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Combining optimization methods with response spectra curve-fitting toward improved damping ratio estimation

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ABSTRACT

The authors have previously shown that many traditional approaches to operational modal analysis (OMA) struggle to properly identify the modal damping ratios for bridges under traffic loading due to the interference caused by the driving frequencies of the traffic loads. This paper presents a novel methodology for modal parameter estimation in OMA that overcomes the problems presented by driving frequencies and significantly improves the damping estimates. This methodology is based on finding the power spectral density (PSD) of a given modal coordinate, and then dividing the modal PSD into separate regions, left- and right-side spectra. The modal coordinates were found using a blind source separation (BSS) algorithm and a curve-fitting technique was developed that uses optimization to find the modal parameters that best fit each side spectra of the PSD. Specifically, a pattern-search optimization method was combined with a clustering analysis algorithm and together they were employed in a series of stages in order to improve the estimates of the modal damping ratios. This method was used to estimate the damping ratios from a simulated bridge model subjected to moving traffic loads. The results of this method were compared to other established OMA methods, such as Frequency Domain Decomposition (FDD) and BSS methods, and they were found to be more accurate and more reliable, even for modes that had their PSDs distorted or altered by driving frequencies.

1. Introduction

Obtaining accurate and reliable estimates for damping is one of the more formidable challenges when performing system identification on a structure. The challenge only becomes more arduous when identification, and thus estimation, must be performed in the absence of data about the excitation or input forces. Systems or structures that lack this type of information are commonly known as “output-only” because any identification efforts must rely upon only the output. The family of techniques and methods that have been created to perform system identification or parameter estimation for output-only systems are often referred to as operational modal analysis (OMA).

A detailed review of system identification methods for OMA may be found in [1], but some well-known OMA techniques include Frequency Domain Decomposition (FDD) [2], Stochastic Subspace Identification (SSI) [3] and the natural excitation

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technique (NExT) [4], as well as their associated variants [5–7]. A more recent addition to the OMA family is "blind" identification, sometimes called blind source separation (BSS), which is a time domain based set of techniques for system identification. While widely used in other fields [8–10], a direct connection between BSS methods and structural dynamics has more recently been established [11,12] and promising results for OMA applications have been shown [13]. One of the more popular BSS variants is second-order blind identification (SOBI) [14] and recent works [15–17] have shown promise for various applications of SOBI to modal analysis. Additionally, SOBI methods have been successfully used to recover modal damping ratios [18] and perform identification for non-ambient excitation [19].

The ability to overcome non-ambient excitation is especially important because many OMA methods rely upon the assumption that the excitation is uniform broad-band noise. One of the more difficult environments for OMA is bridges under traffic loading because that assumption is likely violated by the high variability of traffic conditions created by car, truck and train crossings. Modeling traffic loads crossing a bridge structure is well-studied within the engineering community and has often been reduced to problems involving loads or masses on beams [20–25].

In the authors' previous work [26], simulations of traffic loads traveling across a bridge structure were conducted using the analogy of moving loads and masses on a beam. The finite element model for the bridge consisted of a series of simply-supported (SS) stringer beams resting on top of a larger, continuous girder (Fig. 1). The stringer-girder beam system was used in order to capture the jointed nature between bridge panels. The traffic excitation was separated into cars and trains, where cars were modeled as traveling point loads and the trains as moving masses. For the traffic simulations, several cars and trains simultaneously traveled across the bridge model, and nine different traffic simulations were conducted. Modal parameters for the bridge model, i.e., the natural frequencies and damping ratios for the first ten modes, are shown in Table 1. More detailed information on the bridge model, including section properties and dimensions, and the nature of the traffic simulations may be found in [26].

The vertical acceleration responses of the bridge were recorded at eleven equally-spaced locations along the bridge span during each simulation. These acceleration responses were treated as the input for the variety of OMA techniques used to estimate the damping ratios of the first few bridge modes, which were originally modeled using Rayleigh damping. A sample response spectra from a traffic simulation produced by the FDD method is shown in Fig. 2a [26], where the term "response spectra" is used to denote the singular values of the cross-power spectral density function computed within the FDD algorithm. The response spectra shows obvious distortion in some regions, where the term distortion is used to refer to the sharp gains and losses in power over certain frequency ranges in Fig. 2a. A modified SOBI method was also utilized for OMA on the acceleration responses due to its demonstrated ability to perform modal parameter identification for an earthquake-excited structure [19]. However, the power spectral densities (PSDs) of the recovered modal responses displayed similar patterns of distortion (Fig. 2b) [27].

In both cases, this distortion led to extremely large errors for the damping ratio estimates for certain modes. When using the FDD method, the estimates relied upon taking inverse Fast Fourier Transforms (IFFTs) of isolated modal peaks from the response spectra and the more severely distorted peaks produced the least accurate estimates [26]. Damping ratios were estimated for the SOBI method using two approaches: taking IFFTs of the modal response PSDs and using the random decrement (RD) technique [28,29] on the modal response time histories. Both methods produced equally inaccurate estimates with similar results to the FDD method [27,30]. An important consequence from these analyses was that the errors were equally prevalent using identification in the frequency domain (FDD), time domain (SOBI – RD) and combined time-frequency domains (BSS – IFFT), i.e., the problem was not relegated to a specific domain.

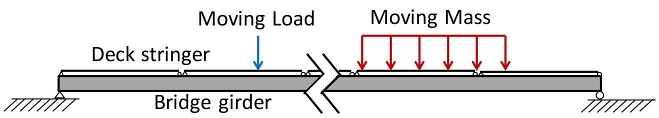

Fig. 1. Sample bridge model set-up (actual model used later in simulations has 100 stringers).

Table 1
Modal properties.

Mode	Natural frequency (Hz)	Damping ratio (%)
1	0.2192	0.0300
2	0.8767	0.0089
3	1.9725	0.0066
4	3.5066	0.0077
5	5.4789	0.0103
6	7.8891	0.0140
7	10.7365	0.0185
8	14.0202	0.0239
9	17.7375	0.0300
10	21.8830	0.0369