Approaches to convective scale data assimilation

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Outline

► Convective scale data assimilation characteristics
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- Convective scale data assimilation characteristics
- Our approach of addressing non-Gaussianity:
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- Convective scale data assimilation characteristics
- Our approach of addressing non-Gaussianity: Ensemble data assimilation scheme with constraints
Convective scale data assimilation characteristics

Our approach of addressing non-Gaussianity: Ensemble data assimilation scheme with constraints

Illustrate approach on simple examples

Explore which constraints should be included
Convective scale data assimilation
Convective scale data assimilation

- Data assimilation on convective scales needs to capture fast changing processes and many scales of motion that are resolved in high resolution models.
- Convection develops/evolves quickly, results in different covariance structures depending on whether or not convection is present.
- Rapid updates are essential (for example radar reflectivity, radial wind data assimilation 5-15 min). However, leading to problems of balance and noise.
- Observations such as radar reflectivity or cloud products are important for prediction on these scales, but difficult to assimilate with the EnKF due to background errors which are non-Gaussian in nature (for example location error).
- Predictability of convective storms is couple of hours (Durran and Weyn 2016, Durran and Gingrich, 2014).
Convective scale DA at DWD

- Kilometre-scale Ensemble Data Assimilation (KENDA) based on LETKF (Schart et al. 2016)
  1. 40-member ensemble
  2. adaptive localization in horizontal, in vertical 0.075–0.5 in ln p
  3. adaptive inflation
  4. RTPP scheme with 0.75 (Zhang et al. 2004)

- COSMO model (Baldauf et al. 2011) in the domain over Germany, 8km horizontal resolution, 50 hybrid levels. Deep convection explicit, shallow convection parametrized.
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- 1h updates

- Each member consists of the prognostic variables of velocity, temperature, pressure perturbation, specific humidity, cloud water and ice.

- The prognostic variables of turbulent kinetic energy, rain, snow, and graupel are excluded from the analysis update.
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- For radar data, LHN in all ensemble members
Idealized radar data assimilation

- Challenges of radar data assimilation will be illustrated using idealized example
- Lange and Craig 2014 setup is used with 32 ensemble members
- The non-hydrostatic COSMO model is employed with a 2 km horizontal resolution and 50 vertical levels
- Six moisture variables: specific humidity, specific cloud liquid water, specific cloud ice, prognostic rain, prognostic snow and prognostic graupel.
- Simulated observations of radar data are taken from a true run and assimilated every 5 minutes.
Experiments

After analysis is done physical consistency checks are made that include setting the negative values of rain, graupel and snow to 0 in each ensemble member.

The following experiments assimilate every 5 minutes:

- **Cntrl**  Velocity with the STD observation error of 1 m/s and reflectivity STD of 5 dBZ;
- **PosR5**  In addition to previous setup no-reflectivity data is assimilated with 5 dBZ STD following Aksoy et al. 2009;
- **PosR20** The previous experiment is repeated with assigned STD to no-reflectivity data of 20 dBZ;
Motivation

Nature run (top left). The analysis means for experiments Cntrl (top right), PosR5 (bottom left) and PosR20 (bottom right).
Motivation

Relative mass bias is calculated

\[
\frac{|S(\mathbf{w}_k^a)_i - S(\mathbf{w}_k^t)_i|}{S(\mathbf{w}_k^t)_i}
\]

\[
[S(\mathbf{w}_k^a)]_i = \int \rho(x, y, z)q_i(x, y, z)dxdydz, \quad i = 1, \ldots 6,
\]

discretized domain integrated values for every hydrometeor \(q_i\) where \(\rho\) is density.

Relative mass bias for rain and graupel of analyses mean.
Characteristics of the problem

- Non-Gaussian background error
- Nonlinear observation operator, non-Gaussian observation error
- Prognostic variables that are nonnegative
- Sources or sinks
- Numerical discretization of the dynamics is physically plausible, in case of no sources and sinks evolution through time should conserve mass and the mass should be nonnegative.
- Frequent updates
Characteristics of the problem

In this talk we first discuss:
  ▶ Non-Gaussian background error, non-Gaussian observation error
  ▶ prognostic variables that are nonnegative
  ▶ linear dynamics
and present the solution from Janjic et al. 2014.

Second we consider:
  ▶ nonlinear dynamics
— EnKF with constraints —
Preserving physical properties

Forecast replicates, true, mean location

EnKF analysis replicates, obs, true, mean location
QPEns algorithm

Inverse of ensemble derived analysis error covariance can be used to minimize the cost function to obtain the analysis

\[
\mathbf{w}^{a,i}_k = \mathbf{w}^{b,i}_k + \arg\min_{\delta \mathbf{w}^i} \frac{1}{2} [\delta \mathbf{w}^i^T (P^b)^{-1} \delta \mathbf{w}^i + \mathbf{f}^i^T R^{-1} \mathbf{f}^i]
\]

subject to

\[
\delta \mathbf{w}^i \geq -\mathbf{w}^{b,i}_k.
\]

where

\[
\delta \mathbf{w}^i = \mathbf{w}^{a,i}_k - \mathbf{w}^{b,i}_k, \quad \mathbf{f}^i = \mathbf{w}^{o,i}_k - \mathbf{H}_k \mathbf{w}^{b,i}_k - \mathbf{H}_k \delta \mathbf{w}^i - \bar{r}^o_k.
\]
$\rho = \text{Rank}(P^b)$, which is no larger than $N - 1$

$\delta w^i = L \eta^i$

$P^b = LQL^T$
QPEns algorithm in ensemble space

\[ \rho = \text{Rank}(P^b), \text{ which is no larger than } N - 1 \]

\[ \delta w^i = L \eta^i \]

\[ P^b = LQL^T \]

QPEns Algorithm in ensemble space

\[ \eta^i = \arg\min_{\eta^i} \frac{1}{2}[\eta^i T \eta^i + f^i T R^{-1} f^i] \]

subject to the following non-negativity constraint:

\[ -L \eta^i \leq w^{f,i}_k. \]

The algorithm reduces to EnKF if there are no constraints present.
Preserving physical properties

QPEns analysis in ensemble space with positivity constraint. Both mass conservation and positivity constraint improve analysis.
EnKF vs. QPEns analysis with positivity and mass constraint for modified shallow water model (Wuersch and Craig 2014).
RMSEs

<table>
<thead>
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<th>Forecast</th>
<th>Analysis</th>
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<td>EnKF</td>
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<td>QF</td>
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<td>QP-Ens</td>
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**RMSE velocity u**

**RMSE height h**

**RMSE mass h**

**RMSE rain r**

**RMSE mass r**

Assimilation cycles
— Other constraints? —
RMSE

LETKF: rmse of ana. mean for $u$

Obs $u$, $v$ and $h$

LETKF: rmse of ana. mean for $u$

Obs $u$ and $v$

LETKF: rmse of ana. mean for $h$

Obs $h$
Energy and Enstrophy
Prediction

RMSE for $u$

RMSE for $h$
Mean Absolute Vertical Velocity 850 hpa (MUC domain average)
Conclusion

- QPEns a method for addressing non-Gaussianity
- Improves accuracy and bias in simple problems
- Although total energy of the analysis ensemble mean converges towards the nature run value with time, enstrophy does not.
- Assimilation of velocity observations bounds enstrophy.
- Next steps: use QPEns to constrain energy and enstrophy


Extra references


