An Iterative Ensemble Kalman Smoother

Marc Bocquet[a,b] and Pavel Sakov[c]

[a] *Université Paris-Est, CEREA joint laboratory École des Ponts ParisTech and EdF R&D, France*
[b] *INRIA, Paris Rocquencourt research center, France*
[c] *Bureau of Meteorology, Melbourne, Australia*

Two main classes of data assimilation methods have taken the lead in geophysical data assimilation [1]. As a nonlinear smoother, 4D-Var is a powerful method found to outperform filters in strongly nonlinear conditions. But its background statistics suboptimally rely on a climatology. Besides, it technically requires the long endeavor of building adjoints of the models.

The ensemble Kalman filter (EnKF) easily propagates the uncertainty with the use of an ensemble of model trajectories, which gives it an advantage over variational methods in a sequential data assimilation context. Yet, it is not a smoother and might not handle nonlinearity within a data assimilation window as well as 4D-Var would. Besides, the finite-size of the ensemble technically often requires the use of inflation and localization to counteract sampling errors.

We have recently introduced the iterative ensemble Kalman smoother (IEnKS) that has the potential of getting the best of both methods [2,3,4]. It is not an hybrid method as it does not run two distinct data assimilation systems. Like 4D-Var, as a nonlinear smoother, it solves for an underlying variational problem, but without the use of the tangent linear and adjoint model. Like the EnKF, it is a flow-dependent method and propagates the uncertainty.

This ensemble variational (EnVar) method will be explained. Differences with other EnVar systems (Environment Canada, Météo-France, Met-Office) and hybrid approaches will be discussed. We will show on low-order meteorological models that, at a scalable computational cost, the method systematically outperforms 4D-Var, the EnKF and even a standard ensemble Kalman smoother. Not only does it lead to a much better re-analysis, but it also leads to a better analysis and forecast, even in the typical mild nonlinearity of current synoptic meteorological models.

However, as an ensemble method, it is still plagued by sampling errors. We shall discuss the obstacles to a well-suited localization scheme, as it is a fundamental issue in such EnVar context.

References

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