FORWARD MODELING AND ATMOSPHERIC COMPENSATION IN HYPERSPECTRAL DATA: EXPERIMENTAL ANALYSIS FROM A TARGET DETECTION PERSPECTIVE

Stefania Matteoli\textsuperscript{a}, Emmett J. Ientilucci\textsuperscript{b}, and John P. Kerekes\textsuperscript{b}

\textsuperscript{a}Department of Information Engineering, University of Pisa, Pisa, Italy
\textsuperscript{b}Center for Imaging Science, Rochester Institute of Technology, Rochester, NY, USA

ABSTRACT

Taking into account atmospheric effects is crucial in target detection of airborne/satellite hyperspectral images. In regard to this, two physics-based approaches to atmospheric radiative transfer modeling are considered here: Atmospheric Compensation (AC) and Forward Modeling (FM). An experimental analysis is presented that encompasses target detection both relying upon an atmospherically compensated reflectance image and by generating predicted radiance target spaces through a forward modeling approach. Real hyperspectral imagery that embodies a very challenging, cluttered, mixed pixel detection problem is used to compare AC and FM approaches from an operational target detection perspective. On this data, detection in the radiance domain through FM has proven to be as effective as the standard AC plus reflectance domain processing. Experiments have also highlighted several aspects of FM approach (e.g. its intrinsic simplicity, flexibility, and applicability) that should be considered when performing target detection, especially for targets affected by high variability.

Index Terms— Sub-pixel target detection, Forward modeling, Atmospheric compensation, physics-based modeling, target space

1. INTRODUCTION

Atmospheric effects play an important role and have to be taken into account in order to efficiently exploit the information provided by hyperspectral data. Specifically, in target detection applications, targets have to be detected relying upon the available radiance imagery and reflectance spectral signatures of the targets. Therefore, in order to successfully accomplish the detection task, radiative transfer within the atmosphere, along with viewing and illumination conditions, needs to be accounted for. This has been typically achieved through Atmospheric Compensation (AC) techniques [1], which aim at retrieving a ground-leaving reflectance image from the sensor-acquired radiance image. More recently, Forward Modeling (FM) approaches [2-3] have been proposed that convert target measured reflectance into predicted sensor-reaching radiance spectra. Specifically, they seem to promise higher flexibility and applicability than AC, especially when applied to highly variable scenarios and when only partial knowledge concerning acquisition information is available. As is evident, in this paper we are interested in physics-based techniques rather than scene-based empirical approaches [4]. In this framework, though much work has been performed in this area [3, 5, 6], there is still not enough work that critically discuss differences and advantages of both AC and FM approaches to target detection (i.e., with emphasis on the final detection step in the processing chain).

In this work, which is part of a larger study, the FM approach is compared to the standard AC approach, from a target detection perspective. Real hyperspectral imagery from the HyMap sensor is used in order to explore the tractability, applicability, and flexibility provided in a target detection scenario. The goal is investigating into whether there is any advantage to processing in the radiance domain (i.e. through the FM) over the reflectance domain (i.e. by relying upon AC), so as to highlight aspects that should be considered when the choice is to be made as to which is the preferred domain to use for a given situation.

The paper is organized as follows: Section 2 briefly introduces the radiative transfer modeling, the data employed are described in Section 3, Section 4 deals with the design of the experiments, results are shown and discussed in Section 5, Section 6 outlines summary and conclusions.

2. RADIATIVE TRANSFER MODELING

Radiative transfer modeling methods basically follow the physical model [4] shown in equation (1), though each technique can account for different details:

\[ L_s(\lambda) = \left[ E_s(\lambda) \tau_1(\lambda) \cos(\phi) + E_s(\lambda) \tau_2(\lambda) \frac{L_s(\lambda)}{\pi} + L_s(\lambda) \right] \]

where the surface is assumed Lambertian and

- \( E_s(\lambda) \) exoatmospheric solar spectral irradiance;
- \( \tau_1(\lambda), \tau_2(\lambda) \) spectral Sun-target and target-sensor path atmospheric transmissions;
- \( \phi \) Sun zenith angle;
- \( E_s(\lambda) \) spectral irradiance from the sky;
- \( r(\lambda) \) spectral reflectance of the target;
- \( L_s(\lambda) \) spectral path radiance.
Given the physical model as in (1), a radiative transfer code such as MODTRAN (MODerate resolution TRANsmi ssion, [7]) can be used to solve for each of the radiometric terms, by making use of user-supplied parameters related to atmospheric, illumination, and viewing conditions at acquisition time.

In target detection applications, available data consist of sensor-acquired radiance imagery and spectral reflectance of the targets, either field or laboratory measured. Hence, atmospheric effects can be accounted for through two possible approaches, exemplified in Figure 1 and summarized below.

2.1. Atmospheric compensation

AC techniques [1] aim at retrieving ground-leaving reflectance images by removing atmospheric effects from radiance imagery, in order to carry out detection in the reflectance domain. Since they are applied to the whole hyperspectral cube, they can be computationally expensive. More importantly, no spatial variability can be easily accounted for, and the information required concerning acquisition has to be as accurate as possible.

2.2. Forward modeling

More recently, a Forward Modeling (FM) approach [2, 3] has been proposed that converts target measured reflectance into predicted sensor-reaching radiance spectra to be used for target detection in the radiance domain. Its intrinsic simplicity and flexibility is basically due to the fact that only target reflectances, rather than a whole image cube, have to be converted through equation (1). Therefore, a certain degree of variability about atmospheric, viewing, and illumination acquisition conditions can be allowed [3] by generating, for each target reflectance, a target space, i.e. a range of possible predicted radiance spectra under the variety of conditions considered. Following the same principle, also shape factor and target orientation effects can be introduced in the model [3]. Any variation introduced simply manifests itself as an additional spectrum in the target space. Hence, even strongly spatially-variable scenarios can be accounted for using a FM approach.

3. DATA SET DESCRIPTION

The hyperspectral data used in this research were acquired by the airborne HyMap sensor over Cooke City, MT, USA [8]. The image consists of 126 spectral channels in the Visible Near InfraRed-Short Wave InfraRed (VNIR-SWIR) and 280 x 800 pixels with Ground Sampling Distance (GSD) of about 3 meters. During acquisition, several fabrics were placed in the scene, and their spectral reflectances were accurately measured and collected in a spectral library. A true-color representation of the scene can be seen in Figure 2 (a), whereas Figure 2 (b) reports target ground-truth map. As is evident from Table I, fabric target sizes were comparable to, and sometimes much smaller than, the GSD, thus resulting in sub-pixel targets. This strong sub-pixel situation, along with the complexity of the background, characterized by many objects and classes, makes the target detection process quite challenging.

4. EXPERIMENTAL DESIGN

Experimental analysis was designed on the basis of the scheme represented in Figure 1. An atmospherically compensated reflectance image was obtained through the HyCorr software [9], designed specifically for HyMap products AC and provided with accurate information concerning acquisition. This compensated reflectance image was used, along with the fabrics library reflectances, to perform target detection in the reflectance domain. In regards to the FM approach, target spaces were generated, for
each target reflectance, by accounting for a certain degree of variability around acquisition conditions, and enriching the available a-priori information through the use of environmental and meteorological data. Variability due to shape factor and target orientation effects [3] was also included in the model. For each target space, a target subspace was generated via Singular Value Decomposition (SVD) [4], and variability around acquisition conditions, and enriching the each target reflectance, by accounting for a certain degree of

detectors for employing two Generalized Likelihood Ratio Test (GLRT) results can be found in Table III, whereas Table IV and Table

tested results: #FAs (‘med’ is the median result computed over the values of #FAs =17) is achieved by SBM-GLRT (with k_{back}=25).

5. EXPERIMENTAL RESULTS

Due to the low number of target pixels, which would hinder any reliable estimate of the detection probability, thus leading to a sparse Receiver Operating Characteristic (ROC) curve, detection performance is evaluated here by counting the number of False Alarms (#FAs) arising from the detection of the pixel with highest test statistic for a given target. The lower #FAs, the better the performance.

Reflectance domain (i.e. AC plus target detection) results can be found in Table III, whereas Table IV and Table V report results in radiance domain (i.e. FM plus target detec-

$\text{Algorithm}$ | $\text{Detector formula}$ | $\text{Reference}$
--- | --- | ---
SBM-GLRT | $ \left\| \frac{x^T P x}{x^T P_f x} \right\|_2 $ | [10]
UBM-GLRT (Kelly) | $ \frac{x^T C_b^{-1} (x^T C_b^{-1} S_f x)^T C_b^{-1} S_f x}{N + x^T C_b^{-1} S_f x} $ | [11]

<table>
<thead>
<tr>
<th>Obj.</th>
<th>$k_{\text{back}}=10$</th>
<th>$k_{\text{back}}=25$</th>
<th>$k_{\text{best}}=10$</th>
<th>$k_{\text{best}}=25$</th>
</tr>
</thead>
<tbody>
<tr>
<td>F1</td>
<td>11</td>
<td>0</td>
<td>15</td>
<td></td>
</tr>
<tr>
<td>F2</td>
<td>59</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>F3</td>
<td>712</td>
<td>2</td>
<td>71</td>
<td></td>
</tr>
<tr>
<td>F4</td>
<td>64</td>
<td>2</td>
<td>22</td>
<td></td>
</tr>
</tbody>
</table>

Table III. Reflectance domain - target detection results: #FAs

<table>
<thead>
<tr>
<th>Obj.</th>
<th>$k_{\text{back}}=10$</th>
<th>$k_{\text{back}}=25$</th>
<th>$k_{\text{best}}=10$</th>
<th>$k_{\text{best}}=25$</th>
</tr>
</thead>
<tbody>
<tr>
<td>F1</td>
<td>1</td>
<td>2</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>F2</td>
<td>0</td>
<td>5.5</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>F3</td>
<td>3308</td>
<td>726.5</td>
<td>755</td>
<td>17</td>
</tr>
<tr>
<td>F4</td>
<td>91.50</td>
<td>32.50</td>
<td>24</td>
<td>3</td>
</tr>
</tbody>
</table>

Table IV. Radiance domain - target detection SBM-GLRT results: #FAs (‘med’ is the median result computed over the values of #FAs =17) is achieved by SBM-GLRT (with k_{back}=25).

As to the radiance domain (Table IV-V), since many target subspace configurations were tested, results are reported by means of the median #FAs computed over all the values of $k$ adopted. The best results, obtained with a specific $k$, are shown as well. As is evident, sometimes few components (even just one) are enough to characterize the target space for a given target. On the other hand, depending on the particular target-background situation, more variability may be necessary for proper detection of a given target (i.e., more components may be required). For instance, with respect to the two detector analyzed here, the best result obtained for the difficult target F3 in the radiance domain (#FAs =17) is achieved by SBM-GLRT (with k_{back} = 25).
Here, a rather large number of target subspace components ($k=20$) was used. For the median results, SBM-GLRT and Kelly yield comparable performance, whereas, when looking at the best results obtained by each algorithm, SBM-GLRT outperforms Kelly, especially in $k_{\text{bak}}=25$ configuration.

When examining the algorithm behavior across the two domains, SBM-GLRT performance obtained with $k_{\text{bak}}=10$ is globally comparable in both domains, whereas it is better in radiance if the best results, achieved with $k=3$, are considered. Much better results are obtained by adopting $k_{\text{bak}}=25$, especially in the reflectance domain, where (nearly) perfect detection of all the fabrics is accomplished. 25 SVD components can probably more accurately account for such a complex background variability. Detection obtained with Kelly’s algorithm are comparable in both domains.

6. CONCLUSION

In this paper, work has been presented that addresses physics-based target detection. An experimental analysis was performed that encompasses detection both relying upon an atmospherically compensated reflectance image and by generating predicted radiance target spaces through a forward modeling approach. The goal of this study was to explore, from an operational viewpoint, both atmospheric compensation and forward modeling approaches within the target detection framework. To this aim, a subspace-based (SBM) and a covariance-based (Kelly’s) GLRT detector were adopted to perform detection on airborne hyperspectral imagery that embodied a very challenging, cluttered, mixed pixel detection problem.

Very good results were obtained, on this data set, through the SBM-GLRT, which seems capable of working with a single reflectance spectrum, as well as able to exploit the higher variability provided by a predicted-radiance target space, of course on condition that an appropriate number of background components is employed. Less user assistance, instead, is required by Kelly’s detector, which characterizes the background by means of its covariance matrix. This detector performed, on this data, similarly in both domains. Its local application may, in general, lead to better performance, but was not pursued here due to the highly local background complexity of the scene.

Processing in the radiance domain was found to require more user interaction, as to target space characterization through a subspace of suitable dimension. On the other hand, the desired variability was managed to be incorporated into the model without any extra processing, a thing that would not have been possible to perform when pursuing the atmospheric compensation approach.

In these data, detection in radiance domain through FM has been shown to be as effective as the standard AC plus reflectance domain processing. However, since the fabric targets were placed onto a flat terrain in a wide open area, comparable results were expected by both approaches. The presence of targets affected by more variability (e.g. shadowed, differently oriented with respect to the sun, etc.) would have allowed the potential and flexibility of the FM to be better exploited. In regards to this, a much larger study was performed using this data, which addresses (i) weak links in the image chain specifically pertinent to this data set (e.g. calibration, atmospheric uncertainty, and variability in measured reflectance spectra) [12], and (ii) detection of much more difficult vehicle targets across multiple images [13]. Furthermore, application of a much larger database of detection algorithms in a variety of configurations is still work in progress.

7. REFERENCES