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Virtual microphone sensing through vibro-acoustic modelling and Kalman filtering

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ABSTRACT

This work proposes a virtual microphone methodology which enables full field acoustic measurements for vibro-acoustic systems. The methodology employs a Kalman filtering framework in order to combine a reduced high-fidelity vibro-acoustic model with a structural excitation measurement and small set of real microphone measurements on the system under investigation. By employing model order reduction techniques, a high order finite element model can be converted in a much smaller model which preserves the desired accuracy and maintains the main physical properties of the original model. Due to the low order of the reduced-order model, it can be effectively employed in a Kalman filter. The proposed methodology is validated experimentally on a strongly coupled vibro-acoustic system. The virtual sensor vastly improves the accuracy with respect to regular forward simulation. The virtual sensor also allows to recreate the full sound field of the system, which is very difficult/impossible to do through classical measurements.

1. Introduction

Several approaches exist for obtaining insight in the acoustic characteristics and performance of a product or system. A first possibility is the analysis of experimental data gathered in a measurement campaign. The main advantage of this approach is that experimental measurements reflect the performance of the real system in operating conditions. However, setting up a full measurement campaign can be costly and time-consuming, not all locations of interest are always easily accessible, and the gathered data can be corrupted by measurement noise. While experimental measurements can be used to quantitatively evaluate the acoustic performance of a product, they do not necessarily provide sufficient insight in the underlying sound generating mechanisms. Alternatively, numerical modelling tools are used to analyze the system. While simulations provide clear insight in the underlying physical processes in complex systems and generate full field information, they often only approximately describe the real-world time-evolution of the system.

The virtual sensing approach presented in this paper attempts to combine the best of both worlds by coupling high fidelity numerical models with easily (and low cost) attainable experimental data. This enables the estimation, or virtual measurement, of the sound at any desired location, and blends the real-world accuracy of experimental measurements with the insights and flexibility of numerical models.

Existing work in virtual sensing for (vibro-) acoustics has mainly emerged from active noise control applications [1–5], where a zone of quiet is generated in a small area around an error microphone. In many applications it is not possible to

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mount a physical error microphone sufficiently close to the desired location of attenuation (for example in an observer's ear). A possible solution consists in using a virtual error microphone instead of a physical one for the control action. An overview of virtual sensing algorithms for active noise control can be found in [1]. The Kalman filter emerges as one of the most promising virtual sensing tools, but Moreau et al. claim that the main disadvantages of this method are that a preliminary system identification is required to generate a state-space model and that it is limited to systems of relatively low order.

Petersen et al. implement a Kalman filter approach to virtual sensing on an acoustic duct arrangement and experimentally validate their approach in [3]. While they show the potential of the method, the application only considers a one-dimensional acoustic problem and requires a preliminary identification stage, which both hinder the generalization to larger and more complex systems.

Halim et al. [4] develop a Kalman filter approach to virtual sensing for coupled vibro-acoustic enclosures which relies on structural sensors to generate virtual acoustic measurements. The modal decomposition method [6] is used to generate a state-space model, eliminating the need for a system identification stage and allowing for application to three-dimensional systems. However, this modelling method only employs in-vacuo panel modes and rigid-walled cavity modes to represent the system dynamics, which are strong simplifications and introduce substantial modelling errors. These will in turn have a negative effect on the real-world performance of the virtual sensing algorithm. Any experimental validation of the developed method is lacking in the paper. It is also worth noting that the use of the modal decomposition method inherently restricts the method to enclosed vibro-acoustic systems.

In this paper a virtual sensing method is proposed that combines a high-fidelity, three-dimensional numerical vibro-acoustic model with a limited number of microphone measurements through a Kalman filter. This new approach overcomes the main aforementioned issues related to existing virtual sensing methods. A numerical finite element (FE) model of the considered vibro-acoustic system is used in order to avoid an experimental system identification stage. The finite element method is widely used in industrial practice and is able to provide accurate numerical models for a broad variety of vibro-acoustic systems. It can deal with both interior and exterior acoustic problems, complex geometries and advanced damping descriptions. The main issue is that this often results in very high order systems, rendering it practically impossible to use in a Kalman filter. To this end state of the art model order reduction techniques are used to obtain an accurate system representation of very low order. This approach solves both problems Moreau et al. list in [1] as being the main shortcomings of the Kalman filter for virtual sensing. The introduction of recently developed vibro-acoustic model order reduction techniques in a virtual microphone sensing context is the main novelty in the presented work. The proposed virtual sensing method is real-time capable, and is validated experimentally to verify its real-world performance.

The paper is structured as follows: Section 2 reviews the basic concepts of the Kalman filter for virtual sensing. Next, Section 3 introduces the numerical models and model order reduction techniques that are used. The influence of the choice of model description and instrumentation on the observability of the system is studied in Section 4. Section 5 presents a complete roadmap describing the required steps to create a virtual sensor. Section 6 presents the experimental validation of the proposed method for virtual microphone sensing, and concluding remarks are given in Section 7.

2. Kalman filter for virtual sensing

In this work, the Kalman filter forms the basis for the virtual sensor. The Kalman filter is known to be an optimal estimator for linear systems [7]. Even though this is a relatively simple approach, it allows to obtain an effective trade-off between model based predictions and measurements. In this work we use the regular discrete Kalman filter for linear systems. This filter is defined for a discrete-time state-space system:

$$\mathbf{x}_{k+1} = \mathbf{A}^d \mathbf{x}_k + \mathbf{B}^d \mathbf{b}_k + \mathbf{s}_k \tag{1}$$

$$\mathbf{h}_{k+1} = \mathbf{H}\mathbf{x}_{k+1} + \mathbf{r}_{k+1} \tag{2}$$

where

- $\mathbf{x}_k \in \mathbb{C}^{n_s}$ is the state-space vector for a given model at time k, where n_s is the number of states.
- $\mathbf{A}^d \in \mathbb{C}^{n_s \times n_s}$ is the discrete-time state transition matrix.
- $\mathbf{B}^d \in \mathbb{C}^{n_s \times n_i}$ is the discrete-time input matrix, where n_i is the number of inputs.
- $\mathbf{b}_k \in \mathbb{C}^{n_i}$ is the external input at time k.
- $\mathbf{s}_k \in \mathbb{C}^{n_s}$ is the random model uncertainty at time k with zero mean and covariance $\mathbf{\Sigma}_s \in \mathbb{C}^{n_s \times n_s}$. This uncertainty is caused both by inaccurately modelled effects and by random unknown inputs to the system.
- $\mathbf{h}_k \in \mathbb{C}^{n_o}$ is the measurement value obtained at time k, with n_o being the number of measured outputs.
- $\mathbf{H} \in \mathbb{C}^{n_o \times n_s}$ is the measurement matrix which transforms the states into the measurement outputs[1].
- $\mathbf{r}_k \in \mathbb{C}^{n_o}$ is the random measurement uncertainty at time k with zero mean and covariance $\mathbf{\Sigma}_r \in \mathbb{C}^{n_o \times n_o}$. The uncertainty of these measured outputs is caused (among others) by sensor noise and sensor misplacement.

[1] In this work we do not consider the direct feedthrough contribution from the external input to the measurements, but this can easily be added.