Fusion of astronomical images: application to JWST data

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Introduction: The James Webb Space Telescope (JWST) is a new telescope providing images and spectra of unmatched quality. Amongst its instruments are:
- ➔ the Near InfraRed Spectrograph (NIRSpec): hyperspectral image, high spectral resolution, "low" (~0.2 arcsecond) spatial resolution
- ➔ the Near InfraRed Camera (NIRCam): multispectral image, low spectral resolution in broadband filters, "high" (~0.06 arcsecond) spatial resolution

Goal: merge the information of both instruments to reconstruct the hyperspectral cube X at high spectral and spatial resolutions.

Fusion problem framework

Fusion is formulated as a regularized least-squares, leading to an inverse problem including:
- a forward model, describing instruments physics
- a prior model, encapsulating a priori information on X

Formulation - find the scene X that minimizes the objective function:

$$\gamma_m \|Y_m - L_m W_m(X)\|_F^2 + \gamma_h \|Y_h - L_h W_h(X) S\|_F^2 + \mu \|\nabla X\|_F^2$$

Multispectral fidelity term — Hyperspectral fidelity term — Sobolev spatial regularization

Where Y_m and Y_h are the multispectral and hyperspectral images, respectively. L and W are the forward model matrices (see below). The last term is a regularization, imposing a spatially smooth solution. This is rephrased as a linear system and solved by gradient descent.
This framework has been established in [2] for simulated JWST data.

Forward model

NIRCam and NIRSpec are described via:
- a spatial degradation, W
- a spectral degradation, L

NIRCam point spread function at 3.3µm with high contrasts

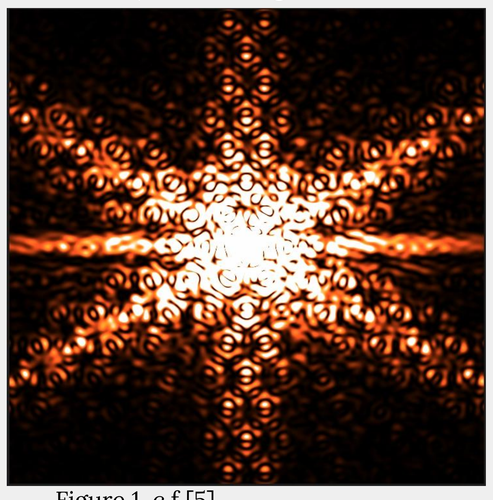

Figure 1, c.f [5]

spatial degradation

$$Y \approx LW(X)$$

spectral degradation

Throughputs

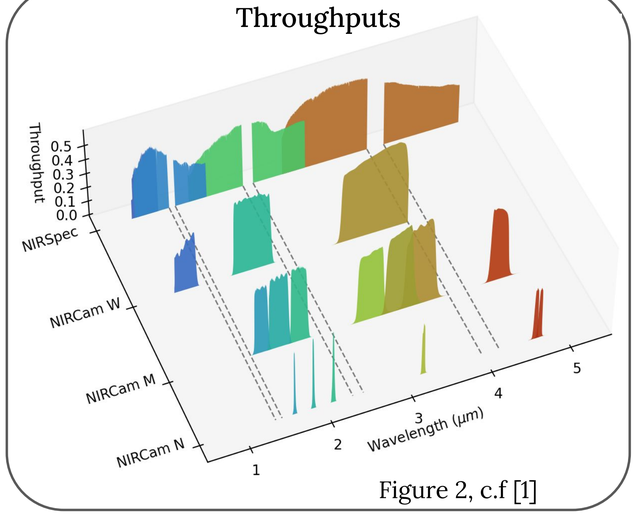

Figure 2, c.f [1]

Prior

Spatial regularization

1st assumption: X is spatially smooth.

Spectral regularization

2nd assumption: observed spectra are linear combinations of a few characteristic spectra.

$$X \approx VZ + \overline{Y_h}$$

Illustration of data fusion

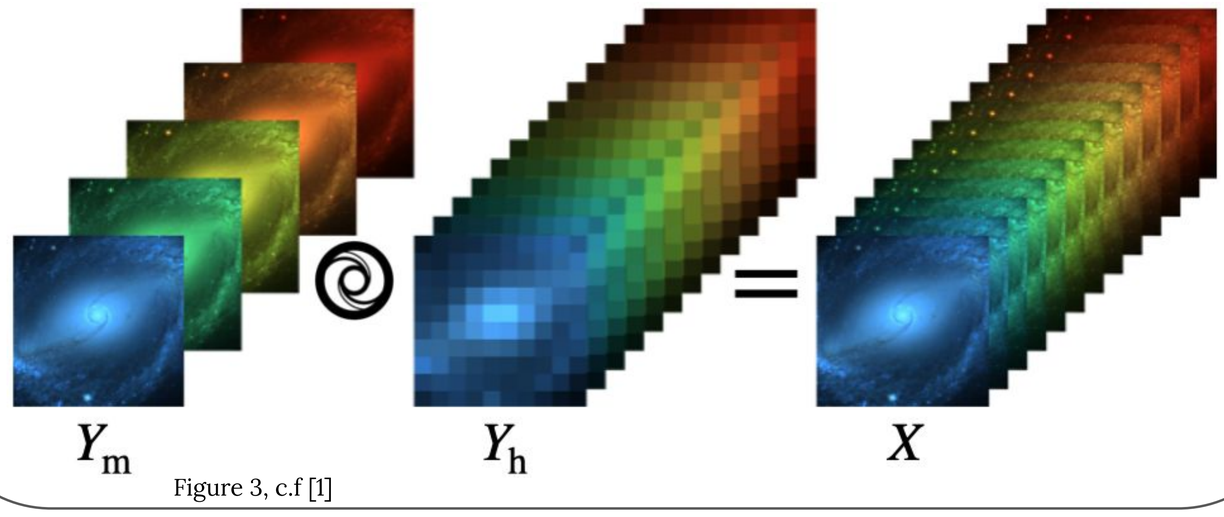

Figure 3, c.f [1]

Results

We performed the first astronomical data fusion using JWST images.

Targets: protoplanetary disk d203-506 in the Orion Bar [3] and Titan [4].

Experimental setup:
- NIRSpec: F170LP, 1616 waves, 1.66 µm to 2.3 µm
- NIRCam: F182M, F187N, F200W, F210M, F212N

Results on d203-506

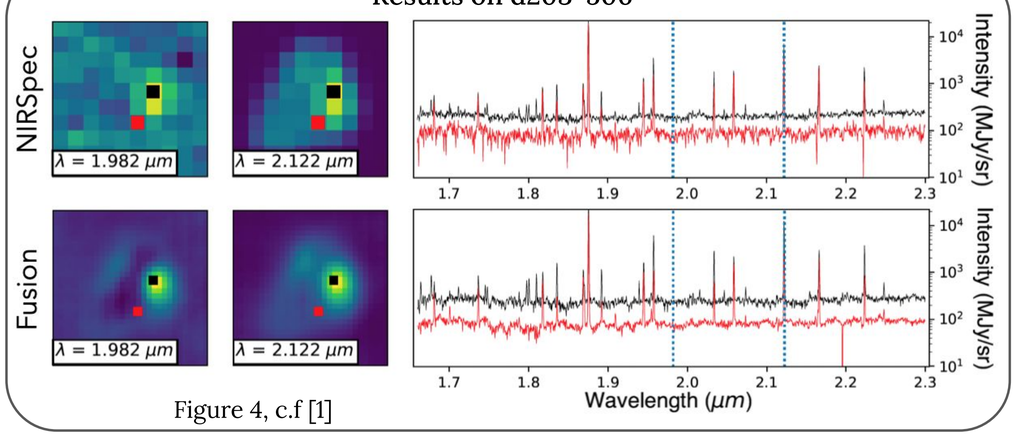

Figure 4, c.f [1]

Results on Titan

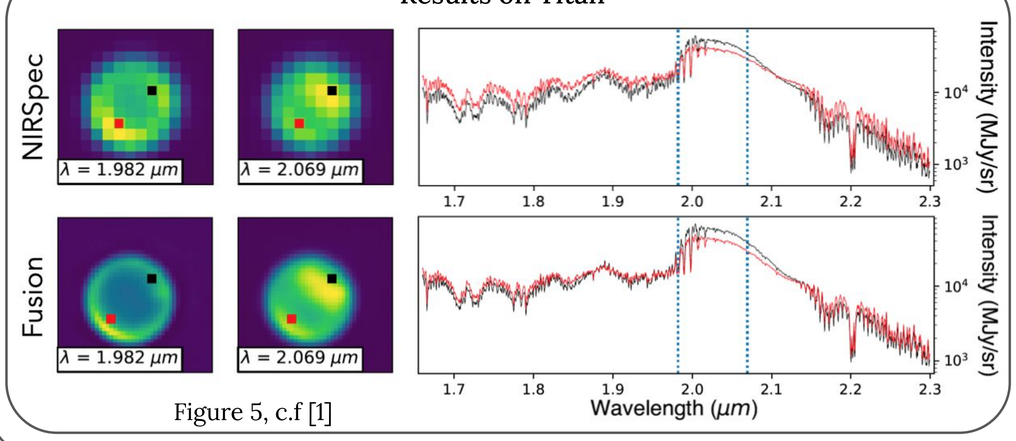

Figure 5, c.f [1]

Analysis of the results

Images:
- Match NIRCam information
- Match NIRSpec tiny variations
- Tiny checkerboard artefacts
- Lost some thin NIRCam textures

Spectra:
- Match NIRSpec emission lines
- SNR better than NIRSpec's
- Absorption line artefact (at 2.2 um on d203-506)

Conclusion and Perspectives

The first successful fusion of astronomical data demonstrated here increased the spatial resolution of NIRSpec from a factor three. Our results are highly consistent with NIRCam and NIRSpec data over the two considered targets. This method opens up the analysing of JWST data at higher resolutions.

Analysing of the current limits of our method leads to two main perspectives.
Improving spatial regularization, by gathering prior information on multispectral image (e.g. using a patch based normalising flow [6]).
Fuse over the entire NIRSpec range, by reconstructing the information even on the NIRSpec gaps, where it is only partial (e.g. using masks on those wavelengths).

References:
[1] L. Marquis et al. submitted
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[3] O. Berné, E. Habart, E. Peters et al. (s.d.). "PDR4all : A JWST Early Release Science Program on radiative feedback from massive stars.", PASP, 2022
[4] Nixon et al., The atmosphere of Titan in late northern summer from JWST and Keck observations, NA, 2025
[5] Perrin et al., Updated point spread function simulations for JWST with STPSF, Proc. SPIE 9143, 2014
[6] F. Altekrüger et al., PatchNR: Learning from Very Few Images by Patch Normalizing Flow Regularization, Inverse Problems, 2023