Journal of Quantitative Spectroscopy & Radiative Transfer 204 (2018) 215–231

Contents lists available at ScienceDirect

Journal of Quantitative Spectroscopy & Radiative Transfer

journal homepage: www.elsevier.com/locate/jqsrt

A demonstration of adjoint methods for multi-dimensional remote sensing of the atmosphere and surface

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ARTICLE INFO

Article history:
Received 4 July 2017
Revised 29 September 2017
Accepted 29 September 2017
Available online 30 September 2017

Keywords:
Adjoint methods
Three-dimensional vector radiative transfer
Linearization
Remote sensing
Parameter derivatives
Searchlight functions

ABSTRACT

In previous work, we derived the adjoint method as a computationally efficient path to three-dimensional (3D) retrievals of clouds and aerosols. In this paper we will demonstrate the use of adjoint methods for retrieving two-dimensional (2D) fields of cloud extinction. The demonstration uses a new 2D radiative transfer solver (FSDOM). This radiation code was augmented with adjoint methods to allow efficient derivative calculations needed to retrieve cloud and surface properties from multi-angle reflectance measurements. The code was then used in three synthetic retrieval studies.

Our retrieval algorithm adjusts the cloud extinction field and surface albedo to minimize the measurement misfit function with a gradient-based, quasi-Newton approach. At each step we compute the value of the misfit function and its gradient with two calls to the solver FSDOM. First we solve the forward radiative transfer equation to compute the residual misfit with measurements, and second we solve the adjoint radiative transfer equation to compute the gradient of the misfit function with respect to all unknowns.

The synthetic retrieval studies verify that adjoint methods are scalable to retrieval problems with many measurements and unknowns. We can retrieve the vertically-integrated optical depth of moderately thick clouds as a function of the horizontal coordinate. It is also possible to retrieve the vertical profile of clouds that are separated by clear regions. The vertical profile retrievals improve for smaller cloud fractions. This leads to the conclusion that cloud edges actually increase the amount of information that is available for retrieving the vertical profile of clouds. However, to exploit this information one must retrieve the horizontally heterogeneous cloud properties with a 2D (or 3D) model.

This prototype shows that adjoint methods can efficiently compute the gradient of the misfit function. This work paves the way for the application of similar methods to 3D remote sensing problems.

1. Introduction

Remote sensing technologies provide data products that guide predictive modeling efforts [1–4]. Images at solar wavelengths measure the intensity of light from the sun that has been transmitted through or scattered by the clouds and aerosols in the atmosphere and reflected by the Earth's surface. Generally, the images must be processed by a retrieval algorithm to obtain maps of the properties of the clouds, aerosols, and surface that are of interest [5–11]. Persistent issues with remote sensing technologies are caused by approximating radiative transfer with a one-dimensional (1D) model. The 1D approximation neglects all horizontal variability of scattering material in the atmosphere. So, it is not possible to model the effects of horizontal cloud edges with 1D radiative transfer calculations that are used to transform radiometric measurements into retrievals of cloud, aerosol and surface properties [12]. In cloudy regions the properties of the clouds are retrieved [6], and in clear regions the properties of aerosols are retrieved [8,9,13,14]. At the interface between cloudy and clear regions we would like to recover both the cloud properties and the aerosol properties, but without modeling the three-dimensional (3D) radiative effects caused by cloud edges there are wide swaths along the cloud edge where neither aerosols nor clouds can be retrieved [15,16]. Shadows on the surface can also affect the retrieval of surface properties. Slightly farther from the cloud edge it is possible to retrieve aerosol properties, but they are often biased [15,17]. There is also bias in the retrieved cloud properties due to horizontal variability that is not resolved by 1D models [18,19]. To retrieve cloud and aerosol properties together in regions near cloud edges, we need to model radiative transfer in 3D.

Going from 1D to 3D retrievals increases the problem size and complexity dramatically. Both the number of measurements and

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https://doi.org/10.1016/j.jqsrt.2017.09.031
0022-4073/© 2017 Published by Elsevier Ltd.

Nomenclature

Remote sensing problem

N	Number of unknowns
M	Number of measurements
$\boldsymbol{a}$	State vector
a^n	State vector elements
$\boldsymbol{y}_{\mathrm{data}}$	Measurements vector
y^m_{data}	Measurement vector elements
$\boldsymbol{F}(\boldsymbol{a})$	Forward model vector
$y^m(\boldsymbol{a})$	Forward model elements
$\Phi_{\mathrm{d}}(\boldsymbol{a})$	Measurement misfit function
$\Phi_{\mathrm{r}}(\boldsymbol{a};\ \gamma)$	Regularized misfit function

Domain

$\boldsymbol{x} = (x, z)$	Position in space
φ	Angle counter-clockwise from x
$\mathbb{S}^1$	Unit circle
D	Spatial domain
Γ_+	Outgoing boundary
Γ_-	Incoming boundary
$D \times \mathbb{S}^1$	Interior set

Basis for numerical methods

$X_j(\boldsymbol{x})$	Basis for cloud retrieval
$\tilde{X}_i(\boldsymbol{x})$	High resolution solver basis
$(\tilde{\mathrm{X}}\tilde{\mathrm{X}}\mathrm{X})_{ii'j}$	Triple products, Eq. (70)
$\overset{\mathrm{surf}}{(\mathrm{XX})}_{ii'}$	Surface products, Eq. (74)

Radiative transfer solutions

$u(\boldsymbol{x},\ \varphi)$	Forward intensity, Eq. (61)
U^i_0	Coefficient array for direct sunlight
f	Internal source solution
g	Incoming source solution
$w(\boldsymbol{x},\ \varphi)$	Adjoint intensity, Eq. (84)
$\tilde{w}^{m_x m_\varphi}$	Searchlight functions, Eq. (62)
$\tilde{w}_0$	Adjoint direct beam, Eq. (79)
$\mathrm{W}^{im_\varphi}_0$	Coefficient array for $\tilde{w}_0$, Eq. (80)
p	Adjoint internal source solution
q	Adjoint outgoing source solution

Linear operators

$\mathcal{Z}[\cdot]$	Scattering operator
$\mathcal{R}[\cdot]$	Reflection operator
$\mathcal{T}[\cdot]$	Streaming operators, Eqs. (28)-(36)
$\mathcal{Z}^*[\cdot]$	Adjoint scattering operator
$\mathcal{R}^*[\cdot]$	Adjoint reflection operator
$\mathcal{T}^*[\cdot]$	Adjoint streaming, Eqs. (46)-(51)

the number of unknown parameters (for each retrieval) increase by 2–3 orders of magnitude. The scalability of the retrieval algorithm becomes a significant concern. This issue of scalability was noticed in 1984 by the seismic imaging community and led to the development of adjoint methods for 3D imaging of the solid earth with pressure waves [20]. Later, in the medical imaging community adjoint methods were used to retrieve tissue properties in two dimensions (2D) [21,22] and 3D [23]. In comparison to the radiative transfer equation used for medical imaging, the equations for modeling multiangle measurements of the atmosphere are complicated by the singularity of incoming solar radiation (in direction) and the near singularity of the detector response functions for measurements (in both direction and space) [24]. Computational codes for solving the forward radiative transfer problem in 3D are available [25–29], and a theoretical framework for 3D remote sensing of the atmosphere with adjoint methods was described by Martin et al. [30]. However, the computational implementations of adjoint methods for atmospheric remote sensing are still limited to 1D [31], spherical [32,33], and pseudo-spherical domains [34,35].

The objective of this paper is to show a computational demonstration of adjoint methods for atmospheric remote sensing in multiple spatial dimensions. To this end, we have developed a radiative transfer solver for a simplified 2D domain which maintains the key implementation challenges caused by the singularity of solar light sources and measurement response functions [24]. This approximate 2D setting has been used to demonstrate other radiative transfer ideas for atmospheric remote sensing [36] and has been used to test new algorithms for rendering 3D animations [37]. Our forward solver models measurements of intensity at multiple angles across the top of a 2D domain. A non-linear least-squares misfit function is defined to setup the retrieval of the cloud extinction field as a function of the horizontal and vertical coordinates. The challenges caused by the singularities in the solar light source and detector response functions are overcome by modifying the source function integration technique used by SHDOM [27] to develop the searchlight function integration technique. This enables us to implement the adjoint method and compute the misfit function and its gradient with a total of two calls to the radiative transfer solver. The fast gradient calculations allow us to use gradient-based numerical optimization methods to retrieve the 2D field of cloud properties from multiangle measurements [38].

Readers who are primarily interested in the performance of the adjoint method may wish to skim Section 2 and then skip to Section 5, where we present synthetic retrievals using an approximate 2D radiative transfer code. Section 2 describes the retrieval algorithm and motivates the use of adjoint methods as a tool for calculating the gradient of the misfit function. The efficient calculation of the gradient is essentially a technical subproblem, and we discuss it in detail in Sections 3 and 4. Section 5 shows three different synthetic retrieval studies, and Section 6 sums up results and discusses plans for future research.

2. Remote sensing of the atmosphere

Let's consider a brief illustration of the problem of interest. Suppose that we are on an airplane flying over a field of fair-weather cumulus clouds and that we take several pictures of one particularly interesting cloud formation. Upon returning home we want to build a 3D model of the cloud with cotton balls and glue. Each picture gives a new perspective of the cloud and by carefully examining all the pictures together, we can make a 3D model of the cloud's shape. In the process of building a cotton-ball cloud model like this, we actually face many of the same challenges that make multidimensional remote sensing difficult. Firstly, if we try to make the cloud model too large it will require too much cotton to fill in the cloud. Analogously, on a computer it takes many unknown parameters to define the spatial variability of a cloud in multiple dimensions. Even in the 2D demonstration shown here, the number of unknowns is larger than 4500 for fairly small regions 10km wide and 3km high. Secondly, to check that the cotton-ball cloud model matches the cloud formation in our pictures, we must shine a light