Analysis of the unmixing on thermal hyperspectral imaging

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Thermal hyperspectral remote sensing in geology

Emissivity Strip over Virginia City (NV) (RGB = 11.08, 9.6 and 9.02 μm)

Photograph of the trimodal tailings site on the up-right.

Studied area composed of Quartz, Jarosite and Clay mixture.

*Vaughan, Calvin et Taranik, SEBASS hyperspectral thermal infrared data: surface missivity measurement and mineral mapping, in RSE 2003
### Outline

1. **Introduction**
   - Context of the work

2. **Unmixing strategies on mixed pixels**
   - FCLS-R - Unmixing on the radiance image
   - FCLS-E - Unmixing on the estimated emissivities
   - TRUST - Thermal Remote sensing Unmixing for Subpixel Temperature

3. **Results on synthetic and real data**
   - Assessment of the three unmixing strategies on a supervised approach
   - Towards an unsupervised approach

4. **Conclusions and perspectives**
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Introduction to thermal hyperspectral remote sensing
Objective of the thesis

Material parameters

Emissivity (optical property), temperature and abundance (material proportion on pixels)

**Pure pixel**: estimation of temperature and emissivity of the material composing the pure pixel.

**Mixed pixel**: dependent of emissivity, temperature and abundance of each material composing the pixel.

**Main Goal**

Estimate the temperature, the emissivity and the abundance of materials on pure and mixed pixels.
State-of-art of the unmixing methods in TIR domain

Two different approaches

- First approach: Unmixing on a co-registered VIS image
  - Increase the spatial resolution of the thermal image *
  - Temperature study of classes of material †

- Second approach: Considering isothermal pixels ‡
  ⇒ Same approach as in VIS domain.§

Lack of a general approach to solve the unmixing in the TIR domain.

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† Deng et al. Examining the impacts of urban biophysical compositions on surface urban heat island: A spectral unmixing and thermal mixing approach, in RSE 2013
‡ Colins et al. Spectral mixture analysis of simulated thermal infrared spectrometry data: An initial temperature estimation bounded tessa search approach, in IEEE TGRS 2001
§ Vaughan et al., SEBASS hyperspectral thermal infrared data: surface emissivity measurement and mineral mapping, in RSE 2003
Radiative transfer model - pure pixel

\[ R_{\text{sens}}^\lambda = \varepsilon^\lambda \cdot B^\lambda(T) \cdot \tau_{\text{atm}}^{\lambda,\uparrow} + (1 - \varepsilon^\lambda) \cdot R_{\text{atm}}^\lambda \cdot \tau_{\text{atm}}^{\lambda,\downarrow} \cdot \tau_{\text{atm}}^{\lambda,\uparrow} + R_{\text{atm}}^\lambda \]

Estimation of temperature and emissivity

1. Atmospheric Compensation
   - Known atmosphere

2. Decoupling Temp. and Emiss.
   - **Ill-posed problem**: \( N \) equations and \( N + 1 \) unknowns (\( N \) spectral bands number)
   - Methods exist (TES*, SpSm†, ...)

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† Borel et al. Surface emissivity and temperature retrieval for a hyperspectral sensor, in IGARSS 1998
Radiative transfer model - mixed pixel 1/2

\[ R_{\text{sens},m}^{\lambda,x,y} = \sum_{m=1}^{M} \left( \left( \varepsilon_m^\lambda \cdot B^{\lambda}(T_m^{x,y}) + (1 - \varepsilon_m^\lambda) \cdot R_{\text{atm},\downarrow}^\lambda \right) \cdot \tau_{\text{atm},\uparrow} + R_{\text{atm},\uparrow}^\lambda \right) \cdot S_m^{x,y} \]

**Estimation of abundance**

- **Three steps:**
  - the number of **endmembers**,  
  - the endmembers themselves,  
  - their **abundances**.

**How to define the endmembers?**

V-NIR = reflectance. TIR = ???

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*Bioucas-Dias et al. Hyperspectral unmixing overview: Geometrical, statistical and sparse regression-based approach, in IEEE JSTARS 2012*
Radiative transfer model - mixed pixel 2/2

\[ R_{\text{sens}}^{\lambda,x,y} = \sum_{m=1}^{M} R_{\text{sens},m}^{\lambda,x,y}(\varepsilon_{m}^{\lambda}, T_{m}, \text{atm}) \cdot S_{m}^{x,y} \]

Three definitions of endmember

- A unique couple of emissivity and temperature
  \[ \Rightarrow \text{FCLS-R: To unmix the radiance at sensor level} \]

- A unique emissivity spectrum
  \[ \Rightarrow \text{FCLS-E: To unmix the emissivity estimated with TES method} \]

- A unique emissivity spectrum and a range of temperature
  \[ \Rightarrow \text{TRUST: To unmix the radiance at sensor level knowing the emissivity}^{*} \]
Three definitions of endmember

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- A unique emissivity spectrum and a range of temperature
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\[
R_{\text{sens}}^{\lambda,x,y} = R_{\text{sens}}^{\lambda,x,y} \left( \sum_{m=1}^{M} \varepsilon_m^\lambda \cdot S_{m}^{x,y}, < T >^{x,y, \text{atm}} \right)
\]
Radiative transfer model - mixed pixel 2/2

\[
R_{\text{sens}}^{\lambda,x,y} = \sum_{m=1}^{M} R_{\text{sens},m}^{\lambda,x,y}(\varepsilon_{m}^{\lambda}, T_{m}^{x,y}, \text{atm}) \cdot S_{m}^{x,y}
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Three definitions of endmember

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*Cubero-Castan et al. A physics-based unmixing method to estimate subpixel temperatures on mixed pixels, in IEEE TGRS 2015*
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4. Conclusions and perspectives
FCLS-R: Linear unmixing model on at-sensor radiances

\[
R_{\text{sens}}^{\lambda,x,y} = \sum_{m=1}^{M} R_{\text{sens},m}^{\lambda,x,y}(\varepsilon_{m}^{\lambda}, T_{m}, \text{atm}) \cdot S_{m}^{x,y}
\]

Linear mixing model on at-sensor radiance  \(\Rightarrow\) Linear unmixing method

**FCLS-R**  Fully Constrain Linear Square Unmixing (FCLS Unmixing)* applied on at-sensor radiances

*Heinz et Chang, Fully Constrain least squares linear spectral mixture analysis method for material quantification in hyperspectral imagery, in IEEE TGRS 2001
FCLS-E: Aggregation Principle

\[ R_{sens}^{\lambda,x,y} = \sum_{m=1}^{M} R_{sens,m}^{\lambda,x,y}(\varepsilon_m^\lambda, T_m^{x,y}, atm) \cdot S_m^{x,y} = R_{sens}^{\lambda,x,y}(\langle \varepsilon^\lambda \rangle, \langle T \rangle, atm) \]

\[ R_{sens}^{\lambda,x,y} \text{ leads to aggregation models } \langle \varepsilon \rangle \text{ & } \langle T \rangle^*. \]

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*Cubero-Castan et al. Physic based aggregation model for the unmixing of temperature and optical properties in the infrared domain, in IEEE WHISPERS 2012*
FCLS-E: Linear aggregation model for emissivity

\[
\sum_{m=1}^{M} \left( \varepsilon_{m}^{\lambda} \cdot B(T_{m,x}^{x,y}) + (1 - \varepsilon_{m}^{\lambda}) \cdot R_{atm,\downarrow}^{\lambda} \right) \cdot S_{m}^{x,y} = \langle \varepsilon \rangle \cdot B(\langle T \rangle) + (1 - \langle \varepsilon \rangle) \cdot R_{atm,\downarrow}^{\lambda}
\]

Aim: To build aggregation models identifying each radiative term.*

\[
\begin{align*}
\langle \varepsilon \rangle &= \sum_{m} \varepsilon_{m}^{\lambda} \cdot S_{m}^{x,y} \\
\langle T \rangle &= (B^{\lambda})^{-1} \left( \frac{\sum_{m} \varepsilon_{m}^{\lambda} \cdot B(T_{m,x}^{x,y}) \cdot S_{m}^{x,y}}{\sum_{m} \varepsilon_{m}^{\lambda} \cdot S_{m}^{x,y}} \right)
\end{align*}
\]

- Linear model on $\langle \varepsilon \rangle$
- Linear unmixing methods

* Cubero-Castan et al. Physic based aggregation model for the unmixing of temperature and optical properties in the infrared domain, in IEEE WHISPERS 2012
FCLS-E: General Structure

\[ R_{\text{sens}}^{\lambda,x,y} = R_{\text{sens}}^{\lambda,x,y} \left( \sum_{m=1}^{M} \varepsilon_m^{\lambda} \cdot S_m^{x,y}, <T>^{x,y,\text{atm}} \right) \]

A two steps process

1. Estimation of emissivity and temperature
2. Linear unmixing on emissivity
   - FCLS Unmixing

Is this aggregation model similar to the TES estimations of emissivity and temperature?
FCLS-E: Comparison with TES structures

**Aim:** To compare the aggregation models with TES estimation.*

**Observation:** Good agreement (RMSE on $\varepsilon < 1.5\%$ and RMSE on $T < 1K$) between TES estimations and aggregation models, for mixed pixels with $T_{max} - T_{min} < 15K$.

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*Cubero-Castan et al. The comparability of aggregated emissivity and temperature of heterogeneous pixel to conventional TES methods, in IEEE WHISPERS 2013*
TRUST: General structure

A two-step process

- Estimation of the mean temperature and the emissivity on pure pixels, with a supervised or unsupervised localization.
- Estimation of the subpixel temperature and the abundances with TRUST method.
TRUST: A two-estimation unmixing algorithm

A two-estimation unmixing algorithm

- Estimation of the **subpixel temperature** $T_{i}^{x,y}$ knowing the **abundance** $S_{i}^{x,y}$,
- Estimation of the **abundances** using the subpixel temperature estimator.
TRUST: Estimation of the subpixel temperatures

**Aim:** To estimate the subpixel temperatures on a mixed pixel knowing the abundances, the emissivity and the mean temperature of materials.*

- Liberalization of the Black Body law $B^λ(T_i)$ around the mean temperature for each material.
- Best Linear Unbiased Estimator (BLUE).

$$\Delta T = (A^t \cdot C^{-1} \cdot A)^{-1} \cdot A^t \cdot C^{-1} \cdot \Delta R$$

$$\begin{align*}
\Delta R^λ_j &= R_{BOA}(T_i) - R_{BOA}(\bar{T}_i) \\
\lambda^T_j &= \varepsilon_i \cdot S_i \cdot \frac{\partial B^λ_j(T)}{\partial T} \bigg|_{T_i} \\
\Delta T_i &= \bar{T}_i - T_i
\end{align*}$$

**Results:** Good estimation (RMSE < 2K) with few materials within the mixed pixels and sufficient abundances.

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* Cubero-Castan et al. An unmixing-based method for the analysis of thermal hyperspectral images, in IEEE ICASSP’14
TRUST: Impact of a misestimation of the abundances

**Aim:** To analyse the impact of an error on the abundance.

**Simulation:** A mixed pixel with **two** materials (50%/50%, ASTER lib., 285K-330K, TASI sensor with 0.03 W.sr$^{-1}$.m$^{-2}$.µm$^{-1}$ noise level). **Shift on abundance** between -20% and +20%.

Study of the reconstruction error (RMSE).

- Big impact of the accuracy of the abundance in the reconstruction error.
- Minimum of the reconstruction error with the good abundance.

**Idea**  
Estimate the abundance by minimizing the reconstruction error
**TRUST: Joint estimation of the temp. & the abund.**

**Aim:** To jointly estimate the subpixel temperatures and the abundances on mixed pixels.*

- Use of the previous BLUE estimator.

\[
D(S_{i}^{x,y}, T_{i}^{x,y}) = \sqrt{\frac{1}{N} \cdot \sum_{\lambda} \left( R_{BOA}^{\lambda} - R_{BOA}^{\lambda}(S_{i}^{x,y}, T_{i}^{x,y}) \right)^2} + \gamma \cdot \sqrt{\frac{1}{M} \sum_{i} \left( T_{i}^{x,y} - \overline{T}_{i} \right)^2}
\]

- **Data dependency:** simulation of BOA radiance with \(S_{i}^{x,y}\) and \(T_{i}^{x,y}\).
- **Physical constraint:** Temperature \(T_{i}^{x,y}\) has to be close to \(\overline{T}_{i}\).

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* Cubero-Castan et al. A physics-based unmixing method for thermal hyperspectral images, in IEEE ICIP’14
Different strategies to unmix TIR data

- **FCLS-R**
  - Unmixing on rad.
  - $R_{sens}^\lambda, x, y$
  - $S_m^{x, y}$
  - $e_m^\lambda$
  - $T_m$

- **FCLS-E**
  - Atm. Comp. + TES
  - $<\epsilon>^{\lambda, x, y}$
  - $<T>^{\lambda, x, y}$
  - Unmixing on emiss.
  - $e_m^\lambda$
  - $S_m^{x, y}$

- **TRUST**
  - Atm. Comp. + TES
  - Unmixing
  - $e_m^\lambda, T_m^{x, y}$
  - $S_m^{x, y}$
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Results on synthetic and real data

Two main results

- Assessment of the three unmixing strategies on a supervised approach
  - On synthetic data - global comparison and impact of the spatial temperature distribution
  - On real data - DUCAS campaign

- Towards an unsupervised approach
  - Estimation of the number of endmembers,
  - Estimation of the endmembers.
Aim: To compare the TRUST method with supervised unmixing on at-sensor radiances and emissivity spectra.

Simulation: A two-material scene (asphalt & gravel - DUCAS campaign) with a Gaussian temperature distribution. Atmosphere and TASI sensor as DUCAS campaign.
Synthetic scene: Comparative study 2/3

Root Mean Square Error (RMSE) on abundance estimation ($E_S$ in %) using the three unmixing methods.

<table>
<thead>
<tr>
<th></th>
<th>$E_S$ (%)</th>
<th>$E_T$ (K)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Asph.</td>
<td>1.8</td>
<td>1.1</td>
</tr>
<tr>
<td>Grav.</td>
<td>2.0</td>
<td>1.3</td>
</tr>
<tr>
<td>Mixed</td>
<td>3.1</td>
<td>1.7</td>
</tr>
<tr>
<td>Total</td>
<td>2.4</td>
<td>0.7</td>
</tr>
</tbody>
</table>

Observation

- TRUST performs a **better** unmixing
- Access to **subpixel temperature**
Synthetic scene: Comparative study 3/3

**Simulation:** Variation of temperature parameters: standard deviation $\sigma_T = [0, 5]$ K and temperature difference $d_T = [0, 40]$ K.

**FCLS-R Method**
Increase of $E_S$ with $T$ distribution parameters.

**FCLS-E Method**
No impact of $T$ distribution but constant error.

**TRUST Method**
No impact of $T$ distribution with good performances.
**DUCAS: Comparative study 1/2**

**Aim:** To study the unsupervised unmixing on the DUCAS data.

**Image:** TASI sensor (32 bands, 8-12 $\mu m$) with 1m of spatial resolution. Campaign DUCAS (EDA) at Zeebruges, Belgium (2011).

Localisation of pure (RGB) and mixed pixels.

<table>
<thead>
<tr>
<th></th>
<th>Asph.</th>
<th>Grav.</th>
<th>3rd Roof</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_{mean}$</td>
<td>333.2</td>
<td>315.3</td>
<td>316.6</td>
</tr>
<tr>
<td>$T_{std}$</td>
<td>1.3</td>
<td>1.4</td>
<td>0.4</td>
</tr>
</tbody>
</table>

TES Estimation of Emiss. & Temp. (K)
DUCAS: Comparative study 2/2

**Aim:** To estimate the abundances using the three unmixing strategies.

- **FCLS-R Method**
- **FCLS-E Method**
- **TRUST Method**

**Observation**

- TRUST method favors **sparsity** and provides the best results.
- FCLS-R and TRUST find **nearly similar** abundances on the mixed pixels.
- FCLS-E gives the poorest results, mainly on Asphalt & 3rd floor mixing abundances.
DUCAS: Subpixel $T$ estimation

**Objective:** Study the estimation of the temperature using TRUST method applied on at-sensor radiance.

![Temperature maps](image)

- **Asphalt Sub. Temp. (K)**
- **Gravel Sub. Temp. (K)**
- **3rd roof Sub. Temp. (K)**

**Observation**

- **Coherent** estimation of subpixel temperatures
Unsupervised unmixing chain design

Three steps to design an unsupervised unmixing chain:

- Estimation of the number of endmembers,
  - A parameter-free method: **HySime**$^*$,
- Identification of the endmembers,
  - Geometrical approach (good solution for high Signal to Noise Ratio (SNR) and without dictionary available): **VCA**$^†$,
- Estimation of the abundances of each endmember,
  - Knowing endmembers leads to **FCLS Unmixing**$^‡$.

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$^*$ Bioucas-Dias et al., Hyperspectral subspace identification, in IEEE TGRS 2008
$^†$ Nascimento et al., Vertex Component Analysis: A fast algorithm to unmix hyperspectral data, in IEEE TGRS 2005
$^‡$ Heinz et al., Fully constrained least square linear spectral mixture analysis method for material quantification in hyperspectral imagery, in IEEE TGRS 2001
Estimation of the number of endmembers

**Strategy:** Unsupervised (Hysime + VCA + FCLS) on radiance.

\[ \text{FLCS-R with 5 materials} \]

\[ \text{TES estimation} \]

\[ \text{Radiance (W m}^{-2} \text {m}^{-2} \text {um}^{-1}) \]

\[ \text{Emissivity} \]
Estimation of the number of endmembers

**Strategy**: Unsupervised (Hysime + VCA + FCLS) on emissivity.
Estimation of the endmembers

**Aim:** Study the Principal Component Analysis (PCA) projection on radiance on a synthetic three-material scene (temperatures and emissivities extracted from DUCAS data).

- Single material is well distributed in the **corner** of the vertex.
- The spatial distribution of $T$ **blurs** the PCA projection.
Estimation of the endmembers

**Aim**: Study the Principal Component Analysis (PCA) projection on *emissivity* on a synthetic three-material scene (temperatures and emissivities extracted from DUCAS data).

\[
\sigma_T = 0
\]

- Single material on a manifold distribution, regardless of the temperature distribution.

\[
\sigma_T \neq 0
\]

- Asphalt
- Gravel
- 3rd roof
- Asph. & Grav.
- Asph. & 3rd roof
- Grav. & 3rd roof
- All materials
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Performances of the three unmixing methods - 1/2

**FCLS-R** Good estimation of abundances (2.4% error with 2 materials), except with high temperature distribution (RMSE > 50% with $\sigma_T = 5K$ and $\bar{T}_1 = \bar{T}_2$).

**FCLS-E** No impact of temperature distribution but emissivity maps are too noisy (5% to 10% error with 2 materials)

**TRUST** Good estimation of abundance (0.7% error with 2 materials) and independence of temperature distribution.

- Computation time: 30 s with TRUST, 0.50 s with FCLS-E and 0.12 s with FCLS-R (320 pixels with 3 materials)
TRUST  A new method to unmix thermal infrared images.

- New estimation of the **subpixel temperature**
- **Validation** on **synthetic** data
  - Good with 1 or 2 materials composing the pixel but not with 3 or more materials.
- **Application** on **real** data
  - DUCAS - Zeebruges, 2011
  - AHS-EUFAR - Salon de Provence, 2010

Which method is the most relevant and in which context using it to unmix an hyperspectral image on TIR domain?
Recommendations

Recommendation for the supervised unmixing in TIR domain

- No spatial distribution of temperature (low $\sigma_T$ and high $d_T$)
  - Supervised unmixing on at-sensor radiances: FCLS-R
- High spatial distribution of temperature (high $\sigma_T$)
  - Joint supervised strategy with unmixing on at-sensor radiances and TES estimation: TRUST

Recommendation for an unsupervised approach

- With small spatial distribution of temperature, a classical unsupervised approach works on at-sensor radiances.
  - Overdetermination of the number of endmembers $\Rightarrow$ post-processing of data to merge similar classes (same emissivity but different temperature)
Contributions

International peer-review articles


International conference participations


Other participation (french symposium)

TRUST improvement

- Unsupervised algorithm on two steps:
  - Selection of pure pixels for each material,
- Speed of the TRUST algorithm

Classification method based on TRUST

- Utilisation of Support Vector Machine (SVM) algorithm.
- Application of TRUST with few materials (no spectral feature, silicate absorption, etc.).
- SVM Classifier = abundance maps estimated by TRUST.
Temperature as a manifold variation

- Variation of temperature as intraclass variability of endmember.
- Apply new unmixing method to diminish the temperature effect on unmixing results.

(On-going collaboration with L. Drumetz - GIPSA-Lab)

Combine both images acquired on V-NIR and on TIR domain

- SYSIPHE: Same spatial resolution VNIR & TIR
- THIRSTY: High spatial resolution in VNIR but few spectral bands ⇒ Spatial information on VNIR image could help TIR image processing
And then ...

... any questions?