5G/6G Radio Localization Tutorial

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Goals of This Tutorial

1. Gain familiarity with different radio-based positioning systems
2. Mathematically describe the corresponding signal models
3. Derive fundamental performance bounds via Fisher information theory
4. Formulate optimization, positioning, and tracking problems and develop algorithms
5. Know current SOTAs and emerging topics for B5G/6G localization
6. Get to know the role of AI in localization systems

Outline

1. Introduction (definition, taxonomy, why 5G/6G localization)
2. Localization basics
   - System (GPS, Wifi, 3G/4G, UWB)
   - Signal Model (OFDM, signal strength, time/delay, angle/direction)
   - Performance Bound (Fisher information matrix, CRB, EFIM)
   - Algorithms (LS, MLE, MAP, convexification)
3. 5G/6G localization
   - Channel Model (delay, AOA, AOD)
   - Selected SOTA works (high frequency, multipath, orientation, RIS)
   - Challenging Scenarios (hardware impairment, near-field, learning-based)
4. Conclusion

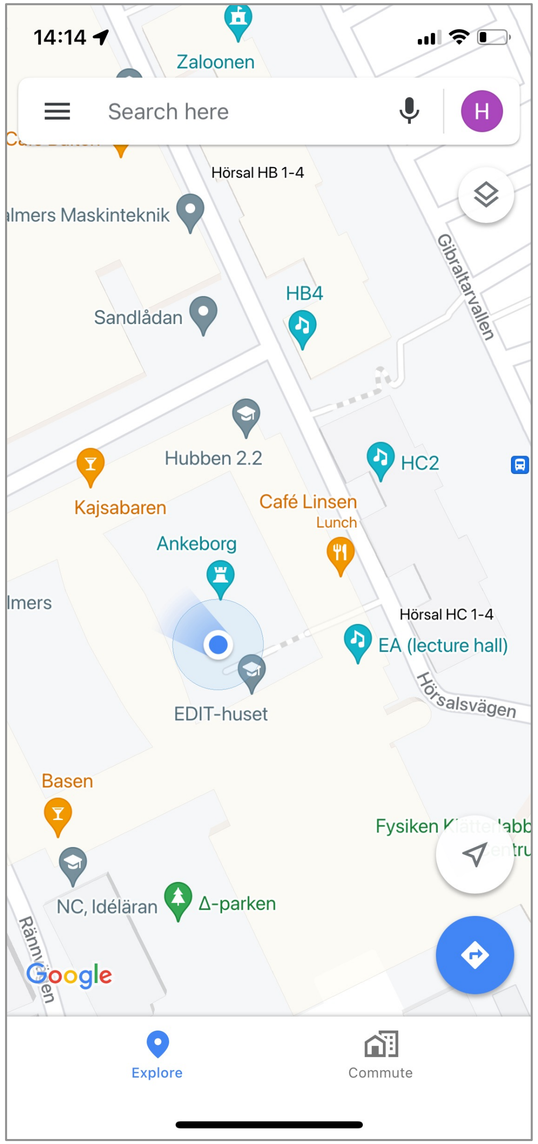
Localization: What? Why? How?

What is localization?

- Localization is the process of estimating the position and orientation of a target.

Why do we need localization?

- Know your location for decision making and planning, e.g., looking for a restaurant, giving lecture via virtual reality, driving to an unknown place :)



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How to know the location?

- Animals have "magic powers" (e.g., salmon via smell, dolphins via sea floor, birds via magnetic fields)
- We also do (celestial navigation, compass, GPS)

"Any sufficiently advanced technology is indistinguishable from magic" [1]

Sockeye salmon© Darryl Leniuk/Getty

Manx shearwaters. © Neil Bowman/Getty

Navvigation satelites. © NOAA

[1] Clarke's three laws. https://en.wikipedia.org/wiki/Clarke%27s_three_laws#:~:text=The%20laws%20are%3A,past%20them%20into%20the%20impossible.

Localization-related Terms

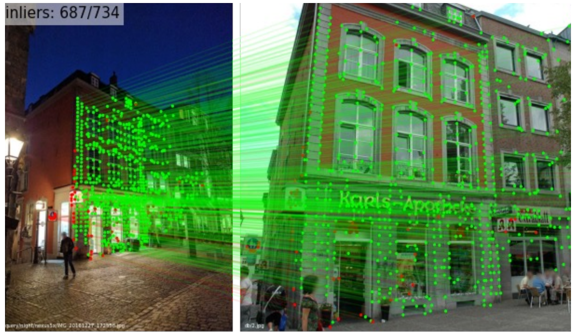
Taxonomy of Localization Techniques

Criteria	Types
Application Scenario	Ourdoor, Indoor
Wireless Technology	GPS, Cellular systems, WLAN, Wifi, Bluetooth
Localization Technique	Geometry-based, Learning-based, Hybird
Signal Type	Radio waves, LED signal, LIDAR, Image
Functionality	Passive, Active
System Structure	Centralized, Distributed, Clustered
Position Information	Absolute position, Relative position
Information-sharing	Cooperatie, Non-cooperative

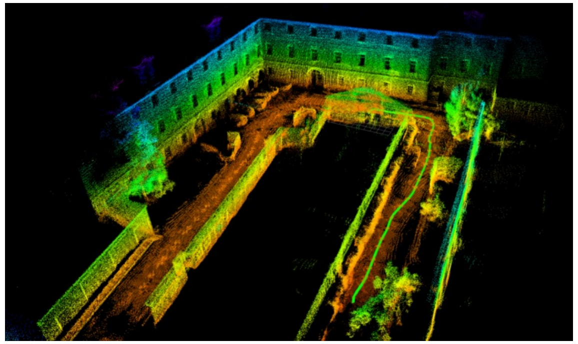
Other localization related topics:

Mapping: The estimation of incidence points of the NLOS paths.
Sensing (system point of view): Localization, mapping, channel/environment change.
Calibration: The estimation of anchor (e.g., BS) states.
SLAM: Simultaneous localization and mapping (relatively mature in computer vision)

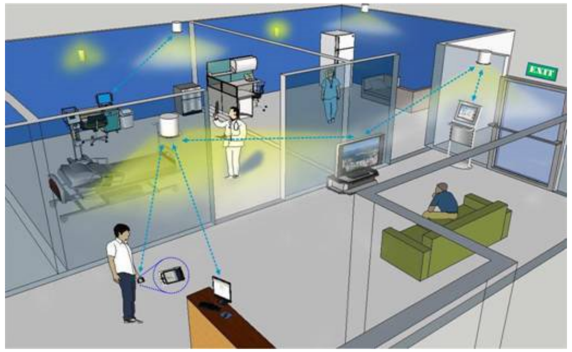
This lecture: Geometry-based, Radio waves, Absolute position



Visual localization. © CVG Lab ETH



Lidar SLAM © Luigi Freda

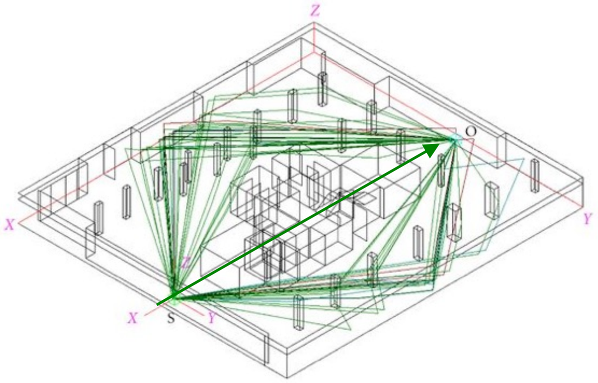


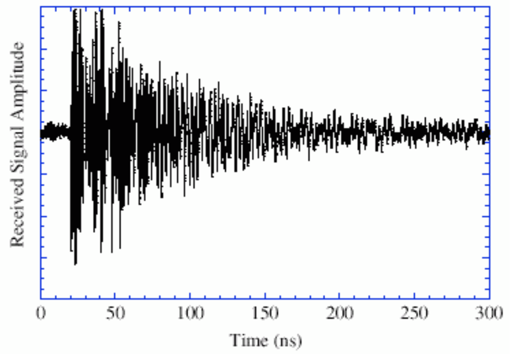
WLAN localization. © Fizmon

Why Radio-based Localization

Why radio localization?

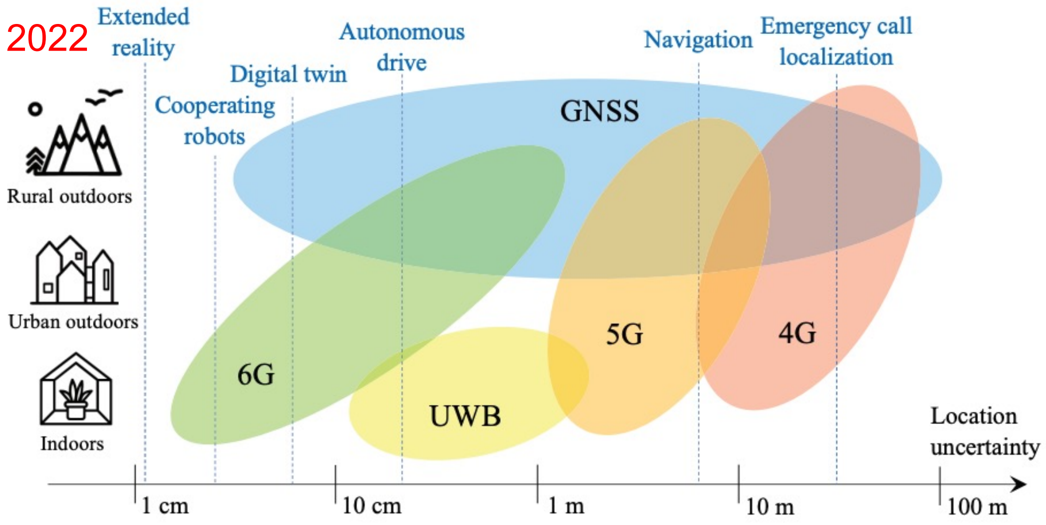
- Waveform conveys information about geometry
- No extra hardware cost (using existing infrastructure)
- Flexible signal design and power control





Why 5G/6G radio localization?

- Array size (better angle estimation, less BSs, orientation)
- Bandwidth (better delay estimation)
- Mapping (multipath, deterministic channel)
- Standardization across devices (3GPP TR38.855)
- Controllable channel (RIS)
- Promising direction/~~secured career (7G/8G/9G… localization)~~



Localization is a software addon from the communication infrastructure !

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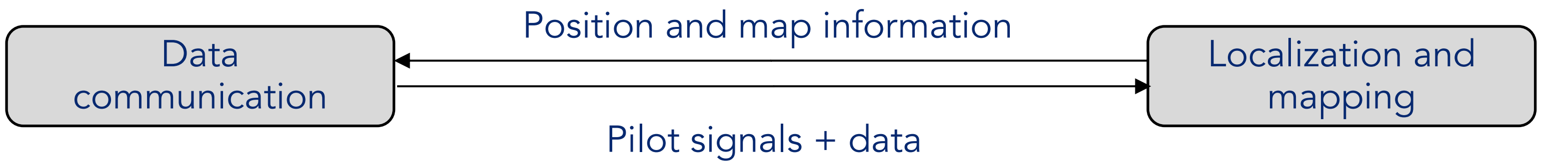
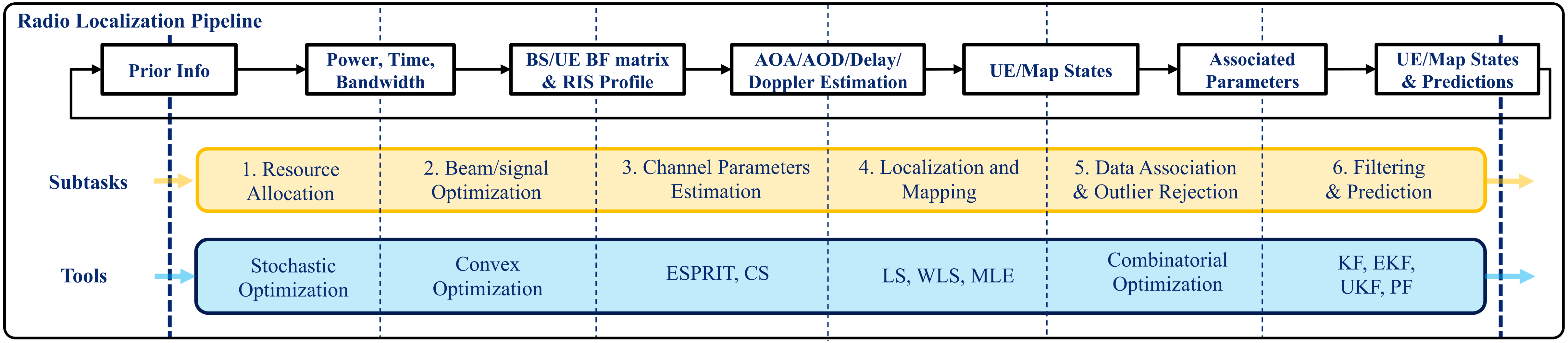
Localization Systems

Joint communication and localization



Radio localization pipeline (4 is a narrow definition of localization)

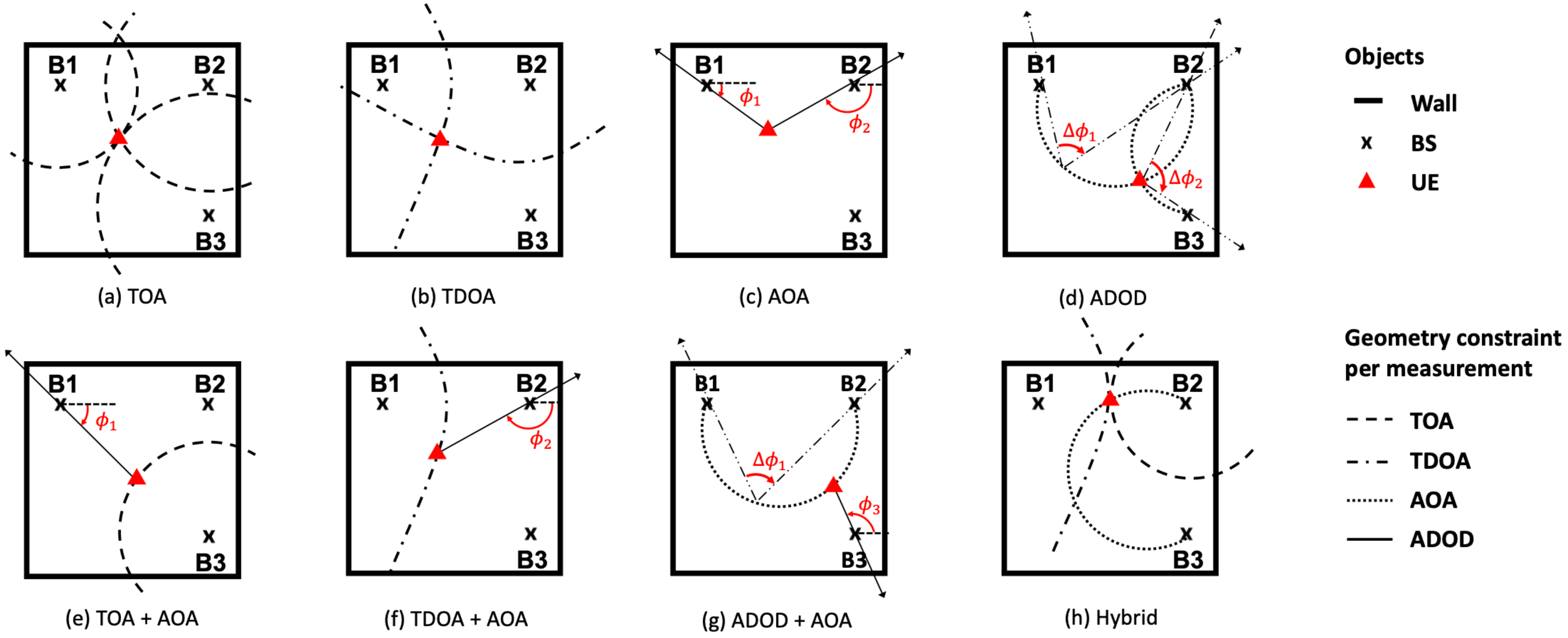


- Direct localization: Received signals → position. (No information loss, but complex.)
- Layered localization: Received signals → geometric parameters → position. (Less accurate, practical)

Geometry Relationship

Channel/geometric parameters

- Signal strength: received signal strength (RSS), fingerprinting (for learning-based methods)
- Time: time of arrival (TOA), time difference of arrival (TDOA)
- Angle: angle of arrival (AOA), angle of departure (AOD), and angle difference of departure (ADOD)



Position estimation from different geometry information (uplink)

Localizability of a System (A Rule of Thumb)

A rule of thumb (*Technical conditions apply)

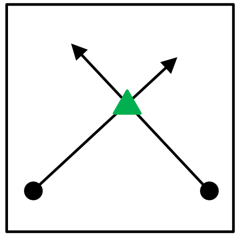
- All localization problems are estimation problems: "estimate **x** from **y**"
- N_Y geometric parameters: Extracted from the channel information (e.g., delays and angles).
- N_X location-related parameters: Usually contains a location part, an orientation part, a clock bias part

For the localization problem to be solvable*, you need $N_X \leq N_Y$

Examples:

- 3D position + 1 clock offset, 1 BS can provide 1 delay estimation, how many are needed? (4 BSs)
- 2D position + 1 clock offset. Will 2 BSs with 2 angles estimations work?

(Yes, line intersection. But the target cannot be located on the line between two BSs)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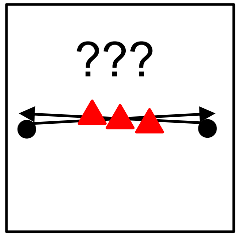
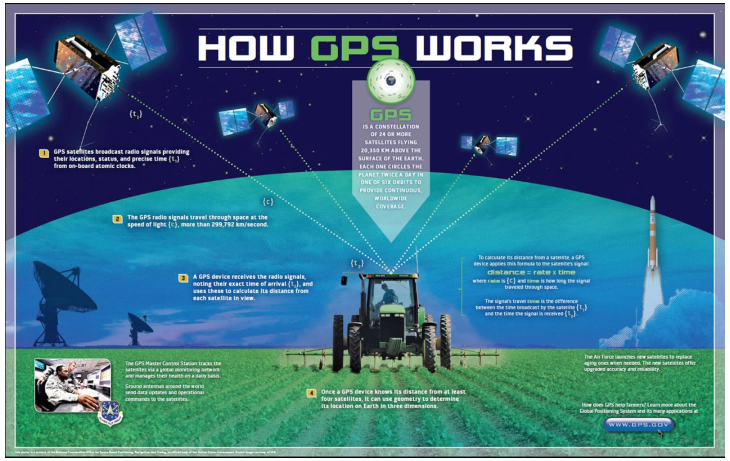


✗

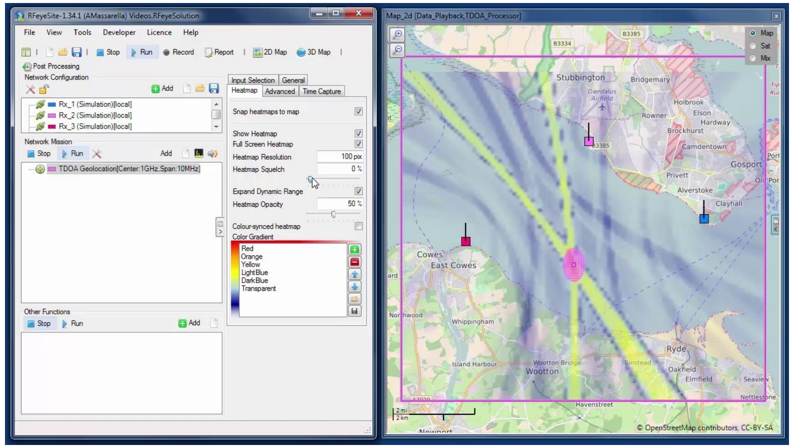
This rule may not always work:
- Clock bias is related to delay-based estimation
- UE orientation is related to downlink AOA (or uplink AOD) only
- UE position is related to AOA, AOD, and delay
- Ask the Fisher information matrix, it knows everything (almost)

Existing Radio-based Localization Systems

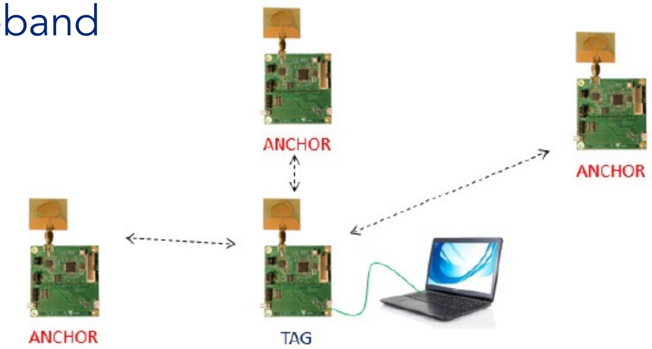
GNSS (Global navigation satellite system):
GPS (US)
Galileo (EU)
GLONASS (Russia)
Beidou (China)



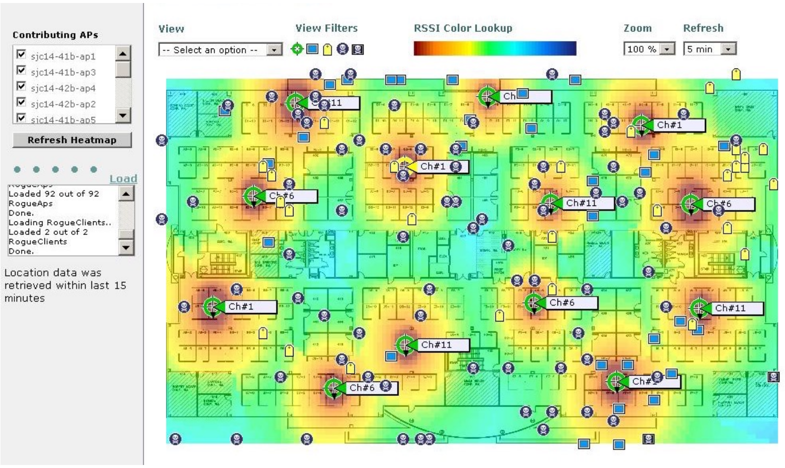
3G/4G Cellular



UWB: Ultra wideband



Wifi



But we need more:
- Better performance (accuracy, delay)
- Orientation (autonomous driving, VR)

Let's start from basics

Source: http://media.defenceindustrydaily.com/images/PUB_How_GPS_Works_lg.jpg; https://www.crfs.com/; https://www.researchgate.net/figure/DecaWave-UWB-localization-system-SDK-5_fig4_281346001

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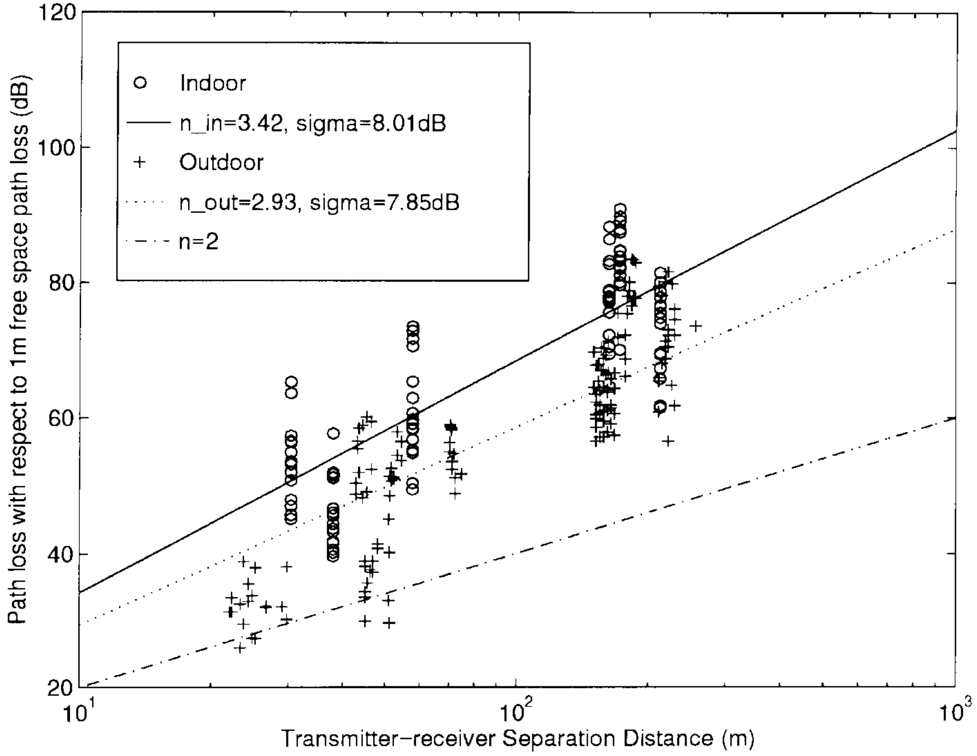
Signal Strength

Principle

- Path loss equation $P_r[\mathrm{dBm}] = P_t[\mathrm{dBm}] + K[\mathrm{dB}] - 10\gamma \log_{10} \frac{d}{d_0}$
- Learn parameters from data
- Map received power to distance



Challenges

- Not one-to-one mapping
- Many meters distance uncertainty
- More common with fingerprinting (machine learning)

Durgin, Greg, Theodore S. Rappaport, and Hao Xu. "Measurements and models for radio path loss and penetration loss in and around homes and trees at 5.85 GHz." *IEEE Transactions on Communications* 46.11 (1998): 1484-1496.

Time/delay

- We consider OFDM pilot transmission, transmitted signal over N subcarriers

$$\mathbf{s} = [s_0, \ldots, s_{N-1}]^\top$$

- Received signal after unknown delay, in receiver frame of reference

$$r_n = \alpha s_n \exp\left(-\jmath 2\pi n \tau/(NT_s)\right)$$

Subcarriers have different wavelengths, resulting different phases:

$$\exp(-\jmath 2\pi (f_c + \Delta_n)\tau), \ \Delta_n = n/(NT_s).$$

- Vectorize

$$\mathbf{r} = \alpha \mathbf{s} \odot \mathbf{a}(\tau)$$

$$[\mathbf{a}(\tau)]_n = \exp\left(-\jmath 2\pi n \tau/(NT_s)\right)$$

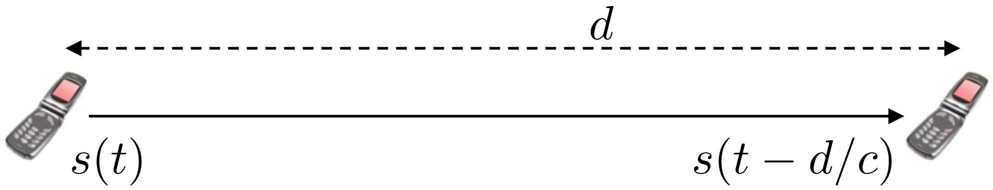
- We then need to estimate channel gain (nuisance parameters) and delay (location-related parameter)

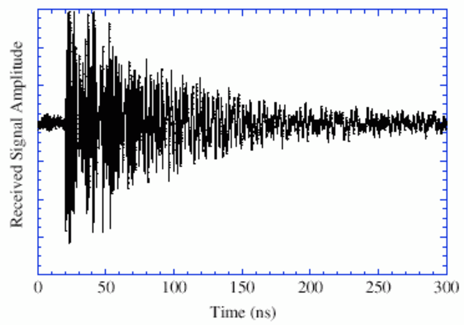
We may have time of arrival (TOA), round trip time (RRT), or time-difference-of-arrival (TDOA), depending on the system hardware.

Time of Arrival (TOA)

Parameter / Numerlogy (u)	0	1	2	3	4
Subcarrier Spacing (Khz)	15	30	60	120	240
OFDM Symbol Duration (us)	66.67	33.33	16.67	8.33	4.17
Cyclic Prefix Duration (us)	4.69	2.34	1.17	0.57	0.29
OFDM Symbol including CP (us)	71.35	35.68	17.84	8.92	4.46

Operation





1 ns time error * 3e8 m/s = 30 cm

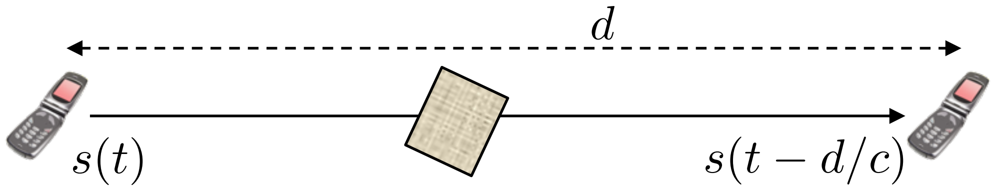
Localization SYNC requirement is much more strigent than Commun.

Estimated in the clock of the receiver

$$\hat{\tau} = \frac{d}{c} + B + n$$

Challenges

- Clock bias must be removed before converting to distance
- Obstacles: non-line-of-sight (NLOS)



- Weakens LOS path, or can block completely (large positive range bias)

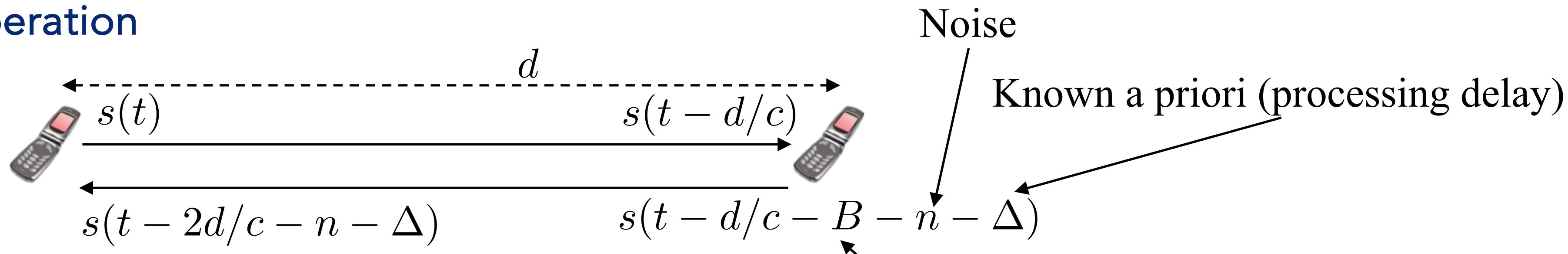
You can treat TOA estimation as 2 channel parameters (round trip) for estimating distance + clock offset.

Be aware of the synchronization between BSs:

- 1 clock offset between the UE and the system
- Several clock offsets between UE and other BSs)

Time: Two-way TOA, or Round-Trip-Time (RTT)

Operation



- Estimated in the clock of the original transmitter

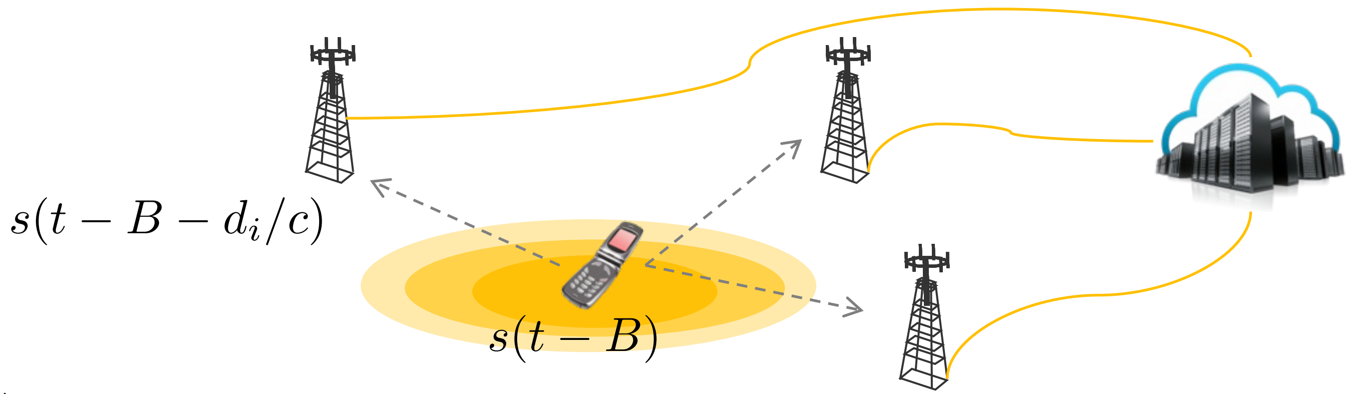
$$\hat{\tau} = \frac{2d}{c} + n + \Delta + w$$

Challenges

- Dedicated transaction per node pair (Need to remove processing time)
- Relies on dedicated hardware

Time: Time Difference of Arrival (TDOA)

Operation



- Estimate $\hat{\tau}_i = d_i/c + B + n_i$
- Differential measurement $y_i = \hat{\tau}_i - \hat{\tau}_0, i > 0$ no longer depends on B
- One transmission per device

Challenges

- Requires tight synchronization among base stations
- Requires central processing unit
- Measurement noise of differential measurements is correlated
- Performance depends on choice of reference base station

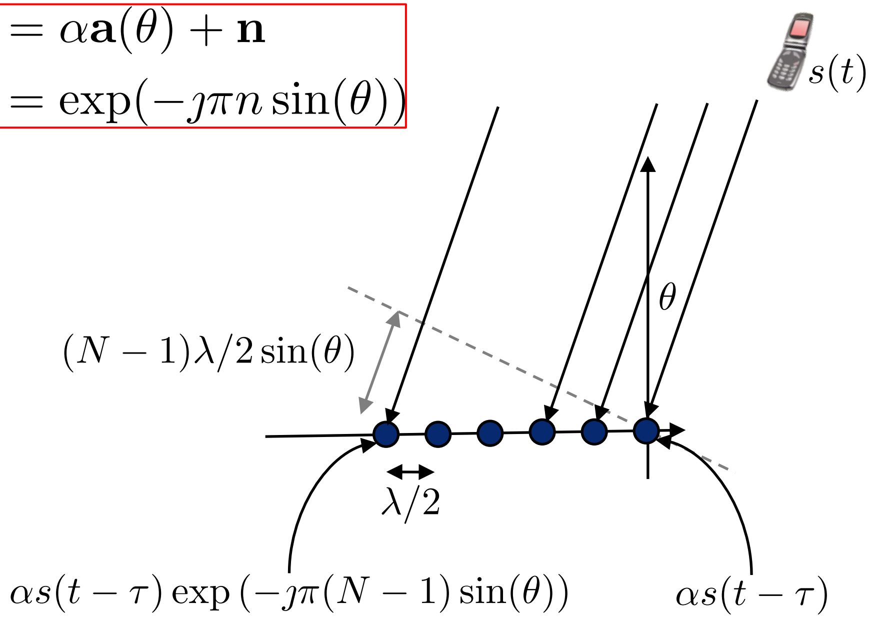
Large bandwidth results in a better delay resolution

Angle: Angle of Arrival (AOA) and Angle of Departure (AOD)

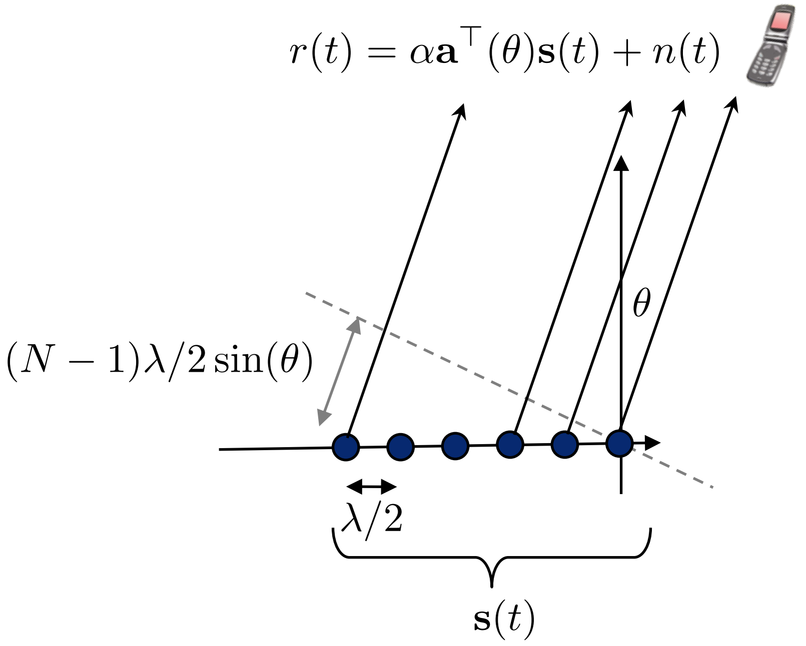
Operation: narrowband signal plane wavefront

AOA: Discrete time observation

$$\boxed{\begin{aligned}\mathbf{r} &= \alpha\mathbf{a}(\theta) + \mathbf{n}\\ [\mathbf{a}(\theta)]_n &= \exp(-\jmath\pi n\sin(\theta))\end{aligned}}$$



AOD: Discrete time observation $\boxed{r_t = \alpha\mathbf{a}^\top(\theta)\mathbf{s}_t + n_t}$



Challenges

- Antenna array required (more hardware cost and computations)
- Array orientation must be known or estimated
- Error propagates with distance

Large array size results in a better angle resolution

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Performance Bound

Purpose

- When developing an algorithm, how to know if it is good enough?
- How should we design a system (e.g., anchor placement) or signal (power allocation)
- Fisher information theory can be used to answer these questions.

Problem: estimate deterministic unknown $\mathbf{x}$ from observation $\mathbf{z}$ given statistical model $p(\mathbf{z}|\mathbf{x})$

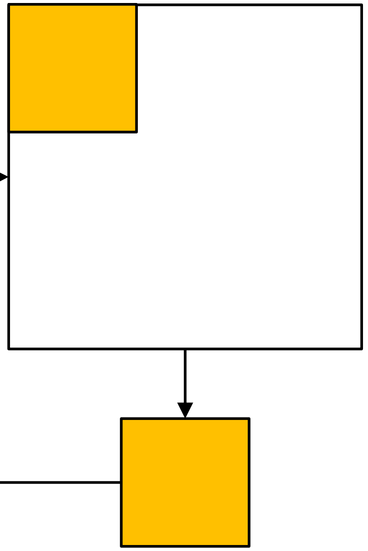
- The Fisher information matrix (FIM): measures "the amount of information the observation carries about the unknown"
$$\mathbf{J}(\mathbf{x}) = \mathbb{E}_{\mathbf{z}}\{\nabla_{\mathbf{x}} \log p(\mathbf{z}|\mathbf{x})\ \nabla_{\mathbf{x}}^{\mathrm{T}} \log p(\mathbf{z}|\mathbf{x})\}$$
- FIM relates to estimation error covariance of any unbiased estimator $\hat{\mathbf{x}}(\mathbf{z})$
$$\mathbb{E}\{(\mathbf{x}-\hat{\mathbf{x}})(\mathbf{x}-\hat{\mathbf{x}})^{\mathrm{T}}\} \succeq \mathbf{J}^{-1}(\mathbf{x})$$
- Cramér-Rao bound: lower bound on estimation error variance
$$\mathbb{E}\{||\mathbf{x}-\hat{\mathbf{x}}||^2\} \geq \mathrm{tr}(\mathbf{J}^{-1}(\mathbf{x}))$$
- Gaussian noise case is easier:
$$\mathbf{z} = \mathbf{m}(\mathbf{x}) + \mathbf{n}, \mathbf{n} \sim \mathcal{CN}(0, \boldsymbol{\Sigma})$$
$$\boxed{\mathbf{J}(\mathbf{x}) = \Re\left\{\nabla_{\mathbf{x}}\mathbf{m}^{\mathrm{H}}(\mathbf{x})\boldsymbol{\Sigma}^{-1}\nabla_{\mathbf{x}}\mathbf{m}(\mathbf{x})\right\}}$$

FIM: More Topics

Equivalent FIM of a sub-vector:

$$\mathbf{J}(\mathbf{x}_1, \mathbf{x}_2) = \begin{bmatrix} \mathbf{A} & \mathbf{B} \\ \mathbf{B}^{\mathrm{T}} & \mathbf{C} \end{bmatrix}$$

invert



invert

$$\mathbf{J}^{\mathrm{E}}(\mathbf{x}_1) = \mathbf{A} - \mathbf{B}^{\mathrm{T}}\mathbf{C}^{-1}\mathbf{B}$$

Insights from EFIM:

1. If x_2 is known, the FIM of x_1 will be A. If x_2 is unknown, the FIM of x_1 will be reduced.
2. EFIM helps to reduce the complexity of matrix inverse if we do not care about x_2
   - Inverse of FIM and get the top left submatrix
   - Or inverse of EFIM describes the information about x_1 when x_2 is unknown

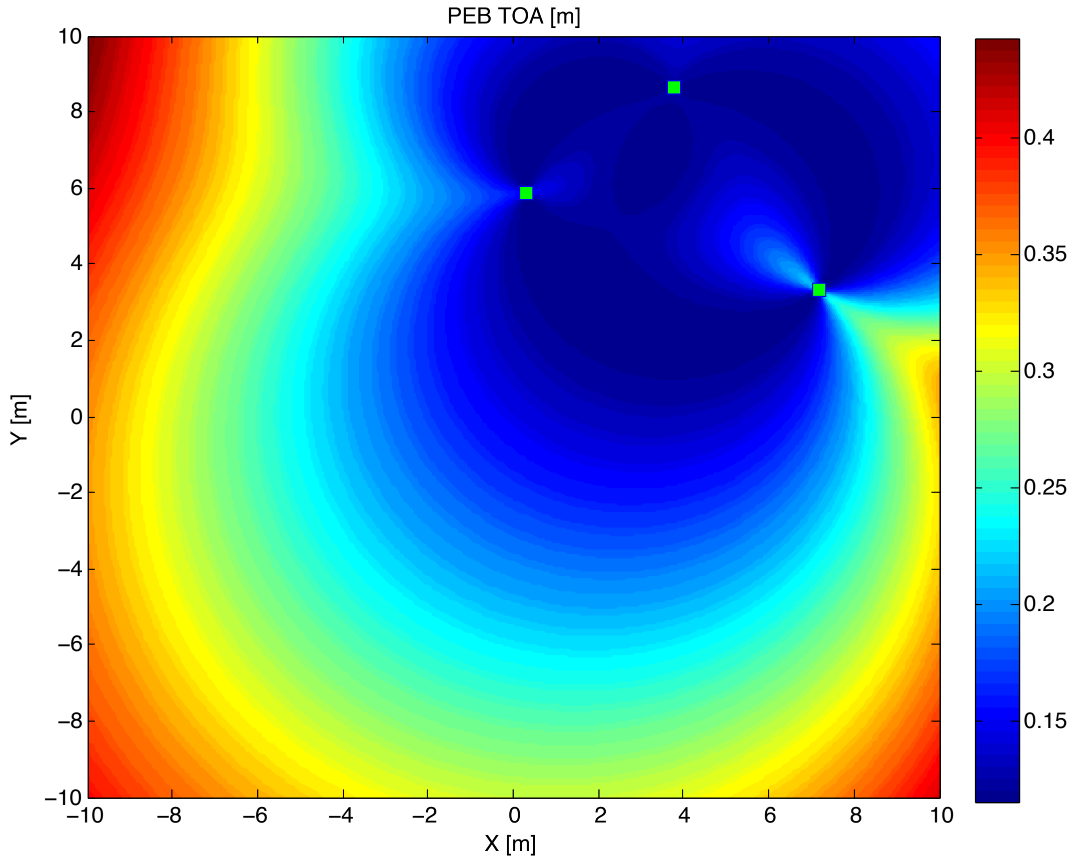
Transformation of variables $\mathbf{x} = \mathbf{f}(\boldsymbol{\eta})$ using Jacobian

$$\mathbf{J}(\boldsymbol{\eta}) = \mathbf{T}^{\mathrm{T}}\mathbf{J}(\mathbf{x})\mathbf{T}, [\mathbf{T}]_{i,j} = \partial x_i / \partial \eta_j$$

Position Error Bound (PEB)

3 anchors, visualize PEB for different positions

$$\mathcal{P} = \sqrt{\mathrm{tr}(\mathbf{J}^{-1}(\mathbf{x}))}$$



Other error bounds can also be defined based on the certain indices of the CRB (inverse of the FIM)

For example, in 6D localization, the state vector

$$\mathbf{s} = [\mathbf{p}^\top, \mathrm{vec}(\mathbf{R})^\top, B, \rho_1, \beta_1, \ldots]^\top$$

Position error bound: $\sqrt{\mathrm{tr}(\mathbf{J}^{-1}(\mathbf{s})_{[1:3,1:3]})}$

Orientation error bound: $\sqrt{\mathrm{tr}(\mathbf{J}^{-1}(\mathbf{s})_{[4:12,4:12]})}$

Clock error bound: $\sqrt{\mathrm{tr}(\mathbf{J}^{-1}(\mathbf{s})_{[13,13]})}$

*Constrained CRB (CCRB) for 3D orientation
*Misspecified CRB (MCRB) for model mismatch
*Posterior CRB (PCRB) for tracking

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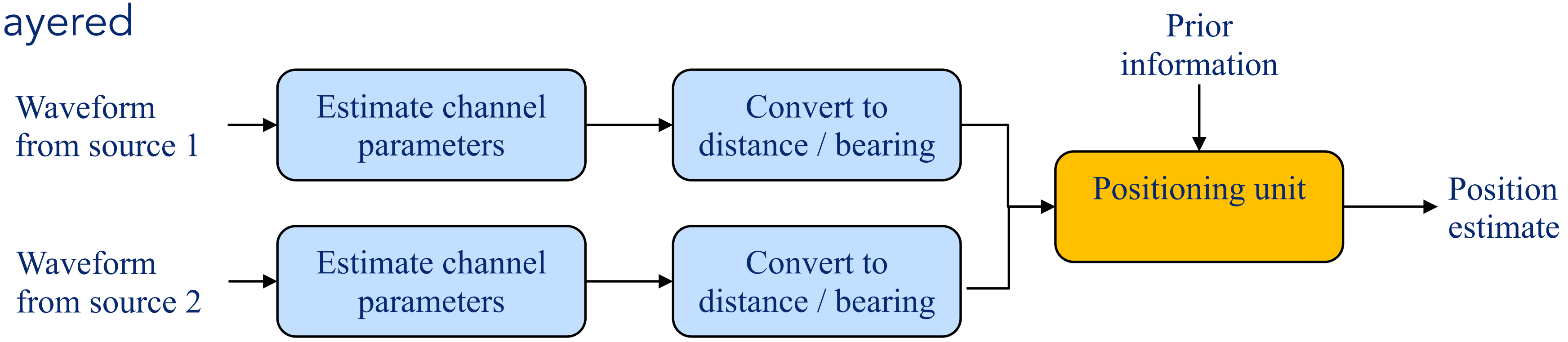
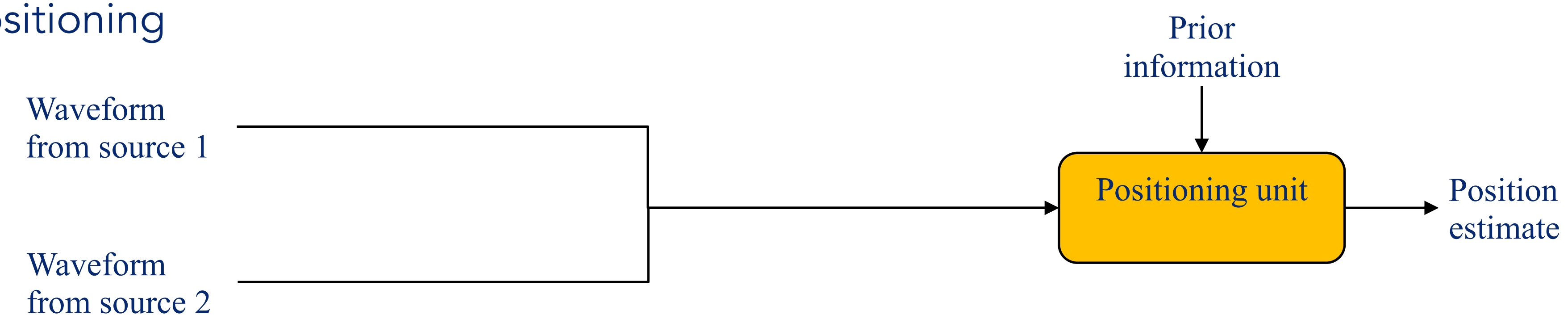
Localization Algorithms

Typically layered



Direct positioning



- Prior information provided in tracking mode, in terms of position/orientation and channel parameters
- Prior information can also be used for signal design, resource allocation, etc.

Estimation Basics

Observation model $\mathbf{r} = \mathbf{f}(\mathbf{x}) + \mathbf{n}$ with Gaussian noise

Least squares (LS) estimator

$$\hat{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{r} - \mathbf{f}(\mathbf{x})\|^2$$

Maximum likelihood (ML) estimator

$$\begin{aligned}\hat{\mathbf{x}} &= \arg\max_{\mathbf{x}} p(\mathbf{r}|\mathbf{x}) \\ &= \arg\max_{\mathbf{x}} -(\mathbf{r} - \mathbf{f}(\mathbf{x}))^{\mathrm{T}} \boldsymbol{\Sigma}^{-1} (\mathbf{r} - \mathbf{f}(\mathbf{x}))\end{aligned}$$

Maximum a posteriori (MAP) estimator

$$\begin{aligned}\hat{\mathbf{x}} &= \arg\max_{\mathbf{x}} p(\mathbf{x}|\mathbf{r}) \\ &= \arg\max_{\mathbf{x}} -(\mathbf{r} - \mathbf{f}(\mathbf{x}))^{\mathrm{T}} \boldsymbol{\Sigma}^{-1} (\mathbf{r} - \mathbf{f}(\mathbf{x})) + \log p(\mathbf{x})\end{aligned}$$

Optimization generally not convex

Usually channel parameter estimation can use LS, because we assume independent and identically distributed (iid) Gaussian noise.

Localization usually requires prior information, and some weighting factors for different parameters.

Example: AOD Estimation (Channel Parameters)

Using maximum likelihood

$$\mathbf{r} = \alpha \mathbf{S}^H \mathbf{a}(\theta) + \mathbf{n}$$

$$(\hat{\alpha}, \hat{\theta}) = \arg\min \underbrace{\|\mathbf{r} - \alpha \mathbf{S}^H \mathbf{a}(\theta)\|^2}_{d(\alpha,\theta)}$$

$\frac{\partial d}{\partial \alpha} = 0$ implies

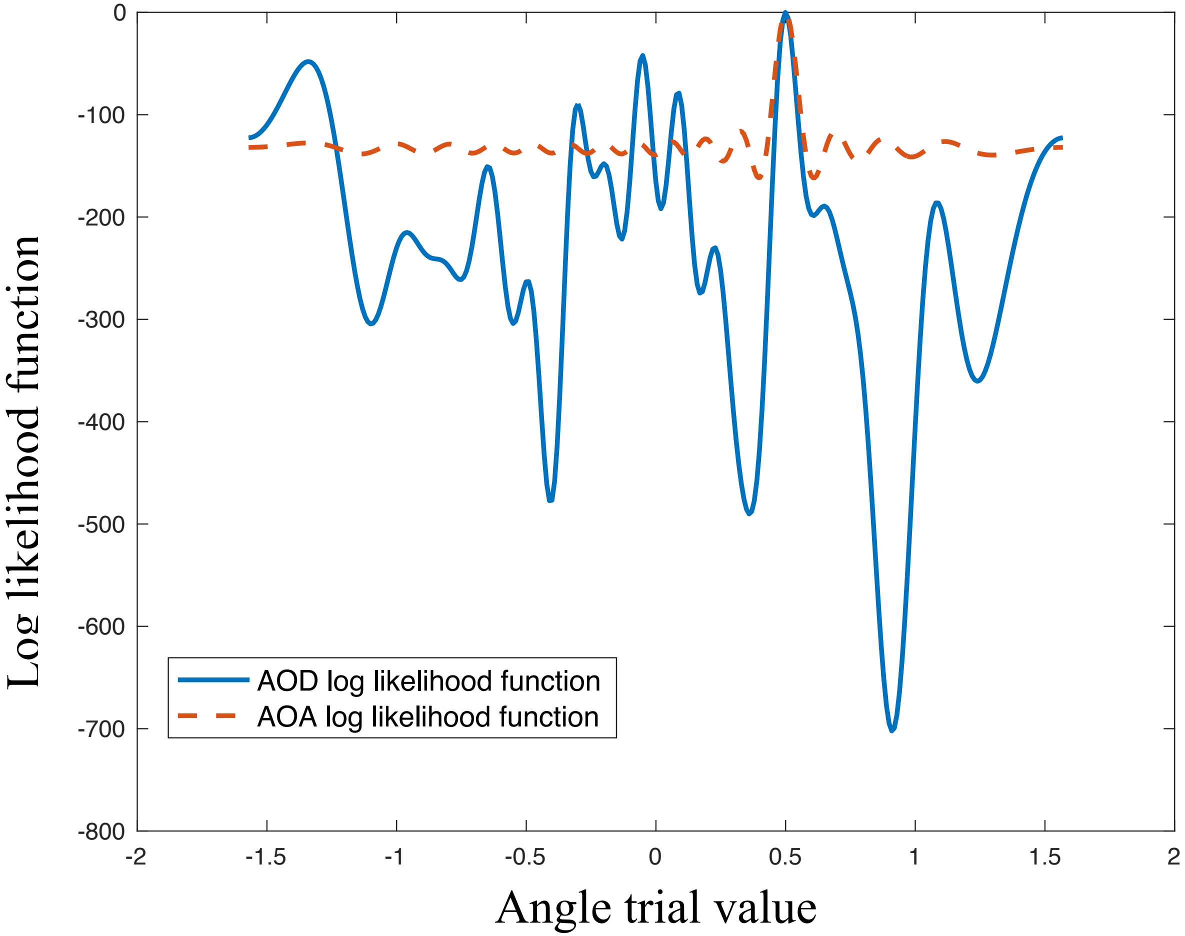
$$\hat{\alpha}(\theta) = \frac{\mathbf{a}^H(\theta)\mathbf{S}\mathbf{r}}{\|\mathbf{S}^H \mathbf{a}(\theta)\|^2},$$

which can be substituted so that

$$\hat{\theta} = \arg\min d\left(\frac{\mathbf{a}^H(\theta)\mathbf{S}\mathbf{r}}{\|\mathbf{S}^H \mathbf{a}(\theta)\|^2}, \theta\right)$$

- Multiple transmissions needed
- Channel gain can be expressed as a function of theta (simplified problem)

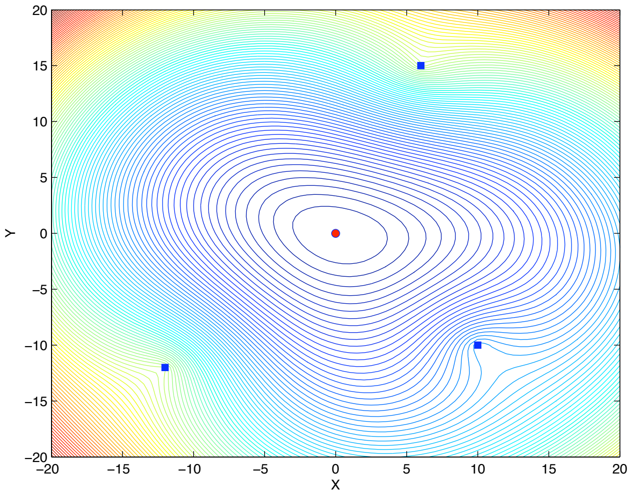
16 antennas ULA, T=3 transmissions, high SNR

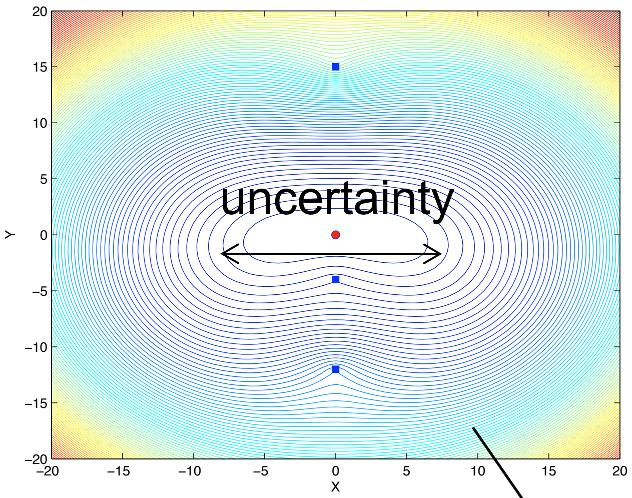


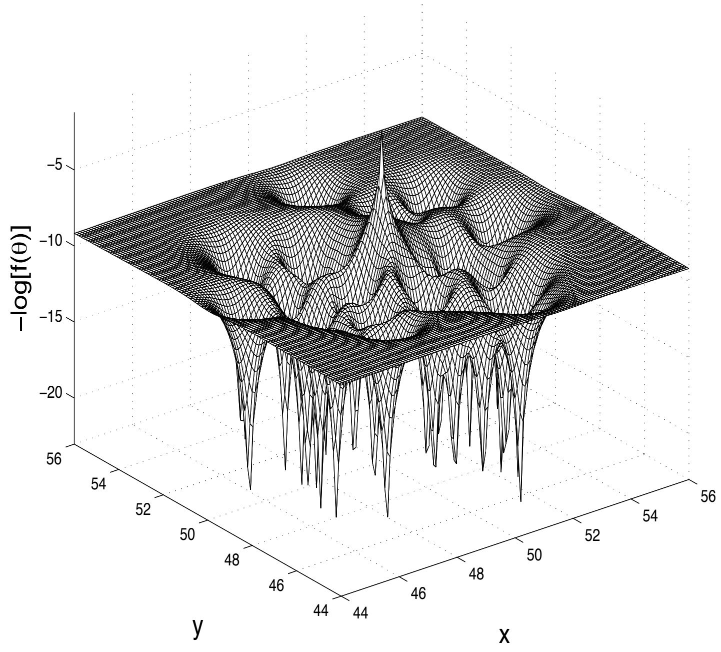
Example: ML Positioning (Localization Parameters)

Hero III, Alfred O., and Doron Blatt. "Sensor network source localization via projection onto convex sets (POCS)." *Acoustics, Speech, and Signal Processing, 2005. Proceedings.(ICASSP'05). IEEE International Conference on*. Vol. 3. IEEE, 2005.

Can be nice, but also very nasty







Gradient descent needs good initial guess

- Convexification
- Use problem structure

Placing three BSs on one line is a bad example.

Solving the LS Problem

Consider a system with one agent, two-way TOA measurements

$$r_k = \|\mathbf{x} - \mathbf{x}_k\| + n_k$$

LS cost function

$$f_{\mathrm{LS}}(\mathbf{x}) = \sum_k (r_k - \|\mathbf{x} - \mathbf{x}_k\|)^2$$

Gradient descent:

$$\hat{\mathbf{x}}^{(k)} = \hat{\mathbf{x}}^{(k-1)} - \epsilon \nabla f_{\mathrm{LS}}(\hat{\mathbf{x}}^{(k-1)})$$

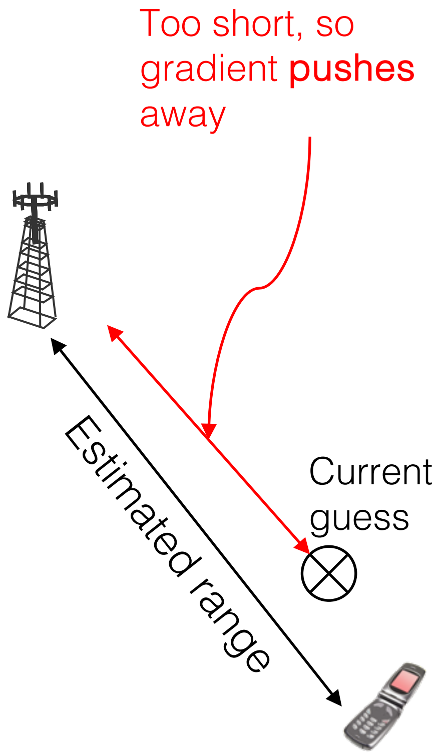
$$\nabla f_{\mathrm{LS}}(\mathbf{x}) = \sum_k \nabla (r_k - \|\mathbf{x} - \mathbf{x}_k\|)^2$$

$$= -2 \sum_k (r_k - \|\mathbf{x} - \mathbf{x}_k\|) \frac{\mathbf{x} - \mathbf{x}_k}{\|\mathbf{x} - \mathbf{x}_k\|}$$

Recall from CRB

$$\nabla_{\mathbf{x}} \|\mathbf{x} - \mathbf{x}_k\| = \frac{\mathbf{x} - \mathbf{x}_k}{\|\mathbf{x} - \mathbf{x}_k\|}$$

Needs an initial estimate



Initial Guess through Convexification

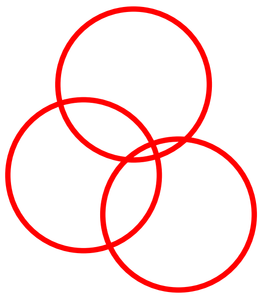
LS reformulations

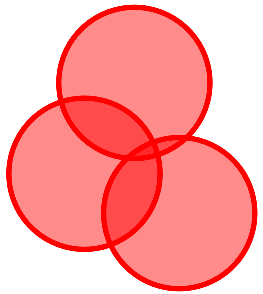
$$\begin{aligned} \underset{\mathbf{x},\mathbf{z},\boldsymbol{\varepsilon}}{\text{minimize}} \quad & \|\boldsymbol{\varepsilon}\|^2 \\ \text{s.t.} \quad & \|\mathbf{x}-\mathbf{x}_k\| = z_k \\ & |z_k - r_k| \leq \varepsilon_k \end{aligned}$$

$$\begin{aligned} \underset{\mathbf{x},\boldsymbol{\varepsilon}}{\text{minimize}} \quad & \sum_{k=1}^{N} \varepsilon_k \\ \text{s.t.} \quad & (\|\mathbf{x}-\mathbf{x}_k\| - r_k)^2 = \varepsilon_k \end{aligned}$$

Nonlinear equality constraint

Relax circle to disk $\|\mathbf{x}-\mathbf{x}_k\| \leq z_k$ leads to second order cone program





Can be solved efficiently. Solution can be initial guess for gradient LS solver

Initial Guess through Problem Structure

- Convexified problem can still be computationally demanding
- Lazy approach: make a few educated guesses and see which work out in terms of cost
- Example:
  - 1 user with distance estimates to 100 anchors. Very nonconvex likelihood function
  - Initial guess:
    - take 2 or 3 good anchors (with good separation and low error variance) and compute intersection of circles
    - Run gradient descent until convergence
    - Try it a few times with different 2 or 3 anchors
- Tends to work very well for many problems

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    - Algorithms (LS, MLE, MAP, convexification)
3. 5G/6G localization
    - Channel Model (delay, AOA, AOD)
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    - Challenging Scenarios (hardware impairment, near-field, learning-based)
4. Conclusion

Signal Model (Typical mmWave Channel)

- 3D, analog, MIMO system
- Stationary Model (Doppler later)
- K subcarriers, G transmissions

Received symbol: $y_{g,k} = \mathbf{w}_g^\top \mathbf{H}_k \mathbf{v}_g x_{g,k} + n_{g,k}$

$$\mathbf{H}_k = \underbrace{\alpha d_k(\tau)\mathbf{a}_\mathrm{R}(\boldsymbol{\varphi}_\mathrm{R})\mathbf{a}_\mathrm{T}^\top(\boldsymbol{\varphi}_\mathrm{T})}_{\text{LOS path}} + \underbrace{\sum_{p=1}^{P} \alpha_p d_{p,k}(\tau_p)\mathbf{a}_\mathrm{R}(\boldsymbol{\varphi}_{\mathrm{R},p})\mathbf{a}_\mathrm{T}^\top(\boldsymbol{\varphi}_{\mathrm{T},p})}_{\text{NLOS paths}},$$

LOS Channel matrix: $\mathbf{H}_k = \alpha d_k(\tau)\mathbf{a}_\mathrm{R}(\boldsymbol{\varphi}_\mathrm{R})\mathbf{a}_\mathrm{T}^\top(\boldsymbol{\varphi}_\mathrm{T})$

Steering vector at Tx (Angle of Departure)

Steering vector at Rx (Angle of Arrival)

Phase change across subcarriers (Delay)

Complex channel gain (nuisance unknown)

3xN Antenna Position Matrix

$$\mathbf{a}(\boldsymbol{\varphi}) = e^{j\frac{2\pi f_c}{c}\mathbf{Z}^\top \mathbf{t}(\boldsymbol{\varphi})}$$

$$d_k(\tau) = e^{-j2\pi k \Delta_f \tau}$$

$$\alpha = \rho e^{-j\xi}$$

Direction Vector

Subcarrier Spacing

UE-related parameters can be used for localization (LOS + NLOS)
Incidence points–related parameters can be used for mapping (NLOS)
* In low frequency systems, H_k would be i.i.d. Gaussian without much geometric structure

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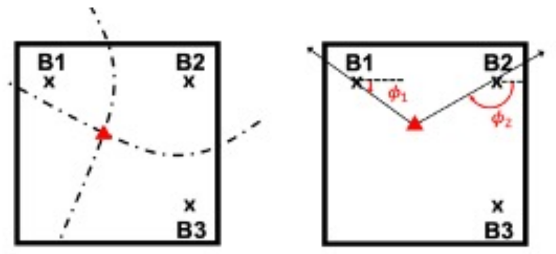
State-of-the-Art

Selected Topics Localization in 5G/6G systems

a) 3D Orientation Estimation
b) 6D Localization (3D Pos + 3D Ori)
c) Single-BS Localization
d) Single-BS 6D Localization
e) Localization and Mapping under Mobility
f) Cooperative localization
g) RIS-aided Localization

<u>Basic Scenario:</u>
Delay- and Angle-based localization



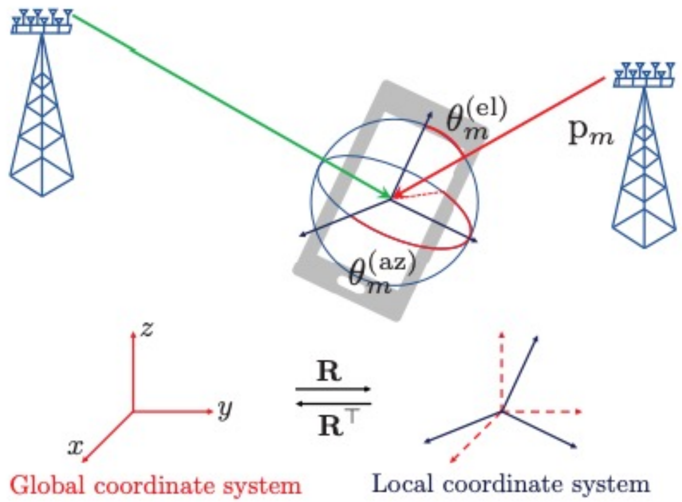
<u>Rule of Thumb:</u>
X <= Y

# of State Unknowns
<=
# of Channel Parameters

3D Orientation Estimation

State Unknowns	Channel Parameters
3D Orientation	2 AOD at BS * 2
Total: 3	Total: 4

UE is equipped with an antenna array



Maps a vector from local to global:

$$\boldsymbol{t}_g = \mathbf{R}\boldsymbol{t}_l$$
$$\boldsymbol{t}_l = \mathbf{R}^{\mathrm{T}}\boldsymbol{t}_g = \mathbf{R}^{-1}\boldsymbol{t}_g$$

An example:

$$R = R_z(\alpha)\,R_y(\beta)\,R_x(\gamma) = \overbrace{\begin{bmatrix}\cos\alpha & -\sin\alpha & 0\\ \sin\alpha & \cos\alpha & 0\\ 0 & 0 & 1\end{bmatrix}}^{\text{yaw}}\overbrace{\begin{bmatrix}\cos\beta & 0 & \sin\beta\\ 0 & 1 & 0\\ -\sin\beta & 0 & \cos\beta\end{bmatrix}}^{\text{pitch}}\overbrace{\begin{bmatrix}1 & 0 & 0\\ 0 & \cos\gamma & -\sin\gamma\\ 0 & \sin\gamma & \cos\gamma\end{bmatrix}}^{\text{roll}}$$
$$= \begin{bmatrix}\cos\alpha\cos\beta & \cos\alpha\sin\beta\sin\gamma - \sin\alpha\cos\gamma & \cos\alpha\sin\beta\cos\gamma + \sin\alpha\sin\gamma\\ \sin\alpha\cos\beta & \sin\alpha\sin\beta\sin\gamma + \cos\alpha\cos\gamma & \sin\alpha\sin\beta\cos\gamma - \cos\alpha\sin\gamma\\ -\sin\beta & \cos\beta\sin\gamma & \cos\beta\cos\gamma\end{bmatrix}$$

CRB does not work, use constrained CRB (CCRB)!

$$\mathbb{E}\left\{(\boldsymbol{\eta}-\hat{\boldsymbol{\eta}})(\boldsymbol{\eta}-\hat{\boldsymbol{\eta}})^\top\right\} \succeq \mathcal{I}_{\text{const}}^{-1}(\boldsymbol{\eta}),$$

η contains 9 unknowns

$$\mathcal{I}_{\text{const}}^{-1}(\boldsymbol{\eta}) = \mathbf{M}(\mathbf{M}^\top\mathcal{I}(\boldsymbol{\eta})\mathbf{M})^{-1}\mathbf{M}^\top, \qquad \mathbf{M} = \begin{bmatrix}-\mathbf{r}_3 & \mathbf{0}_{3\times1} & \mathbf{r}_2\\ \mathbf{0}_{3\times1} & -\mathbf{r}_3 & -\mathbf{r}_1\\ \mathbf{r}_1 & \mathbf{r}_2 & \mathbf{0}_{3\times1}\end{bmatrix}.$$

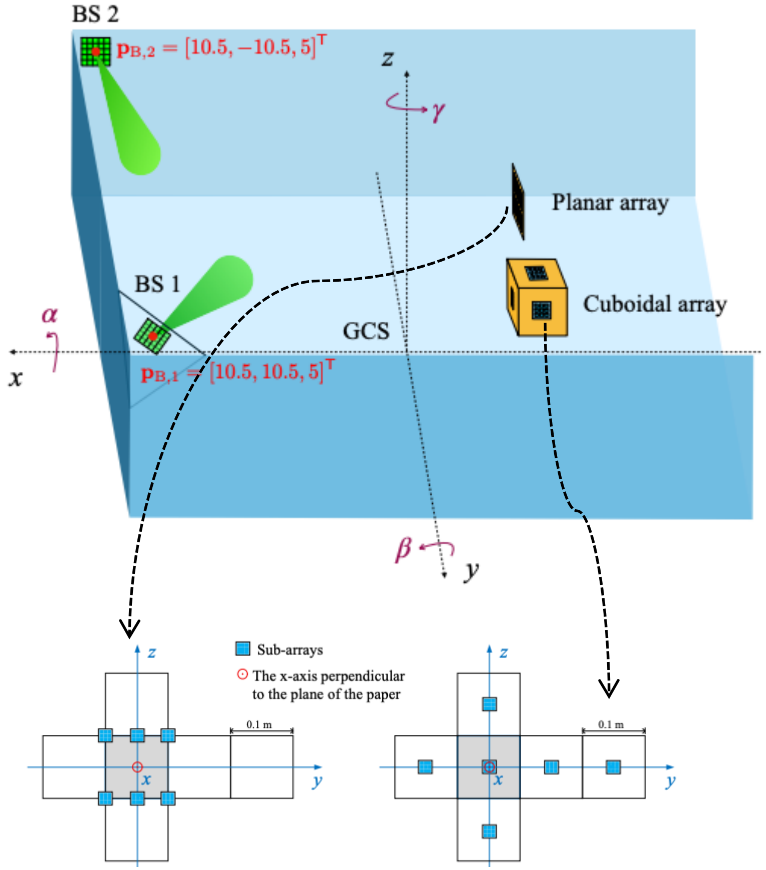
$$\mathrm{OEB} = \sqrt{\mathrm{trace}(\mathcal{I}_{\text{const}}^{-1}(\mathbf{r}))}$$
$$\leq \sqrt{\mathbb{E}\{\|\mathbf{r}-\hat{\mathbf{r}}\|\}} = \sqrt{\mathbb{E}\left\{\|\mathbf{R}-\hat{\mathbf{R}}\|_F^2\right\}}$$

OEB is defined as the error of all matrix element

Nazari, Mohammad A., Gonzalo Seco-Granados, Pontus Johannisson, and Henk Wymeersch. "3D orientation estimation with multiple 5G mmwave base stations." In ICC 2021-IEEE International Conference on Communications, pp. 1-6. IEEE, 2021.

6D Localization (3D Pos + 3D Ori)

Both Pos and Ori are unknown

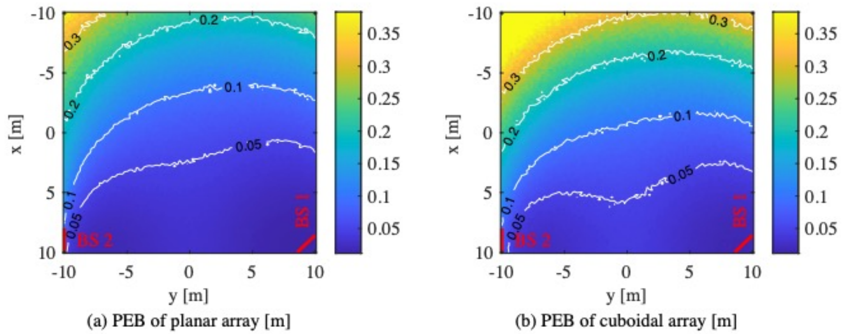


2D layout

3D layout

State Unknowns	Channel Parameters
3D Position	2 AOD at BS * 2
3D Orientation	2 AOA at UE * 2
1 clock offset	2 delay
Total: 7	Total: 10

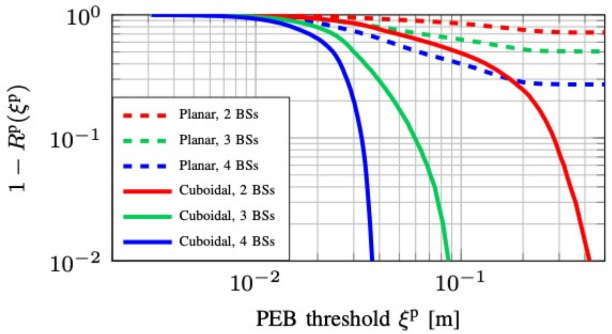
3D array vs 2D array (pros and cons)



(a) PEB of planar array [m]

(b) PEB of cuboidal array [m]

2D array has better peak performance (left figure)



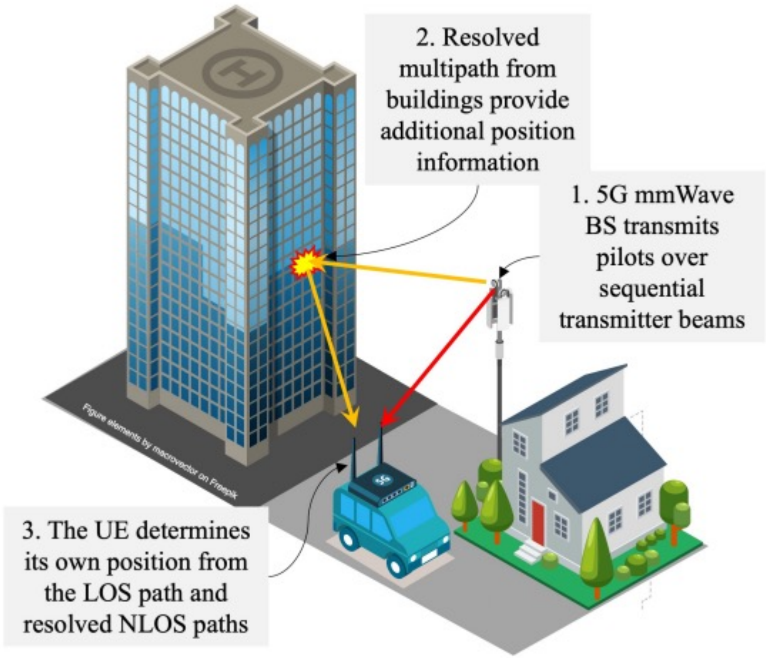
3D array has better coverage (solid curve)

Zheng, Pinjun, Tarig Ballal, Hui Chen, Henk Wymeersch, and Tareq Y. Al-Naffouri. "Coverage analysis of joint localization and communication in THz systems with 3D arrays." IEEE Transactions on Wireless Communications (2023).

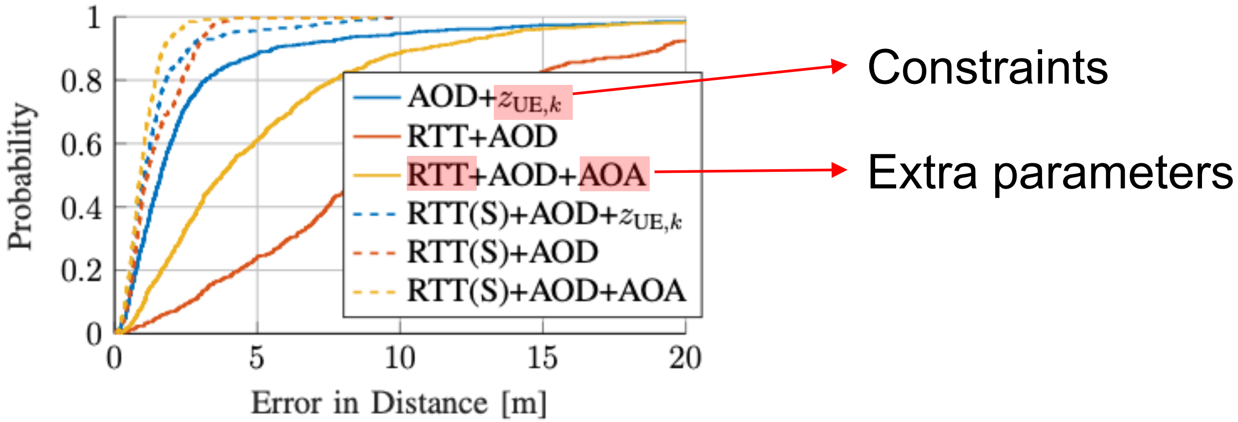
Single-BS Localization

State Unknowns	Channel Parameters
3D Position 1 Clock offset	2 AOD at BS 1 Delay
Total: 4	Total: 3

MISO: Reduced state unknowns or extra channel parameters



Extra information helps
If we know the map, channel parameters = 6
If we know the height, state unknowns = 4

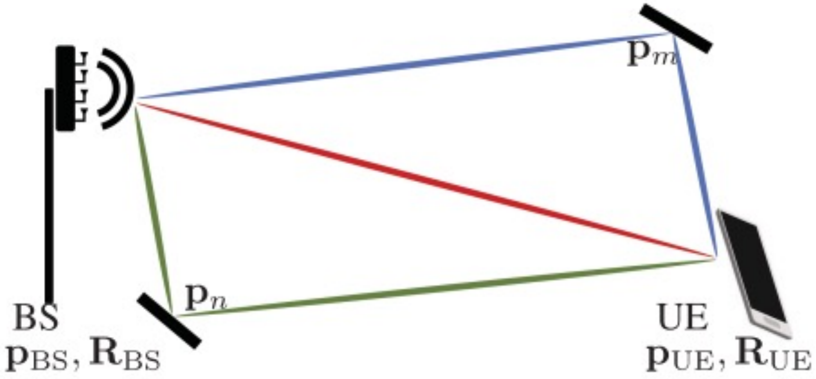


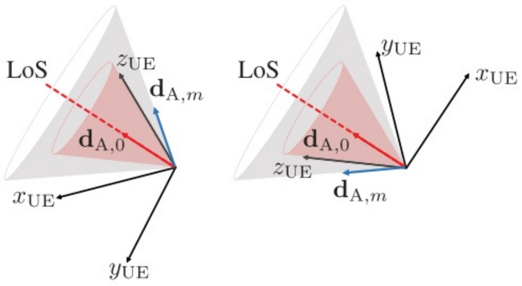
Ge, Yu, Hedieh Khosravi, Fan Jiang, Hui Chen, Simon Lindberg, Peter Hammarberg, Hyowon Kim et al. "Experimental validation of single BS 5G mmWave positioning and mapping for intelligent transport." *arXiv preprint arXiv:2303.11995* (2023).

Single-BS Localization and Mapping

MIMO: 6D localization and mapping

State Unknowns	Channel Parameters
3D Pos + 3D Ori	2 AOD per path
1D clock offset	1 Delay per path
3D Pos * # NLOS	2 AOA per path
Total: 7+3L	Total: 5(L+1)





1D search Ad-hoc algorithm is proposed

Resolvable NLOS paths provide net information gain

$$\mathbf{J}^{\mathrm{e}}_{\breve{\eta}_{\mathbf{p},\alpha}} = \underbrace{\mathbf{A}\mathbf{J}_{\bar{\eta}_{\mathrm{LOS}}}\mathbf{A}^{\mathrm{T}}}_{\triangleq \tilde{\mathbf{A}}^{(\mathrm{G})} \text{ - LOS info gain}} + \underbrace{\mathbf{B}\mathbf{J}_{\bar{\eta}_{\mathrm{NLOS}}}\mathbf{B}^{\mathrm{T}}}_{\triangleq \tilde{\mathbf{B}}^{(\mathrm{G})} \text{ - NLOS info gain}} \underbrace{- \mathbf{B}\mathbf{J}_{\bar{\eta}_{\mathrm{NLOS}}}\mathbf{D}^{\mathrm{T}}(\mathbf{D}\mathbf{J}_{\bar{\eta}_{\mathrm{NLOS}}}\mathbf{D}^{\mathrm{T}})^{-1}\mathbf{D}\mathbf{J}_{\bar{\eta}_{\mathrm{NLOS}}}\mathbf{B}^{\mathrm{T}}}_{\triangleq \tilde{\mathbf{B}}^{(\mathrm{L})} \text{ - NLOS info loss}}.$$

Each NLOS path provides 1D Fisher information (2D in 3D space)

We define $\tilde{\mathbf{B}}^{(N)} \triangleq \sum_{k=1}^{K-1} \boldsymbol{\Psi}_{\mathbf{s}_k}$, where

$$\boldsymbol{\Psi}_{\mathbf{s}_k} \triangleq \epsilon_{\mathbf{s}_k}\boldsymbol{\Upsilon}_{0,0}(\theta_{\mathrm{TX},0},0,0) + \beta_{\mathbf{s}_k}\boldsymbol{\Upsilon}_{1,1}(\theta_{\mathrm{RX},k},\pi/2,\|\mathbf{p}-\mathbf{q}\|) + \gamma_{\mathbf{s}_k}\mathbf{B}^{(\mathrm{L})}_k.$$

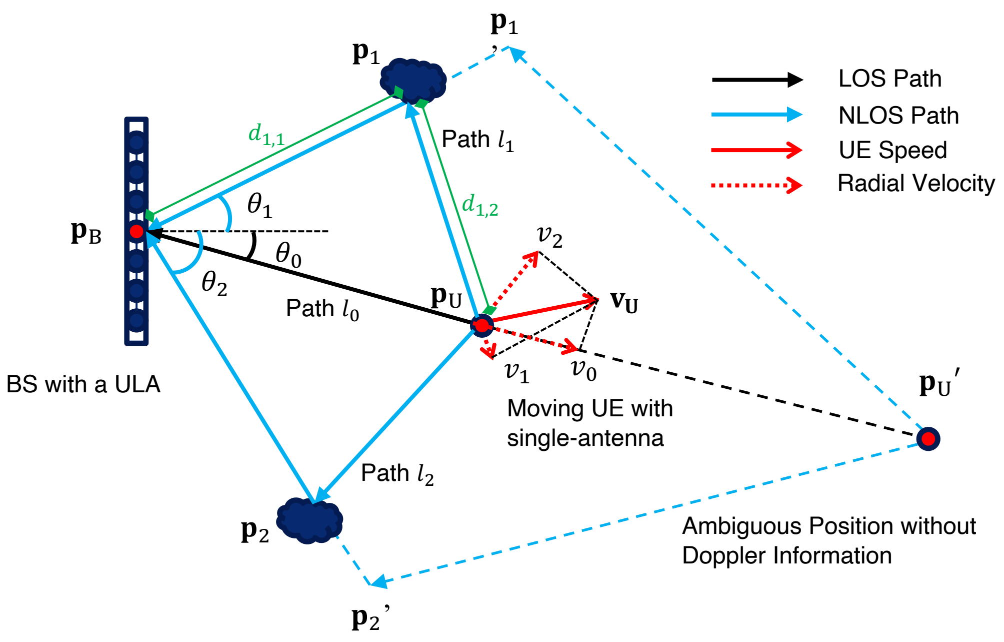
Nazari, Mohammad A., Gonzalo Seco-Granados, Pontus Johannisson, and Henk Wymeersch. "MmWave 6D radio localization with a snapshot observation from a single BS." IEEE Transactions on Vehicular Technology (2023).

Mendrzik, Rico, Henk Wymeersch, Gerhard Bauch, and Zohair Abu-Shaban. "Harnessing NLOS components for position and orientation estimation in 5G millimeter wave MIMO." IEEE Transactions on Wireless Communications 18, no. 1 (2018): 93-107.

Localization and Mapping under Mobility

State Unknowns	Channel Parameters
2D Position 1 Clock offset 2D Velocity 2D Pos of SPs	1 AOA per path 1 Delay per path 1 Doppler per path
Total: 5+2L	Total: 3+3L

MISO: Localization and mapping under mobility



Single-antenna SLAM with UE-BS clock offset?

- Not possible when stationary. ☹
- Possible with mobility! ☺

Doppler provide extra dimension of infomation

$$\mathbf{h}_{g,k} = \sum_{l=0}^{L} \rho_l \mathbf{a}_\mathrm{B}(\theta_l) e^{-j2\pi\Delta_f k\tau_l} e^{j2\pi g T_\mathrm{int} v_l/\lambda}$$

Phase changes accross transmissions (Doppler)

Phase changes across subcarriers (Delay)

Steering vector (Angle of Departure)

Channel gain (nuisance unknown)

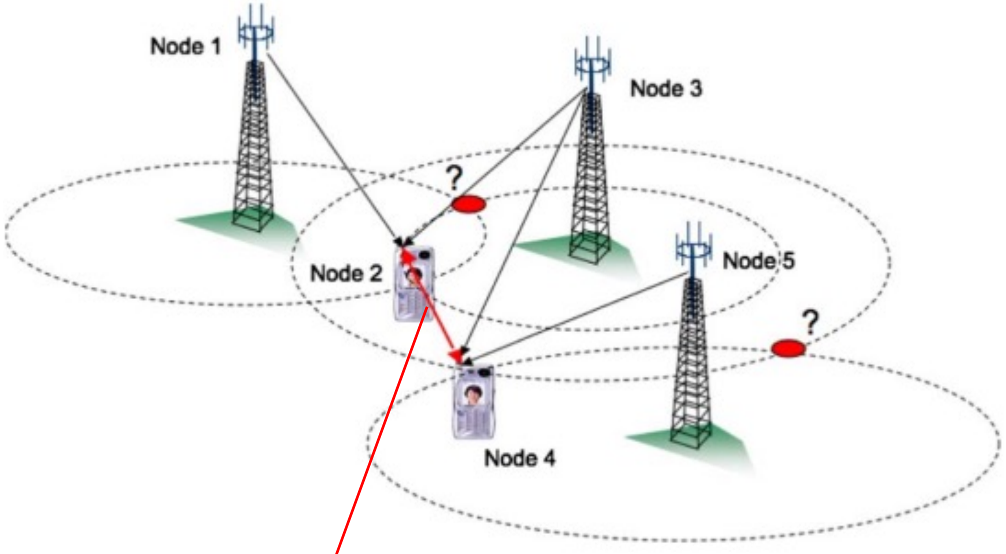
LOS path ($l = 0$) and NLOS paths

Chen, Hui, Fan Jiang, Yu Ge, Hyowon Kim, and Henk Wymeersch. "Doppler-enabled single-antenna localization and mapping without synchronization." In GLOBECOM 2022-2022 IEEE Global Communications Conference, pp. 6469-6474. IEEE, 2022.

Single-BS and multiple UEs

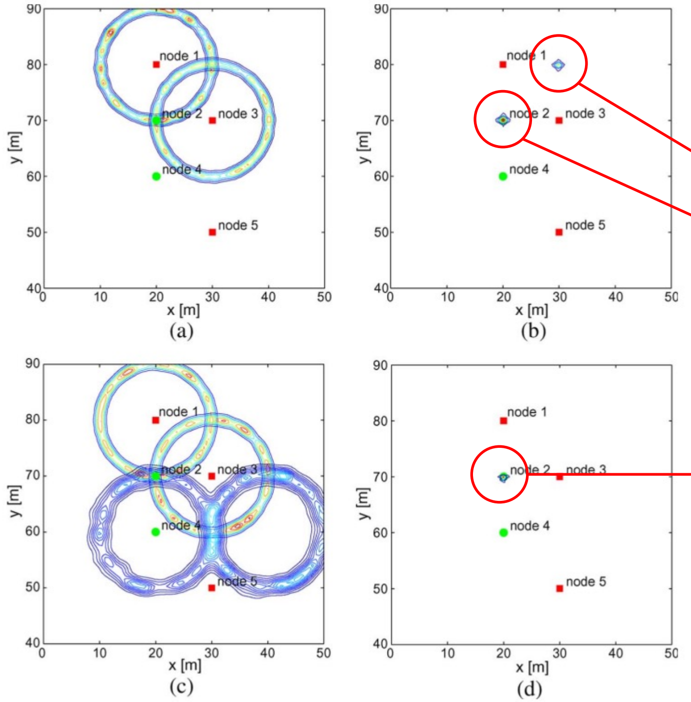
State Unknowns	Channel Parameters
N*3D Position N Clock offset	N delay at BS N choose 2 links
Total: 4N	Total: N + $C(N,2)$

Cooperative Localization



Extra information between UEs can assist localization.

An example of removing ambiguity:



Ambiguity can be removed by an extra node (of course there is a lot of math behind it)

Wymeersch, Henk, Jaime Lien, and Moe Z. Win. "Cooperative localization in wireless networks." *Proceedings of the IEEE* 97, no. 2 (2009): 427-450.

RIS-aided Localization

State Unknowns	Channel Parameters
3D Position 1 Clock offset	2 Delays 2 AOD at RIS
Total: 4	Total: 4

SISO: but RIS works as an anchor with an antenna array

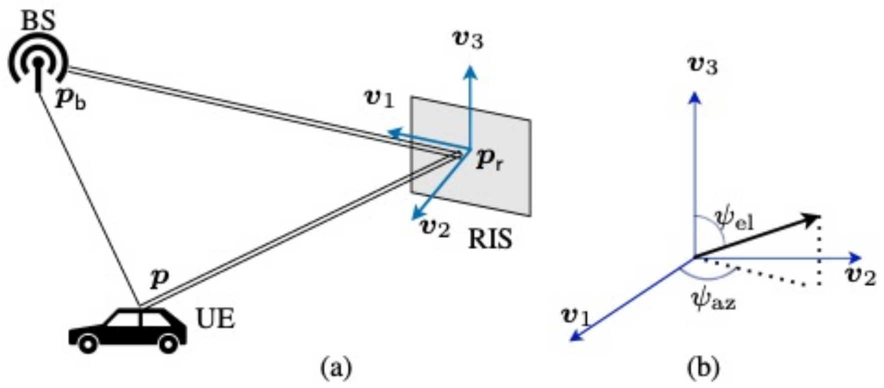


Fig. 1: (a): System setup, (b): Elevation and azimuth angles of a vector.

With known RIS and BS states, signal directions between RIS and UE can be obtained (e.g., beam sweeping).

Signal model:

$$\boldsymbol{Y} = g_{\mathrm{b}}\sqrt{E_{\mathrm{s}}}\boldsymbol{d}(\tau_{\mathrm{b}})\boldsymbol{1}_T^\top + g_{\mathrm{r}}\sqrt{E_{\mathrm{s}}}\boldsymbol{d}(\tau_{\mathrm{r}})\boldsymbol{u}(\boldsymbol{\phi})^\top + \boldsymbol{N},$$

LOS + RIS path

$$\boldsymbol{d}(\tau) = [1, e^{-j2\pi\tau\Delta f}, \dots, e^{-j2\pi\tau(N-1)\Delta f}]^\top$$

Delay

$$\begin{aligned}[\boldsymbol{u}(\boldsymbol{\phi})]_t &= (\boldsymbol{a}(\boldsymbol{\theta}))^\top \operatorname{diag}(\boldsymbol{\gamma}_t)\boldsymbol{a}(\boldsymbol{\phi}) \\ &= \left(\boldsymbol{\gamma}_t^\top \odot (\boldsymbol{a}(\boldsymbol{\theta}))^\top\right)\boldsymbol{a}(\boldsymbol{\phi})\end{aligned}$$

AOD & AOA at RIS

Keykhosravi, Kamran, Musa Furkan Keskin, Gonzalo Seco-Granados, and Henk Wymeersch. "SISO RIS-enabled joint 3D downlink localization and synchronization." In ICC 2021-IEEE International Conference on Communications, pp. 1-6. IEEE, 2021.

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Near-field Localization and Sensing

Recall the rule of thumb, will it always work?

It works for simple estimation models (linear phase change across a certain dimension) under some technical constraints (e.g., 'resolvable').

- Delay resolution: 1/bandwidth
- Angular resolution: wavelength/physical array size

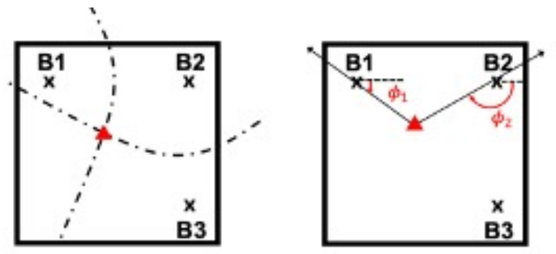
It does not work (or performance degrades) for:

- Complicated environment (rich-scattering, non-resolvable)
- Non-linear phase change (e.g., near-field model)
- Other non-geometrical unknowns (e.g., hardware impairment)

What to do then?

1. New model   2. AI-based solution

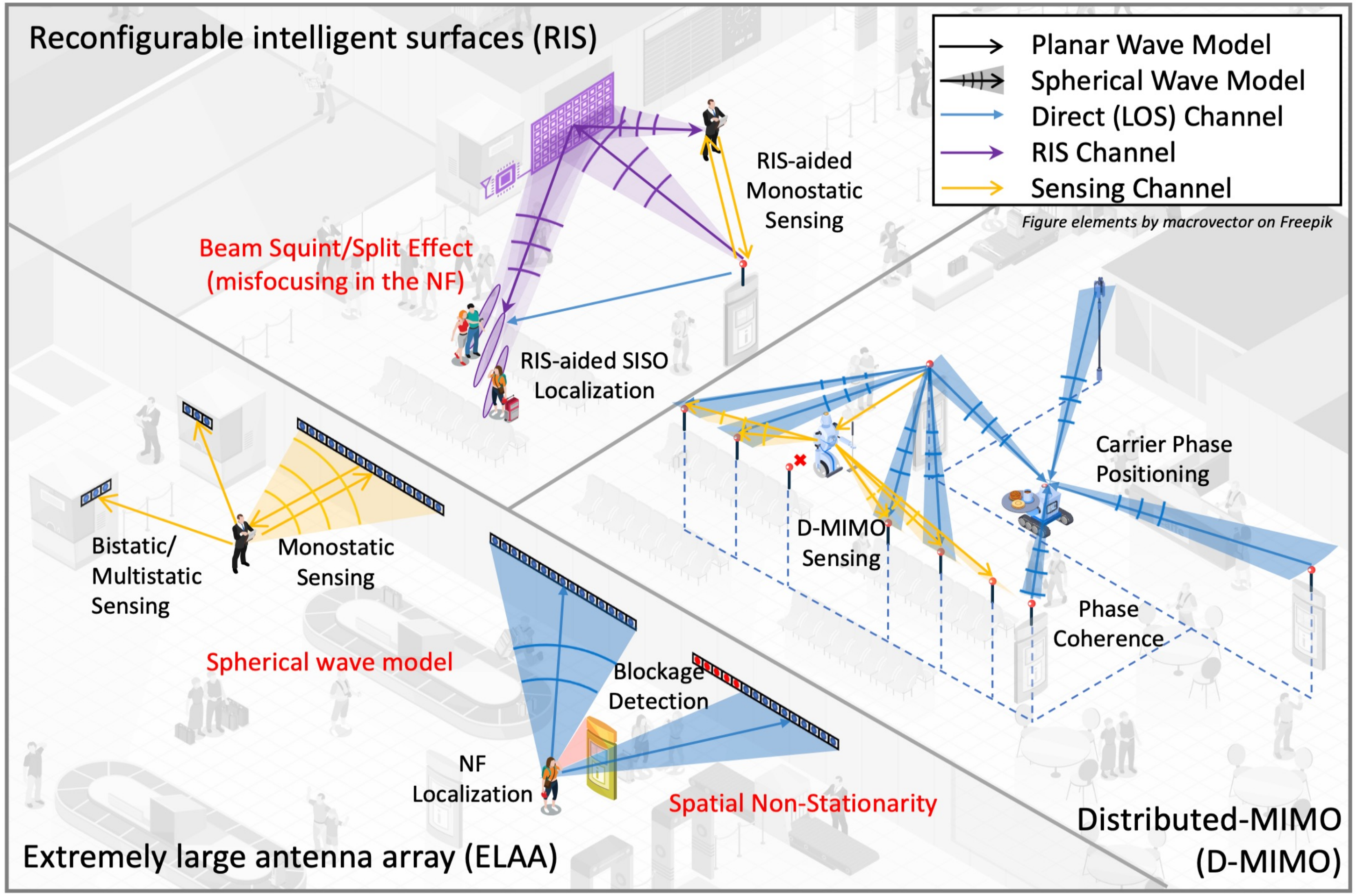
Basic Scenario:
Delay- and Angle-based localization



Rule of Thumb:
X <= Y

# of State Unknowns
<=
# of Channel Parameters

Near-field Localization and Sensing



Is conventional simplified model still sufficient?

- SNS: Spatial non-stationarities
- SWM: Spherical wave model
- BSE: Beam squint effect

Ignore NF features:

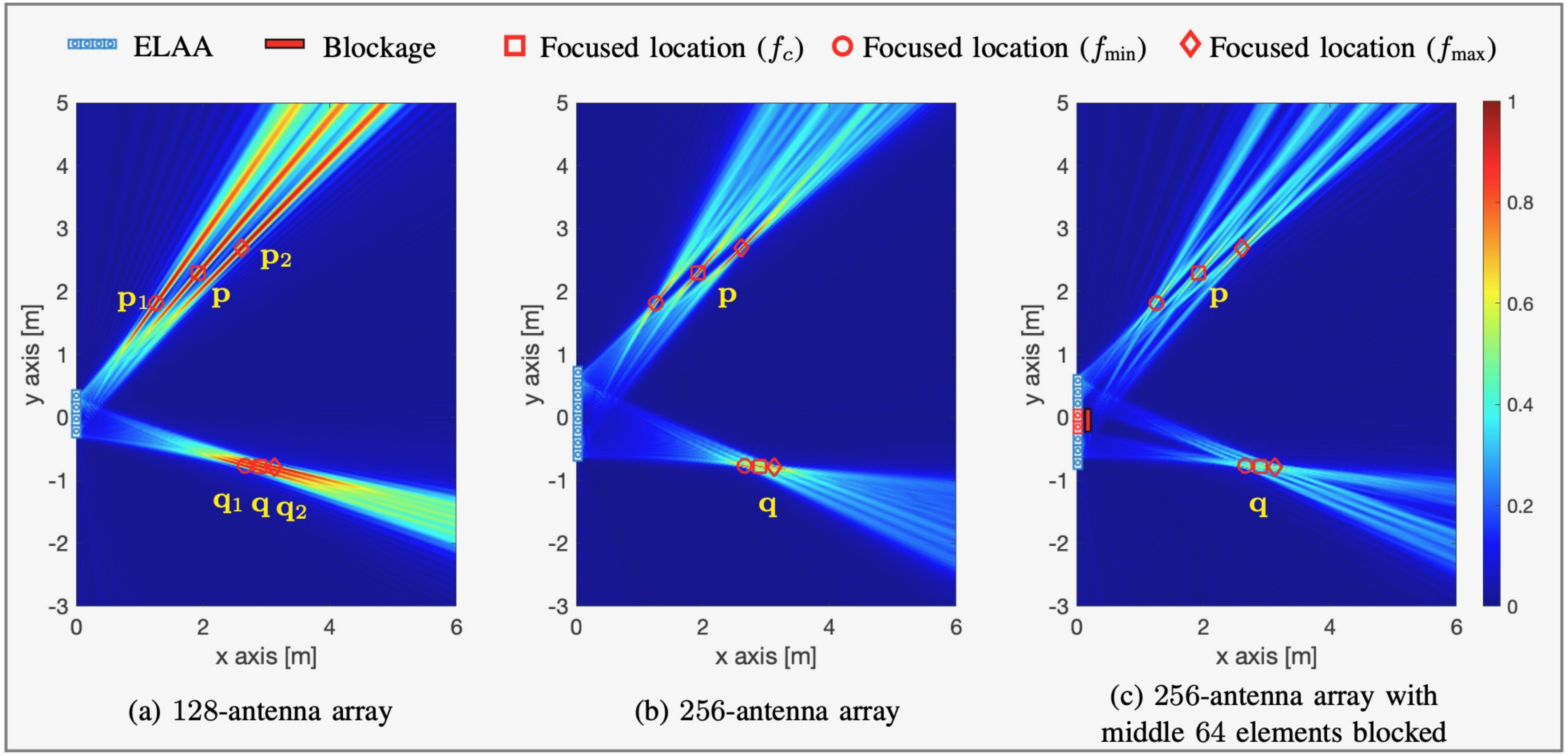
- Performance degradation caused by model mismatch

Take advantage of NF features:

- Performance gain and new application

Chen, Hui, Musa Furkan Keskin, Adham Sakhnini, Nicoló Decarli, Sofie Pollin, Davide Dardari, and Henk Wymeersch. "6G localization and sensing in the near field: Fundamentals, opportunities, and challenges." IEEE Wireless Communications (2023).

Near-field Localization and Sensing



30 GHz carrier frequency

4G bandwidth

Target at **p** and **q**

- SWM: beam focusing with small angles and large arrays
- BSE: large angles, edge subcarrier
- SNS: affect beam focusing performance

Chen, Hui, Musa Furkan Keskin, Adham Sakhnini, Nicoló Decarli, Sofie Pollin, Davide Dardari, and Henk Wymeersch. "6G localization and sensing in the near field: Fundamentals, opportunities, and challenges." IEEE Wireless Communications (2023).

Near-field Localization and Sensing

- 2D uplink SIMO system, LOS only
- Perfectly synchronized
- K subcarriers, G transmissions

Received symbol vector: $\mathbf{y}_{g,k} = \mathbf{W}_g^\top \mathbf{h}_k x_{g,k} + \mathbf{W}_g^\top \mathbf{n}_{g,k}$

Mismatched model (MM)

Channel gain (nuisance unknown)

Steering vector (Angle of Arrival)

Phase changes across subcarriers (Delay)

$$\mathbf{h}_k^{\mathrm{MM}} = \alpha \mathbf{a}(\vartheta) D_k(\tau)$$

$$\alpha = \rho e^{-j\xi} = \frac{\lambda_c}{4\pi\|\mathbf{p}\|} e^{-j\xi}$$

$$\mathbf{a}(\vartheta) = [e^{-j\pi\frac{N-1}{2}\sin(\vartheta)}, \dots, 1, \dots, e^{-j\pi\frac{1-N}{2}\sin(\vartheta)}]^\top$$

$$D_k(\tau) = e^{-j2\pi(f_c + k\Delta_f)\tau} = D_k(\mathbf{p}) = e^{-j\frac{2\pi}{\lambda_k}\|\mathbf{p}\|}$$

True model (TM)

$$\mathbf{b}_n = [0, (2n-N-1)\lambda_c/4]^\top$$

Include SNS, SWM, BSE

$$\mathbf{h}_k^{\mathrm{TM}} = \boldsymbol{\alpha}_k(\mathbf{p}) \odot \mathbf{d}_k(\mathbf{p}) D_k(\mathbf{p}),$$

$$\alpha_{k,n}(\mathbf{p}) = \alpha\, c_{k,n}(\mathbf{p}), \quad c_{k,n}(\mathbf{p}) = \frac{\lambda_k \|\mathbf{p}\|}{\lambda_c \|\mathbf{p} - \mathbf{b}_n\|},$$

SNS

$$d_{k,n}(\mathbf{p}) = e^{-j\frac{2\pi}{\lambda_k}(\|\mathbf{p}-\mathbf{b}_n\| - \|\mathbf{p}\|)}$$

BSE

SWM

Chen, Hui, Ahmed Elzanaty, Reza Ghazalian, Musa Furkan Keskin, Riku Jäntti, and Henk Wymeersch. "Channel model mismatch analysis for XL-MIMO systems from a localization perspective." In GLOBECOM 2022-2022 IEEE Global Communications Conference, pp. 1588-1593. IEEE, 2022.

Simulation – Estimators vs. Lower Bounds

Estimators vs. Lower Bounds

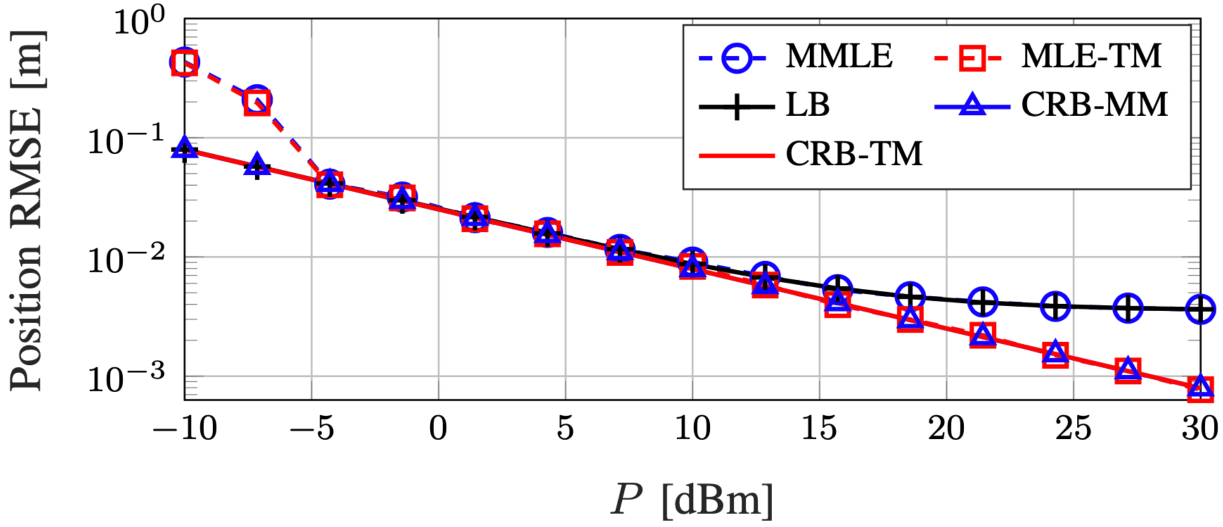
- MMLE and MLE
- LB, CRB-MM, CRB-TM
- UE located at [2, 2]
- 500 simulations per point

Main findings

- CRB-TM and CRB-MM are similar for this scenario (blue triangle and red solid curve)
- LB saturates at a certain level of transmit power (around 20 dBm)
- The derived LB aligns well with the estimator (MMLE), verifying the effectiveness of using MCRB as an analysis tool.

Lower Bound under Mismatch

$$\mathrm{LB} = \mathrm{LB}(\bar{\boldsymbol{\theta}}, \boldsymbol{\theta}_0) = \underbrace{\mathbf{A}_{\boldsymbol{\theta}_0}^{-1}\mathbf{B}_{\boldsymbol{\theta}_0}\mathbf{A}_{\boldsymbol{\theta}_0}^{-1}}_{\mathrm{MCRB}(\boldsymbol{\theta}_0)} + \underbrace{(\bar{\boldsymbol{\theta}} - \boldsymbol{\theta}_0)(\bar{\boldsymbol{\theta}} - \boldsymbol{\theta}_0)^\top}_{\mathrm{Bias}(\boldsymbol{\theta}_0)}$$

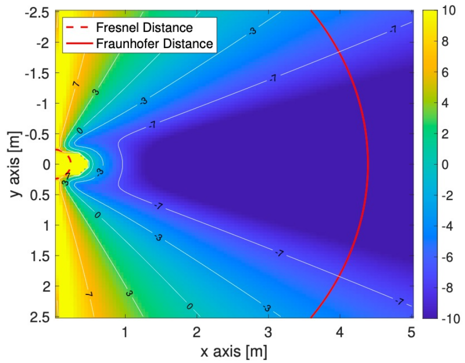


Comparison between simulation results and the derived lower bounds (LB, CRB-TM, and CRB-MM).

Numerical Results – Different System Parameters

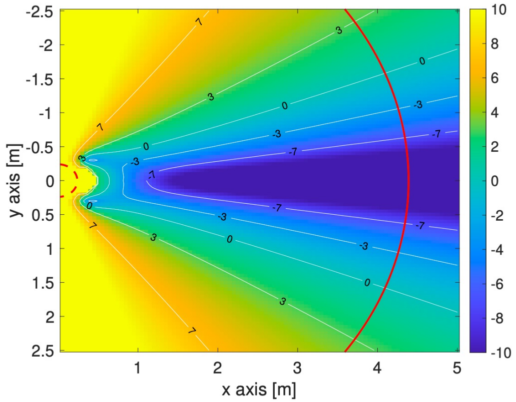
MME for Different System Parameters

- Benchmarked by
  - Digital
  - G = 1
  - P = 20 dBm
  - N = 64

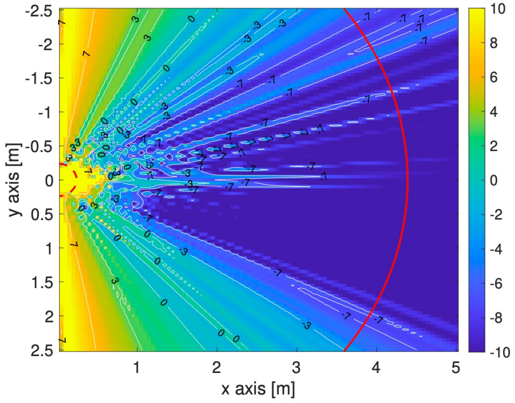


Main findings:

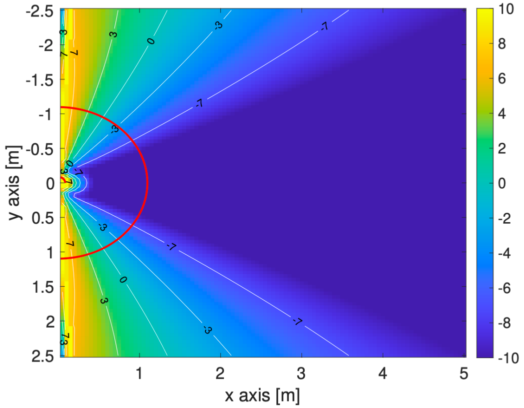
- Mismatch is getting larger with a large P
- Similar pattern can be seen in an analog array when compared with a digital array
- Mismatch area (yellow) reduced with a small N
- Mismatch area (yellow) reduced with a small bandwidth



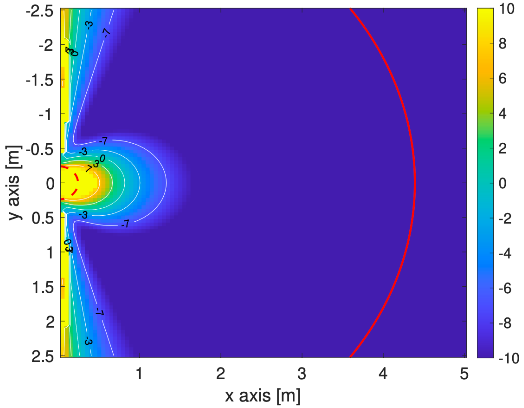
(a) $P = 30\,\mathrm{dBm}$



(b) Analog, $G = 50$



(c) $N = 32$



(d) $W = 100\,\mathrm{MHz}$

Visualization of relative mismatch error MME-PEB (benchmarked by the MME-PEB in Fig. 3 (a)) for different scenarios:

Localization under Hardware Impairment

Motivation

- Hardware impairments (HWIs) will be a crucial factor limiting the performance of (beyond 100 GHz) 6G joint localization and communication systems
  - Communication: HWIs affect end-to-end channel
  - Localization: HWIs affect geometric information in the channel
- Several Questions:
  - What are the relevant HWIs and how to model them?
  - How to evaluate the effect of HWIs on system performance?
  - How do different types of HWIs degrade system performance?

Solution: HWI modeling and performance analysis (overall and individual HWIs)

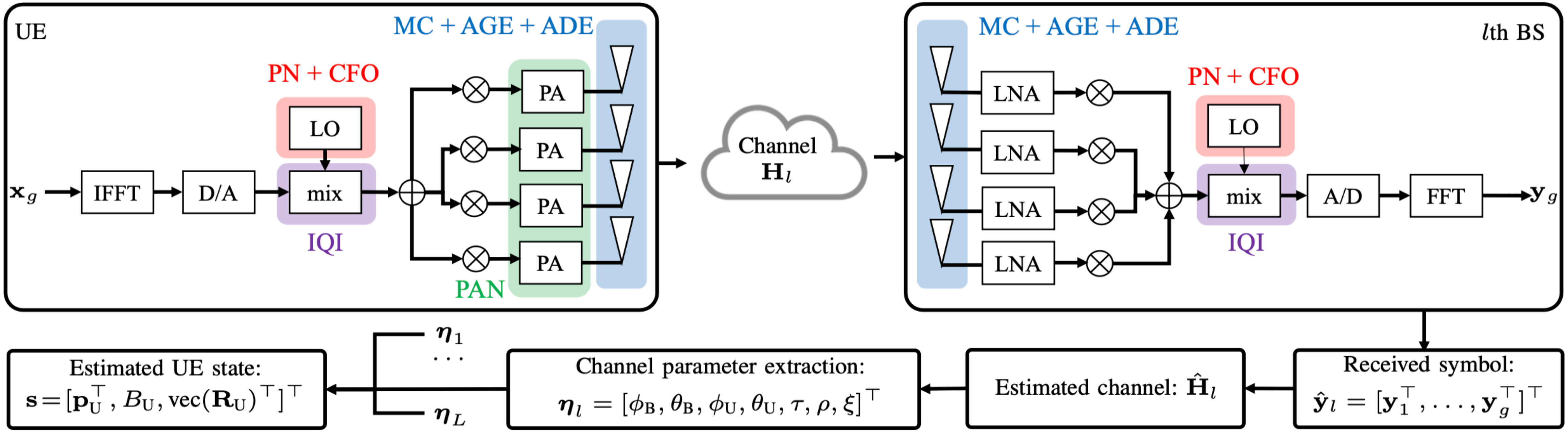
- Localization: analyze error lower bound under mismatch misspecified CRB (position and orientation error)
- Communication: approximate into additive Gaussian noise (symbol error rate)

Chen, Hui, Musa Furkan Keskin, Sina Rezaei Aghdam, Hyowon Kim, Simon Lindberg, Andreas Wolfgang, Traian E. Abrudan, Thomas Eriksson, and Henk Wymeersch. "Modeling and Analysis of OFDM-based 5G/6G Localization under Hardware Impairments." *IEEE Transactions on Wireless Communications* (2023).

System Model

3D, uplink, analog, MIMO: L BSs + 1 UE with clock offset

PN: Phase Noise
CFO: Carrier Frequency Offset
PA: Power Amplifier Nonlinearity
MC: Mutual Coupling
AGE: Array Gain Error
ADE: Antenna Displacement Error
IQI: In-phase and Quadrature Imbalance



System Model - HWI-free model

- 3D uplink, analog, MIMO system
- Multiple BSs, 1 UE
- K subcarriers, G transmissions

HWI-free channel model (for a specific BS-UE link)

Received symbol: $y_{g,k} = \mathbf{w}_g^\top \mathbf{H}_k \mathbf{v}_g x_{g,k} + n_{g,k}$

Channel matrix: $\mathbf{H}_k = \alpha D_k(\tau) \mathbf{a}_\mathrm{B}(\phi_\mathrm{B}, \theta_\mathrm{B}) \mathbf{a}_\mathrm{U}^\top(\phi_\mathrm{U}, \theta_\mathrm{U})$

Steering vector at UE(Angle of Departure) $\mathbf{a}_\mathrm{U}(\theta_\mathrm{U}, \phi_\mathrm{U}) = e^{j\frac{2\pi f_c}{c}\tilde{\mathbf{D}}_\mathrm{U}^\top \tilde{\mathbf{t}}_\mathrm{U}}$

Steering vector at BS (Angle of Arrival) $\mathbf{a}_\mathrm{B}(\theta_\mathrm{B}, \phi_\mathrm{B}) = e^{j\frac{2\pi f_c}{c}\tilde{\mathbf{D}}_\mathrm{B}^\top \tilde{\mathbf{t}}_\mathrm{B}}$

Phase change across subcarriers (Delay) $D_k(\tau) = e^{-j2\pi k \Delta_f \tau}$

Complex channel gain (nuisance unknown) $\alpha = \rho e^{-j\xi}$

Very well structured in the HWI-free model ! ☺

System Model - Impaired model

Signal model with the considered HWIs

$$\underbrace{\mathbf{y}_g}_{(\in\mathcal{C}^{K\times 1})} = \mathbf{F}\big(\underbrace{\alpha_\mathrm{B}}_{\text{IQI, Rx}}\big(\underbrace{\mathbf{E}_{\mathrm{B},g}\boldsymbol{\Xi}_{\mathrm{B},g}}_{\text{PN+CFO, Rx}}\mathbf{F}^\mathsf{H}(\underbrace{\check{\mathbf{X}}_g\check{\mathbf{H}}^\top\mathbf{w}_g\odot\mathbf{d}(\tau)}_{\check{\mathbf{y}}_g=(\mathbf{w}_g^\top\check{\mathbf{H}}\check{\mathbf{X}}_g^\top)^\top\odot\mathbf{d}(\tau)})\big)\big) + \underbrace{\beta_\mathrm{B}}_{\text{IQI, Rx}}\big(\underbrace{\mathbf{E}_{\mathrm{B},g}\boldsymbol{\Xi}_{\mathrm{B},g}}_{\text{PN+CFO, Rx}}\mathbf{F}^\mathsf{H}(\check{\mathbf{X}}_g\check{\mathbf{H}}^\top\mathbf{w}_g\odot\mathbf{d}(\tau))\big)^*\big) + \mathbf{n}_g$$

$$\underbrace{\check{\mathbf{H}}}_{(\in\mathcal{C}^{N_\mathrm{B}\times N_\mathrm{U}})} = \alpha\underbrace{\mathbf{C}_\mathrm{B}}_{\text{MC, Rx}}\Big(\underbrace{\overbrace{\boldsymbol{b}_\mathrm{B}(\boldsymbol{\varphi}_\mathrm{B})}^{\text{AGE, Rx}}\odot e^{j\frac{2\pi}{\lambda}\overbrace{\tilde{\mathbf{D}}_\mathrm{B}^\top}^{\text{ADE, Rx}}\tilde{\mathbf{t}}_\mathrm{B}(\boldsymbol{\varphi}_\mathrm{B})}}_{\text{steering vector at Rx, }\tilde{\mathbf{a}}_\mathrm{B}(\boldsymbol{\varphi}_\mathrm{B})}\Big)\Big(\underbrace{\overbrace{\boldsymbol{b}_\mathrm{U}(\boldsymbol{\varphi}_\mathrm{U})}^{\text{AGE, Tx}}\odot e^{j\frac{2\pi}{\lambda}\overbrace{\tilde{\mathbf{D}}_\mathrm{U}^\top}^{\text{ADE, Tx}}\tilde{\mathbf{t}}_\mathrm{U}(\boldsymbol{\varphi}_\mathrm{U})}}_{\text{steering vector at U, }\tilde{\mathbf{a}}_\mathrm{U}(\boldsymbol{\varphi}_\mathrm{U})}\Big)\underbrace{\mathbf{C}_\mathrm{U}^\top}_{\text{MC, Tx}}$$

$$\underbrace{\check{\mathbf{X}}_g}_{(\in\mathcal{C}^{K\times N_\mathrm{U}})} = \mathbf{F}^H\underbrace{\mathbf{h}_\mathrm{PA}}_{\text{PA, only Tx}}\big(\underbrace{\overbrace{\mathbf{E}_\mathrm{U}\boldsymbol{\Xi}_\mathrm{U}}^{\text{PN+CFO, Tx}}(\overbrace{\alpha_\mathrm{U}}^{\text{IQI, Tx}}\mathbf{F}^\mathsf{H}\mathbf{x}_g + \overbrace{\beta_\mathrm{U}}^{\text{IQI, Tx}}\mathbf{F}^\mathsf{H}\mathbf{x}_g^*)\mathbf{v}_g}_{\text{time domain signal before PA}}\big)$$

PN: Phase Noise
CFO: Carrier Frequency Offset
MC: Mutual Coupling
PA: Power Amplifier Nonlinearity
AGE: Array Gain Error
ADE: Antenna Displacement Error
IQI: In-phase and Quadrature Imbalance

The impairment level (except PA) is controlled by a coefficient.

E.g., Residual PN $\omega_{g,k}\sim\mathcal{N}(0,\sigma^2_\mathrm{PN})$, Residual CFO $\epsilon\sim\mathcal{N}(0,\sigma^2_\mathrm{CFO})$

More complicated than the previous one ! ☹

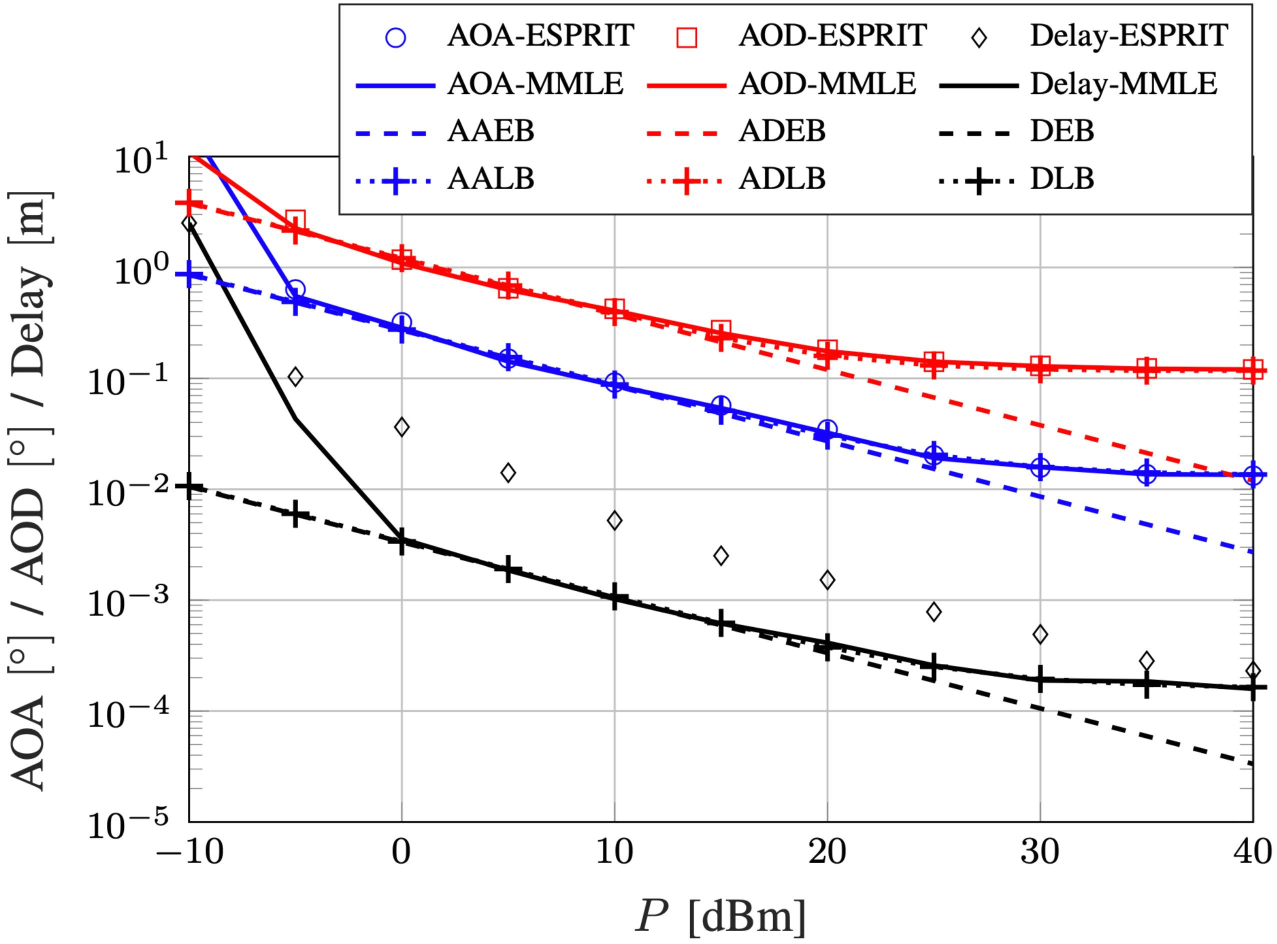
Initial Results: Channel Parameter Estimation

Bounds vs. estimators for channel estimation

- Two estimators: ESPRIT, MMLE (markers vs. solid)
- Two bounds: CRB, LB (dashed vs. dotted cross)

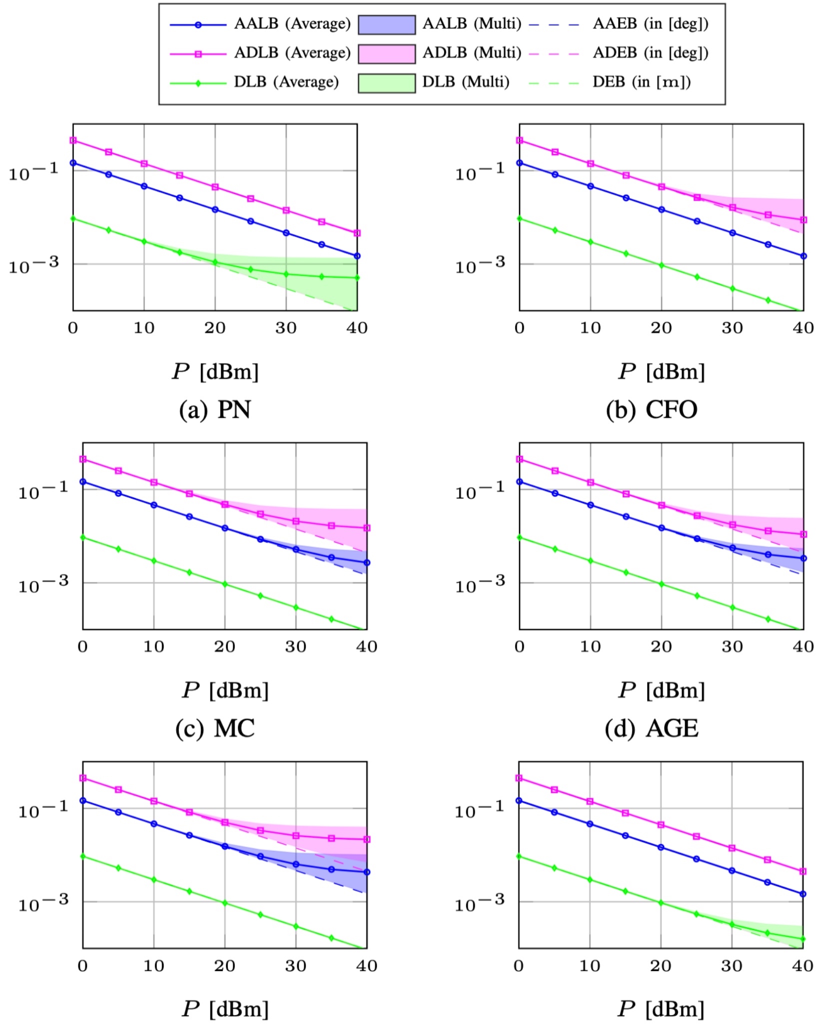
Main findings

- CRBs (AAEB, ADEB, DEB)of the ideal model decrease with transmit power
- LBs will saturate (equals to a constant) in high transmit power
- Refined results using MMLE (initialized with ESPRIT estimation) can attach the derived LB



AOA, AOD, Delay estimation

Localization under Hardware Impairment



(a) PN (b) CFO (c) MC (d) AGE (e) ADE (f) IQI

TABLE III
THE EFFECTS OF HWIS ON LOCALIZATION AND COMMUNICATIONS

Type of HWI	AOD	AOA	TOA	SER
Phase Noise	L	L	H	H
Carrier Frequency Offset	H*	H*	L	L
Mutual Coupling	H	H	L	L
Power Amplifier Nonlinearity	H*	H*	H*	H*
Array Gain Error	H	H	L	L
Antenna Displacement Error	H	H	L	L
IQ Imbalance	L	L	H	H

*The effect of CFO on angle estimations depends on the sweeping order and number of transmissions. The effect of PAN depends on the transmit power and the nonlinear region of the amplifier.

Chen, Hui, Musa Furkan Keskin, Adham Sakhnini, Nicoló Decarli, Sofie Pollin, Davide Dardari, and Henk Wymeersch. "6G localization and sensing in the near field: Fundamentals, opportunities, and challenges." IEEE Wireless Communications (2023).

Model-based vs. learning-based

Model-based localization:
Channel contains geometry information, which can be used to estimate the position of the UE (and possibly surrounding objects)

y = h(p)x + n --> h(p) --> p

Learning-based:
depending on dataset and problem formulation

1. Supervised learning: Fingerprinting (FP) to learn p = f(h)
   Train: {y + p}, Test: {y --> p}

2. Unsupervised learning: Channel charting (CC) to learn p' = f(h)
   FP: CC: Train: {y}, Test: {y --> p'}

3. Semi-supervised learning: CC with side (or label) information to learn p = f(h)
   SSL: Train: {y + some p} | Test: {y --> p, p'}

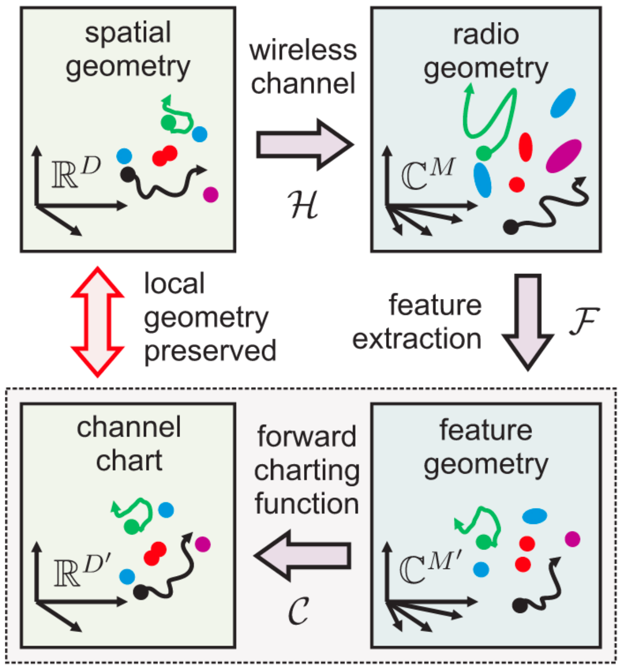
4. Reinforcement learning: trail and error for optimization problem to learn x such that E(p) is maximized
   RL: Environment {y = h(p)x + n, state {p}, action {x} + Reward {p error/CRB} | Test: {p --> x}

y (or h)	-->	h'	-->	p'	-->	p
Received signal		ambient feature		latent feature		position

Estimation: From supervised learning to semi-supervised learning.

Optimization: Reinforcement learning can help.

Channel Charting



$|\mathcal{S}| = N$. Given another space $\mathcal{Y} \subset \mathbb{R}^d$ with $d < D$, classical dimensionality reduction consists in assigning coordinates $\boldsymbol{y}_i \in \mathcal{Y}$ to the i-th sample of X (denoted by $\boldsymbol{x}_i$), such that

$$\|\boldsymbol{y}_i - \boldsymbol{y}_j\| \approx d(\boldsymbol{x}_i, \boldsymbol{x}_j), \quad \text{for } (i,j) \in \mathcal{T} \subset \mathcal{S}^2 \qquad (1)$$

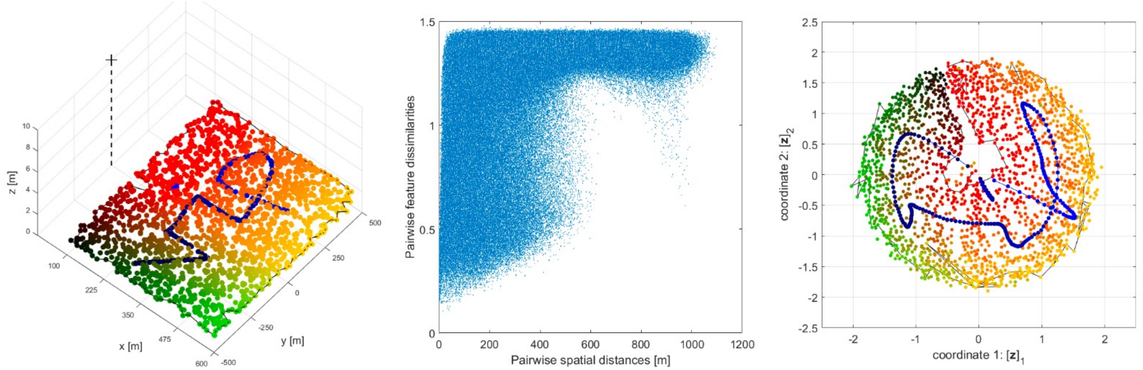
where $\|\cdot\|$ denotes the Euclidean norm on the latent space $\mathbb{R}^d$, and $d(\cdot,\cdot)$ denotes a distance in the ambient space $\mathbb{R}^D$.

$$E = \frac{1}{2N}\sum_{n=1}^{N} \|\mathbf{f}_n - \mathcal{C}^{-1}(\mathcal{C}(\mathbf{f}_n))\|_2^2 + \frac{\beta}{2}\|\mathbf{W}_{\text{enc}}^{(5)}\|_F^2$$

Algorithms:
principal component analysis, Sammon's mapping, autoencoder

Performance metrics:
Continuity measures whether neighbors in the original space are preserved in the representation space.
Trustworthiness measures how well the feature mapping avoids introducing new neighbor relationships.

Pros and Cons:
- Without labeling data, useful for handover
- Cannot provide absolute position



(a) 3D view on the considered system scenario. (b) True distances vs. feature dissimilarities. (c) Learned channel chart.

Studer, Christoph, Saïd Medjkouh, Emre Gonultaş, Tom Goldstein, and Olav Tirkkonen. "Channel charting: Locating users within the radio environment using channel state information." *IEEE Access* 6 (2018): 47682-47698.

Siamese Neural Network

Sammon's mapping:

- high->low dimension, retaining pairwise distance
- Non-parametric, high complexity

$$L(\mathcal{Y}) = \sum_{n=1}^{N-1} \sum_{m=n+1}^{N} w_{n,m} \left(\|\mathbf{x}_n - \mathbf{x}_m\| - \|\mathbf{y}_n - \mathbf{y}_m\| \right)^2.$$

Dataset

New space

De-weight the importance of pairs of vectors that are dissimilar in high-dimensional space.

$$w_{n,m} = \|\mathbf{x}_n - \mathbf{x}_m\|^{-1}$$

Siamese Neural Network:

$$L(\boldsymbol{\theta}) = \sum_{n=1}^{N} \sum_{m=n+1}^{N} w_{n,m} \left(\|\mathbf{x}_n - \mathbf{x}_m\| - \|f_{\boldsymbol{\theta}}(\mathbf{x}_n) - f_{\boldsymbol{\theta}}(\mathbf{x}_m)\| \right)^2,$$

Extension to semi-supervised learning:

Extra loss function $\|f_{\boldsymbol{\theta}}(\mathbf{x}_n) - \underline{\mathbf{y}}_n\|^2$

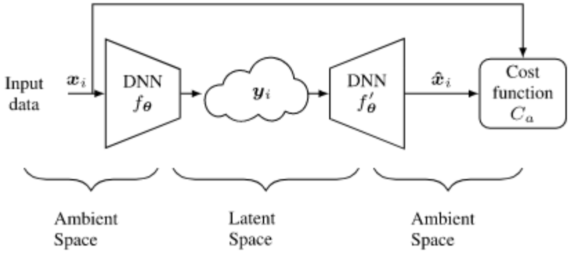
TABLE V
SEMISUPERVISED TEST-SET PERFORMANCE

		Q-LoS		Q-NLoS	
		AE	Siamese	AE	Siamese
MDE [m]		13.35	**10.62**	21.70	**17.59**
KS		0.324	**0.275**	0.491	**0.327**
TW	$K = 1$	**0.976**	**0.976**	**0.942**	0.932
	$K = 40$	0.977	**0.986**	**0.961**	0.953
	$K = 80$	0.981	**0.988**	**0.965**	0.961
CT	$K = 1$	0.979	**0.980**	0.953	**0.954**
	$K = 40$	0.979	**0.987**	0.954	**0.958**
	$K = 80$	0.982	**0.989**	0.957	**0.965**

Lei, Eric, Oscar Castañeda, Olav Tirkkonen, Tom Goldstein, and Christoph Studer. "Siamese neural networks for wireless positioning and channel charting." In *2019 57th Annual Allerton Conference on Communication, Control, and Computing (Allerton)*, pp. 200-207. IEEE, 2019.

Triplet-based Wireless Channel Charting

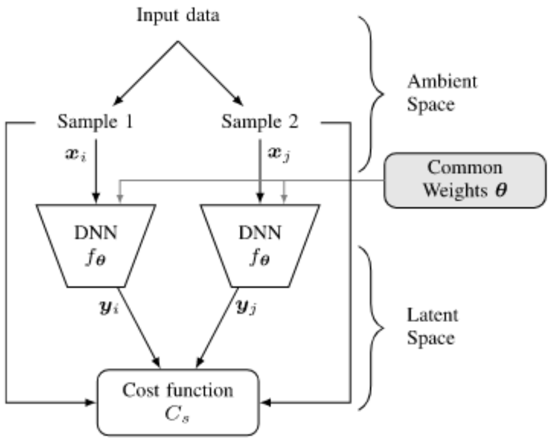
Autoencoder



$$C_a \equiv \frac{1}{|\mathcal{S}|} \sum_{i \in \mathcal{S}} \|x_i - \hat{x}_i\|^2.$$

Euclidean distance between the input and output

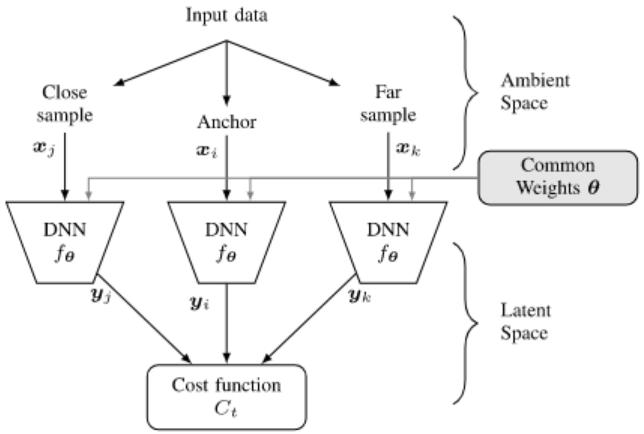
Siamese network



$$C_s \equiv \frac{1}{|\mathcal{T}|} \sum_{(i,j) \in \mathcal{T}} \left(\|x_i - x_j\| - \|y_i - y_j\|\right)^2$$

Replicate the distance in ambient and latent spaces

Triplet network



$$C_t = \frac{1}{|\mathcal{T}|} \sum_{(i,j,k) \in \mathcal{T}} \Big(\|f_\theta(x_i) - f_\theta(x_j)\| - \|f_\theta(x_i) - f_\theta(x_k)\|\Big)^+$$

Only consider latent space distances

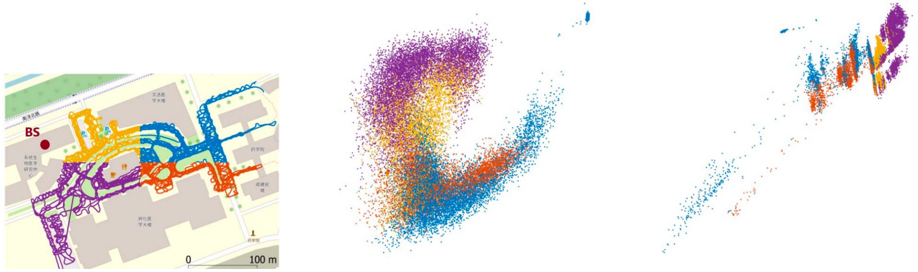
Curse of Dimensionality: large Euclidean distance in high dimension space)

Ferrand, Paul, Alexis Decurninge, Luis G. Ordonez, and Maxime Guillaud. "Triplet-based wireless channel charting: Architecture and experiments." IEEE Journal on Selected Areas in Communications 39, no. 8 (2021): 2361-2373.

Triplet-based Wireless Channel Charting

Dataset 1

Method	KS	TW	CT	SR	EV
MDS	0.524	0.843	0.894	79.2	0.08
UMAP	0.469	0.951	0.923	87.7	0.22
Autoencoder	0.674	0.929	0.889	69.0	0.15
Siamese	0.491	0.846	0.910	77.8	0.20
Triplets (exp)	0.205	0.957	0.975	162.5	**-0.03**
Triplets (margin)	**0.194**	**0.967**	**0.977**	**33.7**	-0.04

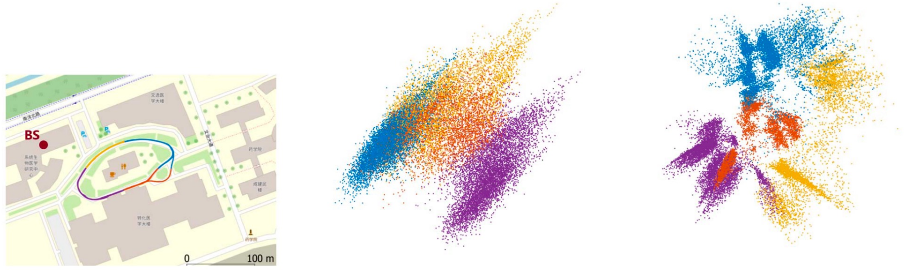


(a) Geographic position (b) Principal component analysis (PCA) (c) Autoencoder

(d) Siamese network (e) UMAP (f) Triplets (margin cost)

Dataset 2

Method	KS	TW	CT	SR	EV
MDS	0.401	0.789	0.863	34.7	0.56
UMAP	0.360	0.975	0.972	72.3	0.38
Autoencoder	0.428	0.937	0.916	37.4	0.63
Siamese	0.887	0.723	0.812	$\gg$ 100	$\gg$ 1
Triplets (exp)	**0.359**	0.969	0.979	**29.2**	**-0.03**
Triplets (margin)	0.404	**0.985**	**0.985**	39.9	0.04

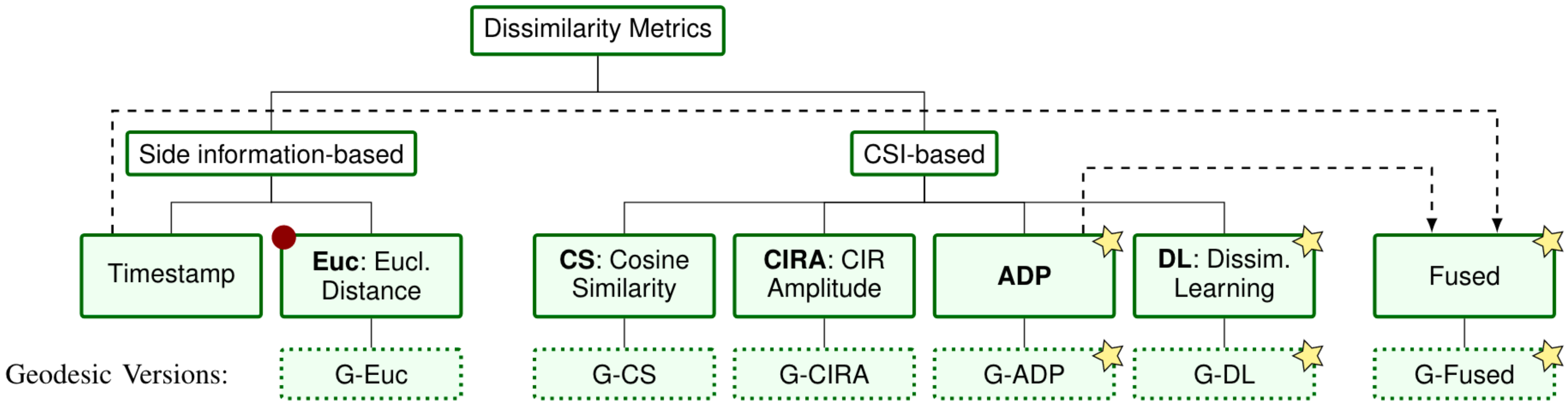


(a) Geographic position (b) Principal Component Analysis (PCA) (c) Autoencoder

(d) Siamese network (e) UMAP (f) Triplets (margin cost)

Ferrand, Paul, Alexis Decurninge, Luis G. Ordonez, and Maxime Guillaud. "Triplet-based wireless channel charting: Architecture and experiments." IEEE Journal on Selected Areas in Communications 39, no. 8 (2021): 2361-2373.

Dissimilarity Metrics



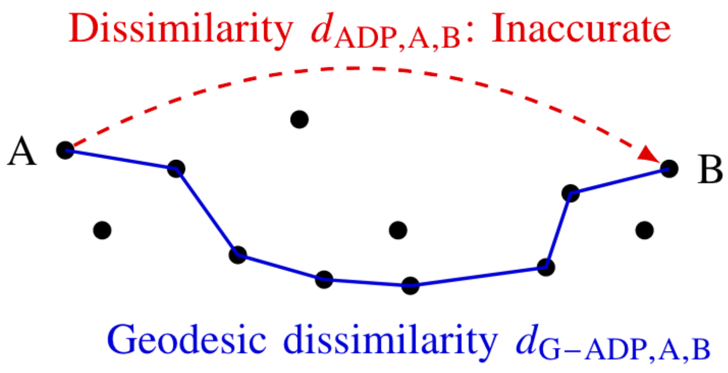
Dissimilarity matrix

- CIR amplitude
- Cosine similarity
- Angle-delay profile

$$d_{\mathrm{CIRA},i,j} = \sum_{b=1}^{B} \sum_{m=1}^{M} \sum_{\tau=\tau_{\min}}^{\tau_{\max}} \left\| \tilde{\mathbf{H}}_{b,m,\tau}^{(i)} \right| - \left| \tilde{\mathbf{H}}_{b,m,\tau}^{(j)} \right\|$$

$$d_{\mathrm{CS},i,j} = \sum_{b=1}^{B} \sum_{n=1}^{N_{\mathrm{sub}}} \left(1 - \frac{\left| \sum_{m=1}^{M} \left(\mathbf{H}_{b,m,n}^{(i)} \right)^{*} \mathbf{H}_{b,m,n}^{(j)} \right|^{2}}{\left(\sum_{m=1}^{M} \left| \mathbf{H}_{b,m,n}^{(i)} \right|^{2} \right) \left(\sum_{m=1}^{M} \left| \mathbf{H}_{b,m,n}^{(j)} \right|^{2} \right)} \right)$$

$$d_{\mathrm{ADP},i,j} = \sum_{b=1}^{B} \sum_{\tau=\tau_{\min}}^{\tau_{\max}} \left(1 - \frac{\left| \sum_{m=1}^{M} \left(\tilde{\mathbf{H}}_{b,m,\tau}^{(i)} \right)^{*} \tilde{\mathbf{H}}_{b,m,\tau}^{(j)} \right|^{2}}{\left(\sum_{m=1}^{M} \left| \tilde{\mathbf{H}}_{b,m,\tau}^{(i)} \right|^{2} \right) \left(\sum_{m=1}^{M} \left| \tilde{\mathbf{H}}_{b,m,\tau}^{(j)} \right|^{2} \right)} \right)$$



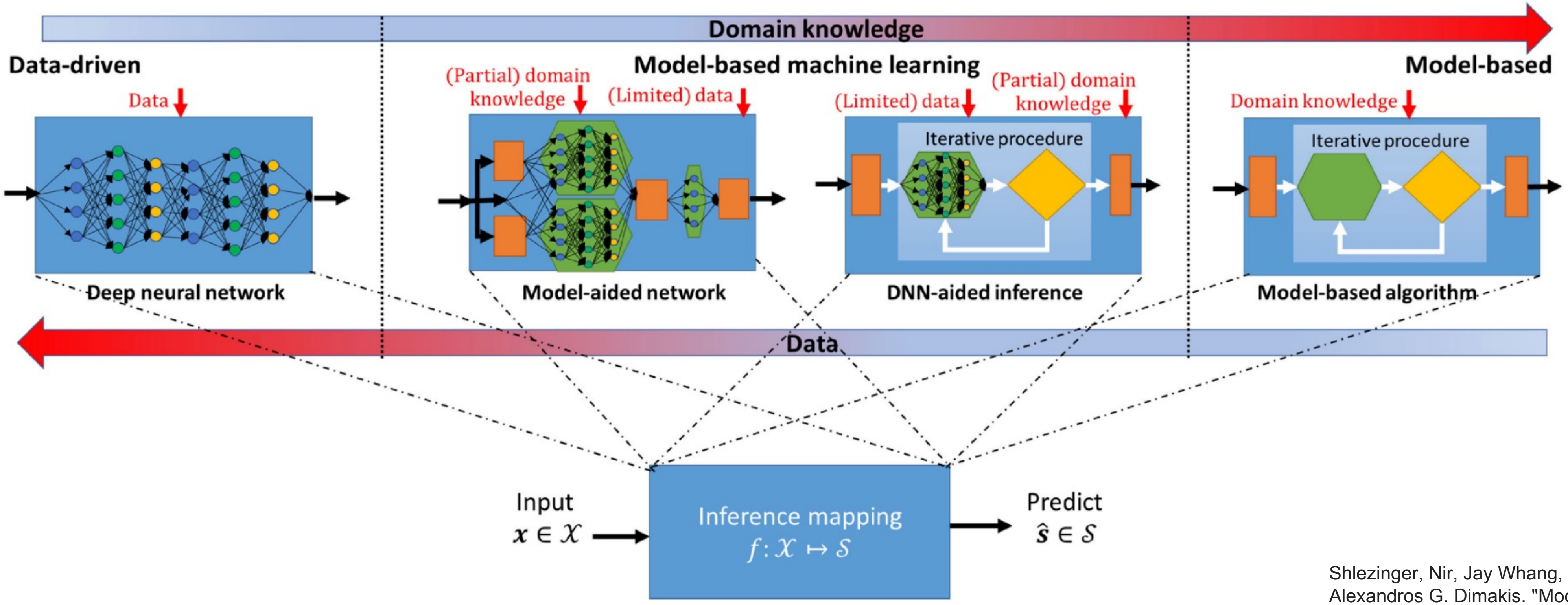
If two datapoints are separated widely in physical space, CSI-based dissimilarity metrics are rarely indicative of the true physical distance.

Stephan, Phillip, Florian Euchner, and Stephan ten Brink. "Angle-delay profile-based and timestamp-aided dissimilarity metrics for channel charting." *arXiv preprint arXiv:2308.09539* (2023).

Model-based Deep Learning

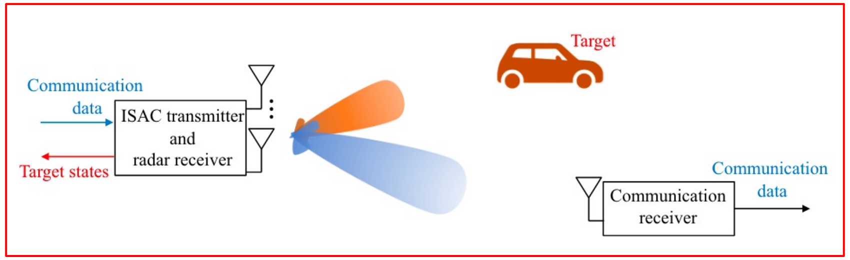
How do we see ML/AI in localization?

- When model-based method works, no need to use fancy ML algorithms
- If the existing method does not work or does not work well (high complexity), try ML
- When using ML, do not leave our expertise behind



Shlezinger, Nir, Jay Whang, Yonina C. Eldar, and Alexandros G. Dimakis. "Model-based deep learning." *Proceedings of the IEEE* (2023).

Learning-based ISAC



End-to-end learning

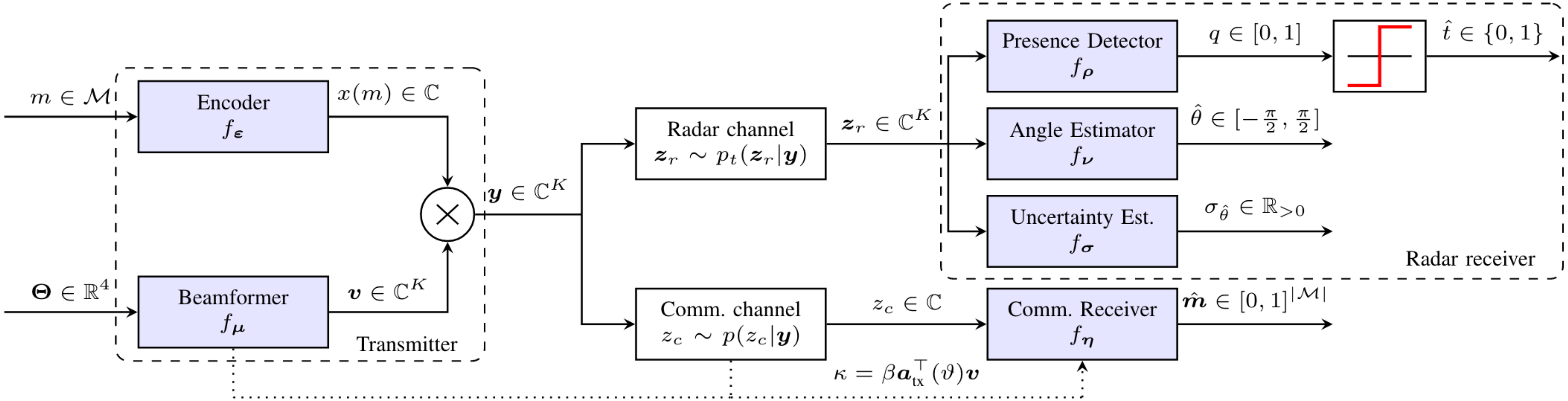


Fig. 1: Block diagram of the ISAC system model. The blocks highlighted in blue are implemented as trainable NNs as part of the proposed AE. The radar receiver is assumed to be co-located with the transmitter, while the communication receiver is remote.

Radar: $\mathcal{J}_{\text{NLL}}(\boldsymbol{\varepsilon},\boldsymbol{\mu},\boldsymbol{\rho},\boldsymbol{\nu},\boldsymbol{\sigma}) = \mathcal{J}_{\text{TD}} + p(t=1)\mathcal{J}_{\text{TR}}.$

Communication: $\mathcal{J}_{\text{CE}}(\boldsymbol{\varepsilon},\boldsymbol{\mu},\boldsymbol{\eta}) = -\mathbb{E}\left[\sum_{j=1}^{C} m_j^{\text{enc}} \log(\hat{m}_j)\right].$

ISAC: $\mathcal{J}_{\text{ISAC}}(\boldsymbol{\varepsilon},\boldsymbol{\mu},\boldsymbol{\rho},\boldsymbol{\sigma},\boldsymbol{\nu},\boldsymbol{\eta}) = \omega_r \mathcal{J}_{\text{NLL}} + (1-\omega_r)\mathcal{J}_{\text{CE}}$

Mateos-Ramos, José Miguel, Jinxiang Song, Yibo Wu, Christian Häger, Musa Furkan Keskin, Vijaya Yajnanarayana, and Henk Wymeersch. "End-to-end learning for integrated sensing and communication." In ICC 2022-IEEE International Conference on Communications, pp. 1942-1947. IEEE, 2022.

Learning-based ISAC

End-to-end learning

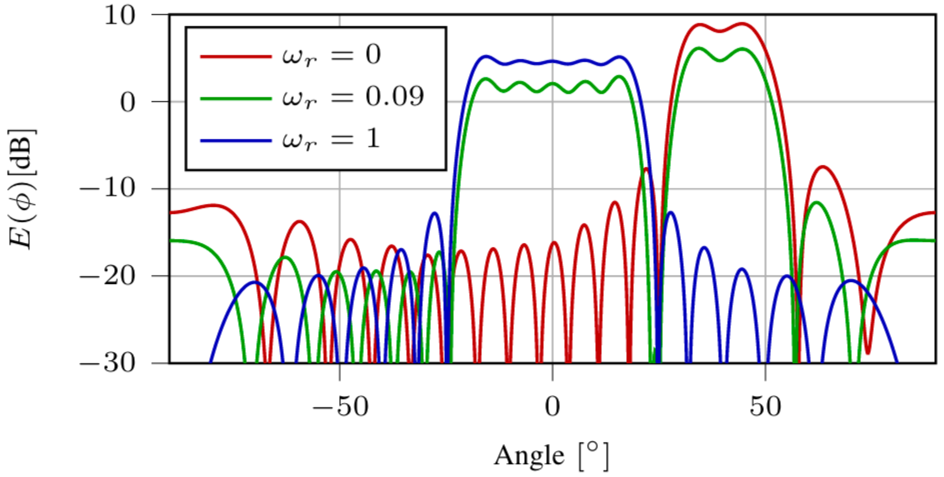


Fig. 3: Learned beampatterns (without hardware impairments) generated by the AE for different values of the hyper-parameter ω_r, where the communication receiver and the radar target reside, respectively, in the intervals $(30°, 50°)$ and $(-20°, 20°)$. The function $E(\phi) = |\boldsymbol{a}_{\text{tx}}(\phi)^\top \boldsymbol{y}|^2$ accounts for how much energy is transmitted in a certain direction.

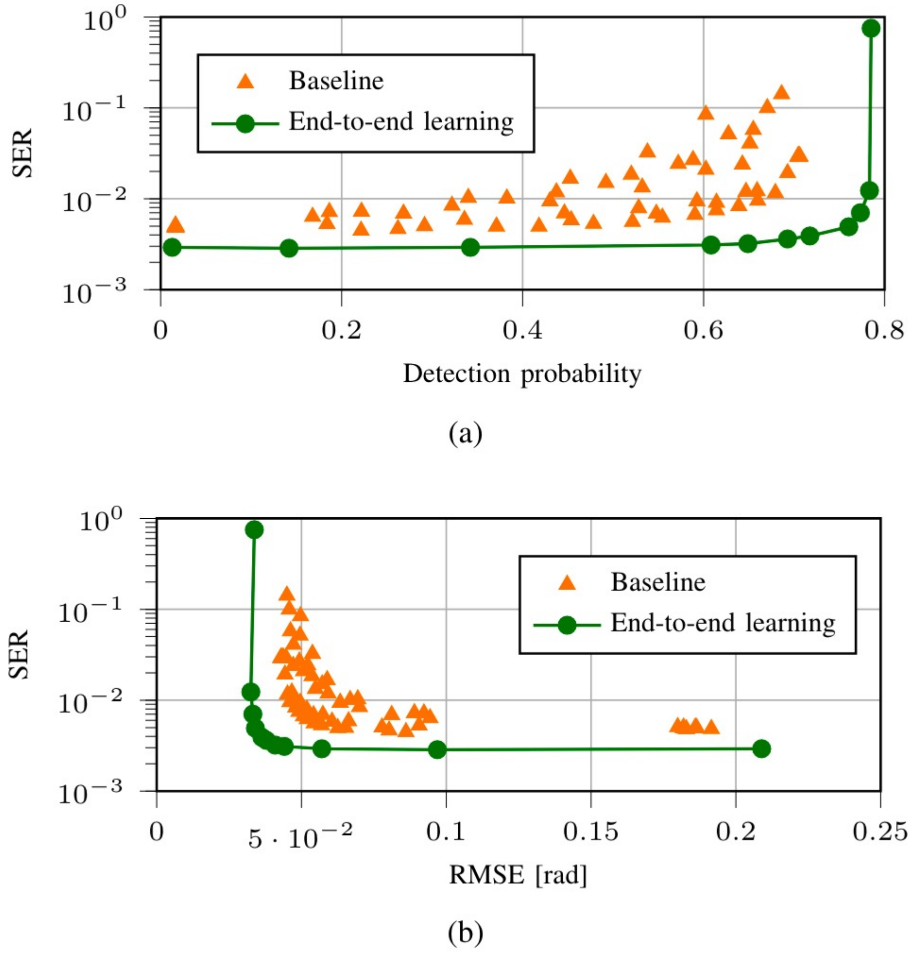
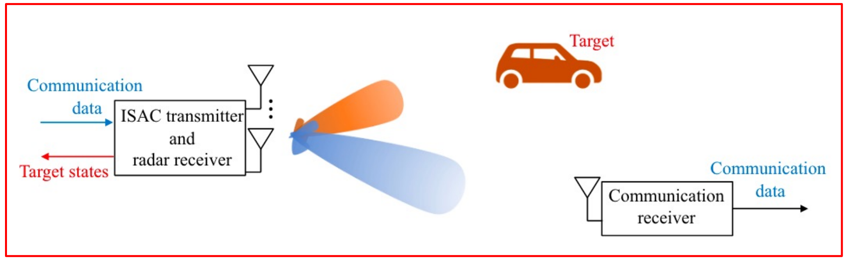


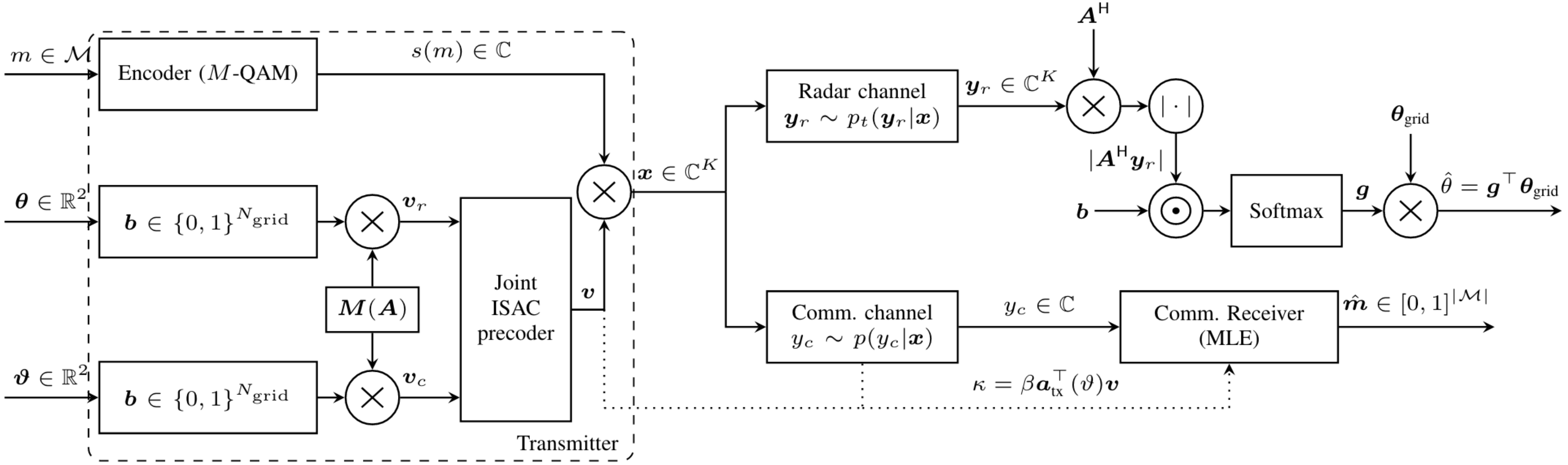
Fig. 5: Results (with hardware impairments) for a fixed empirical false alarm probability of $P_{\text{fa}} = 10^{-2}$, $\text{SNR}_c = 20$ dB, and $\text{SNR}_r = 0$ dB.

Mateos-Ramos, José Miguel, Jinxiang Song, Yibo Wu, Christian Häger, Musa Furkan Keskin, Vijaya Yajnanarayana, and Henk Wymeersch. "End-to-end learning for integrated sensing and communication." In ICC 2022-IEEE International Conference on Communications, pp. 1942-1947. IEEE, 2022.

Learning-based ISAC



Model-driven



Beam pattern

$$[\boldsymbol{b}]_i = \begin{cases} K, & \text{if } \theta_i \in \boldsymbol{\theta}_{\text{range}} \\ 0, & \text{otherwise.} \end{cases}$$

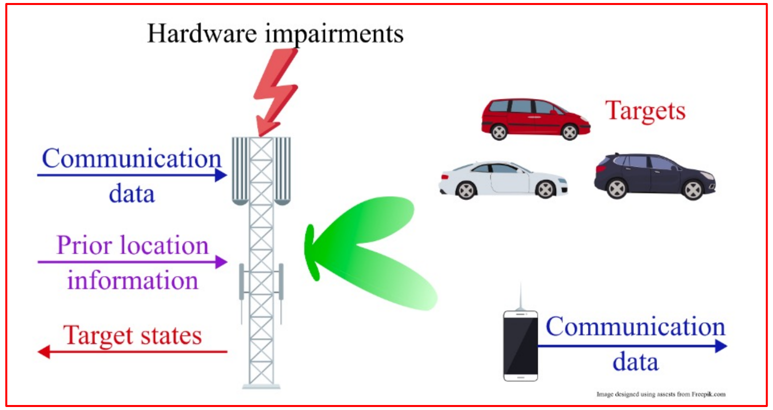
Least-squares

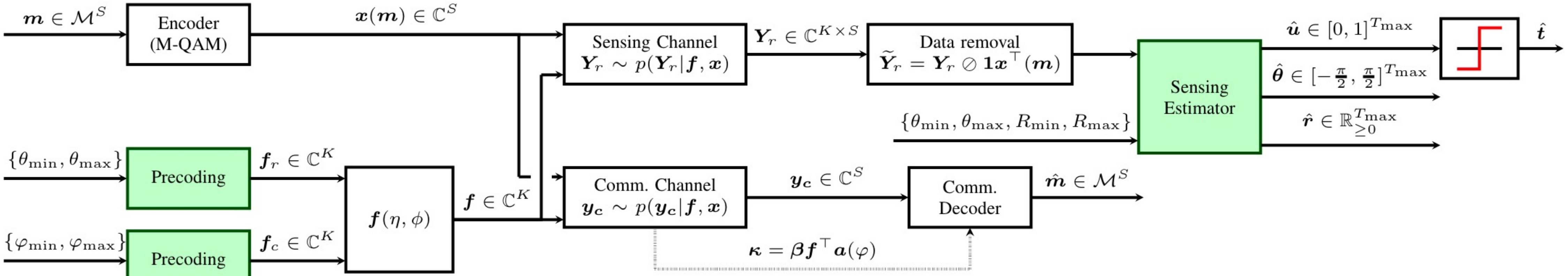
$$\boldsymbol{x} = (\boldsymbol{A}^* \boldsymbol{A}^\top)^{-1} \boldsymbol{A}^* \boldsymbol{b}$$

Mateos-Ramos, José Miguel, Christian Häger, Musa Furkan Keskin, Luc Le Magoarou, and Henk Wymeersch. "Model-driven end-to-end learning for integrated sensing and communication." In ICC 2023-IEEE International Conference on Communications, pp. 5695-5700. IEEE, 2023.

Learning-based ISAC

Multi-target + Differentiable OMP





GOSPA (generalized optimal sub-pattern assignment) Loss Function:

$$d_p^{(\gamma,\mu)}(\mathcal{P},\hat{\mathcal{P}}) = \left(\min_{\pi\in\Pi_{|\hat{\mathcal{P}}|}} \sum_{i=1}^{|\mathcal{P}|} d^{(\gamma)}(\boldsymbol{p}_i,\hat{\boldsymbol{p}}_{\pi(i)})^p + \frac{\gamma^p}{\mu}(|\hat{\mathcal{P}}|-|\mathcal{P}|)\right)^{\frac{1}{p}}.$$

Distance # of Targets

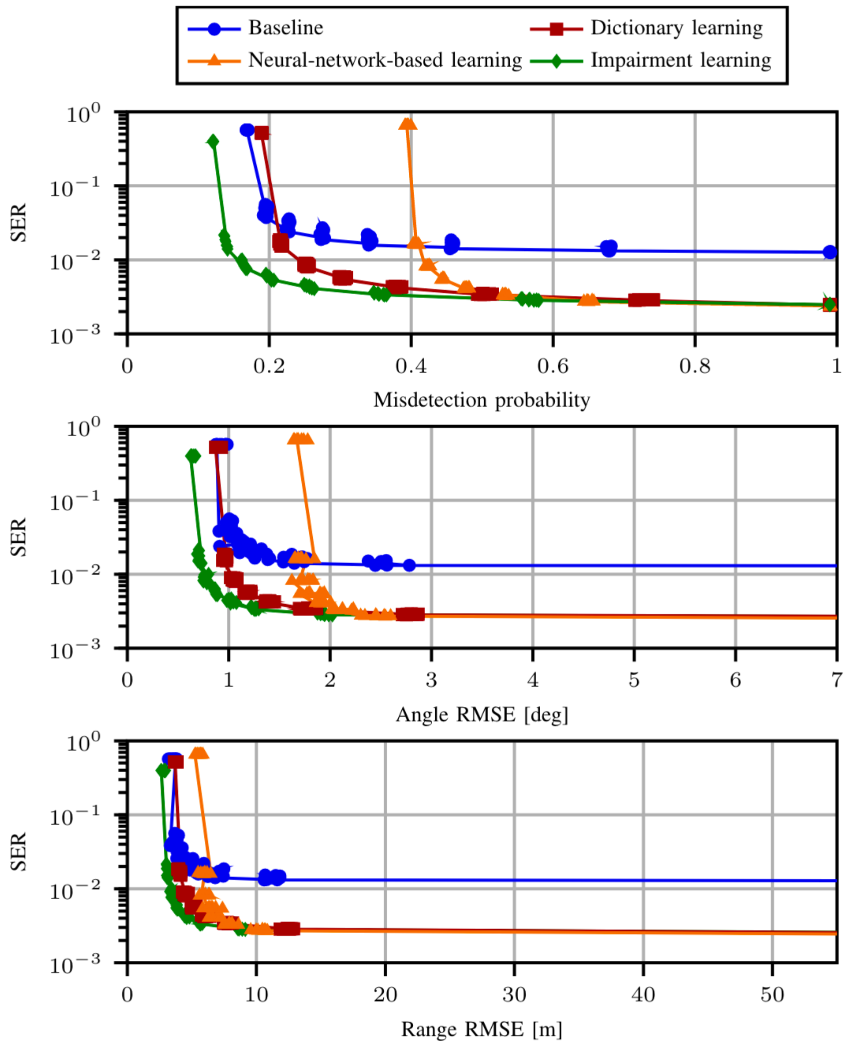
Mateos-Ramos, José Miguel, Christian Häger, Musa Furkan Keskin, Luc Le Magoarou, and Henk Wymeersch. "Model-based end-to-end learning for multi-target integrated sensing and communication." *arXiv preprint arXiv:2307.04111* (2023).

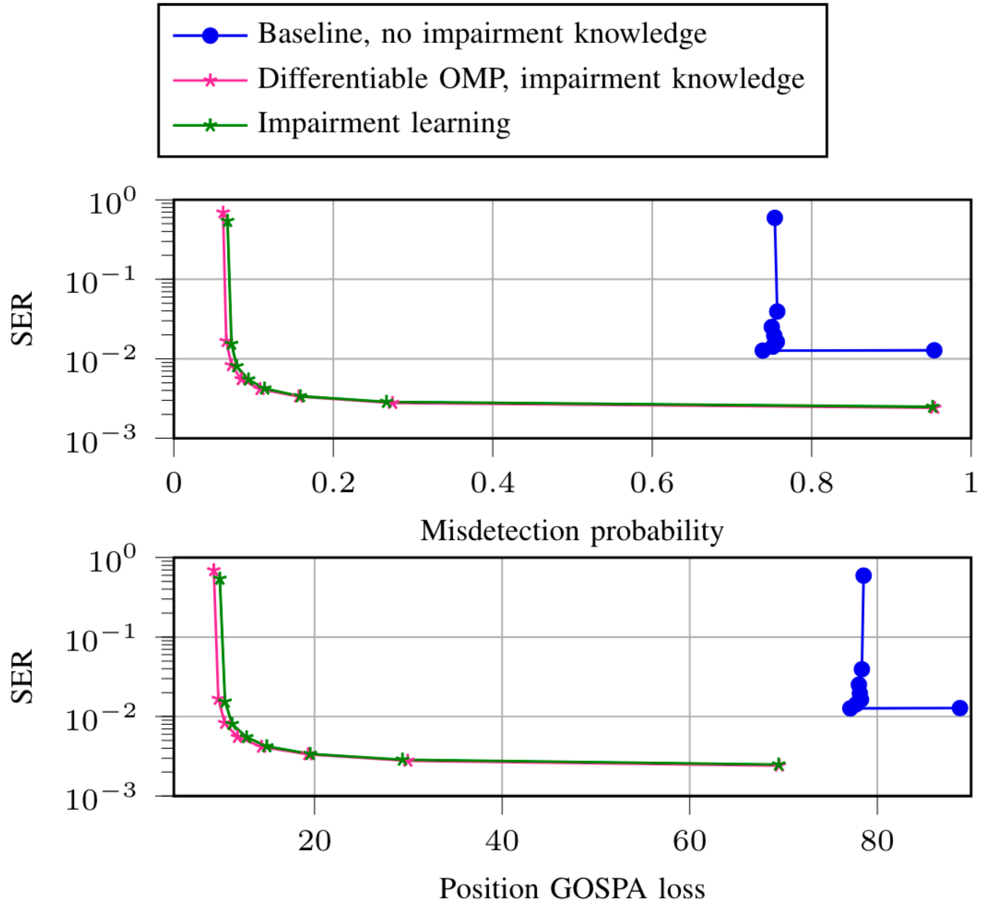
Learning-based ISAC

Impairment learning:

- Outperforms neural network-base learning (overfitting)
- Close to the performance with impairment knowledge

Note: Require correct domain knowledge

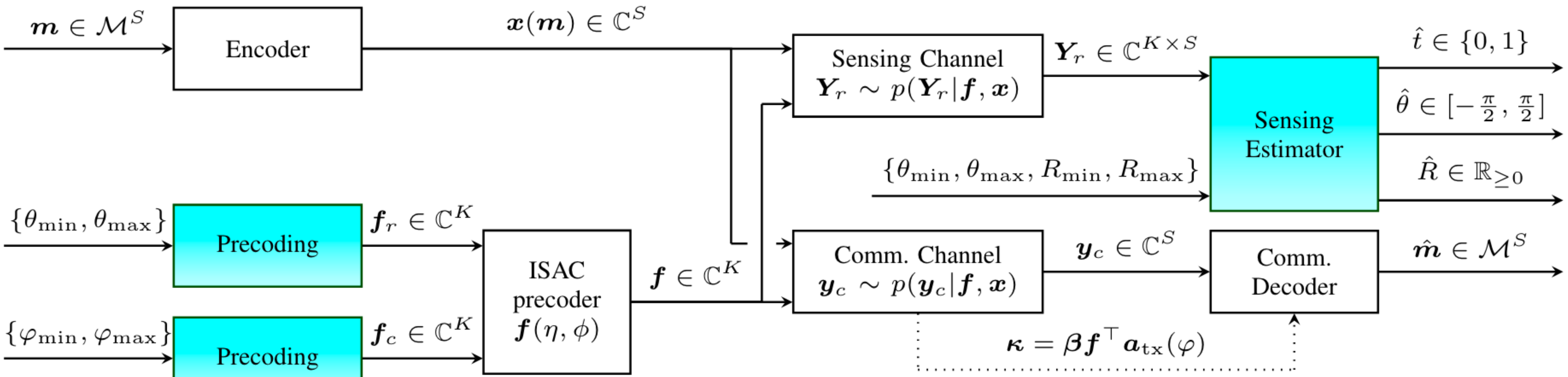




Mateos-Ramos, José Miguel, Christian Häger, Musa Furkan Keskin, Luc Le Magoarou, and Henk Wymeersch. "Model-based end-to-end learning for multi-target integrated sensing and communication." *arXiv preprint arXiv:2307.04111* (2023).

Learning-based ISAC

Semi-supervised/ Unsupervised Learning



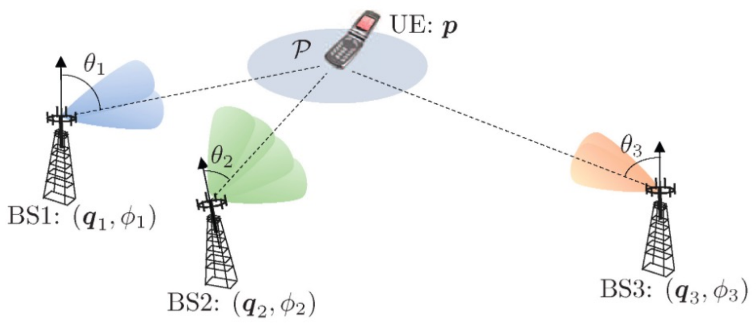
Supervised: $\mathcal{J}_{\text{SL}} = \mathbb{E}\left[\|\boldsymbol{p} - \hat{\boldsymbol{p}}\|^2\right].$

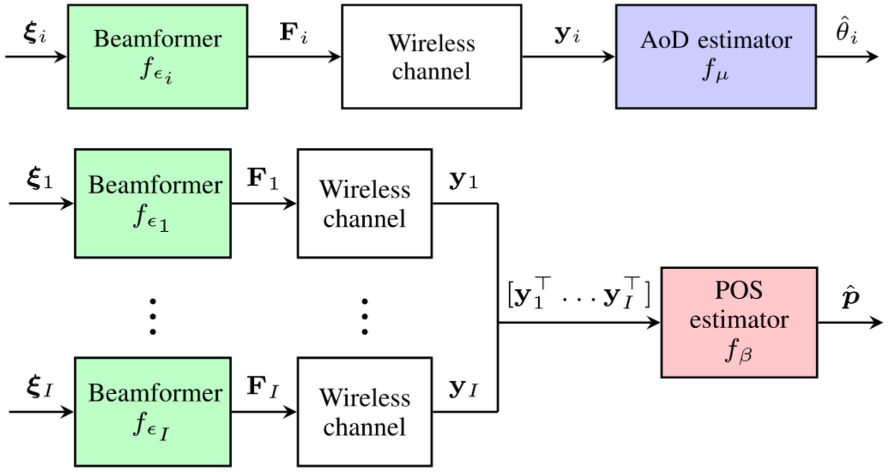
Unsupervised: $\mathcal{J}_{\text{UL}} = -\max_{i,j} [\boldsymbol{\mathcal{L}}(\widetilde{\boldsymbol{Y}}_r)]_{i,j}.$

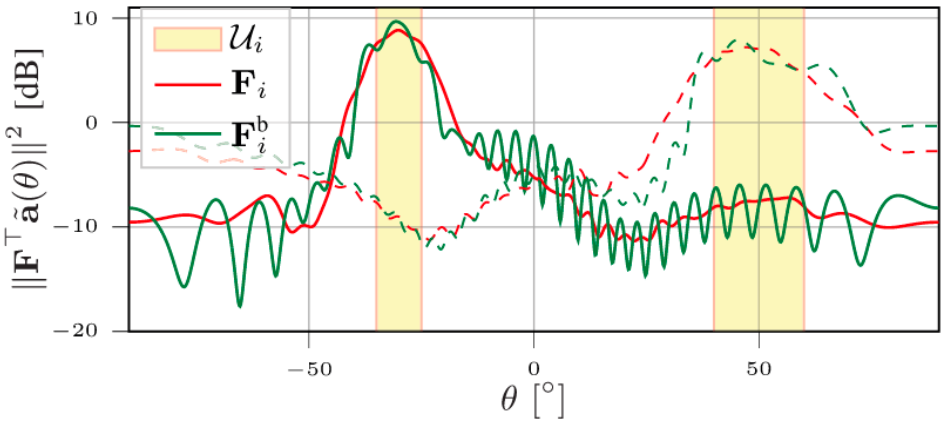
Mateos-Ramos, José Miguel, Baptiste Chatelier, Christian Häger, Musa Furkan Keskin, Luc Le Magoarou, and Henk Wymeersch. "Semi-Supervised End-to-End Learning for Integrated Sensing and Communications." arXiv preprint arXiv:2310.09940 (2023).

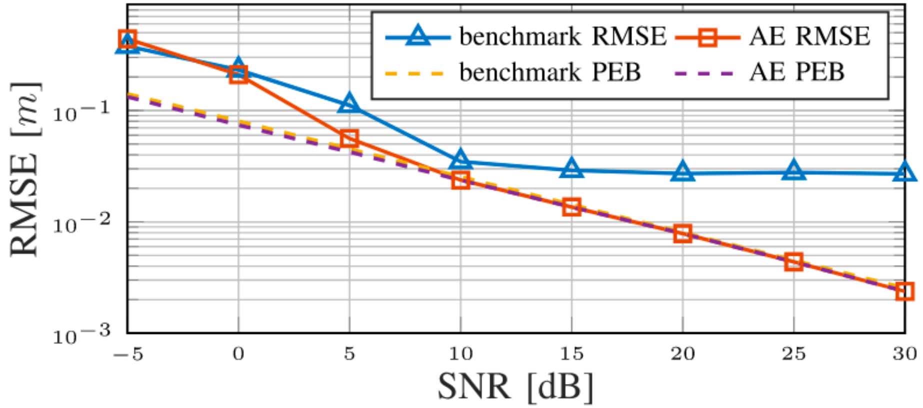
Learning-based ISAC

Multi-BS positioning task









Learned beam pattern differs from the benchmark and provides better performance

Rivetti, Steven, José Miguel Mateos-Ramos, Yibo Wu, Jinxiang Song, Musa Furkan Keskin, Vijaya Yajnanarayana, Christian Häger, and Henk Wymeersch. "Spatial signal design for positioning via end-to-end learning." *IEEE Wireless Communications Letters* 12, no. 3 (2023): 525-529.

Outline

1. Introduction (definition, taxonomy, why 5G/6G localization)
2. Localization basics
   - System (GPS, Wifi, 3G/4G, UWB)
   - Signal Model (OFDM, signal strength, time, angle)
   - Performance Bound (Fisher information matrix, CRB, EFIM)
   - Algorithms (LS, MLE, MAP, convexification)
3. 5G/6G localization
   - Channel Model (delay, AOA, AOD)
   - Selected SOTA works (high frequency, multipath, orientation, RIS)
   - Challenging Scenarios (hardware impairment, near-field, learning-based)
4. Conclusion

Conclusion

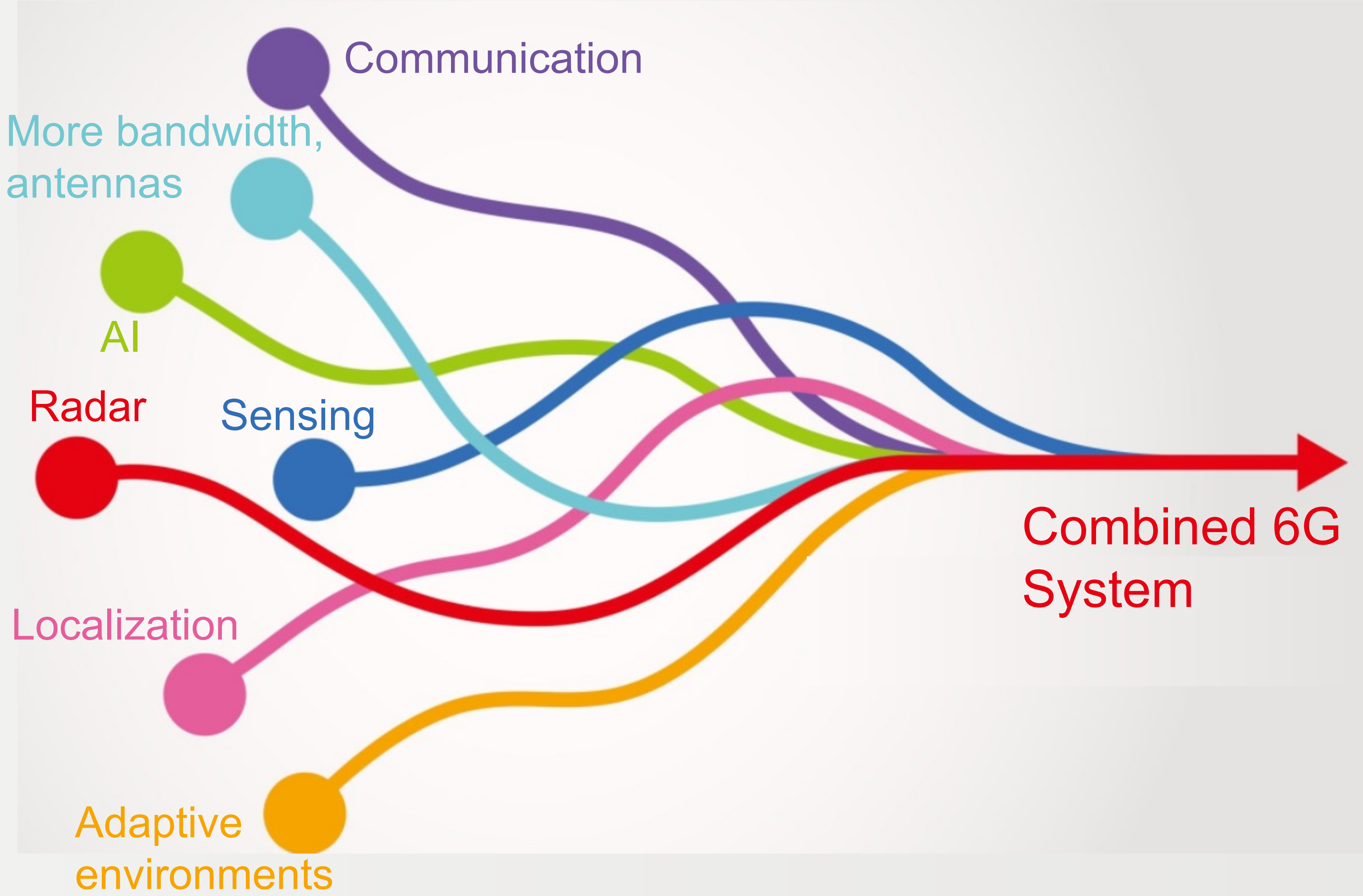
- Localization systems can be realized by a lot of techniques, all have their pros and cons
- Radio signals can provide location information (e.g., delay and angle information)
- Fisher information theory is an important tool for performance analysis
- Maximum likelihood estimator is a good benchmark (at least in simulation, to evaluate the CRB)
- High frequencies, large bandwidth, many antennas is an interesting regime.
  - **5G:** single-anchor positioning, heading estimation, synchronization, environment mapping. Can be a new type of radar. 5G mmWave positioning is now a study item in 3GPP.
  - **Beyond 5G/6G:** potential for RIS to boost localization performance.

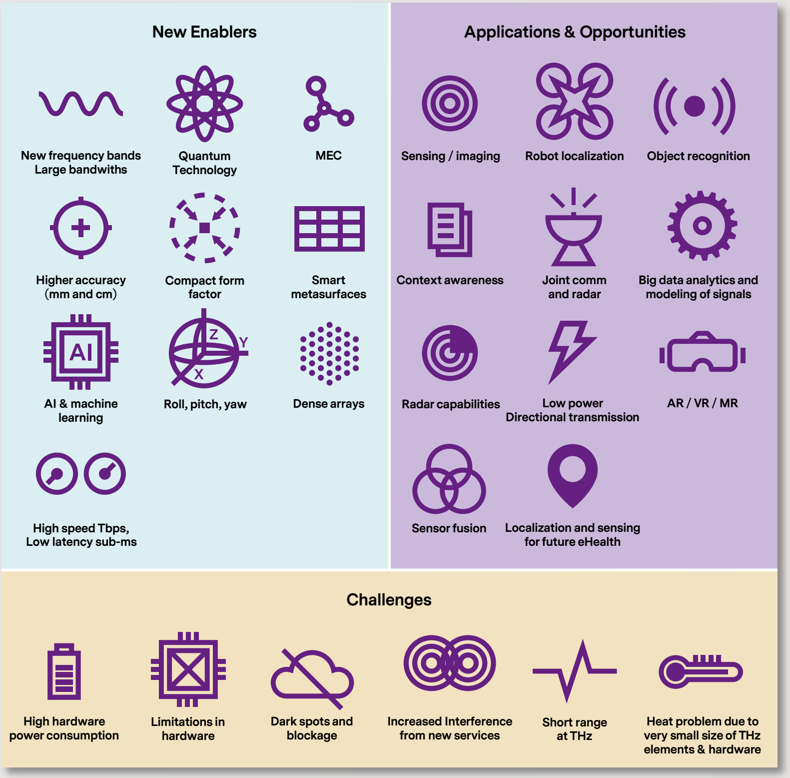
- Many challenges and unanswered questions.
- A long way to go towards the expected performance in 6G

(A longer way to go towards 7G/8G/9G …😂)

FFI Strategic Vehicle Research and Innovation
VINNOVA Swedish Energy Agency TRAFIKVERKET SWEDISH TRANSPORT ADMINISTRATION
FKG SCANIA VOLVO
Vetenskapsrådet
Horizon 2020 European Union Funding for Research & Innovation
WASP WALLENBERG AUTONOMOUS SYSTEMS PROGRAM
MARIE CURIE ACTIONS

What is next?





https://arxiv.org/abs/2006.01779

Q & A?

5G/6G Radio Localization Tutorial

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