

6G Beyond Communications: Positioning, Sensing, and Wireless Power Transfer

Klaus Witrisal, 1-9-2022

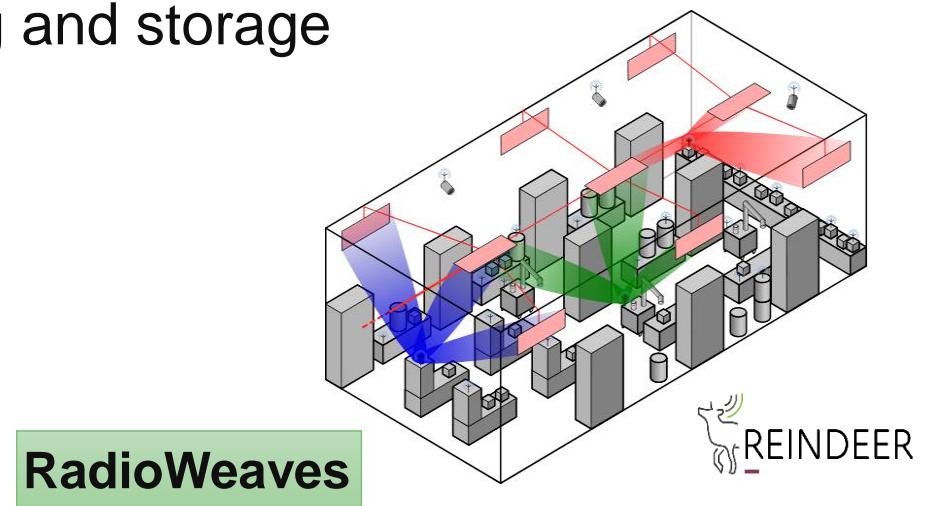
Summer School: "Defining 6G", Linköping, SE

Joint work with my research team and alumni:

Erik Leitinger, Thomas Wilding, Benjamin Deutschmann, Alexander Venus, Lukas Wielandner, Andreas Fuchs, Agnes Koller, Mate Toth, Jakob Möderl, Anh Nguyen, Stefan Grebien, Michael Rath, Josef Kulmer, Paul Meissner

Technologies for 6G:

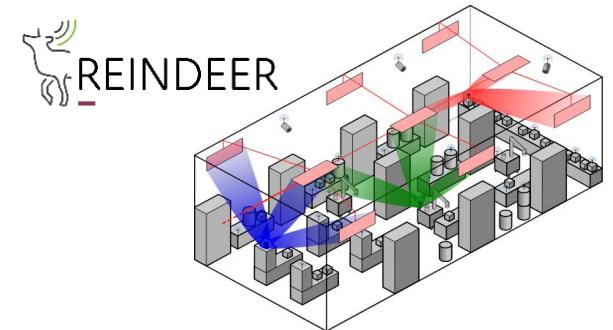
- **BW / frequency** scaling: microwave → mmWave → THz
- **Cell** scaling: small cells → cell-free; coordinated multi point
- **Antenna** scaling / diversity: mMIMO → physically large arrays; distributed mMIMO
- **Channel** control: reconfigurable intelligent surfaces
- Edge cloud: local computing and storage



RadioWeaves: Features and Use Cases

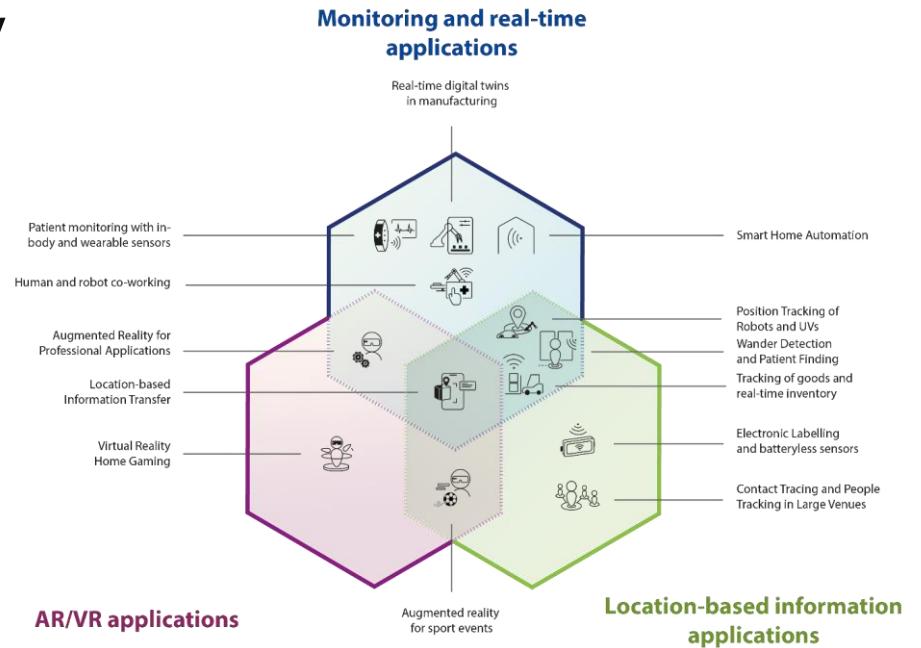
Superior performance:

- Throughput, reliability, latency
- **Energy efficiency**
- **Position accuracy, reliability**



New features:

- **Sensing:** device-free localization
- Mapping; environment awareness
- **Wireless power transfer**



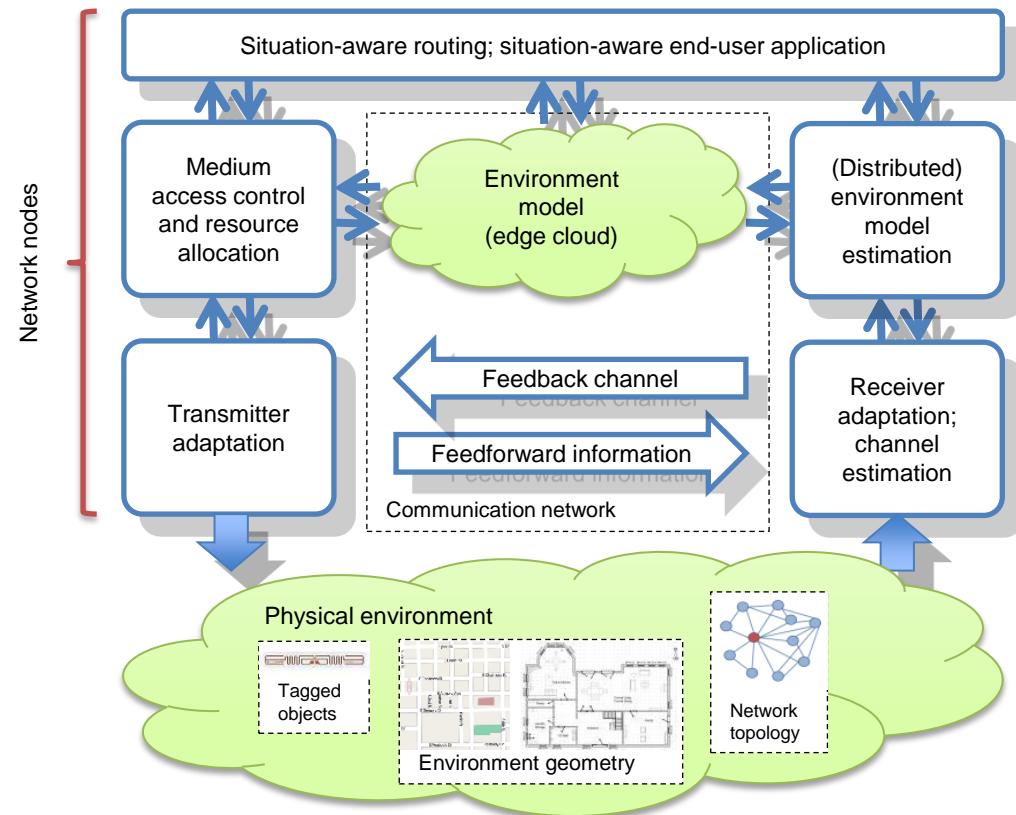
Environment awareness / situational awareness

Awareness of:

- **own location and pose**
- **other users / agents / nodes**
- **environment (sensing; channel state information)**

Benefits for:

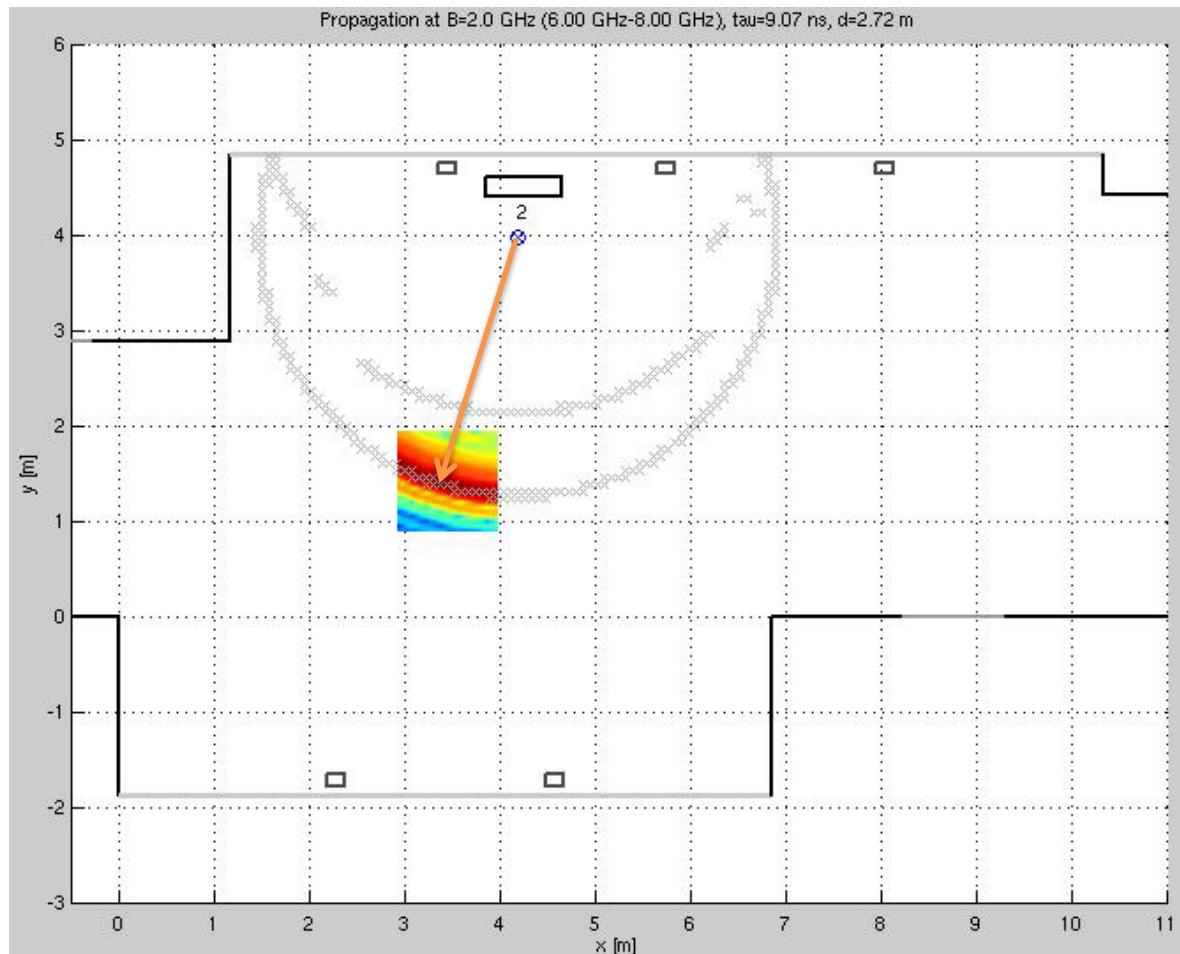
- energy efficient resource allocation
- massive deployment
- predictable reliability
- imperceivable latency
- robust position tracking



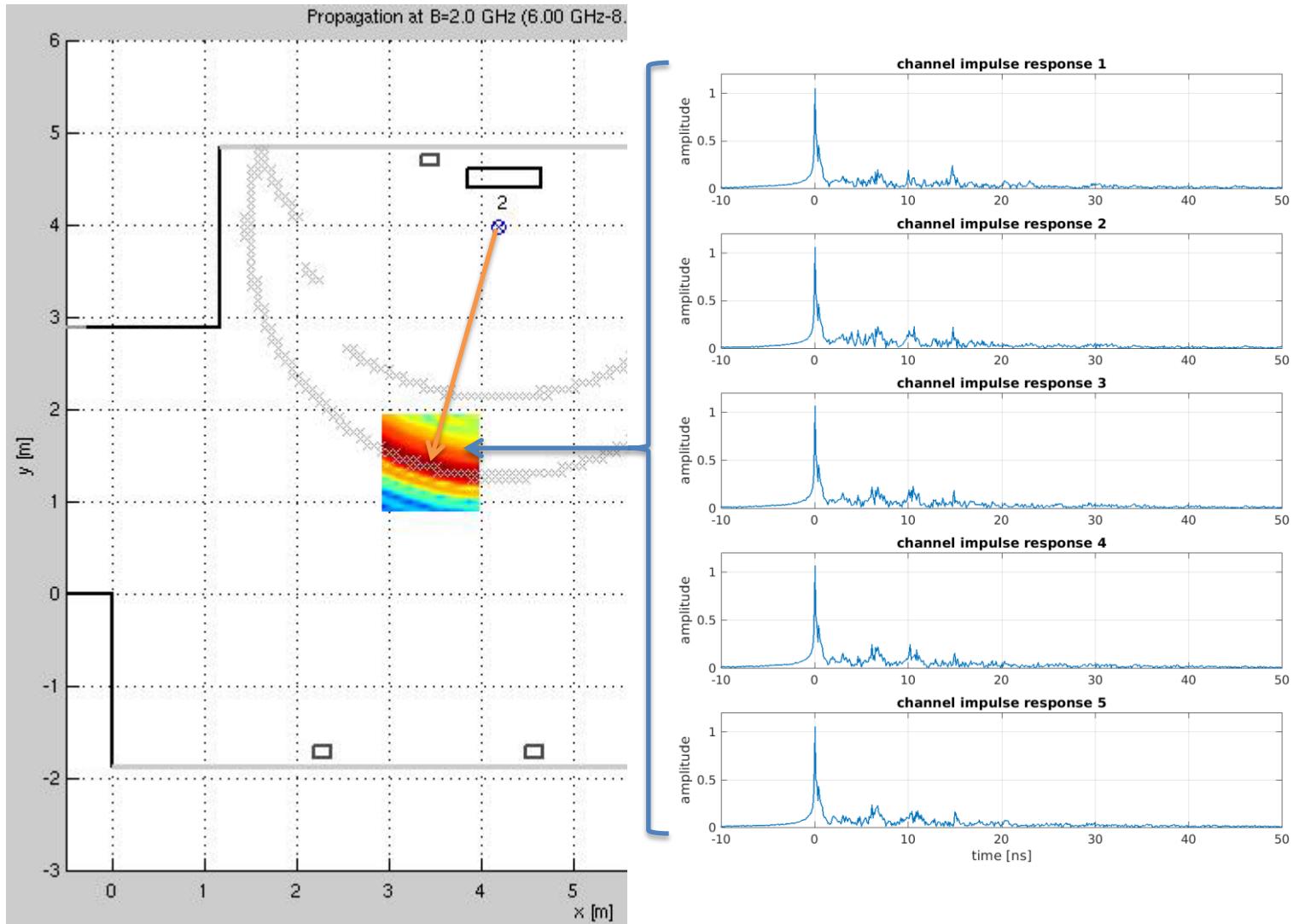
Outline

- Introduction
- **Ranging and positioning in dense multipath**
 - **Bandwidth scaling and MIMO gain**
- Sensing
 - Multipath-assisted indoor positioning
 - Environment modeling
- Wireless Power Transfer
 - With physically large arrays
- Conclusions

An experiment: *transmission of a (UWB) pulse in an indoor environment*

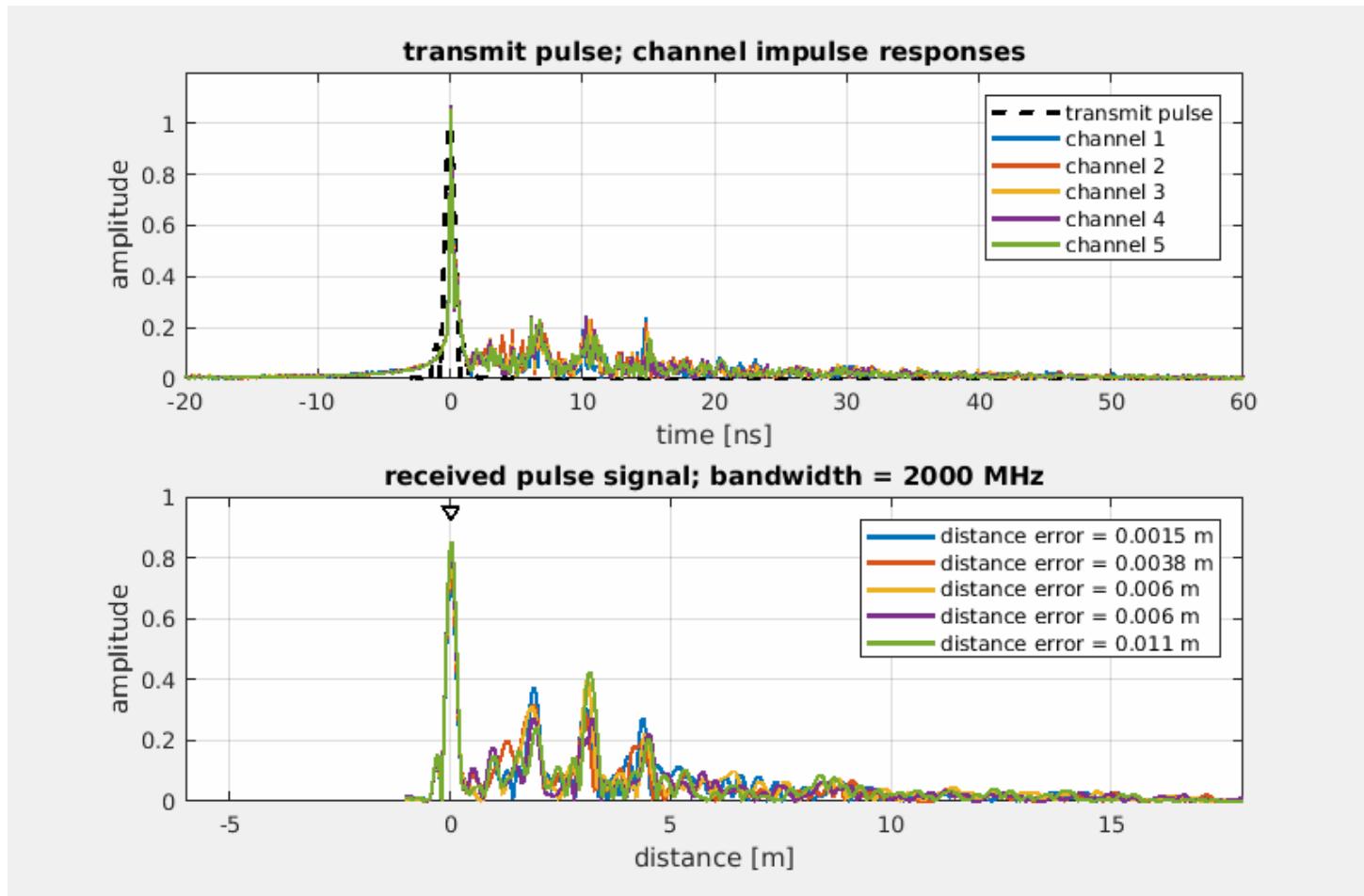


Time-of-flight Ranging



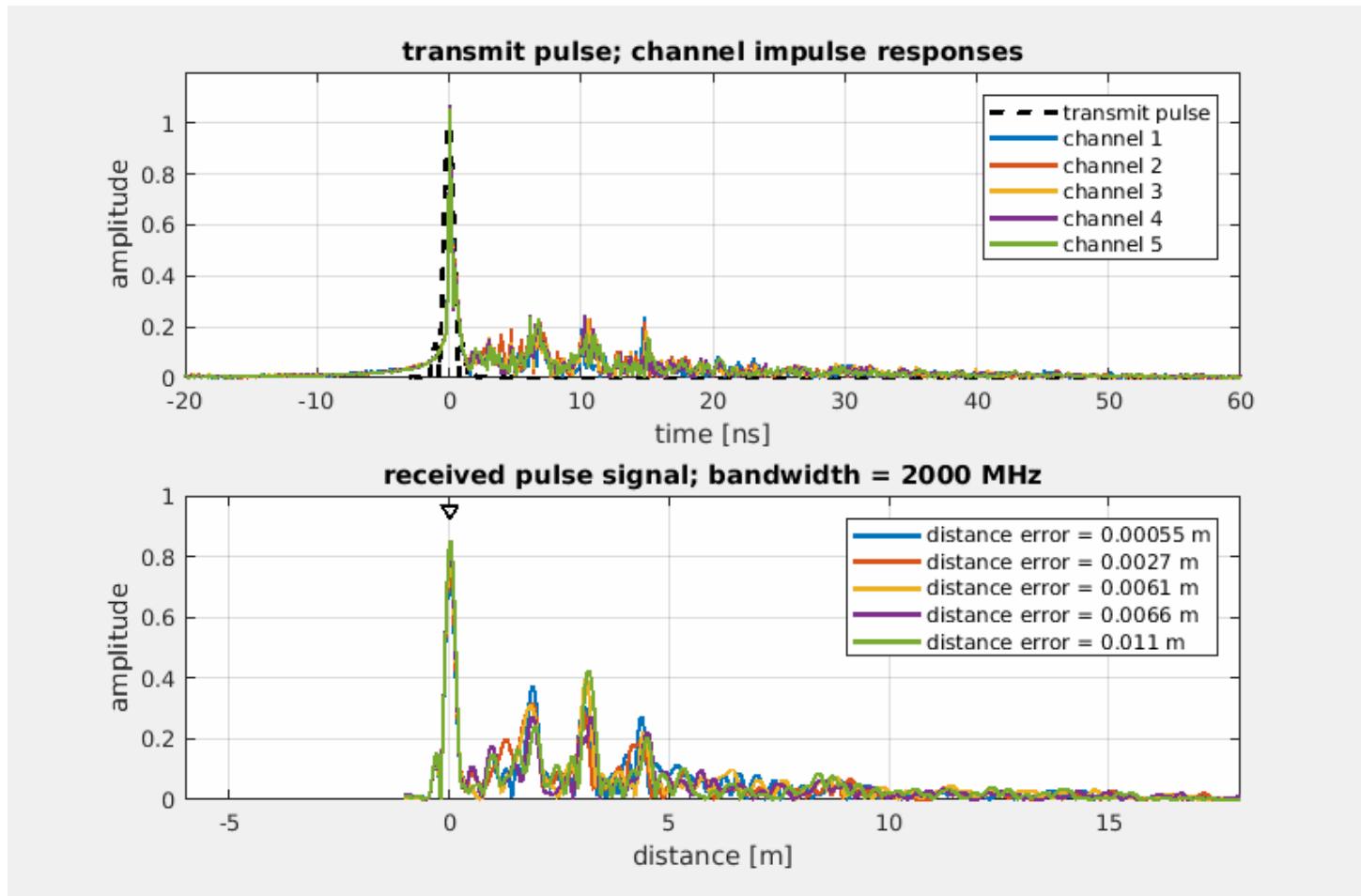
Time-of-flight Ranging:

Problem: Multipath Radio Propagation



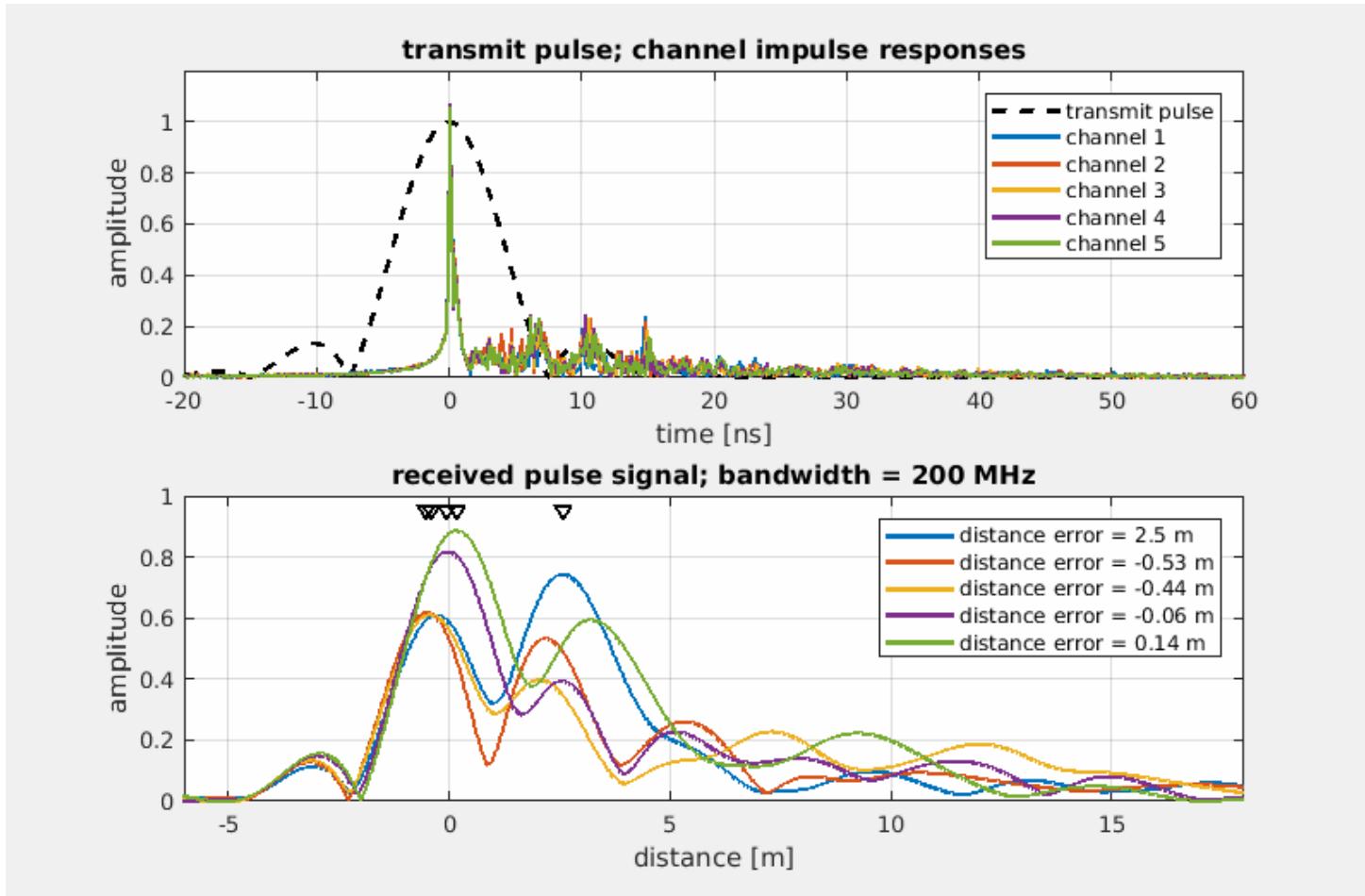
Time-of-flight Ranging:

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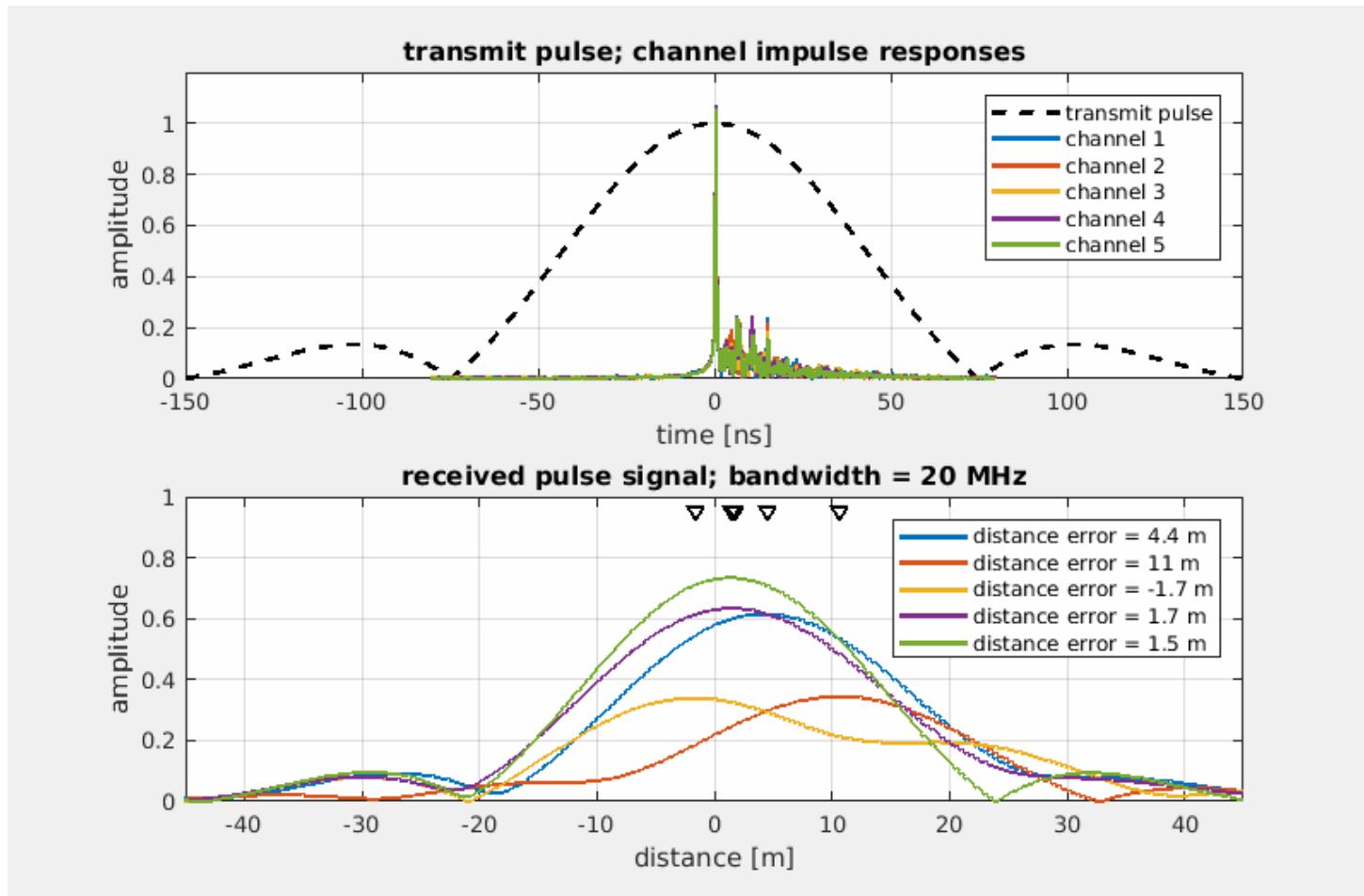
Time-of-flight Ranging:

Problem: Multipath Radio Propagation

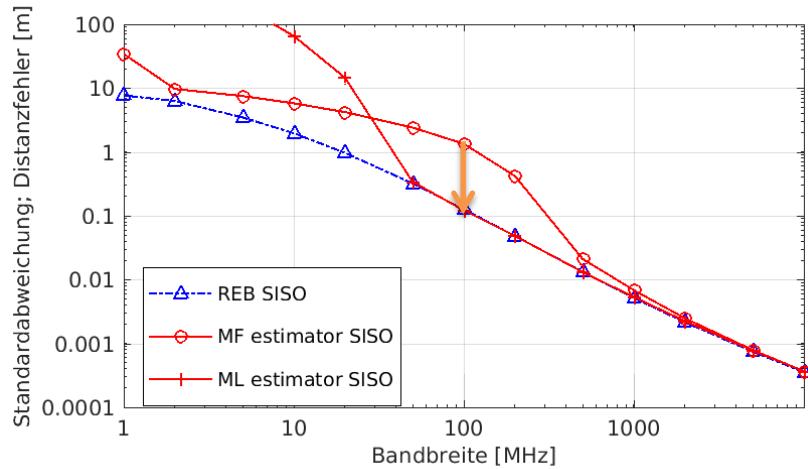
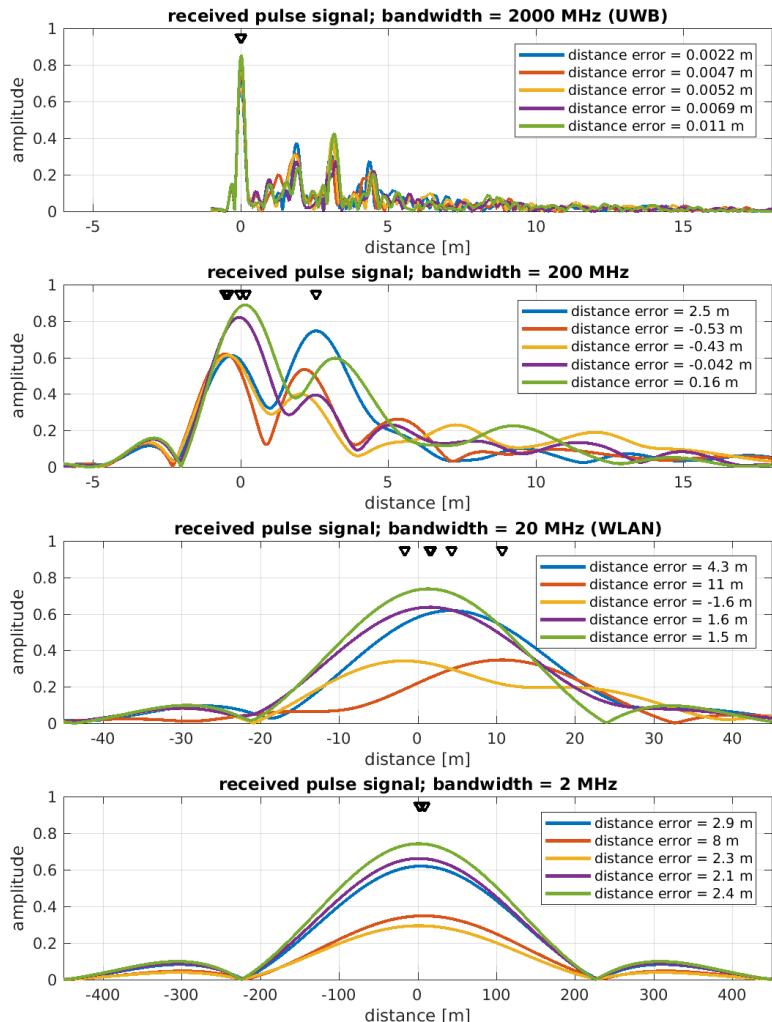


Time-of-flight Ranging:

Problem: Multipath Radio Propagation



Signal Processing for Robust Ranging (& Pos.)



- Experiment
- Modelling
- Performance limits
- Algorithms

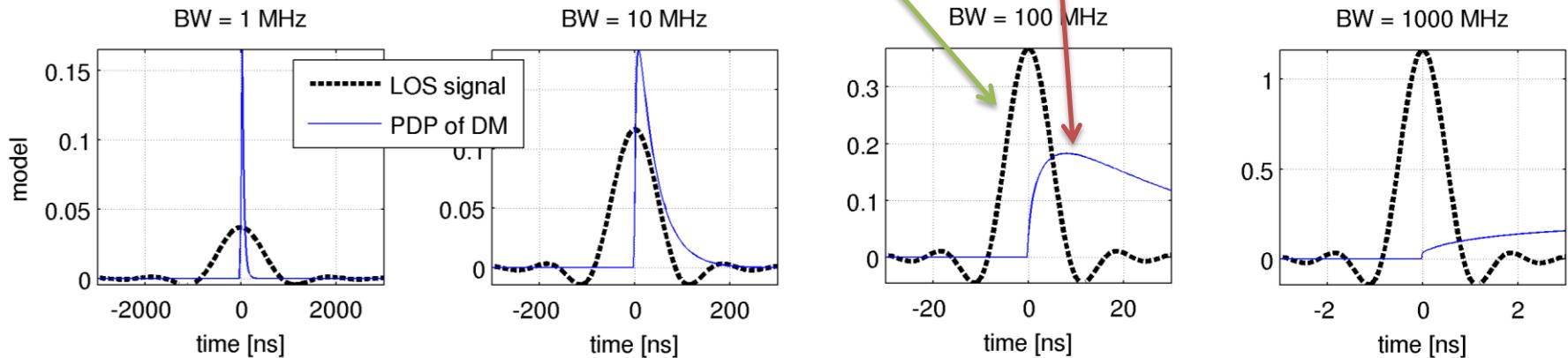
Modeling the dense multipath to derive the theoretical limit (CRLB)

Received signal from anchor j located at $\mathbf{p}^{(j)}$: ($s(t)$: TX signal)

$$r^{(j)}(t) = \underbrace{\alpha^{(j)} s(t - \tau^{(j)})}_{\text{useful signal}} + \underbrace{(s * \nu^{(j)})(t)}_{\text{interference}} + \underbrace{w(t)}_{\text{noise}}$$

$$\tau^{(j)} = \frac{1}{c} \|\mathbf{p} - \mathbf{p}^{(j)}\|$$

$$\mathbb{E}\{\nu(\tau)\nu^*(u)\} = S_\nu(\tau)\delta(\tau - u)$$



Likelihood function for ranging (in DM)

- **Vector** signal model
 - noise and DM modeled as a Gaussian process

$$\mathbf{r} = \alpha \mathbf{s}(\tau_0) + \boldsymbol{\nu} + \mathbf{w} \quad \mathbf{C}_n = \mathbb{E}\{(\boldsymbol{\nu} + \mathbf{w})(\boldsymbol{\nu} + \mathbf{w})^H\}$$

- **Likelihood** for delay estimation (ranging, ToA)

$$f(\mathbf{r}; \tau, \alpha) \propto \exp \left\{ -(\mathbf{r} - \mathbf{s}(\tau)\alpha)^H \mathbf{C}_n^{-1} (\mathbf{r} - \mathbf{s}(\tau)\alpha) \right\}$$

- Allows for derivation of:

Cramer-Rao

lower bound (CRLB):

$$\text{var}(\hat{\tau}) \geq \frac{1}{-\mathbb{E} \left[\frac{\partial^2 \ln f(\mathbf{r}; \tau)}{\partial \tau^2} \right]}$$

**Maximum likelihood (ML)
estimator:**

$$\hat{\tau} = \arg \max_{\tau} f(\mathbf{r}; \tau)$$

ML estimation (in AWGN)

- Maximizing the LHF for model parameters; **AWGN**

$$\begin{aligned}(\hat{\tau}, \hat{\alpha}) &= \arg \max_{\tau, \alpha} \exp \left\{ -(\mathbf{r} - \mathbf{s}(\tau)\alpha)^H \mathbf{C}_n^{-1} (\mathbf{r} - \mathbf{s}(\tau)\alpha) \right\} \\&= \arg \min_{\tau, \alpha} \|\mathbf{r} - \mathbf{s}(\tau)\alpha\|^2\end{aligned}$$

- nuisance parameter α : **projection theorem**

$$\mathbf{s}^H(\tau)(\mathbf{r} - \mathbf{s}(\tau)\hat{\alpha}) = 0 \quad \hat{\alpha}(\tau) = \frac{\mathbf{s}^H(\tau)\mathbf{r}}{\|\mathbf{s}(\tau)\|^2}$$

- yields

$$\hat{\tau} = \arg \min_{\tau} \|\mathbf{r} - \mathbf{s}(\tau)\hat{\alpha}(\tau)\|^2$$

$$= \arg \max_{\tau} |\hat{\alpha}(\tau)|$$

$$= \arg \max_{\tau} |\mathbf{s}^H(\tau)\mathbf{r}|$$

This is a **matched filter!**

ML estimation in AWGN: Matched Filter

- TX and RX signals:

$$s(t) \quad r(t) = (s * h)(t) + w(t)$$

Channel IR

- Matched filter:

$$\overleftarrow{s}(t) = s^*(-t)$$

- Yields **filtered channel impulse response**:

$$\begin{aligned}\hat{\alpha}(\tau) &= (s * h * \overleftarrow{s})(\tau) + (w * \overleftarrow{s})(\tau) \\ &= (h * \rho_s)(\tau) + \tilde{w}(\tau)\end{aligned}$$

Signal ACF

received pulse signal; bandwidth = 2000 MHz (UWB)

received pulse signal; bandwidth = 200 MHz

For **sensing** (the channel impulse response), the autocorrelation function of the TX signal needs to be properly designed!
I.e.: well-defined main lobe; low side lobes; high bandwidth

distance [m]

distance [m]

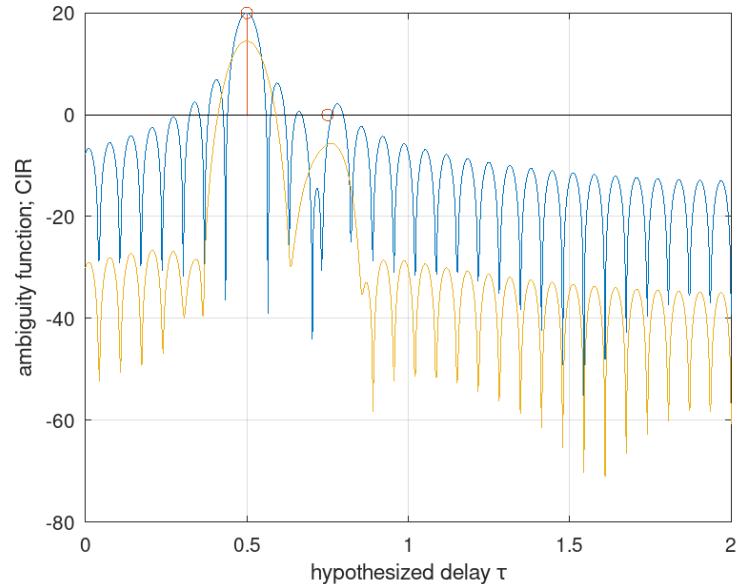
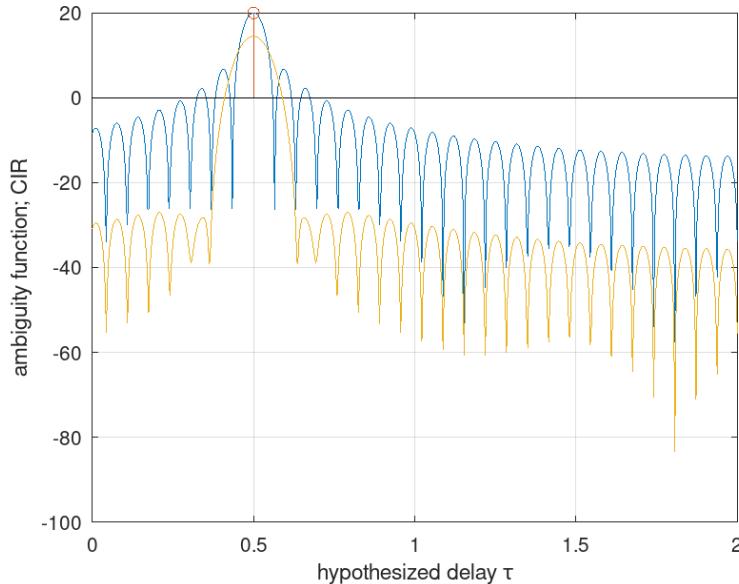
Signal design for ranging in AWGN: OFDM

- TX signal by IFFT $\mathbf{s} = \mathbf{F}^{-1}\tilde{\mathbf{s}}$
- RX signal after FFT
$$\begin{aligned}\tilde{\mathbf{r}} &= \mathbf{F}\mathbf{H}\mathbf{F}^{-1}\tilde{\mathbf{s}} + \mathbf{F}\mathbf{w} \\ &= \tilde{\mathbf{H}}\tilde{\mathbf{s}} + \tilde{\mathbf{w}}\end{aligned}$$
- with (**diagonal!**) channel frequency response matrix
$$\begin{aligned}\tilde{\mathbf{H}} &= \text{diag}[H(0), H(\Delta_f), H(2\Delta_f), \dots, H(-\Delta_f)] \\ &= \alpha \text{diag}[e^0, e^{-j2\pi\Delta_f\tau_0}, e^{-j4\pi\Delta_f\tau_0}, \dots, e^{j2\pi\Delta_f\tau_0}]\end{aligned}$$
- where second line is for **delay channel**
$$h(t) = \alpha\delta(t - \tau_0)$$
- The ML estimator: project $\tilde{\mathbf{r}}$ onto
$$\tilde{\mathbf{s}}(\tau) = [e^0, e^{-j2\pi\Delta_f\tau}, e^{-j4\pi\Delta_f\tau}, \dots, e^{j2\pi\Delta_f\tau}]^T$$
- this is **Fourier transform of rectangular pulse!**
- can use insight in **windowing** to optimize pulse design

Range ambiguity function

for ToA estimation with an OFDM pilot

- OFDM signal: 48 SCs at 0.3125 kHz spacing (BW = 16 MHz)
- Channel: one tap at 0.5 μ s, $\alpha = 10$; **second** at 0.75 μ s, $\alpha = 1$
- Window: Rectangular, Hamming



Likelihood function for ranging (in DM)

- **Vector** signal model
 - noise and DM modeled as a Gaussian process

$$\mathbf{r} = \alpha \mathbf{s}(\tau_0) + \boldsymbol{\nu} + \mathbf{w} \quad \mathbf{C}_n = \mathbb{E}\{(\boldsymbol{\nu} + \mathbf{w})(\boldsymbol{\nu} + \mathbf{w})^H\}$$

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$$f(\mathbf{r}; \tau, \alpha) \propto \exp \left\{ -(\mathbf{r} - \mathbf{s}(\tau)\alpha)^H \mathbf{C}_n^{-1} (\mathbf{r} - \mathbf{s}(\tau)\alpha) \right\}$$

- Allows for derivation of:

**Cramer-Rao
lower bound (CRLB):**

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**Maximum likelihood (ML)
estimator:**

$$\hat{\tau} = \arg \max_{\tau} f(\mathbf{r}; \tau)$$

CRLB for ranging in DM: derivation

- CRLB for parameter vector $\psi = [\tau, \Re\alpha, \Im\alpha]^T$

$$\text{var}(\hat{\tau}) \geq [\mathcal{I}_\psi^{-1}]_{1,1} \quad \mathcal{I}_\psi = \mathbb{E}_{\mathbf{r}|\psi} \left\{ \left[\frac{\partial}{\partial \psi} \ln f(\mathbf{r}|\psi) \right] \left[\frac{\partial}{\partial \psi} \ln f(\mathbf{r}|\psi) \right]^T \right\}$$

- elements of the **Fisher information matrix:**

$$[\mathcal{I}_\psi]_{1,1} = 2|\alpha|^2 \dot{\mathbf{s}}(\tau)^H \mathbf{C}_n^{-1} \dot{\mathbf{s}}(\tau) + \text{tr} \left[\mathbf{C}_n^{-1} \frac{\partial \mathbf{C}_n}{\partial \tau} \mathbf{C}_n^{-1} \frac{\partial \mathbf{C}_n}{\partial \tau} \right]$$

$$[\mathcal{I}_\psi]_{1,2} = [\mathcal{I}_\psi]_{2,1} = 2\Re\{\alpha\} \mathbf{s}(\tau)^H \mathbf{C}_n^{-1} \dot{\mathbf{s}}(\tau)$$

$$[\mathcal{I}_\psi]_{1,3} = [\mathcal{I}_\psi]_{3,1} = 2\Im\{\alpha\} \mathbf{s}(\tau)^H \mathbf{C}_n^{-1} \dot{\mathbf{s}}(\tau) \quad \dot{\mathbf{s}}(\tau) = \partial \mathbf{s}(\tau) / \partial \tau$$

$$[\mathcal{I}_\psi]_{2,2} = [\mathcal{I}_\psi]_{3,3} = 2\mathbf{s}(\tau)^H \mathbf{C}_n^{-1} \mathbf{s}(\tau)$$

$$[\mathcal{I}_\psi]_{2,3} = [\mathcal{I}_\psi]_{3,2} = 0$$

- **yields:**

$$\mathcal{I}_\tau = 2 \frac{|\alpha|^2}{\sigma_n^2} \|\dot{\mathbf{s}}(\tau)\|_{\mathcal{H}}^2 \left(1 - \frac{|\langle \dot{\mathbf{s}}(\tau), \mathbf{s}(\tau) \rangle_{\mathcal{H}}|^2}{\|\dot{\mathbf{s}}(\tau)\|_{\mathcal{H}}^2 \|\mathbf{s}(\tau)\|_{\mathcal{H}}^2} \right) + \text{tr} [\bullet]$$

$$\begin{aligned} \langle \mathbf{x}, \mathbf{y} \rangle_{\mathcal{H}} &= \sigma_n^2 \mathbf{y}^H \mathbf{C}_n^{-1} \mathbf{x} \\ \|\mathbf{x}\|_{\mathcal{H}}^2 &= \langle \mathbf{x}, \mathbf{x} \rangle_{\mathcal{H}} \end{aligned}$$

CRLB for ranging (in dense multipath (DM))

AWGN only

$$r_\ell(t) = \alpha_\ell s(t - \tau_\ell) + w(t)$$

CRLB

$$\text{var}\{\hat{\tau}\} \geq (8\pi^2 \beta^2 \text{SNR})^{-1}$$

- mean-squared bandwidth

$$\beta^2 = \int_f f^2 |S(f)|^2 df$$

- signal-to-noise ratio

$$\text{SNR} = \frac{E_{\text{LOS}}}{N_0}$$

➤ CRLB scales with **squared bandwidth** and SNR

AWGN + **dense multipath**

$$r_\ell(t) = \alpha_\ell s(t - \tau_\ell) + \underline{(s * \nu_\ell)(t)} + w(t)$$

CRLB → interference

$$\text{var}\{\hat{\tau}\} \geq (8\pi^2 \beta^2 \widetilde{\text{SINR}})^{-1}$$

- whitening *gain*

$$\beta_w^2 = \beta^2 \gamma; \quad \gamma \geq 1$$

- reduced* SNR due to DM

$$\text{SINR} = \frac{E_{\text{LOS}}}{N_0 + \text{DM}} \leq \text{SNR}$$

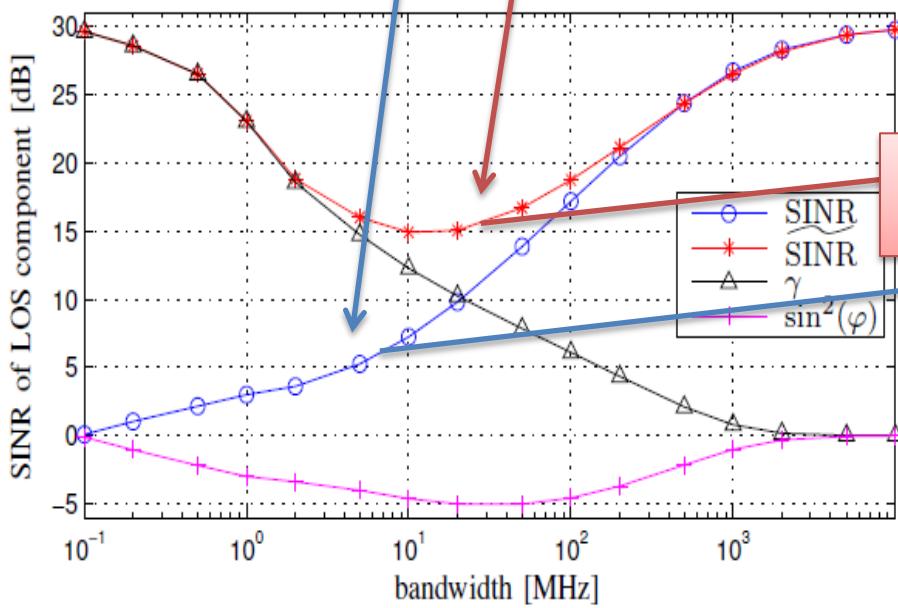
- cost* for nuisance estim.

$$\sin^2(\varphi) \in [0, 1]$$

Ranging error bound and SINR shows the *bandwidth scaling*

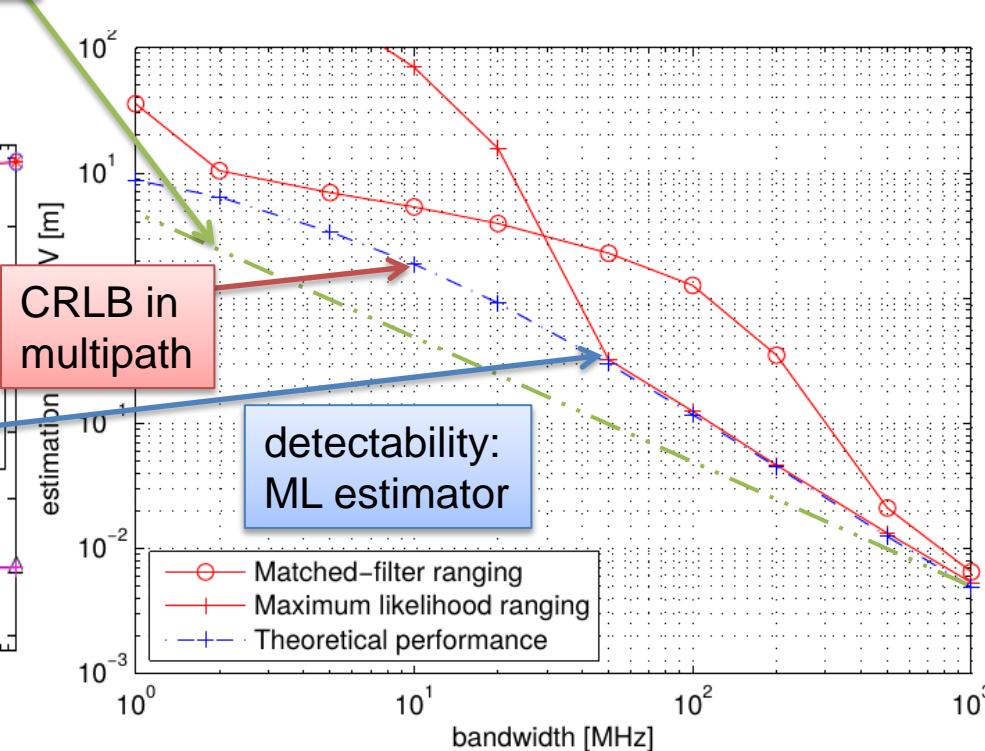
$$\text{var}\{\hat{\tau}\} \geq (8\pi^2 \beta^2 \widetilde{\text{SINR}})^{-1}$$

$$\widetilde{\text{SINR}} = \gamma \text{SINR} \sin^2(\varphi)$$



Parameters

- $\text{SNR} = 30 \text{ dB}$
- $K_{\text{LOS}} = 1 \dots \text{LOS-to-DM-power}$



Position error bound

Equivalent Fisher information \mathbf{J}_P

Position error variance (CRLB):

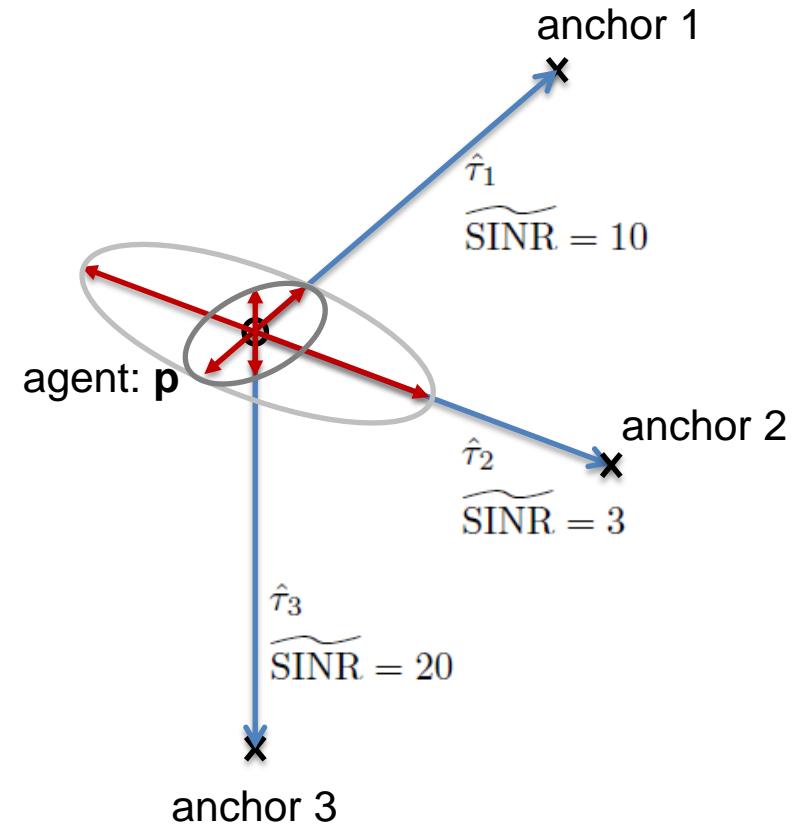
$$\text{var}\{\hat{\mathbf{p}}\} \geq \text{tr}\{\mathbf{J}_P^{-1}\}$$

- J independent measurements:

ranging direction matrix

$$\mathbf{J}_P = \frac{8\pi^2\beta^2}{c^2} \sum_{j=1}^J \widetilde{\text{SINR}}^{(j)} \mathbf{J}_r(\phi^{(j)})$$

geometry of nodes



Diversity (MIMO) gain

Fisher information \mathbf{J}_p

- J independent measurements:

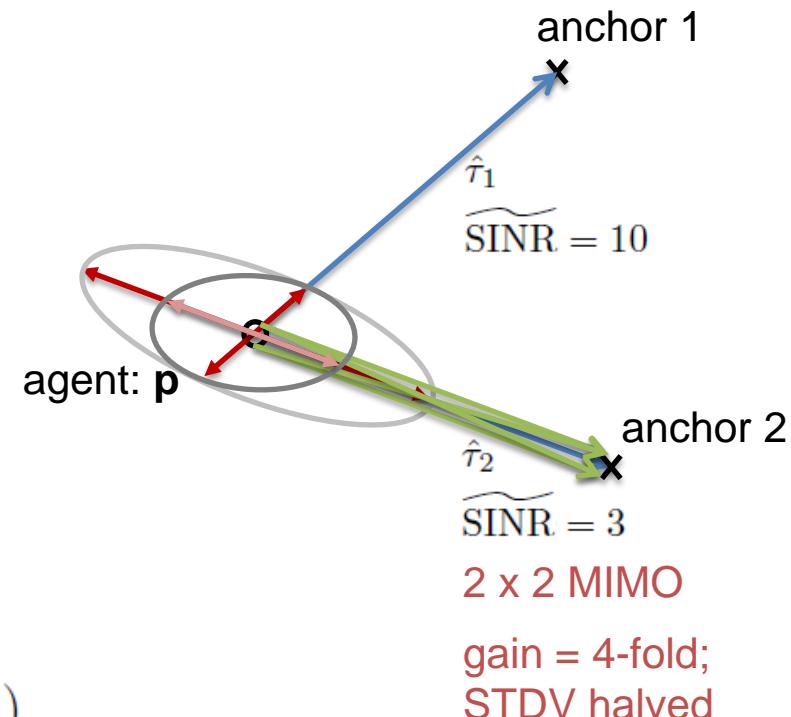
$$\mathbf{J}_p = \frac{8\pi^2\beta^2}{c^2} \sum_{j=1}^J \widetilde{\text{SINR}}^{(j)} \mathbf{J}_r(\phi^{(j)})$$

Diversity combining (SIMO, MISO, MIMO):

- approx. equal geometries
- effective SINRs are added up:

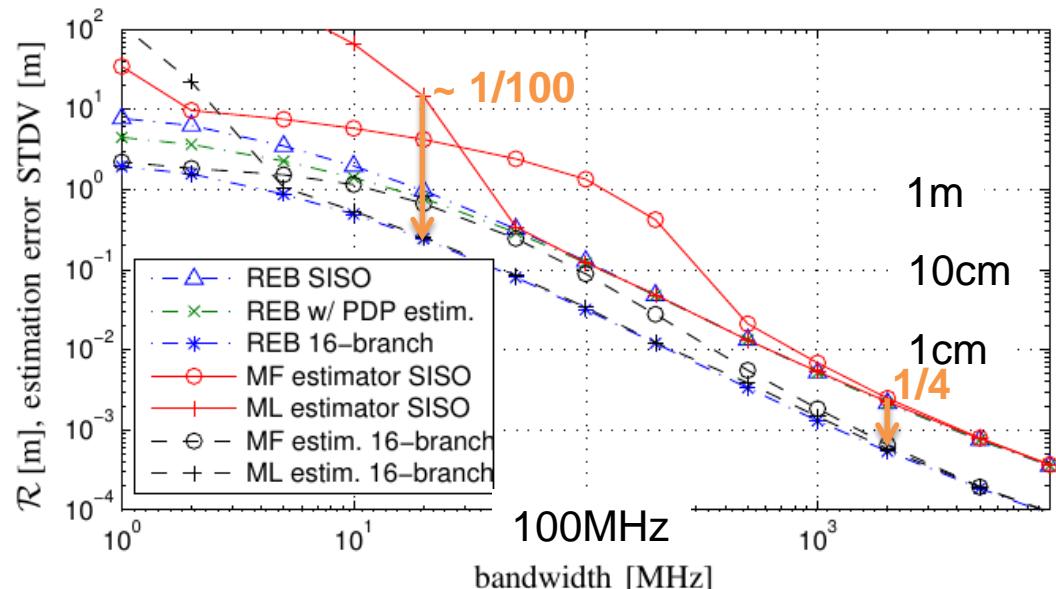
$$\mathbf{J}_p = \frac{8\pi^2\beta^2}{c^2} \sum_{\ell=1}^L \left[\sum_{j \in \mathcal{N}_\ell} \widetilde{\text{SINR}}^{(j)} \right] \mathbf{J}_r(\phi_\ell)$$

SINR gain



Multi-antenna configurations – diversity (MIMO) gain for ranging

- **4 x 4 MIMO** vs. SISO (1 x 1)
- 16 independent measm.
- 16-fold SINR (LOS-to-multipath-power-ratio):
- theoretical limit reduced by **factor 4**
- **detection probability** strongly improved



Position error bound and MIMO gain: applied to multistatic RFID positioning

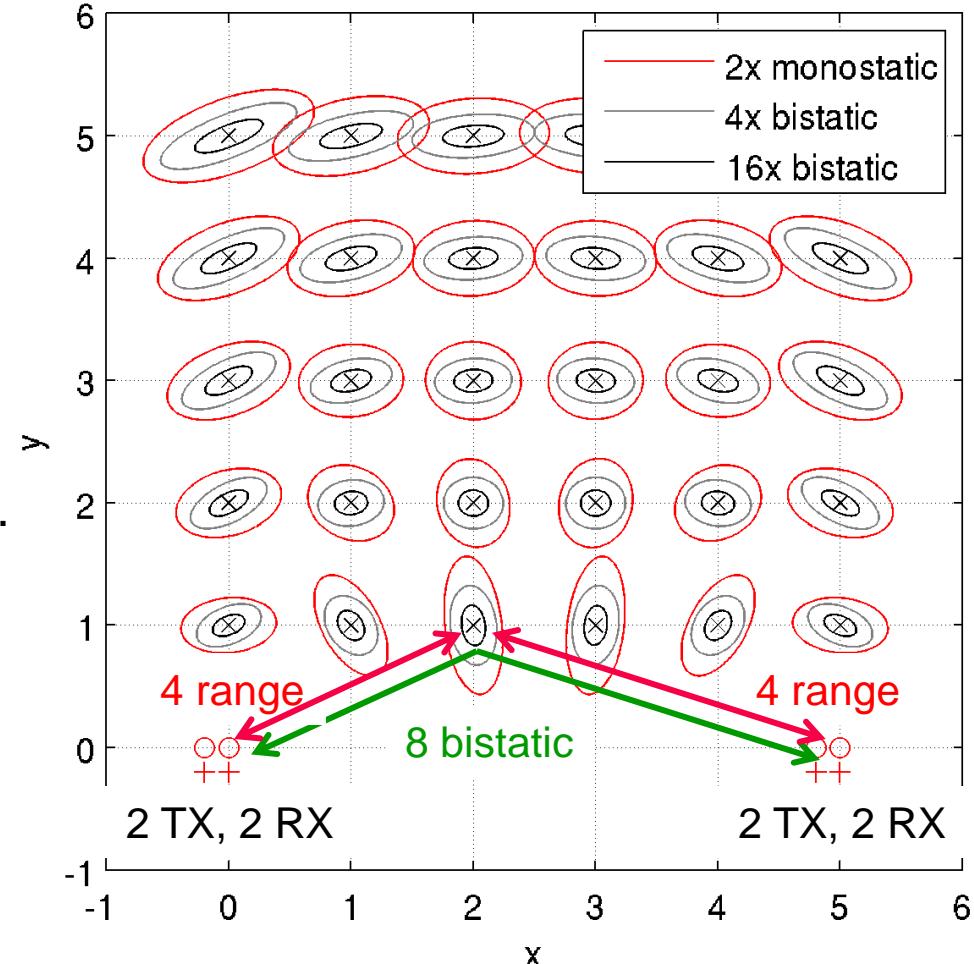
Three configurations are compared:

1. Each reader has:
 - 1 antenna for TX and RX (1 TRX)
 - yielding **2 range** measurements

2. Each reader has:
 - separated TX/RX antennas
 - yielding **2 range + 2 bistatic** meas.

3. Each reader has
 - 2 pairs of separated TX/RX ant.
 - yielding **8 independent** range plus **8 independent** bistatic measurem.

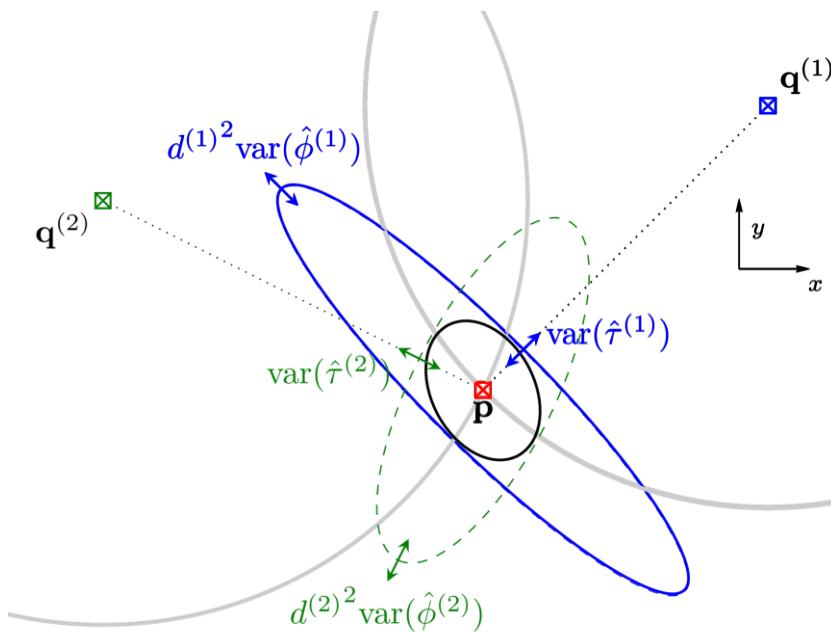
2 Fold Error Ellipses for different TX/RX settings and BW = 50 MHz



Positioning Performance Bounds

- Multiple anchors; delay and angle information from LOS

$$\mathbf{I}(\mathbf{p}) \approx \sum_{l=1}^L \underbrace{\frac{8\pi^2 \text{SINR}^{(l)} D_\lambda^2(\phi^{(l)}) M}{(c\tau^{(l)})^2} \mathbf{U}_r^\perp(\phi^{(l)})}_{\text{AoA}} + \underbrace{\frac{8\pi^2 \beta^2 \widetilde{\text{SINR}}_\tau^{(l)} M}{c^2} \mathbf{U}_r(\phi^{(l)})}_{\text{ToA}}$$



Angle of arrival (AoA) estimation with antenna arrays

- Received signal (NB) :

$$\begin{aligned} \mathbf{r} &= \mathbf{h}s + \mathbf{w} \\ &= \alpha[e^{j2\pi f_c \tau_1(\phi_0)}, e^{j2\pi f_c \tau_2(\phi_0)}, \\ &\quad \dots, e^{j2\pi f_c \tau_M(\phi_0)}]^T s + \mathbf{w} \end{aligned}$$

- MF estimation:

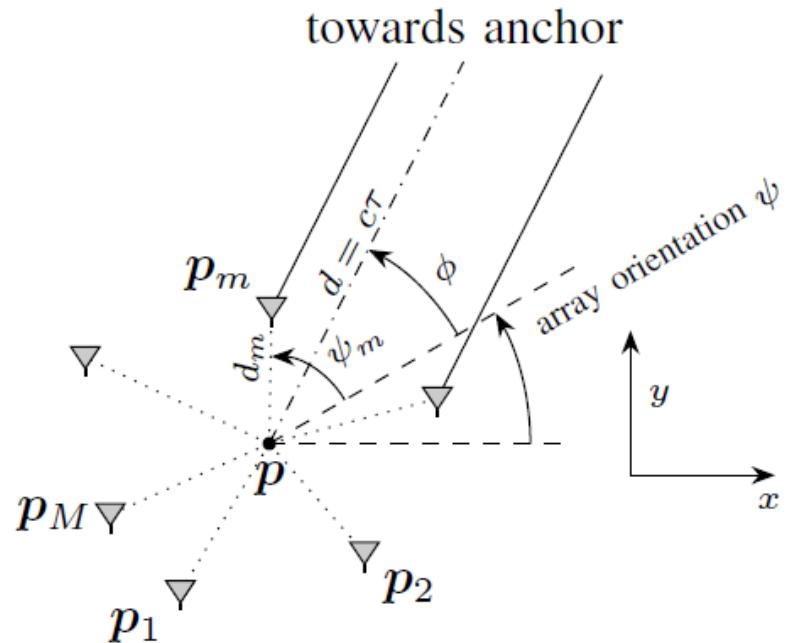
$$\hat{\phi} = \arg \max_{\phi} |\mathbf{a}^H(\phi)\mathbf{r}|$$

- array response vector

$$\mathbf{a}(\phi) = [e^{j2\pi f_c \tau_1(\phi)}, e^{j2\pi f_c \tau_2(\phi)}, \\ \dots, e^{j2\pi f_c \tau_M(\phi)}]^T$$

Scenario:

- 1 TX antenna (in direction ϕ)
- M RX antennas:



CRLB for angle estimation (phased array)

AWGN only

$$r_m(t) \approx \alpha e^{-j2\pi f_c \tau_m} s(t) + w(t)$$

CRLB for AoA

$$\text{var}\{\hat{\phi}\} \gtrsim (8\pi^2 f_c^2 D^2(\phi) \text{SNR})^{-1}$$

- squared effective aperture

$$D^2(\phi) = \sum_{m=1}^M \left[\frac{d_m}{c} \sin(\phi - \psi_m) \right]^2$$

- signal-to-noise ratio

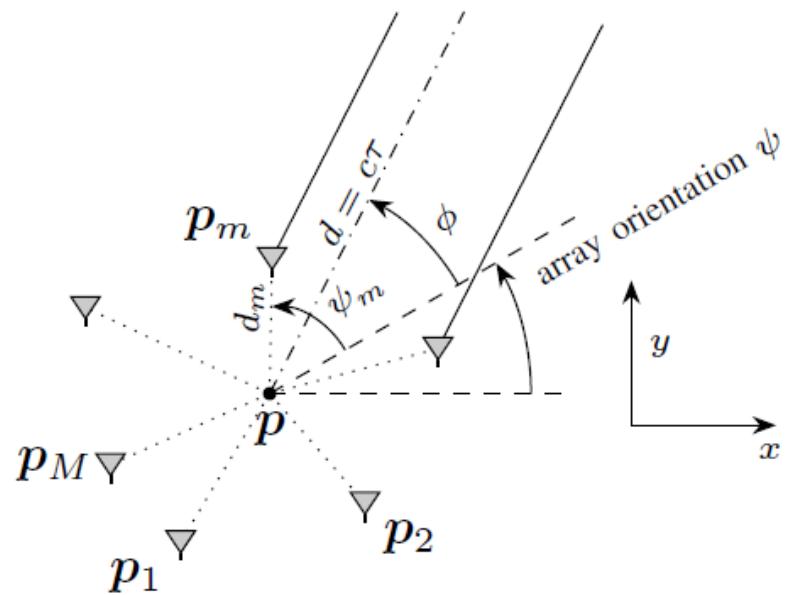
$$\text{SNR} = \frac{E_{\text{LOS}}}{N_0}$$

➤ CRLB scales with f_c (carrier), **squared aperture** and SNR

AWGN + dense multipath

$$r_m(t) \approx \alpha e^{-j2\pi f_c \tau_m} s(t) + (\underline{s * \nu_m})(t) + w(t)$$

towards anchor

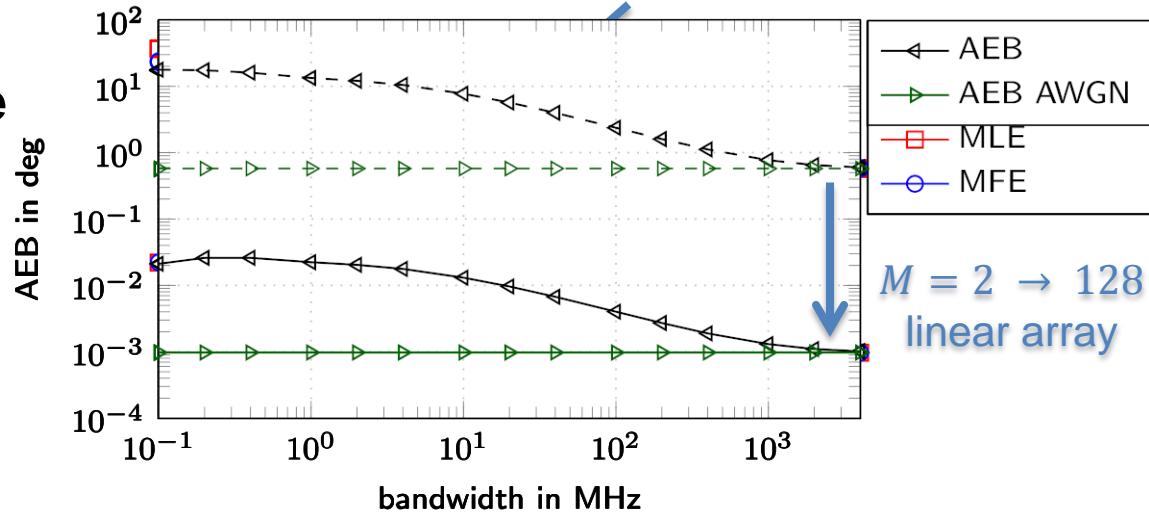


➤ **multipath interference** limits the performance

Physically large arrays –

Performance scaling for angle estimation in dense multipath

- **CRLB for AoA**
 - uniform linear array (ULA)
 - **bandwidth** scales SINR
→ increase of array **aperture**
- **AoA estimators**
 - matched filter diverges from CRLB
 - **minimum SINR** needed for maximum likelihood
→ **detectability** improved



- Large arrays offer tremendous **accuracy gain!**
- **How to exploit it?**

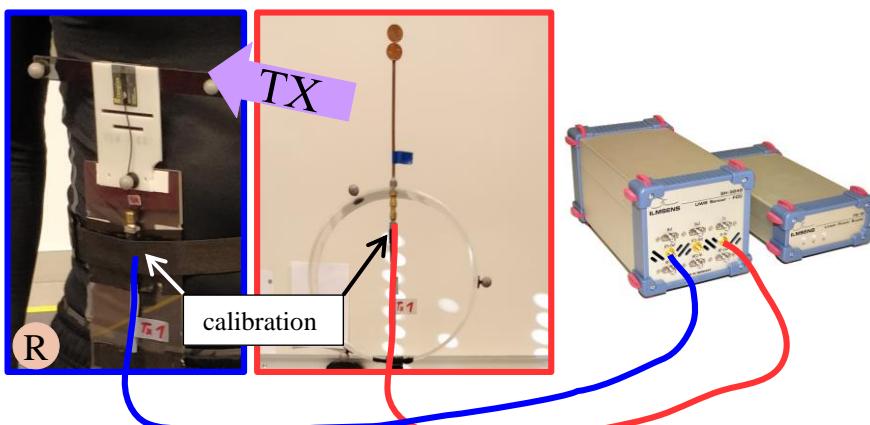
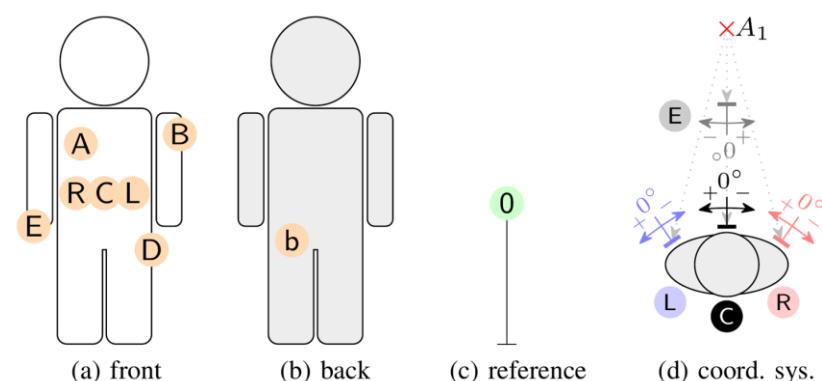
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 - **Multipath-assisted indoor positioning**
 - **Environment modeling**
- Wireless Power Transfer
- Conclusions

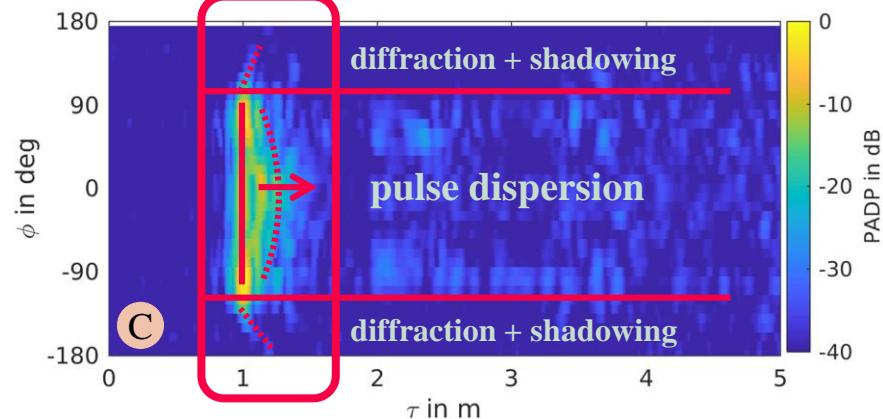
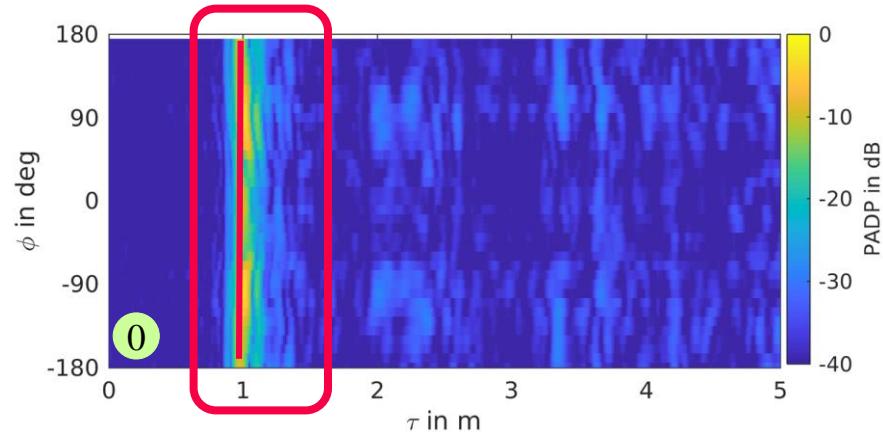
Reliance on Line-of-Sight

Measurement of body influence (off-body channel)

Measurement Setup



Characterization of LOS

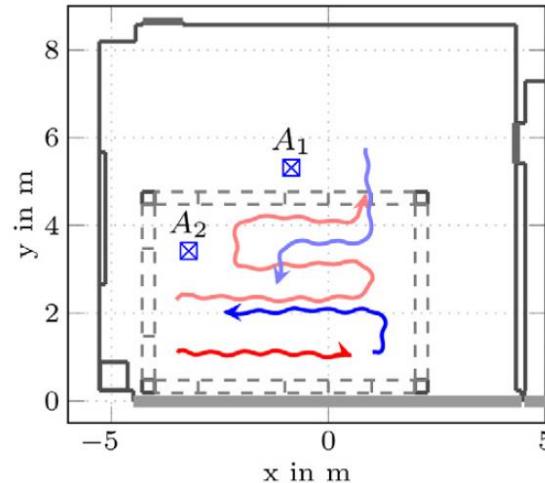
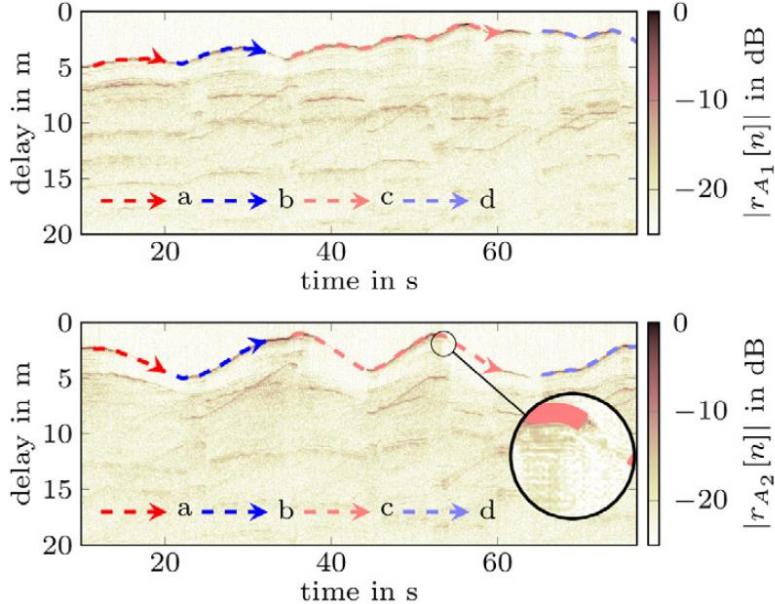


Reliance on Line-of-Sight

Impact of body shadowing

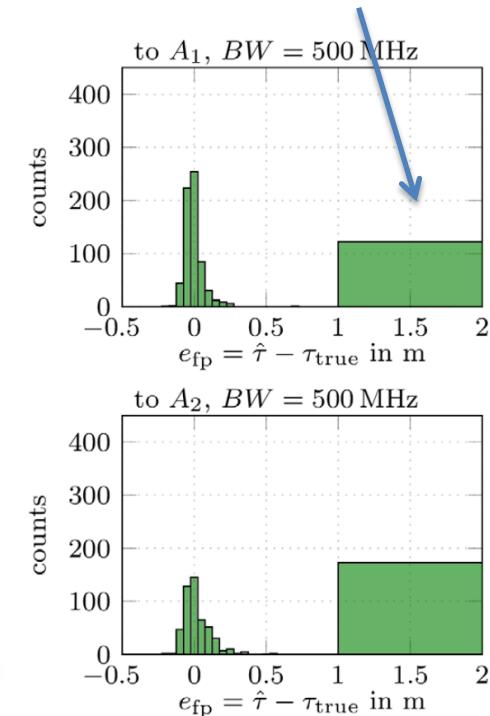
Walking along trajectory

- two fixed anchors



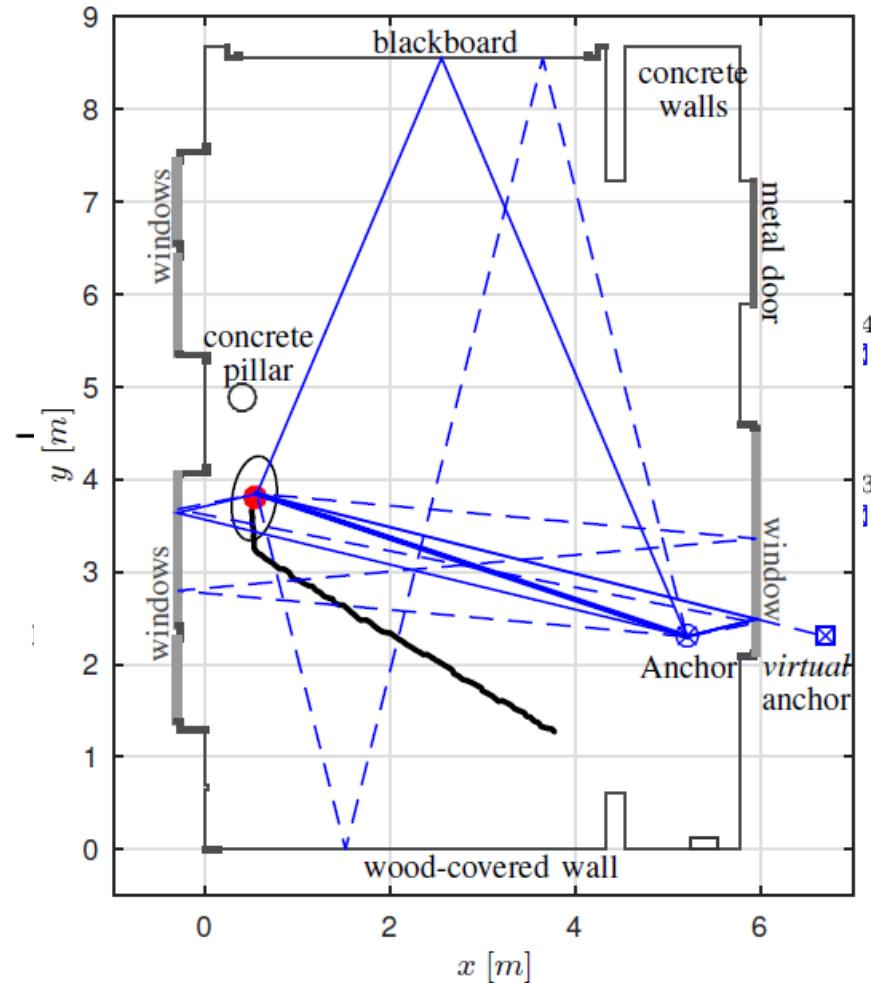
Ranging

- outliers



Multipath-assisted Indoor Navigation and Tracking (MINT) – *concept and geometric model*

- **Idea:**
 - exploit range/position information from *reflected* multipath
- **Benefits:**
 - less anchor nodes;
 - more redundancy, i.e. robustness in NLOS;
 - higher accuracy
- **Geometric model (GPEM):**
virtual anchors (VAs) (mirror sources)



Signal Model

(Geometry-based stochastic channel model - GSCM)

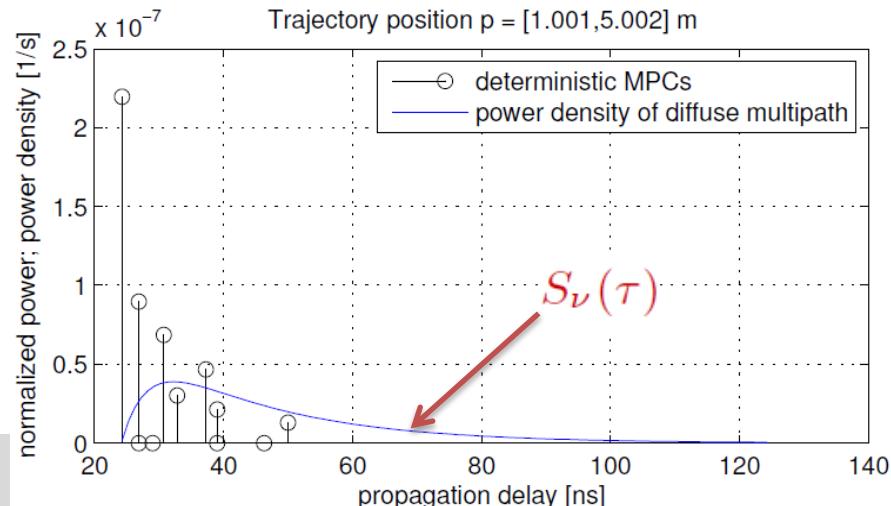
- Received signal: ($s(t)$: TX signal)

$$r(t) = \underbrace{\sum_{k=1}^K \alpha_k s(t - \tau_k)}_{\text{useful signal}} + \underbrace{\int_{-\infty}^{\infty} s(\lambda) \nu(t - \lambda) d\lambda}_{\text{interference}} + w(t)$$

noise

- K deterministic multipath components**
 - Anchor (LOS), virtual anchors (NLOS), deterministic scatterers
 - Diffuse multipath $\nu(t)$**
 - PDP $S_\nu(\tau)$
- MPCs characterized by**

$$\text{SINR}_k := \frac{|\alpha_k|^2}{N_0 + T_s S_\nu(\tau_k)}$$



Position error bound for MINT

(Cramér-Rao lower bound derived from LHF)

- Position error variance is bounded by $\text{var}\{\hat{\mathbf{p}}\} \geq \text{tr}\{\mathbf{J}_P^{-1}\}$
 - If no “path-overlap” occurs (orthogonal signals from VAs)

$$\mathbf{J}_P = \frac{8\pi^2\beta^2}{c^2} \sum_{k=1}^K \text{SINR}_k \mathbf{J}_r(\phi_k)$$

- effective SINR_k determines ranging information intensity
 - for MPC from k -th virtual anchor

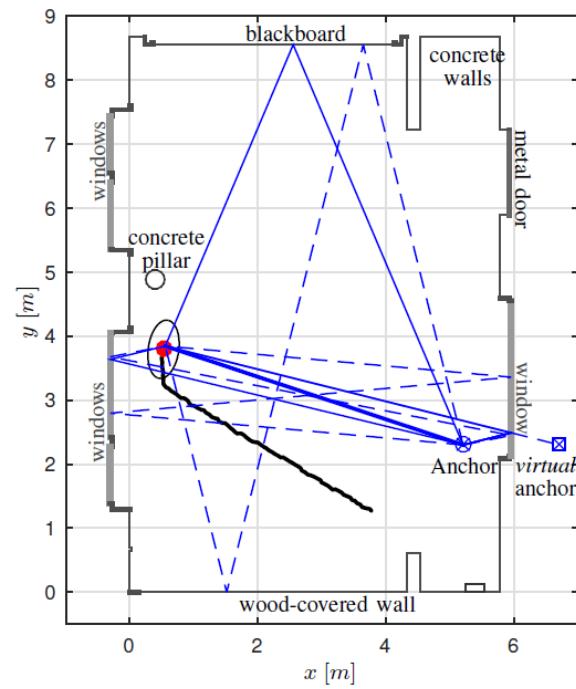
$$\text{SINR}_k := \frac{|\alpha_k|^2}{N_0 + T_s S_\nu(\tau_k)}$$

- Ranging direction matrix accounts for geometry

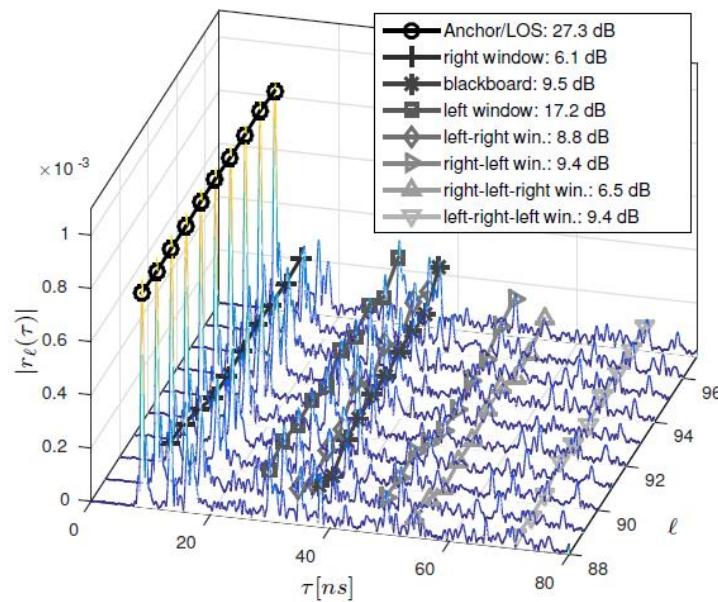
Multipath-resolved environment model

- Exploit (specular) multipath components and location
 - Environment model: **predictability** of multipath
 - Yields **robust tracking** (here)

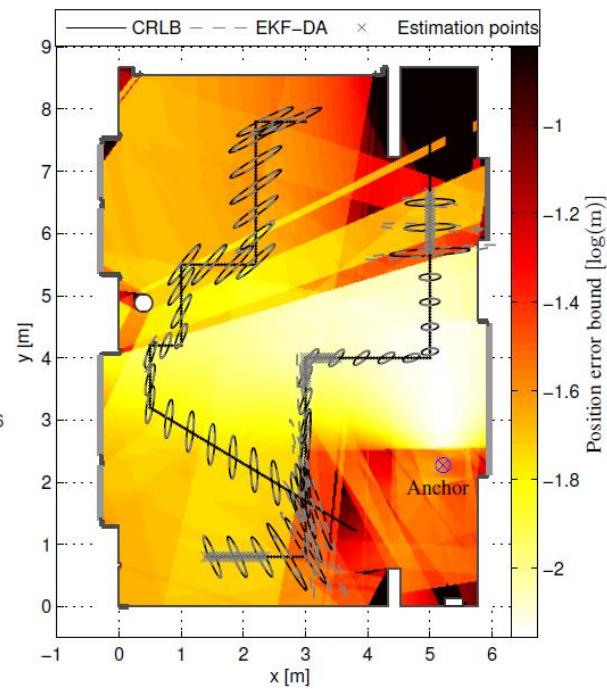
Geometric model:



Signals / Quality (SINR):

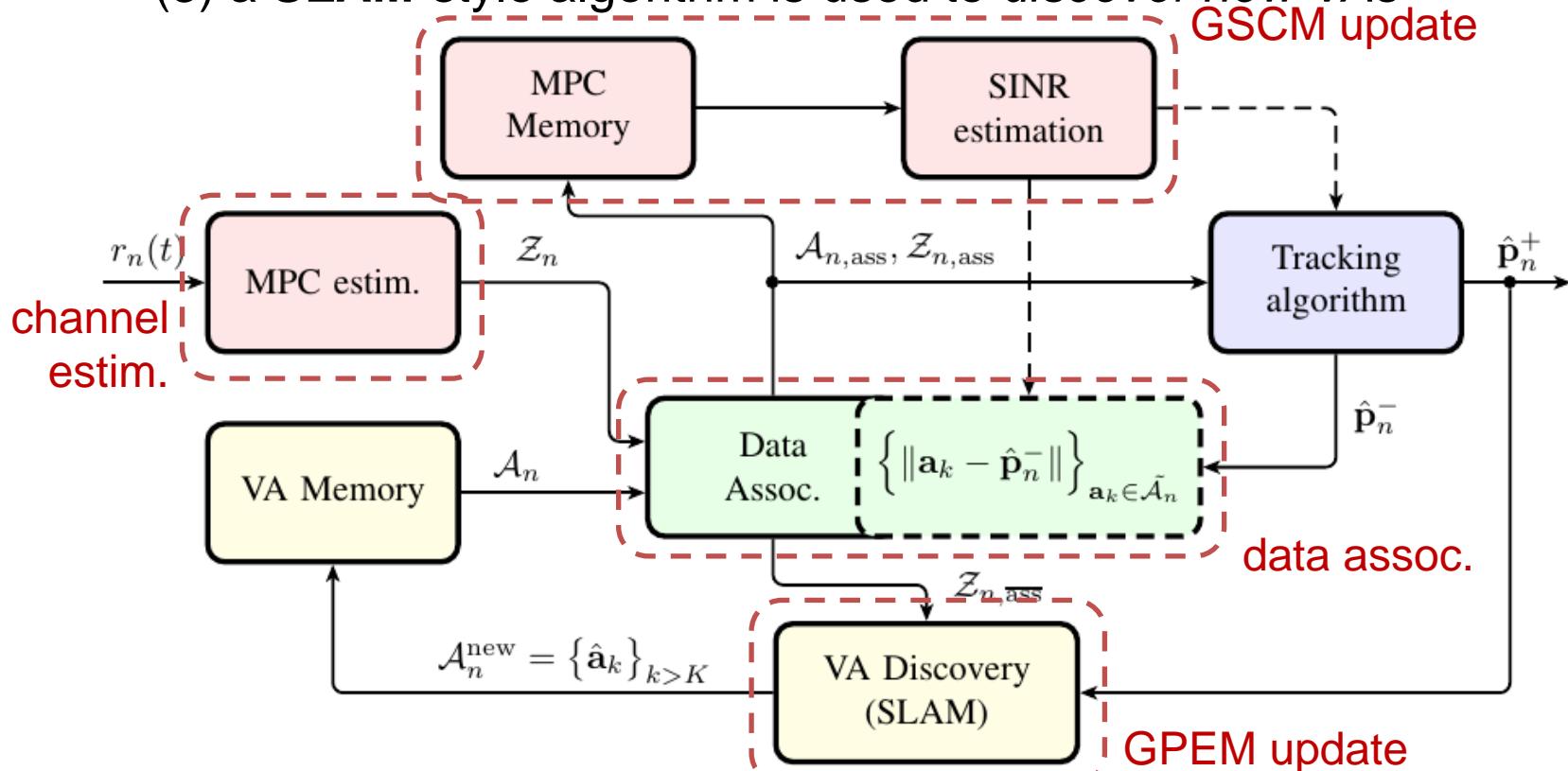


Environment model:



Tracking algorithms exploiting multipath

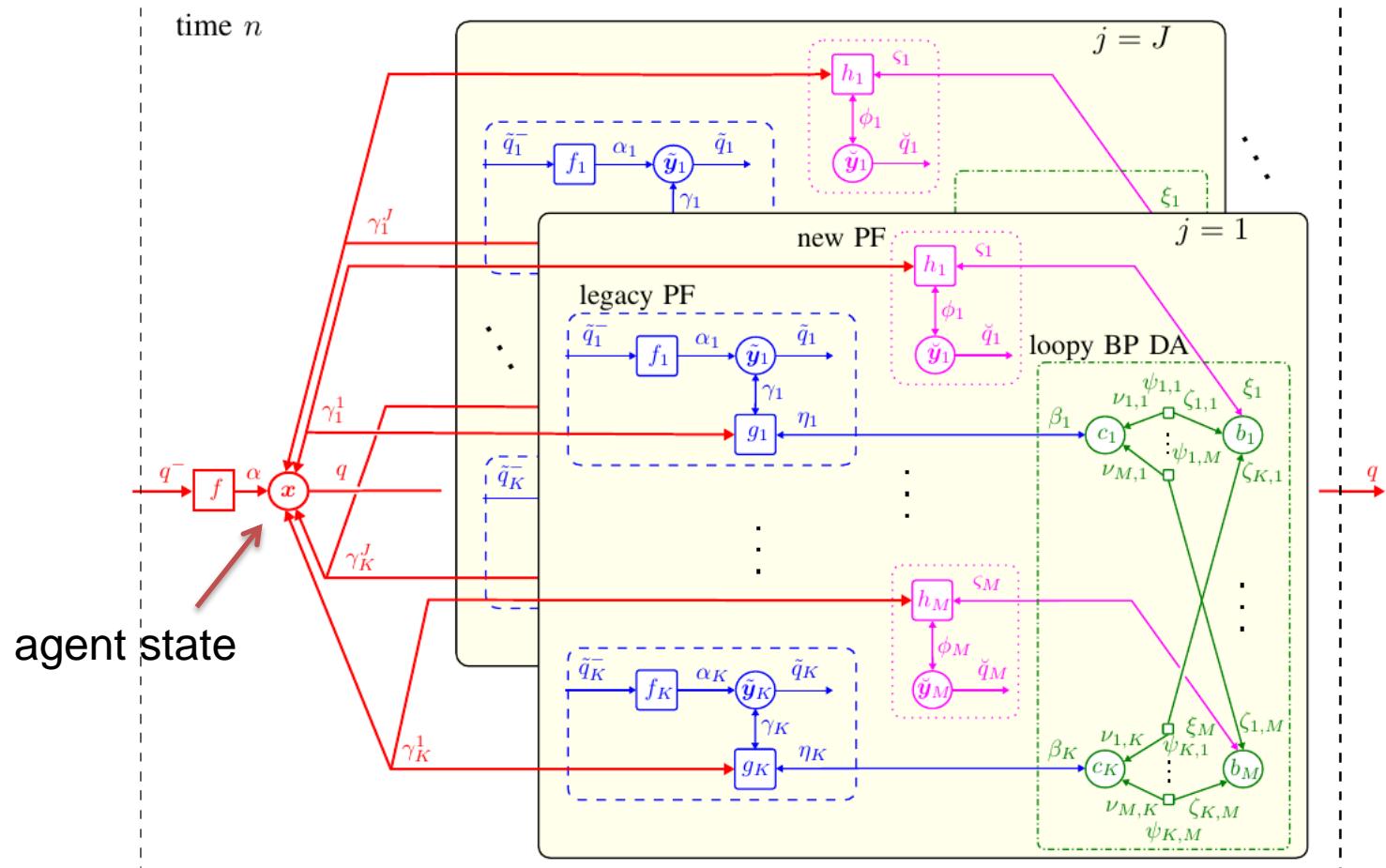
- (0) multipath parameters (ToA/AoA) estimated from **received signals**
- (1) ***data association*** of multipath ranges and *state-space tracking*
- (2) **ranging uncertainty** is estimated from multipath amplitudes
- (3) a **SLAM-style algorithm** is used to *discover new VAs*



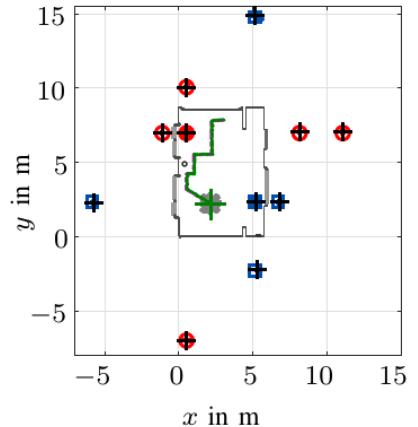
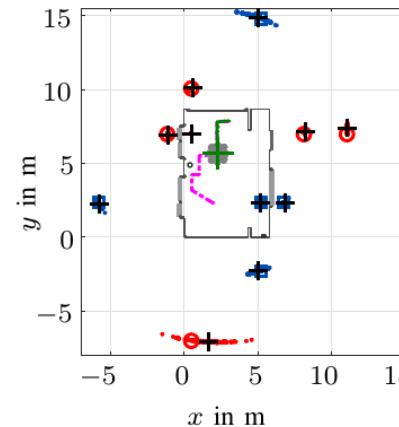
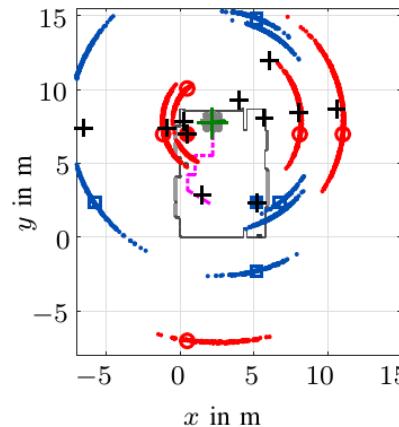
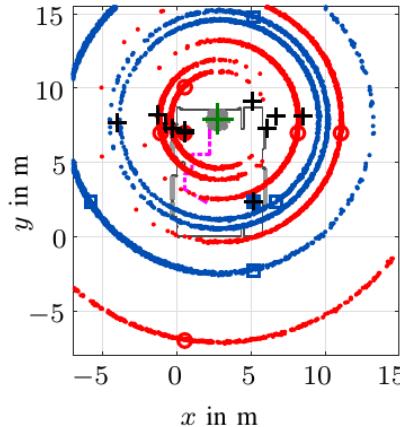
Multipath-based SLAM

Bayesian inference on factor graph

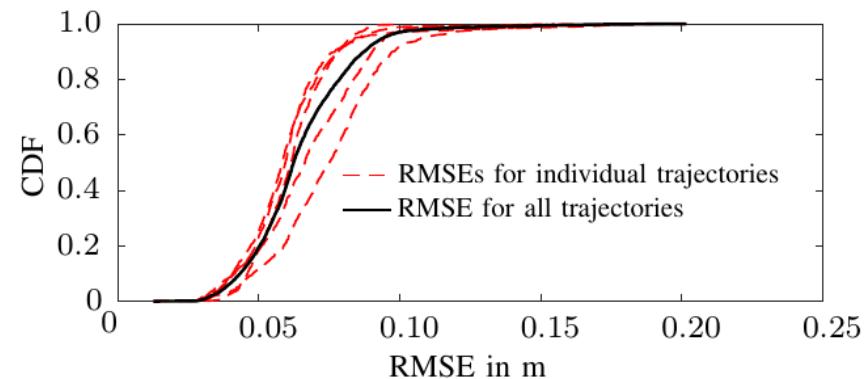
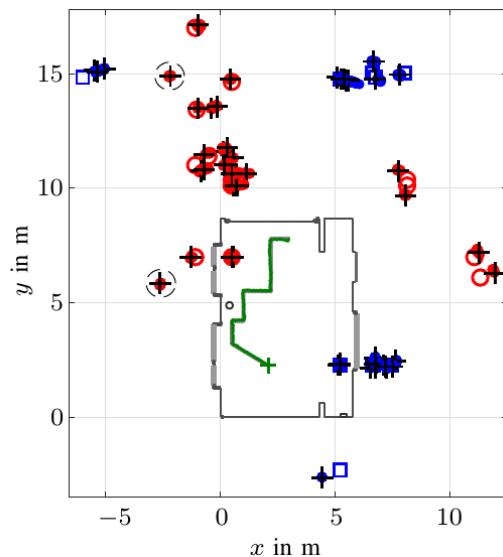
PF: potential feature



Multipath-based SLAM – range-only Particle convergence

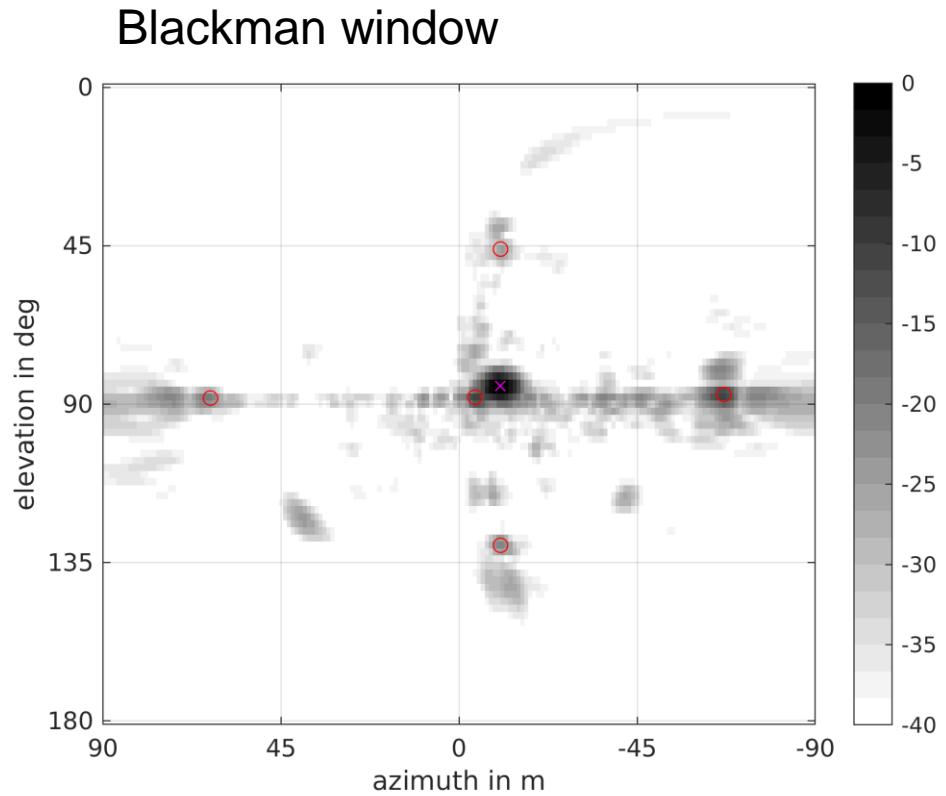
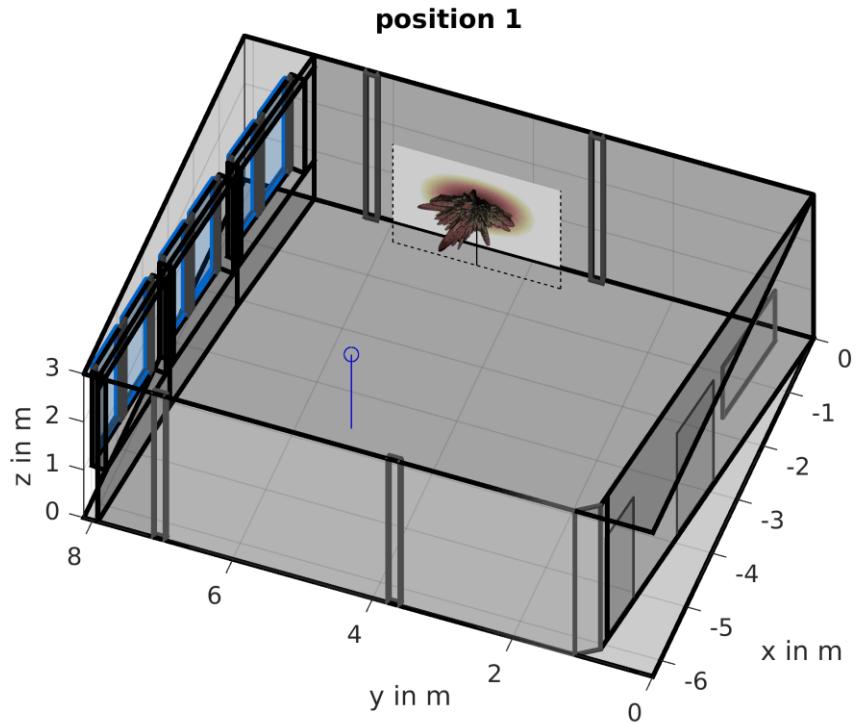


For real data:



Environment sensing with physically large array

2.4 m x 1.6 m virtual array measurement (8400 elements) @ 7 GHz

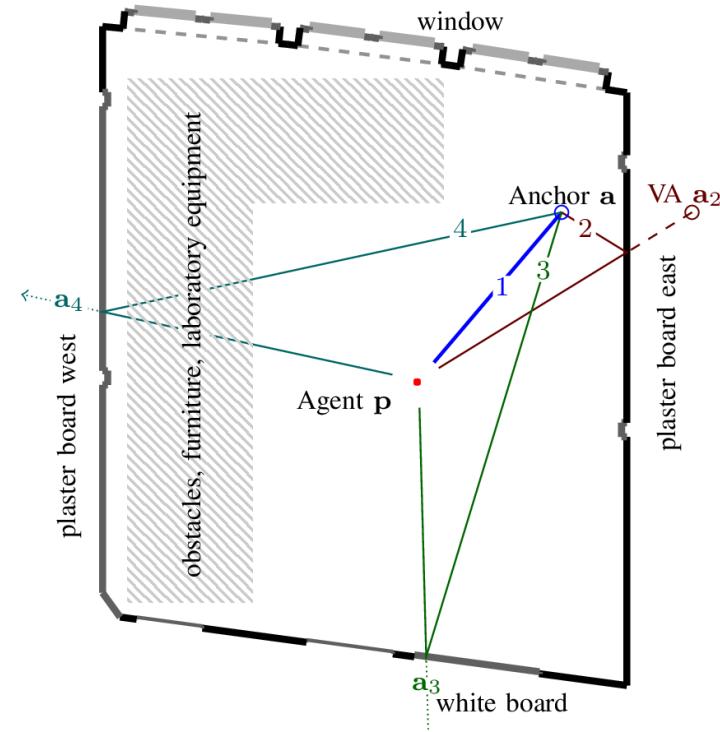
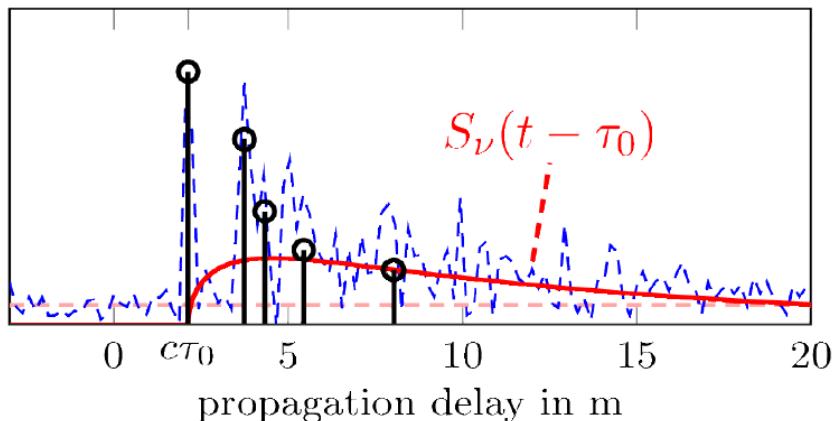


Channel Parameter Estimation

Utilizing Sparse Bayesian Learning

Measured data:

- 3x3 antenna array (2cm spacing)
- Pulse RRC
 - pulse duration 1 ns; roll-off-factor 0.6; center frequency 6 GHz
- AWGN: 30 dB SNR
- **DMC: Double exponential PDP**

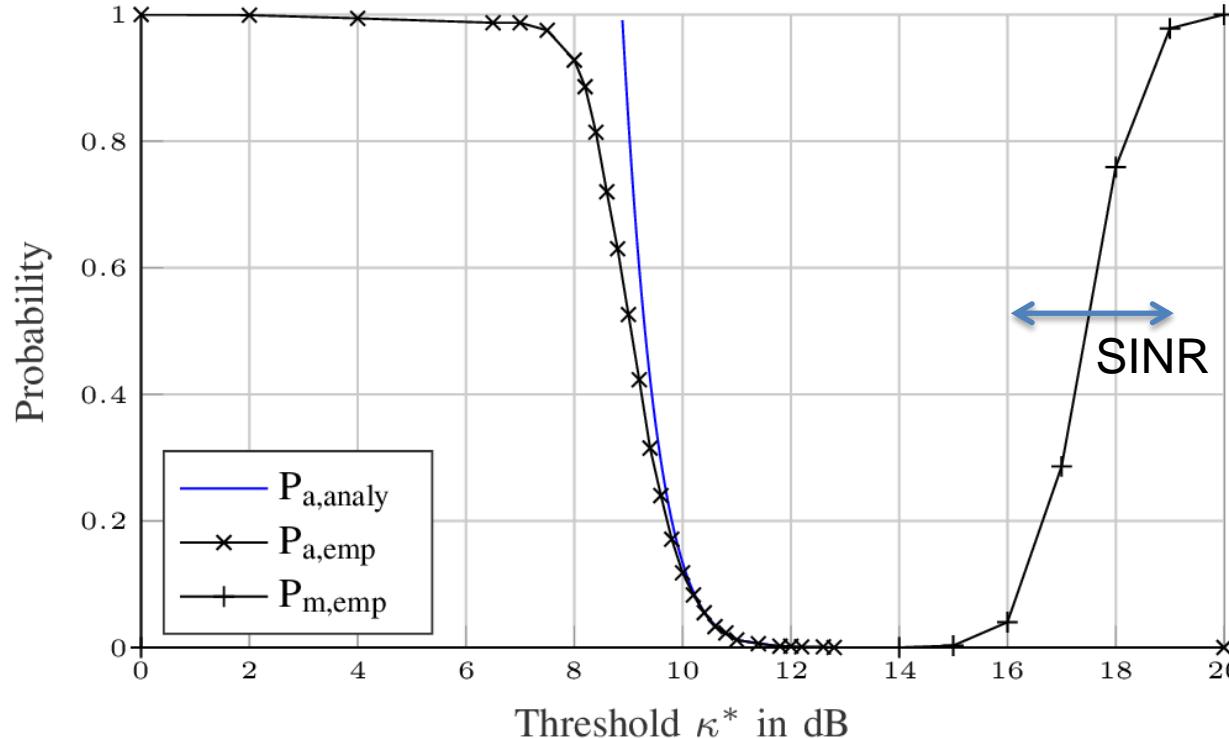


Channel Parameter Estimation

Utilizing Sparse Bayesian Learning

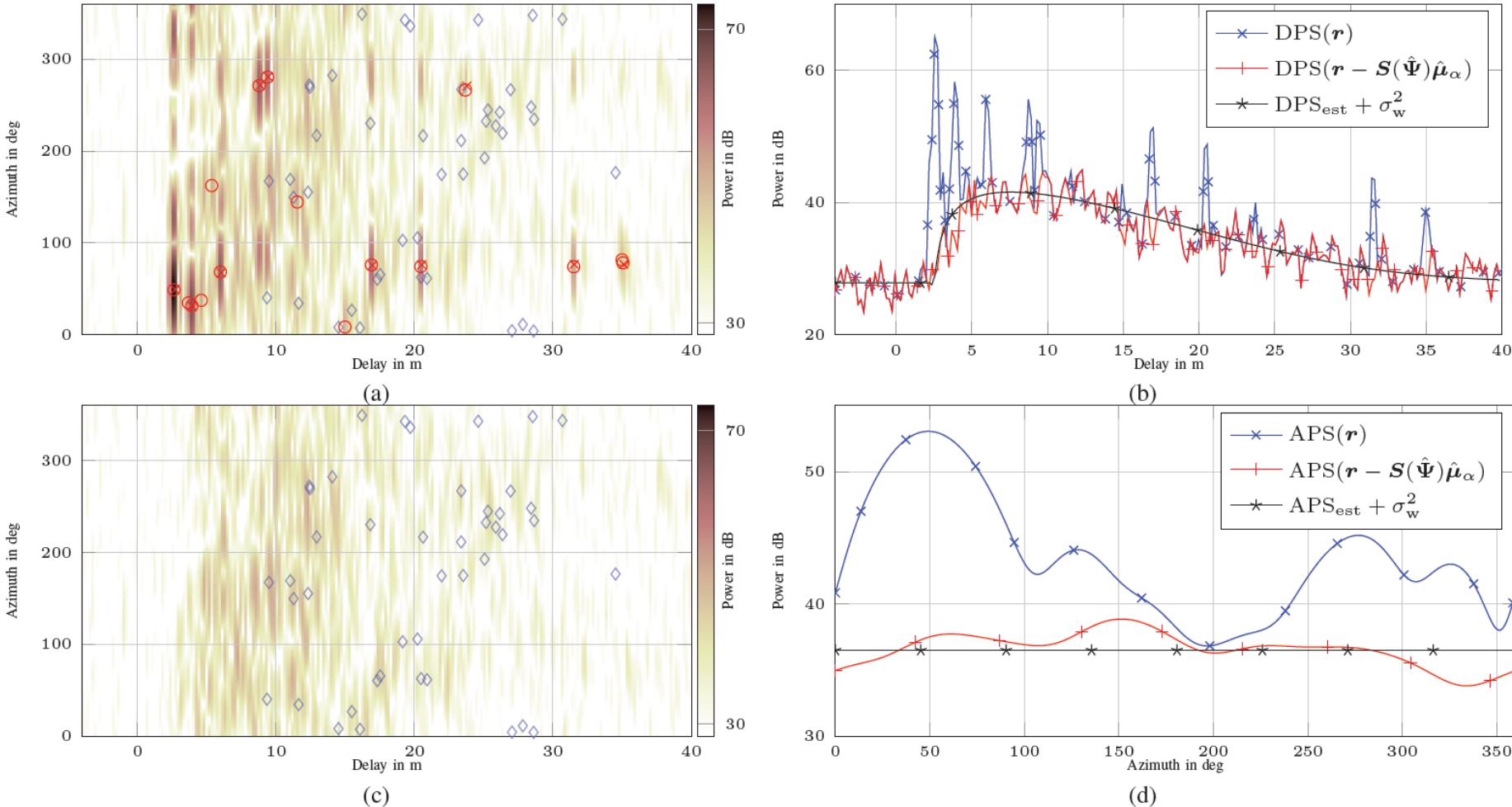
Probability of Artifact and Probability of Detection - ROC

- Single component in DMC plus AWGN



Channel Parameter Estimation

Utilizing Sparse Bayesian Learning



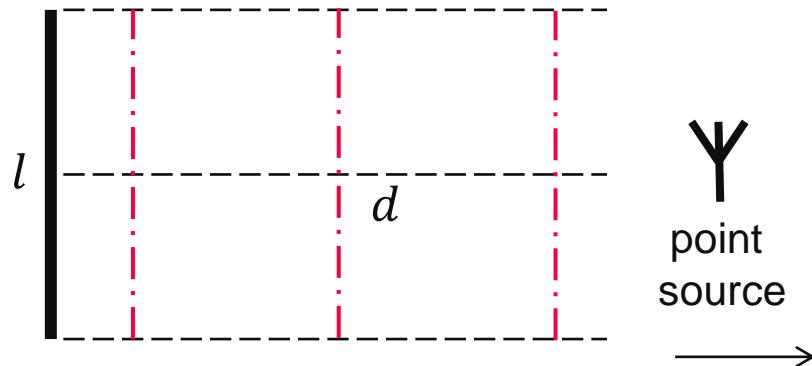
Outline

- Introduction
- Ranging and positioning in dense multipath
 - Bandwidth scaling and MIMO gain
- Sensing
 - Multipath-assisted indoor positioning
 - Environment modeling
- **Wireless Power Transfer**
 - **With physically large arrays**
- Conclusions

Physically Large Antennas/Arrays – What's different?

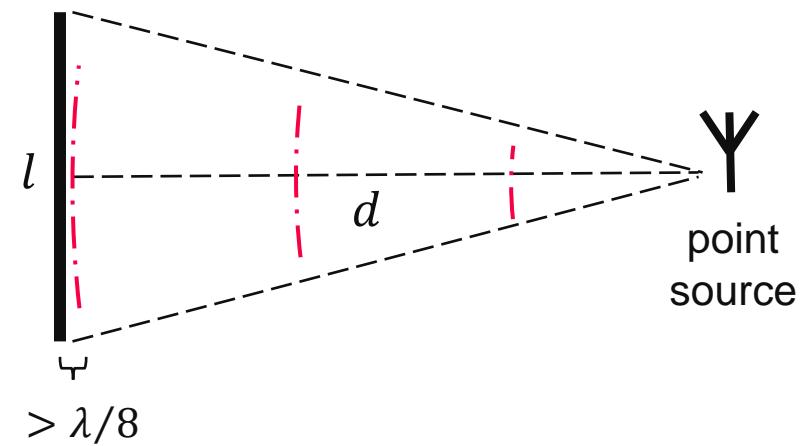
User in “far field”

- **Plane wave**
- $d \gg d_F$... Fraunhofer distance



User in “near field”

- Spherical wave
- $d \leq d_F = 2 l^2 / \lambda$



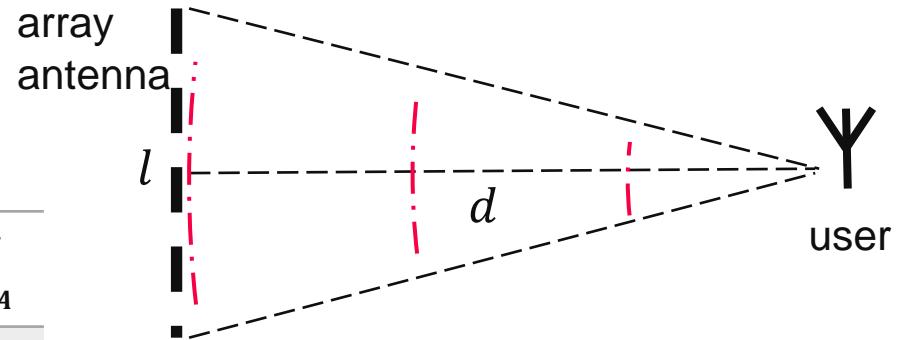
- Field distribution: $E, H \propto \frac{1}{d} f(\theta, \phi)$
- Radiation pattern

- Field distribution: $E, H = f(d, \theta, \phi)$
- Distance dependent → focusing

Physically Large Arrays

Example: user in “near field” $d_{FA} = 2l^2/\lambda$

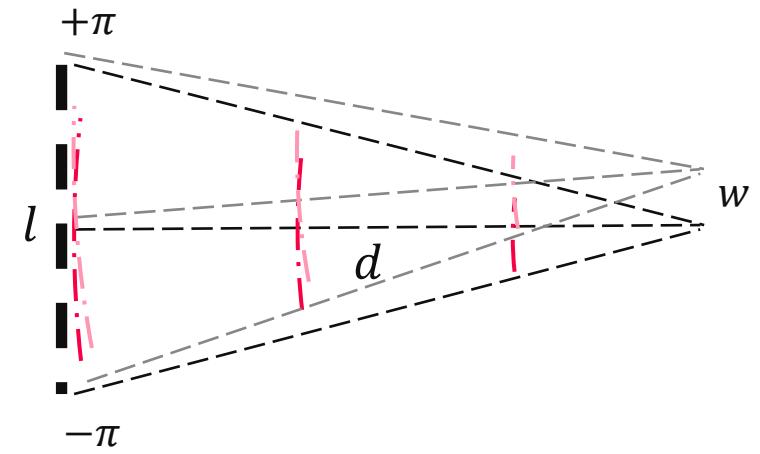
frequency f_c	wavelength λ	array length l	Fraunhofer distance d_{FA}
2.4 GHz	12.5 cm	$2.5 \text{ m} = 20 \lambda$	100 m
6 GHz	5 cm	$2.5 \text{ m} = 50 \lambda$	250 m



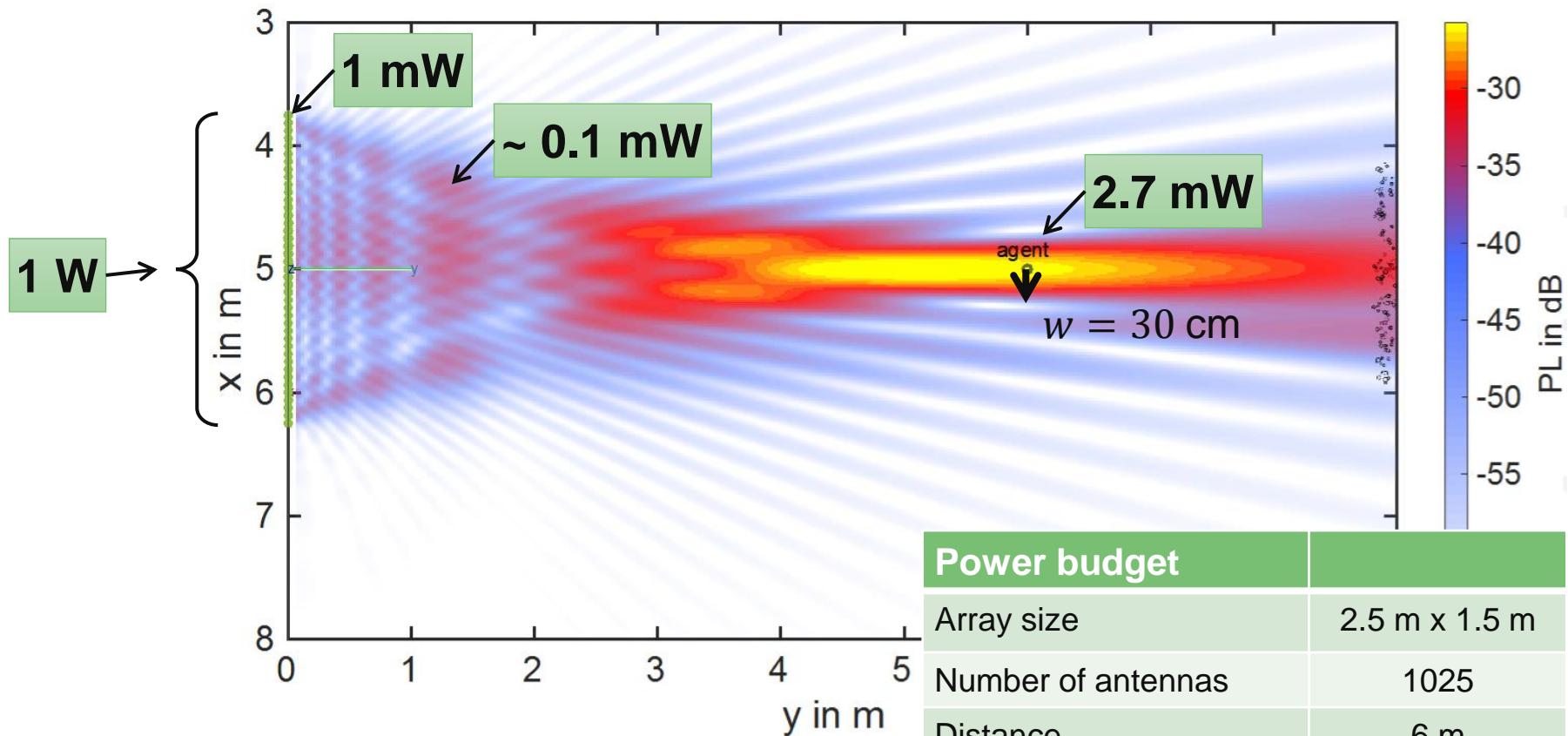
Beam focusing – width of focal point

- $w = d \lambda / l$

wavelength λ	distance d	array length l	focal point w
12.5 cm	6 m	2.5 m	30 cm
5 cm	6 m	2.5 m	12 cm



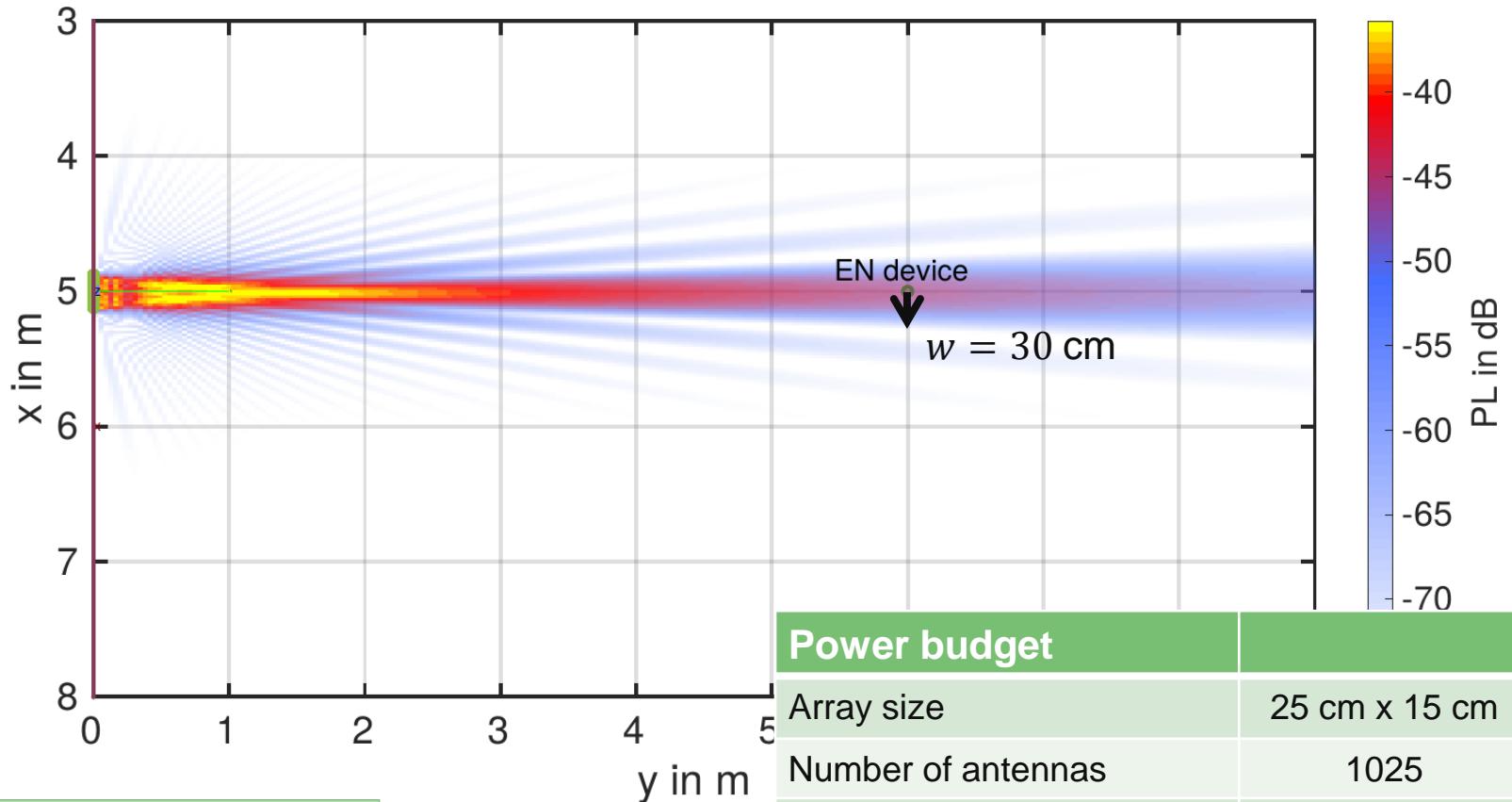
Beam focusing: user in the near field (@ 2.4 GHz)



Power converges towards user:
a radical shift

Power budget	
Array size	2.5 m x 1.5 m
Number of antennas	1025
Distance	6 m
Single-antenna path loss	55.6 dB
Array gain	30.1 dB
Array path loss (simul.)	25.7 dB

Beam focusing: user in the far field (@ 24 GHz)



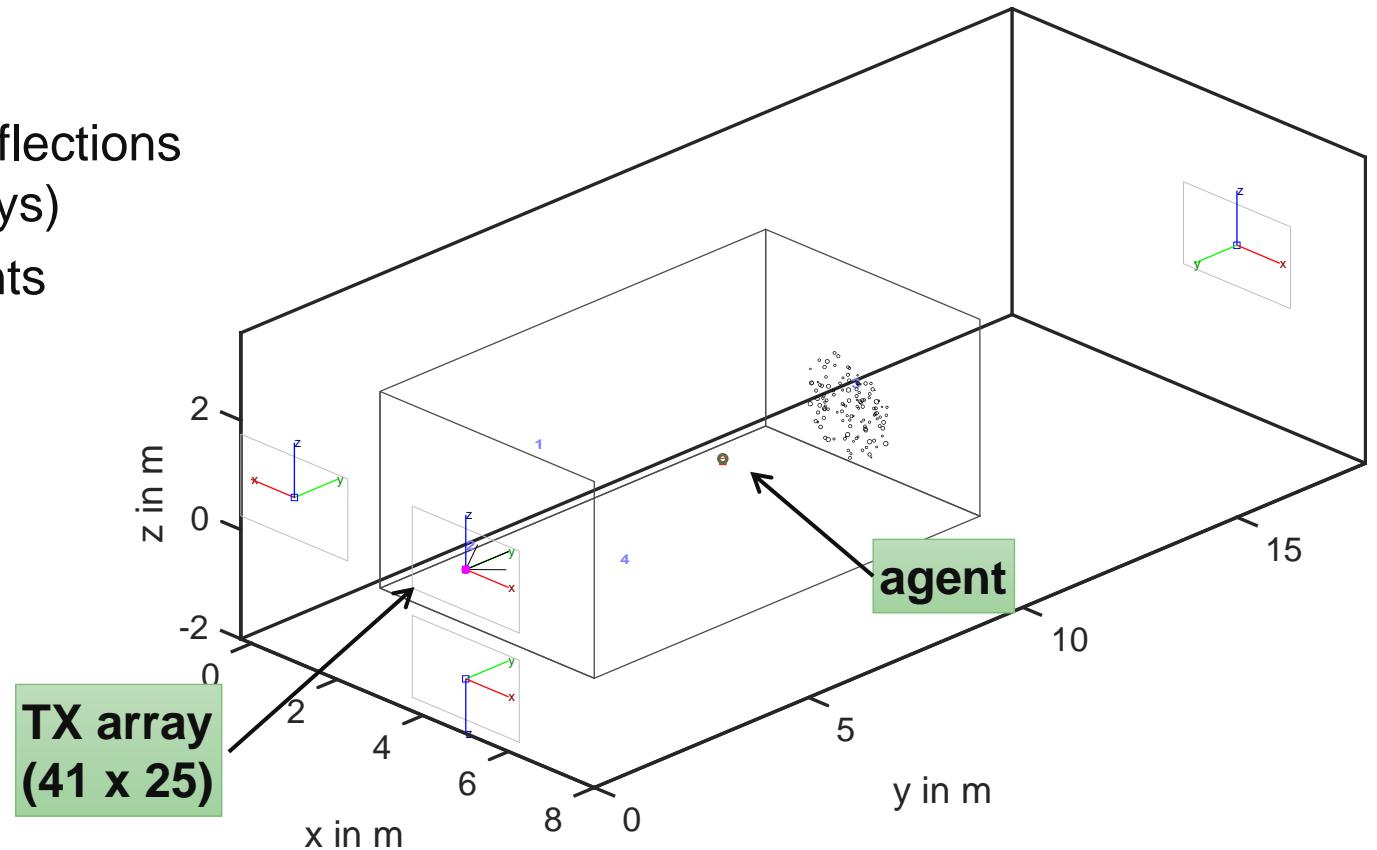
Conventional situation:
Power diverges from array

Channel Modeling for physically large arrays

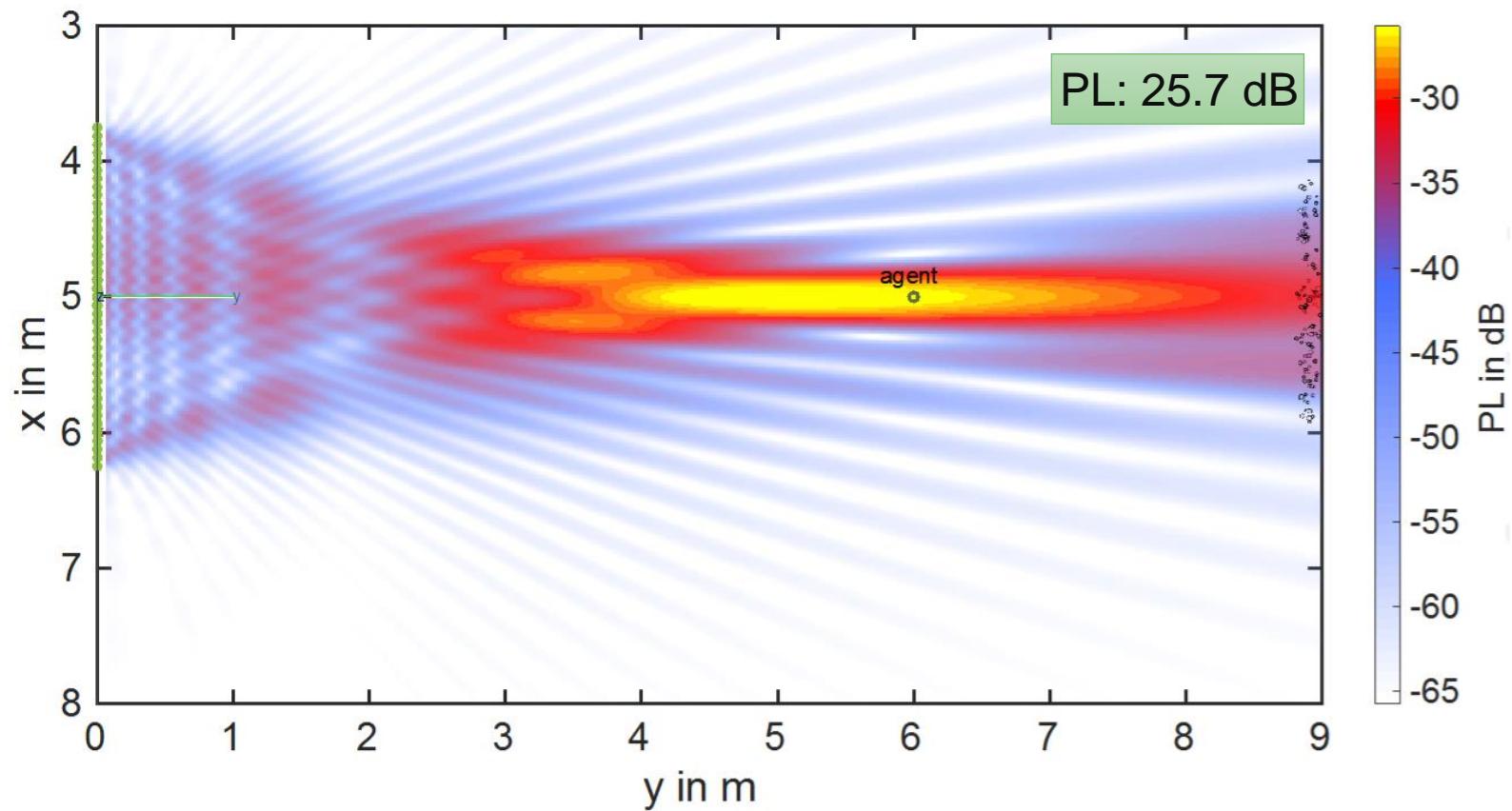
Illustration of propagation mechanisms

Simulation environment:

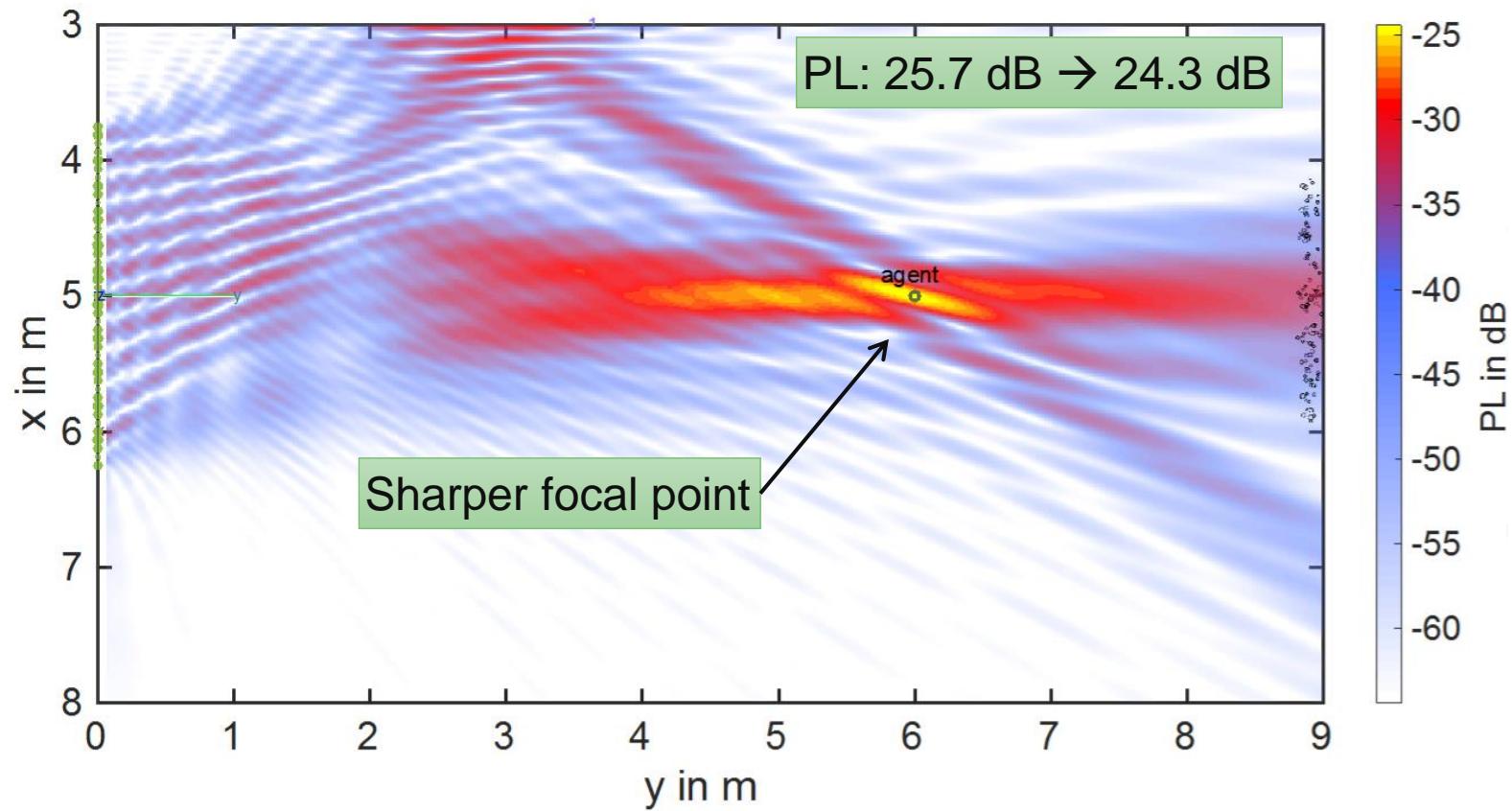
- Specular reflections (virtual arrays)
- Scatter points



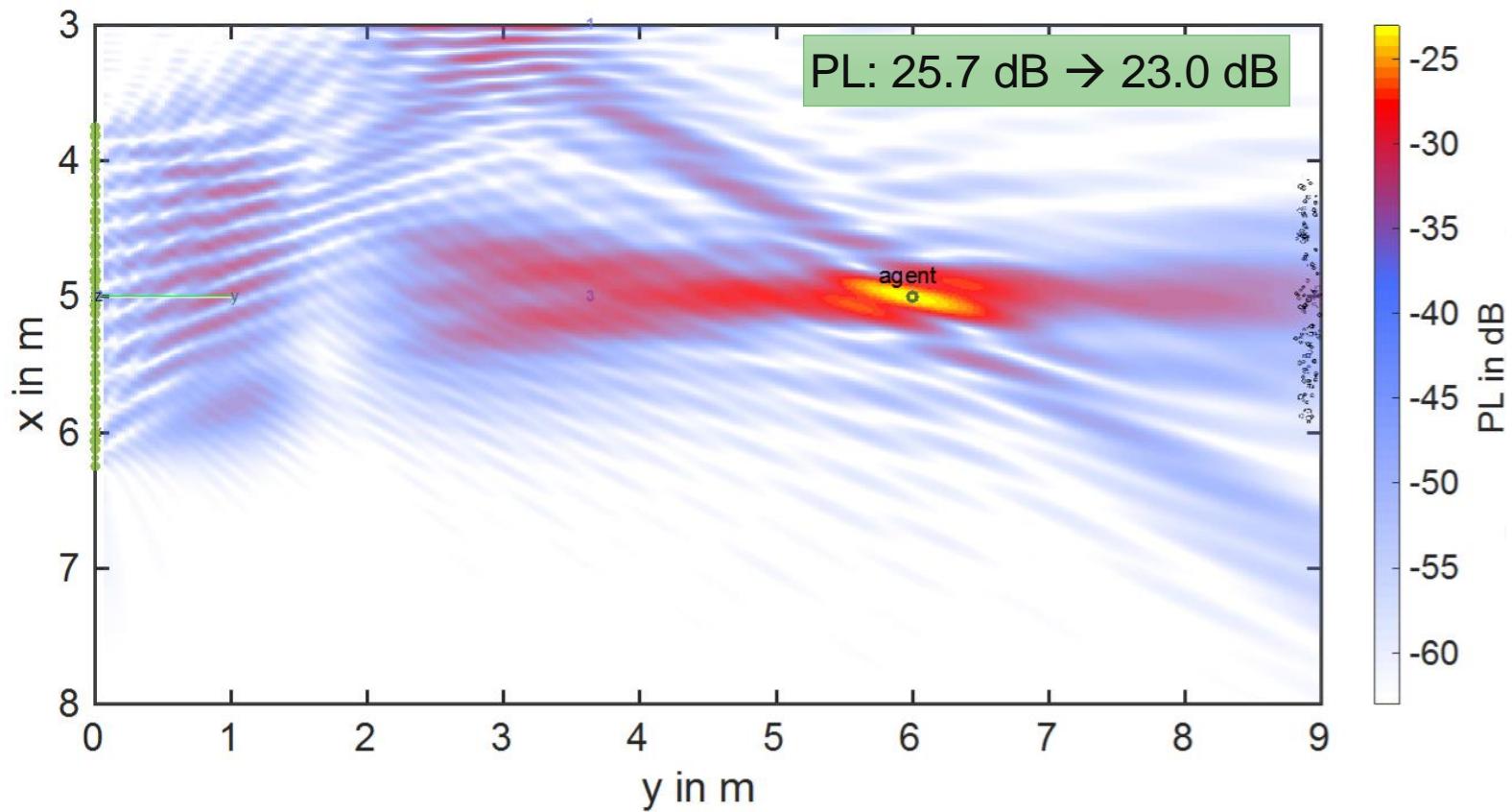
Line-of-sight only



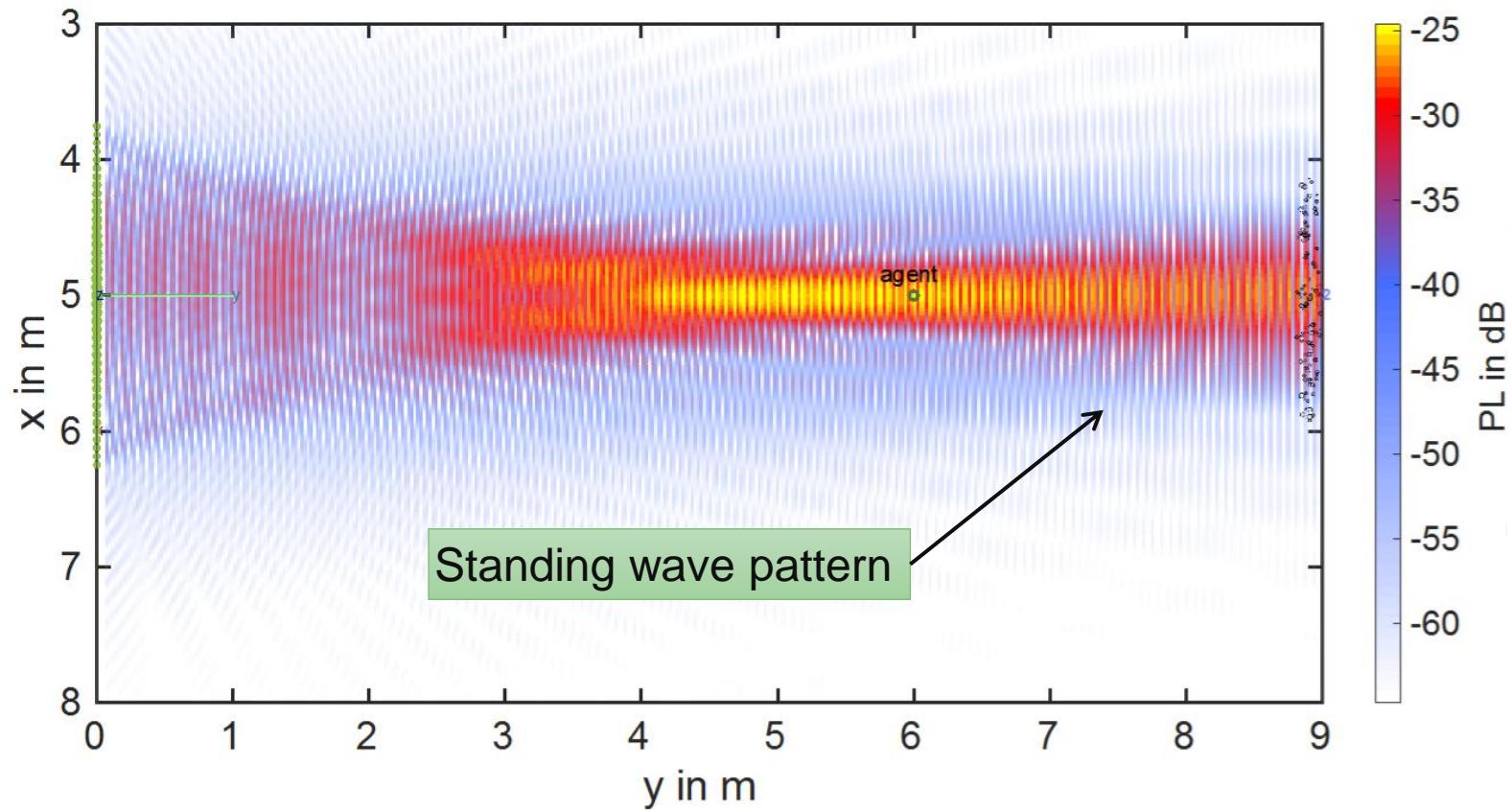
Line-of-sight + one specular component



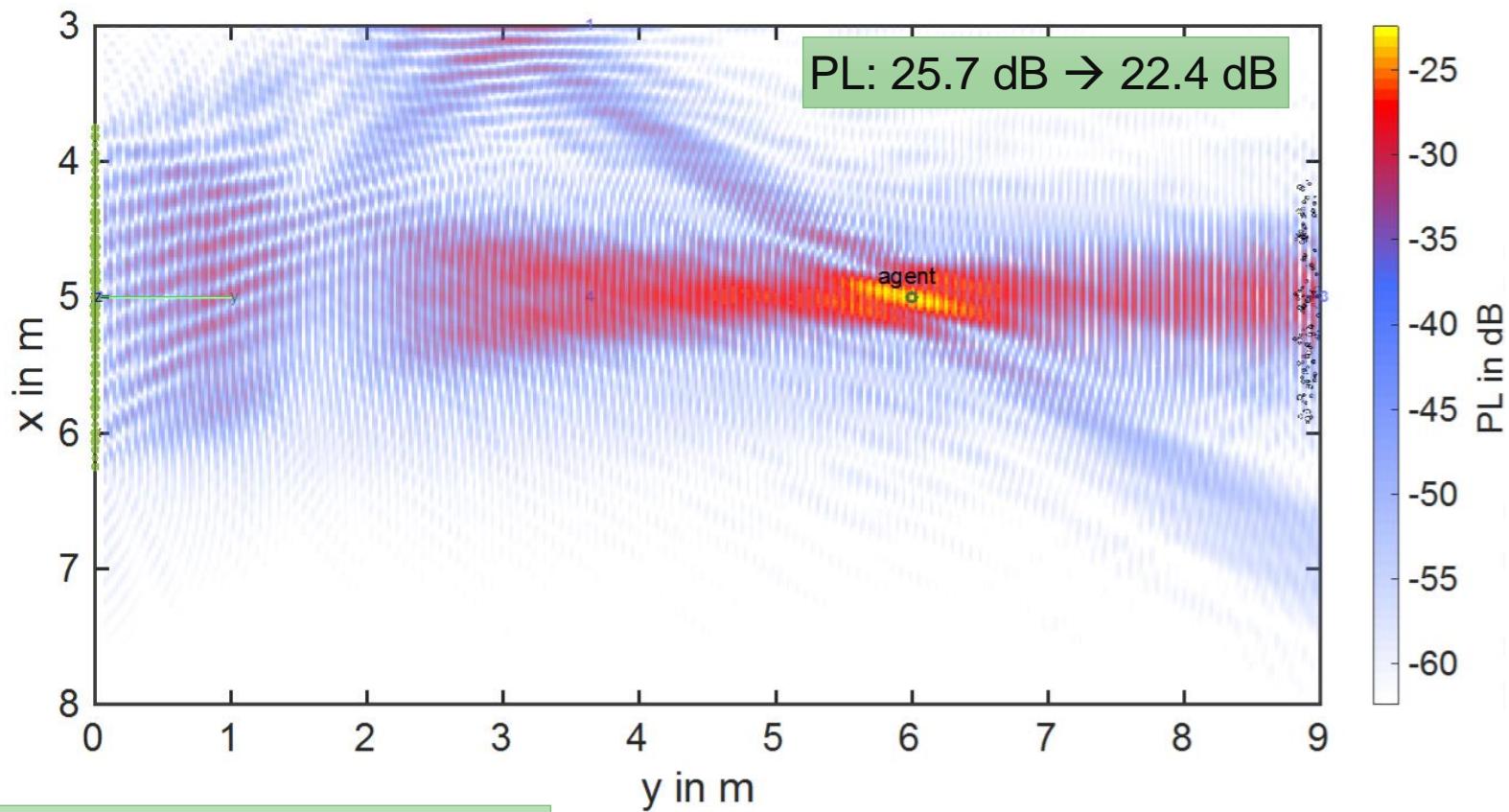
Line-of-sight + 1 Wall + Floor (2 specular components)



Line-of-sight + facing wall

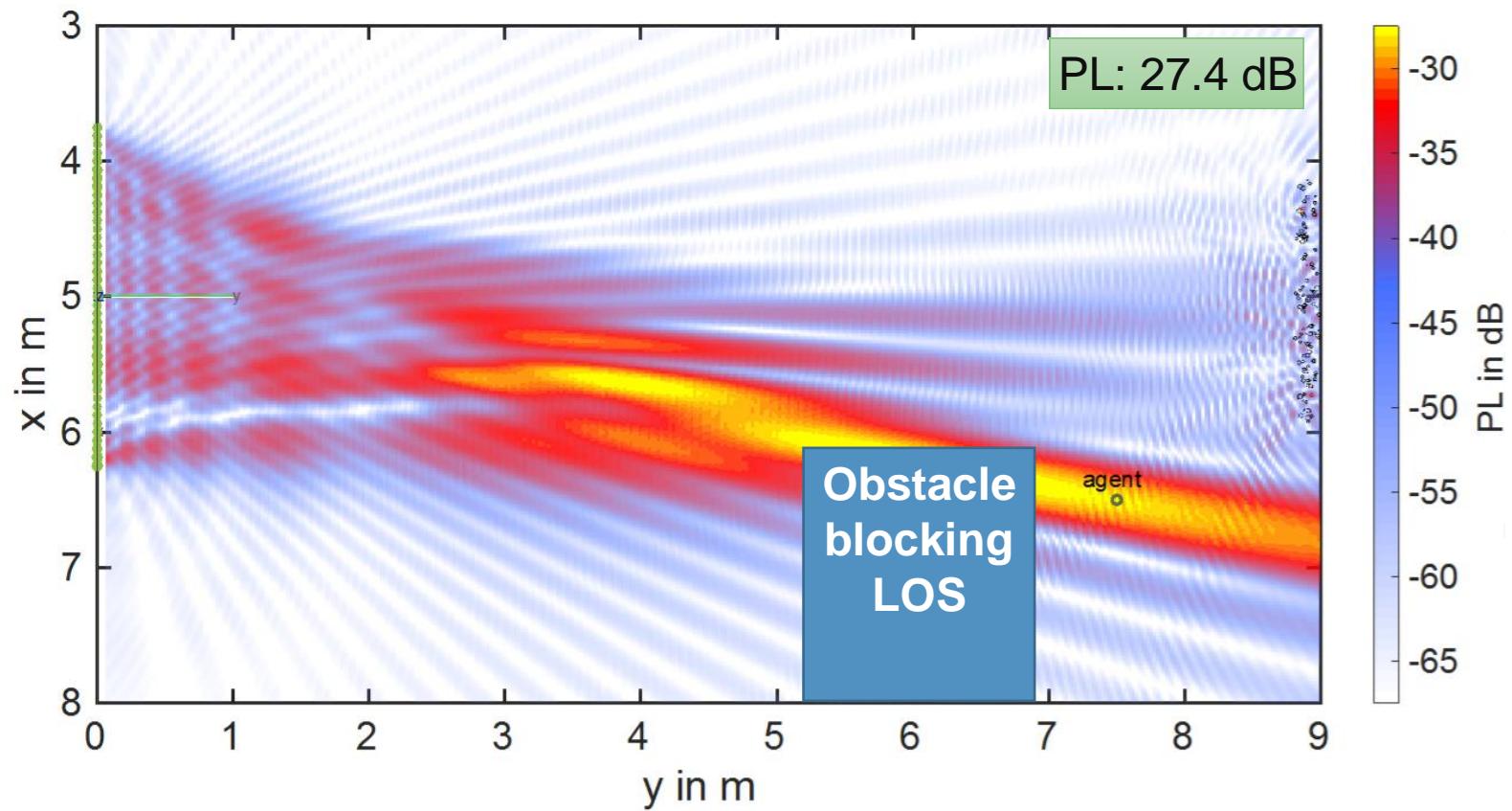


Complete example (LOS + 3 SMCs + scattering)

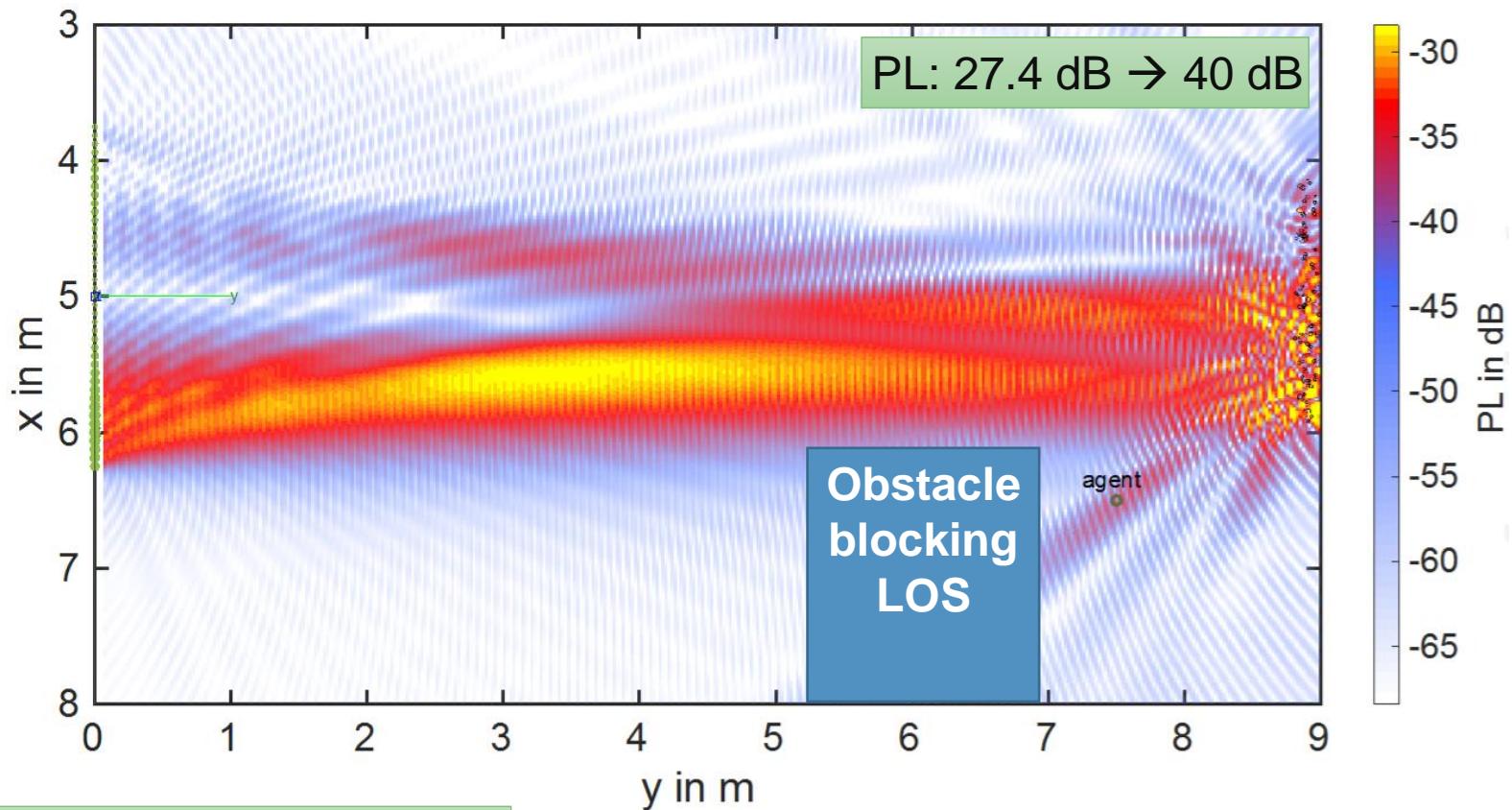


Specular multipath components
enhance the focusing

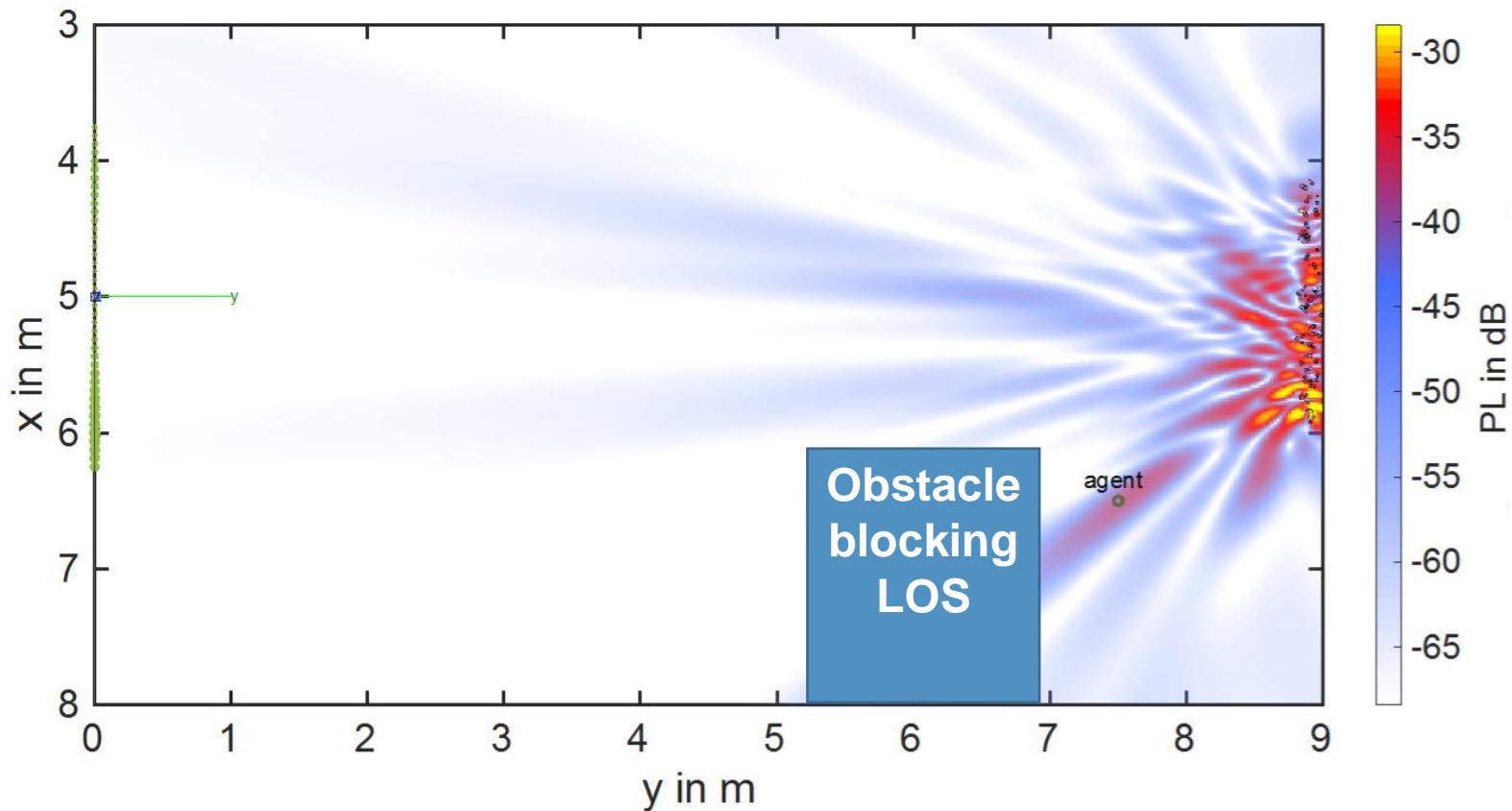
Example 2: Line-of-sight + scatter points



Line-of-sight **blocked** + scatter points

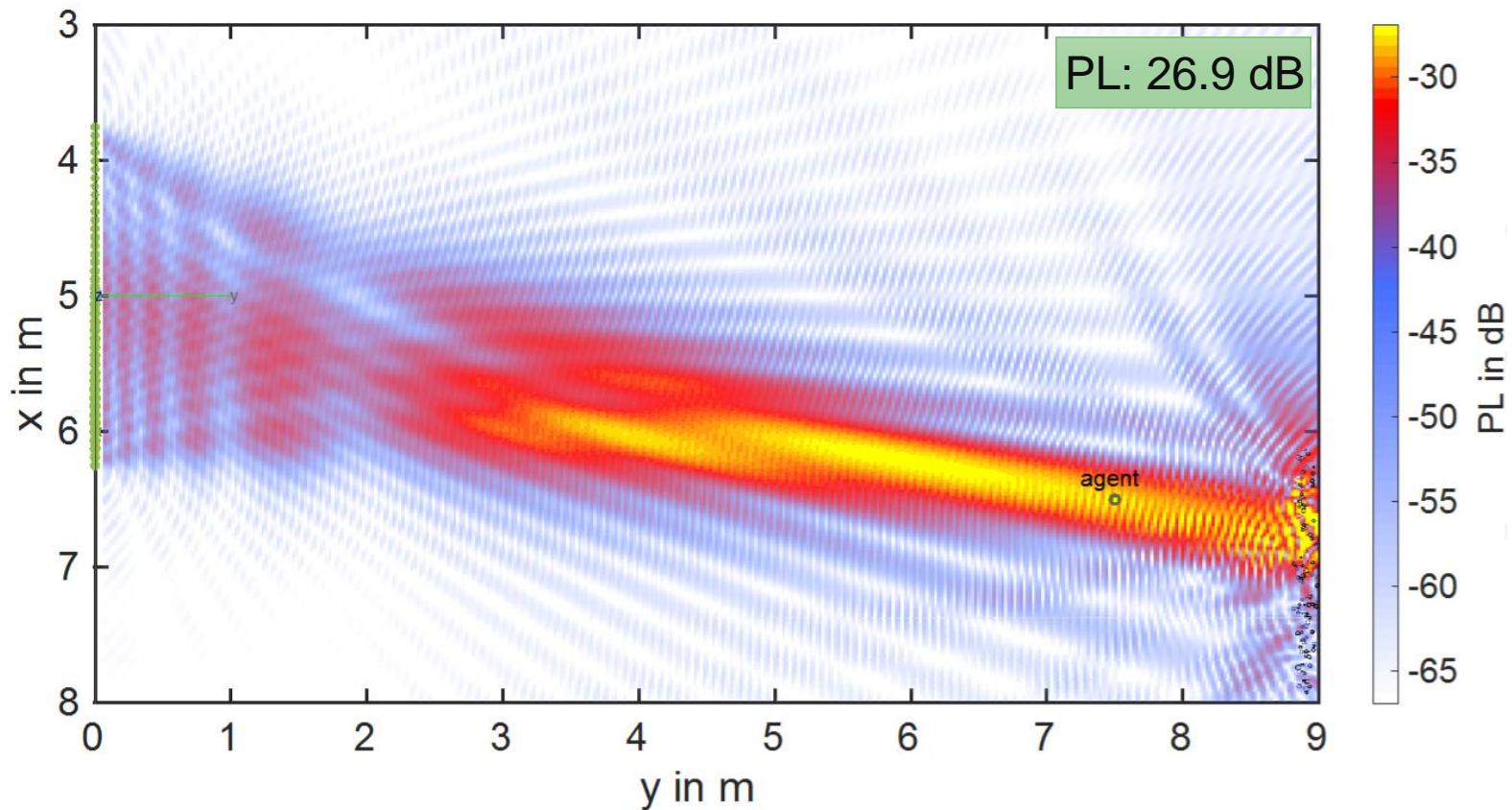


Scattered component, only



Diffuse reflection from
scatter points: **Rayleigh fading**

Example 3: beam illuminates scatter points



Diffuse reflection from
scatter points: **Rayleigh fading**

Applications

(physically large arrays; distributed mMIMO; RadioWeaves)

- Conclusions from channel modeling:
 - Power **converges** towards user
 - High angle resolution; depth resolution (specular components!)
- Applications:
 - Energy efficient communications; low interference to other users
 - Wireless power transfer (WPT)
 - Positioning and sensing

Conclusions and Outlook

- Distributed massive MIMO (RadioWeaves)
 - A candidate technology for 6G with **unique features**
 - Fundamentally shifted **channel properties**
 - Unprecedented **efficiency** and performance
 - Massive deployment including **batteryless nodes**
- 6G wireless networks will include **sensing** and (robust) positioning
 - **Environment awareness** for long-term predictability
 - Data acquisition for **digital twinning**