Balancing and data assimilation – a review

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- Brief historical review
- Balancing in HIRLAM 4D-Var
- Hybrid variational ensemble DA and balancing
- Problems at convection permitting scales

Aims of balancing in data assimilation

- Utilize dependencies between different model variable for mutual improvements, mass-wind for example
- Avoid high frequency oscillations and drift away from the observed state due to adjustment processes





• Ideally these two aims should be handled simultaneously (initialization and analysis in one go)

History of "initialization procedures" (in memory of Jean-Francois Geleyn)



How did we start? Example – Sweden in the 1960's

QG models; Successive corrections analysis (Bergthorsson and Döös, 1955):

• Geopotential analysis only; Use wind observations to estimate geopotential gradients between stations and gridpoints

• Separate analysis of wind and geopotential in successive scans, variational blending with assumption on gradient or geostrophic wind (Sasaki, 1958)

In collaboration with Stockholm University (Sundqvist, Lejenäs) the SMHI analyses data were also tried as initial data for the primitive equation model of Hinkelmann (1959). Initialization by the non-linear balance equation on sigmalevels – no data assimilation cycling.

OI developments 1970-1987

3-dimensional multivariate OI (Rutherford, 1976, Lorenc, 1981)

Used successfully by ECMWF together with non-linear normal mode initialization for operational global NWP
Multivariate co-variances could include separation into divergent and rotational winds, latitude dependent geostrophy and frictional effects

3-dimensional uni-variate OI with variational blending of mass- and wind-fields

(1) Used together with the non-linear balance equation and the ECMWF LAM for operational LAM NWP; High frequency oscillations in the +6h forecasts made "finalization" necessary

(2) Non-linear normal mode initialization solved the problem + ECMWF OI => HIRLAM (1985) ; Digital filter initialization added later (Lynch and Huang, 1992)

Other early assimilation schemes: 1) The Hough mode spectral analysis (Flattery) 2) Time continuous data assimilation or nudging

Example of 2); Impact of aircraft data in two very different data assimilation system (Barwell and Lorenc,1985)

ECMWF

•Multivariate, wind influences mass, and vice versa (dominance by nondivergence)

•3D, one wind observations influences several model levels

Assimilation every 6 hNormal mode initialization

UKMO

Univariate, wind influences only wind, mass only mass (u and v separately => 50 % divergence)
2D, only level closest to the observation is influenced
Continuous with nudging
Divergence damping



UKMO with aircraft winds

UKMO without aircraft winds

showing contours at 10 dam intervals, isotachs and wind observations. Charts are for with-aircraft analysis (a), without-aircraft analysis (b) and ECMWF IIIb analysis (c).

ECMWF with aircraft winds Figure 5. More detailed charts of 250mb analyses over the central North Pacific, 00 corr 11 November 1979.

Analysis fields at 250 hPa over the Pacific

11 November 1979 00UTC

Differences between analyses with and without aircraft data



Differences between analyses and forecasts from these analyses with and without aircraft data



UKMO analysis 11 November 1979 00UTC



Figure 9. Impact of aircraft observations over the Pacific Ocean. (a) Closs-up of part of Fig. 4(b): (b) same after 6-hour forecast.

UKMO forecast 11 November 1979 00UTC + 6h

UK Met Office used this example to improve their assimilation!

3D-Var: Statistical balance background constraint (Berre, 2000)

Spatial covariances between forecast errors are estimated thanks to multiple linear regressions (Parrish and Derber, 1992):

$$\begin{aligned} \zeta &= \zeta \\ \eta &= MH\zeta + \eta_u \\ (T, P_s) &= NH\zeta + P\eta_u + (T, P_s)_u \\ q &= QH\zeta + R\eta_u + S(T, P_s)_u \end{aligned}$$

where $\zeta, \eta, (T, P_s), q$ are respectively the forecast errors on vorticity, divergence, temperature, the logarithm of surface pressure and specific humidity. M, N, P, Q, R, S are matrices containing the linear regression coefficients. $\eta_u, (T, P_s)_u, q_u$ are the residual fields of the respective regressions.

Refinements:

- Take spatial variations of the Coriolis parameter into account.
- Non-linear balance equation
- Tropical mode structure functions (Zagar et al., 2004)

ECMWF: Similar balance in global geometry!

Example of statistical balance background error statistics

HIRLAM RCR version 15 km resolution with 4D-Var September-November 2008 36h – 12h forecasts valid at the same time

Temperature variance explained by vorticity and unbalanced divergence



"Noise" level from OI and 3D-Var -The "Sundquist" parameter mean abs (dpsdt) hPa/3h



Fig. 18. Model area average of the absolute surface pressure tendency as a function of forecast length with the grid point HIRLAM model. Initial time is 5 March 1998 12 UTC. Statistical interpolation without initialization (curve marked oi-noinit) and with initialization (oi-init); 3D-Var without initialization (3dvar-noinit) and with initialization (3dvar-init).

Basic HIRLAM 4D-Var components:

- Tangent linear and adjoint of the semi-Lagrangian spectral HIRLAM.
- Simplified physics packages: Meteo France (Janiskova) package (vertical diffusion only).
- Multi-incremental minimization (gridpoint HIRLAM in outer loops).
- Tangent linear normal mode initialization (talks by Kleist and Parrish)
- Weak digital filter constraint.

(Gustafsson, et al., 2012)

Weak digital filter constraint

$$J_c = \frac{\gamma_{df}}{2.0} (\delta X_{N/2} - \delta X_{N/2}^{df})^T C^{-1} (\delta X_{N/2} - \delta X_{N/2}^{df})$$

$$\delta X_{N/2} - \delta X_{N/2}^{df} = \delta X_{N/2} - \sum_{n=0}^{N} f_n \delta X_n = \sum_{n=0}^{N} h_n \delta X_n$$

Try to come close to the "slow manifold" at the same time as minimization of Jo helps us to come close to the observations! Note the un-known coefficient γ_{df} .

Tuning of the weak digital filter constraint by testing different values of $\gamma_{\rm DFI}$



Does this help to prevent "noise" in the nonlinear model integration?



Horizontal average of the absolute value of the surface pressure tendency.

Versions of Hybrid 4D-Var ensemble data assimilation

$$J = \frac{1}{\beta_{3dvar}} J_{3dvar} + \frac{1}{\beta_{ens}} J_{ens} + J_o + J_{dfi}$$

 $4\mathbf{D}\text{-}\mathbf{Var}:\delta x(t_k) = M_k \delta x(t_0)$

4D-Var Hybrid: $\delta x(t_k) = M_k(\delta x_{3dvar}(t_0) + \sum_{l=1}^N \alpha_l \delta x_l^{ens}(t_0))$

4D-En-Var Hybrid: $\delta x(t_k) = \delta x_{3dvar}(t_*) + \sum_{l=1}^{N} \alpha_l \delta x_l^{ens}(t_k)$ N = number of ensemble members

 δx_l^{ens} Ensemble perturbations, generated by ETKF for example α_l Localized ensemble weights

 $t_0 \leq t_k, t_* \leq t_K$ assimilation time window

(Gustafsson and Bojarova, 2014)

Example of single observation experiments with 4D-Var, 4D-Var Hybrid and 4D-En-Var

Background states



Position of simulated observation V500

Single observation assimilation increments

4D-Var



4D-En-Var







- 4D-Var Hybrid Control is essentially noise-free
- 4D-En-Var control has a slightly increased noise level
 Noise based on 4D-En-Var control increments and ETKF rescaling of ensemble perturbations adds up

Verification of the HARMONIE AROME 2.5km forecasts for extreme weather event (from Xiaohua Yang (DMI) & Lisa Bengtsson et al (SMHI))

Radar data 31.08 00UTC - 12UTC



HARMONIE AROME + 30h (MetCoOp)





The HARMONIE AROME **is capable** in many cases to predict convective precipitation events (severe high impact weather events);

Stochastic nature of the convective phenomena should be taken into account both for verification and in post-processing (timing and location uncertainty);

The quality of the short-term forecasts in the operational runs is not satisfactory: **3D-Var data assimilation partly to be blamed – 4D-Var in progress**

HARMONIE 3D-Var -(potential) problems

• Background error (BGE) statistics (spectra and balances) based on down-scaling of ECMWF ensembles => spectral spin-up problems !

• Very "noisy" forecasts; One reason is that horizontal diffusion has been re-tuned to avoid aliasing of explicit convection on larger scale super-cells

• Significant model surface pressure bias => difficult to assimilate surface pressure observations.

• Assumptions on stationarity, homogeneity and isotropy of BGE are less valid at the meso scale

Thanks to Jelena Bjarova, Nedjeljka Zagar and Magnus Lindskog!



Spectral densities for unbalanced humidity, August 2011, 10 ensemble members

Downscaling +3h, +6h, +12h

EDA +3h, +6h, +12h

Downscaling +12h – EDA 12h



Sensitivity to perturbations in different initial state variables (inspired by Fabry and Sun, 2010) Evolution of random perturbations generated from the structure of B-matrix covariance.

Surface pressure, Member 1 – Control, 13 08 2012 03UTC



Percentage of surface pressure variations explained by vorticity and unbalanced divergence



Preliminary results using **cubic grid truncation** (Mariano Hortal) show encouraging results : **increased numerical stability of the scheme and longer time stepping in the semi-Lagrangian forward propagation**. Processes are resolved in the grid-point space and smoothed in the spectral space.





Climatological structure functions (6 EDA based HarmonEPS perturbations; 06UTC + 12h)





Climatological structure functions (6 EDA based Harmony EPS perturbations; 06UTC + 12h)



Concluding remarks on the mesoscale

• Balancing continues to be crucial also on the convective scale.

•We cannot come much further forward without flowdependent structure functions!=> Stationarity, homogeneity and isotropy assumptions about the forecast error statistics do not hold for the convective scale phenomena.

• Small scales structures and noise is a poor combination => Go for "cubic grid" truncation, possibly low-resolution orography; We need to rethink about initialisation on convective scales

• Ensembles have potential for data assimilation on convective scales (processes driven by surface and PBL conditions) => Go for Ensemble Variational techniques using convection permitting ensembles