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A non-linear method for channel selection

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A non-linear method for channel selection

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Introduction

- Satellite data needs to be thinned so that it can be efficiently stored, transmitted and assimilated.
- Current methods rely on the assumption that the observation operator (the mapping between observation and state space) can be linearised accurately.
 - however satellite data is often a highly non-linear function of the atmospheric state

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 - however satellite data is often a highly non-linear function of the atmospheric state
- Within this talk I'll discuss a new method which does not rely on the linearisation of the observation operator.

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Mutual information

- The first step is to choose an objective measure to quantify the information in the observed data.
- Mutual information measures the reduction in the uncertainty of the state when an observation is made:

$$MI = \int p(\mathbf{y}) \int p(\mathbf{x}|\mathbf{y}) \ln \frac{p(\mathbf{x}|\mathbf{y})}{p(\mathbf{x})} d\mathbf{x} d\mathbf{y}.$$
 (1)

• where \mathbf{x} is the state vector, \mathbf{y} is the observation vector.



Linear approximation

- In many studies of impact for satellite data a linear approximation of *MI* has been used which is consistent with the variational data assimilation scheme (e.g. Rabier et al. 2002)).
- In this case, an analytical expression for mutual information can be given when the prior and likelihood are both Gaussian:

$$MI = \ln |\mathbf{B}^{-1}\mathbf{P}_{\mathbf{a}}|,\tag{2}$$

• where B is the error covariance matrix of the prior estimate of the state and P_a is the error covariance matrix of the analysis estimate of the state.



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- \blacktriangleright where B is the error covariance matrix of the prior estimate of the state and P_a is the error covariance matrix of the analysis estimate of the state.
- Research questions:
 - How does the linear approximation affect the estimate of information in satellite data?
 - What impact could this have on channel selection?



A non-linear estimate

- ▶ It is not possible to give an analytical expression for *MI* when the observation operator is non-linear.
- ▶ But can approximate *MI* using a sampling method which accounts for the non-linear observation operator.
- ▶ This involves taking *M* samples from the likelihood, $p(\mathbf{y}|\mathbf{x})$, and *N* samples from the prior, $p(\mathbf{x})$.

$$MI = \sum_{i=1}^{M} p(\mathbf{y}_i) \left(\sum_{j=1}^{N} w_{i,j} \ln(Nw_{i,j}) \right),$$
(3)

• where $w_{i,j} = \frac{p(\mathbf{y}_i | \mathbf{x}_j)}{p(\mathbf{y}_i)}$ represents the posterior distribution.

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Comparison

Comparison of linear (solid lines) and non-linear (stars) estimate of mutual information



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Comparison

Linearisation error



Figure : Linearisation error= $h(x + \delta x) - h(h) - H\delta x$.



Channel selection algorithm

- 1. Remove channels which are known to be poorly modelled by the radiative transfer model (RTTOV) from the channels available for selection,
- 2. Calculate *MI* for the remaining channels.
- 3. Select the channel with the greatest MI.
- 4. Update the prior given the information from this channel choice.
- 5. Repeat steps 2-4 until the desired number of channels have been selected.



Initial Results

Initial results for IASI data simulated by RTTOV



Figure : Channel selection for ten channels shown to be important by Collard 2007, M = 100, N = 5000.

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Effective sample size			

The effective sample size



Figure : effective sample size = $\left(\sum_{i}^{N} 1/w_{i}^{2}\right)^{-1}$

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Gaussian mixture resampling			

Gaussian mixture resampling

- ► To keep the effective sample size large we have decided to resample from posterior distribution after each channel selection has been made.
- ► Each member of the new sample has equal weight and so the effective sample size is restored to *N*.
- ▶ To resample from the posterior we need to make some assumptions about its distribution.
 - However we wish to maintain any non-Gaussian structure caused by the non-linear observation operator.
 - ▶ This can be done by fitting a Gaussian mixture to the weighted sample with the number of components, *G* dependent on the exact structure.

$$p(\mathbf{x}|\mathbf{y}) \approx \sum_{i=1}^{G} a_i N(\mu_i, \Sigma_i)$$
(4)

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Summary

- Satellite observations are a non-linear function of the state variables of interest. As such a linear approximation to their information content may be misleading.
- ► A sampling approximation to *MI* has been demonstrated which is free from assumptions about linearity. This has shown that for some channels the linear approximation to *MI* is indeed poor.
- ► Although this estimate is free from assumptions about the linearity it does suffer from under sampling when the region of uncertainty is small.
- Resampling from the posterior distribution after each channel is selected can alleviate this problem.

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References

- Rabier et al., 2002: Channel selection methods for IASI radiances. Q. J.
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- Collard, 2007: Selection of IASI channels for use in NWP. Q. J. R. Met. Soc., 133, 1977-1991.

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Thank you for listening, any questions?

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Weighting functions



Figure 4: Weighting functions normalised by the observation error standard deviation, for the ten channels used in the channel selection. a) Sensitivity to changes in temperature. b) Sensitivity to changes in humidity.