

BLUEBILD UPDATE

The background features a complex, abstract design. On the left, there are vertical, wavy lines in shades of light blue and white, resembling a textured surface or a stylized profile. On the right, there are vertical, wavy lines in shades of red and orange, also resembling a textured surface or a stylized profile. The overall effect is a layered, 3D-like appearance with a color gradient from blue on the left to red on the right.

Emma Tolley

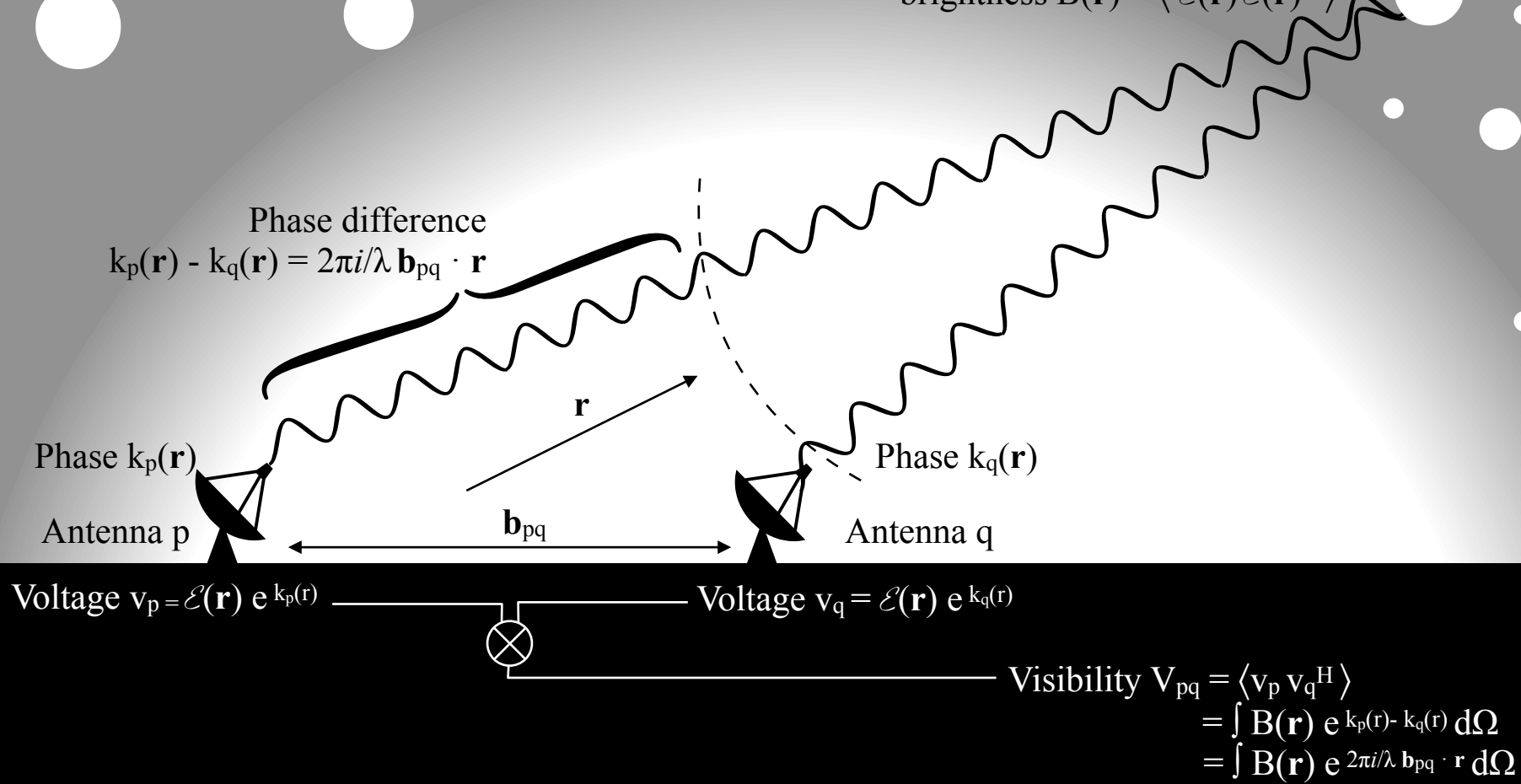
EPFL

SKACH Winter meeting

January 27, 2025

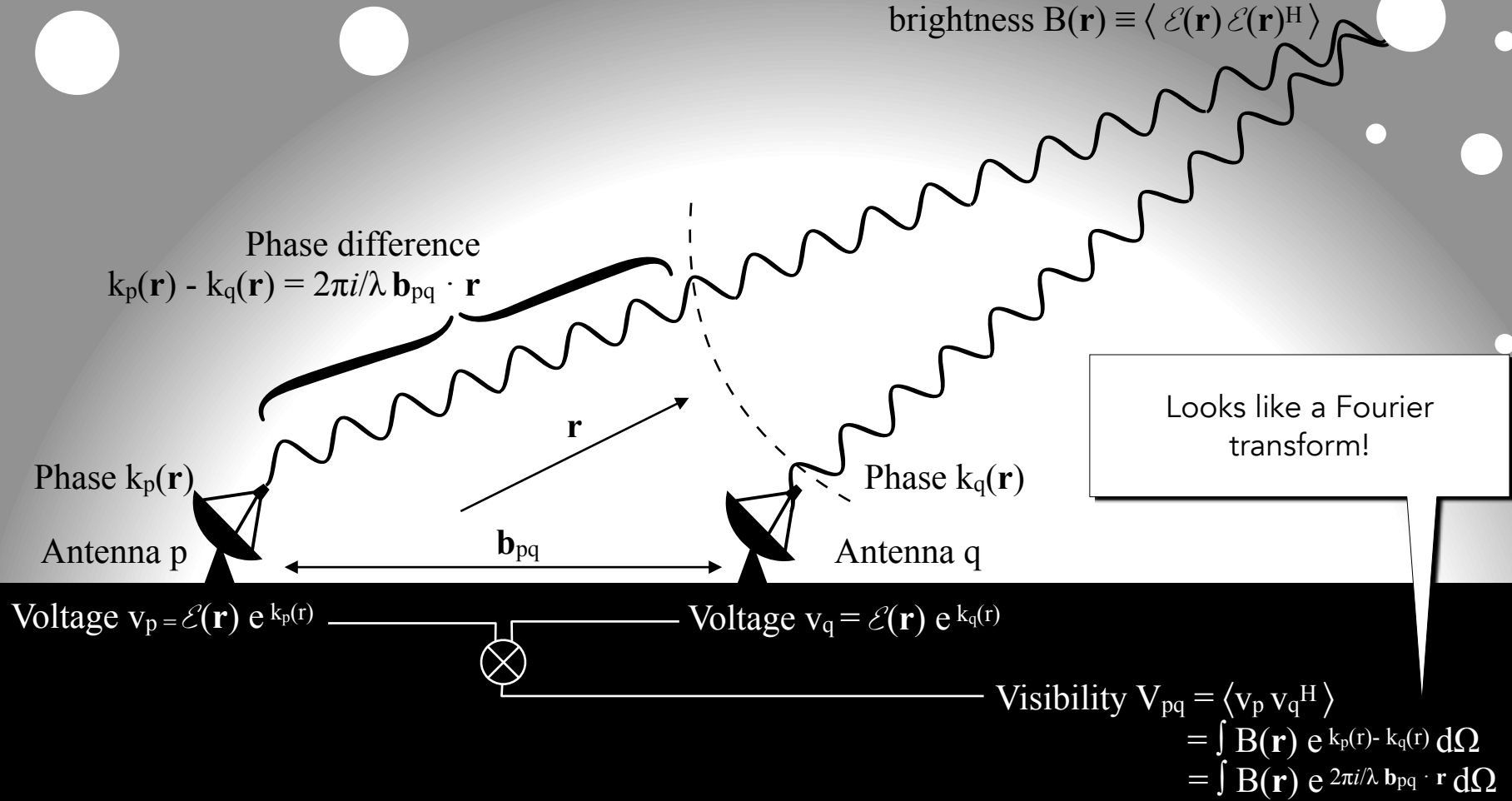
Electric field $\mathcal{E}(\mathbf{r})$

with diagonal covariance matrix $\mathbf{B}(\mathbf{r}_1, \mathbf{r}_2)$ and
brightness $\mathbf{B}(\mathbf{r}) \equiv \langle \mathcal{E}(\mathbf{r}) \mathcal{E}(\mathbf{r})^H \rangle$



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Sampling & Interpolation Operators

Write v and V in a compact form using the sampling operator Ψ^* :

$$v = \Psi^* \mathcal{E} + n, \quad V = \langle v v^* \rangle = \Psi^* B \Psi + \eta$$

Backprojection: $B' = \Psi V \Psi^*$

starting point for CLEAN algorithms,
but does not not minimize

$$\|\Psi^* \tilde{B} \Psi - V\|^2$$

Least-squares: $B' = \Psi (G_\Psi)^{-1} V (G_\Psi)^{-1} \Psi^*$,

where $G_\Psi = \Psi^* \Psi$

Bluebird Algorithm

Find a decomposition of B' in a compact orthogonal basis using functional PCA:

$$B' = \sum_a \lambda_a |\epsilon_a|^2 = \sum_a \lambda_a |\Psi \alpha_a|^2$$

Eigenvectors/values found from the generalized eigenvalue problem:

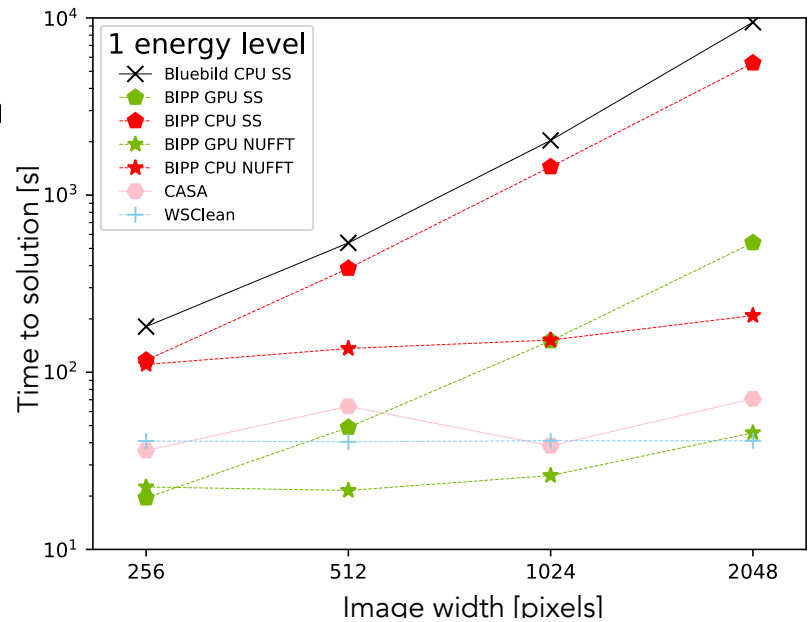
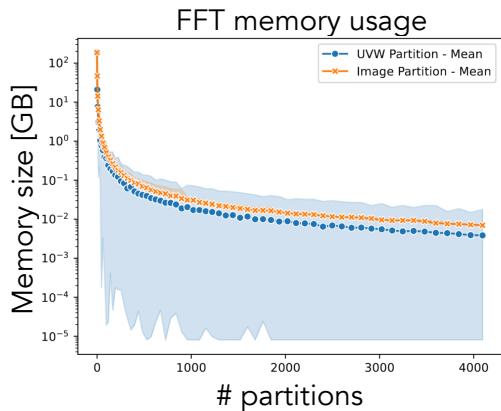
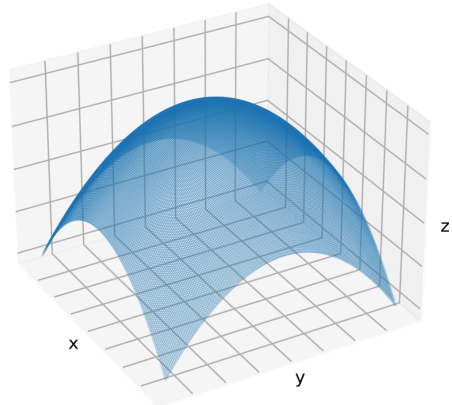
$$V \alpha_a = \lambda_a G_\Psi \alpha_a$$

A least-squares solution without inverting G_Ψ

HPC Implementation of Bluebild

Bluebild Imaging++ (BIPP): Reconstruct images on the celestial sphere using fPCA & 3D type-3 non-uniform FFT (NUFFT). CPU & GPU implementation with CUDA & HIP, funded by PASC 2021-2025. Now published: <https://doi.org/10.1016/j.ascom.2024.100920>

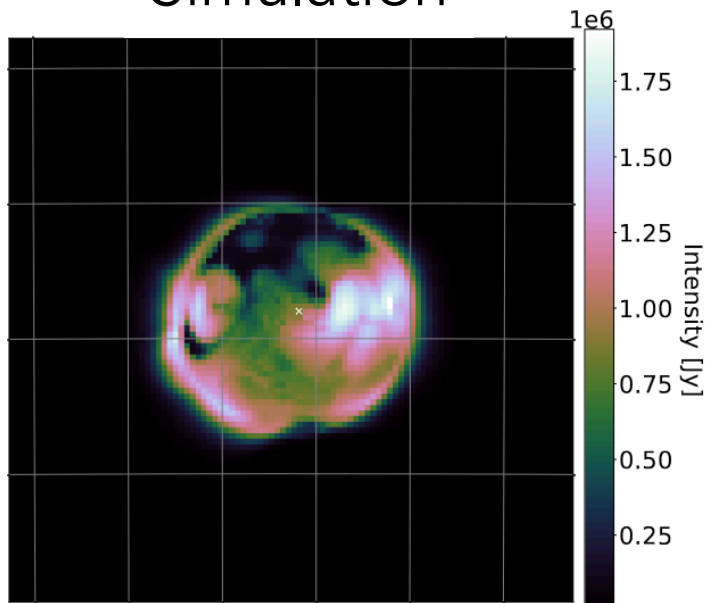
Use **domain partitioning** to take advantage of sparse input & output domains, reduce memory consumption improve performance



fPCA & energy levels

$$B' = \sum_a \lambda_a |\epsilon_a|^2 = \sum_a \lambda_a |\Psi \alpha_a|^2$$

Simulation

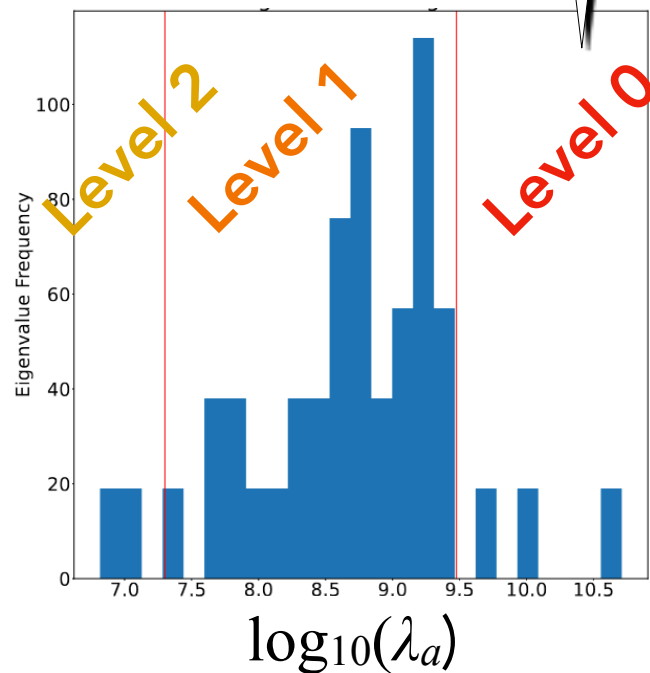


Plots by Shreyam Krishna

Emma Tolley SKACH Winter Meeting 27 Jan. 2025

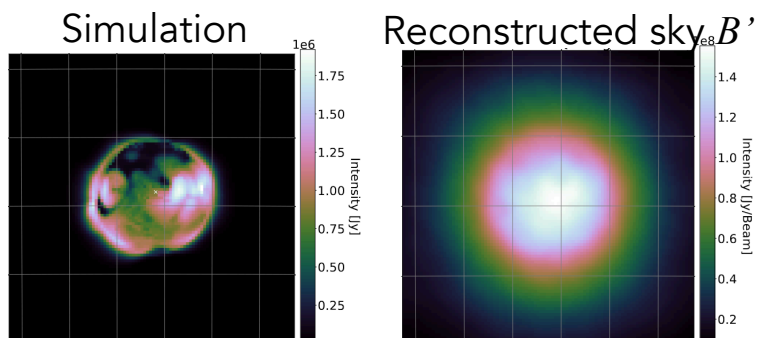
Cluster the eigenvectors/
eigenimages based on
eigenvalue

Eigenvalues



fPCA & energy levels

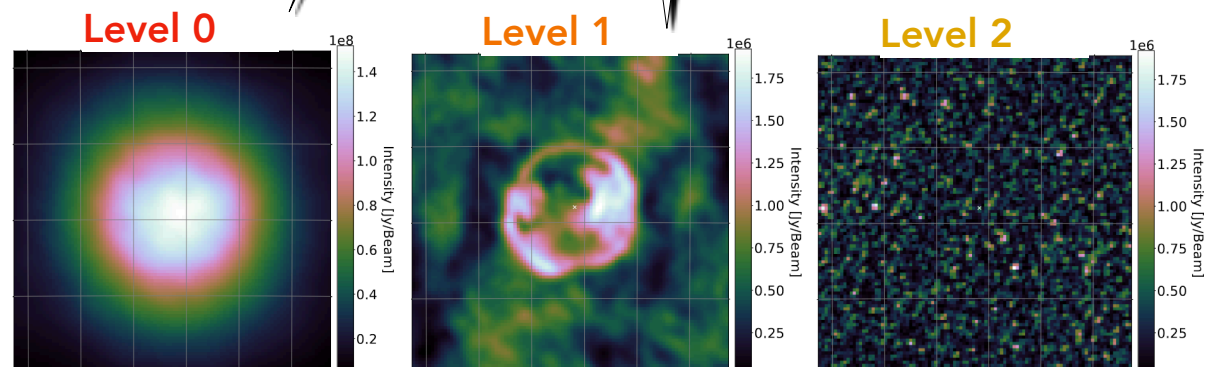
$$B' = \sum_a \lambda_a |\epsilon_a|^2 = \sum_a \lambda_a |\Psi \alpha_a|^2$$



Cluster the eigenvectors/
eigenimages based on
eigenvalue

Diffuse structure
becomes apparent

Plots by Shreyam Krishna



A trivial example

- Assume that we have a sky composed only of point sources, with # sources = # antenna elements = N . In this case:
- Voltages $v_p = \sum_{\text{sources } s} \mathcal{E}_s e^{k_p(\mathbf{r}_s)}$, $\mathbf{v} = \Psi^* \mathcal{E}$, Ψ is an $N \times N$ square matrix with element at index (p,s) given by $e^{k_p(\mathbf{r}_s)}$
- For simplicity assume that $\Psi^* \Psi = \mathbf{I}$. Then:

$$\mathbf{V} = \Psi \mathbf{B} \Psi^*$$

B is a diagonal covariance matrix, Ψ is a square matrix

$$\mathbf{V} \Psi = \Psi \mathbf{B}$$

Equivalent to eigenvalue decomposition!

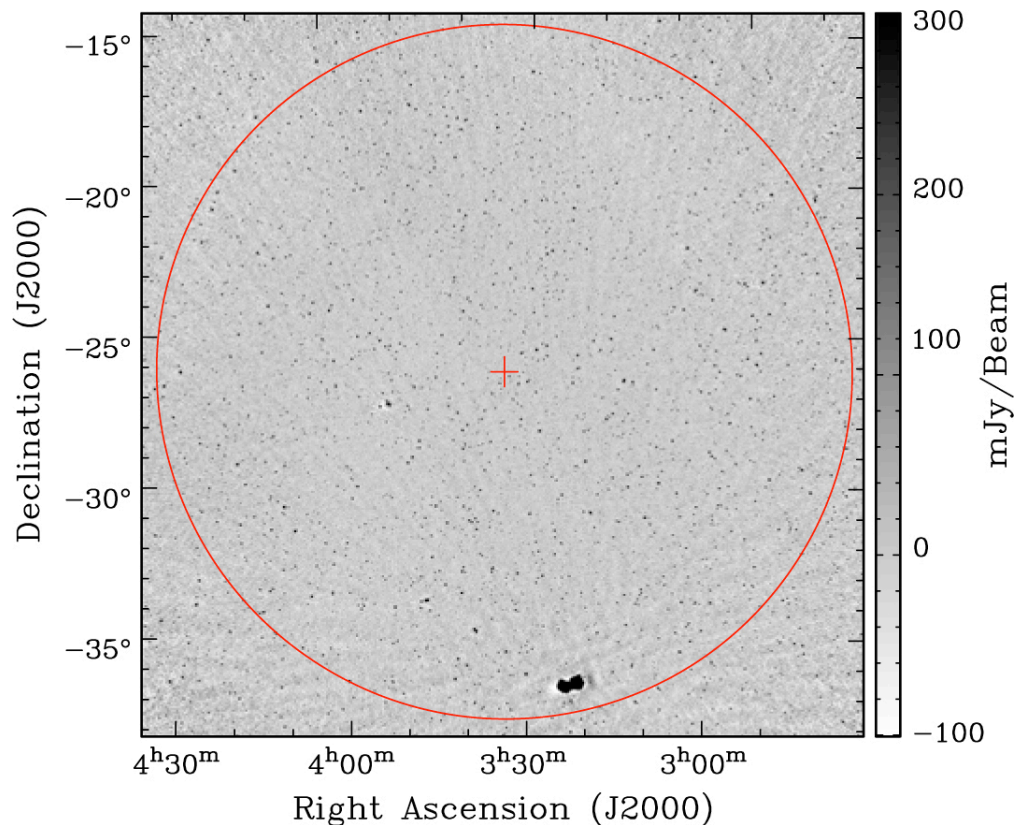
Eigenvectors are given by $e^{k_p(\mathbf{r}_s)}$

Eigenvalues by \mathcal{E}_s

$$\mathbf{V} \alpha^s = \lambda^s \alpha^s.$$

This holds even if the instrument isn't calibrated, ie sampling operator includes unknown complex gain terms $g_p(\mathbf{r}_s)$

A less trivial example

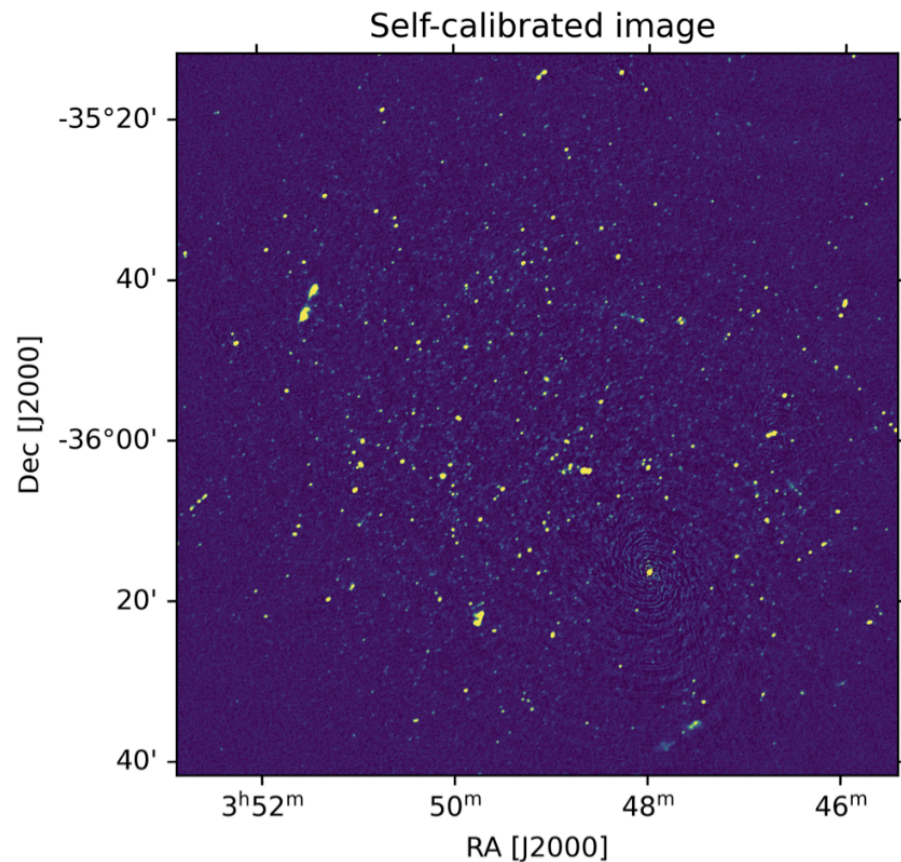
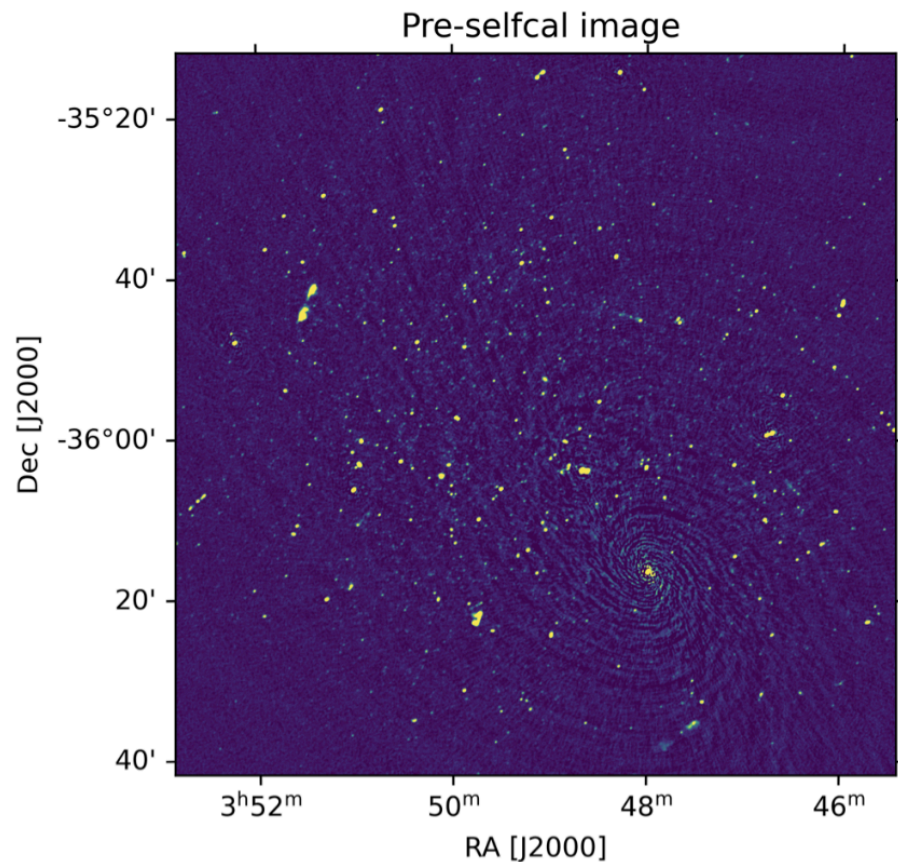


- In reality sky is not just point sources and $\# \text{ sources} \gg \# \text{ antenna elements}$
- However, usually there are just a few bright sources in the FoV, and we still expect first eigenvector to “point” to direction of highest flux:

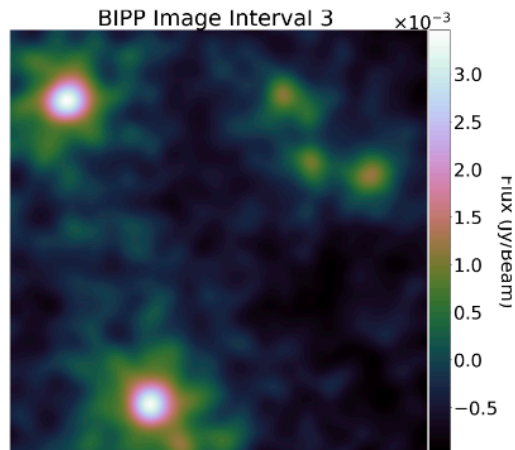
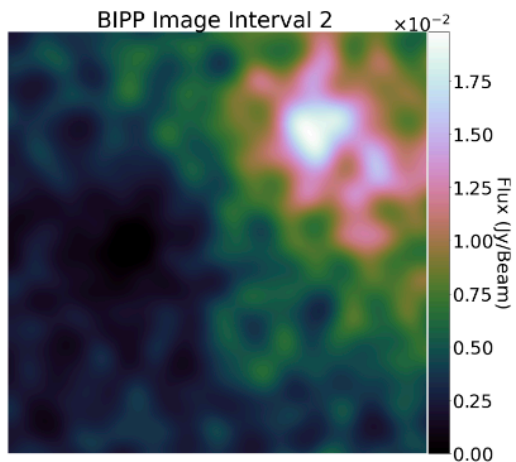
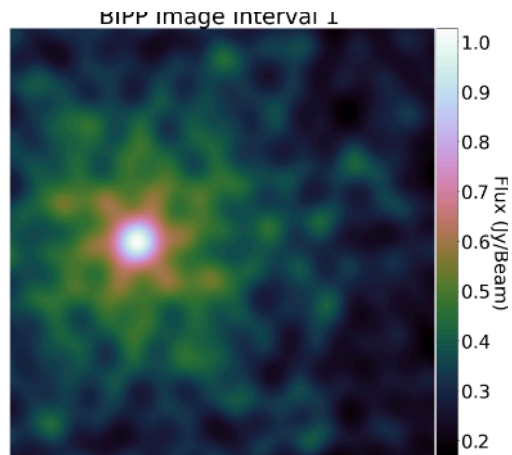
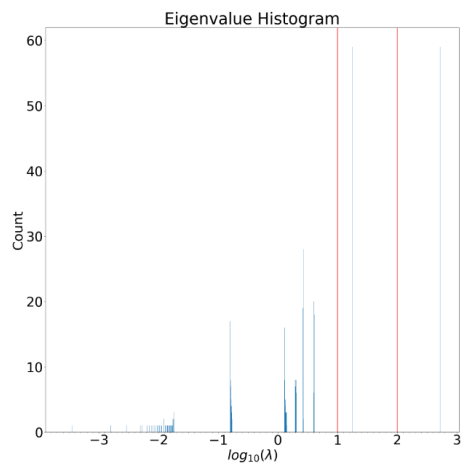
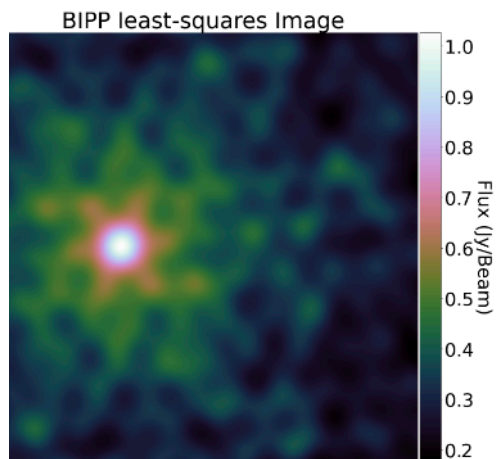
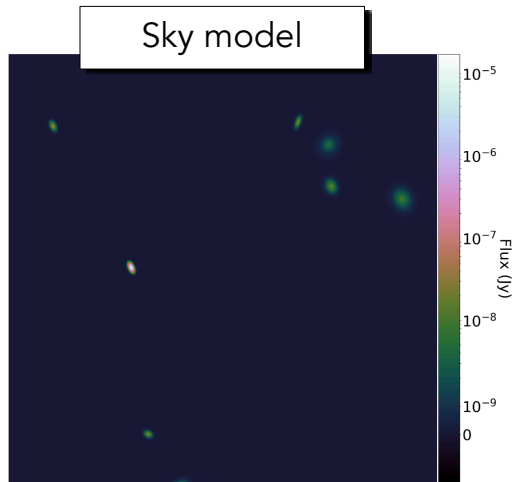
$$(\alpha^1)^* V \alpha^1 = \lambda^1$$

- Note that this acts like super resolution source finding
- Method breaks down with bright diffuse sources, multiple sources with same flux value

Peeling bright sources

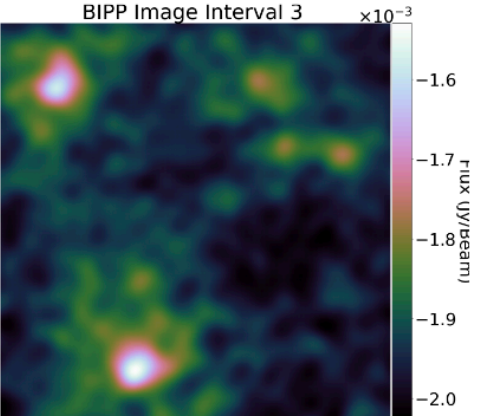
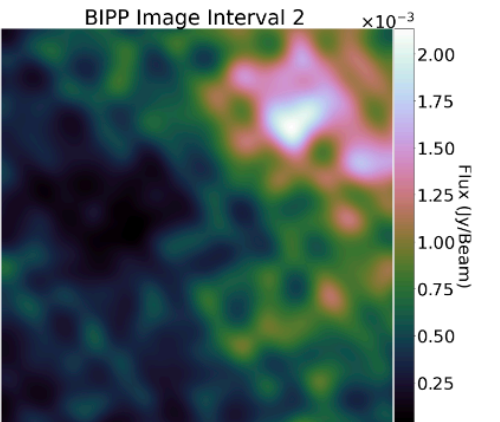
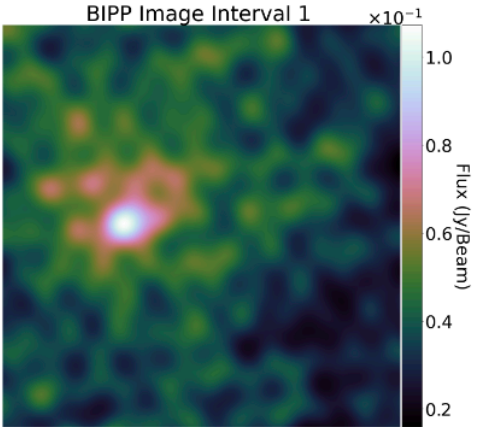
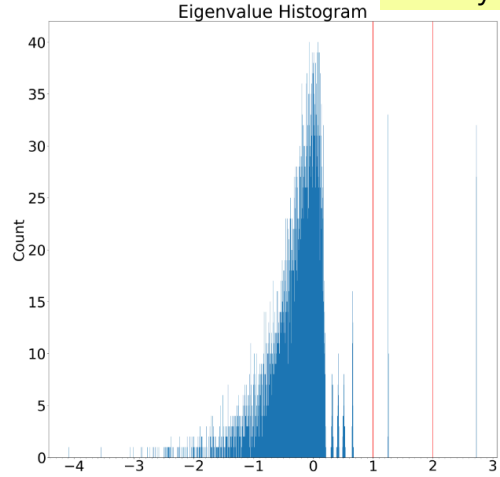
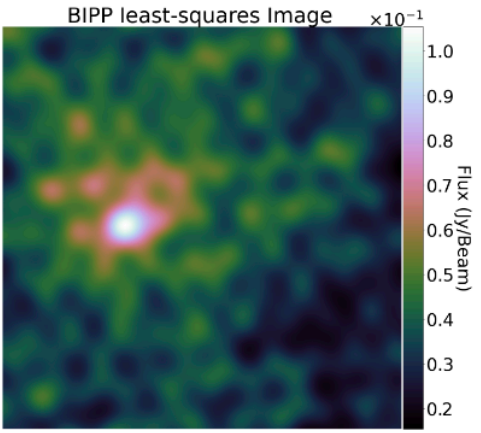
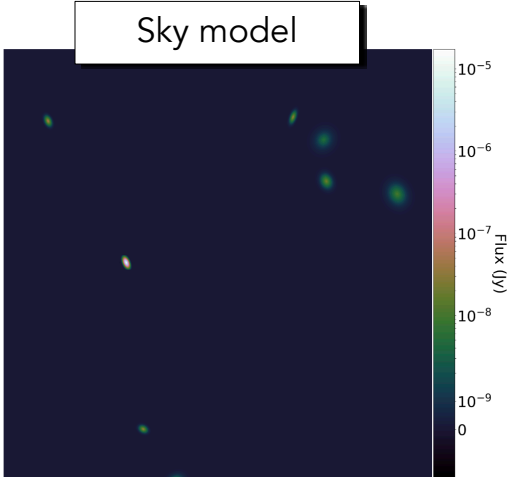


A simulated example



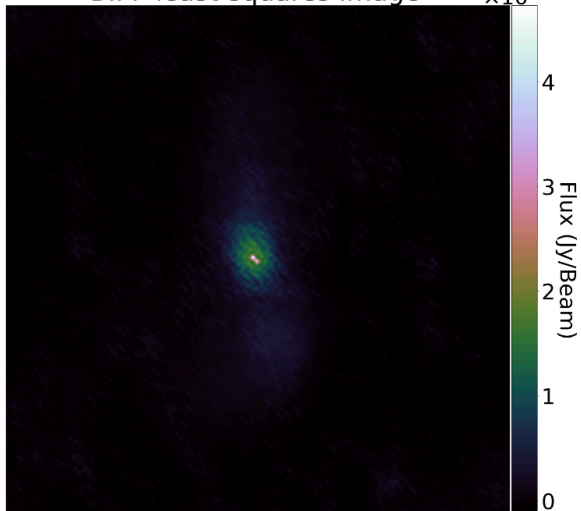
A simulated example with noise & gain errors

Plots by Shreyam Krishna



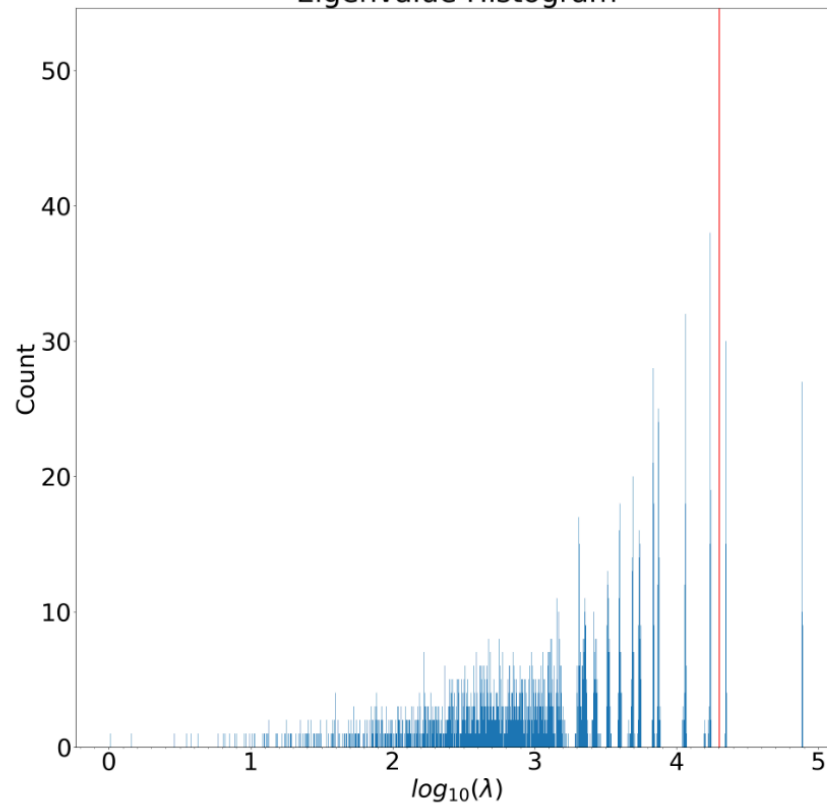
An example on real MWA data

BIPP least-squares Image

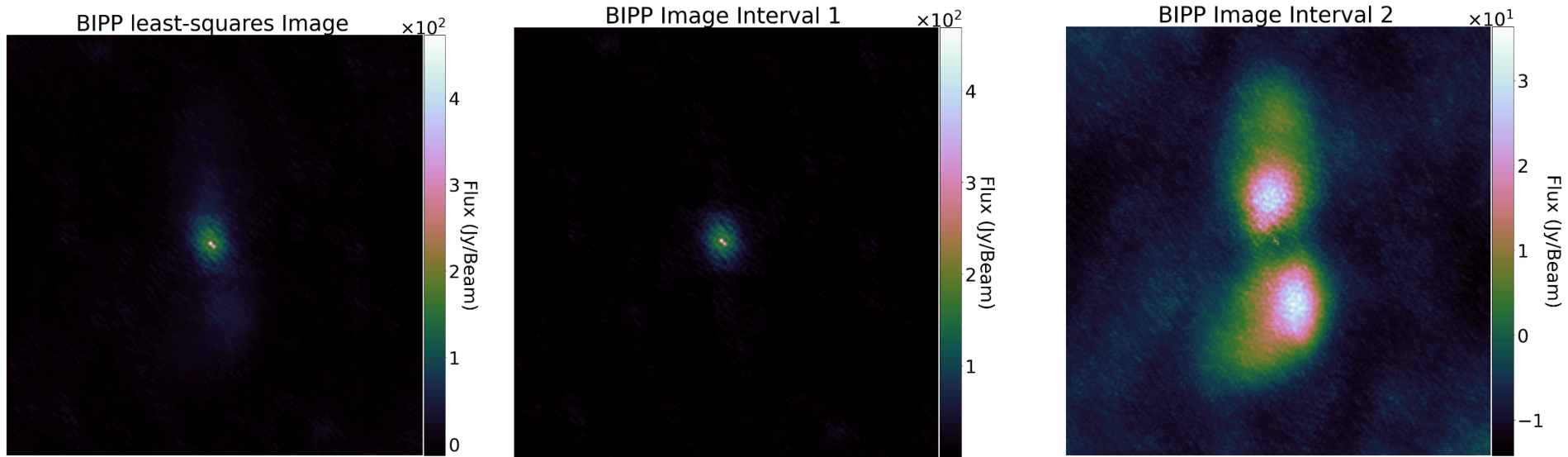


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Eigenvalue Histogram

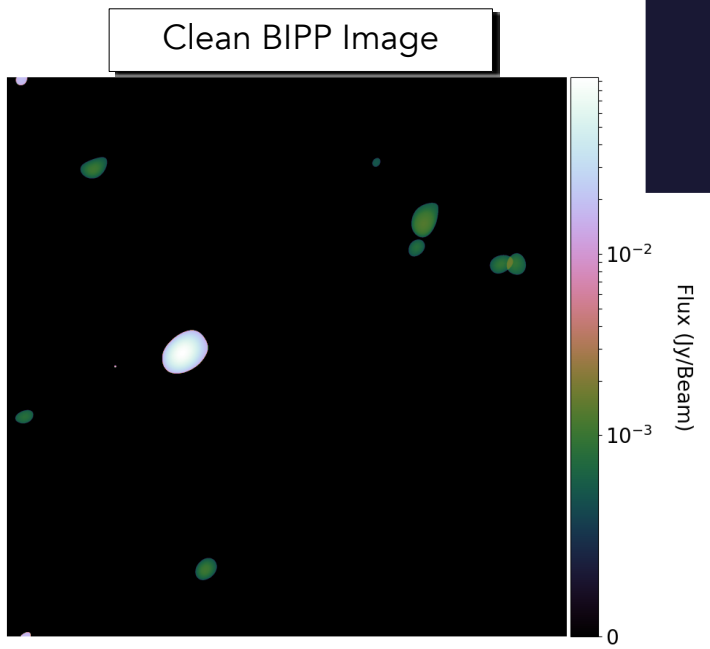
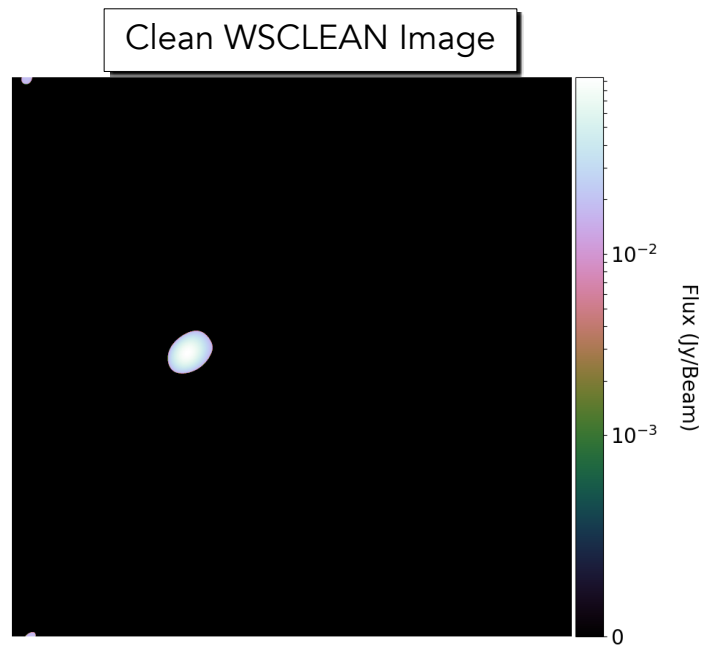


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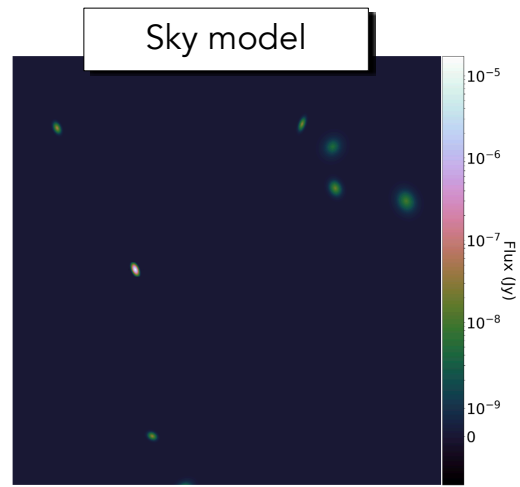


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Better SNR?

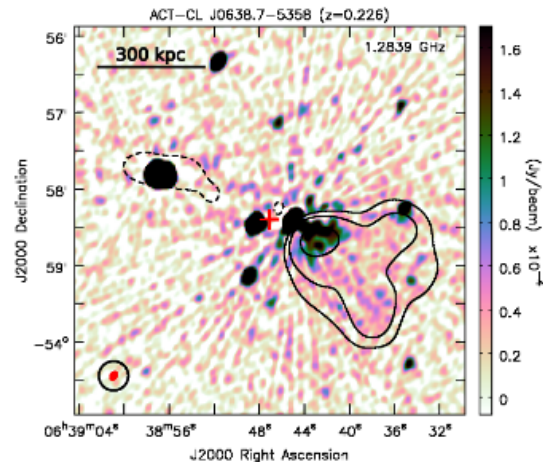


(Levels cleaned separately)



Next steps

- Would like to check the impact of this peeling on a few scientific use cases
 - Using it in the MeerKAT calibration pipeline (R. Kincaid)
 - Seeing if peeling can improve measurements of diffuse flux (R. Poitevineau)
 - If peeling can improve EoR foreground removal, or make fields contaminated by bright A-team sources useful for EoR measurements (S. Krishna)
- Also working on our own NUFFT library, separating eigenvalue decomposition from imaging



If you are interested in using this for your own work the code is publicly available on GitHub: <https://github.com/epfl-radio-astro/bipp>

