Quantifying observation error correlations in remotely sensed data

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Quantifying observation error correlations in remotely sensed data

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### Talk structure

- **Introduction and theory**
  - Motivation
  - Variational data assimilation
  - Observation error covariance matrices

- **Quantifying observation error correlations**
  - Desroziers’ method of statistical approximation
  - Application to IASI data
  - Results

- **Modelling observation error correlation structure**
  - Approximate structures for $R$
What are observation error correlations?

Every observation $y$ of a atmospheric variable $x$ has an associated error $\epsilon$: $y = Hx + \epsilon$

→ observation error correlations are present when components of the error vector $\epsilon$ are related

→ measurement errors are attributed to 3 sources: instrument noise, forward model error and representativity error
Error sources

- **Instrument noise**
  - temperature converted \( \text{ne} \delta t \text{ value} \)
  - regular calibrations ensure noise is uncorrelated between channels

- **Forward model error**
  - errors in discretisation of radiative transfer equation
  - errors in mis-representation of gaseous contributors
  - errors from undetected cloud

- **Representativeness error**
  - contrasting model and observation resolutions
  - observations resolve spatial scales or features that the model cannot
  - contributes to cross channel observation error correlations
Why are correlations important?

**Problems**
-ve magnitude and behaviour relatively unknown
-ve reduce weighting of observations in analysis
-ve for an observation vector of size $10^6$, difficult to store and invert observation error matrix if correlations are included

**Benefits**
+ve increase accuracy of gradients of the observed field represented in the analysis
+ve works with the prior error covariance to specify how observation features should be smoothed
+ve more information available from observations
Observation error correlation and Shannon Information Content

Figure: The SIC under different approximations of $R$
Variational data assimilation

Assimilation objective

Model forecast + Observation data $\rightarrow$ State of atmosphere

Assimilation method Minimise a cost function which measures distance of a solution state $x$ from the observations $y^o \in \mathbb{R}^m$ and the background field $x^b \in \mathbb{R}^n$

Cost Function

$$J(x) = \frac{1}{2} (x - x^b)^T B^{-1} (x - x^b) + \frac{1}{2} (y^o - H(x))^T R^{-1} (y^o - H(x))$$

where $B$ and $R$ are the background and observation error covariance matrices respectively.
An error covariance matrix structure

The observation error covariance matrix takes the form:

\[ R = D^{1/2}CD^{1/2} \]

where \( C \) is the error correlation matrix

\[
C = \begin{pmatrix}
1 & \rho_{12} & \ldots & \rho_{1m} \\
\rho_{12} & 1 & \ldots & \rho_{2m} \\
\vdots & \vdots & \ddots & \vdots \\
\rho_{1m} & \rho_{2m} & \ldots & 1
\end{pmatrix}
\]

and \( D \) is the error variance matrix

\[
D = \begin{pmatrix}
\sigma^2_1 & 0 & \ldots & 0 \\
0 & \sigma^2_2 & \ldots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \ldots & \sigma^2_m
\end{pmatrix}
\]
A desirable error covariance matrix

Main issue in observation error correlation modelling

- need to calculate matrix-vector product $\mathbf{R}^{-1}(\mathbf{y}^o - H\mathbf{x})$ every time we calculate cost function $J$
- relatively easy if $\mathbf{R} = \mathbf{D} \equiv m$ scalar multiplications
- BUT $\mathbf{y} \in \mathbb{R}^{10^6}$ and so $\mathbf{R} \in \mathbb{R}^{10^6 \times 10^6}$ which, if dense, is impossible to store and invert

The perfect partner: what do we want from $\mathbf{R} \neq \mathbf{D}$?

- structure resulting in an $\mathbf{R}^{-1}$ suitable for storage / can be used cheaply in a matrix-vector product
- representative of the true error correlation structure
- greater access to information from the observations and improved analysis accuracy

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Quantifying cross-channel correlations: a study

Objective

Generate the true observation error correlation structure for a sample set of remotely sensed data typical of NWP

Data type

- IASI (infrared atmospheric sounding interferometer) observations
- measurements of the infrared radiation emitted by the earth’s surface and atmosphere at different wavelengths

Method

We use a post analysis diagnostic derived from variational data assimilation theory [Desroziers, 2005]
Desrozier’s method of statistical approximation

Recall the background state, \( x_b \), and observation vector, \( y \), are approximations to the true state of the atmosphere, \( x_t \),

\[
\begin{align*}
y &= Hx_t + \epsilon^o \\
x_t &= x_b + \epsilon^b
\end{align*}
\]

where \( \epsilon^o \) and \( \epsilon^b \) are the observation and background errors respectively.

The best linear unbiased estimate of the true state, \( x_a \), is given by

\[
\begin{align*}
x_a &= x_b + K(y - Hx_b) = x_b + Kd^o_b \\
K &= BH^T(HBH^T + R)^{-1}
\end{align*}
\]
Desrozières’ method of statistical approximation

**Innovation vector**

\[ d^o_b = y - Hx_b = Hx_t + \epsilon^o - Hx_b \]
\[ \approx \epsilon^o + H\epsilon^b \]

**Analysis innovation vector**

\[ d^o_a = y - Hx_a = y - H(x_b + Kd^o_b) \]
\[ \approx (I - HK)d^o_b \]
\[ \approx R(HBH^T + R)^{-1}d^o_b \]
Desroziers’ method of statistical approximation

Taking the expectation of the cross product of $d_a^o$ and $d_b^o$, and assuming

$$ \mathbb{E}[\epsilon^o (\epsilon^b)^T] = \mathbb{E}[\epsilon^b (\epsilon^o)^T] = 0, $$

we find a statistical approximation for the observation error covariances

$$ \mathbb{E}\left[ d_a^o (d_b^o)^T \right] \approx \mathbb{E}\left[ R (HBH^T + R)^{-1} d_b^o (d_b^o)^T \right] $$

$$ \approx R (HBH^T + R)^{-1} \mathbb{E}\left[ (\epsilon^o + H\epsilon^b) (\epsilon^o + H\epsilon^b)^T \right] $$

$$ \approx R (HBH^T + R)^{-1} (R + HBH^T) $$

$$ \approx R $$
Application to IASI data

Figure: Assimilation process
Application to IASI data

**Methodology**

- aim to identify correlations between 139 IASI channels used in 4D-Var assimilation
- only use clear sky, sea surface observations from night and day
- $\mathbf{R}$ matrix is calculated using $\mathbb{E}\left[ d_a^o (d_b^o)^T \right]$
Observation error correlation matrix

Figure: Error correlation matrix for 139 channels used in Var
Observation error correlation matrix

Figure: Error correlation matrix for (a) temperature sounding channels; (b) water vapour channels
Operational and diagnosed error variances

Figure: Operational error variances (black line), diagnosed error variances (red line), and first off-diagonal error covariance (green line)
Diagnosed error variances: comparison with Hollingsworth-Lonnberg (H-L) method

Figure: Diagnosed error variances (red line), H-L diagnosed error variances for 84.8km (blue and black line) and 61.9km (green line) separation. Plot provided by James Cameron, UK Met Office.
Quantifying cross-channel correlations: a summary

★ Strong off-diagonal correlations are present between channels with similar spectral properties
★ Channels highly sensitive to water vapour have large observation error variances and covariances
★ The observation error variance is being overestimated in current assimilation algorithms
★ Diagnosed error variances are comparable with those using the H-L diagnostic
★ Non-symmetric matrices! → future work
What next?

Investigate how to approximate the true error correlation structure within operational assimilation methods...

Current approaches

- a diagonal matrix approximation
- diagonal variance inflation

Alternative approaches

- a Markov error covariance approximation
- a truncated eigendecomposition approximation [Fisher, 2005]
- a Toeplitz to circulant matrix approximation [Healy, 2005]
Consider a Markov covariance matrix of the form

\[ R_{ij} = \sigma^2 \rho^{|i-j|}, \quad \rho = \exp\left(-\frac{\delta z}{h}\right) \]

where \(\sigma^2\) is the error variance, \(\delta z\) is the level spacing, and \(h\) is the length scale.

This is equivalent to a correlation matrix of the form

\[
C = \begin{pmatrix}
1 & \rho & \rho^2 & \ldots & \rho^n \\
\rho & 1 & \rho & \ldots & \rho^{n-1} \\
\rho^2 & \rho & 1 & \ldots & \rho^{n-2} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
\rho^n & \ldots & \rho^2 & \rho & 1
\end{pmatrix}
\]
A Markov error covariance approximation

The benefit of this choice is that $C$ has a tri-diagonal inverse

$$C^{-1} = \frac{1}{1 - \rho^2} \begin{pmatrix}
1 & -\rho & 0 & \ldots & 0 \\
-\rho & 1 + \rho^2 & -\rho & \ldots & 0 \\
0 & -\rho & 1 + \rho^2 & \ldots & 0 \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
0 & \ldots & -\rho & 1 + \rho^2 & -\rho \\
0 & \ldots & 0 & -\rho & 1 \\
\end{pmatrix}$$

and therefore as does $R$: $R^{-1} = \frac{1}{\sigma^2} I \times C^{-1}$

No need to store and invert $R$!
An eigendecomposition approximation

Describe $C$ by a truncated eigendecomposition using its leading eigenpairs

$$\tilde{R} = D^{1/2} \tilde{C} D^{1/2} = D^{1/2} \left( \alpha I + \sum_{k=1}^{K} (\lambda_k - \alpha) v_k v_k^T \right) D^{1/2}$$

where $(\lambda_k, v_k)$ is an eigenvalue, eigenvector pair of $C$, $K$ is the number of eigenpairs used, and $\alpha$ is chosen such that $\text{trace}(\tilde{R}) = \text{trace}(D)$ [Fisher, 2005]

This matrix also has an easily attainable inverse

$$\tilde{R}^{-1} = D^{-1/2} \left( \alpha^{-1} I + \sum_{k=1}^{K} (\lambda_k^{-1} - \alpha^{-1}) v_k v_k^T \right) D^{-1/2}$$

No need to store and invert $R$!
Observation error correlations are often created because of contrasting model and observation resolutions.

Including observation error correlation structure can increase analysis accuracy and information content.

In IASI data, observation error correlations are strongest between channels with similar spectral properties.

In IASI data, the largest observation error covariances are between channels highly sensitive to water vapour.

In order to include observation error correlation structure in data assimilation algorithms, the $R$ matrix must be suitably structured.
Future work

★ Working with a symmetric matrix, eg. fitting a correlation function to the data, taking the symmetric part
★ Investigation using the diagnostic update in a identical twin 1D shallow water model experiment
References