Spectrum-matching Algorithms

We are going to use radiometrically calibrated and atmospherically corrected $R_{rs}$ spectra to simultaneously retrieve bottom depth, bottom reflectance (bottom type), and water column absorption and scattering properties via “spectrum matching” to the full spectra.

Two basic types of “radiative-transfer-based” algorithms for spectrum matching:

- **Semianalytical:** Start with radiative transfer theory and derive an approximate analytical model relating $R_{rs}$ to bottom depth, reflectance, etc. Then use the image $R_{rs}$ determine best-fit values for the parameters of the model via nonlinear optimization (Lee et al., 1998, 1999, Applied Optics)

- **Database Search:** First use a radiative transfer code to create a database of $R_{rs}$ spectra that correspond to all possible combinations of water absorption and scattering properties, bottom depths, and bottom reflectances that might be found in the area being studied. Then match image spectra to the database spectra. (Mobley et al., 2005, Applied Optics)
Use a radiative transfer code to create a database of $R_{rs}$ spectra that correspond to all possible combinations of water absorption and scattering properties, bottom depths, and bottom reflectances that might be found in the area being studied.

Each $R_{rs}$ spectrum in the database corresponds to a known set of water properties ($a$, $b$ and $b_b$ spectra), a bottom reflectance spectrum (bottom type), and a water depth.

Then search the database to find the closest-matching database spectrum to the given image spectrum.

The retrieved environmental properties are then whatever values were used to create the closest-matching database spectrum.
The following results were generated using CRISTAL.

CRISTAL (Comprehensive Reflectance Inversion based on Spectrum matching and Table Lookup) is a software package developed by me to handle the creation of $R_s$ databases, retrieval of environmental properties (water IOPs, bottom depth, and bottom reflectance or type) from hyperspectral imagery, and display of retrieved results.

Parts of CRISTAL are covered by U.S. Patent 7369229.
$R_{fs}$ Database Creation: IOPs

For the Bahamas use

- 6 Chl values: 0.0, 0.05, 0.10, 0.15, 0.20, 0.30 mg m\(^{-3}\)
- 11 $a_{\text{CDOM}}$ values: 0.0 to 0.1 m\(^{-1}\) by 0.01 m\(^{-1}\)
- 5 mineral concentrations: 0.0, 0.05, 0.1, 0.2 and 0.3 gm m\(^{-3}\)

$6 \times 11 \times 5 = 330$ IOP sets
$R_{rs}$ Database Creation: Bottom Reflectance

32 different bottom reflectance spectra (pure bottom types and mixtures of bottom types)

The bottom was placed at 56 depths:
$z_b = 0.25, 0.50, 0.75, 1.0, ..., 14.75, 15.0, 16.0, ..., 19, 20, \infty$

The database creation run shown here (for Bahamas waters) used 330 sets of water properties x 32 bottom reflectances x 56 depths, so $330 \times (32\times55 + 1) \approx 581,130$ RTE solutions to create $R_{rs}$ spectra from 380 to 750 nm by 5 nm (about a week of computer time on a 2 GHz PC). Database creation is a one-time calculation for a given environment.
Each $R_{rs}$ spectrum in the database corresponds to a known set of water properties ($a$, $b$ and $b_b$ spectra), a bottom reflectance spectrum (bottom type), and a water depth.
Image Processing
(after atmospheric correction)

retrieval:
Depth 2.75 m
80% sand, 20% grass
IOP set #17

pixel $R_{rs}$ extraction
database search

spectrum match
database of $R_{rs}$ spectra
Example: Airborne Hyperspectral Image of Very Clear Water in the Bahamas

Lee Stocking Island, Bahamas

Horseshoe Reef

NRL-DC PHILLS image from ONR CoBOP program, May 2000

501x899 pixels at ~1.3 m resolution
Validation with Acoustic Bathymetry

Black: NRL acoustic survey for ONR CoBOP program
Color: CRISTAL depth retrieval
These retrieval errors also include errors due to latitude-longitude calculations in mapping acoustic ping locations to image pixels (horizontal errors of several meters or more due to failure of built-in navigation instrument), and due to whitecaps.
$R_B(488)$ is what you would need for performance evaluation of a 488 nm bathymetric lidar.
Retrieval Information

Keep in mind that a database spectrum matching retrieval retrieves full spectral information at each pixel.
Bull kelp (*Nereocystis luetkeana*) is very important for food, medicines, sheltering of fish, and recreational diving. Harvesting is strictly managed in the US.

http://www.bestpicturesof.com/misc/pictures%20of%20bull+kelp/?page=2#Google

http://www.beachwatchers.wsu.edu/ezidweb/seaweeds/Nereocystis.htm
Mapping of Kelp Coverage California Coast

images courtesy of Paul Bissett, FERI
Mapping of Kelp Coverage
California Coast

images courtesy of Paul Bissett, FERI
HSI determined eel grass distributions, previously unknown.
Error Analysis

Being able to place error bars or confidence estimates on retrievals is often as important as the retrieved value itself.

Can do this statistically from the distribution of retrieved values for the $k$ closest matching spectra ($k$ Nearest Neighbors, or kNN).

The 30 closest matches give a histogram of retrieved depths, and the average or median gives a better estimate of the depth, plus an error estimate.
The closest and most frequently retrieved bottom reflectance spectrum was 30% sand and 70% seagrass. The other bottoms are similar mixtures of sand and grass, sargassum, turf algae, and macrophytes. So we can be fairly certain that the bottom is dense vegetation, probably sea grass.
The retrieval is very certain about the absorption coefficient.

The retrieval is fairly certain about the scattering coefficient.

The retrieval is uncertain about the backscatter coefficient.

Error Analysis
Error Analysis: A Shallow-water Pixel

- **Absorption**: constant across all depths; very confident.
- **Scattering**: uncertain.
- **Backscatter**: very uncertain.

### Pixel Data
- **Pixel (58, 187)**
- **K = 30**
- **Bin size = 0.25 m**
- **Acoustic closest match = 0.37 m**
- **Average = 0.37 m**
- **Median = 0.37 m**
- **Std. dev. = 0.00 m**

### Graphs
- **Absorption**
- **Scattering**
- **Backscatter**

### Bottoms Description
- **Bottoms very similar** (sand or grapestone); very confident.
Does This Make Sense?

- In these very clear waters, the water absorption determines how much light gets to the bottom and back to the surface. Water-column scattering and backscatter contribute less to the water-leaving radiance in shallow water than does the bottom reflectance.

- The retrieval was therefore most certain about the absorption coefficient, and least certain about backscatter.

- The bottom reflectances all had similar reflectance spectra because it’s the reflectance that is important. The retrieval wasn’t able to distinguish between sea grass, turf algae, *sargassum*, and macrophytes, which all have similar reflectances.

- In very shallow (<5 m) clear water, the retrieved bottom reflectance becomes very certain and the water scattering and backscatter very uncertain (i.e., least important in determining $R_{rs}$)
## Comparison of Database & SA Algorithms

<table>
<thead>
<tr>
<th>Feature</th>
<th>CRISTAL</th>
<th>Semianalytical</th>
</tr>
</thead>
<tbody>
<tr>
<td>Algorithm basis</td>
<td>exact solution of the RTE as expressed in the $R_{s}$ database spectra</td>
<td>approximate solution of the RTE as expressed in the semi-analytical model</td>
</tr>
<tr>
<td>Fundamental advantage</td>
<td>accounts for wavelength fine structure of spectra, thus allowing for species-level identification of biota</td>
<td>applicable to any water body without the need for pre-computing underlying databases</td>
</tr>
<tr>
<td>Fundamental limitation</td>
<td>Retrievals are good only if the $R_{s}$ database is representative of the environment</td>
<td>Retrievals are good only if the semianalytical model is representative of the environment</td>
</tr>
<tr>
<td>Convergence to a solution</td>
<td>no convergence problems because a closest-matching database spectrum is always found (even if the match is poor because the database is not representative of the environment)</td>
<td>the optimization may not converge or may converge to a local minimum if the initial guess parameter values are not sufficiently accurate or if the model is not representative of the environment</td>
</tr>
<tr>
<td>Applicable environment</td>
<td>any water body described by the $R_{s}$ database</td>
<td>any water body described by the semianalytical model</td>
</tr>
<tr>
<td>Imagery required</td>
<td>$R_{s}$ spectra must be well calibrated and atmospherically corrected</td>
<td>$R_{s}$ spectra must be well calibrated and atmospherically corrected</td>
</tr>
<tr>
<td>Preprocessing</td>
<td>An $R_{s}$ database must be pre-computed for the given environment before image processing</td>
<td>No preprocessing is required</td>
</tr>
<tr>
<td>Image processing time</td>
<td>fast when optimized database searches are used</td>
<td>fast or slow, depending on search algorithm and implementation</td>
</tr>
</tbody>
</table>
Comparison of Algorithms
preprocessing time / image processing time / pixels per sec

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Retrieval Depth</th>
<th>rms</th>
<th>r²</th>
<th>Preprocessing Time</th>
<th>Image Processing Time</th>
<th>Pixels per Sec</th>
</tr>
</thead>
<tbody>
<tr>
<td>HOPE (Lee, semi-analytic)</td>
<td>0/48 m/156</td>
<td>1.12 m</td>
<td>0.85</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BRUCE</td>
<td>0/12 h/10</td>
<td>0.86 m</td>
<td>0.91</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SAMBUCA</td>
<td>0/1147 h/0.1</td>
<td>1.3 m</td>
<td>0.85</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CRISTAL</td>
<td>45 h/23 m/326</td>
<td>1.14 m</td>
<td>0.88</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ALUT</td>
<td>4 m/2 h/62</td>
<td>2.36 m</td>
<td>0.81</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lyzenga</td>
<td>4 m/2 h/62</td>
<td>1.68 m</td>
<td>0.72</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Comparison of Algorithms

Other Issues

- What is the best metric for spectrum matching?
- What is the best metric for quantifying results?
- How to do glint and whitecap removal?
- Constrained inversions
- How to do atmospheric correction (previous lecture)
## Computational Issues: Metrics for Spectrum Matching

<table>
<thead>
<tr>
<th>Name</th>
<th>Key word</th>
<th>Description</th>
<th>Quantity Computed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Euclidean</td>
<td>EUC</td>
<td>sum of squared differences</td>
<td>$\sum_{k=1}^{N_w} e^2(\lambda_k) [R_{rs}^{im}(\lambda_k) \odot R_{db}^{im}(\lambda_k)]^2$</td>
</tr>
<tr>
<td>Manhattan</td>
<td>MAN</td>
<td>sum of absolute differences</td>
<td>$\sum_{k=1}^{N_w} e(\lambda_k) | R_{rs}^{im}(\lambda_k) \odot R_{db}^{im}(\lambda_k) |$</td>
</tr>
<tr>
<td>Chebyshev</td>
<td>CHE</td>
<td>largest absolute difference</td>
<td>$\max_k w(\lambda_k) | R_{rs}^{im}(\lambda_k) \odot R_{db}^{im}(\lambda_k) |$</td>
</tr>
<tr>
<td>Canberra</td>
<td>CAN</td>
<td>sum of absolute differences divided by sum of values</td>
<td>$\frac{\sum_{k=1}^{N_w} e(\lambda_k) | R_{rs}^{im}(\lambda_k) \odot R_{db}^{im}(\lambda_k) |}{\sum_{k=1}^{N_w} e(\lambda_k) | R_{rs}^{im}(\lambda_k) | R_{db}^{im}(\lambda_k) |}$</td>
</tr>
<tr>
<td>Bray-Curtis</td>
<td>BRA</td>
<td>sum of absolute differences divided by sum of absolute values</td>
<td>$\frac{\sum_{k=1}^{N_w} e(\lambda_k) | R_{rs}^{im}(\lambda_k) \odot R_{db}^{im}(\lambda_k) |}{\sum_{k=1}^{N_w} e(\lambda_k) | R_{rs}^{im}(\lambda_k) | R_{db}^{im}(\lambda_k) |}$</td>
</tr>
<tr>
<td>Spectral Angle</td>
<td>COS</td>
<td>cosine of the angle between the spectra</td>
<td>$\frac{\sum_{k=1}^{N_w} e^{im}(\lambda_k) R_{db}^{db}(\lambda_k)}{\left{\sum_{k=1}^{N_w} e^{im}<em>{rs}(\lambda_k)^2 \sum</em>{k=1}^{N_w} e^{db}_{rs}(\lambda_k)^2\right}^{1/2}}$</td>
</tr>
<tr>
<td>Correlation Coefficient</td>
<td>COR</td>
<td>cosine of the angle between the spectra after the spectra are centered on their means</td>
<td>$\frac{\sum_{k=1}^{N_w} e^{im}<em>{rs}(\lambda_k) \odot R</em>{rs}^{im}(\lambda_k) [R_{db}^{db}(\lambda_k) \odot R_{rs}^{db}(\lambda_k)]}{\left{\sum_{k=1}^{N_w} e^{im}<em>{rs}(\lambda_k)^2 \sum</em>{k=1}^{N_w} e^{db}_{rs}(\lambda_k)^2\right}^{1/2}}$</td>
</tr>
</tbody>
</table>

There is no unique way to say which two spectra are “closest”.

The simple Euclidean and Manhattan metrics run the fastest and usually give the best results.

Spectral angle and correlational metrics run slowly and often give poor results because they discard the magnitude information (they compare only the spectral shapes), but are less sensitive to bad atmospheric correction.
## Computational Issues:
### Metrics for Validation of Retrievals

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
<th>Quantity Computed</th>
</tr>
</thead>
<tbody>
<tr>
<td>pct diff</td>
<td>average signed relative difference in retrieved vs true depth, in per cent</td>
<td>( \frac{100}{N_t} \sum_{i} \frac{e_r z_i^r - z_i^t}{z_i^r} ) / ( \sum_{i} e_r z_i^r / z_i^r )</td>
</tr>
<tr>
<td>z diff</td>
<td>average signed difference in retrieved vs true depth, in meters</td>
<td>( \bar{z}<em>{\text{diff}} = \frac{1}{N_t} \sum</em>{i} e_r z_i^r - z_i^t ) / ( \sum_{i} e_r z_i^r - z_i^t )</td>
</tr>
<tr>
<td>z sd</td>
<td>standard deviation between retrieved and true depths, in meters</td>
<td>( \sqrt{\frac{1}{N_t-1} \left( \sum_{i} e_r z_i^r - \bar{z}_{\text{diff}} \right)^2} )</td>
</tr>
<tr>
<td>r^2</td>
<td>square of linear correlation coefficient</td>
<td>( \left( \frac{1}{N_t} \sum_{i} e_r z_i^r - z_i^t \right)^2 / \left( \sum_{i} e_r z_i^r - z_i^t \right)^2 )</td>
</tr>
<tr>
<td>pct ± 1 m</td>
<td>percent of pixels with a retrieved depth within ± 1 m of the true depth</td>
<td>( \frac{1}{N_t} \sum_{i}</td>
</tr>
<tr>
<td>pct ± 25 %</td>
<td>percent of pixels with a retrieved depth within ± 25 % of the true depth</td>
<td>( \frac{1}{N_t} \sum_{i} \frac{</td>
</tr>
</tbody>
</table>

There is no unique way to say which retrieval is “best”.

What is “best” often depends on the application.
Glint and Whitecap Removal

Sun glint can usually be avoided, but background sky glint is always present. Whitecaps and clouds may be present. All raise the spectrum magnitude at all wavelengths.
Glint and Whitecap Removal

Glint removal algorithms for deep water look at the magnitude of $R_{rs}$ at NIR wavelengths, and flag if too high. However, uncontaminated shallow-water spectra can also be high because of bottom reflectance.

glint-contaminated deep water (red, orange, brown)

uncontaminated shallow-water, bright-bottom (purple, blue)

uncontaminated shallow-water dark bottom (green)
Glint and Whitecap Removal

Correct and incorrect glint removal using a single-spectrum NIR threshold algorithm

deeper areas correctly removed

shallow areas incorrectly removed
Glint and Whitecap Removal

Can use spatial filtering. Look at bright pixel and surrounding pixels. Replace bright pixel with median or average of surrounding dark pixels. Can remove most glint, but degrades spatial resolution.

Original (dark is bright pixels)

Spatially filtered with 5x5 pixel block; discard brightest 2 spectra
Constrained Inversions

Usually do not know anything about the imaged area, so must do simultaneous retrieval of depth, bottom reflectance, and water IOPs.

However, if some information is known (e.g., depth from acoustics or a bathymetric lidar, or IOPs from measurement), we can make use of that information and do a constrained inversion. This adds information to the inversion, and should improve the retrievals of the remaining unknowns.
Depth-constrained Inversions

file: C:\LUT\PHILLS\Horseshoe\HR2000_bathy_subsection_LUT_23Aug06_adj2a_L5bb_Rb6-122.bil

acoustic bathymetry for Bahamas image
Depth-constrained Inversions

file: C:\LUT\PHILLS\Horseshoe\HR2000_bathy_subsection_LUT_23Aug06_adj2a\Slbb_Rb6-122.bil

file: C:\LUT\PHILLS\Horseshoe\HR2000_bathy_subsection_LUT_23Aug06_adj2a\Slbb_Rb6-122_zco.bil

acoustic bathymetry interpolated to each image pixel

depth (m)

0–2
2–4
6–8
8–10
10–12
>12
no acoustic
Now consider the depth known at each pixel where acoustic info was available for interpolation.

Search the database at each pixel only for spectra that correspond to a depth close to the known depth. Retrieve just bottom reflectance and IOPs.
unconstrained bottom-type retrieval. Overall pretty good, but lots of “noise” over deep, dark bottoms, probably due to glint. Not sure what is a coral and what isn’t.
Depth-constrained Inversions

depth-constrained bottom-type retrieval. Less “noise” over deep, dark bottoms, and now picks up the corals on Horseshoe Reef.
dots and squares: two sets of ac9 data from the Horseshoe Reef area.
lines: similar $a$ and $b$ from the LUT IOP database; the four backscatter curves have particle backscatter fractions of 0.01, 0.02, 0.03, and 0.04

To constrain the IOPs, assume that $a$ and $b$ are constant over the image area (probably wrong: CDOM decreases as go off shore, and resuspended sediment likely higher near shore)
IOP-constrained Inversions

Unconstrained inversion for depth

IOP-constrained inversion for depth. Not much different because the unconstrained depth retrieval was already very good.
Computer Processing Times

Even if constrained inversions do not greatly improve the remaining retrievals because the unconstrained inversion were already good, constraining the retrieval does greatly speed up the image processing time because less of the $R_{rs}$ database needs to be searched for each pixel.

For the Horseshoe Reef image (on a 2 GHz PC):

- unconstrained inversion: 71 minutes ($>10^{10} R_{rs}$ comparisons)
- depth-constrained inversion: 25 min
- IOP-constrained inversion: 27 min
- depth- and IOP-constrained inversion: 3.5 min
The Bottom Line

+ Spectrum-matching has proven to be extremely powerful because it makes of both spectral shape and magnitude over all available wavelengths.

- MUST have radiometrically well calibrated and atmospherically well corrected imagery

Matching to semianalytical models:
+ do not require pre-computations
- may not converge; model may not capture the relevant environmental conditions

Matching to database spectra:
+ no convergence problems
- require precomputing a data base of $R_{rs}$; database may not capture the relevant environmental conditions
Kayaking Doesn't Get Any Better Than East Greenland
Sea Kayaking in Panamá, Feb 2012