Spatial RFI mitigation with Phased Array Feeds

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CSIRO Astronomy and Space Science

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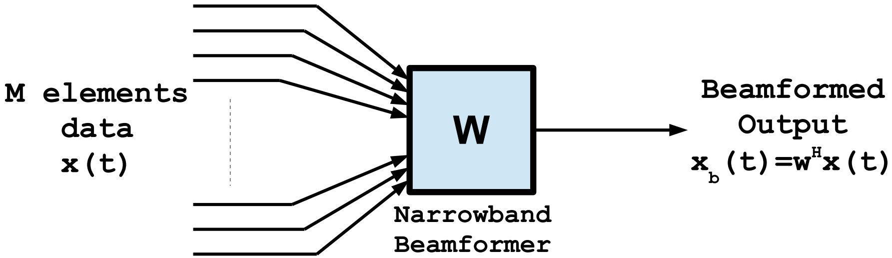
Important dates:

Abstract submission:	15 August 2016
Author registration:	15 September 2016
Conference:	17-20 October 2016
IEEE proceeding submission:	11 November 2016

Single beamformer



$$\mathbf{w}_{opt} = \underset{\mathbf{w}}{\text{argmax}}\, f(\mathbf{w}, \mathbf{x}(t), ?)$$

(yet another slide about beamforming...)

Narrowband data model:

$$\begin{cases} x_1(t) = a_{s_1} s(t) + n_1(t) \\ x_2(t) = a_{s_2} s(t) + n_2(t) \\ \quad \vdots \\ x_M(t) = a_{s_M} s(t) + n_M(t) \end{cases} \Rightarrow \quad \mathbf{x}(t) = \mathbf{a}_s s(t) + \mathbf{n}(t)$$

Beamforming:

$$y_b(t) = w_1.x_1(t) + \cdots + w_M.x_M(t) \Rightarrow \quad y_b(t) = \mathbf{w}^H \mathbf{x}(t) = \mathbf{w}^H \mathbf{a}_s s(t) + \mathbf{w}^H \mathbf{n}(t)$$

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Optimum beamforming

Data model and beamforming

$$\mathbf{x}(t) = \mathbf{a}_s s(t) + \mathbf{n}(t) \quad \Rightarrow \quad \mathbf{w}^H \mathbf{x}(t) = \left[\mathbf{w}^H \mathbf{a}_s\right] s(t) + \left[\mathbf{w}^H \mathbf{n}\right](t)$$

Optimum beamformer (= matched filter)

$$\mathbf{w}_{\text{opt}} = \underset{\mathbf{w}}{\text{argmax}}\, \mathbb{E}\left\{\left|\mathbf{w}^H \mathbf{a}_s s(t)\right|^2\right\} = \mathbf{a}_s$$

(for fixed $\|\mathbf{w}\|$*)*

Additional source (e.g. RFI)

$$\mathbf{x}(t) = \mathbf{a}_r r(t) + \mathbf{a}_s s(t) + \mathbf{n}(t) \quad \Rightarrow \quad \mathbb{E}\left\{\left|{\mathbf{w}_{\text{opt}}}^H \mathbf{a}_r r(t)\right|^2\right\} = ??$$

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Adaptive beamformer

Data model

$$y_{\text{adapt}}(t) = \mathbf{w}_{\text{adapt}}{}^H \mathbf{x}(t)$$
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Adaptive filter:

$$\mathbf{w}_{\text{adapt}} = \underset{\mathbf{w}}{\text{argmax}} \quad \mathbb{E}\left\{\left|\mathbf{w}^H \mathbf{a}_s s(t)\right|^2\right\}$$
$$\text{subject to} \quad \left[\mathbf{w}_{\text{adapt}}{}^H \mathbf{a}_r\right] = 0$$

Requires knowledge of:

- $\mathbf{a}_s$ (≈ direction / pattern of interest)
- $\mathbf{a}_r$ (≈ ?? - a priori knowledge? primary / side lobe?...)

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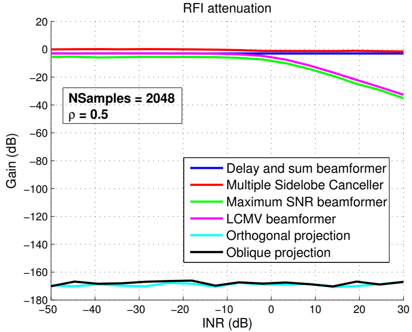
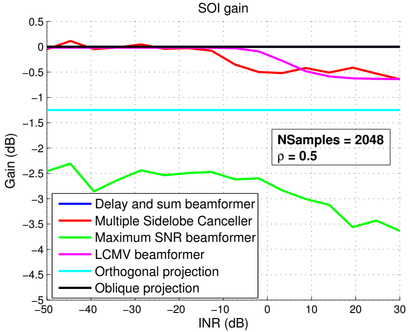
Adaptive beamformer vs. Subspace projection





10 antennas ULA - $\frac{\lambda}{2}$ spacing

RFI spatial information

Time series

$$\mathbf{x}(t) = \mathbf{a}_r r(t) + \mathbf{a}_s s(t) + \mathbf{n}(t)$$

Array covariance *(instantaneous and narrow band)*

$$\begin{aligned}\mathbf{R} &= \mathbb{E}\left\{\mathbf{x}(t)\mathbf{x}^H(t)\right\} \\ &= \sigma_r^2 \mathbf{a}_r {\mathbf{a}_r}^H + \sigma_s^2 \mathbf{a}_s {\mathbf{a}_s}^H + \mathbf{R}_n\end{aligned}$$

When $\sigma_r^2 \gg \sigma_s^2$

$$\mathbf{R} \approx \underbrace{\sigma_r^2 \mathbf{a}_r {\mathbf{a}_r}^H}_{rank=1} + \underbrace{\mathbf{R}_n}_{rank=dim}$$

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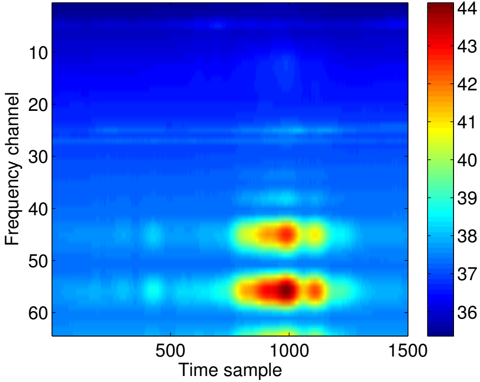
RFI spatial information

ASKAP - Galileo satellite “drift scan”



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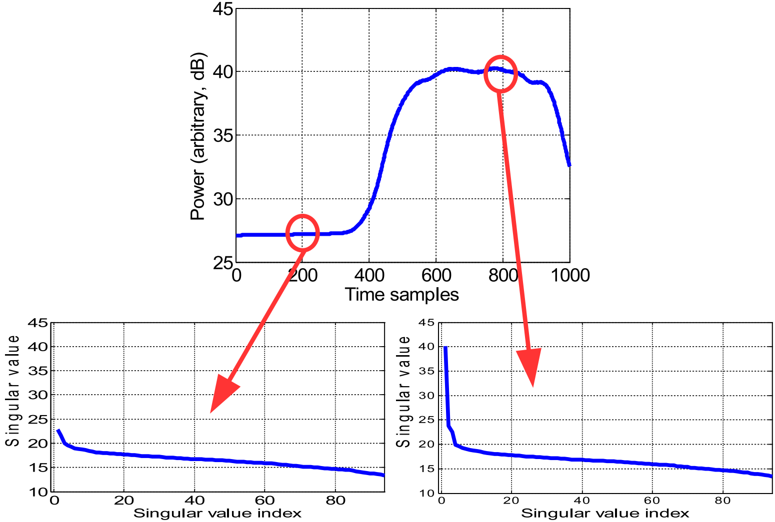

RFI subspace projection

Covariance decomposition

$$\mathbf{R} \approx \sigma_r^2 \mathbf{a}_r \mathbf{a}_r{}^H + \mathbf{R}_n$$

$$= \begin{bmatrix} \mathbf{u}_1 & \mathbf{U}_{M-1} \end{bmatrix} \begin{bmatrix} s_1 & & 0 \\ & \ddots & \\ 0 & & s_M \end{bmatrix} \begin{bmatrix} \mathbf{u}_1{}^H \\ \mathbf{U}_{M-1}{}^H \end{bmatrix}$$

Projection *operator*

$$\mathbf{P} = \mathbf{I} - \mathbf{u}_1 \mathbf{u}_1{}^H$$

Projection *operation*

$$\mathbf{R}_{\text{proj}} = \mathbf{PRP}$$

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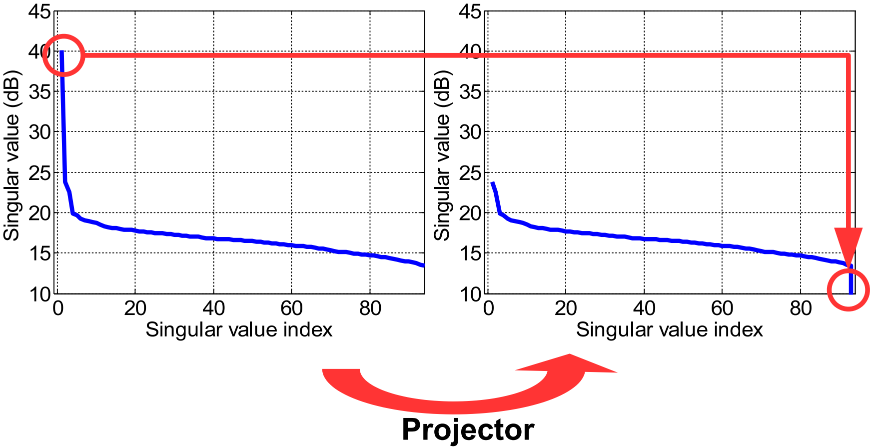

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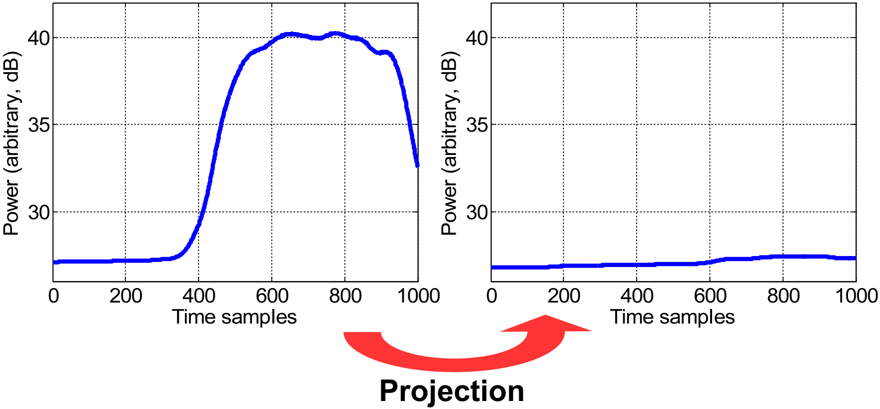

A few comments on projection operators

$$\mathbf{P} = \mathbf{I} - \mathbf{a}_r \mathbf{a}_r{}^H \qquad \mathbf{R}_P = \mathbf{P}\mathbf{R}\mathbf{P}^H$$

- Rank-deficiency of $\mathbf{R}$: $\mathrm{rk}(\mathbf{R}_P) < \mathrm{rk}(\mathbf{R})$
- Modifies $\mathbf{R}_{\mathrm{astro}}$ and $\mathbf{R}_{\mathrm{noise}}$ *(correction possible)*
- Requires the knowledge (estimation) of $\mathbf{a}_r$
- For *strong RFI*, *weak astro sources* and *"calibrated" array*, $\mathbf{a}_r$ is the principal component of $\mathbf{R}$ (what if not?)
- Nulls all sources with spatial signature $\propto \mathbf{a}_r$
  $\Rightarrow$ Inefficient if RFI share same time, frequency and spatial slot as astro source

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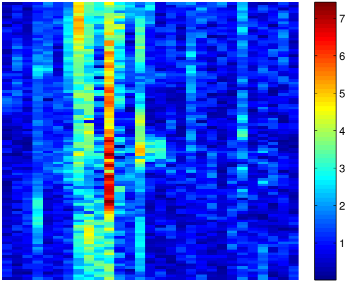
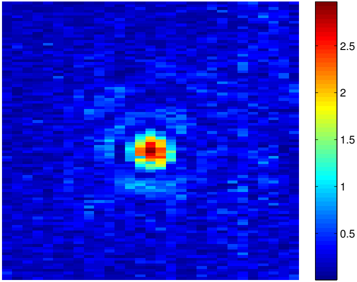
Example : Holographic measurement “cleaning”

Corrupted beam:



Beam after projection:



On INR limitations

EigenValue Decomposition applied to $\mathbf{R}$:

$$\begin{aligned}\mathbf{R} &= \mathbf{U}\mathbf{S}\mathbf{U}^H \\ &= \begin{pmatrix}\mathbf{U_r} & \mathbf{U_n}\end{pmatrix}\begin{pmatrix}\mathbf{S_r} + \sigma_n^2\mathbf{I}_{N_r\times N_r} & \mathbf{0} \\ \mathbf{0} & \sigma_n^2\mathbf{I}_{(M-N_r)\times(M-N_r)}\end{pmatrix}\begin{pmatrix}\mathbf{U_r}^H \\ \mathbf{U_n}^H\end{pmatrix}\end{aligned}$$

Real data:

$$\mathbf{R} = \begin{pmatrix}\mathbf{A_r} & \mathbf{A_c}\end{pmatrix}\begin{pmatrix}\mathbf{R_r} & \mathbf{0} \\ \mathbf{0} & \mathbf{R_c}\end{pmatrix}\begin{pmatrix}\mathbf{A_r}^H \\ \mathbf{A_c}^H\end{pmatrix} + \mathbf{R_n}$$

$\Rightarrow$ Impossible to isolate the RFI subspace from the cosmic sources subspace

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Subspace estimation

Separation between SOI and RFI:

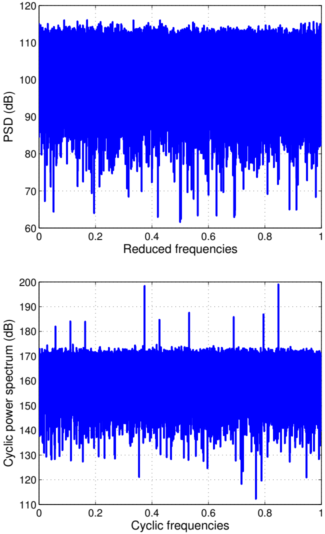
$$\mathbf{R}(t,\tau) = \mathbf{R}_{\text{cosmic}}(t,\tau) + \mathbf{R}_{\text{RFI}}(t,\tau) + \mathbf{R}_{\text{noise}}(t,\tau)$$
$$\Rightarrow \tilde{\mathbf{R}}(t,\tau) = \cancel{\tilde{\mathbf{R}}_{\text{cosmic}}(t,\tau)} + \tilde{\mathbf{R}}_{\text{RFI}}(t,\tau) + \cancel{\tilde{\mathbf{R}}_{\text{noise}}(t,\tau)}$$

$\Rightarrow$ various communication signals' features to be exploited

Adaptive processing - feature extraction

Exploitable features include:

- Interference-to-Noise Ratio
- Higher order statistics
- Polarization
- Non-/cyclo-stationarity
- Non-circularity
- Signal bandwidth
- Sparsity
- Dispersion
- Near / Far field
- Spatial location
- ...??



Coloration exploitation

- Astro sources and system noise : white stochastic processes
- RFI : colored / band-limited processes

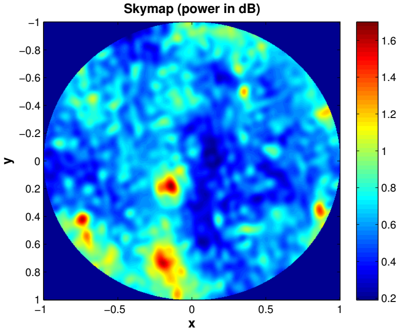
For $\tau_0 \neq 0$:

$$\mathbf{R}(t, \tau_0) = \mathbf{A_c} \underbrace{\mathbf{R_c}(t, \tau_0)}_{\to \mathbf{0}} \mathbf{A_c}^H + \mathbf{A_r} \mathbf{R_r}(t, \tau_0) \mathbf{A_r}^H + \underbrace{\mathbf{R_n}(t, \tau_0)}_{\to \mathbf{0}}$$

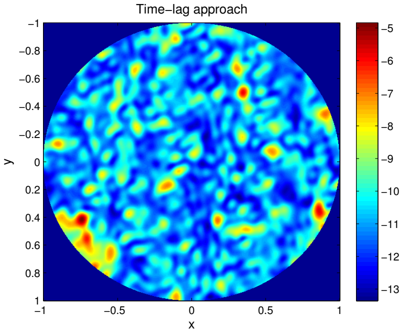
$$\sim \mathbf{A_r} \mathbf{R_r}(t, \tau_0) \mathbf{A_r}^H$$

Time-lag approach

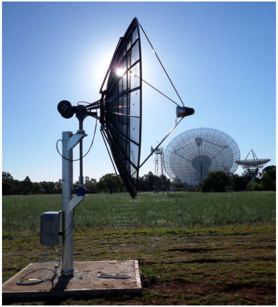
'Standard' data:



'Time-lagged' data:



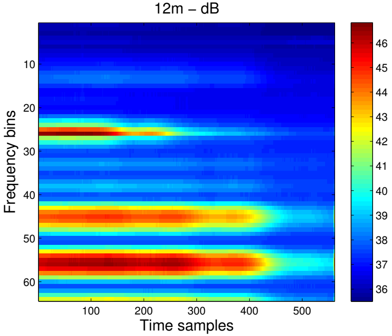
Spatial knowledge



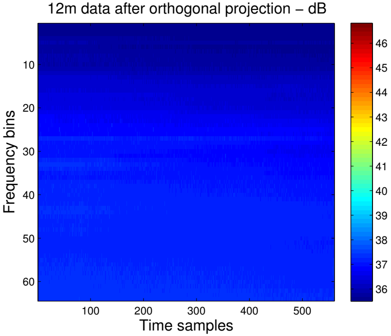
$$\mathbb{E}\left\{\mathbf{x}(t)x_{\text{ref}}^{*}(t)\right\} = \gamma_{\text{ref}}\ \mathbf{a}_{\mathbf{r}}$$

Spatial knowledge - single target

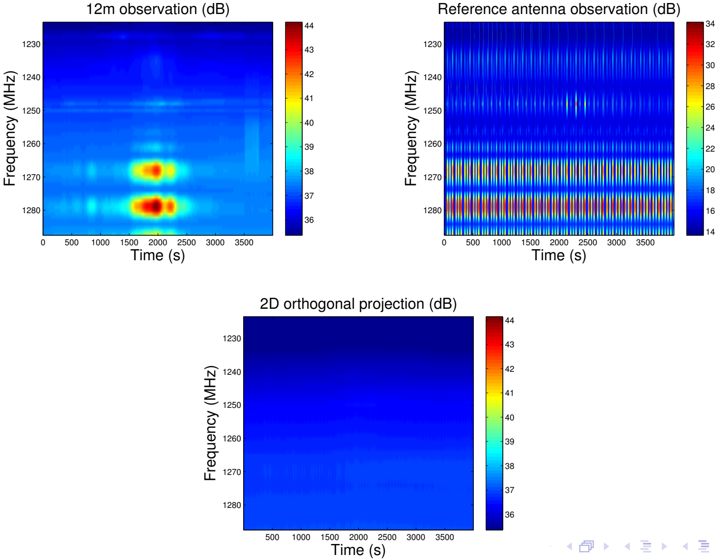
Corrupted data:



Result after projection



Spatial knowledge - multi target



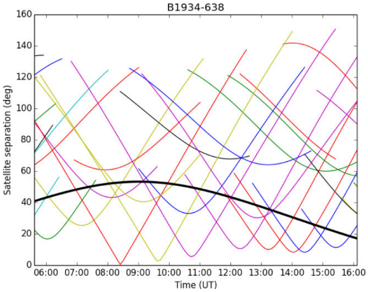
Spatial RFI mitigation implementation

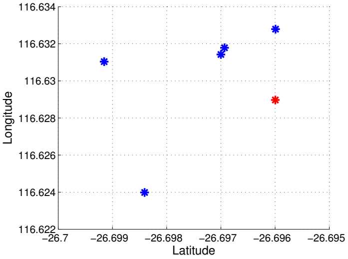
ASKAP / Phased Array Feeds

- 36 $\times$ 12m dishes
- 700 MHz - 1.8 GHz
- FoV 30 sq.deg.@1.8GHz
- 36 independent beams
- 94$\times$2 PAF elements

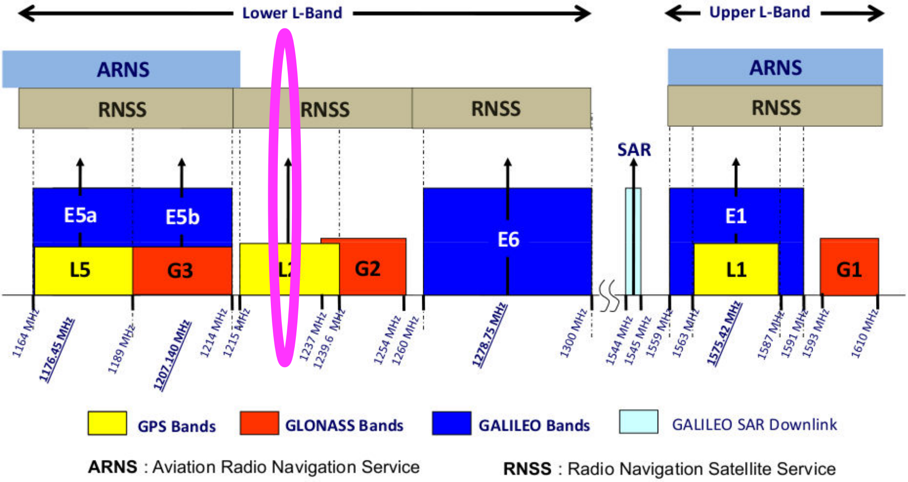
PAF processing - BETA experiment

- 1 MHz bandwidth processed at $f_0 = 1{,}225$ MHz (GPS L2 band)
- 10 h observation of PKS B1934-63
- 5 BETA antennas - baselines = 36 - 916 m
- 9 beams/antenna initialized by same MaxSNR beamformer
- Covariance integrated over 2 s, 50% duty cycle

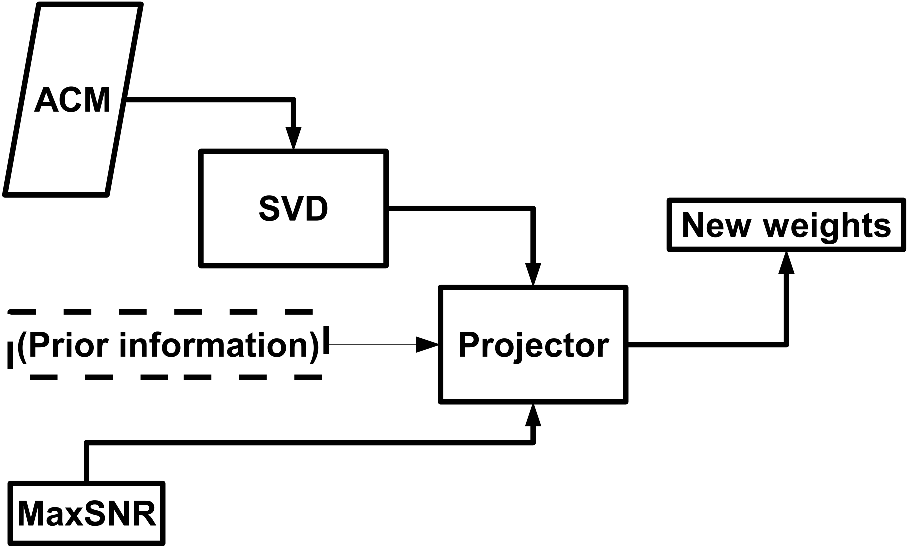




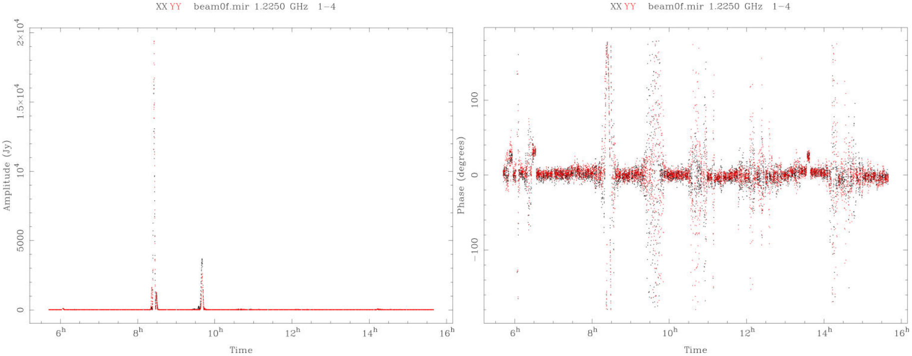
GNSS Frequencies



Algorithm as implemented

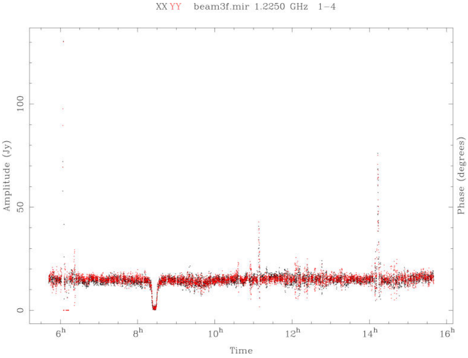


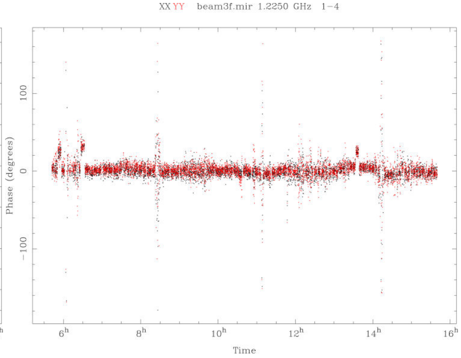
Experiment : 10h @ 1,225 MHz (calibrated, unprocessed)



AK01 - AK06

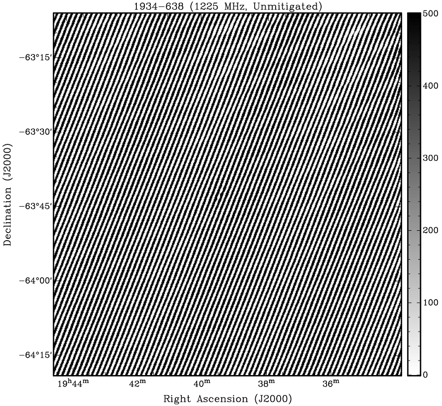
Experiment : 10h @ 1,225 MHz (calibrated, processed)

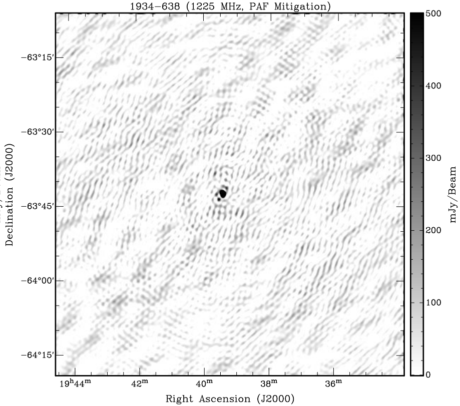




AK01 - AK06

Imaging results



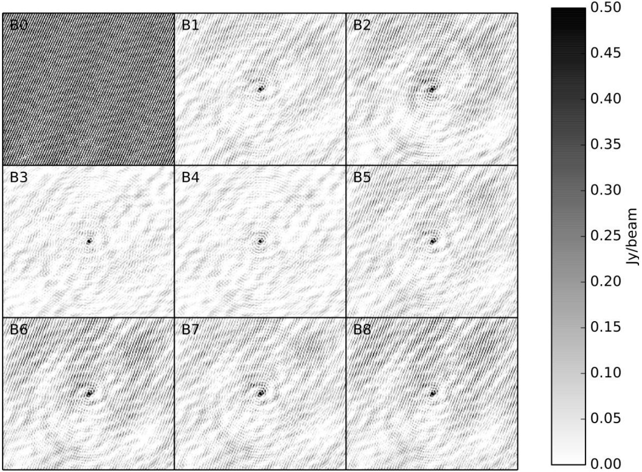


Algorithms variations

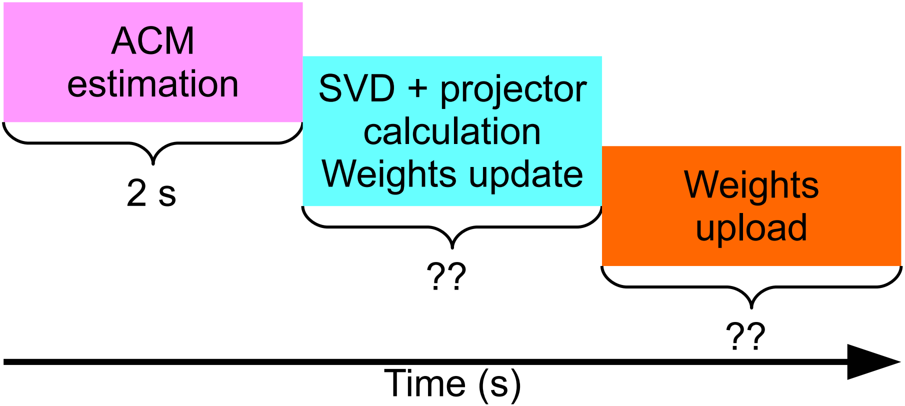
- B0 : MaxSNR beamformer
- B1 : Orthogonal, $n = 1$, $m = 1$
- B2 : Oblique, $n = 1$, $m = 1$
- B3 : Orthogonal, $n = 1$, $m = 10$
- B4 : Oblique, $n = 1$, $m = 10$
- B5 : Orthogonal, $n = n_a$, $m = 1$
- B6 : Oblique, $n = n_a$, $m = 1$
- B7 : Orthogonal, $n = n_b$, $m = 1$
- B8 : Oblique, $n = n_b$, $m = 1$

n = # of Dim projected out, m = # of "historical" vectors

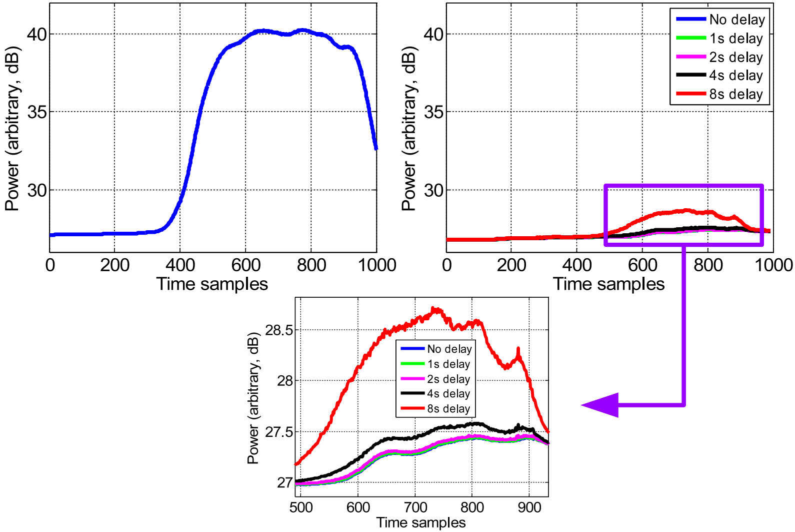
Imaging results



Limitation #1 : Time delay

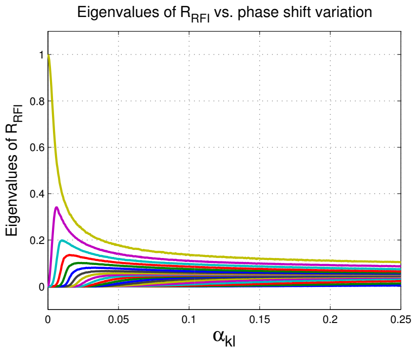


Limitation #1 : Time delay



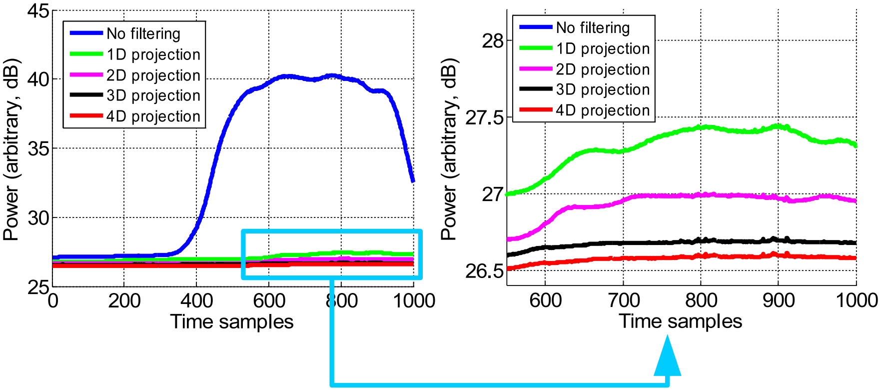
Limitation #2 : Subspace smearing

$$\mathbf{R}_{\mathrm{RFI}} = \iiint \sigma_r^2 \mathbf{a}_r \mathbf{a}_r^H \, dt df d\theta$$



- RFI asymptotically spans the whole observational vector space
- Makes it harder (impossible) to detect (and spatially estimate) RFI
- Projection impossible

Limitation #2 : Subspace smearing



Conclusion

- Theory meets practice - performance quantification tbc
- Experiment improvements:
  - RFI subspace prediction (Kalman? Neural nets?)
  - Subspace smearing compensation
- Science cases to be adressed
- Large arrays / high frequencies (i.e. timed arrays) to be addressed
  - Uncorrelation between elements
  - Central correlator (hardware/software) - computational load to minimize
- Encouraging results with ASKAP on synthesis imaging
- Requires deeper analysis on image deconvolution / corruption

http://go.nrao.edu/rfi2016

RFI 2016

Coexisting with Radio Frequency Interference

October 17-20, 2016

Hosted by the
National Radio Astronomy Observatory (NRAO)
at the New Mexico Tech Macey Center
in Socorro, New Mexico (USA)

Important dates:

Abstract submission:	15 August 2016
Author registration:	15 September 2016
Conference:	17-20 October 2016
IEEE proceeding submission:	11 November 2016