

# Extremal Real Entire Functions of Exponential Type for Blind Spectral Coexistence

*Ellit Focus Period 2026: Wireless Sensing Technologies for Emerging Applications*



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# Motivation

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IEEE Radar band	VHF/UHF [30 MHz – 1 GHz]	L [1-2 GHz]	S [2-4 GHz]	C [4-8 GHz]	X [8-12 GHz]	Ku, K, Ka, V, W [12-300 GHz]
Examples of radar usage	FOPEN	ARSR	ASR, NEXRAD	TDWR	CASA	Automotive radars, cloud radars
Co-existing comms	TV/broadcast/802.11a h/f	WiMAX, JTIDS	LTE	802.11a/ac	LTE	802.11ad, mmwave comm

## Shared spectrum is here to stay

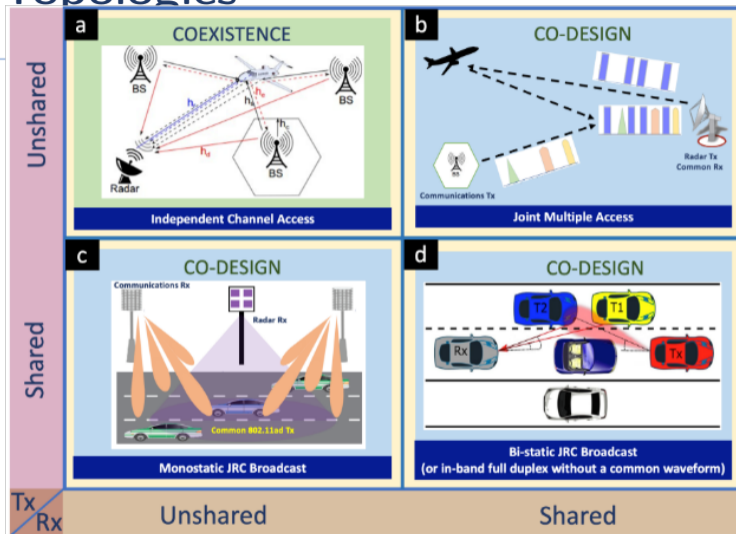
Radar and wireless systems (5G, Wi-Fi, automotive) are being pushed into *the same* frequency bands. The receiver sees a **superposition** of echoes and messages.

## The blind regime

- ▶ radar **waveform** is unknown ,
- ▶ communications **message** is unknown,
- ▶ **channels** (delays, Dopplers, DoAs) are unknown.

⇒ severely ill-posed unless we exploit structure.

# ISAC Topologies



# Blind Co-design Receiver

## What the receiver observes

$$y(t) = \underbrace{x_r(t) * h_r(t)}_{\text{radar trail}} + \underbrace{x_c(t) * h_c(t)}_{\text{comms trail}} + \xi(t)$$

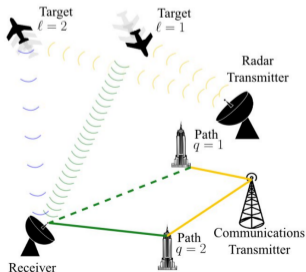
with, after processing, the discrete model

$$[\mathbf{y}]_{\tilde{n}} = \sum_{\ell} [\boldsymbol{\beta}]_{\ell} [\mathbf{s}]_n e^{-j2\pi(n\Delta f[\tau_r]_{\ell} + p[\nu_r]_{\ell})} + \sum_q [\boldsymbol{\omega}]_q [\mathbf{g}]_{\tilde{n}} e^{-j2\pi(n\Delta f[\tau_c]_q + p[\nu_c]_q)} + [\boldsymbol{\xi}]_{\tilde{n}}$$

## Unknowns

- ▶ Radar:  $\{\tau_r, \nu_r, \beta\}$  –  $L$  targets
- ▶ Comms:  $\{\tau_c, \nu_c, \omega\}$  –  $Q$  paths
- ▶ Waveforms:  $s$  (radar),  $g$  (OFDM symbols)

Recover  $2(L + Q)$  continuous parameters **plus** waveforms from  $MP$  noisy samples.



# Prior Art & Our Contributions

## Prior dual-blind deconvolution (DBD) approaches

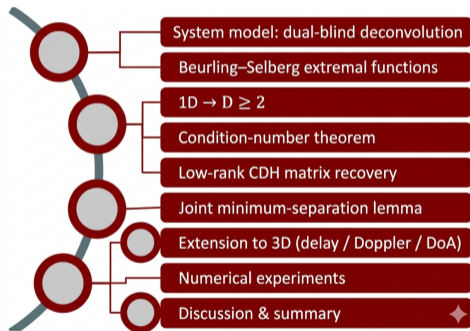
- ▶ **SoMAN minimization** (Vargas *et al.*, J-SAIT 2023): sum of multivariate atomic norms; SDP relaxation; separation requirements *independent* for radar and comms:  
 $\min(\delta_{\tau,r}, \delta_{\nu,r}, \delta_{\tau,c}, \delta_{\nu,c}) \geq c / \min(M, P)$ .
- ▶ **Factor-graph EM** (Jacome *et al.*, CAMSAP 2023): tracks a linear state-space model; Gaussian assumption; no Doppler.

## This work

1. A **joint separation** condition  $\delta$  in the delay–Doppler plane, with  $\delta \geq O(1/\sqrt{MP})$  instead of  $O(1/\min(M, P))$ .
2. A **unified** nuclear-norm recovery of a single low-rank *concatenated  $D$ -fold Hankel* (CDH) matrix.
3. **Multidimensional** Beurling–Selberg extremal functions  $\Rightarrow$  bound on  $\kappa(\mathbf{W})$  for any  $D \geq 2$ .
4. **Extension to 3D** (delay, Doppler, DoA) with ULA receivers.

# Outline

- System model: dual-blind deconvolution
- Beurling–Selberg extremal functions  
 $1D \rightarrow D \geq 2$
- Condition-number theorem
- Low-rank CDH matrix recovery
- Joint minimum-separation lemma
- Extension to 3D (delay / Doppler / DoA)
- Numerical experiments
- Discussion & summary



# Dual-Blind Deconvolution: System Model

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# Transmit Model

## Radar (Pulse-Doppler, Swerling-I)

$$x_r(t) = \sum_{p=0}^{P-1} s(t - pT), \quad 0 \leq t \leq PT$$

Channel with  $L$  targets:

$$h_r(t, \tau) = \sum_{\ell=0}^{L-1} [\beta]_{\ell} \delta(\tau - [\tau_r]_{\ell}) e^{-j2\pi[\nu_r]_{\ell} t}$$

## Communications (OFDM)

$$x_c(t) = \sum_{m=0}^{P-1} x_m(t - mT), \quad x_m(t) = \sum_{k=0}^{K-1} [\mathbf{g}_m]_k e^{j2\pi k \Delta f t}$$

Channel with  $Q$  paths:

$$h_c(t, \tau) = \sum_{q=0}^{Q-1} [\boldsymbol{\omega}]_q \delta(\tau - [\tau_c]_q) e^{-j2\pi[\nu_c]_q t}$$

## Low-rank structural assumption

Waveform and messages live in a *low-dimensional* subspace:  $\mathbf{s} = \mathbf{B}\mathbf{u}$ ,  $\mathbf{g}_p = \mathbf{D}_p\mathbf{v}_p$ ,  $\mathbf{B}, \mathbf{D}_p \in \mathbb{C}^{M \times J}$ ,  $J \ll M$ .

# Concatenated Vandermonde–Khatri–Rao Model

After DFT along range bins and stacking  $P$  pulses,

## Linear measurement model

$$\mathbf{y} = \mathbf{W}(\boldsymbol{\tau}, \boldsymbol{\nu}) \boldsymbol{\eta} + \boldsymbol{\xi} \quad \mathbf{W} \in \mathbb{C}^{MP \times J(L+Q)}$$

$$\mathbf{W} = [\mathbf{W}_r, \mathbf{W}_c], \quad \boldsymbol{\eta} = [[\beta]_0 \mathbf{u}^T, \dots, [\omega]_{Q-1} \mathbf{v}^T]^T$$

## Why the condition number of $\mathbf{W}$ matters

- ▶ Noise stability of waveform recovery minimize $_{\boldsymbol{\eta}} \|\mathbf{y} - \mathbf{W}\boldsymbol{\eta}\|_2^2$  is governed by  $\kappa(\mathbf{W}) = \sigma_{\max}/\sigma_{\min}$ .
- ▶  $\mathbf{W}$  has a *Vandermonde–Khatri–Rao* structure; its columns are entry-wise weighted 2D Vandermonde vectors.
- ▶ We need a **separation condition** on  $(\boldsymbol{\tau}, \boldsymbol{\nu})$  that guarantees  $\mathbf{W}$  is well conditioned.

# Beurling–Selberg Extremal Functions

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# Extremal Real Entire Functions, $D = 1$

## Definition

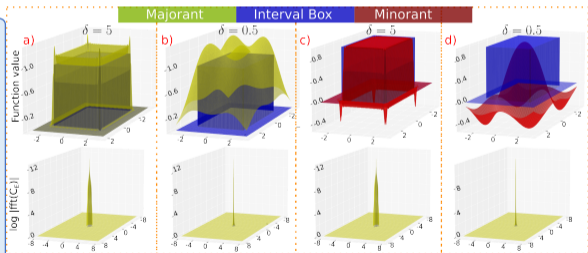
$F : \mathbb{C} \rightarrow \mathbb{C}$  is a real entire function of exponential type  $2\pi$  iff

- C1  $F$  is entire,
- C2  $F|_{\mathbb{R}}$  is real-valued,
- C3  $|F(z)| \leq C e^{(2\pi+\varepsilon)|z|}$  for every  $\varepsilon > 0$ .

## Beurling–Selberg bound

For the interval  $E = [a, b]$ ,  $I_E(t) = \mathbf{1}_{[a,b]}(t)$ , there exist entire functions  $c_E(\delta t) \leq I_E(t) \leq C_E(\delta t)$  with:

- ▶ Fourier support in  $[-\delta, \delta]$ ,
- ▶  $\int (C_E - I_E) dt = 1/\delta = \int (I_E - c_E) dt$ ,
- ▶ *extremal*: minimise the error integral.



# Other Approximations to $I_E(t)$

Approach	Expression	Property	$D \geq 2?$
Beurling–Selberg	$C_E(t) = \frac{1}{2}\{B^+(t-a) + B^+(b-t)\}$	$C_E \geq I_E$ , extremal	Yes
Babenko	Zeros of Bernstein $B(t)$	Approximation on $[-\pi, \pi]$	No
Stenger	$S(t) = \frac{1}{1+k}[1 + k\phi(t)]$	Analytic, $(-1, 1)$ only	No

## Why we pick Beurling–Selberg

Only BS functions (i) **bound**  $I_E$  from both sides, (ii) have **compact Fourier support**, and (iii) **generalise** to  $D \geq 2$  while keeping the two-sided bound – exactly what we need to bound  $\kappa(\mathbf{W})$ .

# Generalisation to $D \geq 2$

## Paley–Wiener (higher dimension)

$f(\mathbf{z})$  entire on  $\mathbb{C}^D$  is the FT of a function supported in the ball  $\{|\mathbf{z}| \leq R\}$  iff for every  $N$ ,

$$|f(\mathbf{z})| \leq \frac{C_N e^{R|\mathbf{z}|}}{(1 + |\mathbf{z}|)^N}.$$

## Majorant and (Todd) minorant on a box $E = \prod_d [a_d, b_d]$

$$C_E(\mathbf{t}) = \prod_{d=1}^D C_E(t_d), \quad c_E^3(\mathbf{t}) \text{ (Todd)} : I_E(\mathbf{t}) \geq c_E^3(\mathbf{t}).$$

FT of  $C_E(\delta\mathbf{t})$ ,  $c_E^3(\delta\mathbf{t})$  supported in  $\prod_d [-\delta_d, \delta_d]$ . With  $\delta = \delta\mathbf{1}$  the error integrals become

$$\int (C_E - I_E) d\mathbf{t} = \int (I_E - c_E^3) d\mathbf{t} = \prod_d \left( b_d - a_d + \frac{1}{\delta} \right) - \prod_d (b_d - a_d).$$

## Key consequence

Plugging this error integral into the 2D (and 3D) receive-signal energy bound produces a *non-trivial* range of delay–Doppler (and DoA) separations for which  $\mathbf{W}$  is well conditioned.

# Condition Number Bound

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# Joint Minimum Separation

## Wrap-around distance

$$d(a, b) = \min(|a - b|, 1 - |a - b|).$$

## Joint separation

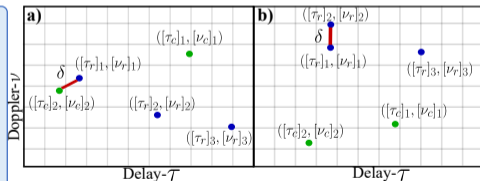
With  $\boldsymbol{\tau} = [\boldsymbol{\tau}_r^T, \boldsymbol{\tau}_c^T]^T$ ,  $\boldsymbol{\nu} = [\boldsymbol{\nu}_r^T, \boldsymbol{\nu}_c^T]^T$ ,

$$\delta = \min_{i \neq j} \psi(d([\boldsymbol{\tau}]_i, [\boldsymbol{\tau}]_j), d([\boldsymbol{\nu}]_i, [\boldsymbol{\nu}]_j))$$

where  $\psi(x, y) = \max(x, y)$  or  $\sqrt{x^2 + y^2}$ .

## Why "joint"?

Two entries with *identical delay* can still be recovered if their Dopplers differ – and vice-versa. SoMAN cannot handle this.



# Main Theorem – Condition Number Bound

Theorem (Monsalve, Vargas, Mishra, Sadler, 2025)

Let  $\gamma(\delta) = \delta P + \delta(M - 1) + 1$ . Then

$$\kappa^2(\mathbf{W}) \leq \frac{MP + \frac{\gamma(\delta)}{\delta^2} - P}{MP - \frac{\gamma(\delta)}{\delta^2} - P}$$

Non-triviality ( $\mathbf{W}$  full column rank) requires

$$M > \frac{\delta P(\delta + 1) - \delta + 1}{\delta(\delta P - 1)}, \quad P > \frac{1}{\delta}.$$

Taking  $P = c/\delta$  with  $c > 1$  yields  $M > (3 + \delta)/\delta$  for  $c = 2$ .

Comparison with SoMAN (Vargas *et al.* 2023)

- ▶ SoMAN:  $\min(\delta_\tau, \delta_\nu) \geq O(1/\min(M, P))$ .
- ▶ Here:  $\delta > O(1/\sqrt{MP})$ .

# Proof Sketch

## Idea (delay–Doppler case)

Sample with a 2D Dirac comb  $h(n, p) = \sum_{i,j} \delta(n - i, p - j)$  and bound  $\|\mathbf{y}\|^2$  above/below by  $\int h(n, p) C_E(n, p) |Y(n, p)|^2 dn dp$  and the analogous minorant integral.

## Key step

Expand  $Y(n, p)$ : cross terms involve  $\alpha^{([\tau_r]_\ell - [\tau_c]_q)n + ([\nu_r]_\ell - [\nu_c]_q)p}$ . Because  $\tilde{C}_E$  is supported in  $(-\delta, \delta)^2$  and any two distinct atoms are *jointly*  $\delta$ -apart, all cross-terms vanish. Only the diagonal survives, and

$$\tilde{C}_E(\mathbf{0}) = MP + \frac{\gamma(\delta)}{\delta^2} - P, \quad \tilde{c}_E(\mathbf{0}) = MP - \frac{\gamma(\delta)}{\delta^2} - P.$$

## Conclusion

Sandwiching  $\|\mathbf{y}\|^2$  between these constants times a positive  $\gamma$  factor yields the  $\kappa^2$  bound because  $\kappa(\mathbf{W}) = \max \|\mathbf{W}\boldsymbol{\lambda}\| / \min \|\mathbf{W}\boldsymbol{\lambda}'\|$ .

# Low-Rank CDH Matrix Recovery

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# From Measurements to a Low-Rank Matrix

## Hidden data matrices

Stack radar/comms unknowns pulse-by-pulse:

$$\mathbf{X}_r = [\mathbf{u}\mathbf{h}_{r,0}^T, \dots, \mathbf{u}\mathbf{h}_{r,P-1}^T], \quad \mathbf{X}_c = [\mathbf{v}_0\mathbf{h}_{c,0}^T, \dots, \mathbf{v}_{P-1}\mathbf{h}_{c,P-1}^T]$$

with  $\mathbf{h}_{r,p} = \sum_{\ell} [\boldsymbol{\beta}]_{\ell} \mathbf{a}([\boldsymbol{\tau}_r]_{\ell}) e^{-2j\pi[\nu_r]_p}$  and analogous for comms. Then  $\mathbf{y} = \mathcal{A}(\mathbf{X})$ ,  $\mathbf{X} = [\mathbf{X}_r^T, \mathbf{X}_c^T]^T$ .

## Two-fold vectorised Hankel lift

Choose  $N_1 + N_2 = M + 1$ ,  $P_1 + P_2 = P + 1$ . Define

$$\mathcal{H}_2(\mathbf{Z}) = \begin{bmatrix} \mathcal{H}(\mathbf{Z}_0) & \cdots & \mathcal{H}(\mathbf{Z}_{P_2-1}) \\ \vdots & \ddots & \vdots \\ \mathcal{H}(\mathbf{Z}_{P_1-1}) & \cdots & \mathcal{H}(\mathbf{Z}_{P-1}) \end{bmatrix}$$

and the Concatenated  $D$ -fold Hankel (CDH) operator

# Factorisation and Nuclear-Norm Recovery

## Low-rank factorisation

$$\mathcal{C}(\mathbf{X}) = \mathbf{L} \operatorname{diag}(\boldsymbol{\psi}) \mathbf{R}^T, \quad \operatorname{rank}(\mathcal{C}(\mathbf{X})) \leq L + P_2 Q$$

with explicit  $\mathbf{L} \in \mathbb{C}^{JP_1 N_1 \times L + P_2 Q}$  and  $\mathbf{R} \in \mathbb{C}^{2N_2 P_2 \times L + P_2 Q}$  built from Vandermonde blocks and waveform/message subspaces.

## Proposed convex recovery

$$\underset{\mathbf{X}}{\text{minimize}} \quad \|\mathcal{C}(\mathbf{X})\|_* \quad \text{s.t.} \quad \mathbf{y} = \mathcal{A}(\mathbf{X})$$

then:

- ▶ MUSIC / ESPRIT on  $\mathcal{H}_2(\mathbf{X}_r)^T, \mathcal{H}_2(\mathbf{X}_c)^T \Rightarrow (\boldsymbol{\tau}_r, \boldsymbol{\nu}_r), (\boldsymbol{\tau}_c, \boldsymbol{\nu}_c)$ ;
- ▶ Form  $\mathbf{W}$  and solve  $\min_{\boldsymbol{\eta}} \|\mathbf{y} - \mathbf{W}\boldsymbol{\eta}\|_2 \Rightarrow$  waveforms.

# Recovery Guarantee

## Assumptions on $\mathbf{B}$ and $\mathbf{D}$ (columns i.i.d.)

P1 Isotropy:  $\mathbb{E}[\mathbf{b}\mathbf{b}^*] = \mathbf{I}$ .

P2 Incoherence:  $\max_j |[\mathbf{b}]_j| \leq \mu_0$ .

P3 Lower boundedness:  $\|\mathbf{b}\|_2^2 \geq 1$ .

P4 Uncorrelated messages:  
 $\mathbb{E}[\mathbf{v}_i^* \mathbf{v}_j] = 0, i \neq j$ .

## Theorem (Chen *et al.* 2022, applied here)

If  $\sigma_{\min}(\mathbf{L}^* \mathbf{L}) \geq N_1 P_1 / \mu_1$ ,  $\sigma_{\min}(\mathbf{R}^* \mathbf{R}) \geq N_2 P_2 / \mu_1$  with  $\mu_1 > 1$ , and  $MP \geq \mu_0 \mu_1 J(L + Q) \log^5(JMP)$ , then nuclear-norm minimisation recovers  $\mathcal{C}(\mathbf{X})$  with probability  $\geq 1 - c_0(JMP)^{-c_1}$ .

## Lemma 8 (Monsalve *et al.* 2025)

The singular-value conditions above hold provided

$$\delta \geq \frac{\mu_1(2P + 2M)}{(\mu_1 - 1)(M + 1)(P + 1)}$$

which is  $O(1/\min(M, P))$  in the worst case and  $O(1/\sqrt{MP})$  for balanced regimes.

Extension to 3D: Delay / Doppler / DoA

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# ULA Receiver: Adding Direction of Arrival

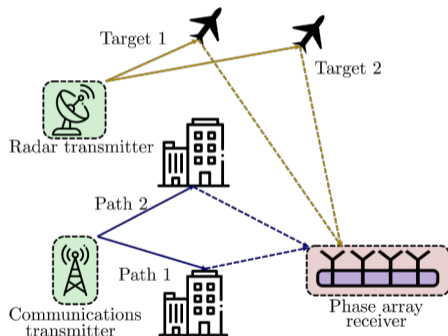
Signal at antenna  $\eta \in \{0, \dots, N_a - 1\}$

$$y(t, \eta, p) = \sum_{\ell} [\boldsymbol{\beta}]_{\ell} s(t - [\boldsymbol{\tau}_r]_{\ell}) e^{-j2\pi[\boldsymbol{\nu}_r]_{\ell} t} e^{-j2\pi[\boldsymbol{\omega}_r]_{\ell} \eta}$$

+ comms term with  $[\boldsymbol{\omega}_c]_q$ ,

where  $[\boldsymbol{\omega}_r]_{\ell} = \sin([\boldsymbol{\theta}_r]_{\ell}/2)$ . The 3D Vandermonde matrix:

$$\mathbf{V}_r = \mathbf{a}_{N_a}(\boldsymbol{\omega}_r) \odot \mathbf{a}_P(\boldsymbol{\nu}_r) \odot \mathbf{a}_M(\boldsymbol{\tau}_r).$$



# Condition Number in 3D

## Theorem (3D bound)

With  $\tilde{\gamma}(\delta) = 2NP\delta^2 + 2NN_a\delta^2 + 2N\delta + PN_a\delta^2 + P\delta + N_a\delta + 1$ ,

$$\kappa^2(\mathbf{W}) \leq \frac{MPN_a + \frac{\tilde{\gamma}(\delta)}{\delta^3} - PN_a}{MPN_a - \frac{\tilde{\gamma}(\delta)}{\delta^3} - PN_a}$$

## How we got there

Replace the 2D box  $[-\delta, \delta]^2$  by the 3D box  $[-\delta, \delta]^3$  in the Dirac-comb argument, use the  $D \geq 2$  Beurling–Selberg bounds (Section II) and propagate the  $1/\delta^3$  volume scaling.

## Natural scaling

Same structure in 2D ( $1/\delta^2$ ), 3D ( $1/\delta^3$ ), and higher – the theory is *dimension-aware*.

# Numerical Experiments

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# Experiment 1 – Condition Number Validation

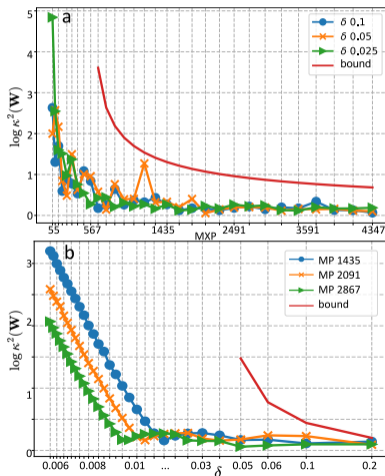
## Setup

$\mathbf{B} = \mathbf{D}_i$  are random columns of a DFT matrix (*worst case*: highly correlated columns of  $\mathbf{W}$ ).  $J = 3$ ,  $L = Q = 2$ ,  $\mathbf{u}, \mathbf{v} \sim \mathcal{U}(0, 1]$ .

- ▶ (a) Vary  $MP$  for  $\delta \in \{0.025, 0.05, 0.1\}$ .
- ▶ (b) Fix  $MP = 2867$ ; sweep  $\delta$ .

## Take-away

Empirical  $\kappa(\mathbf{W})$  lies *under* our theoretical bound for every  $(M, P, \delta)$  tested; larger  $\delta$  hits the well-conditioned regime with far fewer measurements.



# Experiment 2 – Phase Transition vs. SoMAN

## Protocol

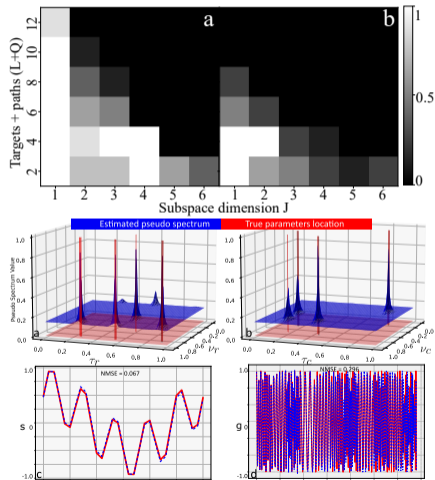
$P = 11, M = 31$ , 20 Monte-Carlo trials. Success:  $\|\tilde{\mathbf{X}} - \mathbf{X}\|_F / \|\mathbf{X}\|_F < 10^{-1}$ . Sweep subspace dimension  $J$  and  $L + Q$  on both axes.

## Result

The proposed low-rank CDH recovery achieves a visibly *higher* phase transition curve than SoMAN-SDP [?], for the same computational budget.

## Single-instance example (noiseless)

$L = Q = 4, M = 31, P = 11, J = 2$ . Parameters recovered to  $\sim 10^{-3}$ ; waveform/message NMSE  $\approx 0.30$  and  $0.30$  respectively.



# Experiment 3 – Noise Robustness

## NMSE vs. $M$

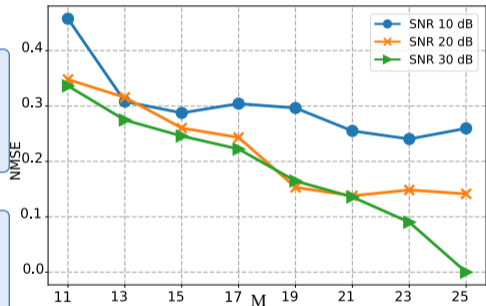
$P = 11$ ,  $\delta = 0.1$ ,  $J = 2$ ,  $L = Q = 2$ . SNR  $\in \{10, 20, 30\}$  dB. NMSE of  $\mathbf{X}$  decreases monotonically and saturates near the noise floor.

## Parameter recovery under noise

For  $\delta = 0.0125$ :

- ▶ SNR 30 dB:  $|\hat{\tau}_r - \tau_r| \leq 10^{-3}$ .
- ▶ SNR 10 dB:  $\leq 10^{-2}$  on a grid of step  $10^{-3}$ .

Message NMSE: 0.030 (30 dB), 0.034 (10 dB).



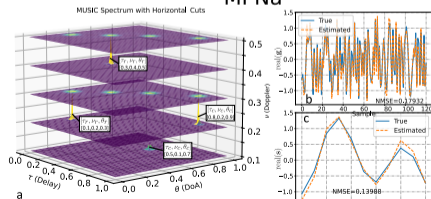
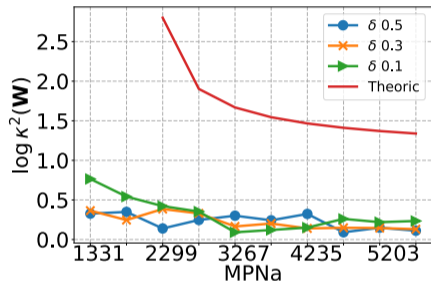
# Experiment 4 – 3D Simulation

## Setup

ULA with  $N_a = 11$ ,  $M = 11$ ,  $P = 11$ ,  $J = 2$ ,  $L = Q = 2$ .  $\mathbf{B}$  random DFT columns (worst-case).

## Observations

- ▶  $\kappa^2(\mathbf{W})$  below the 3D bound for  $\delta \in \{0.1, 0.3, 0.5\}$  as  $M$  grows from 11 to 47.
- ▶ Horizontal cuts of the 4D pseudo-spectrum exhibit *exact* delay–Doppler–DoA localisation.
- ▶  $\text{NMSE}(s) \approx 0.14$ ,  $\text{NMSE}(g) \approx 0.18$ .



# Summary

## What we established

1. A **joint** delay–Doppler separation condition via Beurling–Selberg interpolation theory.
2. An explicit **condition-number bound** on the Vandermonde–Khatri–Rao matrix  $\mathbf{W}$ .
3. A **unified nuclear-norm** recovery of a single CDH matrix – better phase transition and lower cost than SoMAN–SDP.
4. A **three-dimensional** extension (delay–Doppler–DoA) with the same structural bound.

## Open directions

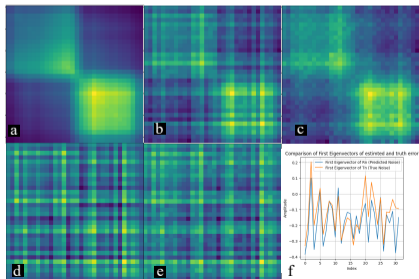
- ▶ Noise-perturbation bounds using second-order BS functions.
- ▶ Scaling to wideband / MIMO waveforms (cf. CLuP line of work).
- ▶ Complexity reduction of the SDP – reweighting, APG, block  $\ell_1$ , low-rank Hankel factorisations.

# Other Ongoing Works

## Diffusion Models Gradient Preconditioning

**Problem.** In CS partitioning data into  $p$  subsets improves FIM conditioning but *injects noise* into the gradient.

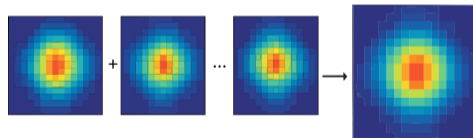
**Key insight.** The accumulation of gradient noise resembles a *forward diffusion process*:  
$$\text{Error}[\nabla \tilde{f}(\Sigma)] = -\sum_{i=1}^p \mathbf{P}_i \mathbf{P}_i^T \mathbf{R}_i \mathbf{P}_i \mathbf{P}_i^T.$$
  
Train a CNN to *reverse* it.



## Group Theory Radar Waveforms Design

**Problem.** Design *MIMO wideband* waveforms with low ambiguity-function sidelobes.

**Key insight.** The wideband AF is indexed by the *affine group*  $(a, b) \in \mathbb{R}_+ \times \mathbb{R}$ :  
$$(U_{\mathcal{A}}(a, b)f)(t) = \frac{1}{\sqrt{a}} f\left(\frac{t-b}{a}\right).$$
  
**Almost Difference Set (ADS)**  $\rightarrow$  near-Welch-bound cross-correlation.



# Thank you!

Questions & discussion

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