PhD defense:

Optimization Methods for Active and Passive Localization

PhD candidate: Nil Garcia

Advisors: Dr. Alexander M. Haimovich

Dr. Martial Coulon

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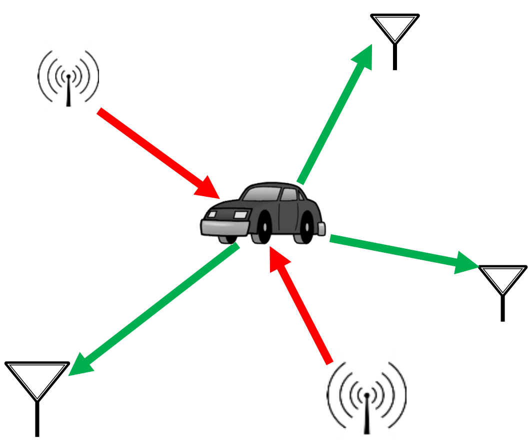
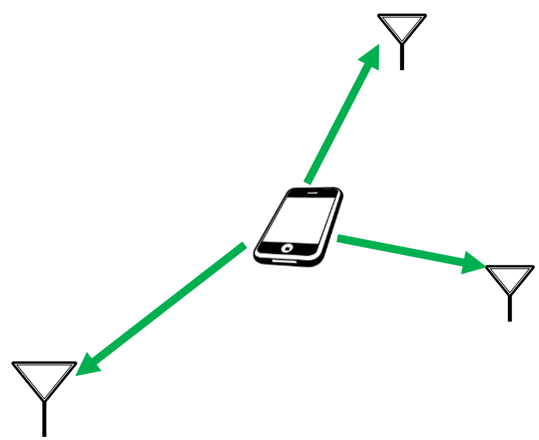
Outline

- Resources Allocation for Active Localization
  - Summary
- High Precision Passive Localization
  - Introduction and context
  - Problem statement and signal model
  - Proposed approach
  - Numerical results
- Summary

Active vs. Passive Localization with Widely Distributed Sensors

Active Localization	Passive Localization
Transmitters illuminate target(s). Application example: MIMO radar	Source(s) emit their own signals Application example: localization of mobile equipment in cellular networks

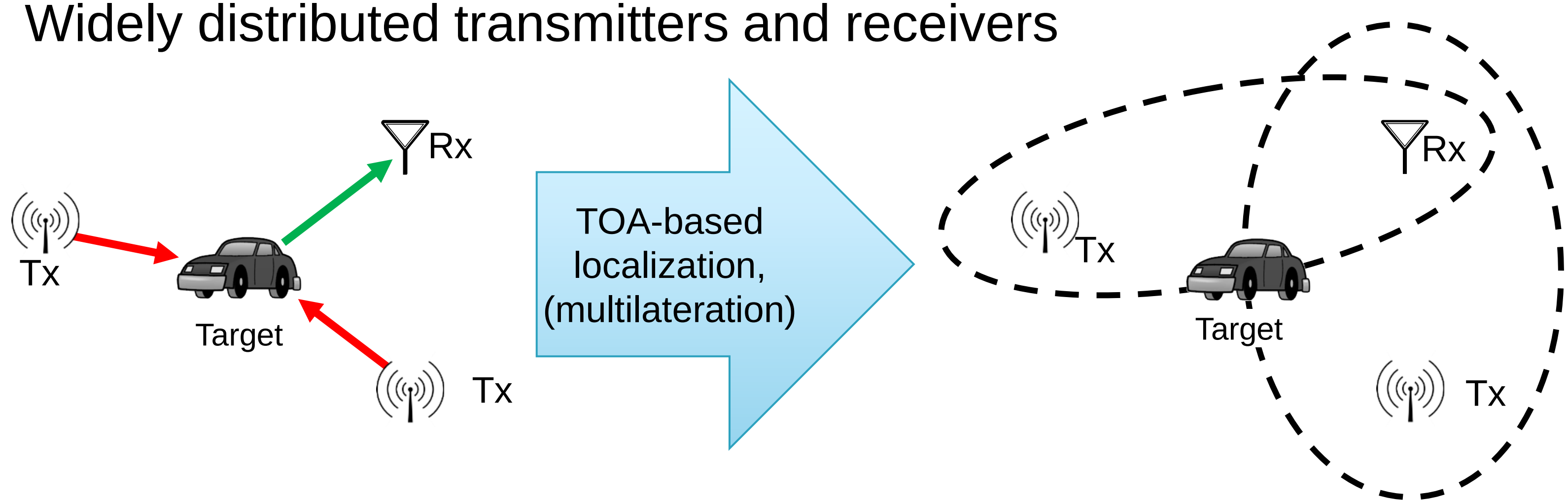




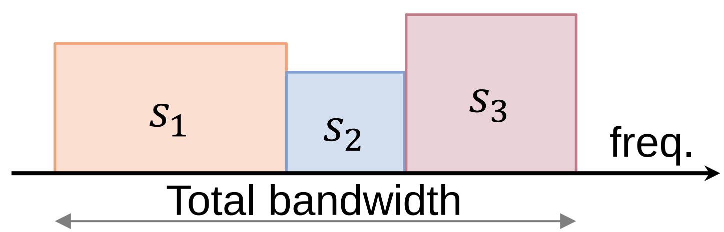
Resources Allocation for Active Localization

Problem Statement

- Widely distributed transmitters and receivers



- Transmitters access the medium using disjoint bandwidths of the spectrum.



- CRLB on the target positions which depends on…
  - Transmitter’s **power**
  - **Bandwidth** of the signals

Proposed Approach

Assuming prior knowledge on the targets locations $\{\hat{\mathbf{p}}_q\}_{q=1}^{Q}$

Minimize: CRLB on target positions

Given constraints on power and/or bandwidth

Optimization variables: transmitters powers and bandwidths

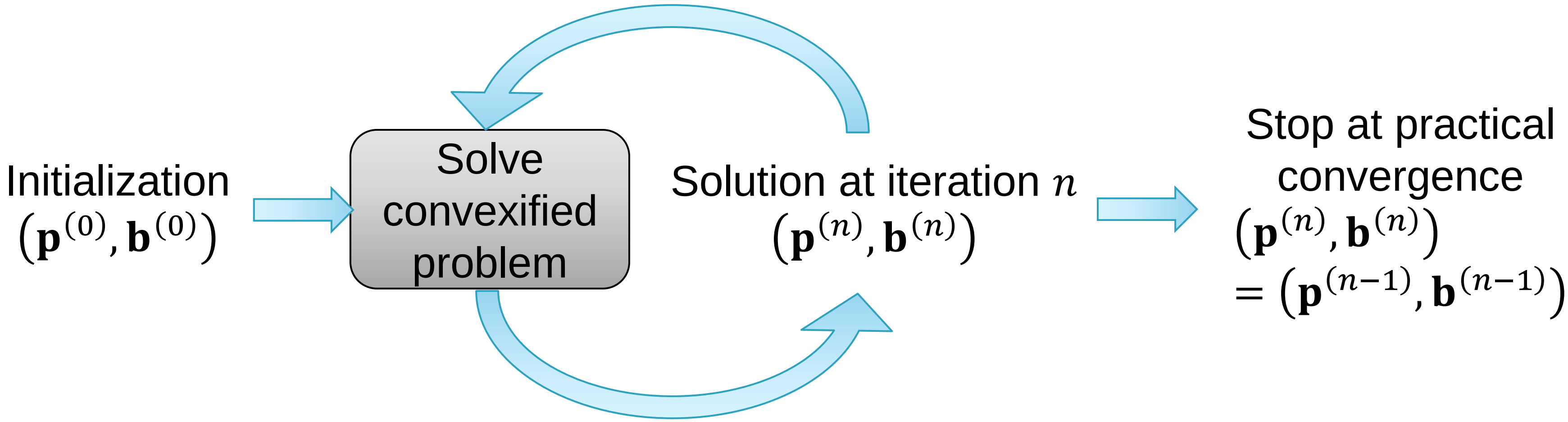
- Power and bandwidth allocation:
  - Power vector: $\mathbf{p} = [p_1, \dots, p_M]^T$
  - Bandwidth vector: $\mathbf{b} = [b_1, \dots, b_M]^T$

$$
\begin{aligned}
\min_{\mathbf{p},\mathbf{b}}: \quad & \max_{q=1,\dots,Q} \mathrm{CRLB}_q(\mathbf{p}, \mathbf{b}) \\
\text{subject to:} \quad & 1^T\mathbf{p} \leq P \\
& 1^T\mathbf{b} \leq B
\end{aligned}
$$

- Similarly we can formulate **optimization problems** for…
  - Power allocation only
  - Bandwidth allocation only

Convexification of the Optimization Problems

- ✗ $\mathrm{CRLB}_q(\mathbf{p}, \mathbf{b})$ not convex ⇨ ~~convex optimization methods~~
- ✓ Sequential convex approximation
  1. Convex approximation of the problem
  2. Uses the solution for the next convex approximation
  3. Stops upon practical convergence



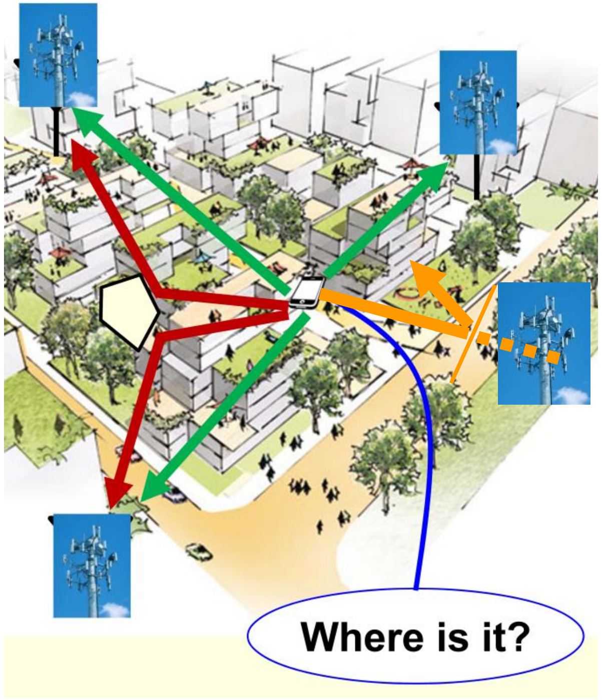
With 5 transmitters, **10%, 50% and 70% reduction** in localization error in power, bandwidth and joint power-bandwidth allocating, respectively, compared to uniform allocation.

High Precision Passive Localization in Multipath

At a Glance

- Goal: Localization (geolocation) of RF emitters in multipath environments

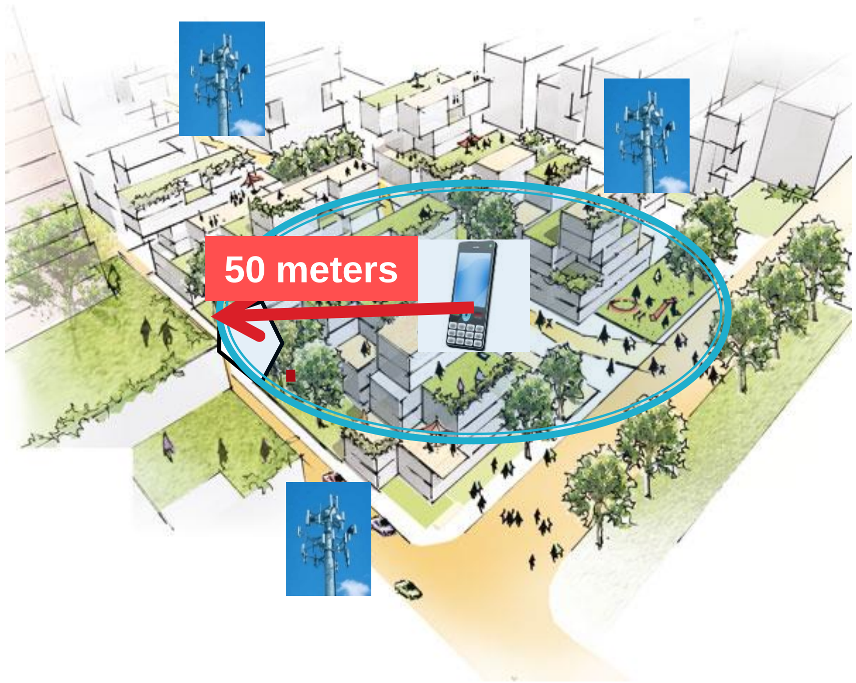
- Challenges:
  - Line-of-sight (LOS) paths
  - Non-line-of-sight (NLOS) paths
  - Blocked LOS paths (e.g. indoor)



- Applications:
  - Indoor positioning
  - Defense/first responders
  - Location based services
  - E911

New FCC Rules

- *"Most 911 calls are currently made from wireless phones, and most wireless calls are made from indoors. This increases the likelihood that wireless 911 calls will come from indoor environments where traditional location accuracy technologies, optimized for outdoor calling, may not work. To close this gap in performance, the Commission today updated its E911 rules to include requirements focused on indoor location accuracy."* FCC News Release 1/29/2015

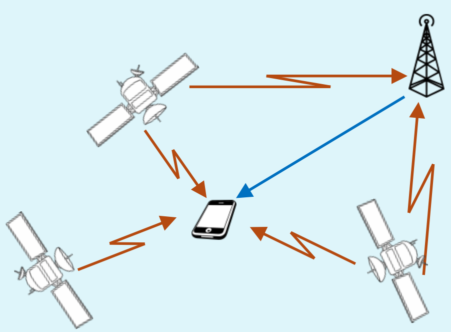


- In two years: Reach a caller's indoor position within 50 meters in 40% of cases.
- In six years: Accurate to 50 meters in 80% of cases.

Context - LTE Positioning Methods (I)

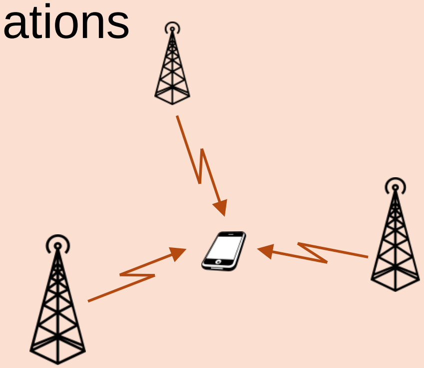
Assisted Global Navigation Satellite System (A-GNSS) Positioning

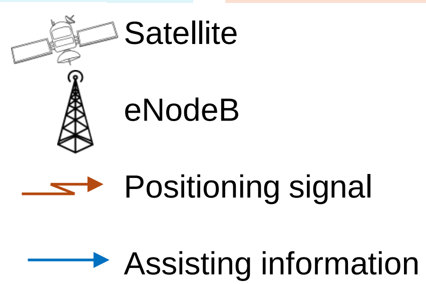
- Relies on TOA's
- ✓ The eNodeB assists the UE so it can synchronize with the GNSS signals faster.
- ✗ Not more accurate than GNSS
- ✗ Challenged in dense urban and indoor situations



Advanced Forward Link Trilateration (AFLT)/TDOA

- Relies on TOA/TDOA or signal strength
- ✓ Does not require GPS
- ✗ Requires synchronization among base stations.
- ✗ Requires signals from at least 3 eNodeB
- ✗ Challenged in dense urban and indoor situations

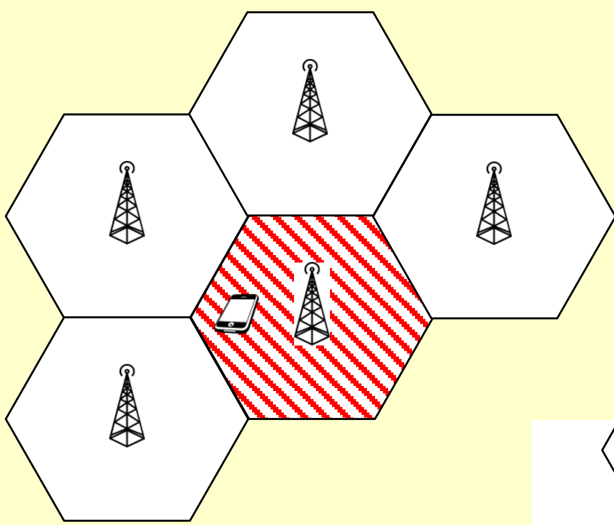


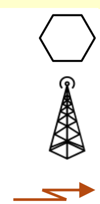


LTE Positioning Methods (II)

Cell-ID-based Positioning

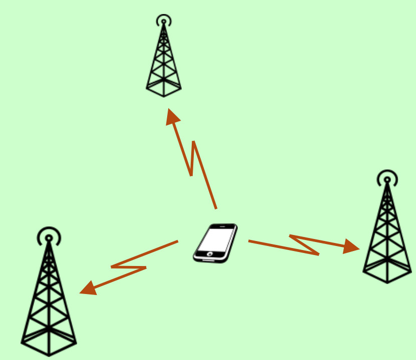
- ✓ Connection needed to only a signle eNodeB
- × Very coarse accuracy



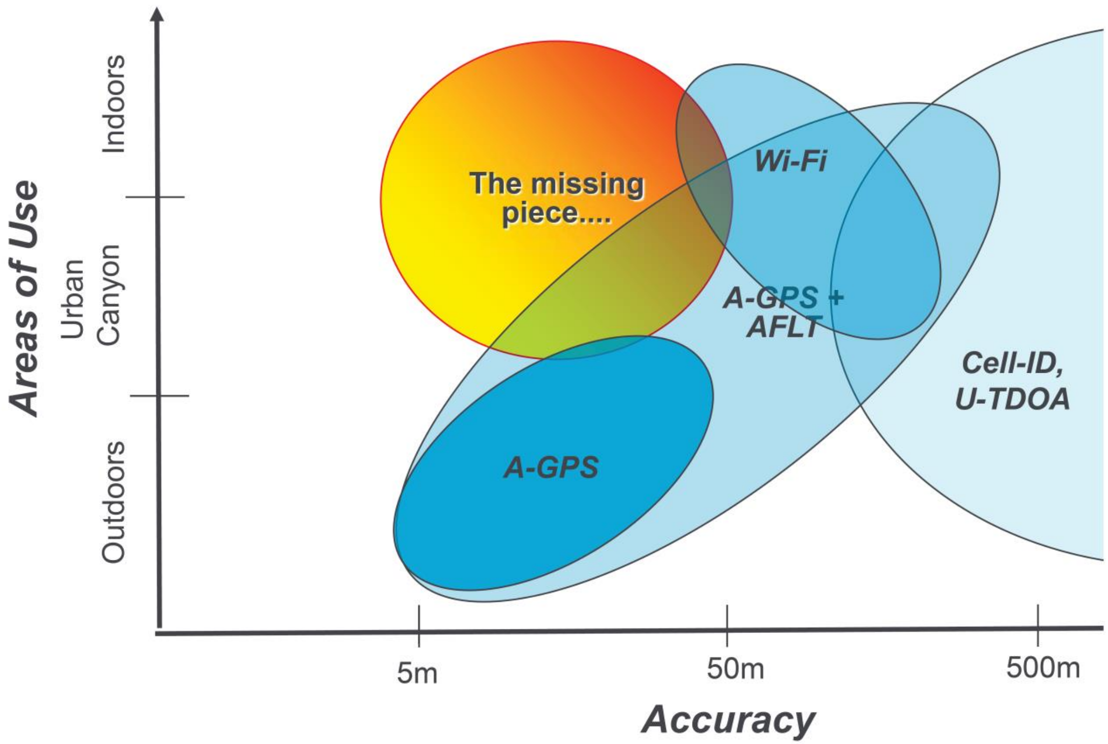


Uplink TDOA (RAN)

- Relies on TDOA’s
- Uses uplink signals
- ✓ Computation done in the eNodeB’s instead of the UE.
- × Requires synchronization among eNodeB’s
- × Challenged in dense urban and indoor situations



Positioning Technology State of the Art

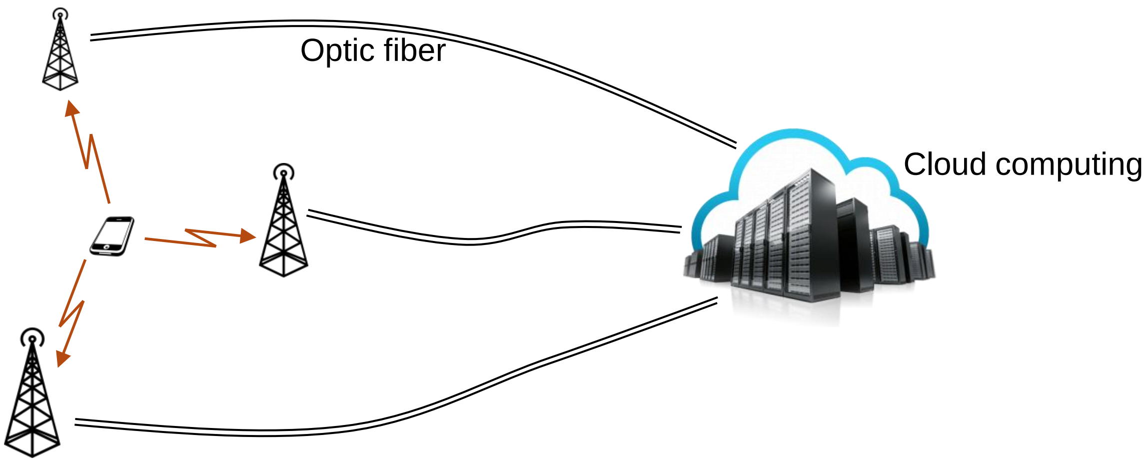


Source: Nextnav 2012

- Methods designed for open outdoor spaces do not work well in congested urban areas and indoors.

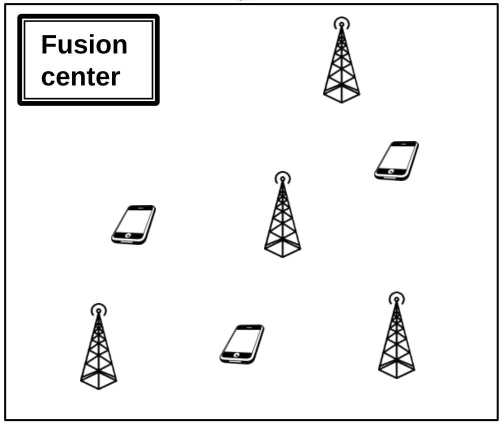
Cloud-RAN Positioning

- Emerging technology of Cloud Radio Access Network (Cloud-RAN or C-RAN) shifts processing and complexity to the cloud thus simplifying the design of sensors.
- Concept of relatively simple sensors linked to the cloud may be ported to applications other than cellular, for example first responders.



Localization over multipath channels still an open problem!

Problem Statement



Goal

- Estimate sources' locations

Assumptions

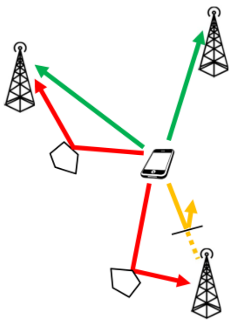
- Network of distributed sensors with fixed, known locations
- Sensors have ideal communication with fusion center
- Emitters' waveforms and their timing are known
- Synchronization
  - Time synchronization between sensors and emitters
  - No phase synchronization
- Observation time << channel coherence time

  ☞ Time-invariant multipath channel
- No prior information on multipath channel

Signal Model

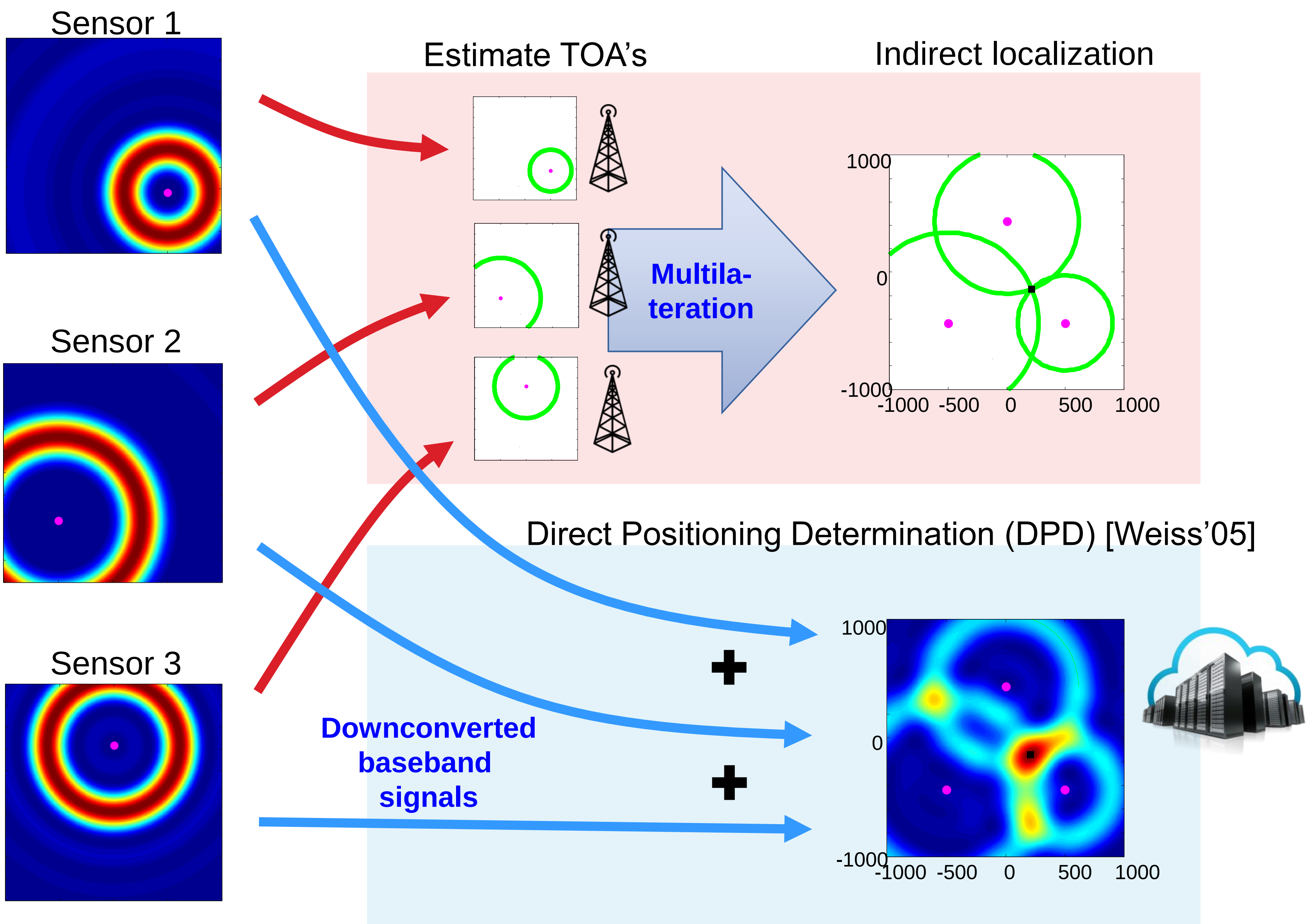
Signal at the l-th sensor:

$$y_l(n) = \sum_{q=1}^{Q} \alpha_{lq} s_q\left(n - \tau_l(\mathbf{p}_q)\right) + \sum_{q=1}^{Q} \sum_{m=1}^{M_{lq}} \alpha_{lq}^{(m)} s_q\left(n - \tau_{lq}^{(m)}\right) + n_l(t)$$



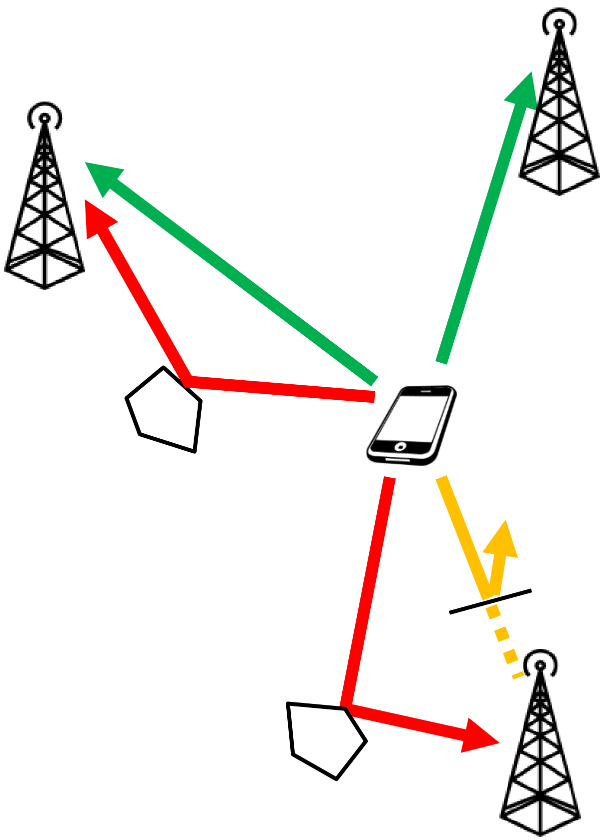
- Q emitters and L sensors
- $s_q(t)$: the signal of the q-th emitter
- LOS parameters:
  - α_{lq}: complex amplitude of the LOS path between emitter q and sensor l
  - $\tau_l(\mathbf{p}_q)$: propagation time from location $\mathbf{p}_q$ to sensor l
- NLOS parameters
  - $\alpha_{lq}^{(m)}$: complex amplitude of the m-th NLOS path between emitter q and sensor l
  - $\tau_{lq}^{(m)}$: propagation time of m-th NLOS path from between emitter q and sensor l

Indirect and Direct Localization



Multipath: the Challenge

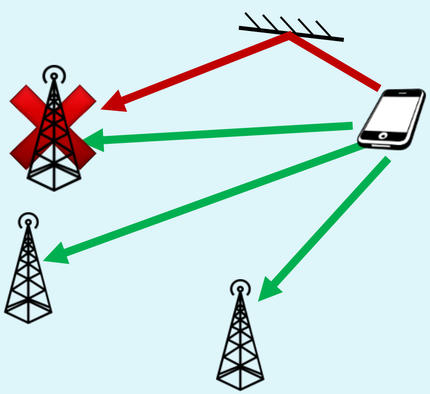
- Direct positioning determination (DPD) is asymptotically optimal in the maximum likelihood sense for ideal LOS channels
- DPD performs better than multilateration at low SNR
- DPD does not address localization in multipath:
  - Non-line-of-sight (NLOS) paths
  - Blocked LOS paths



Ad-Hoc Multipath Mitigation Methods

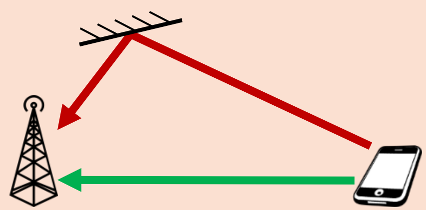
Mitigate/reject contribution from sensors with strong NLOS [Chen’99]

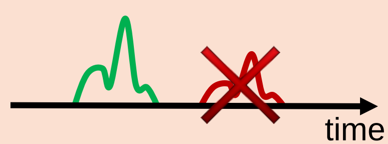
- Various metrics were suggested



Measure TOA of 1st arrival [Lee’02]

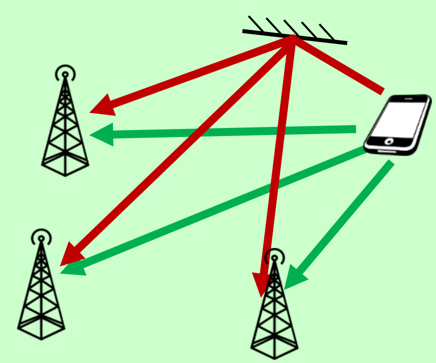
- Works only for discrete MP contributions
- If LOS is blocked
  ☞ error





Single-bounce geometric model [Liberti,Rappaport’96]

- NLOS signals bounce only once
- Known number of reflectors
- Joint estimation of reflectors and emitters locations.



ML estimation in white Gaussian noise

- Measurements
- Unknown parameters related to LOS paths
- Unknown parameters related to NLOS paths

$$\min_{\substack{\mathbf{p}_1,\dots,\mathbf{p}_Q \\ \alpha_{11},\dots,\alpha_{LQ} \\ M_{11},\dots,M_{LQ} \\ \tau_{11}^{(1)},\dots,\tau_{LQ}^{(M_{LQ})} \\ b_{11}^{1},\dots,b_{LQ}^{M_{LQ}}}} \sum_{l=1}^{L}\sum_{n=1}^{N}\left\| y_l(n) - \sum_{q=1}^{Q}\alpha_{lq}s_q\left(n-\tau_l(\mathbf{p}_q)\right) - \sum_{q=1}^{Q}\sum_{m=1}^{M_{lq}}\alpha_{lq}^{(m)}s_q\left(n-\tau_{lq}^{(m)}\right)\right\|^2$$

- ✗ Large unknown parameters pool
- ✗ Infeasible complexity
- ✗ Overfitted solution even if problem could be solved

Proposed Approach

	Deconvolution	Localization
Goal	**Multipath mitigation**	**Estimate sources locations**
Key info	• LOS path is **first** arrival • MP paths are **sparse**	• Sources are **sparse** • LOS paths originate from **common** location • Multipath is **local**
Procedure	• Estimate **TOA's** : $\hat{\tau}_1 < \hat{\tau}_2 \ldots < \hat{\tau}_T$ and their amplitudes $\hat{a}_1, \hat{a}_2, \ldots, \hat{a}_T$ at each sensor. • Exploit **sparsity** • **Remove** 2nd and later estimated arrivals from signals $\hat{r}_l(t) = r_l(t) - \sum_{i=1}^{T} \hat{a}_i s(t - \hat{\tau}_i)$	• **Direct** approach relies directly on observations • **Cloud**-based • Formulate and solve a **convex optimization** problem • **Least number** of sources and NLOS that describe the measured signals

- MP mitigation
  (1) Sparse number of arrivals
  (2) At each sensor, estimate propagation delays of MP paths
  (3) Subtract out from data

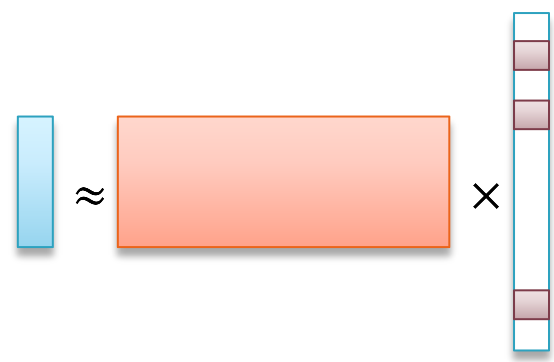
- For sensor l, propagation delays are solution to problem

$$\min_{\mathbf{x}} \quad \left\|\mathbf{y}_l - \mathbf{A}\mathbf{x}\right\|_2 + \lambda\|\mathbf{x}\|_1$$

  Here, the $N \times DQ$ matrix $\mathbf{A}$ is a dictionary of the received signals for all possible delay discrete MP delays and waveforms:

$$\mathbf{A} = \left[\mathbf{s}_1(0) \quad \cdots \quad \mathbf{s}_1\big((D-1)\tau_{res}\big) \quad \cdots \quad \mathbf{s}_Q(0) \quad \cdots \quad \mathbf{s}_Q\big((D-1)\tau_{res}\big)\right]$$

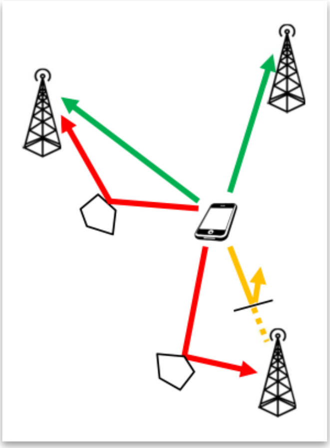
- Lasso optimization problem
  - Solved by convex optimization methods.
  - Yields sparsest solution.



Signal Model in Matrix Form

- All measurements are contained in a single matrix of size $N \times L$:

$$
\begin{array}{cc}
 & \text{Sensors} \\
\mathbf{R} = & \begin{bmatrix} y_1(0) & \cdots & y_L(0) \\ \vdots & \ddots & \vdots \\ y_1(N-1) & \cdots & y_1(N-1) \end{bmatrix}
\end{array}
\quad \text{Samples}
$$



$$
= \sum_{q=1}^{Q} \left[\alpha_{1q} \mathbf{s}_q\left(\tau_1(\mathbf{p}_q)\right) \quad \cdots \quad \alpha_{Lq} \mathbf{s}_q\left(\tau_L(\mathbf{p}_q)\right) \right]
$$

$$
+ \sum_{q=1}^{Q} \sum_{l=1}^{L} \sum_{m=1}^{M_{ql}} \left[\cdots \quad 0 \quad \alpha_{lq}^{(m)} \mathbf{s}_q\left(\tau_{ql}^{(m)}\right) \quad 0 \quad \cdots \right] + \mathbf{W}
$$

- $\mathbf{s}_q(\tau)$ stacks N times samples of the emitted signal delayed by τ:

$$
\mathbf{s}_q(\tau) = \left[s_q(0 - \tau) \quad \cdots \quad s_q\left((N-1)T - \tau\right) \right]^T
$$

Compressive Sensing Localization Approach

$$\mathbf{R} = \sum_{q=1}^{Q} \left[\alpha_{1q}\mathbf{s}_q(\tau_1(\mathbf{p}_q)) \quad \cdots \quad \alpha_{Lq}\mathbf{s}_q(\tau_L(\mathbf{p}_q))\right]$$
$$+ \sum_{q=1}^{Q}\sum_{l=1}^{L}\sum_{m=1}^{M_{ql}} \left[\cdots \quad 0 \quad \alpha_{lq}^{(m)}\mathbf{s}_q\left(\tau_{ql}^{(m)}\right) \quad 0 \quad \cdots\right]$$

- How to decide on the number of NLOS paths M_{ql} and estimate the sources' location? ☞ Apply tools from compressive sensing

"Simple" Model for Localization (I)

- Simplicity [Chandrasekaran,Recht,Parrilo,Willsky'12]
  - Generalizes the notion of sparsity.
  - The dictionary (atomic set) contains the **known** atoms or *building blocks* of the received signals.
  - Dictionaries may contain **atoms of different types** and be **infinite**.

- We wish to distinguish between LOS and NLOS paths
  ☞ two types of building blocks

$$\mathbf{R} = \sum_{q=1}^{Q} \left[\alpha_{1q}\mathbf{s}_q(\tau_1(\mathbf{p}_q)) \quad \cdots \quad \alpha_{Lq}\mathbf{s}_q(\tau_L(\mathbf{p}_q))\right] + \sum_{q=1}^{Q}\sum_{l=1}^{L}\sum_{m=1}^{M_{ql}} \left[\cdots \quad 0 \quad \alpha_{lq}^{(m)}\mathbf{s}_q\left(\tau_{ql}^{(m)}\right) \quad 0 \quad \cdots\right]$$

LOS atom

$$\mathbf{L}_q(\mathbf{b},\mathbf{p}) = \left[b_1\mathbf{s}_q(\tau_1(\mathbf{p})) \quad \cdots \quad b_L\mathbf{s}_q(\tau_L(\mathbf{p}))\right]$$

NLOS atom

$$\mathbf{N}_{ql}(\tau) = \mathbf{s}_q(\tau)\mathbf{u}_l^T$$

"Simple" Model for Localization (II)

- Simple model of the data is

$$\mathbf{R} = \sum_{k=1}^{K} c_k \mathbf{A}_k$$

- …where the atoms $\mathbf{A}_k$ belong to the dictionary $\mathcal{A}$

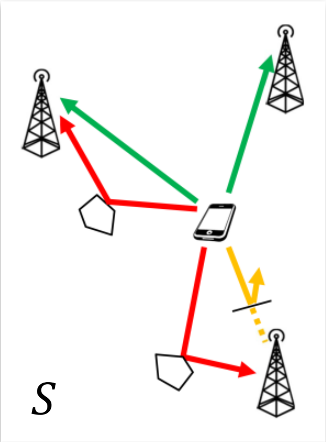
$$\mathbf{A}_k \in \mathcal{A} = \mathcal{A}_{LOS} \cup \mathcal{A}_{NLOS},$$

- composed of LOS atoms…

$$\mathcal{A}_{LOS} = \bigcup_{q=1}^{Q} \{\mathbf{L}_q(\mathbf{b}, \mathbf{p}) : \mathbf{b} \in \mathbb{C}^L, \mathbf{p} \in S\}$$

- …and NLOS atoms:

$$\mathcal{A}_{NLOS} = \bigcup_{q=1}^{Q} \bigcup_{l=1}^{L} \{\mathbf{N}_{ql}(\tau) : \tau \in [0, \tau_{max}]\}$$



Finding the Simplest Solution

The received signals are **assumed simple** in the sense that they can expressed by a relatively small number of atoms

Finding the **simplest explanation** (smallest linear combination of atoms) of the data is an **NP-hard problem**.

- The **atomic norm** $\|\cdot\|_{\mathcal{A}}$ is the ℓ_1-norm $\|\cdot\|_1$ when $\mathcal{A}$ is the set of unit-norm one-sparse vectors.

$$\left\|\hat{\mathbf{R}}\right\|_{\mathcal{A}} = \min \textstyle\sum_k |c_k| \quad \text{such that} \quad \hat{\mathbf{R}} = \textstyle\sum_k c_k \mathbf{A}_k$$

- Simplicity is induced by minimizing the atomic norm:

$$\min_{c_k} \quad \sum_k |c_k|$$

Induces low number of atoms

$$\text{subject to:} \quad \left\| \mathbf{R} - \sum_k c_k \mathbf{A}_k \right\|_2 \leq \epsilon$$

Approximate explanation in presence of noise

$$\min_{c_k} \quad \sum_k |c_k|$$

$$\text{subject to:} \quad \left\| \mathbf{R} - \sum_k c_k \mathbf{A}_k \right\|_2 \leq \epsilon$$

Solution: $c_k^* > 0$

Simple explanation of the data:

$$\hat{\mathbf{R}} = \sum_k c_k^* \mathbf{A}_k$$

Create dictionary $\mathcal{A}$ from:

- Search area
- Largest MP delay
- Sensors locations
- Waveforms

Does this procedure yield the correct sources' locations?

pansion in LOS
d NLOS atoms

$$\hat{\mathbf{R}} = \sum_{q=1}^{Q} \sum_k c_k^{q*} \mathbf{L}_q\left(\mathbf{b}_k^q, \mathbf{p}_k^q\right) + \sum_{q=1}^{Q} \sum_{l=1}^{L} \sum_k c_k^{ql*} \mathbf{N}_{ql}\left(\tau_k^{ql}\right)$$

LOS atoms are a proxy for locations: $\{\mathbf{p}_k^q\}$

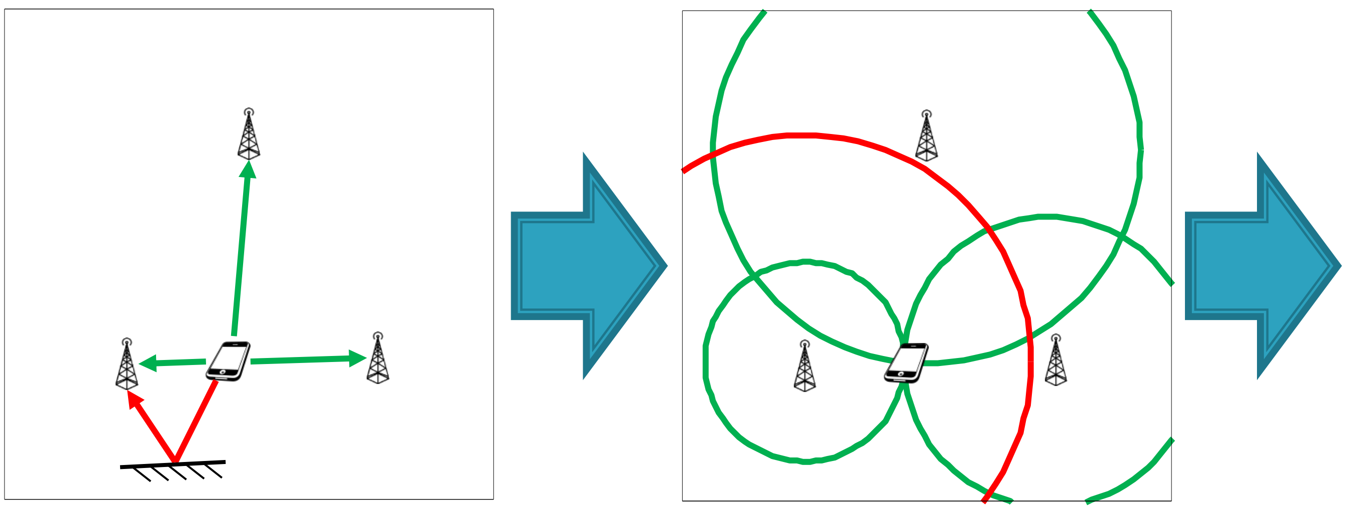
The Notion of Consistency

Definition: A location $\mathbf{p}$ is said to be consistent with X paths (LOS or NLOS) if the propagation delays of such paths, say $\tau_1, \ldots, \tau_X$, satisfy

$$\tau_x = \tau_{l_x}(\mathbf{p}) \text{ for } x = 1, \ldots, X,$$

where $\{l_1, \ldots, l_X\} \subseteq \{1, \ldots, L\}$ are the indexes of the destination sensors of the X paths, and $\tau_{l_x}(\mathbf{p})$ is the delay of the direct path between location $\mathbf{p}$ and sensor l_x.

- Example:



Phone's location is consistent with 3 paths.

Enforcing Consistency

Assumptions:

(1) The number of LOS paths S_q from the q-th source is known.

(2) Noiseless

Lemma 1:

- If the size of the LOS atoms $\mathbf{L}_q(\mathbf{b}, \mathbf{p})$ is normalized to

$$||\mathbf{b}||_2 = u_q$$

- where u_q is such that

$$u_q < \frac{1}{\sqrt{S_q - 1}},$$

- then any output location for the q-th source will be consistent with S_q paths or more.

Interpretation: given a solution that produces a location with less than S_q paths, and if $u_q < 1/\sqrt{S_q - 1}$ is met, there exists another lower cost solution, , implying that a solution with fewer than S_q paths cannot be optimal.

Ensuring a Location is Output

Assumptions:

(1) The number of LOS paths S_q from the q-th source is known.

(2) Noiseless

Lemma 2:

- If the size of the LOS atoms $\mathbf{L}_q(\mathbf{b}, \mathbf{p})$ is normalized to

$$\|\mathbf{b}\|_2 = u_q$$

- where u_q is such that

$$u_q > \frac{1}{\sqrt{S_q}},$$

- then **at least one location** will be output for the q-th source .

Interpretation: given a solution that does not produce a location for the q-th source, and if $u_q > 1/\sqrt{S_q}$ is met, there exists another lower cost solution that produces a location for the q-th source.

Guarantee for Correct Recovery

Assumptions:

(1) The number of LOS paths S_q from the q-th source is known.

(2) Noiseless

(3) Only the true location of the q-th source is consistent with S_q paths.

Theorem:

- If the size of the LOS atoms $\mathbf{L}_q(\mathbf{b}, \mathbf{p})$ is normalized to

$$\|\mathbf{b}\|_2 = u_q$$

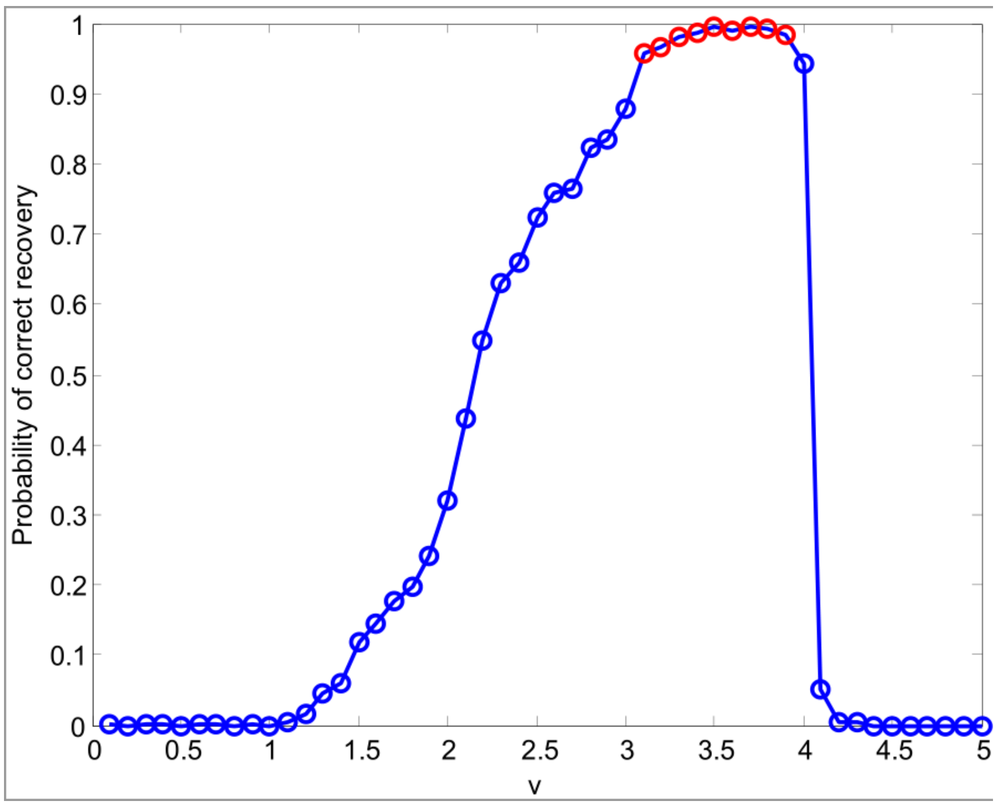
- where u_q is such that

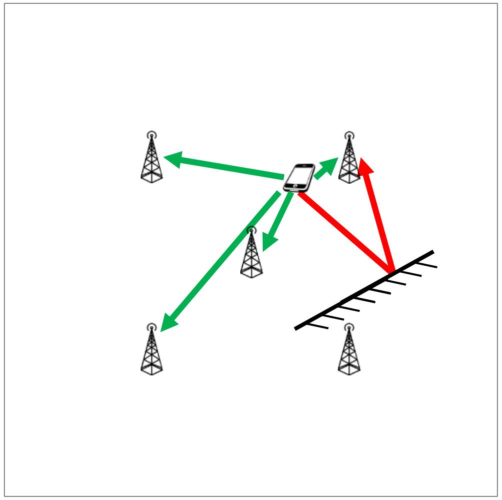
$$\frac{1}{\sqrt{S_q - 1}} < u_q < \frac{1}{\sqrt{S_q - 1}},$$

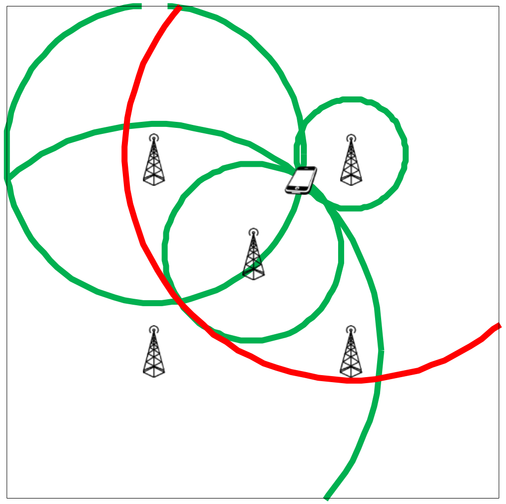
- then by Lemma 1 and 2, a location will be output for the q-th source that is consistent with S_q paths, and by Assumption (3) it must be the <u>correct location</u>.

Numerical Example of the Guarantee

- $S_1 = 4$
- Define $v = {}^{1}/_{(u_1)^2}$
- By Theorem: $S_1 - 1 < v < S_1$



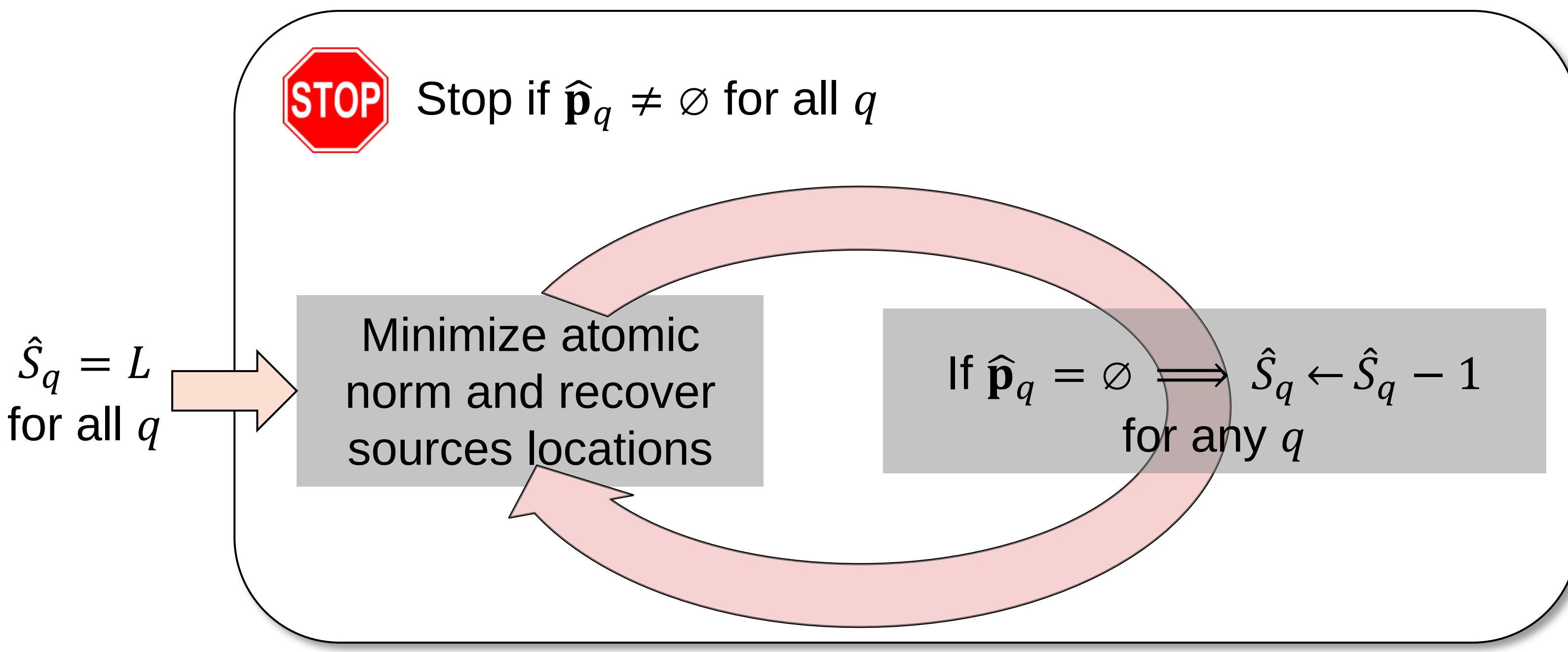




Algorithm Development

- Relaxing assumption S_q is known.
  - $\hat{S}_q$ ➞ initial guess # LOS paths for source q.
  - If u_q is chosen such that $\frac{1}{\sqrt{\hat{S}_q-1}} < u_q < \frac{1}{\sqrt{\hat{S}_q-1}}$ where $\hat{S}_q > S_q$…

    …no location will be output for source q.



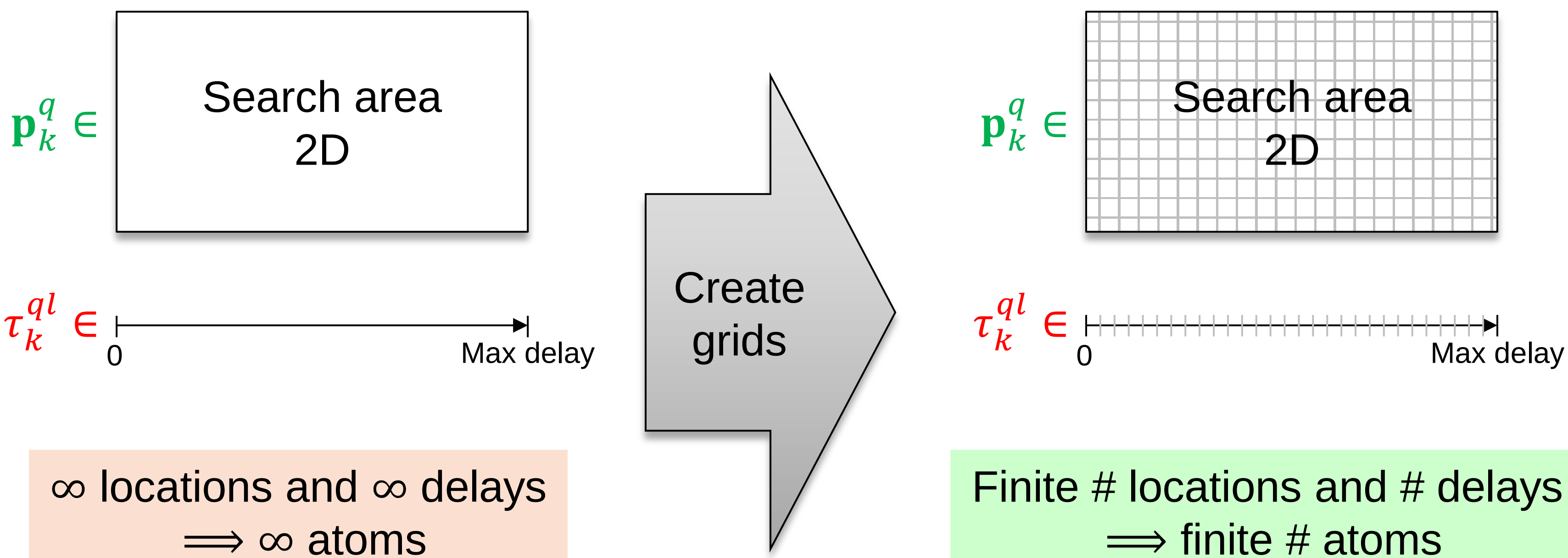
Grid Approximation

- Optimization problem is ∞-dimensional:

$$\min_{c_k^q, c_k^{ql}} \quad \sum_k |c_k^q| + \sum_k |c_k^{ql}|$$

$$\text{subject to:} \quad \left\| \mathbf{R} - \sum_{q=1}^{Q} \sum_k c_k^q \mathbf{L}_q(\mathbf{p}_k^q) + \sum_{q=1}^{Q} \sum_{l=1}^{L} \sum_k c_k^{ql} \mathbf{N}_{ql}(\tau_k^{ql}) \right\|_2 \leq \epsilon$$

- ✓ Grid approach (converges to original problem [Rang,Bhaskar,Recht'13])

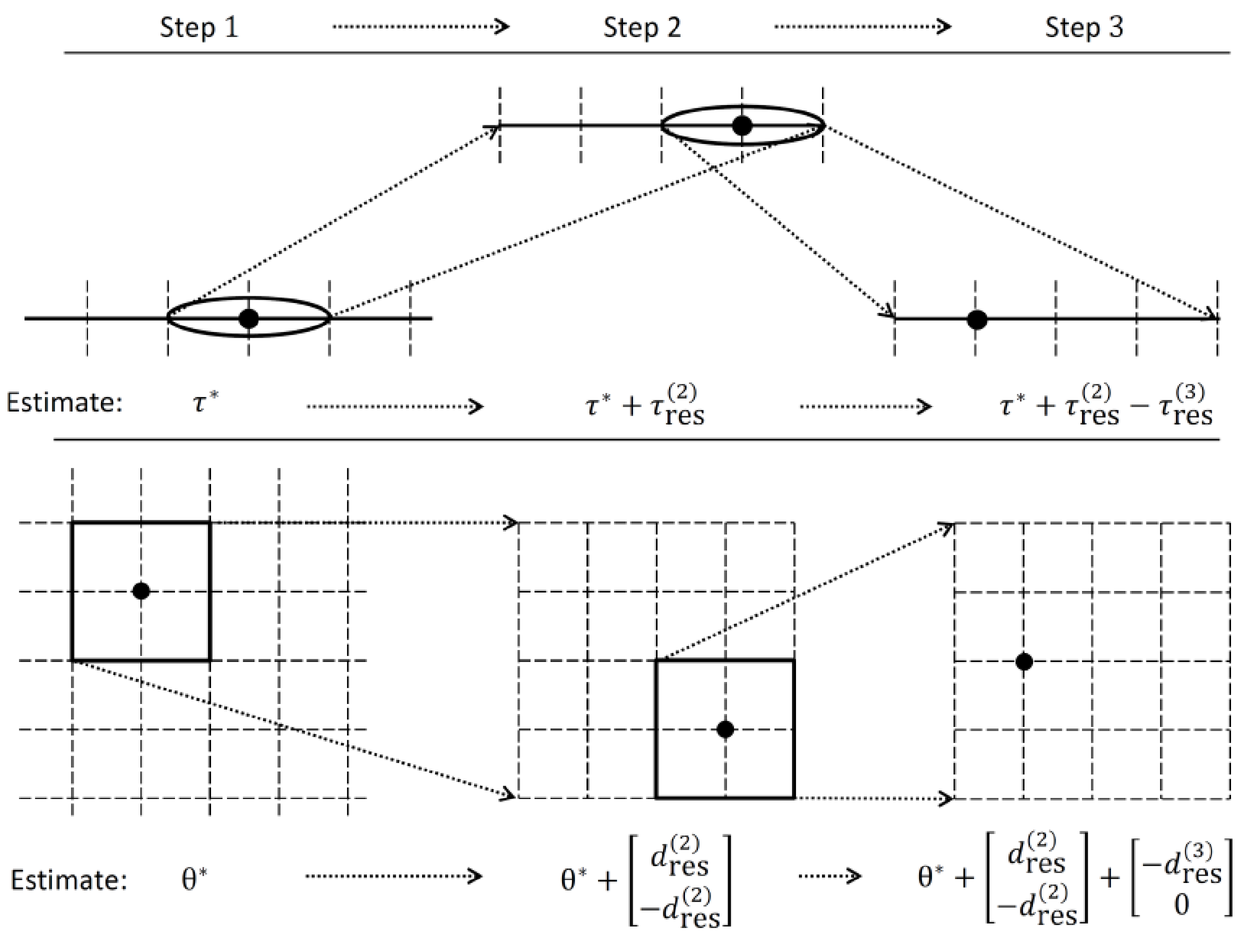


∞ locations and ∞ delays
$\Longrightarrow$ ∞ atoms

Finite # locations and # delays
$\Longrightarrow$ finite # atoms

Grid Refinement

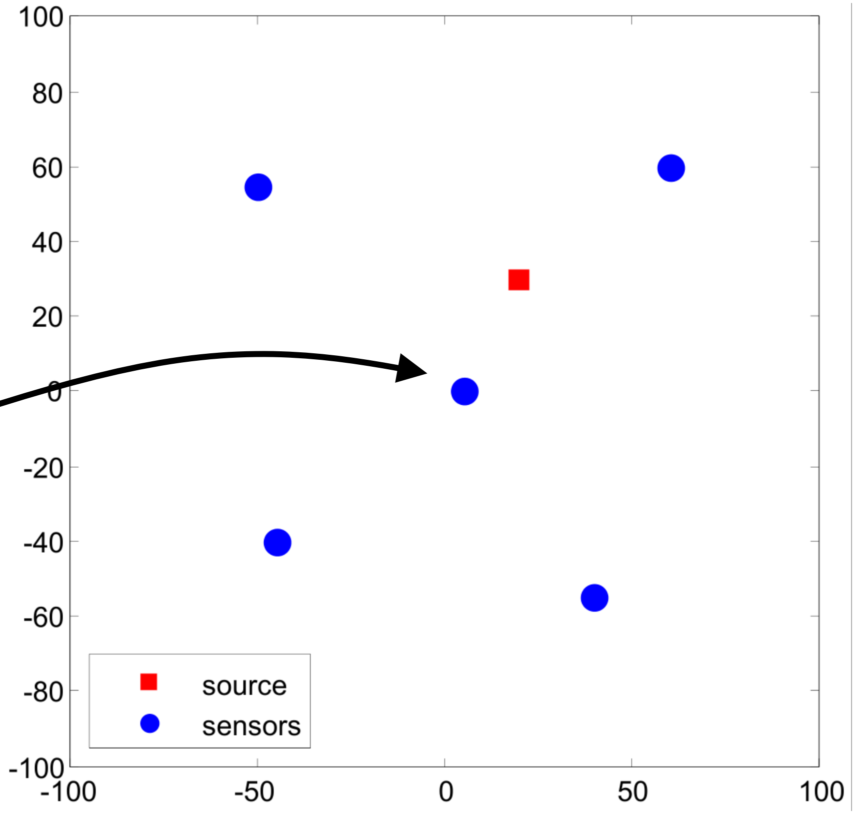
- Two types of grids
- Reduces computational complexity



Simulation Scenario

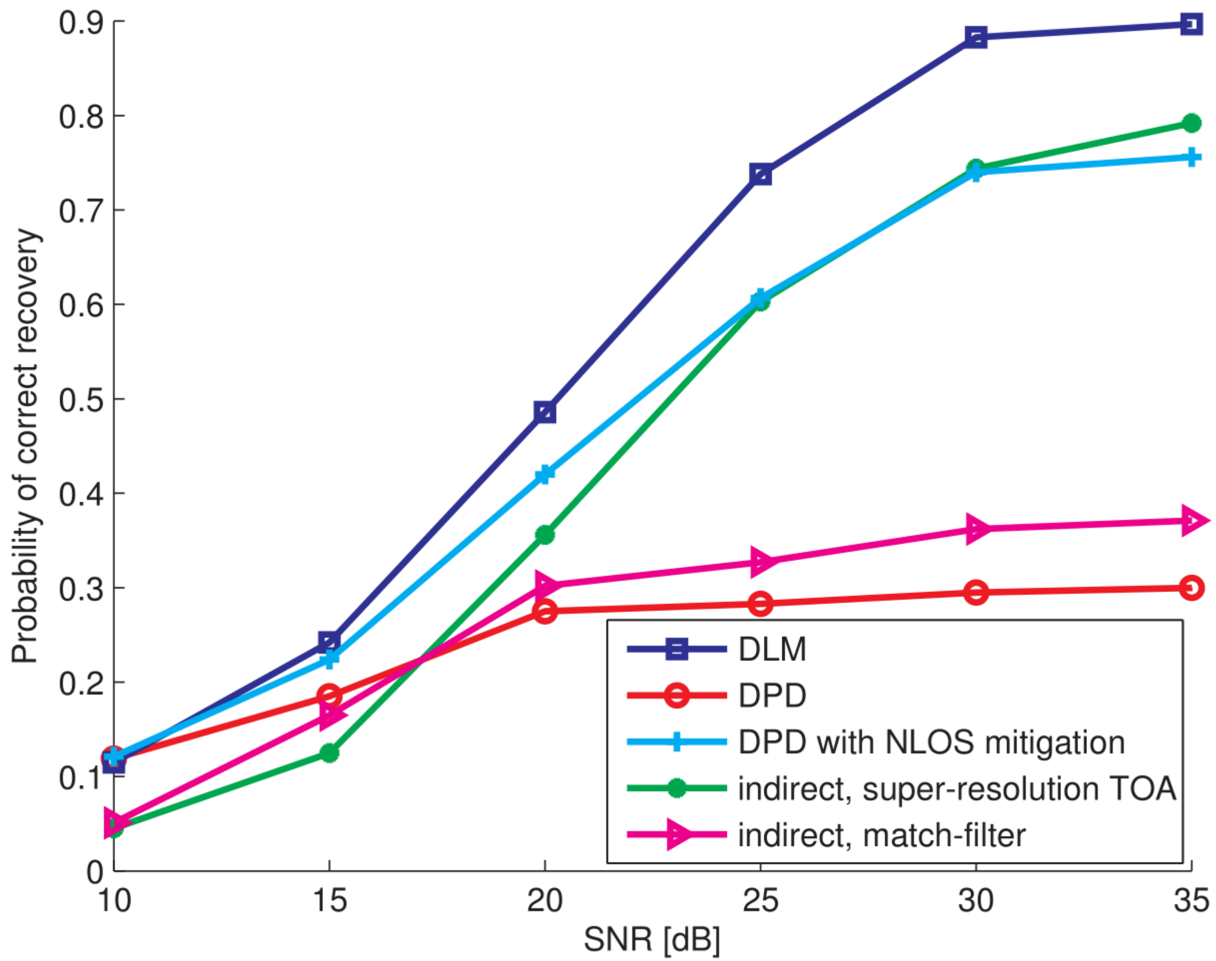
- 10 MHz emitter (30 m ranging resolution)
- Multipath channel RMS delay spread is 500 ns (exponential profile, Poisson arrivals)
- Search area: 200 x 200 m
- 5 base stations and 1 UE
- 100 samples/sensor

Sensor with blocked LOS



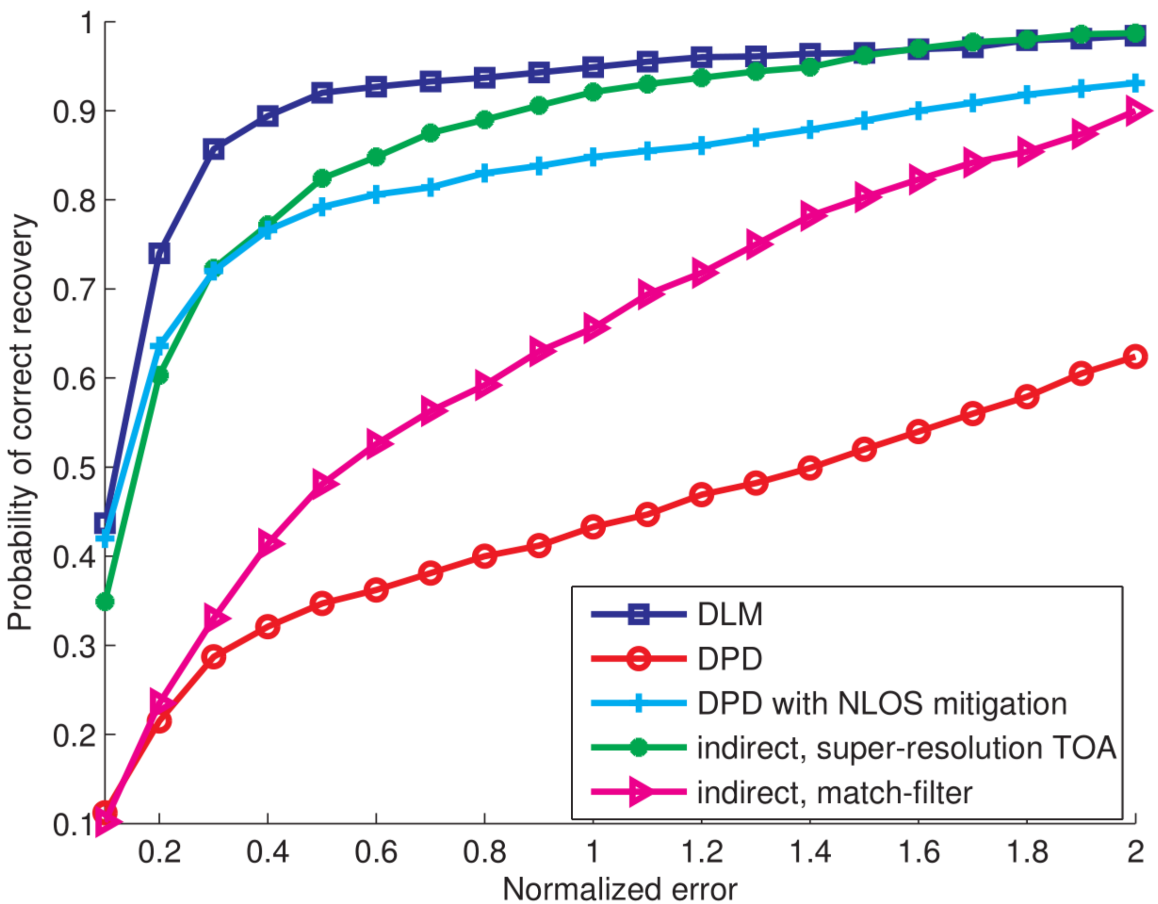
Probability of Correct Recovery vs. SNR

- Correct recovery if error is smaller than 10 m



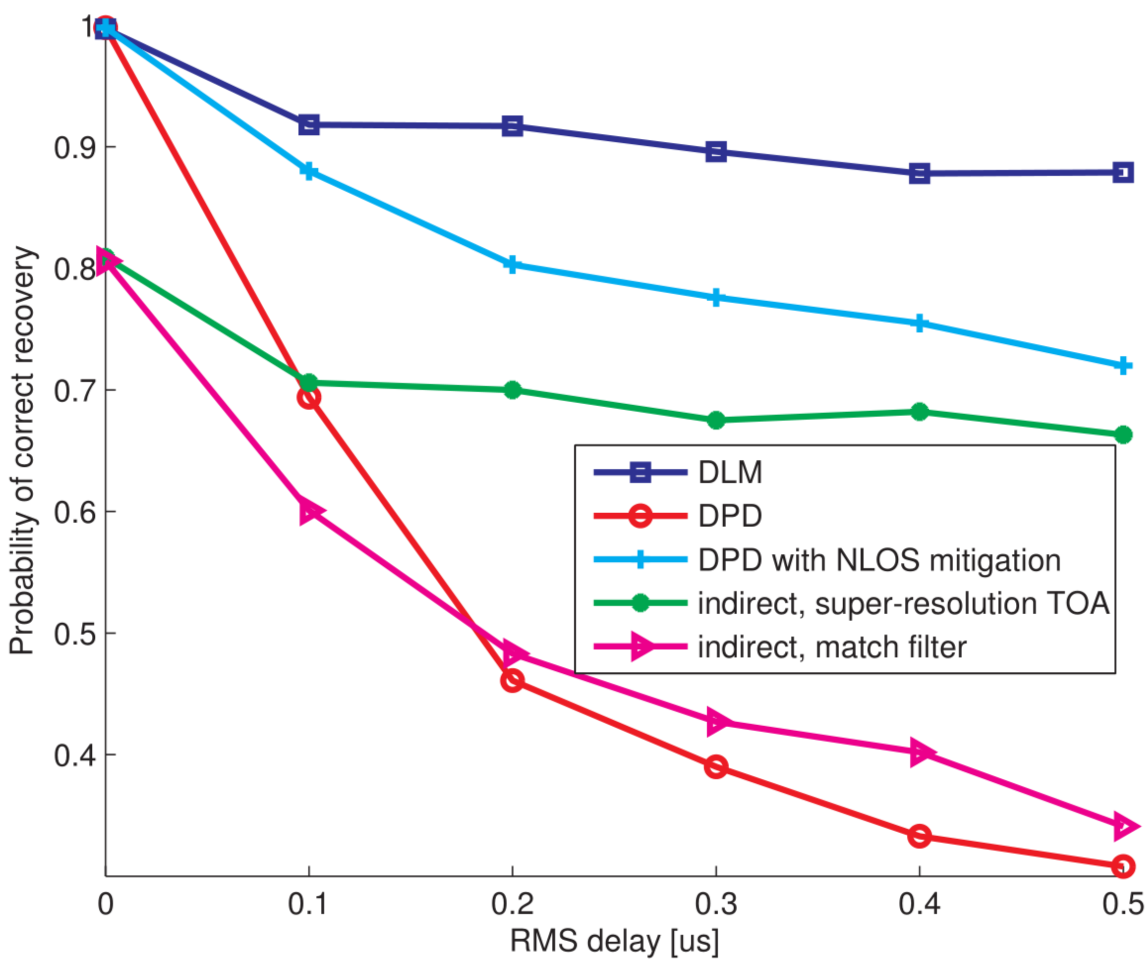
Probability of Correct Recovery vs. Error

- Error normalized to 30 m
- SNR $=$ 30 dB per observation window (100 samples and 5 sensors)

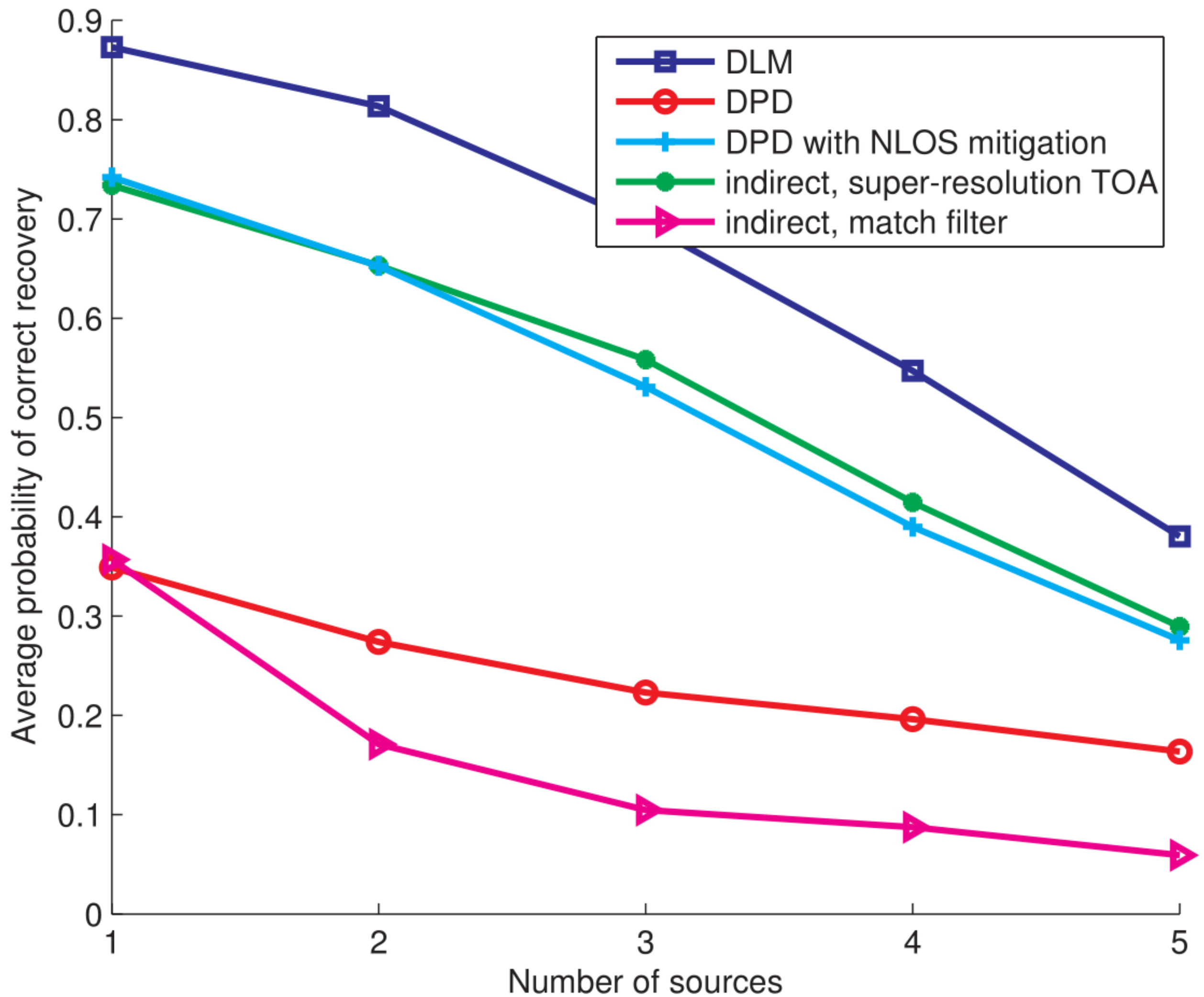


Prob. of Correct Recovery vs. Delay Spread

- SNR = 30 dB per observation window



Multiple Sources



SNR = 30 dB per observation window

Summary (I)

- Resources allocation for MIMO radar
  - ✓ Algorithms for power and/or bandwidth allocation in the presence of multiple targets are provided.
  - ✓ Bandwidth allocation shown to be more valuable than power allocation.

- A **novel approach** for localization of emitters in multipath featuring
  - ✓ **Direct localization** outperforms classical TOA indirect localization
  - ✓ An approximation of **ML** estimator
  - ✓ + novel framework captures **additional information:**
    - ✓ **Sparse** multipath
    - ✓ LOS are **first arrivals**
    - ✓ **Sparse** # sources
    - ✓ LOS signals originate from a **common** emitter location
    - ✓ Multipath is **local**

Summary (II)

- ✓ **Does not require channel state information**, such as power delay profile
- ✓ **Cloud**-based
- ✗ **Computationally more expensive** than indirect techniques but…
  - ✓ …Grid refinement approach proposed for reduced complexity

Thank you for you attention.