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Atmospheric Chemistry and Physics Discussions

Interactive comment on "Elimination of hidden a priori information from remotely sensed profile data" *by* T. von Clarmann and U. Grabowski

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report **Final response to Reviewer #1:**

Response to the first remark:

The reviewer argues that we overstate the problem arising through a priori knowledge in the data and claims that the knowledge of the averaging kernels (along with the covariances, of course) is sufficient to solve all arising problems. We object not only because there are a considerable number of data users who are not part of the retrieval community and thus cannot be expected to be familiar with the characteristics of constrained, hence oversampled profile retrievals, but mainly because there are a couple of problems where even the averaging kernel does not provide an obvious solution:

- Estimation of the smoothing error (or smoothing error difference in comparison of two measurements) requires a climatological co-variance matrix. This often is not available, e.g. for trace gases not routinely measured.
- The averaging kernels of regularized retrievals typically depend on the state variables themselves and thus vary along orbit. The use of conventionally regularized retrievals does not even allow a straight forward comparison of two subsequent profiles of the same instrument, because these typically are characterized by different (sometimes very different) averaging kernels. With our method we can easily represent a whole orbit at the same altitude resolution, allowing direct comparison without risk of artefacts in time series through changing averaging kernels. The same applies to comparison, ratios (e.g. CH_4/N_2O-correlation) or sums (total chlorine) of different trace gases at the same geolocation. Contrary to profiles based on a priori constraints, in data represented according to our suggestion the altitude resolution remains constant, and only the error bars are a function of the state itself. This, however, can easily be handled by standard error statistics.
- Many applications of statistics rely on independent data points. Data points which contain a priori are never independent. This is important, e.g. in data assimilation, where results will be biased towards the a priori information in the assimilated measurements, if the same a priori is used for the set of measurements. Beyond this, statistical testing may suffer from common a priori in the statistical ensemble. Even operations as simple as averaging fail in such cases.

With respect to this, we still think that our suggested method offers more than only a minor simplification. In particular, we disagree with the reviewer about the receipe he suggests for comparison of regularized data with models:

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- First, it is valid only if the model represents an ideal profile representing infinitesimal altitude steps. This is not typically the case, since models also represent a smoothed version of the truth, and the approach suggested by the reviewer is at best an approximation as discussed near our Eq. 48.

- Further, suggested simple multiplication of the modeled profile by the averaging kernel matrix of the retrieval ignores that the a priori profile is not necessarily zero.

- Beyond this, this receipe does not solve the problem that there may be common components in the a priori of the retrieval and the background information in variational data assimilation.

- Further, the suggested formalism does not help if the altitude range of the measurement (and thus the altitude range of the averaging kernels) exceeds the one of the model.

In our paper we discuss how our proposed method helps to solve these problems. We will rearrange the paper to clearer communicate our points as outlined above, such that the motivation of our study becomes more obvious before the mathematical details are introduced. This will also allow to omit sections 4.2–4.4. Furthermore, we will try to avoid any wording which may sound unscientific. One month of MIPAS NO_2 data as generated at IMK including full diagnostics (for target and auxiliary retrieval variables, on the fine retrieval grid, including averaging kernels and error covariance matrices but **without** the S_y measurement covariance matrices) is 350 GB (compressed). The same for HOCl amounts at about 1.4 TB. Therefore, we consider the handling of these data amounts still a challenge.

Response to the second remark:

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- The reviewer suspects that the trace of the averaging kernel can be artificially high, and the solutions will be influenced by the noise of the instrument. We disagree: We do not suggest to use a very weak constraint, but we basically maintain the "strength" of the constraint of the original regularized fine-grid retrieval. We just redistribute the strength of the regularization slightly in altitude, while we approximately maintain (in fact decrease by a number smaller than one) the degrees of freedom of the profile. Thus the noise error does not substantially increase. We intend to report the singular values to prove this, but in first place we will present the estimated noise errors, which give the direct answer to the question raised.

- The ability of the forward model to accurately describe the radiation levels seen by the instrument is mainly controlled by the number of degrees of freedom of the forward model input. This number is changed only marginally by our re-regularization method. The details in the fine-grid regularized profile are only determined by the regularization, because this information is not included in the measurement. If the forward model was significantly sensitive to these changes of the fine structure, the initial regularization of the retrieval on the fine grid would have been too strong. There is no reason why one particular profile shape should be better than the shape of the coarse grid profile. Sub-grid effects are not resolved by the measurement and it is not clear to us why our representation should be worse. The actual loss of information when going from the fine grid to the coarse grid is limited to a fraction of a degree of freedom.

- At no point we make any MIPAS- or limb sounding specific assumptions in our theory part. The only precondition to a meaningful application of our method is that the difference between the actual number of degrees of freedom and its integer approximation can be considered as small. This caveat will be reworded for clarity in the paper. Further the MIPAS instrument will be introduced in the new version only in the case study after the theory part, in order not to mislead the reader such that the theory might be misunderstood MIPAS-specific.

Response to the third remark:

We agree on this one and will add a receipe on how to use remotely sensed data as provided in our representation.

The dashed line in Fig. 1 is, as mentioned in the figure caption, the re-regularized resampled profile.

Response to the fourth remark:

There is a fundamental misunderstanding: Eq. 19 is represented in the **fine** grid, and **R** is **not** zero but chosen such that the product $W^T RW$ is (non-trivially) zero. We don't do an unregularized maximum likelihood retrieval on the coarse grid but we do a regularized retrieval on the fine grid which, after transformation, is equivalent to a maximum likelihood retrieval on the coarse grid. We will add some lines to make this clear.

Response to the fifth remark:
We agree: The triangualr representation will be included and discussed.

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