Joint Unmixing and Demosaicing Methods for Snapshot Spectral Images

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Explore Exciting Imaging Topics!

Presentation Overview

Even if the title sounds technical, this presentation covers a range of interesting topics with something for everyone.

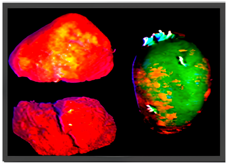
Key Topics

- **Hyperspectral imaging**
- **Demosaicing (Super-resolution)**
- **Unmixing (Non-supervised classification)**
- **NMF (Non-negative matrix factorization)**
- **Image inverse problems**

Evolution of Machine Vision

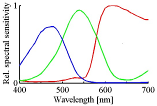
Monochromatic Image

Color Image



Hyperspectral Image

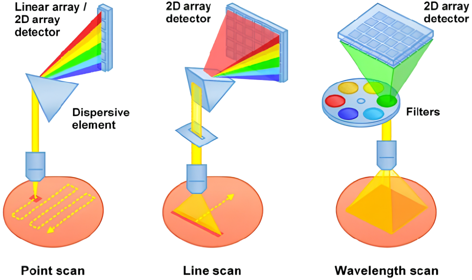
Monochromatic Camera



RGB Camera

Hyperspectral Camera

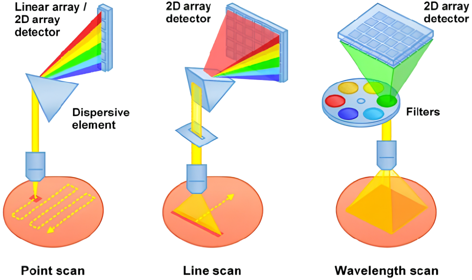
Hyperspectral Cameras



Hyperspectral Cameras Cons

- Current spectral camera systems are slow, usually taking seconds to minutes to scan an object.
- Not portable to be placed on drones or unmanned aerial vehicles (UAVs).
- Expensive!

Hyperspectral Cameras



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Low cost, Portable and Fast cameras are required!

Compact Hyperspectral Cameras

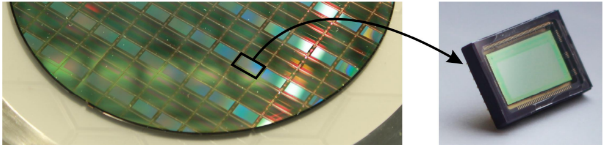

Figure: Wafer including CMOS image sensors with integrated filter mosaics (left) and a packaged sensor (right). (Source Geelen et al.)

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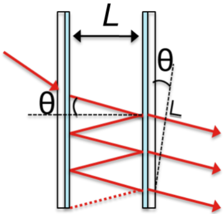
Compact Hyperspectral Camera



Fabry Perot Interferometer

Snapshot Spectral Cameras

- No scan= real-time HSI data acquisition
- Spatial vs. spectral resolution trade-off (e.g. 16 band images of 512x272 resolution today)
- Potential resolution reconstruction increase by demosaicing algorithms

Figure: The SnapShot SWIR camera from IMEC using a mosaic pattern of 16 SWIR filters.

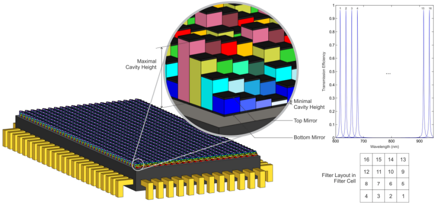
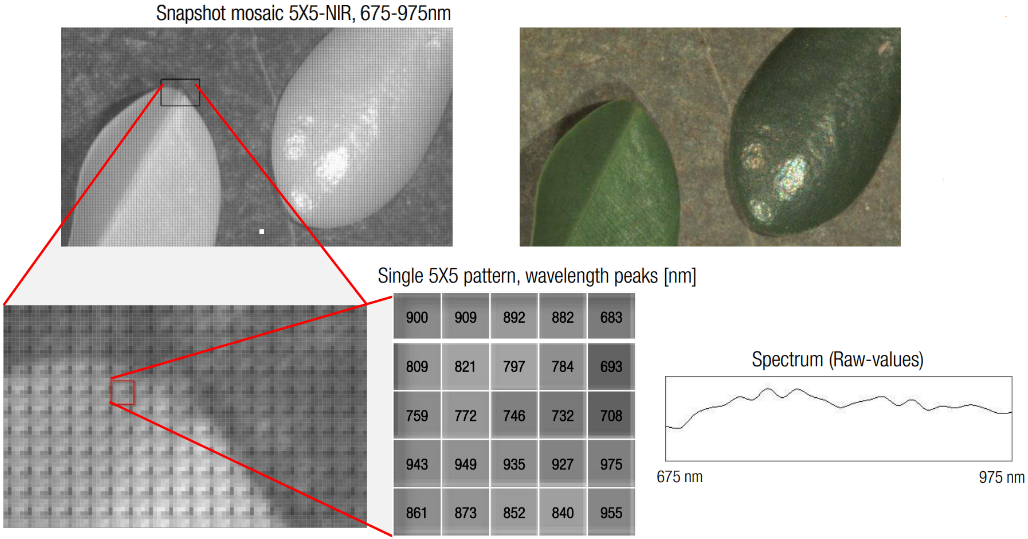
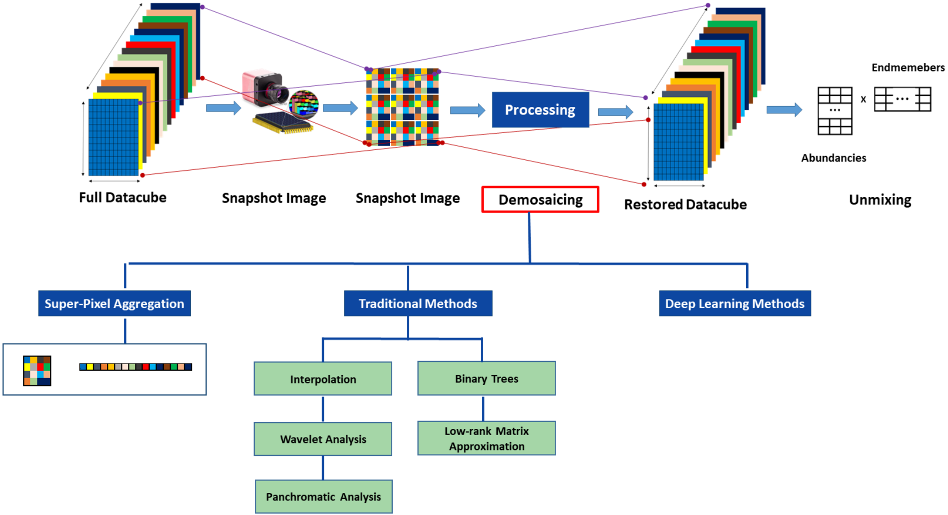


Figure: SSI cameras associate each spatial pixel with a specific spectral band.

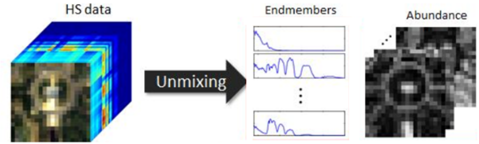
Snapshot Spectral Cameras



Demosaicing



Unmixing



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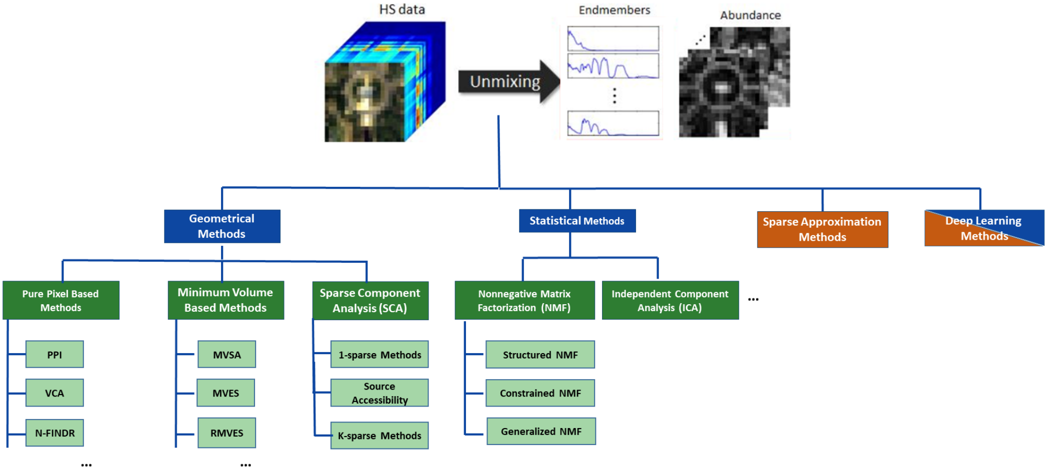

HS data
Unmixing
Endmembers
Abundance
Geometrical Methods
Statistical Methods
Sparse Approximation Methods
Deep Learning Methods
Pure Pixel Based Methods
Minimum Volume Based Methods
Sparse Component Analysis (SCA)
Nonnegative Matrix Factorization (NMF)
Independent Component Analysis (ICA)
...
PPI
VCA
N-FINDR
...
MVSA
MVES
RMVES
...
1-sparse Methods
Source Accessibility
K-sparse Methods
Structured NMF
Constrained NMF
Generalized NMF

Nonnegative Matrix Factorization

- Factorize a non-negative matrix $Y \in \mathbb{R}_{\geq 0}^{(m \cdot n) \times k}$ into $G \in \mathbb{R}_{\geq 0}^{(m \cdot n) \times p}$ and $F \in \mathbb{R}_{\geq 0}^{p \times k}$:

$$Y \approx G \cdot F$$

Constraints: $G, F \geq 0$, $p < \min(m \cdot n, k)$.

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- **Solving NMF**: Multiplicative updates minimize $\|Y - G \cdot F\|_F^2$:

$$G \leftarrow G \circ \frac{YF^T}{GFF^T}, \quad F \leftarrow F \circ \frac{G^T Y}{G^T GF}$$

  Stop when error $< 10^{-5}$ or max iterations (e.g., 1000).

Weighted Nonnegative Matrix Factorization (WNMF)

- **Definition**: Factorize a non-negative matrix $Y \in \mathbb{R}_{\geq 0}^{(m \cdot n) \times k}$ into $G \in \mathbb{R}_{\geq 0}^{(m \cdot n) \times p}$ and $F \in \mathbb{R}_{\geq 0}^{p \times k}$, with a weight matrix $W \in \mathbb{R}_{\geq 0}^{(m \cdot n) \times k}$:

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- **Solving WNMF**: Minimize the weighted Frobenius norm $\|W \circ (Y - G \cdot F)\|_F^2$, where $\circ$ denotes element-wise multiplication. Two approaches:
  - *Direct Method*: Multiplicative updates:

$$G \leftarrow G \circ \frac{(W \circ Y)F^T}{(W \circ (GF))F^T}, \quad F \leftarrow F \circ \frac{G^T(W \circ Y)}{G^T(W \circ (GF))}$$

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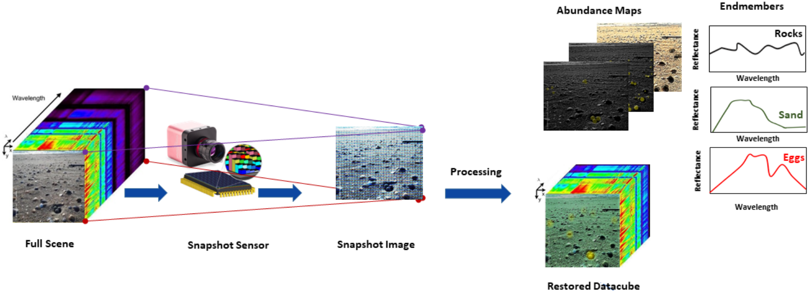
    Stop when weighted error $< 10^{-5}$ or max iterations (e.g., 1000).
  - *EM Strategy*:
    - **E-step**: Estimate missing or uncertain entries in Y to form $\hat{Y}$, using current G and F, with weights in W reflecting confidence:

$$\hat{Y} = W \circ Y + (\mathbf{1}_{m \cdot n \times k} - W) \circ (G \cdot F)$$

      Adjust W to reflect confidence in estimates (e.g., lower weights for imputed values).
    - **M-step**: Apply WNMF update rules (above) to updated $\hat{Y}$ and W to refine G and F.
    - Iterate: After convergence or fixed iterations, update $\hat{Y}$ and W in a new E-step using latest G and F.

What are we trying to solve?



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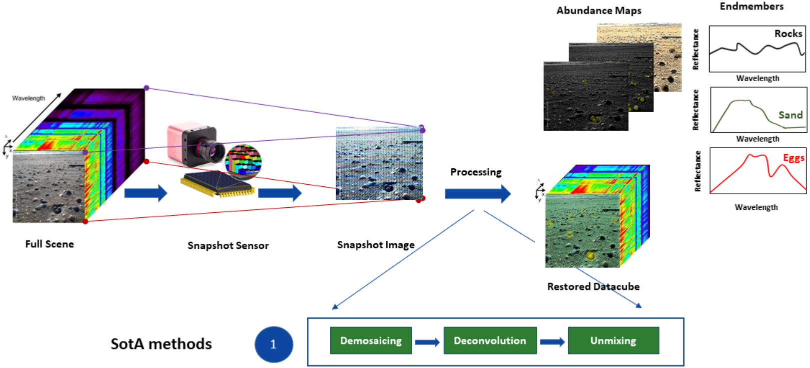

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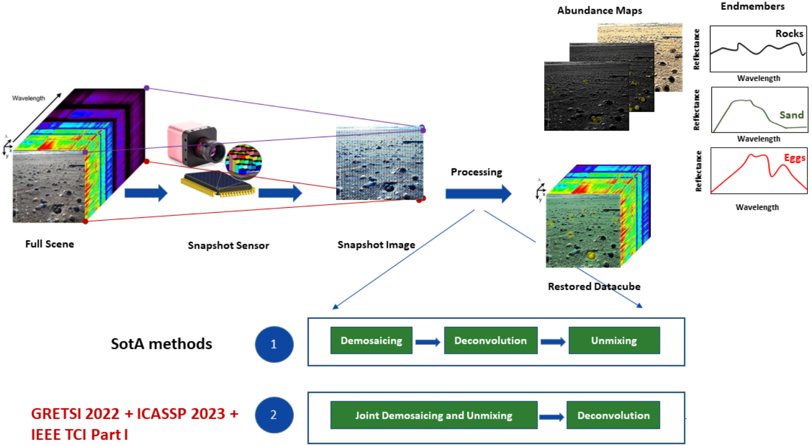

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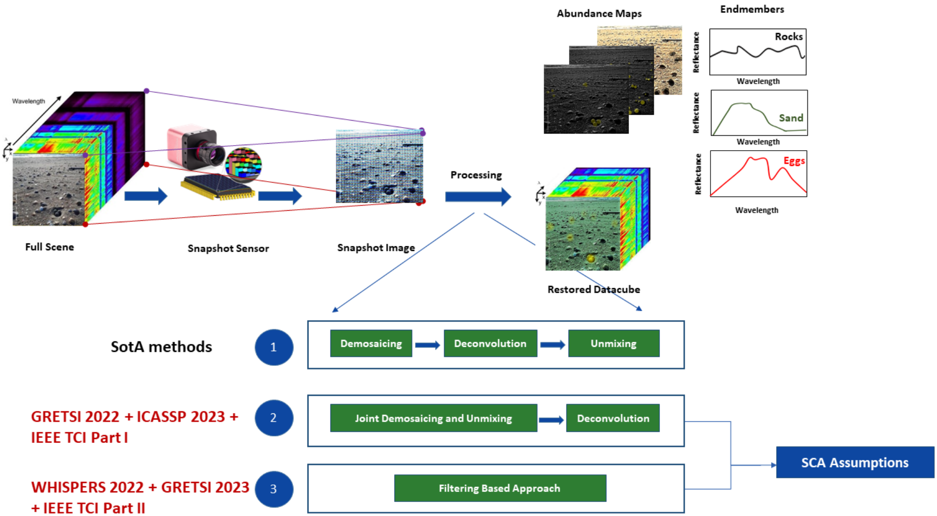
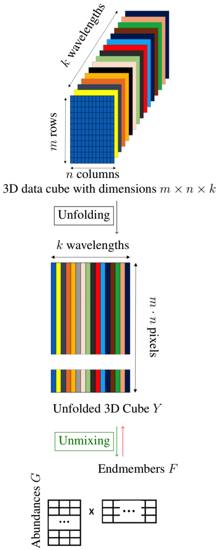


Problem Statement: Joint Demosaicing and Unmixing for SSI



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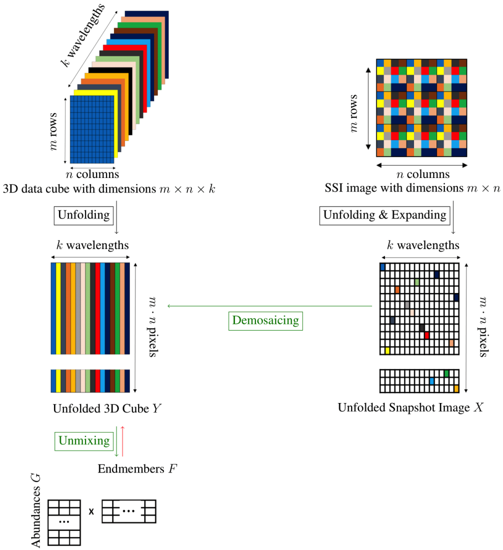

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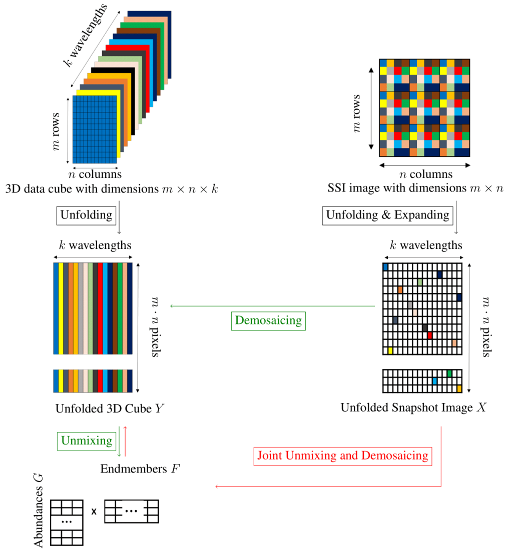

- **Goal**: Reconstruct 3D data cube ($m \times n \times k$) from 2D projection.
- **Demosaicing**: Recover Y from partial matrix X:

$$W \circ X = W \circ Y$$

where W is a binary weight matrix, $\circ$ denotes the Hadamard product.

- **Unmixing**: Decompose Y as:

$$Y \approx G \cdot F$$

where G ($m \cdot n \times p$) is abundances, F ($p \times k$) is endmembers.

- **Joint Model**: Combine processes:

$$W \circ X \approx W \circ (G \cdot F)$$

Recover $\hat{Y}$:

$$\hat{Y} = W \circ X + (\mathbf{1}_{m \cdot n \times k} - W) \circ (G \cdot F)$$

Similar to the Weighted Non-negative Matrix Factorization (WNMF) problem.

Weighted Nonnegative Matrix Factorization

- **Solving WNMF**: EM framework with NeNMF:
  - *E-step*: Estimate $\hat{Y}$ using prior $G^{(t-1)}, F^{(t-1)}$:

$$\hat{Y} = W \circ X + (\mathbf{1}_{(m \cdot n) \times k} - W) \circ (\hat{G}^{(t-1)} \cdot \hat{F}^{(t-1)})$$

  - *M-step*: Apply NeNMF updates to $\hat{Y}$ for $\hat{G}^{(t)}, \hat{F}^{(t)}$.
- **Constraints**: Non-negativity ($G, F \geq 0$); Abundance Sum-to-One (ASC) via augmented matrices:

$$\bar{Y} = [\hat{Y}, \delta \mathbf{1}_{(m \cdot n) \times 1}], \quad \bar{F} = [\hat{F}, \delta \mathbf{1}_{p \times 1}]$$

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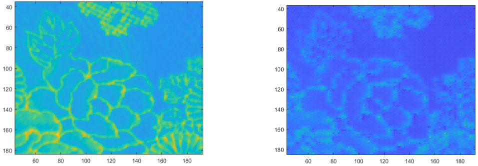

Ground truth

Naive WNMF (PSNR=35.1dB)

Figure: Demosaiced image obtained with Naive method a for the 4 $\times$ 4 patch.

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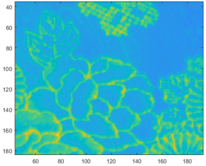

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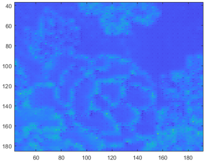


Naive WNMF (PSNR=35.1dB)

- Naive method's performance is lower than expected.
- Highly sensitive to initial matrices F and G.
- Can pre-estimating F improve results?

Figure: Demosaiced image obtained with Naive method a for the 4×4 patch.

Matrix-Completion Framework

K-means Patch-based Weighted Nonnegative Matrix Factorization (KPWNMF)

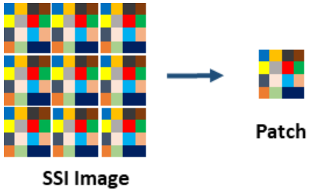
Steps of the proposed method

1. Consider the sensor "patches" as the zones to analyze .
2. Sparse Component Analysis - Sources are accessible: for each source, there exist some small areas to find where only one source is active, e.g., [Deville, 2014]
3. Find "zones" where only one endmember is active
4. Estimate tentative endmembers in all these zones using Rank-1 WNMF

$$W_i \circ X_i \approx W_i \circ (\underline{g}_i \cdot f_i), \quad (1)$$

where $\underline{g}_i$ represents a $k \times 1$ column vector and f_i represents a $1 \times k$ row vector.

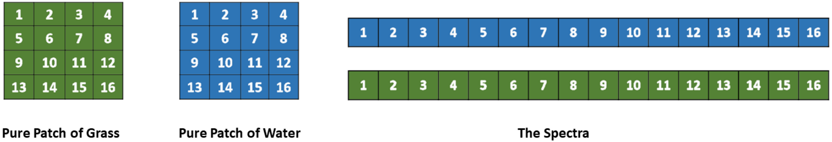
5. Derive actual endmembers from the above estimates (clustering stage)
6. Estimate the abundances from the observed data and the endmembers using WNMF



Assumptions Required for the Proposed Method

Assumption 1 (Pure Patch Assumption)

For each endmember, there exists at least one sensor "patch" where only this endmember is present.



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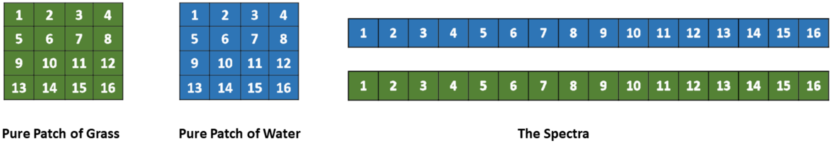

Single-source Confidence Measure

$$\|W_i \circ X_i - W_i \circ (\underline{g}_i \cdot f_i)\|_F^2 \approx 0.$$

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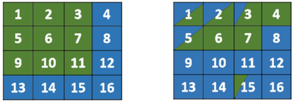
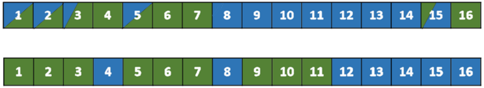
Assumption 2

In the patches where several endmembers are present, their abundances should significantly vary over each patch.



Grass and water abundancies vary



Wavelength-dependent mixture of endmembers

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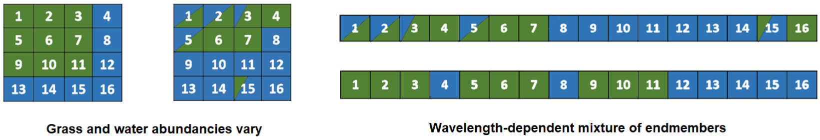
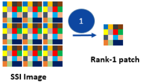


Single-source Confidence Measure

$$\| W_i \circ X_i - W_i \circ (\underline{g}_i \cdot f_i) \|_F^2 \gg 0$$

K-means Patch-based Weighted Nonnegative Matrix Factorization (KPWNMF)



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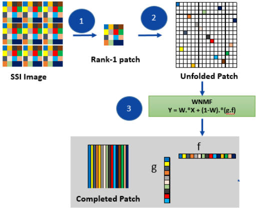

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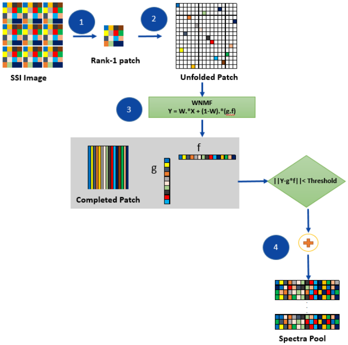

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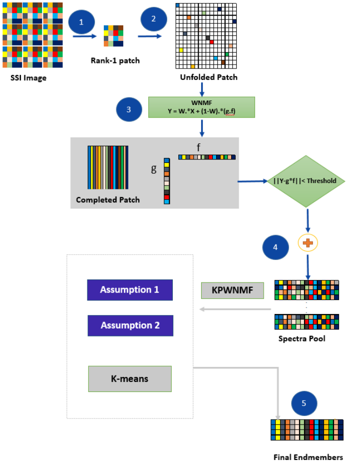

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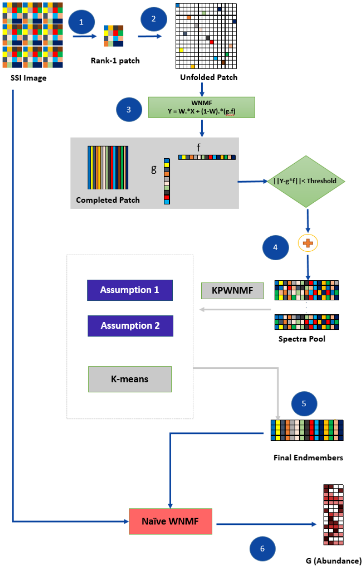

VCA Patch-based Weighted Nonnegative Matrix Factorization (VPWNMF)

- This method follows the same processing steps. However, it relaxes the Assumption 2.

Grass and Water abundancies don't vary

Wavelength-independent mixture of endmembers

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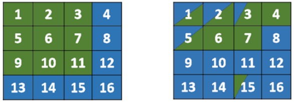
Assumption 3

In the patches where several endmembers are present, their abundances may or may not vary over each patch.



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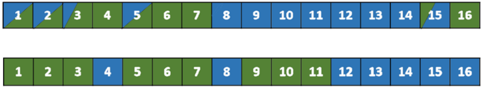


Wavelength-dependent mixture of endmembers

VCA Patch-based Weighted Nonnegative Matrix Factorization (VPWNMF)

In practice, **a rank-1 patch is not necessarily a pure patch**

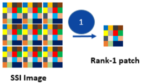
➪ Several scenarios:

- When one unique endmember is present in the patch, the rank-1 approximation error is **low**
  $\| W_i \circ X_i - W_i \circ (\underline{g}_i \cdot f_i) \|_F^2 \gg 0$
- When several endmembers are present in the patch,
  - the rank-1 approximation error is **high** is the abundances **vary** over the patch (We ignore it!)
  - the rank-1 approximation error is **low** if the abundances are **constant** over the patch (We collect it!)

➪ The value of the loss allows to detect rank-1 patches

- We collect all the vectors f_i with sufficiently low errors in a matrix $\mathbb{X}$.
- The recovered spectra in low-error rank-1 patches may be seen as linear mixtures of the endmembers
  $$\mathbb{X} \approx \underbrace{G}_{\text{Abundances}} \cdot \underbrace{F}_{\text{Endmembers}} .$$
- The pure-patch assumption means that each row of F can be found in $\mathbb{X}$.
- The VCA algorithm is then used to derive the final endmembers.

VCA Patch-based Weighted Nonnegative Matrix Factorization (VPWNMF)



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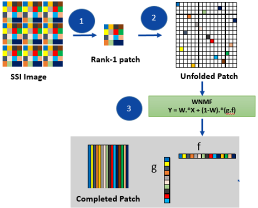

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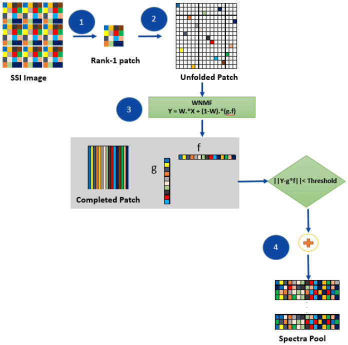
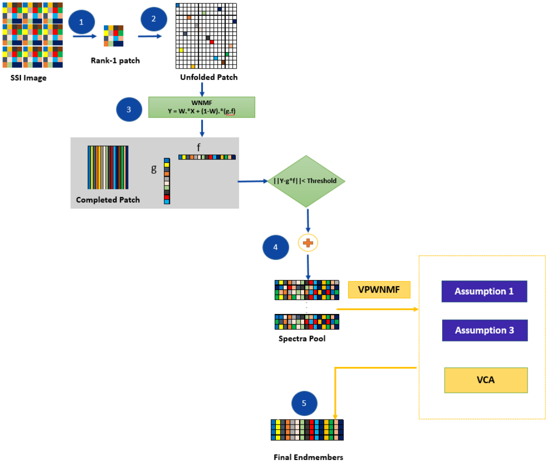
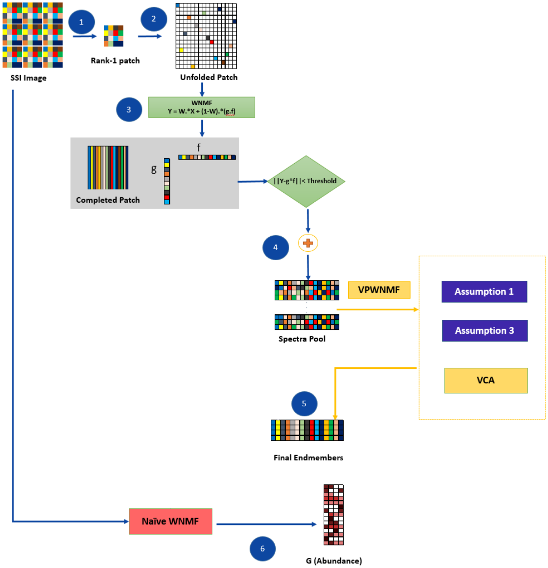


VCA Patch-based Weighted Nonnegative Matrix Factorization (VPWNMF)



VCA Patch-based Weighted Nonnegative Matrix Factorization (VPWNMF)

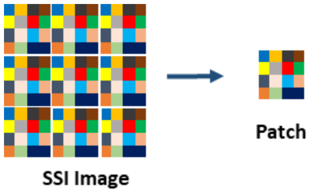


Filtering-Based Approaches

K-means Patch-based Weighted Nonnegative Matrix Factorization (KPWNMF)

Steps of the proposed method

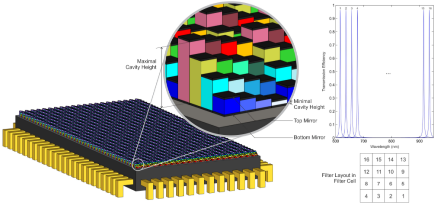
1. Consider the sensor “patches” as the zones to analyze .
2. Sparse Component Analysis - Sources are accessible: for each source, there exist some small areas to find where only one source is active, e.g., [Deville, 2014]
3. Find “zones” where only one endmember is active
4. Estimate tentative endmembers in all these zones by Inverting the filter response.
5. Derive actual endmembers from the above estimates (clustering stage)
6. Estimate the abundances from the observed data and the endmembers using WNMF



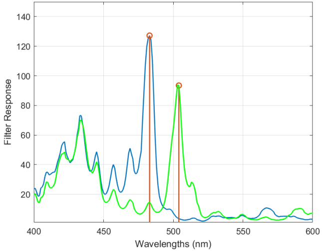
Snapshot Spectral Camera

- Theoretically, the SSI cameras associate each spatial pixel with a specific spectral band.
- In reality, the value at each pixel is a filtered version of the materials that exist in the pixel.

$$y_i(\lambda_i) = \sum_{j=1}^{k} h_i(\lambda_j) \cdot x_i(\lambda_j) + \omega_i, \qquad (2)$$



Snapshot mosaic filter (Source Geelen et al.)



Ideal (in red) and real (in blue and green) spectral response of two Fabry-Perot filters of the 4×4 IMEC SSI camera.

Filtering Based Approach - Problem Statement

- Fabry-Perot filters introduce additional harmonics around each wavelength of interest in real implementation

$$y_i(\lambda_i) = \sum_{j=1}^{k} h_i(\lambda_j) \cdot x_i(\lambda_j) + \omega_i, \tag{3}$$

- These filters $h_i(\lambda)$ are known and are provided by the camera manufacturer
- Over the whole patch, we get k observed values $\underline{y} \triangleq [y_1(\lambda_1), \ldots, y_k(\lambda_k)]^T$, which depend on a $k \times k$ data matrix

$$X \triangleq \begin{bmatrix} x_1(\lambda_1) & \ldots & x_1(\lambda_k) \\ \vdots & & \vdots \\ x_k(\lambda_1) & \ldots & x_k(\lambda_k) \end{bmatrix} \tag{4}$$

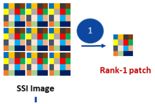
- Supposing the patch is pure (aka rank-1 patch), X reduces to a single vector $\underline{x}^T$
- The filters can be collected as a matrix H s.t.

$$\underline{y} \approx H \cdot \underline{x}^T. \tag{5}$$

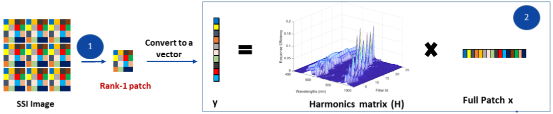
- And $\underline{x}$ can be estimated in such a patch solving

$$\min_{\underline{y} \geq 0} \frac{1}{2} \|\underline{x} - H \cdot \underline{y}^T\|_2^2 + \frac{\alpha}{2} \|D \cdot \underline{y}^T\|_2^2, \tag{6}$$

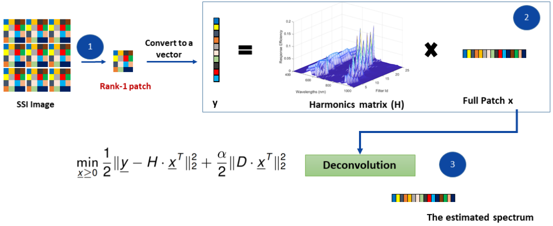
Filtering-based Framework



Filtering-based Framework

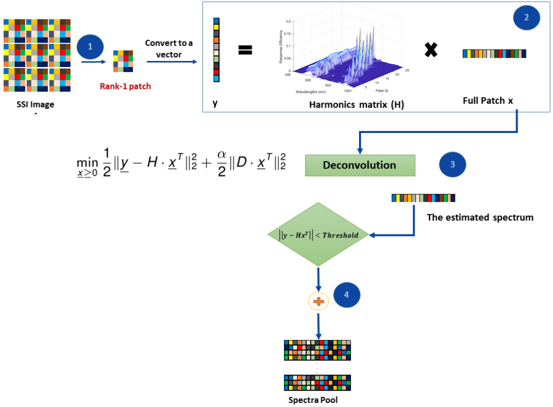


Filtering-based Framework

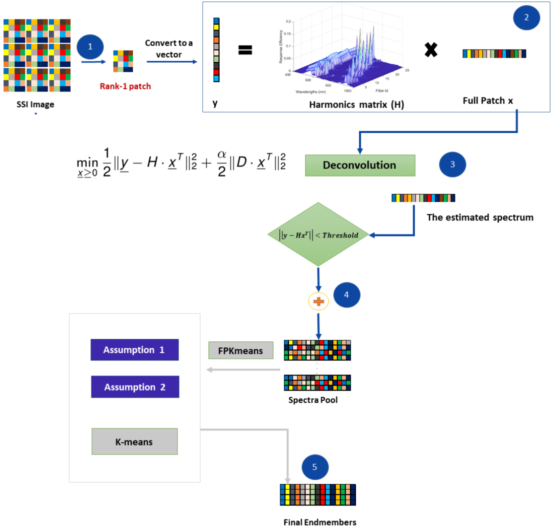


$$\min_{\underline{x}\geq 0} \frac{1}{2}\|\underline{y} - H \cdot \underline{x}^T\|_2^2 + \frac{\alpha}{2}\|D \cdot \underline{x}^T\|_2^2$$

Filtering-based Framework



Filtering-based Framework



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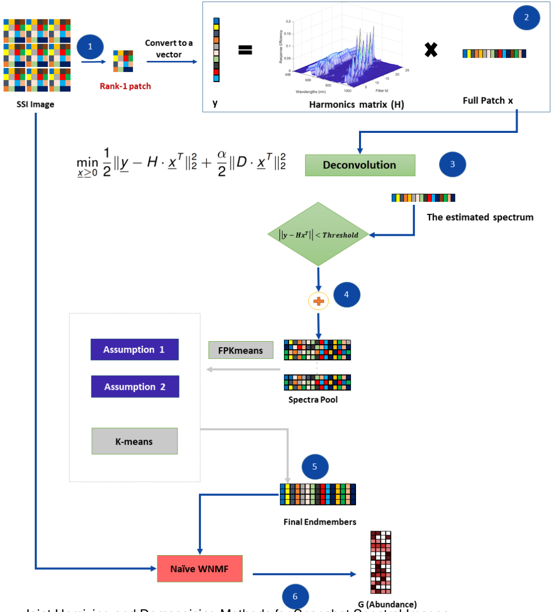

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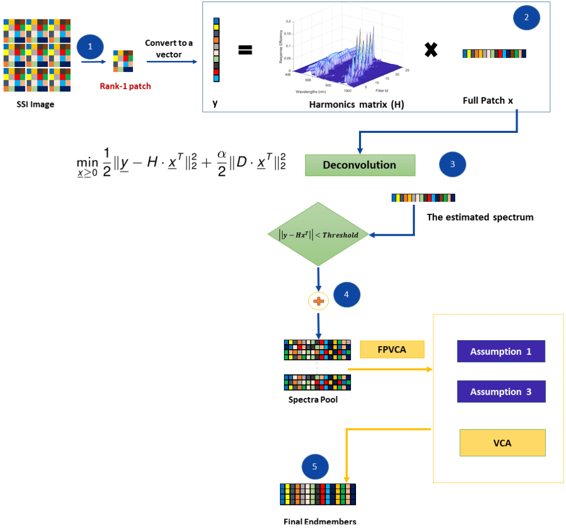
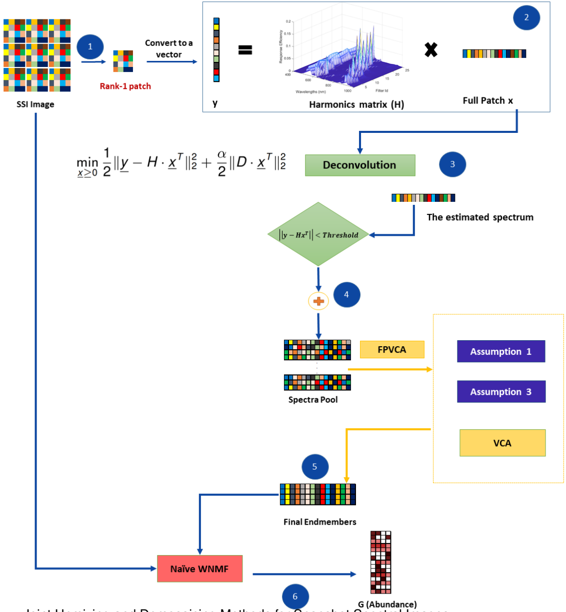
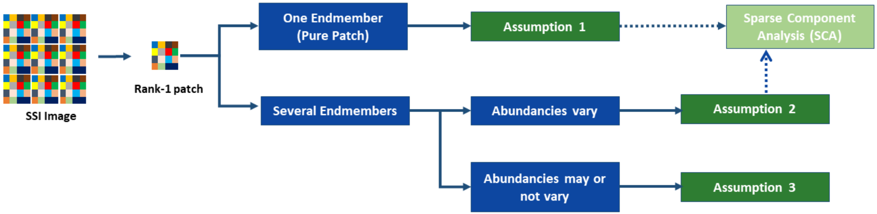


Filtering-based Framework



A review of the proposed methods



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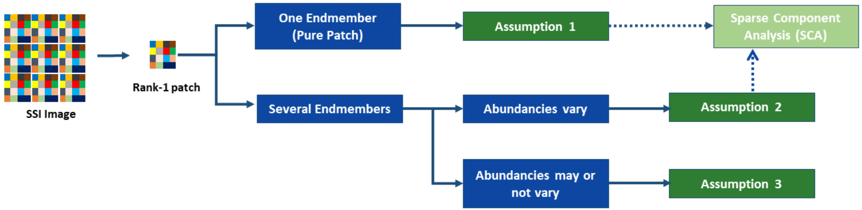
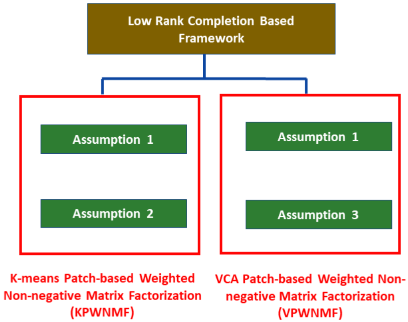
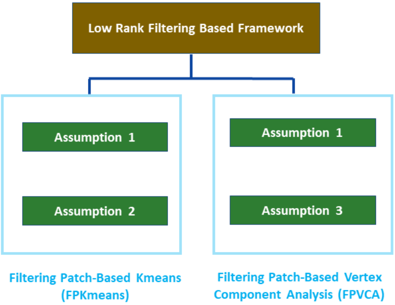






Experiments on Synthetic Data

- To assess the performance of the proposed method, we conduct experiments on SSI simulations derived from synthetic images.
- We assume that the hyperspectral imagery is acquired using a SSI camera system, equipped with 5×5 spectral filter patterns.
- Reconstruction quality is measured in terms of Peak Signal-to-Noise Ratio (PSNR, in dB) while the unmixing enhancement is measured using Signal-to-Interference Ratio (SIR, in dB), Mixing Error Ration (MER, in dB), Spectral Angel Mapper (SAM) and Root Mean Square Error(RMSE).

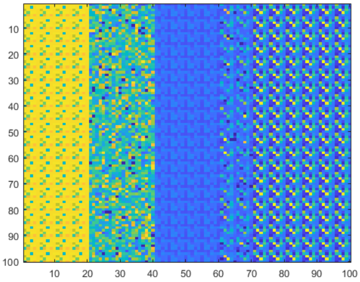


Figure: Image 1, assumption 1 & 2

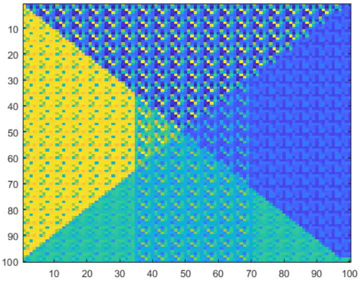
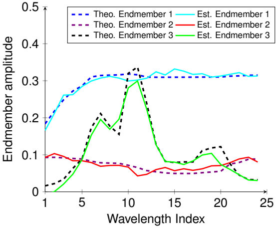
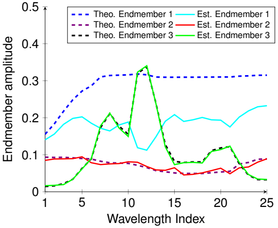


Figure: Image 2 , assumption 1 &3

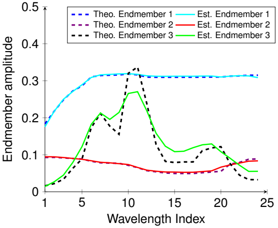
Restored Spectra for Image 2



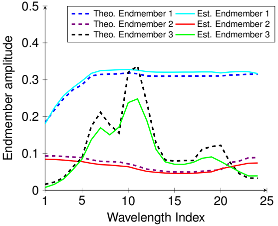
PPID



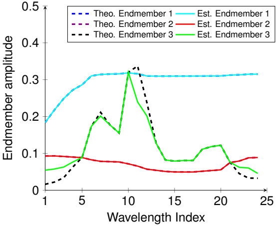
SAND



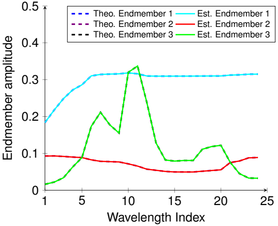
KPWNMF



VPWNMF



FPKmeans



FPVCA

Performance evaluation on real SSI images

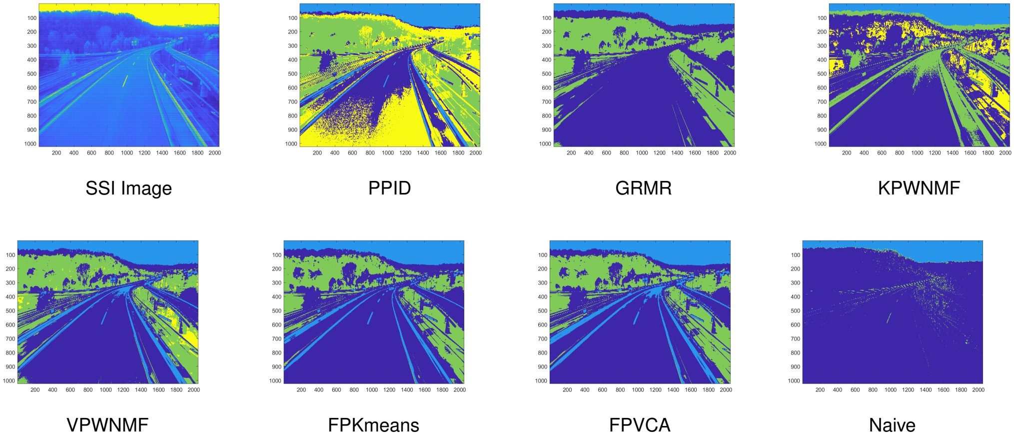


Figure: Segmentation of a Hyko 2 database image for different demixing methods

Conclusion

Main Findings

- In ideal scenarios with varying noise levels, KPWNMF and VPWNMF, which belong to the Low-rank framework, exhibited the highest performance.
- When real filters were introduced, FPKmeans and FPVCA (Filtering based framwork) demonstrated superior performance.
- Although the performance of both KPWNMF and VPWNMF methods declined compared to ideal situations, they still outperfmed 3-stage approaches.

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Take-home Messages

- Employing a joint unmixing and demosaicing approach within the low-rank completion framework proves superior to 3-stage approaches in both ideal and real-world scenarios.
- Obviating the spectral correction step and starting the deconvolution process directly from the raw SSI images improved unmixing and demosaicing results while simplifying the overall processing pipeline.

Future Work

Perspectives

- Take into account endmember spectral variability.
- Take into account Fabry-Perot filter variability.
- Improving the computational efficiency of the frameworks e.g., compressed learning techniques.

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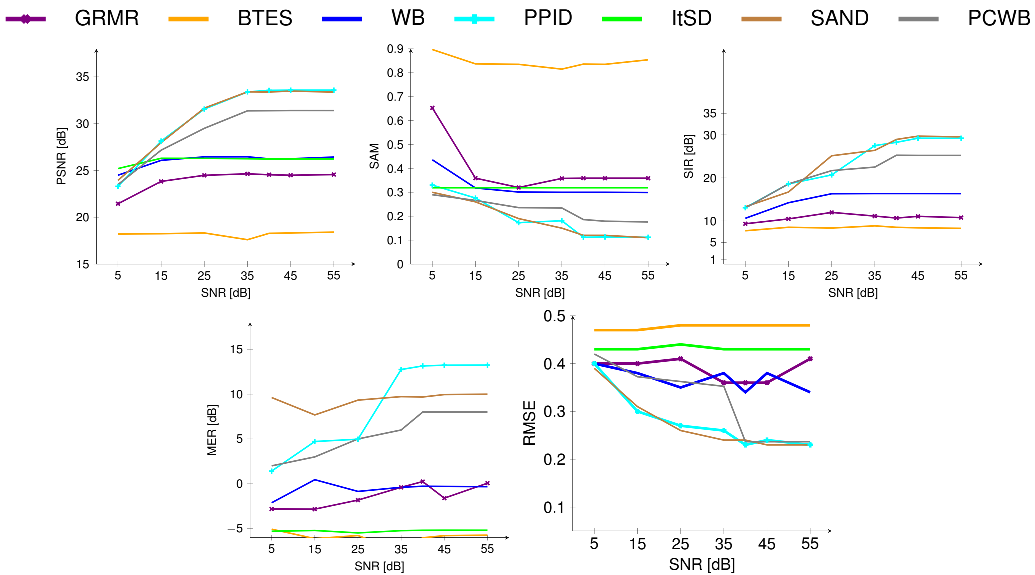
Publications

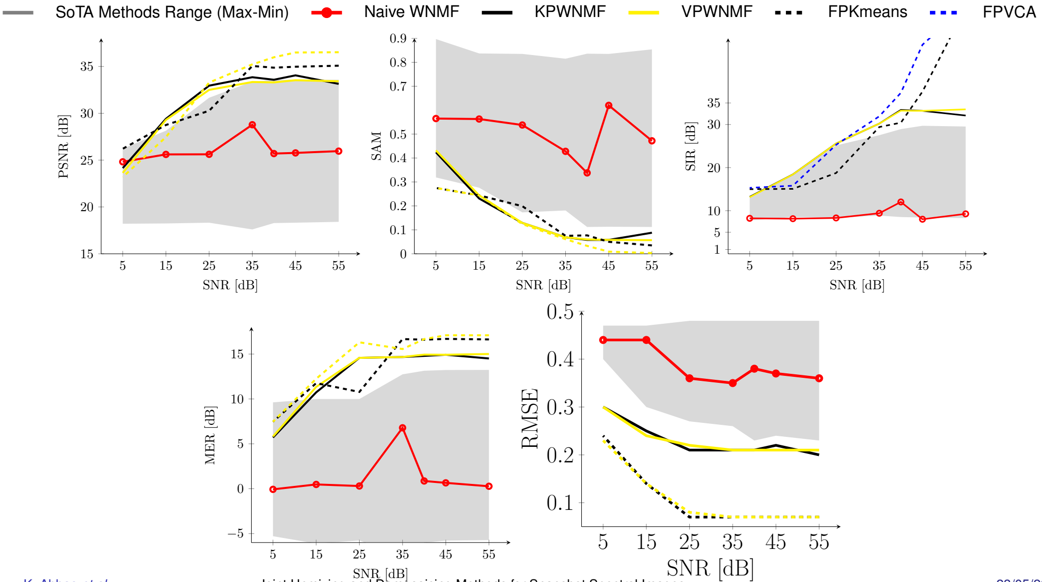
1. **K. Abbas**, M. Puigt, G. Delmaire, G. Roussel, *Locally-Rank-One-Based Joint Unmixing and Demosaicing Methods for Snapshot Spectral Images. Part II: a Filtering-Based Framework*, IEEE Trans. Computational Imaging 10 (2024), pp. 806-817.
2. **K. Abbas**, M. Puigt, G. Delmaire, G. Roussel, *Locally-Rank-One-Based Joint Unmixing and Demosaicing Methods for Snapshot Spectral Images. Part I: a Matrix-Completion Framework*, IEEE Trans. Computational Imaging 10 (2024), pp. 848-862.
3. **K. Abbas**, P. Chatelain, M. Puigt, G. Delmaire, G. Roussel, *Fabry-Perot Spectral Deconvolution with Entropy-weighted Penalization*, IEEE Sensors Letters, vol. 8, no. 9, pp. 1-4, Sept. 2024. *Filtering-based endmember identification method for snapshot spectral images*, Proc. IEEE WHISPERS, 2022. (Outstanding Paper Award)
4. **K. Abbas**, M. Puigt, G. Delmaire, and G. Roussel, *Joint Unmixing and Demosaicing Methods for Snapshot Spectral Images*, in Proc. IEEE ICASSP'23, Rhodes, Greece, June 2023.

Thank You!

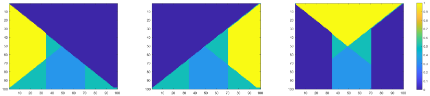
Performance Evaluation on Image 2 — SotA Methods



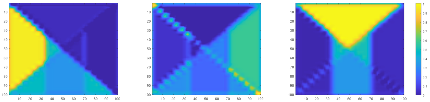
Performance Evaluation on Image 2



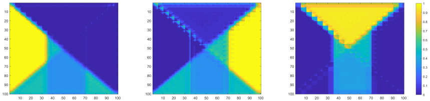
Abundance Maps for Image 2



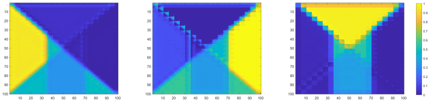
Ground truth



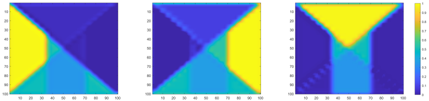
PPID



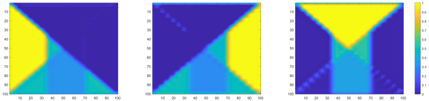
KPWNMF



VPWNMF

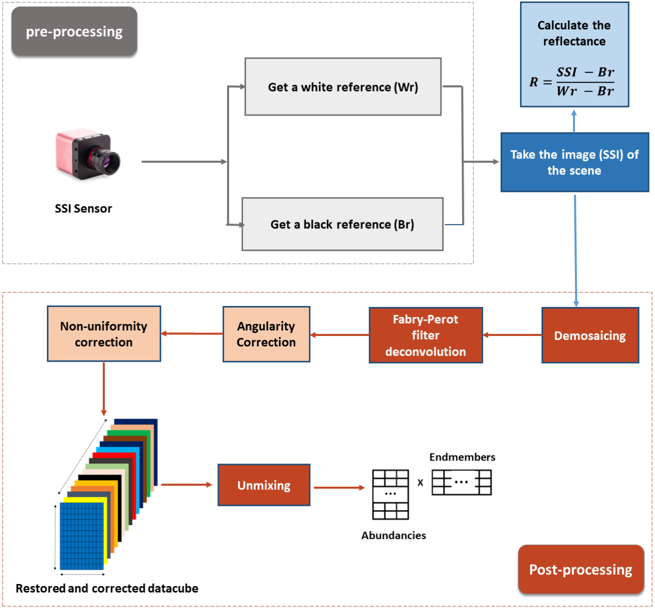


FPVCA



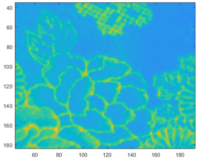
FPKmeans

Processing the SSI Image

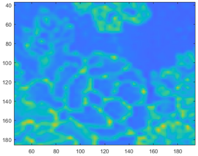


Assuming a Linear Mixture Model (LMM), deconvolution can be performed either before or after unmixing.

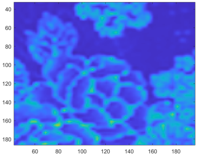
Results on CAVE dataset



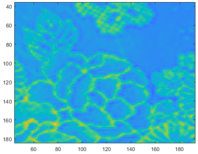
Ground truth



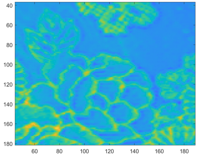
PPID (PSNR=37.1dB)



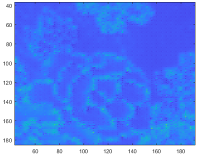
SAND (PSNR=37.1dB)



KPWNMF(PSNR=37.7dB)



VPWNMF(PSNR=37.7dB)



Naive WNMF (PSNR=35.1dB)