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A dual adaptive filtering approach for nonlinear finite element model updating accounting for modeling uncertainty

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ABSTRACT

This paper proposes a novel approach to deal with modeling uncertainty when updating mechanics-based nonlinear finite element (FE) models. In this framework, a dual adaptive filtering approach is adopted, where the Unscented Kalman filter (UKF) is used to estimate the unknown parameters of the nonlinear FE model and a linear Kalman filter (KF) is employed to estimate the diagonal terms of the covariance matrix of the simulation error vector based on a covariance-matching technique. Numerically simulated response data of a two-dimensional three-story three-bay steel frame structure with eight unknown material model parameters subjected to unidirectional horizontal seismic excitation is used to illustrate and validate the proposed methodology. Geometry, inertia properties, gravity loads, and damping properties are considered as sources of modeling uncertainty and different levels and combinations of them are analyzed. The results of the validation studies show that the proposed approach significantly outperforms the parameter-only estimation approach widely investigated and used in the literature. Thus, a more robust and comprehensive identification of structural damage is achieved when using the proposed approach. A different input motion is then considered to verify the prediction capabilities of the proposed methodology by using the FE model updated by the parameter estimation results obtained.

1. Introduction

Calibration of models of structural systems is an important topic with application in different problems in the fields of structural engineering and engineering mechanics. Improving the predictive capabilities of models, providing a tool for damage identification, and verifying and improving modeling techniques are some significant problems that are assisted by model calibration. Although most efforts in model calibration have been dedicated to linear systems, as linear finite element (FE) model updating represents an important field of research [1], calibration of nonlinear models has also attracted significant attention from the community. The work by Distefano and co-workers [2–4] represents, to the authors' knowledge, the first attempt to calibrate nonlinear models under dynamic loading. They employed numerically simulated data [2,3] and experimental data from a shake table test [4] to calibrate single-degree-of-freedom (DOF) and 3-DOFs shear-type building models with restoring force versus relative displacement at the story level characterized by cubic polynomials. Yun and Shinozuka [5] used the Extended Kalman filter (EKF) and the iterated linear filter-smoother to identify, using simulated data,

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the hydrodynamic matrix of a 2-DOF linear system subjected to wave forces. Hoshiya and Saito [6] proposed a weighted global iteration method with the EKF (EK-WGI) to solve identification problems of structural systems under seismic excitation. They used numerical examples of 2-DOFs and 3-DOFs linear systems and a single DOF system with bi-linear hysteretic response to verify the proposed approach. Bittani et al. [7] also used the EKF to estimate parameters of a two-dimensional (2D) frame with localized nonlinearities at the column ends characterized by elasto-plastic cross-sectional behavior. In [8], Hoshiya and Sutoh applied a Kalman filter-weighted local iteration procedure (EK-WLI) to FE models of geotechnical systems. They considered numerical examples of homogeneous and nonhomogeneous stochastic fields in plane strain problems of geomechanics.

The FE method, originally introduced in the 1950's [9,10], is still an active area of research that has made significant progresses in the modeling and simulation of large and complex structures by developing high-fidelity nonlinear models. From experimental-analytical correlation studies, these models have proven to predict with reasonable accuracy the response of civil structures when properly calibrated (e.g., [11,12]). All the developments in the area of FE modeling and simulation can benefit from the field of model calibration, which provides more insights into the modeling aspects of complicated nonlinear phenomena and also offers a powerful tool for damage identification of structures. In recent years, a number of researchers have developed methods to calibrate mechanics-based nonlinear FE models of civil structures. Nasrellah and Manohar [13] proposed to combine the FE method with particle filtering to identify unknown model parameters. They verified the approach by estimating three parameters of a rubber sheet model, the stiffness parameters of a simple supported beam tested in the laboratory, and the modulus of elasticity and spring parameters of a 2D FE model of an arched bridge using field test data. In [14], the authors used numerical data to calibrate the nonlinear FE model of a reinforced concrete shear wall. Astroza et al. [15] and Ebrahimian et al. [16] used the Unscented Kalman filter (UKF) and EKF, respectively, to calibrate mechanics-based nonlinear FE model of 2D and three-dimensional (3D) frame structures. Astroza et al. [17] proposed a hybrid method combining simulated annealing with the UKF for the identification of parameters of linear and nonlinear FE models. In [18], the adaptive quadratic sum-square error with unknown inputs was utilized to update a FE model with lumped plasticity of a reduced-scale frame structure tested in laboratory conditions. In [19], the authors proposed a methodology to jointly estimate the parameters and input excitation of mechanics-based nonlinear FE models subjected to earthquake base excitation. Eftekhar et al. [20] proposed a dual Kalman filter approach for joint input-state estimation of linear systems. The approach proposed in [15] was extended in [21] to reduce the computational cost of the updating procedure, allowing its use in hybrid simulation applications.

Since every FE model is an idealized representation of the structure to be modeled, the selected classes of models never contain the real structure [22,23]. The sources of uncertainty are usually categorized into model parameter uncertainty, model structure uncertainty (referred to as modeling uncertainty hereafter), and measurement error/noise. Different methods and comprehensive studies related to model parameter uncertainty and measurement errors are available in the literature (e.g., [15,24]). However, although it has been recognized that modeling uncertainty is the most critical aspect when updating FE models [25–27], only limited studies of its effects have been performed and only for linear structural models (e.g., [27–30]). It is noted that modeling uncertainty can be due to, for example, the presence of nonstructural components, inappropriate modeling of energy dissipation mechanisms and boundary conditions, etc. For mechanics-based nonlinear FE models, Astroza and Alessandri [31] carried out parametric analyses to investigate the effects of modeling uncertainty in parameter estimation results and also in measured (observed) and unobserved response quantities predicted using state-of-the-art distributed plasticity FE models of building structures updated using the parameter estimation results. They found that in the presence of modeling uncertainty, a good match between the measured and FE-predicted response can be achieved after the updating process, but unobserved response quantities (at both the global and local levels) can be subjected to significant errors because the estimated parameters are biased (in agreement with the results reported in [27]) due to modeling uncertainty, even achieving non-physical parameter values.

Recognizing modeling uncertainty as one of the main challenges in FE model updating, this paper proposes a novel approach based on adaptive filtering to account for this source of uncertainty when updating mechanics-based nonlinear FE models. In the proposed approach, the diagonal terms of the covariance matrix of the simulation error vector are considered time variant and estimated together with the model parameters of the nonlinear FE model. Similar approaches for estimating time-invariant variances of state and measurement noises have been proposed in the literature for linear (e.g., [32–35]) and nonlinear systems (e.g., [36–40]). In this paper, the covariance matrix of the simulation error vector is considered time variant because the modeling uncertainty may vary in time and a covariance-matching approach is used to estimate its diagonal terms, similarly to the idea presented in [33] and [37].

2. Problem statement

The dynamic response of a structural system can be modeled using a discrete-time equation of motion of a nonlinear FE model. This allows to predict the dynamic behavior of the structure and also to detect, localize, and quantify the potential damage it can suffer during an extreme event (e.g., earthquake, hurricane). The equation of dynamic equilibrium of a nonlinear FE model (which is constructed based on the best estimation of the actual properties of the structure) at time $t_{k+1} = (k+1)\Delta t$, where $k = 0, 1, \ldots$ and Δt is the time step, is usually expressed as

$$\mathbf{M}(\mathbf{p})\,\ddot{\mathbf{q}}_{k+1}(\mathbf{p}) + \mathbf{C}(\mathbf{p})\,\dot{\mathbf{q}}_{k+1}(\mathbf{p}) + \mathbf{r}_{k+1}(\mathbf{q}_{k+1}(\mathbf{p}), \mathbf{p}) = \mathbf{f}_{k+1}(\mathbf{p}) = -\mathbf{M}(\mathbf{p})\mathbf{L}(\mathbf{p})\ddot{\mathbf{u}}_{k+1} \tag{1}$$