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Maximum Likelihood Ensemble Filter (MLEF)

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Projects' web-sites:
http://www.cira.colostate.edu/nsf/
http://www.cira.colostate.edu/thorpex/default.asp

Outline

- MLEF
  - Forecast error covariance
  - Hessian preconditioning
  - Analysis error covariance

- Ongoing work

- Future research directions

MLEF Forecast Error Covariance

- Forecast model

$$\boldsymbol{x}^f = \mathcal{M}(\boldsymbol{x}^a)$$

$$\boldsymbol{x}_i^f = \mathcal{M}(\boldsymbol{x}^a + \boldsymbol{p}_i^a)$$

- Forecast (prior) error covariance

$$\boldsymbol{P}_f^{1/2} = [\boldsymbol{p}_1^f \quad \boldsymbol{p}_2^f \quad \cdots \quad \boldsymbol{p}_{N_E}^f]$$

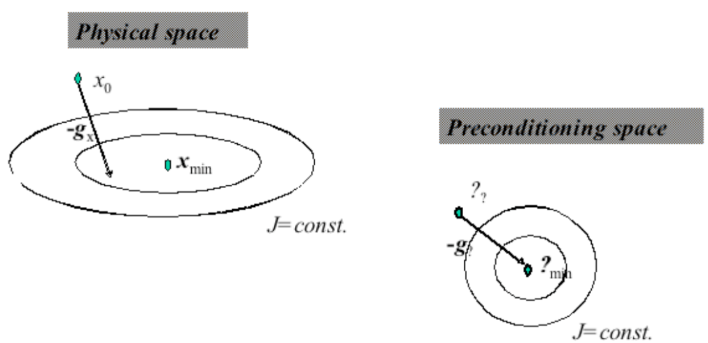
$$\boldsymbol{p}_i^f = \mathcal{M}(\boldsymbol{x}^a + \boldsymbol{p}_i^a) - \mathcal{M}(\boldsymbol{x}^a)$$

- **Control forecast is the *most likely* forecast, not the ensemble mean**
- **No sampling of error covariance**

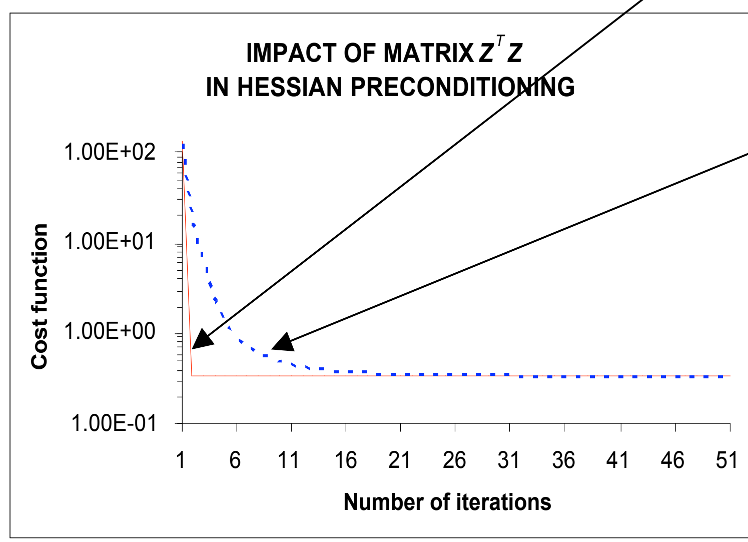
MLEF Hessian Preconditioning

Minimize cost function in ensemble subspace

$$J = \frac{1}{2}[x - x^f]^T P_f^{-1}[x - x^f] + \frac{1}{2}[y_{obs} - \mathcal{H}(x)]^T R^{-1}[y_{obs} - \mathcal{H}(x)]$$



$$H^{-1} \approx P_f^{1/2}(I + Z^T Z)^{-1} P_f^{T/2}$$



$$H^{-1} \approx P_f$$

Superior Hessian preconditioning allows efficient minimization

MLEF Analysis Error Covariance

$$P_a^{1/2} = P_f^{1/2}(I + Z^T Z)^{-1/2}$$

$$P_a^{1/2} = [\, p_1^a \quad p_2^a \quad \cdots \quad p_{N_E}^a \,]$$

$$z_i = R^{-1/2}\mathcal{H}(x^a + p_i^f) - R^{-1/2}\mathcal{H}(x^a)$$

- ***Analysis error covariance*** **is estimated from minimization algorithm, as the inverse Hessian at the minimum**

- ***Good*** **Hessian preconditioning and minimization solution important**

Overview of the MLEF

(*Zupanski* 2005, *MWR*; *Zupanski and Zupanski* 2005, *MWR*)

1 - Estimate of the *conditional mode* of the posterior PDF

2 - Ensembles used to estimate the *uncertainty* of the conditional mode

3 - *Non-differentiable* minimization with Hessian preconditioning
(Generalized conjugate-gradient, BFGS quasi-Newton algorithms)

4 - *Non-Gaussian* errors allowed (minimization of non-Gaussian cost-function)

5 - Augmented control variable

- *initial conditions*
- *model bias*
- *empirical parameters*
- *boundary conditions*

Ongoing work

❑ **Ensemble data assimilation and control theory (NSF)**

- Steven Fletcher (CSU/CIRA), David Randall (CSU/ATS)
- Bahri Uzunoglu, Michael Navon (FSU)
- Dacian Daescu (PSU)

• Apply MLEF with CSU global shallow-water model
• Non-Gaussian framework
• Non-derivative minimization methods
• NCAR bluesky computer (IBM SP)

❑ **Development of Methods for Data Assimilation with Advanced Models and Advanced Data Sources (NASA)**

- D. Randall, G. Stephens, S. Denning (CSU/ATS)
- D. Zupanski (CSU/CIRA)
- W-K. Tao, R. Atlas (NASA)

• Apply MLEF with NASA GEOS AGCM + super-parameterization
• Examine ensemble based DA with Multiscale Modeling Framework (MMF)
• NASA AMES Columbia computer (SGI)

Ongoing work

❑ NCEP Global Forecasting System model and real data (NOAA/THORPEX)

- Arif Albayrak (CSU/CIRA)
- Zoltan Toth, Yucheng Song, Mozheng Wei (NOAA/NCEP)

• Apply MLEF with NCEP GFS and real observations
• Evaluate the conditional mean and mode estimates within ensemble DA
• Develop and test double-resolution MLEF
• NCEP computers (IBM SP)

❑ Microscale ensemble data assimilation (CGAR/DoD)

- Tom Vonder Haar (CSU/CIRA)
- Bob Dumais, Patrick Haines (ARL)

• Apply MLEF with Univ. of Purdue non-hydrostatic model
• Apply MLEF with RAMS model
• Assimilation of real data
• Collaboration with the Army Research Laboratory
• Army supercomputers (IBM SP, Cray-SGI)

Future Research Directions

Algorithmic and theoretical aspects:

Development of a fully non-Gaussian algorithm
- Allow for non-Gaussian *state variable* errors (initial conditions, parameters)
- Generalized algorithm with a list of PDFs

Improved efficiency and algorithm robustness
- Ensemble size reduction and enrichment
- Improved account of degrees of freedom – ensemble space vs. its complement

Assimilation of challenging observations
- Nonliner (and nondifferentiable) observation operators
- Satellite radiances, hyper-spectral instruments
- Clouds, precipitation

Predictability
- Climate and coupled-model predictions
- Probabilistic aspect of the transfer between scales
- Estimate of attractor subspace for realistic models