Initial Trials of 4D-Ensemble-Var... and the impact of observation density on localisation

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Introduction

The UK Met Office’s operational global forecasts are currently based on a hybrid four-dimensional variational assimilation (hybrid 4DVar). In this scheme, the background error covariance (B) at the beginning of the assimilation window is specified as a weighted sum of a fixed (but full-rank) climatological part and a flow-dependent (but limited-rank) contribution derived from the MOGREPS-G ensemble. However, the perturbation-forecast (PF) and adjoint model of 4DVar uses to evolve covariances over time impose significant computational and maintenance cost, and may not scale well on future massively-parallel computer systems. The Met Office is therefore testing an alternative scheme, called 4D-Ensemble-Var (4DEnVar), in which the temporal correlations are taken from the ensemble, whilst the climatological part of the hybrid reverts to a three-dimensional formulation.

Impact on deterministic forecasts

Several trials have been run to compare the performance of deterministic forecasts initialised using 4DEnVar with other approaches. Notable features of the trial setup include:
- Analysis increments calculated at N216 resolution (60km typical grid spacing).
- Ensemble covariances from the operational 44-member MOGREPS-G ensemble, again at N216 resolution, which calculates initial perturbations using a local Ensemble Transform Kalman Filter (ETKF), centred around the analysis from the existing operational hybrid 4DVar.
- Climatological weights: 0.8 climatological, 0.5 ensemble (sum exceeding 1.0 to make the fit to the background). A Gaussian horizontal localisation with half-width of 5 gridpoints is used.
- Initialisation uses 6h Incremental Analysis Update (IAU) for 3DVar. An ‘IAU-like’ approach filters the climatological but not the ensemble modes in 4DVar, whilst 4DVar uses a climatological but not the ensemble modes in 4DVar.

Figure 1. Traditional 4DVar (top) defines a fixed B at the beginning of the assimilation window, which is evolved and readjusted by a flow-dependent using PF and adjoint models. Hybrid 4DVar (middle) augments the climatological B with a flow-dependent contribution from a separate ensemble, but still uses both PF and adjoint models to evolve this in time. 4DEnVar (bottom) uses the 4D covariance predicted by the ensemble, together with a 3D climatological contribution, as no PF or adjoint model are required. In the current implementation, a single set of ensemble member coefficients is chosen for the whole assimilation window, so there is no time localisation (only spatial localisation).

Figure 2. 3DVar uses a standard IAU in which the 3D increment is split over a 6h window to filter out high frequency features which are presumed to be noise. 4DEnVar reduces an increment which combines a constant 3DVar-like climatological contribution with an evolving ensemble contribution. The ‘IAU-like’ application of this increment again filters high-frequency features from the climatological contribution, together with time-uncorrelated noise from the ensemble data, but leaves the coherent ensemble evolution unfiltered.

Figure 3. Performance of 4DEnVar compared to hybrid 4DVar. These have similar background error specifications, except that hybrid 4DVar ignores the time evolution of the ensemble data. The general reduction in RMS error indicates that this time evolution is generally beneficial.

Figure 4. Performance of 4DEnVar compared to hybrid 4DVar representing the performance of the current operational system degraded to the same analysis and forecast resolution as the other trials. Possible reasons for the inferior performance of 4DEnVar include the loss of flow-dependence in the climatological part of the hybrid, the fact that the ensemble localisation does not move with the flow, and initialisation issues. These are explored more fully in Andrew Lorenz’s talk.

Future work

We are currently investigating the impact of waveband localisation on 4DVar. Flow-adaptive localisation may also help to improve its performance. Trials with increased weight on the ensemble covariances, even if not optimal, may simplify the interpretation of results by making the methods more comparable.

The reduced cost of 4DEnVar makes it an attractive method for ensemble initialization. It has theoretical advantages over the ETKF currently used by MOGREPS-G, in areas such as localization, re-linearization, the use of balanced variables, and greater consistency with the way PO-assimilation analysis is produced (Bowler et al., 2013). A single system serving both purposes should also reduce maintenance costs. Trials of a 4DVar-based ensemble are currently ongoing. We may also test a system using perturbed observations instead of the deterministic filter approach, since this would remove the assumption that the DA scheme is optimal. Better ensemble perturbations should in turn benefit the hybrid DA, further improving both the deterministic and ensemble forecasts.

Idealised localisation experiments

Another focus of future work will be the interaction of ensembles and DA at convection-permitting scales. Localisation in a parallel computer system. The Met Office is therefore testing an alternative scheme, called 4D-Ensemble-Var (4DEnVar), in which the temporal correlations are taken from the ensemble, whilst the climatological part of the hybrid reverts to a three-dimensional formulation.

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Figure 5. The use of a large 176-member ensemble reduces the RMS error from 4DVar. Both sides of the comparison use covariance weights of 1.0 climatological, 0.3 ensemble, and localisation as above.

Figure 6. RMS error as a function of the half-width of the Gaussian localisation function, for scenarios with observations every 2 (solid) or 4 (dotted) gridpoints. Each line has been normalised by its minimum value to highlight the impact of localisation radius despite the large difference in RMS error between the two different observation densities. The optimal radius is now about twice that for the sparse observations. In this simple case, both observation scenarios are optimised by very similar localisation radii.

Figure 7. A single member regression shows the number of components from a single increment which combines a constant 3DVar-like climatological contribution with an evolving ensemble contribution. The ‘IAU-like’ application of this increment again filters high-frequency features from the climatological contribution, together with time-un correlated noise from the ensemble data, but leaves the coherent ensemble evolution unfiltered.

Figure 8. As Figure 6, except that the observation error variance has been halved to emphasise the result.

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References


Summary of the performance of 4DEnVar for a larger set of variables, levels and lead-times (each combination is termed a component). The right-hand column shows the number of components for which the 4DEnVar RMS error is better/more/less than the specified threshold, where ‘neutral’ is defined as ±2%. The 4DEnVar advantage over hybrid 4DVar is particularly apparent in the Northern Hemisphere, whilst the disadvantage compared to hybrid 4DVar is stronger in the Southern Hemisphere.

Table 1. Summary of the performance of 4DEnVar for a larger set of variables, levels and lead-times (each combination is termed a component). The right-hand column shows the number of components for which the 4DEnVar RMS error is better/more/less than the specified threshold, where ‘neutral’ is defined as ±2%. The 4DEnVar advantage over hybrid 4DVar is particularly apparent in the Northern Hemisphere, whilst the disadvantage compared to hybrid 4DVar is stronger in the Southern Hemisphere.