

DE LA RECHERCHE À L'INDUSTRIE



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Multichannel Compressed Sensing and its application on radioastronomy

Journées des Thésards 2016 - 7 et 8 Juillet

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Cosmostat, Service d'Astrophysique, CEA Saclay

<http://www.cosmostat.org/>



Ming JIANG

● Education

2010 - 2014: Télécom Bretagne (Master of Engineering)

- Information Processing Systems (Option: Signal/Image processing) on 3rd year

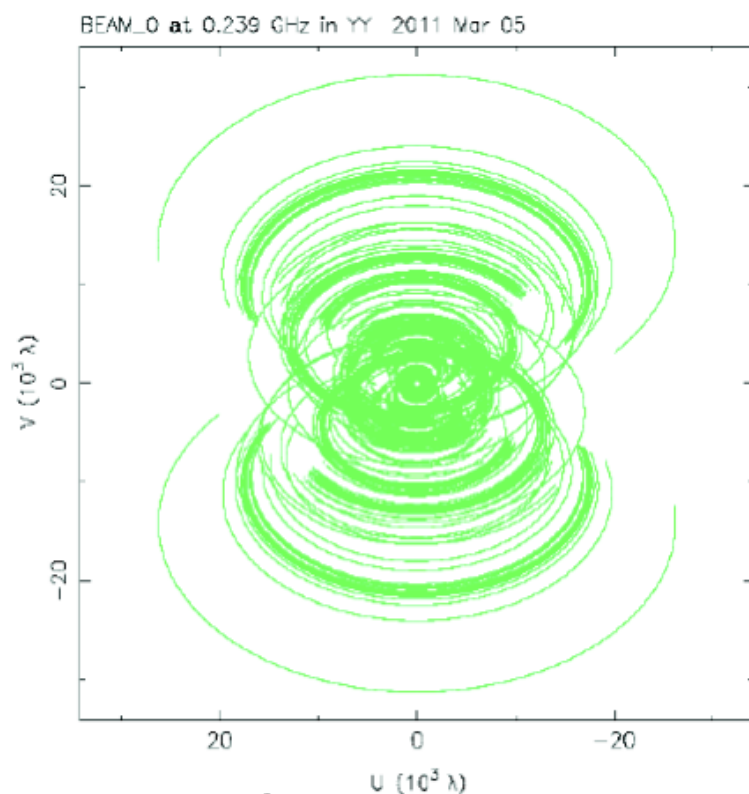
2013 - 2014: Université de Rennes 1 (Master of research)

- SISEA - I(Image processing)

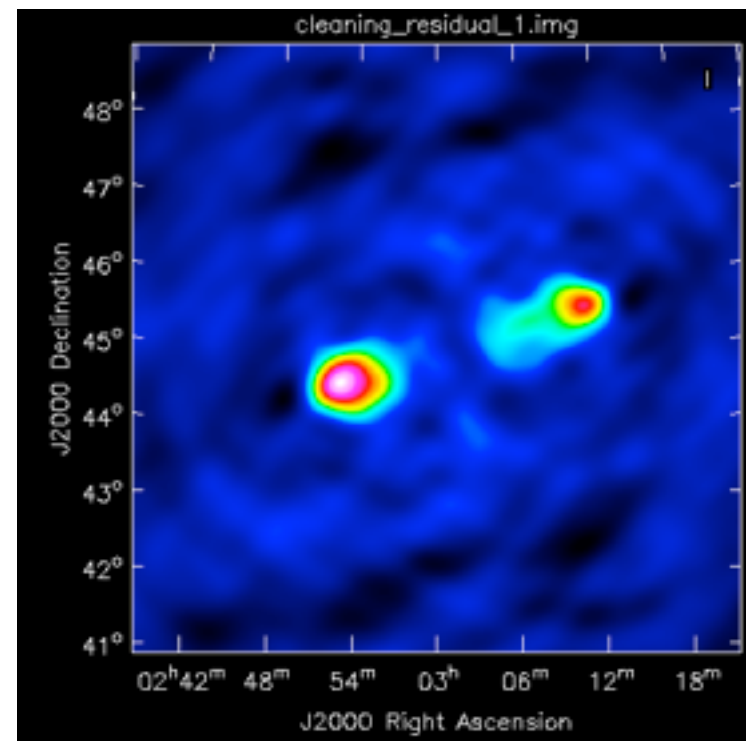
● Ph.D candidate

- Motivation: Interdisciplinary research on signal processing algorithms, applied mathematics, applications in practice, etc.

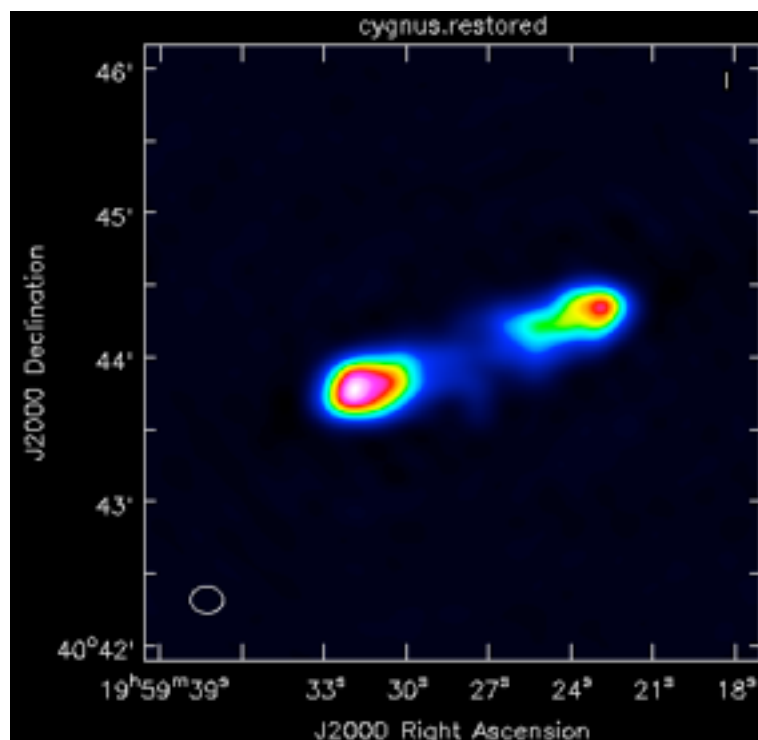
Data



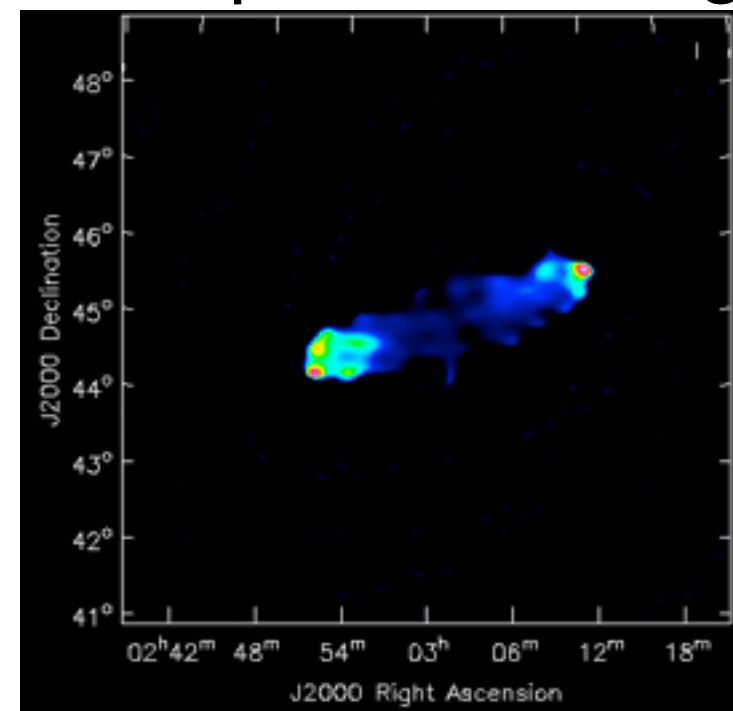
Dirty map



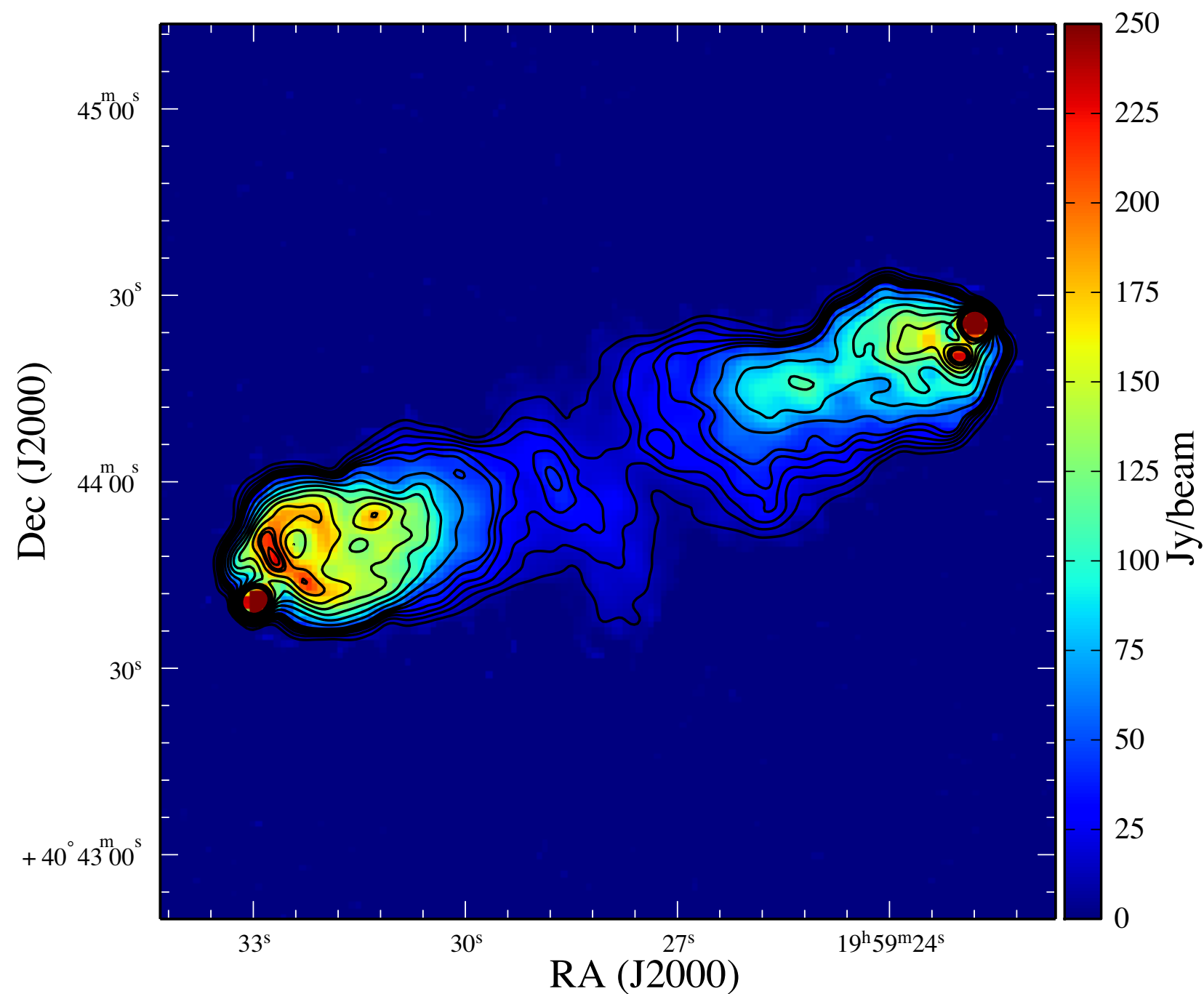
CLEAN



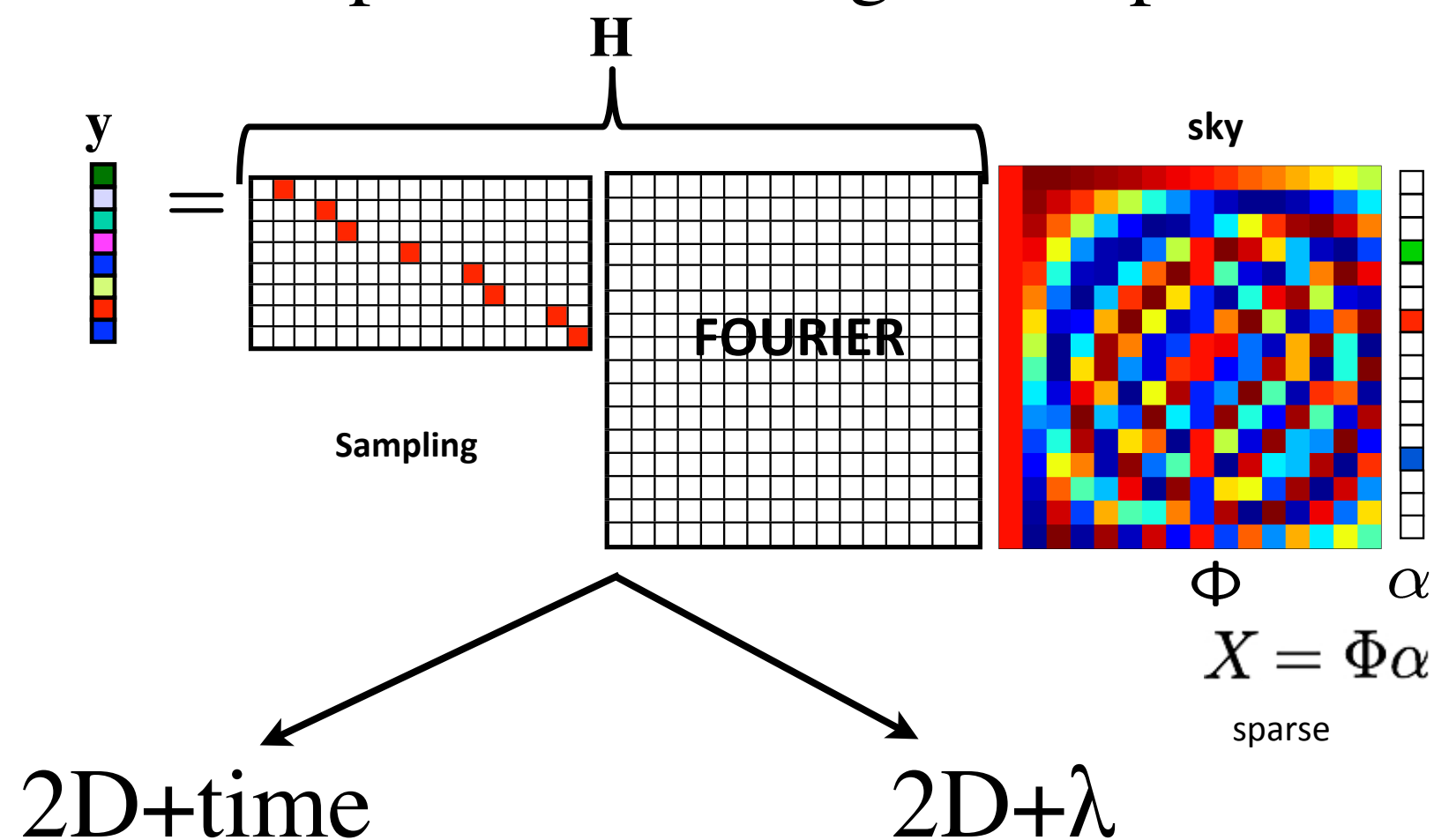
Compressed Sensing



Garsden et al, "LOFAR Image Sparse Reconstruction", A&A, 2015, [ArXiv:1406.7242](https://arxiv.org/abs/1406.7242).



Compressed Sensing Concept



2D-1D sparse reconstruction and transient detection

1st year

Multi/Hyper spectral image restoration

2nd year



Applications

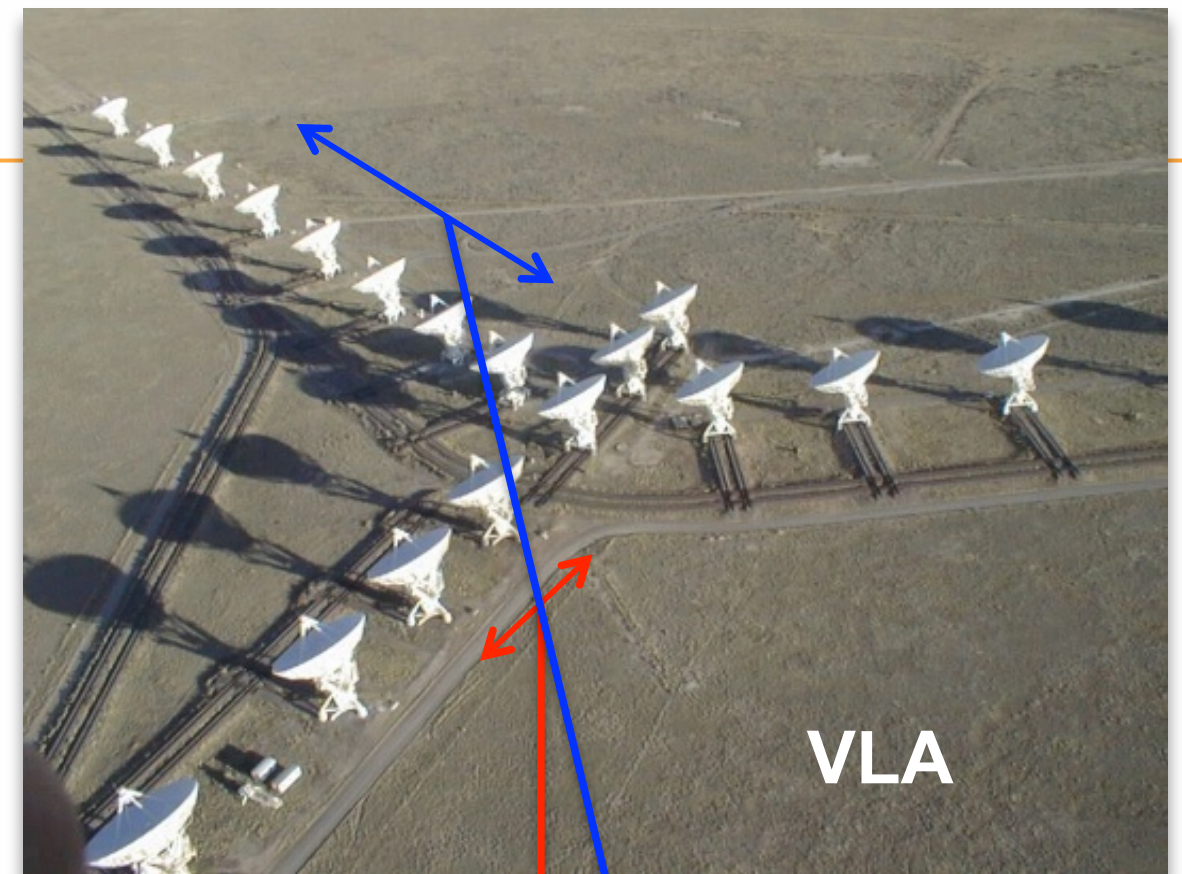


Imaging with interferometry

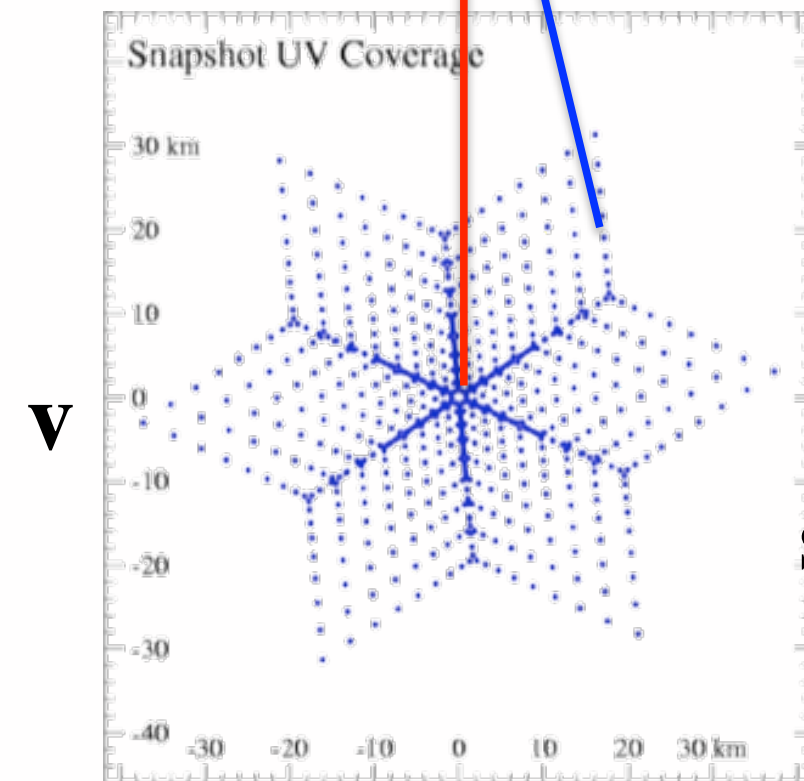
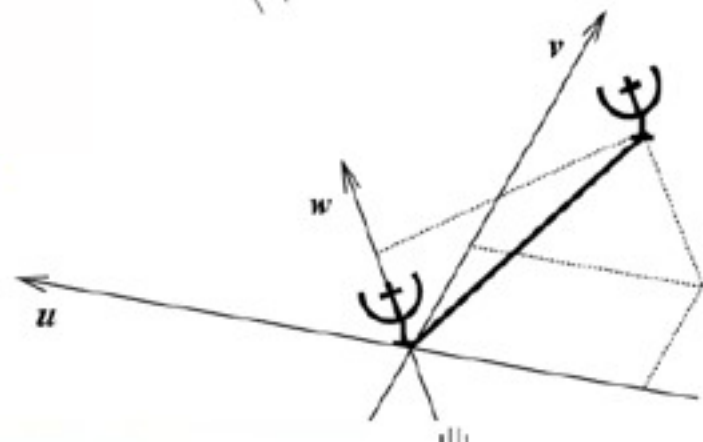
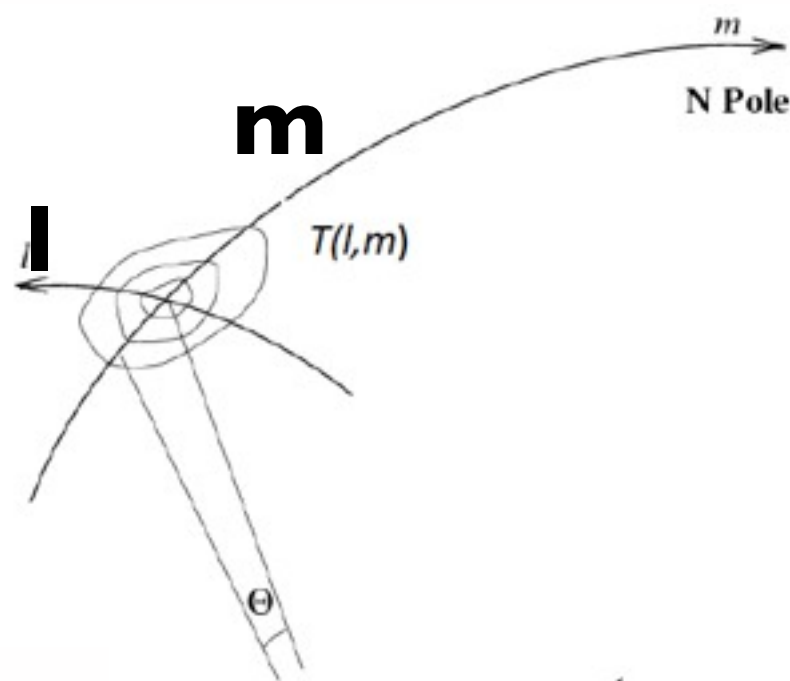
N antennas/telescopes

$\frac{N(N-1)}{2}$ independent baselines

1 projected baseline
= 1 sample in the Fourier « u,v » plane



VLA



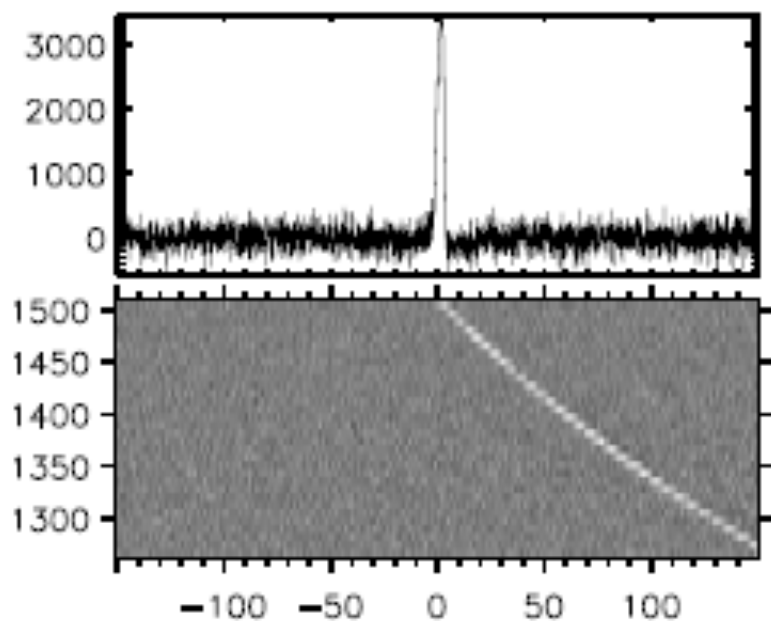
(u,v)
plane
sampling

$$V(u, v) = \iint T(l, m) e^{-i2\pi(ul+vm)} dl dm \longrightarrow T(l, m)$$

The Transient Universe in radio

Timeline diagram showing time scales: <<1ms, 1s, 10s, 1m, 10 m, H, Days, Weeks, M, Y. A vertical line marks 10 m.

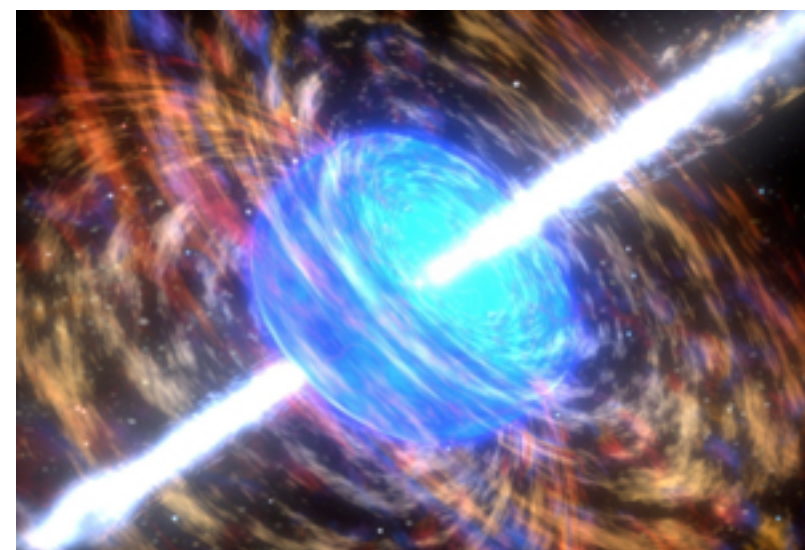
- **Fast transient sources**



- 😊 Good time resolution
- ☹ No/low angular res.
- ☹ Low instantaneous SNR
- ☹ few samples for imaging

- **Slow transient sources**

Variability timescale



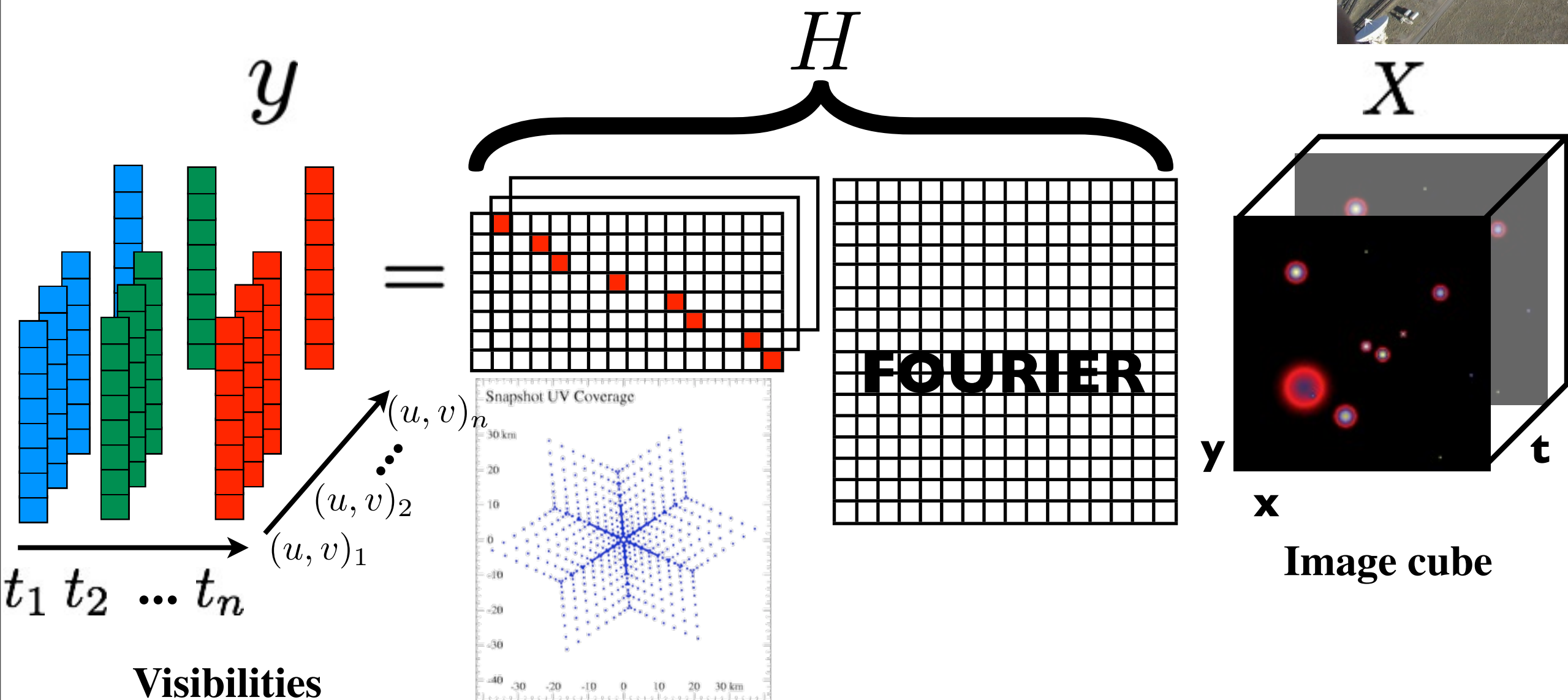
- ☹ **Poor time resolution**
- ☺ **Good angular resolution**
- ☺ **Good integrated SNR**
- ☺ **enough samples for imaging**

+ others problems (instrument stability, ionosphere...)

Extension to 2D-1D sparse reconstruction

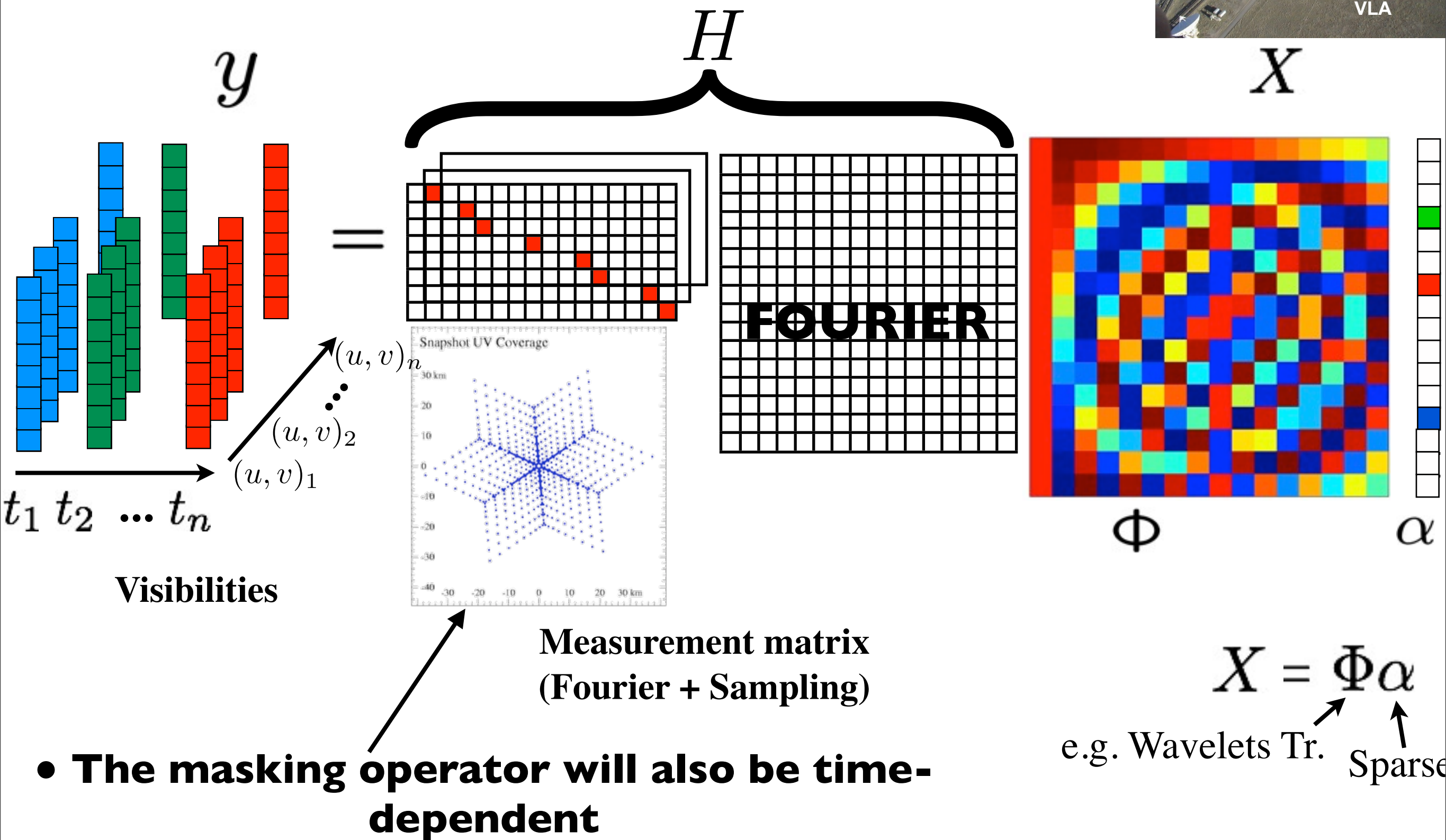


VLA



- The masking operator will also be time-dependent

Extension to 2D-1D sparse reconstruction



• Inverse problem formulation

$$\mathbf{V} = \mathbf{M}\mathbf{F}\mathbf{x} + \mathbf{N}$$

- M: 2D-1D mask
- F: Fourier transform
- N: Gaussian noise

$$\min ||\Phi^t \mathbf{x}||_1 \quad s.t. \quad ||\mathbf{V} - \mathbf{M}\mathbf{F}\mathbf{x}||_2^2 < \epsilon$$

• Analysis framework

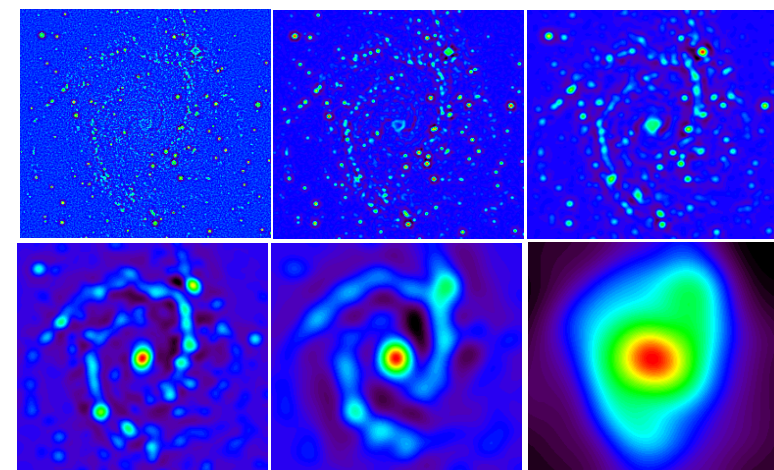
$$\min_x ||V - MFx||_2^2 + ||W \odot \lambda \odot \Phi^t x||_1 + i_{P_+}(x)$$

Data fidelity Positivity
Sparsity constraint

We need dictionaries - space and time are independent

$$\psi(x, y, t) = \psi^{(xy)}(x, y) \psi^{(t)}(t)$$

- for the 2D spatial signal



Starlets [Starck et al. 2011]

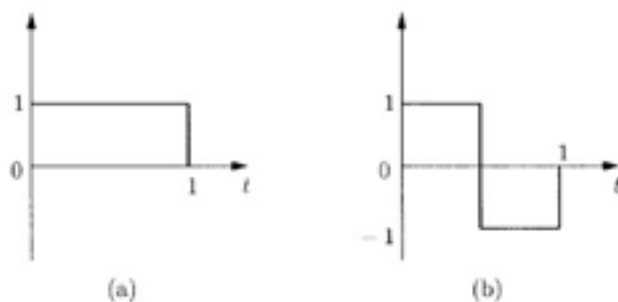
(Isotropic Undecimated Wavelet Transform)

$$\varphi = B_3 - \text{spline}, \quad \frac{1}{2}\psi\left(\frac{x}{2}\right) = \frac{1}{2}\varphi\left(\frac{x}{2}\right) - \varphi(x)$$

$$h = [1, 4, 6, 4, 1]/16, \quad g = \delta - h, \quad \tilde{h} = \tilde{g} = \delta$$

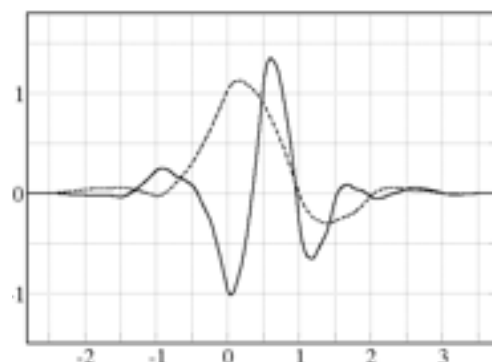
$$I(k, l) = c_{J, k, l} + \sum_{j=1}^J w_{j, k, l}$$

- for the 1D temporal signal



Haar wavelets

Quantified signals



7/9 wavelets

Semi-continuous

...

We need Optimization methods

- **Condat-Vu Splitting Method(Condat 2013; Vu, 2013)**

$$\min_x \|V - MFx\|_2^2 + \|W \odot \lambda \odot \Phi^T x\|_1 + i_{P_+}(x) \quad (1)$$

- Initialize $x^{(0)}, u^{(0)}$
- Iterate $i=1, \dots, \text{Niter}$

- Gradient step to update x

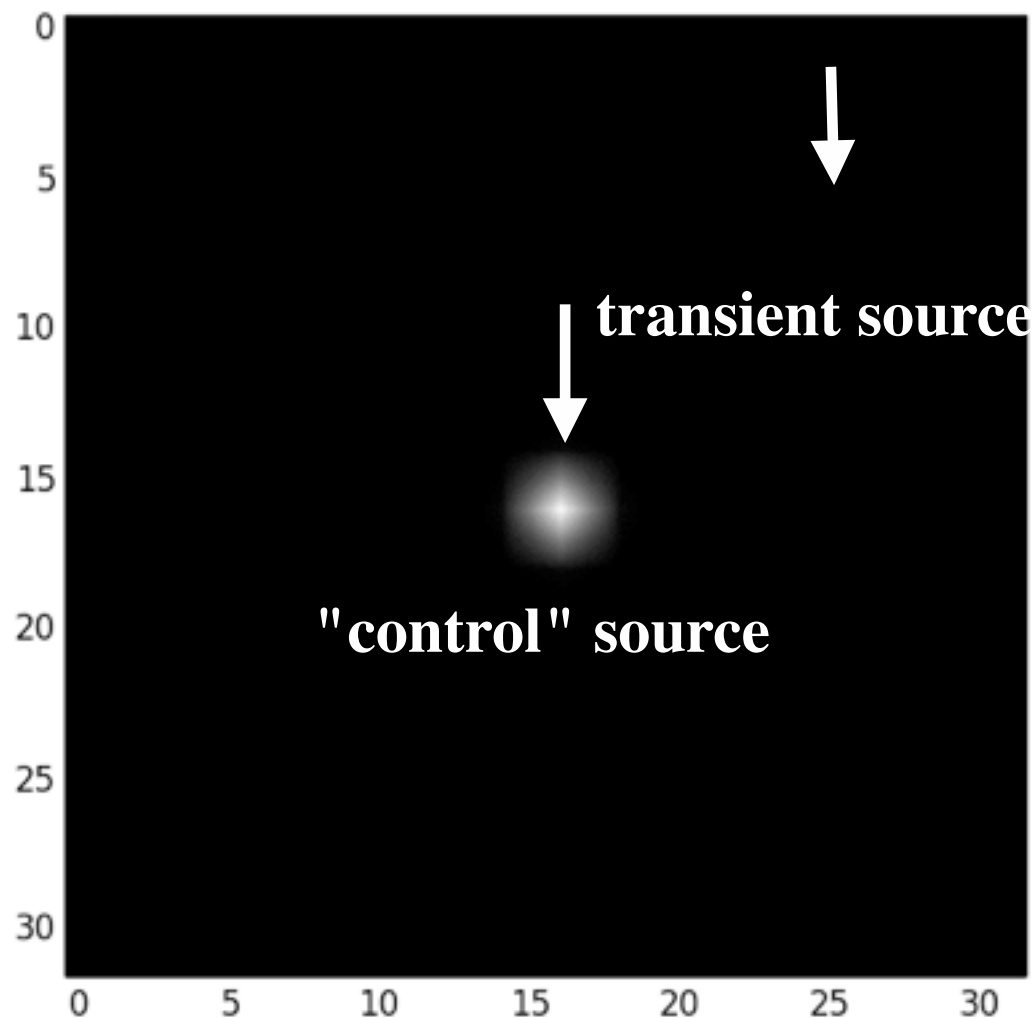
$$x^{(n+1)} = \text{Proj}_{P_+}(x^{(n+1)} - \tau \Phi u^{(n)} + \tau (MF)^*(V - MFx^{(n)}))$$

- Proximity operation to update wavelet coefficient u

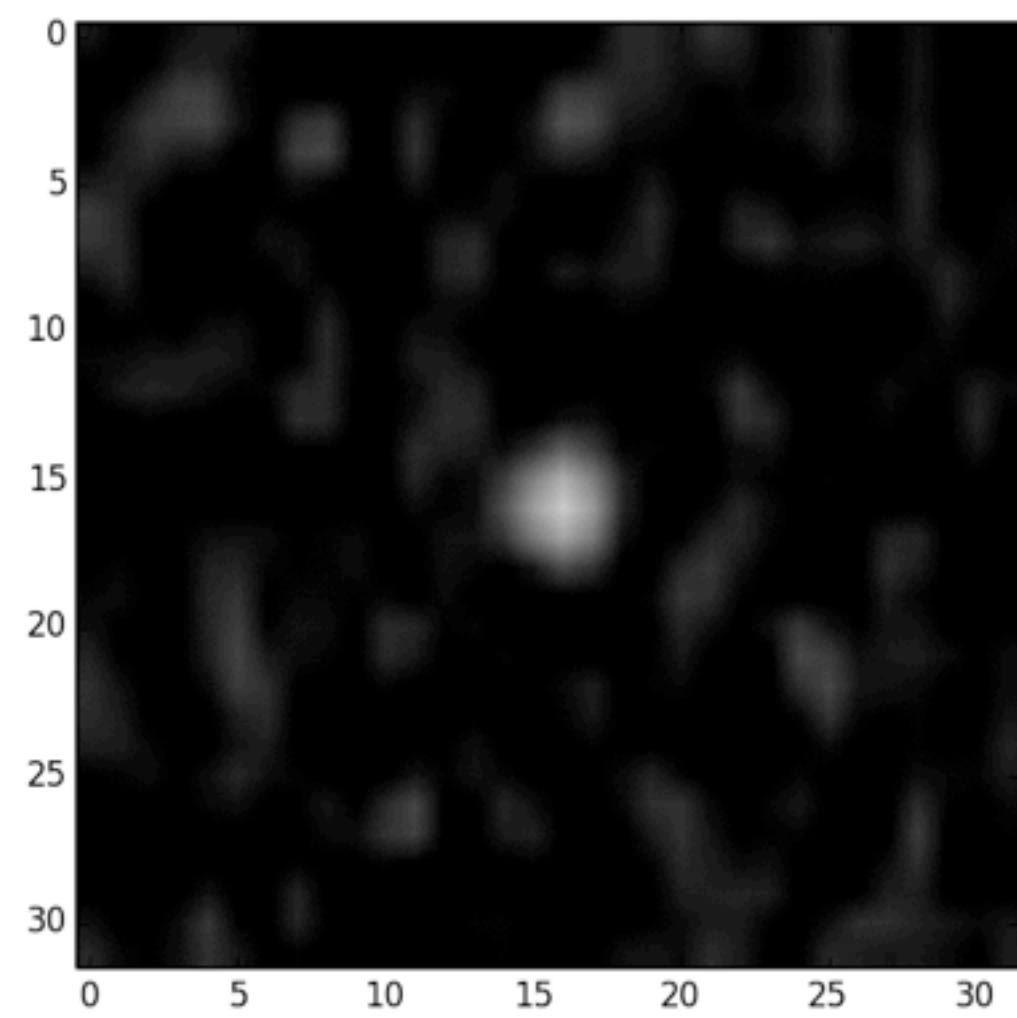
$$u^{(n+1)} = (\text{Id} - \text{ST}_\lambda)(u^{(n)} + \eta \Phi^T (2p^{(n+1)} - x^{(n)}))$$

1) Simulating a transient sky and a radio observation

Sky model



Dirty map



- "control" source: steady

Total flux: 40 FU Max Amp: 10 FU

- transient gaussian source:

Flux: 40 FU maximum Max Amp: 10 FU

*FU = arbitrary flux unit

A new source appeared but side lobes as well !
Need a time-agile deconvolution algorithm

2) Reconstruction for different noisy datasets

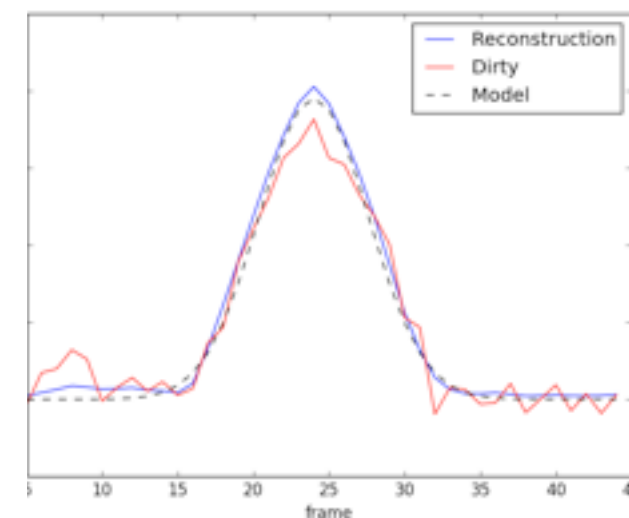
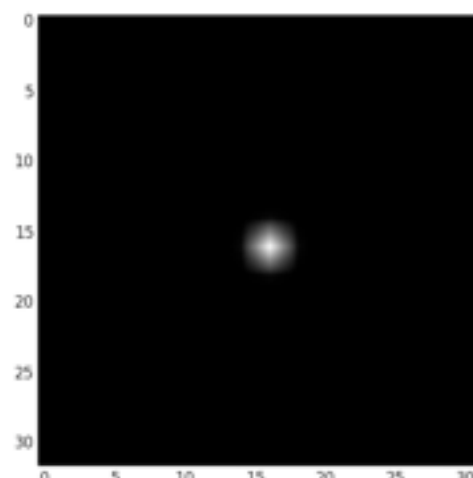
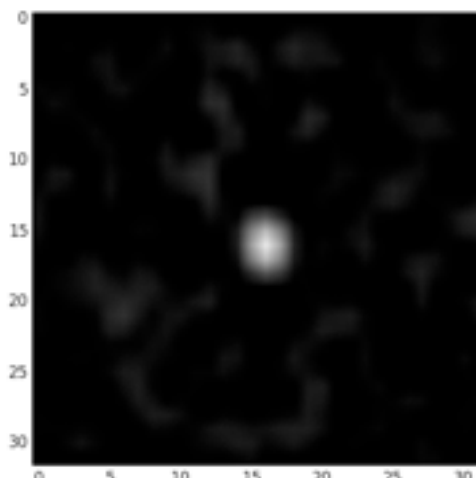
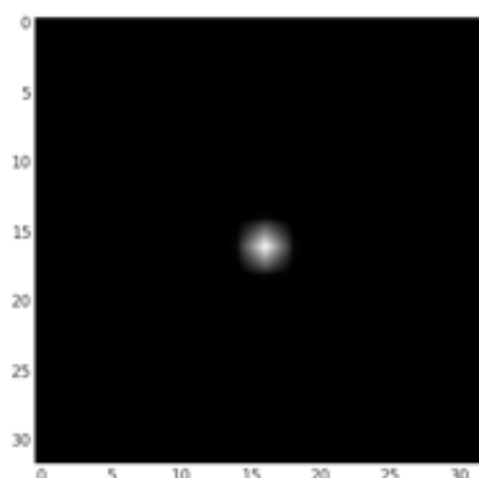
Sky model

Dirty map

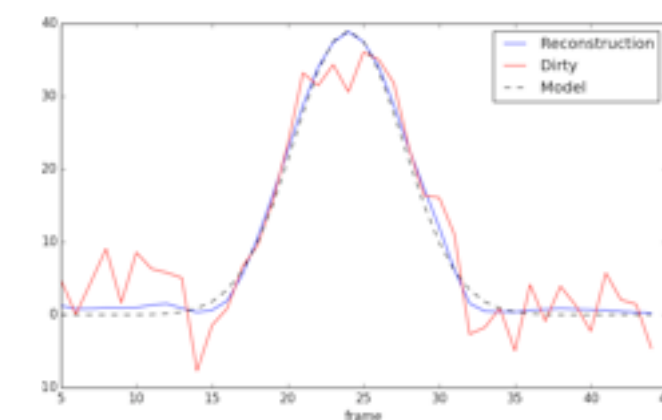
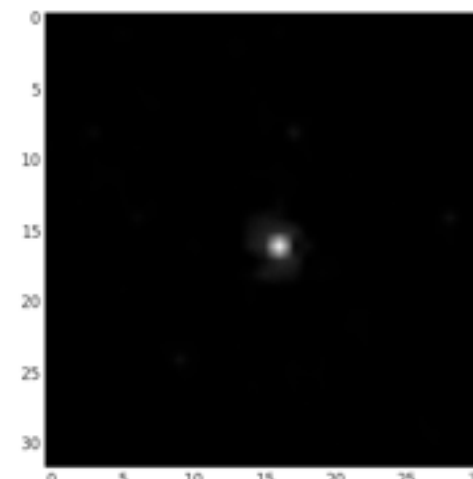
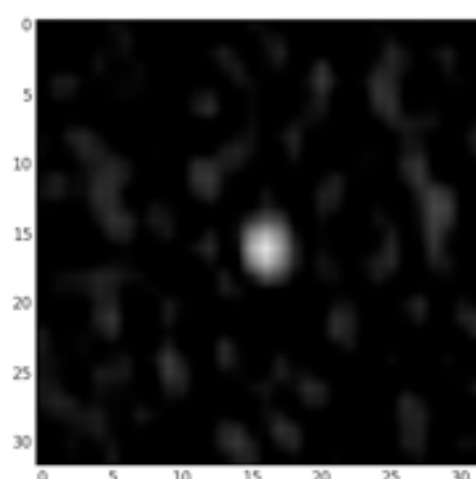
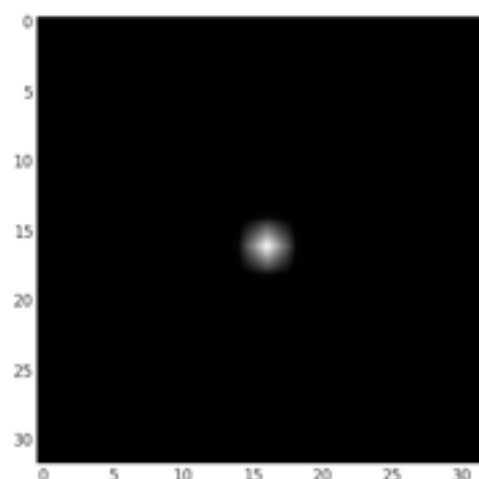
Reconstruction

Time profile of transient

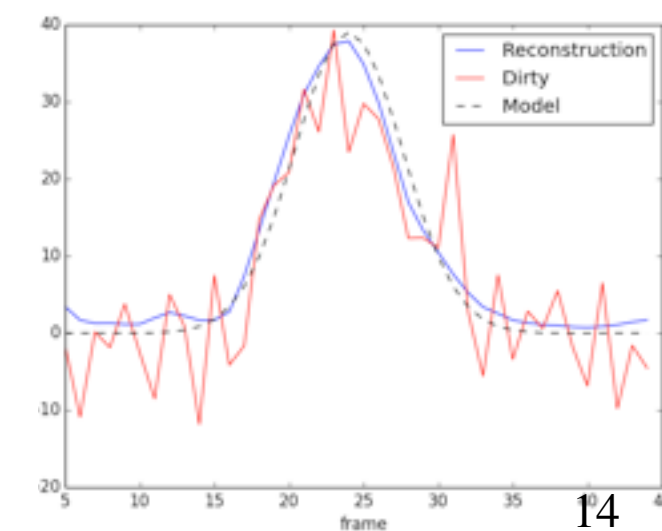
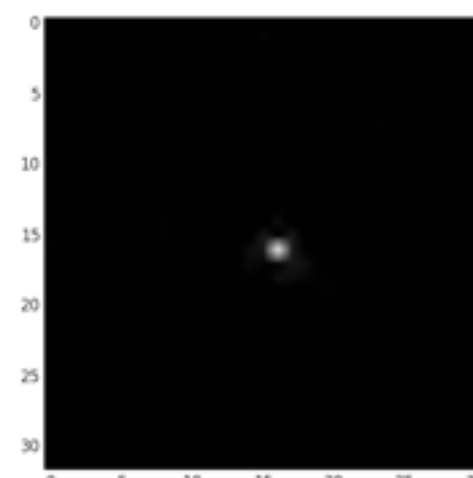
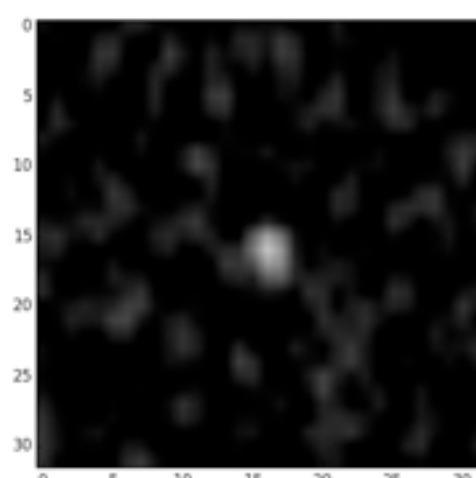
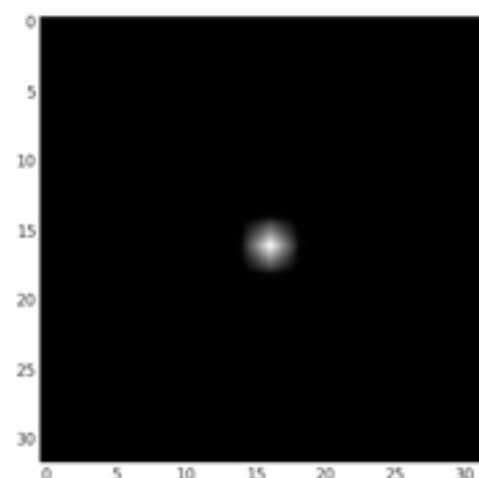
$\sigma=0.5$



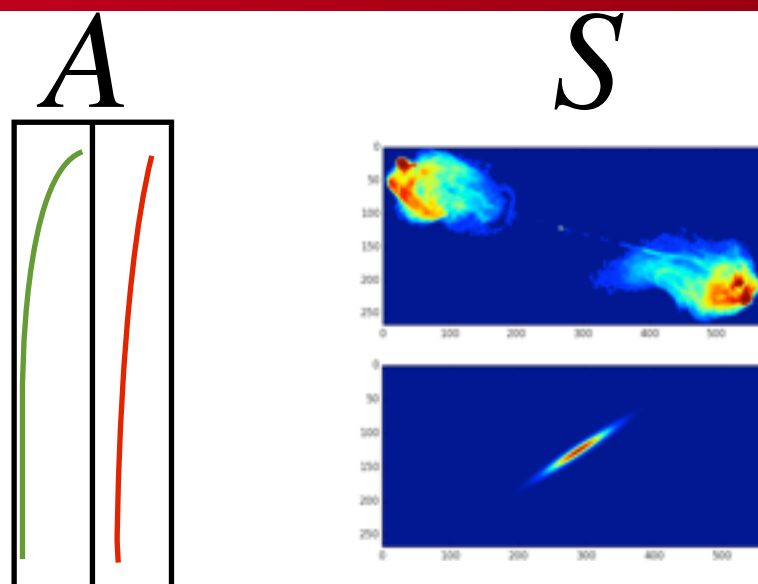
$\sigma = 1.0$



$\sigma = 1.5$

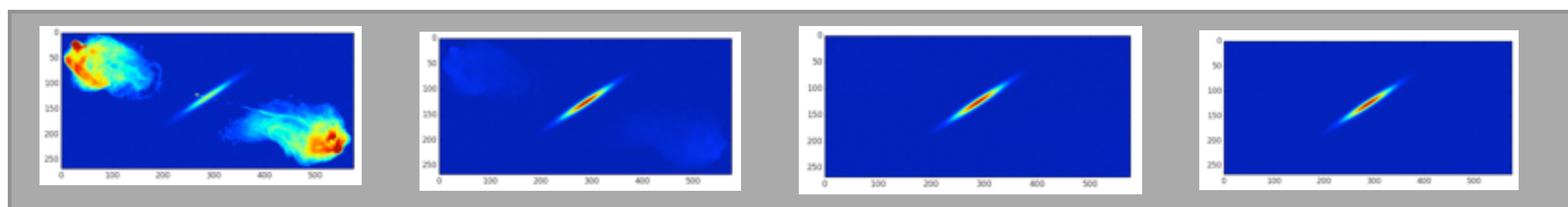


Ground Truth

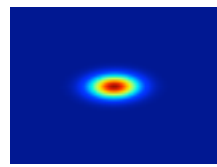
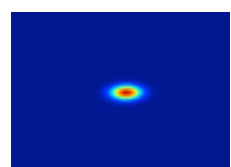


Mixtures

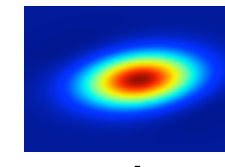
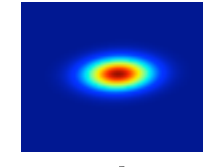
$$X = AS$$



PSF H

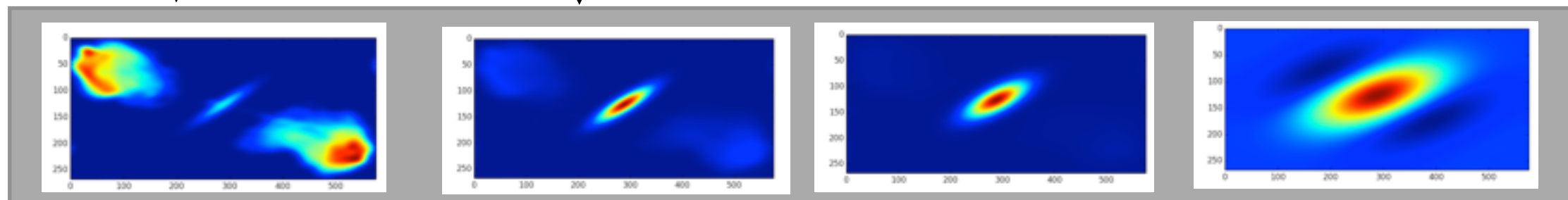


*



Data

$$Y = HX + N$$

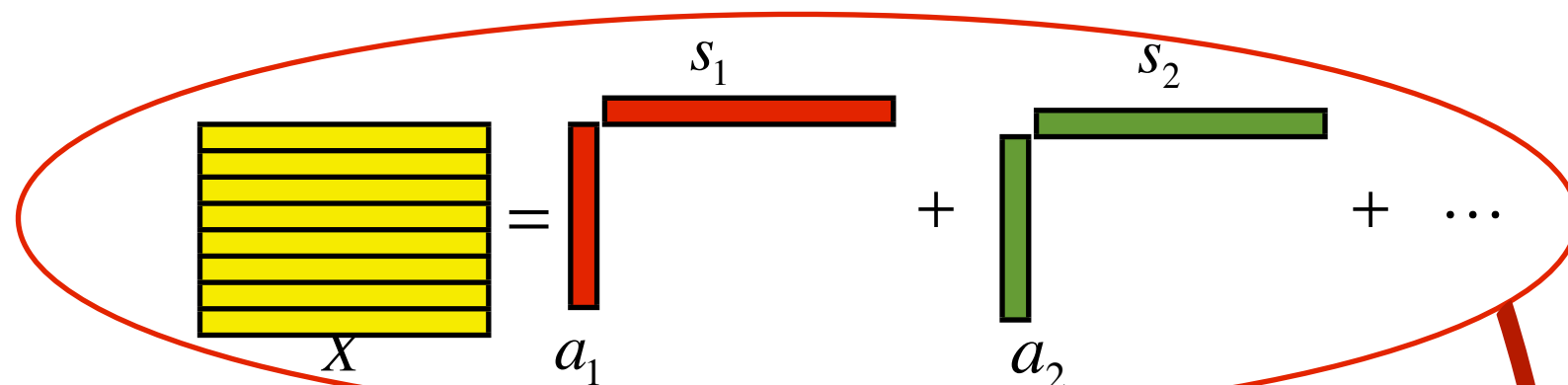


chan 1

chan 4

chan 7

chan 10



- **BSS(Blind Source Separation) problem**

Statistical approach: ICA (FastICA(*A. HYVARINEN et al.*)), etc.

Methods based on morphological diversity: GMCA(*J. BOBIN et al.*) and its variations

- **Deconvolution**

e.g. ForWaRD(*R.N. NEELAMANI et al.*)

$$Y = H(X) \Rightarrow X = H^{-1}(Y)$$

Joint BSS and Deconvolution?

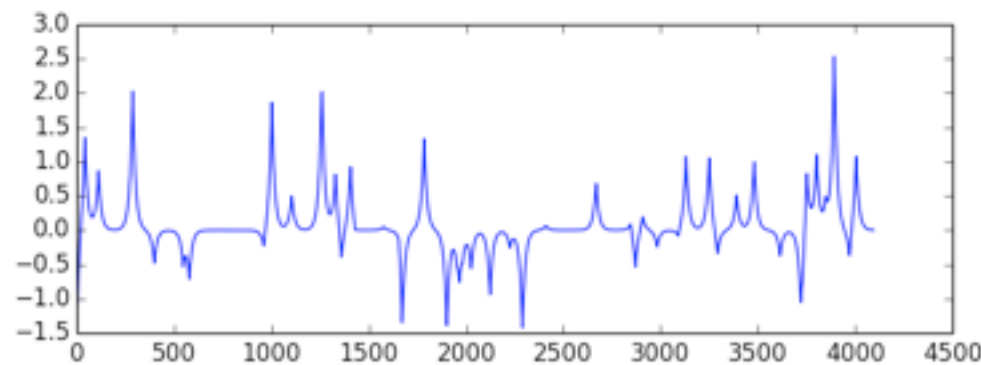
Very few literatures!

Our method: ForWaRD+GMCA = fGMCA

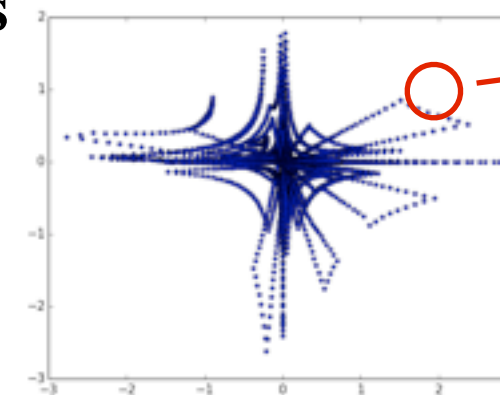
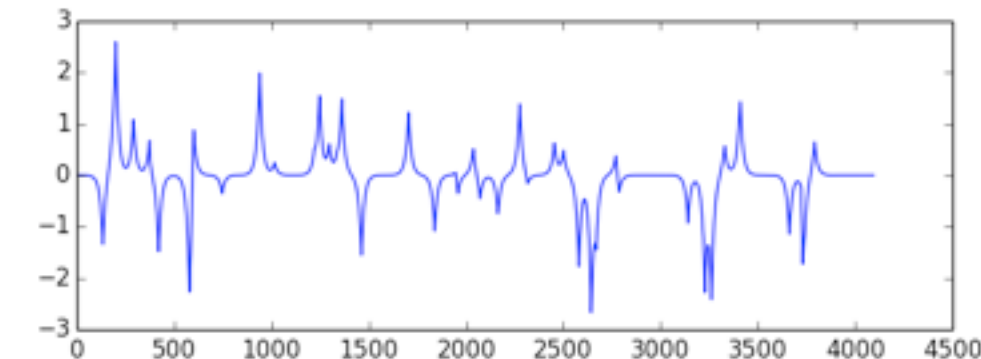
- GMCA: Generalized Morphological Component Analysis**

1-D signals

S1

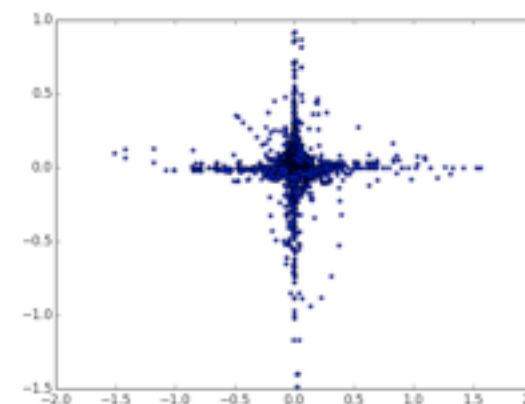


S2



S1 v.s. S2 in direct domain

Correlation

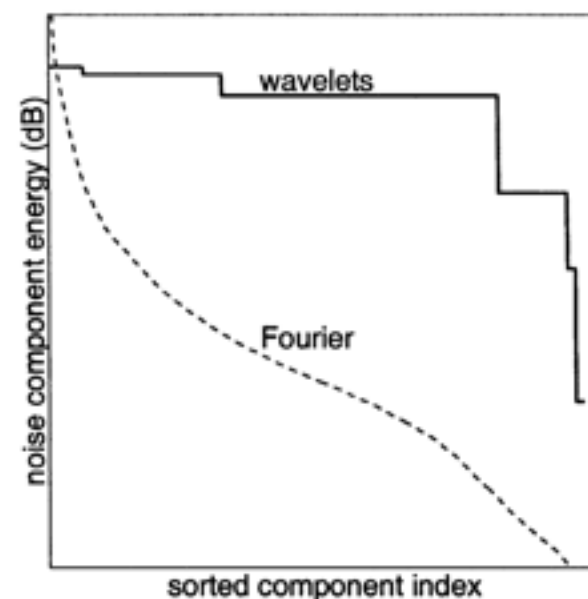


S1 v.s. S2 in wavelet domain

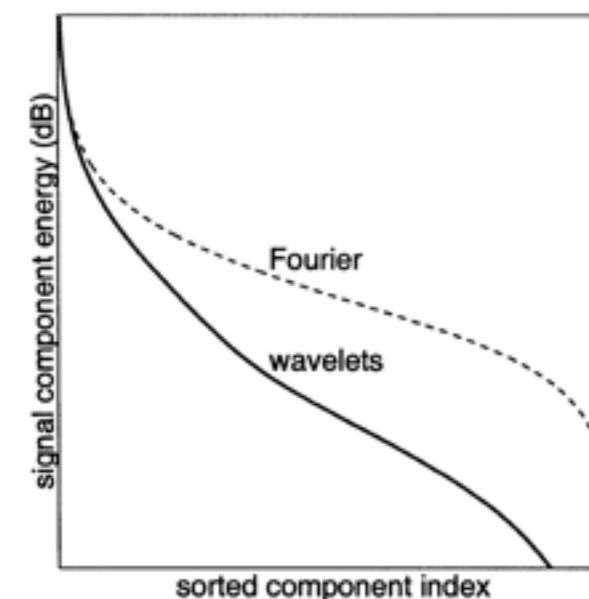
Easier to distinguish sources!

- ForWaRD: Fourier-Wavelet Regularized Deconvolution**

Fourier domain:
Fourier shrinkage and regularize the ill-conditioned system



Wavelet domain:
Wavelet shrinkage searches for smooth signals and images



[R.N. NEELAMANI et al.]

- **ForWaRD-GMCA algorithm**

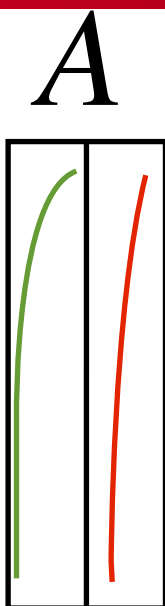
$$\min_{\{S_{j,\cdot}\}, \{A_v\}} \frac{1}{2} \sum_{v,k} \|V_{v,k} - H_{v,k} \mathbf{A}_v \hat{\mathbf{S}}_k\|_2^2 + \sum_j \lambda_j \|S_{j,\cdot} \Phi^t\|_0$$

- Initialize $A^{(0)}$

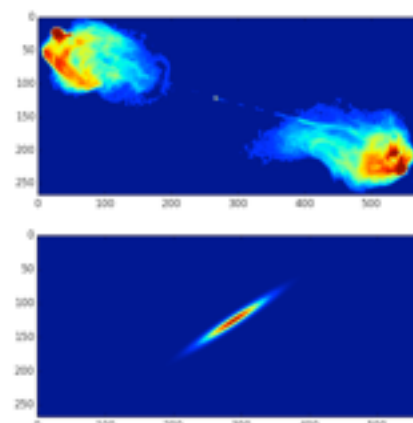
- Iterate $i=1, \dots, \text{Niter}$

- Update S knowing A $\min_{\{S_{j,\cdot}\}} \frac{1}{2} \sum_{v,k} \|V_{v,k} - H_{v,k} \mathbf{A}_v \hat{\mathbf{S}}_k\|_2^2 + \sum_j \lambda_j \|S_{j,\cdot} \Phi^t\|_1$
- Update A knowing S $\min_{\{A_v\}} \frac{1}{2} \sum_{v,k} \|V_{v,k} - H_{v,k} \mathbf{A}_v \hat{\mathbf{S}}_k\|_2^2$
- Decrease the thresholding λ
- Decrease the Tikhonov parameter ε

Ground Truth

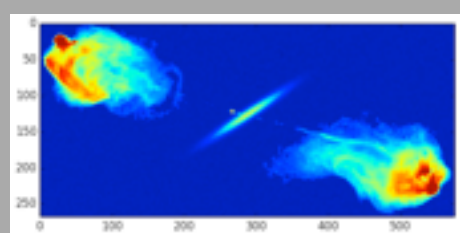


S

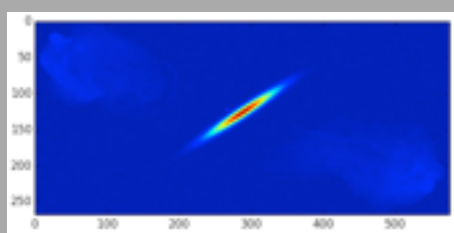


Mixtures

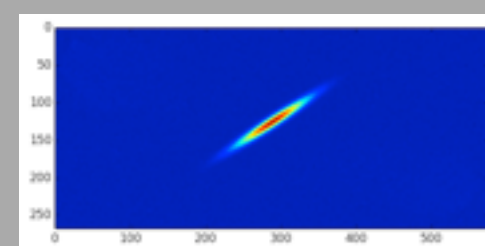
$$X = AS$$



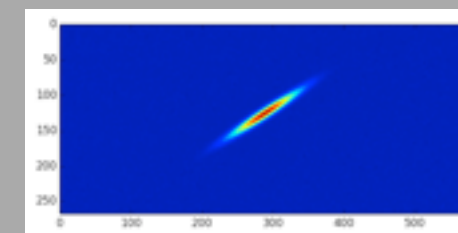
chan 1



chan 4

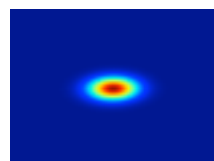
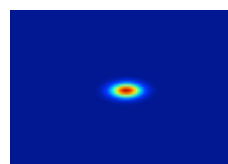


chan 7

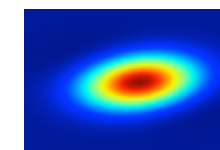
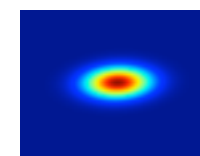


chan 10

PSF H

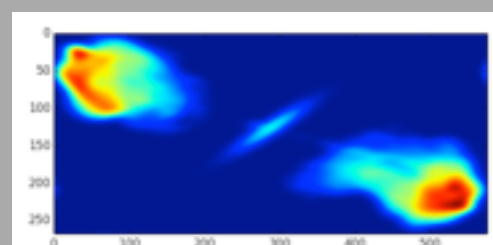


$*$

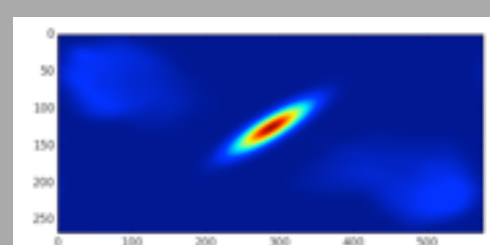


Data

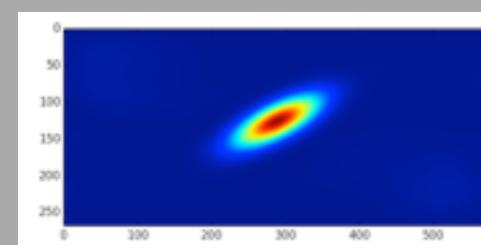
$$Y = HX + N$$



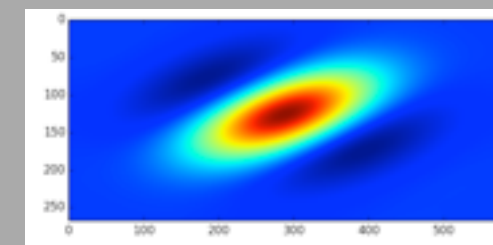
chan 1



chan 4

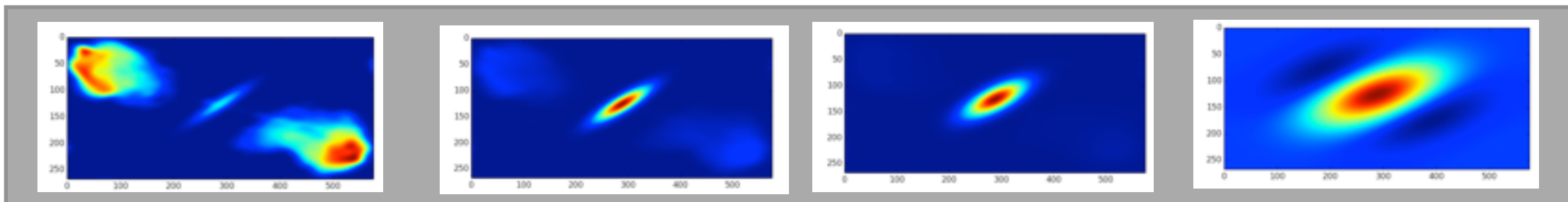


chan 7



chan 10

Data



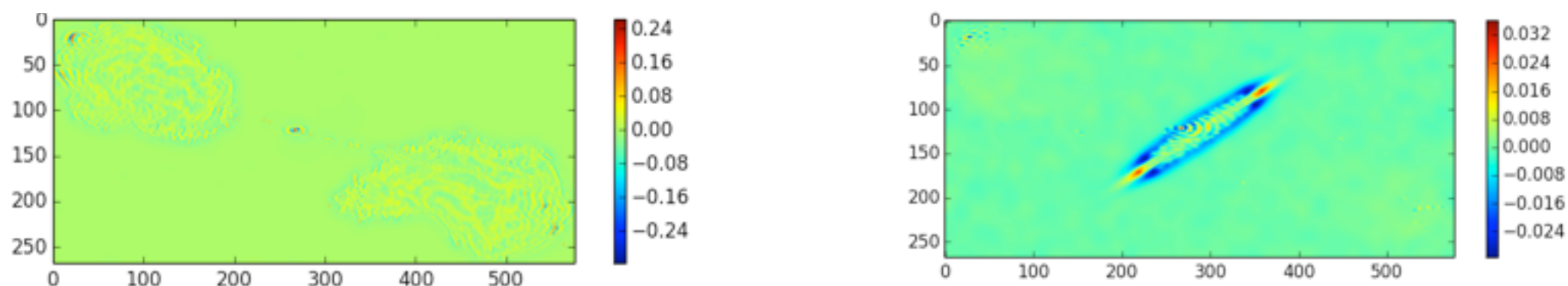
Reconstruction



Truth



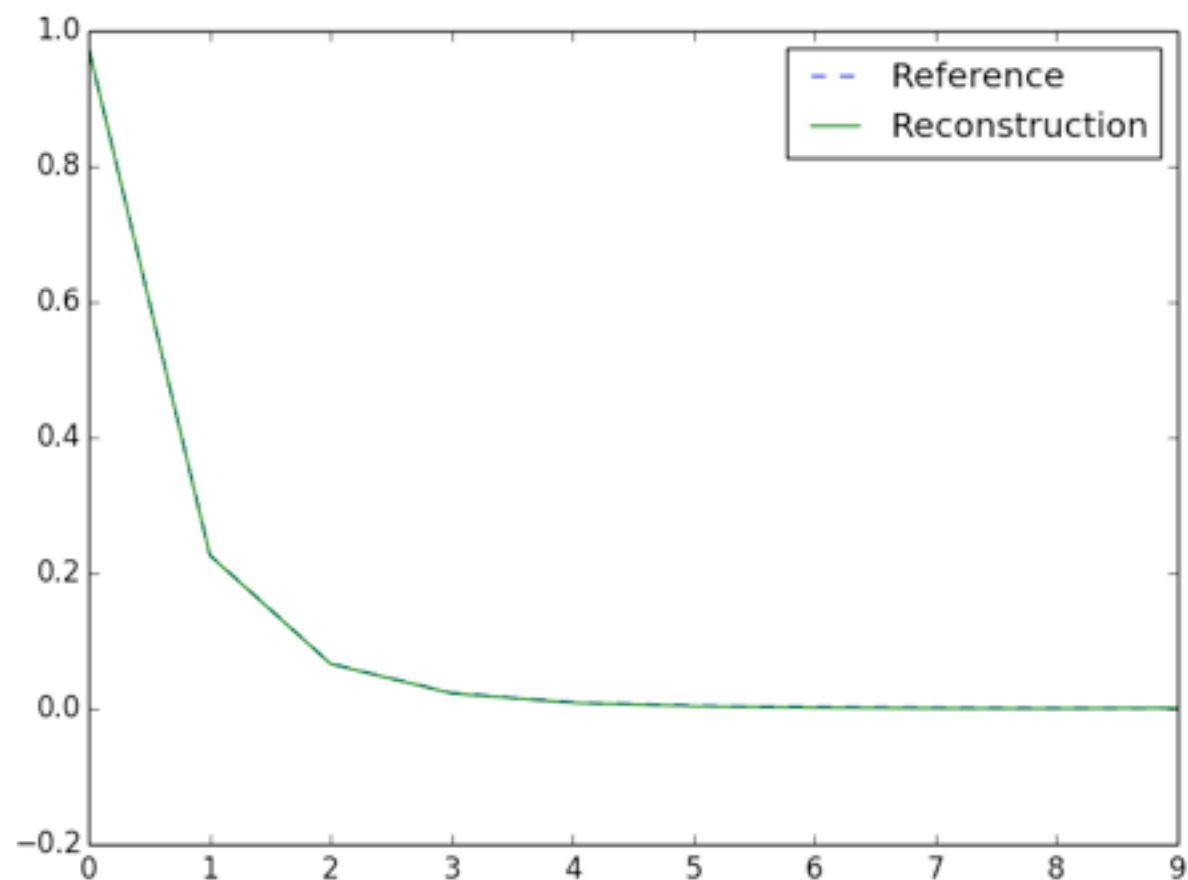
Error



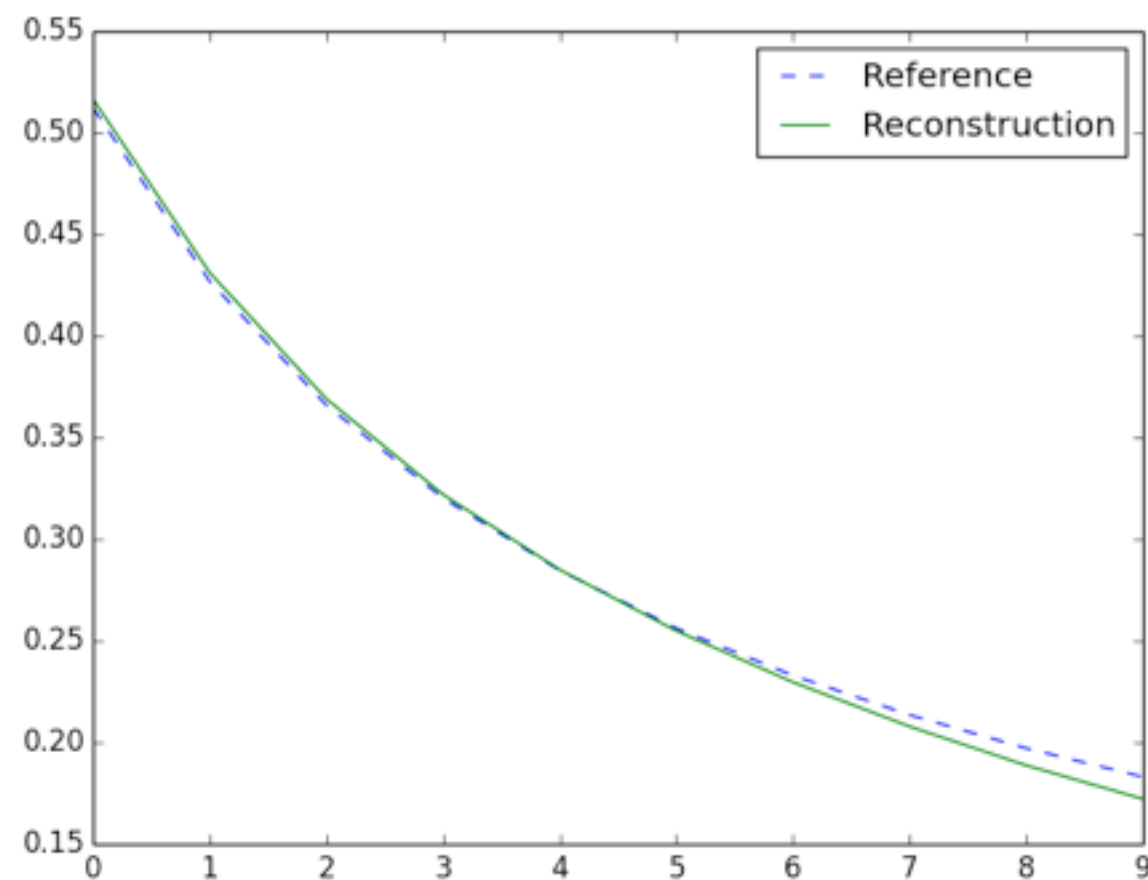
Relative error

0.42%

0.19%

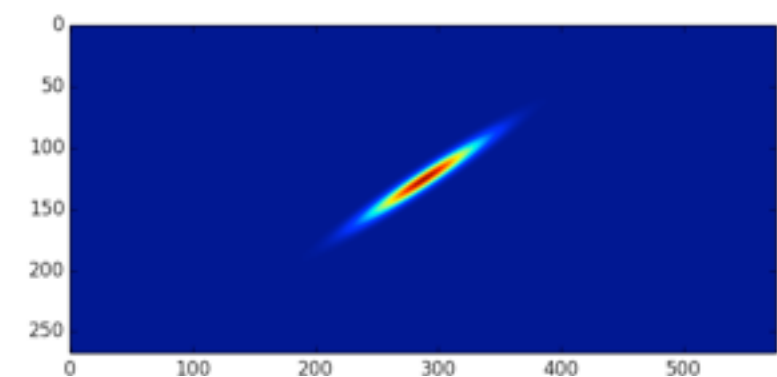
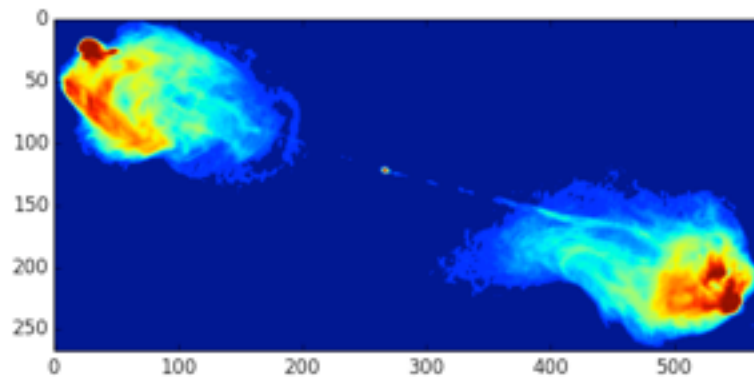


Reconstructed spectrum of S_0 v.s reference

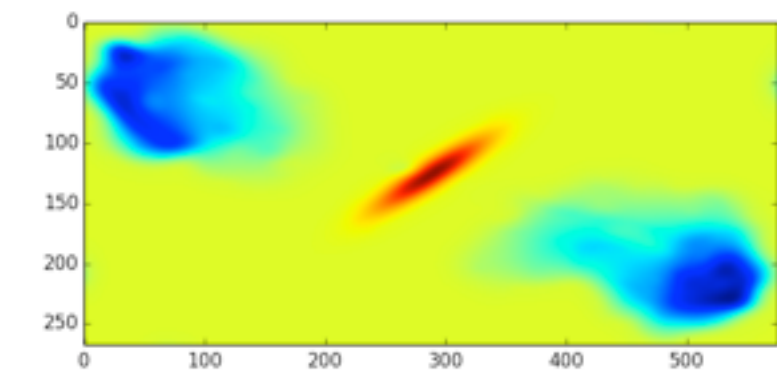
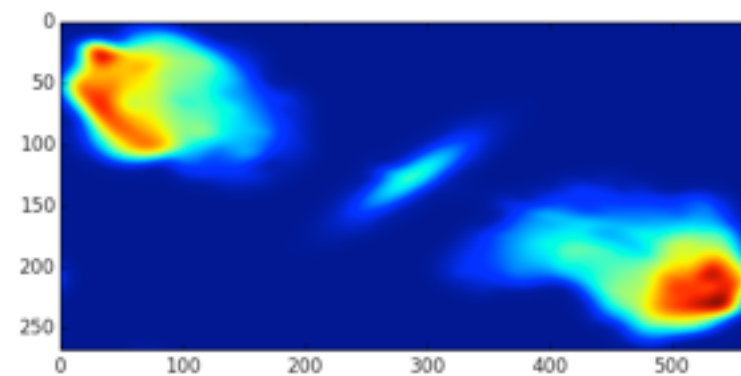


Reconstructed spectrum of S_1 v.s reference

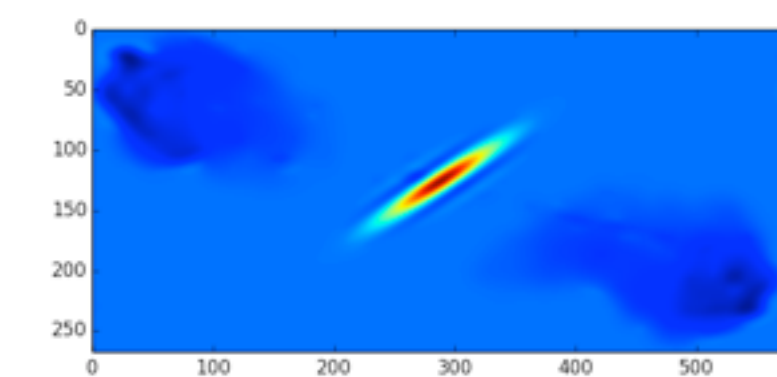
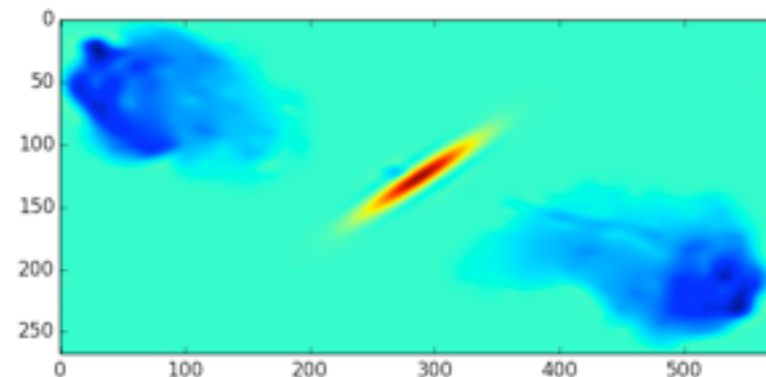
Model sources



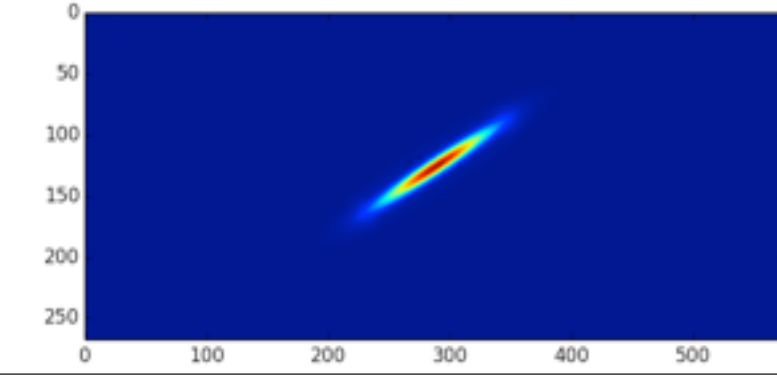
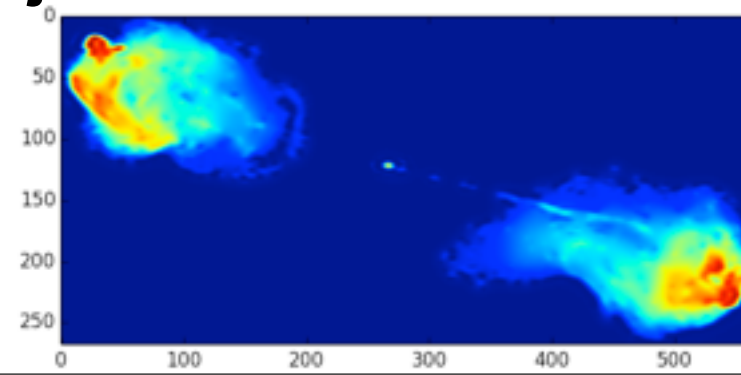
BSS only (GMCA), no deconvolution



Channel by channel deconvolution (ForWaRD) followed by a BSS (GMCA)



Our method fGMCA : joint BSS and deconvolution



Radio sources detection

- Transient study is active in radio astronomy, for the fast transient, detection tool is important
- Proof of compressed sensing concept on 2D image
- Extension to 2D-1D: applied to fast transients search with good angular resolution

Hyperspectral image restoration

- Multi or hyperspectral data generally present channels at different resolution. A rigorous Blind Source Separation method should take into account the different channel resolutions.
- fGMCA is an efficient method to solve jointly the BSS and the deconvolution problems.
- It is shown that taking into account joint BSS and deconvolution gives much better results than applying only a BSS or a channel per channel Deconvolution followed by a BSS.
- Application on radio images(LOFAR, SKA) on 3rd year, study of spectra of radio sources, etc.