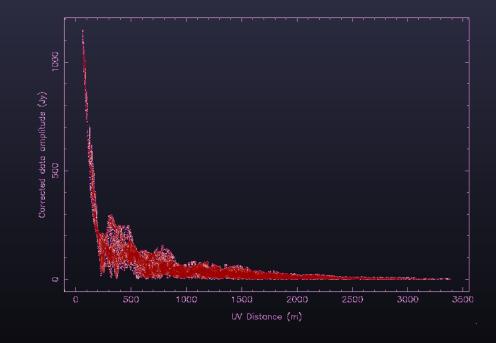
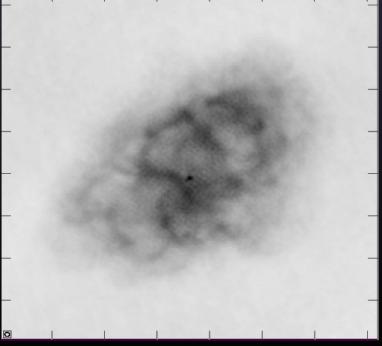
Imaging and deconvolution

S. Bhatnagar, NRAO



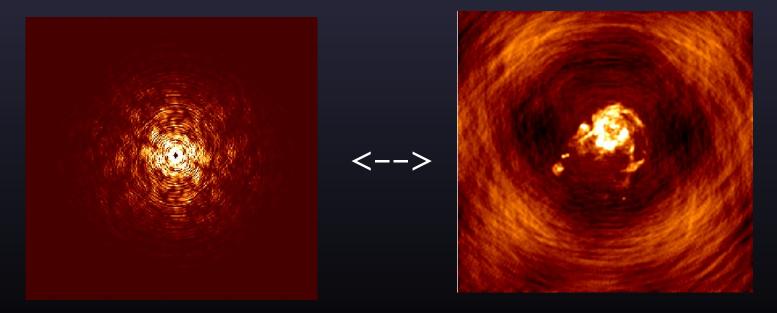




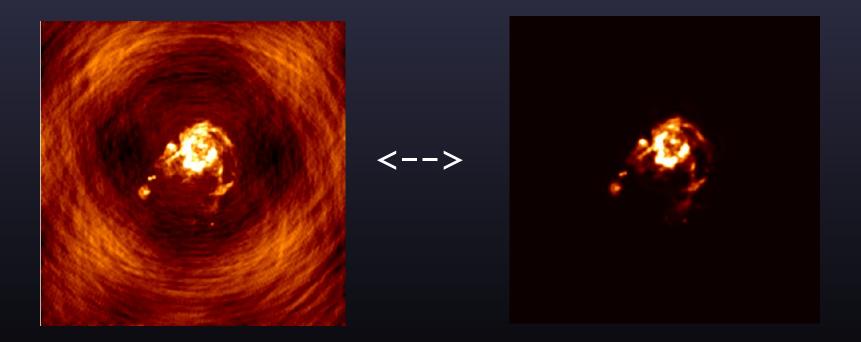
Plan for the lecture-I

- How do we go from the measurement of the coherence function (the Visibilities) to the images of the sky?
- First half of the lecture: Imaging

Measured Visibilities <--> Dirty Image



Second half of the lecture: Deconvolution Dirty image <--> Model of the sky



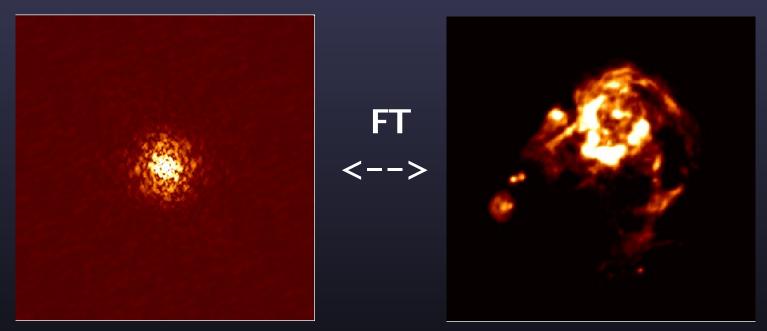
- Interferometers are indirect imaging devices $V^{o}(u, v, w) = \iint P(l, m) I(l, m) e^{2\pi i \left[ul + vm + w \left(\sqrt{1 - l^{2} - m^{2}} - 1 \right) \right]} \frac{dl \, dm}{\sqrt{1 - l^{2} - m^{2}}}$
- For small w (small max. baseline) or small field of view (l² + m² << 1) and P(l,m)~1, l(l,m) is 2D Fourier transform of V(u,v)

$$V^{o}(u,v) = \iint I(l,m) e^{2\pi \iota [ul+vm]} dl dm$$
$$V^{o}(u,v) \Leftrightarrow I(l,m)$$

Imaging: Ideal 2D Fourier relationship

Ideal visibilities(V)

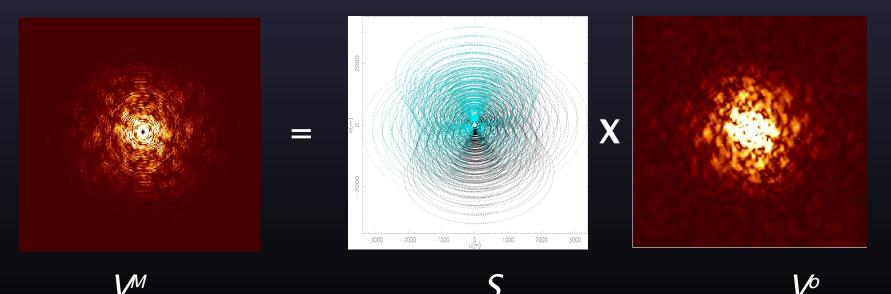
True image(I)



• This is true ONLY if *V* is measured for all *(u,v)*!

 With limited number of antennas, the uv-plane is sampled at discrete points:

 $\overline{S(u, v)} = \sum_{k} \delta(\overline{u_{k}, v_{k}})$ $V^{M}(u, v) = S(u, v) V^{o}(u, v)$



- Effect of sampling the uv-plane: $I^{d}(l,m) = FT^{-1} \Big[V^{o}(u,v) S(u,v) \Big]$
- Using the Convolution Theorem: $I^{d}(l,m) = B(l,m) * I^{o}(l,m)$

The Dirty Image (I^e) is the convolution of the True Image (I^e) and the Dirty Beam/Point Spread Function (B)

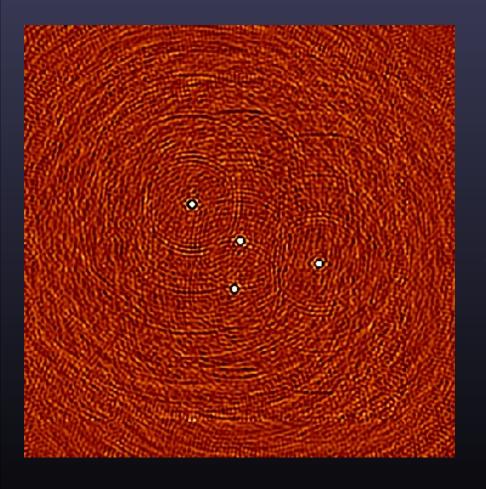
 $B = FT^{-1}(S)$

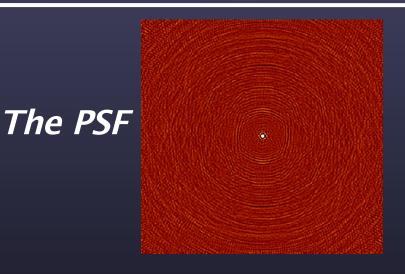
•In practice

 $I^{d} = B^{*}I^{o} + B^{*}I^{N}$ where $I^{N} = FT^{-1}$ (Vis. Noise)

• To recover *P*, we must deconvolve *B* from *P*. The algorithm must also separate *B*P* from *B*P*.

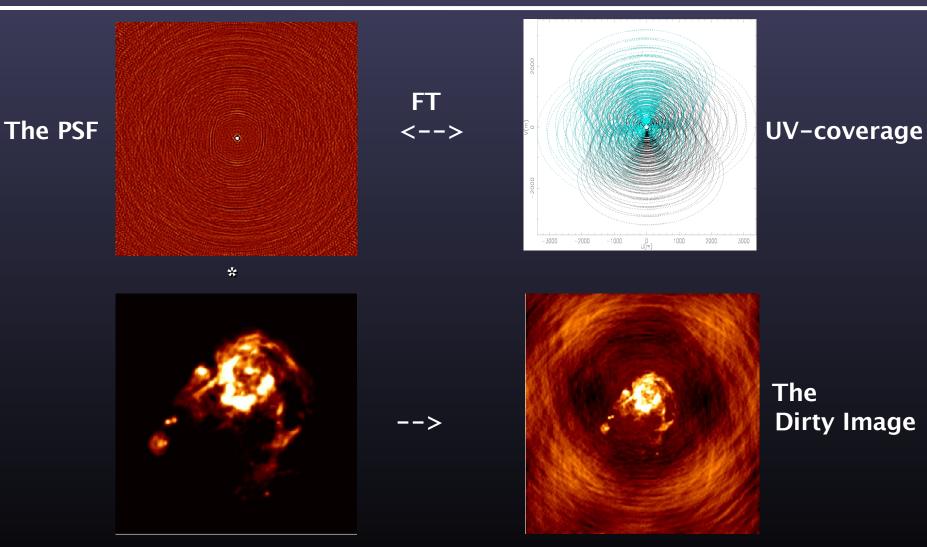
Convolution





 $= I(x_{o})B(x-x_{o}) + I(x_{1})B(x-x_{1}) + \dots$

The Dirty Image



- Fast Fourier Transform (FFT) is used for efficient Fourier transformation. It however requires regularly spaced grid of data.
- Measured visibilities are irregularly sampled (along uv-tracks).
- Convolutional gridding is used to effectively interpolate the visibilities everywhere and then resample them on a regular grid (the Gridding operation)

$$V^{S} = V^{M} * C = (V^{O}S) * C => I^{d} \cdot FT^{-1}(C)$$

• *C* is designed to have desirable properties in the image domain.

 PSF is a weighted sum of cosines corresponding to the measured Fourier components:

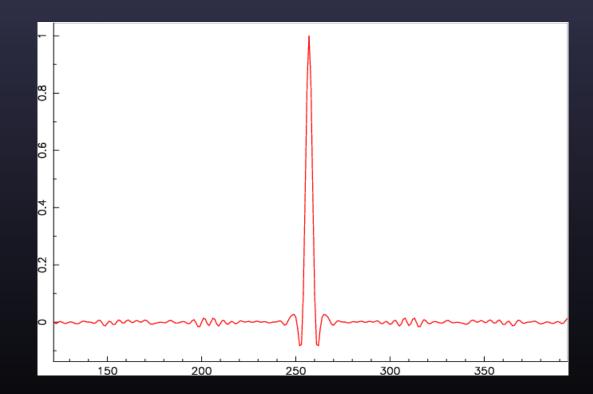
$$B(l,m) = \frac{\sum_{k} W_{k} \cos(u_{kl} + v_{km})}{\sum_{k} W_{k}}$$

Visibility weights (*w*_i) are also gridded on a regular grid and FFT used to compute the Dirty Beam (or the PSF).

- The peak of the PSF is normalized to 1.0
- The 'main lobe' has a size $dx \sim 1/u_{max}$ and $dy \sim 1/v_{max}$

This is the 'diffraction limited' resolution (the Clean **Beam)** of the telescope.

- Side lobes extend indefinitely
- RMS ~ 1/N where N = No. of antennas

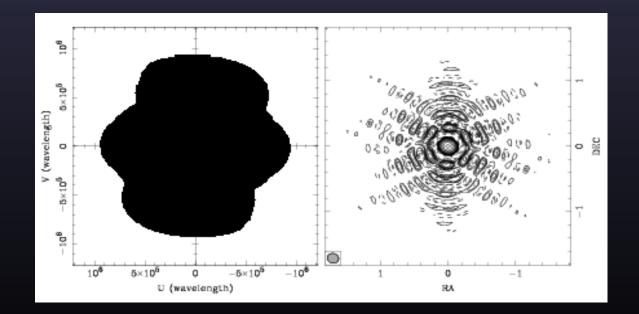


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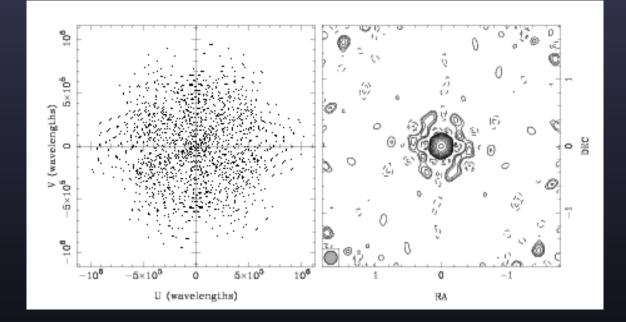
Close-in side lobes of the PSF

• Close-in side lobs of the PSF are controlled by the uv-coverage envelope.

E.g., if the envelop is a circle, the side lobes near the main lobe must be similar to the FT of a circle: Bessel function/Radius



Close-in side lobes: VLA uv-coverage



- Weighting function (W_k) can be chosen to modify the side lobes $B(l,m) = \frac{\sum_k W_k \cos(u_{kl} + v_{km})}{\sum_k W_k}$
- Natural Weighting

 $W_k = 1/\sigma_k^2$ where σ_k^2 is the RMS noise

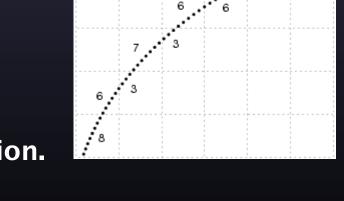
- Best RMS across the image.
- Large scales (smaller baselines) have higher weights.
- Effective resolution less than the inverse of the longest baseline.

Uniform weighting

 $W_k = 1/\rho(u_k, v_k)$ where $\rho(u_k, v_k)$ is the density of uv-points in the *k*th cell.

- Short baselines (large scale features in the image) are weighted down.
- Relatively better resolution
- -Increases the RMS noise.
- Super uniform weighting:

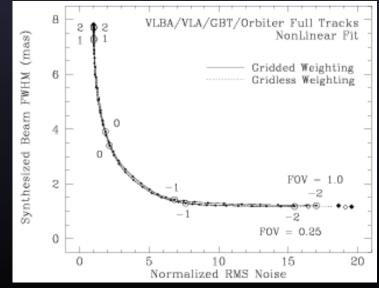
Consider density over larger region. Minimize side lobes locally.



• Robust/Briggs weighting:

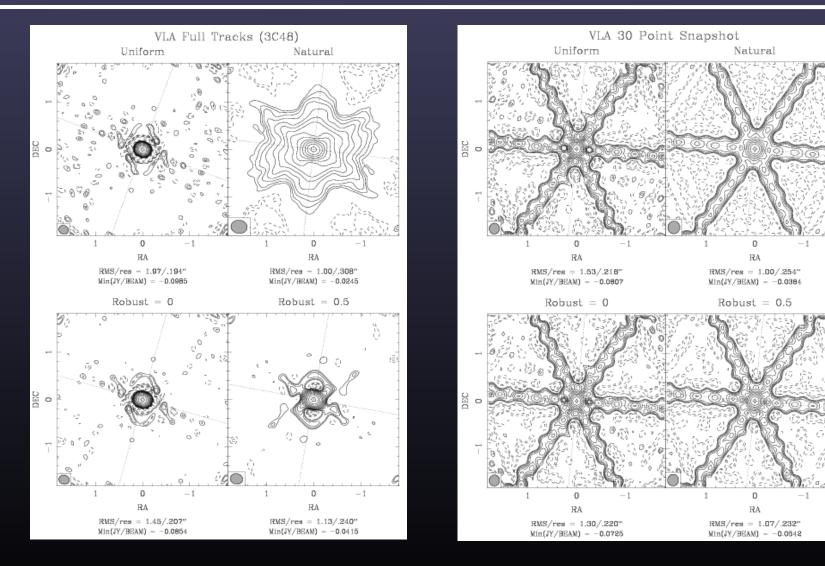
 $W_{k} = 1/[S \rho(u_{k}, v_{k}) + \sigma_{k}^{2}]$

 Parameterized filter – allows continuous variation between optimal resolution (uniform weighting) and optimal noise (natural weighting).



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Examples of weighting



• The PSF can be further controlled by applying a tapering function on the weights (e.g. such that the weights smoothly go to zero beyond the maximum baseline).

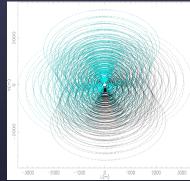
$$W'_{k} = T(u_{k}, v_{k}) W_{k}(u_{k}, v_{k})$$

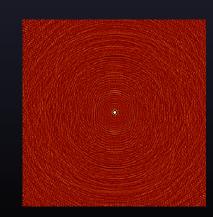
• Bottom line on weighting/tapering:

These help a bit, but imaging quality is limited by the deconvolution process!

The missing information

- As seen earlier, not all parts of the uv-plane are sampled - the 'invisible distribution'
- 1. "Central hole" below u_{min} and v_{min} :
 - Image plane effect: Total integrated power is not measured.
 - Upper limit on the largest scale in the image plane.
- 2. No measurements beyond u_{max} and v_{max} :
 - Size of the main lobe of the PSF is finite (finite resolution).
- 3. Holes in the uv-plane:
 - Contribute to the side lobes of the PSF.





• Missing 'central hole' means that the total flux, integrated over the entire image is zero.

 $V(u=0,v=0) = \iint I^{d}(l,m) dl dm = 0$

- Total flux for scales corresponding to the Fourier components between u_{max} and u_{min} can be measured.
 - In the presence of extended emission, the observations must be designed keeping in mind:
 - > the required resolution ==> maximum baseline
 - the largest scale to be reliably reconstructed ==> minimum baseline

Recovering the missing information

- For information beyond the max. baseline, one requires extrapolation. That's unphysical (unconstrained).
- Information corresponding to the "central hole": possible, but difficult (need extra information).
- Information corresponding to the uv-holes: requires interpolation. The measurements provide constraints

 hence possible. But non-linear methods necessary.

If Z is the unmeasured distribution, then $B^*Z=0$. If I^{M} is a solution to $I^d=B^*I^{M}$, then so is $I^{M} + \alpha Z$ for any value of α .

Deconvolution = interpolation in the visibility plane.

- What can we assume about the sky emission:
 - 1. Sky does not look like cosine waves
 - 2. Sky brightness is positive (but there are exceptions)
 - 3. Sky is a collection of point sources (weak assertion)
 - 4. Sky could be smooth
 - 5. Sky is mostly blank (sometimes justifies "boxed" deconvolution)
- Non-linear deconvolution algorithms search for a model image I^M such that the residual visibilities V^R=V^o-V^M are minimized, subject to the constraints given by the (assumed) prior knowledge.

• Let

A = Measurement matrix to go from the image domain to the visibility domain (the measurement domain).

- I = Vector of the image pixel values
- *V* = Vector of visibilities
- **B** = Operator (matrix) for convolution with the PSF

N = The noise vector

• Then,

$$I^{d} = BI^{o} + BI^{N}$$
 where $BI^{N} = A^{T}AN$
 $V^{M} = AI^{M}$ and $V^{o} = AI^{o} + N$
 $V^{R} = V^{o} - AI^{M}$

• A is rectangular (not square) and is a collection of sines and cosines corresponding to only the measured Fourier components.

A is singular ==> A^{-1} does not exist $I^{M}=A^{-1}V^{M}$ not possible ==> non-linear methods needed

 N is independent gaussian random process. Noise in the image domain = BI^N
 Pixel-to-pixel noise in the image is not independent

- For successful recovery of *I*° given *I*d, prior knowledge must fundamentally separate *BI*° and *BI*^N.
- χ^2 is the optimal estimator. Deconvolution then is equivalent to:

Minimize:
$$\chi^2 = \left| V^m - A I^M \right|^2$$
 where $I^M = \sum_k P_k$; $P_k \equiv Pixel Model$

Deconvolution is equivalent to function minimization

 Algorithms differ in the parameterization of P_k, the type of constraints and the way the constraints are applied. • <u>Scale-less algorithms:</u>

$$\boldsymbol{P}_{k} = \boldsymbol{A}_{k} \, \boldsymbol{\delta} \left(\boldsymbol{x} - \boldsymbol{x}_{k} \right)$$

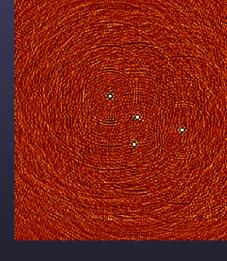
Popular ones: Clean, MEM and their variants

- <u>Scale-sensitive algorithms (new turf!)</u>: $P_k = A_k f(Position, Scale)$ Existing ones: <u>Multi-scale Clean, Asp-Clean</u>
- Image plane corrections (in use)
 Existing ones: w-projection, pb-projection

- Prior knowledge about the sky:
 - is composed of point sources
 - is mostly blank

• Algorithm:

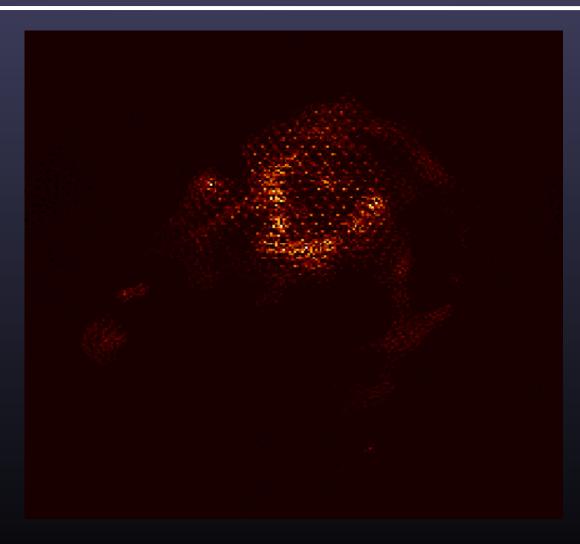
- 1. Search for the peak in the dirty image.
- 2. Add a fraction g (loop gain) of the peak value to I^{M} .
- 3. Subtract a scaled version of the PSF from the position of the peak $I_{i+1}^{R} = I_{i}^{R} g B \max(I_{i}^{R})$
- 4. If residuals are not "noise like", goto 1.
- 5. Smooth *I*^M by an estimate of the main lobe (the "clean beam") of the PSF and add the residuals to make the "restored image"



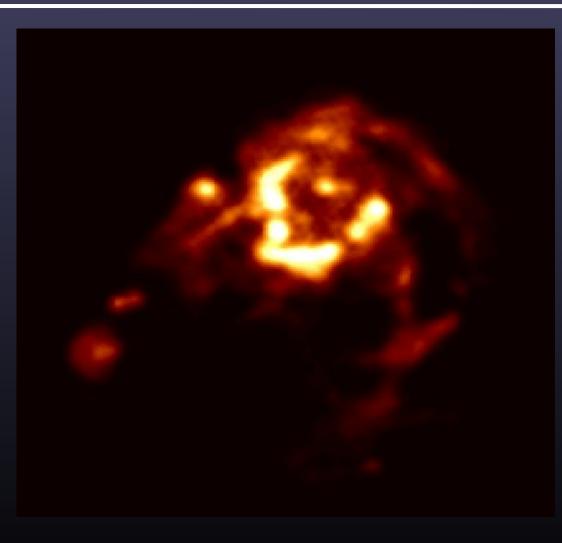
- It is a steepest descent minimization.
- Model image is a collection of delta functions a scale insensitive algorithm.
- A least square fit of sinusoids to the visibilities which is proved to converge (Schwarz 1978).
- Stabilized by keeping a small loop gain (usually g=0.1-0.2).
- Stopping criteria: either the max. iterations or max. residuals some multiple of the expected peak noise.
- Search space constrained by user defined windows.

Ignores coupling between pixels (extended emission) - assumes an orthogonal search space.

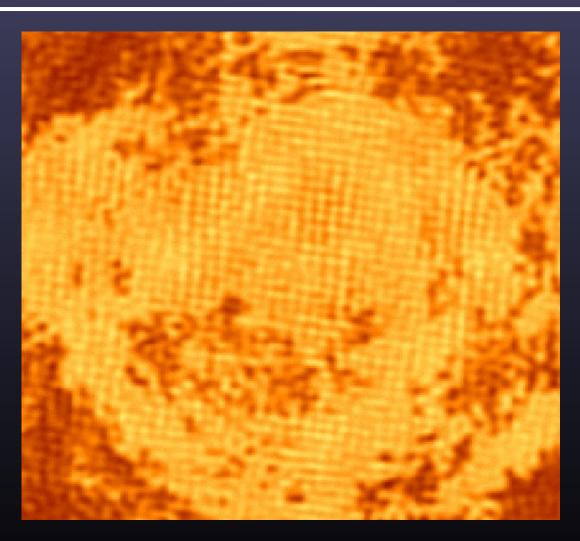
Clean: Model



Clean: Restored



Clean: Residual

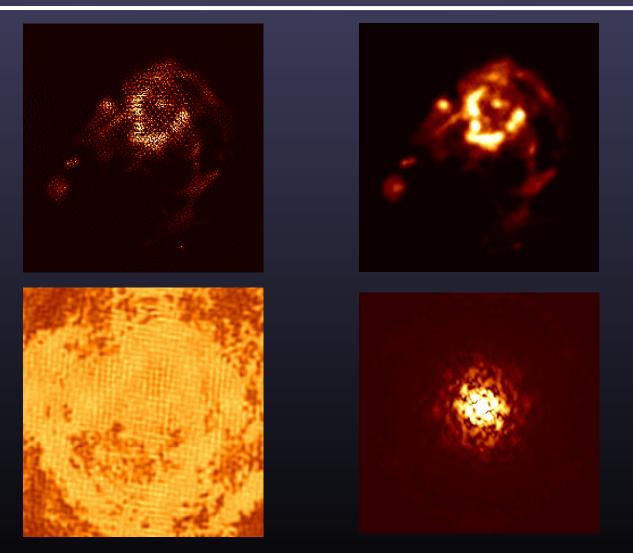


Clean: Model visibilities

Model Vis.

Sampled Vis **Residual Vis** True Vis.

Clean: Example



• Clark Clean – uses FFT to speed up Minor cycle(inexpensive) : Clean the brightest points using an approximate PSF to gain speed Major cycle(expensive): Use FFT convolution to accurately remove the point sources found in the minor cycle

• Cotton-Schwab Clean: A variant of Clark Clean Subtract the point sources from the visibilities directly. Sometimes faster and always more accurate then Clark Clean. Easy to adapt for multiple fields.

- MEM is a constrained minimization algorithm.
- Fast non-linear optimization algorithm due to Cornwell&Evans(1983).
- Solve the convolution equation, with the constrain of smoothness via the 'entropy'

$$H(I) = -\sum_{k} I_{k} - \log \left(I_{k} / m_{k} \right)$$

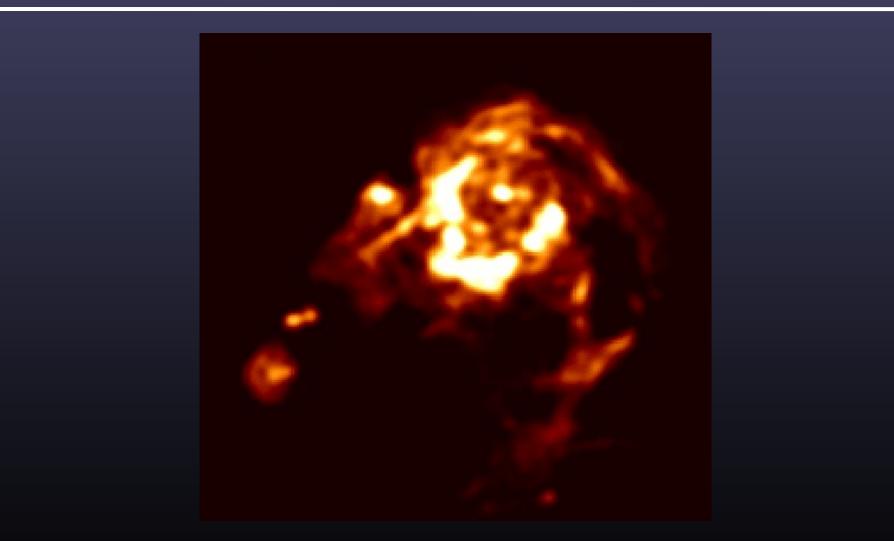
 m_k is the prior image – usually a flat default image.

- Default image is a very useful in incorporating model images from other algorithms etc.
- Naturally useful when final image is some combination of images (like mosaic images).

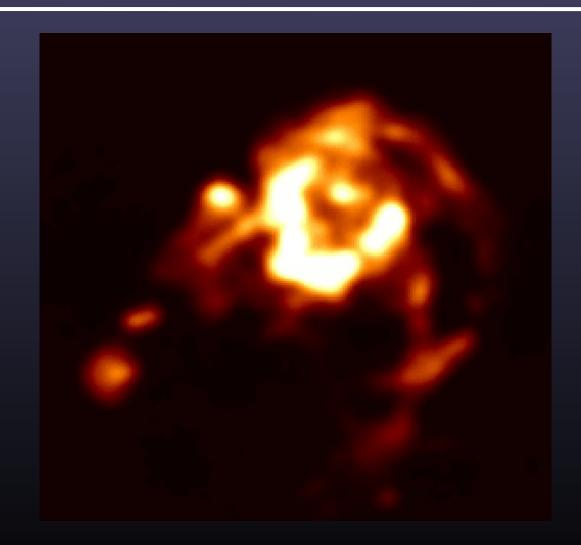
• Works better than Clean for extended emission.

- Every pixel is treated as a potential degree of freedom – a scale insensitive algorithm.
- Point sources are a problem, particularly along with large scale background emission – but can be removed with, say, Clean before hand.
- Easier to analyze and understand.

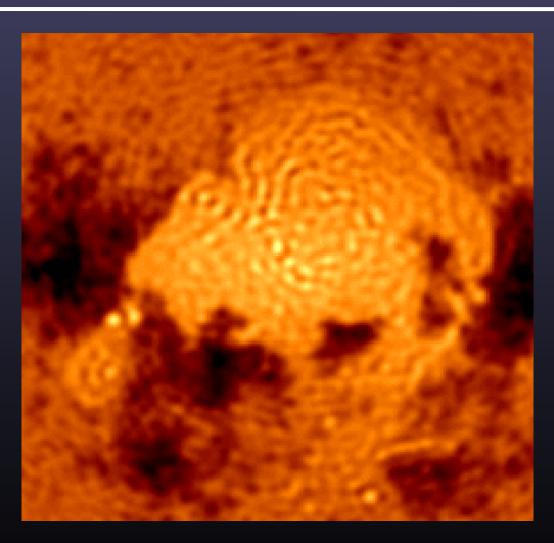
MEM: Model



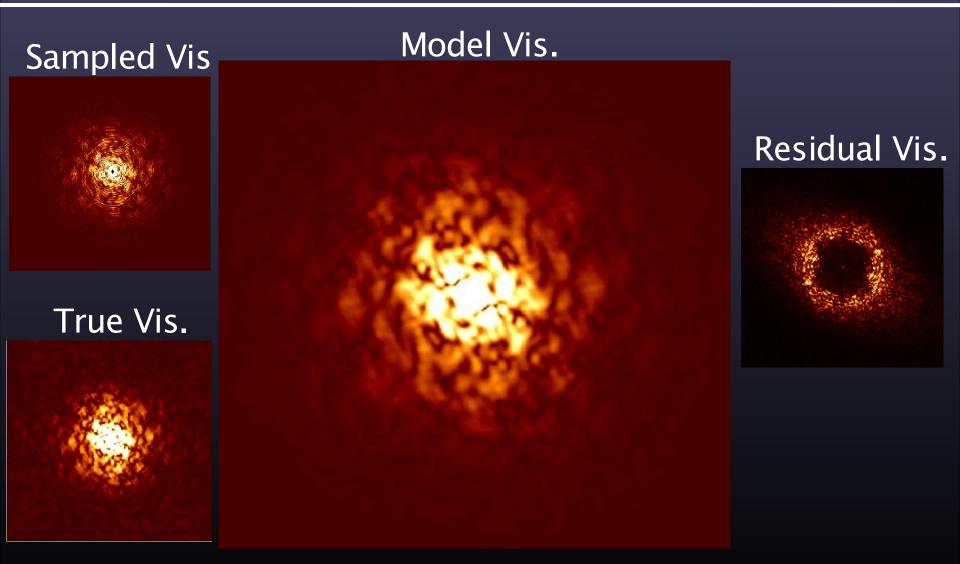
MEM: Restored



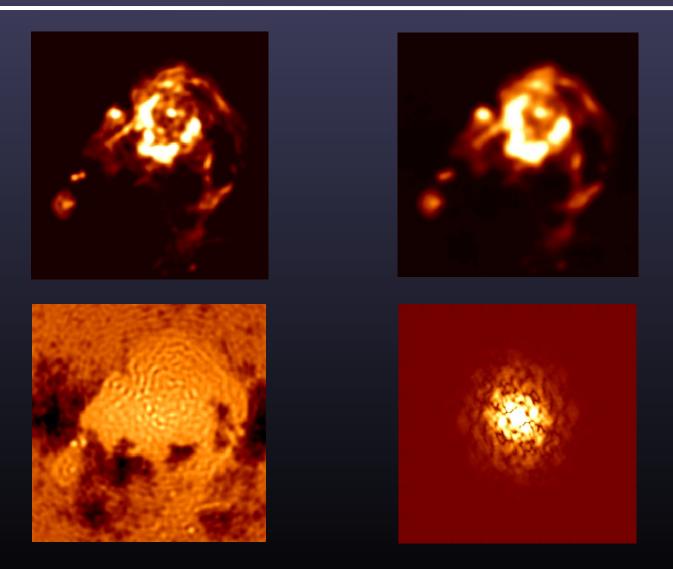
MEM: Residual



MEM: Model visibilities



MEM: Example

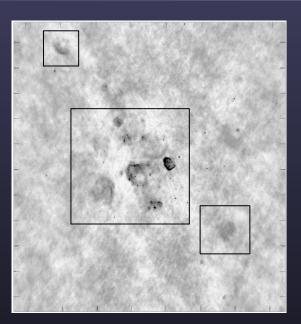


Role of boxes

• Limit the search for components to only parts of the image.

A way to regularize the deconvolution process.

- Useful when small no. of visibilities (e.g. VLBI/snapshots).
- Do not over-Clean within the boxes (over-fitting).



- Deeper Clean with no/loose boxes and lower loop gain can achieve similar (more objective) results.
- Stop when Cleaning within the boxes has no global effect (insignificant coupling of pixels due to the PSF).

Fundamental problem with scale-less decomposition ⁴⁴

• Each pixel is not an independent degree of freedom (DOF).

E.g., a gaussian shaped source covering 100 pixels can be represented by 5 parameters.

- Clean/MEM treats each pixel within a clean-box as an independent degree of freedom.
- Scale fundamentally separates noise and signal.
 - -*Largest* coherent scale in *BI*^N ~ *the size of the resolution element.*
 - -Physically plausible I^M is composed of scales >= the resolution element (smallest scale is of the size of the resolution element).

• Scale-sensitive reconstruction therefore leaves more noise-like (uncorrelated) residuals.

Scale Sensitive Deconvolution: MS-Clean

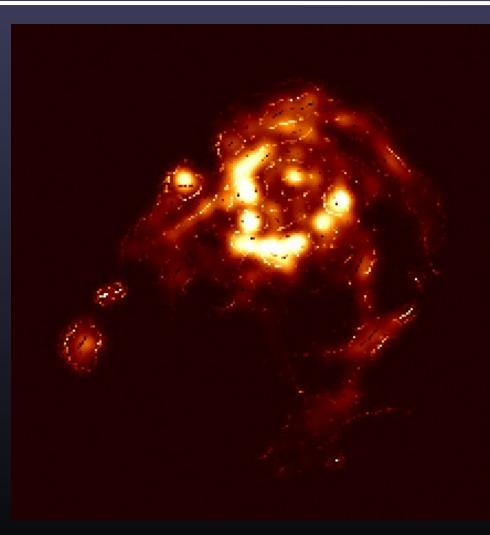
- Inspired by the Clean algorithm (Cornwell & Holdaway).
- Decompose the image into a pre-computed set of symmetric "blobs" at a few scales (e.g. Gaussians).

Algorithm

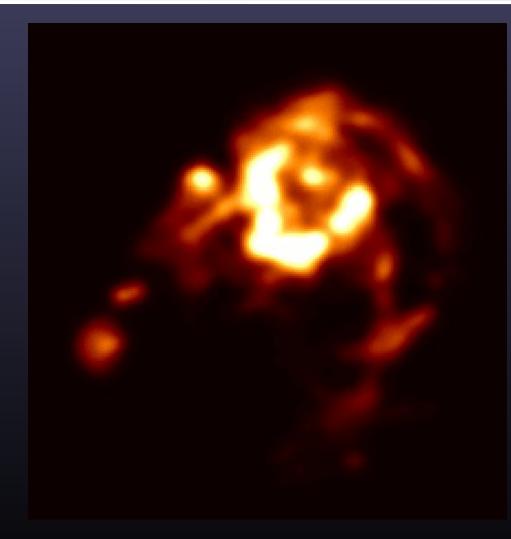
- 1. Make residual images smoothed to a few scales.
- 2. Find the peak among these residual images.
- 3. Subtract from all residual images a blob of scale corresponding to the scale of the residual image which had the peak.
- 4. Add the blob to the model image.
- 5. If more peaks in the residual images, goto 1.
- 6. Smooth the model image by the "clean beam" and add the residuals.

- Deals with compact as well as extended emission better (need to include a blob of zero scale).
- Retains the scale-shift-n-subtract nature of Clean - easy to implement.
- Reasonably fast (for what it does!)
- * Breaks up non-symmetric structures (as in Clean - but the errors are at larger scales than in Clean).
- Ignores coupling between blobs.
 Assumes an orthogonal space and steepest descent minimization.

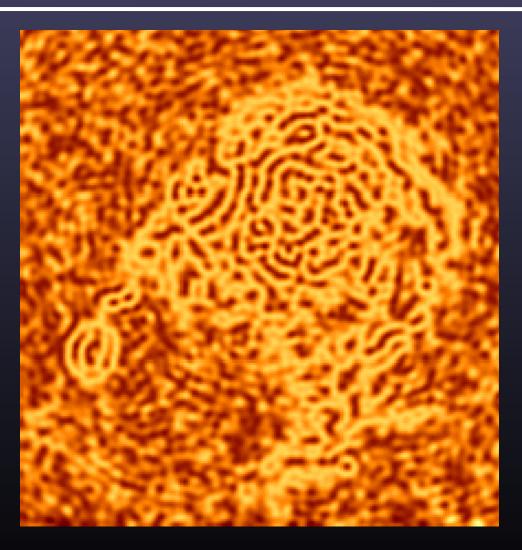
MS-Clean: Model



MS-Clean: Restored



MS-Clean: Residual

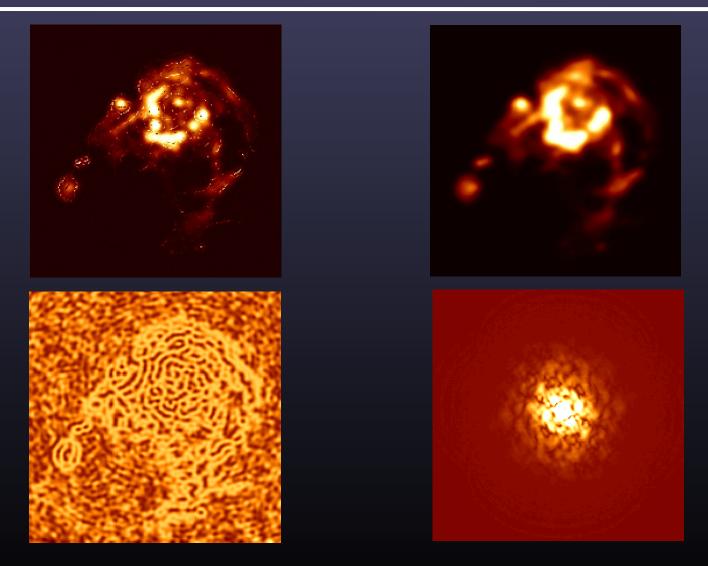


MS-Clean: Model visibilities

Model Vis.

Sampled Vis Residual Vis. True Vis.

MS-Clean: Example



Multi-resolution vs. Multi-scale Clean

- Subtle difference between AIPS and AIPS++ implementations of scale sensitive
 - AIPS++: Each *iteration of the minor cycle* removes the optimal scale (one which reduces the residuals globally). Effectively, this achieves a "simultaneous" deconvolution at various scales [Multi-Scale Clean]
 - AIPS: A decision, based on a user defined parameter, is made at the *start of each minor cycle* about the optimal scale to deconvolve [Multi-resolution Clean].
- MS-Clean naturally detects and removes the scale with maximum power
- Removal of the optimal scale in MR-Clean strongly depends on the value of the user defined parameter.

Scale Sensitive Deconvolution: Asp-Clean

- Inspired by Pixon reconstruction (Puetter & Pina, 1994).
- Decompose the image into a set of Adaptive Scale Pixel (Asp) model (Bhatnagar & Cornwell, 2004).

•Algorithm:

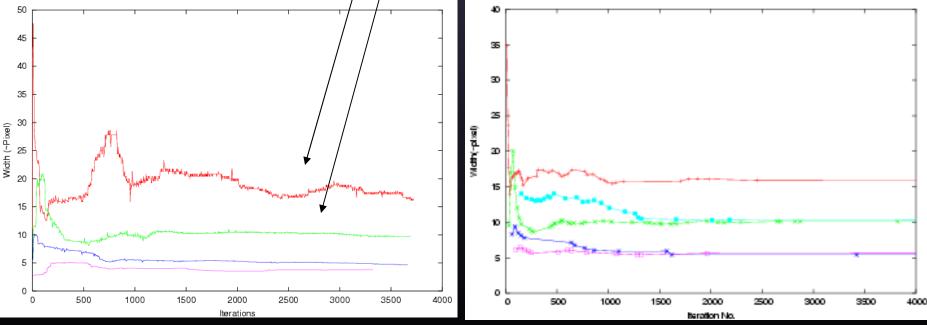
- 1. Find the peak at a few scales, and use the scale with the highest peak as an initial guess for the optimal dominant scale.
- 2. Make a set of active-aspen containing Aspen found in earlier iterations and which are likely to have a significant impact on convergence.
- 3. Find the best fit set of active-Aspen (expensive step).
- 4. If termination criterion not met, goto 1.
- 5. Smooth with the clean-beam. Add residuals if it has systematics.

- Deals with non-symmetric structures better.
- Incorporates the fact that scale changes across the image. Residuals are more noise-like.
- Incorporates the fact that search space is potentially non-orthogonal (inherent coupling between Aspen).
- Aspen found in earlier iterations are not frozen.
- Scales well with computing power.
- **×** Slower in execution speed.

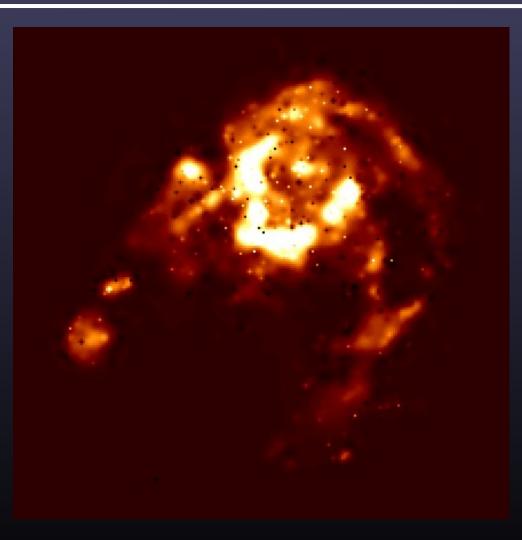
Asp-Clean details: acceleration

Fig 1: All Aspen are kept in the problem for all iterations. Scales all Asp scales evolve as a function of iterations. Not all Aspen evolve significantly for at all iterations.

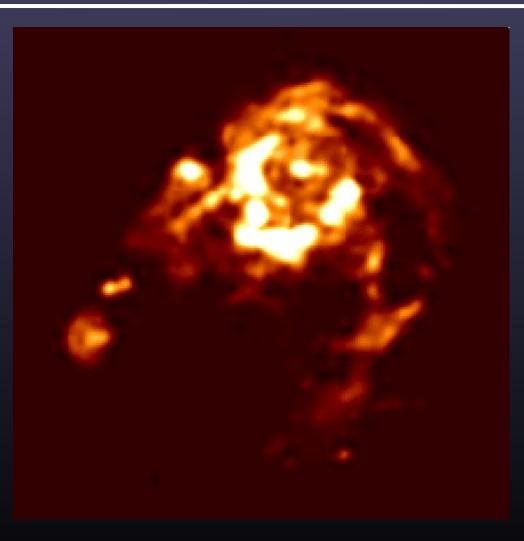
Fig 2: The active-set is determined by thresholding the first derivative. Only those Aspen, shown by symbols, are kept in the problem which are likely to evolve significantly at each iteration.



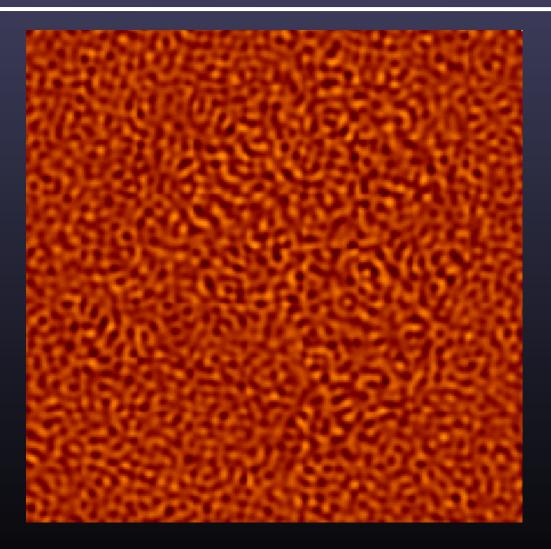
Asp-Clean: Model



Asp-Clean: Restored

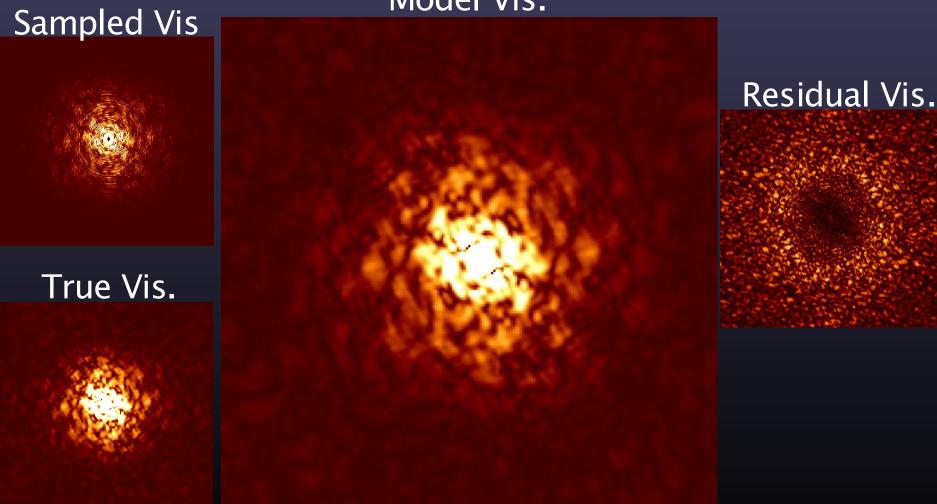


Asp-Clean: Residual

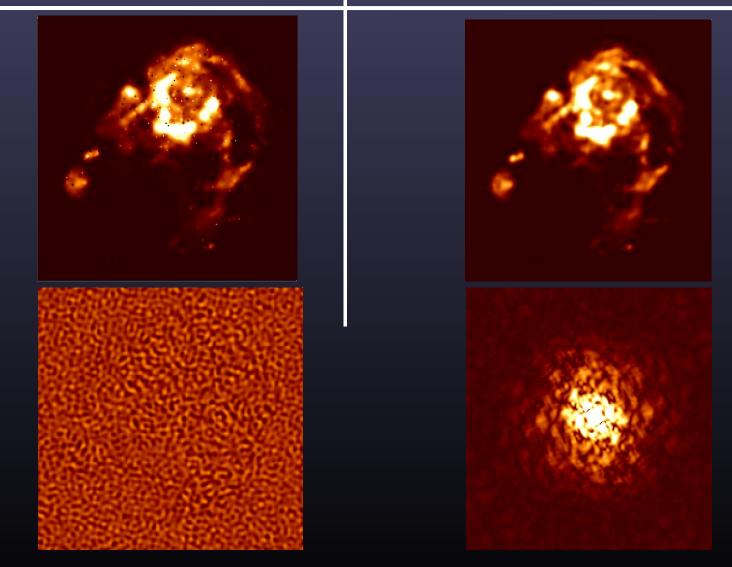


Asp-Clean: Model visibilities

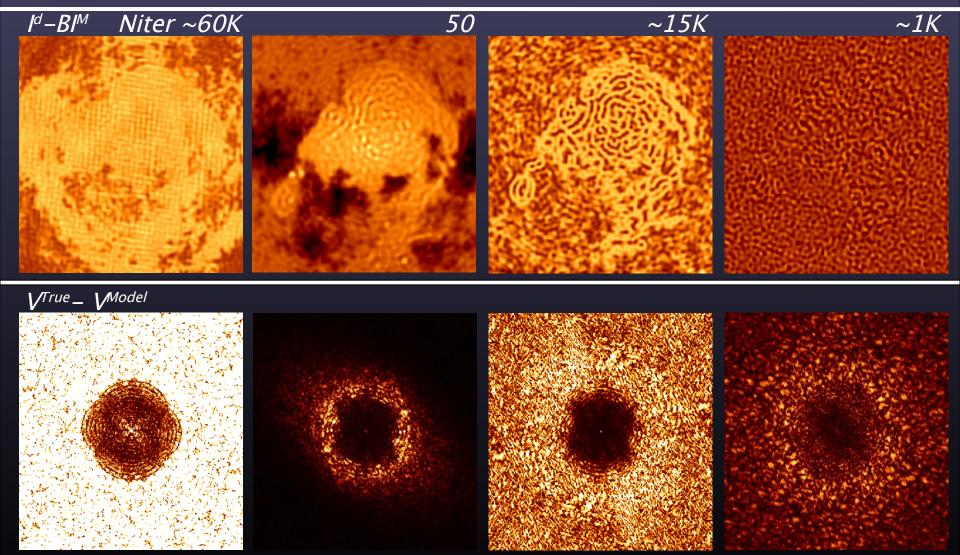
Model Vis.



Asp-Clean: Example



Clean, MEM, MS-Clean, Asp-Clean

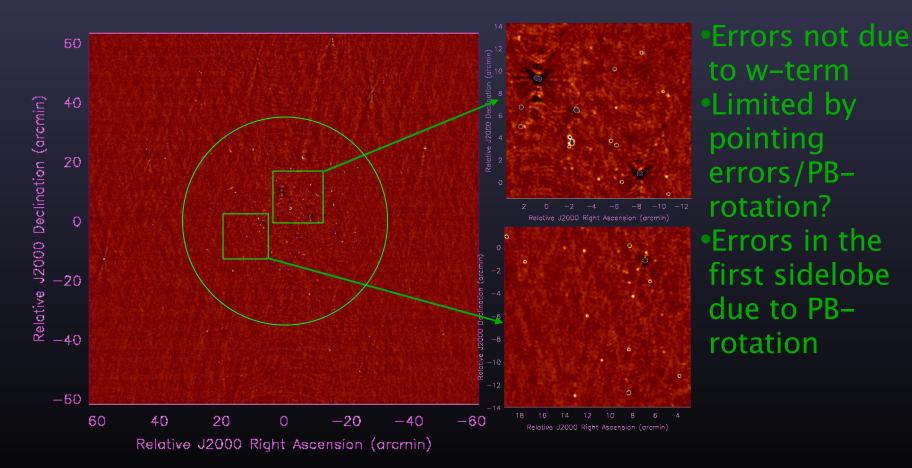


- Full Beam Imaging $V_{ij}^{obs} = J_{ij} \int J_{ij}^{Sky}(\vec{S}) I(\vec{S}) e^{2\pi i \vec{U} \cdot \vec{S}} d\vec{S}$
 - > $J_{ij} \equiv$ Direction independent gains
 - > $J_{ij}^{Sky} \equiv$ Direct dependent gains(e.g. Antenna Power Patterns *P(l,m)*)
 - Rotation of PB on the sky + pointing errors gives time varying direction dependent gains (limits Mosaicking DR).
 - Antenna polarization response is azimuthally asymmetric
 - > VLA polarization squint, full beam full Stokes imaging correction required even for moderate dynamic ranges
 - > Sky and antenna response frequency dependent
 - > EVLA: v_{max} : v_{min} =2:1 PB changes by a factor of 2!

- $V^{obs} = EAI$ where $E = A^T J^{Sky} A$
 - > If E is unitary (or approximately so), use $A^T E^T$ as the inverse operator
 - > Use $A^T E^T$ for update direction (Minor Cycle)
 - > Use *EA* for residuals computation (Major Cycle)
- The modified transforms correct for image place errors
 - > The W-Projection algorithm: Correction for non co-planarity
 - The PB-Projection algorithm: Correction for PB effects (pointing errors, poln., PB rotation)

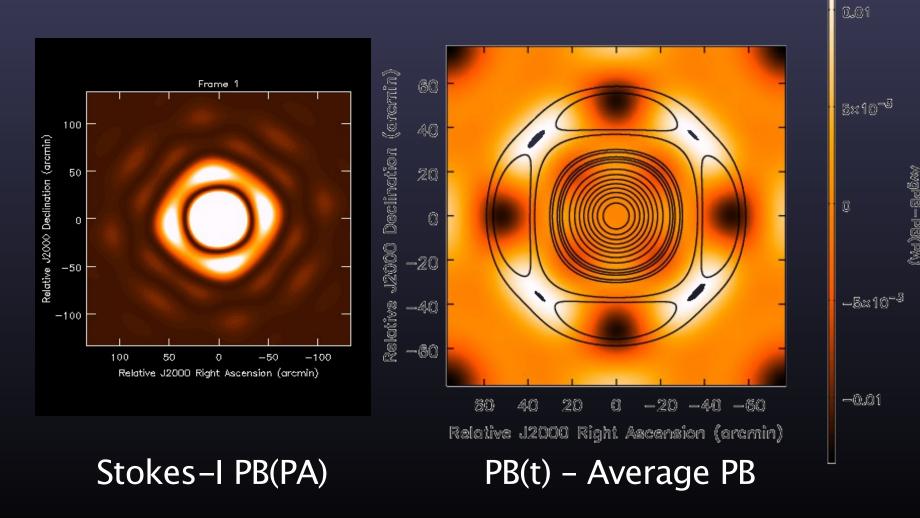
Wide field imaging

• W-projection: w-term = $e^{2\pi i w(\sqrt{1-l^2-m^2}-1)}$



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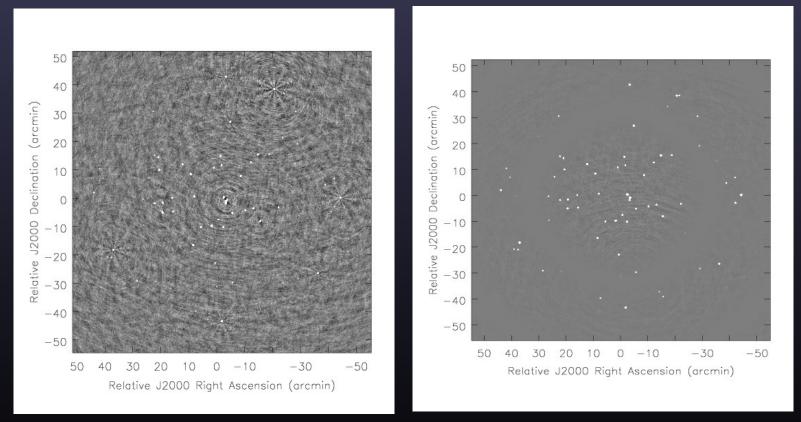
Primary Beams



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Simulations: Stokes-I

 Stokes-I imaging with and without PB effects (Polarization squint, Pointing offsets, PB rotation)



RMS $\sim 15 \mu$ Jy/beam

RMS $\sim 1\mu Jy/beam$

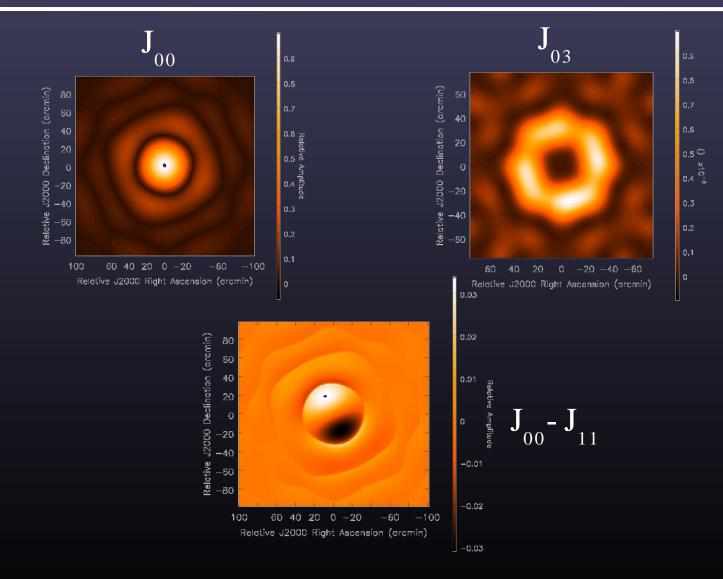
Full-beam full-Stokes imaging

• Full Stokes imaging requires full Sky Muller matrix

$$J_{i}(S) = \begin{bmatrix} J_{i}^{p} & J_{i}^{pq} \\ J_{i}^{qp} & J_{i}^{q} \end{bmatrix}$$
$$\begin{bmatrix} OUT_{pp} \\ OUT_{pq} \\ OUT_{qp} \\ OUT_{qp} \\ OUT_{qp} \end{bmatrix} = \begin{bmatrix} J_{i}^{p} J_{j}^{p^{*}} & J_{i}^{p} J_{j}^{pq^{*}} & J_{i}^{pq} J_{j}^{pq^{*}} & J_{i}^{pq} J_{j}^{qp^{*}} \\ J_{i}^{p} J_{j}^{qp} J_{j}^{qp^{*}} & J_{i}^{q} J_{j}^{qq^{*}} & J_{i}^{pq} J_{j}^{qp^{*}} & J_{i}^{pq} J_{j}^{qp^{*}} \\ J_{i}^{qp} J_{j}^{qp} J_{j}^{qp^{*}} & J_{i}^{qp} J_{j}^{qp^{*}} & J_{i}^{q} J_{j}^{pp^{*}} & J_{i}^{q} J_{j}^{pq^{*}} \\ J_{i}^{qp} J_{j}^{qp^{*}} & J_{i}^{qp} J_{j}^{qp^{*}} & J_{i}^{q} J_{j}^{qp^{*}} & J_{i}^{q} J_{j}^{qp^{*}} \\ J_{i}^{qp} J_{j}^{qp^{*}} & J_{i}^{qp} J_{j}^{qp^{*}} & J_{i}^{q} J_{j}^{qp^{*}} & J_{i}^{q} J_{j}^{qp^{*}} \end{bmatrix} \begin{bmatrix} IN_{pp} \\ IN_{pq} \\ IN_{qp} \\ IN_{qq} \end{bmatrix}$$
$$J_{ij}(S) = J_{i}(S) \otimes J_{j}^{*}(S)$$

- $J_i^p(\vec{S}), J_i^q(\vec{S}) \equiv$ Antenna voltage pattern in orthogonal polarization
- $J_i^{pq}(\vec{S})$, $J_i^{qp}(\vec{S}) \equiv$ Leakage of polarization due to reflection from curved surface
- $J_{ii}(\vec{S})$ is not identity or even diagonal for DR>10⁴

Structure of the Sky-Muller Matrix



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