Journal of Physics: Conference Series

Experimental acoustic modal analysis of an automotive cabin: challenges and solutions

To cite this article: G. Accardo *et al* 2018 *J. Phys.: Conf. Ser.* **1075** 012026

Experimental acoustic modal analysis of an automotive cabin: challenges and solutions

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Abstract. In this paper, a full Acoustic Modal Analysis (AMA) procedure to improve the CAE predictions of the car interior noise level is proposed. Some of the challenges that can be experienced during such an analysis are described and new solutions to face them are proposed. Particular AMA challenges range from the arrangement of the experimental setup to the post-processing analysis. Since a large number of microphones are needed, a smart localization procedure, which automatically determines the microphone three dimensional (3-D) positions and dramatically reduces the setup time, is presented herein. Furthermore, the need for a large number of sound sources spread across the cavity to assure a homogeneous sound field makes modal parameter estimation a nontrivial task. Traditional modal parameter estimators have indeed proven not to be effective in cases where many input excitation locations have to be used. Hence, a more suitable estimator, the Maximum Likelihood Modal Model-based (ML-MM) method, will be employed for such an analysis.

1. Introduction

Nowadays, the automotive industry is asked to fulfil ever more demanding requirements for noise reduction and passenger comfort. Design engineers are asked to face the big challenge of reducing in-vehicle noise and improving passengers acoustic experience by keeping the intervention costs to a minimum. It is clear that the adoption of a numerical method to perform vibration and acoustic analyses is attracting increasing attention because of its merits in saving costs and time. Nevertheless, it is obvious that the effectiveness of this approach greatly depends on the accuracy of the predictions made using such models. So, in order to guarantee reliable simulations of the interior sound field of a vehicle cabin, experimental Acoustic Modal Analysis (AMA) can be considered a must-be-performed step, since it allows for validation and updating of these numerical models, and improvement of the overall modelling know-how.

In this paper, a full procedure to perform an experimental acoustic modal survey of an automotive cabin is proposed, with the goal of providing useful and practical guidelines. The particular challenges of such an analysis, which range from the test preparation to the post-processing analysis, will be shown, and different solutions will be presented.

2. Formulation of the acoustic problem

Consider a cavity of volume $\mathcal{V}$ enclosed by a surface $\Omega = \partial\mathcal{V}$ and excited by a point monopole of volume velocity per unit volume q, located at the arbitrary point r_0. If the surface Ω is acoustically rigid, the governing equation of the system is [3]:

$$\nabla^2 p(\mathsf{r}, t) - \frac{1}{c^2}\frac{\partial^2 p}{\partial t^2}(\mathsf{r}, t) = -\rho\frac{\partial q}{\partial t}\delta(\mathsf{r} - \mathsf{r}_0), \tag{1}$$

where p is the acoustic pressure, which is a function of space r and time t, ∇^2 is the Laplace operator, c is the speed of sound and ρ the density of the medium, and the source function is represented mathematically by a delta function.

Assuming now that a number of point monopoles of known volume velocity per unit volume are placed in the cavity and the sound pressure across the volume is sampled at an appropriate number of points, it can be shown that the continuous wave equation (1) can then be substituted by its discrete equivalent:

$$\mathsf{M}_F\ddot{\mathsf{p}} + \mathsf{C}_F\dot{\mathsf{p}} + \mathsf{K}_F\mathsf{p} = -\rho\dot{\mathsf{q}}, \tag{2}$$

where, to preserve the analogy with a structural finite element model, the matrix M_F is called the acoustic mass matrix; the matrix C_F is the acoustic damping matrix; the matrix K_F is called the acoustic stiffness matrix. In view of this equivalence between acoustics and structural dynamics, it can be concluded that the classical modal parameter estimation approach can be followed also in the acoustic modal analysis case.

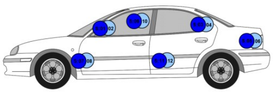
3. Test preparation, test model creation and setup

In this section, the measurement setup and equipment needed for typical AMA tests will be described. Details on the sound sources and their position, on the number of sensors, their spatial distribution, and their mounting inside the cavity will be given.

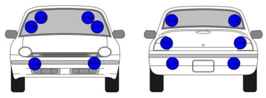
3.1. Sound sources

Calibrated volume velocity sources are necessary to measure acoustic FRFs that are required in AMA tests. The sound sources have to be omnidirectional and have a negligible size in order not to influence the field, especially in the higher frequency range. So the need exists for a dedicated source that is compact, omnidirectional and capable of generating high noise levels. The LMS Qsources Low-Frequency Monopole Sound Source (Q-MED) can fulfil such requirements (Fig. 1). It is a unique monopole sound source that has been developed to acquire acoustic and vibro-acoustic FRFs accurately without disturbing the acoustic behaviour of the passenger compartment.

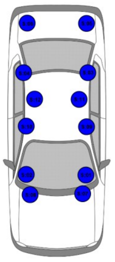
Figure 1: LMS Qsources low-frequency monopole sound source



(a) Side View



(b) Front View (c) Back View



(d) Top View

Figure 2: Reference distribution

As shown in [1, 4, 5], an appropriate source distribution over the entire cabin is required to properly estimate the acoustic modes. With reference to the analysis reported in [1], where up to 12 volume velocity sources were set in geometrically symmetric locations, close to the edges, corners and at the maximum amplitude locations to avoid nodal lines and excite close to pressure maxima on the boundaries, a typical distribution of sound sources is displayed in Fig. 2. Too few sources do not allow for correct identification of the mode shapes as exciter-location-dependent mode shape distortions are clearly visible [1]. For this reason, it is highly advisable to use a rather large number of sources and source locations.

3.2. Sensor Placement

In order to guarantee a good description of the mode shapes and a sufficient number of degrees of freedom for the updating, a sensor layout as the one depicted in Fig. 3 is usually employed.

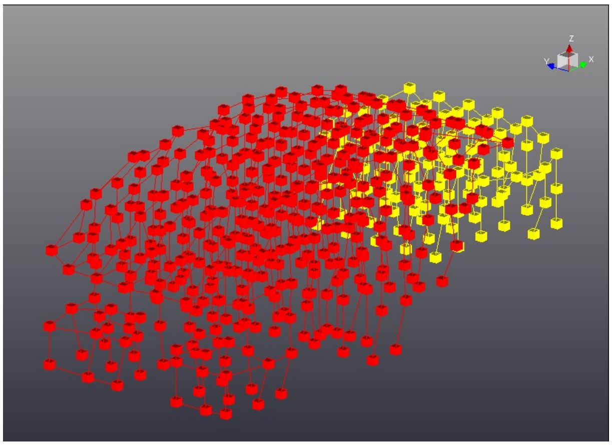


Figure 3: Wireframe model

Sensors need to be uniformly spread across the whole cabin, even in extreme positions, such as in foot regions, between the windshield and the dashboard, and in the hat shelf region. With reference to the test case reported in [1], more than 500 measurement points are required. Determining the exact location of so many sensors by hand would be extremely cumbersome. Hence, automatic methods would be essential for drastically reducing the setup time and localizing microphones in a smarter way. For this purpose, a fast, accurate and cost-effective procedure has been developed and validated [6–8].

3.2.1. Smart localization procedure

The microphone localization procedure employed is based on multilateration: the distances between at least four sources (anchors), whose coordinates are known or estimated *a priori*, and a microphone (target) are utilized to determine the unknown position of the microphone in three-dimensional (3-D) space. However, due to the complex structure and obstructions typical of a car cabin (e.g., seats, dashboard, etc.), the direct path may be obstructed, a so-called Non-Line-Of-Sight (NLOS) condition. As a consequence, acoustic range estimates based on the time-of-arrival (TOA) may have an erroneous positive bias, i.e., the signal arrives at a microphone through reflections instead of through the direct (shortest) path.

The proposed method copes with the problem of NLOS through an identification and discard (IAD) algorithm: the erroneous NLOS measurements are detected and pruned, so that the microphones are localized using the LOS distances only, hence yielding more accurate 3-D localization results. For further details, the reader can refer to [6].

For multilateration, the sound source should ideally be a monopole. It means that, within the frequency range of interest, the characteristic length of the source must be smaller than the minimum wavelength, and the source itself must be always omnidirectional. For this purpose, a new, dedicated and compact LMS Qsources volume source has been utilized (Fig. 4). These LMS Qsources volume velocity sources are designed to be used in a high frequency band (1 to 20 kHz), which is an important bandwidth to ensure accurate TOA measurements [9].

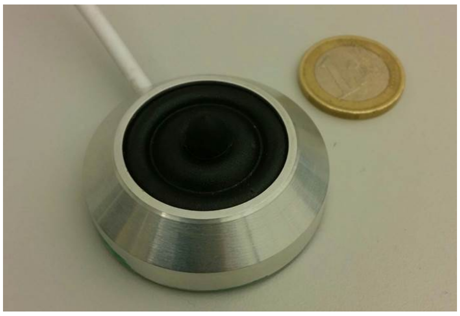


Figure 4: New compact LMS Qsources volume velocity source

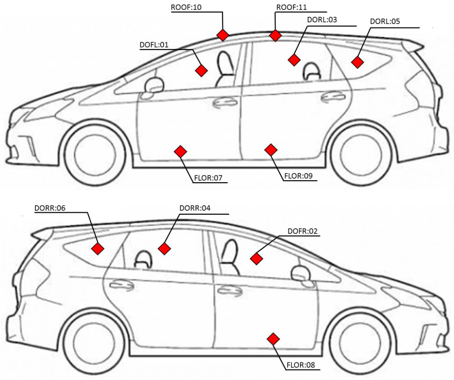


Figure 5: Source Distribution

The anchors should be placed in strategic positions so as to localize the largest number of microphones. With reference to the experimental case reported in [8], where microphones were placed in critical positions, an example of anchors configuration is illustrated[1] in Fig. 5. During the measurements, the averaged temperature of the environment must be recorded in order to calibrate the speed of sound, whereby the temperature is assumed to be constant throughout the cabin.

The linear frequency modulated (chirp) signal have been used for this application.

In order to have a qualitative idea of the effectiveness of the method, the coordinates from the CAD model are assumed as a reference. The discrepancies between the (inaccurate) CAD positions and the acoustically estimated coordinates do not allow for an absolute localization error quantification, but they are sufficient for demonstrating the effectiveness of the approach in a complex scenario, such as a car cabin.

In Fig. 6, a comparison is made between a localization algorithm were the pruning is not applied (i.e. NLOS distances remain present), versus the considered localization algorithm where erroneous distances are identified and discarded[2]. As visible in Fig. 6, the application of the NLOS IAD algorithm is not only effective, but also essential for a correct localization of all microphones.

4. Modal Parameter Identification

It has been observed in [1, 4, 5, 10] that it is quite challenging for classical modal parameter estimation methods to curve-fit an FRF matrix with so many columns (12 references, as reported in § 3.1); typically, not all references are well fitted for a particular sensor location. Therefore, there is a need for a new solver capable to overcome such a difficulty. The Maximum Likelihood Modal Model-based (ML-MM) modal parameter estimator [2] has been proven to be more suitable for such a kind of data [1, 10]. A brief description of the estimator is reported in the follow.

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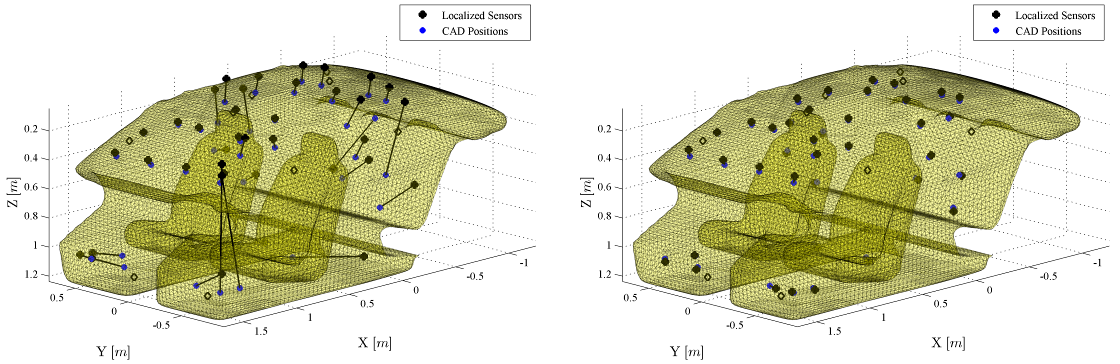
[1] The model of the car is for illustrative purposes only.

[2] The results have been obtained by using all the 11 sources, imposing a threshold $\zeta = 2$ cm, and using as initial guess the centre of gravity of the anchors.



(a) (b)

Figure 6: Localized microphones without (a) and with (b) the application of the NLOS IAD algorithm

4.1. Maximum Likelihood Modal Model-based method

The so-called ML-MM method is a multiple-input, multiple output (MIMO) frequency-domain estimator providing global estimates of the modal model parameters. Since it is an iterative method based on solving a non-linear optimization problem, initial values for the modal model parameters (i.e., poles, participation factors, mode shapes, lower and upper residuals) are needed to start the optimization process. In the first step, the Polymax method [**?**] is applied to the FRFs to obtain the initial estimates for the poles and the participation factors of the physical modes within the analysis band. Then, initial values for the mode shapes and the lower and upper residuals are estimated in a complementary step using the so-called Least-Squares Frequency Domain (LSFD) estimator [11]. In the next step, once the initial values for the entire modal model parameters are obtained, the ML-MM solver starts minimizing the error between the modal model equation and the measured data in a maximum-likelihood sense. Assuming the different measured FRFs to be uncorrelated, the ML-MM cost function to be minimized can be formulated as:

$$K_{\text{ML-MM}}(\theta) = \sum_{o=1}^{N_o} \sum_{i=1}^{N_i} \sum_{k=1}^{N_f} \frac{\left|H_{oi}(\omega_k) - \hat{H}_{oi}(\theta, \omega_k)\right|^2}{\sigma^2_{H_{oi}}(\omega_k)}, \tag{3}$$

where N_0 is the number of outputs, N_i the number of inputs, N_f the number of frequency lines, $\omega_k = 2\pi f_k$ the circular frequency at frequency f_k [Hz], $H_{oi}(\omega_k) \in \mathbb{C}$ is the measured FRF, $\hat{H}_{oi}(\theta, \omega_k) \in \mathbb{C}$ the modelled FRF, and $\sigma^2_{H_{oi}}(\omega_k) = \text{var}[H_{oi}(\omega_k)] \in \mathbb{R}$.

Assuming volume acceleration FRFs, $\hat{\mathsf{H}}(\theta, \omega_k) \in \mathbb{C}^{N_o \times N_i}$ can be represented using the modal model formulation [11]:

$$\hat{\mathsf{H}}(\theta, \omega_k) = \sum_{r=1}^{N_m} \left(\frac{\phi_{\mathrm{r}} \mathsf{l}_r}{j\omega_k - \lambda_r} + \frac{\phi_{\mathrm{r}}^* \mathsf{l}_r^*}{j\omega_k - \lambda_r^*} \right) + \frac{\text{LR}}{(j\omega_k)^2} + \text{UR}, \tag{4}$$

where N_m is the number of the identified modes, $\phi_r \in \mathbb{C}^{N_o \times 1}$ is the r-th mode shape, λ_r is the r-th pole, $(\bullet)^*$ stands for the complex conjugate of a complex number, $\mathsf{l}_r \in \mathbb{C}^{1 \times N_i}$ is the r-th participation factors vector, $\text{LR} \in \mathbb{R}^{N_o \times N_i}$ and $\text{UR} \in \mathbb{R}^{N_o \times N_i}$ are the lower and upper residual terms used to compensate for the out-of-band modes, and θ is the parameters vector (i.e., $\theta = \{\phi_r, \mathsf{l}_r, \lambda_r, \text{LR}, \text{UR}\}$). The maximum likelihood estimates of θ are obtained by using a Gauss-Newton optimization. Furthermore, to ensure convergence, the Gauss-Newton optimization is implemented together with the Levenberg-Marquardt approach, which forces the cost function to decrease. More details about the ML-MM method are presented in [2].

4.2. Considerations and results

The ML-MM method has been proven to outperform more classical modal parameter estimators with such a kind of data.

With reference to the test case in [1], the initial values generated by applying the Polymax method to the full 526 × 12 FRF matrix were improved by applying the ML-MM method. The analysis was stopped after 20 iterations. Nine pure acoustic modes are well identified in the frequency range from 0-200 Hz (Fig. 8). The initial mean fitting error between measured FRFs and Polymax synthesized FRFs was around 9%. The mean fitting error after applying the ML-MM method reduced to only 2%. This improved overall curve fit is illustrated using two typical elements from the full FRF matrix in Fig. 7.

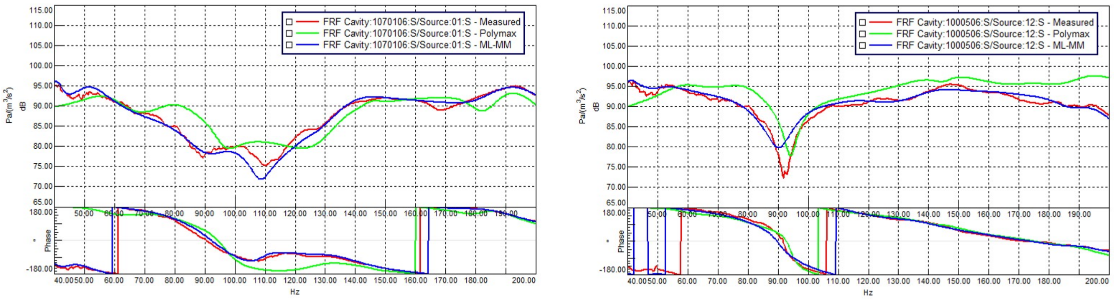


Figure 7: Improved FRF curve-fitting quality shown for two typical FRFs; - Measured (red), Polymax synthesis (green), ML-MM synthesis (blue)

5. Conclusions

A full Acoustic Modal Analysis (AMA) procedure to improve the CAE prediction of the the car interior noise level has been proposed and successively validated. The challenges of typical AMA tests are described in details. The huge amount of sensors required to have a good description of the acoustic cavity, and the large number of sound sources to properly excite the cavity of a car cabin make such tests extremely time-consuming and demanding. In order to have a good description of the dynamic behaviour of the system, many sensors are indeed placed inside the cabin. In such a complex environment, determining the microphone positions by hand is not only tedious, but also inaccurate and cumbersome. Furthermore, where many input excitation locations have to be used, it has been observed that traditional modal parameter estimators have proven not to be effective.

In order to face such typical challenges, different solutions are proposed. Firstly, a smart approach capable to automatically localize microphones in such a complex scenario is presented. The method is based on acoustic distance measurements between a microphone and (at least 4) sources. With the introduction of novel algorithms coping with reflections and non-line-of-sight issues, the localization procedure has been proven to be effective, providing reliable results and drastically reducing the measurement set-up time. Secondly, modal parameters are estimated in the frequency range between 40 and 200 Hz, by applying a new modal parameter estimation method, the so-called ML-MM estimator. Nine acoustically dominant modes are identified. Although Polymax still yields good modal parameter estimates, ML-MM provides superior FRF synthesis results and, hence, more reliable values.

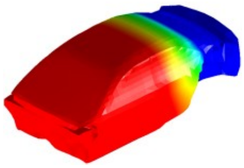
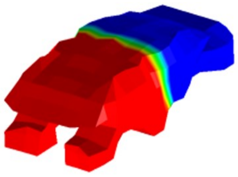
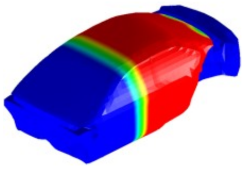
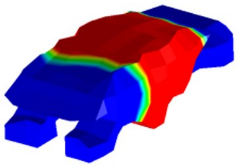
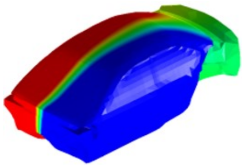
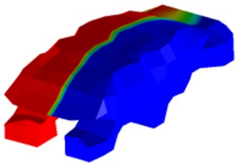
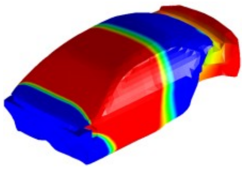
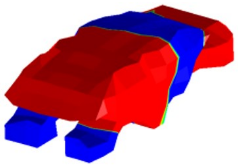
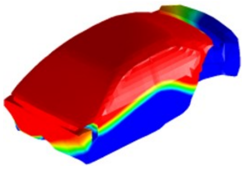
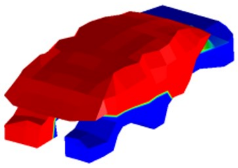
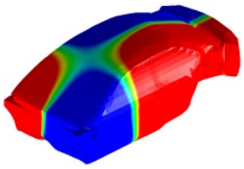
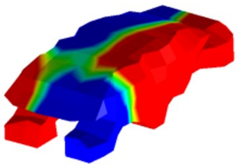
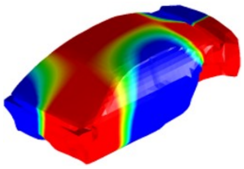
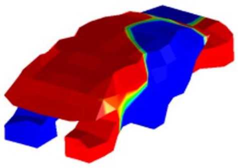
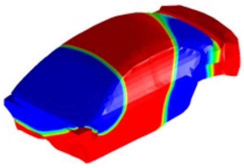
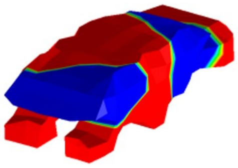
#	**Numerical Modes**	**#**	**Experimental Modes**	**Mode Shapes (Frequency, Damping)**
2		2		I Longitudinal (51.06 Hz, 13.82%)
3		3		I Longitudinal & Rigid-Body Trunk (81.44 Hz, 14.94%)
4		4		I Lateral (97.24 Hz, 10.65%)
5		5		II Longitudinal & Rigid-Body Trunk (137.79 Hz, 7.25%)
7		6		I Vertical (148.66 Hz, 13.70%)
6		7		I Longitudinal & I Lateral (149.34 Hz, 6.57%)
8		8		I Longitudinal & I Lateral & I Lateral Trunk (150.74 Hz, 11.79%)
9		9		III Longitudinal (195.13 Hz, 6.05%)

Figure 8: Identified mode shapes using 12 references (rigid-body mode not shown)

Acknowledgements

This work was supported by the Marie Curie ITN project ENHANCED (joined Experimental and Numerical methods for HumAN CEntered interior noise Design). The project has received funding from the European Union Seventh Framework Programme under grant agreement No. 606800. The whole consortium is gratefully acknowledged.

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