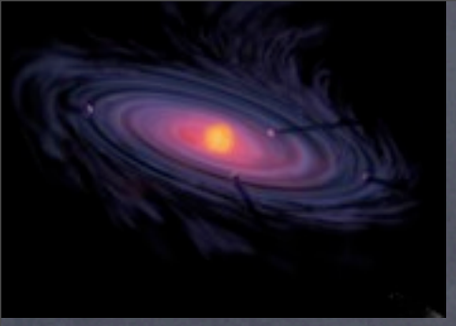
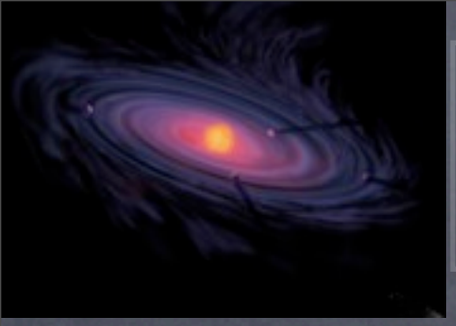




Séparation de composantes dans les données IFU HERSCHEL/PACS

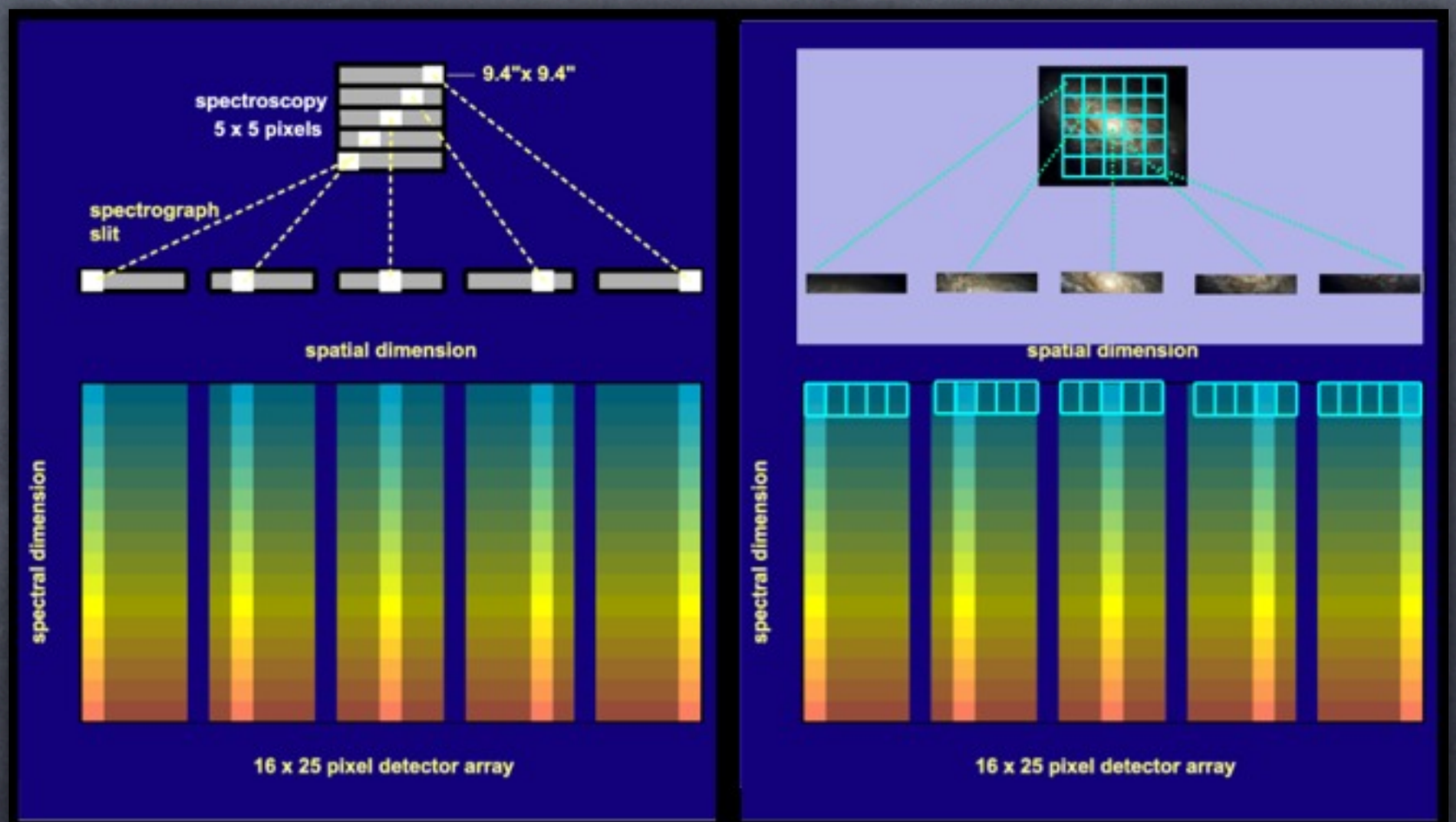
E. Pantin
L.E. Meunier
N. Hara
GASPs KP team



Context

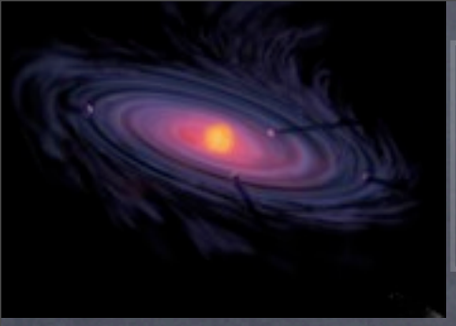


HERSCHEL-PACS
integral-field spectro-imaging data (IFU)
60-220 μm



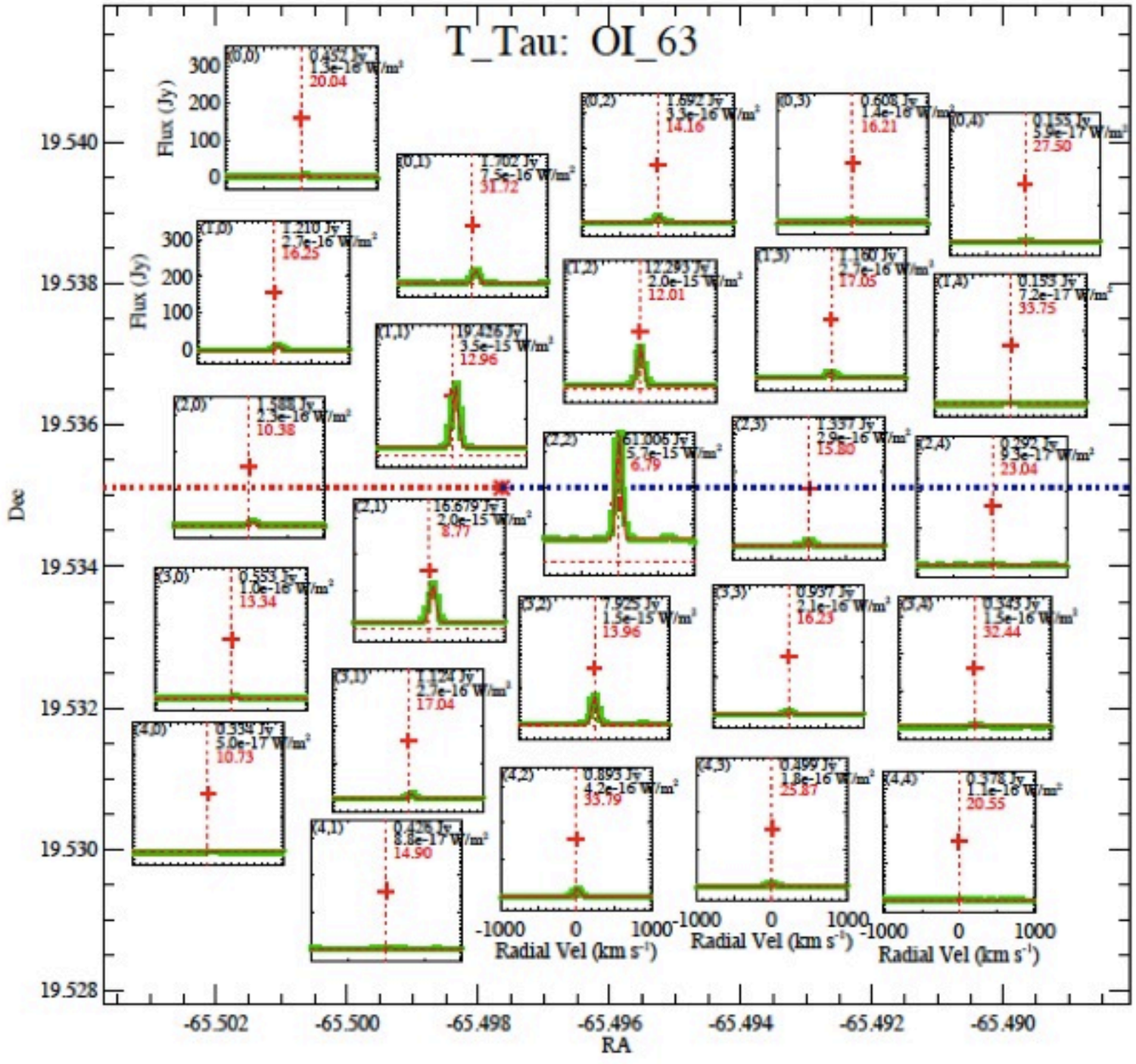
Principe du spectromètre à intégrale de champ
Source : PACS Observer's Manual

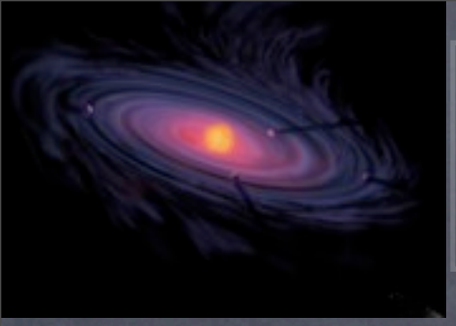
PACS spectrometer observations





40”

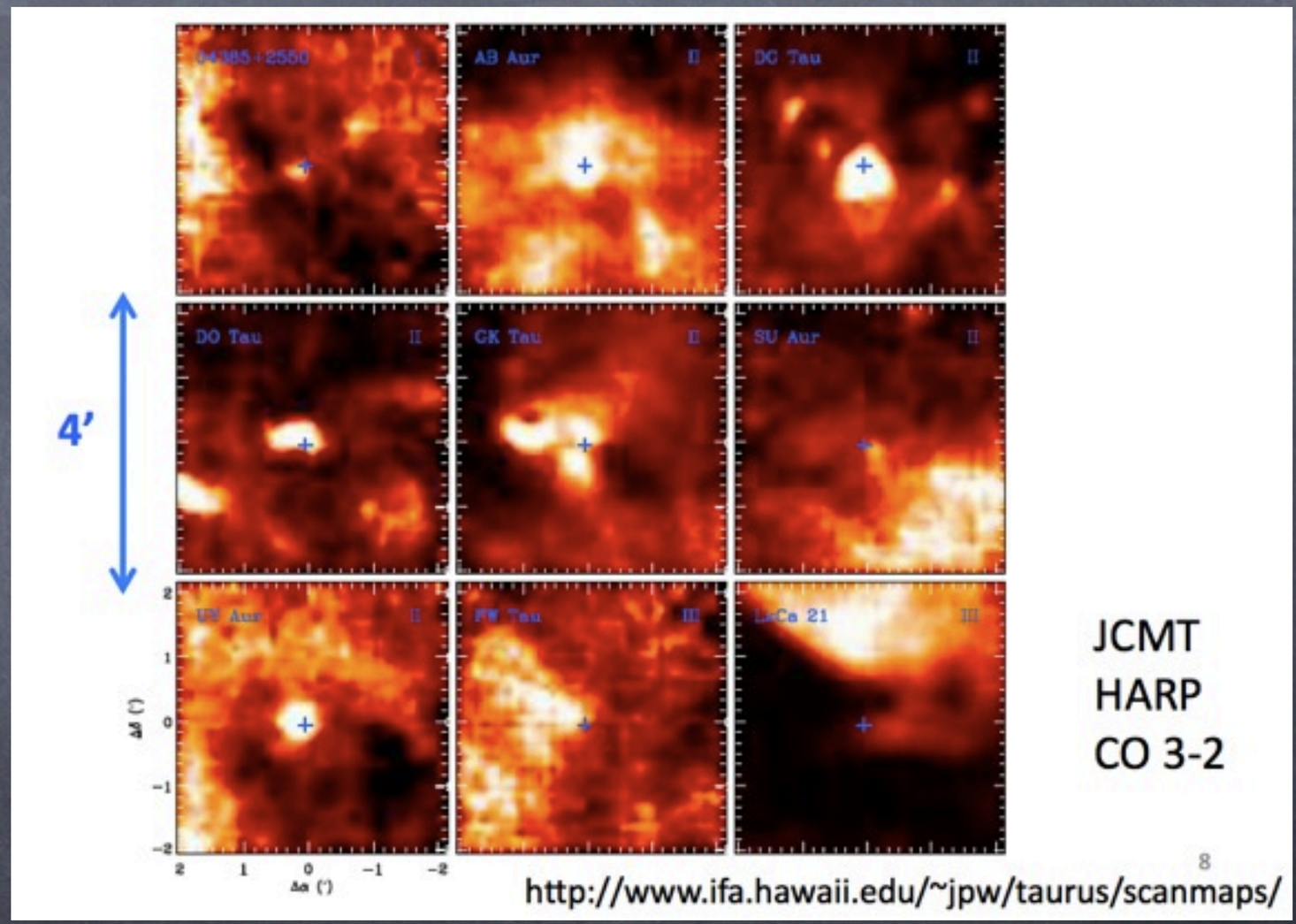




Observations of protoplanetary disks embedded in cloud remnants



- Disks and cloud are made of, more or less, the same stuff
- Diffuse cloud material can stick around for ~1 Myr or more
- Herschel beam size ~10" > disk size ~5"
- Cloud emission is potentially a major contaminant to Herschel observations of young disks

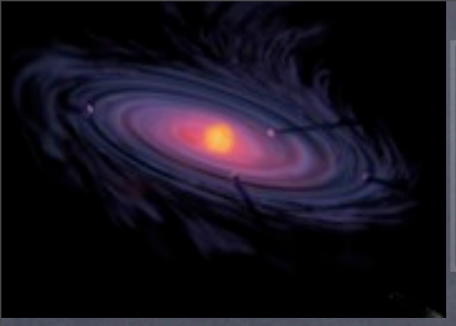


Spatially non-uniform structures ➜ chopping/nodding background subtraction methods won't work, producing spurious fake «lines»



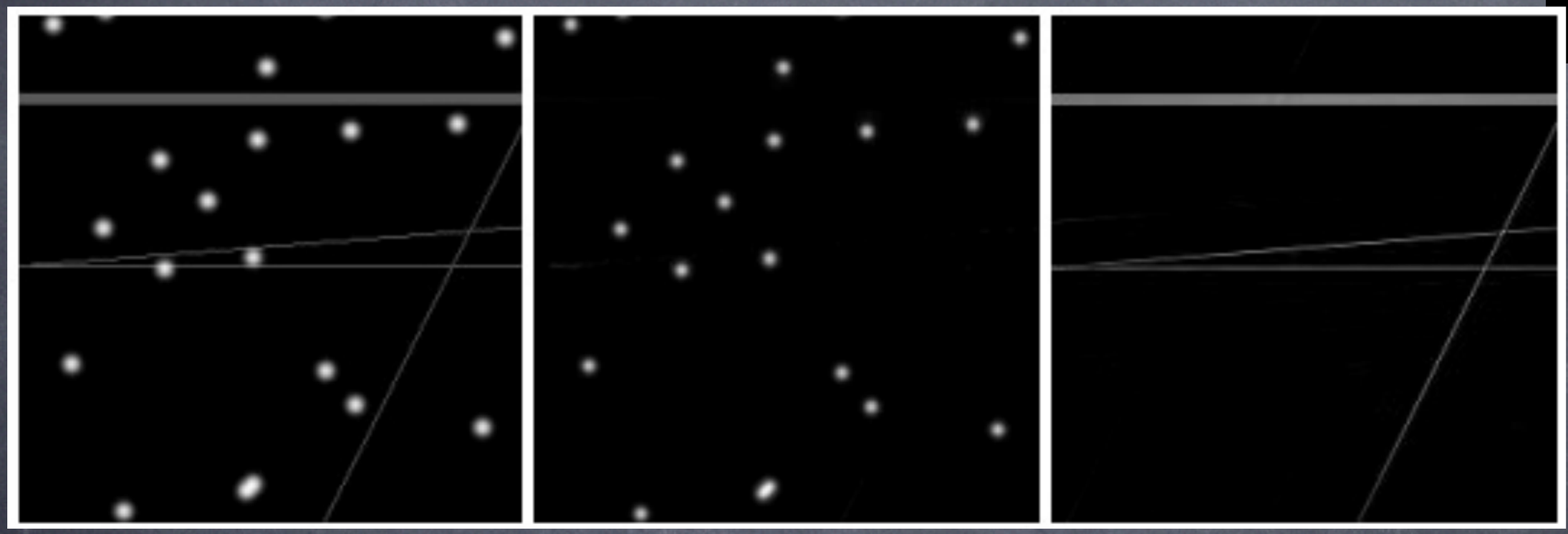


Inpainting and morphological components analysis (MCA)

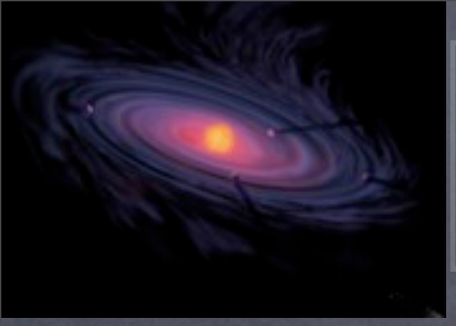


What is morphological components analysis/decomposition (MCA) ?



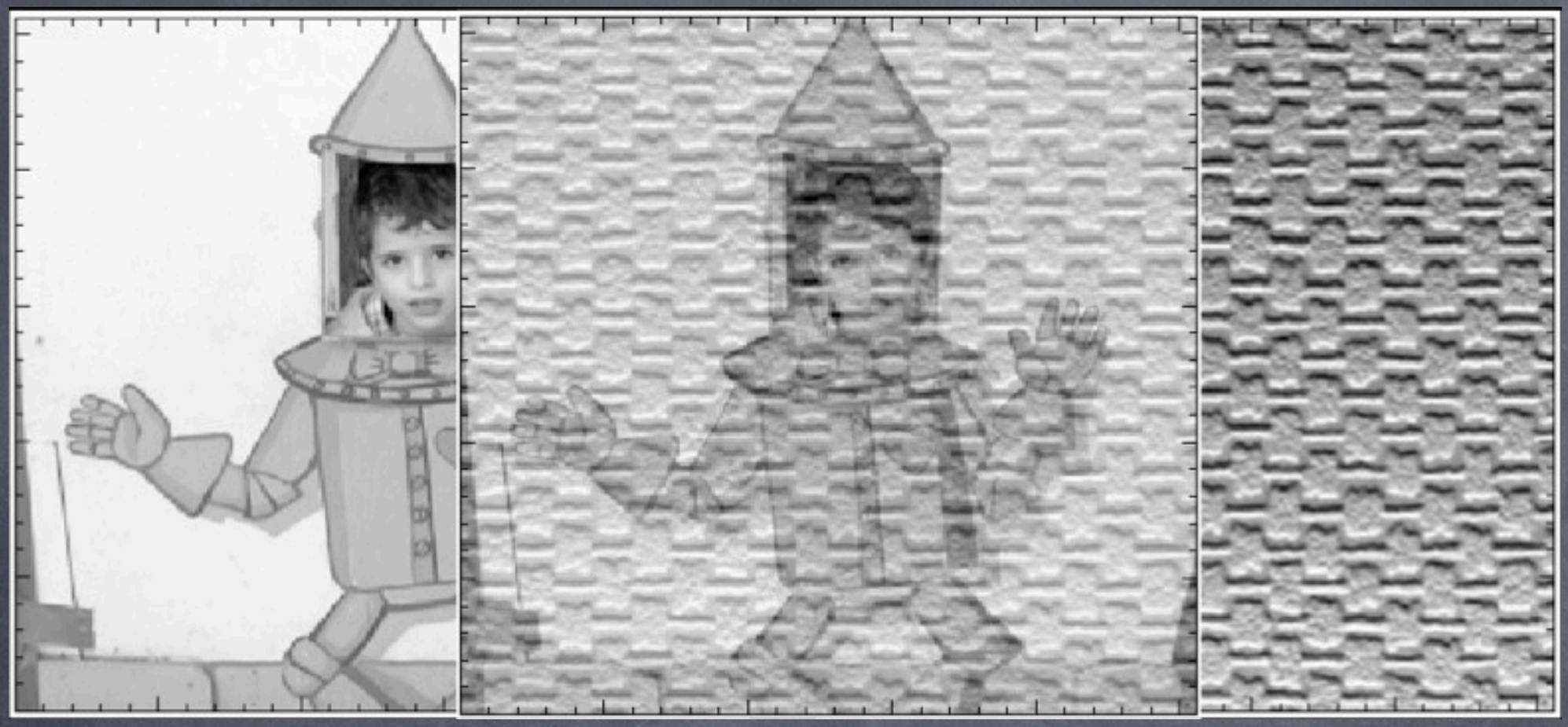


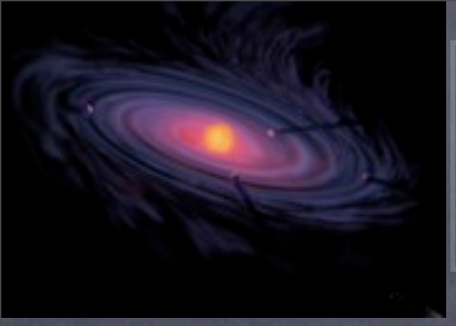
Wavelets basis Ridgelets basis



MCA analysis : DCT and ridgelets

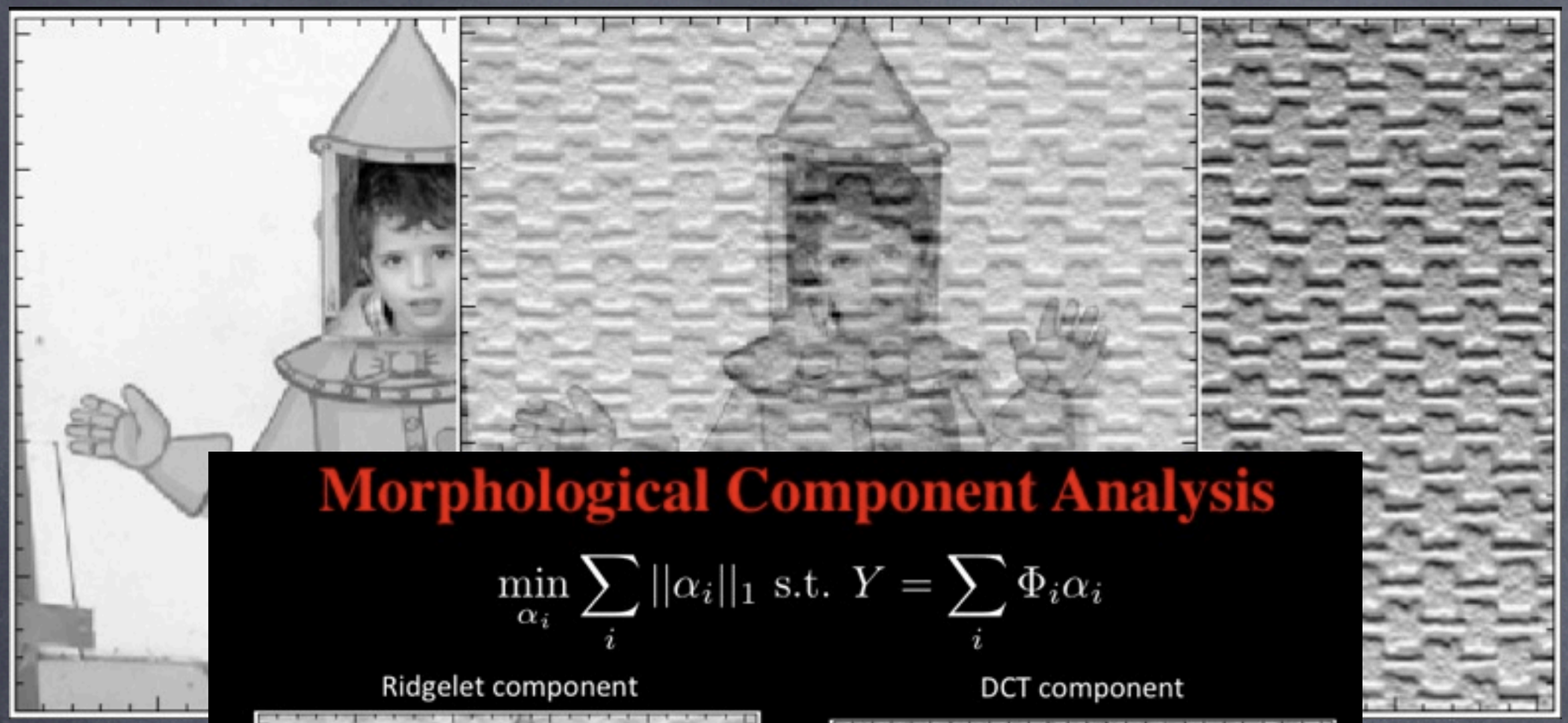






MCA analysis : DCT and ridgelets





Morphological Component Analysis

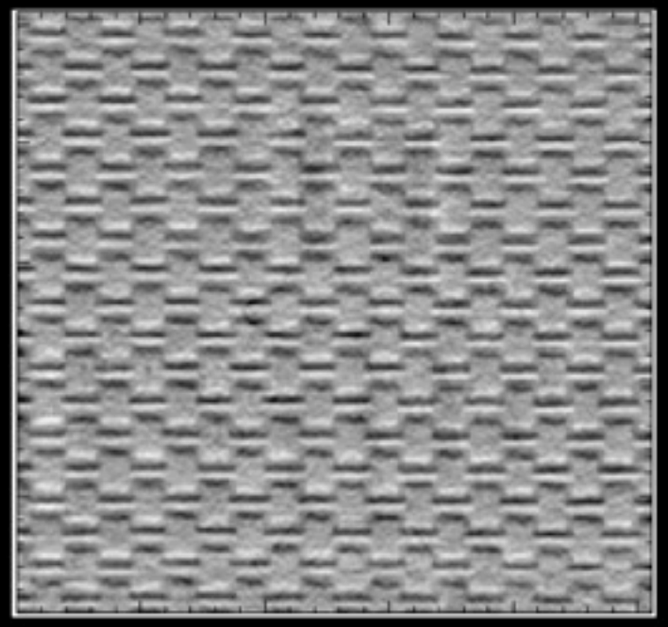
$$\min_{\alpha_i} \sum_i ||\alpha_i||_1 \text{ s.t. } Y = \sum_i \Phi_i \alpha_i$$

Ridgelet component



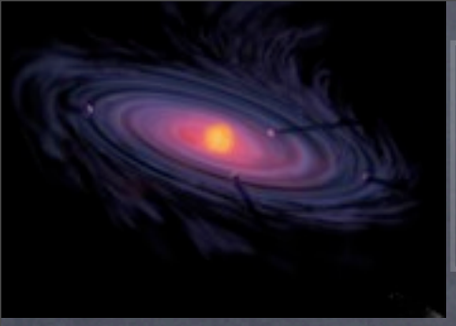
Contour image

DCT component



Texture

Starck et al., 2004
Elad et al., 2005
Pires, 2012



What is inpainting ?



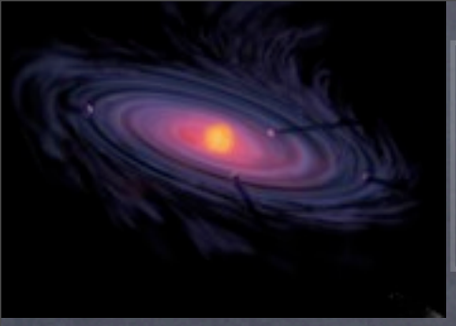
Reconstruction/interpolation usually based on :

- ★ texture
- ★ contours continuity





Exemples d'inpainting Source : Douglas Lanman, « *Texture Synthesis and Manipulation* »

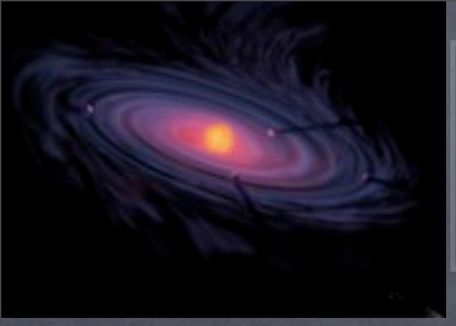


inpainting - MCA



= MCA with missing data (hyp. sparsity) :

→ selection of most relevant MR coefficients to represent the dataset → 2D interpolation

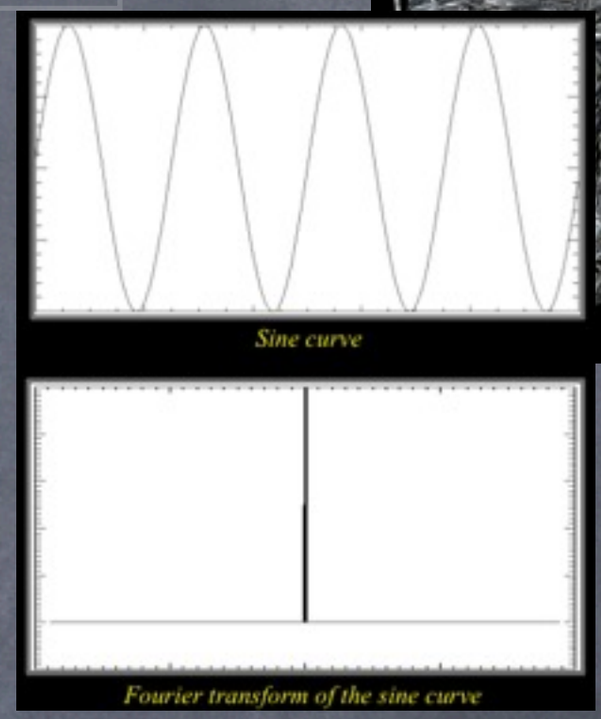


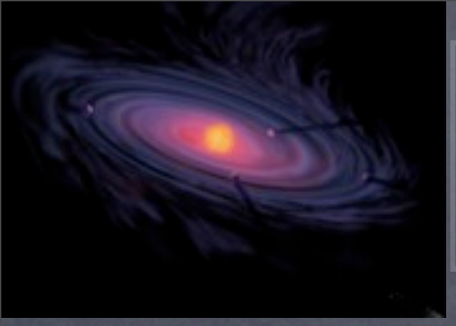
inpainting - MCA



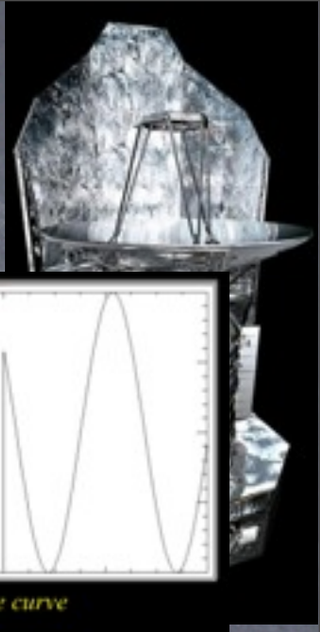
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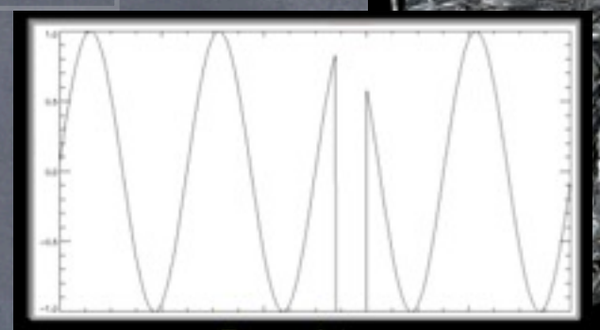


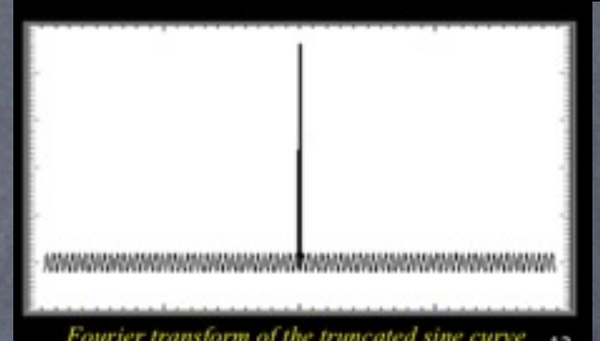
inpainting - MCA

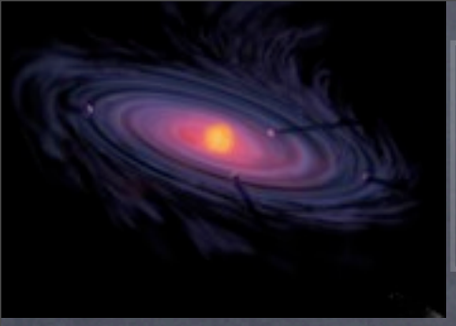


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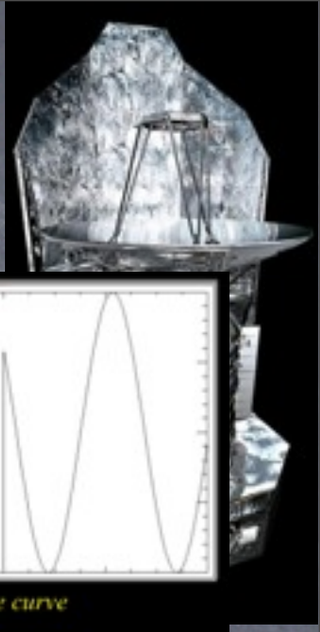
→ selection of most relevant MR coefficients to represent the dataset → 2D interpolation





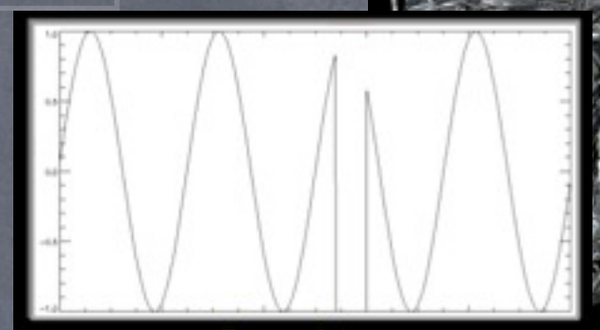


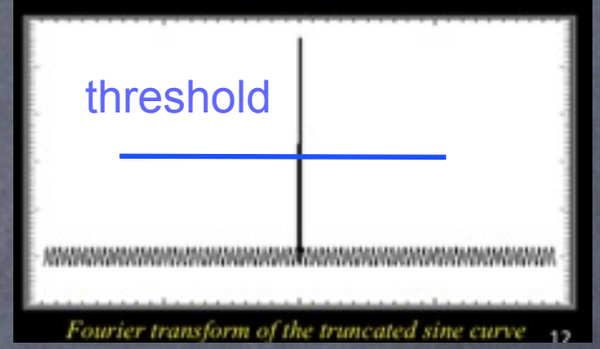
inpainting - MCA

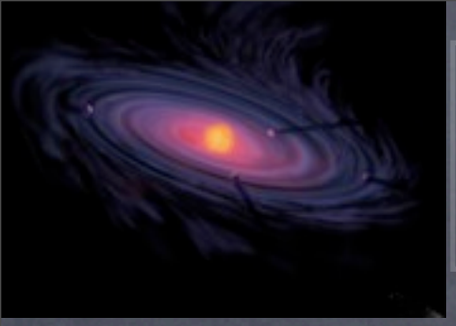


= MCA with missing data (hyp. sparsity) :

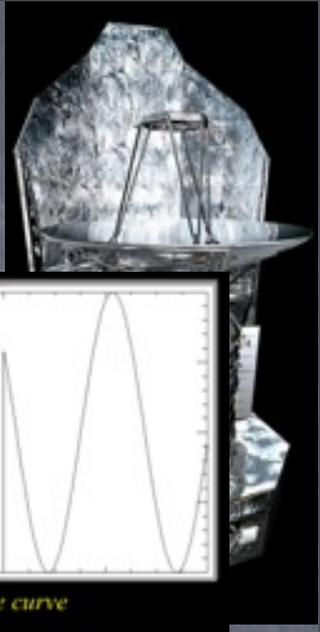
→ selection of most relevant MR coefficients to represent the dataset → 2D interpolation

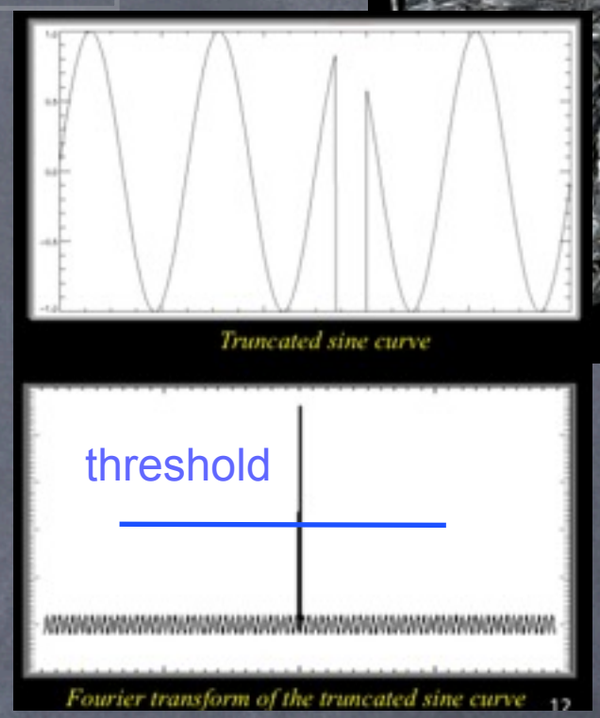






inpainting - MCA





= MCA with missing data (hyp. sparsity) :

→ selection of most relevant MR coefficients to represent the dataset → 2D interpolation

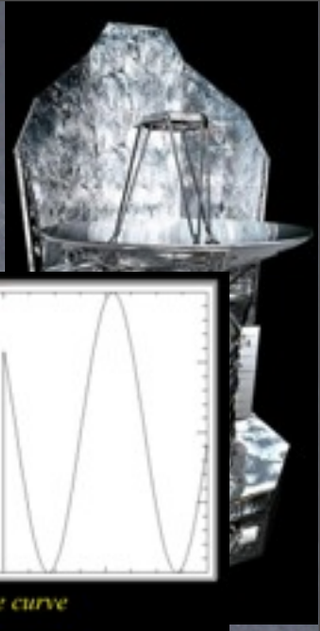
One complex problem (2D interpolation of a complex image) ➜ **serie of «simple»** problems in projection spaces

More robust and unbiased way to interpolate 2D data

Only «a priori» (or parameter) : the choice projection basis(s) (= dictionaries : wavelets, curvelets, ridgelets, Fourier etc ...)

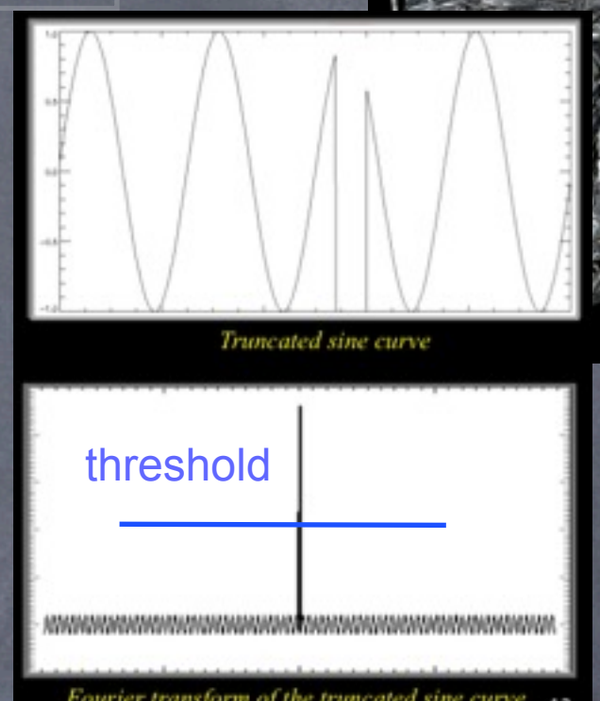


inpainting - MCA



= MCA with missing data (hyp. sparsity) :

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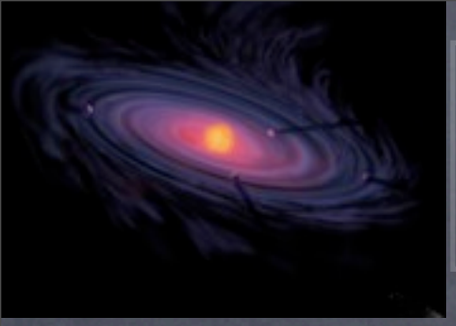
Only «a priori» (or parameter) : the choice projection basis(s) (= dictionaries : wavelets, curvelets, ridgelets, Fourier etc ...)







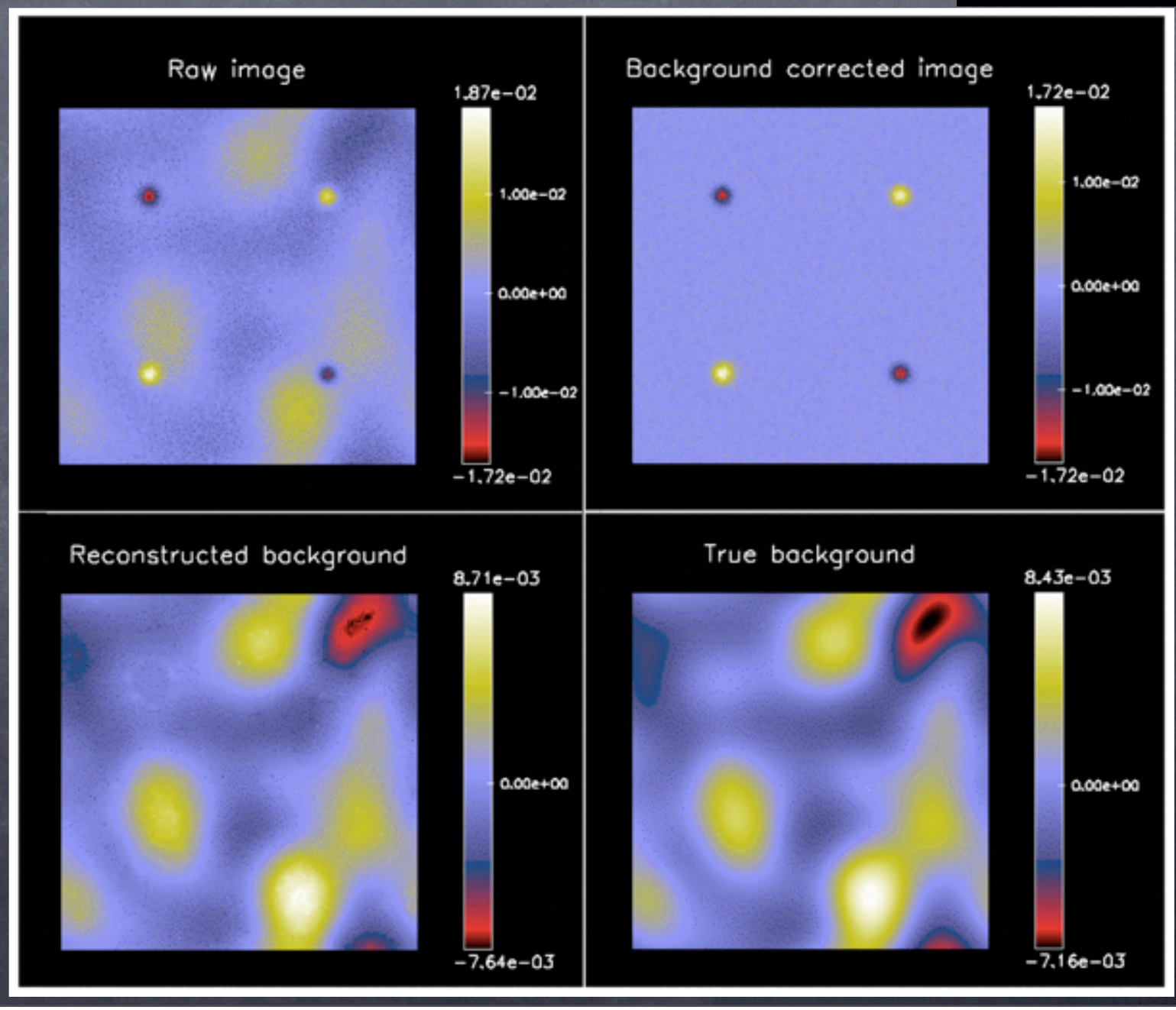
A 3D inpainting method

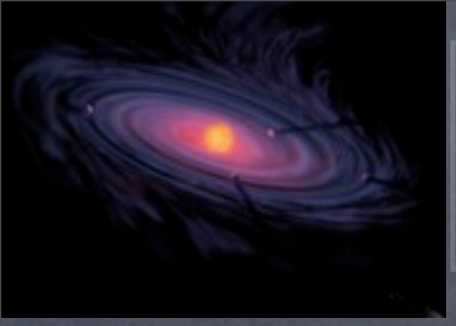


2D inpainting example on astronomical data : inpainting/MCA 2D



multi-scale inpainting method for background correction of 10 μm imaging data



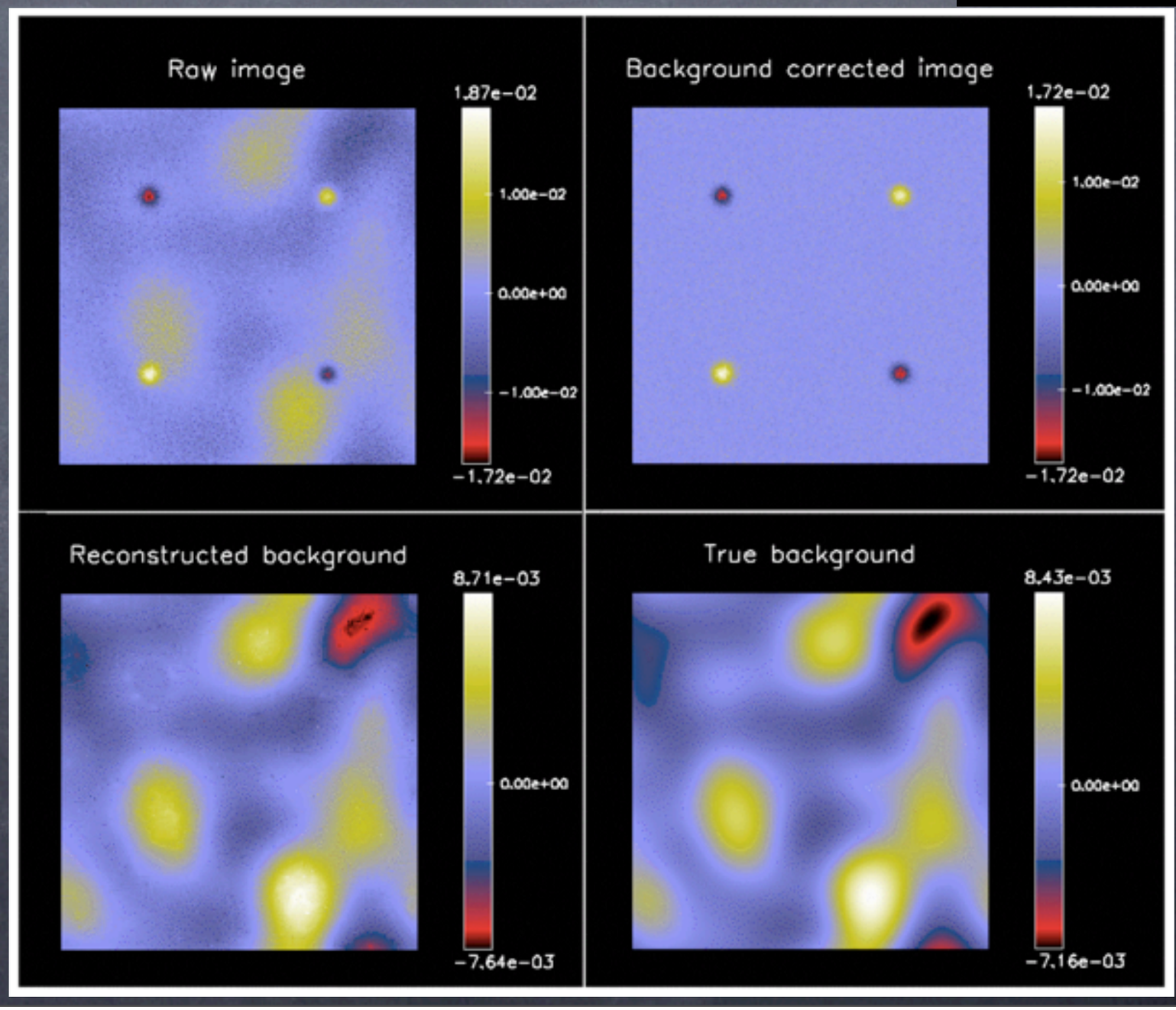


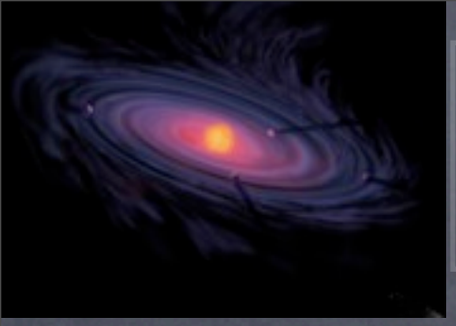
2D inpainting example on astronomical data : inpainting/MCA 2D



multi-scale inpainting method for background correction of 10 μm imaging data

key step: get most accurate source «support»



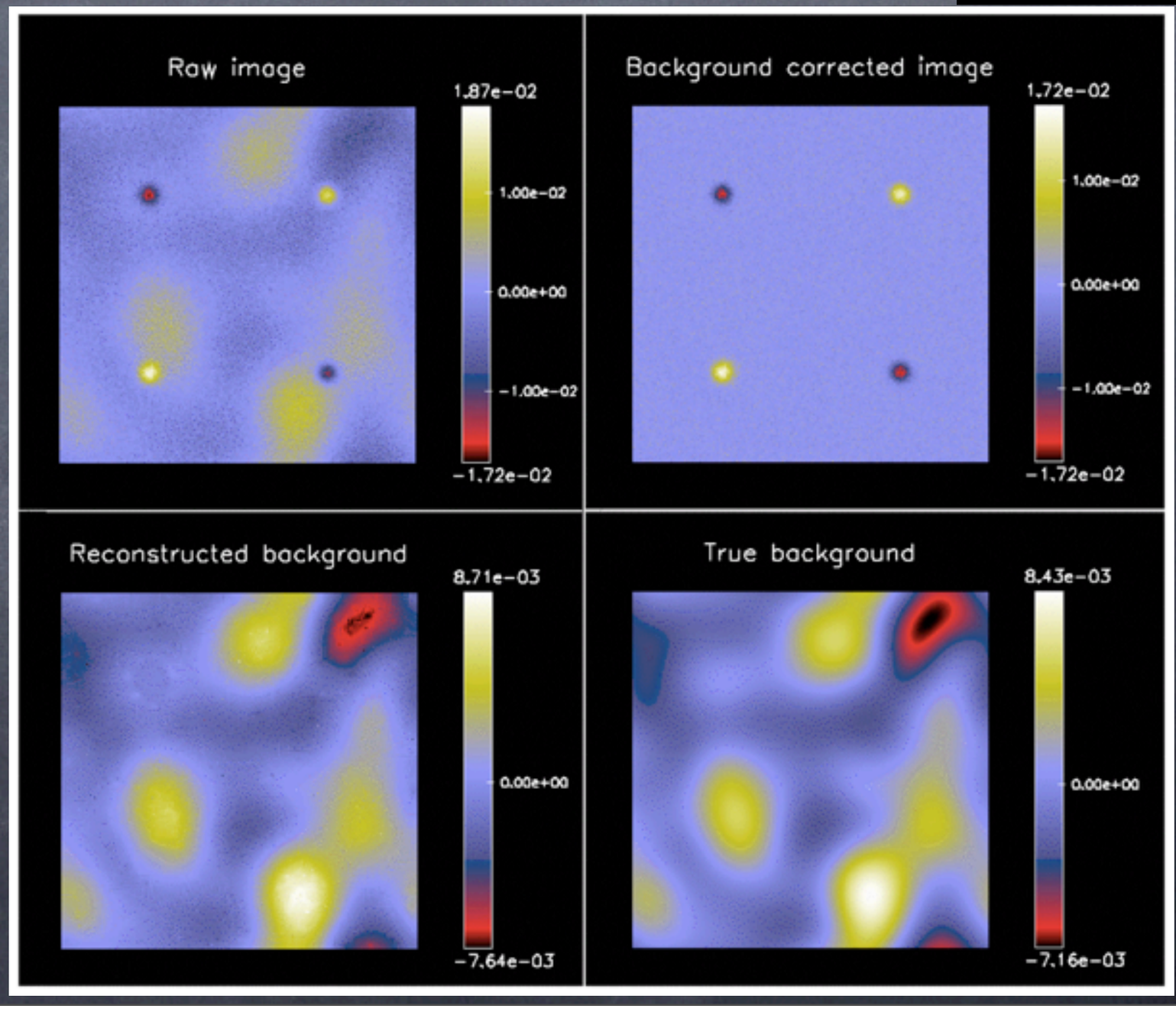


2D inpainting example on astronomical data : inpainting/MCA 2D



multi-scale inpainting method for background correction of 10 μm imaging data

key step: get most accurate source «support» → mask(s)



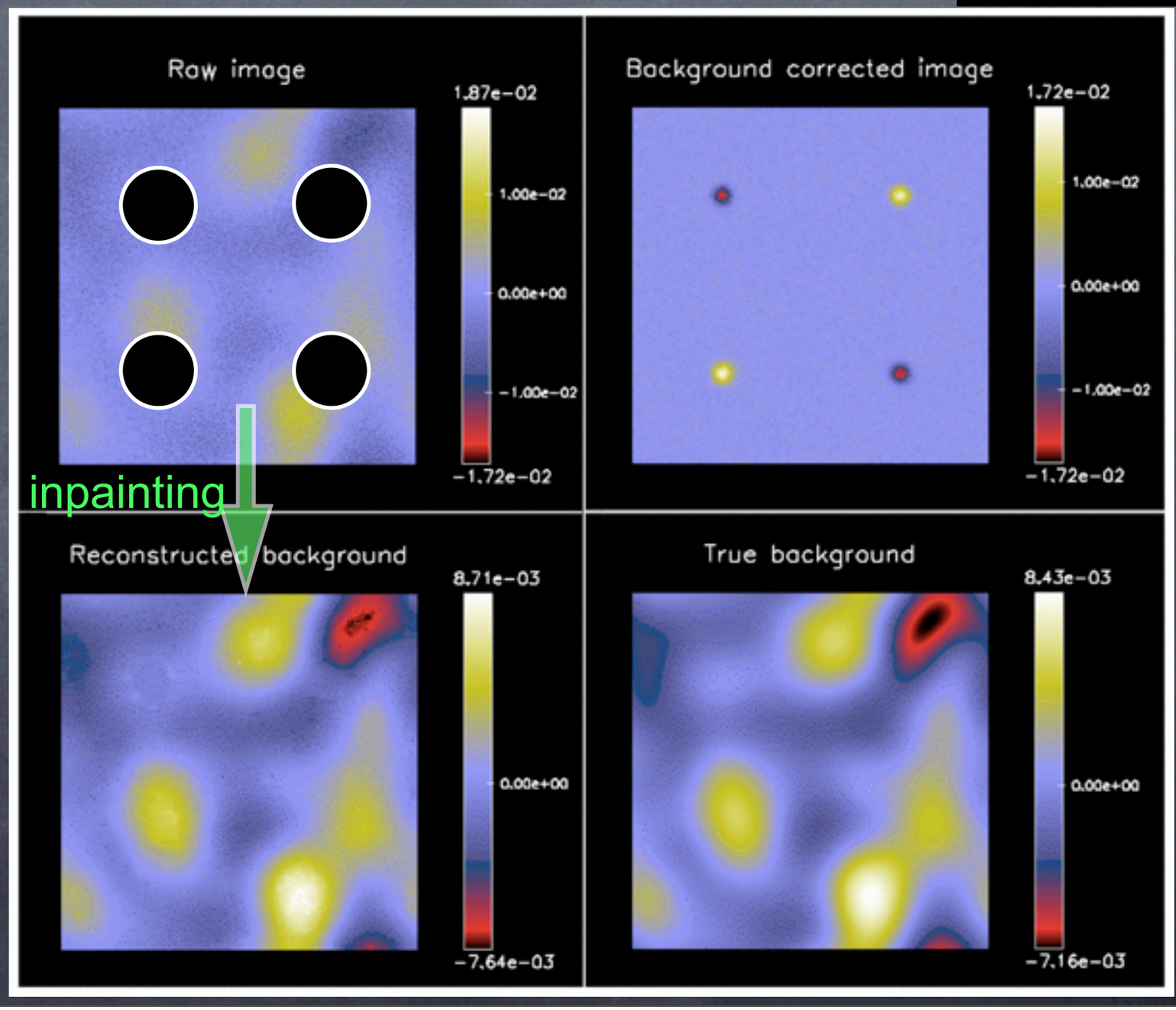


2D inpainting example on astronomical data : inpainting/MCA 2D



multi-scale inpainting method for background correction of 10 μm imaging data

key step: get most accurate source «support»
→ mask(s)
→ reconstruct background using inpainting/MCA (used to correct data)





2D inpainting example on astronomical data : inpainting/MCA 2D

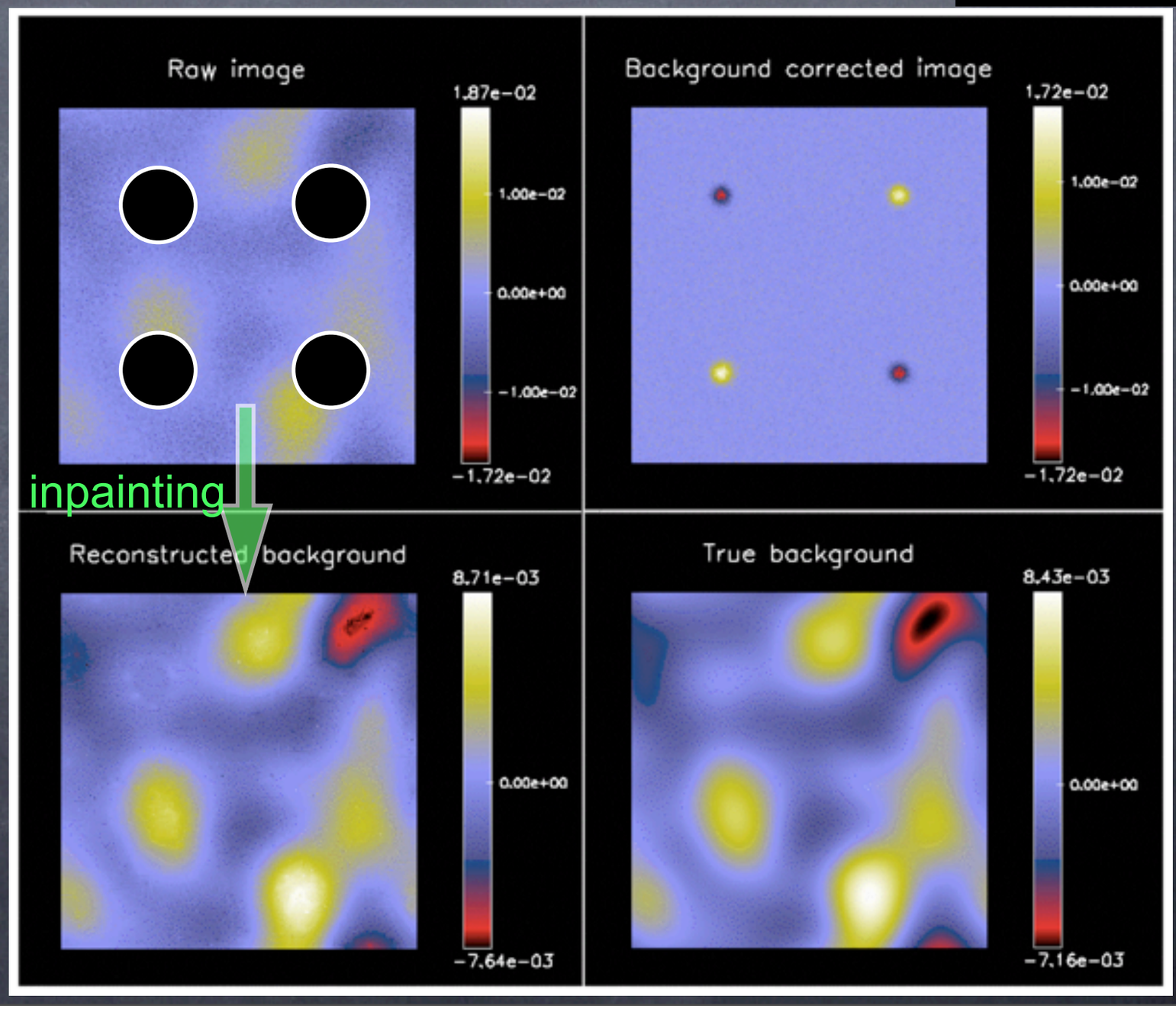


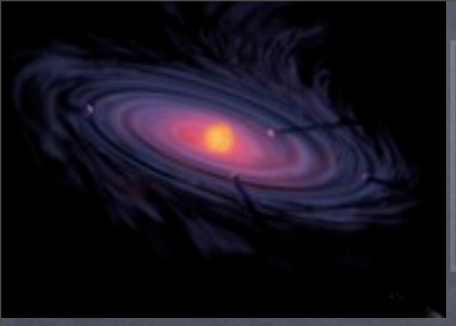
multi-scale inpainting method for background correction of 10 μm imaging data

key step: get most accurate source «support»
→ mask(s)
→ reconstruct background using inpainting/MCA (used to correct data)

caveats :

- too large a mask → large reconstruction error
- too small a mask → photometric loss

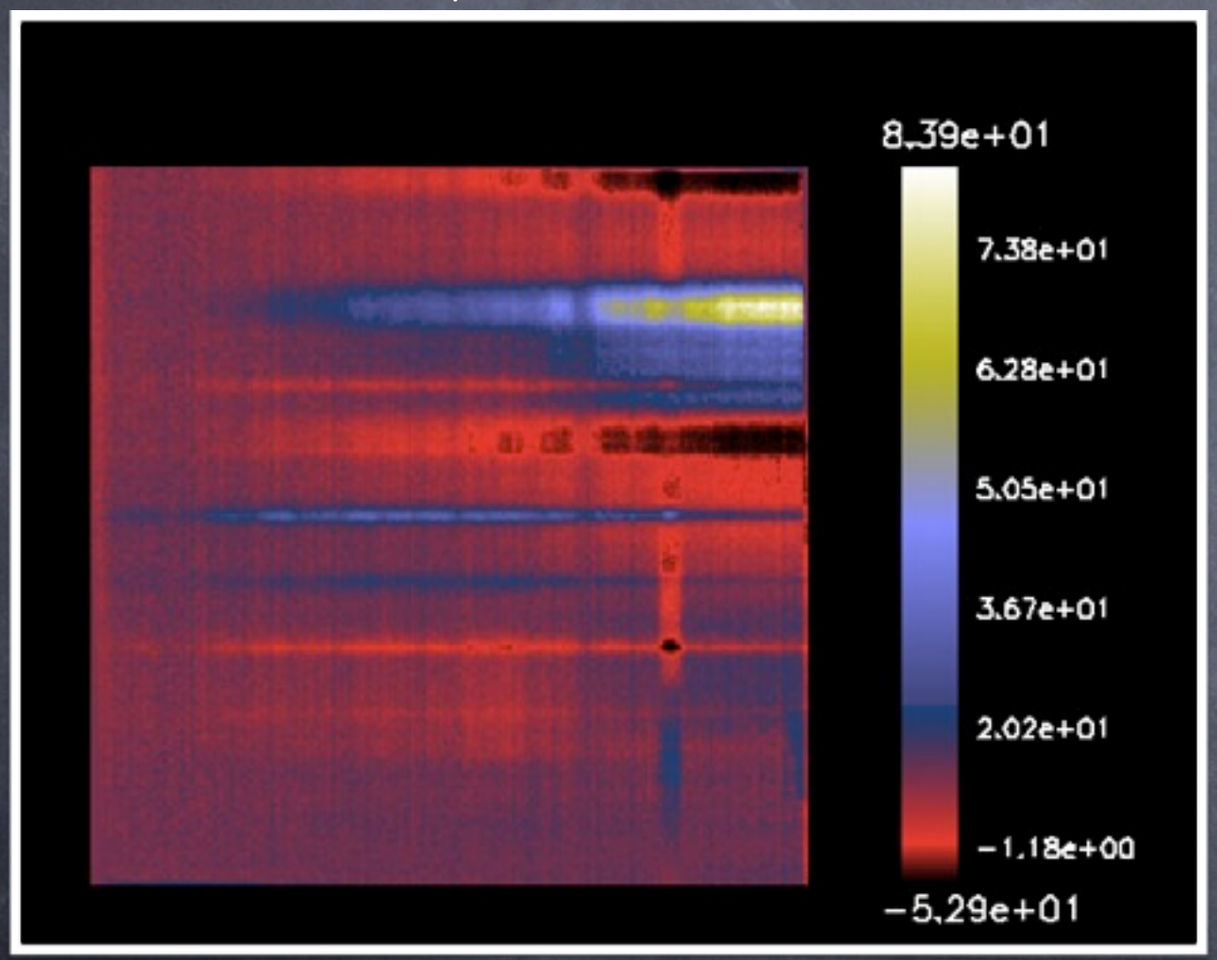


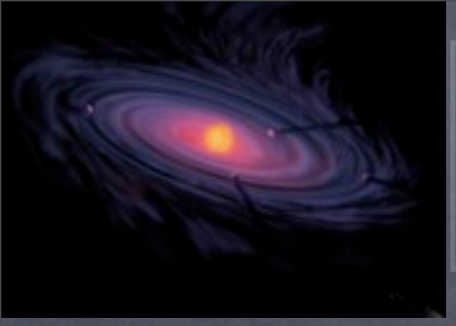


2D inpainting example on astronomical data



multi-scale inpainting method for object extraction in 10 μm

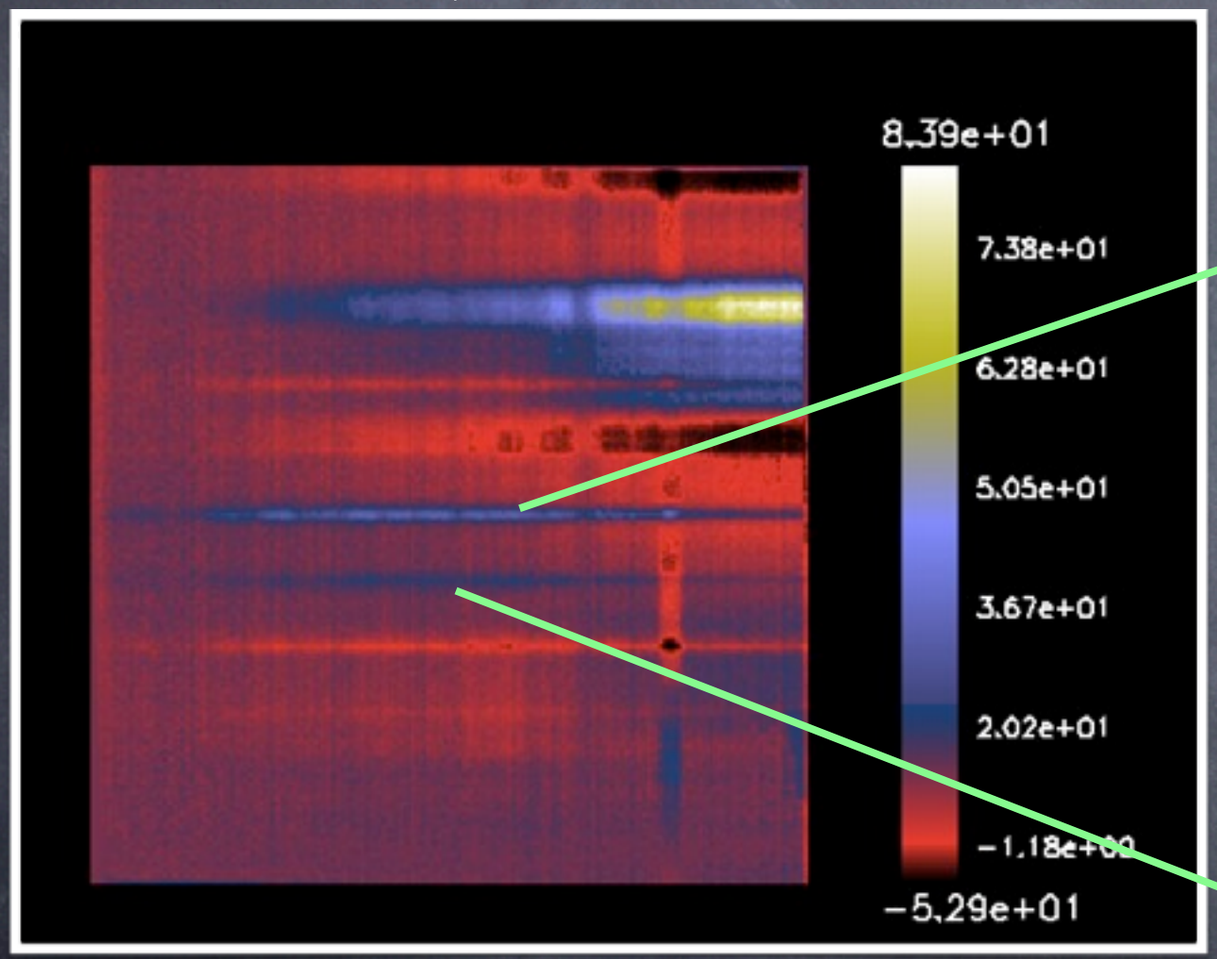


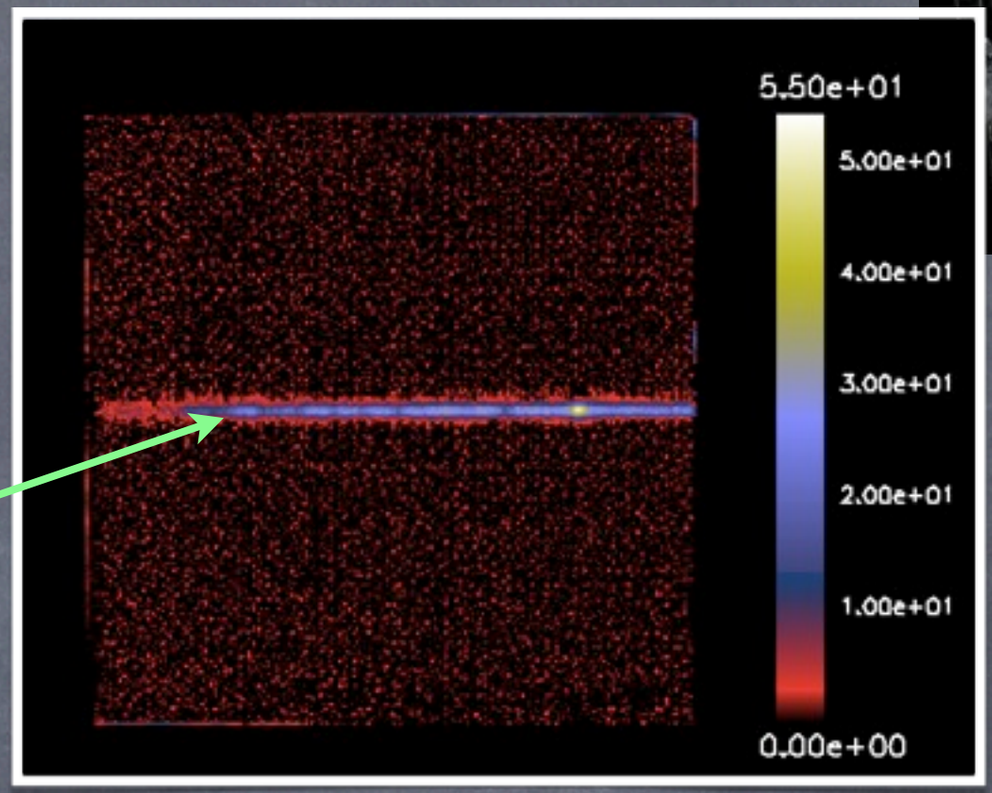


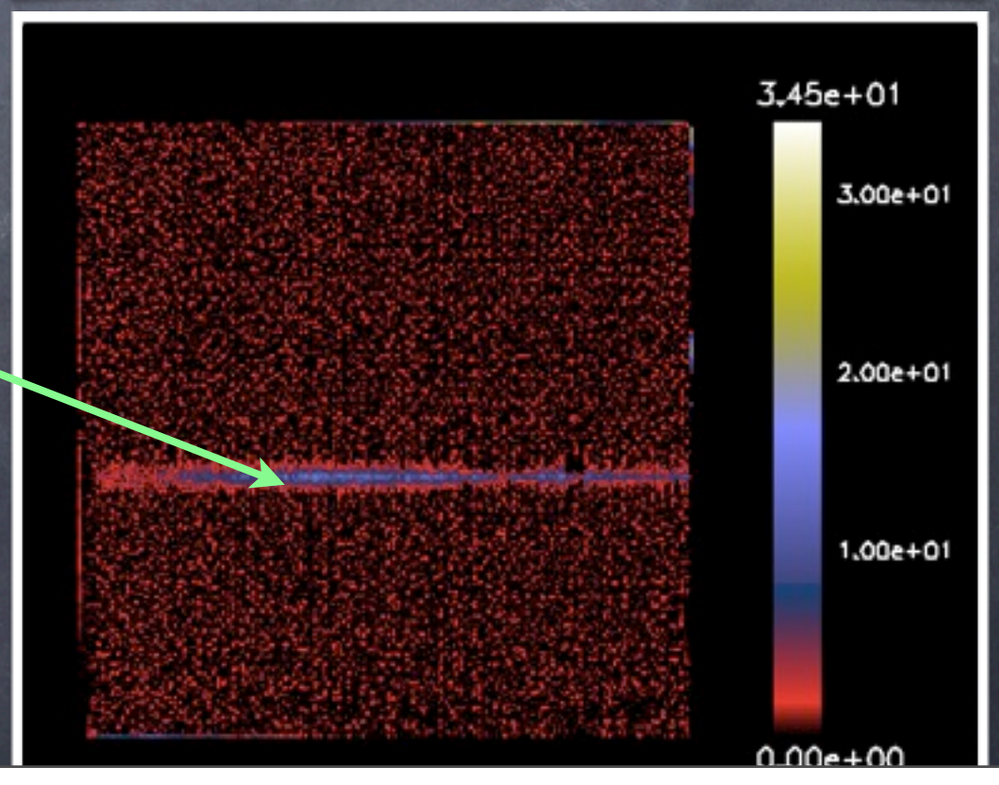
2D inpainting example on astronomical data

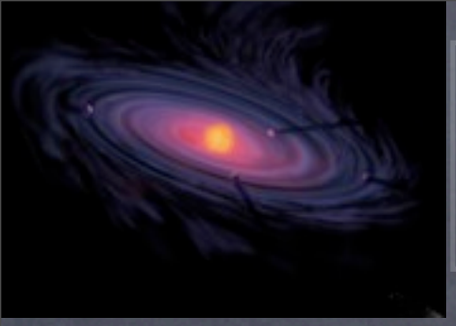


multi-scale inpainting method for object extraction in 10 μm



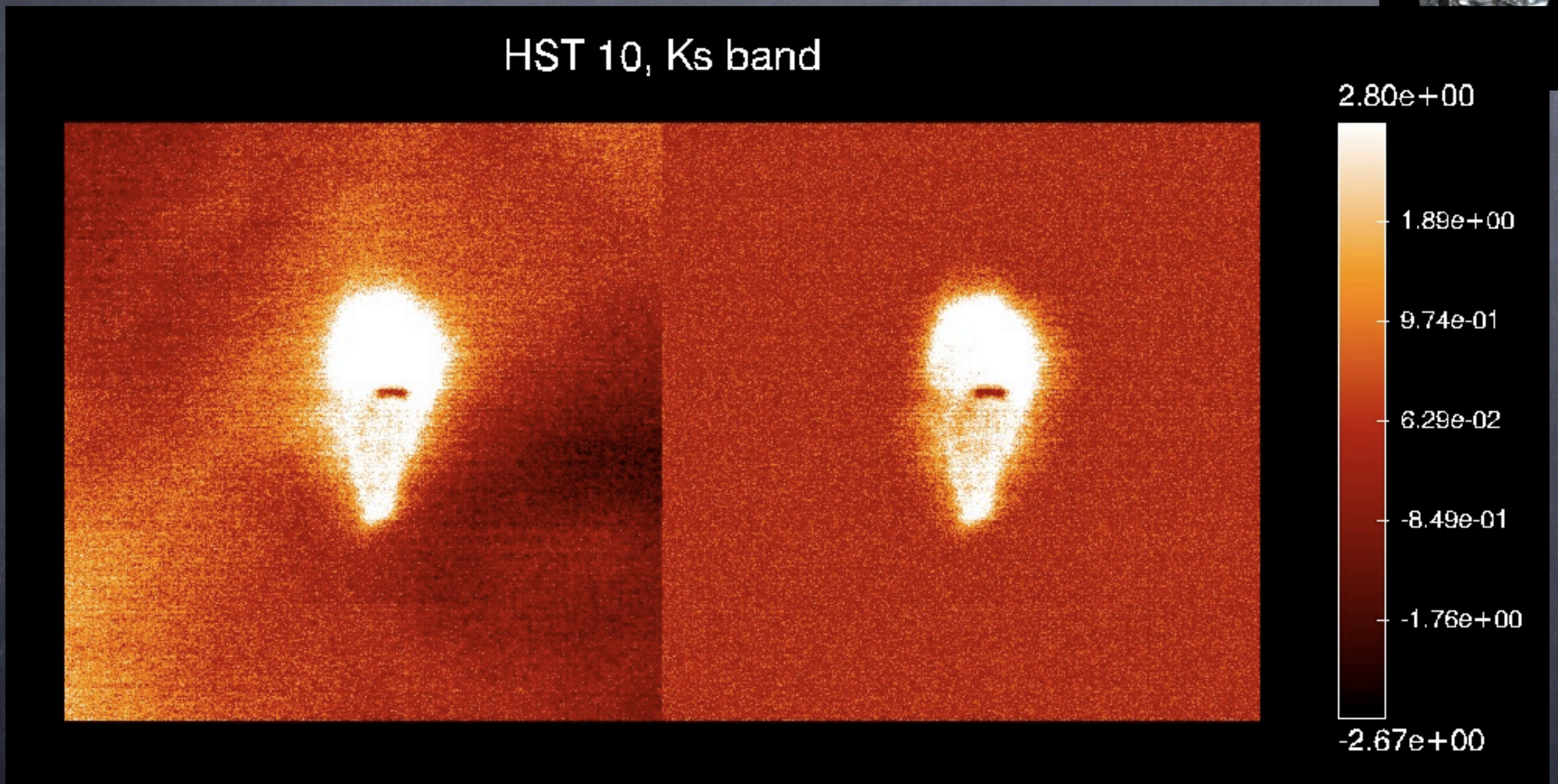




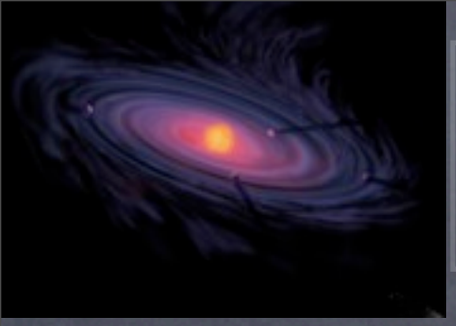


Bgnd correction con't





NaCo data, courtesy of S. Vincente



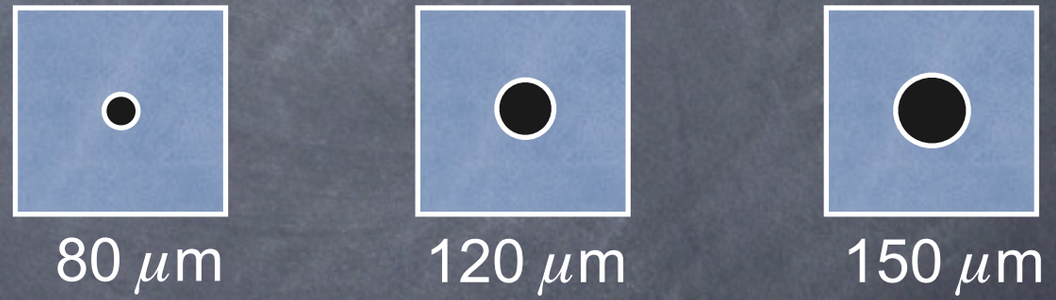
3D spatial/frequency data : inpainting/MCA 3D



Additional constraints one can add:

- same object position in all slices

- angular resolution $\propto \lambda$: correlation between source size (λ) (quasi-unresolved sources)



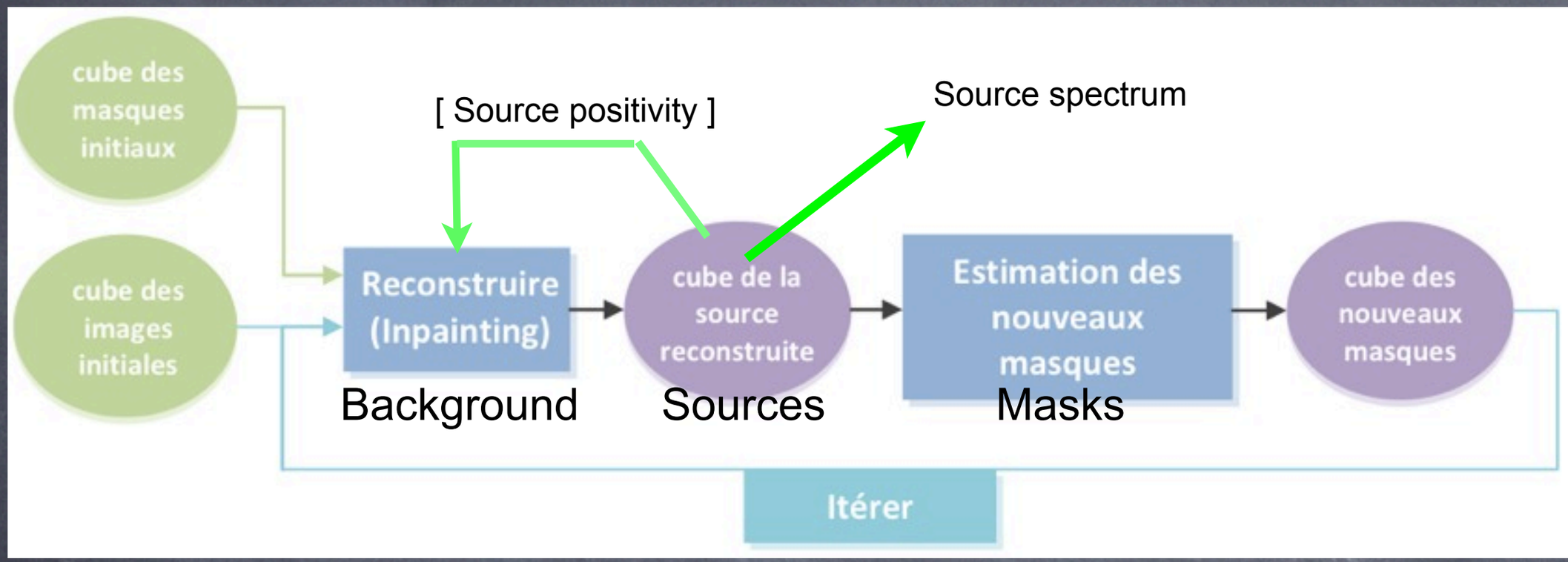
- [upper/lower bounds on disk SED]

- [upper/lower bounds on cloud SED]



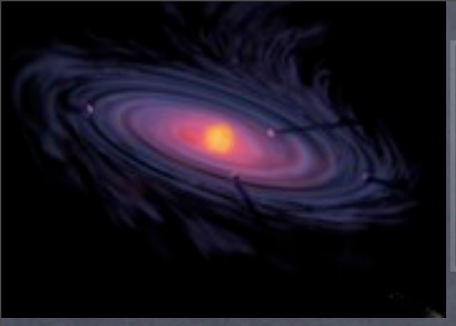
iterative scheme to optimize the masks size



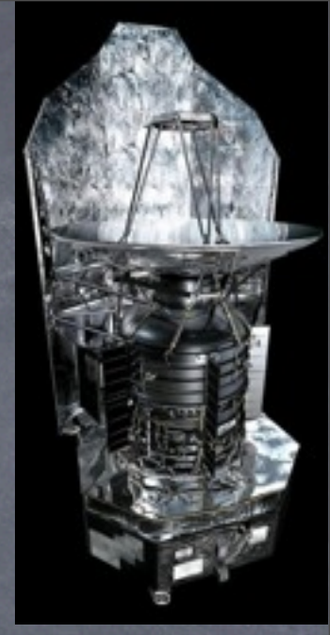


masks ↔ source position and spatial size

- Too small masks → photometric losses
- Too large masks → increase of background error
- Offset masks → both errors

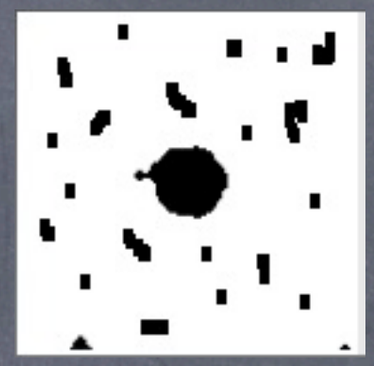


key step: masks estimates



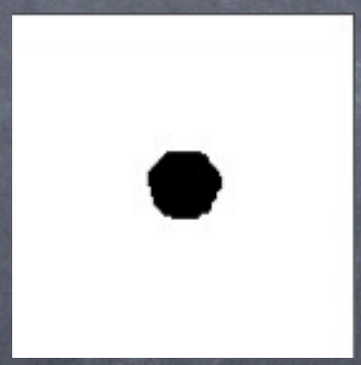
@iteration i,

- source thresholding, level ↘ with i until reaching 3σ noise level ➜ «dirty» masks



- masks correction :
  - erosion/dilation regularization
  - [circular or elliptic fitting]
  - mask size constraint (diffraction)

➜ «clean» mask





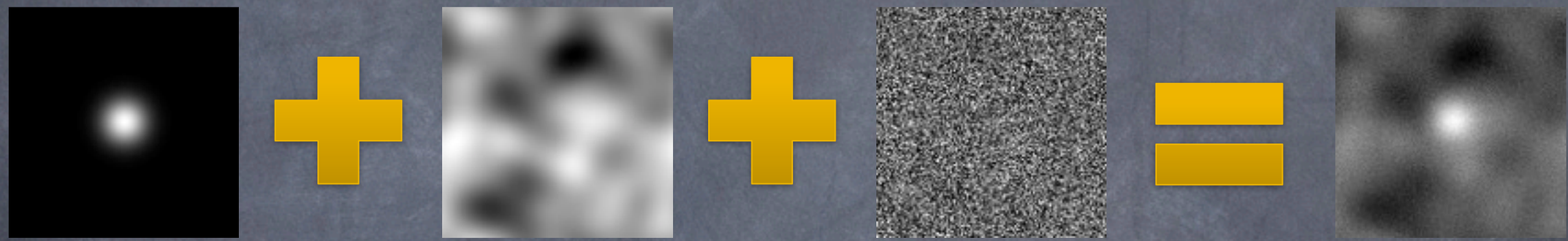
News masks are then injected in inpainting at next iteration until convergence



Tests on simulated data



Données simulées = **Cube d'image à ≠ λ**



Source Ponctuelle = Disque protoplanétaire

Fond Diffus = nuage

Bruit blanc instrumental

Image simulée

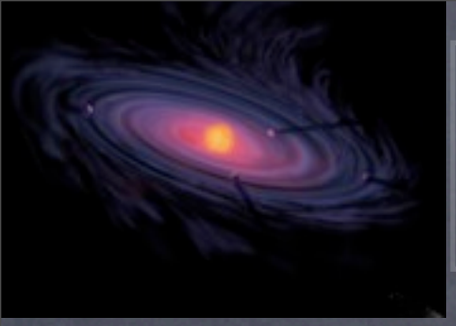
Gaussienne 2D

Taille ∝ diffraction

Amplitude (λ) ∝ spectre de corps noir à 30K

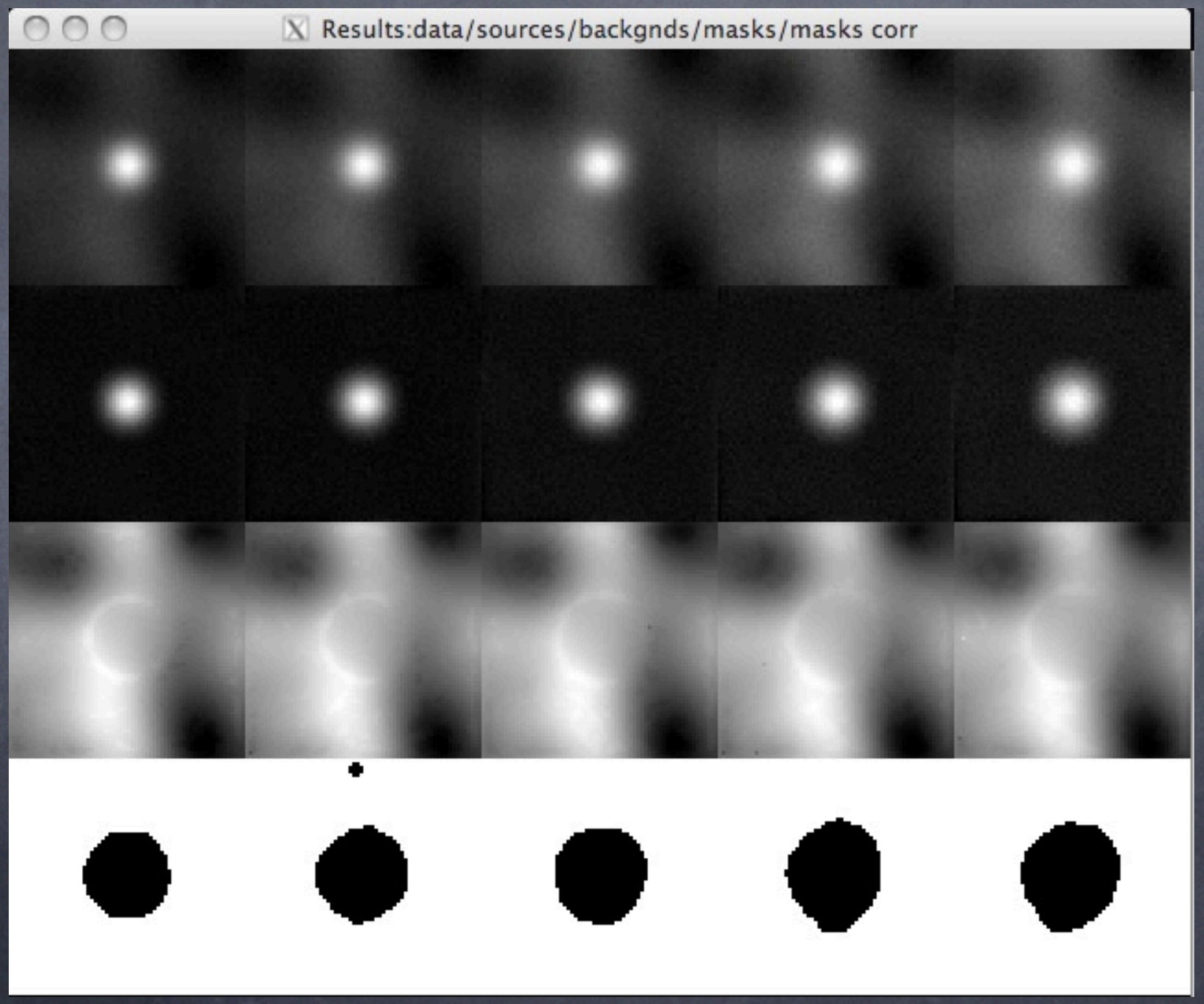
Bruit blanc ∗ gaussienne 2D (large)

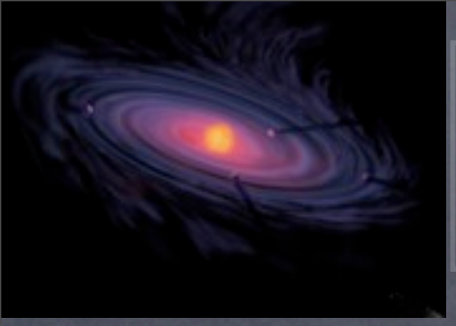
Amplitude(λ) ∝ spectre de corps noir à 15K



snapshot after few iterations

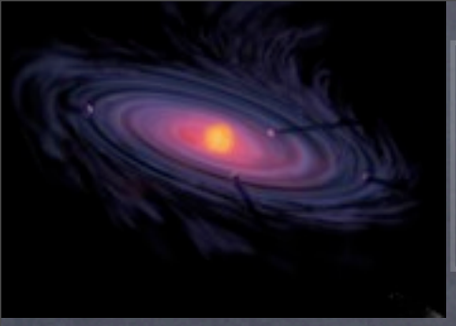






Perspectives

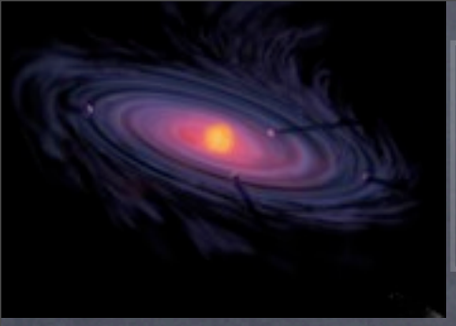




Perspectives



On-going work :

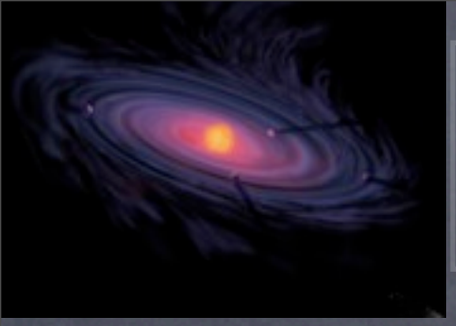


Perspectives



On-going work :

- optimization of method parameters (masks estimation and cleaning)



Perspectives



On-going work :

- optimization of method parameters (masks estimation and cleaning)
- most suited MCA basis

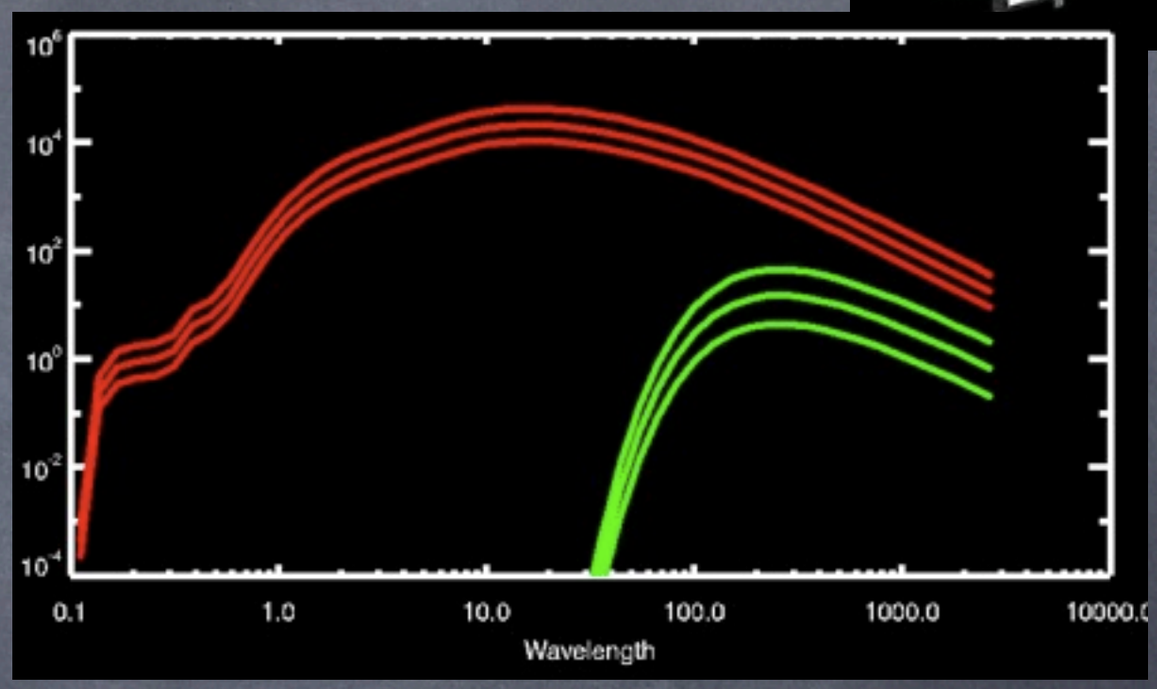


Perspectives



On-going work :

- optimization of method parameters (masks estimation and cleaning)
- most suited MCA basis
- incorporate additional constraints (upper/lower bounds on source/ background SEDs)



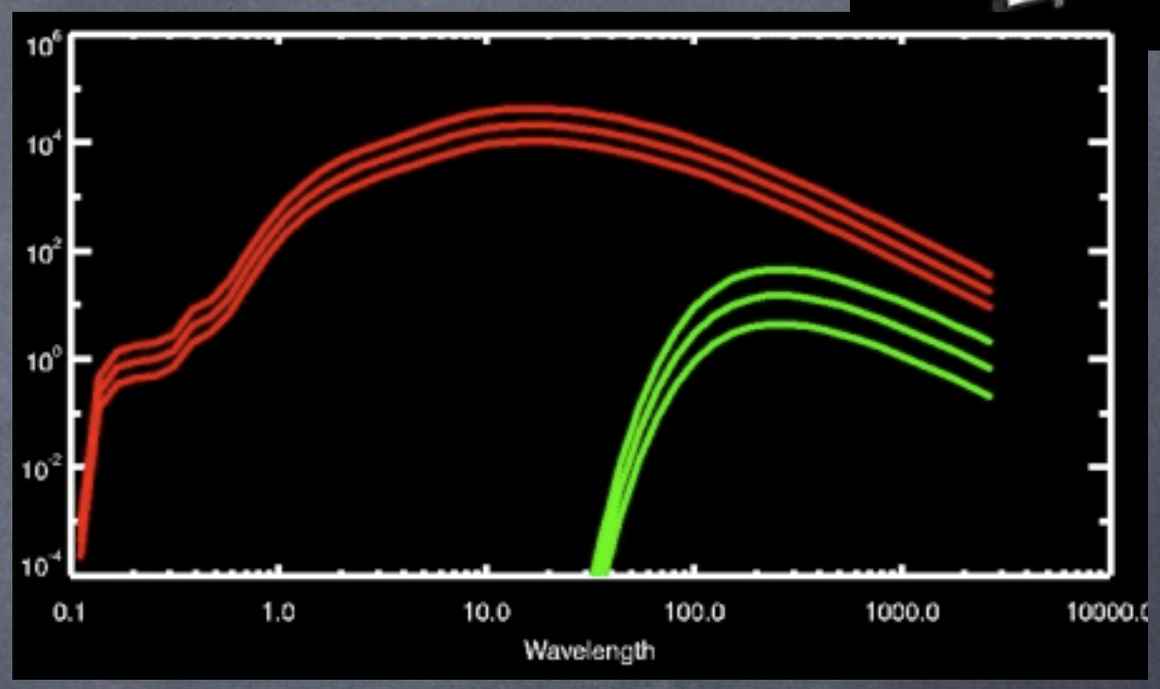


Perspectives

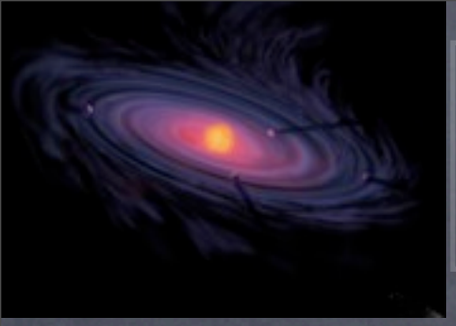


On-going work :

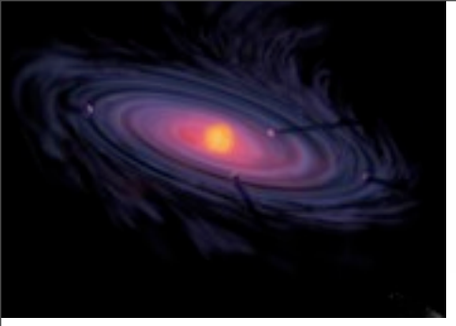
- optimization of method parameters (masks estimation and cleaning)
- most suited MCA basis
- incorporate additional constraints (upper/lower bounds on source/ background SEDs)



... ALMA : inpainting/MCA 3D could be and interesting approach for interferometric data (missing frequencies, sparse data)









Iterative multiresolution scheme aiming at separating the background and the source signals, based on sources separation through a L1-norm minimization :

$$S_{n+1} = P_{S,\lambda}(S_n + CN_R^{-1}(D - CN_R(S_n) - B_n))$$

$$B_{n+1} = P_{B,\lambda}(B_n + SM(D - CN_R(S_n) - B_n))$$

CN_R : 4 beams splitting operator
S_n : reconstructed source signal at iteration n
B_n : reconstructed background at iteration n
D : data (VISIR detector image)
SM : 4 beams masking operator
$P_{S,\lambda}$: Projection operator onto source solution space : positivity + wavelets $\lambda x \sigma$ filtering
$P_{B,\lambda}$: Projection operator onto background solution space : wavelets +curvelets $\lambda x \sigma$ filtering, keeping only lowest frequencies

The process is iterated, decreasing from a value computed w.r.t. the maximum in data, until = 3.5