INVESTIGATION AND DEVELOPMENT OF MODE BASED VARIATIONAL BIAS CORRECTION SCHEME FOR WINDOW CHANNELS ON MICROWAVE AND INFRARED SOUNDERS

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Abstract

The current variational bias correction (VarBC) scheme for satellite data from microwave and infrared sounders (e.g. AMSU-A and HIRS) in the ECWMF operational data assimilation system (cycle 36R3) is adaptive based on the mean. It was found to be sensitive to adverse interactions with quality control and cloud detection. Based on the initial work of Han and McNally (2008), a mode based variational bias correction scheme has been developed which uses mirror weighting of the cost function to construct a symmetric pdf whose mean is effectively the mode of the original pdf. This scheme has been tested in the real 4D-Var operational assimilation system and the tests show that this scheme can find the true biases with respect to the mode, correct them very effectively and converge very quickly within the VarBC framework for microwave and infrared window channels. It results in a smaller bias correction and avoids over correction problems in some channels, e.g. channel 3 of the AMSU-A instrument on NOAA-18 and METOP leading to more accurate data rejection for quality control of other active channels in the same instrument. It has a positive impact on the operational forecast accuracy and will be implemented in the operational system.

INTRODUCTION

Exploiting their enhanced sensitivity to cloud, window channels on microwave and infrared sounders, such as AMSU-A and HIRS, are not assimilated actively but instead are used to detect and reject scenes that are contaminated by cloud and/or precipitation for clear sky assimilation of data. In other words, data from window channels are used for quality control of other channels in the same instrument but they do not directly affect model state variables. The quality control may be as simple as a threshold on first guess departures (observed radiance minus clear sky calculated radiance) in a window channel; or more complex such as using window channels inside a multichannel gradient-based cloud detection scheme (Kelly 2007). In either approach, window channels have an important role to play due to their more acute sensitivity to cloud and rain than the sounding channels of the same instrument.

Just like any other channels, window channels are also subject to systematic errors either due to instrument or radiative transfer calculations. For example, Han and McNally (2008) demonstrated that the biases are different in AMSU-A channel-4 on two NOAA platforms than that of AMSU-A channel-4 on METOP, related to different antenna correction and calibration. Therefore data from window channels themselves need to be bias corrected before they can be used for quality control. The accuracy of the bias correction applied to window channels will have a strong impact on the screening of other active channels and thus on the quality of analysis.

Auligné et al (2007a) described the operational implementation of the Variational Bias Correction scheme (VarBC henceforth) in the ECMWF 4D-Var data assimilation system. Radiance data bias correction is done by removing the mean of first guess departure. The system is adaptive in that it is updated every 12 hour assimilation cycle and can accommodate automatically for any sudden shift in instrument performance without the need of human intervention (also see Dee 2004, 2005, Dee and Uppala 2008). The global mean of first guess departure after bias correction is close to zero. For
window channels, VarBC only has a flat global offset and a globally constant scan dependent correction.

It is known that the presence of clouds will lead to observations from a microwave instrument such as AMSU-A channel-4 having warm outliers in the histogram plot of first guess departures, i.e. there are significantly more observations on the warmer side of the mode of the histogram than on the colder side, whereas observations from an infrared instrument such as HIRS channel-8 exhibit a cold tail. These asymmetric distributions and the physics behind them were demonstrated and explained by Han and McNally (2008). These asymmetric distributions of the observation population will adversely lead mean based bias correction scheme to give an estimated bias that drifts toward the warm population in the AMSU-A channel-4 case and toward the cold population in the HIRS channel-8 case. When such a bias is removed, it actually ‘corrects’ cloud signal and thus reduces the ability of this channel to detect clouds. To alleviate the drift problem, some strict, delicate and carefully tested quality control thresholds have to be used.

The sensitivity of bias correction to quality control thresholds has been documented by Auligné and McNally (2007b) and is further demonstrated here. Figure 1 is the histograms of the first guess departures before bias correction (right) and bias corrected analysis departure (left) from the current ECMWF operational 4D-Var assimilation system (36R3) for AMSU-A channel-3 on METOP (very similar for NOAA-15, not shown). It can be seen that, for the selected observations (3K < FG departure < 3K), the current mean based VarBC indeed found the analysis solution on the mean with the mean of the corrected analysis departure very close to zero, -0.01K for METOP data for example. However the mode is at near -1K indicating the solution shifted toward the warm tail resulting in an over correction. As the mode in both AMSU-A channel-4 (and HIRS channel-8) are considered the representative of clear sky conditions, this over correction will lead to more cloud contaminated data on the far right (left) side of the mode to be allowed in and some clear data on the far left (right) to be excluded and thus cause error in the analysis. Therefore it is very important to get the estimate of the bias in window channels correct and ideally the scheme that is doing this bias correction should not be sensitive to quality control and cloud detection. The motivation of the research presented in this paper is to design, test and implement such a scheme in the operational system and hopefully to improve forecast accuracy.

<table>
<thead>
<tr>
<th>TOVS-1C Met-OP AMSU-A Tb Globe Channel-3</th>
<th>Active and passive Tb METOP-A AMSU-A</th>
</tr>
</thead>
<tbody>
<tr>
<td>Analytic departure (°-a)</td>
<td>Background depo (no bias corr)</td>
</tr>
<tr>
<td>r= 11.475  min=-1.35</td>
<td>r= 11.475  min=-5.90</td>
</tr>
<tr>
<td>mean=-0.131E01  std= 1.26</td>
<td>mean=-0.61  std= 1.42</td>
</tr>
<tr>
<td>min=-3.60  max=-4.66</td>
<td>min=-0.179E-01  max=-7.10</td>
</tr>
</tbody>
</table>

Figure 1: Image and table captions should be kept underneath the respective image or table, in size 8 point bold regular, only the labels in bold and italics.

FORMULATION OF MODE BASED VARIATIONAL BIAS CORRECTION

To avoid the problems discussed above, a mode based bias correction has been proposed (Auligné and McNally 2007b) and tested in a simple toy model. In the real assimilation environment using a tight quality control was
shown to be equivalent to mode (Han and McNally 2008). However this suffered from very slow convergence rates. An improved theoretical formulation of this mode based variational bias correction will be described here.

If radiance departures \( d \) are defined as:

\[
d = y - H(x)
\]  

(1)

where \( y \) is the observation vector, \( x \) is the NWP model state vector, and \( H(x) \) is the observation operator including bias correction, the VarBC bias estimation is incorporated inside the main analysis cost function as:

\[
J(x, \beta) = (x - x_b)^T B_x^{-1} (x - x_b) + (\beta - \beta_b)^T B_{\beta}^{-1} (\beta - \beta_b) + [y_o^i - H(x_b)]^T R^{-1} [y_o^i - H(x_b)]
\]  

(2)

Where the observation operator now includes a bias correction with parametric form based on \( K \) state-dependent predictors \( p_k(x) \) and coefficient \( \beta_k \):

\[
H(x) = H'(x) + b
\]  

(3)

\[
b = c_0 + \sum_{k=1}^{K} \beta_k p_k(x)
\]  

(4)

with \( c_0 \) representing a global offset and \( H'(x) \) representing the basic observation operator not including bias correction.

If we ignore the background constraints (e.g. by setting \( B_x \) and \( B_{\beta} \) to infinity) and think about a single observation type (e.g. one satellite channel) and ignore the state-dependent predictors (e.g. \( K=0 \) in (4)), the observation penalty term (2) can be written as minimising :

\[
\sum_{i=1}^{N} \frac{\left( d_i' - b \right)^2}{\sigma^2}
\]  

(5)

meaning that:

\[
b = \frac{1}{N} \sum_{i=1}^{N} d_i'
\]  

(6)

Where \( d' \) is the first guess departure (FG) before bias correction, \( d_i' = y_o^i - H'(x_b) \), \( \sigma \) is the standard deviation of observation error; \( N \) is the number of observations. In the following text, index \( i \) will always be used for observations.

This simplified penalty function represents adaptive updating of bias correction defined by the mean of the selected observation population when the constraints from inertia and influence of other observations are ignored. We can simulate a formulation of this to derive a VarBC based on use of the mode.

The mode estimation can be written as:

\[
m = \arg \max (f(d'))
\]  

(7)

Where \( f(d') \) is the PDF of FG departures before bias correction. We can add a weighting derived from the mode estimation to the cost function of (5) and thus minimise a proxy:

\[
J(b) = \frac{1}{2N} \sum_{i=1}^{N} \frac{(d_i' - b)^2}{\sigma^2} w_i
\]  

(8)

Where \( w_i \) is a weighting derived from the PDF of FG departures chosen in such a way that \( b \) becomes equal to the mode \( m \). It can be seen that this proxy cost function for the mode is still based upon the mean, but by
carefully design of the weighting, we hope a solution can be found where the estimated mean is effective converge to the mode and this convergence will not be sensitive to quality control and cloud contaminations.

CHOICES AND TESTS OF VARIOUS WEIGHTING

From the formulation in the section above, the crux of the issue now is to find a proper weighting that meets our requirements. We hope this weighting can sharpen the histogram around the mode, i.e. to up-weight the observation near the mode and down weight the outliers so that the mean based VarBC can find a solution at the mode. Three weightings have been designed. After testing a mirror weighting was found to meet the full requirements for our mode based VarBC, with direct weighting and symmetric weighting being excluded (details of these excluded weighting will not be discussed here).

The mirror weighting can be written as:

\[ P_j^{\text{max}+j} = \frac{n_j^{\text{max}+j}}{N} \quad j = 1, M/2 \quad (9) \]

Where \( n_j \) is the observation population in the \( j \)th bin of a histogram of FG departures before bias correction. In practice, the ratio of each bin population to the total population is calculated and stored. The weighting of each bin is the probability ratio of the bin on the other side of the mode with same distance, i.e. the ratio of the mirror bin (mirrored against the bin which has the maximum observation population, i.e. the mode). Applying this weighting to the cost function, the resulting distribution will be near symmetric with the mode effectively coincident with the mean. The biases estimated by VarBC after applying this weighting should result in a solution close to the mode of the original first guess departure histogram. This solution should not depend on quality control or cloud detection.

It needs to be pointed out that any weighting will imply that the observation signal of the first guess departures has been changed. As discussed in previous sections, data from the window channels are passive, i.e. they do not directly affect the model state variables themselves, since they are only used for quality control and cloud detection for the other channels in the same instrument. As long as the biases are corrected properly and there is a consequent improvement of data selection for the other channels, the observation signal change does not matter. For data from other channels that directly affect the profile of the state variable, the use of the above kinds of weight will not be appropriate.

IMPACTS OF THE MODE BASED BIAS CORRECTION ON DATA ASSIMILATION AND ON MODELPREDICTIONS

In this section, we will examine the impacts of implementing the mode based VarBC using the mirror weighting in ECMWF’s 4D-Var assimilation system. We will show that the new mode based VarBC can converge to the mode, rather than the mean under the operational VarBC environments and that this solution is not sensitive to quality control and cloud detection. AMSU-A channel-3 on the METOP platform and on NOAA-15 will be used to demonstrate our results (NOAA-15 results not shown).

Figure 2 is the corresponding histograms to figures 1 but with the mode based VarBC applied in the 4D-Var assimilation. The analysis solution is at the mode with mean analysis departure now about 1.1K, correcting the problem of the solution shifting toward the warm tail. Also it is worth pointing out that the quality control was relaxed to 6.5K (compared to 3K in the control of figures 1), yet the scheme is still able to find a solution at the mode, demonstrating that mode based VarBC is not sensitive to the quality control in the real assimilation environment.
Figure 2: Histograms of bias corrected analysis departure (left) and non-bias corrected first guess departure (right) from the experiment run with mode based VarBC for AMSU-A channel-3 on METOP.

Figure 3a shows latitude-longitude plot of the bias estimate in the control experiment, averaged over a month period, for AMSU-A on METOP. Figure 3b is equivalent to 3a but from the experiment with mode based VarBC switched on for AMSU-A channel-3 on all platforms. Both control and experiment runs are operational CY36R3 configurations. It can be seen that though there are geographical variations, the bias estimated from the control run is at 3.7K, versus 3.1K for the experiment run. About 0.6K smaller bias is estimated by the experiment than by the control, consistent with the estimat

Figure 3: Latitude-longitude distribution of the averaged bias estimate over period from 1 June 2009 to 30 June 2009. 3a(top): By the control and 3b (lower) by the experiment with mode VarBC switched on for AMSU-A channel-3 on all platforms.
from the histogram of the last section and the time series plots (not shown) that the current mean based VarBC over corrected biases by about 0.5 to 1K.

The latitude-longitude distributions of mean analysis departure for AMSU-A channel-3 on METOP averaged over 1 June to 30 June 2009 from both control and the experiment (figures not shown) are also checked. The large negative analysis departures from the control run in the clear areas by over correction of mean based VarBC scheme are significantly reduced. The wrong ‘correction’ of cloud signals by the mean based bias correction in the climatologically cloudy areas around west of South American coast (90W,10S) and along the latitude circle of mid-high southern latitudes is now significantly improved by the mode based VarBC with the increased analysis departures.

The data usage in the actives channels, of which the data selections are controlled by AMSU-A channel-3, is also checked. A prominent feature is that for the clear areas where the large negative departures were reduced, more observations are used with the mode base VarBC scheme, indicating that some clear data are now correctly allowed into the assimilation system whereas they were previously (wrongly) excluded using the MEAN bias correction. Similarly in cloudy areas (with analysis departures correctly increased by the mode based VarBC scheme), less data were used with the MODE scheme leading to better exclusion of cloud contaminated data. These are exactly improvements we are looking for with the new mode based VarBC scheme and should lead to good impacts on forecast accuracy.

From the above discussions, we are able to show that the mode base VarBC scheme we introduced can indeed estimate the correct biases and they are physically sound. We would expect the use of this mode based VarBC lead to improvement of model forecast accuracy. The same experiment (ff4k) as discussed above with mode based VarBC is switched on for AMSU-A channel 3 only on all platforms) has been run for 3 months in order to produce stable verification statistics to compare with the control run. The same quality control criterion of 3K for active channels is used as in the control. Figure 4 shows the verification results of 500mb geopotential height. It shows differences of rms errors of experiment (ff4k) minus rms errors of control (fbir) each calculated against operational analysis. Negative indicates that the experiment has smaller forecast error or better forecast accuracy than the control and positive indicate the opposite. Figure 4 is for Europe and it shows that that the impacts are positive for all forecast ranges, with statistically significant impact over 4-day to 5-day range. For northern hemisphere the impacts on forecast accuracy are overall neutral. The impacts for southern hemisphere are slightly positive, with nearly statistically significant positive impact over forecast range 2-day to 6-day and neutral over the other ranges. The impacts over North American are mixed, with slightly positive impacts until day-8 and significantly negative impacts for forecast of longer range (not shown).

![Figure 4: Verification results of 500mb geopotential height: differences of rms error of experiment (ff4k) minus rms errors of control (fbir) each calculated against operational analysis for Europe; Both experiment and the control are operational 36R3](image-url)
To gain the full picture of the impacts of this mode based VarBC on the forecast accuracy, the verification for other fields and on different pressure levels are also looked at. Figure 5 shows latitude-pressure distribution of differences of rms errors (experiment minus the control each verified against its own analysis) for temperature. A blue colour indicates the experiment has small forecast errors and red otherwise, with a plus sign indicating the differences are statistically significant. It can be seen that for temperature in figure 5, the blue colour completely dominates over the red on all levels, all regions and all forecast ranges and some of these blue areas are statistically significant, e.g. in T+72 southern hemisphere mid-latitude and in tropical area of T+120 and T+144. The only exception is over T+144 southern polar area between 200—400hPa where it is slightly negative. The same verification plots for relative humidity, vector winds and geopotential height are also check and they are very similar to the temperature (not shown).

**Figure 5:** Latitude-pressure distribution of differences of root mean square error in temperature forecast (experiment minus control with each verified against each own analysis.

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**SUMMARY**

From the discussion in the above sections, we have demonstrated that a mirror weighting of the cost function constructs a symmetric pdf which has a mean and mode approximately in the same place as the mode of the original pdf. This technique allows a mode based variational bias correction scheme, enabling us to find the true bias of the data (assuming that the mode of the population corresponds to clear-sky situations). The convergence to the solution is quick and stable. The solution on the mode is not sensitive to quality control and cloud detection.
Window channels of microwave and infrared sounder, such as AMSU-A channel-3 and channel-4 and HIRS channel-8 are passively assimilated and only used for quality control and cloud detection for the other atmospheric channels in the same instrument. They are still subject to systematic errors either from instrument calibration, radiation transfer calculation or model error and have to be bias corrected as well. In such a context and for clear sky radiance assimilation, finding the correct biases and excluding cloud contaminated scenes but not the clear scenes will be crucially important. The mode based VarBC scheme developed in this study, if carefully applied to proper histogram of data samples, is thus a very effective and suitable scheme to these window channel data that are passive, i.e. not affecting the atmospheric profile of model state variables. By switching on the mode based VarBC scheme to AMSU-A window channel 3, we managed to show that the scheme can lead to an overall positive impact on the forecast accuracy on all fields on all levels and in most areas without any change to the quality control criterion to the current system. Therefore we recommend this scheme to be implemented in the operational system.

Through this rather comprehensive investigation on using the mode to improve bias estimates in variational bias correction scheme through probability weighting for satellite data assimilation, various aspects, as to this idea’s advantage of finding the bias that are independent of quality control and cloud detection, the different dependence of mode on data screening for data from different instruments/channels, the sensitivity to bin size due to data sampling in practice, are all better understood. The recommendation is made for operational use of this idea based on the scientific founding of this investigation and also for future reference. More details of this research can be found from ECMWF research memo.

REFERENCES


Kelly G. (2007). The evaluation of the HIRS/4 instrument on Metop 2 by using the ECMWF data assimilation system to provide a reference to compare with other sensors. No. 523. ECMWF Technical Memoranda.