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High-Dimensional Nonlinear Data Assimilation with the Nonlinear Ensemble Transform Filter (NETF) and its Smoother Extension

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Study new Nonlinear Ensemble Transform Filter – NETF (Tödter & Ahrens, MWR, 2015)

- Extend NETF for smoothing
- Test filter and smoother in realistic high-dimensional idealized ocean data assimilation experiments



Ensemble filters – ensemble Kalman filters & NETF

- represent state and its error by ensemble \mathbf{X} of *m* states
- Forecast:
 - Integrate ensemble with numerical model
- Analysis:
 - update ensemble mean
 - update ensemble perturbations

$$\overline{\mathbf{x}}^a = \overline{\mathbf{x}}^f + \mathbf{X}'^f \tilde{\mathbf{w}}$$

$$\mathbf{X}'^a = \mathbf{X}'^f \mathbf{W}$$

(both can be combined in a single step)

- Ensemble Kalman filters & NETF: Different definitions of
 - weight vector $\tilde{\mathbf{w}}$
 - Transform matrix ${f W}$



Nonlinear ensemble transform filter - NETF

- Ensemble Kalman:
 - Transformation according to KF equations
- NETF (Tödter & Ahrens, MWR, 2015)
 - > Mean update from Particle Filter weights: for all particles *i* $\tilde{w}^i \sim \exp\left(-0.5(\mathbf{y} - \mathbf{H}\mathbf{x}_i^f)^T \mathbf{R}^{-1}(\mathbf{y} - \mathbf{H}\mathbf{x}_i^f)\right)$
 - Ensemble update
 - Transform ensemble to fulfill analysis covariance (like KF, but not assuming Gaussianity)
 - Derivation gives

$$\mathbf{W} = \sqrt{m} \left[\operatorname{diag}(\tilde{\mathbf{w}}) - \tilde{\mathbf{w}} \tilde{\mathbf{w}}^T \right]^{1/2} \Lambda$$

(Λ: mean-preserving random matrix; useful for stability)
 (Almost same formulation: Xiong et al., Tellus, 2006)
 Nonlinear Ensemble Transform Filter & Smoother



Ensemble Smoothers – ETKS & NETS

- Smoother: Update past ensemble with future observations
- Rewrite ensemble update as



• Smoother at time i < k

$$\mathbf{X}_{i|k}^{a} = \mathbf{X}_{i|k-1}^{f} \hat{\mathbf{W}}_{k}$$

- works likewise for ETKS and NETS
- also possible for localized filters

See, e.g., Nerger, Schulte & Bunse-Gerstner, QJRMS 140 (2014) 2249-2259



Performance of NETF – Lorenz-96

- Performance for small model (Lorenz-96)
- In Tödter & Ahrens (MWR, 2015)



• NETF beats ETKF for m=20 and larger

How do NETF and NETS perform in a more realistic case?



Assimilation into NEMO

European ocean circulation model

Model configuration

- box-configuration SEABASS
- ¼° resolution
- 121x81 grid points, 11 layers (state vector ~300,000)
- wind-driven double gyre

 (a nonlinear jet and eddies)
- medium size SANGOMA benchmark



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DAF Parallel Data Assimilation Framework

PDAF - Parallel Data Assimilation Framework

- a program library for data assimilation
- provide support for ensemble forecasts
- provide fully-implemented filter and smoother algorithms (LETKF, LSEIK, LESTKF, ...)
- easily useable with (probably) any numerical model (applied with NEMO, MITgcm, FESOM, MPI-ESM, HBM)
- makes good use of supercomputers
- first public release in 2004; continued development

Open source: Code and documentation available at

http://pdaf.awi.de



L. Nerger, W. Hiller, Computers & Geosciences 55 (2013) 110-118

Online coupling: Minimal changes to NEMO



Observations and Assimilation Configuration

Observations

- Simulated satellite sea surface height SSH (Envisat & Jason-1 tracks), 5cm error
- Temperature profiles on 3°x3° grid, surface to 2000m, 0.3°C error

Data Assimilation

- Ensemble size 120
- ETKF and LETKF
- Localization: weights on matrix R⁻¹ (Gaspari/Cohn'99 function, 2.5° radius)
- Assimilate each 48h over 360 days



Application of LETKF



Estimated SSH at 1st analysis time





Application of LETKF (2)



Filter performances in NEMO

- RMS errors reduced to 10% (velocities to 20%) of initial error
- Slower convergence for NETF, but to same error level as LETKF
- CRPS (Continuous Rank Probability Score) shows similar behavior



Tödter, Kirchgessner, Nerger & Ahrens, MWR 144 (2016) 409 – 427

Applying the smoother

- Smoother reduces filter errors by ~10%
- Can be useful as smoothing is cheap to compute
- Roughness of estimated trajectory is strongly reduced (smoothed)



Different smoothing impact



- Similar behavior for ssh (sea surface height)
- Distinct for T
 - Effect of distinct update schemes (NETF uses observation values for both state and ensemble update)

Summary

- Nonlinear ensemble transform filter/smoother (NETF/S)
 - Update state estimate as particle filter
 - Transform ensemble using covariance matrix
- NEMO ocean test case
 - NETF filtering performance similar to LETKF
 - Slower convergence
 - Sensitive on ensemble size
 - Successful smoothing
 - Dependence on lag distinct for LETKS & NETS (due to different update schemes)

Thank you!

