

Calibration of the SKA-low antenna array using drones

Loïc VAN HOOREBEECK

March 25, 2019



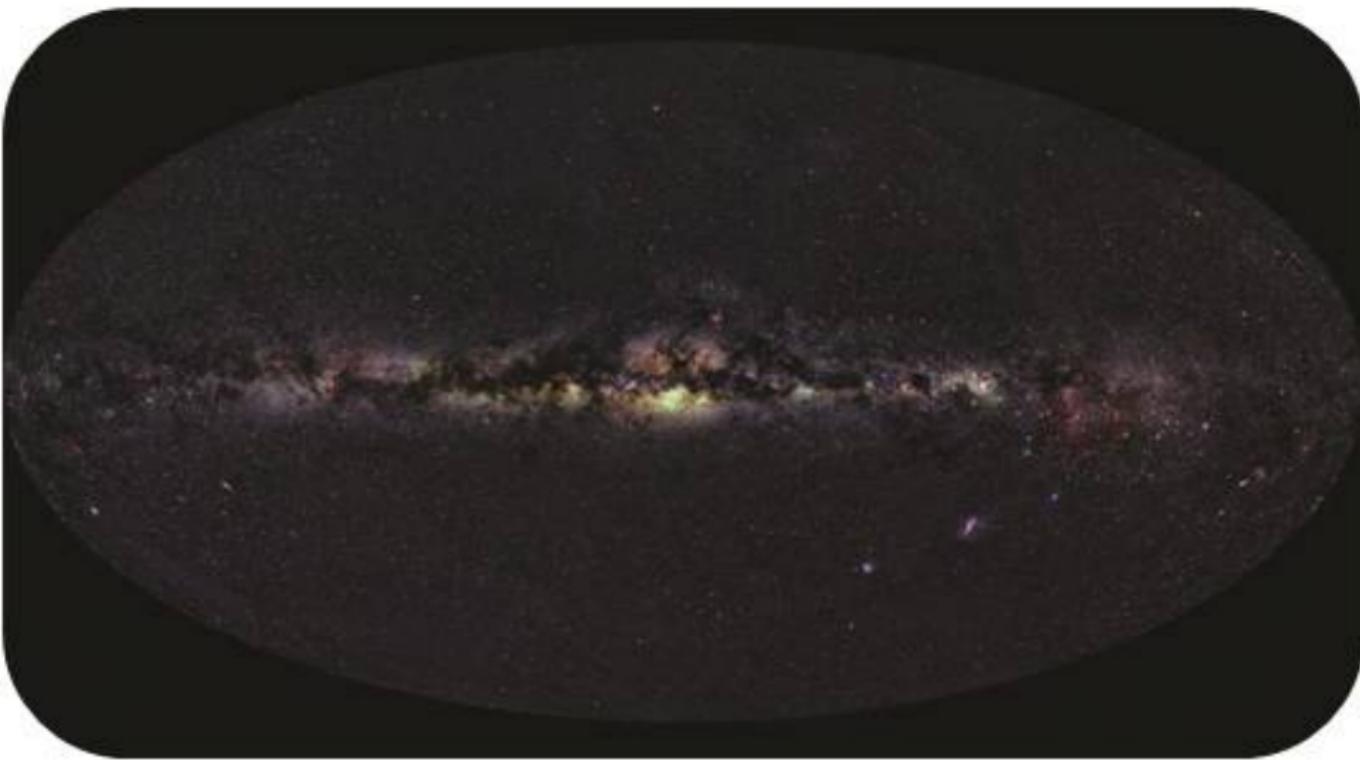
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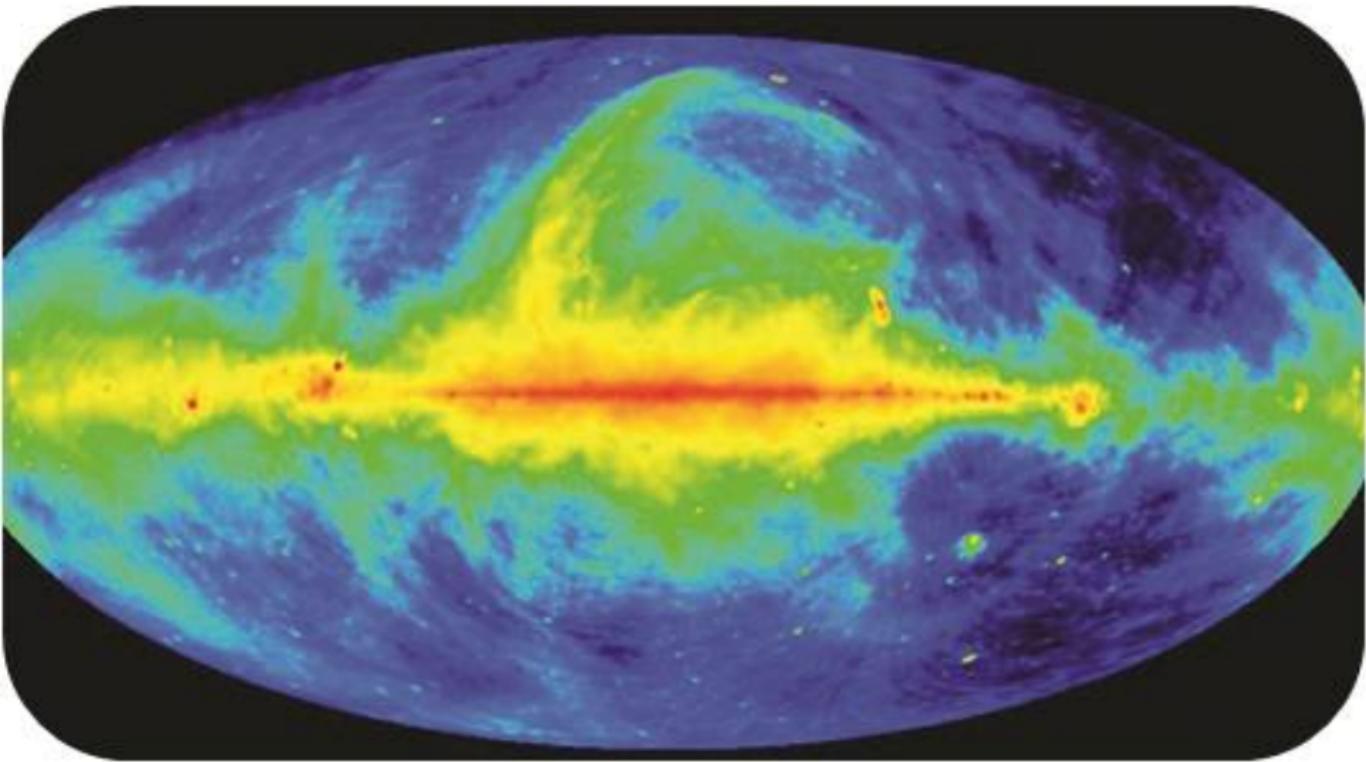
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Optical telescope



Radio telescope



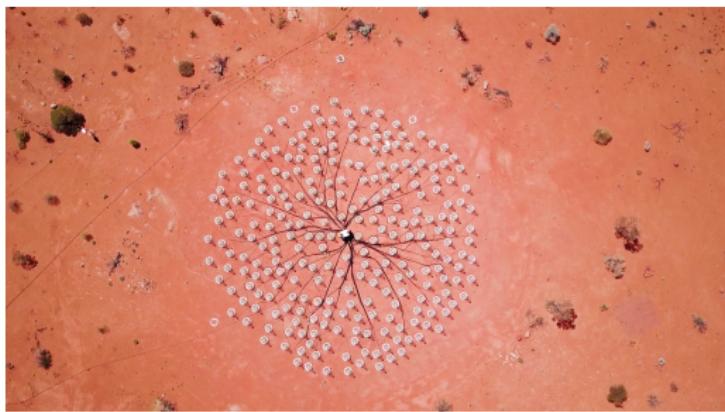
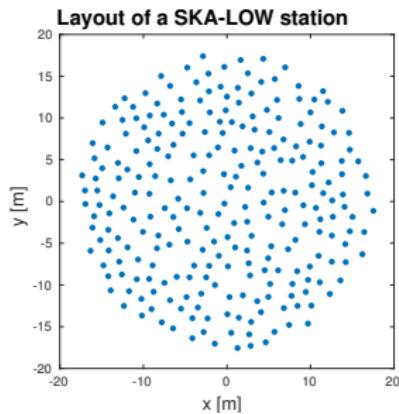
Calibration of the SKA-low antenna array using drones

- ▶ **Square Kilometer Array**
- ▶ Frequency range of [50; 350]MHz
- ▶ 130000 antennas spread between 500 stations
- ▶ Compared to the best similar instrument :
 - 25% better resolution
 - 8× more sensitive
 - 135× the survey speed



Calibration of the SKA-low antenna array using drones

A first station overview



$N_a = 256$ antennas irregularly arranged. The Aperture Array Verification System 1 (AAVS1).

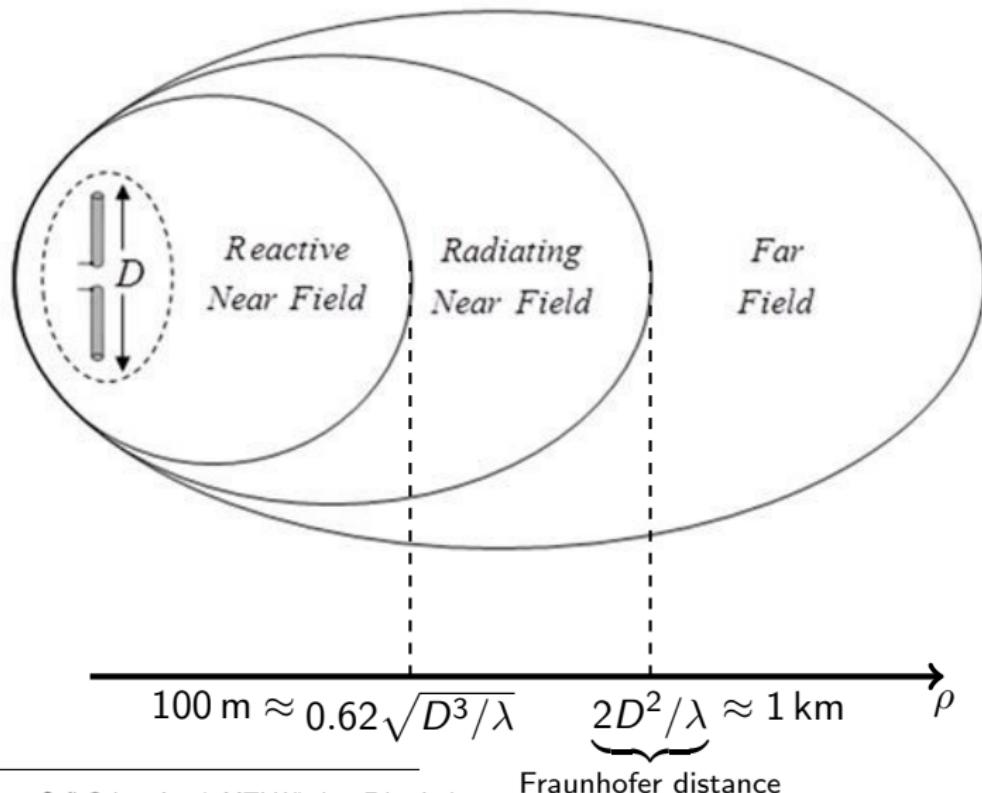
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An example of a wired antenna

Sketch of the running of antenna by converting a sine electric current into a EM wave.

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Field regions



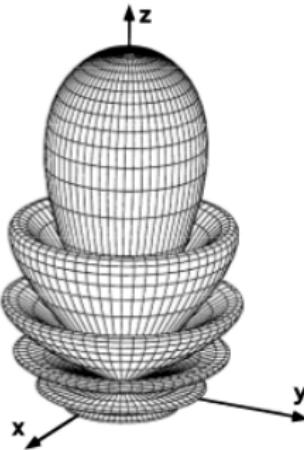
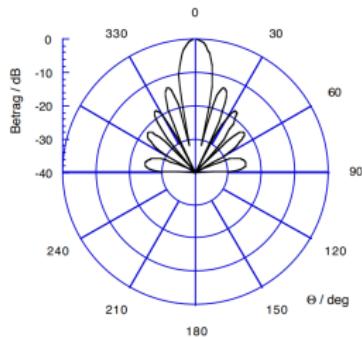
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Radiation Pattern

$$\mathbf{F}(\theta, \varphi) = \lim_{\rho \rightarrow \infty} \frac{\mathbf{E}(\rho, \theta, \varphi)}{\max_{\theta, \varphi} \mathbf{E}(\rho, \theta, \varphi)} = F_v \mathbf{e}_\theta + F_h \mathbf{e}_\varphi$$

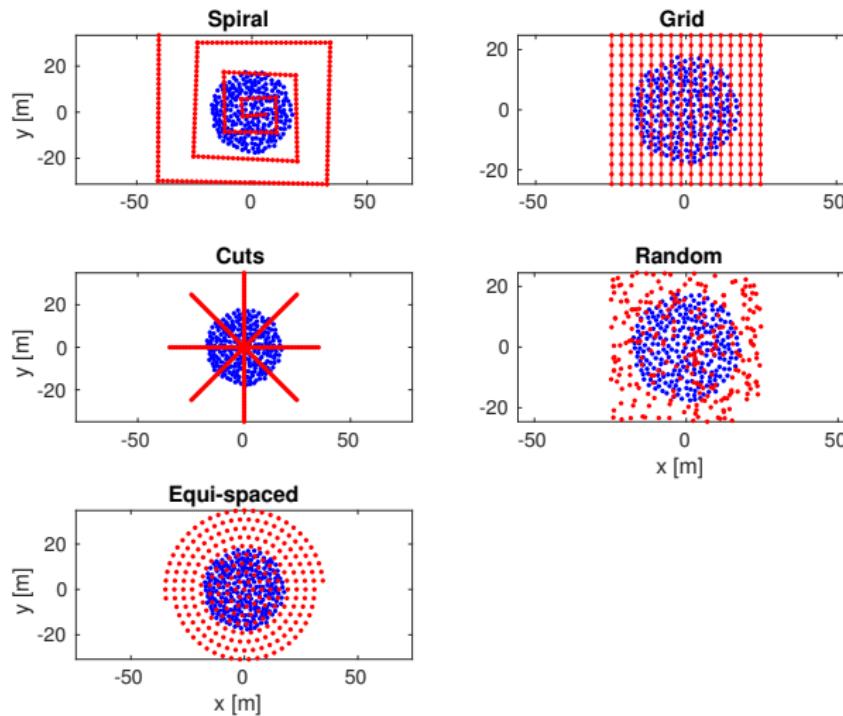
Embedded Element Pattern (EEP)

Radiation pattern when an antenna i is on with the other passively terminated.



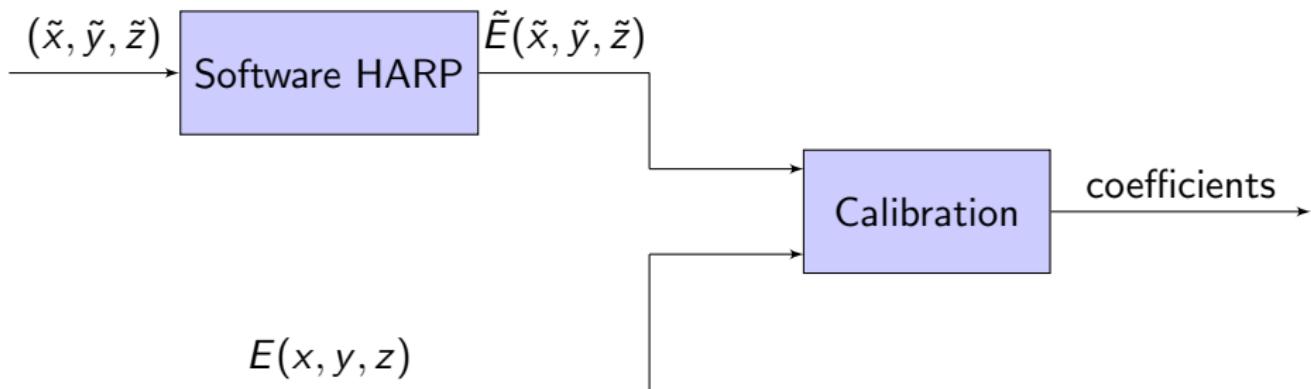
Calibration of the SKA-low antenna array using drones

Flight strategies



Calibration of the SKA-low antenna array using drones

Calibration procedure



Calibration methods

Calibration of the SKA-low antenna array using drones

- ▶ Sum of every EEP of ON antenna i
 - ▶ Computed pattern
- $$\bar{\mathbf{F}}_v = \sum_{i=1}^{N_a} \sum_{j=1}^{N_a} \underbrace{\mathbf{B}_{v,j}^i c_j^i}_{\bar{\mathbf{F}}_v^i} \in \mathbb{C}^{N_e \times 1}$$
- ▶ Basis vectors $\in \mathbb{C}^{N_e \times N_a}$
 - ▶ Calibration coefficients $\in \mathbb{C}^{N_a}$

Calibration of the SKA-low antenna array using drones

Formulation as N_a convex optimization problems

$$\min_{\mathbf{c}^i \in \mathbb{C}^{N_a}} \|\mathbf{F}_v^i - \bar{\mathbf{F}}_v^i\|_2^2 + \|\mathbf{F}_h^i - \bar{\mathbf{F}}_h^i\|_2^2 \quad \forall i = 1 \dots N_a$$

This is a **least-square** problem and its optimal solution satisfies

$$\begin{pmatrix} \mathbf{B}_h^i \\ \mathbf{B}_v^i \end{pmatrix}^H \underbrace{\begin{pmatrix} \mathbf{B}_h^i \\ \mathbf{B}_v^i \end{pmatrix}}_{\mathbb{C}^{2N_{\text{mes}} \times N_a}} \underbrace{\mathbf{c}^i}_{\mathbb{C}^{N_a}} = \begin{pmatrix} \mathbf{B}_h^i \\ \mathbf{B}_v^i \end{pmatrix}^H \underbrace{\begin{pmatrix} \mathbf{F}_h^i \\ \mathbf{F}_v^i \end{pmatrix}}_{\mathbb{C}^{N_a}} \quad \forall i = 1 \dots N_a$$

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Error definition in dB

$$e_{\theta,\varphi} = 10 \log_{10} \left(|\mathbf{F}_v - \bar{\mathbf{F}}_v|^2 + |\mathbf{F}_h - \bar{\mathbf{F}}_h|^2 \right) - 10 \log_{10} \max_{\theta,\varphi} \{ |\mathbf{F}_v|^2 + |\mathbf{F}_h|^2 \}$$

Metrics

$$\text{Maximum error} \quad e_M \triangleq \max_{\theta,\varphi} e_{\theta,\varphi}$$

$$\text{Mean error} \quad \mu_e \triangleq \mathbb{E}\{e_{\theta,\varphi}\}$$

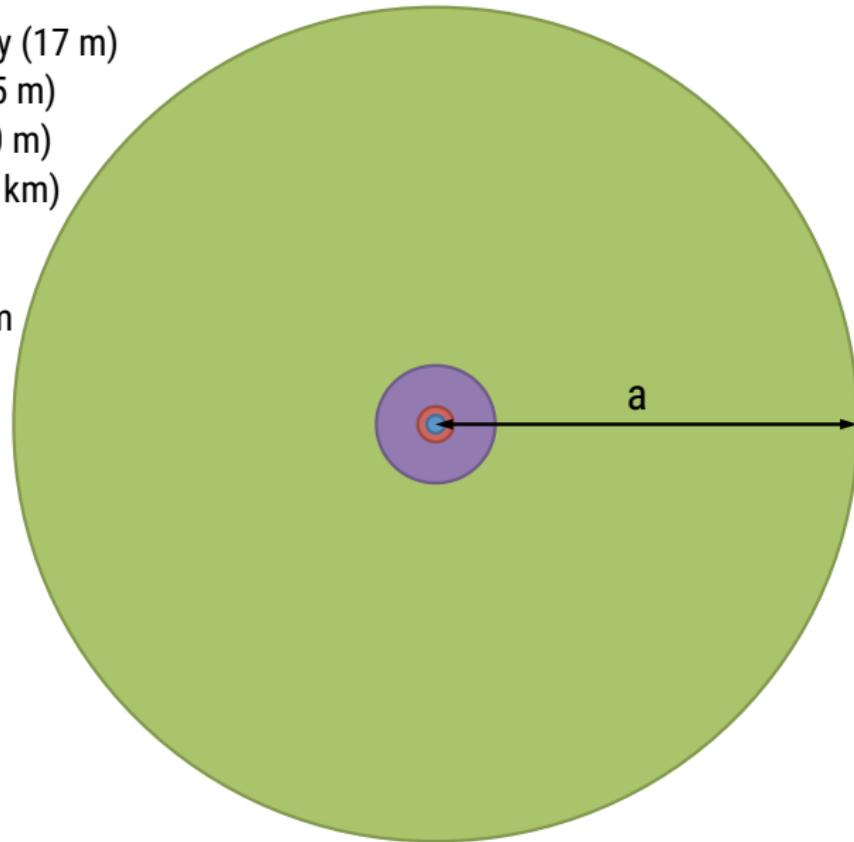
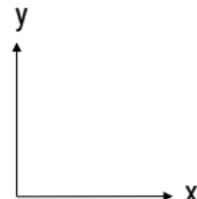
Results

Results

- Antenna array (17 m)
- Near field (25 m)
- Far field (200 m)
- Far field (1.7 km)

$f = 140 \text{ MHz}$

$a = \text{distance from}$
 array center



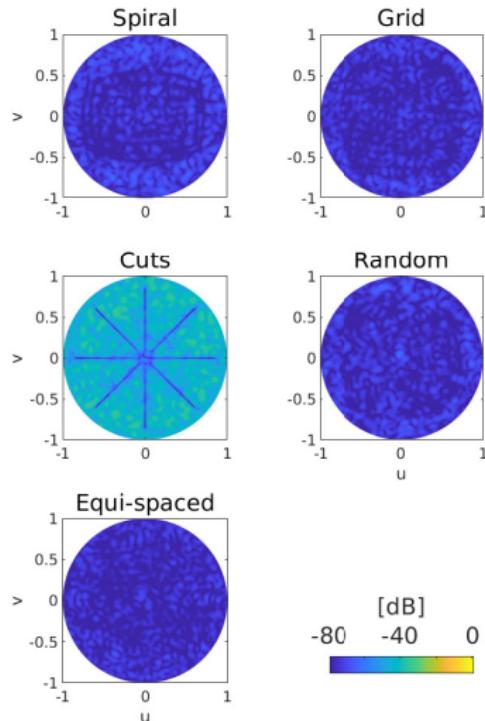
Far-field calibration

No flight restriction

- $h \triangleq 1 \text{ km}$ height to reach Fraunhofer distance
- $a = 1.7 \text{ km}$

| Flight strategy | e_M (dB) | μ_e (dB) |
|-----------------|------------|--------------|
| Spiral | -60.9 | -74 |
| Grid | -63.4 | -75.5 |
| Cuts | -29.8 | -45.3 |
| Random | -60 | -74.3 |
| Equi-spaced | -64.3 | -76.5 |

Good behavior for all strategies except cuts

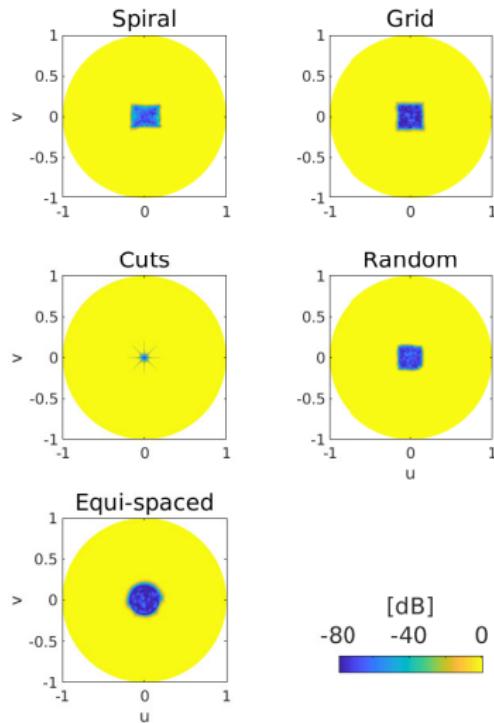


Far-field calibration

200 m flight restriction

- $h = 1 \text{ km}$
- $a = 200 \text{ m}$

Small error along the drone path
Large error anywhere else

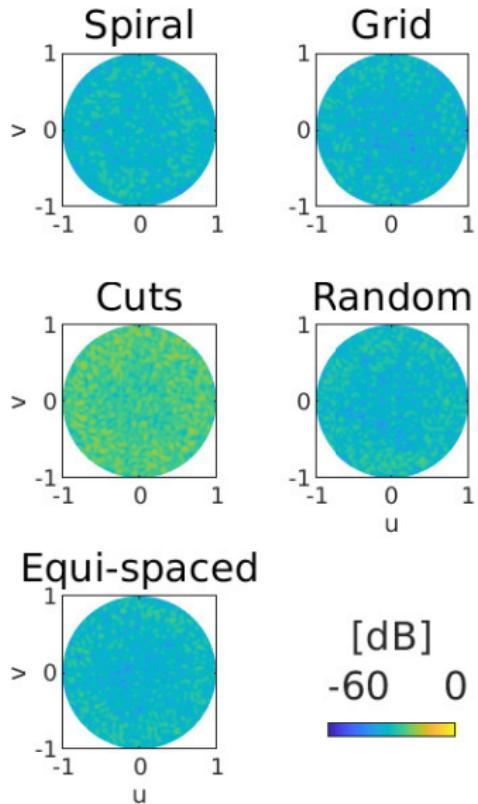


Near-field calibration

- $h = 10 \text{ m}$
- $a = 25 \text{ m}$

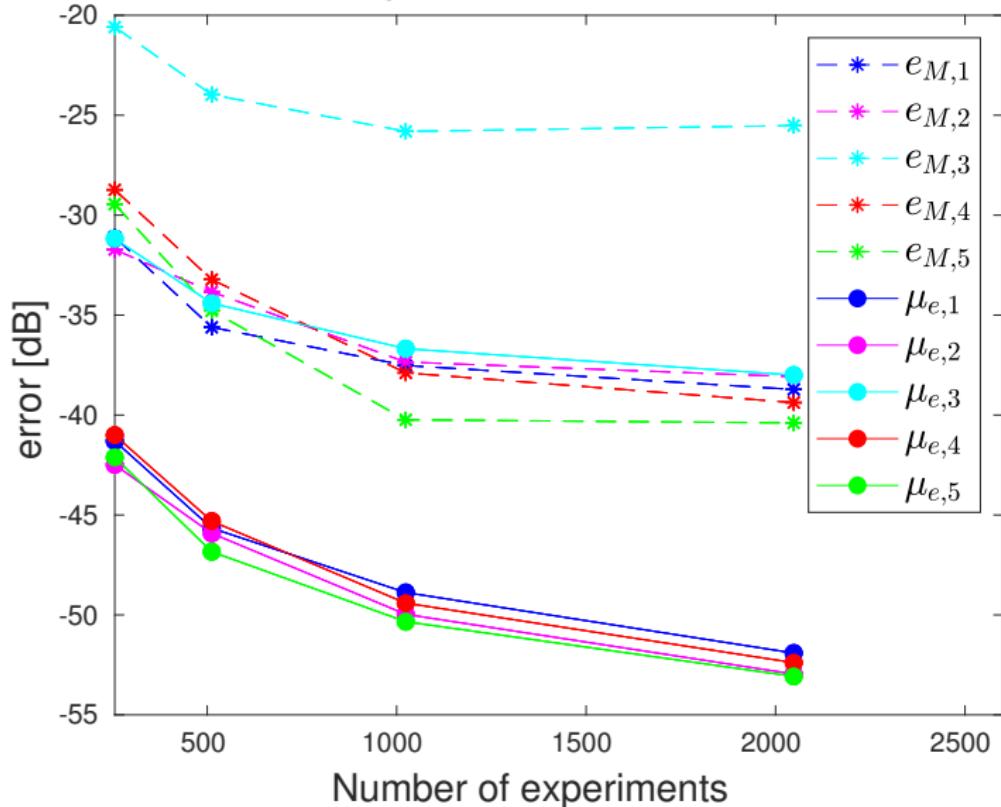
| Flight strategy | e_M (dB) | μ_e (dB) |
|-----------------|------------|--------------|
| Spiral | -31.1 | -41.3 |
| Grid | -31.72 | -42.5 |
| Cuts | -20.6 | -31.2 |
| Random | -28.7 | -41.0 |
| Equi-spaced | -29.7 | -41.1 |

Better than restricted FF but worse
than unrestricted FF



Near Field

Impact of the number of experiments

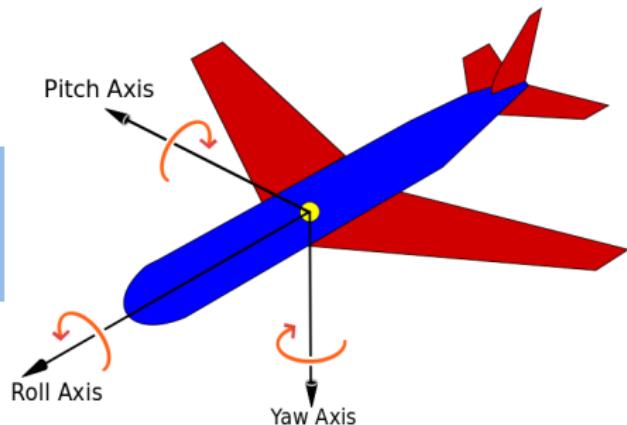


Near field

Drone attitude

| Max error (dB) | Mean error (dB) | σ_y | σ_p | σ_r | (degrees) |
|----------------|-----------------|------------|------------|------------|-----------|
| -48.14 | -57.38 | 2 | 2 | 2 | |
| -48.46 | -59.62 | 2 | 0 | 0 | |
| -54.32 | -65.46 | 0 | 2 | 0 | |
| -54.32 | -65.14 | 0 | 0 | 2 | |

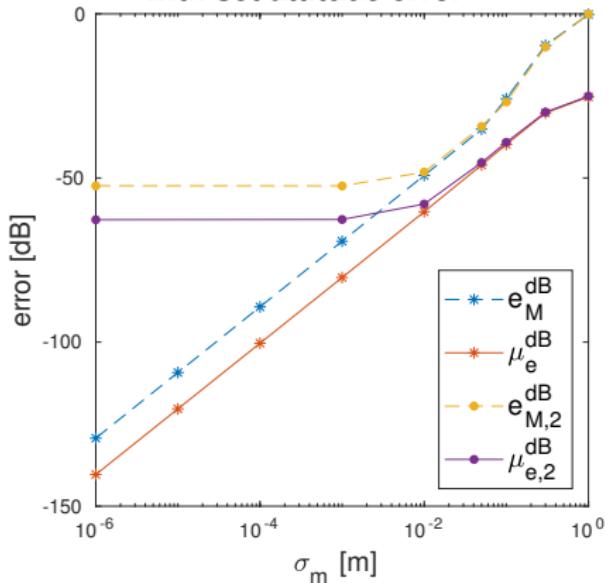
Smaller impact than position noise
Error mainly due to yaw angle



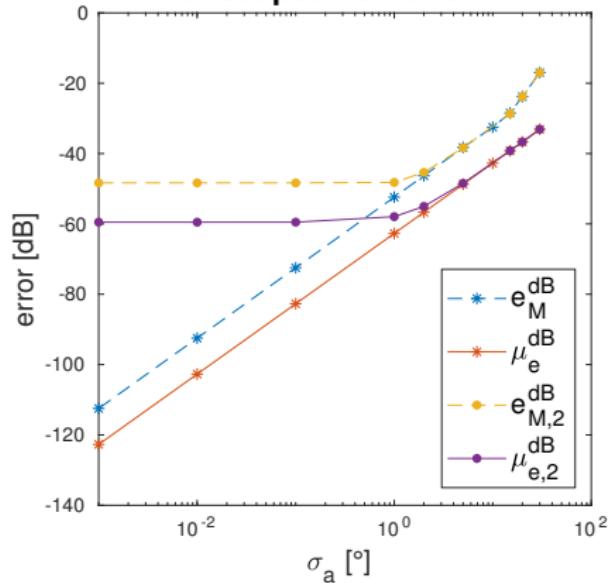
Near field

Combining both noises

**Impact of position error
with set attitude error**



**Impact of attitude error
with set position error**



Linear relationship between error and noise-level in dB scale

When combined, the error is dominated by the more significant noise

Regularization

Regularization

Mathematical formulation

$$\min_{\mathbf{x} \in \mathbb{R}^n} \|\mathbf{Ax} - (\mathbf{b} + \epsilon \mathbf{f})\|_2^2$$

with $\mathbf{A} \in \mathbb{R}^{m \times n}$, $\mathbf{b} \in \mathbb{R}^m$ the data matrix and $\epsilon \mathbf{f}$ the perturbation vector.

A numerical example

Let

$$\mathbf{A} = \begin{pmatrix} 0.16 & 0.10 \\ 0.17 & 0.11 \\ 2.02 & 1.29 \end{pmatrix}, \quad \mathbf{x}^* = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, \quad \mathbf{b} = \mathbf{Ax}^*$$

with $\mathbf{f} = \begin{pmatrix} 1 \\ -3 \\ 2 \end{pmatrix}$ a perturbation with $\epsilon = 0.01$.

Moore-Penrose solution is $\mathbf{x}_\epsilon = (7.0 \quad -8.3)^T$.

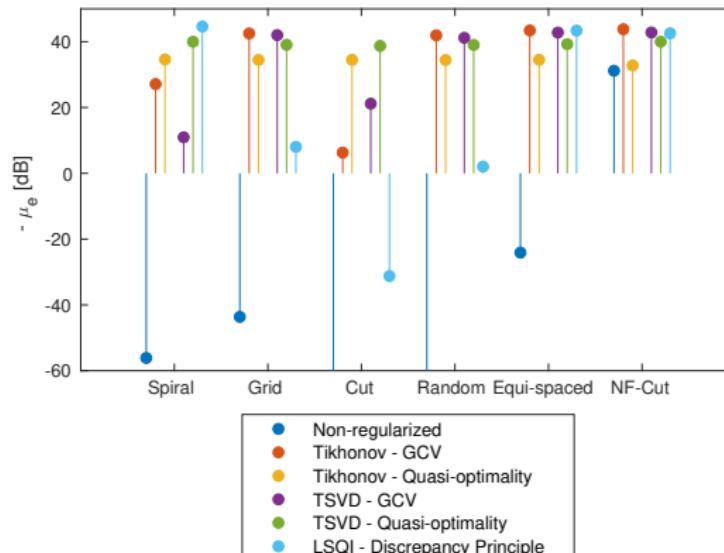
Regularization

Regularization type

Parameter choice strategy

| | |
|---|------------------------------------|
| Tikhonov | Discrepancy principle |
| Truncated SVD (TSVD) | Generalized cross-validation (GCV) |
| Least square minimization with a quadratic inequality constraint (LSQI) | Quasi-optimality criterion (QO) |

Application on SKA-low calibration



Regularization

Regularization type

Tikhonov

Truncated SVD (TSVD)

Least square minimization with a quadratic inequality constraint (LSQI)

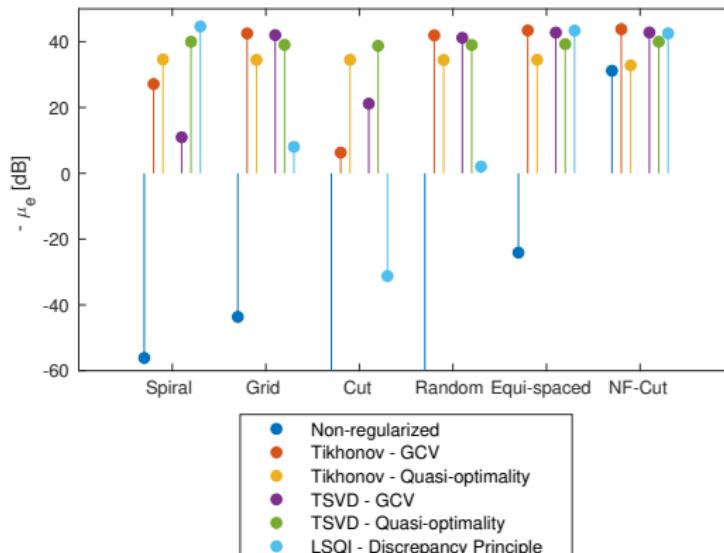
Parameter choice strategy

Discrepancy principle

Generalized cross-validation (GCV)

Quasi-optimality criterion (QO)

Application on SKA-low calibration



Conclusion and future works

Summary

Mean Error μ_e with 256 experiments

| | | Non regularized | | Regularized | | |
|----|--------------|--------------------|---------|--------------|-------------|---------|
| | | Tikh-GCV | Tikh-QO | TSVD- GCV | TSVD- QO | LSQI-DP |
| FF | Restricted | Spiral | 56 | -27 | -35 | -11 |
| | | Grid | 44 | -43 | -34 | -42 |
| | | Cut | 88 | -6 | -34 | -21 |
| | | Random | 63 | -42 | -34 | -41 |
| | | Equi- spaced | 24 | -43 | -35 | -43 |
| | Unrestricted | Spiral | -74 | | | |
| | | Grid | -75 | | | |
| | | Cut | -45 | | | |
| | | Random | -74 | | | |
| | | Equi- spaced | -76 | | | |
| NF | NF | Spiral | -41 | | | |
| | | Grid | -43 | | | |
| | | Cut | -31 | -44 | -33 | -43 |
| | | Random | -41 | | | |
| | | Equi- spaced | -41 | | | |

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| FF | Restricted | Spiral | 56 | -27 | -35 | -11 | -40 | -45 | |
| | | Grid | 44 | -43 | -34 | -42 | -39 | -8 | |
| | | Cut | 88 | -6 | -34 | -21 | -39 | 31 | |
| | | Random | 63 | -42 | -34 | -41 | -39 | -2 | |
| | | Equi-spaced | 24 | -43 | -35 | -43 | -39 | -43 | |
| | Unrestricted | Spiral | -74 | | | | | | |
| | | Grid | -75 | | | | | | |
| | | Cut | -45 | | | | | | |
| | | Random | -74 | | | | | | |
| | | Equi-spaced | -76 | | | | | | |
| NF | NF | Spiral | -41 | | | | | | |
| | | Grid | -43 | | | | | | |
| | | Cut | -31 | -44 | -33 | -43 | -40 | -43 | |
| | | Random | -41 | | | | | | |
| | | Equi-spaced | -41 | | | | | | |

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| | | Random | -74 | | | |
| | | Equi-spaced | -76 | | | |
| NF | NF | Spiral | -41 | | | |
| | | Grid | -43 | | | |
| | | Cut | -31 | -44 | -33 | -43 |
| | | Random | -41 | | | |
| | | Equi-spaced | -41 | | | |

Summary

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| | | Cut | -45 | | | | |
| | | Random | -74 | | | | |
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| NF | NF | Spiral | -41 | | | | |
| | | Grid | -43 | | | | |
| | | Cut | -31 | -44 | -33 | -43 | -40 |
| | | Random | -41 | | | | |
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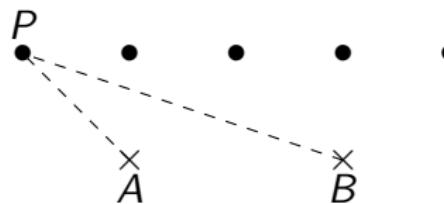
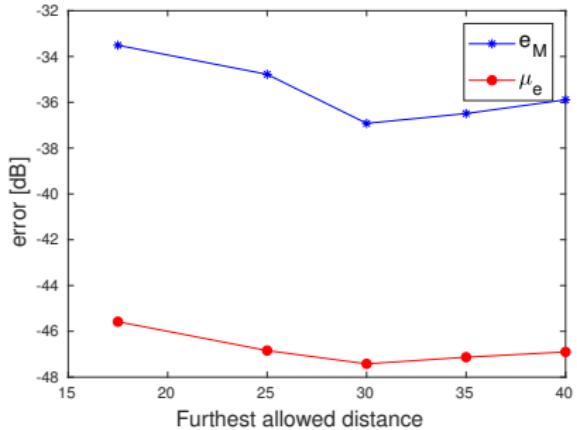
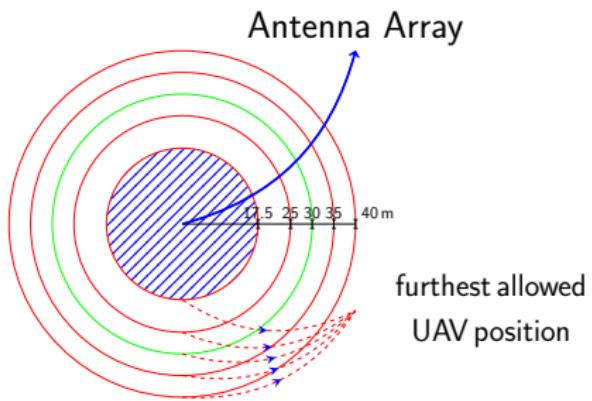
Going further

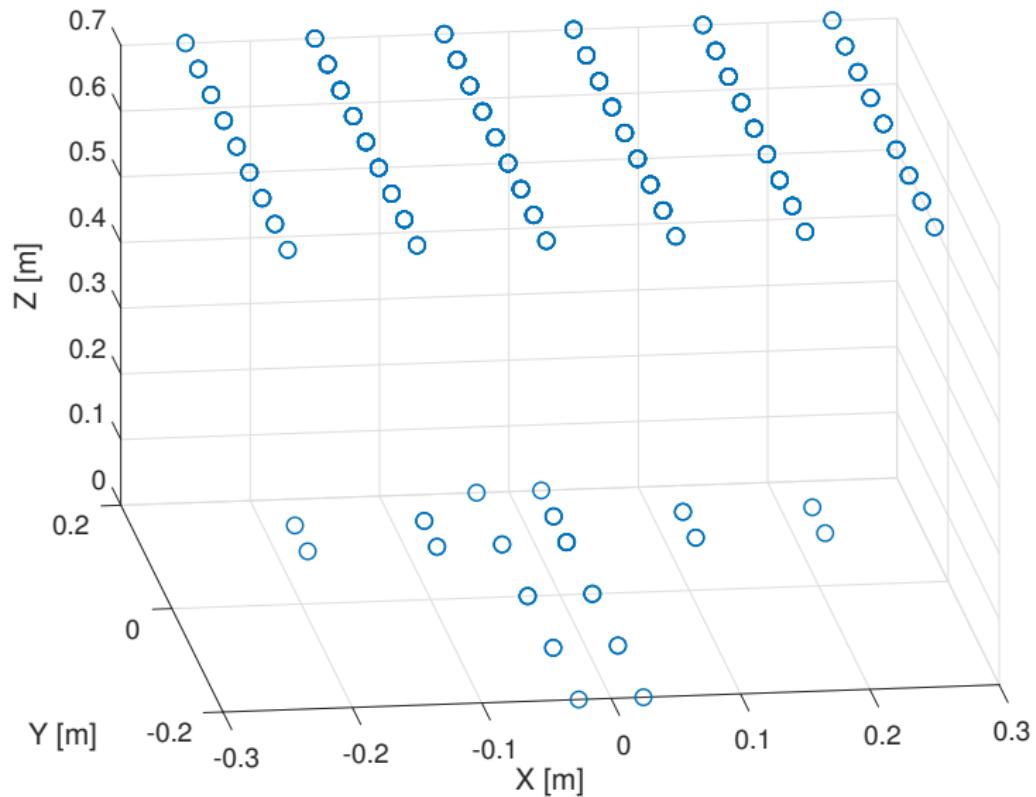
Extending the model

- Adding other noise sources (e.g. during the transmission)
- Taking finite ground plane effects into account

Generalization to $N_a \neq 256$ antennas

- FF case : $N_e \approx \max\{ \underbrace{50}_{\text{Sampling the pattern}}, \overbrace{N_a}^{\text{Unique solution}} \}$
- NF case : Every experiment yields N_a "independent" measurements
⇒ Same behavior for all N_a





Calibration of the SKA-low antenna array using drones

Why using an array of antennas ?

- ▶ Obtaining a better **angular resolution**
- ▶ Increasing the **sensitivity**

Interferometry : Emulation of a single larger dish

