Atmos. Chem. Phys. Discuss., 9, S2398–S2403, 2009 www.atmos-chem-phys-discuss.net/9/S2398/2009/ © Author(s) 2009. This work is distributed under the Creative Commons Attribute 3.0 License.



ACPD

9, S2398–S2403, 2009

Interactive Comment

Interactive comment on "Technical note: Functional sliced inverse regression to infer temperature, water vapour and ozone from IASI data" *by* U. Amato et al.

U. Amato et al.

Received and published: 8 June 2009

Abstract

We thank both referees for the valuable comments, which should hopefully improve the reading and overall quality of the paper. We are now considering a revised version, in which suggestions and comments form the two referees will be handled as described in the item-by-item reply shown below.

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



1 Item-by-item reply to Referee #1

- 1.1 General Remarks
 - the list of references contains 4 citations from reports/proceedings over a total of 21 citations: it is the 19%, and 2 of these 4 citations are science plans (NAST-I and IASI).
 - Envisat: The story we tell relates mostly to meteorological satellites, i.e. satellites intended for Numerical Weather Prediction, which is not the case for ENVISAT. Furthermore the Fourier Transform Spectrometer onboard ENVISAT, MIPAS has been developed for the observations of limb emission spectra in the middle and upper atmosphere. Conversely IASI works in nadir-looking mode and has been mostly designed for the analysis of the troposphere. However, in a revised version of the paper we will make proper reference to MIPAS.
 - The use of relative values for water vapour and ozone can be done. Also to improve reading, we have exploded the three panels of Fig. 2 in the three new figures, which will be numbered Fig. 2, Fig. 3 and Fig. 4, respectively. For temperature we left absolute values, because for temperature, percentage values depend on the temperature units (Kelvin, degrees Celsius and so on), which makes the use of relative values not appropriate. Finally, we have also revised Fig. 7 and 8 (in the new version corresponds to Fig. 9 and 10), which now show relative differences in percentage.
- 1.2 Specific questions/comments
 - p7591/l16 Functional data analysis is about the analysis of information on curves or functions, and the radiance spectrum is a curve evaluated in fixed points that

Interactive Comment

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



depends on the design of the interferometer. Indeed, as written in the paper, in functional regression problems, one has a response variable Y to be predicted by a set of variables R_1, \ldots, R_d that are discretizations of a same curve R at points ν_1, \ldots, ν_d , that is $R_i = R(\nu_i); i = 1, \ldots, d$ where the discretization points ν_i lie in $[\nu_{\min}, \nu_{\max}]$, spectral range of the instrument under examination.

 p7591/l18-20 Chevallier data base documentation can be downloaded from the EUMETSAT SAF (Satellite Application Facilities) Scientific Report web page: http://www.eumetsat.int/groups/pps/documents/document/002197.pdf.

Also proper documentation and the data-base as well can be obtained directly by F.Chevalier at f.chevallier@ecmwf.int

- p7591/l23 NPOESS: National Polar-orbiting Operational Environmental Satellite System.
- p7592/Eq.(1) $R(\nu)$ and $\{\beta_i(\nu), i = 1, \dots, k\}$ are functions belonging to $L_2([\nu_{\min}, \nu_{\max}])$. Moreover the $\{\beta_i(\nu), i = 1, \dots, K\}$ are orthonormal with respect to the usual inner product defined in the space to $L_2([\nu_{\min}, \nu_{\max}])$.
- p7593/l1 m is a smooth link function that indicates what kind of relation exists between the geophysical variable to retrieve and the radiance.
- p7593/l2 in Eq. (1) it is used R(ν), the scalar product is between functions (see p7592/Eq.(1) point).
- p7593/l4 β_i(ν) is a function, and at this point Eq (1) is only saying that the geophysical variable to retrieve in a fixed layer depends on the radiance only through *K* linear functionals of the radiance *R*(ν). The determination of β_i(ν) and the choice of *K* is explained by Eq. (2)-(5) pag. 7594-7595. Obviously the β_i(ν) are determined in the values ν_j, j = 1,..., d.

ACPD

9, S2398-S2403, 2009

Interactive Comment

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



- p7593/l9-l10 Generally this is always possible and the criterion to see if the reduction of dimension is possible is to look at the discretized version of the problem and the spectral decomposition of the matrix defined in Eq. (4).
- p7597 What we show in this paragraph is the mechanics of how *i*_D works and how to perform the computation. These involve the SVD transform and we limit in this paragraph just to define quantities and variables. Thus we think that any cut to this paragraph would make it obscure and not understandable. Concerning the second point, we have built up a transform, which is norm-preserving, and this is not a trivial result.
- p7598/l6 The example has been already given, $i_D = 1$ simply means that we can retrieve only the columnar amount of a geophysical parameter. As far as IASI is concerned, this is, e.g., the case for trace gases such as CO or methane.
- p7600/l4 to l8 The index i_D was evaluated on the whole training dataset consisting of 377 tropical profiles. We give to the term *degrees of freedom* the usual meaning which is given to it in statistics. In its discretized form a given geophysical parameter is represented by a vector, \mathbf{v} of size, say m. Therefore the vector \mathbf{v} lives in a space of dimension m and we need, at least m independent equations, hence m pieces of information, to fully resolve for the geophysical parameter. However, because of data correlated each to other, which means that only some linear combination of the elements of \mathbf{v} has been resolved from the data set. The index i_D says how many independent linear combinations can be resolved from the data, and therefore how many independent pieces of information we have in the retrieved, $\hat{\mathbf{v}}$.
- p7600/I6 The answer is that, yes, FSIR can resolve important small structures in water vapour better than EOF. Of course, this does not mean that FSIR is, in absolute, the best retrieval method, we can only says that it is superior over EOF.

ACPD

9, S2398-S2403, 2009

Interactive Comment

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



- p7602/ paragraph 2. We use temperature difference here. Relative quantities for temperature can be misleading and are avoided in this context. However, we have used relative quantities for water vapour and ozone, where needed.
- 1.3 Technical issues
 - p7591/l13 we have corrected.
 - p7591/l29 we have corrected.
 - p7592/l5 we have corrected.
 - p7593/l6 it is explained: ' Σ_e the covariance operator of the conditional expected value, E(R|Y), of the radiance given the geophysical variable to retrieve.'
 - p7593/l15 we have corrected.
 - p7598/l6 we have corrected.
 - p7600/l12 we have corrected.
 - p7601/l1 we have corrected.
 - p7603/l8 we have corrected.
 - p7603/l9 we have corrected.

ACPD

9, S2398-S2403, 2009

Interactive Comment

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



2 Item-by-item reply to Referee #2

2.1 General Comments

Different methodologies can be used to reduce the dimension in this specific context, i.e. methods different from FSIR but always based on the inverse regression, partial least squares, canonical correlation and variable selection, but most of them are not so diffused in the remote sensing community. This means that the comparisons can be done and they surely are useful, but all the different techniques should be explained in details, and for the sake of brevity this is not possible for the current paper. However this suggestion will be surely taken into account for next work.

2.2 Specific Comments

As regards the sentence on page 7593 line 19 regarding the curse of dimensionality:

Nonparametric statistical techniques are very useful for investigating Y/X, especially when an adequate parsimoniously parameterized model is not available, but the risk or expected squared error of estimation of a nonparametric regression estimator increases rapidly with the dimension p and to maintain a given degree of accuracy of an estimator, the sample size must increase exponentially with the dimension p. This does not happen with parametric technique, i.e. least squares regression, whose risk will decay to zero at a rate of n^{-1} , where n is the number of observations.

ACPD 9, S2398–S2403, 2009

> Interactive Comment

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

