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Fully Automated Operational Modal Analysis using multi-stage clustering

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A B S T R A C T

The interest for robust automatic modal parameter extraction techniques has increased significantly over the last years, together with the rising demand for continuous health monitoring of critical infrastructure like bridges, buildings and wind turbine blades. In this study a novel, multi-stage clustering approach for Automated Operational Modal Analysis (AOMA) is introduced. In contrast to existing approaches, the procedure works without any user-provided thresholds, is applicable within large system order ranges, can be used with very small sensor numbers and does not place any limitations on the damping ratio or the complexity of the system under investigation. The approach works with any parametric system identification algorithm that uses the system order n as sole parameter. Here a data-driven Stochastic Subspace Identification (SSI) method is used. Measurements from a wind tunnel investigation with a composite cantilever equipped with Fiber Bragg Grating Sensors (FBGSs) and piezoelectric sensors are used to assess the performance of the algorithm with a highly damped structure and low signal to noise ratio conditions. The proposed method was able to identify all physical system modes in the investigated frequency range from over 1000 individual datasets using FBGSs under challenging signal to noise ratio conditions and under better signal conditions but from only two sensors.

1. Introduction

Continuous Structural Health Monitoring (SHM) presupposes the automatic extraction of damage sensitive features. In the case of vibration-based Structural Health Monitoring (SHM) these features usually are the modal parameters of the system (natural frequencies, mode shapes and damping ratios). In recent years significant progress has been made in developing and refining modal parameter identification methods that use unmeasured environmental loads as the primary source of structural excitation. These methods are today known under the name of Operational Modal Analysis (OMA) [1]. OMA itself requires manual user interaction but multiple OMA-based automatization algorithms have been proposed and successfully applied to complex structure like bridges [2,3] and wind turbines [4]. Despite some progress, the proper (and ideally fully automatic) choice of automatization parameters and thresholds as well as the identification of complex and heavily damped modes is an area of ongoing research.

The main challenge for Automated Operational Modal Analysis (AOMA) from parametric system identification algorithms

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is the separation between physical and mathematical modes. This challenge is commonly addressed through parameter identification at a large number of system orders n. The approach is based on the empirical observation that physical modes are identified with nearly identical properties at every system order. Their modal properties are stable. Mathematical modes on the other hand are not identified in a consistent way. Traditionally inconsistency thresholds for each modal parameter are provided by the user to separate physical from mathematical modes [5]. Furthermore, additional mode validation criteria like Mean Phase Deviation (MPD), Mode Phase Collinearity (MPC), etc. are often used to single out the physical system modes. This data are then summarized in a stability diagram, which allows the user to manually select the physical modes.

A variety of methods have been proposed to automatize the OMA process. Overviews were published in [3] and [6] and will not be repeated here. The approach to AOMA described in this work can be summarized into the following steps [2,3]:

1. Identify mode candidates from a large number of system orders.
2. Remove as many mathematical modes as possible.
3. Use hierarchical clustering to divide the remaining modes into homogeneous sets.
4. Remove the small sets, which typically consist of mathematical modes.

The method proposed in [2] requires at least one user-defined parameter, the maximum within-cluster distance between representations of the same physical mode from different system orders. Such parameters have to be selected for every new sensor setup and system under investigation and may be sensitive to varying operational and environmental conditions. Their proper choice requires expert knowledge and, depending on the specific application, considerable manual effort may be required. Reynders et al. [3] suggested to automatically derive this parameter from the actual data. However, the proposed algorithm is limited to (nearly) real mode shapes and includes a damping ratio threshold. These are acceptable restrictions for some engineering structures, including e.g. bridges that were investigated in [2] and [3]. However, in aerospace applications damping and complexity are dominated by the fluid-structure interaction and are often substantially larger than under no-wind conditions. For such applications these constraints may be too restrictive.

A Stochastic Subspace Identification (SSI) method is commonly used to identify the mode candidates in a large range of system orders. However, the influence of the utilized system order range has not been investigated in the context of AOMA. Instead, in previous publications [2,3] the maximum system order was chosen to be much larger than the number of expected physical modes in the investigated frequency range. Further, the insensitivity of the proposed methodologies to varying system order ranges was not proven, and no methods were discussed to detect the upper and lower bounds of the usable system order range.

In this work an innovative multi-stage clustering approach for AOMA is introduced that can be used with any parametric system identification algorithm. No user-defined thresholds are required and neither the to-be-identified damping ratios nor the mode shape complexities are limited in any way. Furthermore, the sensitivity of step one of the proposed method to changes of the chosen system order range is explored and compared to existing approaches using a large number of independent datasets and two different measurement setups. One major novel contribution of this work is the consistent formulation of a clustering feature vector to separate between physical and mathematical modes in step two of the investigated method, and the subsequent application of transformation and normalization techniques to the heavily skewed feature vector. It is at this point that the demand for small complexity as well as for a damping ratio threshold can be dropped. For hierarchical clustering we derive a statistically profound threshold value from the measured Probability Density Functions (PDFs) to separate the remaining probably physical modes into homogeneous sets. The performance of the algorithm is assessed using a large number of wind tunnel measurements with a composite cantilever that was equipped with a low number of piezoelectric sensors and a high number of Fiber Bragg Grating Sensors (FBGSs). This presents a challenging data set in terms of a highly damped system with variable noise levels, as well as more broadly representing one possible future utilization scenario for the two sensing technologies in SHM.

2. Methodology

2.1. Experimental data

To assess the performance of the proposed AOMA methodology experimental data from a wind tunnel study are used. The experimental setup is shown in Fig. 1. The investigation was conducted in a closed-loop wind tunnel with an open test section. The investigated specimen was a glass fiber-reinforced polymer plate ($500\ \mathrm{mm} \times 90\ \mathrm{mm} \times 4\ \mathrm{mm}$), which was subjected to different flow conditions. The structural response of the specimen was measured using three sensor types: FBGSs, a unidirectional piezoelectric (PZT) accelerometer and a piezoelectric strain sensor. In addition, the dynamic properties of the inflowing wind were measured using a hot-wire anemometer. A detailed description of the experimental setup was published in [7].

The experimental setup was designed to represent two limiting cases of possible sensor setups. On one hand two piezoelectric sensors, with high dynamic range but only limited spatial information. On the other hand ten FBGSs, with more spatial information but significantly worse dynamic range due to the investigated interrogator, which is based on Charge-Coupled Device (CCD) technology. The differences in the signal-to-noise ratio (SNR) of the two cases are apparent from the