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Review of the ensemble Kalman filter for atmospheric data assimilation

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Overview

After the 6th EnKF workshop (2014), I decided with Prof. Zhang to summarize progress in a review paper. The resulting paper is now in review with Monthly Weather Review.

Many thanks to the participants of the 6th EnKF workshop for their many contributions.

Respecting the experience and knowledge of the two authors, the focus of the review paper is on Atmospheric applications of the EnKF.

The current talk is a personal summary of the review paper and hopefully can serve as a summary of current issues prior to the 7th EnKF workshop.

Purpose of the EnKF

The EnKF is part of a bigger effort to obtain a coherent description of errors in Numerical Weather Prediction systems.

It uses a Monte Carlo procedure towards an ensemble-based simulation of the evolution of errors in a data assimilation cycle.

The origins of the EnKF are in:

1. Early work towards the use of the Kalman-Bucy filter in data assimilation (e.g. Ghil, Cohn, Daley, $\cdots$)
2. The development of ensemble prediction systems.

Normally the improved understanding of error sources in NWP and improvements to the EnKF will go together. In practice, the road from a better understanding towards better results can be difficult.

The Extended Kalman Filter

The Extended Kalman Filter (EKF) is an extension of the Kalman filter for nonlinear systems:

$$x^a(t) = x^f(t) + \mathrm{K}(y^o - \mathcal{H}x^f(t)), \quad (1)$$

$$\mathrm{K} = \mathrm{P}^f\mathrm{H}^T(\mathrm{H}\mathrm{P}^f\mathrm{H}^T + \mathrm{R})^{-1}, \quad (2)$$

$$\mathrm{P}^a = (\mathrm{I} - \mathrm{K}\mathrm{H})\mathrm{P}^f, \quad (3)$$

$$x^f(t+1) = \mathcal{M}(x^a(t)), \quad (4)$$

$$\mathrm{P}^f(t+1) = \mathrm{M}\mathrm{P}^a\mathrm{M}^T + \mathrm{Q}. \quad (5)$$

y^o : vector of observations
x^a : analysis
$\mathcal{H}$: forward operator
$\mathcal{M}$: forecast model
P^a : analysis error covariance
Q : model error covariance
R : observation error covariance
x^f : background
H : forward interpolation matrix
M : linearized forward model
P^f : forecast error covariance

EnKF, maintaining the ensembles with a stochastic filter

In the EnKF, since we don't explicitly compute $\mathrm{P}^{(a,f)}$, we have only three equations:

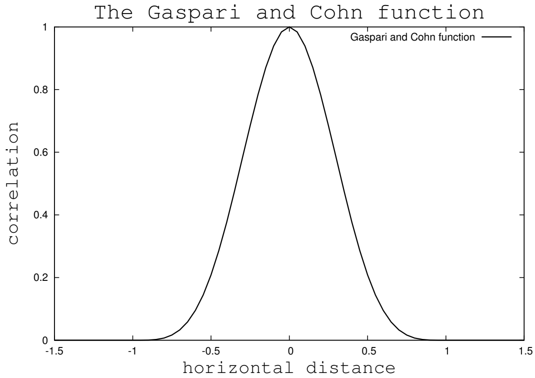
$$
\begin{aligned}
x_i^a(t) &= x_i^f(t) + \mathrm{K}(y_i^o - \mathcal{H}x_i^f(t)), i \in [1, N_{ens}], && (6)\\
\mathrm{K} &= \mathrm{P}^f\mathcal{H}^T(\mathcal{H}\mathrm{P}^f\mathcal{H}^T + \mathrm{R})^{-1}, && (7)\\
x_i^f(t+1) &= \mathcal{M}(x_i^a(t)) + q_i, \quad i \in [1, N_{ens}]. && (8)
\end{aligned}
$$

Equations 6 and 8 do, however, need to be evaluated N_{ens} times.

To have realistic ensemble spread, random perturbations to the observations y^o account for the observation error covariances R and random perturbations q_i to the model state account for the model error covariances Q.

localization of the impact of observations

Localization needs to be used - almost always - in an EnKF due to restrictions on the size of the ensembles. In fact, *localization is the key technique which makes the ensemble approximation to the Kalman filter computationally feasible*.



The most-used (Gaspari and Cohn) function looks Gaussian but becomes exactly zero at finite distance.

Sources of error that are neglected in the EnKF system

System error in an assimilation cycle	
data assimilation error	model error
systematic sampling error	
imbalance due to localization	
assumptions about observation error	
forward operator error	parameterized physics
dissipation due to balancing	model diffusion
spin-up issues	boundary conditions
observation bias	model bias
imperfect coupling of the model and the data assimilation method	
other issues beyond those listed above	

Lacking a quantitative description of the above error sources, covariance inflation methods are used to maintain a realistic ensemble spread.

Balance and window length

In an EnKF system, the ensemble of states carries all information on error statistics from one assimilation cycle to the next. A priori, one would even expect better results with shorter assimilation windows (Fertig et al. 2007).

With a short window:

- Errors evolve over a shorter period. Their evolution will be less non-linear.
- Localization will make more sense for rapidly displacing dynamical features.

The challenge is to introduce analysis increments in such a way that the model balance is respected (avoiding rapid adjustment by e.g. gravity waves).

Limited-area EnKF data assimilation

Limited-area EnKF systems can assimilate radar observations to track and predict active convective systems. High-resolution EnKF systems can also deliver competitive track and intensity forecasts for tropical cyclones.

Nevertheless there are several issues:

- Spin-up issues originate as a consequence of boundary conditions as well as fast error growth at small scales.
- A flexible localization method is necessary to combine information from a diverse observational network (including radar and radiosondes).
- Microphysics are important but are complex and involve many not directly observed variables.
- Radar observations have complex error structures.

Issues with the assimilation in EnKF systems of satellite radiance observations

- Bias correction is of critical importance. It would be desirable to have global probabilistic estimates of bias correction parameters.
- Covariance localization procedures are likely sub-optimal. Brute force could be a solution (N_{ens} O(1000)).
- It is common to use correlated radiance observations at high density. To account for (neglected) observation error correlations, error variances are inflated beyond realistic values. This strategy may have side effects.
- The cycling covariances of the EnKF are affected by the assimilation of large volumes of radiance data. Length scales could (spuriously) become very short.

It is recommended to perform controlled experiments (OSSEs) to explore different hypotheses and strategies.

Quality control of observations

Early EnKF systems (such as operational at CMC) relied for quality control on co-existing variational analysis systems. With differences in observational network, model configurations and observation error statistics, this approach is sub-optimal.

After more than 10 years of operational use, it is time that EnKF systems start doing their own quality control of observations.

For variational systems, the state-of-the-art is to use a Huber norm to give less weight to outlying observations (Tavolata and Isaksen, QJ 2015). Such a norm can also be used towards a robust EnKF (Roh et al. 2013, Sandu 2015).

In an EnKF, it is possible to use the dynamics of the day in the quality control procedure (to not reject observations when the dynamics are active).

More ambitious global EnKF configurations

year	res. km	N_{lon}	N_{lat}	N_{lev}	N_{ens}	N_{obs} 10^6	cost PH^T	cost $\mathcal{M}$
2011	100	400	200	58	192	0.3	0.06	0.42
2014	50	800	400	74	256	0.7	1	5
2022	25	1600	800	94	341	1.6	16	59
2030	13	3200	1600	120	455	3.8	252	686
2032	10	4000	2000	130	500	5.0	612	1513
							GW	GW
2038	6.3	6400	3200	154	606	8.9	0.4	0.8
2046	3.1	12800	6400	196	809	21	6.7	9.8

Current and hypothetical EnKF configurations. Computer power doubles every two years. The analysis scales as $O(N_{model} N_{ens} N_{obs})$. The model $\mathcal{M}$ scales as $O(N_{ens} N_{model}^{4/3})$.

Hybrid gain algorithm

At operational centers, 4D-variational and EnKF algorithms now co-exists. An easy way to combine positive aspects of both algorithms is to use a hybrid gain algorithm (Penny 2014).

Here the EnKF mean analysis $\overline{\mathrm{x}^a_{EnKF}}$ and the deterministic analysis x^a_{det} are recentered using:

$$\mathrm{x}^a_{centered} = \gamma\overline{\mathrm{x}^a_{EnKF}} + (1-\gamma)\mathrm{x}^a_{det}. \quad (9)$$

At ECMWF, Bonavita et al (2015) found that the hybrid gain system performed better than the individual EnKF and 4D-Var components.

A practical advantage is that it permits parallel - fairly independent - development of the two components.

The ultimate global EnKF algorithm

The best possible global EnKF could have the following features:

1. A comprehensive observation preprocessing system that includes bias correction and quality control,
2. A comprehensive treatment of model error (including boundary conditions),
3. Use of prior estimates of weak (remote) correlations,
4. An ensemble size of O(1000) members such that vertical covariance localization can be avoided,
5. A horizontal resolution not better than 10 km,
6. A short assimilation window O(1 h) to permit tracking high-resolution O(10 km) features.

With continued hard work, such a system could become available within the next 20 years.

Thank you for your attention

Thanks to Fuqing Zhang and Dandan Tao

for the organization

Enjoy the 7th EnKF Workshop