

Spatio-Spectral Multichannel Reconstruction from few Low-Resolution Multispectral Data

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Context

The James Webb Space Telescope (JWST) :

Organization	NASA (ESA & CSA)
Expected Launch	March 2021
Primary Mirror	25 m² (> 3× Hubble) 18 hexagonal segments
Wavelength Range	5 — 28 μm (factor of 5)

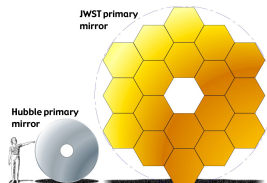


nasa.gov

www.jwst.

Main objectives of the JWST mission :

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



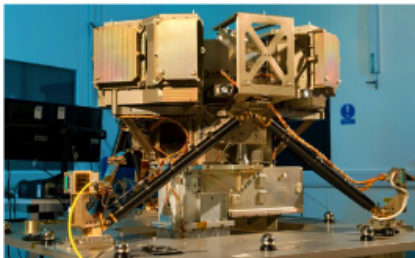
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Instruments on board the JWST

Instrument and Data resolution :

Data	Spatial resolution	Spectral resolution
Imager	✓	✗
Spectrometer	✗	✓



Mid-IR Instrument (MIRI) Imager [Bouchet]

Characteristics :

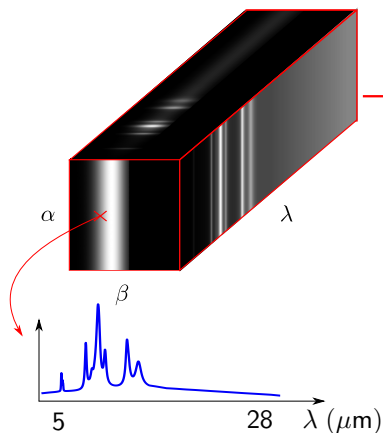
- 9 spectral bands [$5 - 28 \mu\text{m}$]
- $\lambda/\Delta\lambda \sim 5$
- Field of View $74'' \times 113''$
- 2D detector matrix

Outline

- 1 Introduction
 - Objective and Problems
 - Related Works
- 2 Proposed Methodology
 - 1) Instrument Model
 - 2) Forward model
 - 3) Reconstruction
- 3 Results
- 4 Conclusion and Perspectives

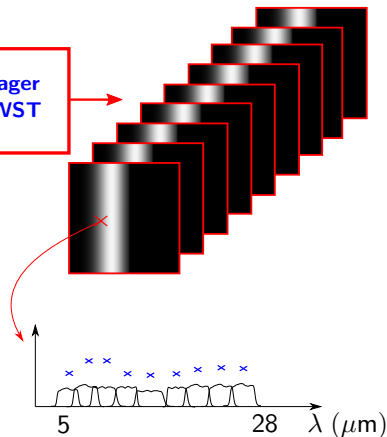
Inverse Problem Application

Continuous Input :
2D+ λ Object



MIRI Imager
of the JWST

Discrete Output :
Set of 2D
Multispectral data



Objective and Problems

Main Objective

- Reconstruction of a high-resolution spatio-spectral object from a small number of degraded multispectral data

Problems

- Dependence of the optical system response (PSF) on the wavelength → Varying blur of the multispectral data
- Integration over broad windows → Low spectral resolution of the multispectral data
- Under-determined problem → Small number of multispectral data (e.g. only nine for the MIRI Imager)

Related Works

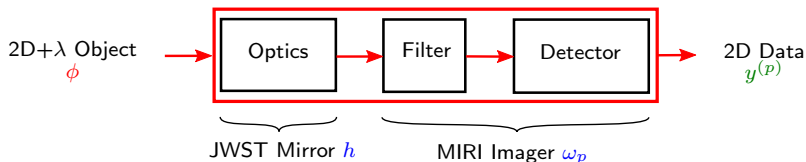
- Methods using stationary/non-stationary PSF :
 - Measured PSF [Guillard], Broadband PSF [Geis & Lutz 2010], PSF linear interpolation [Soulez], PSF approximation [Villeneuve & Carfantan 2014]
 - Neglect the spectral variation of the PSF = inaccurate response
- Processing of the data : Separately band per band [Aniano]
 - Neglect the cross-correlation between the spectral channel
- Our work in [Hadj-Youcef] (*26-th EUSIPCO*)
 - Limitation in the reconstruction of the spectral distribution

Propositions :

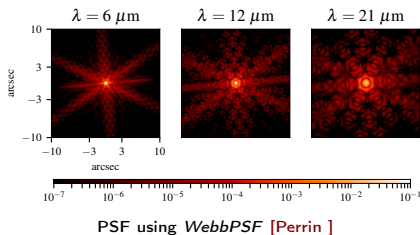
- Modeling the instrument response : spectral integration and variation of the optical response
- Joint processing of all the multispectral data

Modeling of the Instrument Response

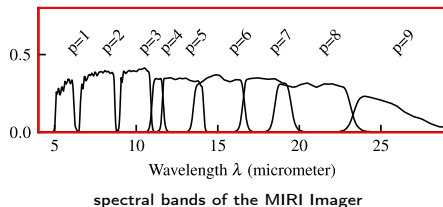
Block diagram of the instrument model :



Spectral Variations of the PSF : h



Spectral Responses : ω_p



Complete Equation of the Model

For p -th spectral band and (i, j) -th pixel :

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

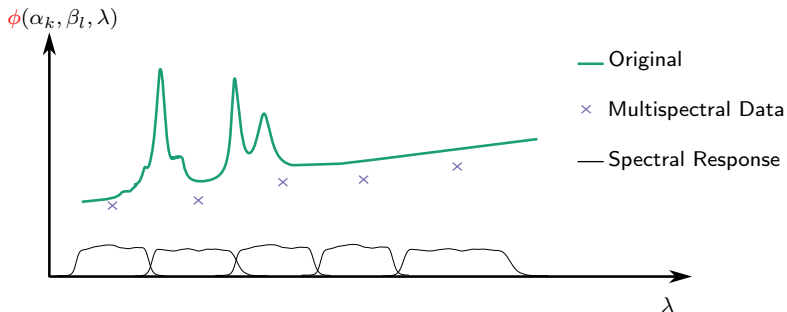
where $p = 1, \dots, P, i = 1, \dots, N_i, j = 1, \dots, N_j$

- N_i and N_j are numbers of rows and columns of the detector matrix
- P is the number of bands
- h is the PSF (Point Spread Function).
- ω_p is the spectral response of the instrument (filter + detector).
- b_{samp} is a spatial sampling function over the pixel area Ω_{pix} and $n_{i,j}^{(p)}$ is an additive noise.

Hypothesis : The non-ideal characteristics of the detector are assumed to be corrected upstream.

Illustration of the Object Model

Spectral distribution at k, l -th pixel with $P = 5$ spectral bands



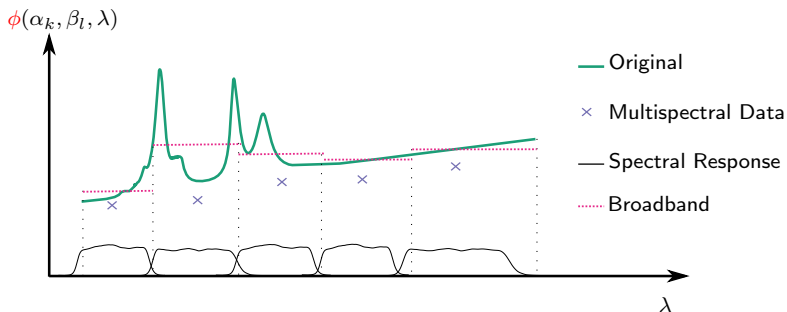
Representation with a piecewise linear function :

$$\phi(\alpha, \beta, \lambda) = \sum_{m=1}^{N_\lambda} \sum_{k=1}^{N_k} \sum_{l=1}^{N_l} x_{k,l}^{(m)} b_{\text{spat}}(\alpha - \alpha_k, \beta - \beta_l) b_{\text{spec}}(\lambda)$$

b_{spat} is a uniform discretization function and b_{spec} a first-order B-spline. N_λ number of wavelengths

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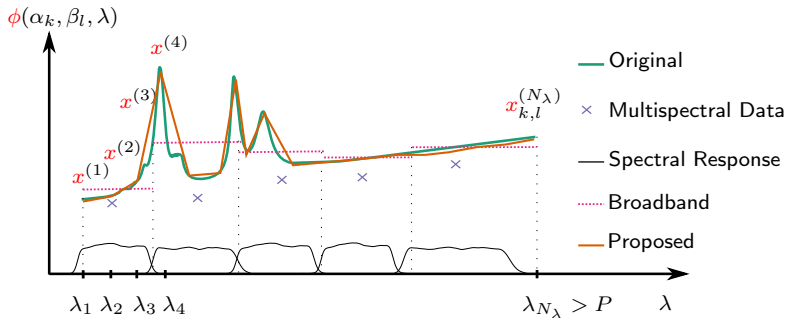
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Forward Model

By substituting the object model in the instrument model we obtain :

$$\mathbf{y}^{(p)} = \sum_{m=1}^{N_\lambda} \mathbf{H}^{p,m} \mathbf{x}^{(m)} + \mathbf{n}^{(p)}, \quad p = 1, \dots, P$$

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

By joint processing of all multispectral data : Multichannel processing

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

$$\mathbf{y} = \mathbf{H} \mathbf{x} + \mathbf{n}$$

Regularized Least-Squares

Convex Minimization :

$$\hat{\mathbf{x}} = \underset{\mathbf{x}}{\operatorname{argmin}} \mathcal{J}(\mathbf{x})$$

where the objective function is

$$\mathcal{J}(\mathbf{x}) = \underbrace{\|\mathbf{y} - \mathbf{H}\mathbf{x}\|_2^2}_{\substack{\mathcal{Q}(\mathbf{x}, \mathbf{y}) \\ \text{Data fidelity}}} + \underbrace{\left\{ \mu_{\text{spat}} \underbrace{\|\mathbf{D}_{\text{spat}}\mathbf{x}\|_2^2}_{\mathcal{R}_{\text{spat}}(\mathbf{x})} + \mu_{\text{spec}} \underbrace{\|\mathbf{D}_{\text{spec}}\mathbf{x}\|_2^2}_{\mathcal{R}_{\text{spec}}(\mathbf{x})} \right\}}_{\text{Quadratic Regularizations}}$$

\mathbf{D}_{spat} and \mathbf{D}_{spec} are 2D and 1D finite difference operator along the spatial and spectral dimensions to enforce smoothness. μ_{spat} and μ_{spec} are regularization parameters.

Solution of the Problem : \mathcal{J} is linear and differentiable

$$\hat{\mathbf{x}} = (\mathbf{H}^T \mathbf{H} + \mu_{\text{spat}} \mathbf{D}_{\text{spat}}^T \mathbf{D}_{\text{spat}} + \mu_{\text{spec}} \mathbf{D}_{\text{spec}}^T \mathbf{D}_{\text{spec}})^{-1} \mathbf{H}^T \mathbf{y}.$$

Computation of the Solution

Computation of the solution requires the inversion of the Hessian matrix :

$$\mathbf{Q}^{-1} = \left(\mathbf{H}^T \mathbf{H} + \mu_{\text{spat}} \mathbf{D}_{\text{spat}}^T \mathbf{D}_{\text{spat}} + \mu_{\text{spec}} \mathbf{D}_{\text{spec}}^T \mathbf{D}_{\text{spec}} \right)^{-1}$$

Computation limit ! $\mathbf{Q} \in \mathbb{R}^{N_\lambda N_k N_l \times N_\lambda N_k N_l}$ is a high-dimensional block-matrix, e.g. 3932160×3932160 ($N_k = N_l = 256, N_\lambda = 60$)

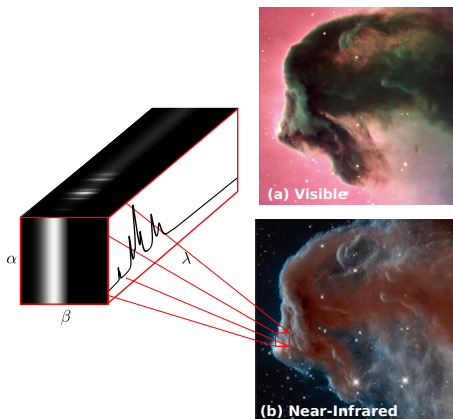
→ heavy to inverse and requires a very large memory.

Proposition :

Computation of the solution iteratively without matrix inversion using an optimization algorithm such as the **Conjugated gradient algorithm**.

$$\mathbf{Q}\mathbf{x} = \mathbf{H}^T \mathbf{y}$$

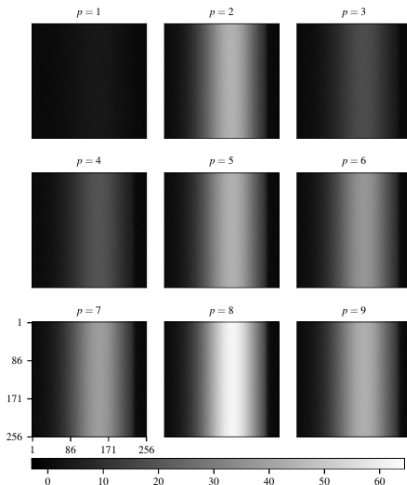
Setup of the Experiment



- Size of the original object
 $1024 \times 256 \times 256$

Simulation Results

Multispectral data of the JWST/MIRI Imager



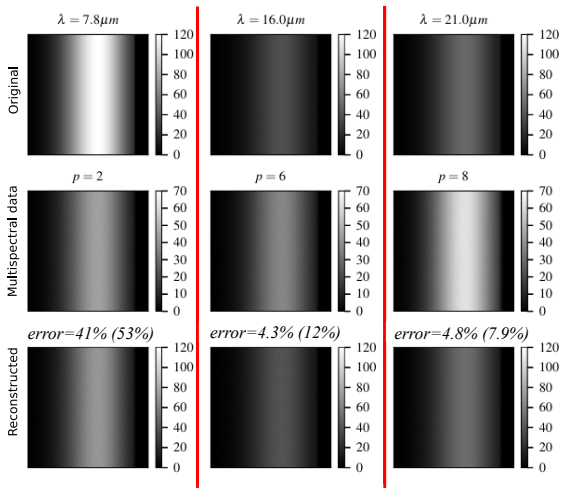
- Size of the multispectral data $9 \times 256 \times 256$

- Additive white Gaussian noise (σ_n) of SNR=30 dB

$$\text{SNR} = 10 \log_{10} \left(\frac{\frac{1}{N} \|\mathbf{y}\|_2^2}{\sigma_n^2} \right)$$

Reconstruction Results

Spatial distribution at $\lambda = 7.8, 16, 21 \mu\text{m}$ with $N_\lambda = 60$

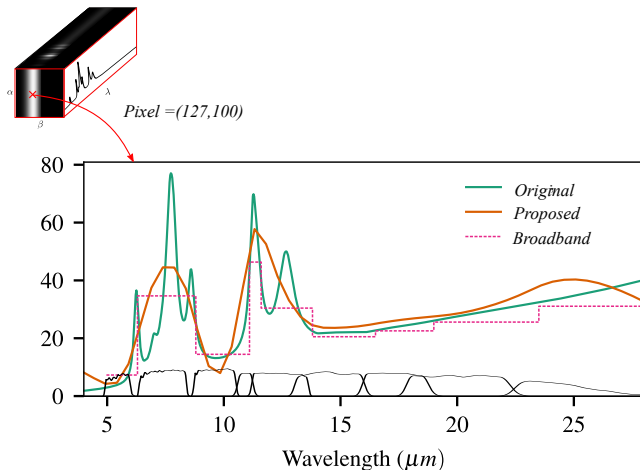


- Reconstruction error :

$$\text{Error} = \frac{\|\mathbf{x}_{orig} - \mathbf{x}_{rec}\|_2}{\|\mathbf{x}_{orig}\|_2}$$

Reconstruction Results

Spectral Distribution at pixel (127, 100)



Conclusion

- Better object reconstruction compared to conventional approaches (Improvement factor up to **2.6**).
- Modeling the response of the JWST/MIRI Imager by accounting for a spectral-variant PSF, detector sampling and integration.
- Representing the object spectral distribution with a first-order B-spline
- Joint processing of the multispectral data from different bands
- Multichannel reconstruction using regularization approach

Perspectives

- Compute the solution in the Fourier space for faster computation
- Propose a solution for tuning N_λ and the regularization parameters
- Explore other object representation (e.g. linear mixing model)

Thank You
for
Your Attention.

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