746 POTENTIAL RETRIEVAL OF AEROSOL PROPERTIES COMBINING THE MULTISPECTRAL, MULTIANGLE RESEARCH SCANNING POLARIMETER (RSP) MEASUREMENTS OF THE INTENSITY AND LINEAR POLARIZATION OF LIGHT.

Alexandra Tsekeri*, Barry Gross, Fred Moshary, Sam Ahmed
Optical Remote Sensing Lab, City College of New York

ABSTRACT

Quantifying the microphysical properties of aerosols is crucial for quantifying global climate forcings. Satellite based aerosol retrievals rely usually on intensity measurements of the scattered light, but this approach has been proven to be quite limited for cases of absorbing aerosols as well as contamination from the ground surfaces. It is with these limitations in mind that we plan to improve the quality and scope of aerosol retrievals by making use of soon to be available polarimetric sensors, such as the Aerosol Polarimetry Sensor (APS) on the GLORY satellite. In order to utilize fully the increased information content on aerosol optical depth (AOD), size distribution and single scattering albedo (SSA), intrinsically available in multispectral-multiangle polarimetric observations, we make use of suitably constructed neural networks and demonstrate the potential of this approach on simulated aircraft instrument data from the Research Scanning Polarimeter (RSP).

1. INTRODUCTION

Aerosols play an important role for the physical and chemical processes in the atmosphere and influence climate by strongly modifying the global energy balance (GEB). In modifying GEB, aerosols may act directly by reflecting or absorbing the sunlight, cooling or heating the earth respectively. This direct interaction is greatly affected by the SSA of the aerosols and a large uncertainty of this direct effect stems from limitations in isolating the SSA from current intensity based retrievals.

In addition, aerosols can modify GEB indirectly by acting as cloud condensing nuclei (CCN), thereby modifying the formation of clouds. The efficiency of particulates as CCN is a function of aerosol size, with coarser modes being more efficient in interacting with water vapor. In addition, aerosol classification is important in these indirect mechanisms since hygroscopic aerosols are more prone to act as CCN. Overall, the aerosol indirect interactions tend to enhance cloud formation thereby driving the earth climate towards lower temperatures. However, due to the complex dependence on aerosol properties, this negative forcing on climate is estimated with a very large uncertainty, due mainly to the non-accurate monitoring of the aerosols. The fact that this uncertainty alone is comparable in magnitude to the positive forcing of the greenhouse gases on the climate highlights the need for better aerosol retrievals (Hansen *et al.* 2005).

* City College of New York, Optical Remote Sensing Lab, NYC, NY 10031

Finally, we should point out that particulates have also serious effects on human health, especially in the heavily polluted environments of big cities, where the majority of the earth population resides. Furthermore, the health impacts are a function of the particulate size, with smaller particles being more likely to cause respiratory and pulmonary distress in certain high risk population groups. This has lead to stringent emission standards from EPA and reinforces the need to provide better satellite observations of fine mode particulates as opposed to overall AOD.

These climate and health issues clearly point to the need of improving existing monitoring strategies in order to achieve minimum SSA and fine/coarse mode estimates. Such retrievals will be a clear improvement over those currently obtained by satellites. The most used satellite sensors of the aerosol retrieval community provide only the intensity of the scattered light in multiple wavelengths (MODIS) and multiple angles (MISR). However, as pointed out by Mishchenko and Travis (1997, 1997a), the multispectral intensity does not provide the information contrast needed for detailed aerosol property retrieval and in general is limited to the total AOD. More successful retrievals are possible with the combination of intensity and polarization of the scattered light, over multiple wavelengths and angles. An instrument with such capabilities is the POLDER instrument on PARASOL. However, the limited spectral range of POLDER makes the retrievals less than optimal. This limitation has lead to the development of the APS instrument on the soon to be launched GLORY satellite (Mishchenko *et al.* 2007), which is optimal in separating out different modes and removing surface contaminations, due to its large spectral range both in the visible and in the IR.

Since data from APS are not available yet, we plan to use data from the RSP instrument (Cairns *et al.* 1999). The RSP measures light intensity and polarization at nine wavelengths in the visible and NIR (410, 470, 550, 670, 865, 960, 1590, 1880 and 2250 nm) and 152 angles from -60^o to +60^o. It has been used in a number of experiments and has produced a wealth of data , the analysis of which supports the promise for more effective aerosol retrievals with the inclusion of polarization (Chowdhary *et al.* 2001, 2002, 2006; Waquet *et al.*, 2009). In this analysis we used simulated measurements as if they were taken from RSP since our work with real RSP data is still in progress.

The inversion of multispectral, multiangle polarized reflectance data for the retrieval of the aerosol properties is not an easy task. For operational purposes, the intensity-only retrievals use look-up-tables which are reasonable when the dimension of the parameter retrieval space is small. However, the inclusion of more variables-dimensions in the parameter space renders this approach unwieldy. On the other hand, direct inversion based on a-priori covariance estimates of signal and parameter uncertainties is possible using the optimal estimator technique (Rodgers 2000, Dubovik 2004), but this approach requires extensive computing time since the inversion process must go through large scale matrix operations on a pixel-to-pixel basis. To avoid this problem, we use a neural network (NN) technique (Haykin 1999), which is specifically designed to handle multi-parameter inversion based on a-priori calculated relations between aerosol and measurement parameters. With such a NN constructed, based on suitable input-output relations, real-time inversion becomes cost-efficient.

NNs have the ability for robust inversion as long as they are built to take into account the real-world variability. This requirement poses the biggest challenge for NNs and for simplicity, we are forced at present to make some assumptions which are discussed more in depth in section 2 and need to be revisited in the future in order to build a more robust retrieval. With this limitation in mind, the current work is closer to a proof of concept of the value of NN inversion in general in extracting a broad set of aerosol parameter retrievals than a fixed algorithm for RSP or APS retrieval.

2. METHODOLOGY

2.1 Simulated dataset characteristics

Our training dataset consists of the intensity and linear polarization of light simulated as if they are measured by the RSP instrument in six visible and NIR channels (410, 470, 550, 865, 1590 and 2250 nm) above atmosphere-and-ocean synthetic scenes. In order to match our simulations with realistic conditions, we acquire the atmospheric and oceanic synthetic scenes properties from various climatologies (Dubovik *et al*. 2002, Smirnov *et al.* 2002). In addition, we consider as done in practice, a simple plane-parallel atmosphere without clouds or aloft plumes, with all the aerosols concentrated in a homogeneous marine boundary layer (MBL) of a variable height from 200 m to 1500 m (Zeng *et al.* 2004). The surface is taken as an open ocean with chlorophyll concentration in the range of 0.07-0.2 mg/m^3, wind speed of 6.5-7.5 m/sec, and no organic dissolved matter.

The aerosol properties in our simulations are taken from the global AERONET dataset (the Level 2 Almucantar Inversion Products) and the information provided in Dubovik *et al*. (2002) and Smirnov *et al.* (2002). The defining aerosol properties for retrieval include the mean radius, width and volume concentration of the fine and coarse modes of the bimodal lognormal size distributions of the particles, and the real and imaginary part of their refractive indices. Their values have characteristic natural distributions for “oceanic” and “mixed” aerosols, as defined in the climatologies. Although not a very realistic simplification, the refractive index is considered constant for all wavelengths, as in all satellite based retrievals. We also do not take into account strongly absorbing aerosols, restricting the maximum value of the imaginary part of the refractive index to 0.01. Furthermore, we make the assumption of spherically shaped particles, which is sufficient for retrieving most aerosol types, except the desert dust (Dubovik *et al*. 2006) and is consistent with the maritime application considered.

Perhaps the most biased factor of our training dataset is the geometry of the simulated measurements, which is taken to be close to the principal plane. We choose this configuration, because the majority of the RSP measurements are made along the principal plane, where there is the most information for the scattering properties of the aerosols. However, this is not going to be the case for the APS measurements, where more out of plane configurations will be realized. Thus, the difference in azimuth angle between the sun and the viewing instrument is taken to be in the range of -10^o to 10^o. The sun zenith angle is in the range of 25^o to 55^o degrees and the viewing angles are from -55^o to -35^o degrees. The viewing angles are chosen outside the domain of serious sun glint contamination.

We also take into account the absorption from water vapor, ozone and nitrogen dioxide. These gases are homogeneously distributed in the atmosphere below the aircraft and their concentrations are in the range of 1.5-3.5 cm/atm, 240-300 Db and 0.05-0.1 ppm, respectively. These values do not cover the whole range of the gases concentrations worldwide –they are only indicative values.

The aerosols, gases and surface properties describe sufficiently the simple synthetic scenes of our simulated dataset. Based on these characteristics we can calculate the intensity and the linear polarization at the aircraft level (4 km) using the adding-doubling vector radiative transfer code (De Haan *et al.* 1987) specifically designed to model the RSP measurements from Dr. Brian Cairns of the Glory team. The vertical structure of the atmosphere is an essential parameter for the accurate modeling of the polarized reflectance, especially when absorbing aerosols are present (Waquet *et al.* 2009). For this reason the information for the vertical structure of the atmosphere from lidar data is important for our retrieval method and will be ingested in it in our future work.

We also take into account the measurement and calibration noise of the RSP. We use the formulas of Waquet *et al.* (2009) to model them as:

$$\sigma_{I_i} = \sqrt{\frac{10^{-7} I_i}{\mu_0}} + 0.03 I_i$$

$$\sigma_{P_i} = \sqrt{\frac{10^{-7} P_i}{\mu_0}} + 0.03 P_i + (0.001 + 0.001 DP_i) P_i$$

where σ_I, σ_P is the noise of intensity and linear polarization measurements respectively, i denotes the measurement at a specific viewing angle and wavelength, μ_0 is the sun zenith angle, I is the light intensity, P is its linear polarization and DP is the degree of its linear polarization (DP = P/I).

The values of the synthetic scenes properties are randomly generated and are taken to be independent from each other. The distributions of the values used for all the properties are in Table 1. The aerosol properties distributions resemble the histograms of the global AERONET data. Although the aerosol properties that fall in the same group of “oceanic” or “mixed” aerosols follow the characteristic properties of the group, their values are randomly generated, independently from the other properties in the group. In this way, the NN is being trained on data which captures the natural variability and diversity expected for the particular region considered.

2.2 Neural network

The NN is a statistical tool which evaluates the inverse function of our retrieval algorithm by finding the statistical relationships between light properties (intensity and linear polarization) and aerosol characteristics. During the training stage we provide the neural network with the simulated RSP measurements of the intensity and linear polarization, paired with the aerosol properties of the corresponding synthetic scenes that generate the simulated signals. Following the common practice, we also use part of the simulated dataset for the testing stage to evaluate the performance of the retrieval. Of course, a better test for the performance and robustness of our neural network is the use of real measurements which is in progress.

We use a one-hidden-layer neural network, which is proved to be able to simulate any continuous function, making the use of more hidden layers unnecessary for our case. The input of our neural network consists of two hundred forty variables, which are the simulated RSP light intensity and linear polarization measurements over twenty viewing angles and six channels. The outputs are the mean radius and width of the fine and coarse modes, the real and imaginary part of the refractive index and the AOD at 550 nm (Table 2). We train the neural network with the neural networks toolbox of MATLAB. Specifically, we use the gradient descent with momentum and adaptive learning rate backpropagation algorithm (traingdx). From the simulated dataset we select randomly six thousand cases for the training and one thousand cases for the testing.

2.2.1 Preprocessing with Principal Component Analysis.

Unfortunately, strong multicollinearities inhibit our neural network performance due to information overlap in the measurement responses, which results in phenomena of competing neural network weights between the correlated variables. Such competition inhibits the predictive ability of the corresponding variables and results in less accurate and less robust evaluation of the outputs (Aires *et al.* 2004). The preprocessing of input variables is thus necessary in this case, but does not come without a cost, since it introduces a bias and decreases the resolution of our retrieval.

Table 1. The distributions of the values used for the simulations

				min-max	distribution type	distribution mean	distribution width
aerosol properties	oceanic aerosols	lognormal bimodal size distribution parameters	fine mode mean radius (μm)	0.1-0.25	lognormal	0.16	0.02
			fine mode width (μm)	0.3-0.7	lognormal	0.48	0.04
			fine mode volume concentration ($\mu m^3/m^3$)	0.01-0.15	lognormal	0.015	0.01
			coarse mode mean radius (μm)	1.7-4	lognormal	2.7	0.16
			coarse mode width (μm)	0.6-0.8	lognormal	0.72	0.04
			coarse mode volume concentration ($\mu m^3/m^3$)	0.01-0.2	lognormal	0.03	0.02
		real part of refractive index		1.33-1.42	normal	1.36	0.01
		imaginary part of refractive index		0-0.01	lognormal	0.0015	0.001
	mixed aerosols	lognormal bimodal size distribution parameters	fine mode mean radius (μm)	0.1-0.25	lognormal	0.18	0.03
			fine mode width (μm)	0.3-0.7	lognormal	0.46	0.04
			fine mode volume concentration ($\mu m^3/m^3$)	0.01-0.15	lognormal	0.03	0.03
			coarse mode mean radius (μm)	1.7-4	lognormal	2.84	0.31
			coarse mode width (μm)	0.6-0.8	lognormal	0.76	0.05
			coarse mode volume concentration ($\mu m^3/m^3$)	0.01-0.2	lognormal	0.038	0.04
		real part of refractive index		1.38-1.55	normal	1.44	0.02
		imaginary part of refractive index		0-0.01	lognormal	0.011	0.007
surface properties (open ocean)		wind speed (m/sec)		6.5-7.5	uniform		
		chlorophyll concentration (mg/m^3)		0.07-0.2	uniform		
atmospheric gases concentrations		water vapor (cm/atm)		1.5-3.5	uniform		
		ozon (Db)		240-300	uniform		
		nitrogen dioxide (ppm)		0.05-0.1	uniform		
		MBL height (m)		200-1500	uniform		
geometry of the measurement		sun zenith angle (degrees)		25^o-55^o	uniform		
		viewing angles (degrees)		20 angles from -55^o to -35^o	none (fixed values)		
		difference in azimuth between the sun and the RSP (degrees)		-10^o - $+10^o$	uniform		
		RSP height (m)		4000	none (fixed value)		

Table 2. Neural Network Input / Output

<table>
<tr><td colspan="3">Input (light properties)</td><td colspan="2">Output (aerosol properties)</td></tr>
<tr><td colspan="2">before PCA (240 variables)</td><td>after PCA (100 PCs)</td><td colspan="2">aerosol optical depth at 550 nm</td></tr>
<tr><td rowspan="2">Intensity</td><td>6 RSP channels (410, 470, 550, 865, 1590, 2250 nm)</td><td rowspan="2">40 PCs of Intensity</td><td rowspan="4">lognormal bimodal size distribution parameters</td><td>fine mode mean radius</td></tr>
<tr><td>20 view angles (from -55^o to -35^o degrees)</td><td>fine mode width</td></tr>
<tr><td rowspan="4">Linear Polarization</td><td>6 RSP channels (410, 470, 550, 865, 1590, 2250 nm)</td><td rowspan="4">60 PCs of Linear Polarization</td><td>coarse mode mean radius</td></tr>
<tr><td rowspan="3">20 view angles (from -55^o to -35^o degrees)</td><td>coarse mode width</td></tr>
<tr><td colspan="2">real part of refractive index</td></tr>
<tr><td colspan="2">imaginary part of refractive index</td></tr>
</table>

For the elimination of collinearities in the input variables we perform Principal Component Analysis (PCA) (Jolliffe 2002) and reduce the redundancy to acceptable levels. The result is the transformation of the input variables to their Principal Components (PCs) which retain the information of the original variables, while they are orthogonal and thus free of any collinearities. We find first the PCs using the noise-free version of the simulated dataset. Then, the input to the NN is the projection of the noisy data on the calculated PCs space. We use the noise-free version of the dataset instead of the noisy dataset, since in this case the calculated PCs are closer to the real dataset structure and are not affected by the noise. This is especially true for the PCs that express the finer structures, although such structures are masked by the noise anyway.

We perform the PCA separately for the intensity and the linear polarization variables. The selection of the PCs is based on the percentage of the total variance they explain (Jolliffe 2002). Thus we keep the first forty PCs of the intensity variables and the first sixty PCs of the linear polarization variables, which are enough to explain practically 100% of the total variance. The noisy data are then projected on the space of the selected PCs and this new dataset is the input to our NN. The output data do not present any collinearities, thus no preprocessing is necessary for them.

3. DISCUSSION OF THE RETRIEVAL RESULTS

We have tested the performance of our neural network on one thousand cases (~15% of the total dataset). We found that all the retrieved aerosol parameters have a RMSE above 0.97. Specifically, the AOD at 550 nm is retrieved with an RMSE of 0.98 (Figure 1). In the figure, the “true values” are the AOD values used for simulating the testing dataset and the corresponding “retrieved values” are the calculated values from the NN. The rest of the aerosol properties are calculated with high accuracies as well (Figure 2). In particular, the imaginary part of the refractive index and the width of the coarse mode are retrieved with a RMSE of 0.99. The real part of the refractive index and the mean radius of the fine and coarse modes are retrieved with a RMSE close to 0.98. Lastly, the width of the fine mode is retrieved with a RMSE of 0.97.

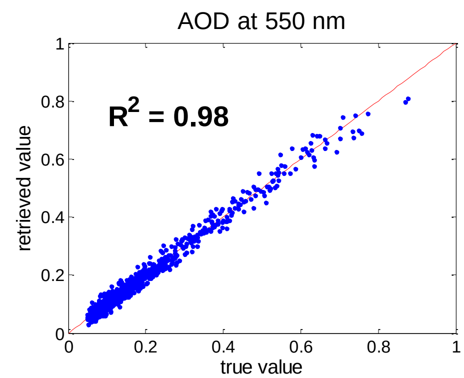

Figure 1. The neural network retrieval of AOD at 550 nm. The red line is the 1-1 line.

The promising preliminary results reported in this work indicate that the proposed retrieval method has the potential for real-time evaluation of the aerosol properties. Further improvements with the use of a more realistic simulated dataset, as well as real RSP and APS data, are expected to cure the deficiencies of this first attempt.

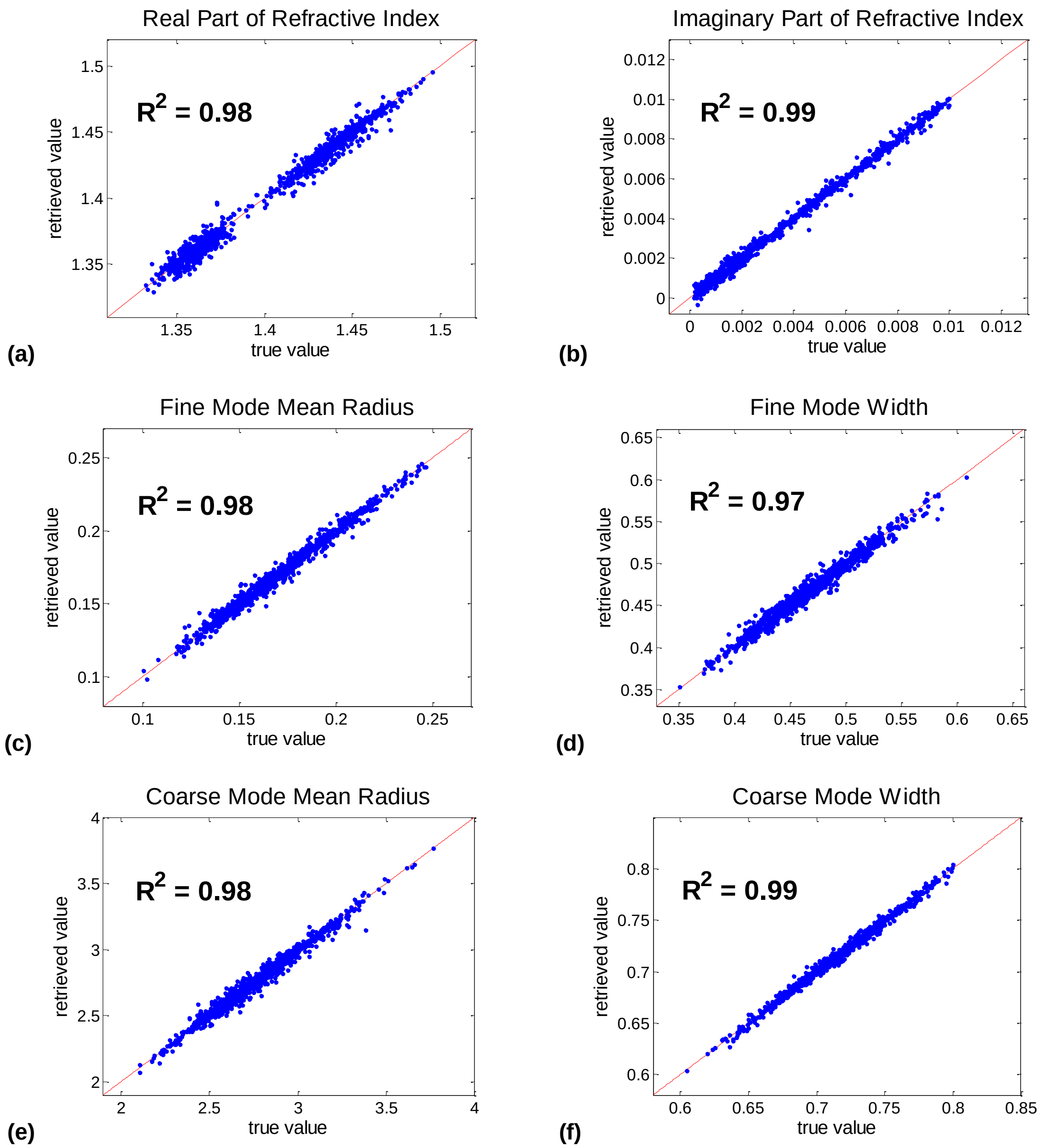

Figure 2. The neural network retrieval of the aerosol microphysical properties: (a) real part of the refractive index, (b) imaginary part of the refractive index, (c) mean radius of the fine mode, (d) width of the fine mode, (e) mean radius of the coarse mode and (f) width of the coarse mode. The red line is the 1-1 line.

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