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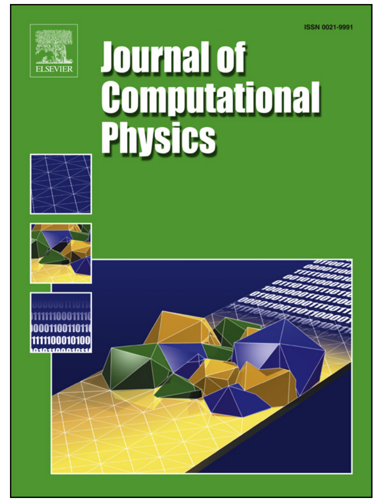

Sequential data assimilation with multiple nonlinear models and applications to subsurface flow

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Sequential data assimilation with multiple nonlinear models and applications to subsurface flow*

Lun Yang[†], Akil Narayan[‡], and Peng Wang[†]

Abstract. Complex systems are often described with competing models. Such divergence of interpretation on the system may stem from model fidelity, mathematical simplicity, and more generally, our limited knowledge of the underlying processes. Meanwhile, available but limited observations of system state could further complicates one's prediction choices. Over the years, data assimilation techniques, such as the Kalman filter, have become essential tools for improved system estimation by incorporating both models forecast and measurement; but its potential to mitigate the impacts of aforementioned model-form uncertainty has yet to be developed. Based on an earlier study of Multi-model Kalman filter, we propose a novel framework to assimilate multiple models with observation data for nonlinear systems, using extended Kalman filter, ensemble Kalman filter and particle filter, respectively. Through numerical examples of subsurface flow, we demonstrate that the new assimilation framework provides an effective and improved forecast of system behaviour.

Key words. Data assimilation, extended Kalman filter, ensemble Kalman filter, particle filter, uncertainty quantification

AMS subject classifications. 62M20, 86A05

1. Introduction.

Mathematical models are essential tools to understand and predict the behaviour of physical systems. However, one's lack of knowledge renders such models as imperfect approximations of physical reality, and may lead to various interpretations and mathematical representations. To reduce the discrepancies between model forecast and physical truth, one can utilise data measurements as an alternative source of information. However, in practice these empirical measurements are often noisy and scant in number, scope and resolution, which may also introduce competing constitutive relations and uncertainty in parameters. A judicious combination of imperfect models and sparse, noisy data is necessary in modern simulation paradigms.

Over the years, data assimilation (DA) has become the primary tool to implement such a combination of models and data. Originally developed for linear systems with noisy measurements, the Kalman filter [20, 19] minimises a quadratic objective and updates prediction by weighing simulation results and the available data at each stage. Further extensions to address nonlinear systems, such as the extended Kalman filter [12, 18], the ensemble Kalman filter [10, 11] and other variants [1, 2, 6, 35, 40], have also been proposed and remain a popular research topic.

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