one6G – Open Lectures

Beam-Space MIMO Radar for Sensing-aided mmWave Communications

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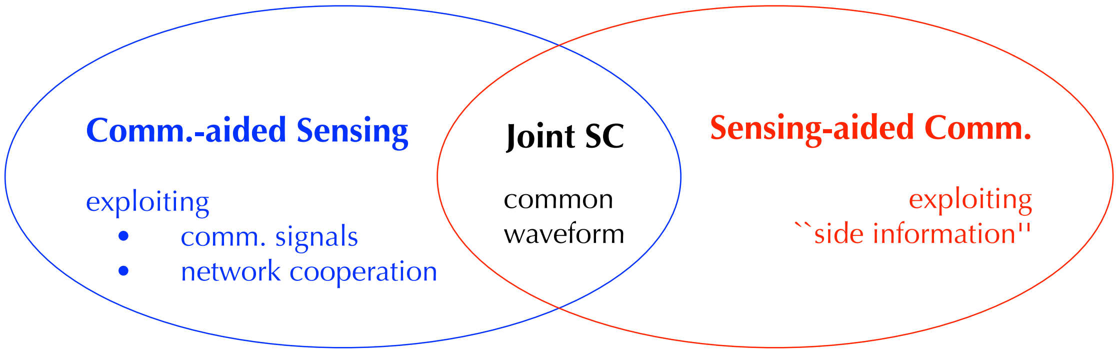
Synergy between Sensing and Communication

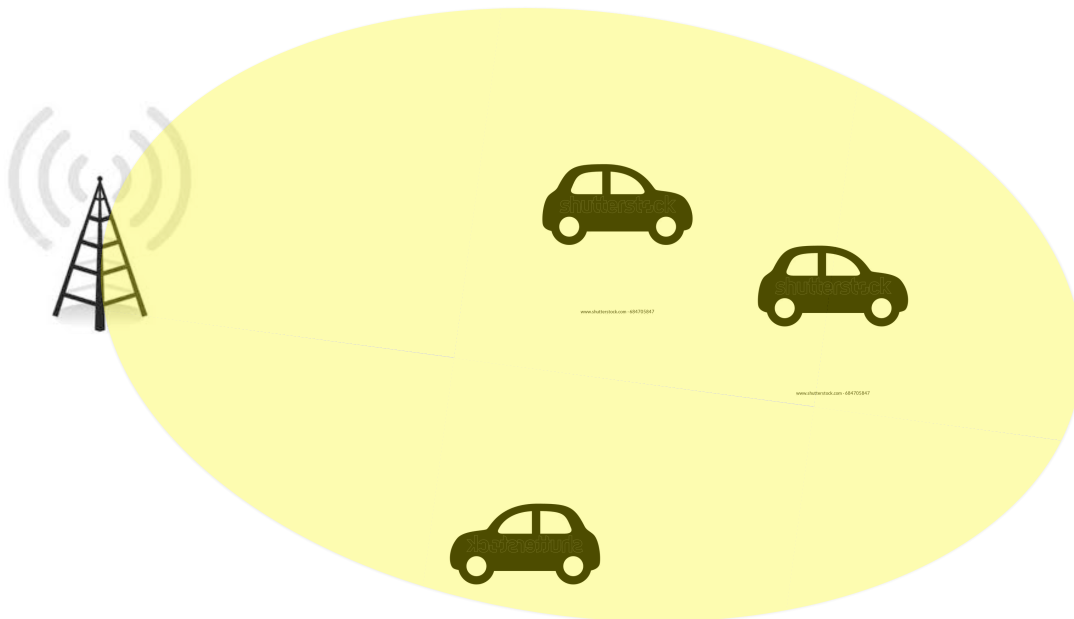


- Sensing can provide "side information" for improving communication functions (beam alignment, refinement, tracking, fast handover, fas user-AP association ...)

- Communication can enhance sensing quality (e.g., multistatic radar, sensor fusion, closed-loop protocols).

- Does it make sense to share the same resource (power, bandwdith, hardware)?

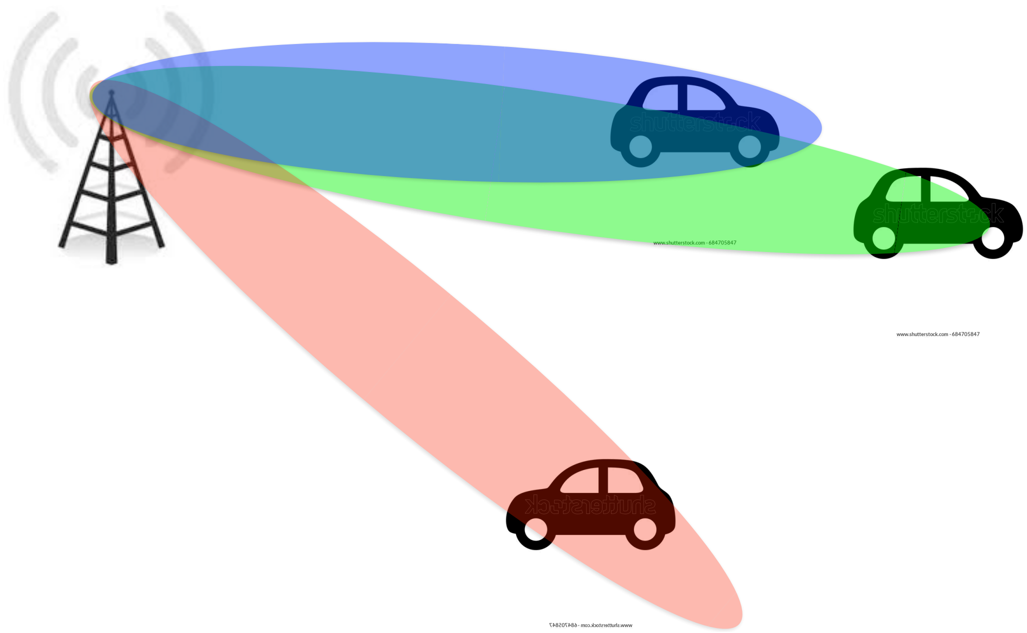
Application Scenarios in mmWave Comm.



- **Scenario 1, Discovery:** wide sector transmission (e.g., low-rate control broadcast channel), unknown targets.

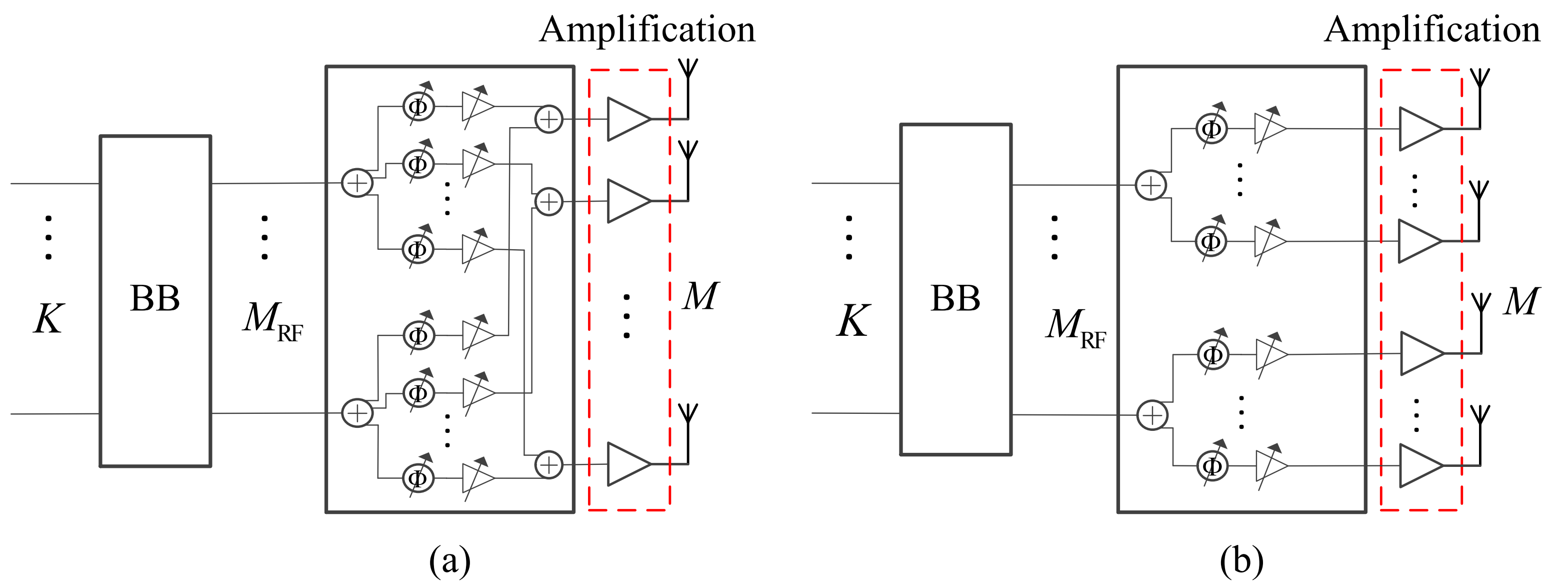
- Goal: target detection, parameter estimation to speed-up BA.

Application Scenarios in mmWave Comm.



- **Scenario 2, Tracking:** beamformed transmission (e.g., individual DL data streams), known targets.
- Goal: parameter estimation for beam refinement/tracking.

RF Beamforming and AoA Estimation

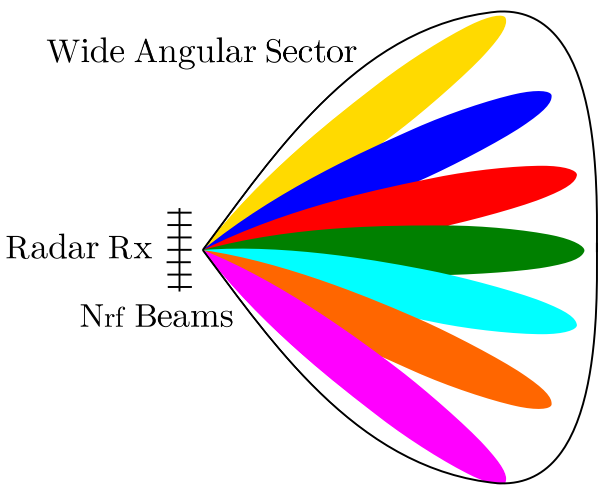


- The number of RF chains (demodulation to BB and ADC) is much smaller than the number of antenna array elements.

- For AoA estimation (both Scenario 1 and 2) we need a vector observation.

Dimensionality Reduction at the Radar Receiver

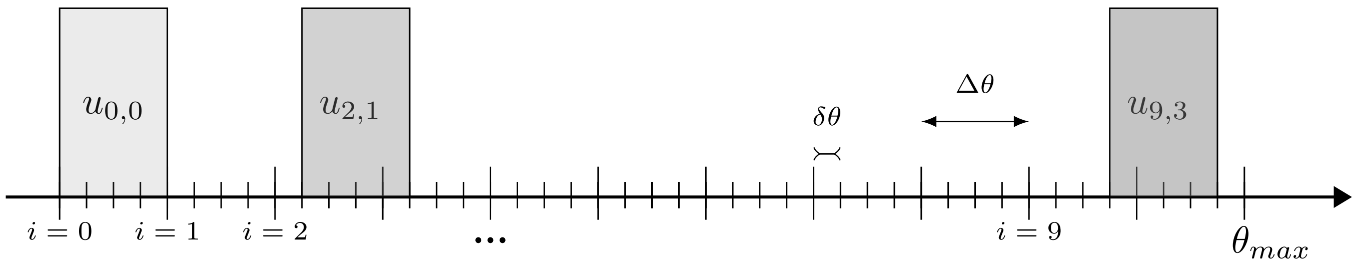
- Because of complexity and power consumption of the A/Ds, a typical mmWave architecture consists of hybrid digital-analog BF.
- A number N_{rf} of RF chains, much smaller than the number of antenna array elements N_{a}, produces a reduced-dimensional “beamspace” baseband channel.

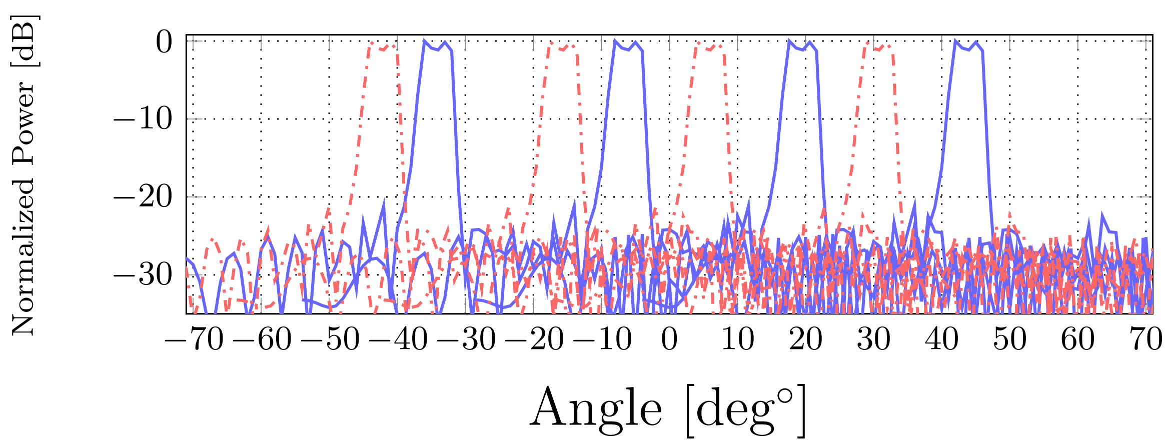


Example of grid of beams for $N_a = 64$.

- Beam-space MIMO radar

$$\mathcal{C} = \{\hat{\mathbf{u}}_{i,j}\} \quad i = 0, 1, 2, ..., \frac{2\theta_{max}}{\Delta\theta} - 1, \; j = 0, 1, 2, ..., \frac{\Delta\theta}{\delta\theta} - 1$$





Multitarget channel model (1)

- Array response vector (simple case: ULA) $\mathbf{a}(\phi) = (a_1(\phi), \ldots, a_{N_a}(\phi))^{\mathsf{T}} \in \mathbb{C}^{N_a}$ with

$$a_n(\phi) = e^{j(n-1)\pi \sin(\phi)}, \quad n = 1, \ldots, N_a.$$

- Backscatter channel model

$$\mathbf{H}(t, \tau) = \sum_{p=0}^{P-1} h_p \mathbf{a}(\phi_p) \mathbf{a}^{\mathsf{H}}(\phi_p) \delta(\tau - \tau_p) e^{j2\pi \nu_p t}$$

- Multicarrier signal with N_s data streams

$$\mathbf{s}(t) = \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} \mathbf{X}_{n,m} g_{\text{tx}}(t - nT) e^{j2\pi m \Delta f (t - nT)}.$$

Multitarget channel model (2)

- Received signal at the radar receiver in block b

$$\mathbf{r}_b(t) = \sum_{p=0}^{P-1} h_p {\mathbf{U}_b}^{\mathsf{H}} \mathbf{a}(\phi_p) \mathbf{a}^{\mathsf{H}}(\phi_p) \mathbf{F} \mathbf{s}(t-\tau_p) e^{j2\pi\nu_p t}.$$

- $\mathbf{U}_b$ is a $N_a \times N_{\mathrm{rf}}$ reduction matrix, whose columns are beamforming vectors.
- After chip matched filtering and sampling, blocks $b = 1, \ldots, B$ of N time symbols and M subcarriers can be compactly written as

$$\underline{\mathbf{y}}_b = \left(\sum_{p=0}^{P-1} h_p \underline{\mathbf{G}}_b(\nu_p, \tau_p, \phi_p) \right) \underline{\mathbf{x}}_b + \underline{\mathbf{w}}_b,$$

where we define the effective channel matrix of dimension $N_{\mathrm{rf}} NM \times N_s NM$ as

$$\underline{\mathbf{G}}_b(\nu, \tau, \phi) \triangleq \left(\mathbf{U}_b^{\mathsf{H}} \mathbf{a}(\phi) \mathbf{a}^{\mathsf{H}}(\phi) \mathbf{F} \right) \otimes \mathbf{\Psi}(\nu, \tau).$$

Target detection in Discovery mode (1)

- We do target detection in sequence: at each step we have a binary hypothesis testing problem with hypotheses $\mathcal{H}_0$ and $\mathcal{H}_1$ correspond to absence or presence of the p-th target only.

$$\underline{\mathbf{y}}_b = \begin{cases} \underline{\mathbf{w}}_b & b = 1, \ldots, B \ \text{ under } \mathcal{H}_0 \\ \mathring{h}_p \underline{\mathbf{G}}_b(\mathring{\nu}_p, \mathring{\tau}_p, \mathring{\phi}_p)\underline{\mathbf{x}}_b + \underline{\mathbf{w}}_b & b = 1, \ldots, B \ \text{ under } \mathcal{H}_1 \, . \end{cases}$$

- The log-likelihood ratio for the binary hypothesis testing problem is given by

$$\ell(h_p, \nu_p, \tau_p, \phi_p) = 2\mathrm{Re}\left\{ \left(\sum_{b=1}^{B} \underline{\mathbf{y}}_b^{\mathsf{H}} \underline{\mathbf{G}}_b \underline{\mathbf{x}}_b \right) h_p \right\} - |h_p|^2 \sum_{b=1}^{B} \|\underline{\mathbf{G}}_b \underline{\mathbf{x}}_b\|^2$$

Target detection in Discovery mode (2)

- Since the true value of the parameters is unknown, we use the Generalized Likelihood Ratio Test

$$\max_{h_p,\nu_p,\tau_p,\phi_p} \ell(h_p,\nu_p,\tau_p,\phi_p) \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} T_r.$$

- The maximization with respect to h_p for fixed τ_p, ν_p, ϕ_p is immediately obtained as

$$\widehat{h}_p = \frac{\left(\sum_{b=1}^{B} \underline{\mathbf{y}}_b^{\mathsf{H}} \underline{\mathbf{G}}_b \underline{\mathbf{x}}_b\right)^*}{\sum_{b=1}^{B} \|\underline{\mathbf{G}}_b \underline{\mathbf{x}}_b\|^2}.$$

- Replacing this into the log-likelihood expression we obtain

$$\ell(\widehat{h}_p,\nu_p,\tau_p,\phi_p) = \frac{\left|\sum_{b=1}^{B} \underline{\mathbf{y}}_b^{\mathsf{H}} \underline{\mathbf{G}}_b \underline{\mathbf{x}}_b\right|^2}{\sum_{b=1}^{B} \|\underline{\mathbf{G}}_b \underline{\mathbf{x}}_b\|^2} \triangleq S(\nu_p,\tau_p,\phi_p)$$

Target detection in Discovery mode (3)

Sequential detection with SIC:

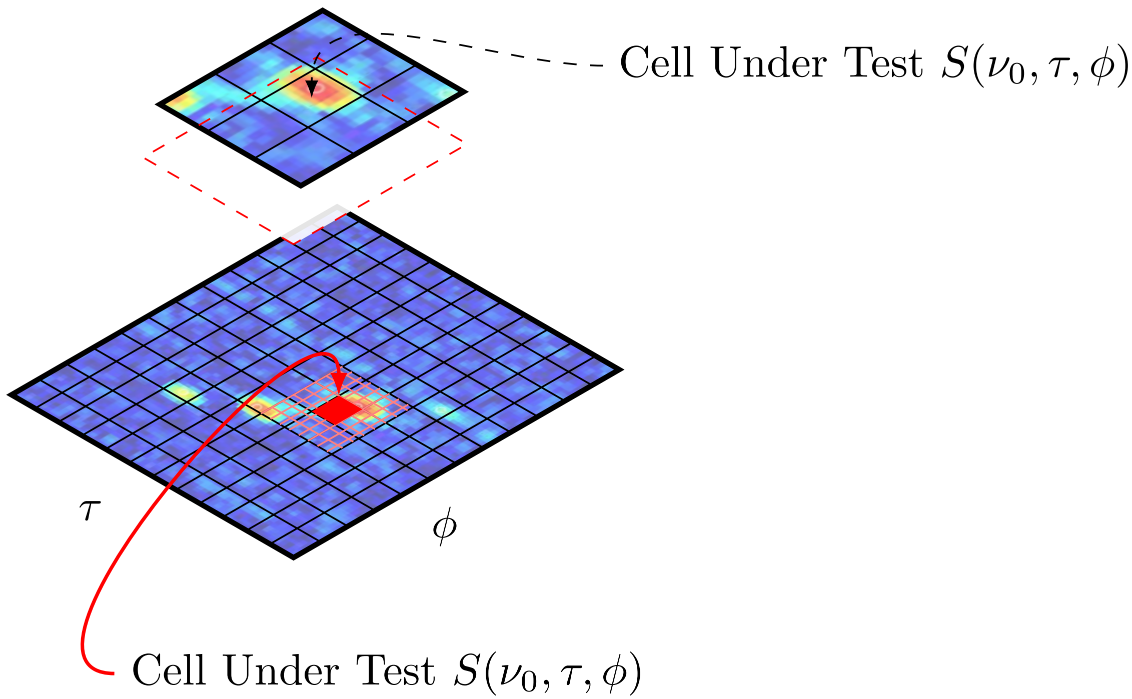
1. Initialize $p = 1$
2. Compare $S(\nu, \tau, \phi)$ with the adaptive threshold $T_r(\nu, \tau, \phi)$, and find the set $\mathcal{T}$ of points in the Doppler-delay-AoA above threshold.
3. If $\mathcal{T} = \emptyset$, exit (no more targets to be found).
4. If $\mathcal{T} \neq \emptyset$, let the p-th target with parameters

$$(\widehat{\nu}_p, \widehat{\tau}_p, \widehat{\phi}_p) = \text{argmax } \{S(\nu, \tau, \phi) : (\nu, \tau, \phi) \in \mathcal{Y}\}$$

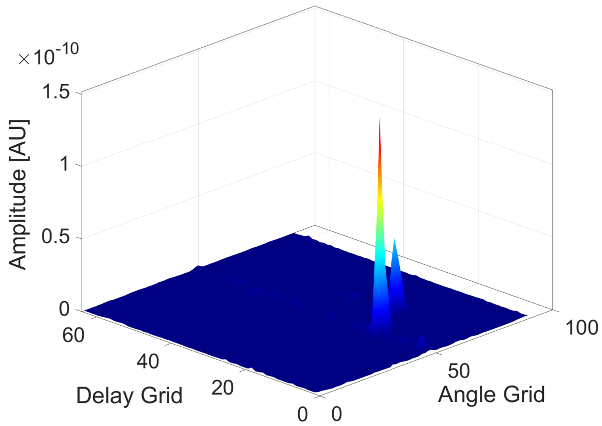
5. Subtract the corresponding signal from the received signal (SIC).
6. $p \leftarrow p + 1$, and go to point 2.

Adaptive threshold for target detection (1)

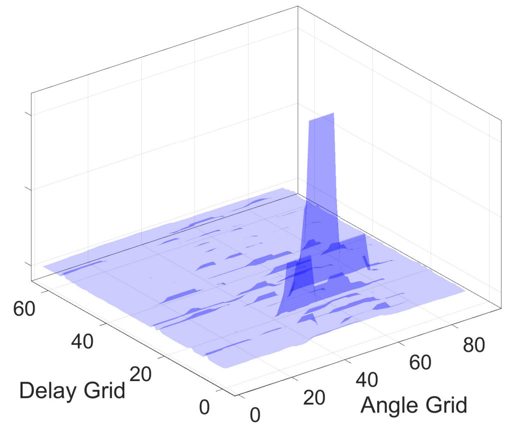
- The decision threshold is set adaptively from the ordered statistics of samples of $S(\nu, \tau, \phi)$ in a window around the decision point.



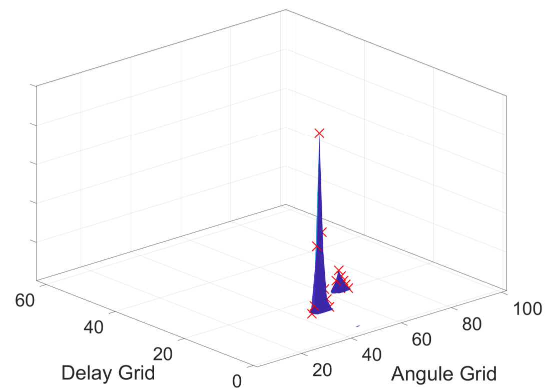
Adaptive threshold for target detection (2)



(a) Signal



(b) Threshold



(c) Threshold-passed Signal points

Parameter estimation in Tracking mode (1)

- The log-likelihood function, neglecting irrelevant terms, is given by

$$\Lambda(\{h_p, \nu_p, \tau_p, \phi_p\}) = 2\mathrm{Re}\{\mathbf{h}^{\mathsf{H}}\mathbf{r}\} - \mathbf{h}^{\mathsf{H}}\mathbf{A}\mathbf{h}.$$

where we define the $P \times 1$ vector of path coefficients $\mathbf{h} = (h_0, \dots, h_{P-1})^{\mathsf{T}}$, the vector of signal correlations $\mathbf{r}$ with p-th element

$$r_p = \sum_{b=1}^{B} \underline{\mathbf{x}}_{b,p}^{\mathsf{H}} \underline{\mathbf{G}}_{b,p}^{\mathsf{H}} \underline{\mathbf{y}}_b,$$

and the $P \times P$ matrix $\mathbf{A}$ with (p,q) element

$$A_{p,q} = \sum_{b=1}^{B} \underline{\mathbf{x}}_{b,p}^{\mathsf{H}} \underline{\mathbf{G}}_{b,p}^{\mathsf{H}} \underline{\mathbf{G}}_{b,q} \underline{\mathbf{x}}_{b,q}.$$

Parameter estimation in Tracking mode (2)

- The maximization with respect to $\mathbf{h}$ is readily obtained as

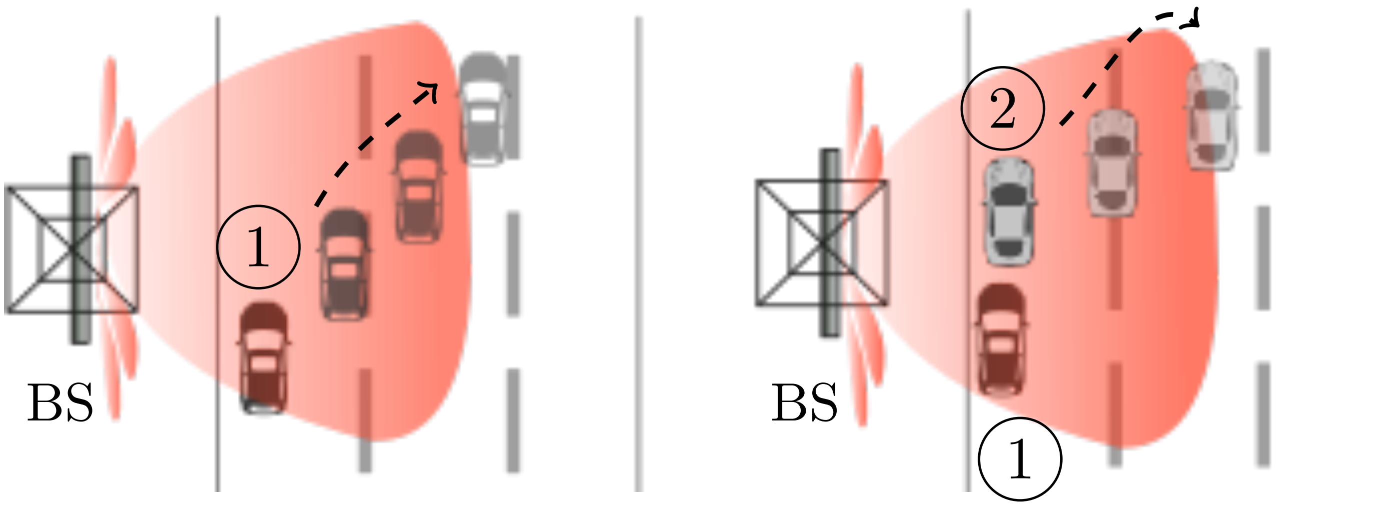
$$\widehat{\mathbf{h}} = \mathbf{A}^{-1}\mathbf{r}$$

- Replacing this, we find $\Lambda_1(\{\nu_p, \tau_p, \phi_p\}) = \mathbf{r}^{\mathsf{H}}\mathbf{A}^{-1}\mathbf{r}$.
- The problem is further simplified by noticing that $\mathbf{A}$ is approximately diagonal. Under this simplification, we obtain

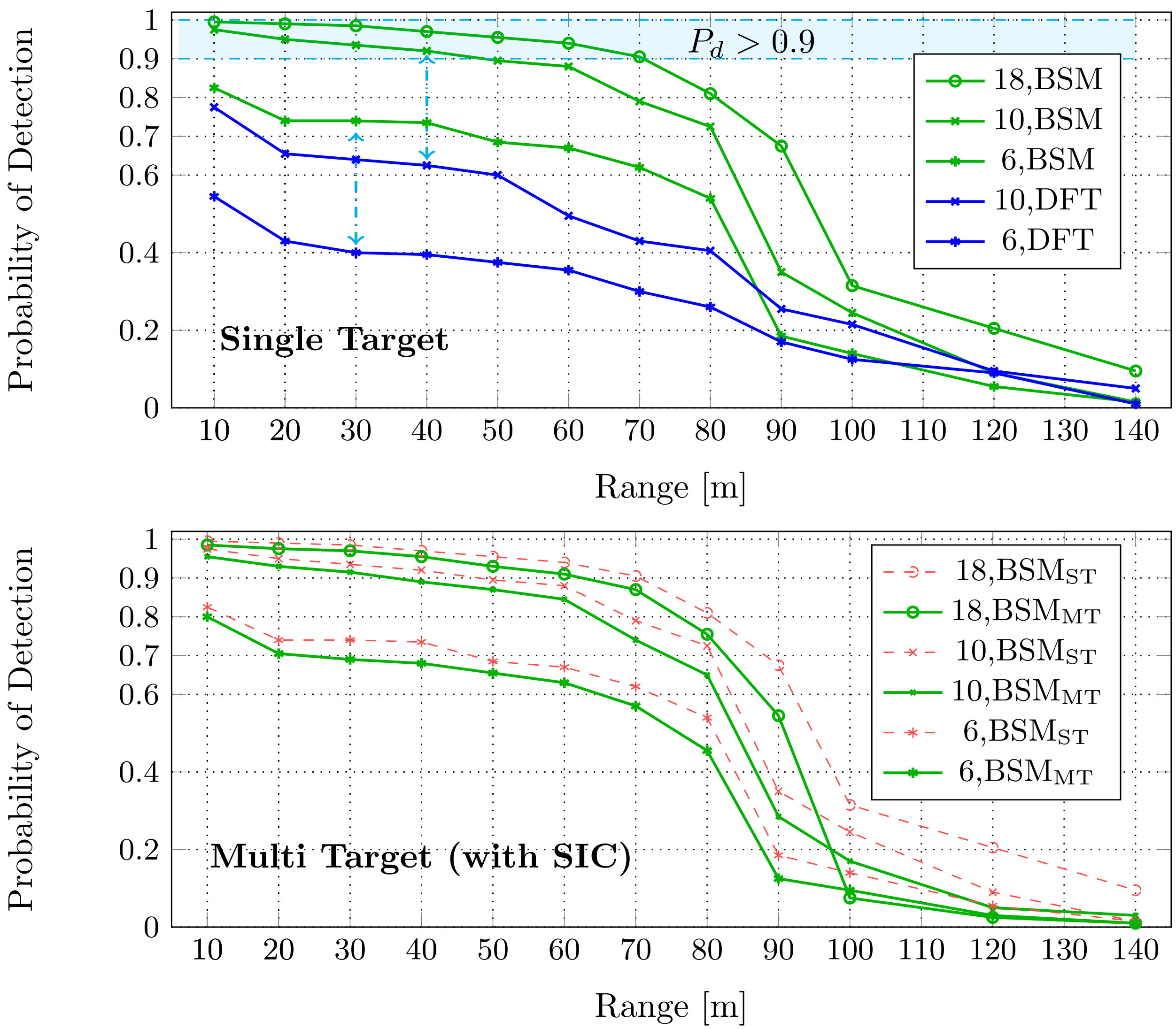
$$\Lambda_1(\{\nu_p, \tau_p, \phi_p\}) = \sum_{p=0}^{P-1} \frac{\left|\sum_{b=1}^{B} \underline{\mathbf{y}}_b^{\mathsf{H}} \underline{\mathbf{G}}_{b,p} \underline{\mathbf{x}}_{b,p}\right|^2}{\sum_{b=1}^{B} \|\underline{\mathbf{G}}_{b,p} \underline{\mathbf{x}}_{b,p}\|^2}.$$

- Each term in the sum has a form similar to the function $S(\nu, \tau, \phi)$ defined before and can be maximized individually with respect to the corresponding parameters $\{\nu_p, \tau_p, \phi_p\}$.

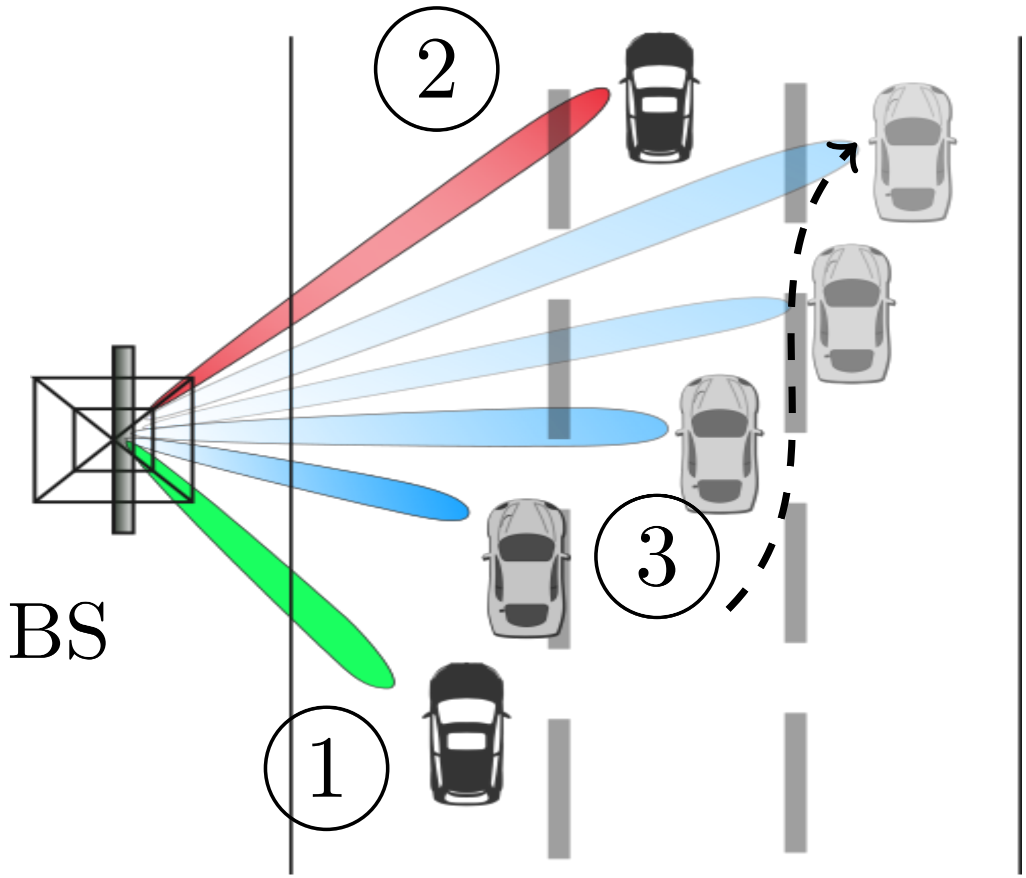
Target discovery (scenario)



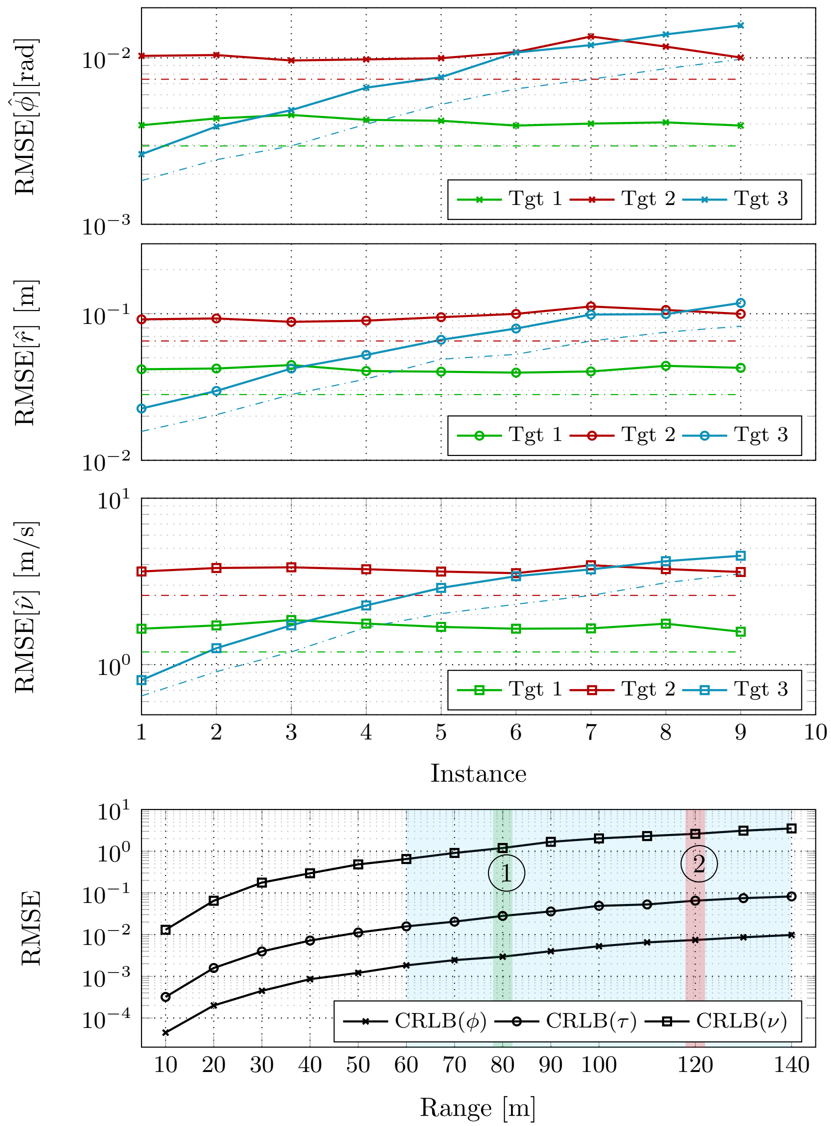
Target discovery (results)



Target parameter estimation (scenario)

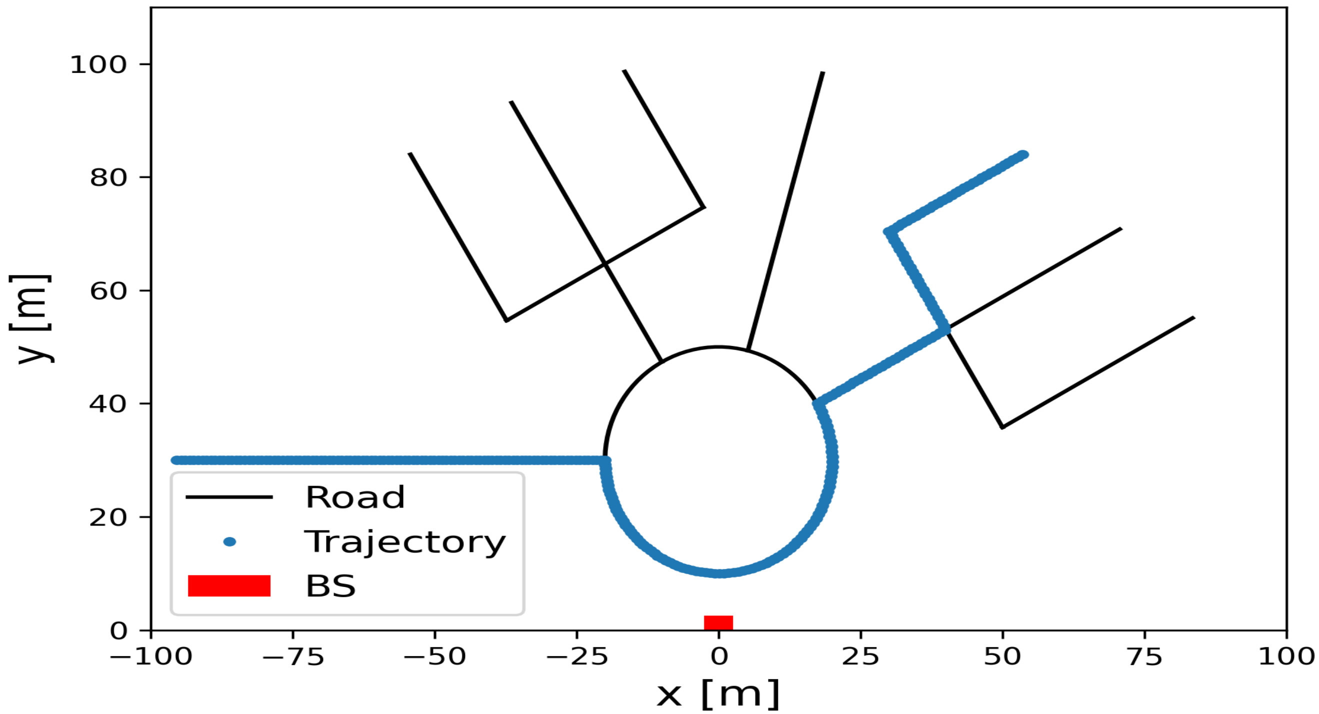


Target parameter estimation (results)



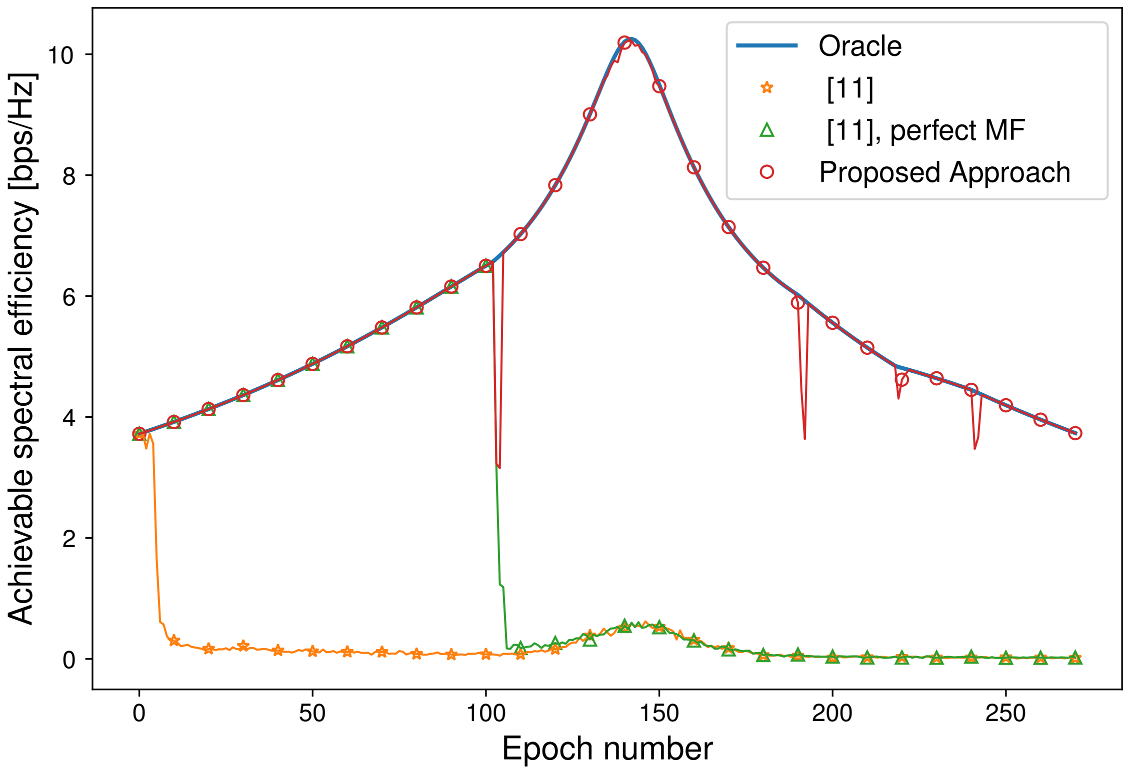
Application to beam tracking in mmWave

- Simulation scenario: cars moving on complicated urban trajectories.



Application to beam tracking in mmWave

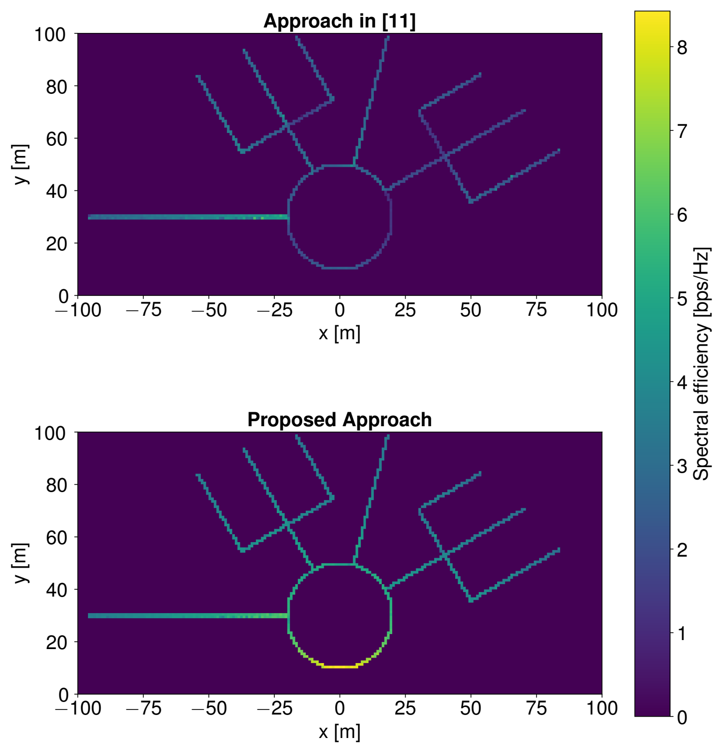
- Rate versus time step for a given trajectory



[11] F. Liu and C. Masouros, “A tutorial on joint radar and communication transmission for vehicular networkspart iii: Predictive beamforming without state models,” *IEEE Commun. Lett.*, vol. 25, no. 2, pp. 332336, 2021.

Application to beam tracking in mmWave

- Average rate versus space (rate map), averaged over many trajectories



Conclusions

- Theoretical results (information theory) show that joint communication and sensing sharing the same transmission resource can be very efficient with respect to resource partitioning.
- Advantage of exploiting the same hardware and not polluting further the RF spectrum.
- For high frequency bands (mmWaves and sub-THz) we propose beam-space MIMO radar as an efficient radar receiver with low A/D front-end complexity.
- Results show that new target detection and parameter estimation for already connected users can be done with performance comparable to state of the art automotive radar.
- Application to beam tracking .. and speed-up of initial beam acquisition (ongoing work).

Thank You