THE IASI PROGRAM IN THE FRAMEWORK OF METEO-FRANCE

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1. INTRODUCTION

The IASI program at Météo-France is called MASSIF (Meteorological Aspects of Studies and Simulations for IASI in France). It is a response to the call of opportunity from Eumetsat and CNES to prepare the IASI mission. It is a shared program between some teams of Météo-France and also a team of LMD (Laboratoire de Météorologie Dynamique).

Our main goal is to be in the best position to assimilate operationally IASI data as soon as they are made available and to improve our knowledge of the atmosphere with IASI data. For this we should go from spectral data provided by IASI to 4D-analysis of the atmosphere.

It is possible to see the MASSIF work through the standard equation of linear estimation:

\[
x-x_0 = (B^{-1} + H^T R^{-1} H)^{-1} [H^T R^{-1} (y_0 - \mathcal{K}(x_0)) + B^{-1} (x_b - x_0)]
\]

where
- \(x\) is the vector of parameters to determine
- \(x_0\) is a set of parameters used to linearize the problem
- \(x_b\) is a set of a priori values for the parameters
- \(y_0\) is the vector of observed values
- \(\mathcal{K}\) is the "observation operator" : it defines the way to compute the observed parameters from the parameters to determine
- \(H\) is the tangent linear operator of \(\mathcal{K}\) (the Jacobian)
- \(B\) is the error covariance matrix on the a priori value \(x_b\)
- \(R = E+F\)
- \(E\) is the error covariance matrix of the observations
- \(F\) is the error covariance matrix of the observation operator

There are ten tasks in MASSIF. One is dedicated to radiative transfer model and deals with \(\mathcal{K}\), \(H\) and \(F\). One is about the development of inversion methods and is concerned with the choice of \(x\), the selection of \(y_0\) and the weight of \(x_0\) in results. It is focussed on theoretical aspects and on the covariance matrix of the errors of the retrieval. One is about coupling with AVHRR to improve \(\mathcal{K}\) and \(H\) in cloudy conditions. One is about noise estimation to improve our knowledge of \(E\) and another tries to determine the information content available in IASI spectra for a given problem when we already have some knowledge (given by \(B\)) on the atmosphere. There is also a task on quality control, one on OSSE (Observing Simulated System Experiment), one on 1DVAR inversion foocussing on retrieval themselves, one on wind estimation and one on cyclone forecasting.

It is not possible to summarize all the work done during the last two years (for more details see the list of papers, reports and databases available). We will only show some main results : the use of neural network to invert IASI spectra, the use of AVHRR to describe cloud parameters at the IASI FOV scale, the way to determine the information content as a compromise between accuracy and vertical resolution and how to evaluate the improvement of IASI on HIRS. This paper will be concluded on our plans for the next two years.
Fig 1: Neural network performance.

The two curves show the result on the learning set (dashed line) and on the generalization set (solid line).

The y-axis is the vertical in pressure coordinates (in hPa), and the x-axis the root mean square of the difference between truth and retrieved temperature (in K).

The neural network is built with a learning phase on all air masses. The curves show the result on the learning set (dashed line) and on the generalization set (solid line).
2. NEURAL APPROACH FOR RETRIEVAL

A neural approach is developed as a sequential method to retrieve surface temperature, temperature profile and humidity profile (Aires et al., 1998).

For extraction of surface temperature information two windows are possible: 800-980 cm\(^{-1}\) and 2500-2750 cm\(^{-1}\). 357 and 262 channels respectively are selected as the most sensitive to surface temperature. We use multilayer perceptron with three layers: 357-20-1 and 262-20-1. The accuracy obtained is about 0.4K.

For temperature profile we retrieve 30 temperatures with a vertical resolution of 1Km up to 10hPa except for the two first levels near the surface. First a band is fixed (545-800 cm\(^{-1}\) or 2100-2500 cm\(^{-1}\)), then Jacobians are studied to select channels with Jacobian extent less than a fixed threshold, also with a width at mid height less than a fixed threshold and which show a single peak. This selection is done on the TIGR database which is built from radiosonde data all over the world. We select for temperature at 15\(\mu\)m: 270 channels, and at 4.3\(\mu\)m: 401 channels. We use multilayer perceptron with three layers with respectively 671, 50 and 30 neurons.

We have checked that the quality of our retrieval is similar to the quality computed in the framework of linear estimation using the spread of TIGR database to determine a priori covariance matrix. If we build neural network dedicated to a given air-mass, for example tropical air-mass we improve the results obtained with standard neural network which learn on the full database. This can be easily explained and quantified by the fact that we introduce more a priori information.

Figure 1 shows the root mean square of the departure between truth and retrieved temperature with a neural network built with a learning phase on all air masses. The two curves show the result on the learning set (dashed line) and on the generalization set (solid line). One can see that, apart from the surface level where the RMS error is 0.4K, the errors are between 0.8 and 1.5K below 20hPa and reach 1.8K at 10hPa. Sometimes the results seem better with the generalization set than with the learning set because the size of the learning set is too small and lacks representativeness.

3. AVHRR COUPLING

We used different softwares to determine at the IASI FOV scale the properties of the surface and of the cloud layers. We tested the approach to simulate cloudy radiances for HIIRS using the clouds properties and an appropriate radiative transfer model. The method is validated now, but the results are still preliminary because not enough cases have been studied.

4. TRADE OFF BETWEEN ACCURACY AND VERTICAL RESOLUTION

Retrieval is a complex algorithm to go from IASI spectra to temperature (and humidity) profiles. There is in fact a balance between accuracy and the vertical resolution of the retrieved profiles. This balance depends of course on the spectral resolution and on the radiometric noise of the data, but also on the a priori information introduced in a way or another in a specific inverse method (Prunet et al., 1999).

We revisit mathematical background to define best linear estimate, in particular we have discussed the impact of a priori information in the context of Tikhonov regularization. We also use Mollifier regularization to deal with vertical resolution. The two approaches are similar from the mathematical point of view but they are used for different purposes.
Fig 2: Vertical resolution with IASI alone and with climatological informations.

The y-axis is the vertical in height coordinate (in Km), and the x-axis is a measurement of the vertical resolution (in Km). There are four curves for IASI (corresponding to different figures of noise) and one for HIRS.

Fig 2a. is for IASI alone, Fig 2b. is with climatological information used.
Vertical discretization of the measured profiles with reasonable accuracy.

**IASI profile vertical resolution**

1 K error. Temperature

(a)

10% relative error. Humidity

(b)

Fig 3: Vertical discretization of a retrieval to reach reasonable accuracy.

The y-axis is the vertical in height coordinate (in Km), and the x-axis is an arbitrary scale to show the resolution at different levels. The accuracy is fixed to 1K for temperature and 10% for humidity. In each figure there are two sets of lines showing the vertical resolution at a given height: one for IASI alone, another with climatological information used.
Fig 4: Measurement of the information content of IASI versus HIRS for numerical weather forecast.

The y-axis is the number of pieces of information in the sense of Shannon theory brought by each eigenvalue of the a posteriori covariance matrix normalized by the a priori covariance matrix, and the x-axis is the rank of these eigenvalues with respect to their contribution. There are four curves for IASI (corresponding to different figures of noise) and one for HIRS. One can fix a threshold of 10% of information coming from the data for a given eigenvector, this threshold is shown by a dashed line.
Using Backus-Gilbert approach, we can define a vertical discretization of the vertical profiles for a given accuracy taking into account a given a priori knowledge of the vertical correlation of the atmosphere. Results are obtained for temperature and humidity and a similar approach is developed for ozone. We show that it is possible to reach 1K/Km if some climatological information is used.

Figures 2a and 2b show the vertical profile of the vertical resolution one can reach with a given accuracy of 1K on retrieved temperature. HIRS curves are shown by dash-dotted lines. For IASI, several scenarios are shown according to noise specification. Figure 2a is for IASI data alone, and figure 2b is when some climatological information is used. In these figures resolution can not be smaller than the discretization used which explains why it goes to zero at lower levels. One can note a major improvement from HIRS.

Figures 3a and 3b show with and without any climatological information the vertical resolution at a given height to have an accuracy of 1K for retrieved temperature (3a) and 10% for retrieved humidity (3b).

5. COMPARISON WITH HIRS

There are two ways to determine the impact of a measurement on the analysis of a specific feature (This work deals primarily with meteorological features determined as the modification of the initial state needed to improve the 48H forecast). The first one is to check if a given feature is greater or not than the a posteriori estimate of the variance. But this approach does not give any information if the answer is yes because the feature is big or because the variance is small and in that case if it is due to good a priori estimate or due to the quality of the measurement. The second approach consists in normalizing the problem by a priori variances and to consider the percentage of diminution of the variance. This quantity is a direct estimate of the information brought by the measurement, and allows to compare measurements done in different ways (Prunet et al., 1998).

In this context it is possible to compute the eigenvalues of the analysis error covariance matrix and to compare these eigenvalues using HIRS data and using IASI data. We find six structures determined by the HIRS data, and eighteen by IASI data. From the eigenvectors structure, it is possible to estimate the vertical resolution obtained.

Figure 4 shows the number of information in the sense of Shannon theory brought by each eigenvalue of the a posteriori covariance matrix normalized by the a priori covariance matrix.

6. CONCLUSION

In this first stage of the study, we have started to look at various issues dealing with the assimilation of IASI radiances. Our scientific objectives for the next two years are:

- to define very fast radiative transfer model efficiency,
- to determine the best way to assimilate IASI data,
- to quantify the impact of IASI on operational meteorology,
- to study the simultaneous use of IASI data and other instruments data,
- to deal with cloudy radiances and surface characteristics.
7. REFERENCES


