A deconvolution scheme for the Murchinson Wide-field Array

Gianni Bernardi
Harvard-Smithsonian Center for Astrophysics
(team: L.J. Greenhill, D.A. Mitchell, S.M. Ord, M. Clark, R. Edgar)

The problem… (see previous Mitchell's talk)

- Well developed selfcalibration & deconvolution rely on ungridded visibilities (u)

- MWA generates time averaged images (up to 10 min)
  - accounting for position dependent synthesized beam
  - pixelization, loss of information limit to the dynamic range

- (you may think that) MWA images cannot be deconvolved, strictly speaking

The problem (cont'd)

Similarities with Rau's & Wijnholds' work

- FORWARD MODELING (FM) needed to subtract sources

▪ any generative model "independent" from the data and <u>related to astrophysical parameters</u>

▪ generate a sky model

▪ generate the model *u*'s (MAPS, Wayth et al. 2010)
  ▪ <u>including atmospheric and instrumental parameters</u>

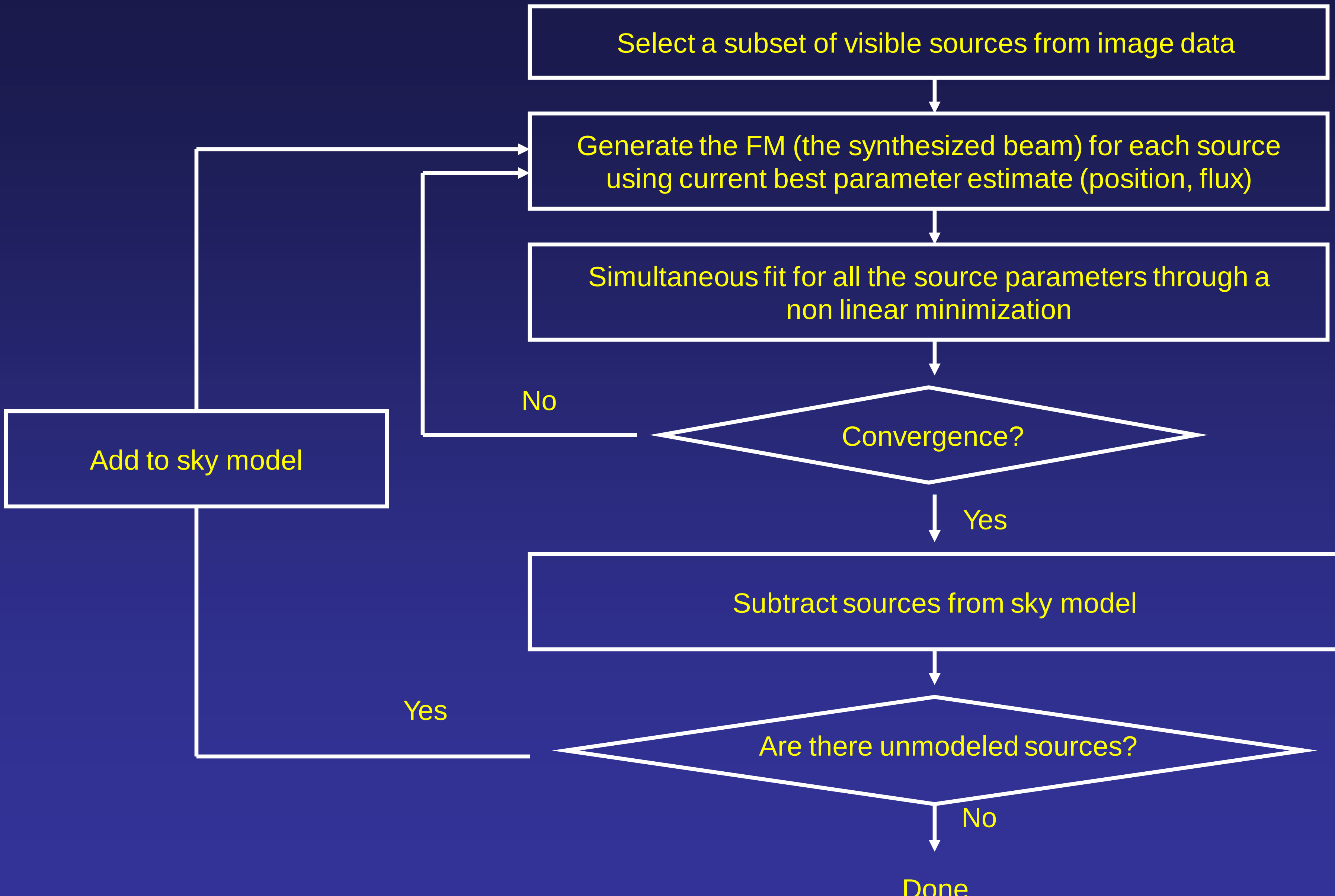
▪ propagate through imaging pipeline

▪ minimize the difference between the sky images and the forward model – fitting for astrophysical parameters & deconvolution

▪ FM is computationally expensive, but does not require original *u*'s

Application to point source deconvolution of MWA images

Flow chart


Select a subset of visible sources from image data
Generate the FM (the synthesized beam) for each source using current best parameter estimate (position, flux)
Simultaneous fit for all the source parameters through a non linear minimization
No
Convergence?
Yes
Add to sky model
Subtract sources from sky model
Yes
Are there unmodeled sources?
No
Done

Some math:

- for M sources and N image pixels, the following system of linear equations is solved at each iteration:

$$\delta x = (J^T W J)^{-1} J^T W \delta m$$

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vector of 3M parameter increments

N x 3M Jacobian matrix (partial derivatives of the FM with respect to the parameters)

Some math:

- for M sources and N image pixels, the following system of linear equations is solved at each iteration:

$$\delta x = (J^T W J)^{-1} J^T W \delta m$$

N x N pixel weight matrix

N-element vector of the difference between the data and the FM

Some math:

- for M sources and N image pixels, the following system of linear equations is solved at each iteration:

$$\delta x = (J^T W J)^{-1} J^T W \delta m$$

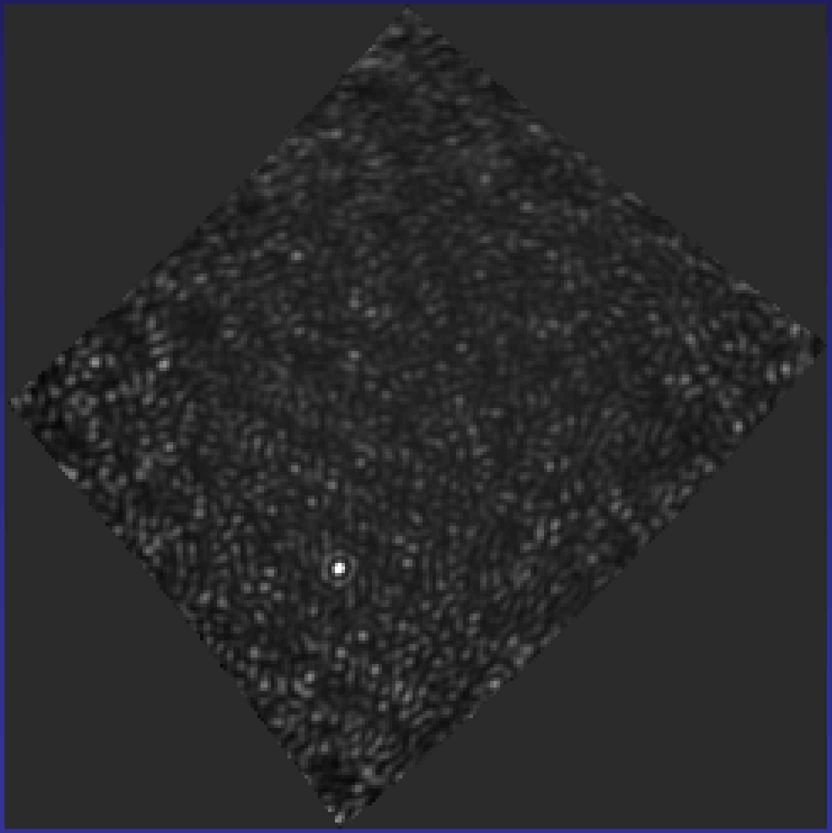
- get a new parameter estimate x_i:

$$x_i = x_{i-1} - \delta x$$

Case 1: 32T 10 min integration

- 16 sources, $S_\nu > 4$ Jy (LogN-LogS distributed)
- thermal noise
- one 40 kHz channel, 32T coverage
- $\alpha = 4^h \quad \delta = -30^\circ$; 20° field of view
- 10 min integration:
  - real-time accumulation of 8^s snapshots to 5^m (Healpix resampling)
  - co-add 5^m integrations to 10^m off-line
  - primary beam correction

Initial image
(16 sources + thermal noise)



Peak: 97 Jy

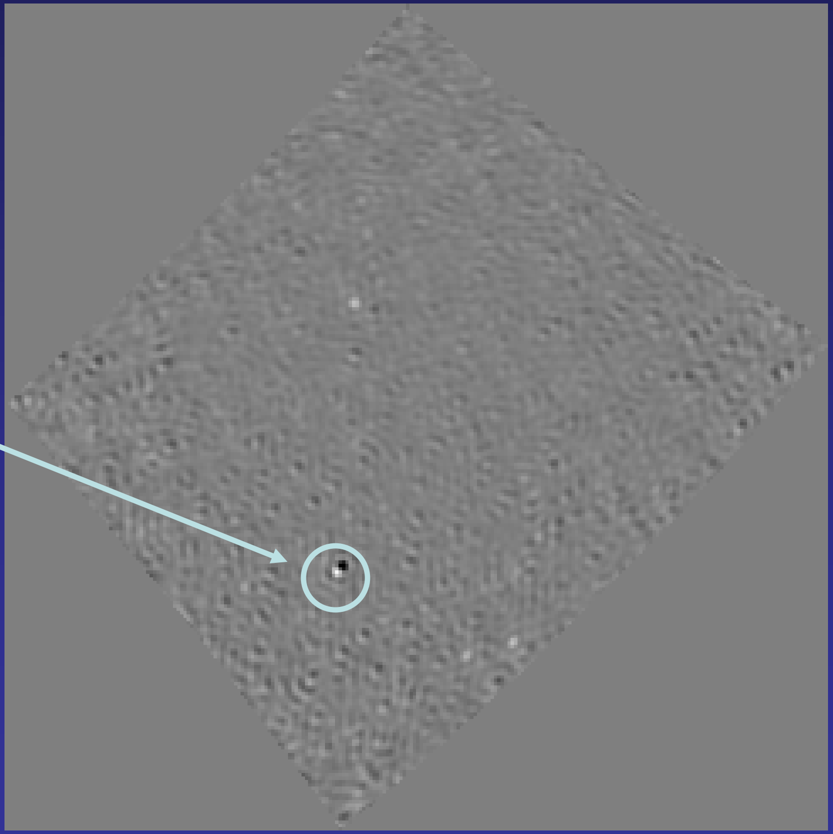
rms: 2.4 Jy/beam

DNR (apparent) ~ 35

One source visible

Initial parameter estimation and subtraction

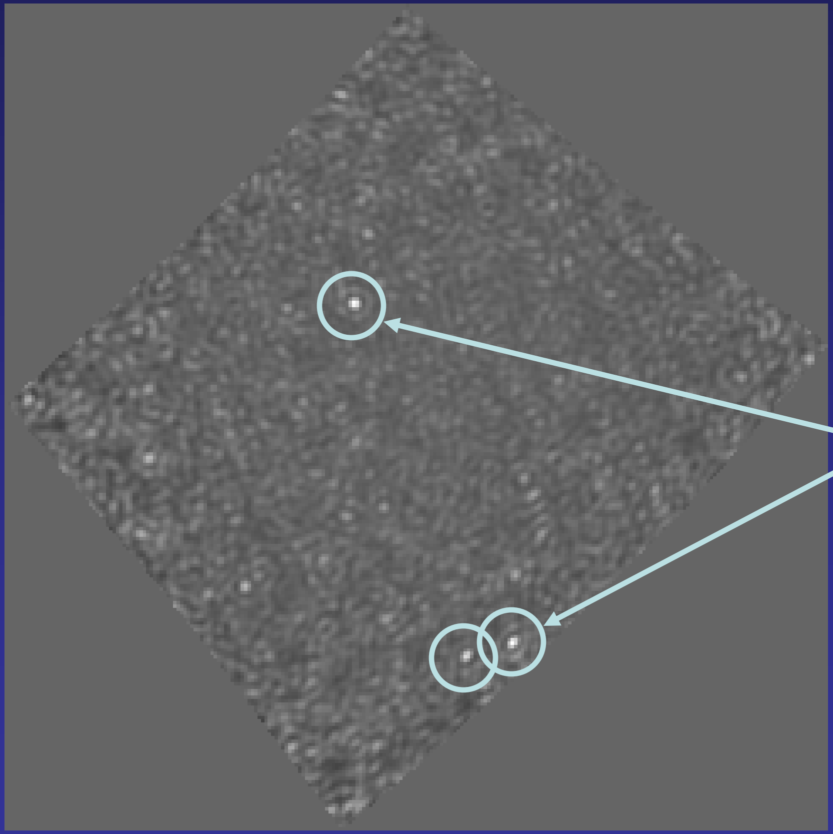
• estimate params. via Gaussian fit
• subtract (S-curve residual indicates pos'n err.)



• Generate the synthesized beam at the estimated position

• Minimize

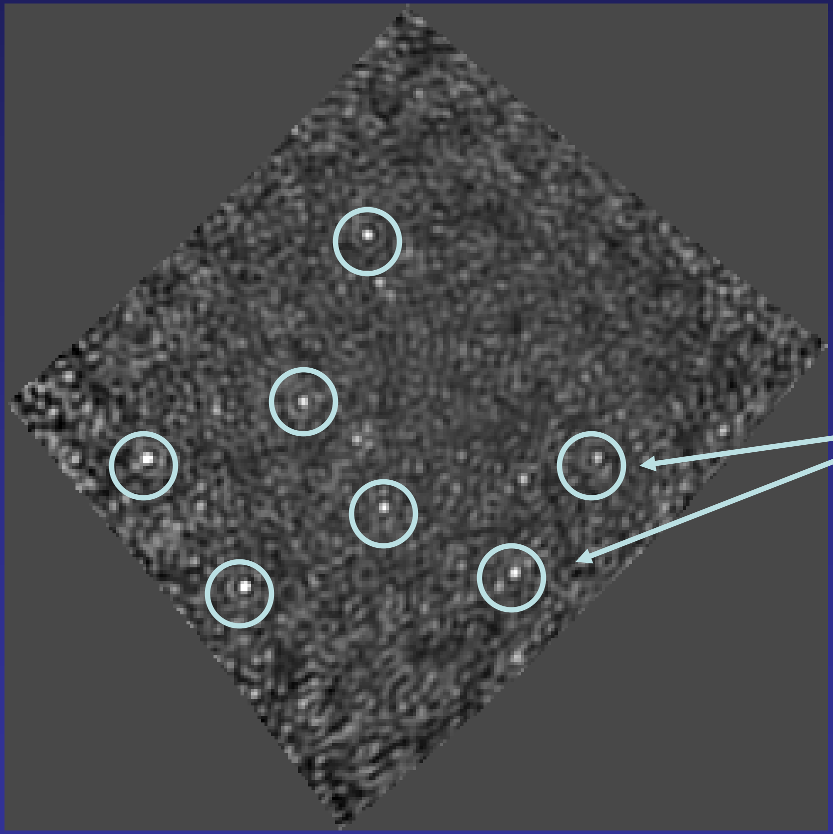
Non linear minimization for the brightest source (3 iterations)



Peak ~ 20 Jy

Fainter sources appear

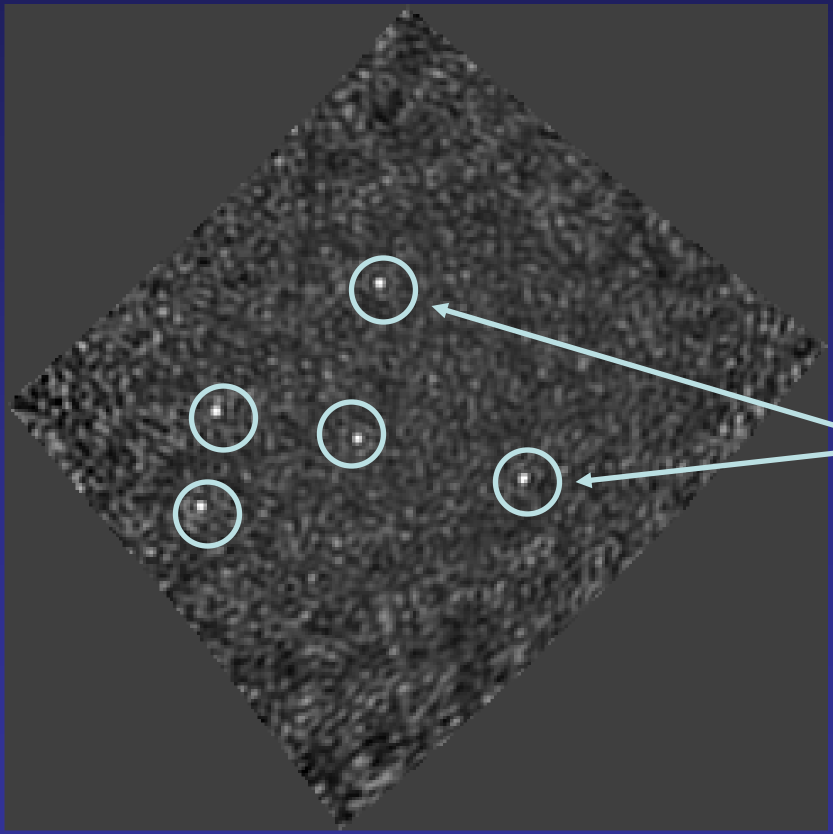
Non linear minimization for the 4 brightest sources (3 iterations)



Peak ~ 8 Jy

Fainter sources appear

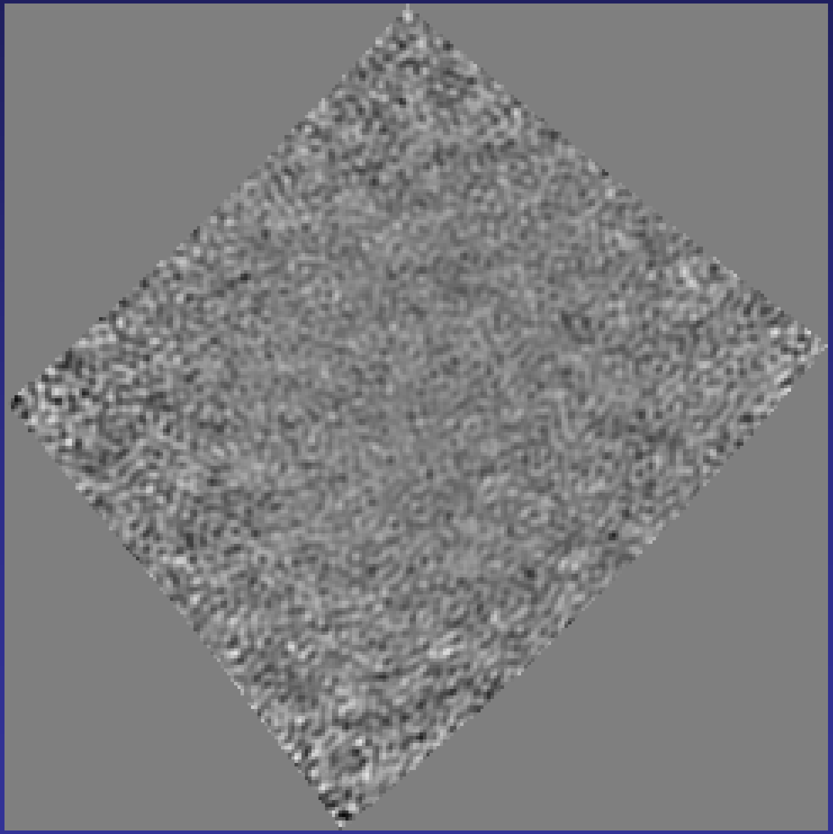
Non linear minimization for the 11 brightest sources (3 iterations)



Peak ~ 4 Jy

Fainter sources appear

Non linear minimization for all the 16 brightest sources (3 iterations)



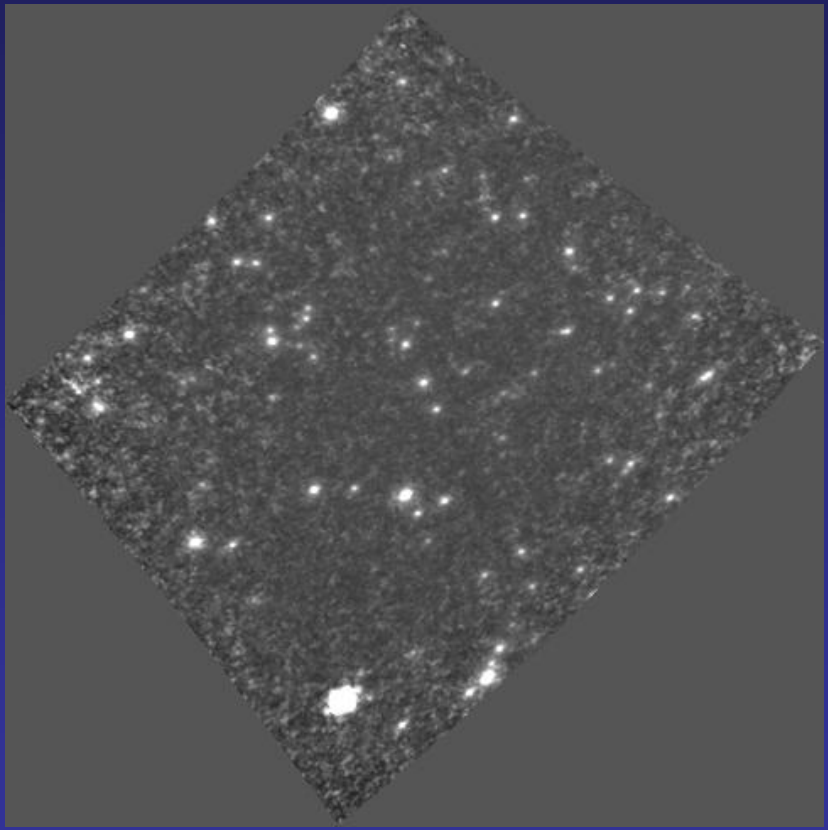
rms ~ 52 mJy/beam

final DNR ~ 1900

Case 2: 512T 8 sec integration

- 101 sources, $S_\nu > 1$ Jy (LogN-LogS distributed)
- thermal noise
- one 40 kHz channel, 512T coverage
- $\alpha = 4^h$ $\delta = -30^\circ$; 20° field of view
- 8 sec integration:
  - Healpix resampling
  - primary beam correction

Initial image
(101 sources + thermal noise)



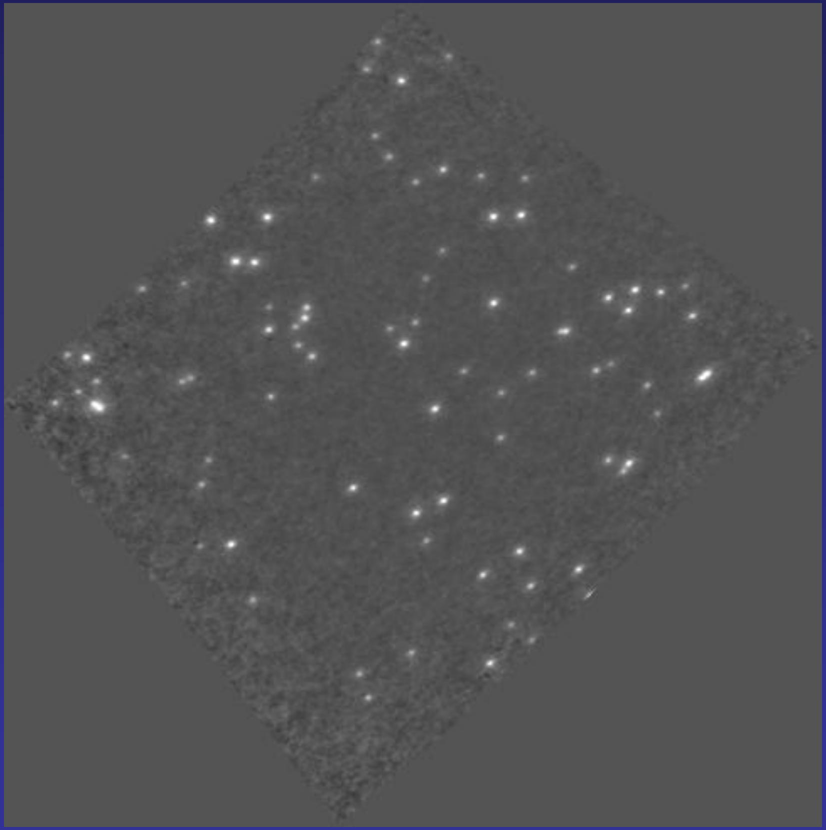
Peak: 87 Jy

rms: 105 mJy/beam

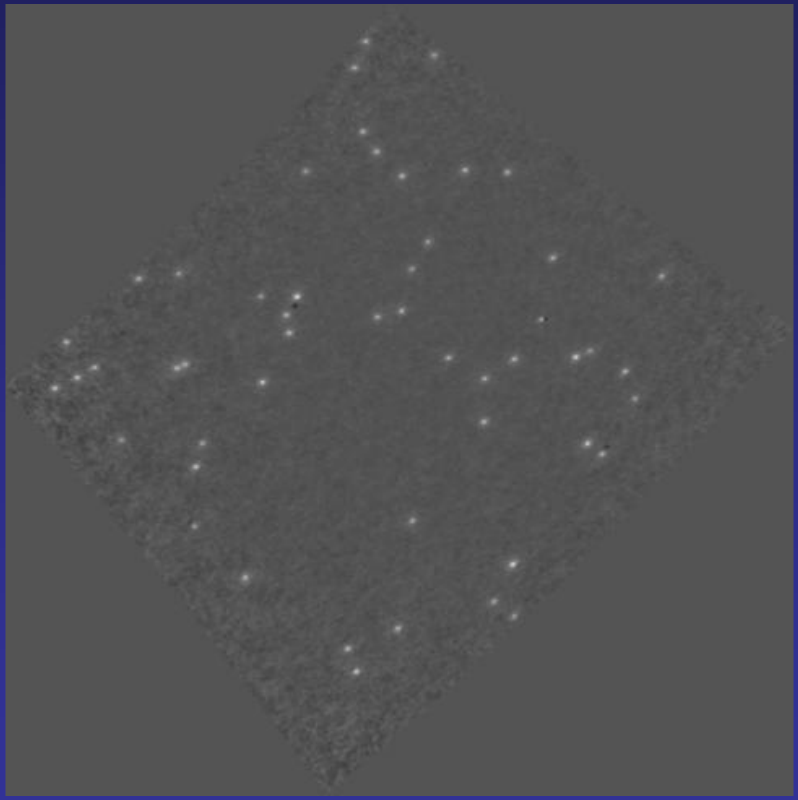
DNR (apparent) ~ 800

Many sources visible

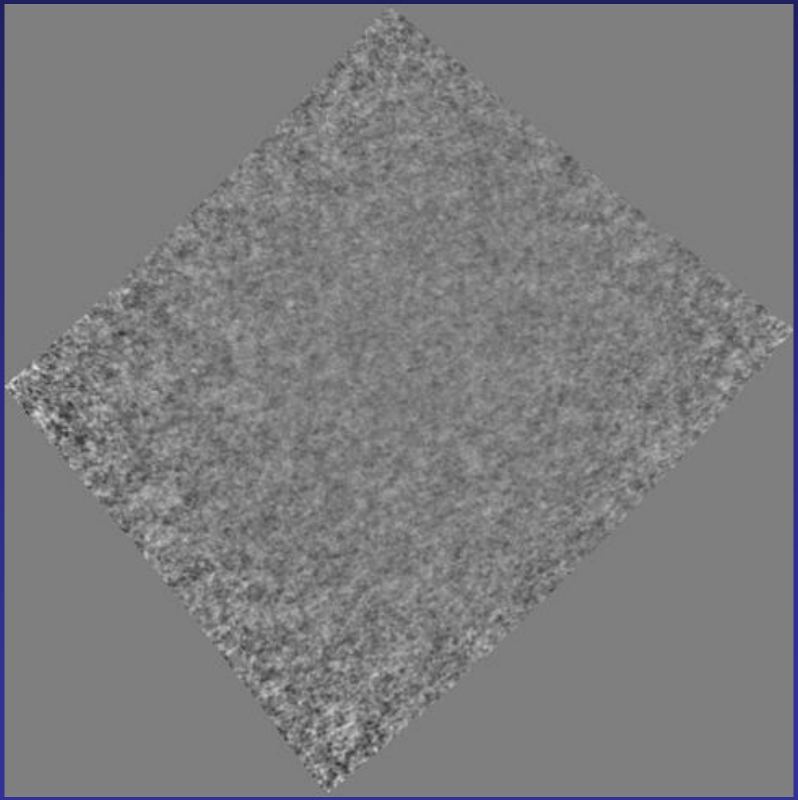
Non linear minimization for the 15 brightest sources (5 iterations)



Non linear minimization for the 50 brightest sources (5 iterations)



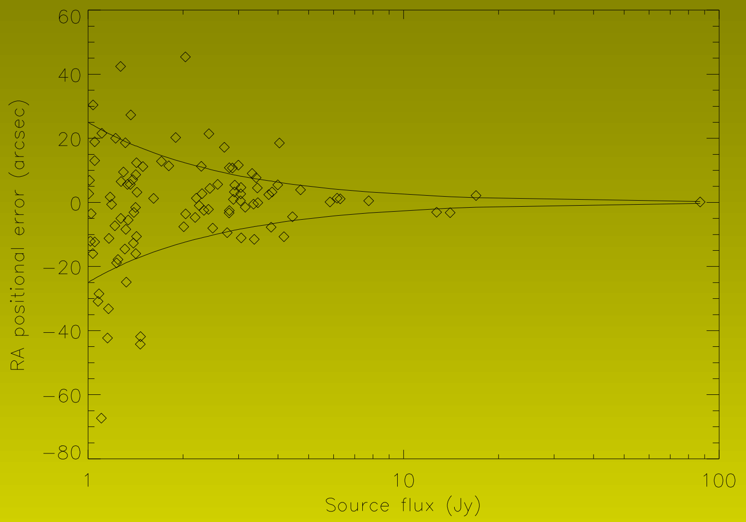
Non linear minimization for all the 101 sources (5 iterations)

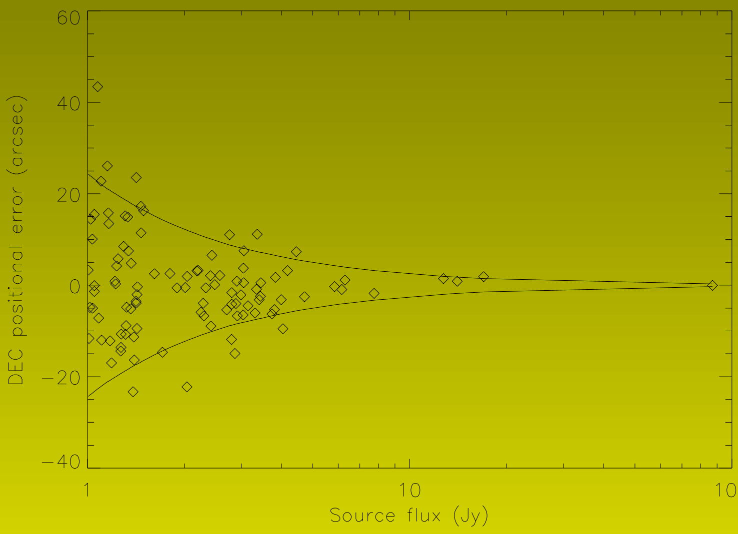


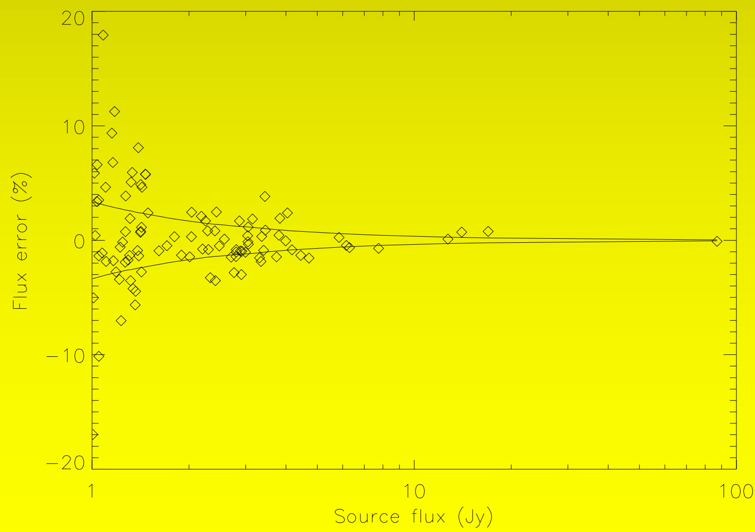
rms ~ 25 mJy/beam

final DNR ~ 3500

How good is FM?

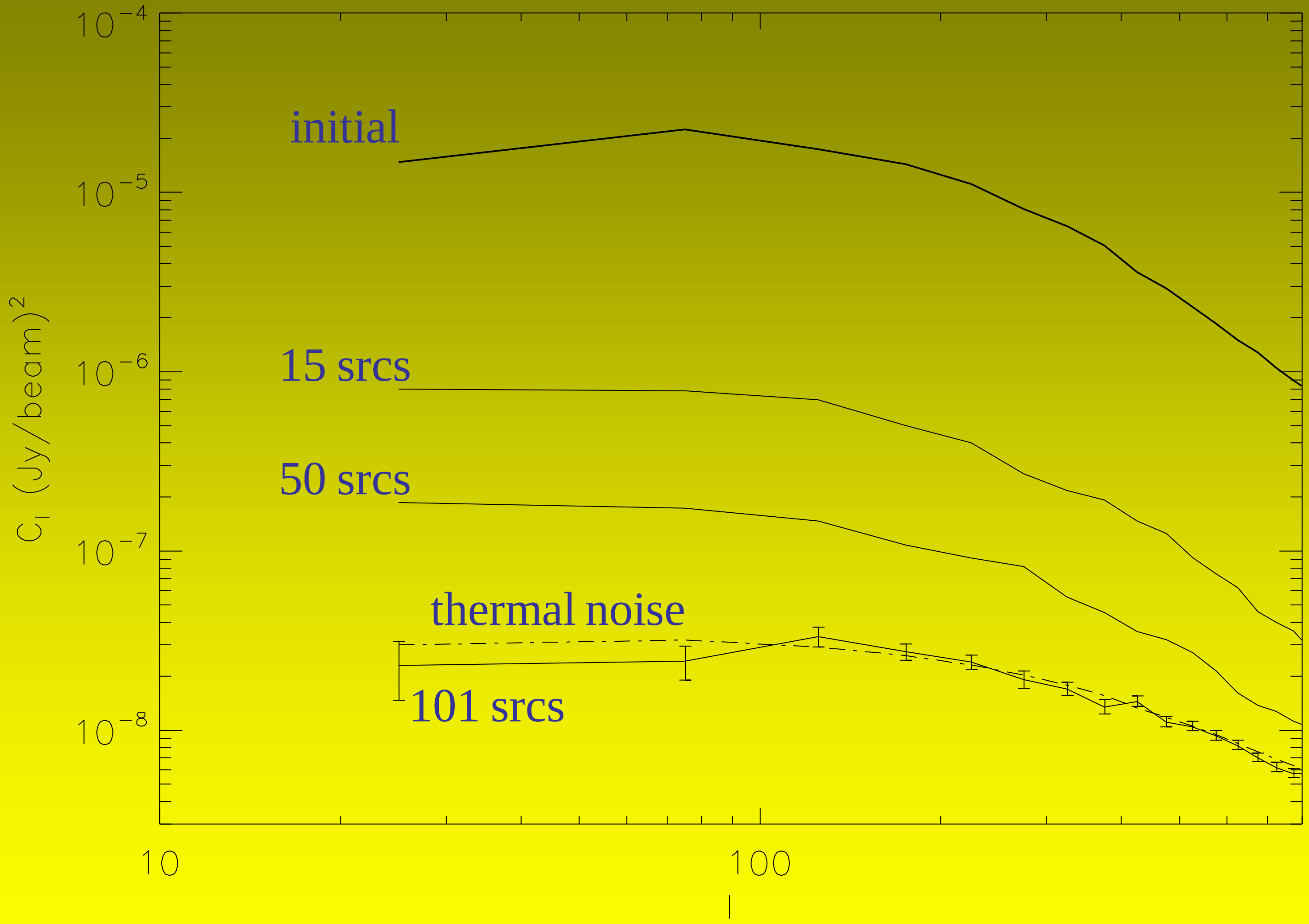






Basically signal-to-noise limited!

How good is FM?



Case 3: out of beam sources

- 7 sources, S_ν > 6 Jy (LogN-LogS distributed, the brightest sources of the previous 512T simulation): 5 within the field of view and 2 outside (out-of-beam sources)

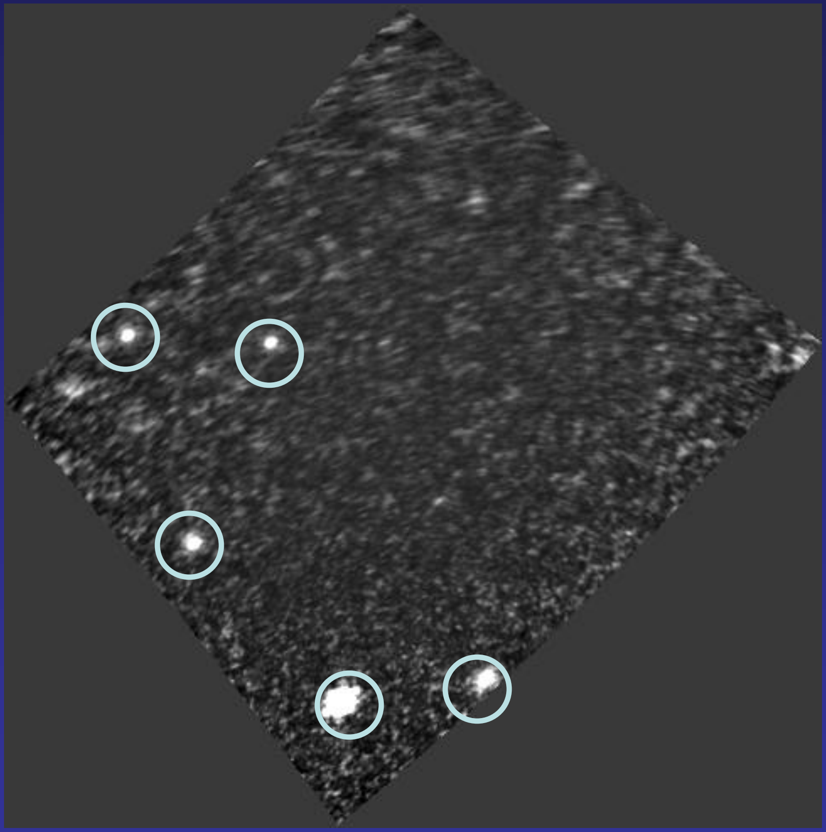
- thermal noise

- one 40 kHz channel, 512T coverage

- $\alpha = 4^h$ $\delta = -30^\circ$; 20° field of view

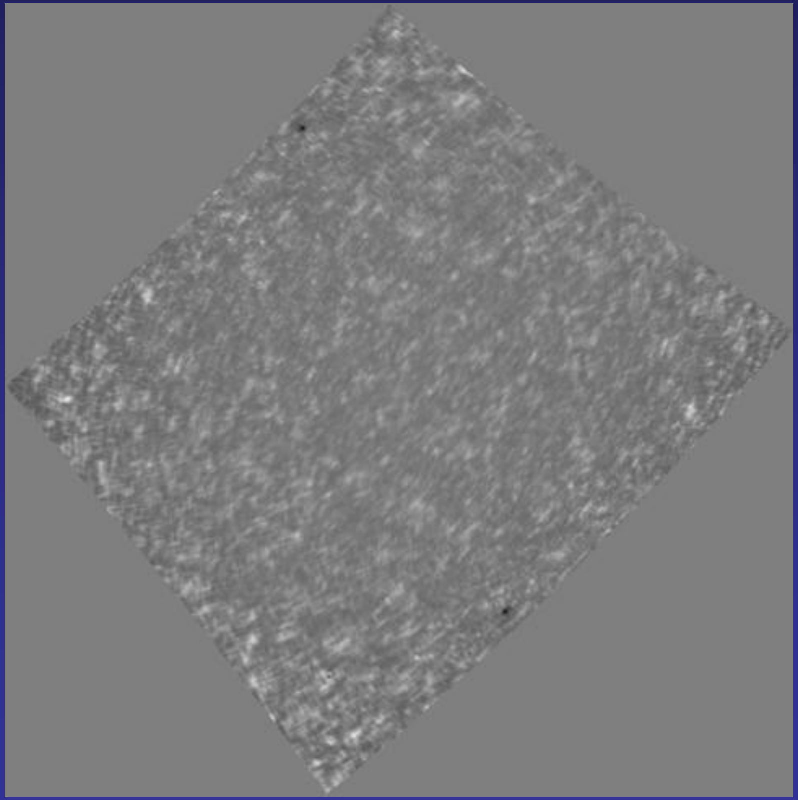
- 10 min integration:
  - real time accumulation of 8^s snapshots to 5^m (Healpix resampling)
  - co-add 5^m integrations to 10^m off-line
  - primary beam correction

Initial image
(7 sources + thermal noise)



Peak: 87 Jy

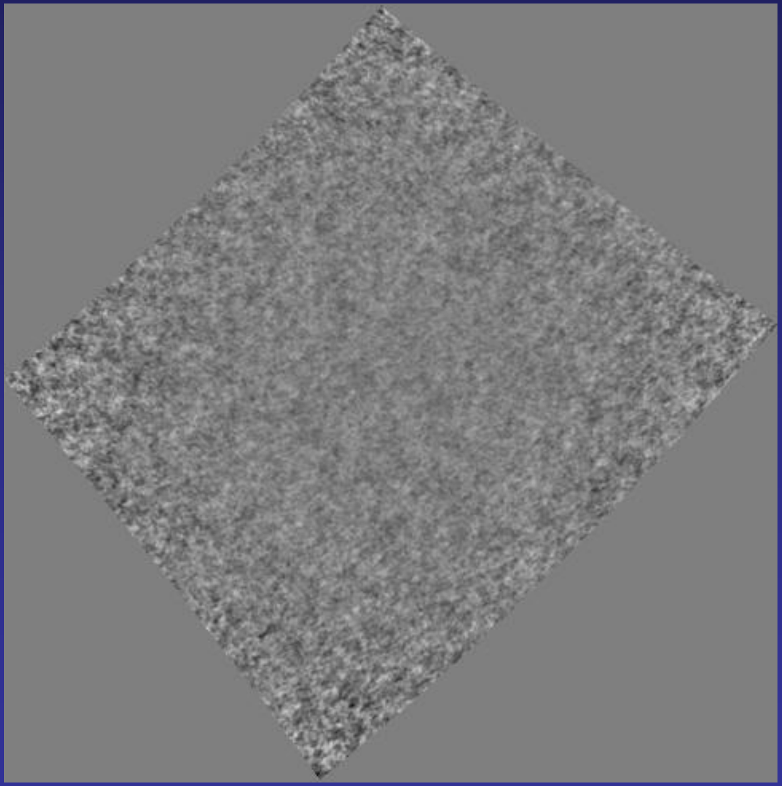
Non linear minimization for the 5 visible sources (5 iterations)



rms: ~14 mJy/beam

the sidelobes of the out-of-beam sources run through the image

Non linear minimization for the 5 visible + 2 oob sources (5 iterations)



rms: ~2.8 mJy/beam
DNR improvement of a factor of ~5

Conclusions

- MWA cannot rely on a traditional selfcalibration & deconvolution
- algebraic non linear minimization can service forward modeling – complement to peeling in visibility space
- demonstrated for point sources in simulated images
  - parameter errors limited by SNR
  - power spectrum consistent with thermal noise
- minimally sensitive to sidelobe contamination
  - all sources fit simultaneously
- natural extension to multi-frequency data, diffuse (localized and non) emission, polarized emission.
- next application to 32T survey data

Thank you!