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Normalization of Environmental Effects in Modal Parameter Tracking

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Abstract. Natural frequencies are appropriate damage-sensitive features to detect structural changes in cables and prestressing tendons as well as in the support displacements of large engineering structures, such as bridges. However, environmental changes often cause variations in the frequencies that are more pronounced than changes due to small structural damages, making it imperative to apply reliable machine learning approaches for the removal of environmental conditions. This case study sets out to demonstrate that small changes in the structural mass and failing bolts in a 30 m steel-concrete composite, the Munich Test Bridge, can be detected despite large temperature variations. During the 21 day-long measurement campaign, no traffic loads are applied to the bridge but the ambient temperature ranged between -10°C and 20°C . An artificial neural network is applied to remove the effect of ambient temperatures on the measured frequencies in a separate preprocessing step. Ultimately, it is demonstrated that, after the removal of temperature effects, the distribution of natural frequencies can be approximated through a normal distribution, paving the way for more advanced analysis techniques that require features to be normally distributed.

Keywords: Operational modal analysis · Environmental and operational variables · Neural networks · Damage detection

1 Introduction

Automated damage detection is an integral part of every structural health monitoring (SHM) system. The diagnostic analysis chain is typically divided into the following steps: the acquisition of measurement data, the extraction of damage-sensitive features, and the statistical evaluation of the features [6]. The statistical evaluation includes the removal of environmental and operational variabilities (EOVs) from the features, as well as the anomaly detection. Modal parameters are often used as damage-sensitive features, and play an important role in vibration-based analysis of structures [13]. However, they are also sensitive to changes in the support displacements and prestressing forces of large engineering

structures, such as bridges. For such structures, changes in temperature, traffic loads, and wind loads often cause a more significant shift in modal parameters than local structural damages. Therefore, it is imperative to identify the confounding effect and to remove it from the features before diagnosing damages. Various methods exist for such a data normalization and they are commonly categorized based on whether the EOVs need to be measured or not.

Belonging to the class of methods without EOV measurements, the most commonly applied methods are linear principal component analysis (PCA) [14], second-order blind identification (SOBI) [10], and kernel PCA [11]. This group of methods is convenient, because no extra sensors are required to measure the EOVs and remove their effect, but the interpretation of the results and the hyper-parameter tuning can be challenging. On the other hand, the method class using measured EOVs comprises multiple linear regression [4], neural networks [3], support vector machines [8], polynomial chaos expansion [12] and Gaussian Process models [1, 2], to name a few. The most thoroughly studied EOVs in the context of bridge monitoring are temperature, traffic loads, and wind loads. In this article, linear regression and neural networks will be applied.

In Section 2, the employed method for data normalization is revisited. In Section 3, the methods are applied to a bridge case study under large temperature variations and small damages, followed by conclusions in Section 4.

2 Methodology

In this section, linear regression and neural networks are revisited for data normalization. In all studies, natural frequencies f are used and the time history of the ambient temperatures T is the considered EOV. It is supposed that training data $\{(T^j, f_i^j)\}$, $j = 1, \dots, n_d$, is available from n_d datasets in the reference state, which reflects the relation between T and each frequency $i = 1, \dots, n_m$, where n_m is the number of modes. The goal is to learn a model $\tilde{f}_i = g_i(T)$ describing this relationship, such that the error $f_i^j - g_i(T^j)$ (in some norm) is small, and to apply this model to new, incoming data for data normalization.

2.1 Linear Regression

Linear regression assumes that the relationship between the dependent variable f_i and the regressors (depending on T) is linear, in the simplest case

$$f_i^j = \mathbf{a}_i^T T^j + b_i + \varepsilon_i^j, \quad (1)$$

where ε_i^j denotes the error. The coefficients of the function $g_i(T) = \mathbf{a}_i^T T + b_i$ are obtained based on the training data using a least-square optimization. In this work, the linear regression model Matlab function `fitlm` is used.

2.2 Artificial Neural Network

Neural networks aim to establish non-linear relationships between input and output variables, $\tilde{f}_i = g_i(T)$. They contain multiple artificial neurons that are

arranged in layers, i.e. one input layer, multiple hidden layers, and one output layer. To set up a neural network, the available data is typically split into two sets, i.e. the training and test set. The training data contains data from the undamaged structure and is used to adjust the weights. Due care should be applied to make sure that it contains a wide range of environmental and operational variations. In this paper, the Matlab `fitrnet` function of the Machine Learning Toolbox is employed. The considered input variables are the ambient temperatures. To account for the thermal inertia, not only the temperature at the time of measurement of the frequency may be used as inputs, but also additional past temperatures. The output variable is one of the natural frequencies. Typically, the input and output variables are linearly scaled to the interval $[0, 1]$ first. This way, values of larger magnitude are not considered more important and emphasis is put on learning the fluctuation behaviour. For each frequency, a fully connected network is created, generally consisting of 2 layers and 10 neurons per layer. A hyperbolic tangent (\tanh) activation function is used.

To avoid overfitting, a k-fold method is used. To do so, the training data is split into ten subsets first. Then, the training is repeated ten times, while nine out of ten subsets are used for training and the remaining subset is used for validation (in a “leave-one-out” fashion). The resulting outputs are then averaged over all ten runs to obtain a robust network. Finally, the outputs are linearly scaled back to the original domain.

The validation of the optimized model is performed based on testing data from the undamaged structure; its intention is to verify how well the algorithm generalizes if it is confronted with new data it has not seen before. The input EOVs from the testing set are fed into the network, and the output are the ANN-based predictions of the frequency, which are compared to the corresponding measured frequencies for validation.

2.3 Data normalization

The ANN-based predictions can be used for data normalization, i.e., to remove the EOV influence from the measured frequencies. For this, a reference value of the EOV T^{ref} is defined, to which the normalized frequencies will correspond to, and let f_i^{ref} be a mean of the frequencies at T^{ref} from the learning data. Alternatively, $f_i^{\text{ref}} = g_i(T^{\text{ref}})$ can be taken. Then, the normalization of a new measurement (T^*, f_i^*) can be carried out by

$$\check{f}_i^* = \frac{f_i^*}{g_i(T^*)} f_i^{\text{ref}}. \quad (2)$$

3 Application to the Munich Test Bridge

In this section, the linear regression and the ANN is applied to the Munich Test Bridge data for data normalization. First, the models are trained based on data from the undamaged structure and validated on testing data. Then, data from the damaged structure is analyzed with and without data normalization to separate the effects of EOVs and damage on the natural frequencies.

3.1 The Munich Test Bridge

The Munich Test Bridge is a composite bridge with a length of 29.9 m and a width of 4.0 m, see Fig. 1. The bridge is placed at the University of the Bundeswehr Munich and was constructed for academic studies in 2007. The bridge deck is composed of 11 removable concrete plates with a height of 20 cm, a width of 4.00 m, and varying lengths. The concrete segments (C30/37) are placed on two main steel girders (HEB1000) which are connected through seven transverse braces (HEB120) at the lower flange and two transverse beams (HEB240) at the abutment. More information on the experimental setup can be found in the literature [7].

Among other sensors, the bridge is instrumented with 16 acceleration sensors, 8 uni-axial ones and 8 tri-axial ones. Data from the reference state was recorded over 21 days. Afterward, four well-defined damage scenarios with changing damage extent are applied, including the removal of bolts, the removal of braces, extra masses on the concrete deck, and settlements of the center support. In this study, only the extra mass of 400kg as a point load on the deck and bolt failure is examined.

The modal parameters are extracted using operational modal analysis, or more precisely, covariance-driven stochastic subspace-based identification (SSI-Cov) [5]. The dynamic tracking is conducted based on a fully automated algorithm that considers the statistical uncertainty in the estimation of the modal parameters [9]. The tracked modal parameters are shown in Fig. 2.

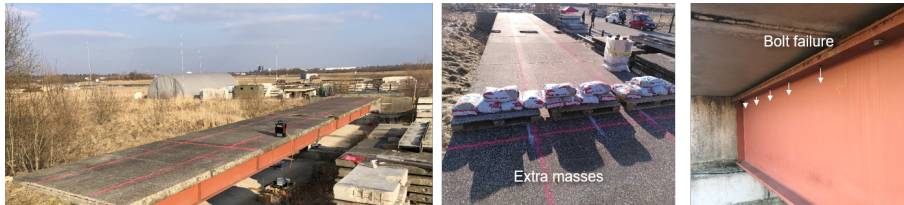


Fig. 1. The Munich Test Bridge: photos of the bridge and analyzed damage scenarios.

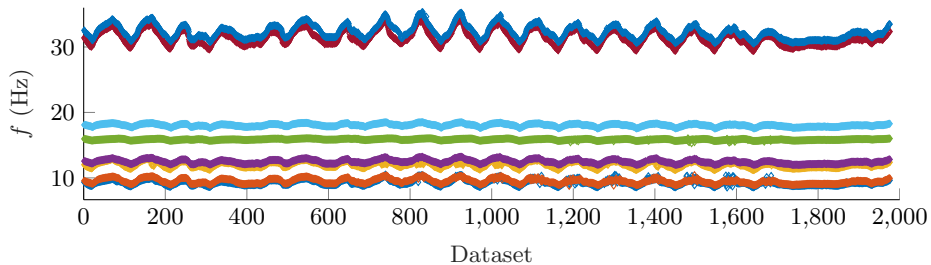


Fig. 2. Tracking the first eight natural frequencies of Munich Test Bridge

3.2 Comparison of Linear Regression and Neural Networks

After determining the parameters of the regression model (1) on the training data, the model is applied to the temperatures of the test data. The outputs (predicted frequencies \tilde{f}) are compared to the actual estimated frequencies f in Fig. 3, showing results for the sixth frequency as an example. The behavior of the other frequencies is similar. Two different cases are considered, namely linear regression without delay between the natural frequencies and the temperature

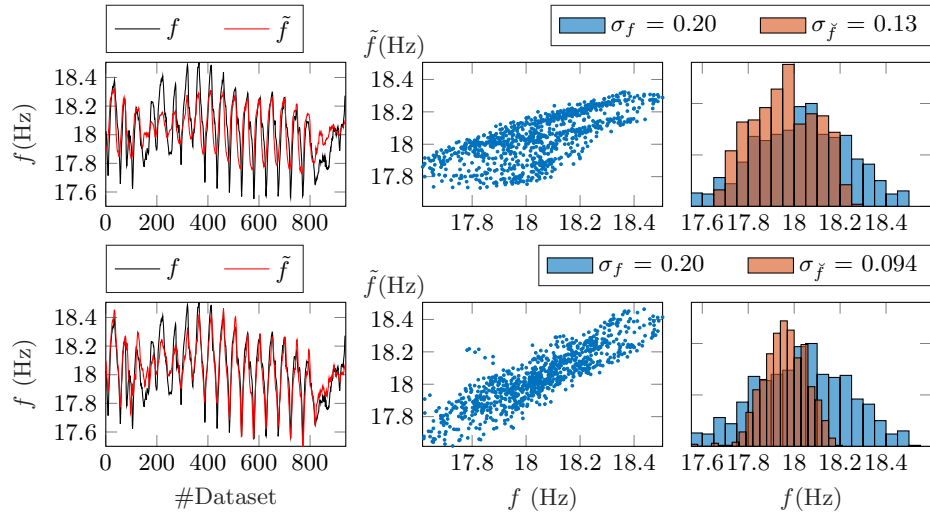


Fig. 3. Top: validation results using linear regression model without any delay between the temperature and the frequencies, bottom: with temperature history until 18 hours. Left: Estimated natural frequencies f from data (black) and predicted frequencies \tilde{f} from regression model (red). Center: frequency estimate f from the data vs the model output \tilde{f} , illustrating the efficiency of the learned model. Right: histogram of estimated frequencies f (blue) and normalized frequencies \tilde{f} (orange).

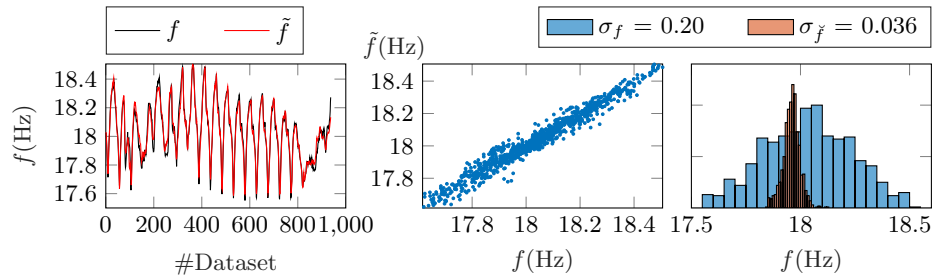


Fig. 4. Validation results using ANN model with temperature history of up to 18 hours; cf. legend of Fig. 3

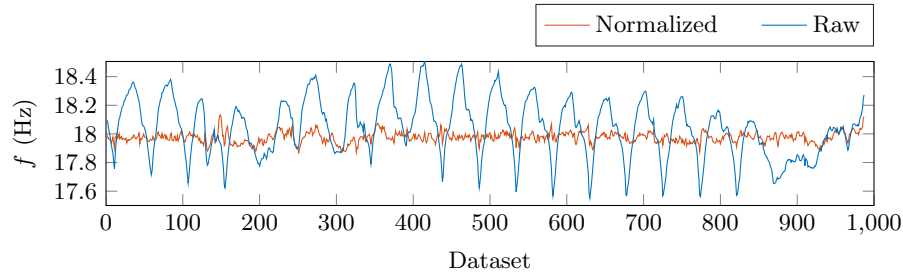


Fig. 5. Sixth natural frequency before and after data normalization.

record (top plots), and with using the whole time history of the temperatures recorded during the last 18 hours (bottom plots). For performance comparison, the left plots show the direct comparison between the predicted and actual frequencies, the center plot shows \tilde{f} vs. f (which should ideally be a diagonal line), and the right plots show the histograms of the actual frequencies f and of the normalized frequencies \tilde{f} from Eq. (2). It can be seen that the consideration of the past temperature data in the bottom plots leads to a better prediction of the frequencies. The standard deviation of the normalized frequencies is reduced by about 50% (right plots) and plotting the measured over the predicted frequencies is closer to a straight line than without considering the temperature history (center plots). The consideration of the thermal inertia is important since ambient temperature and not material temperature is measured. Nonetheless, the linear regression is not able to accurately model the relationship between natural frequencies and ambient temperature in this case, probably due to the non-linear character of the relation. The normal fluctuations due to temperature amount up to over 1% for the sixth frequency, but more than 3% for higher frequencies, and might mask potential damages.

Fig. 4 summarizes the results for the ANN, considering the temperature history. The predicted frequencies match the measured frequency more closely. In contrast to linear regression (cf. Fig. 3), frequency peaks are predicted correctly and the normalized frequencies appear to approximate a normal distribution with a standard deviation before and after normalization that reduces from 0.20 to 0.03, compared to 0.10 for linear regression. Fig. 5 shows the fluctuation of Mode 6 before and after data normalization, where no systematic fluctuation seems to be present after data normalization.

3.3 Analysis of Data from Damage Cases

Data from two damage scenarios is analyzed. Fig. 6 depicts the histograms of the sixth and fifth natural frequencies before data normalization (top) and after (bottom) as examples. The qualitative behavior is similar for the other frequencies, with some minor differences regarding the impact of the damage.

Since EOVs cause a significant scatter in the frequencies (blue histogram), the changes due to bolt failure are partly masked (top left, orange histogram),

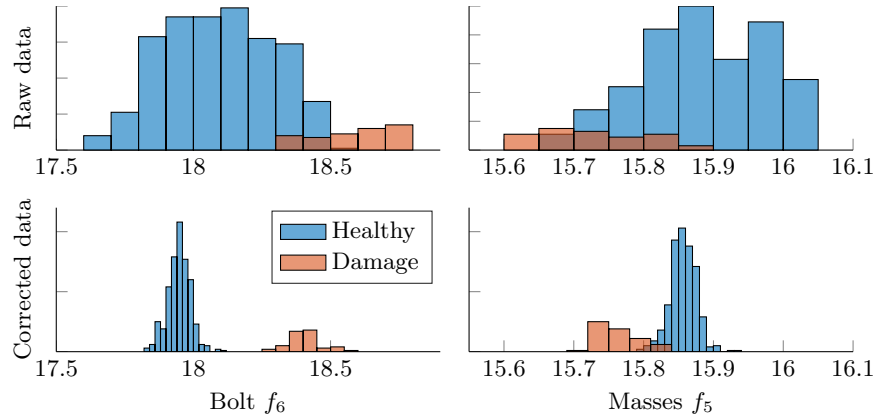


Fig. 6. Histograms for sixth frequency without and with damage for the damage scenario bolt failure (left) and fifth frequency for extra mass (right). The top plots show the frequencies before normalization and the bottom ones afterward.

meaning the damage could not be reliably detected. After normalization (bottom left), the distributions can be clearly distinguished, and structural damage appears to cause a larger shift towards higher frequencies. The situation is even more difficult for the added mass in Fig. 6 (right), where the change due to the mass is nearly completely masked before normalization. Only after normalization changes due to the added mass become well apparent in the distribution.

4 Conclusions

In this article, the vibration data of a 30 m composite bridge was analyzed in order to detect small structural changes, including extra masses on the concrete deck or bolt failure between the concrete deck and the steel girders. The measurement campaign comprises 21 days and the extracted modal frequencies exhibit substantial variation due to environmental changes such as temperature changes. The most important conclusions are listed below:

- The fluctuations in the natural frequencies can be explained through changes in the temperature changes, where a history of up to 18 hours should be considered between the ambient temperature and the material changes.
- Using artificial neural networks, the temperature effect can be reliably removed from natural frequencies. The normalized frequencies approximate a normal distribution. The ANN outperforms the linear regression approach, as the peak frequency is predicted well and the cleansed frequency follows a normal distribution with a small standard deviation.
- Based on natural frequency changes, the damage scenarios bolt failure and extra masses can be detected, and the shift in the frequency distributions is clearly visible after data normalization.

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