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Target detection in hyperspectral imagery using forward modeling and in-scene information

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ABSTRACT

This work addresses the problem of detecting and classifying materials and targets in hyperspectral images based on their reflectance spectrum. Accurate target detection in hyperspectral imagery requires a radiative transfer model that maps between the spectral reflectance domain and the measured radiance domain. Such a model can be employed in two ways for detection – using atmospheric compensation, where the measured hyperspectral radiance image is converted to a reflectance image, and using forward modeling, where the target reflectance spectrum is converted to an at-sensor target radiance spectrum. This work presents a forward modeling detection method that utilizes in-scene information to estimate the parameters in the radiative transfer model. Uncertainty in the radiative transfer model and variability of the target spectra are captured using a constrained subspace model for the target. Target detection using library spectra and target rediscovery are evaluated in hyperspectral images of a complex urban scene.

1. Introduction

Remote hyperspectral sensing is a powerful tool for discriminating between different materials based on their spectral reflectance or emissivity signatures. In contrast to conventional cameras, a hyperspectral sensor measures radiance in a large number of narrow spectral bands where the resulting image contains a detailed spectral signature in each pixel. With this information it is possible to detect and classify surface materials and targets in the image in a pixel-wise fashion, for example by matching the measured spectra to a library of materials with known spectra. There are many different hyperspectral sensors, both airborne and satellite systems, which can obtain measurements of ground spectra. An overview of hyperspectral analysis methods and a table of example sensors can be found in Bioucas-Dias et al. (2013). Here, we focus on target detection using airborne hyperspectral sensors and present results from the visible and near-infrared spectral range.

The main problem for target detection in hyperspectral data is that variations in illumination, atmosphere, and ground geometry modifies the measured at-sensor radiance, complicating comparisons with known spectral appearances, see Fig. 1. For accurate target detection, these factors must be modeled and accounted for.

A radiative transfer model $L(\lambda, \alpha; \Omega)$ describes how the reflectance spectrum of a material $\alpha(\lambda)$ is mapped to the radiance spectrum measured by the sensor. Ω represents a set of model parameters that describe illumination, sun angle, atmosphere effects, ground geometry that give rise to reflections and shadows, sensor inaccuracies, etc. A comprehensive model of $L(\lambda, \alpha; \Omega)$ is complex and many parameters in Ω are unknown or uncertain, making the prediction of the spectral appearance of a material in the image uncertain. Additional sources of variability include sensor noise, sensor calibration errors, and spectral mixing of materials due to a limited spatial resolution. It is key to model this uncertainty and variability in spectral signature matching for target detection. Deterministic or stochastic models, sometimes also referred to as structured and unstructured models, respectively, can be used to this end. A deterministic model is typically implemented using a linear signal subspace that models the main spectral variations as a sum of basis vectors. A common stochastic model is a multivariate Gaussian distribution that describes variability around a mean spectral shape using a variance–covariance matrix. Frequently, spectral variability is modeled as a mix of deterministic and stochastic components. Different modeling choices give rise to a plethora of different detection methods such

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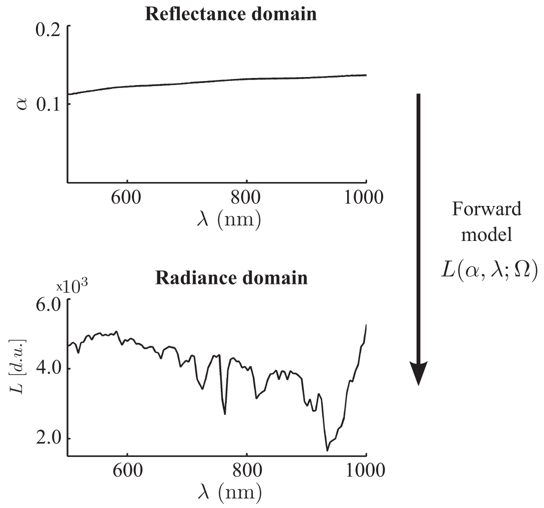

Fig. 1. A forward modeling function describes the radiative transfer from the reflectance domain to the radiance domain.

as Spectral Angle Mapper, Constrained Energy Minimization, Generalized Likelihood Ratio Test, Adaptive Coherence/Cosine Estimator, Adaptive Matched Filter, Adaptive Subspace Detector, and Orthogonal Subspace Detector. Detailed descriptions of these methods are outside the scope of this presentation, good overviews are found in Manolakis and Shaw (2002), Manolakis et al. (2003), Ientilucci (2005), Nasrabadi (2014), and Geng et al. (2016).

Target detection can be performed either in the reflectance domain based on the reflectance spectrum $\alpha(\lambda)$ or in the radiance domain based on the measured radiance spectrum $L(\lambda, \alpha; \Omega)$, see Fig. 1. The former approach requires $L(\lambda, \alpha; \Omega)$ to be inverted to obtain an estimate of the reflectance spectrum $\alpha(\lambda)$ of the material in a pixel. All pixels in the hyperspectral image must be converted, and for target detection a model of the uncertainty in the reflectance spectrum for each individual pixel must be considered. This requires significant computational resources and several authors have therefore advocated that the detection should take place in the radiance domain instead (Healey and Slater, 1999; Ientilucci and Schott, 2005; Haavardsholm et al., 2007; Matteoli et al., 2011). The target reflectance spectrum, in this approach, is mapped through $L(\lambda, \alpha; \Omega)$ to estimate how it would appear if measured by the hyperspectral sensor. Different possible appearances can be predicted by varying the model parameters in Ω within plausible ranges. The target spectral variability can then be summarized in a deterministic or stochastic target model that is used for the subsequent detection. This so-called forward modeling approach is computationally light-weight as only one single model of the target spectral variability is required.

A major component of the radiative transfer model $L(\lambda, \alpha; \Omega)$ is the influence of the atmosphere (Griffin and Burke, 2003; Ben-Dor et al., 2004; Gao et al., 2006; Yuan and Elvidge, 1996), e.g., transmission and scattering parameters. Atmosphere effects are well studied and simulation programs such as MODerate resolution TRANsmission (MODTRAN) (Berk et al., 1989) can give accurate values for these parameters if detailed knowledge of the temperature, humidity, air pressure, aerosol composition, and other factors are available. Generally, this is not the case, and target detection methods that rely on MODTRAN must therefore also handle uncertainty. Most previous forward modeling methods (Healey and Slater, 1999; Haavardsholm et al., 2007; Kolodner, 2008; Matteoli et al., 2011) run a large number of MODTRAN simulations with different parameterizations to generate a number of plausible target radiance signatures. The variability of these is captured using a deterministic or stochastic model as discussed above.

A different approach to estimating atmosphere parameters is to use in-scene information from the actual image. This may be a favorable approach depending on the available knowledge of weather and atmosphere composition parameters. Moreover, as in-scene methods utilize the actual image data, there is also the potential to model and account for sensor characteristics, calibration errors, and noise. Therefore, in the context of target detection, in-scene methods may provide a more compact and accurate model of the uncertainty of spectral signature appearances. A drawback of in-scene methods is that the true reflectance of one or several materials in the scene must be known, or other assumptions about the scene content must be made. Manual interaction may also be required.

Perhaps the most well-known and used in-scene method is the Empirical Line Method (ELM) which estimates atmosphere transmission and scattering parameters using the true reflectance spectra of two or more materials in the scene (Roberts et al., 1986; Conel et al., 1987; Kruse et al., 1990; Eismann, 2012; Mei et al., 2016). In a slightly relaxed method, here referred to as the Empirical Ratio Method (ERM), only one reference material in the scene must be known to estimate the multiplicative atmosphere transmission, while the additive scattering term is found using the Darkest Pixel or Minimum Histogram method (Themistocleous and Hadjimitsis, 2013; Campbell, 1993; Chavez et al., 1977; Teillet and Fedosejevs, 1995). Vegetation Normalization (Eismann, 2012, 2006) is an example of an ERM, in which vegetation is used as reference material.

The Flat Field approach (Roberts et al., 1986) works in a similar fashion, assuming that an operator can identify a material with a flat spectrum in the scene. Methods that assume no knowledge of any specific materials in the scene have also been proposed. The Internal Average Relative Reflectance method (Kruse, 1988) uses the average spectral signature of the entire scene as a mapping factor from the radiance domain to a relative reflectance domain. With a similar idea, the QUick Atmospheric Correction (QUAC) method uses the average of a number of end-member signatures extracted from the scene (Bernstein et al., 2005, 2008) as mapping factor.

In this work, we evaluate a target detection method which captures the spectral variation of the target using forward modeling of in-scene information for estimation of the parameters in the radiative transfer model $L(\lambda, \alpha; \Omega)$. This is an approach that has not been evaluated as intensively as MODTRAN-based approaches in the literature, although the basic idea is not new (Eismann, 2012 p. 30). Target detection using library reflectance signatures and target rediscovery is demonstrated using large hyperspectral data sets acquired over an urban area.

The remainder of the paper is organized as follows. Section 2 detail the forward modeling of the target signature using in-scene information and how the spectral variation is captured in the target model. Section 3 describes the constrained spectral matching. Section 4 introduces the four hyperspectral data sets used in the evaluation. Section 5 presents experimental results from both target detection with library spectra and from target rediscovery using target spectra from an image. Finally, Sections 6 and 7 conclude the paper with discussion and conclusions, respectively.

2. Modeling

2.1. Radiative transfer model

A radiative transfer model describes how the direct solar irradiance and indirect downwelling radiance are reflected at ground objects, and then transmitted and scattered by the atmosphere as