PREDICTING THERMAL RESPONSE FOR STRUCTURAL HEALTH MONITORING USING BLIND SOURCE SEPARATION METHOD

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Abstract
Research in Structural Health Monitoring (SHM) has been rapidly expanding over the last decades. However, data interpretation is still a big challenge for damage detection in SHM applications for civil infrastructure, especially due to the presence of environmental variations. This is the motivation for developing a methodology to separate the prediction of thermal responses from other sources of a structural response. This paper presents a Blind Source Separation (BSS) method for predicting structural thermal responses without any prior knowledge of the structure in-service circumstances. This BSS-based method involves combination and optimization of Ensemble Empirical Mode Decomposition (EEMD), Principal Component Analysis (PCA) and Independent Component Analysis (ICA). Numerical simulation of a truss bridge, inspired from New Joban Line Arakawa Railway Bridge, is used to validate applicability of the method. Results demonstrate that the method can predict temperature effects from the mixed structural responses recorded by a single sensor with sufficient accuracy.

1 INTRODUCTION

Structural Health Monitoring (SHM) system is implemented on civil infrastructures to track structural performance under various in-service conditions. It involves a comprehensive sensor system (i.e. data acquisition system) and advanced data interpretation methods to support decision making. Methods for damage identification can be classified into two categories: model-based methods and model-free methods, distinguished by the utilization or absence of physics-based behavior models \cite{1}. Model-based methods typically use measured data to calibrate models that are able to reflect the real behavior of structures and then compare structural responses with predictions of behavior models. However, when building a finite element model, it is inevitable to use some typical engineering assumptions and idealizations to build the model, which may result in modelling uncertainties. The more complex the structure, the harder it is to develop a good model \cite{2}. On the other hand, model-free methods provide direct interpretation of measurements without geometrical and material information of the measured structure. Considering efficiency, model-free methods are suitable for long term continuous monitoring \cite{3}. General evaluation of model-based and model-free methods has been summarized in the ASCE state-of-the-art report on structural identification of constructed system \cite{1}.

Pattern extraction and data interpretation are specialized fields that represent one of the
most significant challenges for structural damage detection [4]. The basic premise of most popular damage detection methods is that damage alters the structural properties (e.g., stiffness), which in turn will change the measured dynamic response of the system [5]. Damage detection is even more difficult when taking into account the environmental and operational loading conditions, especially the temperature effects [6], as they induce variations in measured data which might conceal damage [6, 7]. For example, Bell et al. found that temperature effects mask the application of load during a laboratory test of the Rollins Road Bridge [8]. Ni et al. reported that the temperature changes limits the successful application of vibration-based methods in real structures, because it is difficult to distinguish the modal changes due to temperature from the changes in modal caused by real structural damage [9]. Relative simulated results and conclusions have also been demonstrated in other papers [10-12].

To address environmental variations, the conventional solution is to fit the algebraic relation between structural responses and environmental conditions and then remove the environmental effects from the measurements. For example, Ni et al. [9] quantified the correlation between modal frequencies and temperature variations, then applied support vector machine method to formulate the models. After that, the research about the thermal distribution on structural frequencies was presented in [13], which use the relation model to verify and update the numerical model. Mahmoud et al. [14] observed the decrease of natural frequencies with the increased wind speed in a suspension bridge. Most recently, Yarnold et al. generated the relation (or baseline) among temperature changes, mechanical strain and structural displacements where the temperature was treated as input load on the structure, while the strain and displacement were treated as output responses [15, 16]. This baseline might be able to identify and characterizing structural abnormal performance [17]. Despite these developments, some drawbacks remain, including the reliability of collecting data, which is the foundation of building relationship between temperature variations and structural response(s). Another difficulty is analyzing the large volume of data. Moreover, even though the existing research of temperature effects has obtained some achievements in controlled experiments (i.e. laboratory test), it is still a challenge in uncontrolled applications (i.e. field tests) [17, 18]. Strategies to overcome such challenges of those existing methods for structure health monitoring under environmental variations are desirable.

On the other hand, the other potential idea is separating temperature variations from mixed structural responses. For example, Liu et al. applied a linear decomposition method, the Singular Value Decomposition (SVD), on ultrasonic data [19]. The SVD method can identify and separate changes produced by a scatter from environmental effects. Another similar method is the application of Principal Component Analysis (PCA) [20]. Recently, the Independent Component Analysis (ICA), the solution for Blind Source Separation (BSS) problem, has been introduced for extracting interesting signals under temperature fluctuations in industry case study [21]. In addition, ICA has also been combined with wavelet transform for extracting damage information [22], but this did not consider temperature effects.

This paper presents a combination method based on Single Channel BSS (SCBSS), which analyses data by applying Ensemble Empirical Mode Decomposition (EEMD), PCA and ICA. This method can be termed as EEPI, which can extract environmental effects from a single sensor record directly without any prior knowledge of structure loading conditions. Despite the successful application on voice separation [23], it has not been applied for extracting temperature effects.

The paper is organized as follows: Section 2 introduces this EEPI method, including brief introduction of BSS. After that a truss bridge case study is used for validate this EEPI
method, followed by the conclusion.

2 THERMAL FEATURE EXTRACTION METHOD

2.1 Blind Source Separation

BSS is to recover original signals from mixed sources, without knowledge of the mixing process and original sources themselves. For example, \( [X] \) is the mixed source of independent sources \( [S] \), see Eq. (1). \( [M] \) is a mixing matrix. In this equation, \( [X] \) can be observed and recorded, while \( [S] \) and \( [M] \) are unknown. BSS is aiming to separate \( [X] \) into a set of new sources \( [Y] \), which is the estimated sources of original sources \( [S] \), see Eq. (2). \( [W] \) is a decomposing matrix.

\[
[X] = [M] [S] \tag{1}
\]

\[
[Y] = [W] [X] \tag{2}
\]

Most of BSS algorithms tackle the separation problem when the channel number of mixture \( [X] \), \( m \), is larger than or equal to the channel number of original sources \( [S] \), \( n \). However, in SHM applications, estimated sources \( [Y] \) of original sources \( [S] \) have to be recovered from a single-channel mixed recording, where \( m \) is equal to 1. This is because, the temperature at various sensor location among the structure are not same, which then results in the unique response, e.g. stress and strain, at each sensor location. Such problem can be defined as Single Channel Blind Source Separation (SCBSS), the extreme case of underdetermined BSS [24, 25]. Several methods have been developed and proposed to solve this single-input-multiple-output (SIMO) problem in other fields such as audio processing and bio-medical [23, 25-27].

2.2 EEPI Method

The EEPI method involves application of Independent Component Analysis (ICA) on the output of Ensemble Empirical Mode Decomposition (EEMD) and Principal Component Analysis (PCA), which is to separate from a single input signal. The procedure of EEPI will be given at the end of this part, after the brief introduction of EEMD, PCA and ICA.

EEMD, Ensemble Empirical Mode Decomposition, was proposed as a noise-assisted version of EMD, Empirical Mode Decomposition, with higher robustness by Wu and Huang [28]. The idea of EEMD is decomposing the complicated time-series signal into a finite set of oscillatory components called Intrinsic Mode Functions (IMFs), as a pre-processing of Hilbert-Huang Transform (HHT). EEMD was developed to avoid a mode mixing problem when running the EMD [29]. The mixing mode problem is the major defect of EMD, which is defined as a single IMF that either contains signals of widely disparate scales, or different IMF components obtain the similar signals with a similar scale. To overcome the mode mixing problem, the EEMD was developed as a noise-assisted data analysis method. EEMD firstly adds independent and identically distributed white noise, with the same standard deviation, into the interest signal to generate a new input, then obtains IMFs by applying the EMD to the new input. The final and true IMFs are defined as the mean of an ensemble of trials, which will cancel the side effect of adding white noise.

Principal Component Analysis, known as PCA, is a mathematical procedure to reduce the dimensionality of the transformed data. It was invented in 1901 by Karl Pearson [30]. PCA uses an orthogonal conversion, to transform a set of observations of possibly correlated variables \( [A] \) into a set of values of uncorrelated variables \( [B] \). The components of \( [B] \) are
called principal components, among which the first principal component has the largest variance. After applying PCA, only the first few principal components will be reserved, which can restructure the original data and as a result, the dimensionality reduction is completed.

To solve BSS problem, the Independent Component Analysis (ICA), which is used to separate a set of mixed signals into independent non-Gaussian signals, was firstly invented by Comon in 1994 [31]. After that, many different methods based on ICA were proposed and proved as efficient tools to recover sources from observed signals. The most popular discovery and development of ICA is the FastICA which has been successfully applied into many different research areas, such as biomedical signal processing, audio processing and image processing [32]. More details of ICA learning rule can be found in [22].

### 2.3 Procedure of EEPI Method

a) As showing in Eq.(1), 

\[ [X] \] 

is the mixed source of independent sources \([S]\), mixing by \([M]\). 

\([S]\) and \([M]\) are unknown, while \([X]\) is the input signal.

b) Decide ensemble cycle times (M) and standard deviation (SD) of the white noise.

c) Add white noise series, \([n]\), to generate the new target data \([Y]\).

d) Decompose the new target data \([Y]\) into a set of IMFs \([c]\) by applying EMD, where \([r]\) is the meaningless residual part.

\[ [Y] = \Sigma [c] + [r] \]  

(3)

e) Repeat step c) and d) for M times.

f) Obtain the means of corresponding IMFs of the decompositions as the final set of IMFs. IMFs are simple oscillatory functions with varying amplitude and frequency.

g) Apply PCA to the whole set of IMFs to reduce the dimensionality of IMFs, except to the first IMF component, because it is the same vision of input signal [33]. The whole set of IMFs are mapped into the reduced space \([Z]\) and just the first L independent components can represent the whole IMFs, so only the first L components will be saved, see Eq. (4), where \([D]\) is the transforming matrix.

\[ [Z] = [D] \Sigma [c] \]  

(4)

h) Applying ICA on the dimensionally reduced IMFs, \([Z]\), to estimate both the decomposing matrix \([W]\) and the sources \([E]\).

\[ [E] = [W] [Z] \]  

(4)

i) Evaluation process. The performance of single-channel blind separation method can be evaluated by the correlation coefficient and relative root mean squared error (RRMSE).

### 3 TRUSS BRIDGE CASE STUDY

The purpose of this simulation is to evaluate the performance of the EEPI method for separating temperature effects from a mixed structural response. To achieve this, a scaled truss bridge model, inspired from the New Joban Line Arakawa Railway Bridge, is used for simulation.

The simplified finite element model of this truss structure is built using ANSYS whose geometry size is given in Figure 1. As shown in the figure, both supports are pinned. The material of this model is aluminum, whose Young’s modulus is 70 GPa, density is \(2.739 \text{ g/cm}^3\), Poisson ration is 0.35 and thermal expansion is \(23.1 \mu \text{m/m K}^{-1}\). To generate
structural response signals, the temperature and traffic load will be applied on this finite element model.

The temperature variation for a year is shown in Figure 2. In this simulation, 365 load steps assumed to simulate for one year, while every 10 load steps, approximately, represents a day cycle. This means only 36 days are simulated among each year. Annual average temperature is 9.7°C, maximum 24-hour temperature difference is 4°C and maximum 12-month temperature difference is 7°C.

The traffic load will be applied as point loads at all 12 bottom nodes of the model. The traffic load will be calculated first based on the full-scale bridge (bridge width: 8.4m). Then a scaled traffic load, according to the model’s geometry size and material properties, will be separated into 12 parts. The applied load on each node is also time-varying to simulate the morning and evening peaks within every single day. Detailed calculation and simulation will be given as follows.

According to EN 1991-2 6.3.2 [34], Load Model 71 is used to represent the static effect under normal rail traffic. The overall traffic load for the scaled model is maximum 60KN approximately, with maximum 5KN on each bottom node (see Figure 3).

The value of traffic load should be time varying within 24 hours to simulate the morning and evening peaks, which is approximately conformed to a normal distribution with double peaks (see Eq. (5)). Where \( \mu \) and \( \sigma \) are the mean or expectation and standard deviation of the distribution, respectively as. Variables \( \mu_1 = 8/24 \) and \( \mu_2 = 17/24 \), which means that the
morning peak is around 8 o’clock and evening peak is around 17 o’clock, while \( \sigma_1 = \sigma_2 = 0.9 \).

\[
f(x) = \frac{r}{\sqrt{2\pi} \cdot \sigma_1} \exp\left( -\frac{(x-\mu_1)^2}{2\sigma_1} \right) + \frac{(1-r)}{\sqrt{2\pi} \cdot \sigma_2} \exp\left( -\frac{(x-\mu_2)^2}{2\sigma_2} \right)
\]

(5)

3.2 Simulation procedure

First of all, temperature and traffic load are applied simultaneously. The elastic strain, \([X]\), of the middle beam at the bottom chord (see Figure 1, marked as BEAM No.82) is saved as an input signal for the next step, shown in Figure 4.

![Figure 4: Structural response, [X], under traffic and temperature variations.](image)

Responses under seasonal temperature variations, daily temperature variations and traffic load are also simulated separately (Figure 5-7) to be compared with final results of the separation procedure using the proposed method.

![Figure 5: Structural response under seasonal temperature variations](image)

![Figure 6: Structural response under daily temperature variations (left) and its partial enlarged detail (right)](image)
The second step of this simulation is the selection of the two parameters of the methodology: the ensemble average times (M) and standard deviation (SD) of noise. Thirdly, EEMD, PCA and ICA are applied sequentially on the input signal [X].

3.3 Results and discussion

In this simulation, two parameters of EEMD, the ensemble average times (M) and standard deviation (SD) of noise should be first determined. However, the EEMD algorithm is an empirical method hence there is no formulation to be followed to calculate the best combination of M and SD. Therefore the current optimal combination was selected through a grid search to evaluate a set of possible combinations of these parameters.

Figure 8-10 show the outcomes of potential combinations for extracting seasonal temperature effect, daily temperature effect and traffic load effect individually. Two criteria, correlation coefficient and relative root mean square error (RRMSE), are used as metrics to evaluate performance. It is noted that for daily temperature variations and traffic loading, decreasing the value of standard deviation (SD) will improve performance (i.e. leads to high correlation coefficient). The best results for each loading are summarized in Table 1.
Figure 10: Evaluation of M and SD for extracting traffic load effects

<table>
<thead>
<tr>
<th>Evaluation criteria</th>
<th>Ensemble average times (M)</th>
<th>Standard deviation of noise (SD)</th>
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</thead>
<tbody>
<tr>
<td>Correlation Coefficient (predicted vs. original)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>seasonal temperature effect</td>
<td>50</td>
<td>0.0631</td>
</tr>
<tr>
<td>daily temperature effect</td>
<td>100</td>
<td><strong>0.0251</strong></td>
</tr>
<tr>
<td>traffic load effect</td>
<td>50</td>
<td>0.0201</td>
</tr>
<tr>
<td>RRMSE (predicted vs. original)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>seasonal temperature effect</td>
<td>200</td>
<td>0.0261</td>
</tr>
<tr>
<td>daily temperature effect</td>
<td>200</td>
<td>0.0261</td>
</tr>
<tr>
<td>traffic load effect</td>
<td>50</td>
<td>0.0201</td>
</tr>
</tbody>
</table>

Table 1: Optimal Combination of two key parameters based on three criteria

As shown in Table 1, the best compromised combination, M=100 and SD=0.0251, of optimal extraction of daily temperature effect is selected, because it is much more difficult to separate daily temperature effect from the mixed signal.

The comparison between the predicted sources and original sources, using the combination above, are given in Figure 11-13 and Table 2 will list their correlation coefficient and RRMSE.

Figure 11: Structural responses under seasonal temperature variation. Predicted and original strain time history.

Figure 12: Structural responses under daily temperature variations. Predicted and original strain time history.
Despite the observed discrepancies, Figure 11 shows that generally this method is able to separate structural response due to seasonal temperature effect from other sources. Figure 12 demonstrates that the structure response under daily temperature variations is also separated well. The estimated source of structural response due to traffic load is also recovered by this single-channel BSS-based method (see Figure 13). Correlation coefficient and the RRMSE between estimated sources and original strain data are presented in Table 2. Ranging from 92% to 99%, the values of correlation coefficient are shown to be quite high. The RRMSE values are also quite good (i.e. 10-12%).

The performance of extracting seasonal temperature effect is quiet well with correlation coefficient at 0.99 and RRMSE at 10%. The correlation coefficient for separating daily temperature effect is also very high, as 0.96, while the RRMSE of it is 16%, which is due to the deviation within signal amplitudes. Finally, this method is also able to recover the time varying strain under traffic load effect, with 0.92 correlation coefficient and 13% RRMSE. In summary, according to the correlation coefficient, this single-channel blind source separation method is quiet stable with a sufficient accuracy for separating temperature effects from a mixed source.

### 4 CONCLUSION

A thermal response predicting method, the combination of EEMD PCA and ICA, based on single channel Blind Signal Separation is presented and validated in this study. Based on the results, the following conclusions are summarized:

- This EEPI method is a useful tool for separating mixed structural responses due to combinations of traffic loading and environmental variations. This method has been shown to perform quite well with high values of correlation coefficient between original and estimated signals.
- High standard deviation (SD) of the noise added to the signal during the separation process using EEPI in SHM applications leads to better estimations of the original sources.

Future study will further explore the relationship between the ensemble average times (M)
and standard deviation (SD) of noise which will also involve strategies to select the best combination of these parameters. The contribution of this paper is the first stage of utilizing temperature variations instead of treating it as noise in SHM field. The EEPI method is the first attempt to apply single-channel BSS technique on temperature effects separation.

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REFERENCES


