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. Due to international legal restrictions on noise and air pollution and the increasing customer's sensitiveness for the acoustic comfort, automotive companies have been driving more and more resources to acoustic treatment and isolation, as well as to environmentally compatible hybrid-electric powertrain concepts. 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.

It is of paramount importance to fine-tune the structural and acoustic design of a vehicle cavity to achieve specific NVH objectives. Structural-acoustic finite element (FE) models of the cavity represent an important tool in this context, because of the freedom given in testing different design strategies targeted at improving the passengers acoustic comfort. They can also be used as a diagnostic tool to identify the potential noise sources and also to evaluate the effectiveness of the proposed design modifications. 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 [1], 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. The first big challenge to face during the test preparation is the creation of a correct, geometrical wireframe model that represents the three-dimensional (3-D) position of the sensors. An acoustic modal analysis test can indeed easily consist of hundreds of degrees of freedom, particularly when the results are used for validating and updating finite element (FE) models, or, more generally, for having a good description of the mode shapes. In current practice, one has to measure the geometry of the test object by hand, which is extremely time-consuming and typically yields inaccurate results. Establishing a precise test geometry then relies on the capability of the operator to instrument exactly at predefined locations. It is clear that in many realistic cases this task can be rather challenging, above all when the structure is complex. Smart methods, which reduce this setup time and yield more accurate results, are therefore highly sought for. In this paper, a fast, accurate and cost-effective procedure to automatically localize microphones in a car cabin [2, 3] is proposed and will be briefly described. The approach, which exploits the same hardware used for AMA tests, provides more accurate 3-D positions compared to manual measurements, and drastically reduces the measurement set-up time.

A further challenge is represented by the high modal damping ratios resulting in highly overlapping modes with complex mode shapes. It has been observed [4–6] that, due to the high damping, a large number of acoustic sources distributed across the cabin are needed to get a sufficiently homogeneous sound field. Nevertheless, traditional modal parameter estimation methods may prove less suited for such data. Thus, a method overcoming the difficulties that the classical methods face when fitting an FRF matrix consisting of many (i.e., 4 or more) columns needs to be used. A Maximum Likelihood Modal Model-based (ML-MM) estimator [7] has been proven to be more suitable for such an analysis [6, 8]. Herein, the new method will be briefly described, and its performance showed by using a real test case.

The paper is organized as follows. Section 2 briefly recalls the formulation for internal acoustic problems. Using a discretized formulation, one can see that an analogy exists between acoustic and mechanical systems. Thanks to this equivalence, the classical approach can be used also in the acoustic modal analysis case. In section 3, with reference to the case study on a fully trimmed car reported in [6], the test preparation, set-up and measurements are described in detail. Sound sources, measurement points, and their respective location will be presented. Furthermore, a smart localization procedure to automatically localize microphones inside a car cabin is proposed. Section 4 discusses the modal parameter estimation. The ML-MM estimator is briefly illustrated and employed. The results will be compared to more classical modal parameter methods in terms of curve fitting, mean error, values of the modal parameters and mode shapes. Finally, in Section 5 some concluding remarks are given.

2 Formulation of the acoustic problem

In this section, the formulation of internal damped acoustic problems is recalled.

The internal acoustic problem considered is illustrated in Fig. 1. It consists of 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. Part of the surface Ω_0 is acoustically rigid and the part Ω_A is covered by a sound-absorbing material. If this material is assumed to be locally reacting, then its properties can be represented by a specific acoustic impedance Z_a.

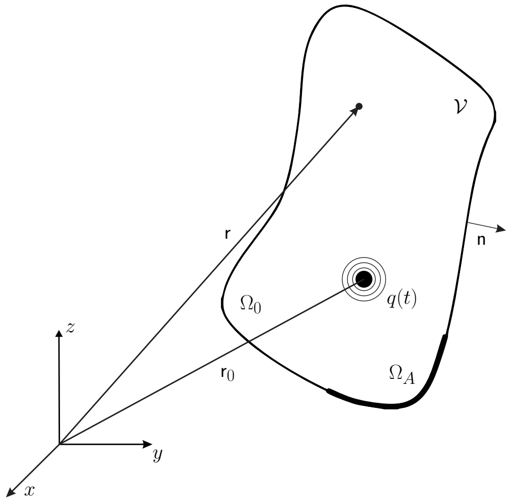


Figure 1: Description of the acoustic problem

Within $\mathcal{V}$, the governing equation of the system is [9]:

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

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. Over the boundary surface, the fluid particle velocity normal to the surface is equal to the normal velocity of the surface. This gives rise to the following boundary conditions:

$$\mathsf{n} \cdot \nabla p = 0 \qquad \text{over } \Omega_0, \tag{2a}$$

where n is the outward-directed unit vector normal to the surface and

$$\mathsf{n} \cdot \nabla p = -j\rho\omega \frac{p}{Z_a} \qquad \text{over } \Omega_A. \tag{2b}$$

The discretization of the continuous acoustic wave equation is based on the finite element formulation. The acoustic domain of volume $\mathcal{V}$ is represented by an assemblage of acoustic finite elements (FEs). The pressure distribution within an element is interpolated in terms of the nodal pressures by using shape functions. Variational formulation based on Eq. (1), boundary conditions (2a), (2b) and FE discretization gives the M_F, C_F and K_F matrices. To preserve the analogy with a structural finite element model, the matrix M_F is called the acoustic mass matrix, although it represents a compressibility matrix, relating the pressure to a displacement; the matrix C_F is the acoustic damping matrix, induced by the impedance boundary condition (2b); the matrix K_F is called the acoustic stiffness matrix, although it represents an inverse mass or mobility matrix, relating the pressure to an acceleration. 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:

$$\mathsf{M}_F\ddot{\mathsf{p}} + \mathsf{C}_F\dot{\mathsf{p}} + \mathsf{K}_F\mathsf{p} = -\rho\dot{\mathsf{q}}. \tag{3}$$

Taking the Laplace-transform and assuming zero initial conditions one gets:

$$\left[s^2\mathsf{M}_F + s\mathsf{C}_F + \mathsf{K}_F\right] \cdot \mathsf{p}(s) = -\rho s\mathsf{q}(s). \tag{4}$$

As usual in structural dynamics, the inverse of the matrix term can be substituted by the frequency response function $\mathsf{H}(s)$:

$$\mathsf{p}(s) = -\rho s\mathsf{H}(s) \cdot \mathsf{q}(s). \tag{5}$$

One can prove that the FRF-matrix can be expressed as a partial fraction expansion of modal parameters [10]:

$$\mathsf{H}(s) = \sum_{r=1}^{N_m} \frac{A_r \phi_r \phi_r^T}{s - \lambda_r} + \frac{A_r^* \phi_r^* \phi_r^{*T}}{s - \lambda_r^*}, \tag{6}$$

where N_m are the number of modes, ϕ_r the r-th modal vector, A_r the modal scaling factor for the r-th mode, and λ_r the system pole for the r-th mode. Substituting now s by $j\omega$ and using Eq. (5) it is obvious that the modal parameters of the system can be gained from the FRF measurements where the sound pressures across the volume are referenced to the volume accelerations of the sources. Notice that Eqs. (4)-(6) are in complete analogy with those being used in structural dynamics, therefore, it can be concluded that the classical modal parameter estimation approach can be followed also in the acoustic modal analysis case.

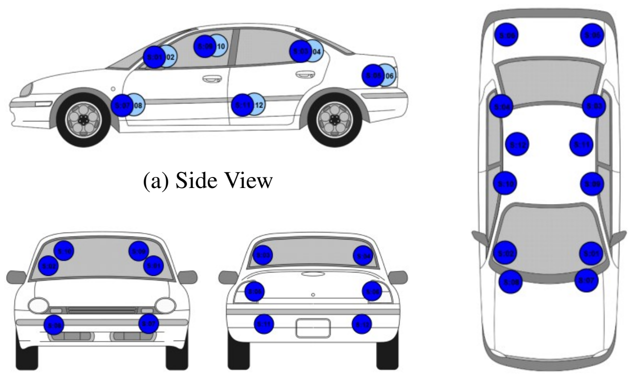
3 Test preparation, test model creation and setup

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. 2). 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 2: LMS Qsources low-frequency monopole sound source

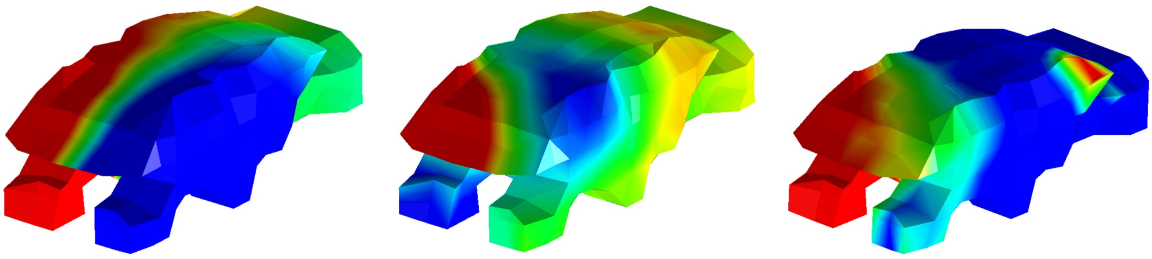


(a) Side View

(b) Front View (c) Back View (d) Top View

Figure 3: Reference distribution

As shown in [4–6], an appropriate source distribution over the entire cabin is required to properly excite the acoustic modes. With reference to the analysis reported in [6], 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. 3. Too few sources do not allow for correct identification of the mode shapes as exciter-location-dependent mode shape distortions are clearly visible. As an illustration of such an effect, Fig. 4 compares the use of all 12 columns (12 source locations) to the use of a single column (either the second or third column was selected). While the 12-source case clearly yields a first lateral mode, the shapes of the single-source cases are severely distorted, and the appearance makes it possible to locate the selected source based on the observed mode shape distortions. For this reason, it is highly advisable to use a rather large number of sources and source locations to excite as many modes as possible.



(a) (b) (c)

Figure 4: Mode shape distortion of I lateral mode when not using enough acoustic source locations: (a) Pure mode shape identified using all 12 sources; (b) Distorted mode shape with one source at Location 2 (front right); (c) Distorted mode shape with one source at Location 3 (rear left)

3.2 Sensor Placement

Over the years, different strategies for the optimal placement of actuators and sensors (OPAS) have been developed for system identification [11–14], in order to obtain an optimal or sub-optimal actuator and sensor layout assuring the goodness of the excitation and the observability of modes with a minimum number of sensors, respectively. Although such methods are extremely useful when only a few sensors are available, in practice they are proven to be effective only when the numerical models have already been calibrated or are close to the real one. It is clear that such conditions are far from being satisfied when the goal of the analyses is the overall improvement of the modelling know-how. Therefore, a large number of sensors is actually needed for this purpose [4, 6, 15]. Nevertheless, information extracted from an initial numerical model, like the number of modes in the frequency range of interest and mode shapes, can still support the decision process, taking into account that most information might be uncertain. An acoustic FE model of an interior car cavity with rigid boundaries (Fig. 5) may indeed be helpful to: i) have an idea on where to properly locate the sound sources to avoid nodal lines; ii) have a preliminary geometry of the measurement points; iii) select meaningful modes and address the dominant acoustic modes in such a coupled system where the FRFs are also influenced by the resonances of the structural system.

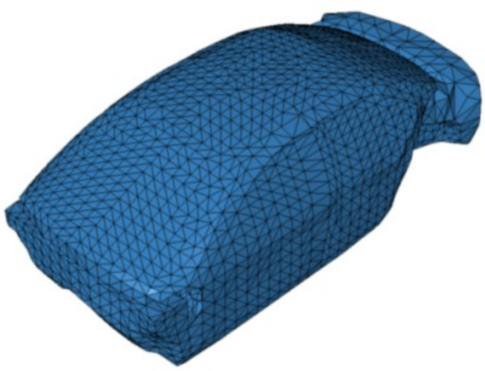


Figure 5: CAE cavity model

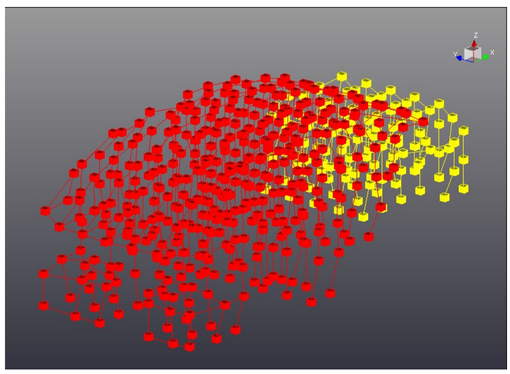


Figure 6: Wireframe model

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. 6 is hence usually employed. 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 [6], 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 [2, 3, 16].

3.2.1 Smart localization procedure

The microphone localization procedure herein proposed 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. Hence the estimation of microphone coordinates comprises two steps (Fig. 7): i) acoustic ranging measurements, ii) multilateration.

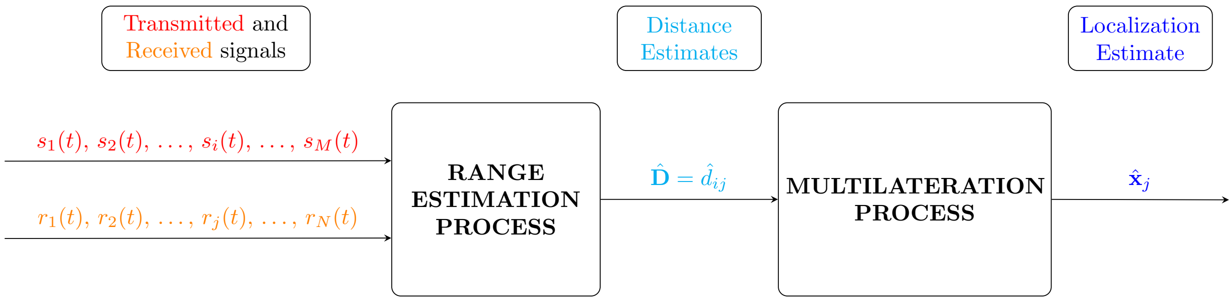
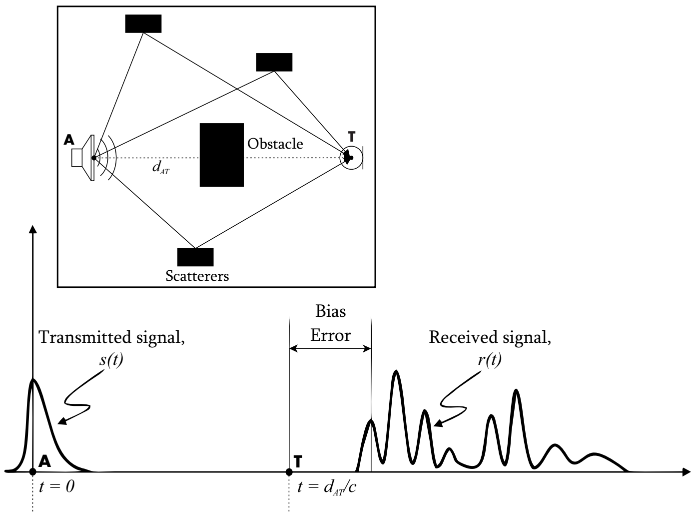


Figure 7: Localization process

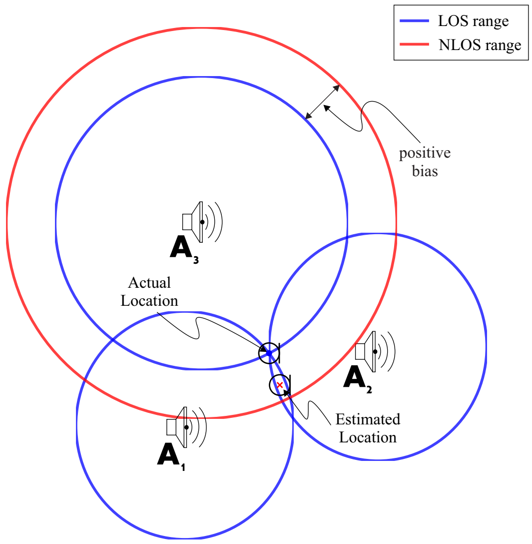
However, due to the complex structure and obstructions typical of a car cabin (e.g., seats, dashboard, etc.), the direct path may be obstructed, a so-called Non-Line-Of-Sight (NLOS) condition. As a consequence, acoustic range estimates based on the time-of-arrival (TOA) may have an erroneous positive bias, i.e., the signal arrives at a microphone through reflections instead of through the direct (shortest) path (Fig. 8a).
Furthermore, estimating the TOA of the direct path (when it exists) can be rather challenging in such a harsh environment. Reflections of the wavefront may indeed cause the strongest path not to be the first, leading to a possible erroneous detection of the actual first path, because of fading. The (overestimated) NLOS distances may subsequently lead to large 3-D position errors (Fig. 8b).
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.

Range Estimation Process

Localization performances are highly dependent on the quality of the range measurements. Hence, particular attention has to be paid to this crucial first phase. The TOA can be simply estimated by cross-correlating the received signal with the transmitted signal template. In ideal propagation conditions, the TOA estimate is given by the time instant corresponding to the maximum absolute peak of the cross-correlation function (CCF) over the observation interval. Nevertheless, in dense multipath scenarios, the TOA estimation actually consists in the correct detection of the first arriving path. In general, while the dominant peaks may correspond to the signal echoes, it is not straightforward to find the correct peak due to the presence of noise and fading. Hence, this ambiguity highlights that TOA estimation in the presence of multipath is not a pure



(a) In the absence of a direct link between the anchor A and the target T, the estimated distance will be larger than the true distance



(b) The positively biased NLOS range may affect the accuracy of the target location estimate

Figure 8: TOA-based localization in NLOS environments

parameter estimation problem, but rather a joint detection-estimation problem [17]. In this approach the TOA estimation problem will be considered as a change detection problem without relying on any threshold. Details on the TOA estimator are available in [16].

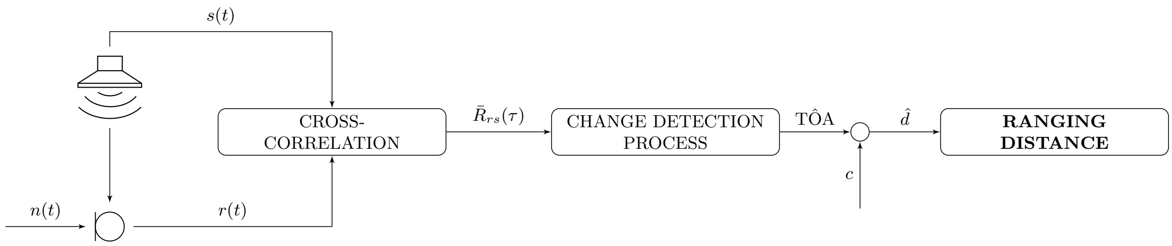


Figure 9: Flowchart of the Ranging Process

Multilateration and NLOS Identify and Discard Algorithm

3-D localization problem is treated as an optimization problem. In absence of noise and NLOS bias, the actual distance d_i between the target and the i-th anchor defines a sphere around the i-th anchor corresponding to possible target locations, i.e.,

$$(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2 = d_i^2, \quad \text{for } i \in \mathcal{M}, \tag{7}$$

where $\{\mathbf{x}_i = [x_i \; y_i \; z_i]^T, \; i \in \mathcal{M}\}$ are the known locations of the M anchors, and $\{\mathbf{x}_j = [x_j \; y_j \; z_j]^T\}$ is the unknown location of the j-th target, which we wish to determine.
The exact location of the target is then found at the unique intersection of all the spheres. In practice however, the noisy distance measurements and NLOS bias yield spheres which do not intersect at the same point, resulting in the inconsistent equations

$$(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2 = \hat{d}_i^2, \quad \text{for } i \in \mathcal{M}. \tag{8}$$

Equation (8) can hence be solved by minimizing the sum of squared residuals, i.e.,

$$\min_{\mathbf{x}} \left\{ \sum_{i=1}^{M} \left(||\mathbf{x} - \mathbf{x}_i|| - \hat{d}_i \right)^2 \right\} \tag{9}$$

whose solution yields the final estimate $\hat{\mathbf{x}}$ of the target location.

In multilateration, at least four LOS anchors are required for a unique 3-D solution. If there are more than four LOS anchors, the redundancy of these sources can be utilized in a least square (LS) sense for a more accurate localization result. Minimizing the non-linear expression in Eq. (9) can be achieved by numerical search methods [18].

Evidently, the optimization method will be most effective in estimating the location when only LOS distance measurements are combined. Therefore, there is a need for a NLOS identification and discard (IAD) algorithm, which is able to identify the NLOS observed distances and discard them in the LS calculation. The method is able to identify the number L of LOS anchors and localize the target with them only. To achieve this, the method exploits the redundancy and compares the squared residual of a set of distances to a predefined threshold, ζ:

$$\left(d_i^* - \hat{d}_i \right)^2 < \zeta^2 \tag{10}$$

where $d_i^* = ||\hat{\mathbf{x}} - \mathbf{x}_i||$ is the estimated distance between the i-th anchor and the target at estimated location $\hat{\mathbf{x}}$.

First, the algorithm begins by using all the available M distances. It estimates the microphone location, $\hat{\mathbf{x}}$, and compares the residuals, as in Eq. (10). If all the M residuals are below the threshold ζ, then $L = M$, otherwise the optimization procedure moves to groups of $(L - 1)$ sources. The algorithm stops when all the residuals of the k-th set of M sources taken L are below the threshold, or when $L = M^{min}$, i.e., the minimum number of sources which are necessary for a unique localization result. For further details, the reader can refer to [2].

Equipment and Localization results

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. 10). Such a source incorporates an internal sound source strength sensor which outputs a realtime volume acceleration signal, and it emits the noise as a monopole source up to several kHz. 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 [19, 20].

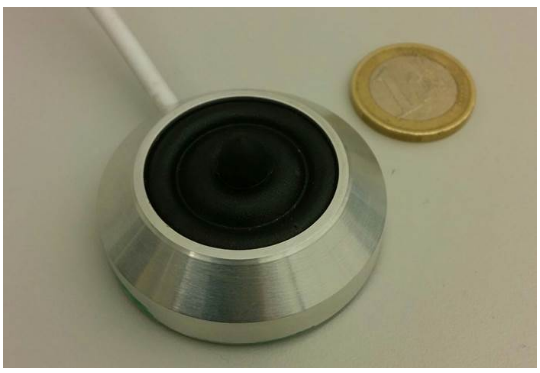


Figure 10: New compact LMS Qsources volume velocity source

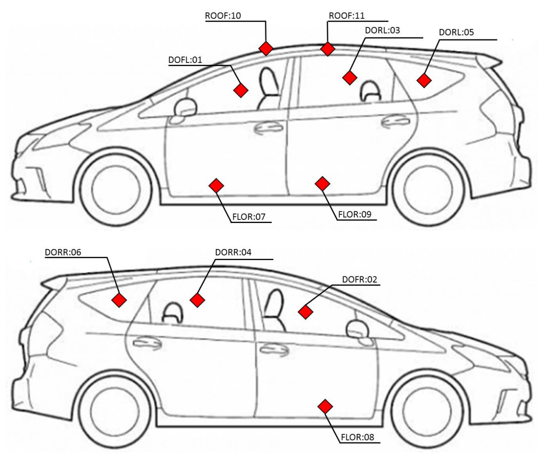


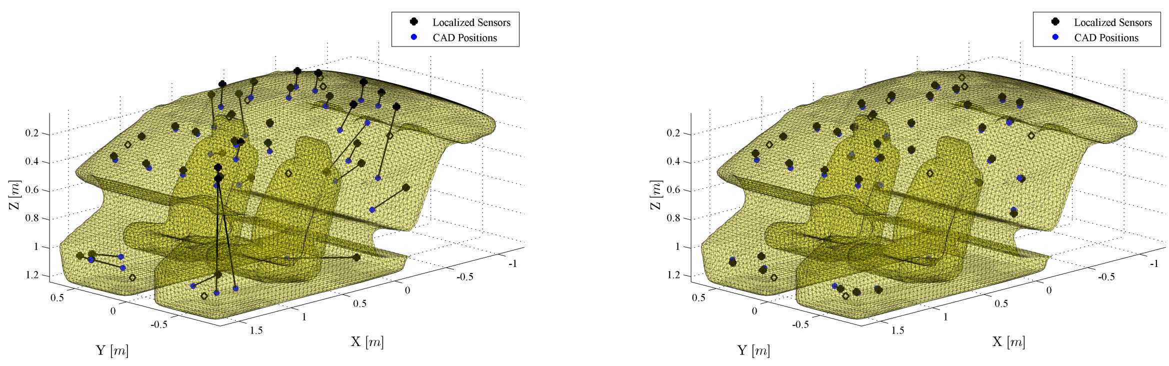
Figure 11: Source Distribution

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 [16], where microphones were placed in critical positions, an example of anchors configuration is illustrated[1] in Fig. 11. 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.

In order to have the highest possible temporal resolution of the CCF, the maximum sampling rate provided by the acquisition system is recommended. Furthermore, the pulse length must be short to avoid the overlapping of near echoes in the CCF. This is not a trivial requirement, as it is difficult to emit sharp pulses for speaker limitations. In addition, the signal has to be emitted with the highest power available in order to increase the signal-to-noise ratio (SNR), and to minimise the Cramer-Rao Lower Bound (CRLB) [19]. Nevertheless the SNR is proportional to pulse duration [21]. The contradiction can be solved by long duration signals which lead to short duration correlation functions, i.e., where the cross-correlation of the received signal and an appropriate template signal leads to a short pulse. A signal commonly used in radar application for this purpose is the linear frequency modulated (chirp) signal.

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. 12, 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. 12, the application of the NLOS IAD algorithm is not only effective, but also essential for a correct localization of all microphones.



(a) (b)

Figure 12: Localized microphones without (a) and with (b) the application of the NLOS IAD algorithm

4 Modal Parameter Identification

It has been observed in [4–6, 8] 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

[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.

estimator [7] has been proven to be more suitable for such a kind of data [6, 8]. A brief description of the estimator is reported in the follow.

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 [22] 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 [10]. 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:

$$K_{\text{ML-MM}}(\theta) = \sum_{o=1}^{N_o} \sum_{i=1}^{N_i} \sum_{k=1}^{N_f} \frac{\left|H_{oi}(\omega_k) - \hat{H}_{oi}(\theta, \omega_k)\right|^2}{\sigma^2_{H_{oi}}(\omega_k)}, \tag{11}$$

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 [10]:

$$\hat{\mathsf{H}}(\theta, \omega_k) = \sum_{r=1}^{N_m} \left(\frac{\phi_{\mathsf{r}} \mathsf{l}_r}{j\omega_k - \lambda_r} + \frac{\phi^*_{\mathsf{r}} \mathsf{l}^*_r}{j\omega_k - \lambda^*_r} \right) + \frac{\text{LR}}{(j\omega_k)^2} + \text{UR}, \tag{12}$$

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 [7].

4.2 Considerations and results

An important issue to be addressed when processing acoustic modal analysis data is to identify predominantly acoustic modes in FRFs with a rather high modal density [4, 15]. Even if purely acoustic FRFs have been measured, the modal density is indeed high since the acoustic cabin is coupled to a flexible body and also the resonances of the structural system (mainly panel vibrations from the windshield, the roof, etc.) show up in sound pressure measurements. So, among the several coupled natural frequencies, the number of effective acoustic eigenvalues must be narrowed down to a level that is around the number of uncoupled acoustic eigenvalues computed analytically or numerically. For this purpose, data acquired by accelerometers placed on strategic positions (windshield, roof, trunk, side windows, etc.) might help to distinguish the dominant acoustic modes: analyzing the structural driving-point FRFs, the main peaks in these FRFs can be considered to be structural modes. If these frequencies are also revealed in the acoustic FRFs, then they can be assumed as not purely acoustic.

Moreover, the high damping of the cabin involves lower and wider peaks in FRFs resulting in highly overlapping modes. Finally, possible data inconsistencies, due to the fact that the different runs are usually performed in different days, can cause resonance frequencies to vary within the test database. When analyzed altogether, these problems can cause a rather unclear stabilization chart, and hence a non-trivial selection of the right stable pole. Or more precisely, the right stable pole does not exist as such since there are multiple stable poles identifying the same mode.
Taking that into account, 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 [6], 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 (Tab. 1 and Fig. 14). 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. 13.

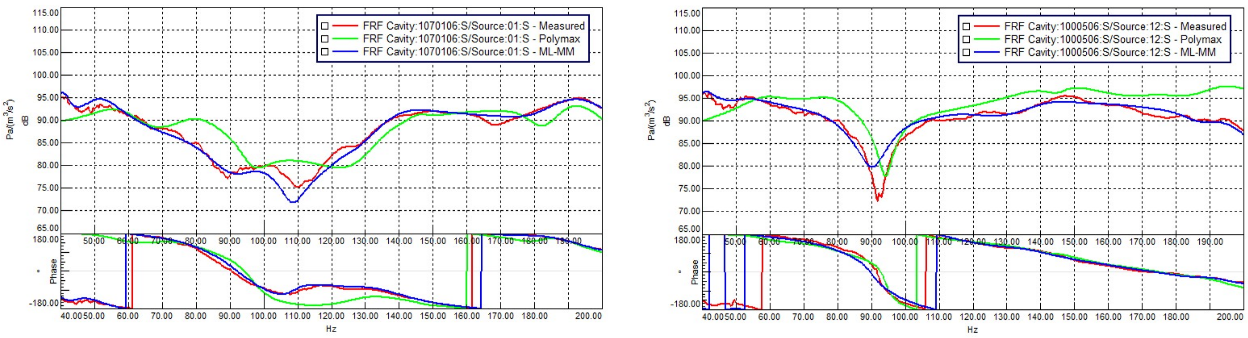


Figure 13: Improved FRF curve-fitting quality shown for two typical FRFs; - Measured (red), Polymax synthesis (green), ML-MM synthesis (blue)

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

Table 1: Modal parameters estimates

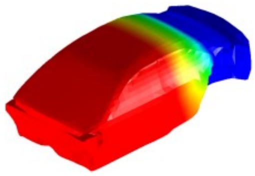
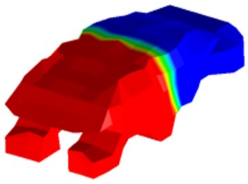
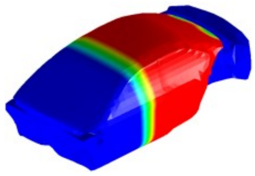
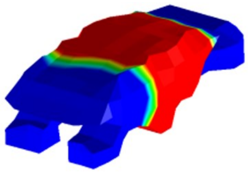
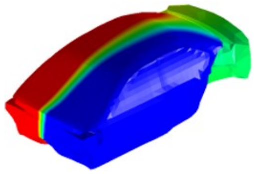
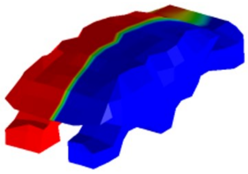
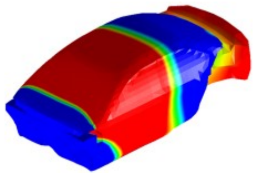
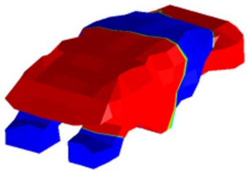
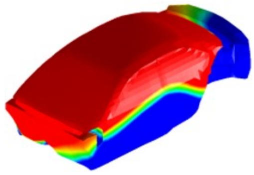
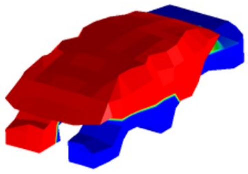
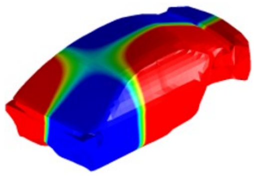
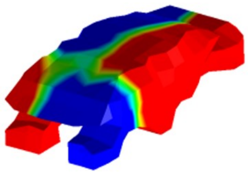
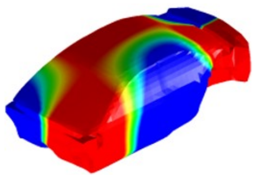
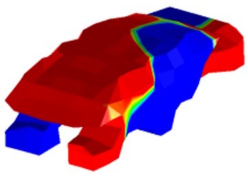
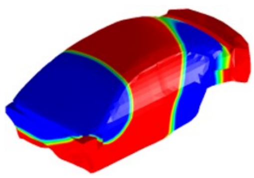
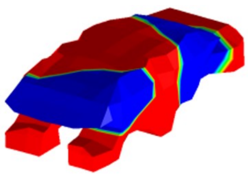
#	Numerical Modes	#	Experimental Modes	Mode Shapes
2		2		I Longitudinal
3		3		I Longitudinal & Rigid-Body Trunk
4		4		I Lateral
5		5		II Longitudinal & Rigid-Body Trunk
7		6		I Vertical
6		7		I Longitudinal & I Lateral
8		8		I Longitudinal & I Lateral & I Lateral Trunk
9		9		III Longitudinal

Figure 14: Identified mode shapes using 12 references (rigid-body mode not shown)

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.

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.

References

[1] M. A. Sanderson and T. Onsay. CAE Interior Cavity Model Validation using Acoustic Modal Analysis. *SAE Technical Paper 2007-01-2167*, 2007.

[2] G. Accardo, B. Cornelis, K. Janssens, and B. Peeters. Automatic microphone localization inside a car cabin for experimental acoustic modal analysis. In *Proceedings of the 22nd International Congress on Sound and Vibration (ICSV 22)*, 2015.

[3] G. Accardo, B. Cornelis, P. Chiariotti, K. Janssens, B. Peeters, and M. Martarelli. A non-line-of-sight identification algorithm in automatic microphone localization for experimental acoustic modal analysis. In *Proceedings of the 44th International Congress and Exposition on Noise Control Engineering*, 2015.

[4] T. Yoshimura, M. Saito, S. Maruyama, and S. Iba. Modal analysis of automotive cabin by multiple acoustic excitation. In *Proceedings of the 25th International Conference on Noise and Vibration Engineering (ISMA2012)*, 2012.

[5] B. Peeters, M. El-kafafy, G. Accardo, T. Knechten, K. Janssens, J. Lau, and L. Gielen. Automotive cabin characterization by acoustic modal analysis. In *Proceedings of JSAE Spring Annual Conference 114-20145437*, 2014.

[6] G. Accardo, M. El-kafafy, B. Peeters, F. Bianciardi, D. Brandolisio, K. Janssens, and M. Martarelli. Experimental Acoustic Modal Analysis of an Automotive Cabin. *Sound & Vibration*, pages 10–18, 2015.

[7] M. El-Kafafy, T. De Troyer, and P. Guillaume. Fast maximum-likelihood identification of modal parameters with uncertainty intervals: A modal model formulation with enhanced residual term. *Mechanical Systems and Signal Processing*, 48(12):49 – 66, 2014.

[8] M. El-kafafy, G. Accardo, B. Peeters, K. Janssens, T. De Troyer, and P. Guillaume. A Fast Maximum Likelihood-Based Estimation of a Modal Model. In *Proceedings of the 33rd International Modal Analysis Conference (IMAC XXXIII)*, 2015.

[9] F. Fahy and P. Gardonio. *Sound and Structural Vibration. Radiation, Transmission and Response*. 2nd edition, 2007.

[10] W. Heylen, S. Lammens, and P. Sas. *Modal Analysis. Theory and Testing*. PMA – K.U. Leuven, 2012.

[11] D.C. Kammer. Sensor set expansion for modal vibration testing. *Mechanical Systems and Signal Processing*, (19):700–713, 2005.

[12] S. Pulthasthan and H. R. Pota. Optimal Actuator-Sensor Placement for Acoustic Cavity. In *Proceedings of the 45th IEEE Conference on Decision & Control*, 2006.

[13] C. Stephan. Sensor placement for modal identification. *Mech. Syst. Signal Process.*, (19):461–470, 2012.

[14] C. He, J. Xing, J. Li, Q. Yang, R. Wang, and X. Zhang. A New Optimal Sensor Placement Strategy Based on Modified Modal Assurance Criterion and Improved Adaptive Genetic Algorithm for Structural Health Monitoring. 2015.

[15] T. Watanabe and T. Yoshimura. Identification of vibro-acoustic coupled modes for vehicle. *SAE International*, 2014.

[16] G. Accardo, B. Cornelis, K. Janssens, and B. Peeters. Smart localization of microphones inside an automotive cabin. In *Proceedings of the 2016 JSAE Annual Congress (Spring)*, 2016.

[17] D. Dardari, A. Conti, U. Ferner, A. Griorgetti, and M.Z. Win. Ranging With Ultrawide Bandwidth Signals in Multipath Environments. *Proceedings of the IEEE*, 97(2):404–426, February 2009.

[18] D. F. Shanno. Conditioning of Quasi-Newton Methods for Function Minimization. *Mathematics of Computing*, 24:647–656, 1970.

[19] J. Zhang, R.A. Kennedy, and T.D. Abhayapala. Cramér-Rao lower bound for the time delay estimation of UWB signals. *Proceedings of the IEEE International Conference on Communications*, 6:3424–3428, 2004.

[20] K. Lauterbach, A.and Ehrenfried, L. Koop, and S. Loose. Procedure for the accurate phase calibration of a microphone array. In *Proceedings of the 15th AIAA/CEAS Aeroacoustics Conference (30th AIAA Aeroacoustics Conference)*, May 2009.

[21] C.E. Cook and M. Bernfeld. *Radar Signals. An Introduction to Theory and Application*. Academic Press, 1967.

[22] B. Peeters, H. Van der Auweraer, P. Guillaume, and J. Leuridan. The PolyMAX frequency-domain method: a new standard for modal parameter estimation? *Shock and Vibration*, 11:395–309, 2004.