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Bottom Estimation In Shallow Water : Solving a High Mixing Level

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Outline

Purpose

Recent works

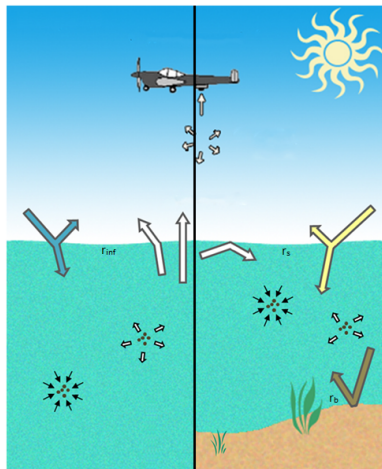
Proposed methods

Conclusion and perspectives

Water column and bottom estimation

Problem

- ▶ Observed image \rightarrow sub-surface reflectance $r_s(\lambda)$
- ▶ **Unknown water column parameters**
 \rightarrow bathymetry H and constituents $\theta = [P, G, X]$,
- ▶ **Unknown bottom reflectance**
 \rightarrow combination of reference spectra from a library



Radiative transfer into the water column

Water column and bottom estimation

Problem

- ▶ Observed image \rightarrow sub-surface reflectance $r_s(\lambda)$
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- ▶ **Unknown bottom reflectance**
 \rightarrow combination of reference spectra from a library
- ▶ Radiative transfer models

Radiative Transfer Models

Maritorena's model [1]:

$$\mathbf{r}_s = \mathbf{r}_\infty + (\mathbf{r}_b - \mathbf{r}_\infty) \mathbf{K} \quad (1)$$

Lee's model [2]:

$$\mathbf{r}_s = \mathbf{r}_\infty + (\mathbf{r}_b \mathbf{K}_b - \mathbf{r}_\infty \mathbf{K}_c) \mathbf{K}_d \quad (2)$$

$$\mathbf{K}_c = \text{diag} [\exp\{-k_{u,c}(\lambda, \theta) H\}]$$

$$\mathbf{K}_b = \text{diag} [\exp\{-k_{u,b}(\lambda, \theta) H\}]$$

$$\mathbf{K}_d = \text{diag} [\exp\{-k_d(\lambda, \theta) H\}]$$

Water column and bottom estimation

Problem

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- ▶ Radiative transfer models

Inversion methods

- ▶ Inversion of the radiative transfer equation if enough knowledge
- ▶ Least squares :

$$[\mathbf{r}_b, \Theta] = \min_{\mathbf{r}_b, \Theta} \sum \|\mathbf{r}^o - \mathbf{r}_{r_b, \Theta}\|^2$$
- ▶ Look up Tables : $[\mathbf{r}_b, \Theta] = \min_{\mathbf{r}_b, \Theta} \sum \|\mathbf{r}^o - \mathbf{r}_{r_b, \Theta LUT}\|^2$
- ▶ Maximum Likelihood

$$[\mathbf{r}_b, \Theta] = \min_{\mathbf{r}_b, \Theta} \mathcal{L}(\mathbf{r}_b; \Theta)$$

Water column and bottom estimation

Problem

- ▶ Observed image \rightarrow sub-surface reflectance $r_s(\lambda)$
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 \rightarrow combination of reference spectra from a library
- ▶ Radiative transfer models

Inversion with a known library: hard points

- ▶ Many parameters
 \rightarrow less accuracy
- ▶ Reference library
 \rightarrow are the reference spectra really adequate ?
- ▶ **Not possible to estimate θ and reflectances (200 s.b.) simultaneously**

Recent method : Iterative E-U algorithm [4]

Separate the estimation of column parameters and bottom spectra

- ▶ Known (fixed) bottom reflectance
→ estimation of the water parameters
- ▶ Known (fixed) water column attenuation
→ unmixing underwater bottom
(optional updating of \mathbf{K})
 - ▶ Combining the eq.(1) radiative model and the mixing model :

$$\mathbf{R}_s - \mathbf{r}_\infty \mathbf{1}_{1N} = \mathbf{K}(\mathbf{S} - \mathbf{r}_\infty \mathbf{1}_{1J})\mathbf{A},$$
 - ▶ Three matrices factorization

$$\tilde{\mathbf{R}} = \mathbf{K}\tilde{\mathbf{S}}\mathbf{A} \quad [3]$$

E-U Algorithm : *Estimation - Unmixing*

Initialization: $\mathbf{R}_b^{(0)}$

while $\epsilon > th$ **do**

$\{\Theta^{(n)}\} \leftarrow$ Estimation ($\mathbf{R}_b^{(n)}$ fixed)

$\mathbf{K}_0^{(n)} = f(\Theta^{(n)})$

$\mathbf{A}^{(n)}, \mathbf{S}^{(n)}, [\mathbf{K}^{(n)}] \leftarrow$ unmixing ($\mathbf{K}_0^{(n)}$ fixed)

$\mathbf{R}_b^{(n)} = \mathbf{A}^{(n)}\mathbf{S}^{(n)}$

$\epsilon = \max_p (|\mathbf{r}_p^{(n)} - \mathbf{r}_p^{(n-1)}| / \mathbf{r}_p^{(n)})$

$n = n + 1$

endwhile

Recent method : Iterative E-U algorithm [4]

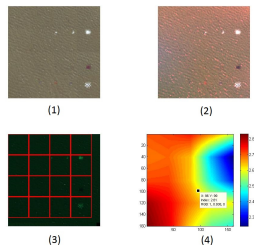
Separate the estimation of column parameters and bottom spectra

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$$\mathbf{R}_s - \mathbf{r}_\infty \mathbf{1}_{1N} = \mathbf{K}(\mathbf{S} - \mathbf{r}_\infty \mathbf{1}_{1J})\mathbf{A},$$
 - ▶ Three matrices factorization

$$\tilde{\mathbf{R}} = \mathbf{K}\tilde{\mathbf{S}}\mathbf{A} \quad [3]$$
 - ▶ Drawback : $\mathbf{K} = [\text{diag}(e^{-2k(\lambda)H})]$ is constant over the pixels in the unmixing step

Example of results



(1) reconstructed bottom with S A, (2) inversion, (3) observed area, (4) bathymetry

NMF with a variable attenuation matrix on each pixel

- ▶ More advanced radiative model : Lee model

$$r_{rs}(\lambda) = \left(1 - e^{-(k_d(\lambda) + k_u^c(\lambda))H}\right) r_\infty(\lambda) + e^{-(k_d(\lambda) + k_u^b(\lambda))H} r_b(\lambda) \quad (1)$$

- ▶ Variable attenuation vector on each pixel

$$\mathbf{r}_{rs,p} = (\mathbf{1} - \mathbf{w}_{p,1}) \odot \mathbf{r}_\infty + \sum_{j=1}^J a_{jp} \mathbf{w}_{p,2} \odot \mathbf{s}_j = \sum_{j=0}^J a_{jp} (\tilde{\mathbf{w}}_{p,j} \odot \mathbf{s}_j)$$

- ▶ Which matrix factorization ?
 - ▶ **Way 1** : factorization of abundances a_{jp} and variable endmembers $(\tilde{\mathbf{w}}_{p,j} \odot \mathbf{s}_j)$
 - ▶ **Way 2** : use $\tilde{\mathbf{r}}_{rs,p} = \mathbf{r}_{rs,p} - (\mathbf{1} - \mathbf{w}_{p,1}) \odot \mathbf{r}_\infty$ as observation
→ simplification
 - ▶ Consider **known attenuation vectors** in a first approach

NMF with a variable attenuation matrix on each pixel

First way

- ▶ Attenuated spectra \equiv variable endmember spectra
 → using a NMF model for spectral variability [5]
- ▶ Construction of structured matrices $\check{\mathbf{S}}, \check{\mathbf{A}}$
 $\check{\mathbf{S}} = [\mathbf{S}_1 \odot \mathbf{S}_{2,1}, \dots, \mathbf{S}_1 \odot \mathbf{S}_{2,p}, \dots, \mathbf{S}_1 \odot \mathbf{S}_{2,P}]$, with
 $\mathbf{S}_1 \odot \mathbf{S}_{2,p} = [\mathbf{r}_\infty \odot (1 - \mathbf{w}_{1,p}), \mathbf{s}_1 \odot \mathbf{w}_{2,p}, \dots, \mathbf{s}_J \odot \mathbf{w}_{2,p}]$,

$$\check{\mathbf{A}} = \begin{bmatrix} \mathbf{a}_1 & 0 & \cdot & \cdot & 0 \\ 0 & \mathbf{a}_2 & 0 & \cdot & 0 \\ 0 & & & & \cdot \\ \cdot & & & & \cdot \\ 0 & \cdot & \cdot & \cdot & \mathbf{a}_P \end{bmatrix}$$

- ▶ Exact NMF formulation $\mathbf{R} = \check{\mathbf{S}} \check{\mathbf{A}}$, but highly structured spectra and abundances matrices (constraints)

NMF with a variable attenuation matrix on each pixel

Second way

- ▶ Lee model : $\mathbf{R} = (\mathbf{1} - \mathbf{W}_1) \odot \mathbf{R}_\infty + \mathbf{W}_2 \odot \mathbf{R}_b$
- ▶ \mathbf{W}_1 and \mathbf{W}_2 attenuation matrices,
- ▶ $\mathbf{R}_b = \mathbf{SA}$ bottom

$$\tilde{\mathbf{R}} = \mathbf{R} - (\mathbf{1} - \mathbf{W}_1) \odot \mathbf{R}_\infty$$

$$\tilde{\mathbf{R}} = \mathbf{W}_2 \odot (\mathbf{SA})$$

with $\mathbf{W}_2 = [\mathbf{w}_{2,1}, \dots, \mathbf{w}_{2,p}, \dots, \mathbf{w}_{2,P}]$

- ▶ NMF formulation \mathbf{SA} with usual spectra and abundances matrices, with a variant of the objective function

Optimization

In a first approach, we suppose the attenuation matrices fixed, and we do not add specific constraints to the objective function

First way

- ▶ Objective function

$$\mathcal{D}_1 = \min_{\mathbf{S}, \mathbf{A}} \|\mathbf{R} - \mathbf{S}\mathbf{A}\|_F^2$$

s. t. $\mathbf{S} \geq 0, \mathbf{A} \geq 0$,
structured matrices.

- ▶ Gradient optimization

$$\nabla_{\mathbf{S}_1} \mathcal{D}_1 = -\mathbf{S}_2 \odot \left[\left(\mathbf{R} - \mathbf{S}\mathbf{A} \right) \mathbf{A}^T \right]$$

$$\nabla_{\mathbf{A}} \mathcal{D}_1 = -\mathbf{S}^T \left(\mathbf{R} - \mathbf{S}\mathbf{A} \right)$$

Second way

- ▶ Objective function

$$\mathcal{D}_2 = \min_{\mathbf{S}, \mathbf{A}} \|\tilde{\mathbf{R}} - \mathbf{W}_2 \odot (\mathbf{S}\mathbf{A})\|_F^2$$

s. t. $\mathbf{S} \geq 0, \mathbf{A} \geq 0$.

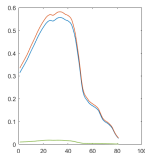
- ▶ Gradient optimization

$$\begin{aligned} \nabla_{\mathbf{S}} \mathcal{D}_2 &= \\ & \left[\mathbf{W}_2 \odot \left(\tilde{\mathbf{R}} - \mathbf{W}_2 \odot (\mathbf{S}\mathbf{A}) \right) \right] \mathbf{A}^T, \\ \nabla_{\mathbf{A}} \mathcal{D}_2 &= \\ & \mathbf{S}^t \left[\mathbf{W}_2 \odot \left(\tilde{\mathbf{R}} - \mathbf{W}_2 \odot (\mathbf{S}\mathbf{A}) \right) \right] \end{aligned}$$

Simulations

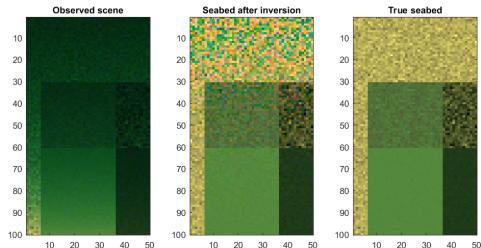
Simulated data

- ▶ Mixing of sand, shell, posidonia, substratum
- ▶ No pure pixel
- ▶ Lee model with variable bathymetry between 0 m and 5 m, fixed water constituents P , G , X
- ▶ Realistic noise added



water attenuation at 5m with

$$C_{\varphi} = 0.7 \mu\text{gL}^{-1}, \quad C_{cdom} = 0.08 \text{m}^{-1}, \quad C_{sm} = 2.8 \text{mgL}^{-1}$$

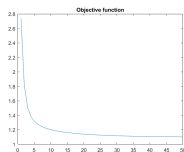


Simulated scene with different mixed zones, and inversion with Lee model.

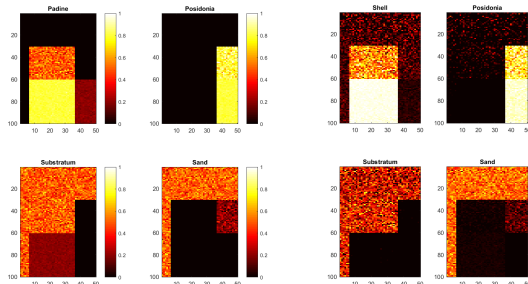
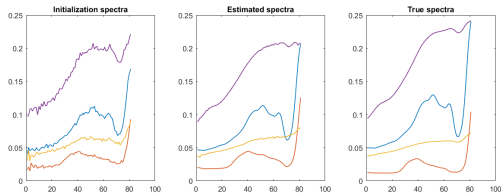
Results

First way

- ▶ $\mathbf{R} = \mathbf{\tilde{S}} \mathbf{\tilde{A}}$
- ▶ No sum-to-one constraint on abundances
- ▶ Initialization : noisy and distorted spectra, FCLS for abundances



Objective function



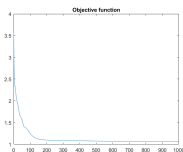
True abundances and estimated abundances

Improvement : 0.2% on abundances, 24% on endmembers spectra (mse)

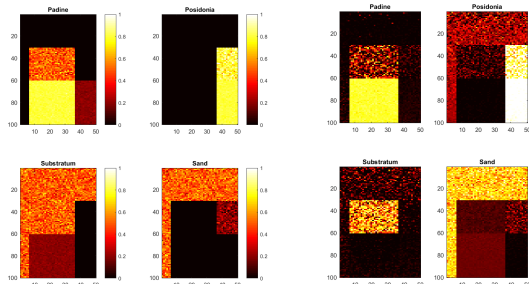
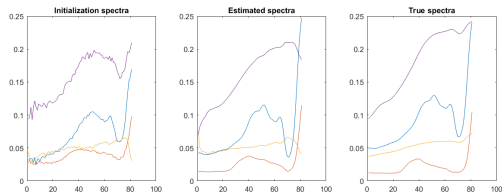
Results

Second way

- ▶ $\tilde{\mathbf{R}} = \mathbf{W}_2 \odot (\mathbf{SA})$
- ▶ No sum-to-one constraint on abundances
- ▶ Initialization : noisy and distorted spectra, FCLS for abundances



Objective function



True abundances and estimated abundances

Improvement : 2% on abundances, 47% on endmembers spectra (mse)

Comments

First Way $\mathbf{R} = \tilde{\mathbf{S}} \tilde{\mathbf{A}}$

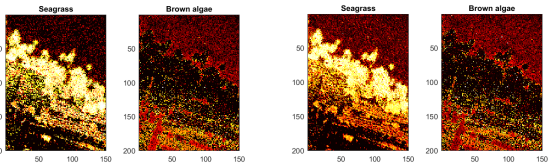
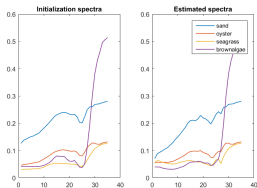
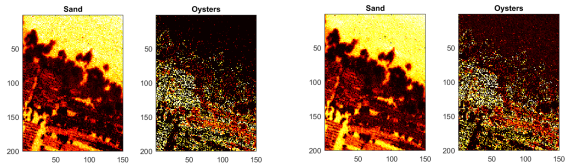
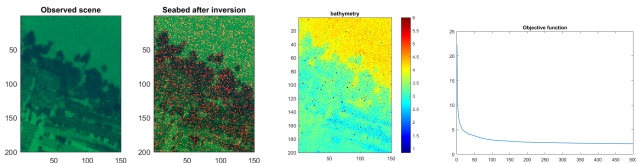
- ▶ Final objective function $E_1 \approx 1.1$
- ▶ Local minimum in few iterations
- ▶ Speed : $\approx 11sec/iter$
- ▶ Endmembers spectra : limited improvement, robust to noisy spectra
- ▶ Abundances : small improvement
- ▶ Able to update the attenuation matrix with the NMF model

Second way $\tilde{\mathbf{R}} = \mathbf{W}_2 \odot (\mathbf{S}\mathbf{A})$

- ▶ Final objective function $E_2 \approx 1.05$
- ▶ Local minimum
- ▶ Speed : $\approx 0.1sec/iter$
- ▶ Endmembers spectra : improvement
- ▶ Abundances : limited improvement
- ▶ Fixed attenuation matrix for NMF model

Generally, the second way is faster and gives better results than the first way. However, the first way is very robust to noisy spectra at initialization and is able to update the attenuation matrix.

Quiberon coast



End members, initial abundances and estimated abundances with the second way

Conclusions

- ▶ Non stationary unmixing the underwater materials for the bottom estimation
- ▶ Two ways explored
- ▶ Limited improvement for spectra and abundances, useful to update the spectral data base

Perspectives

- ▶ Obtain more results with large data
- ▶ Include the non stationary unmixing step into the E-U algorithm.
- ▶ Add adequate constraints (sum to one, etc.)

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