Using time series to improve endmembers estimation on multispectral images for snow monitoring

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Context

Snow cover monitoring using MODIS images
- Low spatial resolution (250-500 m)
- High revisit time (1 day)
- Acquisitions in the visible and NIR domains

Snow cover maps based on Spectral Unmixing
-> based on a library of endmembers (Painter & al, 2010  Sirguey & al, 2009)
  -> Application driven

-> based on estimations done on images
  -> More representative but less interpretable
Spectral Unmixing

Considering \( E = [e_1, ..., e_m] \), \( e_i \in \mathbb{R}^q \) the spectral signature of endmembers in \( q \) spectral bands

The Linear Mixing Model of the spectrum \( r \) of pixel \( p \):

\[
    r_p = \sum_{i=1}^{m} e_i \phi_{i,p} + n_p
\]

Where \( \phi_p = [\phi_{1p}, ..., \phi_{mp}] \) are fractional per pixel abundances and \( n \) is noise

\[
    \hat{\phi}_p = \arg \min_{\phi_p} \left\| r_p - \sum_{i=1}^{m} e_i \phi_{i,p} \right\|_2
\]
Spectral Unmixing

- With Abundance Non-negative ($\phi_i \geq 0$) and Sum-to-one ($\sum_{i=1}^m \phi_i = 1$) Constrain (resp. ANC and ASC)

  -> Full Constrained Least Square Unmixing (FCLSU)

- With parcimonie :

  $$\hat{\phi}_p = \arg \min_{\phi_p} \frac{1}{2} \left\| r_p - \sum_{i=1}^m e_i \phi_{i,p} \right\|_2^2 + \lambda \left\| \phi_p \right\|_1$$

  Example : SUnSAL (Bioucas-Dias and Figueiredo, 2010)

- Spectral variability :

  $$\hat{\phi}_p = \arg \min_{\phi_p} \left\| r_p - \sum_{i=1}^m \phi_{i,p} f_{i,p}(e_i) \right\|_2$$

  where $f_{i,p} = \Psi_{i,p} e_{0,i}$ and $\Psi$ is a matrix gathering all the scaling factors for all P pixels

  Example : ELMM (Drumetz & al., 2015)
Spectral unmixing approaches

**Endmembers estimation**

- Geometrical approaches (e.g., Vertex Component Analysis (VCA)) Nascimento, J. and Bioucas Dias, J., 2005.

- Minimum volume approaches (e.g., Simplex identification via split augmented Lagrangian (SISAL), J. M. Bioucas-Dias, 2009

**Abundances estimation**

- FCLSU

- Sparsity (e.g., SUnSAL) Bioucas-Dias and Figueiredo, 2010

- Spatial regularization (e.g., SUnSAL_vtv)

- Spectral variability (e.g., ELMM (Drumetz & al., 2015)

- Clusters (e.g., AEB Somers & al., 2012, FDN Jin & al., 2010)
Daily estimation

Issue: mixed pixels and spectral variability
Usual approaches

Endmembers estimation
- Vertex Component Analysis (VCA)
- Geometric Cluster (AEB, FDN)

Abundances estimation
- FCLSU
- SUnSAL
- SUnSAL_vtv
- ELMM

Designed for spectral variability

Issue: mixed pixels / time
Proposed approach

Date of interest (d=0, $R_{old}=\infty$)

Set of endmembers used for the abundance estimation

Masking snow

Endmember estimation

Reconstruction Error

100 runs

Set of endmembers $E_{final}$ + Snow endmembers

$R_{new} = r_0 + r_1 + r_2$

If $R_{new} < R_{old}$

$E_{final} = E_{temp}$

$R_{old} = R_{new}$

$r_0$

$r_1$

$r_2$
Experimentation:

- **Endmember estimation**
  - VCA (1 date over all pixels)
  - VCA (1 date over non-snow pixels)
  - VCA with 3 dates
    - Our approach

- **Abundance estimation**
  - FCLSU
  - SUnSAL
  - SUnSAL_vtv
  - ELMM

- Cluster (AEB, FDN)
Tested area: The Alps near Grenoble

30 dates, 320x400 pixels

set up:
- 3 consecutive dates
- 100 test for reconstruction error
- 15 dates considered
Results: visual interpretation
Results: quantitative results

Red: 1 date
Orange: 2 dates
Green: 3 dates
Results: comparison with daily endmembers estimation
Results: comparison on areas without snow
Effect of the number of dates
Conclusions and perspectives

• Large improvement between SU performed daily
  - Easy to implement, stability of the result
  - Limitation: need for consecutive cloud free acquisitions

• Spectral unmixing:
  - Large differences between FCLSU and SUnSAL in case of misfit set
  - Spatial regularisation not fully appropriate for snow cover monitoring
  - ELMM high performance in most of the cases (but time consuming)

• Applications/perspectives:
  - High return time but low spatial and spectral resolution → consider images from different sensors
  - Generalize the proposed spectral unmixing scheme