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Efficient radiative transfer model inversion for remote sensing applications

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ABSTRACT

A simple method for efficient inversion of arbitrary radiative transfer models for image analysis is presented. The method operates by representing the shape of the function that maps model parameters to spectral reflectance by an adaptive look-up tree (ALUT) that evenly distributes the discretization error of tabulated reflectances in spectral space. A post-processing step organizes the data into a binary space partitioning tree that facilitates an efficient inversion search algorithm. In an example shallow water remote sensing application, the method performs faster than an implementation of previously published methodology and has the same accuracy in bathymetric retrievals. The method has no user configuration parameters requiring expert knowledge and minimizes the number of forward model runs required, making it highly suitable for routine operational implementation of image analysis methods. For the research community, straightforward and robust inversion allows research to focus on improving the radiative transfer models themselves without the added complication of devising an inversion strategy.

1. Introduction

Inversion of physics-based radiative transfer models is an area of rapid development in remote sensing of both aquatic and terrestrial environments (Liang, 2007). In these approaches a parameterized forward model for reflectance such as Hydrolight (for aquatic applications) or PROSPECT, PROSAIL or DART (for terrestrial canopies) takes a series of parameters describing the optical properties of participating media or canopy structure and the model defines a mapping from parameter space to spectral space (Fig. 1a) (Darvishzadeh et al., 2008; Gastellu-Etchegorry et al., 2003; Mobley et al., 2005; Zhang et al., 2008). Image analysis then uses a search algorithm to find the parameter space location which minimizes the distance of the corresponding spectral space location from the image pixel reflectance, measured by a distance metric such as Euclidean distance. Two distinct approaches to the search algorithm can be identified: 1) pre-calculation of reflectance look-up tables (LUTs) by repeated runs of the forward model with systematically differing parameter values (Mobley et al., 2005), optionally with interpolation across tabulated points (Gastellu-Etchegorry et al., 2003; Liang et al., 2006) and 2) spectral matching by successive approximation using optimization techniques such as the Downhill Simplex or Levenberg–Marquardt (L–M) algorithm (Brando et al., 2009; Goodman & Ustin, 2007; Klonowski et al., 2007; Lee et al., 1999; Wolfe, 1978), which is feasible only if the forward model is sufficiently fast to permit many runs for each image pixel. With either approach, for a complex radiative transfer model, both the forward modeling and the inversion may take substantial computational effort. Routine or large-scale operational image analysis by physics-based methods therefore demands the development of efficient approaches for both modeling and inversion. Often the forward model is simplified or approximated to facilitate inversion. In contrast, we develop a generic inversion technique which allows the use of any forward model and hence model accuracy need not be compromised.

A key problem in the efficient representation of the parameter to reflectance mapping function is that it is not generally clear a priori how to subdivide the parameter space in order to evenly populate spectral space from the forward model. For example, modeled shallow water reflectance typically has an inverse exponential relationship with depth (Mobley, 1994), so a regular subdivision of a depth parameter would over-sample the deep water spectral space region with similar reflectance spectra produced from unnecessary forward model runs. At the same time the shallow water spectral space region would be relatively under-sampled with a higher discretization error in the tabulated reflectances (Fig. 1b). The interaction between multiple parameters (e.g. depth vs. water clarity) makes the general problem of efficient and accurate LUT construction very hard to tackle by analytical means.

To address this problem we present an automated construction procedure for adaptive look-up trees (ALUTs) that evenly distributes and minimizes the discretization error in spectral space and facilitates fast inversion (Fig. 1). The construction technique can be applied to any forward radiative transfer model that is parameterized by a series of real and integer values. The following sections describe 1) the requirements of a forward model to which the ALUT construction

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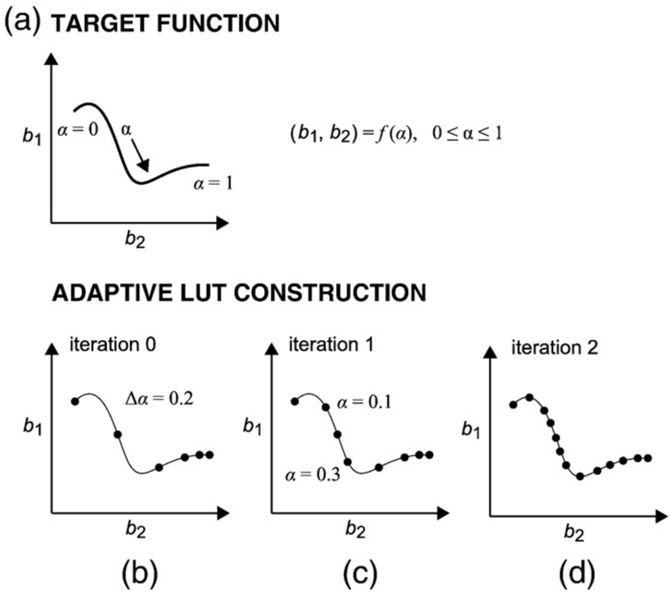

Fig. 1. Adaptive LUT construction for a forward model of one continuous parameter, α, mapping to two spectral bands, $\langle b_1, b_2 \rangle$. (a) The mapping function from parameter space to spectral space which the LUT seeks to accurately represent. (b) Discretization by regular steps in parameter space over-samples some regions of spectral space and under-samples others. (c) and (d) iterative adaptive construction fills in the gaps to approximate an even distribution of points in spectral space and efficiently represent the function.

method can be applied 2) the adaptive construction algorithm, and 3) the methodology for building and searching the tree representation of the ALUT. The subsequent sections present an illustrative example of ALUT construction using a shallow water radiative transfer model (Lee et al., 1999) and its application to hyperspectral airborne imagery of a coral reef.

2. Methods

2.1. Mapping from parameter space to spectral space

The adaptive LUT construction can be applied to any forward model for n-band remote sensing reflectance modeled dependent on a set of set of m real-valued parameters, $\alpha_1, \alpha_2 \ldots \alpha_m$, and any number of discrete integer parameters, $i_1, i_2 \ldots$, etc. As a first step, any discrete valued parameters are combined into a single integer parameter by $i = i_1 + i_2 N_1 + i_3 N_1 N_2 + \ldots$ so that $i = 1, 2 \ldots N$, where $N_1, N_2 \ldots$ are the maximum value each integer parameter can take and N is the product of the maximum values. This gives a set N of mapping functions from the real-valued parameter space to remote sensing reflectance in spectral space,

$$f_i : \mathbb{R}_m \rightarrow \mathbb{R}_n \qquad \langle \alpha_1, \alpha_2 \ldots \alpha_m \rangle \mapsto \mathbf{R}_{rs} \tag{1}$$

where f_i is the forward model for particular discrete value of i and each f_i consists of an assumed continuous mapping from m-dimensional parameter space to n-dimensional spectral space, with $\mathbf{R}_{rs}$ being the spectral remote sensing reflectance in n-vector form. The separation of discrete and continuous parameters is necessary because the adaptive subdivision can only be applied to the continuous parameters. In essence, a series of separate ALUTs are constructed, one for each value of i, this accommodates forward models that contain discrete parameters, for example where a model component is based on a choice of one from a set reflectance spectra. The only additional requirement is that a priori limits for the continuous parameters are defined, so that $\alpha_i^{\mathrm{MIN}} \le \alpha_i \le \alpha_i^{\mathrm{MAX}}$, this is the same as is required for any LUT methodology and is also often used in successive approximation techniques to constrain the mapping function domain.

2.2. Adaptive look-up-table construction

ALUT construction begins with an initial regular subdivision of parameter space (as shown for 1-dimensional parameter space in Fig. 1b), then an iterative algorithm repeatedly assesses which regions in parameter space correspond to currently under-sampled regions of spectral space, the most effective parameter is subdivided in that region, the new points are added to the ALUT and the iteration continues (Fig. 1c,d).

The key to implementing the subdivision algorithm for m-dimensional parameter space is that the ALUT structure is represented as a hierarchical voxelation of the parameter space, where voxels are m-dimensional parameter bounding boxes, the 2^m vertices of which are current points in the LUT (Fig. 2). To assess the local point distribution in spectral space, change in $\mathbf{R}_{rs}$ across the voxel is assessed by taking the mean distance in spectral space when changing

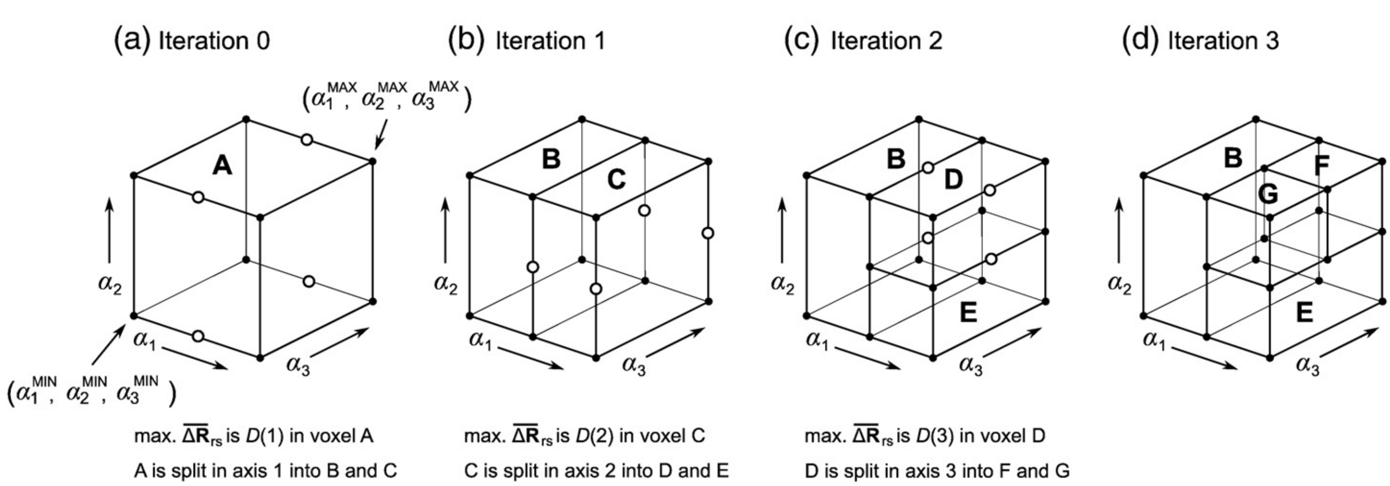

Fig. 2. Hierarchical voxelation of parameter space for a forward model of three continuous parameters $\langle \alpha_1, \alpha_2, \alpha_3 \rangle$. Black dots show the parameter space location of points in the ALUT where $\mathbf{R}_{rs}$ has been calculated, open circles show where subdivision is occurring and points need to be calculated for the next iteration.