

Reconstruction hyperspectrale à partir d'images large bande. Application à MIRI/JWST.

Journée en analyse et traitement d'images en astronomie

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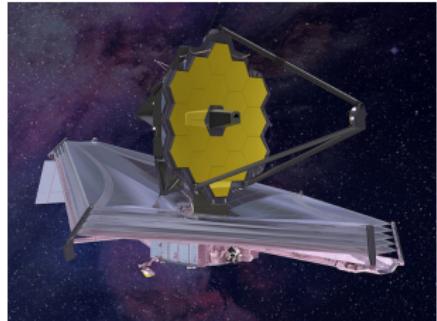


The Spatial Telescope of the Next Decade



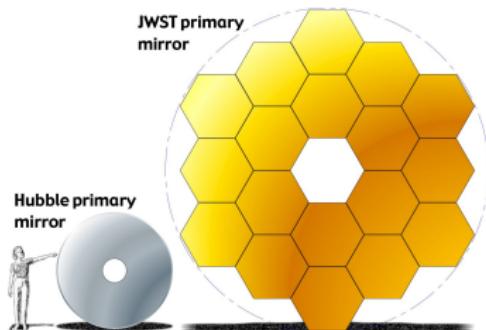
James Webb Space Telescope (JWST)

Organization	NASA (ESA & CSA)
Expected Launch	March 2021
Primary Mirror	6.5 m (2.4 m Hubble)
diameter	18 hexagonal segments
Wavelength Range	0.6 – 28 μm
Budget	10 Billion USD
Flight duration	5 – 10 years



Main objectives of the JWST mission

- Studying the formation and evolution of galaxies
- Understanding formation of stars and exoplanetary system
- ...



The Mid-Infrared Instrument (MIRI) Imager

Instrument and data resolution

Data	Spatial resolution	Spectral resolution
Imager	✓ high	✗ low
Spectrometer	✗ low	✓ high

The Mid-IR Instrument (MIRI) Imager



Characteristics

- **5 – 28 μm (~factor of 5)**
- **9 spectral bands "broads" ($\lambda/\Delta\lambda \sim 5$)**
- **Field of View $74'' \times 113''$**
- **2D infrared detector**
- **HS : ≈ 12000 thin band with $\lambda/\Delta\lambda \approx 3000$**

Objective :

Exploiting the wideband images of the MIRI Imager to reconstruct an object with high spatial and spectral resolution

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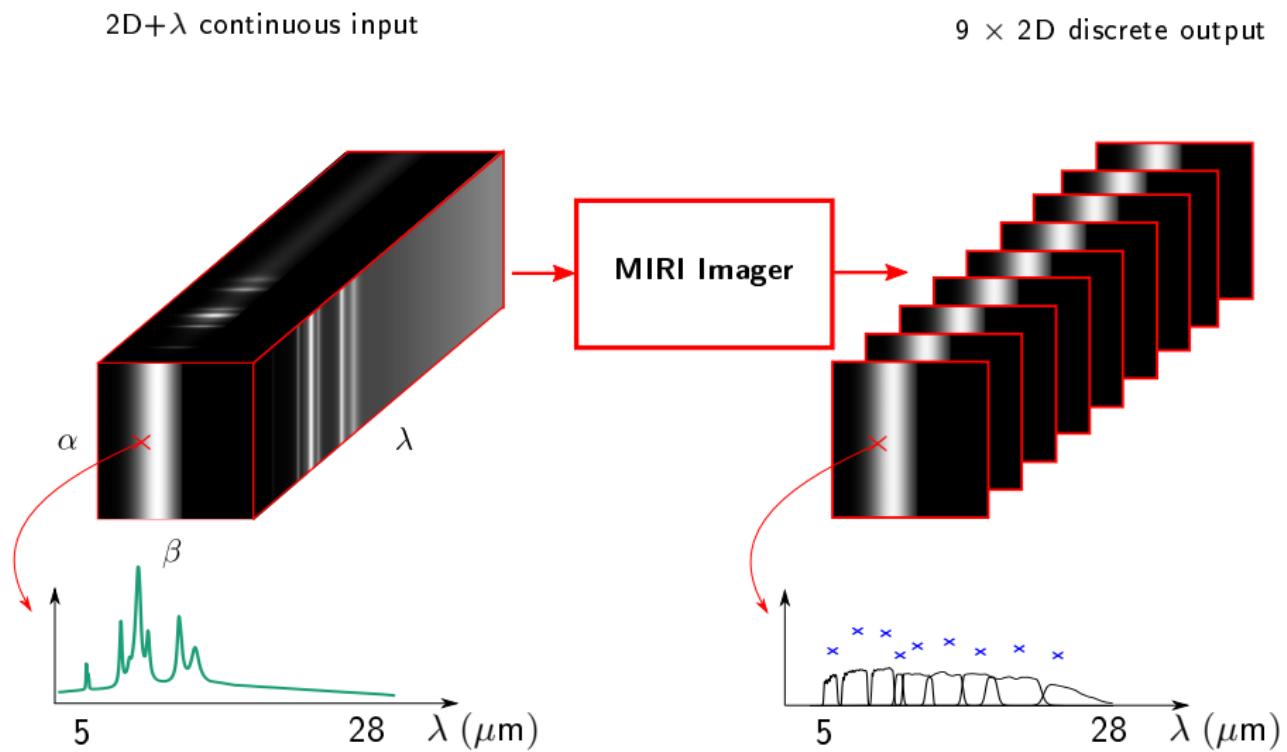
Characteristics

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Data Acquisition



Courtesy to Nathalie Ysard

Problems and Objective

Problems

- Integration over broad bands \Rightarrow Low spectral resolution
- Spectral dependence of the PSF \Rightarrow Varying blur
- Only nine bands \Rightarrow Poor spectral information

Objective

- Reconstruction of a high-resolution spatio-spectral object

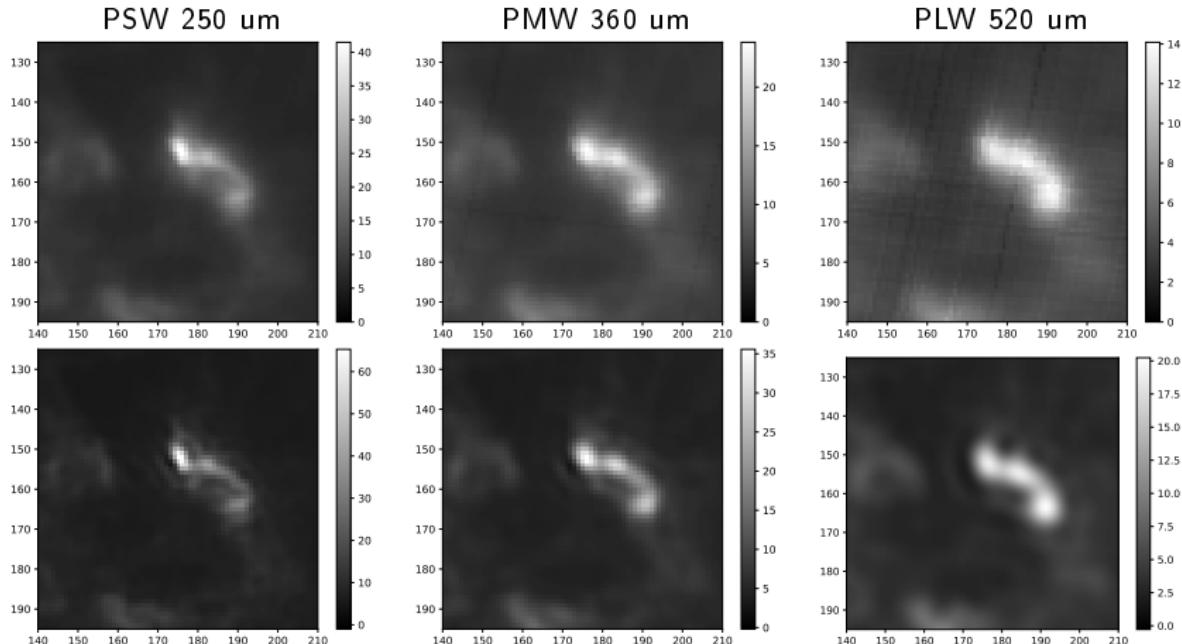
PSF Modeling

- 2D PSF : Measured PSF [Guillard2010], Broadband PSF [Geis2010]
 - PSF linear interpolation [Denis2011, Soulez2013]
 - PSF approximation [Villeneuve2014]
- ⇒ Accuracy of the instrument response

Data Processing

- Separately, band per band [Orieux2012, Bongard2013]
- ⇒ Neglect the cross-correlation between spectral bands
- Data homogenization [Aniano2011, Boucaud2016]
- ⇒ Degrade all the data to the lowest resolution !

Real data ex : SPIRE/Herschel (\approx deconvolution)

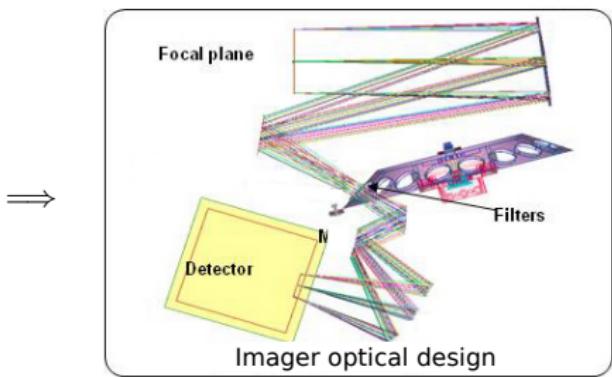


Propositions

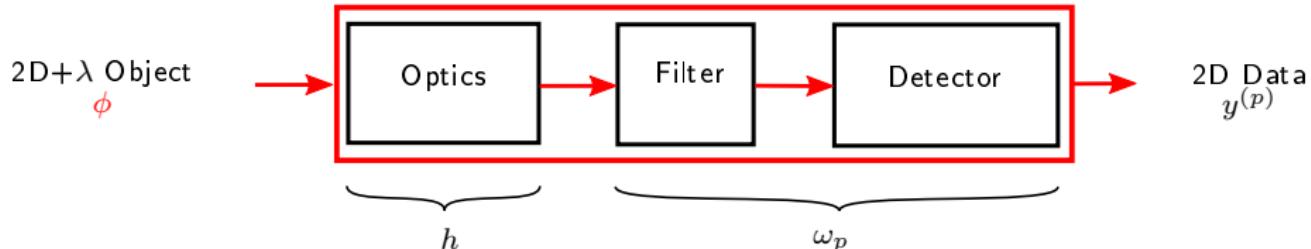
- * Use of a realistic monochromatic PSFs using a simulation tool
- * Develop an instrument model with spectral integration and PSF variation
- * Adapted object representation for the $2D + \lambda$ reconstruction
- * Joint processing of all wideband data.

Modeling of the Instrument Response

MIRI optical design [Bouchet2015]

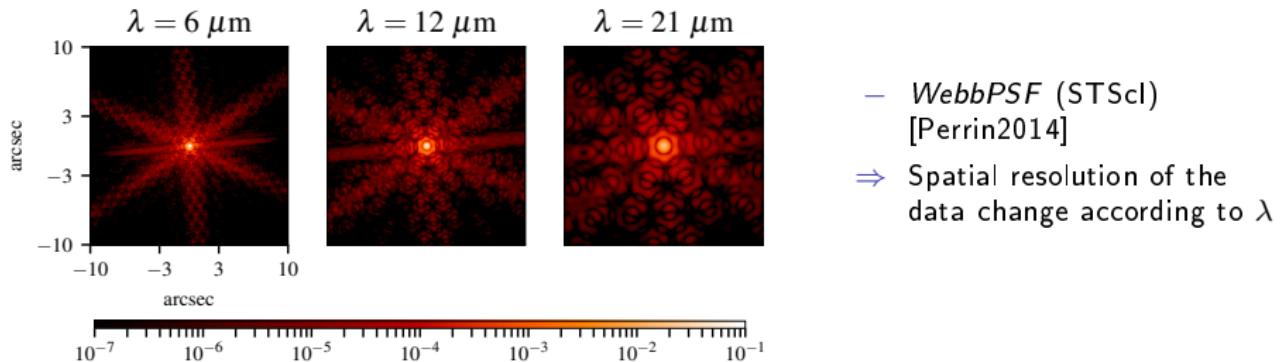


Proposed Instrument Model

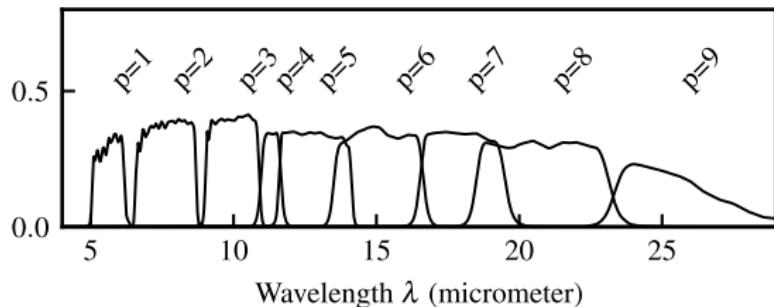


Instrument Parameters

Spectral Variations of the PSF : h



Nine Spectral Responses of the MIRI Imager : ω_p



- ω_p : Filter transmission \times Quantum efficiency
- ⇒ Broad responses + Correlation between the data

Complete Equation of the Model

For the band p and the pixel (i, j)

$$y_{i,j}^{(p)} = \int_{\mathbb{R}_+} \omega_p(\lambda) \times \left(\iint_{\Omega_{\text{pix}}} \left(\iint_{\mathbb{R}^2} \phi(\alpha', \beta', \lambda) h(\alpha - \alpha', \beta - \beta', \lambda) d\alpha' d\beta' \right) b_{\text{samp}}(\alpha - \alpha_i, \beta - \beta_j) d\alpha d\beta \right) d\lambda + n_{i,j}^{(p)}$$

where $p = 1, \dots, P, i = 1, \dots, N_i, j = 1, \dots, N_j$

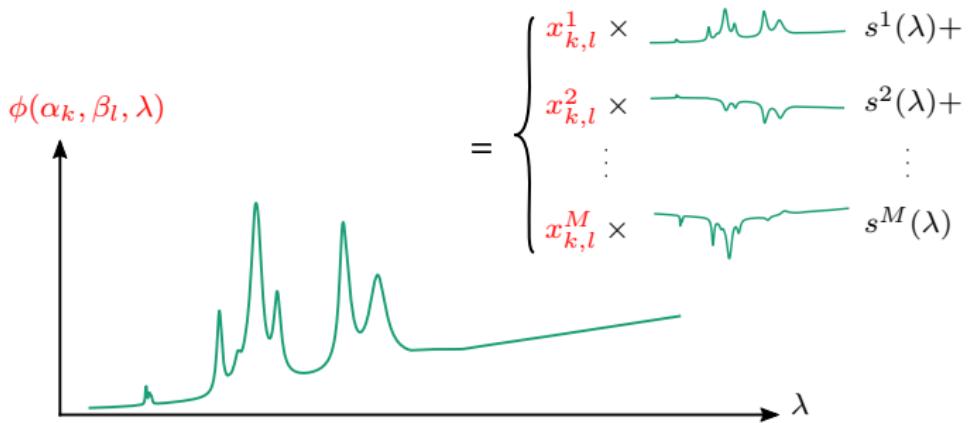
N_i, N_j	Numbers of rows and columns	ω_p	Spectral response of the band p
P	Number of spectral bands	b_{samp}	Spatial integration function over Ω_{pix}
h	Spatial response PSF	$n^{(p)}$	Additive noise

Hypothesis

- Photon noise neglected
- All issues related to the detector are corrected

Object Representation : Linear Mixing Model

For a single spatial position (α_k, β_l)



Object Model

$$\phi(\alpha, \beta, \lambda) = \sum_{m=1}^M \left(\sum_{k=1}^{N_k} \sum_{l=1}^{N_l} x_{k,l}^m b_{\text{rec}}(\alpha - \alpha_k, \beta - \beta_l) \right) s^m(\lambda)$$

x^m	m -th Mixture coefficient
s^m	m -th Spectral component
M	number of components
b_{rec}	Decomposition function

[Adams1986, Berne2007, Dobigeon2009]

Forward Model

Instrument model + object model

$$\mathbf{y}^{(p)} = \sum_{m=1}^M \mathbf{H}^{p,m} \mathbf{x}^{\textcolor{red}{m}} + \mathbf{n}^{(p)}, \quad \text{for the band } p$$

with

$$H_{i,j;k,l}^{p,m} = \iint_{\Omega_{\text{pix}}} \left(\left(\int_{\mathbb{R}_+} \omega_p(\lambda) h(\alpha, \beta, \lambda) s^m(\lambda) d\lambda \right)_{\alpha, \beta} * b_{\text{rec}}(\alpha - \alpha_k, \beta - \beta_l) \right) b_{\text{samp}}(\alpha - \alpha_i, \beta - \beta_j) d\alpha d\beta$$

Joint processing of all data ($M < P$)

$$\underbrace{\begin{pmatrix} \mathbf{y}^{(1)} \\ \mathbf{y}^{(2)} \\ \mathbf{y}^{(3)} \\ \vdots \\ \mathbf{y}^{(P)} \end{pmatrix}}_{\mathbf{y}} = \underbrace{\begin{pmatrix} \mathbf{H}^{1,1} & \mathbf{H}^{1,2} & \dots & \mathbf{H}^{1,M} \\ \mathbf{H}^{2,1} & \mathbf{H}^{2,2} & \dots & \mathbf{H}^{2,M} \\ \mathbf{H}^{3,1} & \mathbf{H}^{3,2} & \dots & \mathbf{H}^{3,M} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{H}^{P,1} & \mathbf{H}^{P,2} & \dots & \mathbf{H}^{P,M} \end{pmatrix}}_{\mathbf{H}} \underbrace{\begin{pmatrix} \mathbf{x}^1 \\ \mathbf{x}^2 \\ \vdots \\ \mathbf{x}^M \end{pmatrix}}_{\mathbf{x}} + \underbrace{\begin{pmatrix} \mathbf{n}^{(1)} \\ \mathbf{n}^{(2)} \\ \mathbf{n}^{(3)} \\ \vdots \\ \mathbf{n}^{(P)} \end{pmatrix}}_{\mathbf{n}}$$

Reconstruction : Estimation of the Mixture Coefficients

Convex Minimization

$$\hat{\mathbf{x}} = \underset{\mathbf{x}}{\operatorname{argmin}} \left\{ \mathcal{J}(\mathbf{x}) = \|\mathbf{y} - \mathbf{Hx}\|_2^2 + \mu \mathcal{R}(\mathbf{x}) \right\}$$

where the multichannel regularization is

$$\mathcal{R}(\mathbf{x}) = \sum_{m=1}^M \left(\sum_{k=1}^{N_k} \sum_{l=1}^{N_l} \varphi(x_{k+1,l}^m - x_{k,l}^m) + \sum_{k=1}^{N_k} \sum_{l=1}^{N_l} \varphi(x_{k,l+1}^m - x_{k,l}^m) \right)$$

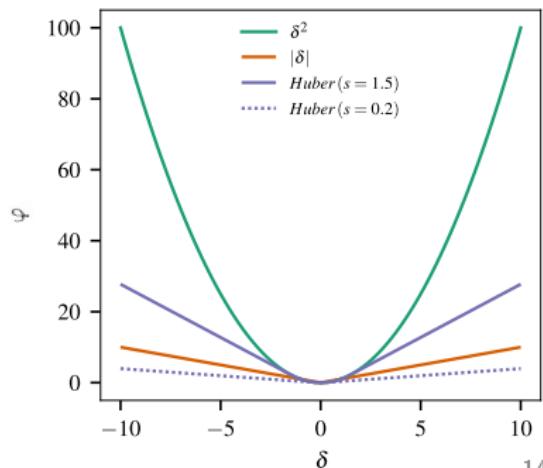
Regularization functions

1) Quadratic (l_2) : $\varphi(\delta) = \delta^2$

2) Half-Quadratic : Huber function (l_2/l_1)

$$\varphi(\delta) = \begin{cases} \delta^2 & \text{if } |\delta| < s \\ 2s|\delta| - s^2 & \text{otherwise} \end{cases}$$

s : Threshold parameter



Half-Quadratic Regularization

Convex Conjugate construction of [Geman1995]

$$\varphi(\delta) = \min_b \left\{ \frac{1}{2}(\delta - b)^2 + \xi(b) \right\}, \quad \forall \delta \in \mathbb{R}.$$

ξ : auxiliary function

b : auxiliary variable

Augmented objective function

$$\begin{aligned} \mathcal{J}_{l_2/l_1}^*(\mathbf{x}, \mathbf{b}_h, \mathbf{b}_v) = & \|\mathbf{y} - \mathbf{H}\mathbf{x}\|_2^2 + \mu \sum_{m=1}^M \left\{ \sum_{k=1}^{N_k} \sum_{l=1}^{N_l} \left(\frac{1}{2} [\mathbf{D}_h \mathbf{x}^m - \mathbf{b}_h^m]_{k,l}^2 + \xi([\mathbf{b}_h^m]_{k,l}) \right) \right. \\ & \left. + \sum_{k=1}^{N_k} \sum_{l=1}^{N_l} \left(\frac{1}{2} [\mathbf{D}_v \mathbf{x}^m - \mathbf{b}_v^m]_{k,l}^2 + \xi([\mathbf{b}_v^m]_{k,l}) \right) \right\} \end{aligned}$$

$\mathbf{D}_h, \mathbf{D}_v \in \mathbb{R}^{N_k, N_l}$: horizontal and vertical first-order finite difference operators.

$$\mathcal{J}_{l_2/l_1}(\mathbf{x}) = \min_{\mathbf{b}_h, \mathbf{b}_v} \mathcal{J}_{l_2/l_1}^*(\mathbf{x}, \mathbf{b}_h, \mathbf{b}_v),$$

Half-Quadratic Algorithm

⇒ Two minimization problems : Quadratic and separable

$$\begin{cases} \hat{\mathbf{b}}_h, \hat{\mathbf{b}}_v = \underset{\mathbf{b}_h, \mathbf{b}_v}{\operatorname{argmin}} \mathcal{J}_{l_2/l_1}^*(\mathbf{x}, \mathbf{b}_h, \mathbf{b}_v) \\ \hat{\mathbf{x}}_{l_2/l_1} = \underset{\mathbf{x}}{\operatorname{argmin}} \mathcal{J}_{l_2/l_1}^*(\mathbf{x}, \hat{\mathbf{b}}_h, \hat{\mathbf{b}}_v) \end{cases}$$

The half-quadratic solution : Updated at each iteration

$$\begin{aligned} \hat{\mathbf{b}}_h &= \overline{\mathbf{D}}_h \mathbf{x}_{l_2/l_1} - \varphi'(\overline{\mathbf{D}}_h \mathbf{x}_{l_2/l_1}) \\ \hat{\mathbf{b}}_v &= \overline{\mathbf{D}}_v \mathbf{x}_{l_2/l_1} - \varphi'(\overline{\mathbf{D}}_v \mathbf{x}_{l_2/l_1}) \\ \hat{\mathbf{x}}_{l_2/l_1} &= \underbrace{\left(\mathbf{H}^T \mathbf{H} + \mu \left(\overline{\mathbf{D}}_h^T \overline{\mathbf{D}}_h + \overline{\mathbf{D}}_v^T \overline{\mathbf{D}}_v \right) \right)^{-1}}_{\mathbf{Q}_{l_2/l_1}} \underbrace{\left(\mathbf{H}^T \mathbf{y} + \mu \left(\overline{\mathbf{D}}_h^T \mathbf{b}_h + \overline{\mathbf{D}}_v^T \mathbf{b}_v \right) \right)}_{\mathbf{q}_{l_2/l_1}} \end{aligned}$$

\mathbf{Q}_{l_2/l_1} is not circulant matrix but block-circulant

Inversion of a block-matrix with circulant blocks

Step 1 : Block-matrix with circulant blocs

$$Q = \begin{pmatrix} \left(\begin{array}{c} Q^{1,1} \\ \vdots \\ Q^{2,1} \\ \vdots \\ Q^{N_x 1} \end{array} \right) & \left(\begin{array}{c} Q^{1,2} \\ \vdots \\ Q^{2,2} \\ \vdots \\ \ddots \end{array} \right) & \dots & \left(\begin{array}{c} Q^{1,N_\lambda} \\ \vdots \\ \ddots \\ \dots \\ Q^{N_x N_\lambda} \end{array} \right) \end{pmatrix}$$

Inversion of a block-matrix with circulant blocks

Step 2 : Diagonalization in Fourier space, $\mathbf{Q}^{i,j} = \mathbf{F}^\dagger \mathbf{\Lambda}^{i,j} \mathbf{F}$

$$\mathbf{\Lambda}_Q = \left(\begin{array}{ccc} \left(\begin{array}{ccc} \Lambda_1^{1,1} & & \\ & \ddots & \\ & & \Lambda_{N_k N_l}^{1,1} \end{array} \right) & \left(\begin{array}{ccc} \Lambda_1^{1,2} & & \\ & \ddots & \\ & & \Lambda_{N_k N_l}^{1,2} \end{array} \right) & \cdots & \left(\begin{array}{ccc} \Lambda_1^{1,N_\lambda} & & \\ & \ddots & \\ & & \Lambda_{N_k N_l}^{1,N_\lambda} \end{array} \right) \\ \left(\begin{array}{ccc} \Lambda_1^{2,1} & & \\ & \ddots & \\ & & \Lambda_{N_k N_l}^{2,1} \end{array} \right) & \left(\begin{array}{ccc} \Lambda_1^{2,2} & & \\ & \ddots & \\ & & \Lambda_{N_k N_l}^{2,2} \end{array} \right) & \ddots & \vdots \\ \vdots & \ddots & \ddots & \vdots \\ \left(\begin{array}{ccc} \Lambda_1^{N_\lambda 1} & & \\ & \ddots & \\ & & \Lambda_{N_k N_l}^{N_\lambda 1} \end{array} \right) & \cdots & \cdots & \left(\begin{array}{ccc} \Lambda_1^{N_\lambda N_\lambda} & & \\ & \ddots & \\ & & \Lambda_{N_k N_l}^{N_\lambda N_\lambda} \end{array} \right) \end{array} \right)$$

NDBD : Non-Diagonal Block Diagonal

Inversion of a block-matrix with circulant blocks

Step 3 : Transformation + Parallel computation

$$\Lambda_Q = \begin{pmatrix} \left(\begin{array}{c} \Lambda_1^{1,1} \\ \vdots \\ \Lambda_1^{2,1} \\ \vdots \\ \Lambda_1^{M,1} \end{array} \right) & \left(\begin{array}{c} \Lambda_1^{1,2} \\ \vdots \\ \Lambda_1^{2,2} \\ \vdots \\ \Lambda_1^{N_\lambda,1} \end{array} \right) & \cdots & \left(\begin{array}{c} \Lambda_1^{1,N_\lambda} \\ \vdots \\ \Lambda_1^{2,N_\lambda} \\ \vdots \\ \Lambda_1^{N_\lambda N_\lambda} \end{array} \right) \\ \Lambda_{N_k N_l}^{1,1} & \Lambda_{N_k N_l}^{1,2} & \cdots & \Lambda_{N_k N_l}^{1,N_\lambda} \\ \Lambda_{N_k N_l}^{2,1} & \Lambda_{N_k N_l}^{2,2} & \cdots & \Lambda_{N_k N_l}^{2,N_\lambda} \\ \vdots & \vdots & \ddots & \vdots \\ \Lambda_{N_k N_l}^{N_\lambda,1} & \Lambda_{N_k N_l}^{N_\lambda,2} & \cdots & \Lambda_{N_k N_l}^{N_\lambda N_\lambda} \end{pmatrix}$$

$\mathbf{R}^{(1)} = \begin{pmatrix} \Lambda_1^{1,1} & \Lambda_1^{1,2} & \cdots & \Lambda_1^{1,N_\lambda} \\ \Lambda_1^{2,1} & \Lambda_1^{2,2} & \cdots & \Lambda_1^{2,N_\lambda} \\ \vdots & \vdots & \ddots & \vdots \\ \Lambda_1^{N_\lambda,1} & \Lambda_1^{N_\lambda,2} & \cdots & \Lambda_1^{N_\lambda N_\lambda} \end{pmatrix}$

Inversion of a block-matrix with circulant blocks

Step 4 : Inversion

$$\left(\mathbf{R}^{(2)} \right)^{-1} = \mathbf{T}^{(2)} = \begin{pmatrix} T_2^{1,1} & T_2^{1,2} & \cdots & T_2^{1,N_\lambda} \\ T_2^{2,1} & T_2^{2,2} & & \vdots \\ \vdots & & & T_2^{N_\lambda N_\lambda} \\ T_2^{N_\lambda 1} & \cdots & \cdots & \end{pmatrix}$$
$$\Lambda_Q^{inv} = \begin{pmatrix} \left(\begin{array}{c} T_1^{1,1} \\ T_2^{1,1} \end{array} \right) & \left(\begin{array}{c} T_1^{1,2} \\ T_2^{1,2} \end{array} \right) & \cdots & \left(\begin{array}{c} T_1^{1,N_\lambda} \\ T_2^{1,N_\lambda} \end{array} \right) \\ \left(\begin{array}{c} T_1^{2,1} \\ T_2^{2,1} \end{array} \right) & \left(\begin{array}{c} T_1^{2,2} \\ T_2^{2,2} \end{array} \right) & \cdots & \vdots \\ \vdots & \cdots & \cdots & \left(\begin{array}{c} T_1^{N_\lambda N_\lambda} \\ T_2^{N_\lambda N_\lambda} \end{array} \right) \\ \left(\begin{array}{c} T_1^{N_\lambda 1} \\ T_2^{N_\lambda 1} \end{array} \right) & \cdots & \cdots & \ddots \end{pmatrix}$$

The diagram illustrates the inverse relationship between the matrix $\mathbf{R}^{(2)}$ and the block-diagonal matrix Λ_Q^{inv} . Red circles highlight specific entries in both matrices. Dashed red arrows point from entries in $\mathbf{R}^{(2)}$ to corresponding entries in Λ_Q^{inv} , illustrating how the inverse is constructed from the blocks.

Inversion of block-matrix with circulant blocks

$$Q = \begin{bmatrix} Q^{1,1} & \dots & Q^{1,M} \\ \vdots & \ddots & \vdots \\ Q^{M,1} & \dots & Q^{M,M} \end{bmatrix}, \quad Q^{i,j} = F^\dagger \Lambda^{i,j} F, \quad i, j \in [1, \dots, M]^2,$$

Then

$$Q = \bar{F}^\dagger \Lambda_Q \bar{F}, \quad \text{and} \quad Q^{-1} = \bar{F}^\dagger \Lambda_Q^{-1} \bar{F}, \quad (1)$$

with

$$\Lambda_Q = \begin{bmatrix} \Lambda^{1,1} & \dots & \Lambda^{1,M} \\ \vdots & \ddots & \vdots \\ \Lambda^{M,1} & \dots & \Lambda^{M,M} \end{bmatrix}, \quad \bar{F} = \begin{bmatrix} F \\ \vdots \\ F \end{bmatrix}. \quad (2)$$

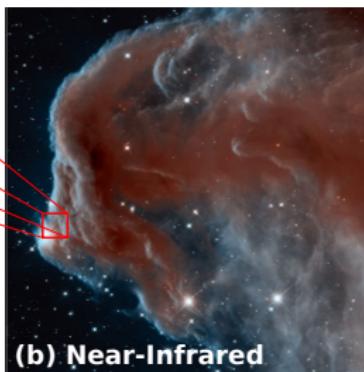
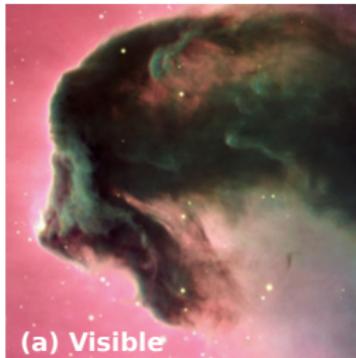
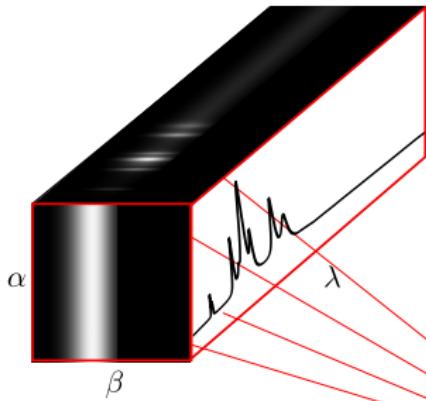
Thanks to the permutation matrices P , the NDBD matrix can be written as

$$\Lambda_Q = P R P = P \text{diag}(R^p) P \quad \text{with} \quad (R^p)_{i,j} = (\Lambda^{i,j})_{p,p}, \quad (3)$$

Then

$$\Upsilon = \Lambda_Q^{-1} = P^T R^{-1} P^T = P^T \text{diag}\left((R^p)^{-1}\right) P^T \quad \text{with} \quad (\Upsilon^{i,j})_{p,p} = \left((R^p)^{-1}\right)_{i,j} \quad (4)$$

Original Spatio-Spectral Object for Simulation

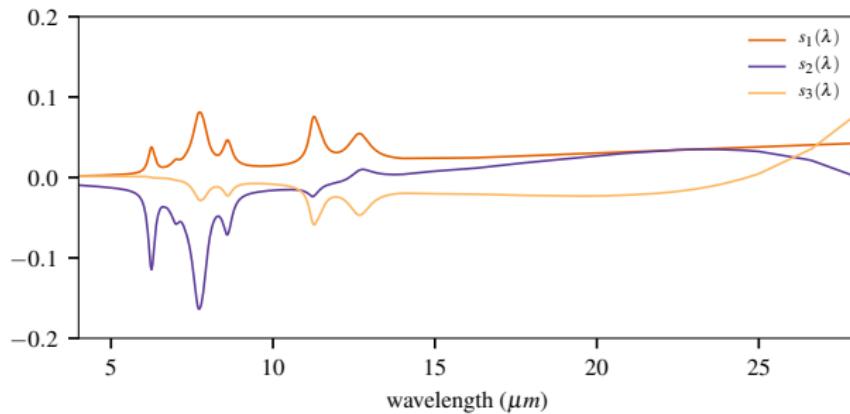


HorseHead nebula
[Abergel2003]

— Size : $1000 \times 256 \times 256$

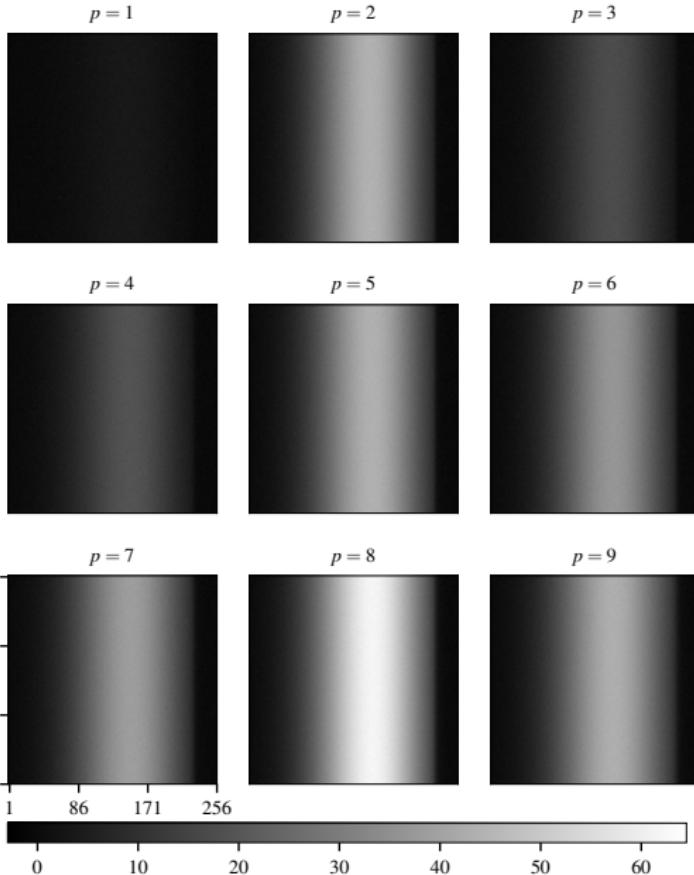
Original Spatio-Spectral Object :

Horsehead Nebula ($M = 3$)



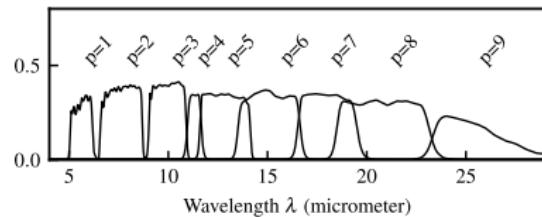
Spectral component are extracted using the **Principal Component Analysis** (PCA) method.

Simulation of Wideband Multispectral Data



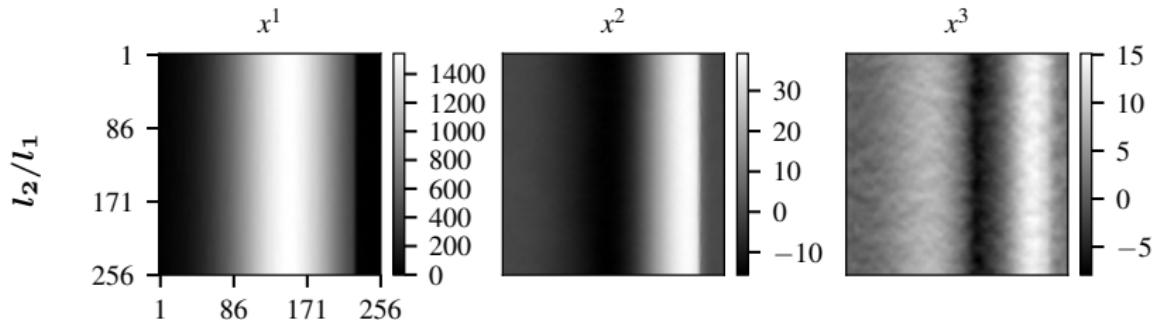
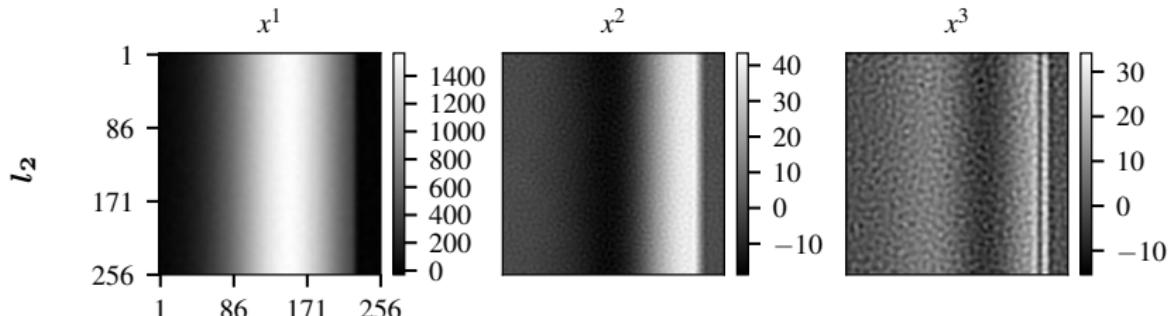
HorseHead

- JWST/MIRI Imager
- $9 \times 256 \times 256$ pixels
- SNR = 30 dB white Gaussian noise

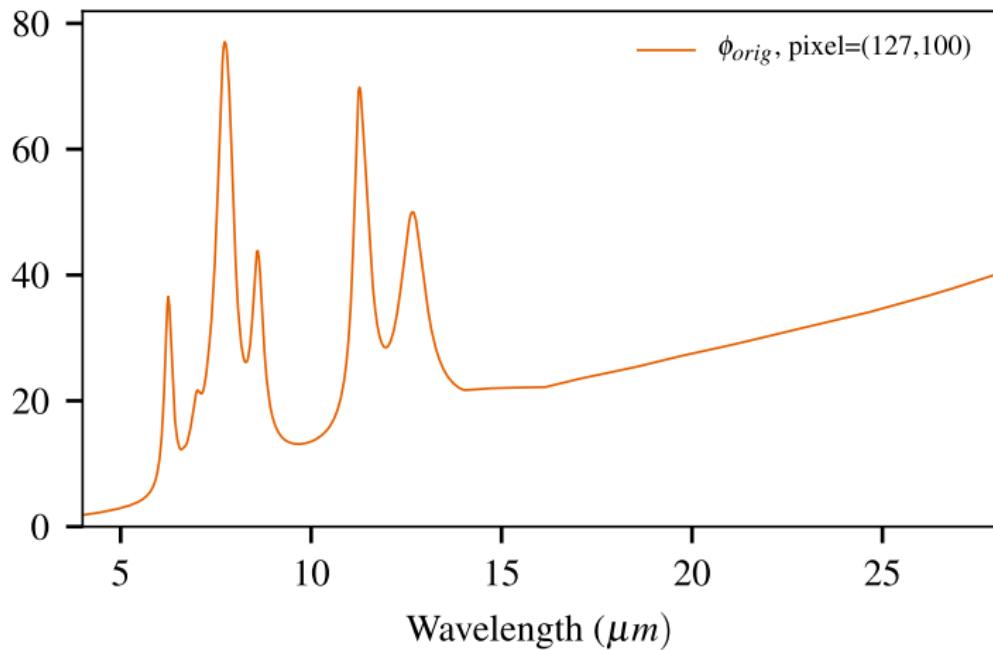


Estimated Mixture Coefficients

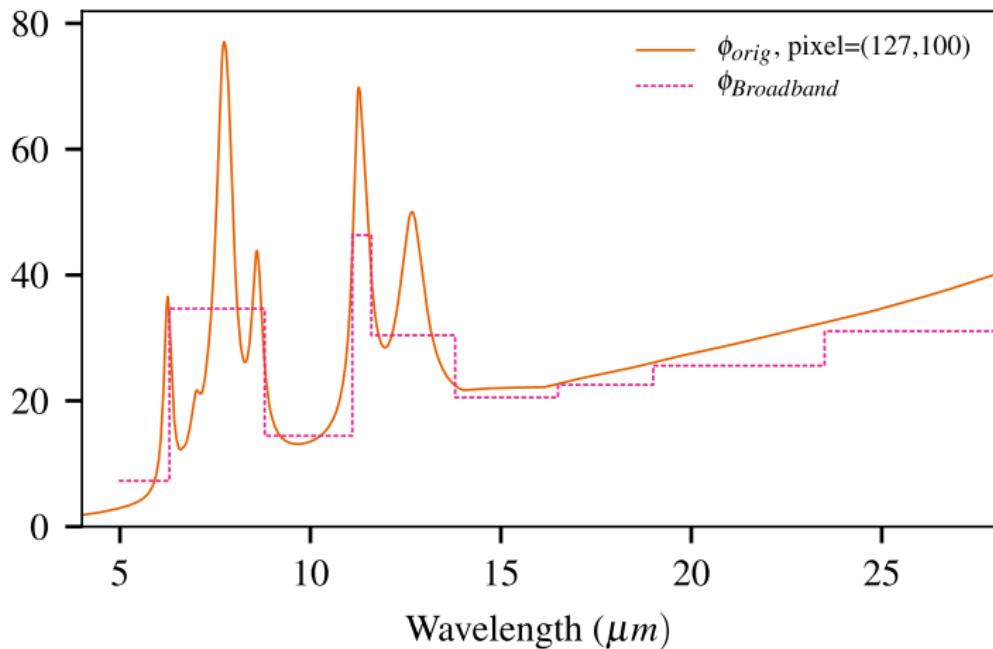
HorseHead



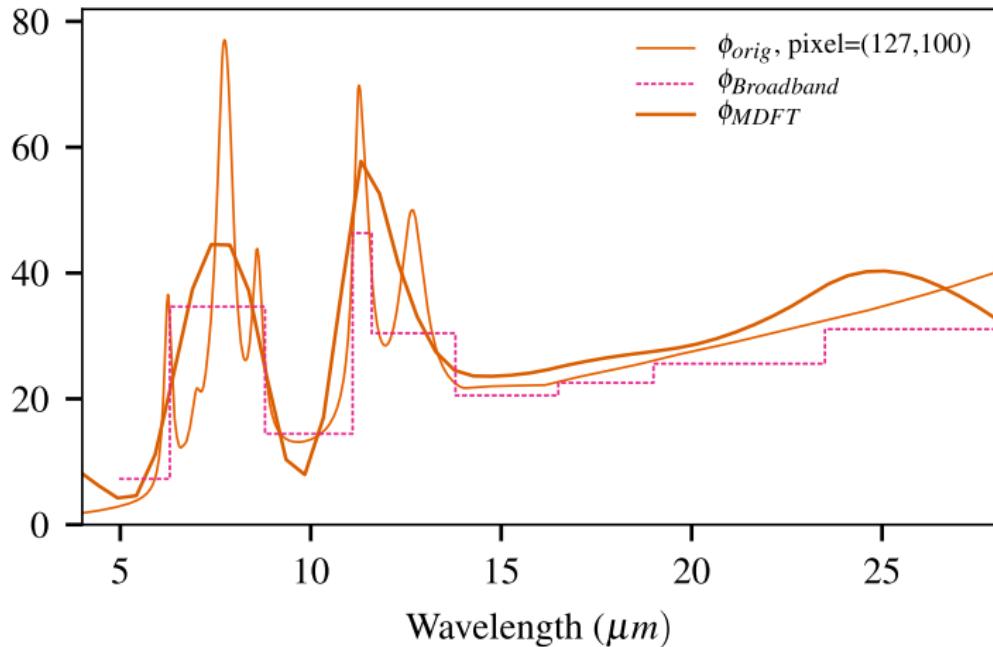
Comparison Between Results



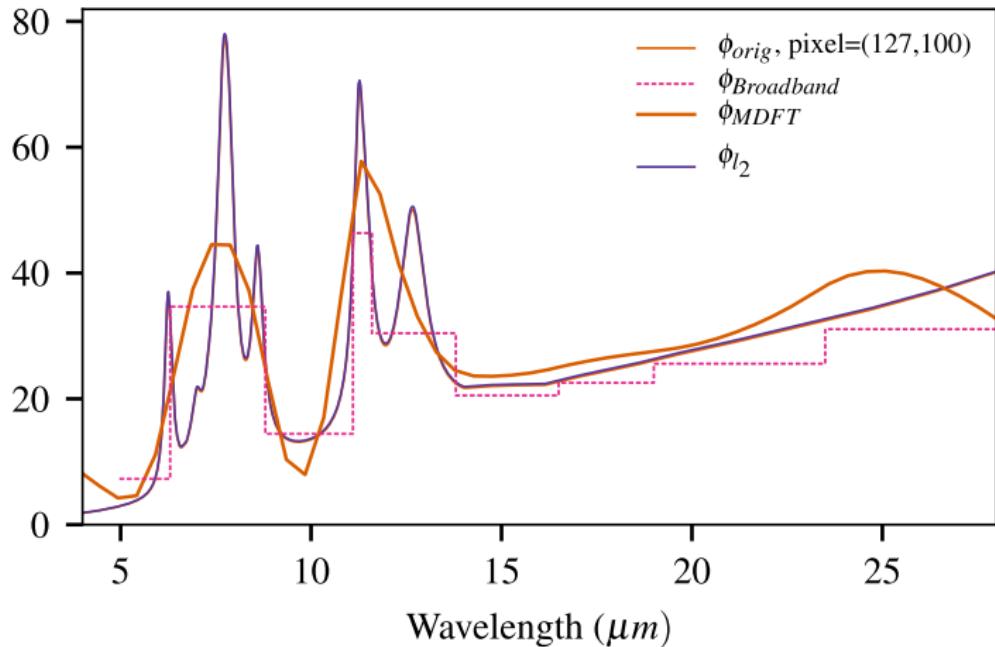
Comparison Between Results



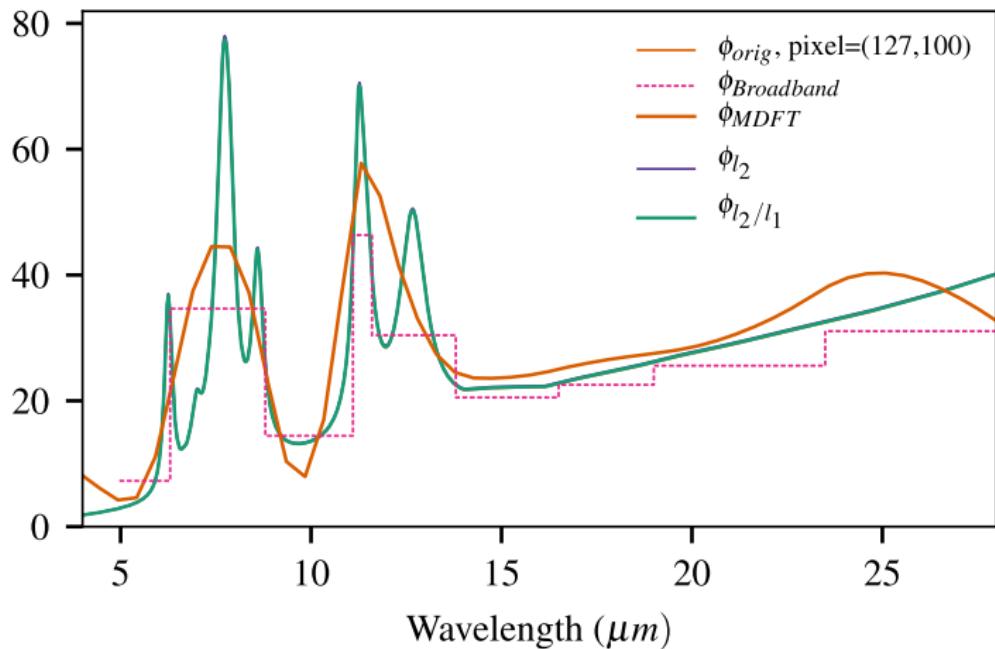
Comparison Between Results



Comparison Between Results



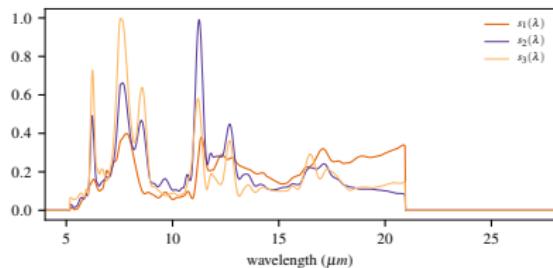
Comparison Between Results



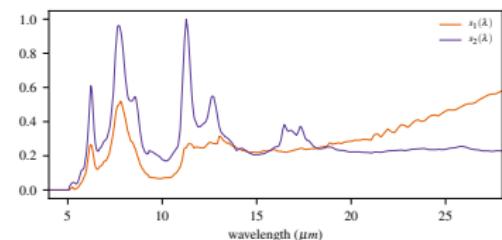
Synthetic Spatio-Spectral Objects : $1000 \times 256 \times 256$

Spectral components

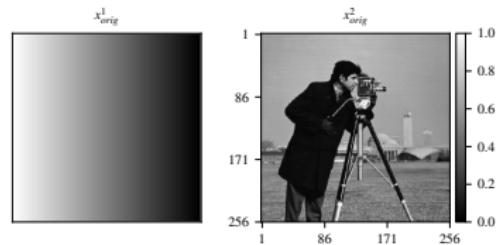
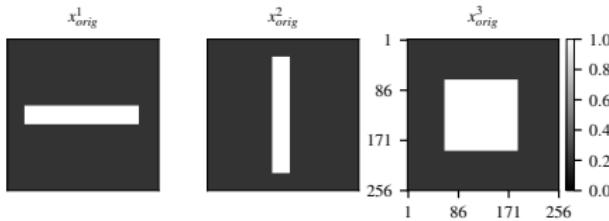
Object₁



Object₂

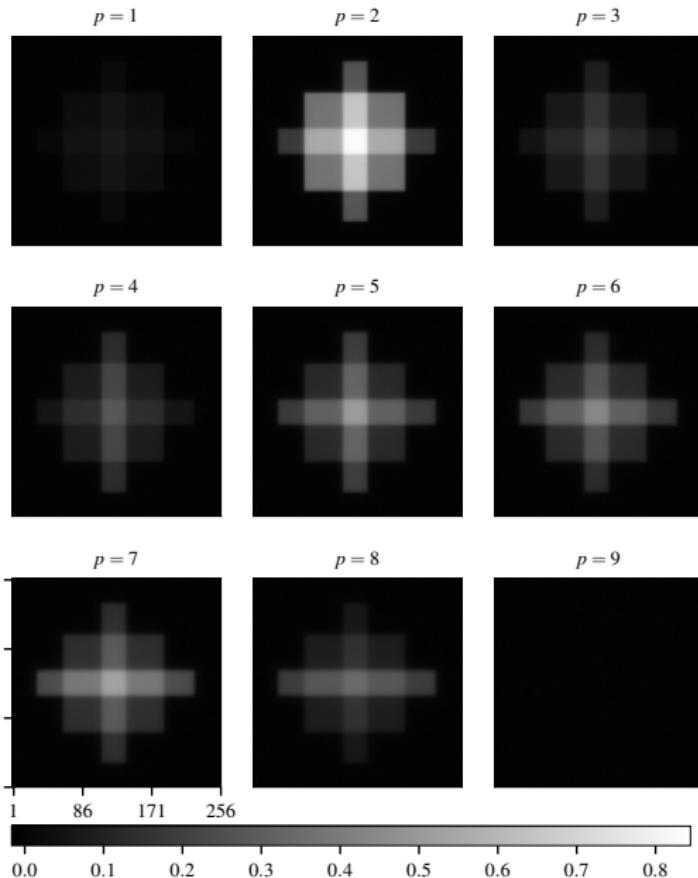


Mixture coefficients



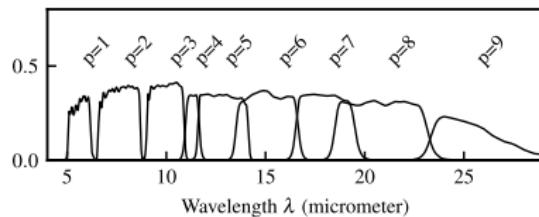
Spectra extracted from real data observed by the Spitzer Telescope [?]

Simulation of Wideband Multispectral Data



Object₁

- JWST/MIRI Imager
- $9 \times 256 \times 256$ pixels
- SNR = 30 dB white Gaussian noise



Simulation of Wideband Multispectral Data

$p = 1$



$p = 2$



$p = 3$



$p = 4$



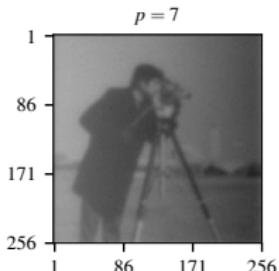
$p = 5$



$p = 6$



$p = 7$



$p = 8$

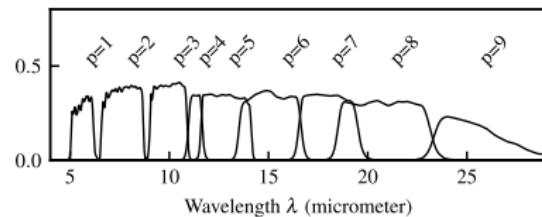


$p = 9$



Object₂

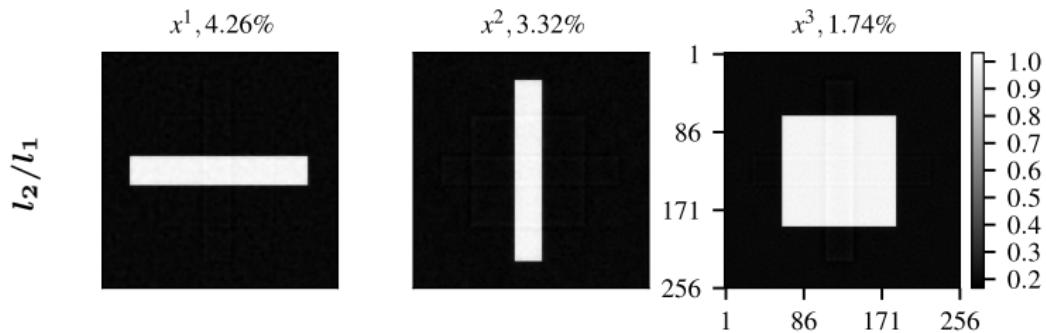
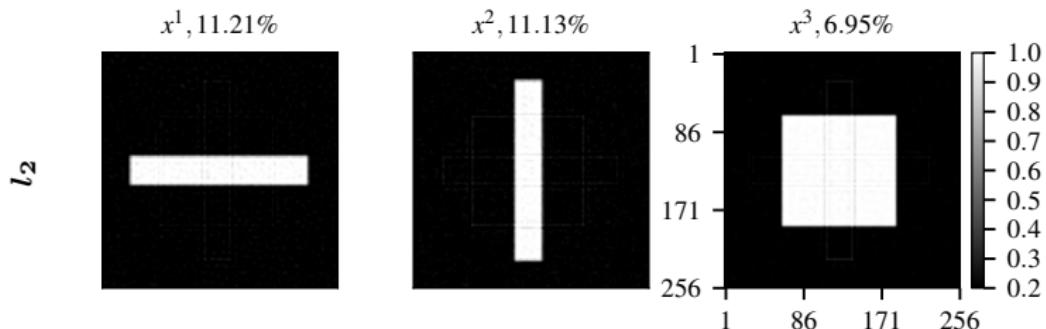
- JWST/MIRI Imager
- $9 \times 256 \times 256$ pixels
- SNR = 30 dB white Gaussian noise



Wavelength λ (micrometer)

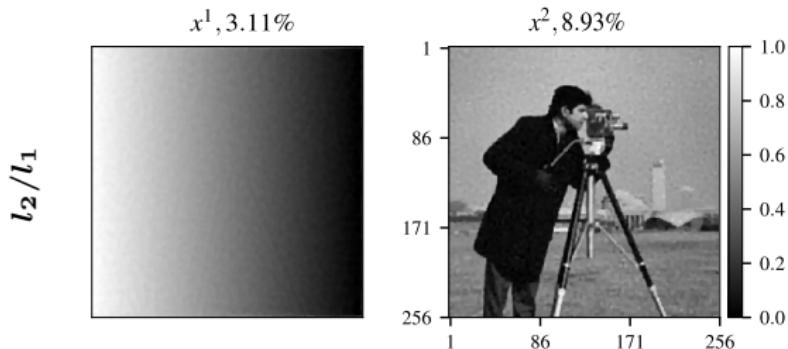
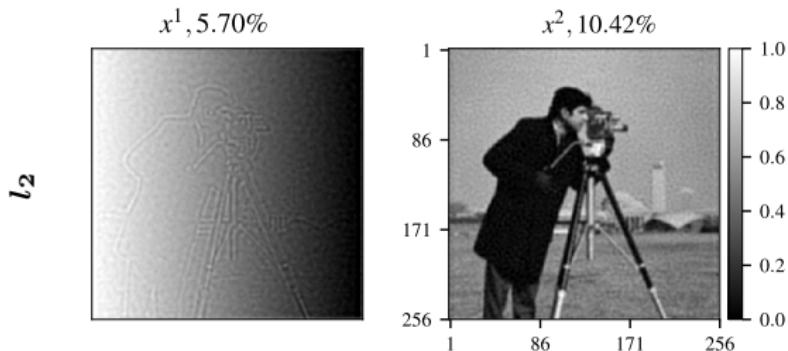
Estimated Mixture Coefficients

Object₁

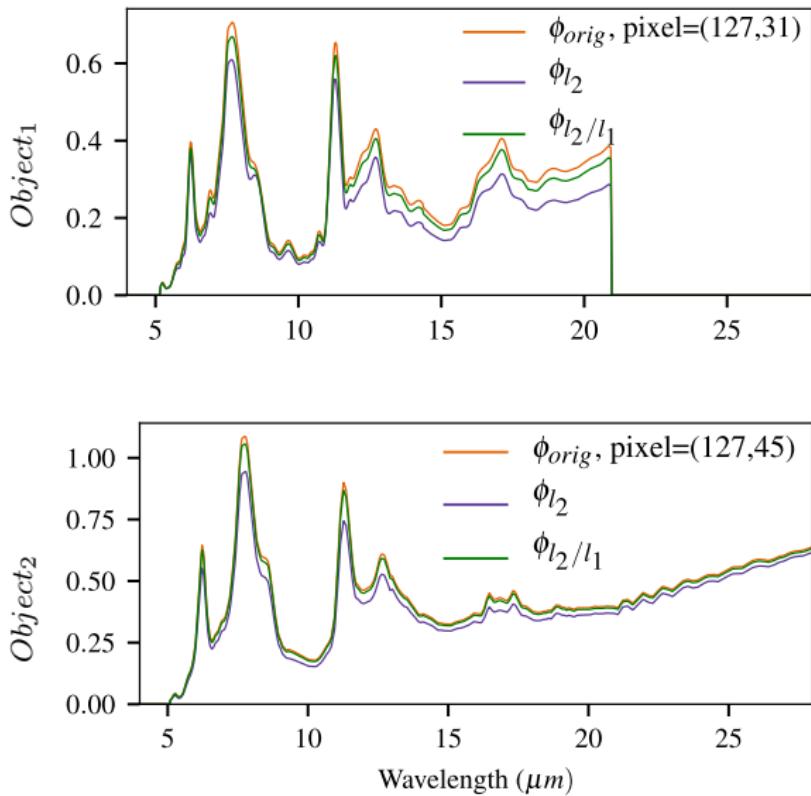


Estimated Mixture Coefficients

Object₂



Reconstruction Results



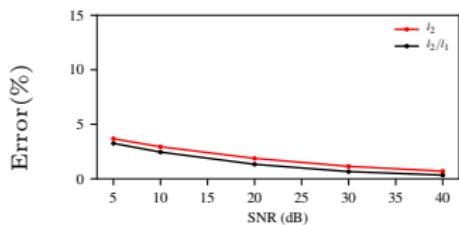
Reconstruction Results

Spatio-Spectral Object	Regularization	Error (%)	Runtime (seconds)	N_{iter}
<i>HorseHead Nebula</i>	l_2	1.14	1.36	
	l_2/l_1	0.66	20.33	50
<i>Object₁</i>	l_2	5.29	1.19	
	l_2/l_1	1.91	19.98	50
<i>Object₂</i>	l_2	5.95	0.97	
	l_2/l_1	4.91	18.50	50

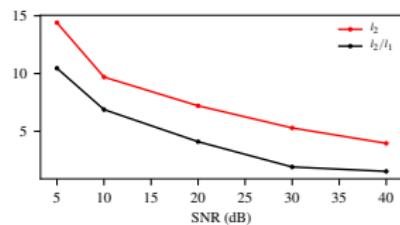
- Reconstructed spatio-spectral objects of size **1000 × 256 × 256**.
- Relative error : $\text{Error}(\%) = 100 \times \frac{\|\mathbf{x}_{orig} - \mathbf{x}_{rec}\|_2}{\|\mathbf{x}_{orig}\|_2}$

Influence of the Noise Level

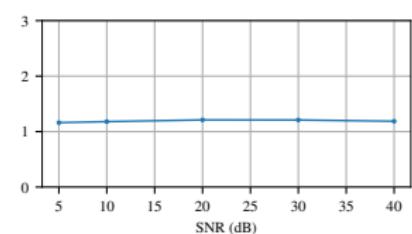
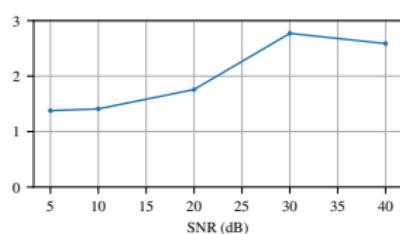
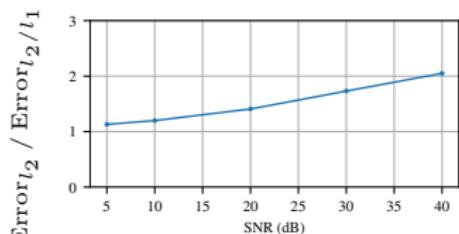
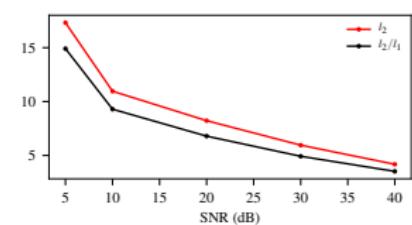
HorseHead



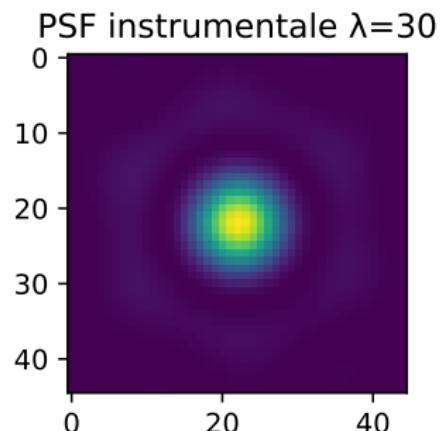
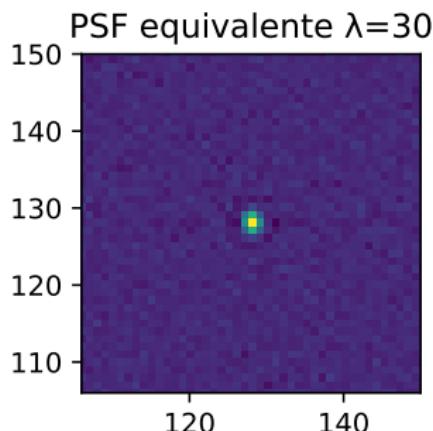
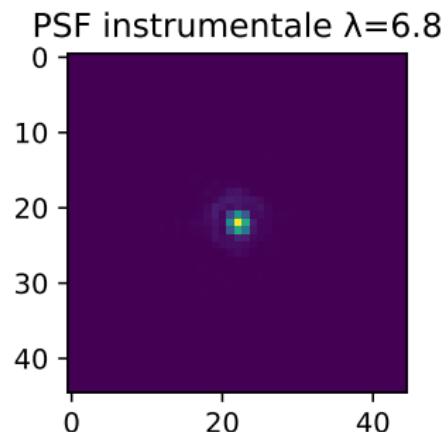
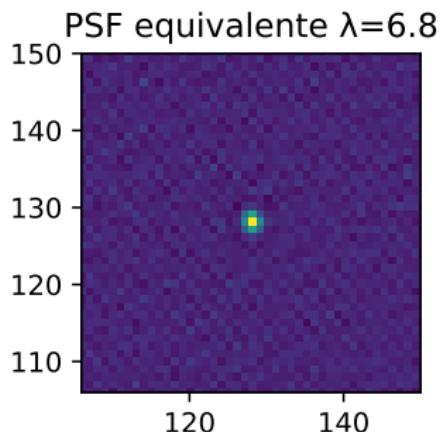
Object₁



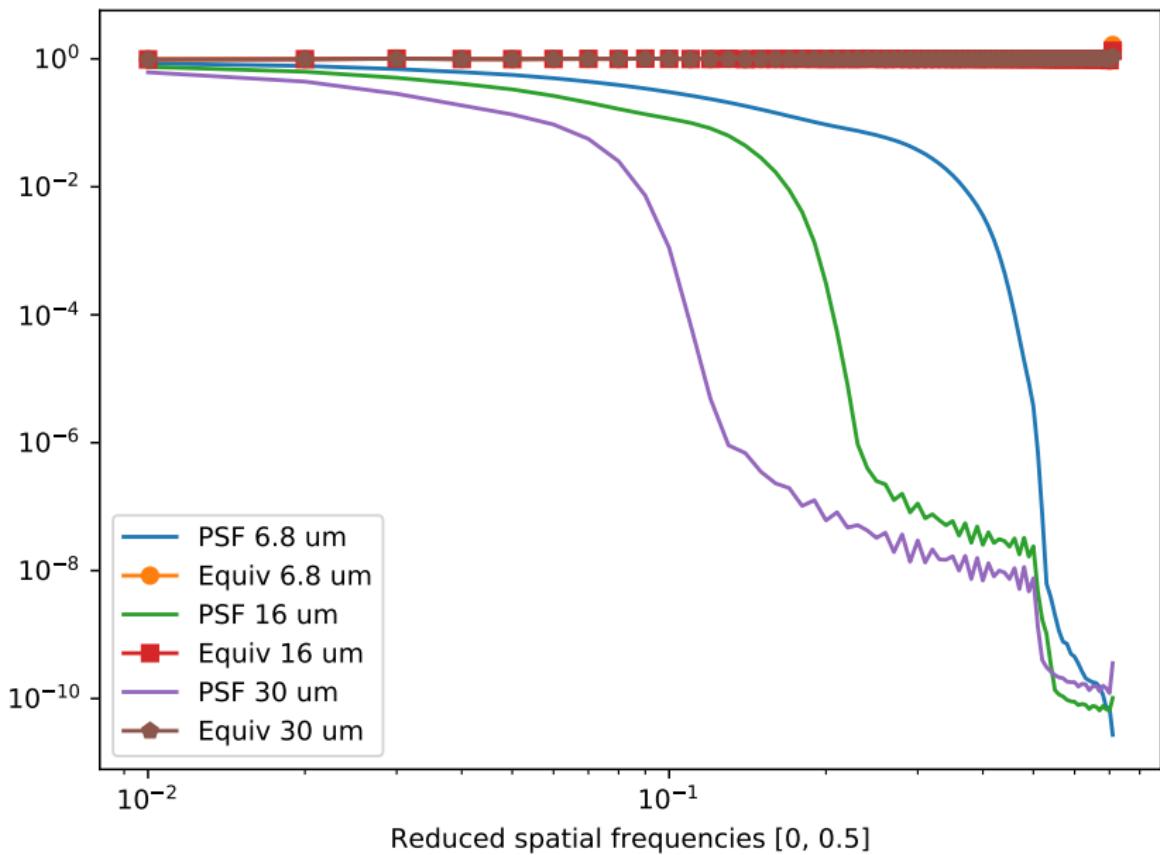
Object₂



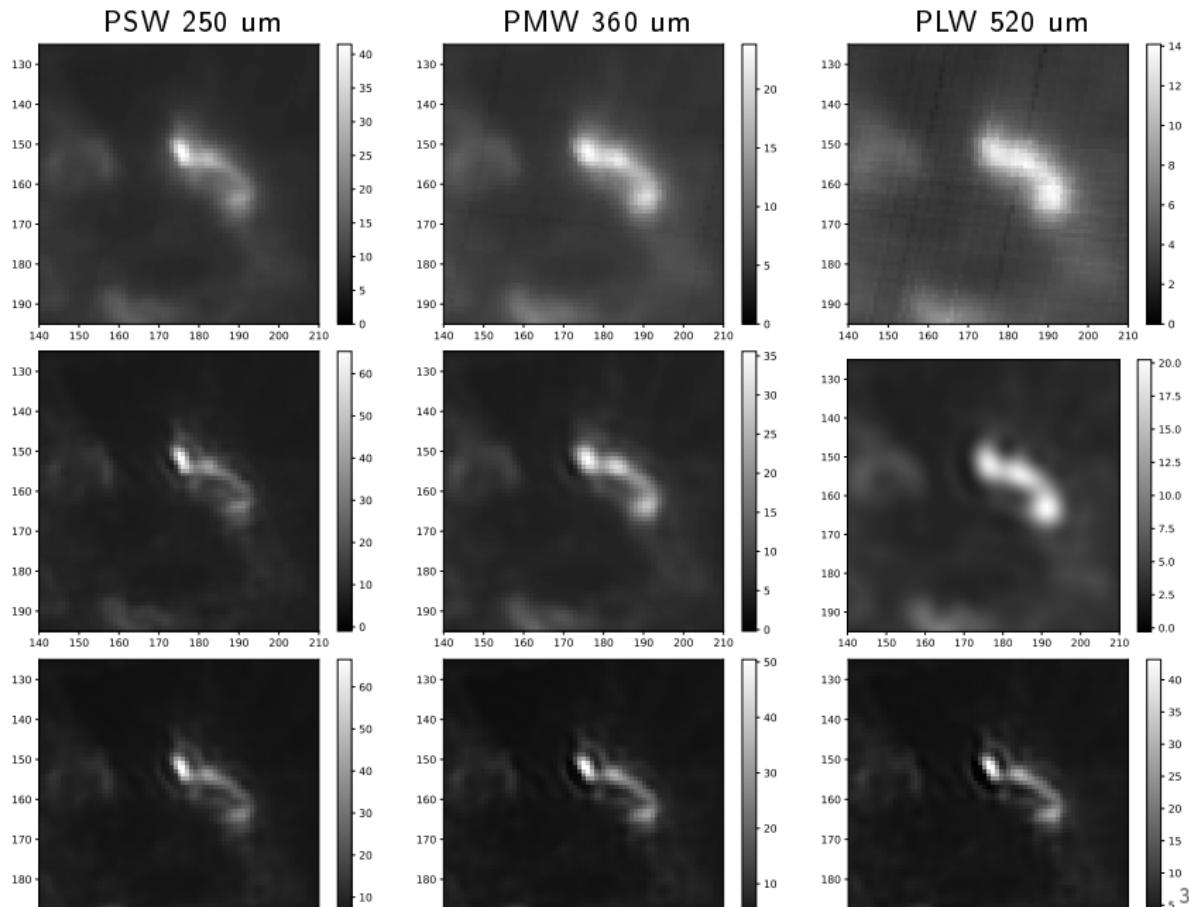
Extra figs : Equivalent PSF



Extra figs : Equivalent OTF



Ex : SPIRE/Herschel real data



Conclusion and Perspectives

Conclusion

- Reconstruction of a $2D + \lambda$ object from a small number of wideband images
- Exploiting all data of the Imager from different bands
- Development of a model for the JWST/MIRI Imager (spectral-variant PSF and the detector integration)
- Proposition of three reconstruction algorithms, $10 \times$ faster than the conjugated gradient algorithm
- Computation of the exact solution thanks to matrix diagonalization in Fourier domain
- Object model is very important for a better reconstruction
- The obtained results outperform the conventional approaches using a piecewise linear function and linear mixing model

Perspectives

- Estimation of the regularization parameters μ , μ_{spat} and μ_{spec}
- Automatic tuning the parameter : N_λ and s
- Enforce prior information for objects with different spatial and spectral distributions (e.g. sparse, piecewise constant, ...)
- Exploit the data of the MIRI spectrometer to extract the spectral components

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