Model updating with a Modified Dual Kalman Filter acting on distributed strain measurements

S. Farahbakhsh*, **L. Chamoin***,† **and M. Poncelet***

* Université Paris-Saclay, CentraleSupélec, ENS Paris-Saclay, CNRS, LMPS
Laboratoire de Mécanique Paris-Saclay
91190, Gif-sur-Yvette, France.

† Institut Universitaire de France (IUF)
1 rue Descartes, 75005 Paris, France

e-mail: sahar.farahbakhsh@ens-paris-saclay.fr, ludovic.chamoin@ens-paris-saclay.fr, martin.poncelet@ens-paris-saclay.fr

ABSTRACT

Following the advances in measurement technology and its vast availability, mechanical systems and structures are increasingly equipped with sensors to obtain continuous information regarding the system state. Coupled with robust numerical models, this information can be used to build a numerical twin of the structure that is linked to its physical twin via a feedback loop. This results in the concept of Dynamic Data Driven Application Systems (DDDAS) that can predict and control the evolution of the physical phenomena at stake on the structure, as well as dynamically updating the numerical model with the help of real-time measurements [1, 2].

The physical evolution control is not addressed here, as the focus is mainly on the model updating part of the DDDAS process. This step requires data assimilation and sequentially solving a potentially ill-posed inverse problem. A robust approach towards solving inverse problems regarding numerical models with experimental inputs is the modified Constitutive Relation Error (mCRE) [3]. One of the critical features of this method is the distinction between reliable and unreliable information so that only reliable ones, such as equilibrium, known boundary conditions, and sensor positions, are strongly imposed in the definition of the functional. In contrast, unreliable information, namely constitutive relation, unknown boundary conditions, and sensor measurements, are dealt with in a more relaxed sense. This energy-based functional can be conceived as a least squares minimization problem on measurement error, regularized by a model error term, aka Constitutive Relation Error (CRE), which accounts for the physical sense of the minimization problem while improving the convexity of the functional. In other words, mCRE can be analyzed as a compromise between measurement and model error, and is adjusted with reference to the level of confidence one has in each of these terms. Hence, it yields impressive results even when confronting noisy and corrupted measurement data [4].

Despite all its advantages, the mCRE method can become computationally expensive and might not be suitable for real-time applications, including DDDAS. Furthermore, it does not comply with the sequential nature of DDDAS. Thus, it makes sense to use it within a sequential data assimilation framework such as Kalman Filters.

Acquired from Bayesian inference, Kalman filtering is a widely known sequential data assimilation method for predicting evolving systems, which incrementally corrects the predictions through assimilated measurements [5]. Various extensions of the Kalman filter have been developed to improve the method performance for different operations. Notably, its nonlinear extensions have been employed to solve inverse problems [6, 7]. Kalman filters are shown to be sensitive to noisy or corrupted measurements [8, 9]. Thereby, integrating the mCRE within this stochastic approach provides a cheap, robust and sequential model updating tool named Modified Dual Kalman Filter (MDKF) [10, 11].

In the present work, sensor data is collected from optic fiber sensors embedded inside a cement-based mortar beam undergoing a quasi-static 4-point bending test. The optic fibers provide longitudinal strain measures along the fiber with a spatial resolution as high as 1500 points per meter [12]. These measurements are then implemented in the MDKF approach to identify model parameters and detect possible damage at each timestep. Furthermore, the CRE part of the functional is analyzed to detect zones with large modeling error and adapt the parametric space accordingly.

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