# IRAP PhD Day 2019
# Taking in account panchromatic data in hyperspectral image unmixing


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# An hyperspectral image

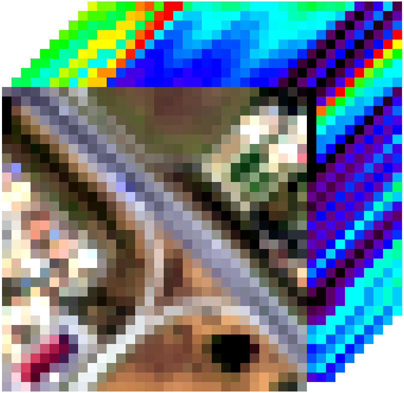
Acquiring a scene with several hundred of spectral bands

**Expectation:**

# An hyperspectral image

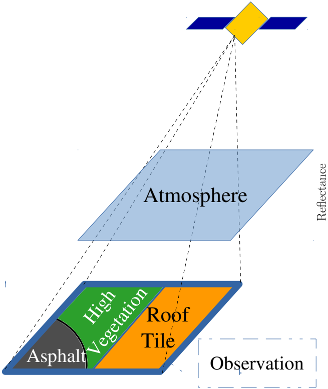
Acquiring a scene with several hundred of spectral bands

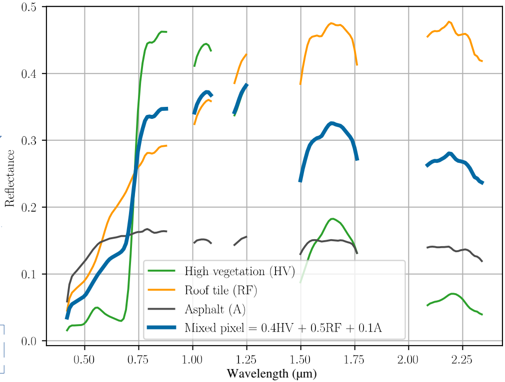
**Reality:**



# Problem statement

Due to the spatial sampling, a hyper-spectral photosite acquires a mix of the material spectra in the covered area.



# Problem statement

## Example: linear mixing model

$$\overrightarrow{y_i} = \sum_{k=1}^{P} x_{ki}\overrightarrow{s_k} + \overrightarrow{w}$$

- The pixel $i$ $\overrightarrow{y} \in \mathbb{R}_+^L$
- The abundance fractions $\overrightarrow{x_k} \in \mathbb{R}_+^P$
- The endmembers $\overrightarrow{s_k} \in \mathbb{R}_+^L$
- A noise $\overrightarrow{w}$

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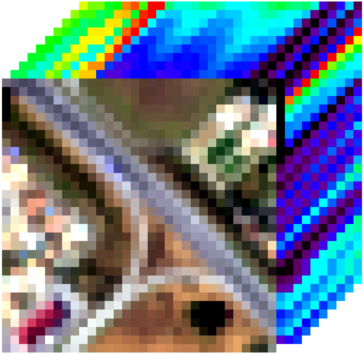
## Unmixing goal

Blindly extract or estimate the endmembers $\overrightarrow{s_k}$ as well as their abundance fractions $\overrightarrow{x_{k,i}}$

# Adding a panchromatic image

Since 2011 the CNES studies the possible outcomes of shipping two co-registered instrument:

- an hyperspectral camera covering the [0.4 - 2.5] µm range whith 10 nm spectral step and a 8 m GSD.
- a 2 m GSD panchromatic camera.

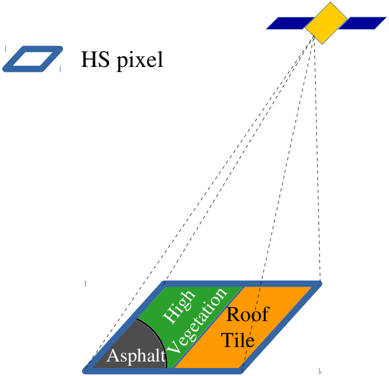


Hyperspectral image (HSI) - 8 m GSD

Panchromatic image (Pan) - 2 m GSD

# Proposed approach

Homogeneity-Based Endmember Extraction (HBEE): A homogeneous panchromatic area leads to a pure pixel



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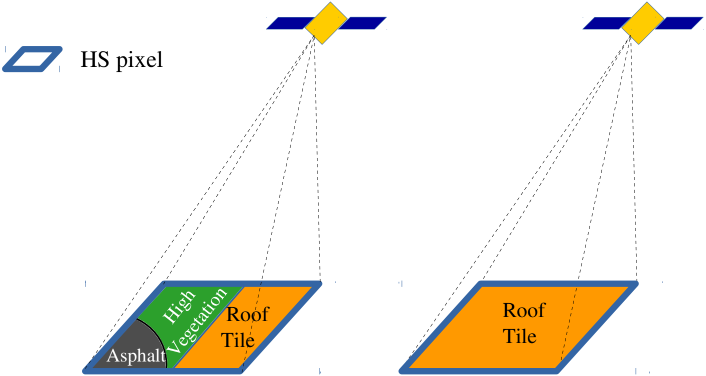
Homogeneity-Based Endmember Extraction (HBEE): A homogeneous panchromatic area leads to a pure pixel



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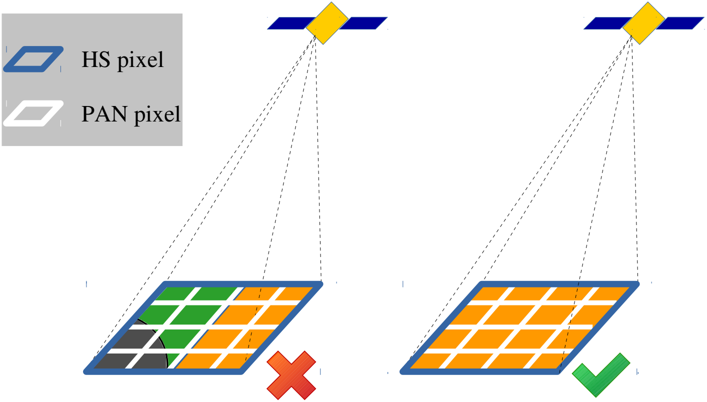
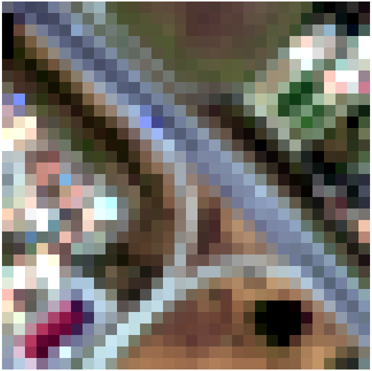
Homogeneity-Based Endmember Extraction (HBEE): A homogeneous panchromatic area leads to a pure pixel



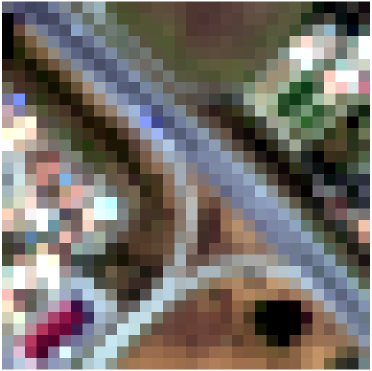
# Homogeneous pixel detection



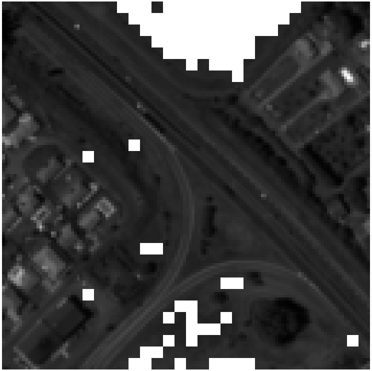
HS image with an 8m GSD

Pan image with a 2m GSD

# Homogeneous pixel detection

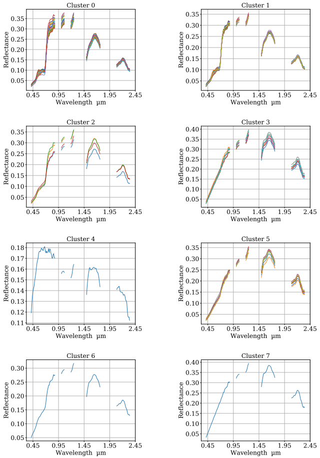


HS image with an 8m GSD

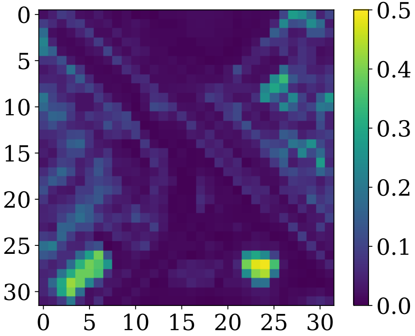


Detected homogeneous area

# HBEE results




Pure spectra clusters




Reconstruction Error (RE) map after the HBEE stage:

$$RE = \frac{||\hat{y_{ij}} - y_{ij}||}{||\hat{y_{ij}}||}$$

# Proposed approach - LSNMF stage

A poorly reconstructed area contains a yet unextracted endmember.

## Locally-Semi-supervised Non-negative Matrix Factorisation (LSNMF)

1. Calculation of the RE map.
2. Selection of the most poorly reconstructed area.
3. Initialisation of the endmember and abundance fraction matrices.
4. Estimation of an unknown endmember by applying an NMF onto the area.
5. Iterate until all the previously detected areas are correctly rebuilt.

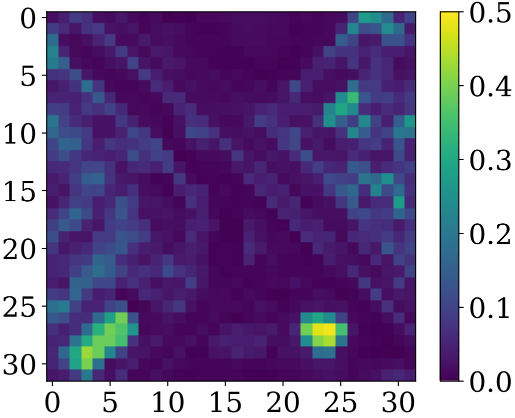
## NMF

To estimate the endmember, the multiplicative update strategy is considered here :

$$X_{k+1} \leftarrow X_k \frac{S_k^T Y}{S_k^T S_k X_k + \epsilon} \qquad S_{k+1} \leftarrow S_k \frac{Y X^T}{S_k X_k X_k^T + \epsilon}$$

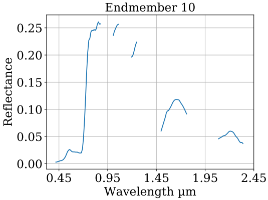
# LSNMF results

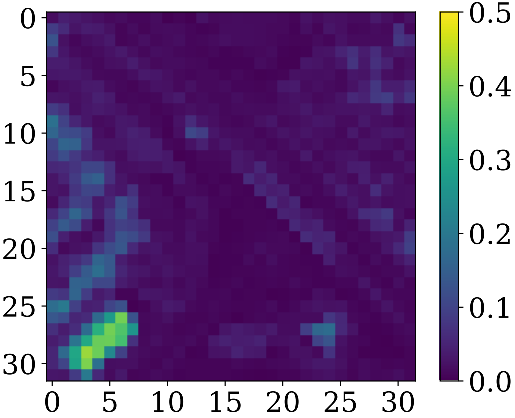
Iteration 0



# LSNMF results

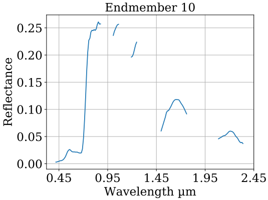
Iteration 1

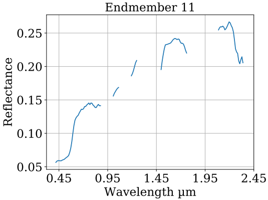


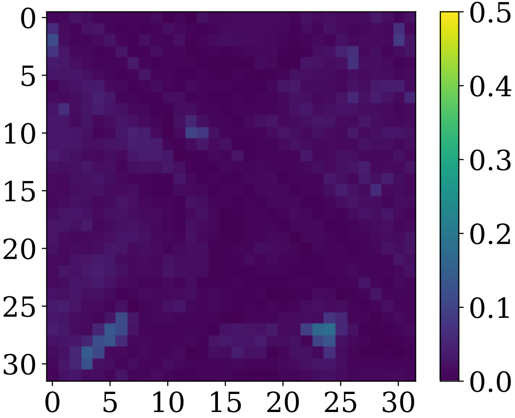



# LSNMF results

## Iteration 2



# Conclusion

## Limitations and possible enhancements

- The parameters depend on the image

## Contribution

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- HBEE extracts truly pure spectra as endmembers.

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- HBEE extracts truly pure spectra as endmembers.
- LSNMF estimates satisfactory unextracted endmembers.

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- HBEE extracts truly pure spectra as endmembers.
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- The overall performances are equivalent to others state of the art methods in a spectral sense.

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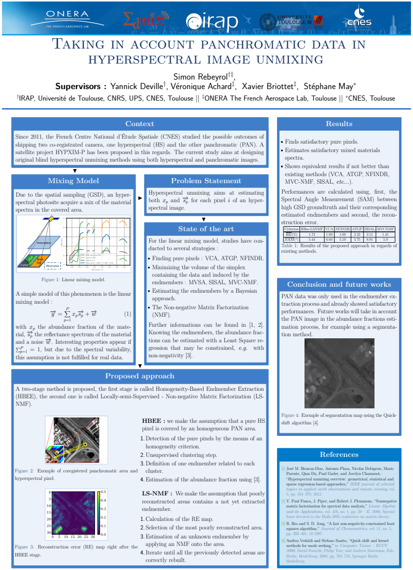
## Contribution

- HBEE extracts truly pure spectra as endmembers.
- LSNMF estimates satisfactory unextracted endmembers.
- The overall performances are equivalent to others state of the art methods in a spectral sense.
- Naturally estimates a satisfactory number of endmember

# Thank you for your attention !



# TAKING IN ACCOUNT PANCHROMATIC DATA IN HYPERSPECTRAL IMAGE UNMIXING

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[†]IRAP, Université de Toulouse, CNRS, UPS, CNES, Toulouse || [‡]ONERA The French Aerospace Lab, Toulouse || [*]CNES, Toulouse

## Context

Since 2011, the French Centre National d'Étude Spatiale (CNES) studied the possible outcomes of shipping two co-registrated camera, one hyperspectral (HS) and the other panchromatic (PAN). A satellite project HYPXIM-P has been proposed in this regards. The current study aims at designing original blind hyperspectral unmixing methods using both hyperspectral and panchromatic images.

## Mixing Model

Due to the spatial sampling (GSD), an hyperspectral photosite acquire a mix of the material spectra in the covered area.

Figure 1: Linear mixing model.

A simple model of this phenomenon is the linear mixing model :

$$\overrightarrow{y} = \sum_{p=1}^{P} x_p \overrightarrow{s_p} + \overrightarrow{w} \quad (1)$$

with $x_p$ the abundance fraction of the material, $\overrightarrow{s_p}$ the reflectance spectrum of the material and a noise $\overrightarrow{w}$. Interesting properties appear if $\sum_{p=1}^{P} = 1$, but due to the spectral variability, this assumption is not fulfilled for real data.

## Problem Statement

Hyperspectral unmixing aims at estimating both $x_p$ and $\overrightarrow{s_p}$ for each pixel $i$ of an hyperspectral image.

## State of the art

For the linear mixing model, studies have conducted to several strategies :

- Finding pure pixels : VCA, ATGP, NFINDR.
- Minimizing the volume of the simplex containing the data and induced by the endmembers : MVSA, SISAL, MVC-NMF.
- Estimating the endmembers by a Bayesian approach.
- The Non-negative Matrix Factorization (NMF).

Further informations can be found in [1, 2]. Knowing the endmembers, the abundance fractions can be estimated with a Least Square regression that may be constrained, *e.g.* with non-negativity [3].

## Proposed approach

A two-stage method is proposed, the first stage is called Homogeneity-Based Endmember Extraction (HBEE), the second one is called Locally-semi-Supervised - Non-negative Matrix Factorization (LS-NMF).

Figure 2: Exemple of coregistered panchromatic area and hyperspectral pixel.

**HBEE :** we make the assumption that a pure HS pixel is covered by an homogeneous PAN area.

1. Detection of the pure pixels by the means of an homogeneity criterion.
2. Unsupervised clustering step.
3. Definition of one endmember related to each cluster.
4. Estimation of the abundance fraction using [3].

Figure 3: Reconstruction error (RE) map right after the HBEE stage.

**LS-NMF :** We make the assumption that poorly reconstructed areas contains a not yet extracted endmember.

1. Calculation of the RE map.
2. Selection of the most poorly reconstructed area.
3. Estimation of an unknown endmember by applying an NMF onto the area.
4. Iterate until all the previously detected areas are correctly rebuilt.

## Results

- Finds satisfactory pure pixels.
- Estimates satisfactory mixed materials spectra.
- Shows equivalent results if not better than existing methods (VCA, ATGP, NFINDR, MVC-NMF, SISAL, *etc*...).

Performances are calculated using, first, the Spectral Angle Measurement (SAM) between high GSD groundtruth and their corresponding estimated endmembers and second, the reconstruction error.

| Criterion | HBee-LSNMF | VCA | NFINDR | ATGP | SISAL | MVCNMF |
|---|---|---|---|---|---|---|
| $RE$(%) | 1.72 | 1.69 | 1.88 | 2.22 | 2.11 | 1.41 |
| $SAM$(°) | 5.44 | 6.60 | 5.19 | 5.75 | 8.85 | 5.9 |

Table 1: Results of the proposed approach in regards of existing methods.

## Conclusion and future works

PAN data was only used in the endmember extraction process and already showed satisfactory performances. Future works will take in account the PAN image in the abundance fractions estimation process, for example using a segmentation method.

Figure 4: Exemple of segmentation map using the Quickshift algorithm [4].

## References

[1] José M. Bioucas-Dias, Antonio Plaza, Nicolas Dobigeon, Mario Parente, Qian Du, Paul Gader, and Jocelyn Chanussot, "Hyperspectral unmixing overview: geometrical, statistical and sparse regression-based approaches," *IEEE journal of selected topics in applied earth observations and remote sensing*, vol. 5, pp. 354–379, 2012.
[2] V. Paul Pauca, J. Piper, and Robert J. Plemmons, "Nonnegative matrix factorization for spectral data analysis," *Linear Algebra and its Applications*, vol. 416, no. 1, pp. 29 – 47, 2006, Special Issue devoted to the Haifa 2005 conference on matrix theory.
[3] R. Bro and S. D. Jong, "A fast non-negativity-constrained least squares algorithm," *Journal of Chemometrics*, vol. 11, no. 5, pp. 393–401, 10 1997.
[4] Andrea Vedaldi and Stefano Soatto, "Quick shift and kernel methods for mode seeking," in *Computer Vision – ECCV 2008*, David Forsyth, Philip Torr, and Andrew Zisserman, Eds., Berlin, Heidelberg, 2008, pp. 705–718, Springer Berlin Heidelberg.

# Main unmixing methods

Several strategies :

## Endmember estimation

- Finding pure pixels : VCA, ATGP, NFINDR.
- Minimizing the volume of the simplex containing the data and induced by the endmembers : MVSA, SISAL, MVC-NMF.
- Estimating the endmembers by a Bayesian approach.
- The Non-negative Matrix Factorization (NMF).

## Abundance fraction estimation knowing the endmembers

- Least-Square
- Non-negatively constraind Least-Square (NCLS)
- Fully-Constrained Least-Square (FCLS)

# Spectral clustering and selection

## Clustering of the extracted spectra

A simple unsupervised algorithm will iteratively build $p$ clusters of the extracted pure spectra using a Spectral Angle Measurement (SAM) criterion :

$$\theta = \left( \frac{\langle s_k, s_l \rangle}{\|s_k\|.\|s_l\|} \right)$$

## Endmembers selection

The chosen endmembers $s_k$ are the ones with the best homogeneity score for each class.

## Abundance fraction estimation

The abundance fractions matrix $X$ is estimated using a Non-negatively Constrained Least-Square algorithm (NCLS)

# Annexes

## Clustering spectra

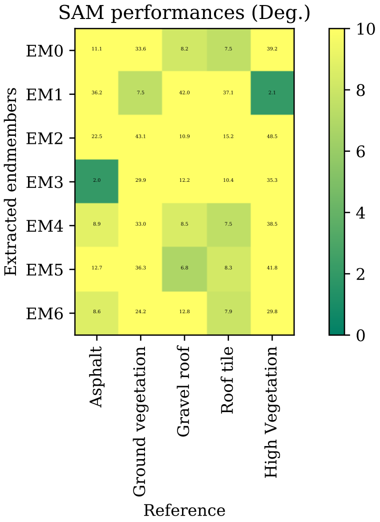
1. The pure spectrum list is sorted by their homogeneity level
2. Création d'une classe $C_k$ à partir du premier spectre de la liste.
3. Agrégation à $C_k$ tous les spectres de la listes présentants une valeur de SAM avec le premier spectre inférieure à $\epsilon_{SAM}$ et suppression de ces spectres de la liste.
4. Recommencer à l'étape 1 jusqu'à ce que la liste soit vide.

# Annexes

## Reconstruction error map criterion

$$RE = \frac{||\hat{y_{ij}} - y_{ij}||}{||\hat{y_{ij}}||} \quad (1)$$

# Annexes


SAM performances (Deg.)
EM0
EM1
EM2
EM3
EM4
EM5
EM6
11.1 33.6 8.2 7.5 39.2
36.2 7.5 42.0 37.1 2.1
22.5 43.1 10.9 15.2 48.5
2.0 29.9 12.2 10.4 35.3
8.9 33.0 8.5 7.5 38.5
12.7 36.3 6.8 8.3 41.8
8.6 24.2 12.8 7.9 29.8
Extracted endmembers
Asphalt
Ground vegetation
Gravel roof
Roof tile
High Vegetation
Reference
10
8
6
4
2
0