Mechanical Systems and Signal Processing 88 (2017) 62–80

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

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

Characterization of identification errors and uses in localization of poor modal correlation

Guillaume Martin[a,b,*], Etienne Balmes[a,b], Thierry Chancelier[c]

[a] Arts et Metiers ParisTech, PIMM, 151 Boulevard de l'Hopital, 75013 Paris, France
[b] SDTools, 44 rue Vergniaud, 75013 Paris, France
[c] Chassis Brakes International, 126 rue de Stalingrad, 93700, Drancy, France

ARTICLE INFO

Keywords:
Modal assurance criterion
Identification error
Localization of poor correlation

ABSTRACT

While modal identification is a mature subject, very few studies address the characterization of errors associated with components of a mode shape. This is particularly important in test/analysis correlation procedures, where the Modal Assurance Criterion is used to pair modes and to localize at which sensors discrepancies occur. Poor correlation is usually attributed to modeling errors, but clearly identification errors also occur. In particular with 3D Scanning Laser Doppler Vibrometer measurement, many transfer functions are measured. As a result individual validation of each measurement cannot be performed manually in a reasonable time frame and a notable fraction of measurements is expected to be fairly noisy leading to poor identification of the associated mode shape components.

The paper first addresses measurements and introduces multiple criteria. The *error* measures the difference between test and synthesized transfer functions around each resonance and can be used to localize poorly identified modal components. For intermediate error values, diagnostic of the origin of the error is needed. The *level* evaluates the transfer function amplitude in the vicinity of a given mode and can be used to eliminate sensors with low responses. A *Noise Over Signal* indicator, product of error and level, is then shown to be relevant to detect poorly excited modes and errors due to modal property shifts between test batches. Finally, a *contribution* is introduced to evaluate the visibility of a mode in each transfer. Using tests on a drum brake component, these indicators are shown to provide relevant insight into the quality of measurements.

In a second part, test/analysis correlation is addressed with a focus on the localization of sources of poor mode shape correlation. The MACCo algorithm, which sorts sensors by the impact of their removal on a MAC computation, is shown to be particularly relevant. Combined with the *error* it avoids keeping erroneous modal components. Applied after removal of poor modal components, it provides spatial maps of poor correlation, which help localizing mode shape correlation errors and thus prepare the selection of model changes in updating procedures.

1. Introduction

Major reasons to perform modal testing are to understand the experimental behavior of a mechanical system and often to

* Corresponding author at: Arts et Metiers ParisTech, PIMM, 151 Boulevard de l'Hopital, 75013 Paris, France.
E-mail address: balmes@sdtools.com (E. Balmes).

http://dx.doi.org/10.1016/j.ymssp.2016.11.006
Received 14 March 2016; Received in revised form 4 November 2016; Accepted 7 November 2016

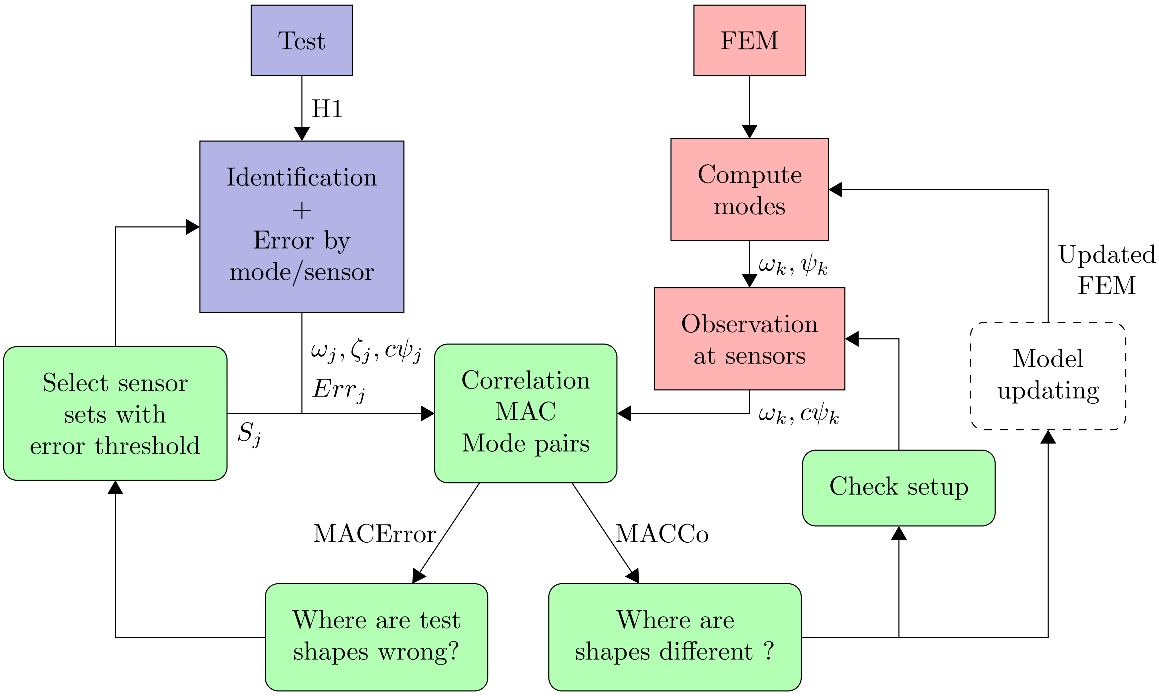

Fig. 1. Correlation evaluation during model updating process.

evaluate the correlation between test and analysis. The Modal Assurance Criterion (MAC) [1] is generally used for such correlation. It allows pairing of test and analysis (usually Finite Element Model (FEM)) mode shapes and provides a quantitative measurement of the difference between test and analysis. In most applications the motivation for the test is to help in the diagnosis of modeling errors and improvement of model parameters through updating [2].

Fig. 1 summarizes the use of the MAC correlation criterion in the model updating process used in this paper. On the one hand, data from test measurements are used to identify modes providing experimental frequencies ω_j, damping coefficients ζ_j and mode shapes $c\psi_j$. On the other hand, computation of the FEM provides numerical frequencies ω_k and mode shapes ψ_k, which need then to be observed at sensors, leading to $c\psi_k$. Identified and observed numerical mode shapes are then compared with the MAC and after pairing give correlation levels per mode pair. This presentation clearly highlights the fact that poor correlation can come from modeling errors, answering the question of where mode shapes are different as usually considered in updating processes, but also from test, thus answering the question of where test shapes are badly identified and not relevant. The objective of the work presented here is therefore to introduce and illustrate strategies for test error quantification and use in poor sensor localization.

Test errors may have different origins. Product variability can play a major role in updating processes and correlation analysis [3–5] but they will not be addressed. Test variability (loading variability, temperature evolution during test,…) are typically controlled through reproducibility tests. Methods involving bootstrap strategies [6,7] can be used to obtain uncertainty on identified parameters from repeated measurements. One important interest of these methods is that no assumption is made on the statistical law, but the major drawback is that all measurements must be saved (no averaging). Comparable results can be achieved using Monte Carlo methods [8] or Maximum Likelihood identification [9,10], but assuming a normal distribution of the measured response. In all of these cases, it is useful to note that any bias introduced by the chosen identification method has uncontrolled effects [7].

Illustrations of the proposed methods are based on 3D scanning laser Doppler vibrometer (3D-SLDV) measurements routinely used by Chassis Brakes International in the model validation process where brake components and assemblies are tested and correlated with FEM. The retained test case is detailed in Section 2.

The first focus of this paper is on a quantification of identification error, rather than building of an uncertainty model for identified parameters. After a description in Section 2 of the test case used as illustration, the identification procedure and notations used in the paper are presented in Section 3.1. An identification error is defined, in Section 3.2, by computing, for each mode and each sensor, the norm of the difference between measured and synthesized transfer functions around the resonance frequency. This criterion does not imply the need to use stochastic methods to estimate uncertainty bounds on modal parameters [9,10] and is as a result more easily used. Three additional indicators, level, contribution, and Noise Over Signal are then introduced to help sorting measurements and in the diagnostic of non-relevant modal contributions. Taking identification results obtained using the pole tuning strategy [11] of the Structural Dynamics Toolbox [12] for MATLAB, these criteria are shown to allow proper diagnostic of measurement problems and the definition of sensor sets retaining reliably measured components of each mode shape.

The second paper contribution is an analysis, in Section 4, of strategies used to build valid sensor sets for different modes. When