From Toy Models to NWP: Leveraging HWRF for Data Assimilation Research

Jonathan Poterjoy

University of Maryland
NOAA Atlantic Oceanographic and Meteorological Laboratory

Wednesday 7th August 2019
Regional modeling at AOML and UMD

HWRF Basin-Scale Data Assimilation and Ensemble Forecasting Project

Main collaborators: Gus Alaka (AOML), Henry Winterbottom (I. M. Systems Group Inc.)

- Ensemble-based hurricane analysis and prediction system using HWRF model and GSI DA.

- Continuously cycles HWRF model states using EnKF and GEFS boundary conditions – with no operational HWRF heuristics.

- Adopts extensive model domain (comparable to the AOML Basin-scale HWRF) to provide 60-member ensemble analyses of tropical weather systems and their environments.
HWRF Basin-Scale Data Assimilation and Ensemble Forecasting Project

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- Maintains all prognostic HWRF variables during DA steps.
- Performs online bias correction for clear-air satellite radiances.
- Uses same software infrastructure as operational HWRF forecast system, including Python run scripts and Rocoto workflow management system.

Summary: run a stand-alone HWRF prediction system that mimics global NWP models as close as possible.
2017 HFIP real-time demo

MSLP (contours) and 850-mb vorticity increments (shading) for member 1

06 UTC 14 Aug 2017
Objectives relevant to today’s discussion:

1. Build a prototype HAFS system for model, DA, and observing system research.

2. Provide a holistic evaluation of HWRF and its various components.

3. Help facilitate a better university collaboration with NOAA for NWP efforts.

4. **Build a testbed for developing new DA strategies with community software.**
Regional modeling at AOML and UMD

HWRF Basin-Scale Data Assimilation and Ensemble Forecasting Project

Why HWRF?

- TCs are complex multi-scale weather systems that encompass almost all challenges relevant to modern NWP: nonlinear dynamics, model error, observability, satellite radiance DA, etc.

- HWRF provides a way of exploring outstanding science problems in a limited-area modeling framework.

- HWRF and its various components already have a large user base and dedicated support.
Regional modeling at AOML and UMD

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Identifying model and DA problems (2017)

Regional average errors (g/Kg)
Northern Hemisphere $q_{\text{vapor}}$

**Obs-space verification uncovered error caused in single-domain configurations of HWRF.**
Problems of this type likely shaped early decisions for operational HWRF forecasting system.

Excerpt from Section 1.1:

The original design for the HWRF initialization (Liu et al. 2006a) was to continually cycle the HWRF large-scale fields and apply the vortex relocation technique (Liu et al. 2000, 2006b) at every model initialization time. However, the results were problematic. Large-scale flows can drift and the errors increased as cycles passed. To address this issue, the environmental fields from the GFS analysis are now used at every initialization time.
Domain average innovations ($q_{vapor}$)

- Regional average errors (g/Kg)
- RMSD
- Expected RMSD
- Bias

Num of obs
Cycle date
Available observations
Assimilated observations
Comparing error profiles over first and last month of 2017 experiment.

Error decrease in $q_{\text{vapor}}$ appears to follow spin up of satellite radiance bias coefficients in cycling system.
Identifying model and DA problems (2018)

Conventional obs at single time. What is missing?
Figure courtesy of Hui Christophersen (AOML/CIMAS)
Regional modeling at AOML and UMD

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Bayesian filtering problem

The goal is to estimate a model state’s probability distribution conditioned on observations.

\[ p(x_t|y_{0:t}) \]

\[ p(x_{t+1}|y_{0:t}) \]

\( x_t \) and \( y_t \) are given by:

\[
\begin{align*}
x_{t+1} &= M(x_t) + \eta_t, \\
y_t &= H(x_t) + \epsilon_t.
\end{align*}
\]
Monte Carlo approach: DA step

Draw $x_t^n$ for $n = 1, 2, \ldots, N_e$, from $p(x_t|y_{0:t})$. 

$p(x_t|y_{0:t})$

$x$
Monte Carlo approach: prediction step

Pass samples through forecast model.

\[ p(x_t | y_{0:t}) \]

\[ x_{n+1}^t = M(x^n_t) + \eta_t^n, \text{ are then samples from } p(x_{t+1} | y_{0:t}). \]
**Particle filters (PFs)** use ensemble members ("particles") to approximate prior and posterior distributions.

In the context of DA schemes currently used for NWP:

- EnKFs apply a sample estimate of mean and covariance – parameters needed for Gaussian density estimation.
- PFs use samples to apply a Dirac delta function approximation of probability densities.
Moving beyond EnKF/Var for DA step

Particle filters (PFs) use ensemble members (“particles”) to approximate prior and posterior distributions.

- Unlike EnKFs, PFs converge to the Bayesian solution as
  i. ensemble sizes increase.
  ii. model and observation errors become more reliable.

- Like EnKFs, PFs require ensemble sizes that increase with the problem size.

- Approximations are needed to prevent ensemble variance from collapsing to zero for NWP; namely, localization and inflation.
Filters that work well for weather prediction:


- Potthast et al. (2019) test the *localized adaptive particle filter* for global weather prediction with ICON.

- NOAA National Severe Storms Laboratory (NSSL) successfully used the Poterjoy (2016) *localized bootstrap particle filter* for multiple convective outbreaks – testing at NSSL, UMD, and OU is ongoing.
By construction, the Poterjoy (2016) local PF algorithm fits easily into community software packages in the US:

- Data Assimilation Research Testbed (DART) maintained by the Data Assimilation Research Section of NCAR
- Ensemble component of operational Gridpoint Statistical Interpolation (GSI) system maintained by DTC
- JEDI?
Serial ensemble square root filters

DART and GSI process obs serially, performing parallel obs- and state-space updates (Anderson and Collins 2007).

For example, consider the 2-D problem:

- **Blue shading**: \( p(x_1, x_2) \)
- **Blue markers**: samples from \( p(x_1, x_2) \)
- **Dashed line**: direct observation of \( x_1 \), denoted \( y_1 \)
Serial ensemble square root filters

DART and GSI process obs serially, performing parallel obs- and state-space updates (Anderson and Collins 2007).

Observation Space
DART and GSI process obs serially, performing parallel obs- and state-space updates (Anderson and Collins 2007).

\[
p(x_1|y_1) \approx N(\bar{x}_{\text{post}}, \sigma^2_{\text{post}}), \quad p(x_1) \approx N(\bar{x}_{\text{prior}}, \sigma^2_{\text{prior}})
\]
DART and GSI process obs serially, performing parallel obs- and state-space updates (Anderson and Collins 2007).

Each $x^n$ is updated via a linear regression from obs-space update:

$$\bar{x} \leftarrow \bar{x} + K(y_1 - x_1)$$

$$x^{n'} \leftarrow \tilde{K}x^{n'}, \text{ for } n = 1, \ldots, N_e$$
Local particle filter

The algorithms described in Poterjoy (2016) and Poterjoy et al. (2019) follow a similar strategy.

**Observation Space**

\[
p(x_1|y_1) \approx \sum_{n=1}^{N_e} w^n \delta(x_1 - x_1^n), \quad w^n \propto p(y_1|x_1^n)
\]

\[
p(x_1) \approx \frac{1}{N_e} \sum_{n=1}^{N_e} \delta(x_1 - x_1^n)
\]
Local particle filter

The algorithms described in Poterjoy (2016) and Poterjoy et al. (2019) follow a similar strategy.

**State Space**

Original EnKF update of each $x^n$ is replaced by:

$$\bar{x} \leftarrow \sum_{n=1}^{N_e} \omega^n \circ x^n,$$

$$x'^n \leftarrow r_1 \circ x'^n + r_2 \circ x'^n,$$

where $\omega^n$, $r_1$, and $r_2$ are formulated to reflect a mix of PF and prior solutions.
Local particle filter

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State Space

Original EnKF update of each $x^n$ is replaced by:

$$\bar{x} \leftarrow \sum_{n=1}^{N_e} \omega^n \circ x^n,$$

$$x^{n'} \leftarrow r_1 \circ x^{n'} + r_2 \circ x^{k_n'}.$$  

$r_1 = f(\omega^{1:N_e})$, $r_2 = g(\omega^{1:N_e})$, and variables are decoupled in $\omega^n$ using localization and regularization.
Failure without localization and regularization

In its standard form, the PF collapses easily for example problem with \( N_y = 2 \) and \( N_e = 80 \).
**Application:** vortex with prior position uncertainty

- Model output is geopotential height for a major hurricane.
- First 5 members of a 6-h ensemble forecast are shown.
A Rankine vortex reproduces non-Gaussian DA problem posed by displacement errors (e.g., tropical cyclones).

- The 1-D wind profile (top panel) is extrapolated to a 2-D grid (bottom panel).

Model state: $\mathbf{x} = \begin{pmatrix} \mathbf{u} \\ \mathbf{v} \end{pmatrix}$
Experiments with Rankine vortex

- **Prior**: 100 vortices with identical structure, but position error.

- **Observations**: radar radial wind measurements observe part of the wind field.
Localization and regularization provide a PF-like solution, while maintaining benefits over Gaussian DA methods (e.g., EnKFs).
Recall that posterior $u$ and $v$ must be inferred from joint obs/model-space statistics.
### Comparison with EnKF

<table>
<thead>
<tr>
<th>Prior members</th>
<th>EnKF members</th>
<th>PF members</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1" alt="Prior members" /></td>
<td><img src="image2" alt="EnKF members" /></td>
<td><img src="image3" alt="PF members" /></td>
</tr>
</tbody>
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**Example**: consider the joint prior pdf of

- obs-space variable $u_r(A)$ [radial wind at $A$]
- model-space variable $u(B)$ [zonal wind at $B$]
Examples for different priors

- First three panels: scatter plots for $10^4$-member ensembles using three different ratios of position standard deviation ($\sigma_p$) with a fixed radius of maximum winds ($R$).

- Fourth panel: $\frac{\sigma_p}{R} = 1$, but with added size and intensity uncertainty.
Month-long experiments from Sept. 2017

MSLP and conventional ob locations every 6 h

MSLP and radiance ob locations every 6 h
Cycling data assimilation tests:

- **Model grid spacing**: 18 km
- **Observation frequency**: 6 h
- **Ensemble DA schemes**: EnKF (Whitaker and Hamill 2002) and a variant of the Poterjoy (2016), Poterjoy et al. (2019) local PF
- **Ensemble size**: 60
Verification:

- **Forecasts**: 5-day 20-mem ensembles initialized every 12 h
- **Spin up**: verification begins 5 d into cycling DA experiments
- **Verifying metric**: volume-average root mean square difference between ensemble mean forecasts and GFS analysis
Ensemble mean forecast RMSE

RMSEs averaged over 52 sets of ensemble forecasts

![Graphs showing RMSEs over time for u-wind and v-wind](image-url)
Ensemble mean forecast RMSE

RMSEs averaged over 52 sets of ensemble forecasts

Temperature

Specific humidity

RMSE (K)

Time (h)

EnKF
Local PF

RMSE (g/kg)

Time (h)

EnKF
Local PF
Ensemble mean forecast RMSE

RMSEs averaged over 52 sets of ensemble forecasts

Vertical vorticity

EnKF
Local PF

MSLP

Ensemble mean forecast RMSE
Impact of data assimilation on wind field
Comparison of vorticity fields (prior)

- 850-mb vertical vorticity fields for region centered on Hurricane Maria.
- Wavelengths > 150 km are removed.
Comparison of vorticity fields (posterior)

- 850-mb vertical vorticity fields for region centered on Hurricane Maria.

- Wavelengths $> 150$ km are removed.

- The local PF produces noticeably fewer small-scale anomalies than the EnKF.
850-mb vertical vorticity fields for region centered on Hurricane Maria.

Wavelengths $> 150$ km are removed.

The local PF produces noticeably fewer small-scale anomalies than the EnKF.

Many of the smaller-scale features dissipate during integration.
Impact on uncertainty estimate from ensemble

Average ensemble spread in domain-mean vertical vorticity from 0 – 120 h.
Summary

The cycling HWRF system provides a testing ground for transitioning new science into community modeling systems:

- Efforts by UMD and NOAA AOML have already produced important community software fixes (e.g., HWRF bugs and missing observation types).

- Framework allows for vigorous testing of new DA techniques (e.g., GSI PF) using an amended version of the HWRF run scripts and workflow.

- Many implications for HAFS.
Formulating PF algorithms that operate efficiently for high-dimensional problems remains an active area of research.

- Poterjoy et al. (2019) highlight some (but not all) recent advancements for filter discussed here.

- Results from month-long regional experiments are encouraging:
  1. First real test for synoptic-scale NWP.
  2. Large room for improvement.

- Some operational centers are already exploring the use of PFs for NWP; e.g., Potthast et al. (2019).
Should we re-think Gaussian assumptions for measurement errors?

- Obs errors estimated online using Gaussian mixture approximation: early tests with Lorenz (1996) model.
  - $N_x = 40$, $N_y = 20$, $\Delta t = 0.05$ time units ($\sim 6$ h)
Looking forward

Should we re-think Gaussian assumptions for measurement errors?

- Obs errors estimated online using Gaussian mixture approximation: early tests with Lorenz (1996) model.

- $N_x = 40$, $N_y = 20$, $\Delta t = 0.05$ time units ($\sim 6$ h)
Looking forward

How can we improve on the current PF methodology?

- **Current strategy:** generate localized particle updates through a single step.

\[
\overline{x} \leftarrow \sum_{n=1}^{N_e} \omega^n \circ x^n,
\]

\[
x^{n'} \leftarrow r_1 \circ x^{n'} + r_2 \circ x^{k_n'},
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Looking forward

Localization for PFs is still an evolving idea.

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\mathbf{x}^{n'} \leftarrow \mathbf{r}_1 \circ \mathbf{x}^{n'} + \mathbf{r}_2 \circ \mathbf{x}^{k'}.
\]
Looking forward

Localization for PFs is still an evolving idea.

- New approach: break original update into a series of intermittent steps.
- Each intermittent step uses particle weights with larger “effective ensemble size” than one single update.
Looking forward

Outstanding questions:

- What are the implications for all-sky radiance DA?
- What can be done with larger ensembles?
- Can nonlinear DA provide additional benefits for modeling systems configured to use rapid updates?
- How should multivariate probabilistic forecasts be verified outside a Gaussian framework?

My contact info

email: poterjoy@umd.edu
url: https://poterjoy.com


Other PF-based strategies using localization


Lee, Y., and A. J. Majda, 2016: State estimation and prediction using clustered particle filters. PNAS.


