

Iterative Kalman Filter using Ensembles

Technical formulation and preliminary test

Tannersvile PA / 8th Adjoint Workshop

Martin Verlaan

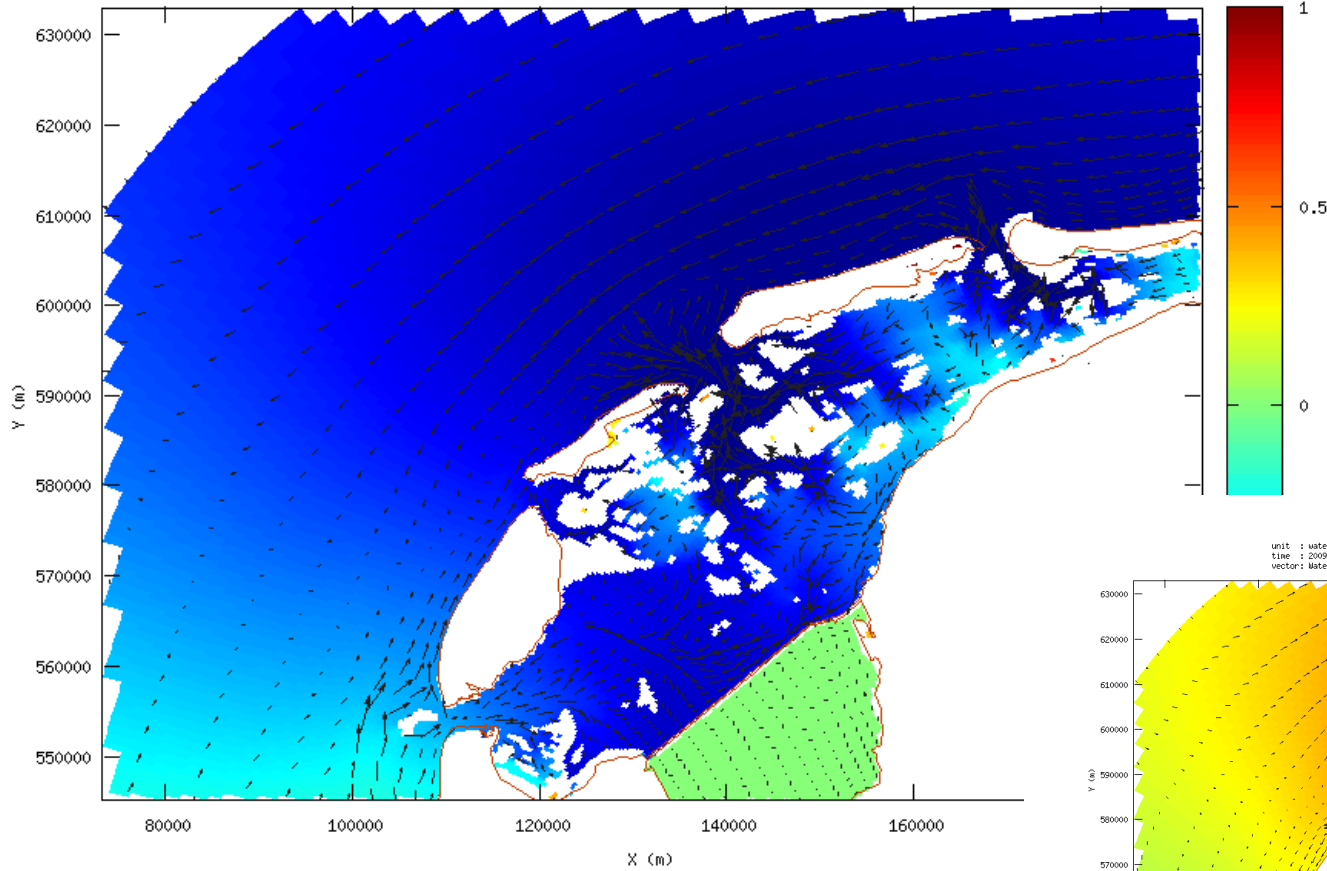
May 21, 2009

1

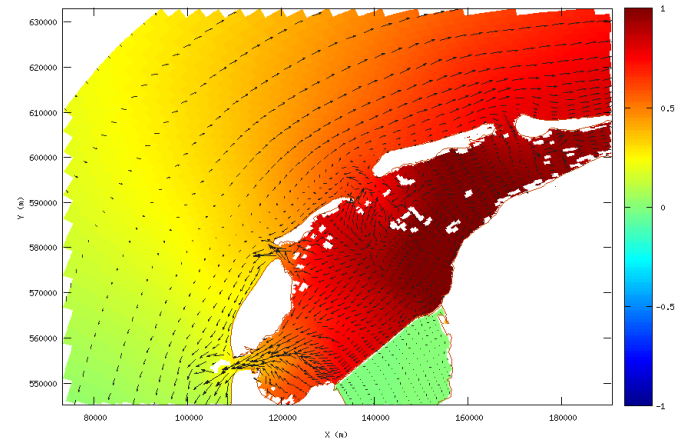
Outline

- " Motivation
- " Notation & review
- " DUD
- " Algorithm
- " Experiment
- " Summary

unit : waterlevel in m source : kustfijn
time : 2009-05-21 11:00:00 analysis: 2009-05-21 01:00:00
vector: Water velocity, 1 cm = 1 m/s



unit : waterlevel in m source : kustfijn
time : 2009-05-21 18:00:00 analysis: 2009-05-21 01:00:00
vector: Water velocity, 1 cm = 1 m/s



Motivation

- " particle filters have nice theoretical properties, but are very expensive to run
- " Kalman Filter analysis is inconsistent with model if operators are non-linear (unlike VAR)

$$\mathbf{y}_k^a \neq H_k[\mathbf{x}_k^a]$$

$$\mathbf{x}_{k+1}^a \neq M_k[\mathbf{x}_k^a] + \mathbf{w}_k^a$$

$$\mathbf{x}_k^a \neq M_{0,k}[\mathbf{x}_0, \hat{\mathbf{p}}]$$

Notation

$$\mathbf{x}_{k+1}^t = M_k [\mathbf{x}_k^t] + \mathbf{w}_k$$

$$\mathbf{y}_k^o = H_k [\mathbf{x}_k^t] + \varepsilon_k$$

$$\mathbf{J}(\mathbf{x}_k) = \frac{1}{2}(\mathbf{x}_k - \mathbf{x}_k^f)'(\mathbf{P}_k^f)^{-1}(\mathbf{x}_k - \mathbf{x}_k^f) + \frac{1}{2}(\mathbf{y}_k^o - H_k[\mathbf{x}_k])'\mathbf{R}_k^{-1}(\mathbf{y}_k^o - H_k[\mathbf{x}_k])'$$

Incremental formulation

$$\mathbf{x} = \mathbf{x}^g + \delta \mathbf{x}$$

$$\mathbf{J}_{incr}(\delta \mathbf{x}) = \frac{1}{2}(\delta \mathbf{x} + \mathbf{x}^g - \mathbf{x}^f)'(\mathbf{P}_k^f)^{-1}(\delta \mathbf{x} + \mathbf{x}^g - \mathbf{x}^f) + \frac{1}{2}(\mathbf{y}^o - H[\mathbf{x}^g] - \mathbf{H}\delta \mathbf{x})'\mathbf{R}_k^{-1}(\mathbf{y}^o - H[\mathbf{x}^g] - \mathbf{H}\delta \mathbf{x})$$

$$\nabla \mathbf{J}_{incr}(\delta \mathbf{x}) = (\mathbf{P}^f)^{-1}(\delta \mathbf{x} + \mathbf{x}^g - \mathbf{x}^f) - \mathbf{H}'\mathbf{R}^{-1}(\mathbf{y}^o - H[\mathbf{x}^g] - \mathbf{H}\delta \mathbf{x})$$

Incremental form and Kalman

$$\delta \mathbf{x} = ((\mathbf{P}^f)^{-1} + \mathbf{H}'\mathbf{R}^{-1}\mathbf{H})^{-1} ((\mathbf{P}^f)^{-1}(\mathbf{x}^g - \mathbf{x}^f) - \mathbf{H}'\mathbf{R}^{-1}(\mathbf{y}^o - H[\mathbf{x}^g]))$$

$$\mathbf{x}^f = \mathbf{x}^g \longrightarrow \delta \mathbf{x} = \mathbf{K}(\mathbf{y}^o - H[\mathbf{x}^g])$$

$$\mathbf{K} = \mathbf{P}^f \mathbf{H}' (\mathbf{H} \mathbf{P}^f \mathbf{H}' + \mathbf{R})^{-1}$$

Ensemble Kalman Filter

$$\mathbf{x}^f \approx \bar{\xi}^f = \frac{1}{n} \sum_{i=1}^n \xi_i^f \quad \mathbf{P}^f \approx \frac{1}{n-1} \sum_{i=1}^n (\xi_i - \bar{\xi}^f)(\xi_i - \bar{\xi}^f)'$$

$$\mathbf{P}^f = \mathbf{A}^f (\mathbf{A}^f)'$$

$$\mathbf{A}^f = \left[\frac{1}{\sqrt{n-1}} (\xi_1^f - \bar{\xi}^f), \dots, \frac{1}{\sqrt{n-1}} (\xi_n^f - \bar{\xi}^f) \right]$$

Ensemble based VAR

$$\mathbf{x} = \bar{\xi}^f + A\mathbf{w}$$

$$\begin{aligned} \mathbf{J}_{incr}(\mathbf{w}) &= \frac{1}{2}(\mathbf{A}^f \mathbf{w})'(\mathbf{P}_k^f)^{-1}(\mathbf{A}^f \mathbf{w}) + \frac{1}{2}(\mathbf{y}^o - H[\bar{\xi}^f] - \mathbf{H}\mathbf{A}^f \mathbf{w})'\mathbf{R}_k^{-1}(\mathbf{y}^o - H[\bar{\xi}^f] - \mathbf{H}\mathbf{A}^f \mathbf{w}) \\ &= \frac{1}{2}\mathbf{w}'\mathbf{w} + \frac{1}{2}(\mathbf{y}^o - H[\bar{\xi}^f] - \mathbf{H}\mathbf{A}^f \mathbf{w})'\mathbf{R}_k^{-1}(\mathbf{y}^o - H[\bar{\xi}^f] - \mathbf{H}\mathbf{A}^f \mathbf{w}) \end{aligned}$$

$$\mathbf{H}\mathbf{A}^f \approx \left[\frac{1}{\sqrt{n-1}}(H\xi_1^f - H\bar{\xi}^f), \dots, \frac{1}{\sqrt{n-1}}(H\xi_n^f - H\bar{\xi}^f) \right]$$

ETKF, ENSR, MLEF, ...

EnRML Gu & Oliver 2007 (SPE)

En3DVAR Liu et. al. 2008

DUD - Does not Use Derivatives

$$\mathbf{J}(\mathbf{w}) = \frac{1}{2}(\mathbf{y}^o - \mathbf{f}[\mathbf{w}])'(\mathbf{y}^o - \mathbf{f}[\mathbf{w}])$$

$$\mathbf{f}(\mathbf{w}) \approx \mathbf{f}(\mathbf{w}_0) + [\mathbf{f}(wb_1) - \mathbf{f}(wb_0), \dots, \mathbf{f}(wb_q) - \mathbf{f}(wb_0)] \\ [wb_1 - wb_0, \dots, wb_q - wb_0]^{-1}(\mathbf{w} - \mathbf{w}_0)$$

Ralston & Jennrich 1978

DUD solve

$$\mathbf{A} = [\mathbf{f}(\mathbf{w}_1) - \mathbf{f}(\mathbf{w}_0), \dots, \mathbf{f}(\mathbf{w}_q) - \mathbf{f}(\mathbf{w}_0)]$$

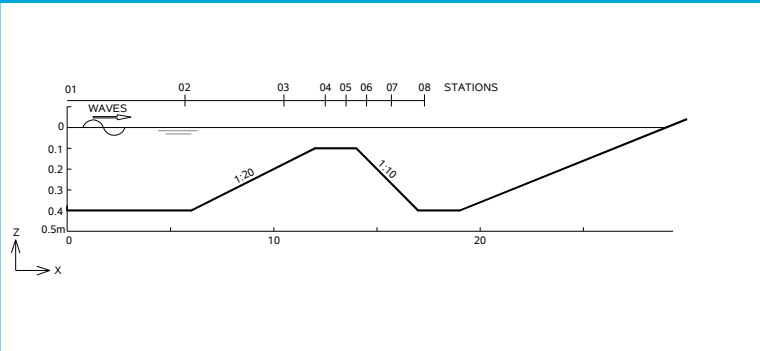
$$\mathbf{B} = [\mathbf{w}_1 - \mathbf{w}_0, \dots, \mathbf{w}_q - \mathbf{w}_0]$$

$$\mathbf{J}_{lin}(\mathbf{w}) = \frac{1}{2} (\mathbf{y}^o - \mathbf{f}(\mathbf{w}_0) + \mathbf{B}\mathbf{A}^{-1}(\mathbf{w} - \mathbf{w}_0))' (\mathbf{y}^o - \mathbf{f}(\mathbf{w}_0) + \mathbf{B}\mathbf{A}^{-1}(\mathbf{w} - \mathbf{w}_0))$$

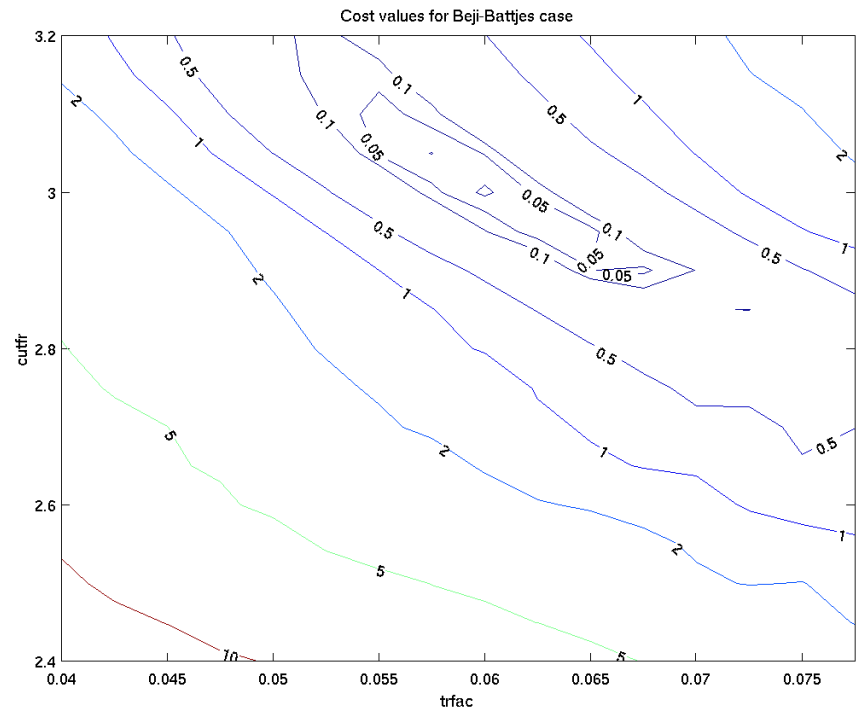
$$\hat{\mathbf{w}} = \mathit{argmin}_{\mathbf{w}} \mathbf{J}_{lin}(\mathbf{w})$$

Now update trial points \mathbf{w}_j

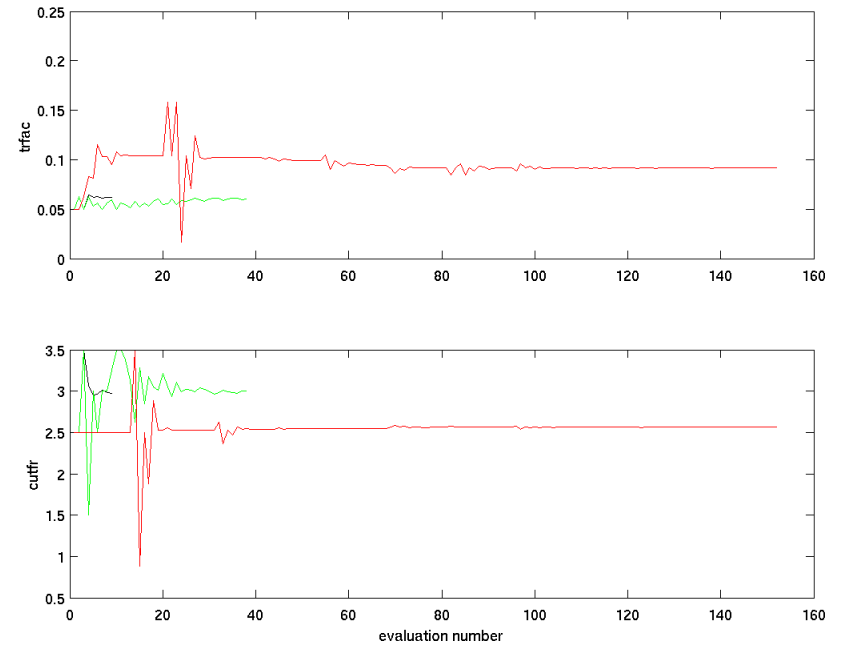
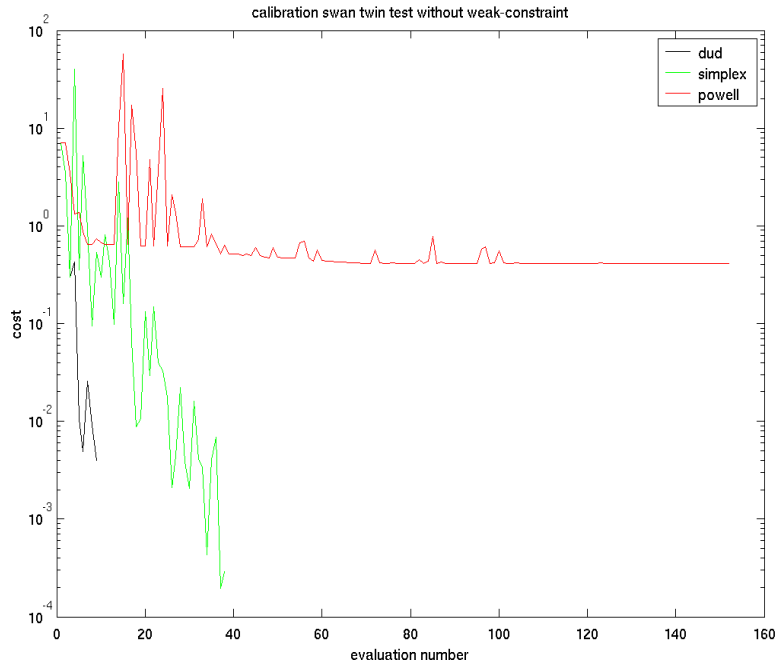
DUD example



$$\frac{DN}{t} + \frac{1}{x}(c_x N) + \frac{1}{y}(c_y N) + \frac{1}{\sigma}(c_\sigma N) + \frac{1}{\theta}(c_\theta N) = \frac{S_{tot}}{\sigma}$$



DUD example



DUDEnKF

substitute $\mathbf{x} = \bar{\xi}^f + A\mathbf{w}$ in non-linear $\mathbf{J}(\mathbf{x}_k)$

$$\mathbf{J}(\mathbf{w}) = \frac{1}{2}\mathbf{w}'\mathbf{w} + \frac{1}{2}(\mathbf{y}^o - H[\bar{\xi}^f + A\mathbf{w}])'\mathbf{R}^{-1}(\mathbf{y}^o - H[\bar{\xi}^f + A\mathbf{w}])$$

$$H_k[\bar{\xi}^f + A\mathbf{w}] \approx H[\bar{\xi}^f + A\mathbf{w}_1^l]$$

$$+ \left[H[\bar{\xi}^f + A\mathbf{w}_2^l] - H[\bar{\xi}^f + A\mathbf{w}_1^l], \dots, H[\bar{\xi}^f + A\mathbf{w}_n^l] - H[\bar{\xi}^f + A\mathbf{w}_1^l] \right] \\ \left[\mathbf{w}_2^l - \mathbf{w}_1^l, \dots, \mathbf{w}_n^l - \mathbf{w}_1^l \right]^{-1} (\mathbf{w} - \mathbf{w}_1^l)$$

MLEF Zupanski 2005

DUDEnKF algorithm

Time loop

" forecast $\xi_{k+1}^f = M_k[\xi_i^a] + \mathbf{w}_{ki}$

" minimize $\mathbf{J}_i(\mathbf{w}) = \frac{1}{2} \mathbf{w}' \mathbf{w}$

$$+ \frac{1}{2} (\mathbf{y}^o + \varepsilon_{ki} - H[\xi_i^f + A\mathbf{w}])' \mathbf{R}^{-1} (\mathbf{y}^o + \varepsilon_{ki} - H[\bar{\xi}^f + A\mathbf{w}])$$

using DUD, $\xi_i^a = \bar{\xi}^f + A\hat{\mathbf{w}}_i$

Lorenz example

$$\frac{dx}{dt} = \sigma(y - x)$$

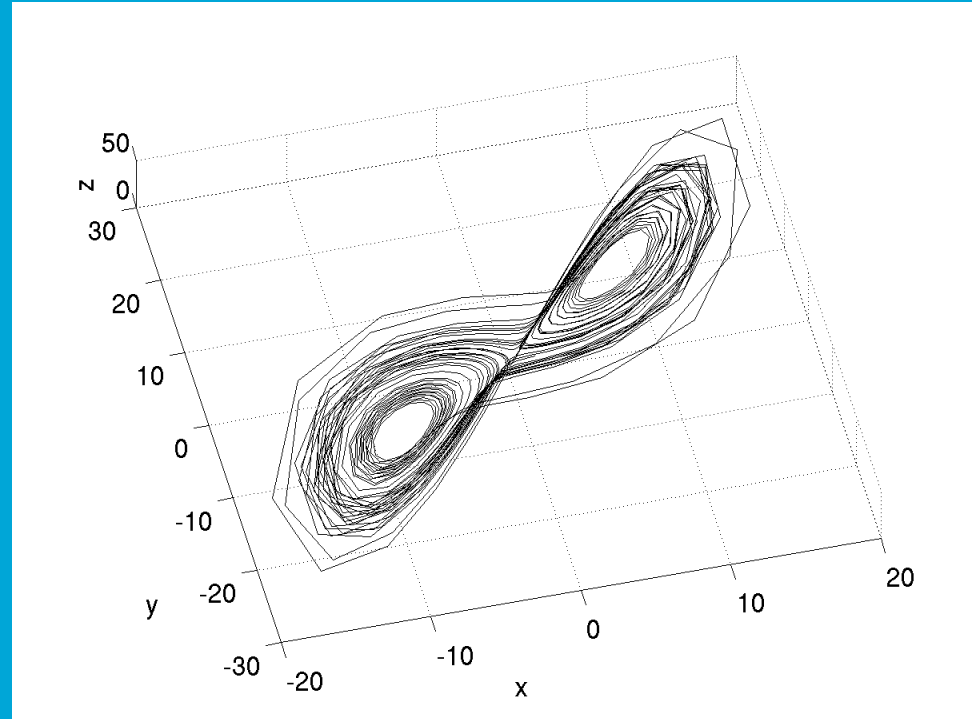
$$\frac{dy}{dt} = \rho x - y - xz$$

$$\frac{dz}{dt} = xy - \beta z$$

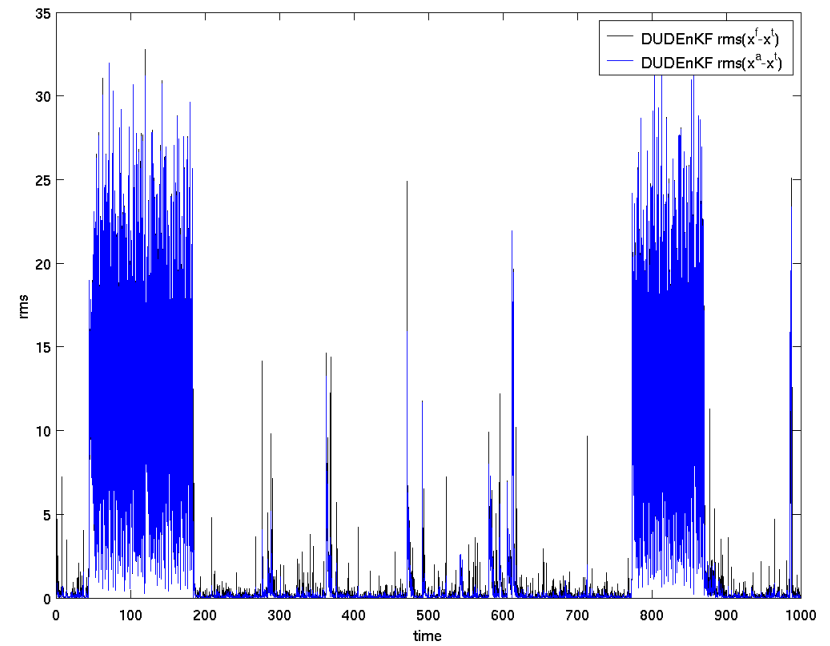
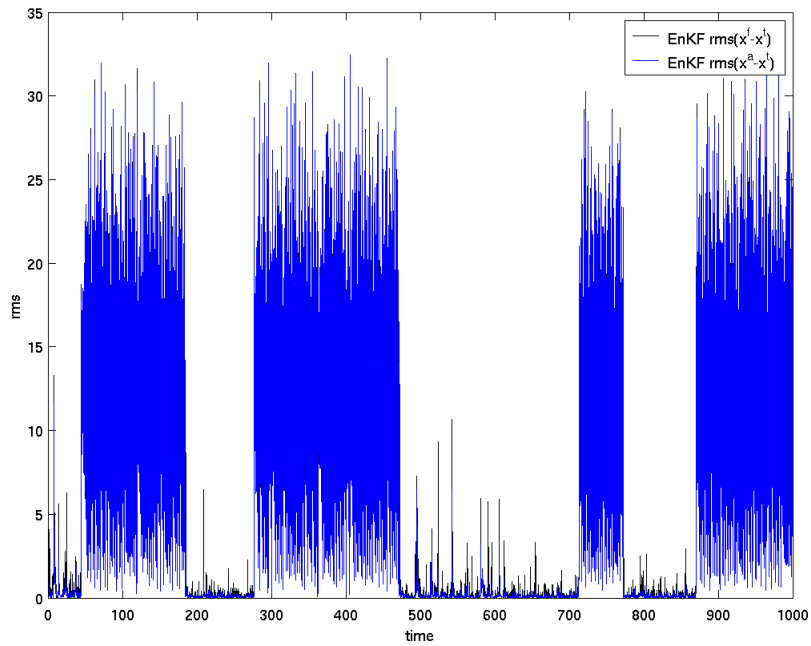
observations x^2, y^2, z^2

$$\Delta t_{obs} = 0.2$$

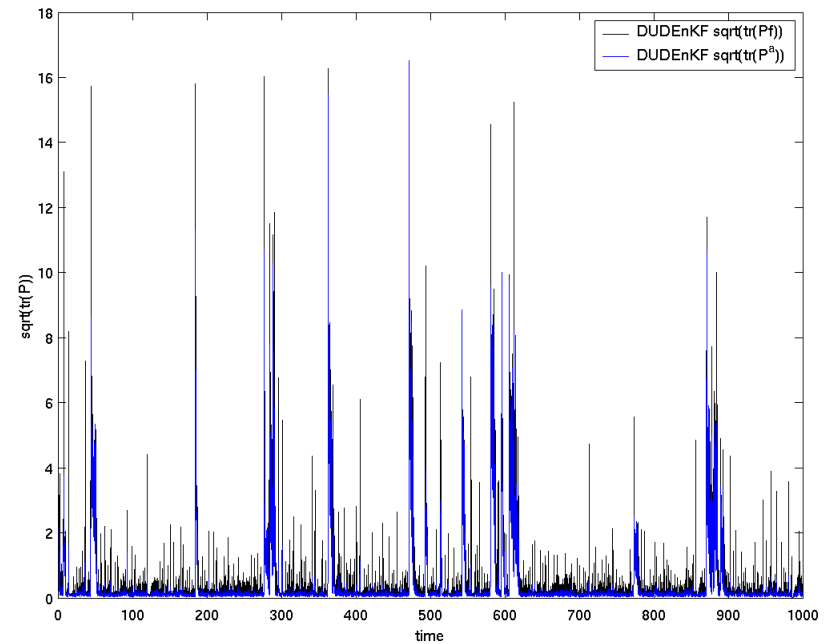
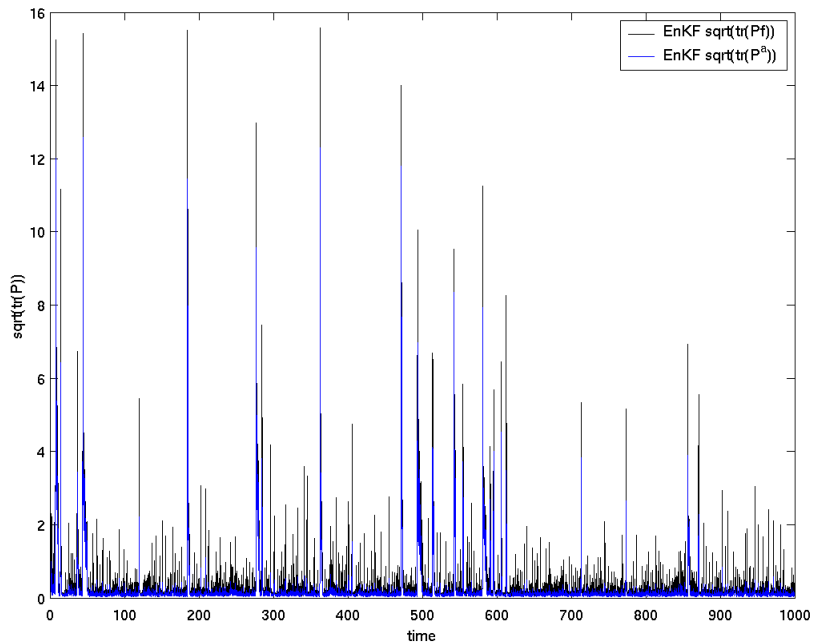
$$\sigma_{obs} = 10.0$$



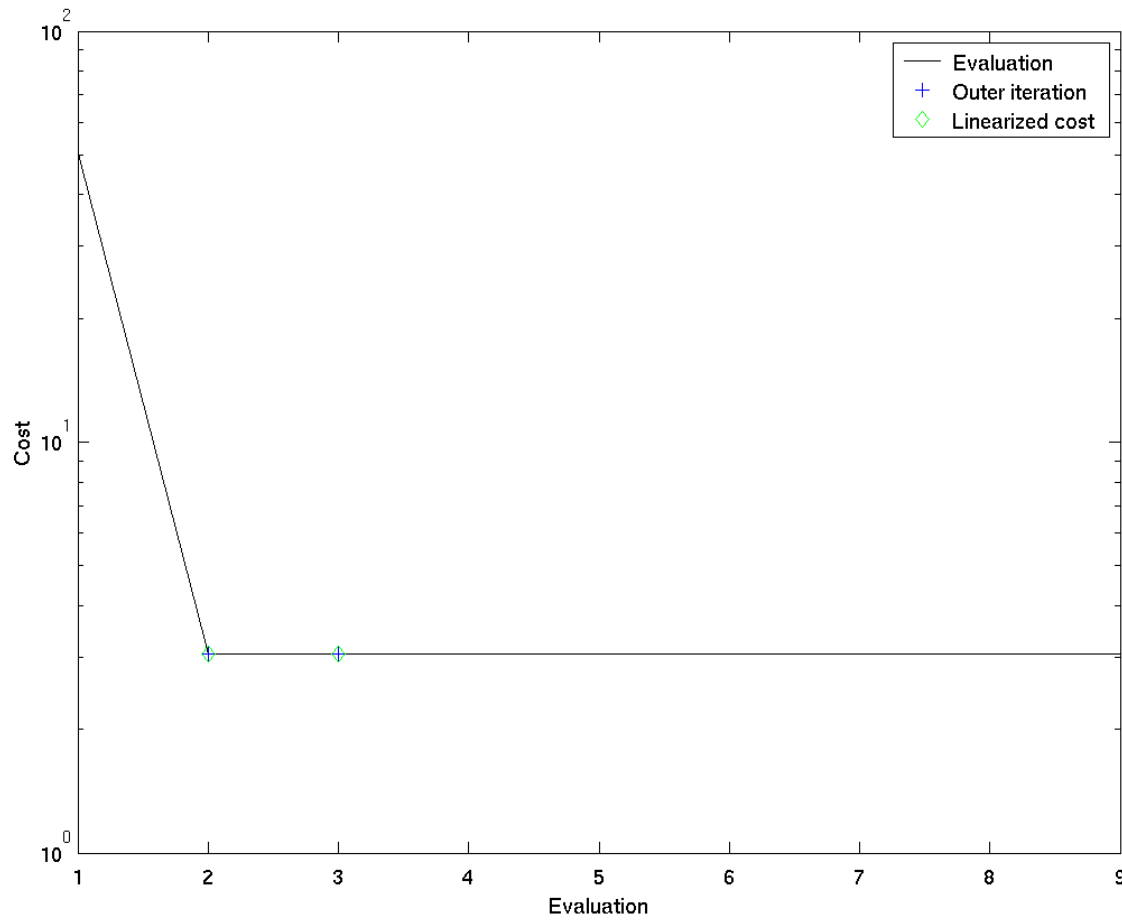
Lorenz example



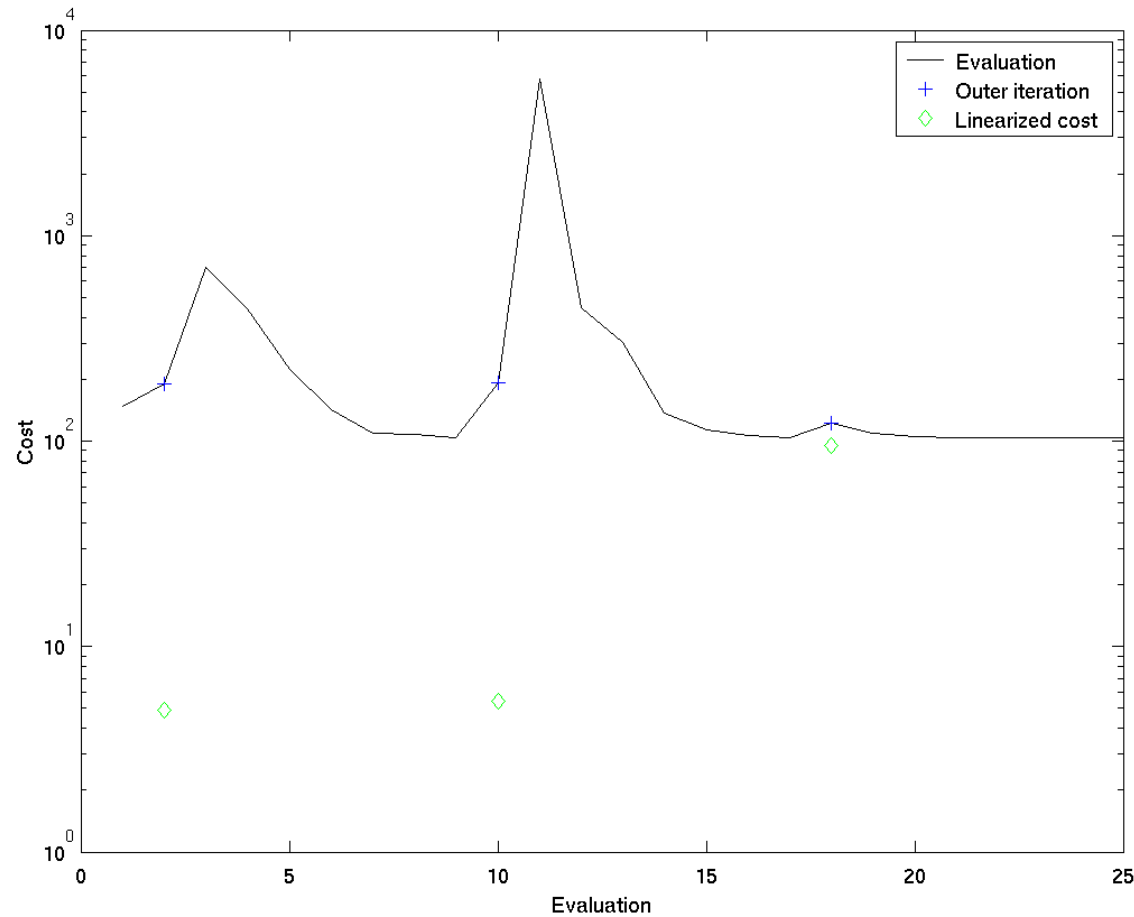
Lorenz example



Iteration – quick convergence



Iteration – slow convergence



Summary / future

- " Iterations in a maximum-likelihood/VAR approach can improve consistency
 - " Iterated Kalman Filter can approach VAR solution
 - " No TLM or adjoint needed (except for efficiency)
-
- " Next: smoothing and parameter estimation and applications

References

- " [Ralston and Jennrich, 1978] Ralston, M. and Jennrich, R. (1978). Dud, a derivative-free algorithm for nonlinear least squares. *Technometrics*, 20(1):7- 14.
- " [Zupanski, 2005] Zupanski, M. (2005). Maximum likelihood ensemble filter: Theoretical aspects. *Monthly Weather Review*, 133:1710-1725.
- " [Chen et al., 2008] Chen, Y., Oliver, D., and Zhang, D. (2008). Efficient ensemble-based closed-loop production optimization. *Society of Petroleum Engineers*
- " [Liu et al., 2008] Liu, C., Xiao, Q., and Wang, B. (2008). An ensemble-based four-dimensional variational data assimilation scheme. part i: Technical formulation and preliminary test. *Monthly Weather Review*, 136:3363-3373.
- " [Liu et al., 2009] Liu, C., Xiao, Q., and Wang, B. (2009). An ensemble-based four-dimensional variational data assimilation scheme. part ii: Observing system simulation experiments with advanced research wrf (arw). *Monthly Weather Review*.
- " [Krymskaya et al., 2008] Krymskaya, M., Hanea, R., and Verlaan, M. (2008). An iterative ensemble kalman filter for reservoir engineering applications. *Comput Geosci*, pages DOI 10.1007/s10596-008-9087-9.
- " [Li and Navon, 1999] Li, A. and Navon, I. (1999). Optimality of 4d-var and its relationship with the kalman filter and kalman smoother. submitted to *Q.J.R. Meteorol. Soc.*