Mechanical Systems and Signal Processing ∎ (∎∎∎∎) ∎∎∎–∎∎∎

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

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

Model validity and frequency band selection in operational modal analysis

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ARTICLE INFO

Article history:
Received 31 December 2015
Received in revised form
31 March 2016
Accepted 31 March 2016

Keywords:
Bandwidth
Modal identification
Maximum entropy
Model class selection
Operational modal analysis

ABSTRACT

Experimental modal analysis aims at identifying the modal properties (e.g., natural frequencies, damping ratios, mode shapes) of a structure using vibration measurements. Two basic questions are encountered when operating in the frequency domain: Is there a mode near a particular frequency? If so, how much spectral data near the frequency can be included for modal identification without incurring significant modeling error? For data with high signal-to-noise (s/n) ratios these questions can be addressed using empirical tools such as singular value spectrum. Otherwise they are generally open and can be challenging, e.g., for modes with low s/n ratios or close modes. In this work these questions are addressed using a Bayesian approach. The focus is on operational modal analysis, i.e., with 'output-only' ambient data, where identification uncertainty and modeling error can be significant and their control is most demanding. The approach leads to 'evidence ratios' quantifying the relative plausibility of competing sets of modeling assumptions. The latter involves modeling the 'what-if-not' situation, which is non-trivial but is resolved by systematic consideration of alternative models and using maximum entropy principle. Synthetic and field data are considered to investigate the behavior of evidence ratios and how they should be interpreted in practical applications.

1. Introduction

Ambient modal identification, conventionally known as 'operational modal analysis' (OMA), aims at identifying the modal properties (primarily, natural frequencies, damping ratios, mode shapes) of a structure using 'output-only' vibration data under ambient conditions [1–3]. The input excitation is not measured (often impractical to do so) but assumed to be 'broadband random' so that the statistical characteristics of measured response reflect primarily the properties of vibration modes rather than excitation. High economy and feasibility in data collection is a major advantage. The approach is promising for response and model updating [4]; and more generally health monitoring of civil structures [5–8]. OMA can be performed in the time or frequency domain, Bayesian or non-Bayesian. Conventional methods are mostly non-Bayesian, e.g., stochastic subspace identification [9] (time domain) and frequency domain decomposition [10] (frequency domain). Bayesian methods have been formulated in the time and frequency domain, e.g., [11,12]. Application was limited until computational problems were solved in the frequency domain [13,14]. Reported cases are more recent, perhaps because the approach is less intuitive and derivation is more mathematically involved; see review in [15].

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http://dx.doi.org/10.1016/j.ymssp.2016.03.025

Please cite this article as: S.-K. Au, Model validity and frequency band selection in operational modal analysis, Mech. Syst. Signal Process. (2016), http://dx.doi.org/10.1016/j.ymssp.2016.03.025

Identifying modal properties without input information is theoretically more involved. Results have much higher variability/uncertainty and sensitivity to algorithmic parameters compared to their counterparts identified with free or forced (known input) vibration data. Frequency domain methods make use of spectral quantities in a selected frequency band for identifying the modes within it. In doing so the identification (ID) model only needs to account for the modes dominating the band and so can be significantly simplified. For well-separated modes the band can be selected to cover only one mode. In general the number of close modes rarely exceeds three. ID results are insensitive to activities in other bands because their spectral data (e.g., FFT) do not enter into the calculation process (e.g., likelihood function in Bayesian approach). This is especially attractive for OMA since ambient data contains a variety of activities in different bands which are irrelevant to identifying the mode(s) of interest or difficult to model.

1.1. Basic questions in frequency domain modal ID

Performing modal ID in the frequency domain, among the first few questions is where the potential modes are, or equivalently, whether a mode exists near a particular frequency. Existing means are empirical. Stabilization diagram [16] observes whether the eigenvalues of system matrix consistently appear near a particular frequency as the model order of a time-domain state-space model increases. Another common tool is singular value (SV) spectrum [17], i.e., a plot of the singular values of sample PSD with frequency. Sample PSD matrix is positive semi-definite Hermitian and so its singular values and eigenvalues are the same. The number of lines significantly above the remaining ones indicates the dimension of the space spanned by the contributing measured mode shapes and their variation with frequency is similar to the dynamic amplification factor.

Given that a mode exists near a particular frequency, the next question is to select the band whose spectral data shall be used for modal ID. This is a trade-off between ID precision and modeling error risk [15]. As the band widens more information in data is included for modal ID, hopefully leading to higher ID precision. This however increases the risk that the ID model may not hold in the additional band, creating modeling error (bias) in results. For well-separated modes with high modal signal-to-noise (s/n) ratios a reasonable band is not difficult to decide based on SV spectrum; ID results are insensitive to the choice. Otherwise, a prudent choice currently relies on experience. Examining ID results with different choice of band is a straight-forward strategy but involves repeated calculations. The variation of results is also subjected to interpretation. For example, even when there is no modeling error, results can still fluctuate as more data is used. Although not directly related, see other issues on modal estimation [18–21]; and achievable precision limits [22,23].

1.2. Problem statement

This paper aims at developing quantitative means for addressing the above concerns for OMA so that modeling error can be effectively suppressed. The problem is approached in a 'Bayesian model class selection' context [28,32], using the FFT of data for probabilistic inference. Bayesian approach provides the basic principle but questions need to be properly formulated to yield useful conclusions while admitting a legitimate mathematical analysis. In this work, the concerns are addressed via the following two questions:

Question 1. Is the modal ID model valid in a band near a particular frequency?

Question 2. If the answer to Question 1 is positive, is the model valid in a wider band?

These questions are illustrated in Fig. 1. Focusing near 0.17 Hz, Question 1 asks if there is a mode in the gray band. If the answer is positive, Question 2 follows up with how wide the band can be expanded to incorporate more FFT data to improve modal ID precision. If one includes the FFT data in the yellow band, will it cause significant modeling error, e.g., with regard to single mode? To keep the questions well-posed, the band in Question 1 (gray area) is assumed to surround a potential

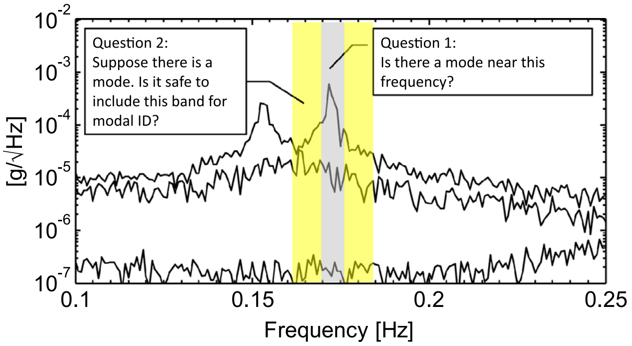

Fig. 1. Illustration of Questions 1 and 2, showing the sample SV spectrum (averaged for visualization) of one hour triaxial ambient acceleration data measured on a tall building roof.

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