Data Assimilation Studies on Typhoon Sinlaku (2008) using the WRF-LETKF system

Takemasa Miyoshi and Masaru Kunii
University of Maryland, College Park
miyoshi@atmos.umd.edu

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Data Assimilation (DA)

Data assimilation best combines observations and a model, and brings synergy.
DA has an impact.

SV w/ 4D-Var  
JMA operational system

LETKF  
under development

Using the same NWP model and observations.  
DA matters!

Miyoshi and Sato (2007)
My approach

- **Local Ensemble Transform Kalman Filter** (LETKF, Hunt et al. 2007)
- **Application to various systems**
- **New ideas for improvements**
  - Examples:
    - Satellite bias correction (Miyoshi et al. 2010, Whitaker and Miyoshi 2011)
    - Adaptive Inflation (Miyoshi 2011)
Ensemble Kalman Filter (EnKF)

Analysis ensemble mean

FCST ensemble mean

\[ P_{t1}^f \approx \frac{\delta X_{t1}^f (\delta X_{t1}^f)^T}{m-1} \]

T=t0

T=t1

T=t2
**LETKF** (Local Ensemble Transform Kalman Filter)

Analysis is given by a linear combination of forecast ensemble:

\[ X^a = \bar{x}^f + \delta X^f_T \]

Ensemble Transform Matrix
(ETKF, Bishop et al. 2001; LETKF, Hunt et al. 2007)

\[ T = \tilde{P}^a (\delta Y)^T R^{-1} (y^o - H(x^f)) + [(m-1)\tilde{P}^a]^{1/2} \]

ensemble mean update  uncertainty update

\[ \tilde{P}^a = [(m-1)I / \rho + (\delta Y)^T R^{-1} \delta Y]^{-1} \]

Analysis error covariance in the ensemble subspace
WRF-LETKF flowchart
# Experimental settings

## LETKF settings

<table>
<thead>
<tr>
<th>Setting</th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ensemble size</td>
<td>20</td>
</tr>
<tr>
<td>Lateral boundary conditions</td>
<td>Unperturbed</td>
</tr>
<tr>
<td>Covariance inflation</td>
<td>Adaptive (Miyoshi 2010) Fixed 20% (smaller above level 20)</td>
</tr>
<tr>
<td>Covariance localization</td>
<td>400 km, 0.4 ln $\rho$</td>
</tr>
<tr>
<td>Analyzed variables</td>
<td>$u, v, w, T, ph, qv, qc, qr$</td>
</tr>
</tbody>
</table>

## WRF settings

<table>
<thead>
<tr>
<th>Setting</th>
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</tr>
</thead>
<tbody>
<tr>
<td>Domain size</td>
<td>136(137) x 108(109) x 39(40)</td>
</tr>
<tr>
<td>Horizontal grid spacing</td>
<td>~ 60 km</td>
</tr>
<tr>
<td>WRF version</td>
<td>WRF-ARW 3.2</td>
</tr>
</tbody>
</table>
6-hr Forecast at 12Z 12 Sep. 2008

(a) NCEP

(b) NOOBS

(c) ADAPT

Accumulated Precip (mm / 6hour)

after 9 days cycle
Adaptive inflation accounts for imperfections such as model errors and limited ensemble size.

Large adaptive inflation > 100 % (2.0) appears occasionally and is appropriate in limited regions.

Miyoshi and Kunii (2011)
Ensemble spread (T500)

Adaptive inflation improves the ensemble spread.

Miyoshi and Kunii (2011)
Adaptive inflation reduces the RMSE and BIAS consistently.

Miyoshi and Kunii (2011)
Impact of SST perturbations

SST perturbations reduce the RMSE and BIAS consistently.
ENSEMBLE SENSITIVITY
— estimating impact of observations —
Ensemble sensitivity

- **Observation impact** is calculated without an adjoint model. *(Liu and Kalnay 2008)*

\[
J = \frac{1}{2} \left( e_{t|0}^T e_{t|0} - e_{t|6|}^T e_{t|6|} \right)
\]

\[
\approx \left[ e_{t|6|} + \frac{1}{2} X_{t|6|}^f \tilde{K}_0 v_0 \right]^T X_{t|6|}^f \tilde{K}_0 v_0
\]
Ensemble sensitivity

- Observation impact is calculated without an adjoint model. (Liu and Kalnay 2008)

- We applied the above method to real observations for the first time! (Kunii, Miyoshi, and Kalnay 2011)

\[
J = \frac{1}{2} \left( e_{t|0}^T e_{t|0} - e_{t|-6}^T e_{t|-6} \right) \\
\approx \left[ e_{t|-6} + \frac{1}{2} x_{t|-6}^f \tilde{K}_0 v_0 \right]^T x_{t|-6}^f \tilde{K}_0 v_0
\]
Observation impact for each type

Observation impact for each observation type (except for satellite radiances) (9/8 12 UTC – 9/12 12UTC, NW Pacific)

All types of observations reduce the forecast error. Upper soundings (ADPUPA) have the largest impact.
Impact of each observation

00UTC Sep. 11 2008

Forecast error reduction (J/kg, KE)

TY Sinlaku

SONDE

AMV

SPSSMI

Degrading

Improving
Impact of dropsondes on a Typhoon

Estimated observation impact

TY Sinlaku

Degrading

Improving
Denying negative impact data improves forecast!

Estimated observation impact

DOTSTAR  00Z 11 SEP 2008

Typhoon track forecast is actually improved!!

36-h forecasts

Improved forecast

Observed track

Original forecast
A new question arises.

Impact of multiple flights

At what stages of TC lifecycle evolution are upper level dropsondes more important?

○ Upper level (> 600 hPa)
□ Lower level (< 600 hPa)

An exciting study on the observing strategies
This is currently ongoing…
FUTURE PLANS
Plans

• **More focusing on TC intensity forecasting**
  – Investigating *air-sea coupled covariance* around TC
  – *Higher-resolution* experiments to resolve TC structures
  – Predictability studies by ensemble prediction
  – More TCS-08 case studies
    • More analysis of the impact of aircraft observations
      – Impacts of lower-level and upper-level flights at each stage
    • Use of **AIRS** retrievals
    • Use of *rapid-scan* cloud images
    • Direct assimilation of **best-track** data
  – Possibly, further **ITOP-10** case studies
    • Cases with joint DOTSTAR and WC-130J missions
The LETKF code is available at:

http://code.google.com/p/miyoshi/