

HYPERSPECTRAL PARTIAL UNMIXING TECHNIQUE FOR OIL SPILL TARGET IDENTIFICATION

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ABSTRACT

In this study, advanced techniques for oil spill detection and oil spill type identification using hyperspectral AVIRIS data are presented. Spectrally complex areas are highly dimensional and are consequently difficult to fully unravel. In our previous study, the Spectral Linear Unmixing (SLU) technique showed many limitations for operational applications, since signatures for all the target materials in the scene must be spectrally identified. Our new methodology emphasizes the ability to distinguish oil slicks from the background using the Partial Unmixing (PU) technique. Both the data reduction and the pixels projection methods are used for distinguishing thick, slick oil from dispersed oil; moderate and thin oil sheens; polluted water; and tarry oil. It was developed in part to partially un-mix the oil target pixels from the background mixed pixels. This method improves on the SLU technique because it does not require prior knowledge of the background material spectral signatures. Our analysis applies to oil spill targets with the assumption that all pixels are pure and they are not mixed with background materials. In the specific case of the Santa Barbara coastal zone event (March, 2002), the changes in the oil slick occurred from the north (oil spill source) to the south due to the high sea waves and strong current effects.

Our study is focusing on target identification for oil slick. We show that oil spill on sea water can be clearly identified.

1. INTRODUCTION

The classification of oil is extremely complicated due to the variance in the optical properties of different oil spill types. Sea waves currently lack positive discrimination and cause poor contrast and mixing of many oil spill types. There is difficulty in optically identifying thick oil slicks spectra from streaks and oiled water. Also, it is difficult some times to optically identify oil slick spectral signatures for oil spills on the scene. A complete spectral mixing of a complicated AVIRIS scene may not always be possible or even desired. High-quality data of spectrally complex areas are very high dimensional and difficult to fully separate. There is a need for a more selective method to increase the ability to identify regions of interest for the desired regions. Therefore, using more advanced techniques such as the Partial Unmixing (PU) is very efficient for increasing the reliability of the analysis.

The improved signal to noise AVIRIS data complemented by new data reduction and processing techniques permits unambiguous oil identification and spectral unmixing of subpixel targets; subtle spectral differences enhanced in the data include oil types and polluted water discrimination. This allows the detailed detection of smaller oil spill areas. The techniques developed so far classify oil spills and verify their effectiveness experimentally, which in turn will make it possible to model water-leaving radiances from different types of oil slicks. Analysis methods focus on classifying each pixel into a single class by identifying the main material in the pixel (Richard, et al. 2002).

Our new methodology emphasizes the ability to distinguish oil slicks from the background using the Partial Unmixing (PU) technique. It was developed in part to partially un-mix the oil target pixels from the background mixed pixels. Our model focuses on distinguishing the abundance of targets under investigation from background features. The PU techniques are used to identify oil spill targets in the presence of a complex background and when there is no ground truth information.

In practice, with multispectral techniques, one method alone is not conclusive in all oil spill detection (Goodman and Fingas, 1988). Often, oil has no specific characteristics that distinguish it from the background. Taylor (1992) studied oil spectra in the laboratory and field and observed flat spectra with no usable features distinguishing it from the background (Taylor, 1992). Techniques that separate specific spectral regions did not increase detection capability.

1.1 Case Study: Santa Barbara

Santa Barbara County is home to the most intensive offshore oil development on the West Coast. For decades, Santa Barbara County has been sensitive to offshore oil drilling. In 1969, California's biggest oil spill fouled the Santa Barbara Channel with about four million gallons of crude oil. Moreover, at least 10,000 gallons of oil have been spilled from an undersea pipe near Santa Barbara. As oil production continues offshore, tourism has grown dramatically, increasing the threat of oil-related injuries.

1.2 AVIRIS Data Set

In our previous study using the AISA sensor, the classification process was performed using 25 bands. The Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) sensor allows more specific spectral analysis with wavelengths from 380 nm to 2500 nm. AVIRIS data with spectral radiance in 224 contiguous spectral channels, spectral resolution of about 10 nm, and a ground pixel size of 18m x 18m were available to this study. The 2001 AVIRIS scene of the Santa Barbara coastal zone was obtained from the NASA Jet Propulsion Laboratory (JPL) in California. The whole track scene consists of 13 segments; each segment consists of 512 x 614 pixels. Four scenes were selected, each one representing an oil spill at a different stage from north to south. AVIRIS data allow the study of different types of oil spills in the ocean, oil spill classification, and quantitative measurements for on apparent oil spill.

2. METHODOLOGY AND RESULTS

In this research study, hyperspectral processing techniques are applied to an AVIRIS image using a total of 224 bands from 0.374 μm to 2.50 μm . This process involved several steps beginning with looking at the change in spectral signatures in both space and time, as the oil spill characteristics changed with time. Three segments were selected to detect the different oil slick shapes. Data browsing was used to look at spatial and spectral changes in reflectance.

2.1 Model Description

In this paper an attempt was made to use newer and simpler techniques for target identification building on the PU technique. This PU method is used for partially unmixed AVIRIS data. High quality data of spectrally complex areas are highly dimensional and are consequently difficult to fully unravel (Boardman, et al., 1995). PU technique provides a method of solving only that fraction of the data inversion problem that directly relates to the specific goals of the investigation. In our previous study, the spectral linear unmixing technique showed many limitations for operational applications, because signatures for all the target materials in the scene must be spectrally identified. The PU method does not require a prior knowledge of the background material spectral signatures. Our investigation included only oil spill targets that were not mixed with other materials except water. The data are subjected to dimensional reduction processes using Minimum Noise Fraction (MNF) technique for reducing high dimensionality of the data.

2.2 Data Reduction

The data reduction phase of the analysis strives to identify Regions of interest (ROIs) in the data set by separating noise from information and reducing the data set to its true dimensionality by applying the minimum noise transform, then determining spectrally pure (extreme) pixels using the Pixel Purity Index (PPI) function on the minimum noise fraction results (Wagtendonk, et. al., 2000). N-dimensional visualization can then be performed using the grand tour of the high PPI value pixels to cluster the purest pixels into image-derived ROIs.

AVIRIS data were put through a dimensionality analysis using the MNF transform. The data are translated to have a zero

mean, and then the data are rotated and scaled so that the noise in every band is uncorrelated and has unit variance. The inherent dimensionality of the data is determined by examining the final eigenvalues and the associated images. The data space is divided into two parts: one part associated with near-unity eigenvalues and coherent eigen-images, and a complementary part with near-unity eigenvalues and noise-dominated images. By using only the coherent portions, the noise is separated from the data, which improves the spectral processing results. Image linking and overlaying are used to identify pixel locations for thick oil slicks to selected oil spill spectra. A target weighting variance for high eigenvalues for each class provides clues to spectral features, contributing to the classification.

2.3 Target Identification Using Partial Unmixing

In our study another experiment was performed using the MNF (principal component) technique for target identification using data reduction and PU. The results indicated good separation of oil slicks, oiled water, and polluted water. Results are here used as a preliminary identification of oil targets, since no ground truth data were available. PU allows mapping of the apparent target abundances in the presence of an arbitrary and unknown spectrally mixed background.

We have developed a partial unmixing technique as a method of mapping target ROIs using two MNF bands in a 2-D scatter plot to separate the oil spill target from the background pixels and to produce ROIs. The purest pixels in the scene are then compared against the target spectra. If any are close matches for the target materials, they are identified and separated from the other purest pixels. High-purity pixels that do not closely match a target spectrum are used to determine the subspace background. This analysis does not require a prior knowledge of the background material signatures. The steps are indicated:

2.3.1 Eigenvector Weighting

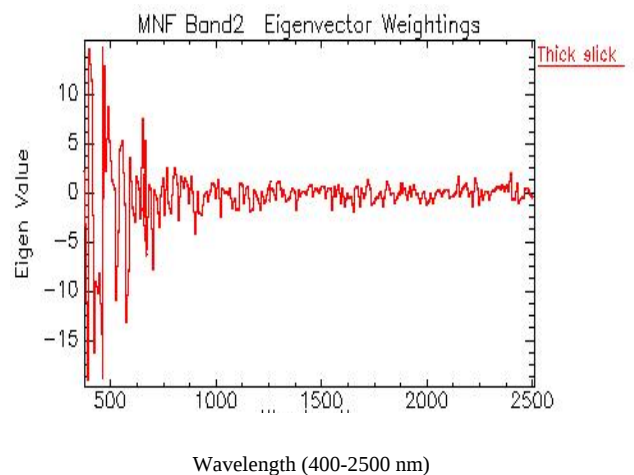


Figure 7. The MNF Spectrum For Thick Oil Slick Bands Shows High Eigenvalues.

Figure 7 shows a plot of the MNF eigenvalues, showing the amount of covariance in each output MNF band. Most of the information is derived from differences in 640 to 890 nm. The output results of data reduction processes are 25 MNFs; some of these bands have significant pixels for oil spills and the

rest are MNFs for other classes. Two MNFs with high variances in oil spill are required to process the PU method to be used in a 2-D scatter plot. Eigenvalue weighting is used to compare the average spectrum of oil in the raw data and the MNF spectra of oil. Both spectra are selected from the same pixel location. The statistics provide clues to spectral features contributing to the classification. The oil slick spectra and the associated spectra in the image are examined for weighting using the high variance (eigenvector) portion of the spectra.

2.3.2 Data Projection

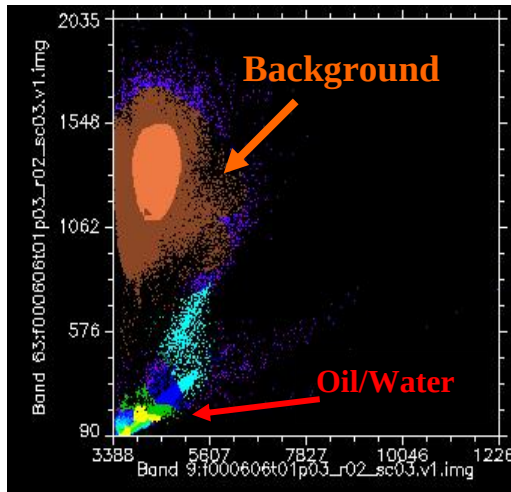


Figure 9 (a) PU Results; Radiance Pixels Projection

In Figure 9 (a), the radiance (raw) data projection is for band 9 (visible) in the X axis and band 63 (near IR) in the Y axis. These two bands were selected with minimum correlation to maximize the variance between targets. It shows a good separation in the background cluster (mountains) appearing in brown and very poor separation between the oil and water clusters appearing in the lower corner in blue, green, and yellow.

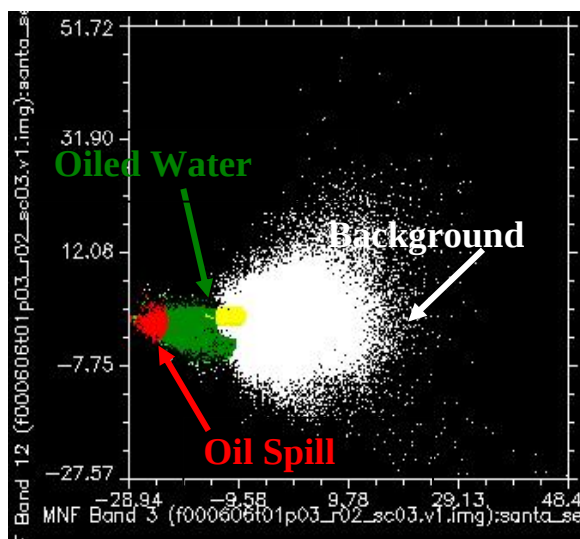


Figure 9. (b) PU Results; MNFs Pixels Projection.

In Figure 9 (b), the vertical axis corresponds to the separation between the targets (green = oiled water, red = thick oil slicks,

yellow = polluted water and streaks) and the background (white cluster), while the horizontal axis maps inter-target separation. The plot shows the optimal projection selected of the data using 2 MNF bands, where the background composite ROIs is centered at the 0, 0 mean.

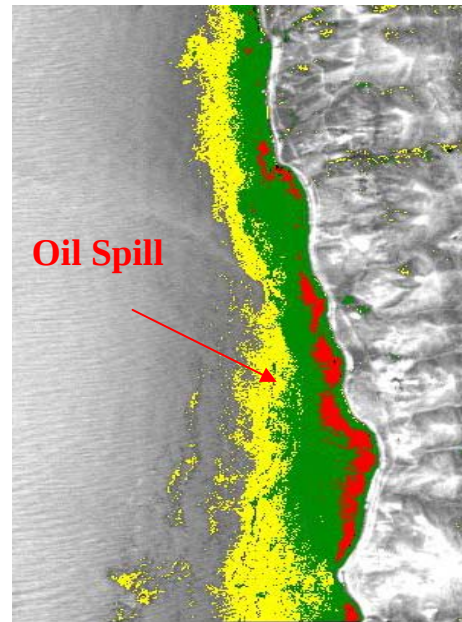


Figure 10. The PU Results; The Abundance of Oil Materials

The agreement between the observed data and the 2-D scatter plot indicates the successful derivation of the optimal projection that the targets are optimally separated, and the multi-component background is fully compressed. Spectral signatures for oil spill types can be generated from the 2-D scatter plot clusters.



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Bands Composite Image for a Complex Stage of the Oil Spill

Figure
A 3

3. RESULTS AND CONCLUSIONS

- The PU method significantly reduces the overall processing complexity and is making analysis easier and more robust for the user.
- The PU method provides a quick and practical operational method for selecting ROIs, without using statistical classification algorithm, where MNF function and 2-D scatter plot are available in all image analysis software packages.

The results indicated good separation of oil slicks, oiled water, and polluted water. Results are used as a preliminary identification of oil targets, as there is no ground truth data available. PU provides a method of resolving only that fraction of the data division problem that directly relates to the specific goals of the investigation. PU allowed mapping of the apparent target abundances in the presence of an arbitrary and unknown spectrally mixed background.

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