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A New Algorithm for Simultaneous Retrieval of Aerosol and Marine Parameters in Coastal Environments

K. Stamnes^a, W. Li^a, Y. Fan^a, B. Hamre^b, Ø. Frette^b, A. Folkestad^c, K. Sørensen^c
and J. J. Stamnes^b

^a*Department of Physics and Engineering Physics, Stevens Institute of Technology, Hoboken, NJ 07030, USA*

^b*Department of Physics and Technology, University of Bergen, N-5007, Bergen, Norway*

^c*Norwegian Institute of Water Research, N-0349, Oslo, Norway*

Abstract. We present simultaneous retrievals of aerosol and marine parameters in coastal areas from ocean color data using the OC-SMART algorithm, *Ocean Color: Simultaneous Marine and Aerosol Retrieval Tool*. OC-SMART uses a one-step nonlinear optimal estimation/Levenberg-Marquardt method instead of the traditional two-step look-up table approach to improve retrieval accuracy, and a radial basis function neural network (RBF-NN) forward radiative transfer model for the coupled atmosphere-water system to increase retrieval speed without loss of accuracy. We discuss applications of OC-SMART to analyze SeaWiFS, MERIS, and MODIS images obtained over coastal waters. Five parameters are obtained from the retrieval: aerosol optical depth, aerosol bi-modal fraction, chlorophyll concentration, CDOM absorption, and backscattering coefficient. The water leaving radiance is provided as a by-product.

Keywords: Ocean color, Remote sensing, Radiative transfer, Coastal water.

PACS: 42.68.-w

INTRODUCTION

Li et al. [1] presented an algorithm for simultaneous retrieval of aerosol and marine parameters which used a linearized coupled atmosphere-ocean radiative transfer model (C-DISORT), and an inverse algorithm based on optimal estimation. Because this algorithm simultaneously used all available visible and near infrared satellite measurements, it provided not only a more accurate retrieval than the traditional two-step approach based on look-up tables for atmospheric correction [2,3], but also retrieval of two aerosol as well as three marine parameters (chlorophyll concentration, CDOM absorption coefficient, and backscattering coefficient). Furthermore, this algorithm [1] is very useful for coastal areas, where the black pixel assumption may not be valid [4], and where more than one parameter is required to adequately describe the water. In contrast, open ocean marine bio-optical properties can be assumed to co-vary with the chlorophyll concentration, so that retrieval of only one marine parameter (chlorophyll concentration) is sufficient. Thus, this forward-inverse algorithm provides a valuable tool for ocean color remote sensing that is expected to be especially useful for retrieval of aquatic parameters in complex turbid waters such as those encountered in lakes and rivers, as well as in estuarine and coastal areas. The accuracy of the retrieval will depend to a large extent on the realism of the atmospheric aerosol model and the aquatic bio-optical model that provide links between the inherent optical properties used in the forward model and the retrieval parameters.

From an operational point of view, the algorithm described by Li et al. [1] is time-consuming because the iterative, non-linear optimal estimation requires a call to the forward radiative transfer (RT) model at each iteration step to simulate the radiances and Jacobians for the current state vector. For fast computation of radiances and Jacobians, we have adopted a neural network function to replace the direct call to the forward RT model [5,6]. In the retrieval part, the Levenberg-Marquardt optimal estimation scheme is used to determine the parameters that best fit the measurements. Here we focus on MODIS image retrieval over the Santa Barbara Channel. The algorithm has been applied to ocean color data obtained from the SeaWiFS and MERIS instruments and could be applied to other ocean color satellite instruments in any coastal area once the corresponding aerosol model and bio-optical ocean model have been established. We used C-DISORT, the DISORT radiative transfer model for the coupled atmosphere-ocean system [7-9] to simulate the radiances measured in the MODIS channels for randomly selected geometries as well as aerosol and marine parameters. Besides the geometry, there are 5 inputs: aerosol optical depth

at 865 nm, aerosol bi-modal fraction, chlorophyll concentration, CDOM absorbing coefficient at 443 nm, and backscattering coefficient at 443 nm.

METHOD

We use the US standard atmospheric model profile and divide it into 24 layers to determine molecular scattering and absorption properties, and added aerosols between altitudes 0 and 2 km. We use the 80 SeaDAS aerosol models based on AERONET data described by Ahmad et al. [10]. The bi-modal aerosol approach used here is based on these 80 aerosol models, which are the same as those currently used in NASA's SeaDAS software package consisting of 8 groups of aerosol models based on relative humidity with 10 models in each group based on the fraction of large versus small particles, but instead of a *discrete* set of 80 aerosol models we use a *continuum* of models with bi-modal (fine mode) fractions between 0 and 95%, and relative humidities ranging from 30 to 95%. The humidity is obtained from ancillary data available as part of the SeaDAS software package.

Based on field measurements obtained in the Santa Barbara Channel (SBC) and compiled in the NOMAD database [11], Li et al. [1] constructed a bio-optical for the SBC coastal waters. In this model the IOPs are derived from wavelength-dependent parameterizations of the phytoplankton absorption coefficient, the detritus and colored dissolved material (CDOM) absorption coefficient, and the total backscattering coefficient. The model is described by three retrieval parameters CHL, CDM, and BBP, and four model coefficients. CHL is the chlorophyll concentration, CDM is the CDOM absorption coefficient at 443 nm, and BBP is the backscattering coefficient at 443 nm. Although this SBC bio-optical model is not a general model, it is representative for a coastal water scenario. Another frequently used bio-optical model is the GSM model, included in NASA's SeaDAS software package, which has the same structure as the SBC model, but with different coefficients.

The traditional two-step retrieval method based on lookup tables cannot be used for simultaneous retrieval of multiple parameters. An iterative, non-linear inversion method can solve this problem by simultaneous use of the information available in all instrument channels. But repeated use of the forward model to compute the required radiances and Jacobians is computationally demanding. In order to circumvent this problem, we replaced the forward RT model with a radial basis function neural network (RBF-NN) to establish a relationship between the retrieval parameters and the simulated spectral radiances. The RBF-NN functions consist of two layers with a radial basis layer of hidden neurons, and a linear layer of output neurons. We trained a RBF-NN to provide an analytic relationship between the retrieval parameters and the simulated radiances, and used this relationship to derive an analytic expression for the Jacobians. Both the radiances and the Jacobians are required in the non-linear optimal estimation retrieval. Using the forward RT model, we calculated 12,000 simulation cases. The input parameters to the forward model were 2 atmospheric parameters (aerosol optical depth at 865 nm, and the aerosol bimodal fraction f), 3 marine parameters (CHL, CDM, and BBP), and 3 solar and satellite sensor geometry angles (solar zenith angle, sensor zenith angle, and azimuth angle). We used a random function to select values for these input parameters for the 12,000 cases. This data set was used for training/testing of the forward NN. The output data were the simulated TOA radiances in all satellite channels.

We use Levenberg-Marquardt (LM) optimal estimation techniques appropriate for non-linear iterative spectral fitting. The details of this approach [12] are described by Li et al. [1].

RESULTS

Figure 1 shows a comparison of retrievals with OC-SMART and the SeaDAS package for a MODIS image obtained over SBC on November 15, 2010. Level 1B radiances, calibrated, cloud-screened, and corrected for white caps and sunglint, were used as input to both algorithms, and the same bio-optical model (GSM) and the same aerosol models (SeaDAS) were used in both algorithms. Thus, the differences between the two retrieval results can be ascribed to the 2-step atmospheric correction approach used by SeaDAS and the 1-step simultaneous retrieval used by OC-SMART.

TOA reflectance residuals are defined as the percentage difference between the measured reflectance at the TOA, and the computed reflectance based on the retrieved IOPs. In Fig. 2 we show reflectance residuals for the OC-SMART retrievals for MODIS channels centered at 412, 443, 488, 531, 547, 667, 678, 748, and 869 nm. We note that the residuals are generally quite small.

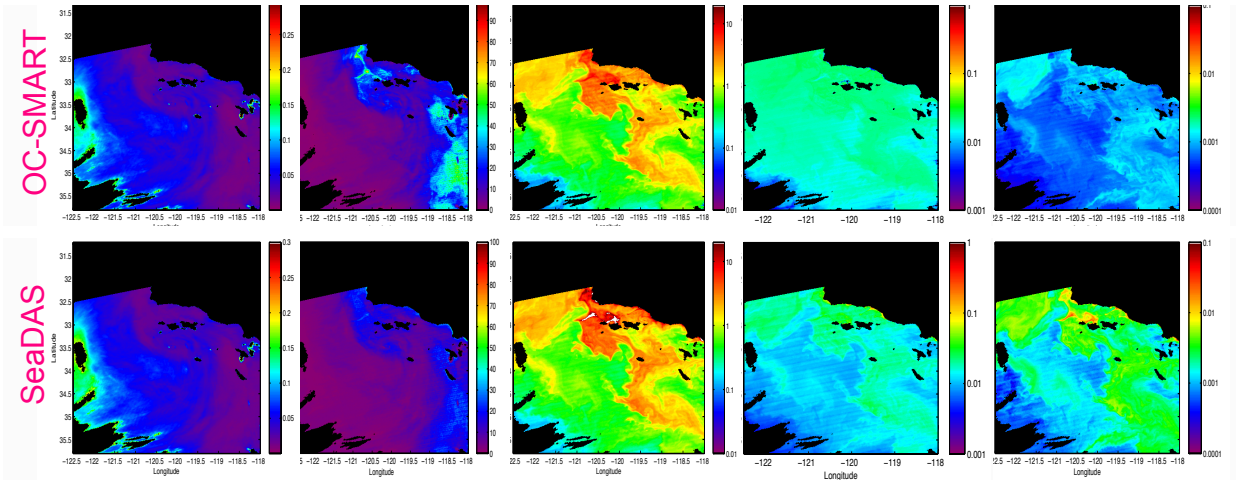


FIGURE 1. Comparison of OC-SMART (upper panels) and SeaDAS (lower panels) retrievals. From left to right: Aerosol optical depth, aerosol fraction, chlorophyll concentration, CDOM absorption coefficient, and backscattering coefficient.

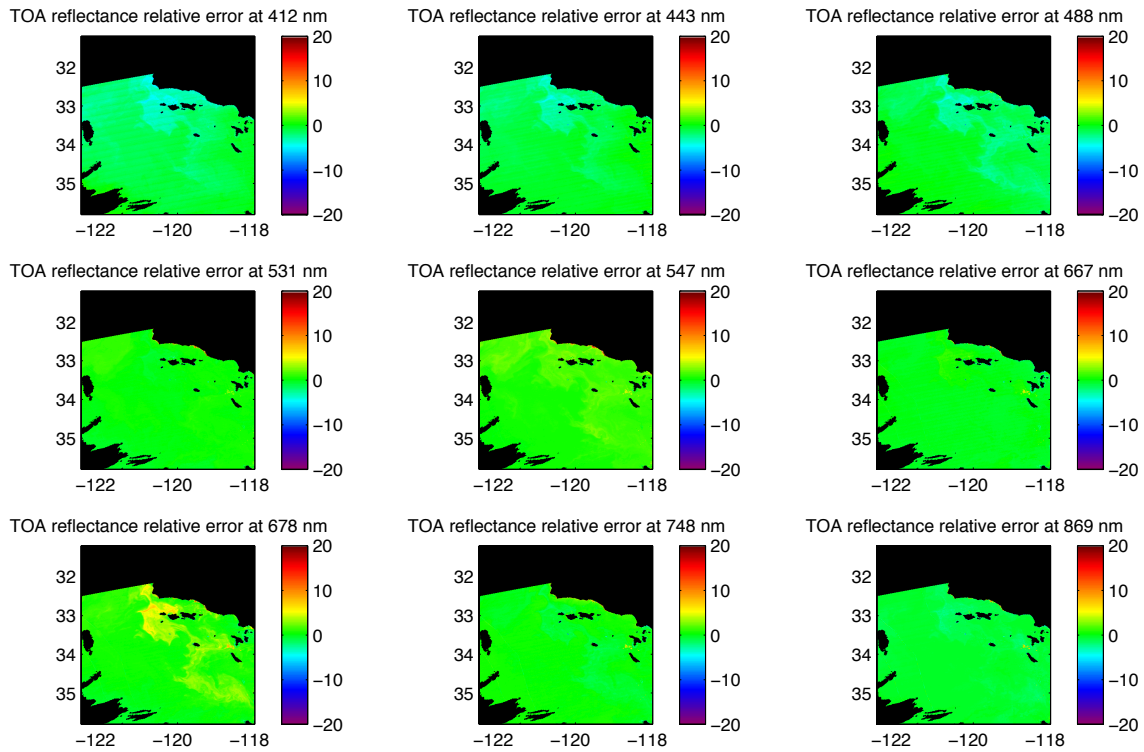


FIGURE 2. TOA reflectance residuals at 9 MODIS channels for the OC-SMART retrievals. The numbers on the horizontal axis indicate Longitudes, and those on the vertical axis indicate Latitudes.

Similar results for the SeaDAS retrievals are shown in Fig. 3. The SeaDAS retrievals have larger residuals than OC-SMART especially for wavelengths 531, 547, 667, and 678 nm, and at the cloud edges. To investigate possible reasons for the differences in the residuals, we found that using OC-SMART inferred aerosol parameters, but SeaDAS inferred marine parameters led to residuals that were considerably reduced.

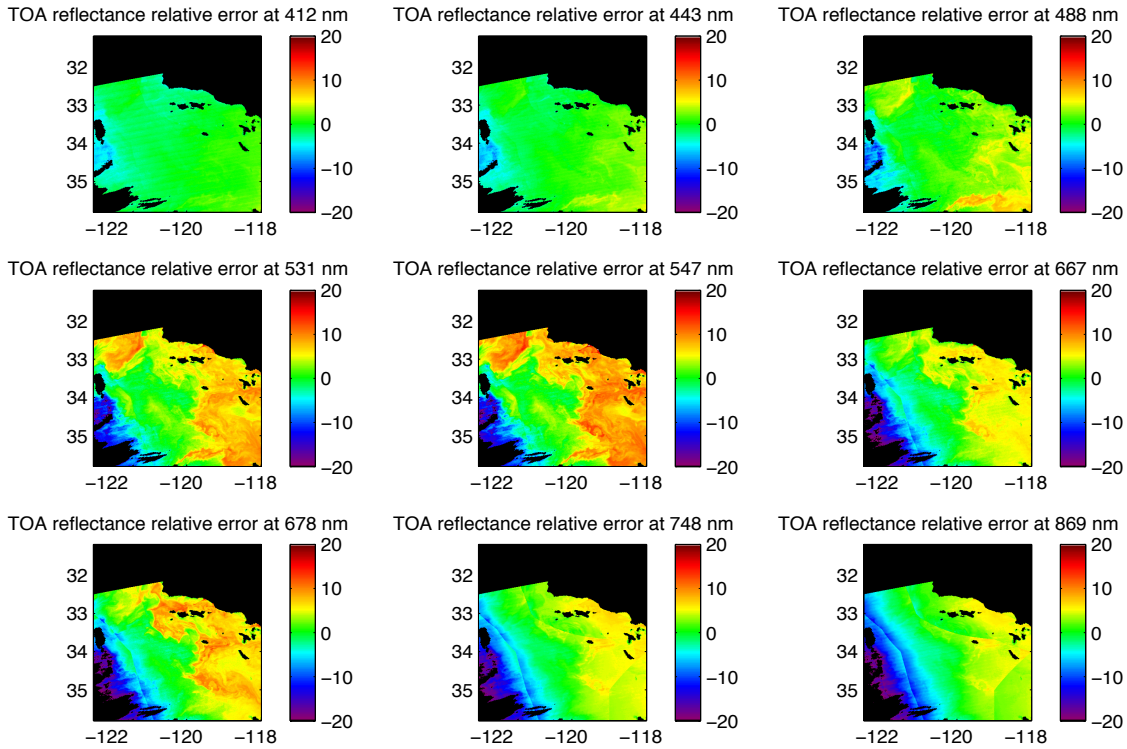


FIGURE 3. TOA reflectance residuals at 9 MODIS channels for the SeaDAS retrievals.

SUMMARY

The salient features of the OC-SMART method may be summarized as follows: (i) C-DISORT provides accurate radiances at both the TOA and the ocean surface (Rrs values); (ii) C-DISORT can be used to estimate residuals and thus check the quality of the retrievals; (iii) the OE/LM inverse method provides simultaneous retrieval of aerosol and several marine parameters; (iv) the aerosol and bio-optical models can be easily changed, which is valuable because a given coastal region may require a *local* marine bio-optical model to represent water IOPs, and a *local* aerosol IOP model; (v) RBF-NN training of the forward RT model provides fast yet accurate retrievals; (vi) OC-SMART has already been applied to different sensors, including MERIS, MODIS, and SeaWiFS and to high-latitude data; (vii) the C-DISORT code used in OC-SMART includes Earth curvature effects, and is therefore suitable for use in polar regions where low solar zenith angles prevail.

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