bridge and developed an ARX model to distinguish normal modal frequency changes due to environmental effects from abnormal changes due to damage. All the reported studies were conducted on general highway bridges, and investigation of long-span cable-supported bridges is still lacking.

The support vector machine (SVM) is a newly emerging technique for learning relationships in data within the framework of statistical learning theory [17,18]. The basic idea of SVM is to transform the data to a higher dimensional feature space and find the optimal hyperplane in the space that maximizes the margin between the classes [19]. As opposed to the empirical risk minimization (ERM) principle that is commonly employed in statistical machine learning methods such as artificial neural networks, SVM follows the structural risk minimization (SRM) principle which equips SVM with a greater potential to generalize the input–output relation and predict the unseen data more accurately. SVM has recently been applied to engineering problems concerning pattern recognition, regression estimation and inverse solution of dynamic systems. Schölkopf et al. [20] and Hayton et al. [21] explored the SVM-based novelty detection and its application to jet engine diagnosis. Worden and Lane [22] conducted vibration-based damage identification of ball bearings and a truss structure using SVM. Mita and Hagiwara [23] proposed a method using SVM and the measured modal frequency change to detect local damage of shear-type building structures. Ge et al. [24] presented an approach for fault diagnosis in sheet metal stamping process by means of SVM. In recognizing that SVM is in reality a universal estimator, we explore the SVM technique in this paper for the modeling of correlation between modal frequencies and temperature for the cable-stayed Ting Kau Bridge based on long-term monitoring data. Making use of one-year acceleration and temperature measurement data from a long-term monitoring system installed on the bridge, modal frequencies are identified at one-hour intervals and correlation with the corresponding temperatures is obtained which covers a full cycle of varying environmental and operating conditions. The SVM technique is then applied to formulate regression models describing the temperature–frequency relationship. In the formulation, all the measurement data are alternately selected to form two subsets: one subset is used to train the models while the other is employed to optimize the SVM coefficients for good generalization performance.

2. SVM for statistical learning

SVM provides a new statistical learning algorithm which employs the SRM principle rather than the commonly used ERM principle [17]. Consider a set of training data $S = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \ldots, (\mathbf{x}_n, y_n)\}$ where $\mathbf{x}_i \in R^P$ is a P-dimensional vector of input variables (attributes) and $y_i \in R$ is the corresponding scalar output (target). The objective is to find a regression function, $y = f(\mathbf{x})$, such that it minimizes the error of predicting new data set S_n, which is derived from the same joint probability distribution $P(\mathbf{x}, y)$ as the training data set. To fulfill the stated goal, SVM considers the following linear estimation function:

$$f(x) = \langle \mathbf{w}, \mathbf{x} \rangle + b \tag{1}$$

where $\mathbf{w}$ and b are weight factors to be adjusted to obtain the best fit, and $\langle *, * \rangle$ denotes the inner product. As opposed to the ERM principle which minimizes the error on the training data set, $R_{\mathrm{emp}}(f)$, the SRM principle which minimizes an upper bound on the generalization error, $R(f)$, is adopted in SVM to avoid over-fitting and thereby improve generalization performance. The relationship between the structural risk $R(f)$ which guarantees good classification on the training data while maximizing the margin, and the empirical risk $R_{\mathrm{emp}}(f)$ can be expressed as [19]

$$\begin{aligned} R(f) &\le R_{\mathrm{emp}}(f) + \lambda \|\mathbf{w}\|^2 \\ &= \frac{1}{n} \sum_{i=1}^{n} L(f(\mathbf{x}_i) - y_i) + \lambda \|\mathbf{w}\|^2 \end{aligned} \tag{2}$$

where λ is a regularization constant; $\|\mathbf{w}\|^2 = \langle \mathbf{w}, \mathbf{w} \rangle$ is the Euclidean norm; and $L(f(\mathbf{x}_i) - y_i)$ is some kind of loss function measuring the empirical risk of the training data. There are various kinds of loss functions with respect to different noise conditions, such as Huber's robust loss, polynomial, ε-insensitive, and Gaussian [25]. The