J1.2 USE OF A NEURO-VARIATIONAL METHOD TO IMPROVE ATMOSPHERE AND OCEAN PARAMETER RETRIEVAL FROM OCEAN COLOR SENSOR

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1. INTRODUCTION

The retrieval of ocean constituents from satellite ocean color measurements is very sensitive to the atmospheric correction. Improved atmospheric correction algorithms, which simultaneously estimate ocean and aerosol optical properties, have recently been developed (Gordon, 1997; Gordon and Wang, 1994, Gordon and al., 1997). These new methods perform well in the presence of absorbing aerosols, but are difficult to include in operational ocean color data processing because they use look-up tables, which are costly in computer-time. Advanced programming techniques such as Neural Network (NN) can facilitate the implementation of such improved atmospheric correction techniques in operational processing.

Our atmospheric correction algorithm relies on a classical variational inversion combined with a set of Multilayered Perceptron (MLP) neural networks (NNs) (Bishop, 1995) . In this paper we describe the methodology and we present the performance of the different NNs, which are the core of the inversion. In final, we discuss the first qualitative results obtained for the East Coast of the United States from SeaWiFS imagery.

2. METHODOLOGY OF THE INVERSION

Once corrected for gaseous absorption and Rayleigh scattering, the reflectance "measured" by an ocean color sensor in the visible and near infrared can be written as $r_{COR} = r_A + t * r_w$, where r_A is the atmospheric reflectance due to the aerosol scattering and the scattering due to the interaction between aerosol and molecules, *t* is the diffuse transmittance and r_W, the water leaving reflectance. In this work, we follow the work of Chomko and Gordon (Chomko and Gordon, 1998), who developed an atmospheric correction algorithm that uses set of Junge power-law size distributions to compute r_A and a semi-analytic model (Gordon and al., 1988) for r_W. For clarity, the method is hereafter described for the Sea-viewing Wide Field-of-view Sensor (SeaWiFS), but note that it would be applicable to every ocean color sensor as well.

Our NN-based method is thus decomposed in two steps: a first inversion relies on the red and near-infrared (NIR) SeaWiFS bands (670, 765, 865 nm) to get a first guess on three keys aerosol parameters (i.e., aerosol size distribution, ν, the real part of the refractive index, m_r, and aerosol optical thickness, τ). At these wavelengths, the intensity of r_{COR} is directly related to τ since the water-leaving reflectance r_w can be neglected, while its spectral variation depends mostly sensitive on the aerosol scattering properties defined by the real refractive index m_r and to ν throughout the Mie theory. The objective of this first step is thus to find the combination of ν, τ and m_r that best match the measured r_{COR}. We trained dedicated MLP classifiers for two values of m_r (1.33 and 1.50) which allow to retrieve, for the given $r_{COR}(NIR)$ and viewing geometry, the three best pairs of (ν, τ) together with their associated probability level. The six best solutions (three pair (n_i, t_i) for each values of m_r) are then retained to be used as different first guess for the second part of the inversion described below. This NIR inversion is summarized in figure 1.

The second step of the method uses visible

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wavelengths (i.e., 412, 443, 490, 510, 555 nm) to retrieve both aerosol and oceanic optical properties. We developed a neuro-variational inversion to do so. This

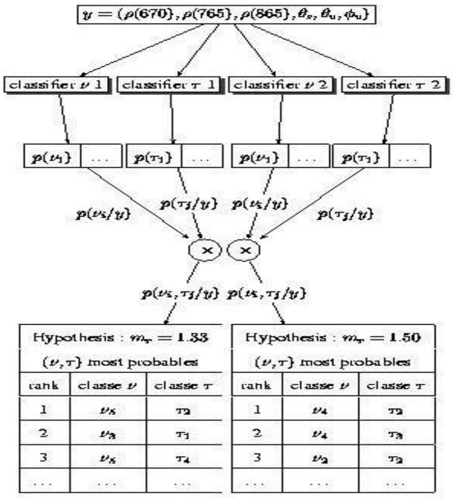

Fig.1: Inversion in the NIR bands

algorithm relies on three NNs (one for each component of r_{COR}, namely r_A, t and r_W; see figure 2), which have been trained using a large set of direct atmospheric and oceanic radiative transfer simulations similar to that of Chomko and Gordon.

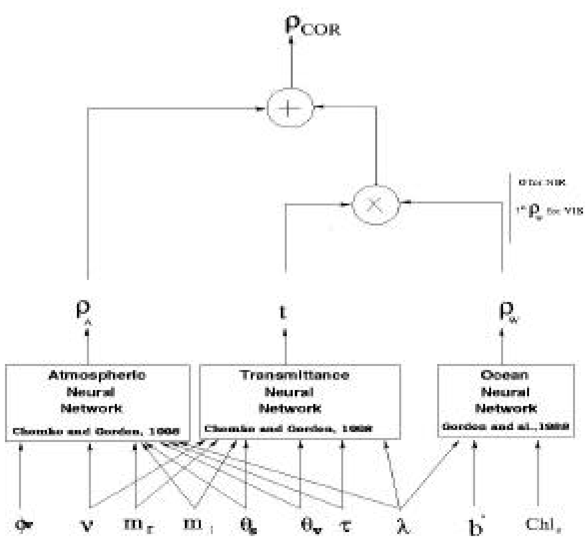

Fig.2: Direct Neural Network in the visible

These NNs are thus capable to compute r_A, t and r_W for a given wavelength in the visible and for the given viewing geometry, aerosol type and concentration, chlorophyll-a concentration (Chl *a*) and marine scattering parameter b°. b° is, with Chl *a*, a parameter of the direct oceanic reflectance model. The principle of this neuro variational inversion is thus to invert this NN-based direct model to retrieve the aerosol and marine parameters by minimizing the distance between observed and computed r_{COR}, taking into account the constraints which come from the NIR inversion. The control parameters of this inversion are the oceanic (b° and the chlorophyll-a concentration Chl-a) and atmospheric (n, m_r, m_i, t) constituents (see Figure 3).

The major advantage of this approach is that the variational method is easy to implement for direct model based on NNs, because the gradients (adjoints) are straightforward to compute (Bishop, 1995). The second advantage of this approach is that it would easily allow to take into account the spatial coherence of the parameters during the inversion.

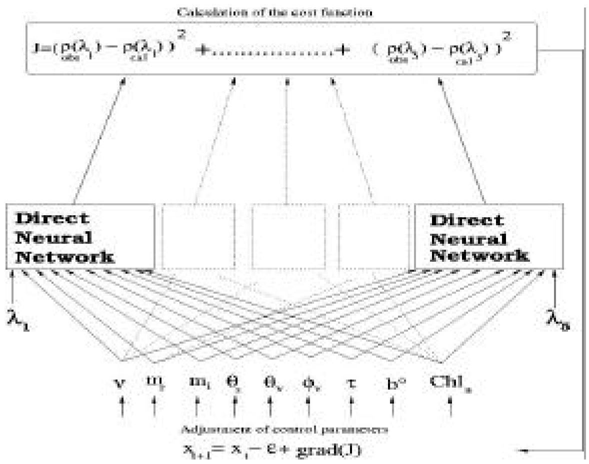

Fig.3: Neuro-variationnal method in the visible

3. TEST OF THE GLOBAL INVERSION

All NNs were developed with the same type of NNs (Multilayered Perceptron, MLP) and were trained using the set of simulations of Chomko and Gordon for low-absorbing aerosols. In this section, we show the respective accuracy of these NN models.

The validation of the inversion in the NIR is done with 20000 different parameter's configurations of the database. When inverting the NIR spectra (first step of the method), the desired value ν and τ are retrieved 87.3% and 97.6% of the time, respectively, whatever the value of m_r . The first pair of (n_1, t_1) corresponds to the desired solution 85% of the time for m_r =1.33 and reaches 89.2% for m_r =1.50. These performances of the direct NIR inversion based on MLP classifiers are very satisfactory and enable to retrieve ν and τ with a sufficient accuracy to efficiently constrain the neuro-variational inversion in the visible. This is of primary importance because the inversion in the visible is highly multi-valuated (i.e., several combinations of the control parameters can lead to a minimum during the inversion procedure). Appropriate initialisation of the aerosol parameters thus helps to avoid wrong inversion results.

The direct radiative transfer m odel in the visible (see Figure 2) is modelled by the combination of three MLPs. The MLP are tested with 20000 differents configurations of aerosol properties, oceanic components and geometry of the view. The accuracy of each Direct Model (MLP) is satisfactory and leads to a good estimate of r_{COR}, as shown in Table 1.

	RMSE	Relative RMSE (%)	R²(%)
NN t	$2.4*10^{-3}$	0.50	99.986
NN r_w	$3.69*10^{-5}$	1	1
NN r_A	$1.16*10^{-3}$	6.9	99.98

Table 1: Performance of the three neural network of the direct model

The global inversion is tested with 1008 differents configurations of viewing geometry, optical aerosol properties and oceanic parameter for different wavelengths. As initial parameter for the variational method, we use the first values of ν, m_r and τ given by the first step of the method. Figure 4 displays the scatterplot of r_{COR}.

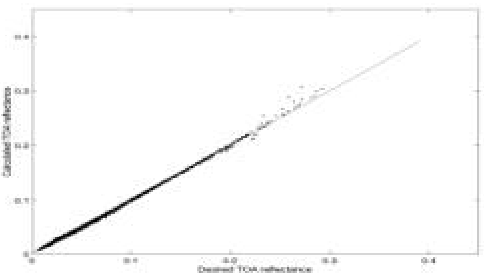

Fig.4: scatterplot of desired vs calculated r_{COR} after inversion when we have a good first-guess (ν, m_r and τ given by the NIR bands).

For this experiment, the root-mean-square (RMS) error computed on the test set is $4.3*10^{-4}$. Table 2 confirms that r_{COR} is retrieved with a much better accuracy when a good first guess on aerosol parameters (ν, m_r , τ) is provided by the NIR inversion. In term of retrieved parameters, we can see a dramatical improvements (Table 2). The chlorophyll-a concentration is retrieved with a relative RMS error of 20% when ν, m_r and τ are known.

	r_{COR}	m_i	b°	[Chl]
rmse	0.00049	0.00079	0.075	0.586
rel rmse (%)	0.88	∞	20	19.7

Table 2: Rmse and relative rmse of the retrieved parameters with the neuro-variational inversion with a good first-guess (ν, m_r and τ known) .

4. QUALITATIVE RESULTS ON THE EAST COAST OF THE USA

In this part we show the capacity of the algorithm to retrieve the spatial aspect and coherence of the pigment concentration. We chose the East Coast of the United States for the tests. The results are given for the case of low-absorbing aerosols, taking as first guess in the second part of the method the most probable couple (ν, τ) given by the first step.

For the chlorophyll-a concentration, we compare our results with the SeaWiFS products (Gordon and Wang, 1994). We choose the 8 October 1997 for our test and we compare with pigment concentration retrieved with SeaWiFS algorithm. This day is characterized by a clear atmosphere.

The SeaWiFS result is showed in figure 6. The retrieved pigment concentration with the neuro-variational method is given in figure 5. This first results provided by our inversion show the ability to retrieve the spatial pattern of the pigment. We are able to retrieve the caracterisctic pattern (Ω form) of the pigment concentration.

Concerning the values of the pigment concentration, our retrieved values are surestimated with regard to the values of SeaWiFS algorithms by a factor 2. For the open ocean, the mean values with our algorithm is of order of 0.4 mg.cm^{-3} , instead of 0.2 for SeaWiFS's algorithms. Around the characteristic pattern of the pigment, we find of order of 1.5 mg.cm^{-3} , instead of 0.5 mg.cm^{-3}. There is an offset between the two method.

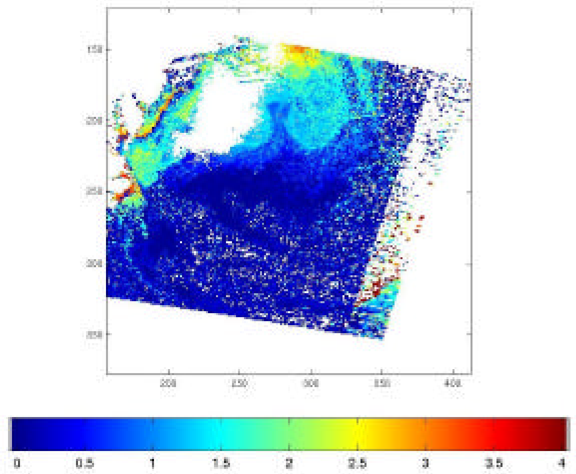

fig.5: Chlorophyll concentration retrieved with the neuro-variational inversion.

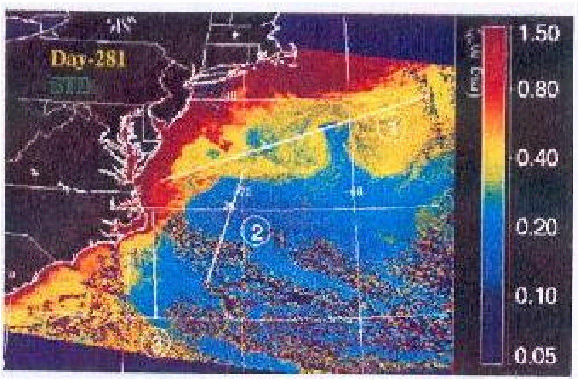

fig.6: Chlorophyll concentration retrieved with the SeaWiFS algorithm for the second decade of April, 1999**.**

5. CONLUSIONS AND PERSPECTIVES

We have developed a methodology to process the ocean color imagery. Retrieval of ocean constituents from these imagery is difficult due to the presence of the atmosphere, which represents a least 80% of the reflectance received by the sensor.

Our method is decomposed in two parts. First, the near infrared wavelength informations are used to give a first estimate of the aerosol optical properties through a direct NN inversion. These aerosol optical properties are retrieved with a sufficient accuracy to provide a robust first guess to the second part of the inversion, which enables to retrieve final oceanic and aerosol optical properties from visible wavelengths. This second step is called the neuro-variationnal inversion. To perform this inversion, we have modelled the oceanic and atmospheric radiative transfer equations with respect to the aerosol and oceanic parameters (the direct model) by using NN. The accuracy is better than 5% in term of root-mean-square error. The variationnal method consists in inverting the direct model to retrieve the aerosol and oceanic parameters. We minimize the distance between the observed reflectance at the top of the atmosphere and this calculated by the NN model, these parameters being the control variables. The calculation of the gradient of the cost function is straightforward due to the proprieties of the NN. We can thus invert a whole image in one time to take into account the spatial coherence of the parameters.

The inversion is tested with SeaWiFS Images for a clear sky day (October, 8th 1999) for the East Coast of Unite States. For clear sky condition, we retrieve the spatial coherence of the pigment concentration. In term of retrieved values, they are surestimated. These first results, which are only qualitative allows us to be confident with the method.

The future work concerns the use of the spatially coherence of the aerosol optical properties, the choice of the best pair (ν, τ) for each pixel and the validation of the algorithm for very absorbing aerosols with regard to SeaWiFS products and Chomko and Gordon's algorithm SOA (Chomko and Gordon, 1998, 2001).

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