Ensemble Filtering for the Atmospheric Mesoscale

Chris Snyder
National Center for Atmospheric Research
Ensemble Filtering for the Atmospheric Mesoscale

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Key Facts

Multiple scales and dynamical regimes:
- Moist convection (< 10 km)
- Coherent structures, organized moist convection (≤ 100 km) … squall lines and outflows, “convective systems,” hurricanes
- Orographic (≤ 100 km) … flow blocking, lee waves, sea breezes
- Fronts (~100 km)
- Larger scales (1000 km to global)

Strong dependence on sub-grid/parameterized processes:
- “Microphysics,” i.e. condensation, precipitation, latent heating
- Turbulent mixing and surface fluxes
Preliminaries

Notation

- $x = \text{state w.r.t. discrete basis, e.g. grid-point values or Fourier coefficients}$
- $x^t = \text{true state}$

True state is unknown

- pdf of $x^t$, $[x^t]$, is most that can be determined

Available information, typically

- recent forecast of $x^t$
- new observations, $y = Hx^t + \epsilon$
The Kalman Filter (KF) 

Assume

- $x^t \sim N(\bar{x}^f, P^f)$; Gaussian forecast errors
- $\epsilon \sim N(0, R)$; Gaussian observation errors

KF analysis implements Bayes rule for Gaussians

- analysis equations:
  
  $\bar{x}^a = \bar{x}^f + K(y - H\bar{x}^f)$ ;
  
  $P^a = (I - KH)P^f$,

- Kalman gain
  
  $K = P^f H^T (HP^f H^T + R)^{-1}$

Computationally difficult unless problem is small

- $P^f, P^a$ are $N_x \times N_x$, w/ $N_x = \text{dim } x$
Ensemble Kalman Filter (EnKF)

- EnKF uses sample (ensemble) estimates in KF update eqns
- EnKF is linear and considers only 1st, 2nd moments; thus, sub-optimal when prior or obs non-Gaussian.
- Converges to BLUE (best linear unbiased est.) as $N_e$ increases
Covariance localization

Doesn’t \( N_e \) need to be huge (again)?

- \( N_x \geq O(10^6) \implies N_e \leq O(10^3) \)
- \( \tilde{P}^f \) extremely rank deficient
- errors in each element only \( O(N_e^{-1}) \)
Effects of Sampling Error

Update for single, scalar observation $y^o$

- let $y^f = Hx^f$; estimate from ensemble
  $$\hat{c} = \text{Cov}(x^f, y^f), \quad \hat{d} = \text{Var}(y^f) + R$$
- update given by
  $$\bar{x}^a = \bar{x}^f + (\hat{c}/\hat{d})(y^o - H\bar{x}^f), \quad P^a = P^f - \hat{c}\hat{c}^T/\hat{d}$$

Worst case is state and obs uncorrelated

- $\hat{c}$ nonzero only because of sampling error
- mean is updated with noise
- posterior variance is systematically underestimated
- problems compounded with few members, many obs
Covariance localization (cont.)

Large spatial separation \(\rightarrow\) small covariances
- allow obs to update only nearby state variables
- multiply sample covariance matrix elementwise by correlation matrix with compact support

A wonder drug!
- decreases detrimental effects of sampling error
- increases effective rank of \(\hat{P}^f\)
- decreases computational cost
Lateral BCs for Atmospheric Limited-Area Models

Tendencies at boundary from external analyses, forecasts

Tendencies near boundary are weighted average of dynamical tendencies and specified (external) tendencies
  - Weighting decreases to zero with distance from boundary

(Strictly, ill posed)
Lateral BCs

In limited-area model, lateral BCs a source of uncertainty

- ensemble forecasts require ensemble of lateral BCs
- global ensemble schemes not designed/tuned for very short range

Possible approaches for ensemble BCs

- ensemble from EnKF on larger domain (‘exterior’ EnKF)
- draw BC perturbations from Gaussian with 3DVar covariances
- draw (scaled) perturbations from climatology
- other ad hoc approaches
Testing of Lateral BC schemes
Testing of Lateral BC schemes

Composite error differences for 500 mb height

Data Assimilation Research Testbed (DART)

A general-purpose software facility for ensemble filtering
- Apply same filtering algorithms to multiple forecast models and obs. Sets
- Developed by J. Anderson, NCAR/IMAGe
- See http://www.image.ucar.edu/DARes/DART/

Interfaces for Weather Research and Forecasting model (WRF)
- Non-hydrostatic, time-split dynamics
- Extensive suite of observation operators, including Doppler radar

“WRF/DART”
Assimilation of Hurricane Position

- Even moderate position errors problematic for assimilation
- Geostationary obs of position almost continuous in time
- Wish to avoid vortex “bogussing” and “relocation” by direct assimilation of position observations
Details of Position Assimilation

- Need operator that returns vortex position given model fields, e.g., location of minimum surface pressure

- For small, Gaussian displacements, errors are Gaussian with covariances related to gradient of original field

\[ \zeta(x + \delta x, y + \delta y) - \zeta(x, y) \approx \nabla \zeta \cdot (\delta x, \delta y) \]

- If position obs are accurate and frequent, can assimilate with a linear scheme
Hurricane Rita (2005)

- 36-km horizontal resolution, 26 ensemble members
- Assimilate position, intensity, and satellite winds hourly during 12-h period
Hurricane Katrina 2005

- 36-km horizontal resolution, 26 ensemble members
- Assimilate position, intensity, and satellite winds hourly during 12-h period
Data Assimilation for Convective Storms

Relatively small scales and short times
- Updraft width ~ 1--5 km
- Time scales of a few 10’s of minutes

Doppler radars provide main observations
- Only observing system with sufficient spatial and temporal resolution

Dynamics fundamentally different than at larger scales
- Driven by condensation, latent heating, evaporation
- No mass-velocity balances; fully three dimensional
WRF/DART for Doppler Radar

Analysis reflectivity (color), obs. (20 dBZ, black contour), 8 May 2003
WRF/DART for Doppler Radar

Background minus observation rms (black), ensemble spread (grey)

Ensemble has too little variance
  • Presently ignores uncertainty in larger scales and in forecast model
Comparison of EnKF and 4DVar

- Simulated observations of radial velocity and reflectivity for supercell storm (perfect model)
- 4DVar: full fields (not incremental), mesoscale background, simple covariance model
- EnKF: 100 members, initialized with noise in T where first scan shows reflectivity

Comparison with 4DVar

- rms errors over entire domain; obs of both $v_r$ and reflectivity
- EnKF (thin) and 4DVar (thick w/ boxes)
  ... EnKF worse than 4DVar over first few cycles, then better
Appeal of Ensemble Filters for (Atmos) Mesoscale

General covariance model
  • Independent of assumptions about nature of flow; e.g. approximate geostrophic balance

Basis for probabilistic forecasts
  • For convective storms, 1 hour is a long-range forecast

Ease of implementation and maintenance
  • Doesn’t require adjoints for sub-grid schemes, which are crucial in these flows but often discontinuous or highly nonlinear
  • … or adjoints of complex observation operators (e.g. radar)

Performance (so far) at least comparable to variational schemes

Straightforward application to domains with multiple nests
Key Outstanding Issues

Wish to estimate and predict across range of scales
• Limited-area models and their lateral boundary conditions
• Influence of larger-scale “environment” on smaller-scale flows
• Choice of localization scale for EnKF? (Similarly, choice of window for 4DVar?)

Imperfect representations of sub-grid processes:
• How should assimilation account for forecast-model error?
• Under examination
  — Covariance “inflation”
  — Additive, spatially correlated noise
  — Multiple configurations of model, using different parameterization schemes
EnKF Analyses Across Multiple Domains

- innovations calculated using finest available grid
- all grid points w/in localization radius are updated
- minor extension to code
Experimental Design

- obs from NA rawinsonde network
- domain (200 km) and obs locations shown
- assimilate $u$, $v$, $T$ every 12 h
- LBCs from GFS analyses
- cycle for Jan 2003
EnKF/3DVar Comparison

- $T$ analysis increment, day 10, single $T$ observation at 850 mb
EnKF/3DVar Comparison

Wind Fit to RAOBS

- Pressure (hPa)
- Bias
- RMS (m/s)

Legend:
- no assimilation
- 3D-Var 12-h forecast
- 3D-Var analysis
- EnKF 12-h forecast
- EnKF analysis
EnKF/3DVar Comparison

Temperature Fit to RAOBS

- no assimilation
- 3D-Var 12-h forecast
- 3D-Var analysis
- EnKF 12-h forecast
- EnKF analysis

Bias (K) vs. Pressure (hPa) vs. RMS
Comparison with GFS Analysis

- 500-hPa heights and winds, 00UTC 31 January
- EnKF (left; $\Delta = 60$ m), GFS (center), difference (right; $\Delta = 20$ m)
EnKF/3DVar Comparison

- rms $\partial p_s / \partial t$ as function of $t$
Bogussing

- ICs for hurricane forecasts often involve some form of bogussing

- A simple, empirical approach to initializing hurricane vortex
  - Obs of intensity, size of vortex (e.g. from reconnaissance flights)
  - Use these to determine parameters in analytic, axisymmetric model of vortex … a “bogus” vortex
  - Information from bogus vortex inserted into ICs at observed location of vortex

- Operational (NHC/GFDL) scheme
  1. Remove existing vortex from ICs
  2. Spin up vortex in an axisymmetric model, constraining low-level winds to match those from specified bogus vortex
  3. Add axisymmetric vortex to ICs at observed location
Vortex Spin-up

Hurricane Ivan 2004
Surface Pressure Tendency

GFS0913

EnKF
Position and intensity Correction

<table>
<thead>
<tr>
<th>RITA 2005-09-20-23Z</th>
<th>Center Lat. (°N)</th>
<th>Center Lon. (°W)</th>
<th>Mini. SLP(mb)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observation</td>
<td>24.00 (0.3)</td>
<td>-82.20 (0.3)</td>
<td>973.0 (5.0)</td>
</tr>
<tr>
<td>Prior mean</td>
<td>23.85 (0.24)</td>
<td>-82.33 (0.23)</td>
<td>988.6 (2.0)</td>
</tr>
<tr>
<td>Posterior mean</td>
<td>23.89 (0.15)</td>
<td>-82.29 (0.18)</td>
<td>986.5 (2.0)</td>
</tr>
</tbody>
</table>
Hurricane Ivan 2004

- 36-km horizontal resolution, 28 ensemble members
- Assimilate position, intensity and satellite winds every 3h for a total of 24h
- Compare forecasts initialized from the EnKF analysis and from the GFS analysis
Rita and Ophelia (2005)

- 36-km horizontal resolution, 26 ensemble members
- Assimilate position, intensity, and satellite winds hourly during 12-h period

Other cases: Track improved for Dujuan (2003), Ivan (2004), Katrina (2004; rel. to both GFS, GFDL)
Radar Observations

Fundamentals

Measurements

▷ reflectivity = power of returned signal; nonlinear dependence on number, size of scatterers
▷ radial velocity = velocity of scatterers along beam (via Doppler shift)

Details

▷ range \( \sim 150 \) km
▷ resolution \( O(1 \) km\)
▷ one volume scan every 5 min
Particle Filter (PF)  

General, non-parametric approach

▷ ensemble of forecasts, \( \{x^f_i, \ i = 1, \ldots, N_e\} \)

▷ approximate pdfs by point masses:

\[
[x^t | y] \approx \sum_{i=1}^{N_e} w_i \delta(x^t - x^f_i)
\]

▷ weights \( w_i \) given by

\[
w_i = \frac{[y|x^f_i]}{\sum_{j=1}^{N_e} [y|x^f_j]}
\]

Widely applied, and effective, in low-dim'l systems
Collapse of Weights

As $N_y$ and $N_x$ increase for fixed $N_e$, $\max \omega_i \to 1$

- PF then provides poor approximation to posterior expectations (mean, etc)
- to avoid in simple examples, require $N_e \sim O(e^{N_x})$
Collapse of Weights

$\triangleright N_e = 10^3, \mathbf{x}^t \sim N(0, I), \mathbf{H} = I, N_y = N_x$ and $\epsilon \sim N(0, I)$
Collapse of Weights

\( N_e \) s.t. PF mean has error less than obs