CAPABILITIES AND LIMITATIONS OF METHODS FOR BRDF CHARACTERIZATION IN IMAGING SPECTROMETRY DATA

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ABSTRACT

Anisotropic reflectance behavior is typical for all natural surfaces. The target- and wavelength-specific characteristics of this physical phenomenon may be expressed by the conceptual quantity of the Bidirectional Reflectance Distribution Function (BRDF).
On the one hand, characterization of the BRDF may enable to better estimate biophysical and biochemical as well as structural parameters of the observed surface. On the other hand, reflectance anisotropy often is considered an interfering effect in airborne or spaceborne Imaging Spectrometry data. Changes in within-scene across-track radiometry, which are caused by the sensor view angle variation, can lead to misclassification or improper estimation of the surface properties of interest. Anisotropy is especially pronounced for sensor systems that feature wide field-of-view optics, as it is the case for a number of current and future instruments, both airborne and spaceborne. Accurate quantitative data analysis most often requires a normalization of the existing reflectance anisotropy, especially for the derivation of albedo products. State-of-the-art sensor systems have implemented dedicated, operational BRDF analysis steps into their data processing chain (e.g. MODIS). Full BRDF characterization requires a number of multi-angular observations; proper correction for reflectance anisotropy therefore is more error-prone and less amenable to validation in airborne single-pass imagery.

This paper reports on present achievements in the analysis of both empirical, scene-based and semi-empirical methods suited for the characterization and quantification of anisotropy and its correction in Imaging Spectrometry data. It summarizes capabilities and limitations of the methods, with respect to sensor properties and acquisition geometry that determine the range of available angular observations and limit the accuracy of BRDF characterization. Furthermore, it focuses on spectral pre-classification, which has authoritative influence on the success of some of the methods. RSL's spectral database SPECCHIO contains a large number of field-measured spectra that can be both used for spectral pre-classification of data and validation of the anisotropy normalization results in the future.

1. REFLECTANCE ANISOTROPY IN IMAGING SPECTROMETRY DATA

All surfaces (especially natural, but most artificial as well) feature an anisotropic reflectance behavior. Magnitude and shape of the BRDF effect basically depend on the target and its neighborhood, the sensor's field-of-view (FOV), and the illumination and view geometry (view zenith and relative view azimuth angle). A contribution comes also from the atmosphere, which is not perfectly isotropic. As reflectance anisotropy is an intrinsic surface property, its effects are present in all remotely sensed images, especially when using recent wide-FOV airborne and spaceborne instruments. Ignoring the influence of BRDF may lead to biased results for a large number of quantitative data analysis methods like estimation of albedo variants or retrieval of terrestrial ECV's.

2. IMPACT OF THE USE OF BRDF AFFECTED DATA

Data of Imaging Spectrometers are nowadays used for a multitude of applications, ranging from regional ecological studies like estimation of biochemicals in a regional forest up to calculations of global albedo, which then drives climate change models. A large percentage of these applications rely on reflectance products. Consistent use of a standardized reflectance terminology plays a crucial role the quality of the final data product. For a consistent and physically well-substantiated nomenclature for this very topic the reader may be referred to Schaepman-Strub [1] or the classic, basal paper of Nicodemus [2].
When a dataset is corrected for atmospheric effects, the assumption of an isotropic ground reflectance model is made. The measured *top-of-atmosphere* radiance is converted into *at-surface* reflectance for the given view and illumination geometry, with the illumination assumed diffuse. Most sensors are measuring a very small cone (IFOV < 0.2 degree), so even if in a strict physical sense one should call the resulting reflectance product "*Hemispherical-Conical Reflectance Factor*, HCRF" in the first place, in practice it highly approximates the according directional configuration "*Hemispherical-directional reflectance factor*, HDRF". These data still contain the effects of target-induced reflectance anisotropy. While for some applications this potential error source can be neglected (depending for

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instance on the within-scene location of the particular region of interest), for others it cannot. If the final product is a variant of albedo, which is calculated through integration over all possible view directions, a relative error of up to 20% is to be expected if the effects of BRDF are not taken into account. ***Figure 1*** presents a general, recommended processing scheme for reflectance products [3].

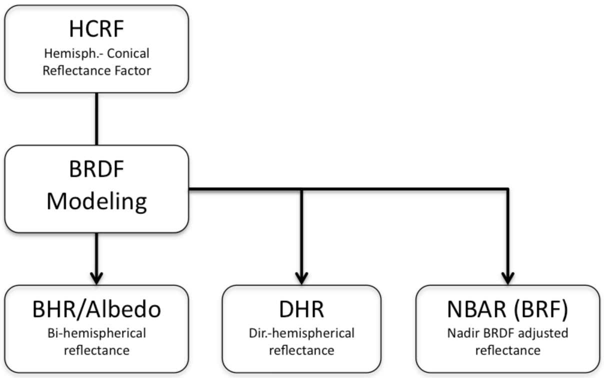

Figure 1: Processing scheme for reflectance products

HCRF as measured by a space- or airborne instrument can only be processed accurately to higher-level reflectance products like albedo, directional-hemispherical reflectance or the nadir BRDF-adjusted reflectance factor, when either a proper BRDF modeling has been performed or (depending on the application) the effects of BRDF have been removed from the data through a correction method.

3. METHODS FOR ANISOTROPY CORRECTION

The choice of a certain BRDF correction method depends on the desired application or product, on the number of observations for each target (pixel), but also a limited time frame for the processing or other computational performance requirements may restrict the user to a certain type of method. From very simple, computationally inexpensive, but also "unphysical" methods up to the physically correct ones based on radiative transfer theory, three basic types may be distinguished. These will be explained in the next sections.

3.1. Physically based methods

A Radiative Transfer Model (RTM) could theoretically be used as a means to correct for effects of the BRDF. There is a large number of RTM's known and appropriate; they all have in common that they require a large number of parameters to be specified by the user in order to produce accurate results. These parameters have either to be measured in the field or estimated from the data. The necessity of a field measurement for each scene is in contradiction with the requirement of simplicity in application and an optional automation. Estimation of all parameters from the data is impossible and would be highly error-prone since a large percentage of it is known to be sensitive to BRDF.

3.2. Semi-empirical methods

Semi-empirical, kernel-based BRDF models are a simplification to physically based methods with a drastically reduced number of input parameters [4]. They try to decompose the reflected radiation into the three components of basic scattering: 1. isotropic scattering; 2. volumetric scattering as caused by small inter-leaf gaps within a horizontally homogeneous vegetation canopy, and 3. geometric scattering, which mainly describes (mutual) shading effects caused by larger gaps within a canopy or sparse stand structures. Each of these kernels (*iso*, *vol*, *geo*) is a nonlinear function of the observation and illumination geometry while the kernels are combined in a linear way, using a waveband specific weighting parameter *f*. The reflectance *R* can then be described by the following formula:

$$R = f_{iso}(\Lambda) + f_{vol}(\Lambda)K_{vol} + f_{geo}(\Lambda)K_{geo}$$

Each of these kernels is a nonlinear function of the observation and illumination geometry while the kernels are combined in a linear way, using a weighting parameter. Dedicated kernel functions have been developed for general use with a number of land surface types. A well-established set of kernels are the so-called Li-Ross kernels [5]; [6], which are in use for the generation of the operational MODIS BRDF-Albedo product [7]. Kernel-based BRDF models in general rely on a number of stable observations for each target, i.e. accurately co-registered pixels of scenes taken from different viewing angles and/or illumination angles. If there are high-quality observations of the targets, i.e. well illuminated, low-noise pixels with the observations well distributed over the viewing and/or illumination hemisphere, an inversion of this three-parameter model is possible with just three parameters. As the quality of observations decreases, more observations are required to achieve the desired level of confidence. The influence of the angular sampling has been assessed in a number of studies [8, 9].
Kernel-based methods are popular, robust and in wide use for more than a decade now. There has also been a successful attempt to use such methods for BRDF-correction of single-pass airborne imagery [10]; however, the study has been carried out on a very limited number of targets and its applicability depends on the spatial distribution of targets within the scene.

3.3. Empirical, scene-based methods

Purely empirical methods can be used in cases where the angular sampling is not sufficient, for instance in single pass (airborne) imagery.
Empirical, scene-based BRDF normalization can be carried out by means of a polynomial fit, following the approach of Kennedy [11]. ***Figure 2*** depicts the workflow of the empirical anisotropy normalization:

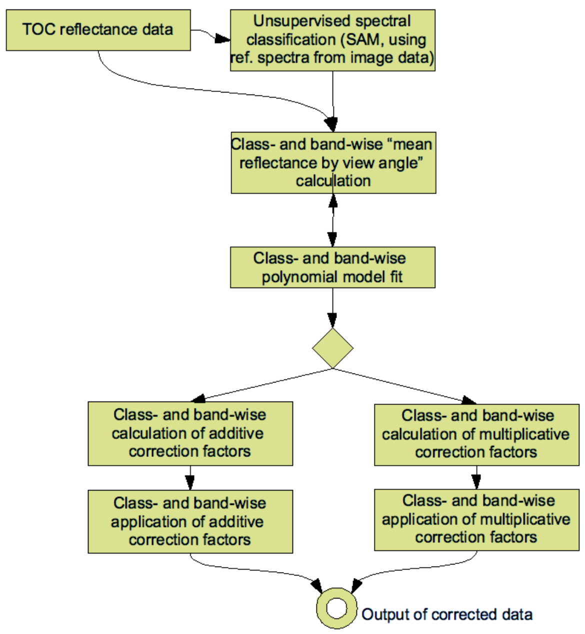

Figure 2: Flow diagram of the empirical anisotropy normalization method.

Using a previously generated spectral classification, a mean reflectance by view angle calculation is performed, per spectral class and waveband, assuming that directional effects are zero when the view angle is zero, for the given illumination geometry. A quadratic model, which optimizes the residual error in a least-squares sense, is then fit to the data. After an offset correction of the fitted mean reflectance at nadir to the calculated TOC reflectance at nadir, the coefficients are transformed into a correction factor per class, waveband and view angle (respective across-track pixel number). Correction factors can then be calculated and applied in either multiplicative or additive manner. Due to the better performance that was evaluated in studies carried out by e.g. Kennedy or Schiefer [12] only the multiplicative approach should be followed.
Purely scene-based methods like the one described here have certain limitations. They can only be used as nadir normalization of view angle effects. There is no extrapolation to arbitrary view angles or another illumination geometry possible. In addition, such a method is not applicable when the data have been acquired in partial hotspot geometry. In other cases, given the spectral pre-classification is reasonable, the data quality will be enhanced for quantitative data analysis through application of such a nadir normalization method.

4. SPECTRAL PRE-CLASSIFICATION

For empirical methods of BRDF characterization and correction, a spectral pre-classification is inevitable. A classification algorithm suitable for this purpose must be either robust to the expected degree of anisotropy or it must be adaptive.
The Spectral Angle Mapper (SAM) classification algorithm [13] uses the spectral angle α to determine the spectral similarity between an image pixel spectrum t and a reference spectrum r in an n-dimensional feature space, with n = number of available spectral bands, using the following equation:

$$\alpha = \cos^{-1}\left(\frac{\sum_{i=1}^{n} t_i r_i}{\left(\sum_{i=1}^{n} t_i^2\right)^{1/2} \left(\sum_{i=1}^{n} r_i^2\right)^{1/2}} \right)$$

Equation 1: Spectral angle calculation

Smaller angles represent closer matches to the reference spectrum; a pixel is assigned to the class that exhibits the smallest spectral angle. Each band of each pixel can be considered as a vector which has a certain length and direction. SAM performs a band-wise comparison only of the vector's direction, so that the length of the vector does not influence the final spectral angle. That makes the SAM relatively robust against variation in the total illumination intensity. However, it is robust only against linear, multiplicative differences between spectra. Target-induced reflectance anisotropy is wavelength-dependent for the majority of targets, especially for natural surfaces, and introduces a non-linear relationship in the total illumination intensity between targets of the same species composition but differing illumination and/or viewing angles. The SAM algorithm therefore *is* sensitive to BRDF effects, as has been shown by other authors before [14].
However, the SAM offers a user-definable threshold in spectral angle to be used as determinant for the assignment of a pixel to a spectral class. Theoretically, any pixel with arbitrary spectrum might be assigned to a spectral class when the approved spectral angle is chosen large enough. A threshold needs to be defined for each of the reference spectra so that it covers all pixels of the intended surface type or spectral class,

neglecting differences caused by reflectance anisotropy, and at the same time excludes those of other spectral classes that exhibit similar spectra.

The nadir-normalization method used for the empirical BRDF correction requires spectra to be separated by their wavelength-dependent distribution of the spectral reflectance factor. A spectral class should contain *all* spectra that for *all* bands show a comparable reflectance factor, with the exception of differences caused by wavelength-specific reflectance anisotropy for this class. The magnitude of the tolerable per-waveband differences of this effect for a specific spectral class is expressed by the spectral angle. With this prerequisite, a suitable classification algorithm needs to separate classes by differences in their respective spectral angle, simultaneously neglecting modification in the magnitude of the spectral reflectance factor, and that ability makes SAM a qualified method for the given problem position.

The SAM should be used for empirical nadir normalization with a limited number of reference spectra for the dominant spectral classes that can be identified in the image, e.g. coniferous forest, a bright photosynthetic vegetation and bare soil for a typical central-European rural scene.

Based on the acquired set of reference spectra, the SAM algorithm can then be applied to the data and the resulting spectral classification is used to control the empirical BRDF correction process.

5. SPECTRAL ANGLE SPACE

There is a unique relationship between BRDF and the spectral angle space. BRDF in general has wavelength-specific characteristics and causes a change in the band ratios for a target. As the spectral angle actually describes differences in band ratio for two targets the "within-class" differences in spectral angle relate to the magnitude of anisotropy for the target under consideration, given the classification being robust against the effects of anisotropy. If within-class differences in spectral angle are computed for just a certain range of wavebands, e.g. only in the NIR region, they might be used in order to make assumptions about structural properties of the surface. High leaf transmittance for vegetation in the NIR region causes high multiple (volumetric) scattering in the canopy, which in turn results in a low reflectance anisotropy for the NIR [15]. For a horizontally homogeneous, rather planophile vegetation canopy, a lower variation in spectral angle would therefore be expected for the NIR when the observation angle is changed, than for a sparse, electophile vegetation canopy.

This concept, however, is true in theory but has yet to be verified on real data. Noise (as e.g. caused by shading effects) is assumed a severe impediment for application to real data.

If information on the spatial distribution of volume scattering can be derived from the data in an authoritative way, this (structural) information can be used to better parameterize kernel-based methods, which then would give more reliable inversion results even with a very limited number of observations and become more applicable also for single-pass imagery with only a single observation.

6. SUMMARY AND CONCLUSIONS

The effect of anisotropic reflectance in Imaging Spectrometry data has an underrated influence on the accuracy and quality of data analysis and products. Depending on the number of angular observations, either semi-empirical or purely empirical methods can be applied to correct for the effects of the BRDF. Semi-empirical, kernel-based methods are popular, effective and fast, but rely on a minimum number of observations, which cannot be provided in single-pass airborne data acquisition. In this case, empirical methods should be used in conjunction with a spectral classification, but these methods have some severe limitations (hotspot, fixed illumination geometry).

The spectral angle space is estimated to provide a means for estimation of vegetation structure based on single pass imagery when a robust classification can be performed. This information could then be used for an improved and more reliable BRDF correction of single-pass imagery using the kernel-based semi-empirical approach.

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