

Ensemble Transform Kalman Filter (ETKF)

Bishop et al. 2001

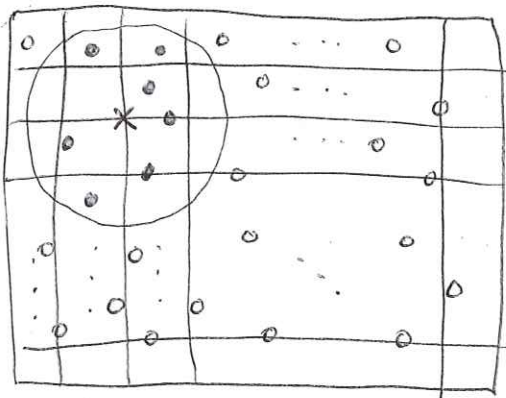
Idea: Instead of looping over observations, $j=1, 2, \dots, p$ and solve for $\bar{x}_{(j+1)} = \bar{x}_{(j)} + \frac{\text{cov}(\bar{x}_{(j)}, y_{(j)})}{\text{var}(y_j^o) + \text{var}(y_{(j)})} (y_j^o - y_{(j)})$ iteratively, (in EnSRF)

we can loop over state variables, $i=1, 2, \dots, n$ and

$$\text{solve for } x_i^a = x_i^b + \frac{\text{cov}(x_i^b, \bar{y}^b)}{\text{var}(\bar{y}^o) + \text{var}(\bar{y}^b)} (\bar{y}^o - \bar{y}^b)$$

⇒ computation for each grid point i can be done independently, which allows parallelization.

⇒ convert the matrix inversion $(HP^bH^T + R)^{-1}$ into ensemble space to speed up computation.



LETKF (Hunt et al. 2007)
⇒ use only local observations to update each state variable.

Intercomparison of EnKF variants:

Perturbed obs EnKF	Filter Type	Assimilation of obs	Tippett 2003	
			↓ Cost	
EnKF	Evenesen 1994 Houtekamer 1998 Mitchell	stochastic	simultaneous	$O(N^3 + N_p^2 + N_n^2)$
EnSRF	Whitaker Hamill 2002	deterministic	serial	$O(N_p + N_{np})$
EAKF	Anderson 2001	deterministic	simultaneous	$O(N^3 + N_p^2 + N_n^2)$
ETKF LETKF	Bishop et al. 2001 Hunt et al. 2007	deterministic	simultaneous	$O(N^3 + N_p^2 + N_n^2)$

The inversion $(HP^bH^T + R)^{-1}$ is a $p \times p$ matrix inversion,
we convert this problem into ensemble space:

Recall ensemble perturbation matrix

$$\mathbf{X}^b = \frac{1}{\sqrt{N-1}} \begin{pmatrix} |x_1^b\rangle & |x_2^b\rangle & \dots & |x_N^b\rangle \end{pmatrix}, \text{ where } x_k^{b'} = x_k^b - \bar{x}^b, \text{ for } k=1, 2, \dots, N$$

$$\bar{x}^b = \frac{1}{N} \sum_{k=1}^N x_k^b$$

Define $\mathbf{Y}^b \approx H\mathbf{X}^b$

$$= \frac{1}{\sqrt{N-1}} \begin{pmatrix} |y_1^b\rangle & |y_2^b\rangle & \dots & |y_N^b\rangle \end{pmatrix}, \text{ where } y_k^b = h(x_k^b)$$

$$\bar{y}^b = \frac{1}{N} \sum_{k=1}^N y_k^b$$

$$y_k^{b'} = y_k^b - \bar{y}^b$$

for $k=1, 2, \dots, N$

Kalman Gain can be rewritten:

$$K = P^b H^T (HP^bH^T + R)^{-1} \text{ use } P^b = \mathbf{X}^b \mathbf{X}^{bT}$$

$$= \mathbf{X}^b \mathbf{Y}^{bT} (\mathbf{Y}^b \mathbf{Y}^{bT} + R)^{-1} \quad \textcircled{1}$$

$$= \mathbf{X}^b \underbrace{(\mathbf{I} + \mathbf{Y}^{bT} R^{-1} \mathbf{Y}^b)^{-1}}_S \mathbf{Y}^{bT} R^{-1} \quad \textcircled{2}$$

S is the local analysis error covariance.

Similar to $(P^b)^{-1} + H^T R^{-1} H$ but with background P^b

factored into the second term: $(\mathbf{I} + \underbrace{(H\mathbf{X}^b)^T}_{\text{"background" error}} R^{-1} \underbrace{H\mathbf{X}^b}_{\text{"observation" error}})^{-1}$

$\rightarrow S$ is a $N \times N$ matrix, which is much easier to find an inverse:

$U \Lambda U^T = \mathbf{Y}^{bT} R^{-1} \mathbf{Y}^b$ is the singular value decomposition of a symmetric matrix.

Note: R is diagonal matrix. So R^{-1} is easy to compute.

$$S = U(\mathbf{I} + \Lambda)^{-1} U^T$$

In step ④ of EnKF, we need to generate new ensemble perturbations that satisfy $P^a = (I - KH)P^b$, this can be done by transforming the ensemble perturbation matrix X^b with the square-root of $I - KH$:

$$\begin{aligned}
 P^a &= X^a X^{aT} = (I - KH)P^b \\
 &= [I - P^b H^T (H P^b H^T + R)^{-1} H] X^b X^{bT} \\
 &= X^b X^{bT} - X^b Y^{bT} (Y^b Y^{bT} + R)^{-1} Y^b X^{bT} \\
 &= X^b (I - \underbrace{Y^{bT} (Y^b Y^{bT} + R)^{-1} Y^b}_{\textcircled{3}}) X^{bT} \\
 &= X^b (\underbrace{I + Y^{bT} R^{-1} Y^b}_{\textcircled{4}})^{-1} X^{bT} \\
 &= X^b S X^{bT}
 \end{aligned}$$

It is much easier to find the square root of $S = \underline{W} \underline{W}^T$ than $(I - Y^{bT} (Y^b Y^{bT} + R)^{-1} Y^b)$

$$\underline{W} = U(I + \Lambda)^{-\frac{1}{2}}$$

$$X^a = X^b \underline{W}$$

Proof that ③ = ④:

$$\begin{aligned}
 \textcircled{3} \textcircled{4}^{-1} &= [I - Y^T (Y Y^T + R)^{-1} Y] [I + Y^T R^{-1} Y] \quad \textcircled{Y Y^T + R - R} \\
 &= I + Y^T R^{-1} Y - Y^T (Y Y^T + R)^{-1} Y - Y^T (Y Y^T + R)^{-1} \textcircled{Y Y^T R^{-1} Y} \\
 &= I + \boxed{Y^T R^{-1} Y} - \underbrace{Y^T (Y Y^T + R)^{-1} Y}_{\textcircled{Y^T (Y Y^T + R)^{-1} Y}} - \underbrace{Y^T (Y Y^T + R)^{-1} (Y Y^T + R) R^{-1} Y}_{\textcircled{Y^T (Y Y^T + R)^{-1} R R^{-1} Y}} \\
 &= I
 \end{aligned}$$

$$\begin{aligned}
 \textcircled{2} = \textcircled{4} \cdot Y^T R^{-1} &= \textcircled{3} Y^T R^{-1} = Y^T R^{-1} - Y^T (Y Y^T + R)^{-1} \textcircled{Y Y^T R^{-1}} \\
 &= Y^T R^{-1} - Y^T \underline{(Y Y^T + R)^{-1}} (\underline{Y Y^T + R}) R^{-1} + Y^T (Y Y^T + R)^{-1} \underline{R R^{-1}} \\
 &= \textcircled{1}
 \end{aligned}$$

LETKF algorithm:

(1) Forecast step $X_{t+1,k}^b = m(X_{t,k}^a)$ for $k=1, 2, \dots, N$

(2)-(8) Analysis step at time $t+1$ independently performed for each $i=1, 2, \dots, n$

(2) Compute ensemble perturbations $\underline{X}_i^b = \frac{1}{\sqrt{N-1}} (x_{1,i}^{b'}, x_{2,i}^{b'} \dots x_{N,i}^{b'})$

(3) compute observation prior perturbations \underline{Y}^b by applying nonlinear observation operator h .

(4) Localization

At each grid point i , select local subset of observations (observations within cutoff radius)

$$y_L^o = \text{subset}(y^o), \quad \bar{y}_L^b = \text{subset}(\bar{y}^b),$$

$$\underline{Y}_L^b = \text{subset}(\underline{Y}^b)$$

$$R_L = \text{subset}(R) \circ \text{diag}(P_L), \text{R-localization function } (P_L)_j = e^{-d_{ij}^2/2L^2}$$

where d_{ij} is distance between i th grid point and j -th observation.

L is the localization length scale

$\rightarrow 3.65L$ is considered the cutoff distance.

(5) compute local analysis error covariance in ensemble space.

$$S = (I + \underline{Y}_L^{bT} R_L^{-1} \underline{Y}_L^b)^{-1}$$

(6) update mean: $\bar{X}_i^a = \bar{X}_i^b + \bar{X}_i^b w$

$$w = S \underline{Y}_L^{bT} R_L^{-1} (y_L^o - \bar{y}_L^b)$$

(7) update ensemble perturbations $\underline{X}_i^a = \underline{X}_i^b \underline{W}$, $\underline{W} = S^{\frac{1}{2}}$

(8) form analysis $X_{k,i}^a = \bar{X}_i^a + X_{k,i}^{a'}$ for $k=1, 2, \dots, N$

\rightarrow analysis is local linear combination of ensemble perturbations, which is limited by the directions defined by ensemble.