Introduction to imaging and self-calibration

Cristiana Spingola

Italian National Institute for Astrophysics (INAF)
Institute for Radioastronomy, Bologna (Italy)

JIVE VLBI SCHOOL 15-19 SEPTEMBER 2025

INAF
ISTITUTO NAZIONALE
DI ASTROFISICA

INTRODUCTION TO IMAGING

The output of an interferometer is basically a table of the correlation (amplitude & phase) measured on each baseline every few seconds.

INTRODUCTION TO IMAGING

The output of an interferometer is basically a table of the correlation (amplitude & phase) measured on each baseline every few seconds.

To get the final image out of our visibilities the steps are:

1) Calibration and data editing (lectures and hands-on so far!)

2) Deconvolution = making CLEANed images and models of your source (this talk)

3) Refining the phase and amplitude calibration using a model of the source = self-calibration (next talk)

BASICS OF IMAGING: FOURIER TRANSFORM

S = sampling function
= 1 where there is a measurement in the uv plane
= 0 otherwise

B = Intrinsic source brightness distribution

Convolution

D = dirty beam = point spread function (PSF)

S = Sampling function

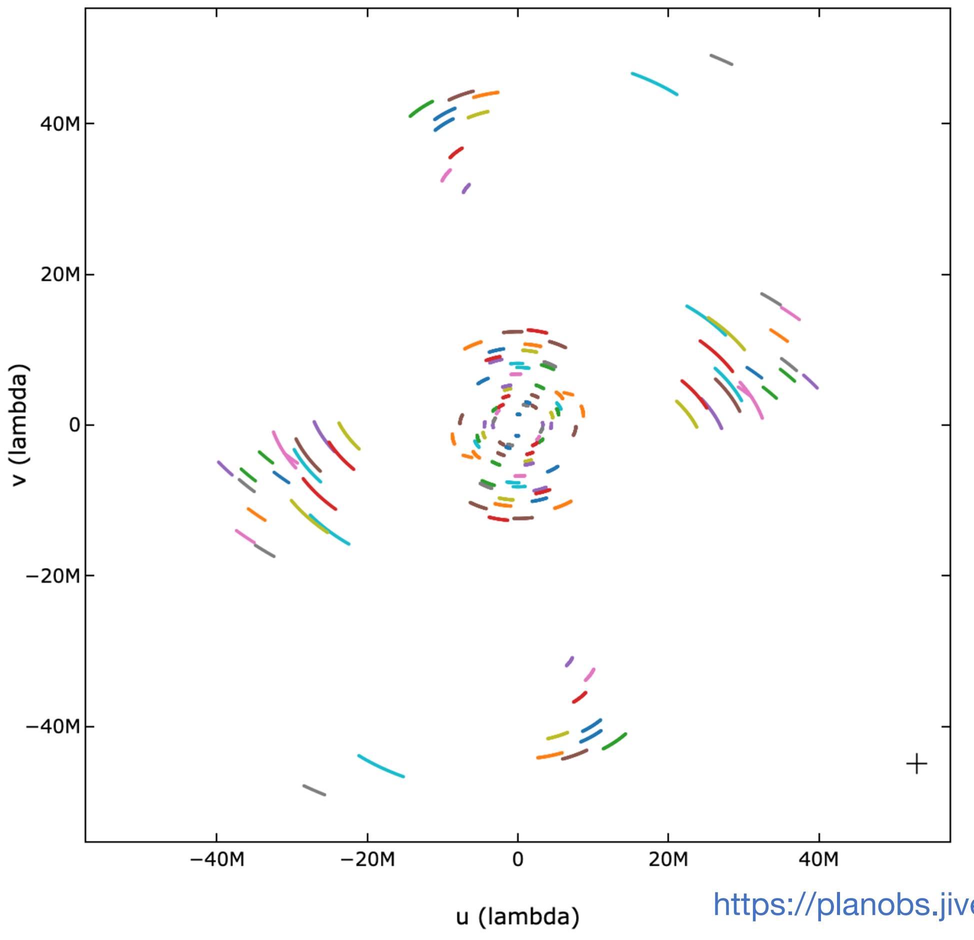
V = True visibilities

Dirty image = $$B(l,m) * D(l,m) \approx \iint_{uv} S(u,v)V(u,v)e^{2\pi i(ul+vm)}dudv$$

$$D(l,m) = \iint_{uv} S(u,v)e^{2\pi i(ul+vm)}dudv$$

Dirty beam D(l,m) = Fourier transform of the sampling function
We know D(l,m) !!!

We need to **deconvolve** B(l,m) from the dirty beam D(l,m)



1 h EVN

https://planobs.jive.eu/

BASICS OF IMAGING: FT and uv-coverage

B = Intrinsic source brightness distribution

D = dirty beam = point spread function (PSF)

S = Sampling function

V = True visibilities

Convolution

$$\text{Dirty image} = B(l,m) * D(l,m) \approx \iint_{uv} S(u,v)V(u,v)e^{2\pi i(ul+vm)}dudv$$

$$D(l,m) = \iint_{uv} S(u,v)e^{2\pi i(ul+vm)}dudv$$

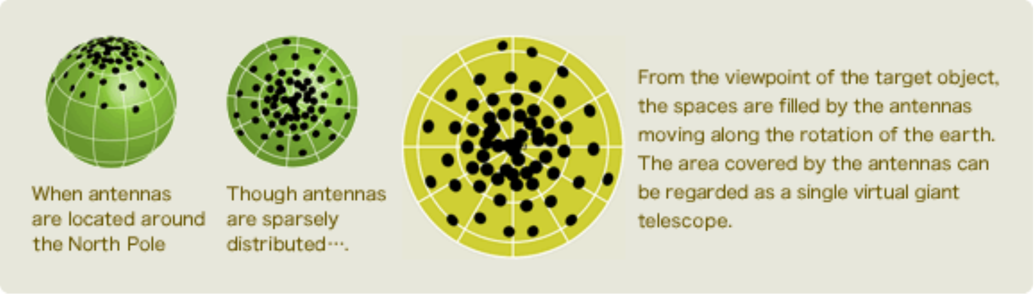
Dirty beam D(l,m) = Fourier transform of the sampling function

An ideal interferometer would deliver
on a regularly highly sampled rectangular grid.
An image of would then be made by simply applying
a Fourier transform

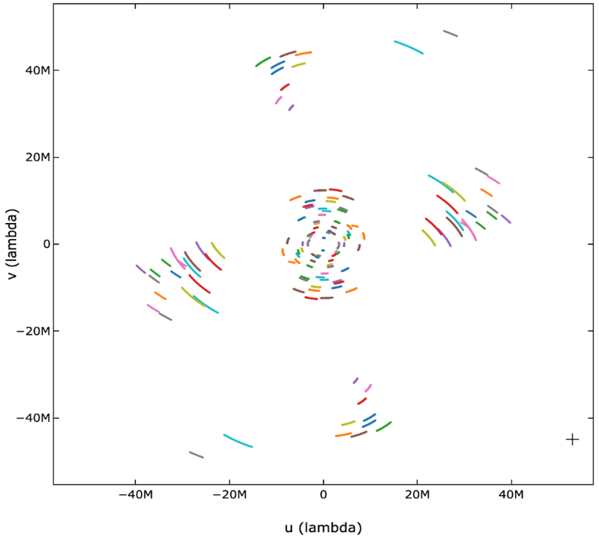
But, arrays provide typically poorly sampled Fourier Transform of the radio brightness region of sky

You need as many V(u,v) points as possible to reconstruct as robustly as possible the surface brightness distribution of the source

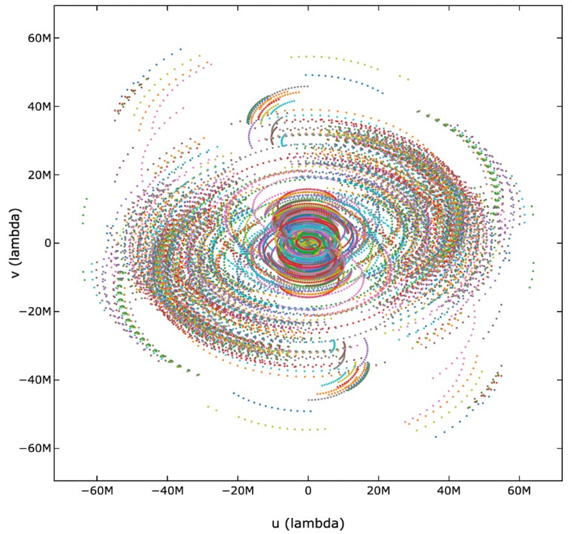
S = sampling function
= 1 where there is a measurement in the uv plane
= 0 otherwise



Credits: B. Koberlein



1 h
<10 antennas



12 h
>30 antennas

https://planobs.jive.eu/

BASICS OF IMAGING: FT and uv-coverage

B = Intrinsic source brightness distribution

S = Sampling function

D = dirty beam = point spread function (PSF)

V = True visibilities

Convolution

Dirty image = $$\mathrm{B}(l,m) * \mathrm{D}(l,m) \approx \iint_{uv} \mathrm{S}(u,v)\mathrm{V}(u,v)e^{2\pi i(ul+vm)}dudv$$

$$\mathrm{D}(l,m) = \iint_{uv} \mathrm{S}(u,v)e^{2\pi i(ul+vm)}dudv$$

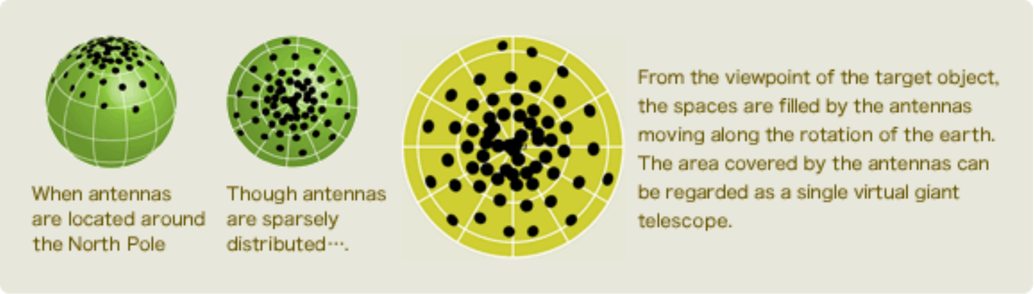
Dirty beam D(l,m) = Fourier transform of the sampling function

An ideal interferometer would deliver
on a regularly highly sampled rectangular grid.
An image of would then be made by simply applying
a Fourier transform

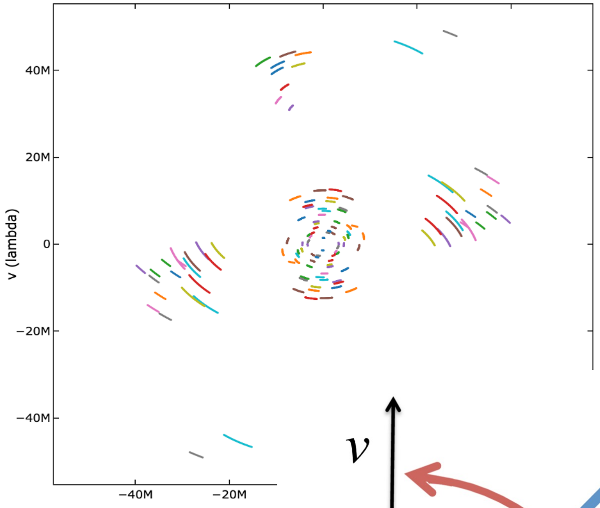
But, arrays provide typically poorly sampled Fourier Transform of the radio brightness region of sky

You need as many V(u,v) points as possible to reconstruct as robustly as possible the surface brightness distribution of the source

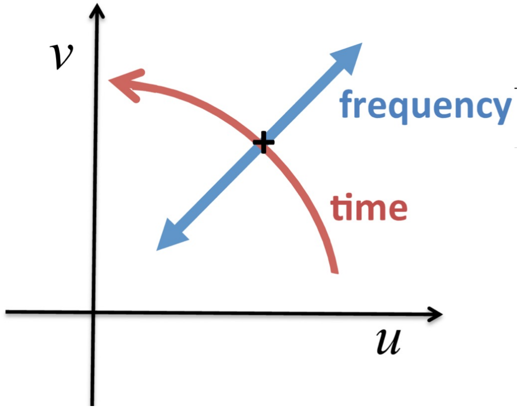
S = sampling function
= 1 where there is a measurement in the uv plane
= 0 otherwise

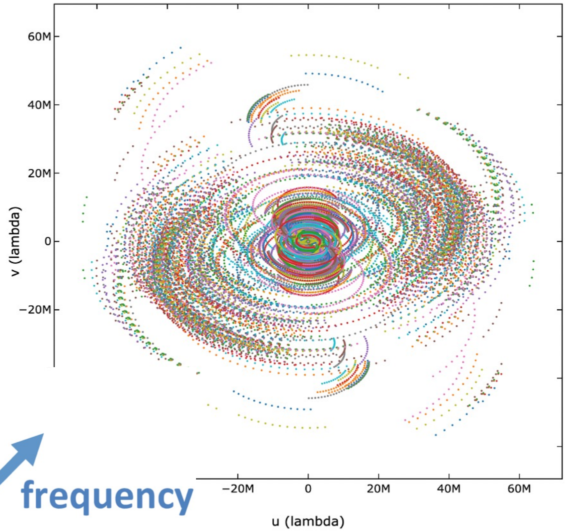


Credits: B. Koberlein



1 h
<10 antennas

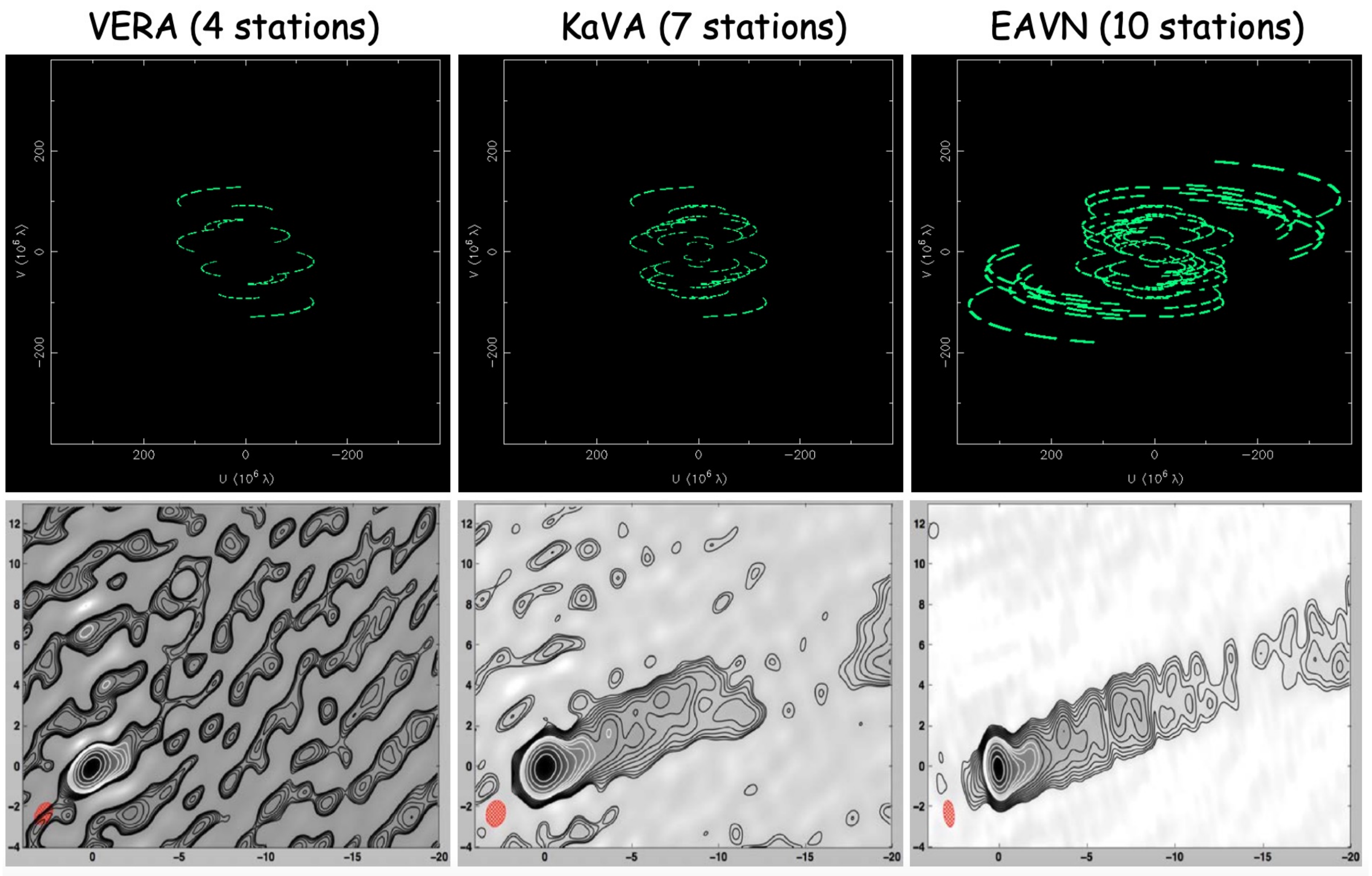




12 h
>30 antennas

https://planobs.jive.eu/

BASICS OF IMAGING: FT and uv-coverage

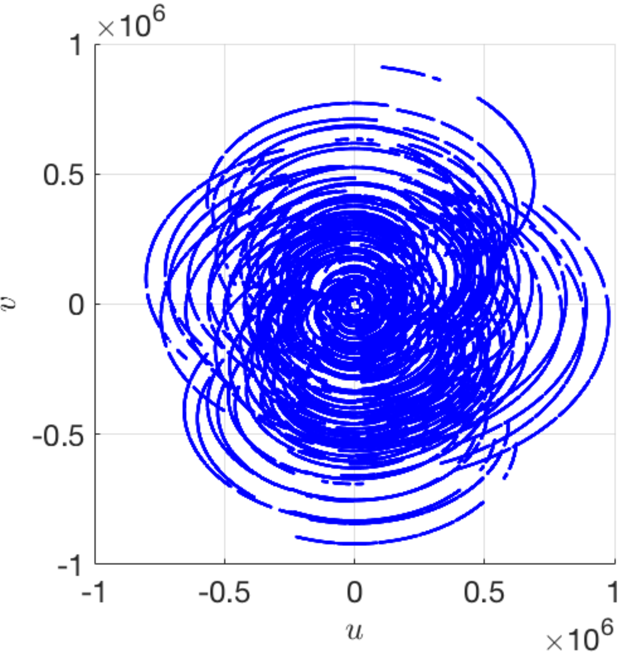


Credits: Prof. Kazuhiro Hada

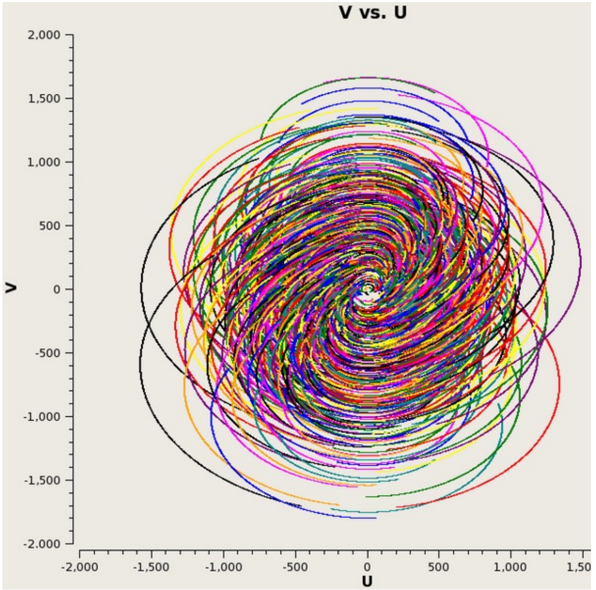
A good uv-coverage is crucial for recovering extended structures

BASICS OF IMAGING: FT and uv-coverage

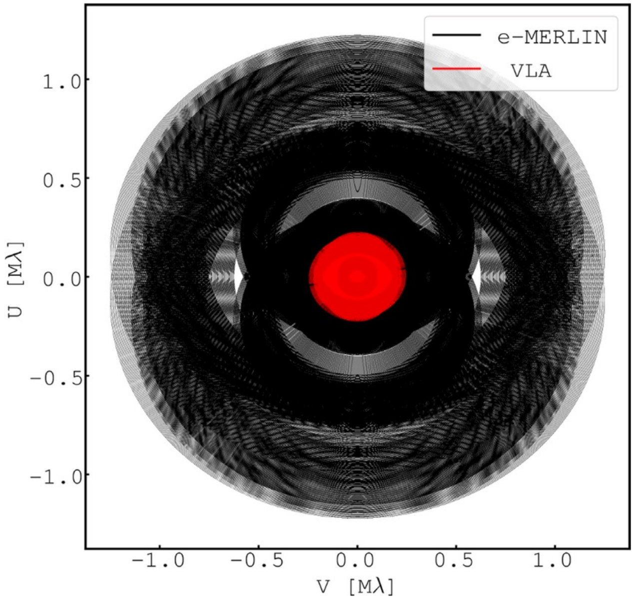
Full-track 8.4 GHz VLA
(A. Abdulaziz PhD thesis)

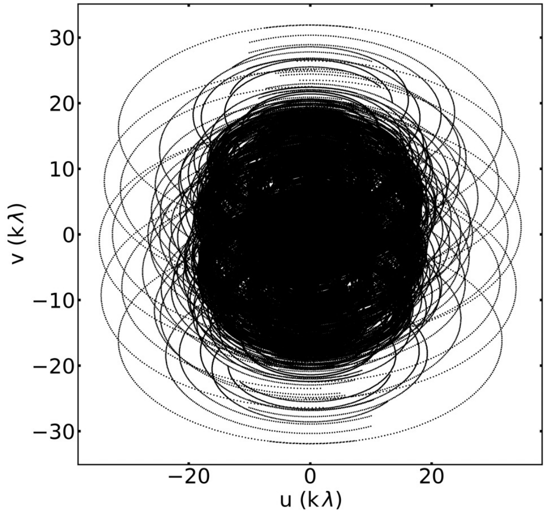


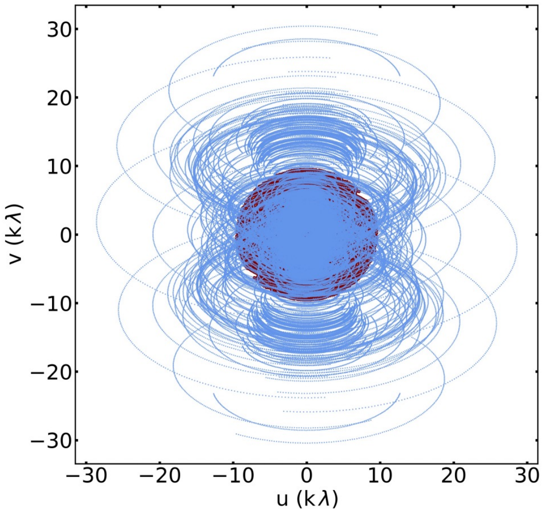
8hr ALMA
Credits: CASA guide



e-MERGE survey
MERLIN+VLA full-track
(Muxlow et al. 2020)





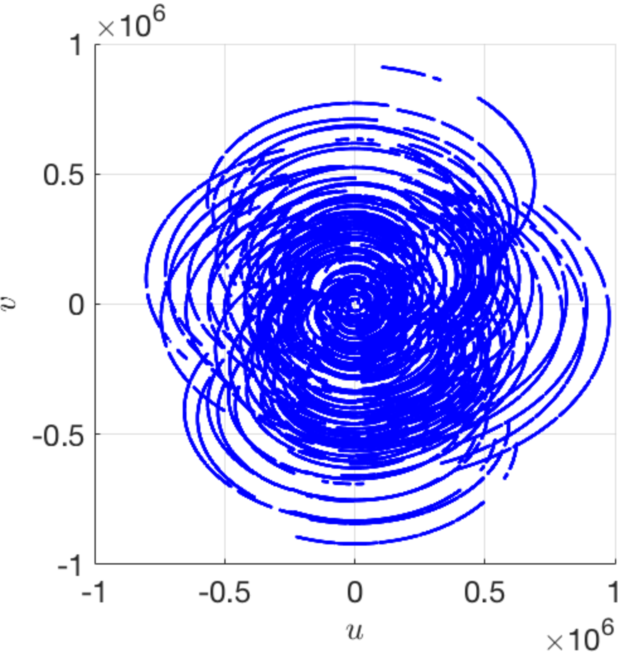


Impressive MeerKAT and ASKAP uv-coverage

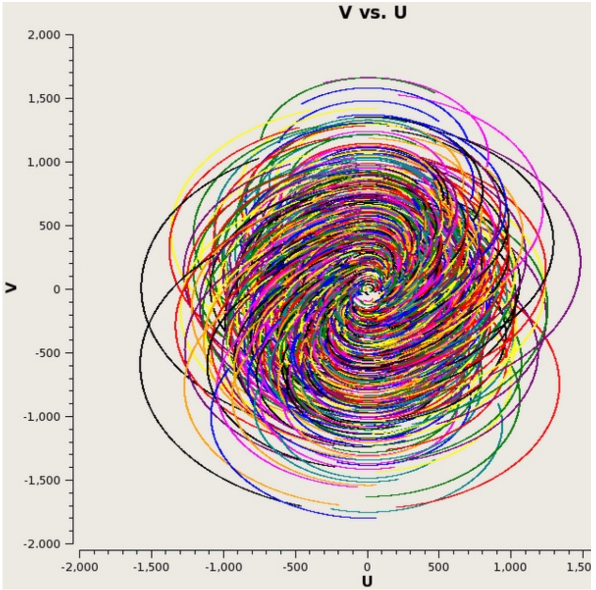
(Bharti et al. 2023)

BASICS OF IMAGING: FT and uv-coverage

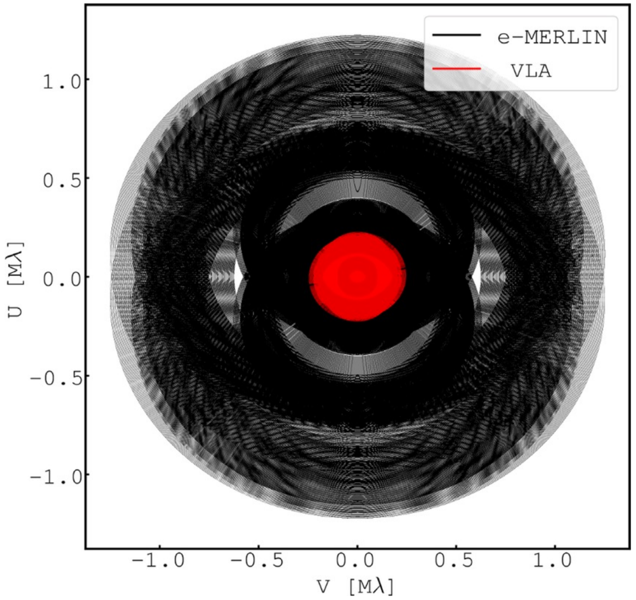
Full-track 8.4 GHz VLA
(A. Abdulaziz PhD thesis)



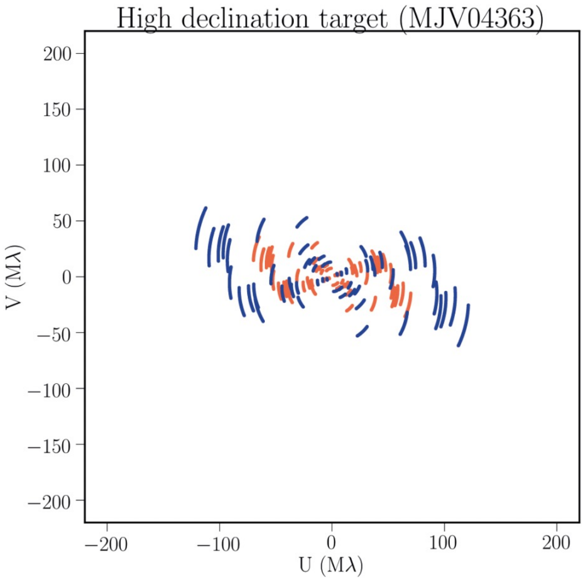
8hr ALMA
Credits: CASA guide

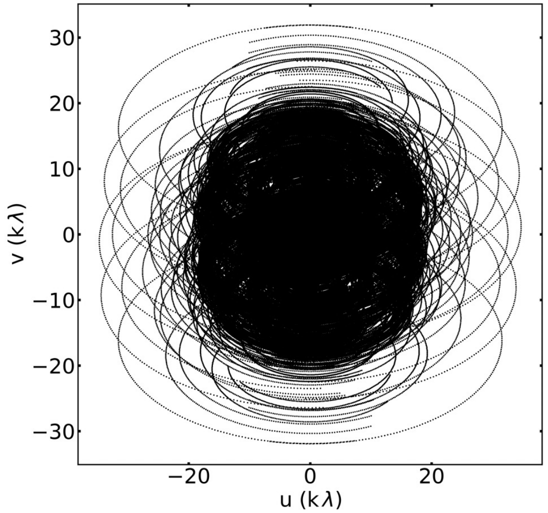


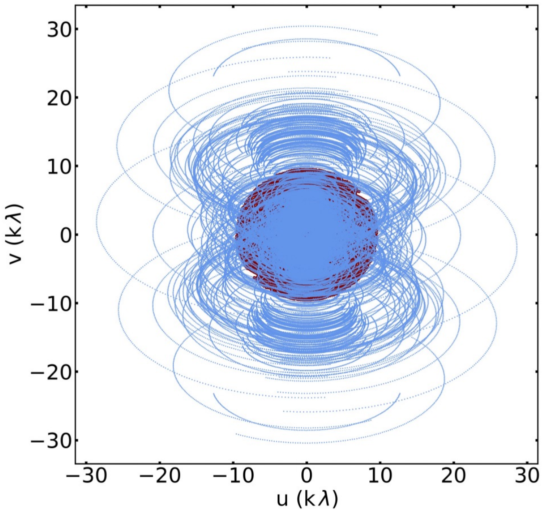
e-MERGE survey
MERLIN+VLA full-track
(Muxlow et al. 2020)



1.5h VLBA L-band
(Spingola et al. 2019a)







Impressive MeerKAT and ASKAP uv-coverage

(Bharti et al. 2023)

BASICS OF IMAGING: gridding

… but there will always be gaps in the uv-plane!
But well filled uv-coverages mitigates this

Two approaches

1) **Direct Fourier Transform (DFT)** = FT evaluated at every point of a rectangular grid – $O(N^2)$ operations

Impractical for a large number of visibilities

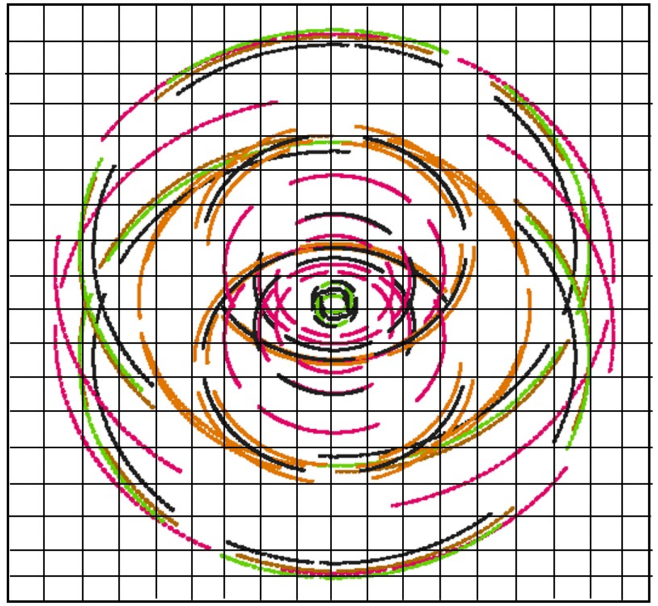
2) **Fast Fourier Transform (FFT)** = interpolate the data onto a rectangular grid – $O(N \log N)$ operations

It saves a lot of computing time!!

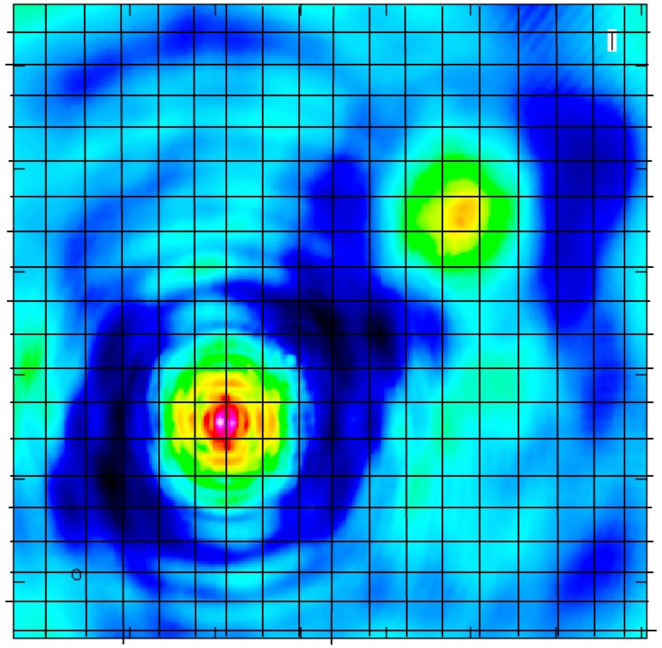
This FFT method requires the observed visibilities to be interpolated on a **regular grid**.

Usually we define the grid in the image plane, where **grid spacing = pixel size**

Field of view is defined by the primary beam
(~ λ/D where D is the diameter of the antenna)



NxN grid

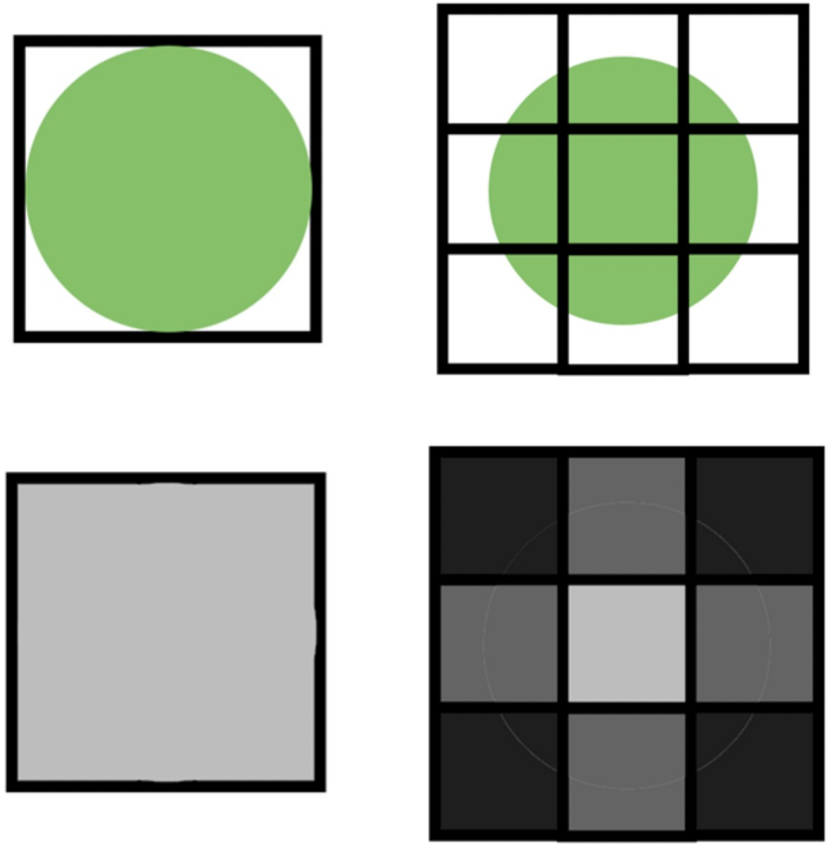


BASICS OF IMAGING: choice of pixel scale

Nyquist sampling theorem in astronomical terms:
The FWHM of the PSF should be sampled by at three least pixels

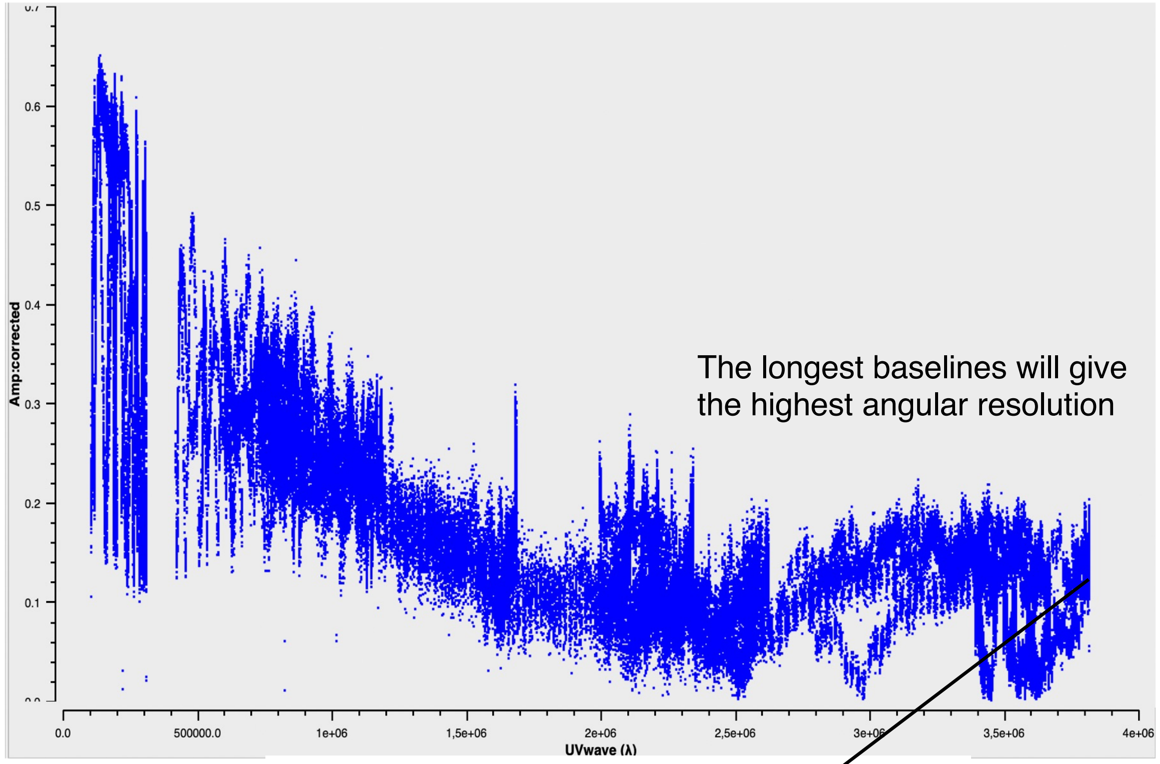
PSF relative to pixels

Output pixels (image)



Credits: HySpex

*Nyquist sampling theorem in **radioastronomical** terms:*

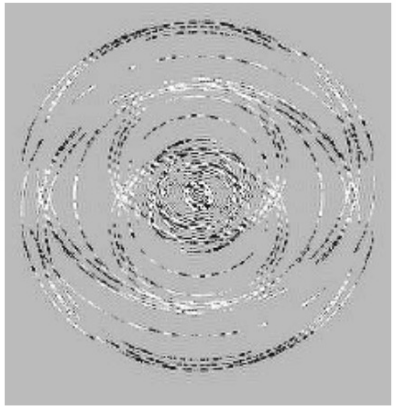


$$\text{cell} \approx \frac{180}{\pi N_s} \times \frac{1}{D_{\max}\,[\lambda]}\ [\text{deg}]$$

N_s at least 3, but typically 5 or 7
(an odd number because the peak needs to correspond to a single pixel)

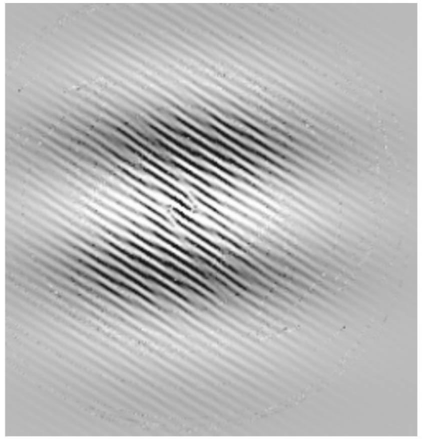
THE NEED FOR DECONVOLUTION

Sampled visibilities V'(u,v)



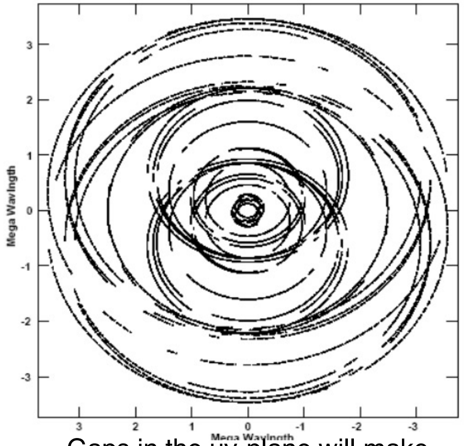
=

True visibilities V(u,v)



X

Sampling function S(u,v)

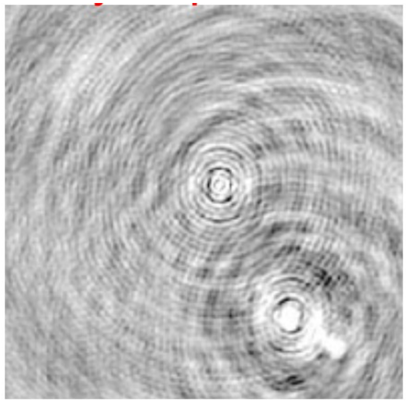


Gaps in the uv-plane will make sidelobes in the dirty beam

«Visibility domain» FT^{-1} FT

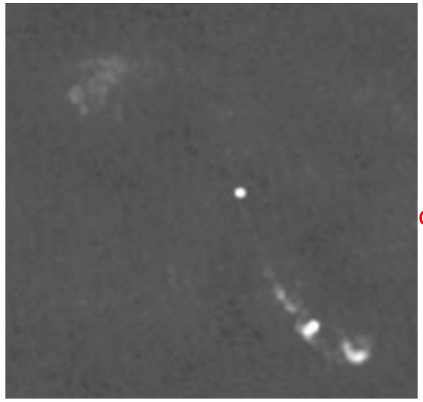
«Image domain»

Dirty image B' (l,m)



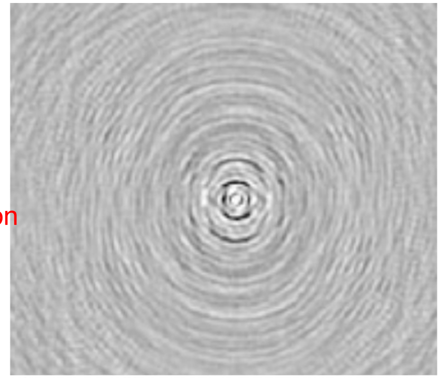
=

True sky B (l,m)



* convolution

Dirty beam D(l,m)



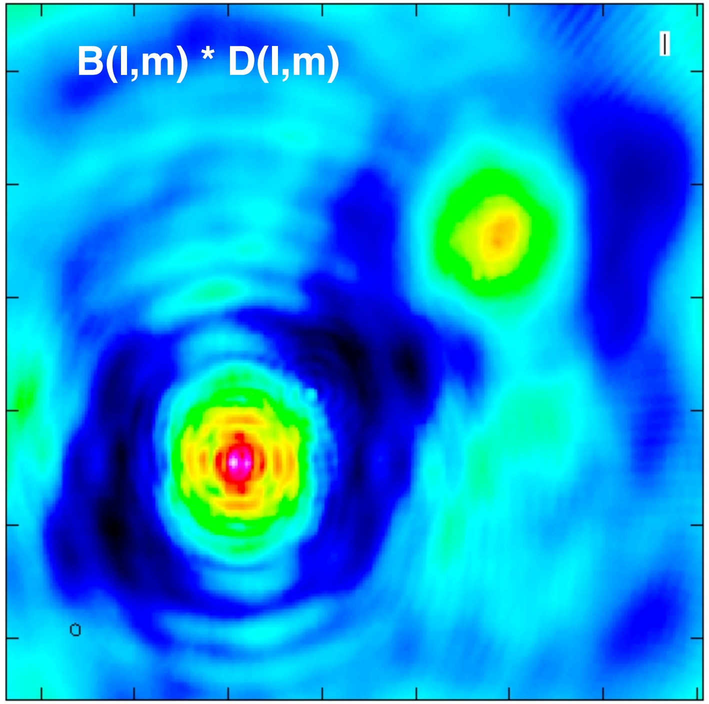
The dirty image is not the true image of the source, since **the sampled visibilities are not the true visibilities**

Corrections of the effect of Fourier sampling deficiencies on the dirty image = CLEAN algorithms

Original slide from Prof. Garrington ERIS 2017

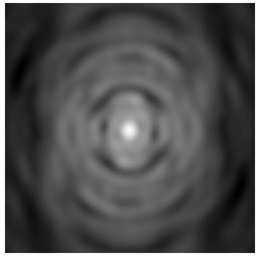
DECONVOLUTION

….Why do we need all of this again?



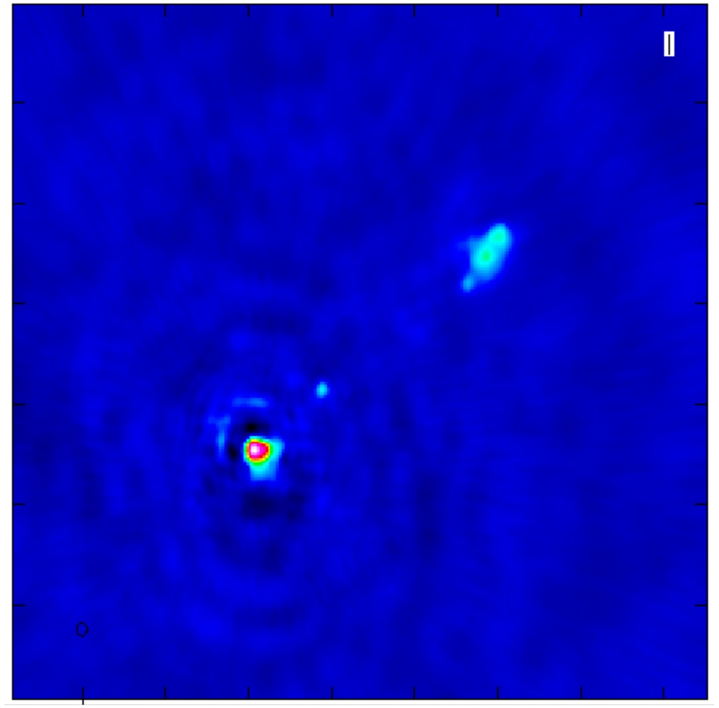
From «dirty image»

Deconvolve the intrinsic source brightness distribution B(l,m) from the **dirty beam** D(l,m)



Dirty beam

The radio
Point Spread Function (PSF)



To «CLEAN image»

DECONVOLUTION

Since only a finite number of (noisy) samples are measured, to recover B(l,m) we need **some stable non-linear approach** + ***a priori* information**:

- **B(l,m) must be positive** (exceptions: absorption lines and polarization)

- **Radio sources do not resemble the dirty beam** (i.e. sidelobes-like patterns)

- **Sky is basically empty** with just a few localised sources

B = Intrinsic source brightness distribution

Convolution

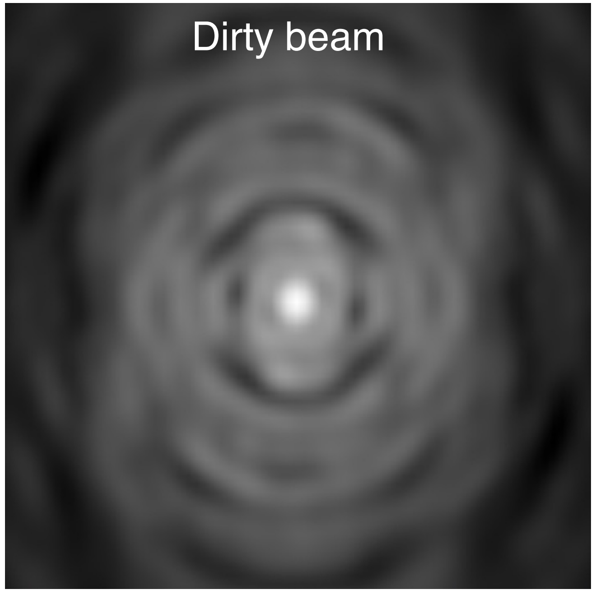
D = dirty beam = point spread function (PSF)

S = Sampling function

$$B(l,m) * D(l,m) \approx \iint_{uv} S(u,v)V(u,v)e^{2\pi i(ul+vm)}dudv$$

$$D(l,m) = \iint_{uv} S(u,v)e^{2\pi i(ul+vm)}dudv$$

We know this!
To recover B we have **"just" to deconvolve** the D(l,m) term



DECONVOLUTION

CLEAN method principal steps (Högbom's algorithm):

1) Initialize a residual map (first image = dirty image)

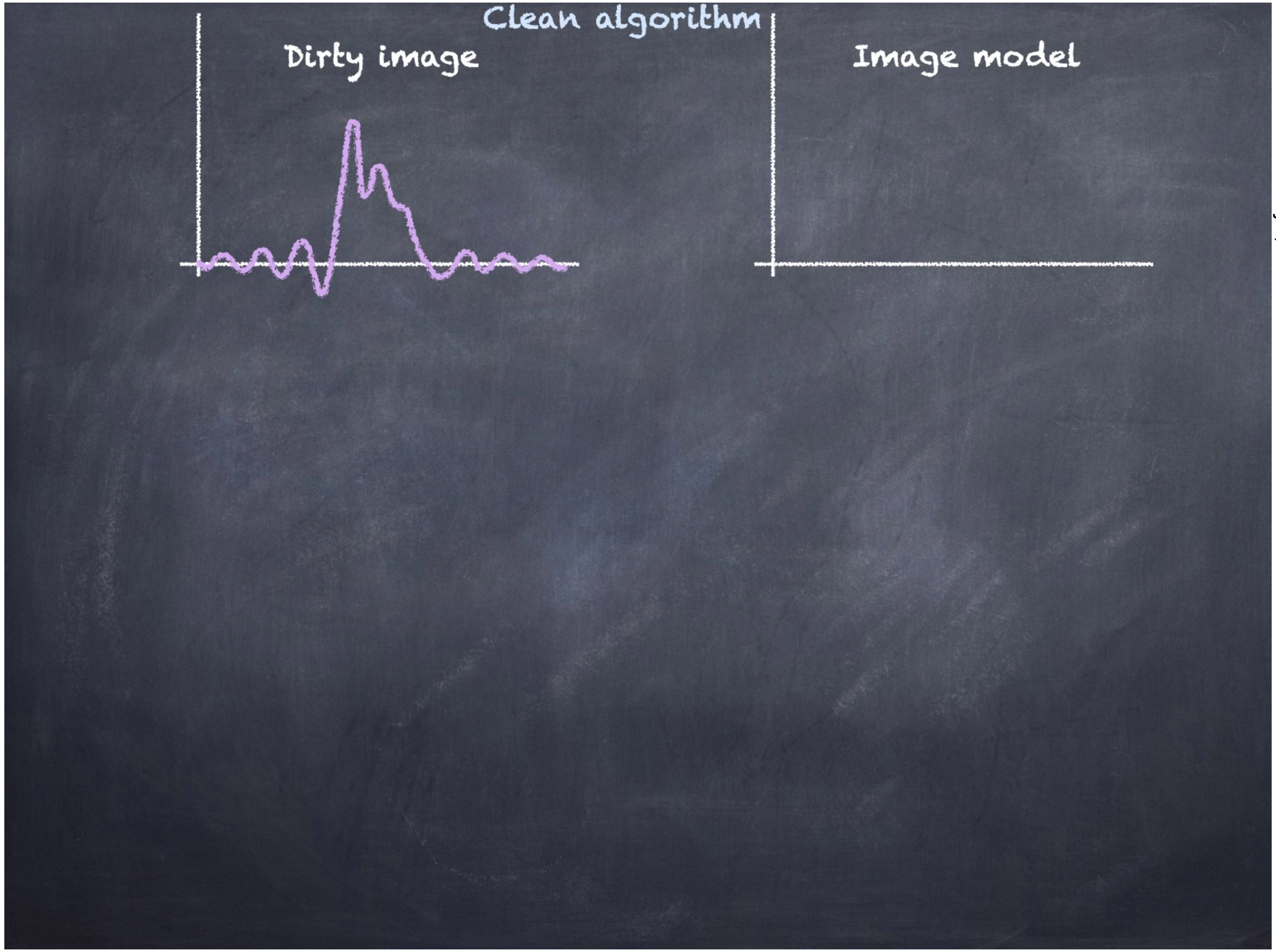
2) Identify strongest peak as a delta component

3) Record the position and magnitude in a model (clean components), subtract it from the dirty image

4) Go to 1) unless you reach the stopping criterion

5) Convolve the model (clean components) with an idealized CLEAN beam (elliptical Gaussian fit of the main lobe of the dirty beam)

6) Add the residual of the dirty image to the CLEAN image



Credits: Daniel Tafoya, ERIS 2019

DECONVOLUTION

CLEAN method principal steps (Högbom's algorithm):

1) Initialize a residual map (first image = dirty image)

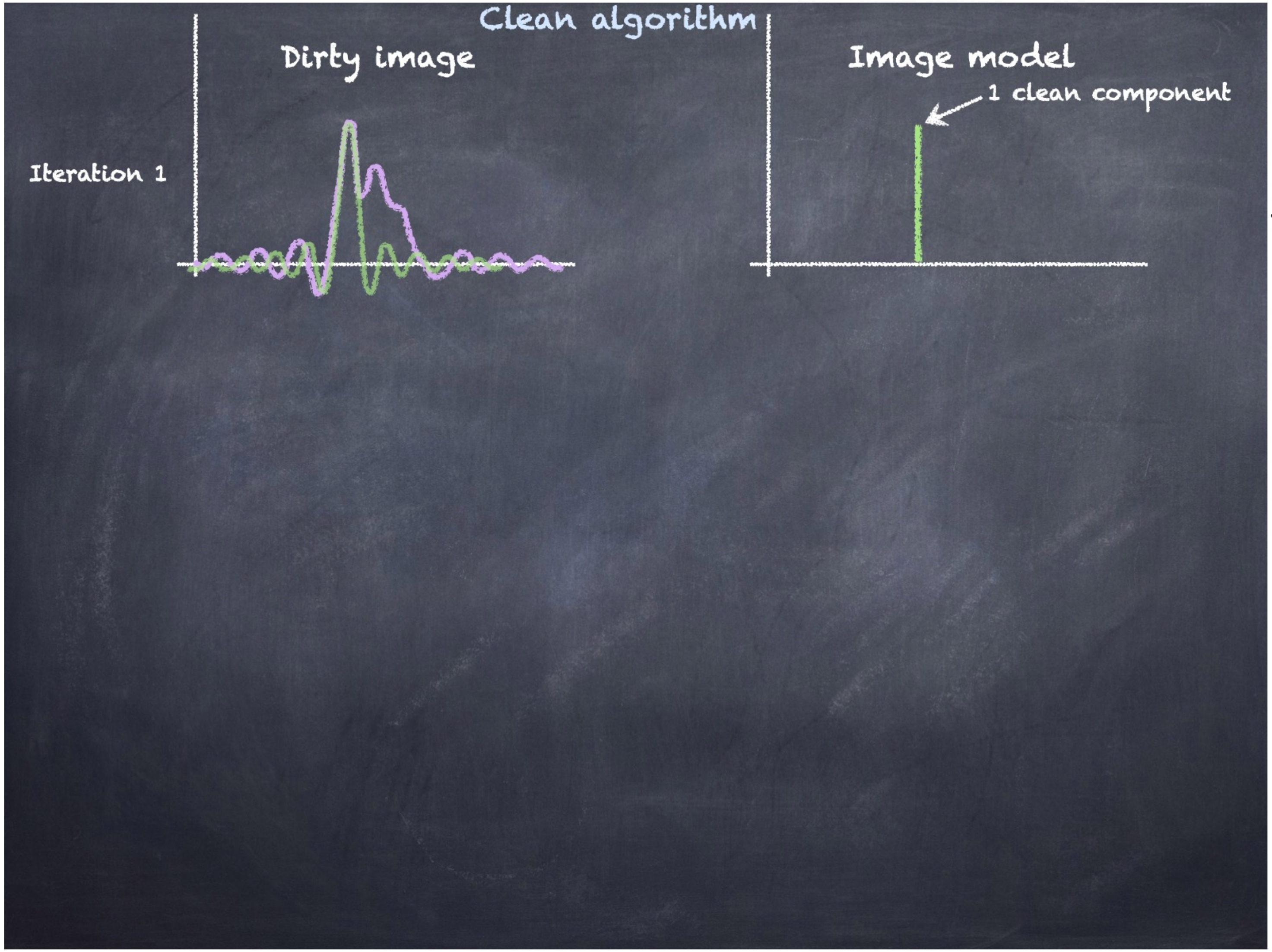
2) Identify strongest peak as a delta component

3) Record the position and magnitude in a model (clean components), subtract it from the dirty image

4) Go to 1) unless you reach the stopping criterion

5) Convolve the model (clean components) with an idealized CLEAN beam (elliptical Gaussian fit of the main lobe of the dirty beam)

6) Add the residual of the dirty image to the CLEAN image



Credits: Daniel Tafoya, ERIS 2019

DECONVOLUTION

CLEAN method principal steps (Högbom's algorithm):

1) Initialize a residual map (first image = dirty image)

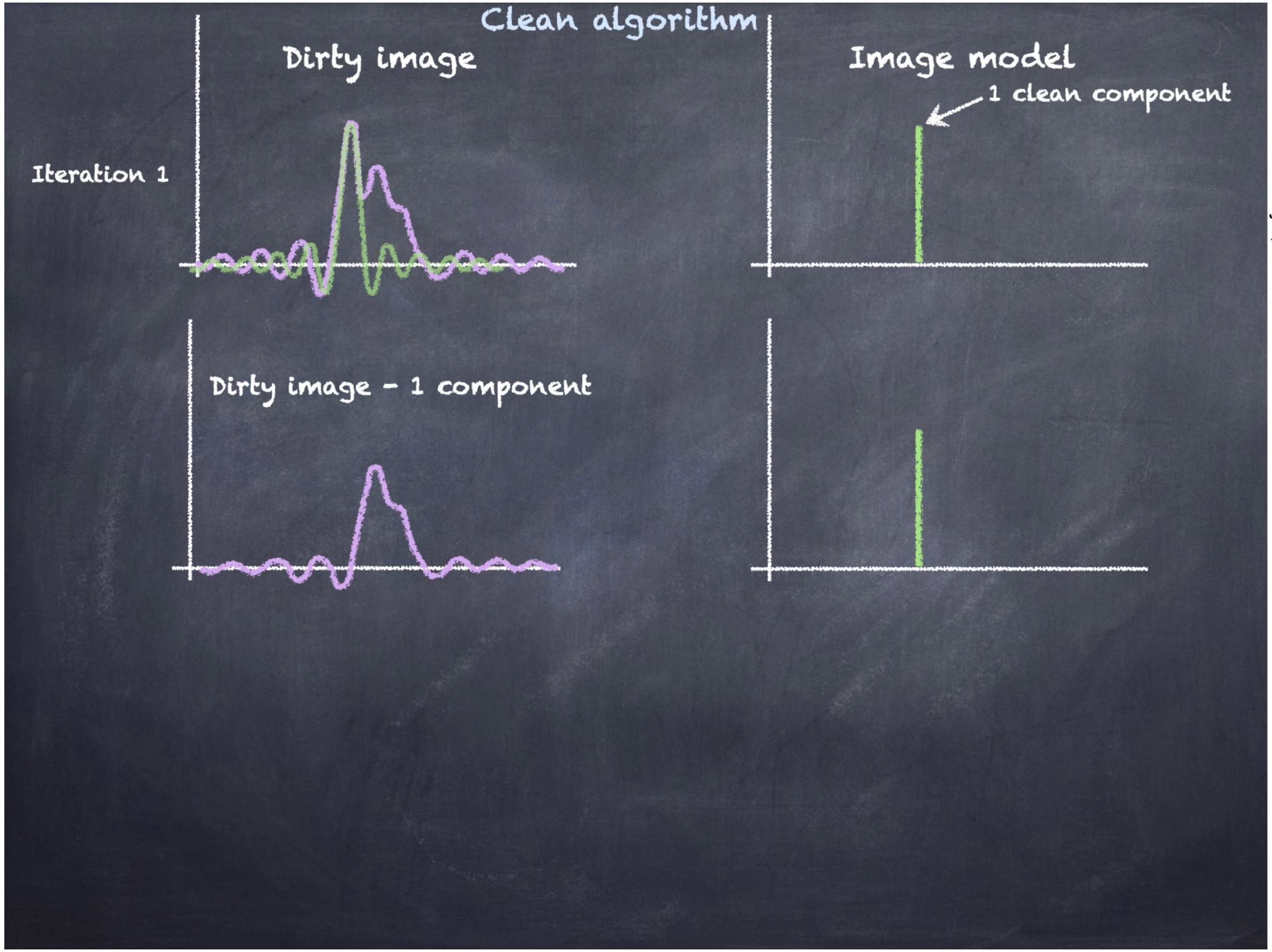
2) Identify strongest peak as a delta component

3) Record the position and magnitude in a model (clean components), subtract it from the dirty image

4) Go to 1) unless you reach the stopping criterion

5) Convolve the model (clean components) with an idealized CLEAN beam (elliptical Gaussian fit of the main lobe of the dirty beam)

6) Add the residual of the dirty image to the CLEAN image



Credits: Daniel Tafoya, ERIS 2019

DECONVOLUTION

CLEAN method principal steps (Högbom's algorithm):

1) Initialize a residual map (first image = dirty image)

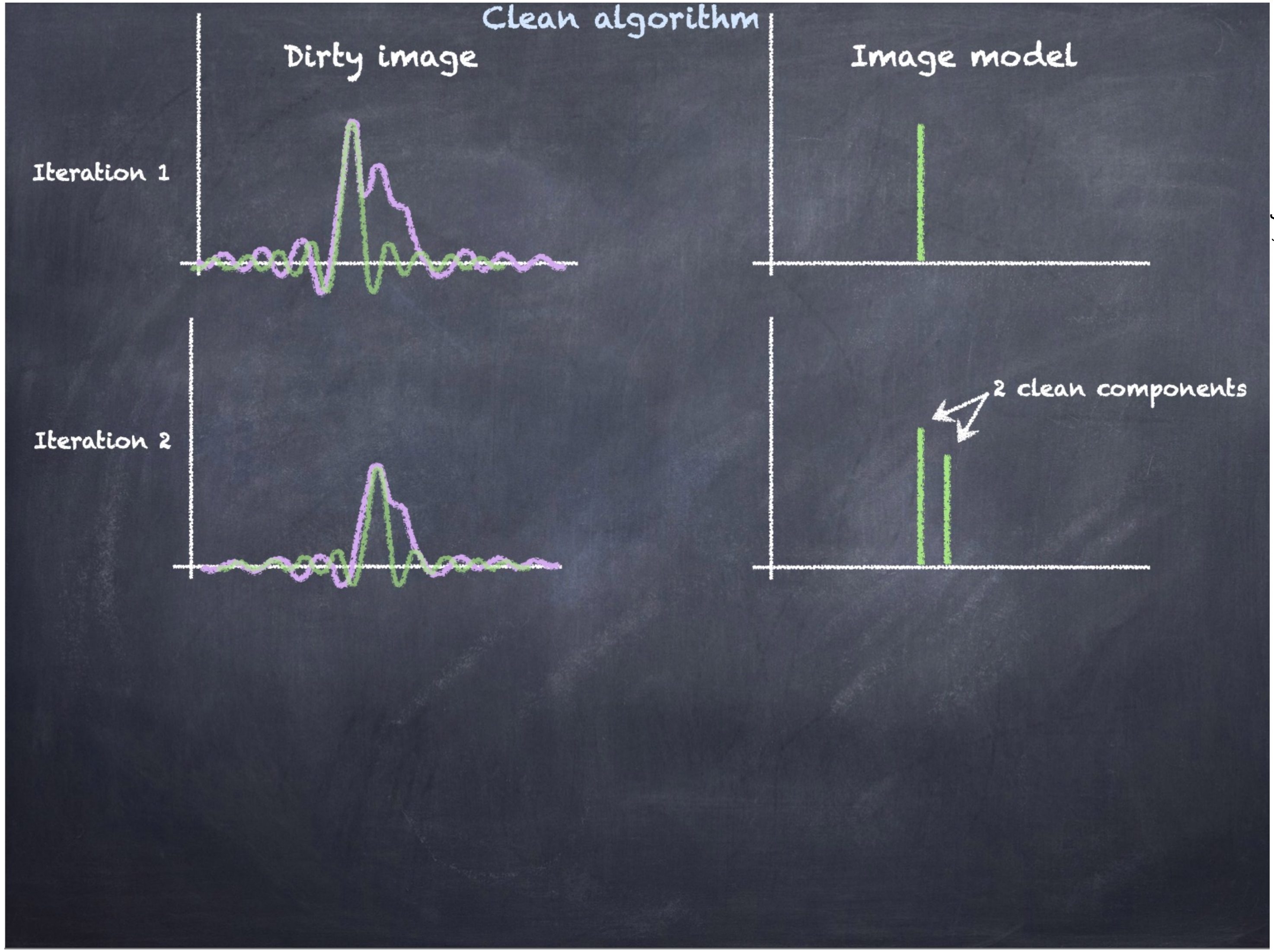
2) Identify strongest peak as a delta component

3) Record the position and magnitude in a model (clean components), subtract it from the dirty image

4) Go to 1) unless you reach the stopping criterion

5) Convolve the model (clean components) with an idealized CLEAN beam (elliptical Gaussian fit of the main lobe of the dirty beam)

6) Add the residual of the dirty image to the CLEAN image



Credits: Daniel Tafoya, ERIS 2019

DECONVOLUTION

CLEAN method principal steps (Högbom's algorithm):

1) Initialize a residual map (first image = dirty image)

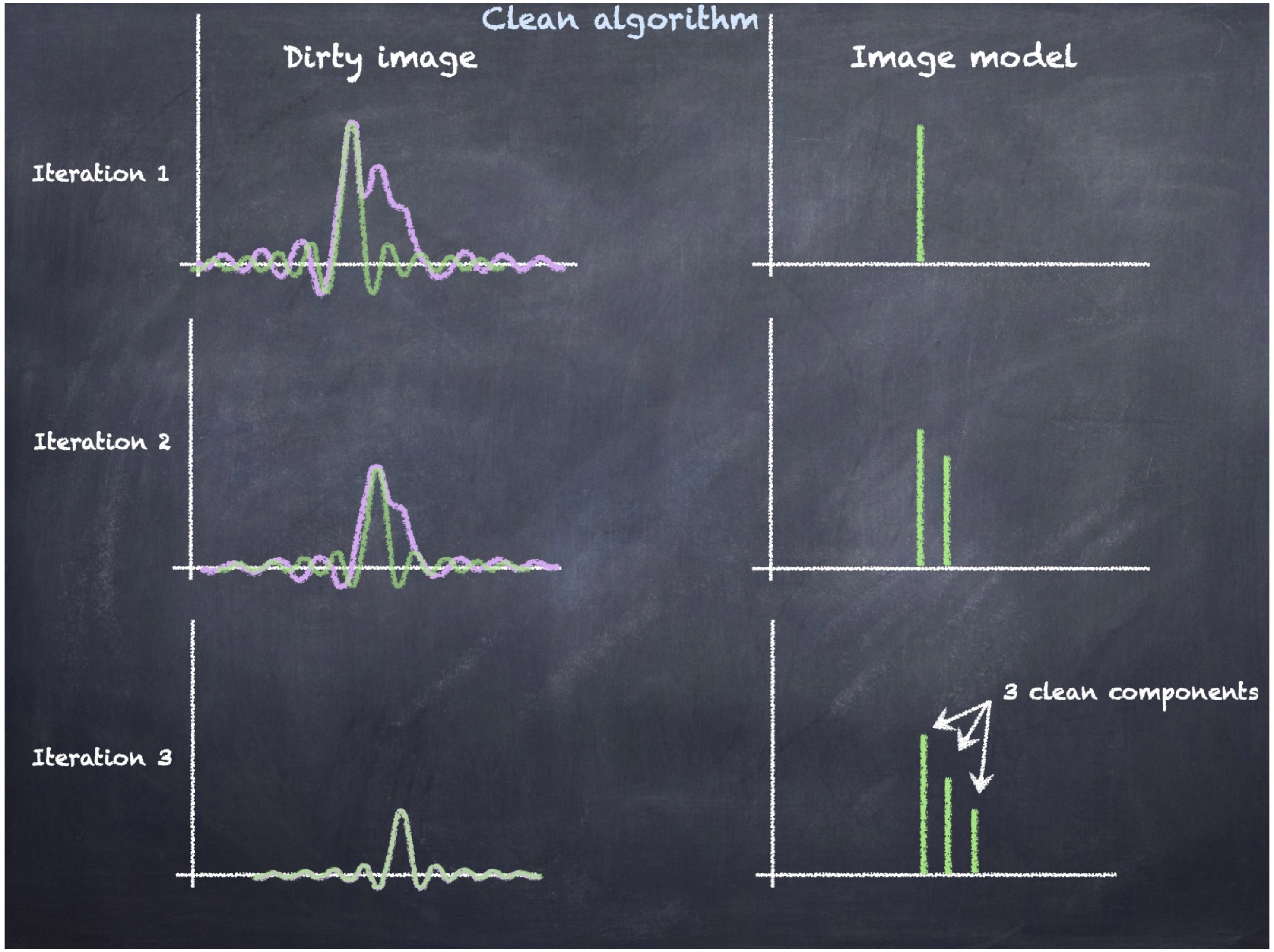
2) Identify strongest peak as a delta component

3) Record the position and magnitude in a model (clean components), subtract it from the dirty image

4) Go to 1) unless you reach the stopping criterion

5) Convolve the model (clean components) with an idealized CLEAN beam (elliptical Gaussian fit of the main lobe of the dirty beam)

6) Add the residual of the dirty image to the CLEAN image



Credits: Daniel Tafoya, ERIS 2019

DECONVOLUTION

CLEAN method principal steps (Högbom's algorithm):

1) Initialize a residual map (first image = dirty image)

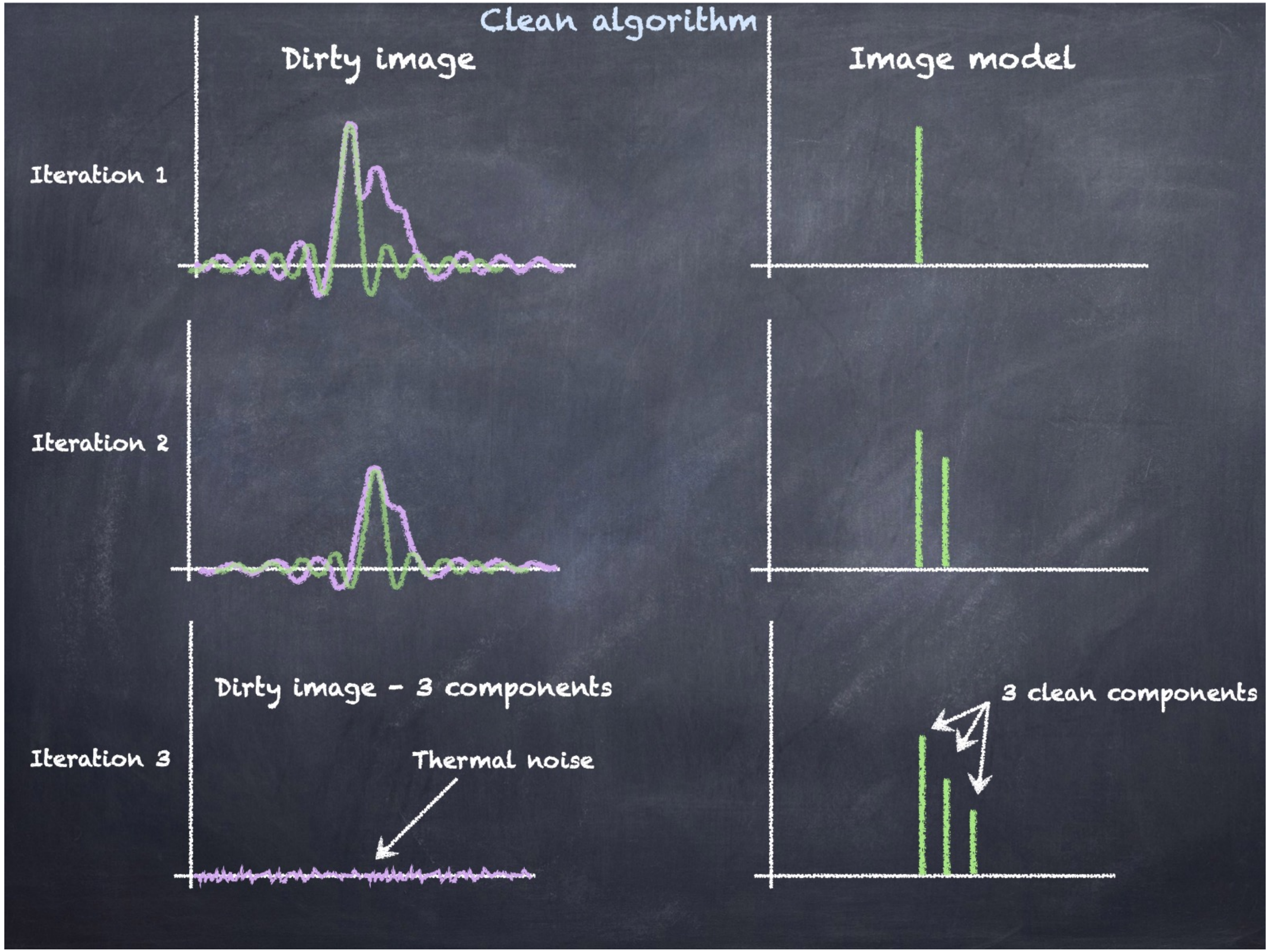
2) Identify strongest peak as a delta component

3) Record the position and magnitude in a model (clean components), subtract it from the dirty image

4) Go to 1) **unless you reach the stopping criterion**

5) Convolve the model (clean components) with an idealized CLEAN beam (elliptical Gaussian fit of the main lobe of the dirty beam)

6) Add the residual of the dirty image to the CLEAN image



Credits: Daniel Tafoya, ERIS 2019

DECONVOLUTION

CLEAN method principal steps (Högbom's algorithm):

1) Initialize a residual map (first image = dirty image)

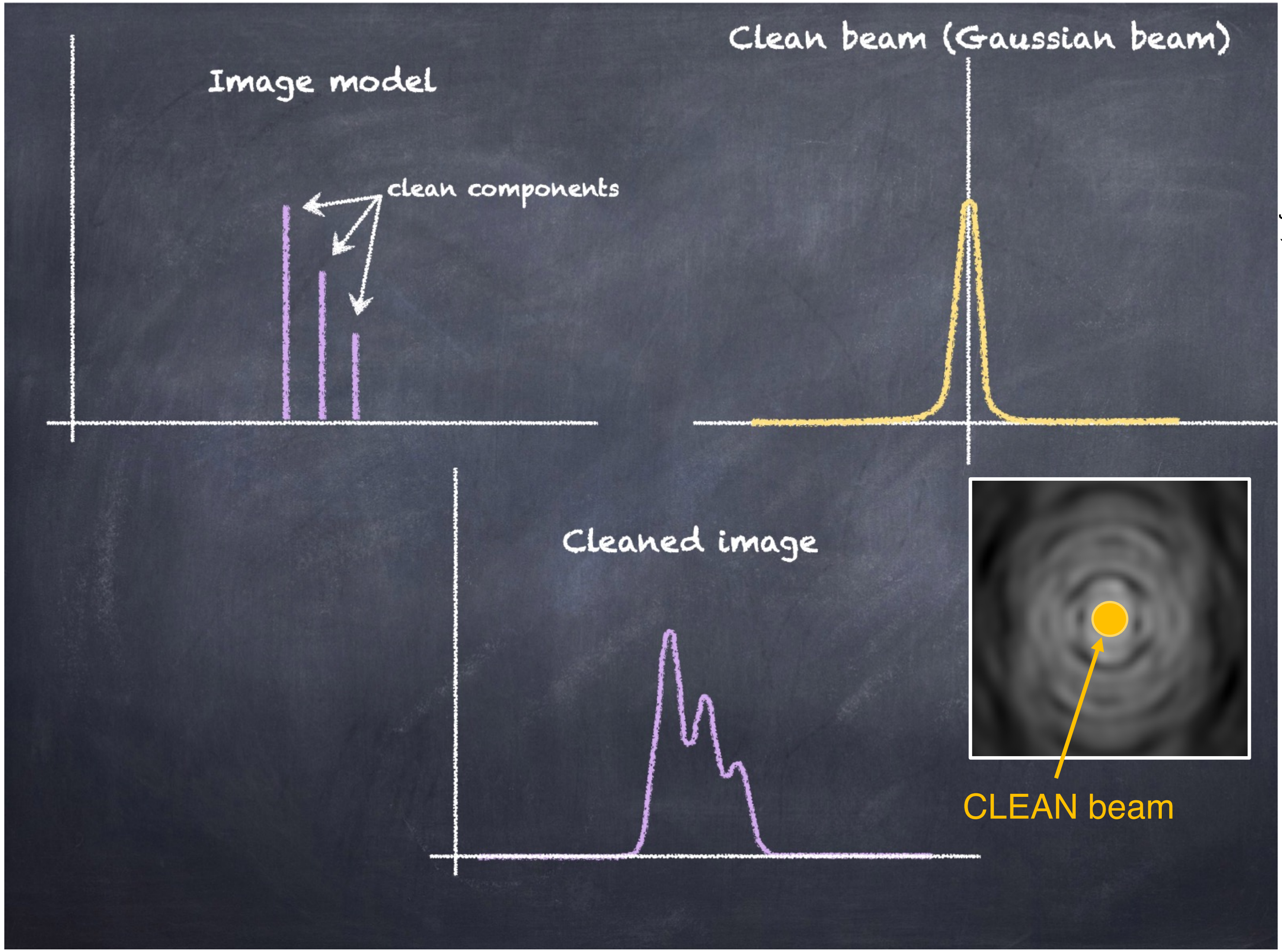
2) Identify strongest peak as a delta component

3) Record the position and magnitude in a model (clean components), subtract it from the dirty image

4) Go to 1) unless you reach the stopping criterion

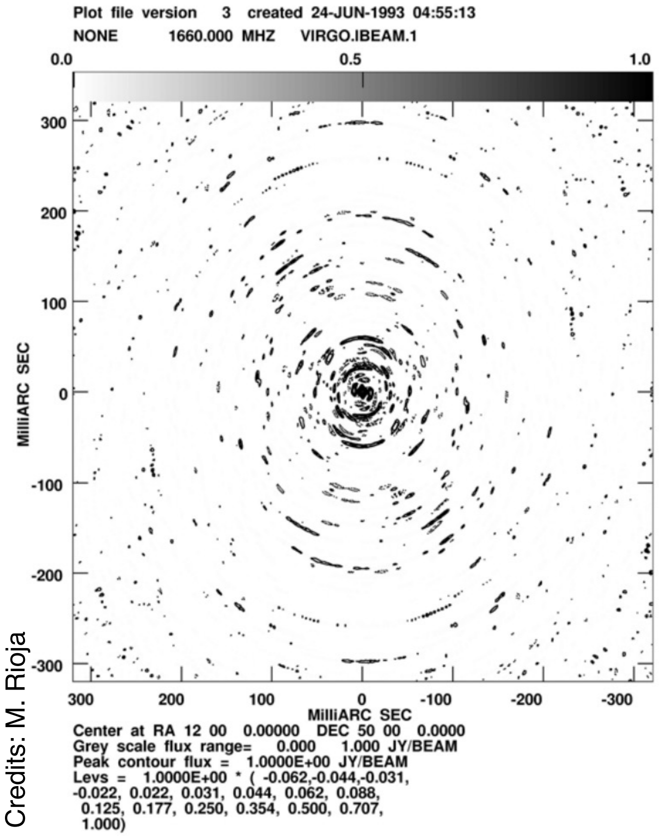
5) Convolve the model (clean components) with an idealized CLEAN beam (elliptical Gaussian fit of the main lobe of the dirty beam)

6) Add the residual of the dirty image to the CLEAN image

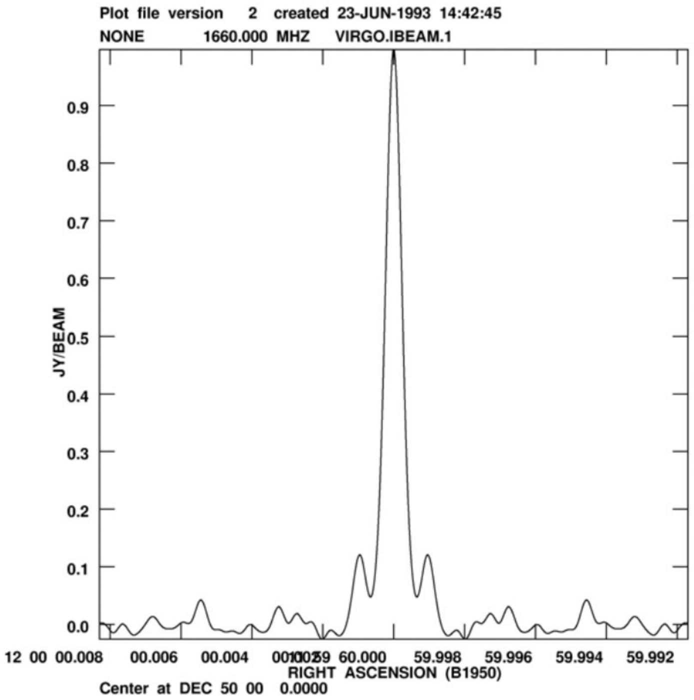


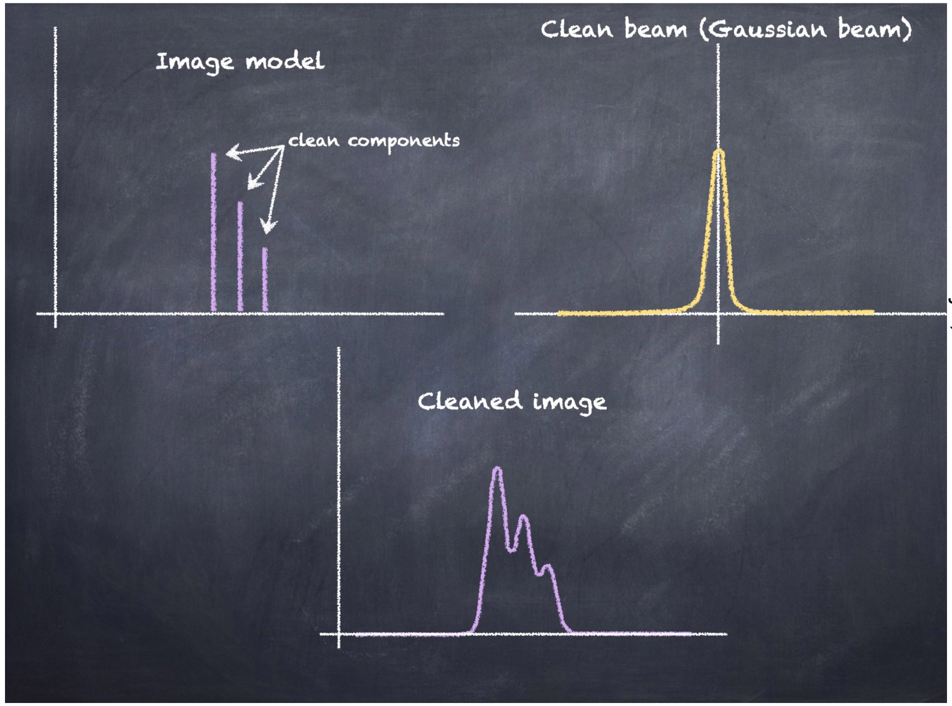
Credits: Daniel Tafoya, ERIS 2019

DECONVOLUTION

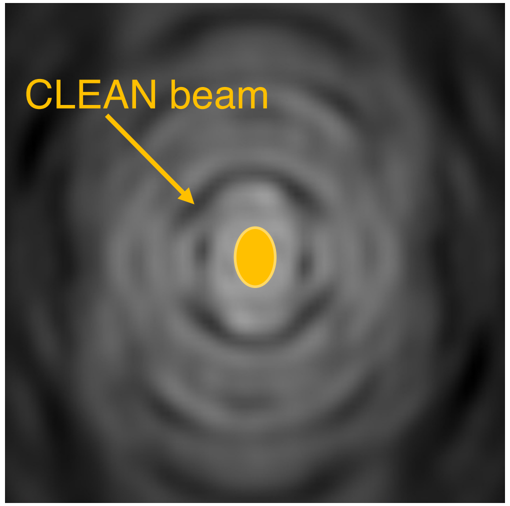


Credits: M. Rioja

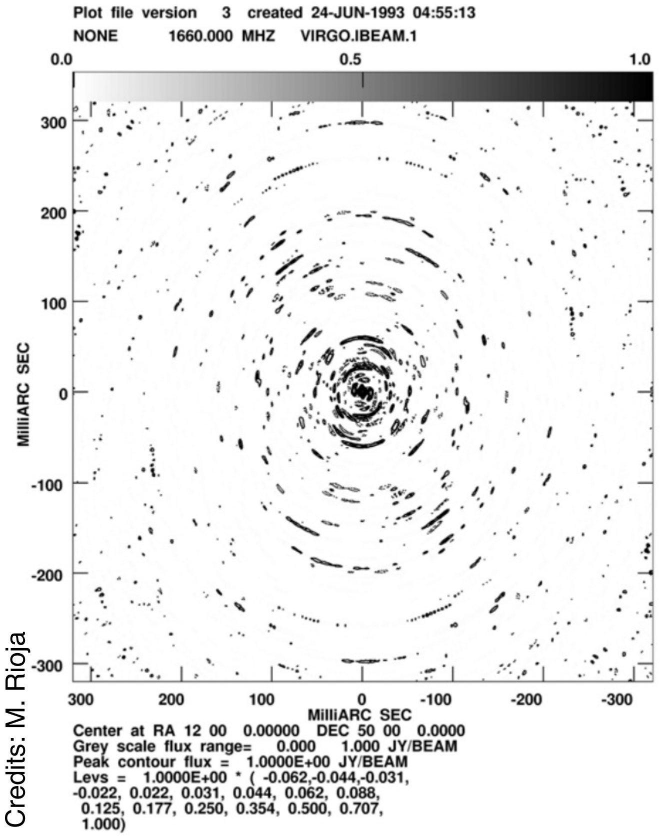




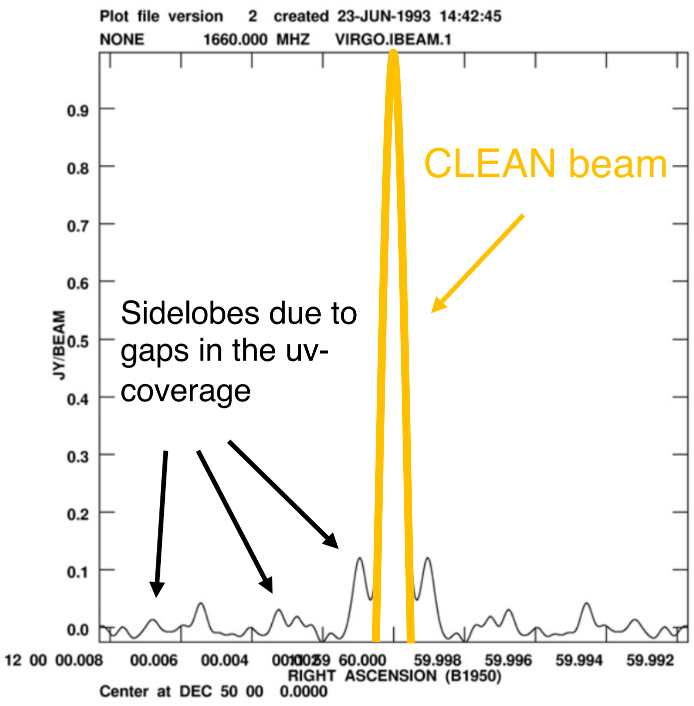
Credits: Daniel Tafoya, ERIS 2019

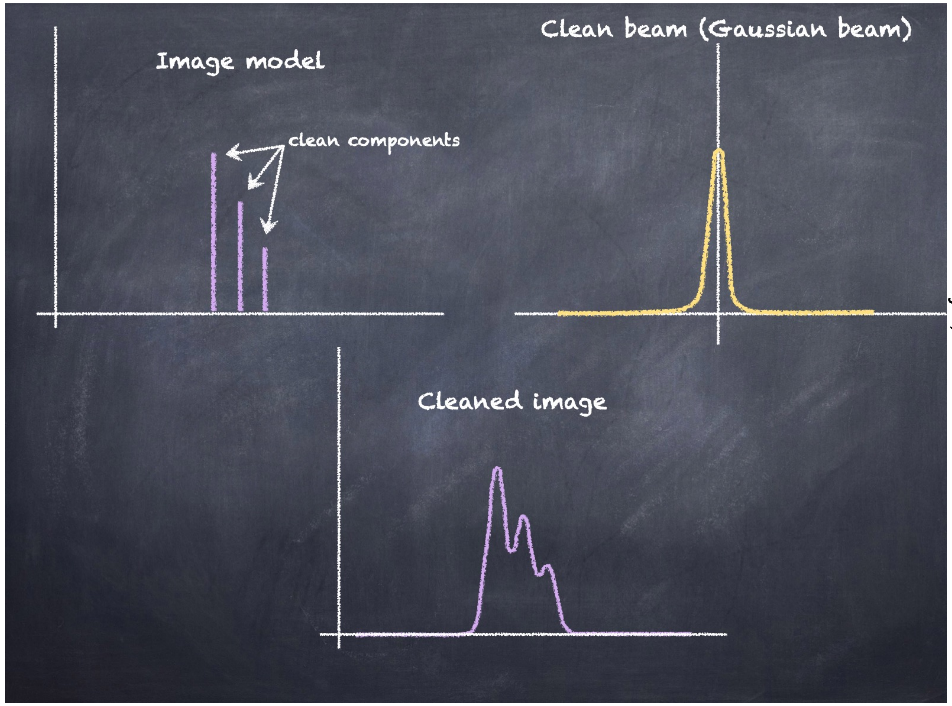


DECONVOLUTION

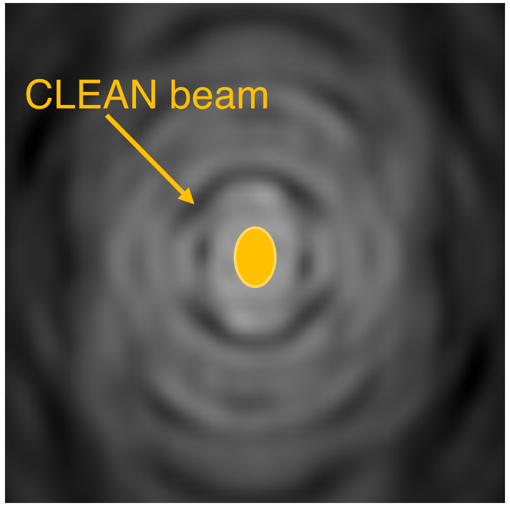


Credits: M. Rioja





Credits: Daniel Tafoya, ERIS 2019

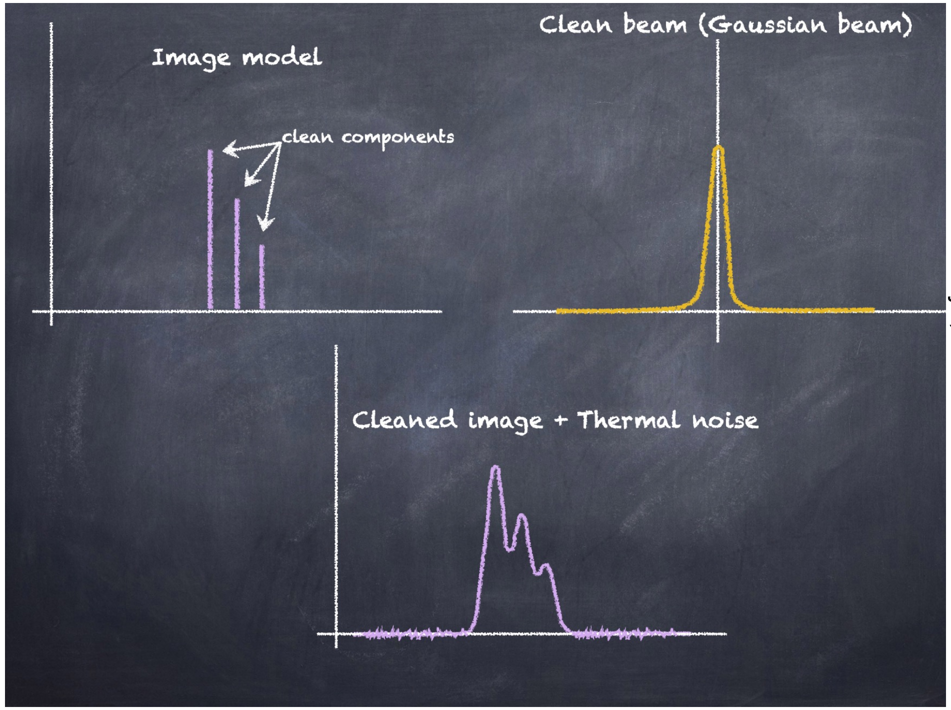


DECONVOLUTION

CLEAN method (Clark's algorithm, a variant of Högbom's algorithm):

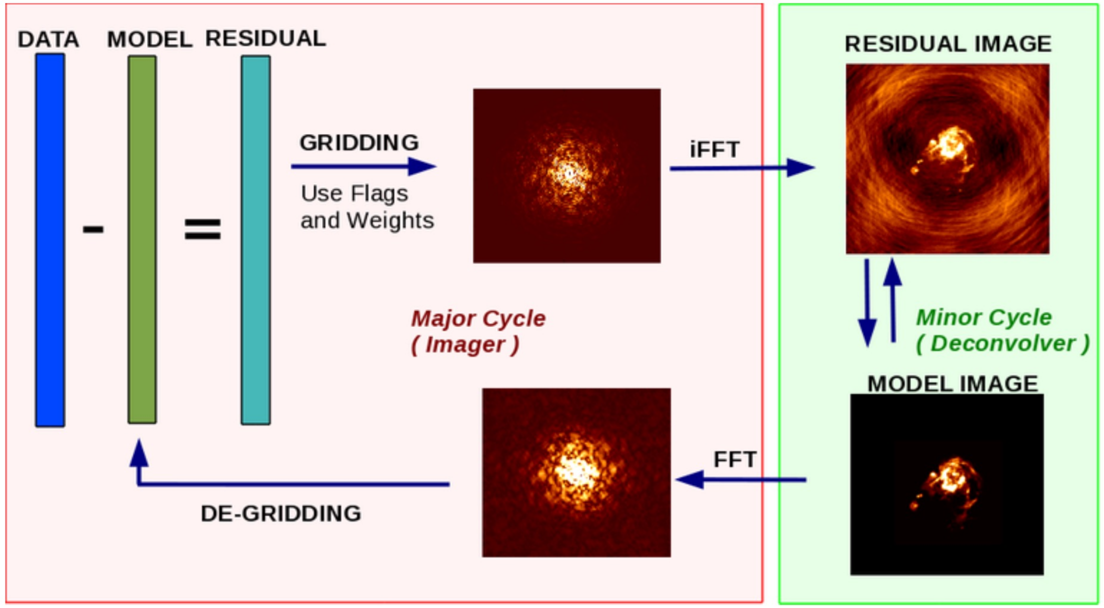
Minor cycle

1) Initialize a residual map (first image = dirty image)
2) Identify strongest peak as a delta component
3) Record the position and magnitude in a model (clean components), subtract it from the dirty image
4) Go to 1) unless you reach the stopping criterion
5) Convolve the model (clean components) with an idealized CLEAN beam (elliptical Gaussian fit of the main lobe of the dirty beam)
6) Add the residual of the dirty image to the CLEAN image



Credits: Daniel Tafoya, ERIS 2019

Credits: Daniel Tafoya, ERIS 2019



The major cycle implements FT between the data and image domains

The minor cycle operates purely in the image domain

(The 2-cycles approach makes the deconvolution faster)

Also, typically we use CLEAN a fraction of the delta function (typically 5-10%), not the entire delta (the illustration is a semplification)

CLEAN in action (based on the ERIS tutorial)

ERIS 2024 - Tutorials

HOME INTRO. TO DATA CALIBRATION IMAGING SELF CALIBRATION ADVANCED IMAGING FULL TUTORIAL

Imaging

Data required

For this section, it is advised to start from the pre-calibrated data (rather than your own from the calibration section). These are contained in the `ERIS24_imaging_tutorial.tar.gz` which you should have already downloaded. Untar this folder and enter the `ERIS24_imaging` folder that should have been created. Please ensure the following are in your current working directory,

1. `1252+5634.ms` - measurement set containing just the 3C277.1 visibilities (this should have been created after the calibration tutorial or untar from the imaging tar bundle (see Home)
2. `3C277.1_imaging_outline2024.py` - imaging script for the next three tutorials (imaging, self-calibration and advanced imaging)
3. `3C277.1_imaging_all2024.py` - cheat script containing the answers

Many thanks to Jack Radcliffe & the team!

BASICS OF IMAGING: field of view

The source size is typically much smaller than the entire Field-of-View (FoV), which corresponds to the primary beam
[single-dish beam ≈ λ/D, where D=antenna diameter, for homogeneous arrays]

It's always good to check what is already known about your target!
For 3C277.1 you may check Lüdke+1998 (MNRAS, 299, 467–478 https://www.jb.man.ac.uk/DARA/ERIS22/plots/299-2-467.pdf)

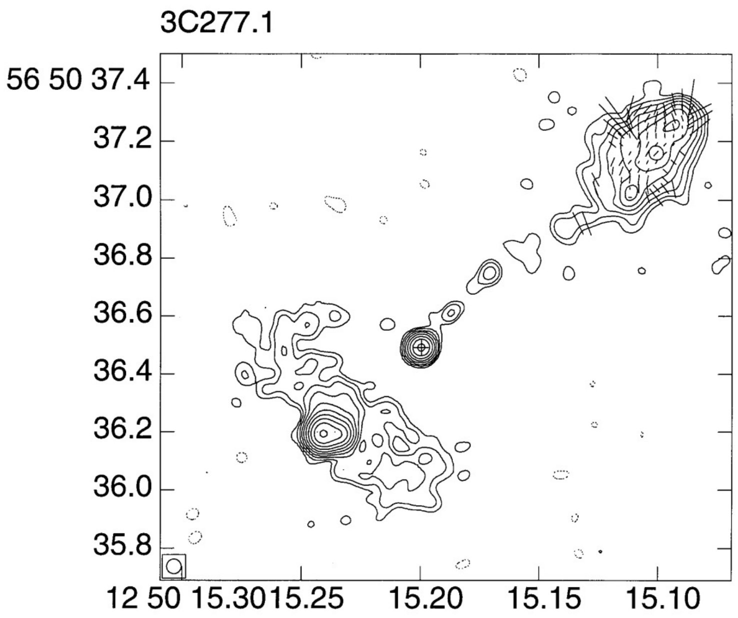
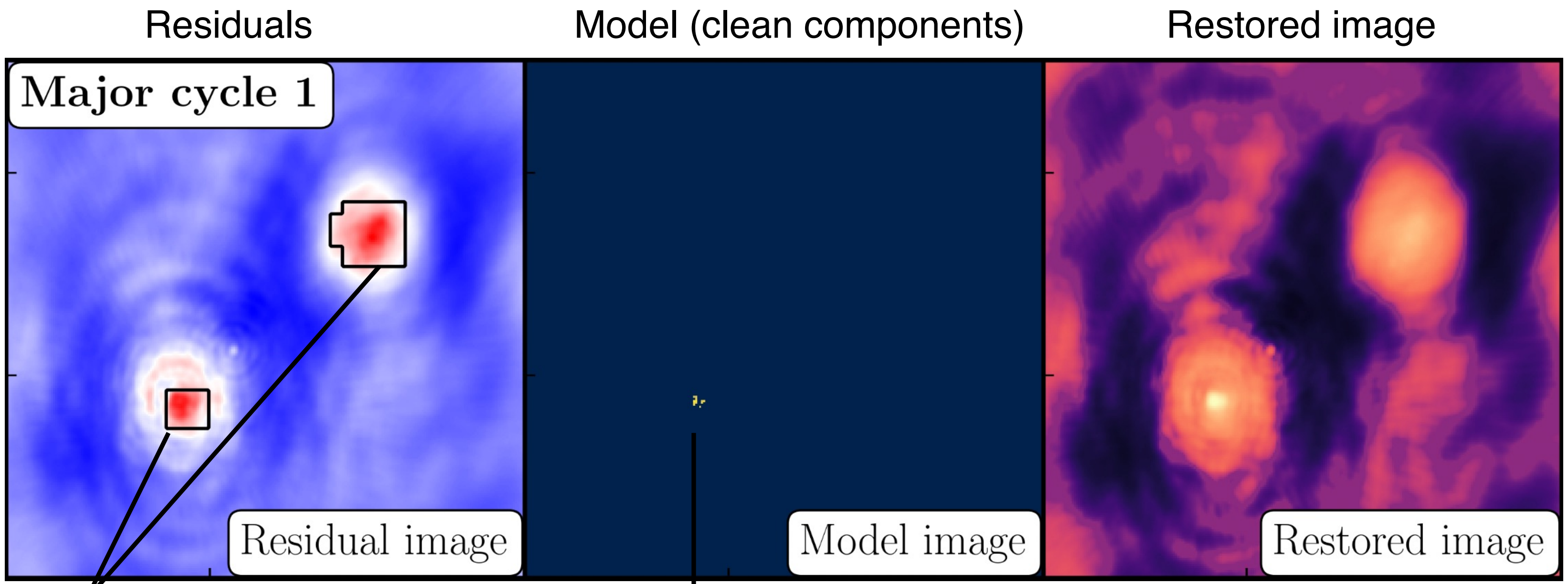


Table 1. Observational parameters and journal of observations. Largest angular sizes (*LAS*), largest linear sizes (*LLS*) and optical identification (G = galaxy, Q = quasar) are given. This table also gives the lowest contour for each of the maps in Fig. 1, along with the scale for the polarization vectors as the percentage polarization represented by a vector 1 arcsec long.

Name	z	Id	LAS arcsec	S_{peak} mJy/beam	*LLS* kpc	ϕ-cal.	Obs. date	Lowest contour mJy/beam	Pol. scale per cent/arcsec
3C 43	1.47	Q	2.6	320	11.1	0149+218	920614	1.7	500
3C 48	0.37	Q	1.3	870	4.0	0202+319	920615	9.0	333
3C 49	0.62	G	1.0	730	3.8	0119+115	921208	0.5	
3C 67	0.31	G	2.5	126	7.0	0234+285	920527	0.5	250
3C 93.1	0.24	G	0.2	423	0.5	0424+414	950709	1.5	5000
3C 119	0.41	G	0.2	2962	0.75	0424+414	950709	5.0	50
3C 138	0.76	Q	0.8	1091	3.3	0528+134	920710	8.0	333
3C 147	0.54	Q	0.7	67	2.63	0532+506	921105	2.5	500
3C 186	1.06	Q	1.2	32	5.1	0739+398	920807	0.3	
3C 190	1.21	Q	2.6	65	11.2	0748+126	920615	0.5	
3C 216	0.67	Q	1.5	671	5.9	0917+449	920620	1.0	500
3C 237	0.88	G	1.3	271	5.6	1005+066	950617	1.0	67
3C 241	1.62	G	1.2	112	5.1	1013+208	921206	1.2	
3C 258	0.17	G	0.10	206	0.2	1119+183	950626	0.75	
3C 268.3	0.37	G	1.3	161	4.0	1226+638	920506	0.5	333
3C 277.1	0.32	Q	1.6	171	4.6	1300+580	950418	0.3	500
3C 286	0.85	Q	3.8	5948	15.8	1308+326	920518	4.0	500
3C 298	1.44	Q	1.5	279	6.3	1408+077	950505	0.75	333
3C 303.1	0.27	G	1.9	21	4.8	1448+762	950530	0.4	208
3C 305.1	1.13	G	10.1	42	10.1	1448+762	950530	0.4	200
3C 309.1	0.90	Q	2.2	1681	9.2	1531+722	920727	2.5	500
3C 318	0.75	G	0.8	288	3.2	1511+238	920616	3.0	500
3C 343	0.99	Q	0.15	423	0.6	1634+604	950629	1.0	133
3C 343.1	0.75	G	0.24	385	1.0	1634+604	950629	1.5	
3C 380	0.69	Q	1.5	2980	5.9	1851+488	921228	3.0	500
3C 454	1.76	Q	0.6	231	2.5	2246+208	921106	0.75	500
3C 454.1	1.84	G	1.60	97	6.66	2251+704	950703	0.3	
4C 13.66	1.45	G	1.2	118	5.1	1749+096	920808	0.75	

Lüdke+1998

CLEAN in action

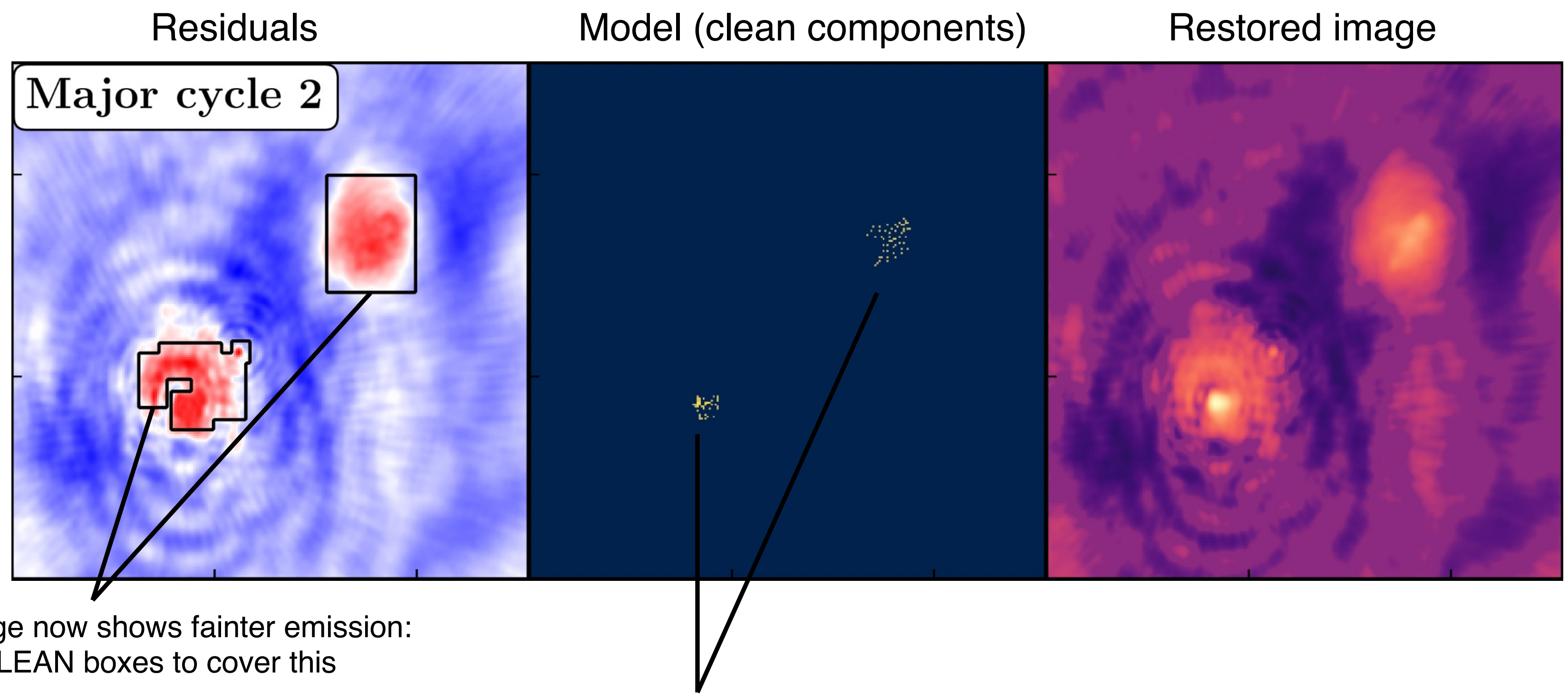


To make this process converge faster we use the so-called CLEAN boxes (mask)

Also useful to not let CLEAN go to sidelobes
(see next slides)

CLEAN components obtained during several minor cycles

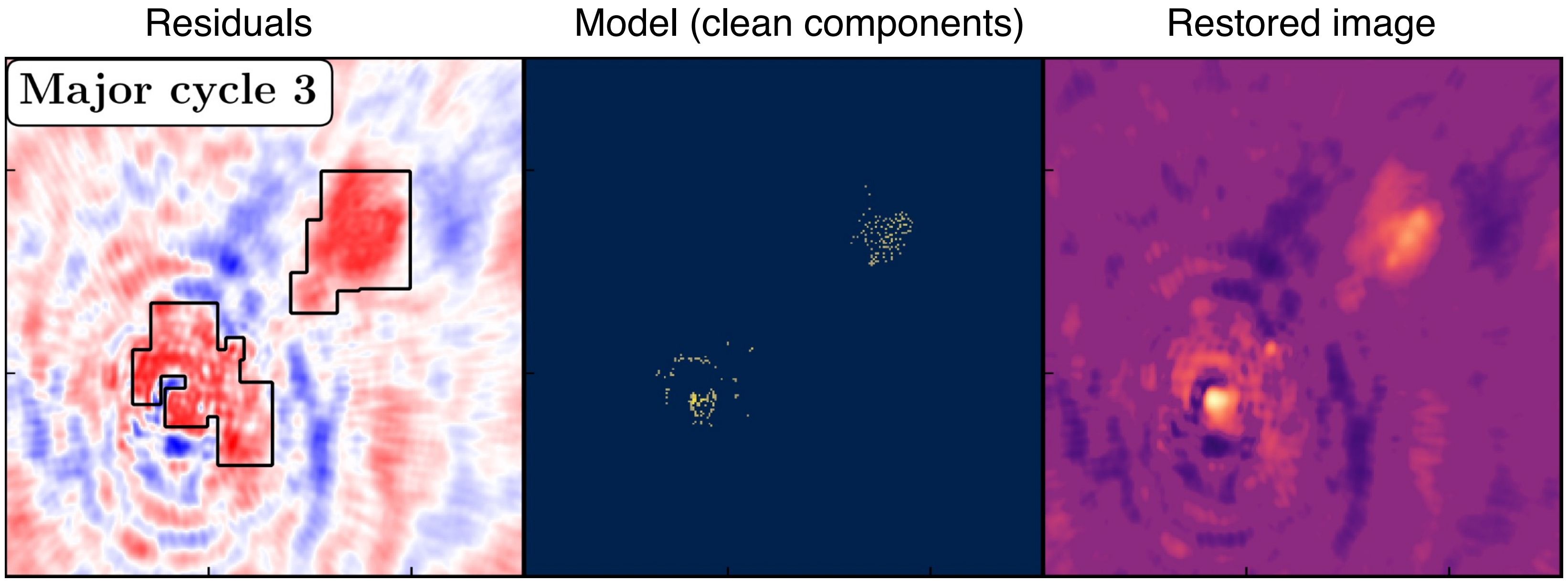
CLEAN in action



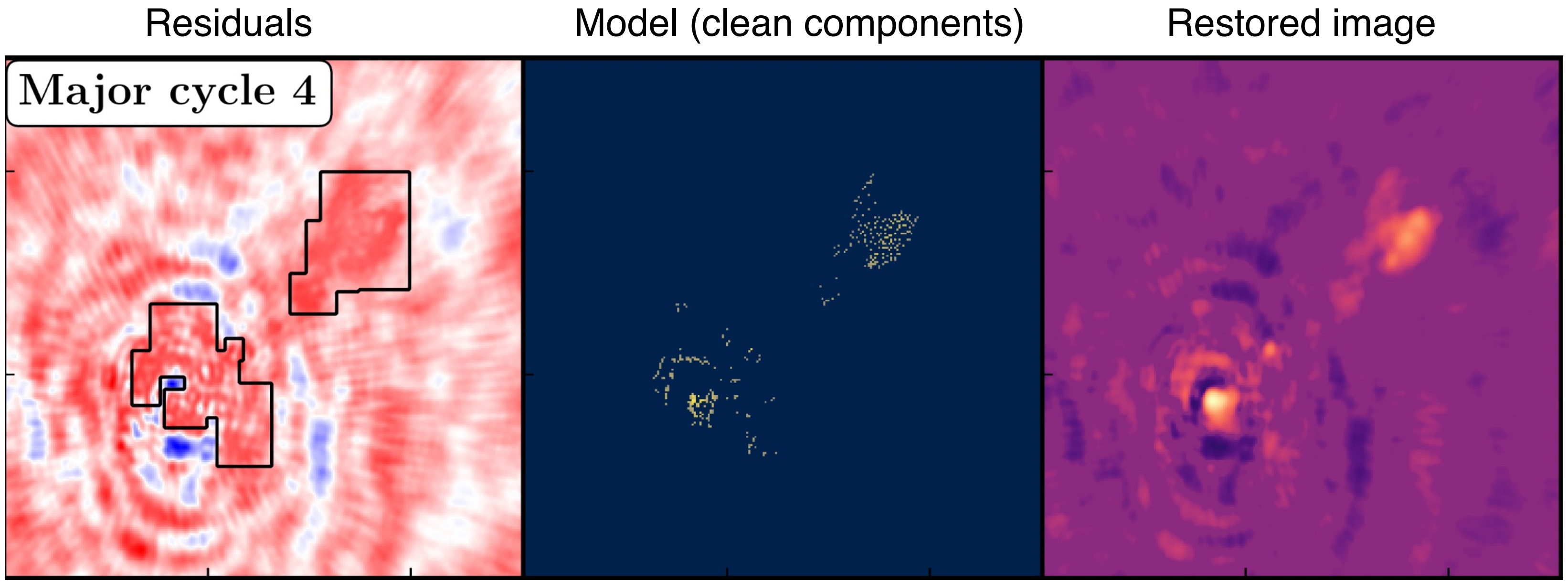
The residual image now shows fainter emission: we enlarge the CLEAN boxes to cover this

New CLEAN components added to the previous ones

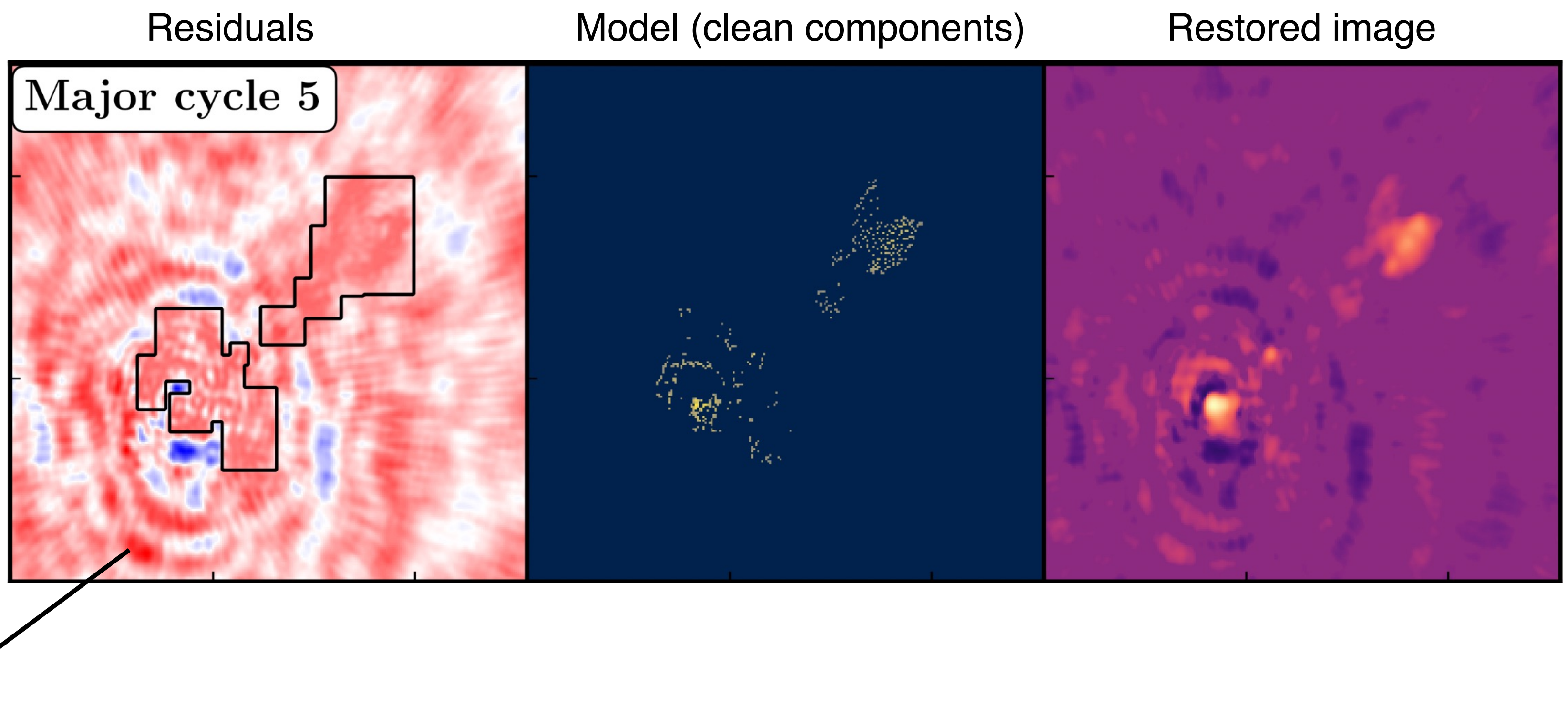
CLEAN in action



CLEAN in action



CLEAN in action



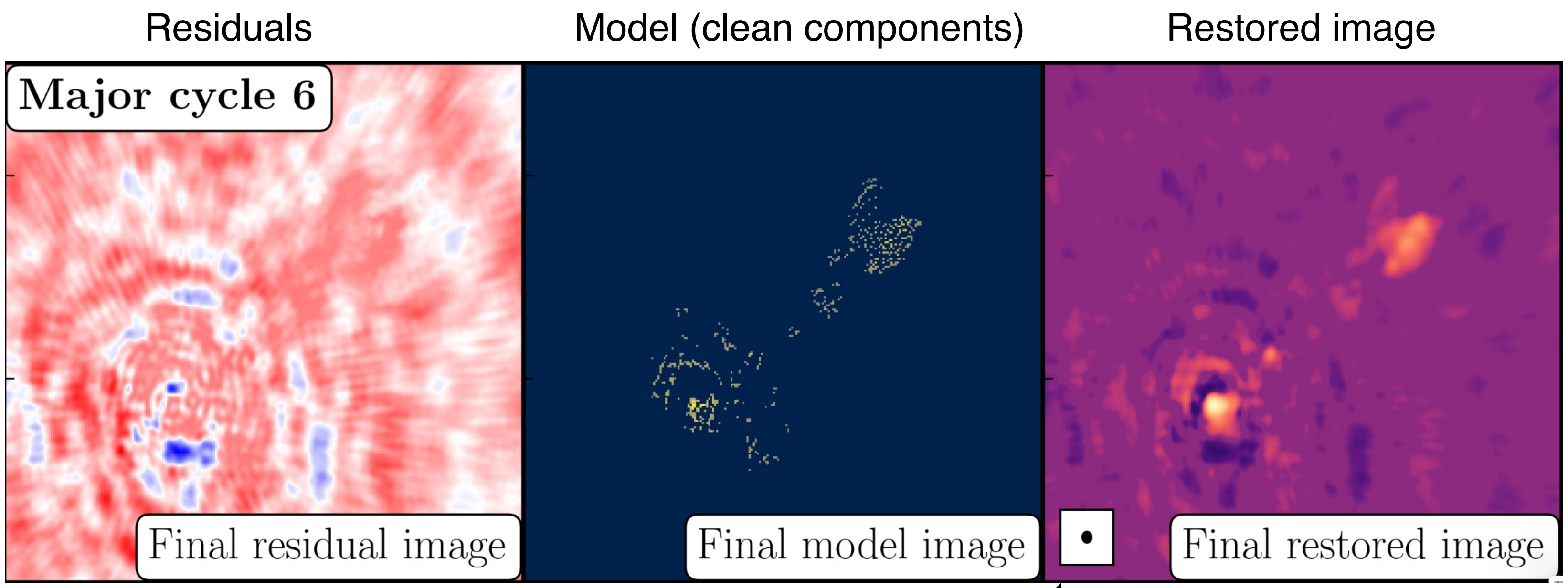
This emission is brighter BUT it's due to sidelobes!

It's always a good idea take a look at the dirty beam before starting cleaning

+ CLEAN boxes prevent the CLEANing of sidelobes

CLEAN in action

This is important for self-calibration!



Residual image should look like «only noise»

STOPPING CRITERION

CLEAN beam

STOPPING CRITERIA

- **Visually**, when your residuals contain only noise – this means that you cleaned all the flux density of the source

- **Convergence**: Check the logger for max-min (possibily symmetrical), total flux density should increase while cleaning (if not, stop), noise level should decrese (if it does not change anymore, stop → overcleaning)

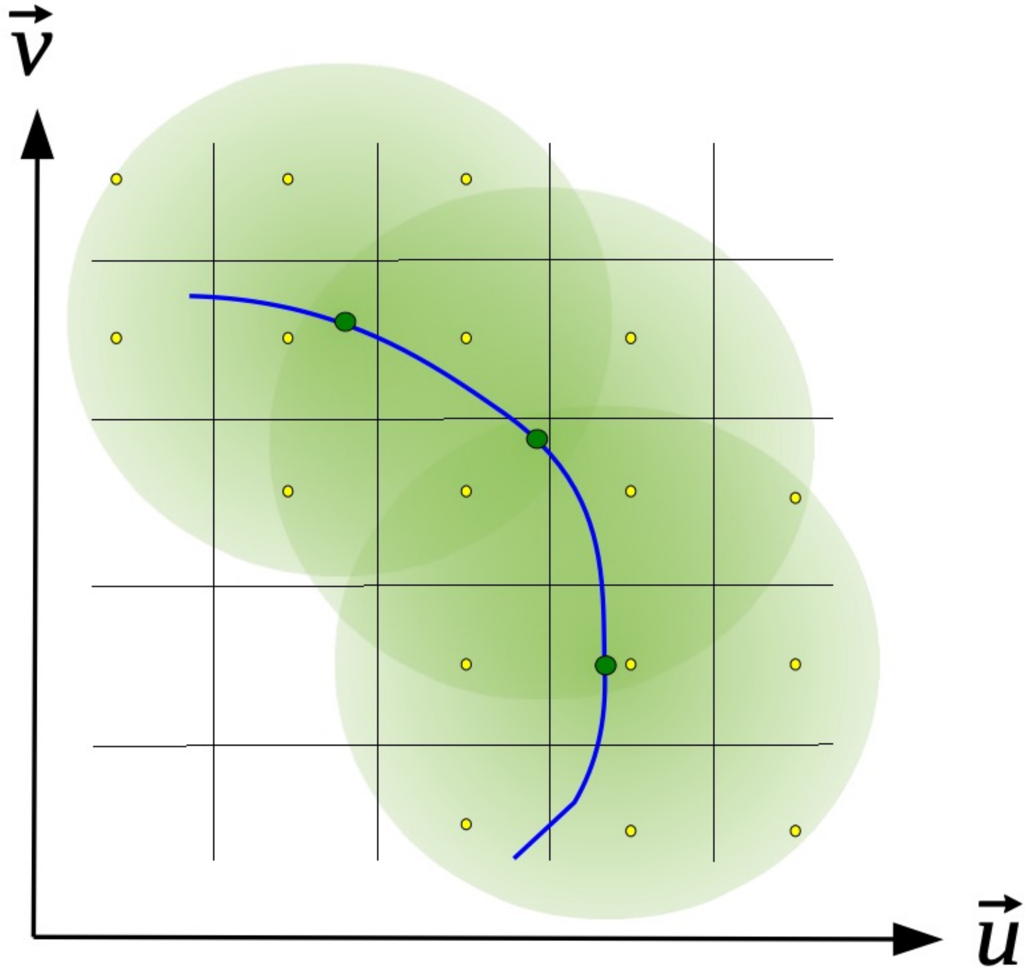
- **Negative peak identified** (negatives can indicate that CLEAN is now working on sidelobes/noise, but it can also indicate that CLEAN is trying to fix earlier mistakes)

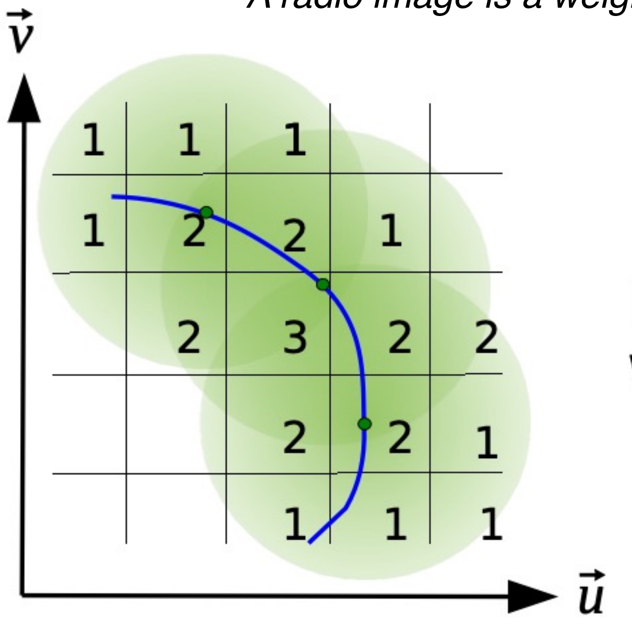
- **Smallest peak identified below a threshold** – which can be noise-based (e.g. 3 x theoretical noise estimated with exposure calculator – thermal noise)

- **Warning: Number of iterations –** be careful when setting «`niter`», as you may end up doing too much or too little cleaning

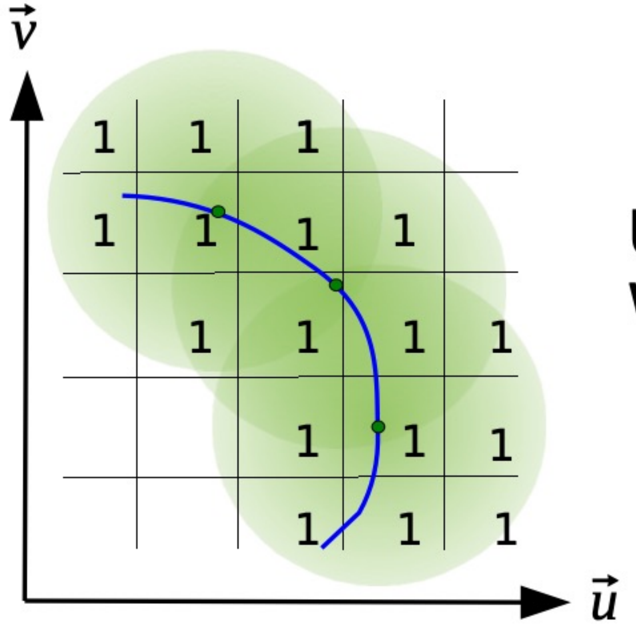
WEIGHTING

A radio image is a weighted-average of the data





Natural Weights



Uniform Weights

Visibility data are recorded onto a regular grid before performing FFT^{-1}

Use weights per visibility (weighted average of all data points per cell)

Slide credits: Urvashi Rau (NRAO)

WEIGHTING

Visibility V_k → AMP(a_k) PHASE(ϕ_k) NOISE(σ_k) WEIGHT (w_k)

Better rms, worse beam

Natural

$w_k = 1 / \sigma_k^2$. «more weights on short baselines», best sensitivity (important for more extended structures) but poor beam shape with overemphasized sidelobes

Robust

(Briggs 1995)

$w_k = 1 / (S^2 + \sigma^2_k)$

$$S^2 = \frac{(5 \times 10^{-R})^2}{\overline{w}}$$

R = robustness
it goes from -2 to 2 in CASA
and from -5 to 5 in AIPS

Average variance weighting factor over the grid cell in the image

Uniform

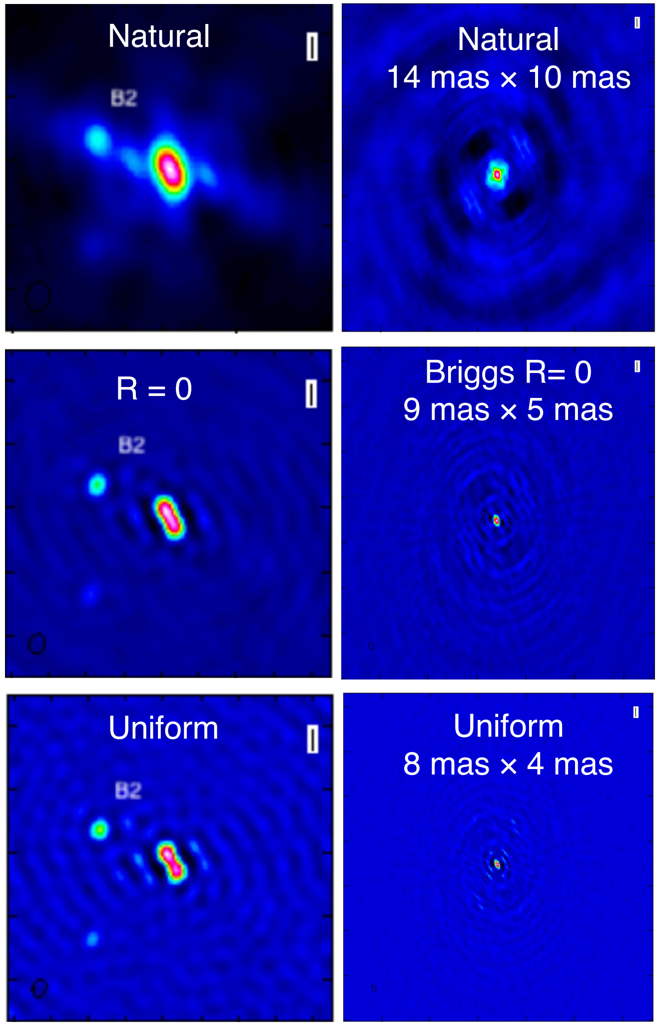
$w_k = 1 / \varrho (u_k, v_k)$

Sampling density function

better resolution (tighter main lobe) and lower sidelobes

Better beam, worse rms

image Dirty beam



Key points

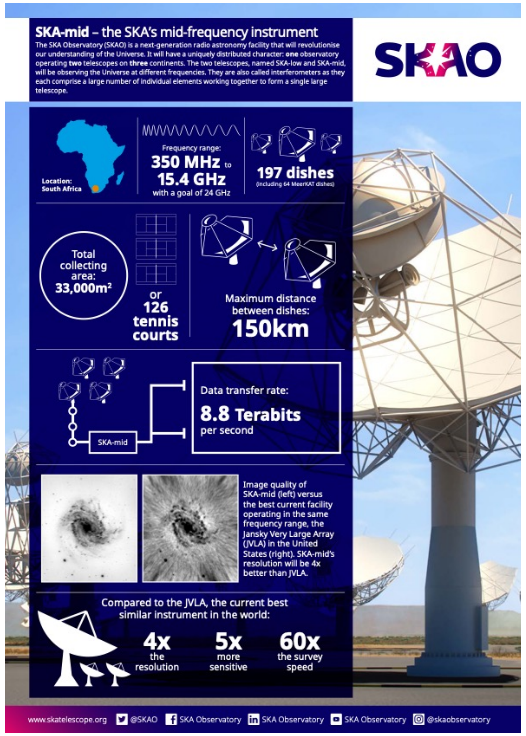
- «Imaging» is a **model-dependent iterative process**
  (~ a χ^2 pixel-by-pixel minimization)

- We use ***a priori*** **information:**
  B(l,m) must be positive; radio sources do not resemble the dirty beam;
  Sky is basically empty with just a few localized sources

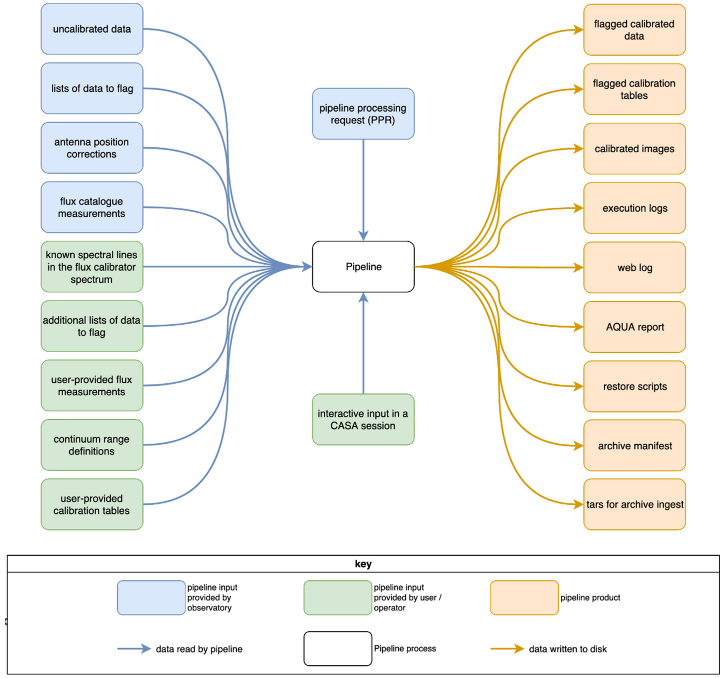
- **Multiple images can be created with a given set of visibilities.**
  Depending on your science goal you may prefer one or another
  (Ideally we should always put at least natural and uniform images in papers)

Imaging issues, recognizing errors and beyond Högbom/Clark methods

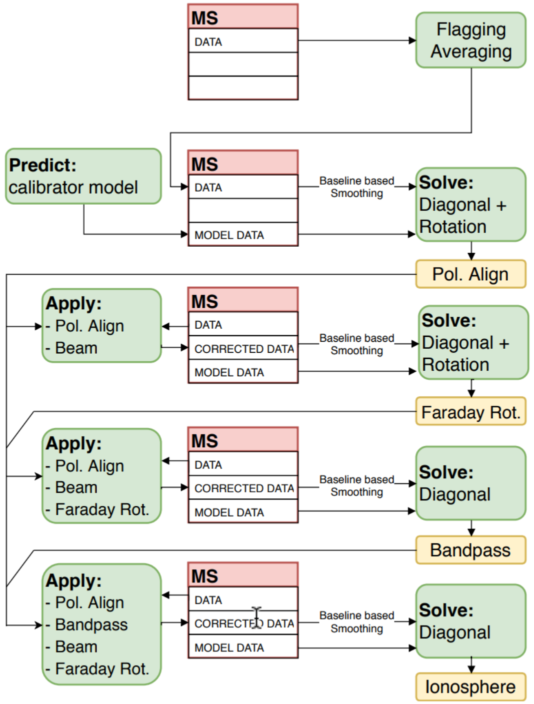
Imaging issues, recognizing errors and beyond Högbom/Clark methods: why?



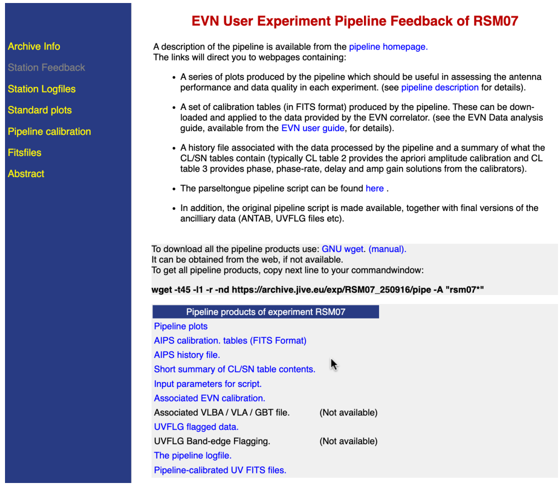
Credits: SKAO



ALMA pipeline (Hunter et al. 2023)

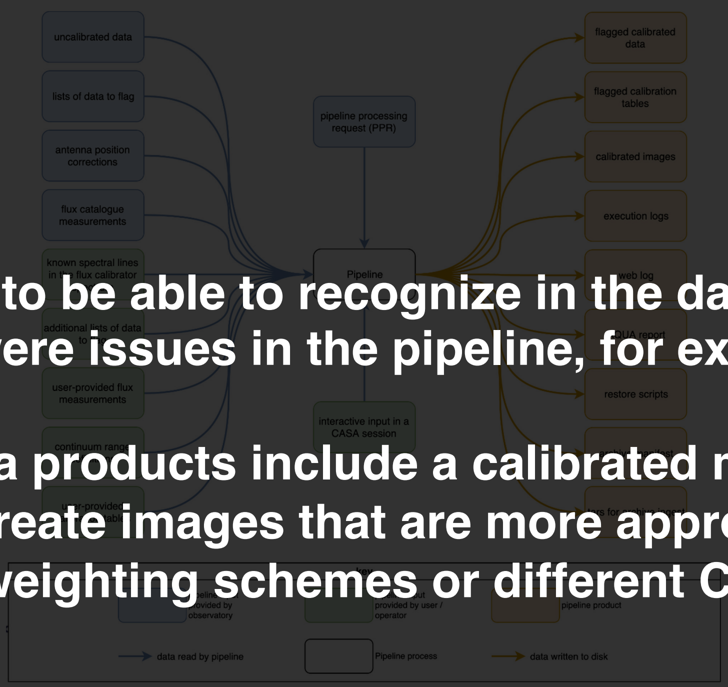


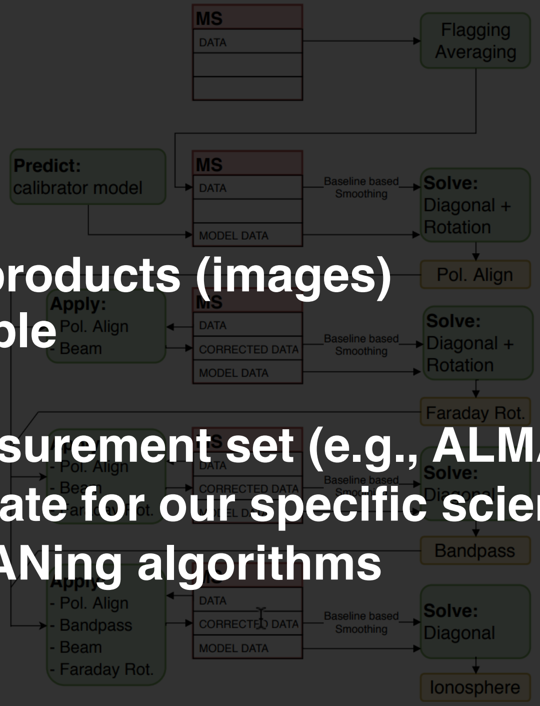
LOFAR LBA and HBA pipeline (De Gasperin et al. 2023)

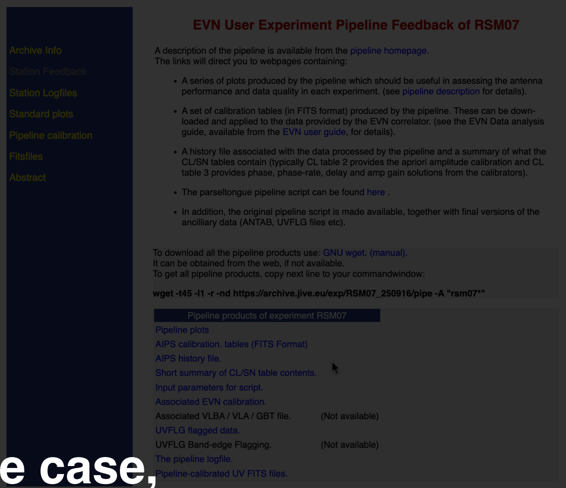


Also EVN pipeline
See Archive talk (J. Oh)

Imaging issues, recognizing errors and beyond Högbom/Clark methods: why?







1) We need to be able to recognize in the data products (images) if there were issues in the pipeline, for example

2) If the data products include a calibrated measurement set (e.g., ALMA) we can create images that are more appropriate for our specific science case, testing weighting schemes or different CLEANing algorithms

Also EVN pipeline
See Archive talk (J. Oh)

Credits: SKAO

ALMA pipeline (Hunter et al. 2023)

LOFAR LBA and HBA pipeline (De Gasperin et al. 2023)

Imaging issues and recognizing errors

1. CLEANing procedure
2. Calibration and data-handling
3. Source-related

ISSUES WITH CLEANING AND RECOGNIZING ERRORS

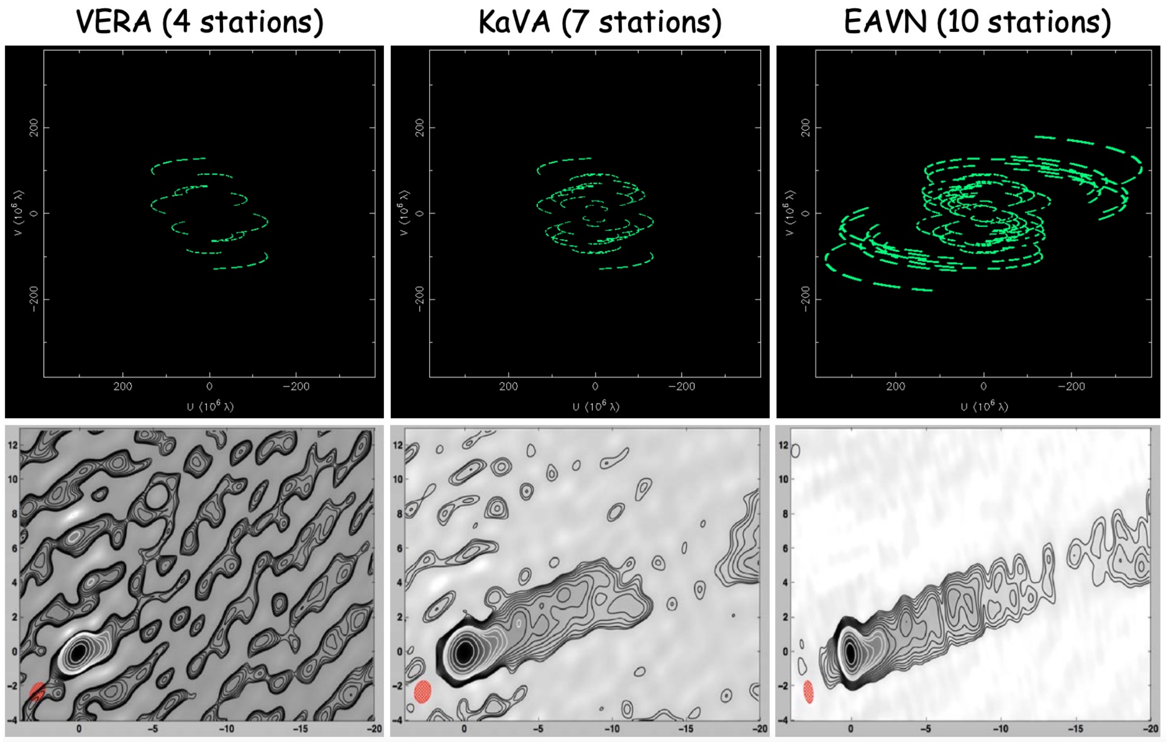
1) CLEANING-related

- Interpolation of **unsampled (u,v) spacings** (in particular short spacings):
  reconstruction of largest spatial scales is always an extrapolation (CLEAN boxes help)

- Assumption of **point-sources for extended structure** is not great

- **Under- and over-cleaning** are often an issue (over-cleaning: rms in logger does not change anymore)

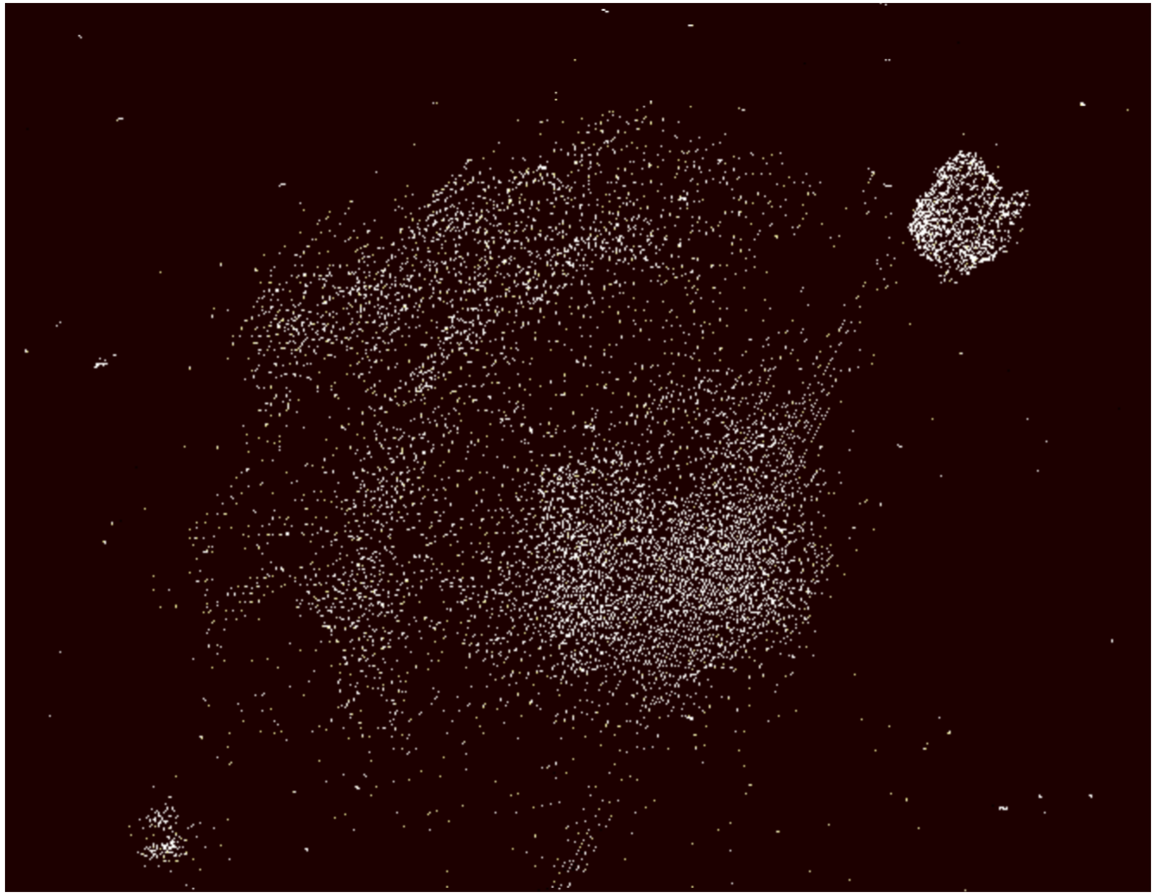
- **Computationally expensive**, as it requires iterative, non-linear fitting process (CLEAN boxes/masks help)



ISSUES WITH CLEANING AND RECOGNIZING ERRORS

1) CLEANING-related

- Interpolation of **unsampled (u,v) spacings** (in particular short spacings):
  reconstruction of largest spatial scales is always an extrapolation (CLEAN boxes help)
- Assumption of **point-sources for extended structure** is not great (but there are solutions)
- **Under- and over-cleaning** are often an issue (over-cleaning: rms in logger does not change anymore)
- **Computationally expensive**, as it requires iterative, non-linear fitting process (CLEAN boxes/masks help)



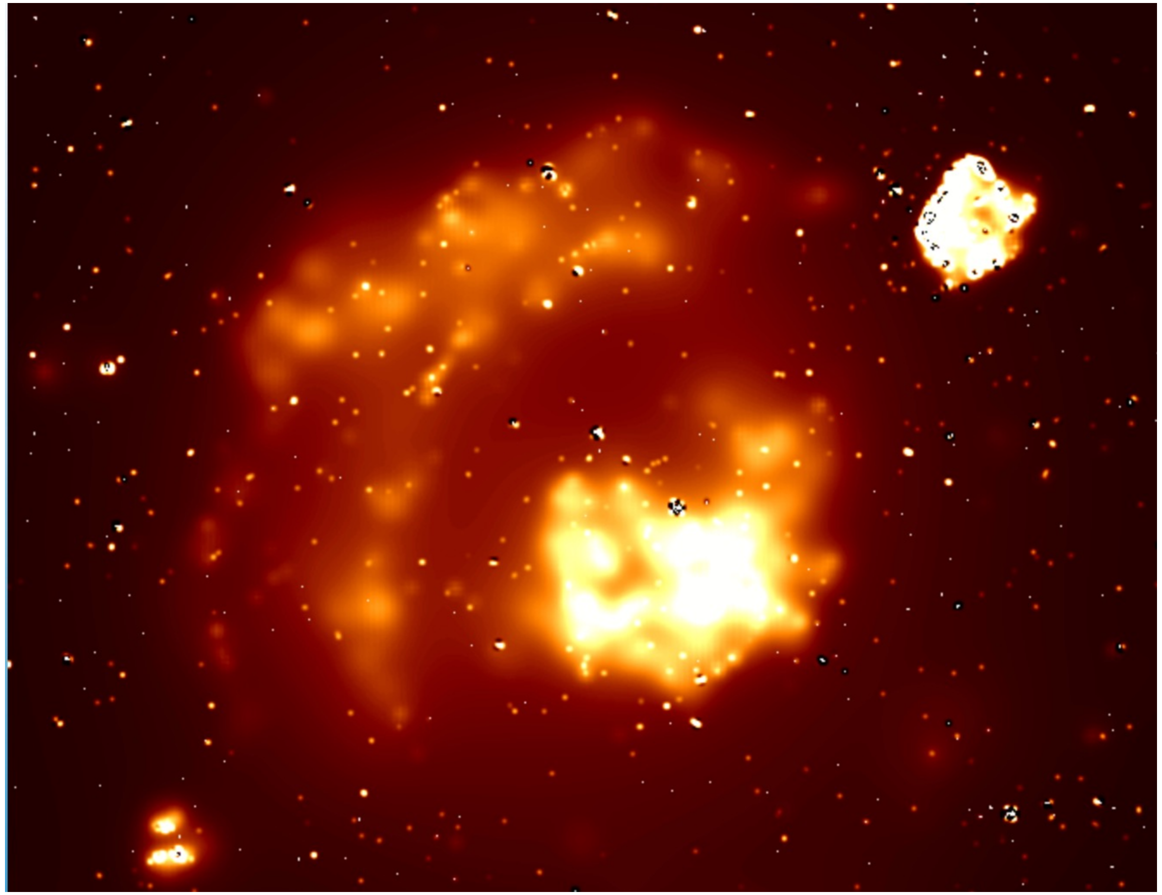
CLEAN method = Högbom

Credits: André Offringa ERIS 2017

ISSUES WITH CLEANING AND RECOGNIZING ERRORS

1) CLEANING-related

- Interpolation of **unsampled (u,v) spacings** (in particular short spacings): reconstruction of largest spatial scales is always an extrapolation (CLEAN boxes help)
- Assumption of **point-sources for extended structure** is not great (but there are solutions)
- **Under- and over-cleaning** are often an issue (over-cleaning: rms in logger does not change anymore)
- **Computationally expensive**, as it requires iterative, non-linear fitting process (CLEAN boxes/masks help)



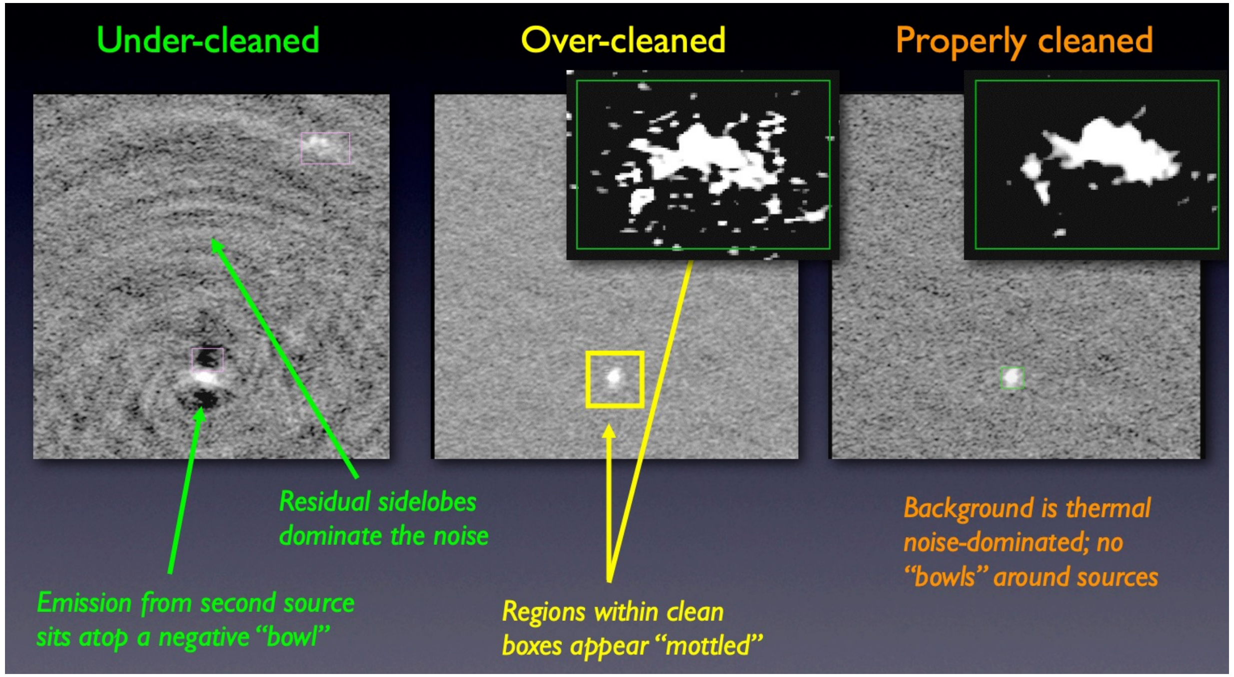
CLEAN method = multi-scale

Credits: André Offringa ERIS 2017

ISSUES WITH CLEANING AND RECOGNIZING ERRORS

1) CLEANING-related

- Interpolation of **unsampled (u,v) spacings** (in particular short spacings): reconstruction of largest spatial scales is always an extrapolation (CLEAN boxes help)
- Assumption of **point-sources for extended structure** is not great (but there are solutions)
- **Under- and over-cleaning** are often an issue (over-cleaning: rms in logger does not change anymore)
- **Computationally expensive**, as it requires iterative, non-linear fitting process (CLEAN boxes/masks help)



Credits: Michael Wise UVA lectures

ISSUES WITH CLEANING AND RECOGNIZING ERRORS

1) CLEANING-related

- Interpolation of **unsampled (u,v) spacings** (in particular short spacings):
  reconstruction of largest spatial scales is always an extrapolation (CLEAN boxes help)

- Assumption of **point-sources for extended structure** is not great (but there are solutions)

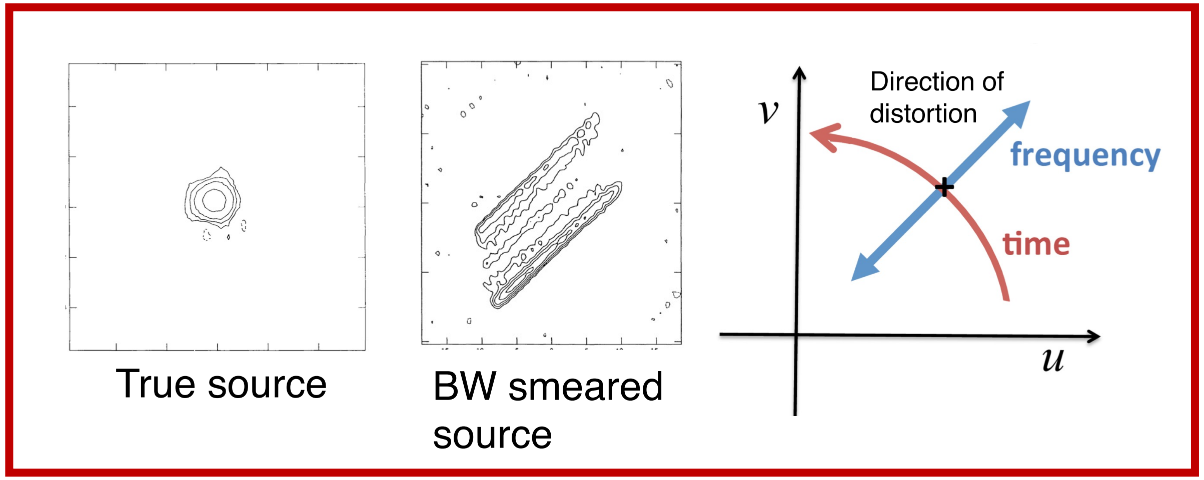
- **Under- and over-cleaning** are often an issue (over-cleaning: rms in logger does not change anymore)

- **Computationally expensive**, as it requires iterative, non-linear fitting process (CLEAN boxes/masks help)

ISSUES WITH CLEANING AND RECOGNIZING ERRORS

2) Calibration and data-handling related

- **Bandwidth** (chromatic aberration) **and time smearing** (de-correlation)
- **Amplitude/phase errors** from previous calibration and/or unflagged data **(symmetric/antisymmetric artefacts)**



Images of sources away from the observing centre are smeared out in the radial direction, reducing the signal-to-noise ratio. The effect of bandwidth smearing increases with the fractional bandwidth $\Delta\nu/\nu$, the square root of the distance to the observing centre, $(l^2 + m^2)^{1/2}$, and with $1/\theta_b$, where θ_b is the FWHM of the synthesized beam.

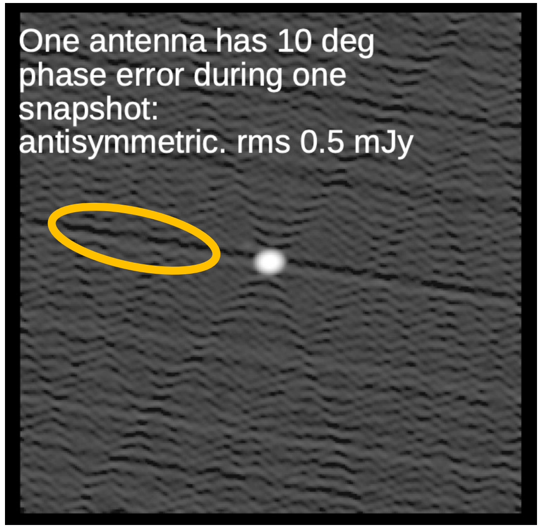
(Middelberg 2012)

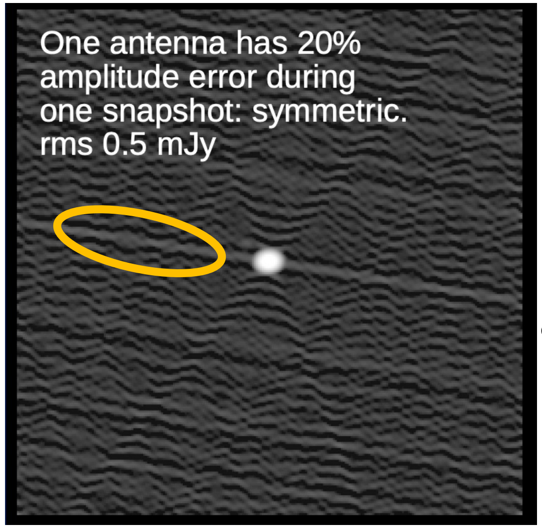
ISSUES WITH CLEANING AND RECOGNIZING ERRORS

2) Calibration and data-handling related

- **Bandwidth** (chromatic aberration) **and time smearing** (de-correlation)

- **Amplitude/phase errors** from previous calibration and/or unflagged data **(symmetric/antisymmetric artefacts)**





Credits: Laing ERIS 2013

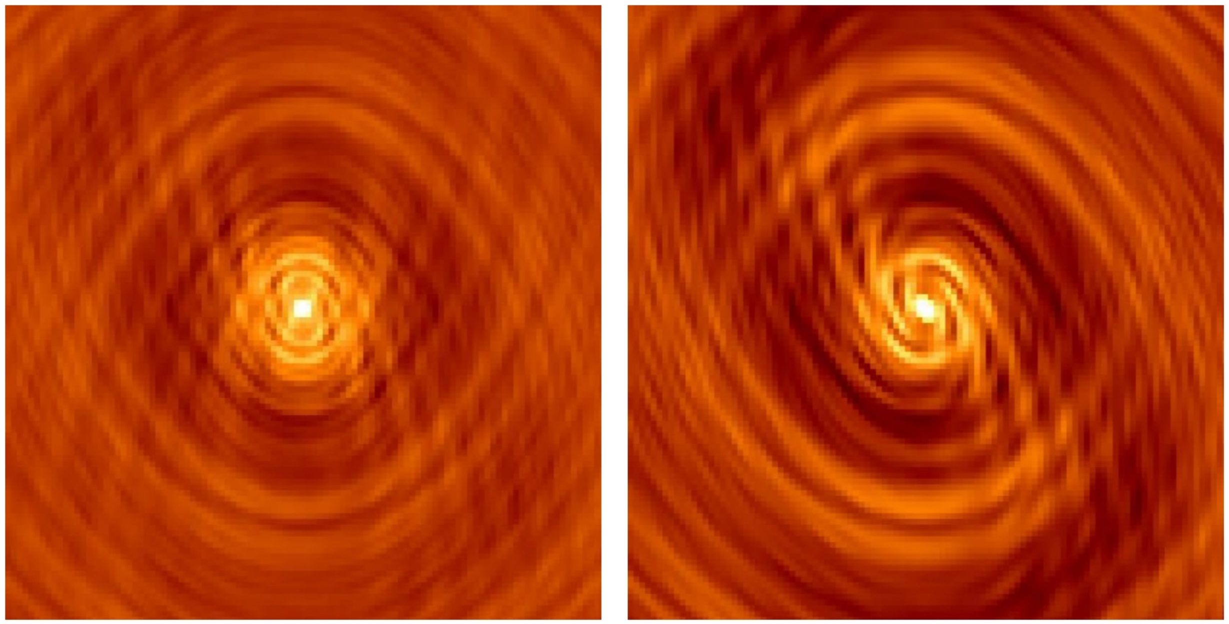
ISSUES WITH CLEANING AND RECOGNIZING ERRORS

3) Source-related

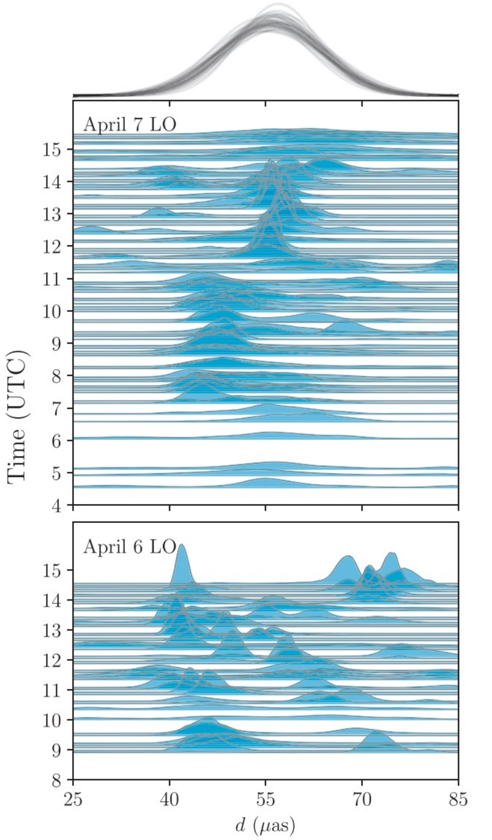
- **Variability** of the source

- **Spectral variations of the source** – mu
  (gridding different frequencies on the san

Source constant in time | Source flux varying with time

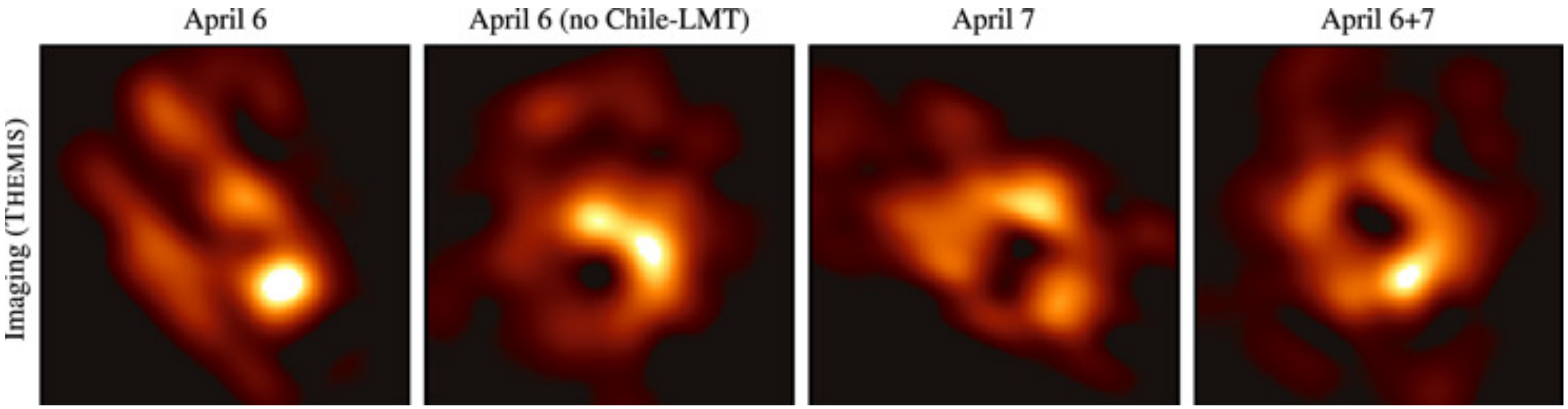


Credits: Stewart 2012 GLOW school



Snapshot images
then stacking/average

Figure 13. Example snapshot modeling results and averaging scheme applied to the Sgr A* April 6 and 7 low-band HOPS data sets. The blue filled regions



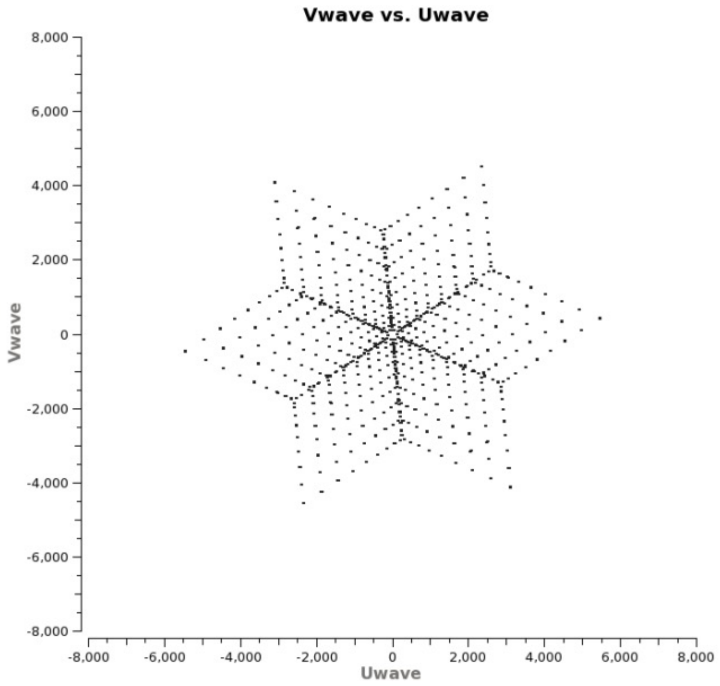
SgrA* EHT Collaboration (2022)

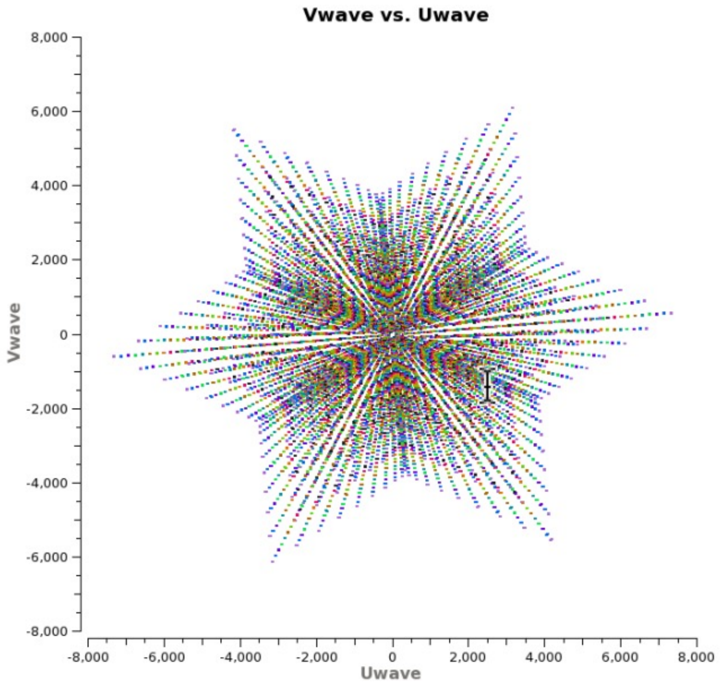
ISSUES WITH CLEANING AND RECOGNIZING ERRORS

3) Source-related

- **Variability** of the source

- **Spectral variations of the source** – multi frequency synthesis (gridding different frequencies on the same (u,v) grid is now standard)





Credits: Michael Wise UVA lectures

BASICS OF SELF-CALIBRATION

MOTIVATION: BEYOND STANDARD CALIBRATION

Standard calibration relies on frequent observations of radio **sources with known structure, flux density and position** (*calibrators*)
to
determine the **empirical corrections** for time-variable instrumental and environmental factors that cannot be measured directly

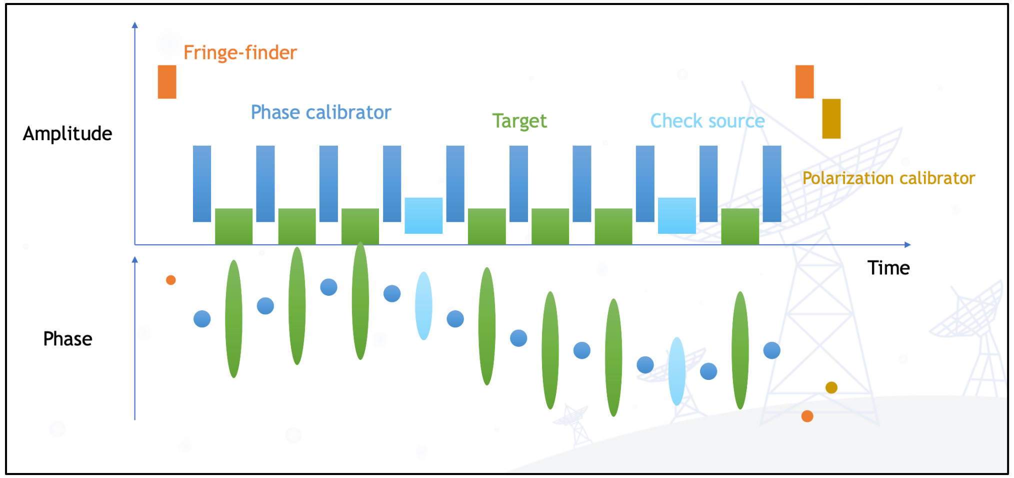
Complex gains of antennas i and j

Thermal noise

$$\widetilde{V}_{ij}(t) = g_i(t)g_j^*(t)V_{ij}(t) + \epsilon_{ij}(t)$$

Observed visibilities at time t

True visibilities



From Benito Marcote’s lecture

MOTIVATION: BEYOND STANDARD CALIBRATION

Using calibrators nearby the target one can solve for the gains as a function of time.

Then, calibration is transferred to the target sources, **which is at a different position**

(troposphere and ionosphere are not uniform across the sky)

and observed at a different time

(troposphere/ionosphere might be variable and electronics too)

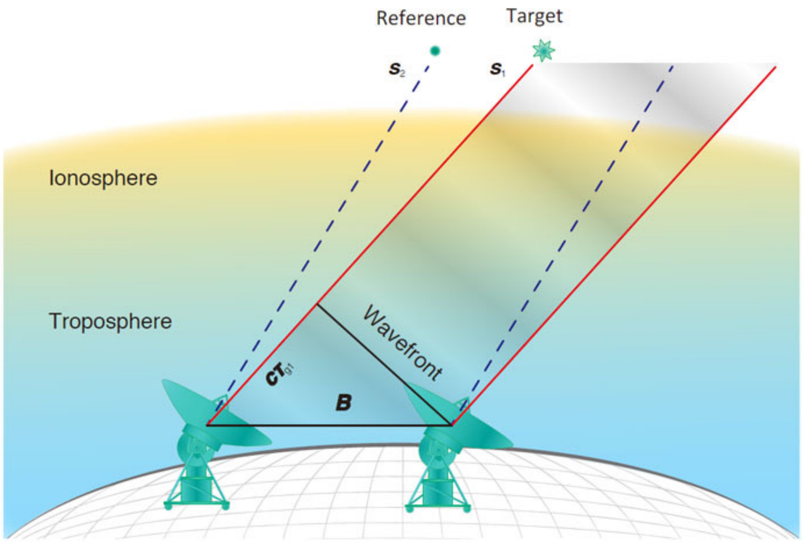
Complex gains of antennas i and j

Thermal noise

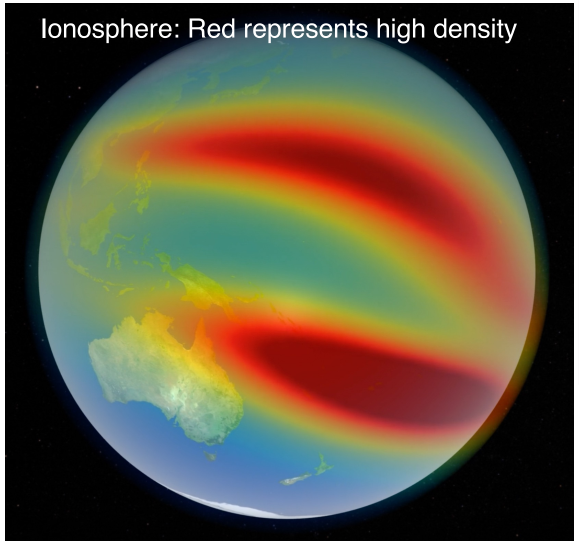
$$\widetilde{V}_{ij}(t) = g_i(t) g_j^*(t) V_{ij}(t) + \epsilon_{ij}(t)$$

Observed visibilities at time t

True visibilities



Reid & Honma 2014



https://svs.gsfc.nasa.gov/4504

Temporal and spatial variations in the atmosphere and electronics will not be properly estimated

Hence the effect of $g_i(t)\, g_j(t)^*$ cannot be removed completely and residual errors remain

MOTIVATION: BEYOND STANDARD CALIBRATION

Using calibrators nearby the target one can solve for the gains as a function of time.

Then, calibration is transferred to the target sources, **which is at a different position**

(troposphere and ionosphere are not uniform across the sky)

and observed at a different time

(troposphere/ionosphere might be variable and electronics too)

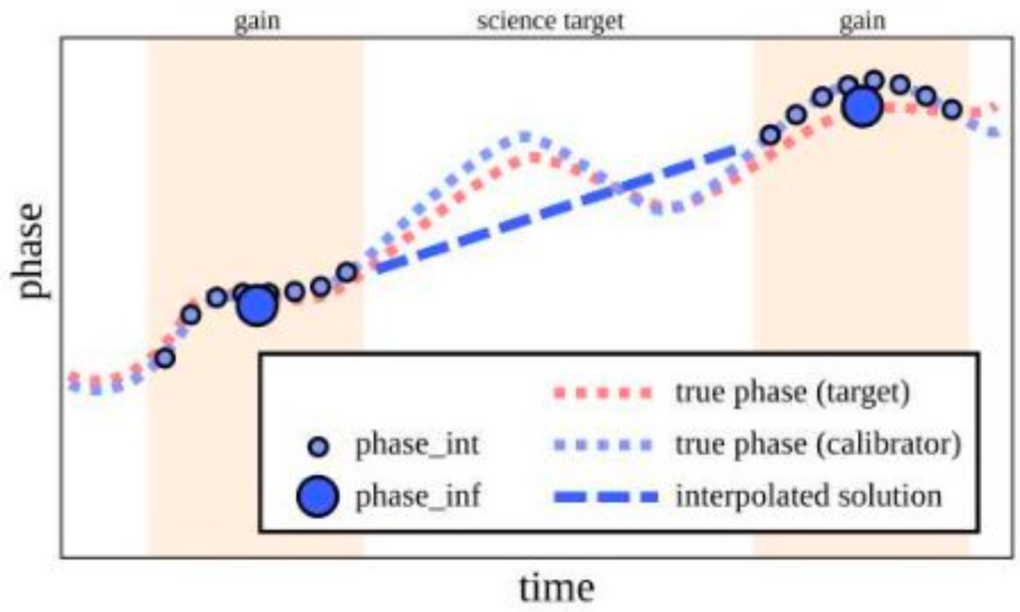
Complex gains of antennas i and j

Thermal noise

$$\widetilde{V}_{ij}(t) = g_i(t) g_j^*(t) V_{ij}(t) + \epsilon_{ij}(t)$$

Observed visibilities at time t

True visibilities



Credits: ALLEGRO team

Temporal and spatial variations in the atmosphere and electronics will not be properly estimated

Hence the effect of $g_i(t)\, g_j(t)^*$ cannot be removed completely and residual errors remain

MOTIVATION: BEYOND STANDARD CALIBRATION

Complex gains of antennas i and j

Thermal noise

$$\widetilde{V}_{ij}(t) = g_i(t)g_j^*(t)V_{ij}(t) + \epsilon_{ij}(t)$$

Observed visibilities at time t

«True» visibilities = MODEL

1) *A priori* knowledge of the source

When we make the first CLEANed image we create a MODEL of the target, which can be used as «True visibilities»

Note: standard calibration is done with simple sources (ideally point-like) at the phase center, while self-calibration is performed on complex sources, to take into account their structure while estimating the residual corrections

2) Redundant calibration

Arrays are designed so that different baselines may measure the same uv-spacings → this **redundancy implies that the complex gains can be solved for** (up to a linear phase slope, e g., Hamaker+ 1977)

MOTIVATION: BEYOND STANDARD CALIBRATION

Complex gains of antennas i and j

Thermal noise

$$\widetilde{V}_{ij}(t) = g_i(t) g_j^*(t) V_{ij}(t) + \epsilon_{ij}(t)$$

Observed visibilities at time t

«True» visibilities = MODEL

2) Redundant calibration

Arrays are designed so that different baselines may measure the same uv-spacings → this **redundancy implies that the complex gains can be solved for** (up to a linear phase slope, e g., Hamaker+ 1977)

2) *A priori* knowledge of the source

When we make the first CLEANed image we create a MODEL of the target, which can be used as «True visibilities»

Note: standard calibration is done with simple sources (ideally point-like) at the phase center, while self-calibration is performed on complex sources, to take into account their structure while estimating the residual corrections

MOTIVATION: BEYOND STANDARD CALIBRATION

Using a good model (obtained from CLEANing) of the target to refine phase and amplitude corrections

SELF-CALIBRATION PROCEDURE

First CLEANed image to get the **initial model** of the target

Determine the residual phase (or amp) corrections using this initial model
= find antenna gains

If OK, apply these antenna gains

Create a new improved model of the target

Determine the residual phase (or amp) corrections using this **new model**
= find antenna gains

If OK, apply these antenna gains

Continue…

Self-cal is an iterative process where we **determine $g_i(t)g_j(t)^*$**, produce an **improved model** of the target and continue the cycle until we reach thermal noise (ideally)

$$g_i(t)g_j(t)^* = \frac{\tilde{V}_{ij}^{obs}}{V_{ij}^{model}}$$

SELF-CALIBRATION PROCEDURE

First CLEANed image to get the **initial model** of the target

Determine the residual phase (or amp) corrections using this initial model **= find antenna gains**

If OK, apply these antenna gains

Create a new improved model of the target

Determine the residual phase (or amp) corrections using this **new model** **= find antenna gains**

If OK, apply these antenna gains

Continue…

Why does it work?

Self-calibration works because we have **over-constrained data** (arrays with many antennas)

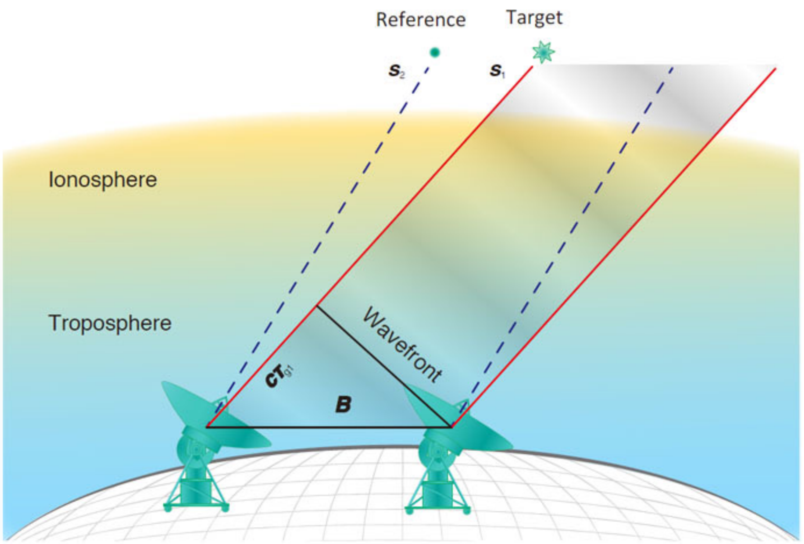
3 antennas = minimum for phase self-cal

4 antennas = minimum for amp self-cal

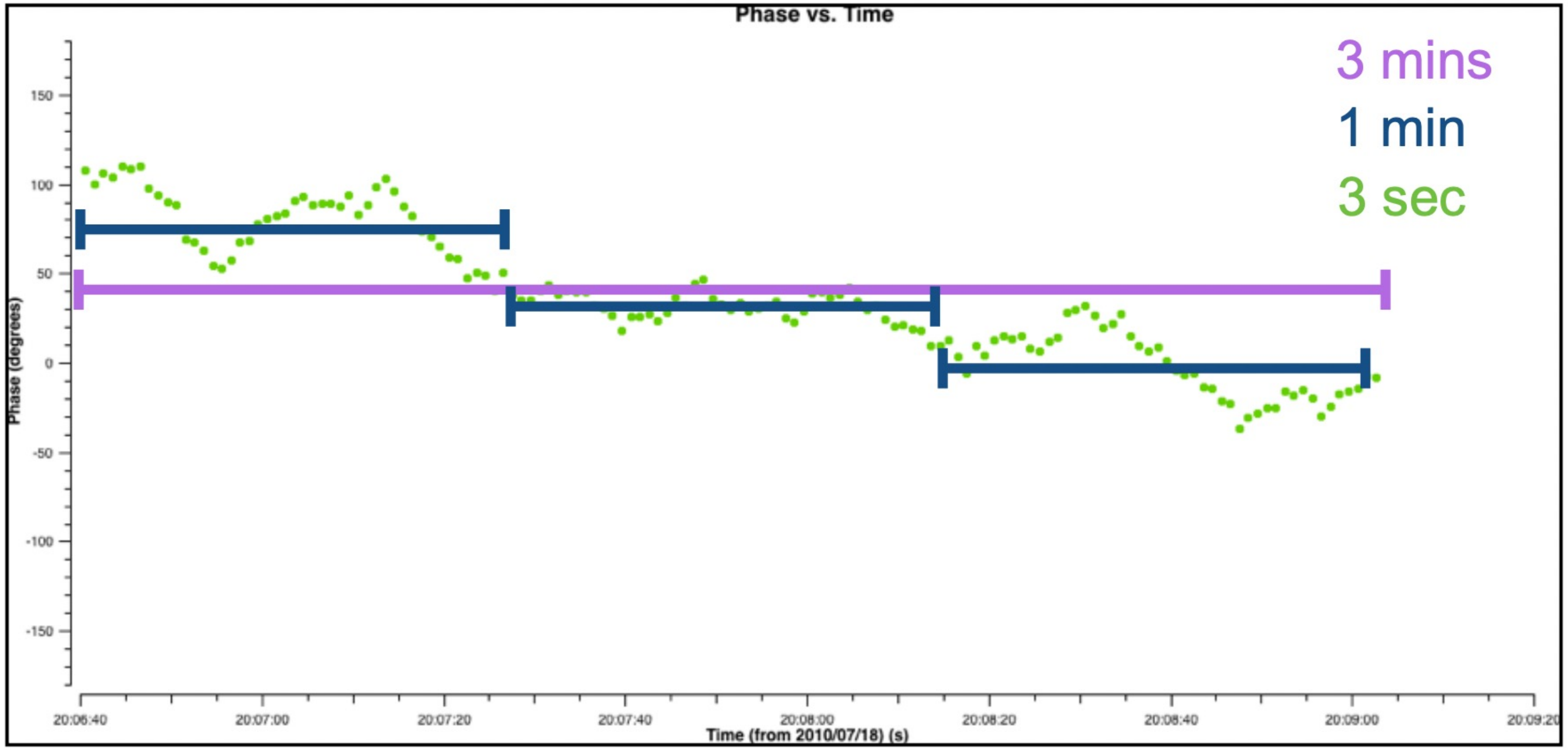
Source structure can be parametrized (typically) in a relatively simple way → we can obtain a **good model**

SELF-CALIBRATION: the choice of solution interval

Solution interval: short enough to track the gain variations, but not too short otherwise the signal-to-noise ratio per solution is too small



Reid & Honma 2014



Credits: McKean ERIS 2017

Typically one decreases the solution interval progressively across the self-cal loops

SELF-CALIBRATION PROs and CONs

- Sources with **enough signal-to-noise ratio** can be used for self-cal to obtain a better image = determining **better gains will lead to a better image** (improving dynamic range)

- You generally want to perform self-cal if the **rms noise is much worse than expected** and/or the dynamic range is not close to the theoretical one

- Learning self-cal is useful as it is rarely included in data reduction pipelines (but see recent ALMA and VLA pipeline developement https://science.nrao.edu/srdp/self-calibration-preview)

SELF-CALIBRATION PROs and CONs

- Sources with **enough signal-to-noise ratio** can be used for self-cal to obtain a better image = determining **better gains will lead to a better image** (improving dynamic range)

- You generally want to perform self-cal if the **rms noise is much worse than expected** and/or the dynamic range is not close to the theoretical one

- Learning self-cal is useful as it is rarely included in data reduction pipelines (but see recent ALMA and VLA pipeline developement https://science.nrao.edu/srdp/self-calibration-preview)

- **Absolute** positional information is **lost** if you apply phase self-cal

- You need a sufficiently **bright source** = it's not always successful

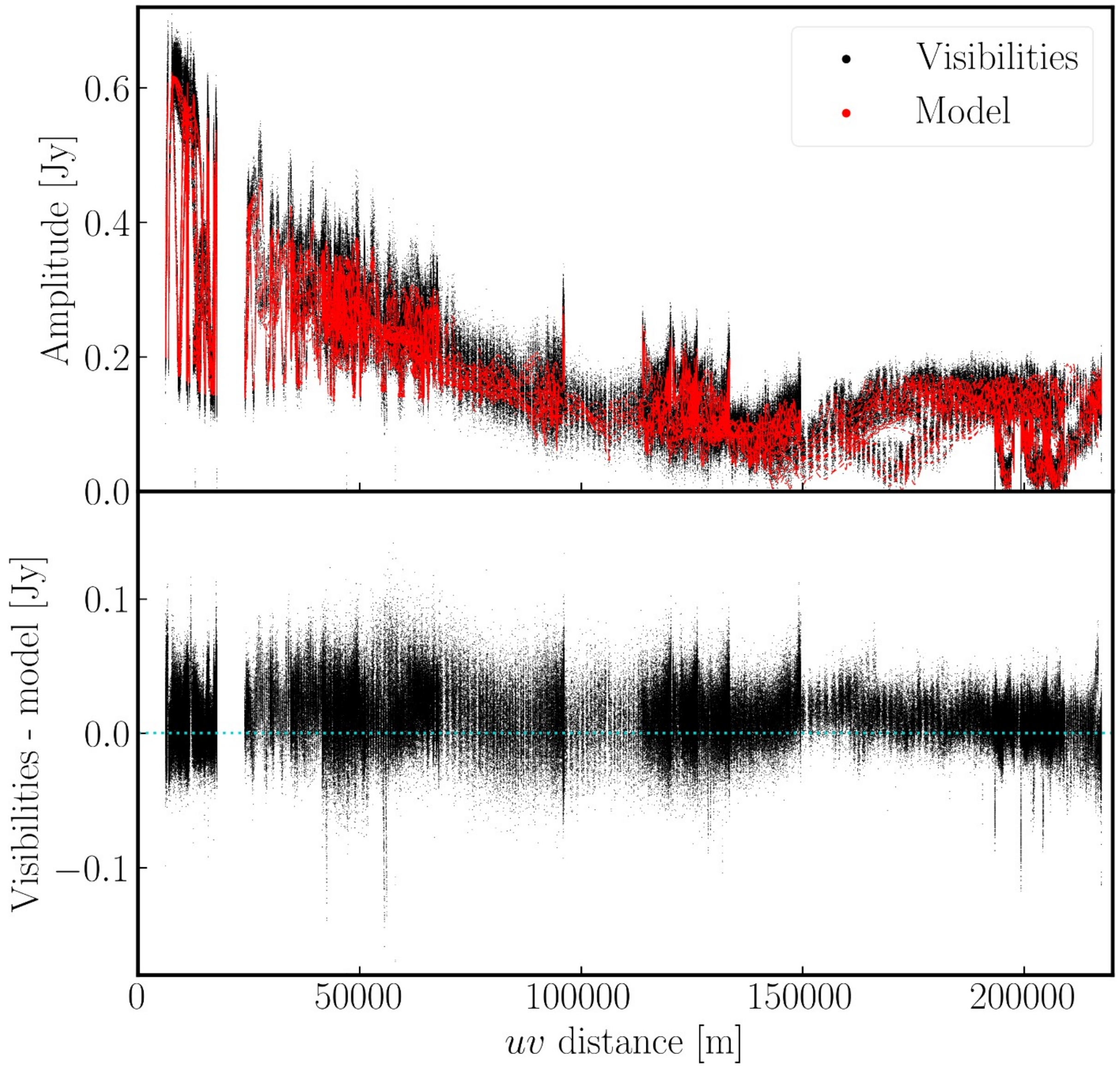
SELF-CALIBRATION: measuring the improvement through image quality

- **Off-source rms** noise: you should obain better rms at each iteration of self-cal → ideally up to theoretical noise (thermal noise)

- **Dynamic range** (peak / off-source rms) -- typical (good) values 10^2 - 10^6, it should improve as self-calibration continues

- Off-source rms **noise structure quite uniform**, close to a Gaussian random field («no stripes»):
  check for any phase and amplitude errors (see previous slides)
  any «weird» structure might be a symptom that something went wrong (at the deconvolution stage and/or during self-cal calibration)

SELF-CALIBRATION: measuring the improvement through visibilities



Credits: Jack Radcliffe,
https://www.jb.man.ac.uk/DARA/ERIS22/selfcalibration.html

SELF-CALIBRATION – when to stop and final notes

- Complex sources may require more cycles than compact (simple) sources

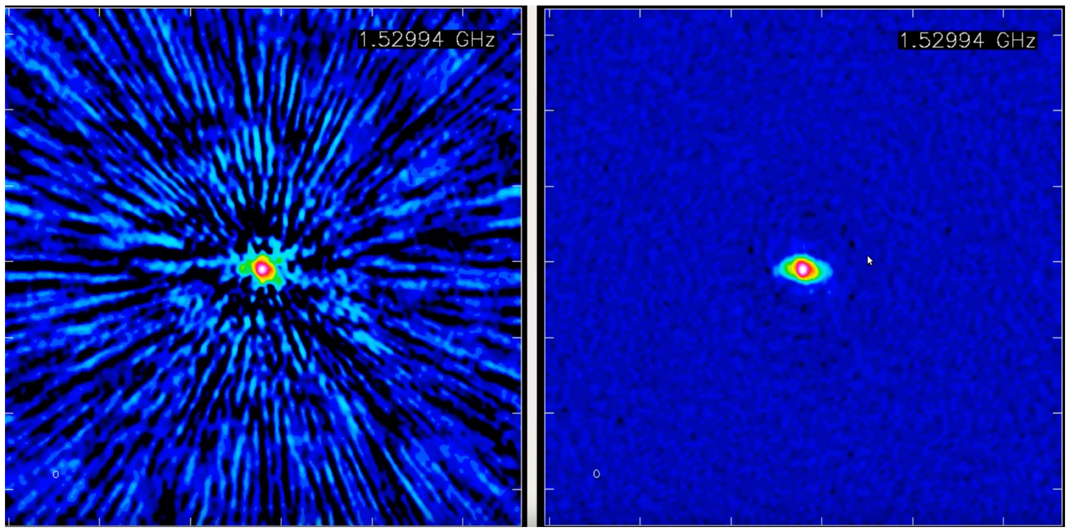
- Try to progressively go down to the lowest solution interval allowed by your dataset (always check failed solutions)

- Construct your model step-by-step: **a wrong model compromises the entire self-calibration process** and may lead to wrong scientific results!

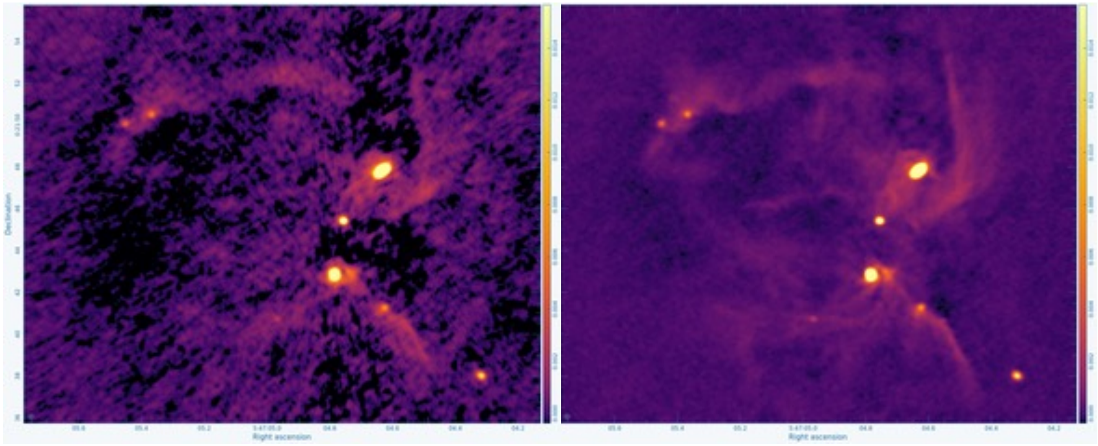
- **Stop** when your dynamic range **(peak / rms) does not improve anymore** – ideally you should have reached the thermal noise

- A little note about **amplitude self-calibration**: it is meant to «fix» time-dependent gain residuals , not to set the flux scale! It is easy to «lose» or «add» flux density → always normalize your solutions (in CASA `solnorm=True`) and use longer solution interval wrt to phase-only self-cal

CLEANed image | Self-calibrated image



Credits: Moldón CASA-VLBI 2023



Credits: NRAO
https://science.nrao.edu/srdp/self-calibration-preview

References

«Synthesis imaging in radio astronomy II» (Edited by Taylor Carilli and Perley)

Campbell 2019 http://old.evlbi.org/user_guide/fov/fovSFXC.pdf

Interferometry and Synthesis in radio imaging (Thompson, Moran and Swenson) https://link.springer.com/book/10.1007/978-3-319-44431-4

Previous ERIS imaging and self-cal lectures can be found here https://www.astron.nl/events/eris-2022/

Lecture on imaging by Michael Wise https://www.astron.nl/astrowiki/lib/exe/fetch.php?media=ra_uva:ra_uva_lecture8.pdf

Self-calibration lecture by Javier Moldón at CASA-VLBI workshop 2023

Richards et al. 2022, ALMA Memo Series «Self-calibration and improving image fidelity for ALMA and other radio interferometers»

DARA tutorials https://www.jb.man.ac.uk/DARA/unit4/Workshops/EVN_continuum.html Complete tutorial using EVN data developed by Jack Radcliffe, Anita Richards and Des Small

African radio interferometry winter school https://www.sarao.ac.za/courses/african-radio-interferometry-winter-school/

ALLEGRO Data Reduction Cookbook - SelfCal https://home.strw.leidenuniv.nl/~alma/doc/allegroDRC/selfcal.html