Journal of Sound and Vibration 413 (2018) 66–78

Contents lists available at ScienceDirect

Journal of Sound and Vibration

journal homepage: www.elsevier.com/locate/jsvi

Adaptive modal identification of structures with equivariant adaptive separation via independence approach

Fereidoun Amini*, Vida Ghasemi

School of Civil Engineering, University of Science and Technology, Tehran, Iran

ARTICLE INFO

Article history:
Received 9 November 2016
Received in revised form 28 August 2017
Accepted 25 September 2017

Keywords:
Adaptive blind source separation
Equivariant adaptive separation via independence algorithm
Modal identification
Output-only system identification

ABSTRACT

An efficient output-only Blind Source Separation (BSS) method was recently introduced for the modal identification of structures. BSS procedures recover a set of independent sources from their unknown linear mixtures when only mixtures are observed. Batch data is required for the separation in traditional blind source separation methods. These algorithms are however unfavorable, as some sets of data are observed one after another. In this paper, an adaptive blind source separation technique - equivariant adaptive separation via independence (EASI) - is introduced to overcome the mentioned disadvantage within the structures. The EASI algorithm is beneficial as it can provide solutions to real time problems, while also update the un-mixing matrix for each step. EASI not only avoids increases in size of the relevant matrices and vectors, but also decreases the analysis time. A synthetic example and a benchmark structure have been used in this paper to better investigate the efficiency of the proposed method. The simulation results demonstrate the effectiveness of the EASI algorithm in on-line identification of modal parameters of structures.

1. Introduction

In recent years, modal analysis has been the most useful and attractive tool to characterize and identify structural systems. Traditional modal identification methods require both input and output signal characteristics. Input forces in many structural systems, such as structures excited by the wind or seismic ground motion excitation are unmeasurable. In these cases, the output-only system identification (SI) methods [1,2], such as blind source separation methods (BSS) [3], are very effective in the estimation of system characteristics.

BSS approaches have been studied widely in SI [4], particularly, in the modal identification of structures [5–7] and mechanical systems [8], heretofore. The main idea behind BSS approaches is to extract the sources from a mixture of output measurements without any knowledge about the source signals or the mixing process. In the structural SI, normal modes of a linear dynamical system can be considered as the virtual sources. Hence, extracting normal modes from the mixture of them becomes a blind identification problem. In addition to modal identification, BSS methods are used in many engineering applications such as damage detection [9] and condition monitoring [10].

According to the literature, BSS performance has been conducted through two popular approaches, namely the independent component analysis (ICA) [11] and the second-order blind identification (SOBI) [3,12]. The presence of structural

* Corresponding author.
E-mail address: f.amini@iust.ac.ir (F. Amini).

https://doi.org/10.1016/j.jsv.2017.09.033
0022-460X/

damping weakens ICA methods, even at the order of 2% critical [5]. SOBI methods on the other hand perform better at high damping [8] due to the utilization of the signal time structure. SOBI based methods are suitable for non-stationary signals such as seismic excitations [13]. In recent years, BSS methods have been improved to handle the blind modal identification of structures, where sensors may be fewer compared to the number of active modes [14–16].

One of the most important challenges in civil engineering is controlling structures to protect against environmental excitations, such as earthquakes and wind forces. Online SI plays the main rule in extracting main parameters to use in the control law.

Traditional BSS methods pose two main disadvantages to online problems. First, these methods are offline and require whole of the signal to perform separation and identification whereas there is no such access in online problems, and new data are observed one after another. Second, utilization of offline BSS methods for online problems wastes a good amount of time. As the size of relevant matrices and vectors increases with the number of given data, so does the analysis time. Due to the inefficiency of traditional offline BSS techniques in online cases, researchers have introduced online BSS methods for separation.

Jutten and Herault initially proposed an adaptive BSS [17], followed by another method based on neural network architecture, which only succeeded in the separation of sources with different symmetric probability density functions [18]. Gaeta and Lacoume [19] and Comon [20] obtained source separation by means of optimizing mutual information as a “contrast function”. Harroy et al. developed an adaptive algorithm based on this contrast function [21]. Cardoso and Laheld proposed another adaptive method [22]. They employed the ‘relative gradient’ adaptive algorithm based on serial updating, where the separating matrix is updated in each step when a new sample is received. These adaptive algorithms are called equivariant adaptive separation via independence (EASI). The EASI algorithm has two main drawbacks: dependence of the convergence on the source statistics [17,23] and complexities of analysis [21,23]. Zarzoso et al. introduced a novel method to overcome these disadvantages [24]. Also, some researchers developed different adaptive BSS methods to improve the available algorithms [25]. Reference [26] proposed an optimized EASI algorithm to increase the convergence speed.

In this study, an equivariant adaptive separation via independence (EASI) method is used to provide a general framework for online structural SI. EASI is a relatively recent method that has been developed in the electrical engineering field, and has not been used in structural SI related problems thus far. The modal matrix and modal coordinates of the structure for each time are determined by the EASI algorithm, and based only on structural output responses received online. The modal parameters are then extracted from information hidden in the modal coordinates and modal matrix. EASI is a good choice for online applications because with increasing data and time, it prevents changes from occurring in the dimension of matrices and vectors, which in effect reduces the computational effort and solving time. . The efficacy of the mentioned algorithm is investigated by utilizing synthetic example simulation studies, and comparing them to the popular BSS based modal identification methods, the Fast-ICA and SOBI, in civil structures. According to the results, EASI performs exceptionally well in low damping structures. In addition, EASI is robust against noise for low damped structures under seismic excitation. However, due to its sensitivity to outliers, its performance can deteriorate, so it is necessary to remove the outliers before separation. The phase I IASC–ASCE benchmark building is also used to verify this method. Results show that the EASI algorithm is efficient and proper for online modal identification.

The remainder of this paper is organized as follows: Section 2 states the problem and details the theoretical background of BSS and its relation to the modal identification of structures. Section 3 presents the EASI method. Section 4 illustrates the numerical simulation of simple three degree-of-freedom (3-DOF) mass, spring, and dashpot system. Section 5 addresses the performance of the proposed method using the phase I IASC–ASCE benchmark building. Finally, section 6 concludes the paper.

2. Problem formulation

2.1. Modal expansion

Motion equations for a linear, classically damped, and lumped-mass n-degree-of-freedom (n-DOF) structural system under an excitation force vector $\mathbf{f}(t)$ is expressed in Eq. (1).

$$\mathbf{M}\ddot{\mathbf{x}}(t) + \mathbf{C}\dot{\mathbf{x}}(t) + \mathbf{K}\mathbf{x}(t) = \mathbf{f}(t) \tag{1}$$

Where, $\mathbf{x}(t)$ is a vector of displacement coordinates at the degrees of freedom, $\mathbf{M}$, $\mathbf{C}$ and $\mathbf{K}$ are symmetric mass, damping and stiffness matrices, respectively. As illustrated in Eq. (2), with the assumption of existing normal modes, the displacement and acceleration responses can be written in terms of vibration mode expansions.

$$\mathbf{x}(t) = \sum_{j=1}^{n} \boldsymbol{\varphi}_j q_j(t) \rightarrow \ddot{\mathbf{x}}(t) = \sum_{j=1}^{n} \boldsymbol{\varphi}_j \ddot{q}_j(t) \tag{2}$$

Where $\boldsymbol{\varphi}_j \in \mathbb{R}^n$ is the jth modal vector, and $q_j(t)$ is the jth modal coordinate of each mode. When the excitation $\mathbf{f}(t)$ is a stationary white noise vector, the $q_j(t)$ modal coordinate is expressed as Eq. (3).