Title: A fast, single-iteration ensemble Kalman smoother for online, sequential data assimilation

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Abstract:

Iterative, ensemble-variational methods form the basis for the state-of-the-art for mildly nonlinear, scalable data assimilation (DA) schemes. These methods seek to combine the benefits of high-accuracy of the iterative solution of the Bayesian maximum a posteriori (MAP) solution to the DA problem with the relative simplicity of numerical model development and maintenance in ensemble-based DA. While iterative ensemble-based schemes are promising for nonlinear, non-Gaussian DA, a barrier to their use in online, sequential DA still lies in the computational bottleneck of simulating the nonlinear, physics-based model to perform the sampling procedure. Even when only a single iteration of the solution for the cost function is necessary, many iterative procedures require multiple runs of the ensemble simulation over the data assimilation window (DAW) to produce the: (i) forecast; (ii) filtering; and (iii) re-analyzed posterior statistics. For online applications in which there is a short operational time-window to produce a forecast for future states, the multiple ensemble simulations may be prohibitively expensive. Particularly for synoptic meteorology, the linear-Gaussian approximation for the evolution of the last posterior to the new prior is often sufficient as the basis for a learning scheme and the cost of an iterative, nonlinear optimization may not be justified by the improvement in forecast accuracy.

We consider a simple hybridization of the classical ensemble Kalman smoother with the iterative ensemble Kalman smoother to produce a fast, fixed-lag, sequential smoother. This scheme derives the benefit of the increased accuracy of the re-analyzed prior with a retrospective analysis, as in the classical EnKS, and utilizes the improved prior estimate in producing the EnKF filter and forecast statistics. For linear-Gaussian systems, this is a fully consistent Bayesian estimator, albeit one that uses redundant model simulations. However, we demonstrate that considerable performance gains can be produced in nonlinear systems by re-initializing the re-analyzed prior for the forecast of the nonlinear model in the next cycle. The resulting scheme is a single-iteration, ensemble Kalman smoother that sequentially solves the filtering, Bayesian MAP cost-function, and produces forecast, filtering and smoothing statistics within a single sweep of the DAW with the ensemble. To handle the increasing nonlinearity over longer forecast ranges, we furthermore derive a method of multiple data assimilation for this hybrid smoother scheme. The result is a two-stage algorithm, estimating the forecast, filtering and posterior statistics, and shifting the smoother forward in time with two sweeps of the DAW.