Derivative Based Bathymetric Algorithms for Hyperspectral Data

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LONG-TERM GOALS

Our long-term goal is the development of spectral analysis tools that fully exploit the information content in hyperspectral image data, particularly as it applies to passive, remote sensing derived bathymetry.

OBJECTIVES

The objective of this work was to develop an effective method for extracting bathymetric information from hyperspectral data.

APPROACH

Our approach involved using a differential form of a simple two-flow model (Philpot, 1989) as the basis for the bathymetric analysis. We chose this approach for several reasons: 1) basing the methodology on a radiative transfer model does not require any presumption of independence of spectral band, nor does it imply a bias toward variables (bands) with a large variance (dynamic range). 2) using the differential form of the equation insured that the emphasis would be on the spectral shape rather than on the magnitude of the spectral signal.

Depth estimates based on the differential form of the model were compared to results based on the standard form of the model using the same synthetic data. At the time of this work, no hyperspectral image data were available that were coincident with bathymetric data. In the absence of these data, a synthetic data set was produced using HYDROLIGHT 3.1 to predict the upwelling spectral radiances for a variety of bottom types and ranges of depth.

The procedure based on the standard form of the model begins with the equation for the upwelling radiance at the remote detector for a homogeneous water column of finite depth:

$$L_d = L_b e^{-gz} + L_\infty \qquad (1)$$

where: $L_d(\lambda)$ = radiance at the airborne detector
$L_b(\lambda)$ = a radiance term representing the contrast between bottom and water reflectance.
$L_\infty(\lambda)$ = the radiance received at the airborne detector of an optically deep water body.
$g(\lambda)$ = an effective two-way attenuation coefficient
z = depth of the water column

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Equation (1) is then linearized, yielding:

$$\ln|L_d - L_\infty| = \ln|L_b| - gz \qquad (2)$$

The absolute values are added to insure appropriate solutions whether the bottom is darker than the water or vice versa. Assuming that the bottom type and water type are uniform over the area under study, one must still know L_d for two different finite depths and for infinite depth (L_∞). Using data corresponding to a single water reflectance and a single bottom reflectance and performing a principal component analysis (PCA) on that data results in a 1st principal component that can be used to minimize the uncertainty (noise) in the depth estimate. If the first principal component is given by a vector, a, then the optimized solution is for depth is of the form:

$$\frac{-\left[\mathbf{a}\cdot\ln\left|L_d - L_\infty\right| - \mathbf{a}\cdot\ln\left|L_b\right|\right]}{\mathbf{a}\cdot\mathbf{g}} = z \qquad (3)$$

where the components of both a and g are the weightings for each spectral band.

An alternative is to use the differential form of Equation (1) and solving for depth, z, yields:

$$\frac{\dfrac{\partial}{\partial\lambda}\left(\ln\left[\dfrac{\left|L_d - L_\infty\right|}{\left|L_b\right|}\right]\right)}{\dfrac{\partial}{\partial\lambda}(-g)} = z \qquad (4)$$

The PCA procedure described briefly above was not as effective when applied to equation (4) presumably because the data distribution in the spectral domain was no longer as strongly linear and small variations in the PCA solution (possibly caused by the outliers) would produce a less than optimal depth estimate. Thus, the crucial task in using equation (4) for depth estimates was outlier removal. After evaluating several approaches, we settled on a method which we call the growth kernal approach (Kohler, 1999, Kohler and Philpot, 1999).

Determining which outliers to remove is not a simple process. Because of the shear volume of signals in an image and the varying number and position of the outliers present for each signal, a sensitive yet automated approach was developed.

After testing several outlier removal techniques, the “outwards” outlier test was chosen due to it robustness. This method starts with a core sample centered around the mean and tests observations close to this core by way of a "t" statistic. Rather than removing unfit data points, this method works by determining whether or not any new observation truly belongs to the trimmed distribution. After each new observation is included the mean and standard deviation are recalculated and used to evaluate the next closest observation to the new core.

Obviously, the selection of an appropriate core sample size is vital. After testing several traditional methods, a hybrid approach was chosen, which is best suited for remotely sensed data. This method starts by using the middle 10% of the sample as its core. If this core size had a standard deviation that was so small that no new observations would be included, the innermost outlying observation was added to the core and the core statistics were recalculated. If this new core was also so selective as not to include at least one new observation, the next closest outlier was added to the core. This procedure continued enlarging the core until at least one new observation passed the t-test and was included in the trimmed sample.

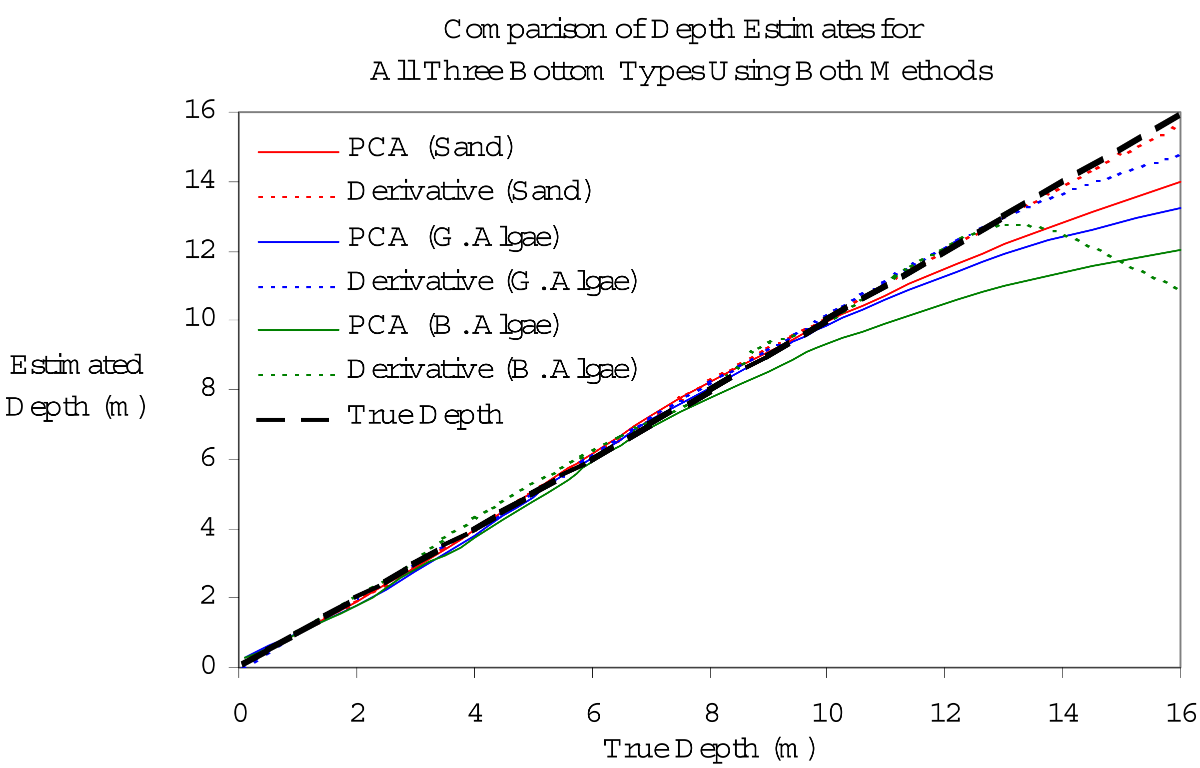
WORK COMPLETED

We developed a procedure for extracting depth from hypersepctral data using the differential form of a simplified two-flow model.

Given a set of upwelling radiances over a single bottom type (constant bottom reflectance) and representing a range of depths, we prototyped a method for estimating the apparent two-way attenuation coefficient, $g(\lambda)$ and the bottom-sensitive radiance term, $L_b(\lambda)$.
We developed a procedure for Outlier Removal from the depth estimates data derived from the differential form of the two-flow model.

RESULTS

Figure 1 illustrates the results of the depth estimate for both methods using three different bottom types. It is clear that for the green algae bottom, brown algae bottom, and the coral sand bottom, the derivative method achieved better results than the standard approach using Principal Components Analysis. This, however, is still a preliminary result based only on synthetic, noise-free data. The PCA methods did produce acceptable results and therefore should not be dismissed.



IMPACT/APPLICATIONS

Obviously, the application of the procedures outlined above to real imagery is in order. While this may seem straight forward, it is not. The determination of the of g and L_b is crucial to the accuracy of the overall estimates. Great care is being given to the development of procedures that will estimate of these parameters. Also, areas such as using multiple rather than one derivative and how each approach handles the situation of misclassification of the bottom type are being currently investigated. Finally, a test to exhaust the algorithms so to better determine the boundary conditions for where they are useful is planned.

TRANSITIONS

None

RELATED PROJECTS

The results and procedures developed in this project are in direct support of the HyCODE project N000149710020

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PUBLICATIONS

Kohler, D.D. (1999) Master's Thesis, Cornell University, Ithaca, NY 14853.

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PATENTS

None.