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Online damage detection in structural systems via dynamic inverse analysis: A recursive Bayesian approach

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ABSTRACT

In this paper, a framework is presented for the joint state tracking and parameter estimation of partially observed structural systems characterized by a relatively large number of degrees of freedom. To pursue this aim in real-time, the order of the system is reduced via an optimal set of bases, or proper orthogonal modes (POMs) obtained through proper orthogonal decomposition. Since the aforementioned POMs are sensitive to damage, which is defined as a change in the stiffness of the structural model, the variation in the characteristics of the POMs themselves is also tracked online. Taking advantage of the linear relationship between the observation process and the components of the POMs, a solution to the whole problem is obtained with an extended Kalman filter or a hybrid extended Kalman particle filter for the joint tracking-estimation purposes, and with a further Kalman filter for the model update purposes. The efficiency of the proposed method is assessed through simulated experiments on a 8-story shear type building.

1. Introduction

Aging of infrastructures in developed countries, performance based design, and environmental changes all call for systems to monitor in real-time the health of structural systems. The current practice to assess the health and integrity of a structure is predominantly based on visual inspections, whose frequency can vary from once a month to once every a few years, depending on factors related to the age and the importance of the structure itself. Such inspections primarily furnish a qualitative awareness on possible structural defects, and once damage is detected a quantitative evaluation of the remaining lifetime of the structure becomes necessary. The reliability of the said visual inspection is thus primarily related to the capability of the inspector. Recent advances in measurement technology, computing power, and signal processing have provided an unprecedented prospect for developing autonomous, robust and continuous structural health monitoring (SHM) systems. Numerous structures across the globe have been already instrumented by sensors that include strain gages, accelerometers and displacement transducers to quantify their responses. State-of-the-art monitoring schemes in the literature are centered on extracting parameters of a model of the structure from the measured signals, so as to be able to update it and detect, localize, and quantify damage from changes in the system characteristics.

In a physics-based SHM framework, the detection of changes in the mechanical properties of structural members is the main objective. A damage in the structure is considered as a degradation of its stiffness and/or load bearing capacity, see [1]; such degradation may be due to a change of the geometry of the members, or to a reduction of their mechanical properties. Accordingly, the detection of damage in a structure can be posed as a system identification problem. Dealing with a linear structure, i.e. assuming that damage can be temporarily frozen within the time window between two subsequent observation instants, several algorithms can provide an offline identification of the system properties. In the time domain, the data driven stochastic subspace identification algorithm is de facto standard for output only identification of structural models, see [2]; the subspace identification algorithm has been widely applied for deterministic input-output systems, see [3]. The aforementioned methods rest on singular value decomposition (SVD) and QR decomposition techniques, see [4]. They have been also adopted for online system identification by operating on a fixed-length window that moves over time: when a new observation becomes available, the subspace is re-identified. The computational costs associated with SVD and QR techniques prevent the real-time application of such methods for large structural systems; to reduce such costs, methods have been proposed to only update the SVD and QR outcomes, see e.g. [3]. It has been also shown that the measurement noise can substantially affect the performance of these methods, especially when the duration of the moving time-window is assumed short.

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To alleviate the issues attributed to modelling and measurement uncertainties in online system identification, recursive Bayesian estimation methods are usually exploited. The online and real-time estimation of the state of a system and of the relevant unknown model parameters is usually obtained by augmenting the state, namely by joining the state to be tracked and the parameters to be tuned into a vector of unknowns, whose dynamics needs to be appropriately modelled. The mentioned unknown model parameters can be the mechanical properties of the system, that for instance vary in time due to variations in the ambient temperature, see [5]. In the literature of online Bayesian estimation, a considerable effort has been devoted to this joint state-parameter estimation problem, whose results are affected by the type of system evolution. For instance, an extended Kalman filter (EKF) has been adopted in [6] for the identification of constitutive parameters of composite materials, to detect possible delamination/damage events. The unscented Kalman filter has been applied in [7] for the parameter identification of a hysteretic model, see also [8]; a parallel implementation scheme for the same unscented Kalman filter has been proposed in [9], still to deal with impact-induced vibrations and delamination of composite materials. A hybrid extended Kalman particle filter (EK-PF) for the identification of nonlinear structural systems has been offered in [10], in order to better catch the evolution of the statistics of the state variables in the mentioned nonlinear frame. A particle filter with mutation schemes has been applied in [11] for the estimation of time-invariant parameters of structural models. Recursive Bayesian filters have been recently considered also for the online and real-time estimation of fatigue damage [12]. For a review of the literature on this topic, readers are referred to [13,14].

In this work, to detect damage in real-time a joint estimation of state and stiffness parameters is proposed, by making use of recursive Bayesian filters. As the number of degrees of freedom (DOFs) of the structural model increases, a bias has been already shown to rapidly pollute the estimates furnished by these filters, see [13]. To cope also with this problem, we provide a scheme for the reduced-order modelling of the system; the joint estimation of state and parameters is then carried out on the obtained reduced-order model (ROM) of the structure, and not on the original full-order one [15]. Unlike the identification of the full-order model, estimating stiffness components related to the ROM does not allow to obtain explicit information concerning the intensity and location of the damage state. However, it is known that the proper orthogonal modes (POMs) of a structure, as provided by the model order reduction technique, contain data concerning the location and intensity of a possible damage, see e.g. [16–20]. This feature of POMs can potentially compensate for the aforementioned shortcoming of the joint estimation at the ROM level, and is here specifically exploited. To this end, we therefore discuss an algorithm for the joint estimation of state and parameters of the ROM, accompanied by an online update of the damage-sensitive POMs of the structure. At each recursion of the (discrete time) Bayesian procedure, a Kalman filter is adopted to update the subspace spanned by POMs retained in the ROM; an EKF, or a hybrid EK-PF is instead used to estimate the joint state vector of the ROM. While the EKF-based approach was already discussed in [20], the EF-PF-based approach is newly proposed in this work. The two approaches are comparatively assessed to ascertain whether the superior performance of the EK-PF in tracking the nonlinear evolution of system statistics can actually deliver a SHM system more sensitive to the state of damage. The offered framework is shown to be able to effectively detect the severity of damage in shear type buildings; the efficiency of the methodology is testified through pseudo-experimental data relevant to a multi-story frame, obtained from direct numerical analyses polluted with ad-hoc measurement noise terms.

The remainder of the paper is organized as follows. In Section 2, the state-space formulation of structural dynamics is reviewed, followed by highlights on the key features of the proper orthogonal decomposition (POD)-based model order reduction technique. In Section 3, peculiarities of the joint estimation of the ROM of a damaging structure are discussed; next, the proposed methodology is presented and the intricated formulation to allow for model update is discussed. In Section 4 the efficiency of the approach is numerically assessed by tracking the damage state in a shear type building; some results are also reported for the full-order structural model, to discuss the detrimental effects of a large number of unknown model parameters on the accuracy of the estimates, and to also compare the performance of the proposed methodology with those based on the EKF or a standard PF. Some concluding remarks on the work done, and suggestions for future developments are then gathered in Section 5. Since the available EKF-based approach is here adotped as a term of comparison, in Appendix A the scheme relevant to this further approach is briefly discussed for completeness, and to provide a uniform notation for the two formulations.

2. Structural dynamics: state-space formulation and reduced-order modelling

Let us consider a space-discretized structural system, whose dynamics is governed by the vectorial equation:

$$\boldsymbol{M}\ddot{\boldsymbol{u}} + \boldsymbol{D}(t)\dot{\boldsymbol{u}} + \boldsymbol{K}(t)\boldsymbol{u} = \boldsymbol{F}(t) \tag{1}$$

where: $\boldsymbol{u}$, $\dot{\boldsymbol{u}}$ and $\ddot{\boldsymbol{u}}$ are the vectors gathering relevant (nodal, in case of e.g. finite element discretizations) displacements, velocities and accelerations; $\boldsymbol{M}$ is the mass matrix; $\boldsymbol{D}$ is the damping matrix; $\boldsymbol{K}$ is the stiffness matrix; $\boldsymbol{F}$ is the external load vector. If the system is supposed to be continuously monitored to sense possible drifts in its response to the external actions due to the inception or growth of a damage process, the mass matrix can be assumed to be time-invariant. On the other hand, since geometrical and/or stiffness characteristics of some structural members can be affected by the aforementioned damage, $\boldsymbol{K}$ varies in time. In the case of a Rayleigh damping as considered in Section 4, for which the damping properties of the structure are proportional to the stiffness and mass ones, coefficients in $\boldsymbol{D}$ turn out to be damage- and also time-dependent too, see also [21].

With a focus on two-dimensional models of shear type buildings, the mass matrix is a diagonal one with non-zero entries corresponding to the story masses, whilst the stiffness matrix has a characteristic tri-diagonal banded structure, ruled by the properties of the interstory columns. The damping matrix might have a more complex structure, depending on the mechanisms inducing dissipation, see e.g. [22]. The external load vector in this case gathers the horizontal loads acting at each single story level.

To move to a state-space formulation, a time discretization and a stepping scheme are needed for the solution of Eq. (1). Through a Newmark explicit time integration procedure, within a generic time interval $[t_{k-1} t_k]$ the solution can be updated in accordance with:

- prediction stage:

$$\tilde{\boldsymbol{u}}_k = \boldsymbol{u}_{k-1} + \Delta t\, \dot{\boldsymbol{u}}_{k-1} + \Delta t^2 \left(\frac{1}{2} - \beta\right) \ddot{\boldsymbol{u}}_{k-1} \tag{2}$$

$$\dot{\tilde{\boldsymbol{u}}}_k = \dot{\boldsymbol{u}}_{k-1} + \Delta t (1-\gamma) \ddot{\boldsymbol{u}}_{k-1} \tag{3}$$

- explicit integration stage:

$$\ddot{\boldsymbol{u}}_k = \boldsymbol{M}^{-1}(\boldsymbol{F}_k - (\boldsymbol{D}_{k-1} \dot{\tilde{\boldsymbol{u}}}_k + \boldsymbol{K}_{k-1} \tilde{\boldsymbol{u}}_k)) \tag{4}$$

- correction stage:

$$\boldsymbol{u}_k = \tilde{\boldsymbol{u}}_k + \Delta t^2 \beta \ddot{\boldsymbol{u}}_k \tag{5}$$

$$\dot{\boldsymbol{u}}_k = \dot{\tilde{\boldsymbol{u}}}_k + \Delta t\, \gamma \ddot{\boldsymbol{u}}_k \tag{6}$$

where: $\Delta t = t_k - t_{k-1}$ denotes the time step size; $\boldsymbol{u}_{k-1}$, $\dot{\boldsymbol{u}}_{k-1}$ and $\ddot{\boldsymbol{u}}_{k-1}$ provide the solution at the beginning of the time step; $\boldsymbol{u}_k$, $\dot{\boldsymbol{u}}_k$ and $\ddot{\boldsymbol{u}}_k$ is