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Virtual sensing of structural vibrations using dynamic substructuring

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ABSTRACT

Virtual sensing techniques use information available from a limited set of physical sensors together with the finite element model to calculate an estimate of the quantity of interest. In structural dynamics applications, analytical mode shapes from the finite element model are typically used as a basis to estimate the response at unmeasured locations by an expansion algorithm. An alternative is to model only the interesting part of the structure using substructuring techniques, in which the natural modes are replaced by component modes consisting of a selected number of fixed interface modes plus the interface constraint modes. They are mutually independent and compose a valid subspace for estimating the unmeasured response. If the number of interface degrees of freedom is large, interface reduction is applied. The main advantage of the proposed approach is that the modelling effort can be substantially decreased, because only part of the structure is modelled and the modelling uncertainties, non-linearities, or changes in the omitted structure can be ignored. The method is validated by numerical simulations of three different structures under unknown excitation. Different types and locations of virtual sensors are studied. Also, the effects of noise and model errors are investigated. The most accurate estimation is obtained if the virtual sensor is located away from the interface and close to a physical sensor.

1. Introduction

Structural monitoring utilizes vibration measurements acquired by a sensor network to assess the condition of structures. Sensors are also needed for vibration control. With current technology, the number of sensors is often limited or some locations may be inaccessible for instrumentation. Analytical virtual sensing techniques use information available from a limited set of physical sensors together with a finite element model to calculate an estimate of the quantity of interest. For example, estimating the stress or strain field from acceleration measurements could be useful for fatigue assessment. Analytical mode shapes from the finite element model are typically used as a basis to estimate the response at unmeasured locations by an expansion algorithm.

Virtual sensing (VS) can be either model-based (analytical) or data-driven (empirical) [1]. Analytical virtual sensing in structural dynamics has been studied e.g. in the following papers. Sestieri et al. [2] estimated rotational degrees of freedom (DOFs) from a limited set of measured translational DOFs. Hjelm et al. [3] estimated stress histories from acceleration measurements. Avitabile [4] applied virtual sensing to correlation of analytical and experimental models using model

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expansion. Iliopoulos et al. [5] applied virtual sensing to fatigue assessment of wind turbines. Full-field dynamic stress/strain field was estimated from limited sets of measurement data [6,7]. Papadimitriou et al. [8] introduced a technique that uses Kalman filter to estimate power spectral density of strain anywhere in the structure for fatigue assessment. Azam et al. [9] developed a dual Kalman filter for estimating the unknown input and states of a linear system. Maes et al. [10] compared three different response estimation algorithms: a joint input-state estimation algorithm, a Kalman filter algorithm, and a modal interpolation algorithm. Empirical virtual sensing is based on training data from a redundant sensor network. It can be used, for example, to replace a temporarily installed or failed sensor [11]. Empirical virtual sensing has also been used for damage or sensor fault detection in structural dynamics [12]. Kullaa introduced combined empirical and analytical virtual sensing [13].

In analytical virtual sensing, a finite element model is needed. For a large and complex structure, generation and validation of an accurate finite element model may be laborious. An alternative is to model only the interesting part of the structure using dynamic substructuring techniques. The natural modes are replaced by component modes, which in the Craig-Bampton method [14] consist of fixed interface modes (substructure natural modes with fixed interface DOFs) plus interface constraint modes (substructure responses, where a single interface DOF in turn is given a unit displacement, while the remaining DOFs are fixed). They are mutually independent and compose a valid subspace for estimation of the unmeasured response. Another set of Ritz vectors is attachment modes (substructure responses to unit interface forces) together with free-interface modes (substructure natural modes with free interface DOFs) [14]. An equivalent set was used by Rixen [15], who used free interface modes together with residual flexibility components as basis vectors. The number of static component modes in the aforementioned methods is equal to the number of interface DOFs.

The main advantage of using component modes instead of the natural modes of the structure is that the modelling effort can be substantially decreased, because only part of the structure is modelled. The unmodelled part may include modelling uncertainties (e.g. joints, boundary conditions, or non-linearities) or structural variability (e.g. varying mechanism configurations or changes in mass or boundary conditions), which can now be ignored. The physical sensors must be located in the domain of the substructure and their number must be higher than the number of component modes. A disadvantage is that the component modes do not represent the true natural modes of the structure. Therefore, model validation by comparison of the modal parameters is difficult. Also, the proposed method is only feasible if the number of interface DOFs is small. If this number is large, a further reduction must be performed. A nice review of reduction methods is given in [16].

The paper is organized as follows. Analytical virtual sensing using an expansion algorithm is outlined in Section 2. Substructuring using the Craig–Bampton method is discussed in Section 3. Also, interface reduction is discussed. In Section 4, the method is validated by numerical simulations of vibration measurements of a plane frame. Different types and locations of virtual sensors are studied. Also, the effects of noise and model error are investigated. Section 5 studies a vehicle crane, which is a time-varying system, showing practical advantages of substructuring. In Section 6, a floor structure with several interface DOFs is investigated applying interface reduction. Concluding remarks are given in Section 7.

2. Virtual sensing in structural dynamics

Analytical virtual sensing combines the physically measured quantities and a physics-based model to estimate an unmeasured quantity of interest. In the present study, virtual sensing is applied to structural vibrations, in which the estimated quantities are displacements, rotations, or strains at unmeasured locations.

The basis vectors in the System Equivalent Reduction Expansion Process (SEREP) algorithm [4] are the natural modes of the structure, which are solved from the finite element model. Often, only a few lowest modes are needed to represent the vibration pattern with reasonable accuracy. In this study, natural modes are replaced with component modes as basis vectors, which is discussed in the following section.

The structural motion of a linear system can be expanded as a sum of modal contributions:

$$\mathbf{x}(t) = \sum_{i=1}^{N} \phi_i q_i(t) \approx \sum_{i=1}^{n} \phi_i q_i(t) = \mathbf{\Phi}\mathbf{q}(t) \tag{1}$$

where $\mathbf{x}(t)$ is the displacement response, N is the number of DOFs in the finite element model, $n < < N$ is the selected number of modes, $\mathbf{\Phi}$ is the modal matrix consisting of the n mode shapes ϕ_i as columns, and $\mathbf{q}(t)$ are the modal, or generalized coordinates.

If $\mathbf{x}(t)$ is divided into measured (m) and unmeasured (u) DOFs, also the mode shapes are divided correspondingly:

$$\mathbf{x}(t) = \begin{Bmatrix} \mathbf{x}_m(t) \\ \mathbf{x}_u(t) \end{Bmatrix} = \begin{bmatrix} \mathbf{\Phi}_m \\ \mathbf{\Phi}_u \end{bmatrix} \mathbf{q}(t) \tag{2}$$

The upper equation in (2) reads

$$\mathbf{x}_m(t) = \mathbf{\Phi}_m \mathbf{q}(t) \tag{3}$$

If the number of sensors is greater than the number of active modes n, the modal coordinates $\mathbf{q}(t)$ can be solved:

$$\hat{\mathbf{q}}(t) = (\mathbf{\Phi}_m^T \mathbf{\Phi}_m)^{-1} \mathbf{\Phi}_m^T x_m(t) \tag{4}$$