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Enhanced sparse component analysis for operational modal identification of real-life bridge structures

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ABSTRACT

Blind source separation receives increasing attention as an alternative tool for operational modal analysis in civil applications. However, the implementations on real-life structures in literature are rare, especially in the case of using limited sensors. In this study, an enhanced version of sparse component analysis is proposed for output-only modal identification with less user involvement compared with the existing work. The method is validated on ambient and non-stationary vibration signals collected from two bridge structures with the working performance evaluated by the classic operational modal analysis methods, stochastic subspace identification and natural excitation technique combined with the eigensystem realisation algorithm (NExT/ERA). Analysis results indicate that the method is capable of providing comparative results about modal parameters as the NExT/ERA for ambient vibration data. The method is also effective in analysing non-stationary signals due to heavy truck loads or human excitations and capturing small changes in mode shapes and modal frequencies of bridges. Additionally, closely-spaced and low-energy modes can be easily identified. The proposed method indicates the potential for automatic modal identification on field test data.

1. Introduction

Operational modal analysis (OMA) is targeted at identifying modal characteristics from only response measurements of structures under ambient or natural excitation [1] and has many applications such as for structural identification, vibration-based health monitoring and damage detection, etc.

Several algorithms have been developed for OMA, including natural excitation technique combined with the eigensystem realisation algorithm (NExT/ERA) [2,3], stochastic subspace identification (SSI) approaches [4] and a general auto-regression moving average (ARMA) model [5] in time domain and frequency domain decomposition [6] in frequency domain. Most of them are parametric identification methods based on a mathematical model representing the physical phenomenon of structural dynamics. Their applications are limited to certain situations (e.g. ambient and free vibration signals) due to the model assumption regarding the nature of excitation forces (e.g. a broadband uncorrelated random process). In addition, the working performance is sensitive to some model parameters (e.g. model order) and the parameter selection is dependent on users' subjective judgement.

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Hilbert Huang transform (HHT) [7–9] is a parameter-free time-frequency analysis tool for modal identification which is capable of dealing with nonlinear and nonstationary signals. One critical step in the HHT is empirical mode decomposition (EMD), i.e. decomposing one multi-component signal into a series of mono-component signals. The decomposition process exploits no joint information between multiple measurement channels and might derive modal responses involving mode mixing [10]. Improved work has been performed by proposing the ensemble EMD [11] and multivariate EMD [12,13] to overcome limitations.

Blind source separation (BSS) offers an alternative for OMA, belonging to non-parametric identification methods. BSS originates from the audio signal processing field for de-mixing audio sources from recordings via a mixing matrix. Its physical interpretation for OMA is that with the modal responses regarded as virtual sources, the mixing matrix is mapped directly to structural vibration modes [14]. BSS is classified into two types, overdetermined and undetermined cases depending on the provided measurement channels compared to the number of active modes. Underdetermined BSS is suitable for civil applications with limited sensors available and has been addressed by different methods such as sparse component analysis (SCA) and tensor decomposition.

The SCA makes use of sparseness in the transformed domain i.e. the time–frequency (TF) domain for decomposition. The sources are assumed to be sparsely represented after the TF transform e.g. short-time Fourier transform (STFT) [15–17], wavelet packet transform [18] and quadratic TF transform [19]. A mixing matrix (or mode shapes) is estimated using clustering algorithms (e.g. hierarchical clustering [15], K-hyperline clustering [16], K-means clustering [17,19] and Fuzzy C-means clustering [20]) on scatter plots of measurement signals in the transformed domain. Given the mixing matrix, source signals can be reconstructed based on the source sparsity using l^1 norm minimisation [16,20], smoothed zero-norm algorithm [15] or subspace-based algorithm (by identifying active sources at TF points and estimating the energy each of these sources contributes) [19]. With the source signals (or modal responses) available, modal frequencies and damping ratios can be estimated using either single-mode curve fitting in frequency domain or logarithmic decrement method in time domain. The SCA has been implemented for OMA on a cantilever beam structure [16], a laboratory tower structure under narrow-band excitations [18] and a column structure in temperature-varying environment [17] with the working performance evaluated against identification using SSI [16].

Tensor decomposition method is an alternative for the underdetermined BSS based on the assumption that source signals are uncorrelated among different channels but correlated individually in time [21]. The main idea is to decompose the third-order tensor representation (i.e. spatial covariance matrices of observation signals for different time lags) into a linear combination of a minimal number of rank-1 terms by means of an alternating least squares algorithm. The derived mixing matrix and auto-covariance of modal responses can be used for modal parameter estimation. The method has been validated at being effective when analysing ambient vibration signals [22], earthquake responses [23] as well as human-induced vibrations [24,25].

Although there are already a few studies implementing the underdetermined BSS for OMA, most of these are numerical and laboratory studies, while field tests are rare except on two footbridges [25,26], one tower structure [27] and two buildings [28,29]. There is no further study to investigate whether the underdetermined BSS method is capable of offering an effective alternative to classic OMA methods on field testing data, especially non-stationary vibration signals.

In this study, an enhanced method based on the SCA is proposed for OMA suitable for field applications. In this method, a novel procedure of the two-step clustering is involved to ensure an automatic and robust estimation of mode shapes that is the basis for the accurate estimation of modal parameters.

The proposed method is validated on two full-scale in-operation bridges in both ambient and non-stationary vibrations (i.e. due to heavy truck loads or passing pedestrians). Wired and wireless accelerometer sensors with different accuracy levels were used for data acquisition to test the sensitivity of the proposed method to noise level. Closely-spaced and low-energy modes that are common for footbridges are considered based on the recorded data. The working performance of the proposed method is evaluated by comparing with the classic OMA methods i.e. NExT/ERA and SSI.

To that end, Section 2 introduces the main methodologies of the proposed OMA method based on the SCA and improvements, mainly in the clustering step, to ensure a robust estimation of mode shapes. Section 3 describes a validation study on ambient vibrations of a short-span road bridge and evaluates the performance through comparing the results with those using the NExT/ERA algorithm. Section 4 describes a load test on the same bridge and investigates the feasibility of the proposed method on non-stationary signals. Section 5 analyses non-stationary vibration data from a footbridge under pedestrian excitation and validates the effectiveness of the proposed method for vibration signals under narrow-band excitation and for extracting closely-spaced modes.

2. Enhanced sparse component analysis for OMA

The BSS is a powerful tool for separating mixed signals when the sources and the mixing methodology are unknown. The simple form of BSS in the noiseless case is to determine a mixing matrix A (using statistical and data structure information [30]) and to recover the M-component source data **s** from their linear mixture in the N-component observational data **X**, expressed as

$$\mathbf{X}(t) = A\mathbf{s}(t). \tag{1}$$