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Separation and identification of structural modes in largely underdetermined scenarios using frequency banding

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ABSTRACT

In recent years, blind source separation (BSS) has gained significant interest in the context of operational modal analysis, as a non-parametric alternative to the identification of mechanical structures from output-only measurements. One persisting limitation of most BSS methods, however, is to they cannot identify more active modes than the number of simultaneously measured outputs. The aim of this work is to propose a solution to the largely underdetermined case – where many more modes are to be identified than the number of available measurements – by dividing the frequency axis in subbands, such that each band provides an (over)determined problem where BSS can be applied separately. The approach comes with the proposal of a new second-order BSS that operates directly in the frequency domain and takes as an input the cross-spectral matrix of the data. A data augmentation technique is also devised to artificially increase the dimension of the measurements in severely undetermined scenarios. Finally, an identification algorithm is introduced that estimates the modal parameters of the separated structural modes. A remarkable aspect of these algorithms is that they are all based on the unified use of multi-filters designed in the frequency domain, yet with different frequency bandwidths. Another particularity of the present paper is to demonstrate the validity of the proposed approach on several benchmark databases with various degrees of difficulty including complex modes, high modal overlap, singular modes, and the presence of engine harmonics. In all cases, the proposed methodology was efficient and, above all, easy to deal with even in largely undetermined cases.

1. Introduction

The scope of operational modal analysis (OMA) is to identify the modal properties of a mechanical structure through the analysis of vibration data measured under operating conditions, when neither initial conditions nor artificial excitations are known. OMA is typically applied when it is complicated and/or expensive to deal with controlled vibration tests, for instance with very large structures (e.g. bridges, buildings) or when in situ excitation is hardly accessible (e.g. wind turbines). Many different techniques have been developed for OMA, from simple peak picking in the Fourier spectra to sophisticated system

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List of symbols[1]

ALS	Alternative least squares
BSS	Blind source separation
CP	Complexity pursuit
CSM	Cross-spectral matrix
DA	Data augmentation
ESD	Energy spectral density
FD-BSS	Frequency-domain blind source separation
GCP	Generalized complexity pursuit
GSM	Generalized spectral moment
ICA	Independent component analysis
JAD	Joint approximate diagonalization
MOF	Modal overlap factor
OMA	Operational modal analysis
PSD	Power spectral density
PARAFAC	Parallel factor analysis
RMS	Root mean square value
SNR	Signal-to-noise ratio
SOBI	Second-order blind identification
SSI	Stochastic subspace identification
M	Number of channels
N	Total number of active modes
N_i	Total number of active modes in band B_i
J	Number of FD-BSS filters in each band
D	Number of GSM filters in each band
A_i	Number of DA filters in band B_i
B_i	i-th frequency band used in FD-BSS
$\boldsymbol{y}(t)$	Vector of measured structural responses (of dimension M)
$\boldsymbol{n}(t)$	Vector of additive noise (of dimension M)
$\boldsymbol{\eta}(t)$	Vector of modal coordinates (of dimension N)
F_s	Sampling frequency (in Hz)
T_s	Sampling period (in s)
Δf	Frequency resolution of Fourier transform (in Hz)
$X(f)$	Fourier transform of signal $\boldsymbol{x}(t)$
$\boldsymbol{Y}_j^{\mathrm{DA}}(f)$	j-th vector of spectra obtained by data augmentation
$\boldsymbol{Y}^{aug}(f)$	Complete vector of augmented data
$\mathbf{S}_{xx}(f)$	Cross-spectral matrix of the signals in vector $\boldsymbol{x}(t)$
$\mathbf{S}_{xx,B_i}(f)$	Cross-spectral matrix of reduced dimension N_i
$\mathbf{S}_{xx,B_i}^{(j)}$	Cross-spectral matrix weighted with j-th frequency gain and integrated in band B_i
$S_{\widehat{\eta}_k}(f)$	Energy spectrum of k-th estimated modal coordinate
$\mathbf{S}_{yy}^{aug}(f)$	Cross-spectral matrix of augmented data
$\mathbf{\Phi}$	Modal matrix
$\mathbf{\Phi}_{B_i}$	Modal matrix of reduced dimension N_i
$\mathbf{A}^{+}$	Pseudo-inverse of matrix $\mathbf{A}$
$\mathbf{A}^{T}$	Transpose of matrix (or vector) $\mathbf{A}$
$\mathbf{A}^{H}$	Transpose conjugate of matrix (or vector) $\mathbf{A}$
$G_{ij}^{\mathrm{BSS}}(f)$	j-th frequency gain of FD-BSS used in band B_i
$G_{ij}^{\mathrm{ID}}(f)$	j-th frequency gain of GSM used in band B_i
$G_j^{\mathrm{DA}}(f)$	j-th frequency gain of DA
B_{kj}^{BSS}	Bandwidth of $G_{ij}^{\mathrm{BSS}}(f)$ (in Hz)
B_{kj}^{ID}	Bandwidth of $G_{ij}^{\mathrm{ID}}(f)$ (in Hz)
B_j^{DA}	Bandwidth of $G_j^{\mathrm{DA}}(f)$ (in Hz)
f_k	Natural frequency of k-th mode (in Hz)
ζ_k	Damping ratio of k-th mode
λ_k	Relaxation time of k-th mode (in Hz)
$\tilde{f}_k$	Damped frequency of k-th mode (in Hz)