Optimisation & AI for image formation in the SKA era

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Outline

- ☛ The image formation challenge
- ☛ The hybrid optimisation & AI algorithms
- ☛ Algorithm variations and real data

The image formation challenge

Aperture synthesis by radio interferometry

Aperture synthesis by radio interferometry provides access to high resolution but forming an image $\boldsymbol{x}$ from visibility data $\boldsymbol{y}$ is an ill-posed inverse problem.

- The combination of correlations between all antenna pairs across the observation time provides an incomplete Fourier sampling of the sky:
- Forward Model:

$$\boxed{\boldsymbol{y} = \boldsymbol{\Phi x} + \boldsymbol{n}}$$

- Reconstruction algorithms are needed, leveraging a prior image model to regularise and solve the problem:

$$\boxed{\boldsymbol{y} \rightarrow \boldsymbol{x}}$$

- Accurate models needed for precision
- Calibration functionalities needed for robustness

The Square Kilometre Array

SKA will target new resolution and sensitivity regimes, leading to EB data volumes and PB wideband image sizes.

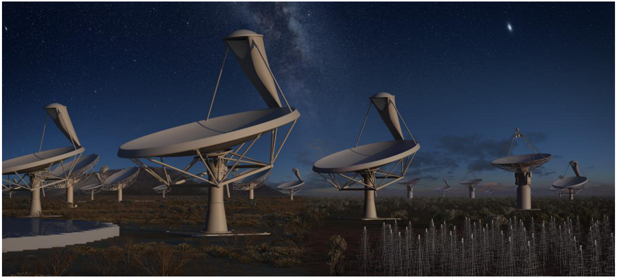


Image credit SKA organisation

- Reconstruction algorithms must be scalable!
- State-of-the-art CLEAN algorithm is scalable but offers sub-optimal precision and robustness

The hybrid optimisation & AI algorithms

Powerful hybrid framework

Convex optimisation provides a powerful framework to solve inverse problems via highly iterative algorithms.

$$\boxed{\boldsymbol{x}^\star \in \underset{\boldsymbol{x}}{\operatorname{argmin}} \Big\{ g(\boldsymbol{x};\boldsymbol{y}) = f(\boldsymbol{x};\boldsymbol{y}) + r(\boldsymbol{x}) \Big\}}$$

- $f(\boldsymbol{x};\boldsymbol{y})$: convex data-fidelity term; $r(\boldsymbol{x})$: convex regularisation term

VERSATILE THEORY:

- Provides convergence guarantees for robustness
- Allows advanced regularisation for precision
- Provides parallel algorithmic structures for scalability
- Generalizes to nonconvex optimisation for robust calibration
- Generalises to learned regularisation for precision and scalability

The Forward-backward optimisation algorithm

The Forward-Backward (FB) algorithmic is a versatile and powerful optimisation structure for imaging.

- $f(\boldsymbol{x}; \boldsymbol{y})$, differentiable: *e.g.* $||\boldsymbol{y} - \boldsymbol{\Phi x}||_2^2$ (Gaussian noise)
- $r(\boldsymbol{x})$, differentiable or not: *e.g.* $||\boldsymbol{\Psi x}||_1$ (sparsity), $\iota_{\mathbb{R}_+^N}$ (positivity)
- Iteration structure (reminiscent of, but much more general than, CLEAN):

$$\boldsymbol{x}^{(t)} = \mathrm{prox}_r \left(\boldsymbol{x}^{(t-1)} + \mu \boldsymbol{\Phi}^\dagger \left(\boldsymbol{y} - \boldsymbol{\Phi} \boldsymbol{x}^{(t-1)} \right) \right)$$

- Regularisation operator prox_r is an image denoiser

The AI variant

The Plug-and-Play Forward-Backward (PnP-FB) is an AI variant enabling to learn the regularisation model.

- $f(\boldsymbol{x};\boldsymbol{y})$, differentiable: *e.g.* $||\boldsymbol{y}-\boldsymbol{\Phi x}||_2^2$ (Gaussian noise)
- The regularisation denoiser is learnt and embedded in a DNN, rather than handcrafted
- Iteration structure:

$$\boxed{\boldsymbol{x}^{(t)} = \mathrm{DNN}\left(\boldsymbol{x}^{(t-1)} + \mu\boldsymbol{\Phi}^{\dagger}\left(\boldsymbol{y}-\boldsymbol{\Phi}\boldsymbol{x}^{(t-1)}\right)\right)}$$

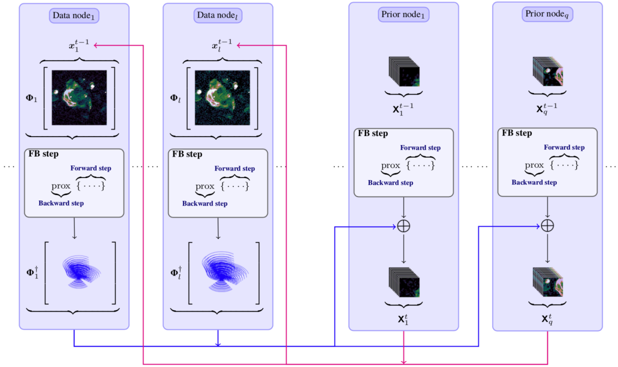
- Learning enables more physical regularisation for precision
- The DNN is typically much faster than complicated prox_r operators

Algorithm variations and real data

Parallel wideband calibration and imaging

Parallel FB deployed on an HPC system to jointly calibrate 7.4GB of VLA data and produce a 15GB wideband image of Cygnus A, with exquisite precision.

- Distributed implementation structure



Thouvenin et al., arXiv:2003.07358; Dabbech et al., arXiv:2102.00065

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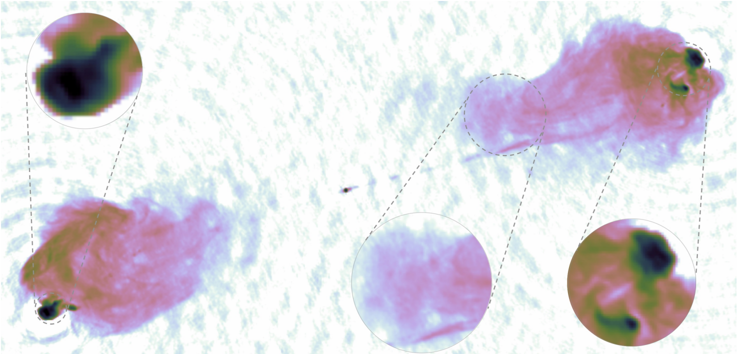
- CLEAN imaging



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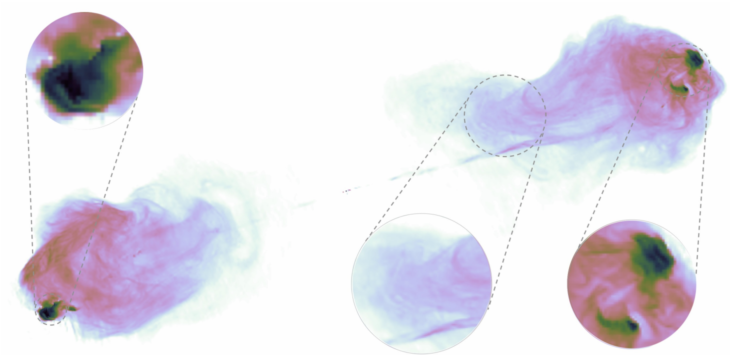

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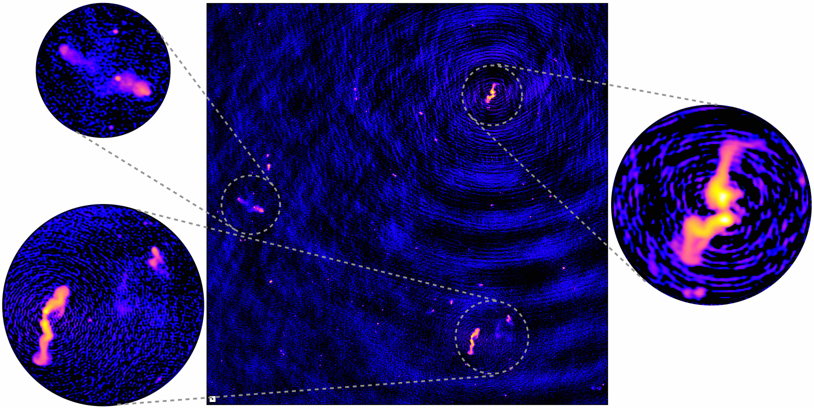
Parallel widefield imaging

Parallel FB deployed to process widefield ASKAP data.

- Merging system Abell 3391/95: CLEAN imaging (0.3GB data)



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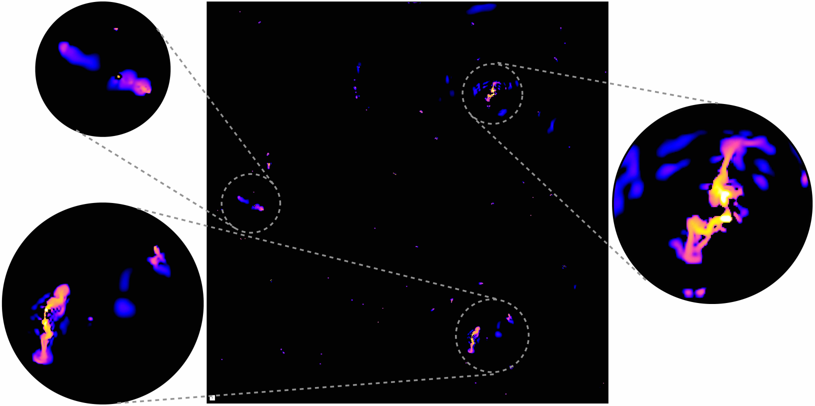

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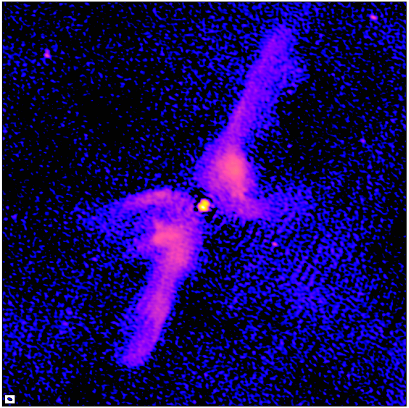
Parallel FB deployed to process widefield ASKAP data.

- X-shaped radio galaxy PKS 2014-55: CLEAN imaging (1GB data)



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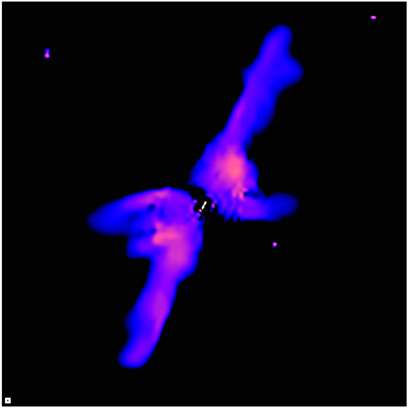

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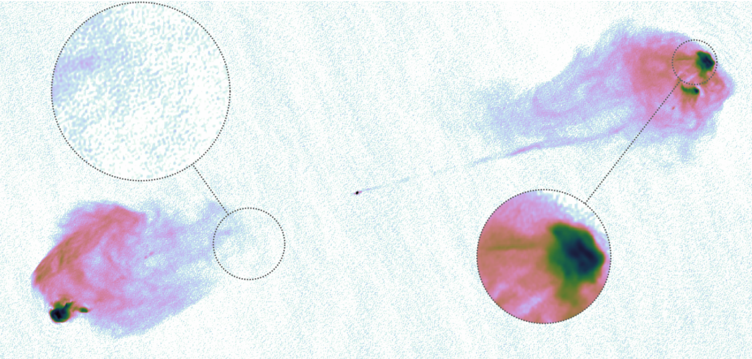
Accelerated imaging with AI

DNN trained on high dynamic range dataset and PnP-FB deployed for Cygnus A imaging (simulation): 22-fold acceleration vs. FB for similar precision.

- CLEAN imaging



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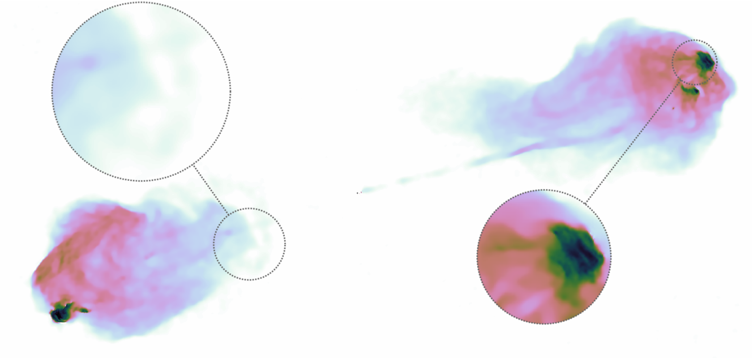
- PnP-FB imaging



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