RETRIEVING THE OCEAN SALINITY FROM SMOS OBSERVATIONS BY THE USE OF NEURAL NETWORKS

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INTRODUCTION

One of the critical issues for the SMOS mission is the inversion algorithm which will be used to retrieve the sea surface salinity (SSS) from the SMOS brightness temperatures (TBs). Most of the scientists have chosen an inversion processing based on a forward model, developed with theoretical or semi empirical models. This forward model allows simulating brightness temperatures, given a triplet of geophysical parameters (sea surface salinity, sea surface temperature and wind speed). The iterative method tries to adjust the cost function between the SMOS measured brightness temperatures and the simulated ones. The development of this physical inversion method is necessary because it allows to take into account pixel by pixel the surface physics and especially to improve our knowledge in surface emissivity modeling.

Nevertheless, one of the main drawbacks of such a method is the use of a forward model. We know that this model does not reproduce perfectly all the physics, especially the influence of the sea surface roughness (foam effect, swell…). All the studies performed with simulated data give errors which meet the GODAE requirements, but all the scientific community acknowledge that, once SMOS in-flight, the retrieval algorithm based on a forward model will provide inaccurate salinities. The improvement of the salinity retrieval can be performed only by improvement of the physics modelling in the forward model. No strategy has been defined yet to perform this task, which needs a large amount of work and can not be achieved in reasonable delays in order to release SMOS products to the users, at the end of the commissioning phase.

In this context, we propose to develop in parallel an empirical inversion algorithm that will provide realistic SSS at the beginning of the mission. For that purpose, we propose an algorithm using neural network methods, built with SMOS measurements (TBs) co-located with in-situ salinities, during the commissioning phase. For pre-launch studies, the feasibility of neural network inversion is demonstrated with simulated data sets. This simulation phase is very important because it allows fixing the architecture of the network and helps to identify the critical issues to build a reliable algorithm. Once SMOS in-flight, the work will consist in two steps. First, the constitution of the learning database, using a suitable editing to make a representative dataset. In a second step, the coefficients of the algorithm will be updated, keeping the architecture and strategy defined during the pre-launch study.

In this context, the objective of this feasibility study was to develop a neural inversion for the subsatellite track, and to evaluate its performances in terms of sensitivity to the input brightness temperatures and to the auxiliary parameters (noise and bias).

SIMULATED DATA

Emissivity model

The forward model used to simulate SMOS measurements is the following. Firstly, the emissivity of a flat surface is obtained from the sea water dielectric constant model proposed by the Klein and Swift [1]. Secondly, the contribution coming from the surface roughness is tabulated as a function of the wind speed following [2] and added to the flat surface emissivity. The effect of foam is not taken into account.

The model simulates L band brightness temperatures for a given set of salinity (SSS), sea surface temperature (SST) and wind speed (U). The incidence angles vary from 0 to 60 degrees, by step of 10°. The polarization H and V are taken into account, leading to a total of 13 brightness temperatures available for the salinity retrieval.

Databases

Learning Database

The choice of the learning database is known to be crucial in the development of a neural algorithm. That is why we used for the training of the neural algorithm a physical database, containing all statistical information between the 3 geophysical parameters (U, SST and SSS). The data are distributed over the 4 seasons. Sea surface salinity and temperature values are extracted from the seasonal WOA97 database (World Ocean Atlas). The wind speed is a daily Quikscat map chosen in the middle of the season. A daily map was chosen to ensure a large range of wind speed, especially allowing for high wind speeds. For each season, data are randomly drawn within the maps to have a uniform distribution in latitude, in order to have equally represented situations in the database. Then the brightness temperatures are simulated using the described emissivity model for incidence angle between 0° and 60°, by step of 10°.

Testing Database

This database has to be independent from the previous one and is constituted with outputs from the Mercator model for one winter day (12 January 2001) to get more variability in surface wind speed. SSS and SST are coming from MERCATOR PSY1V1, and the surface wind speed used in the MERCATOR model is coming from the ECMWF. To lower the number of points, we performed a sampling at a resolution of 1°x1°. This gives a total of 5614 points in the testing database. Note that the histograms for the testing database are quite different from those for the learning database (very low salinity, secondary peak for the wind speed around 13 m/s).

The Neural Network

A neural network is defined by the number of layers, the number of neurons for each layer and the transfer function associated to each neuron. For the salinity retrieval, there are 16 inputs (the 13 brightness temperatures and a priori values for the wind speed, the sea surface temperature and salinity) and one output (the salinity). All the information between two neurons is quantified by a weight. The transfer function we use is the sigmoid function. The network output has a final expression given by the combination of the transfer function with weights and biases. The

determination of the adapted architecture is done in an empirical way, testing for various architectures. Once the network architecture has been settled, the network parameters (the weights and biases associated to each neuron) are iteratively adjusted when presenting the inputs (brightness temperatures and auxiliary parameters) and outputs (salinity) of the learning database to the network. The network learning consists in minimizing a cost function between simulated salinity in the learning database and the network output.

For the learning step, a realistic noise is added to the brightness temperatures to simulate the instrumental error of the SMOS measurements. The noise is gaussian with a zero bias and a standard deviation depending on the incidence angle: 1.9K for 0°, 1.65K for 10°, 1.5K for 20 and 30°, 1.6K for 40°, 1.9K for 50° and 2.35K for 60° (outputs of the SEPS simulator). A noise of 2m/s, 1° and 1 psu is also added to the wind speed, the sea surface temperature and the salinity respectively, in order to simulate the expected error on these parameters.

RESULTS OF THE NEURAL NETWORK RETRIEVAL

The obtained neural network is now tested in several configurations and the performances are assessed on the independent testing database. Parameters to be fixed in each configuration are:

1. Geophysical parameters: the real SSS, SST, U at the surface used to simulate the measured brightness temperatures. This SSS is the reference one.

2. Measured brightness temperatures: simulated brightness temperatures from the geophysical parameters using the forward model. A noise/bias is added to the TBs to take into account instrumental errors.

3. Auxiliary parameters: the SSS, SST, U values used as input parameters for the inversion. They are simulated adding noise/bias to the geophysical parameters or they come from an independent geophysical database.

4. Retrieved parameter: the salinity. The quality of the inversion method is evaluated by comparing the reference salinity in the database (geophysical value) to the retrieved SSS. The bias and the standard deviation between both values are analysed.

Sensitivity to TBs

We can assume that TBs will not be perfectly measured. In this section, we check the robustness of the method to noisy or biased TBs.

The reference test is performed applying the neural algorithm to simulated brightness temperatures without noise. To simulate the auxiliary parameters, a white noise with a standard deviation of (1 psu, 1°C, 2m/s) is added to the geophysical values (SSS,SST,U). In this case, the obtained bias is -0.29 psu and the global standard deviation of 0.52 psu is satisfactory.

Now, the same instrumental noise as the one used for tuning the neural network is added to the brightness temperatures just before running the inversion. Auxiliary parameters are the same as previously. The standard deviation increases slightly (0.6 psu). This test points out the weak sensitivity to noise on TBs with the neural inversion. It can be considered as a reference for SMOS simulation since a realistic noise is added to the brightness temperatures and to the auxiliary parameters.

The brightness temperatures are also artificially biased, adding 1K to all simulated brightness temperatures. A stronger bias is obtained (-0.7 psu) but the standard deviation remains very consistent around 0.5 psu.

Sensitivity to auxiliary parameters

In this part, the objective is to estimate the impact of the auxiliary parameters accuracy on the retrieved salinity. The reference case is obtained, with noisy brightness temperatures and with auxiliary parameters perfectly known (identical to geophysical parameters). The error (standard deviation between retrieved and reference SSS) of 0.44 psu is satisfactory. A “standard” noise on auxiliary parameters of 1 psu, 1°C and 2m/s increases the error to 0.6 psu. A noise twice higher (2psu, 2°C, 4 m/s) is then added to the auxiliary parameters. This case is extreme but locally differences between auxiliary (SSS,SST,U) and real (SSS,SST,U) could be of this order of magnitude. The neural inversion retrieves the salinity with a larger error of 0.8 psu for all the points in the testing database.

When SMOS will fly, the auxiliary parameters will be quite different from the reality and the difference between these two fields will be characterized by a standard deviation around (1psu,1°C, 2m/s) as already tested, but also with local biases for example. To perform an even more realistic test, we are now using auxiliary parameters that are independent of the geophysical parameters. We extracted January Levitus salinity, weekly Reynolds temperatures for one week in January 2001 and Quikscat wind speeds for 12 January 2001 (not yet assimilated in the ECMWF model). Standard deviations between the two are of 1.3°C for the SST and 1.9 m/s for the wind speed (which is within the standard deviation used in our scenario), and as expected, the differences are very different from a white noise (for example, there is a mean bias of 1.3 m/s for the wind speed with a significant slope). Comparison between auxiliary and geophysical SST and wind shows differences ranging between -3 and 3° for the SST and between -5 and 5 m/s for the wind speed. Performances of the neural algorithm remain satisfactory with an error of 0.47 psu which very close to the results obtained with the noisy geophysical parameters, due to the weak dependence on the initial conditions.

CONCLUSIONS

In all simulated cases, we showed the robustness of the neural algorithm to noise and bias on brightness temperatures and auxiliary parameters.

Nevertheless, the results obtained with this neural algorithm are not perfect. In particular, the behavior of the algorithm for low and high salinity that results in a systematic slope, can be greatly improved. The constitution of the learning database used to train the network could be improved, adding cases of extreme values in salinity (low and high) that are not well represented in this learning database.

Overall, available forward models are not accurate enough yet to expect a useful retrieved salinity with an inversion method based on a forward model. In these conditions, it seems clear that only an empirical algorithm will provide salinity accurate enough to meet the SMOS requirements. A neural formulation is particularly adapted to the development of such algorithms.

REFERENCES

[1] Klein, L.A and C.T.Swift, "An improved model for the dielectric constant of sea water at microwave frequencies", IEEE Trans. in Antennas and Propagation, AP-25, (1977), 104-111.

[2] Dinnat, E. P., J. Boutin, G. Caudal, J. Etcheto, and P. Waldteufel, 2002: Influence of sea surface emissivity model parameters at L-band for the estimation of salinity. International Journal of Remote Sensing, 23, 5117-5122.

[3] Reul N. and B. Chapron, 2003: Study on salinity Data processing. report of WP1100, ESA contract 165/01/NL/SF.