High-accuracy Direct Localization in the Presence of Multipath

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Outline

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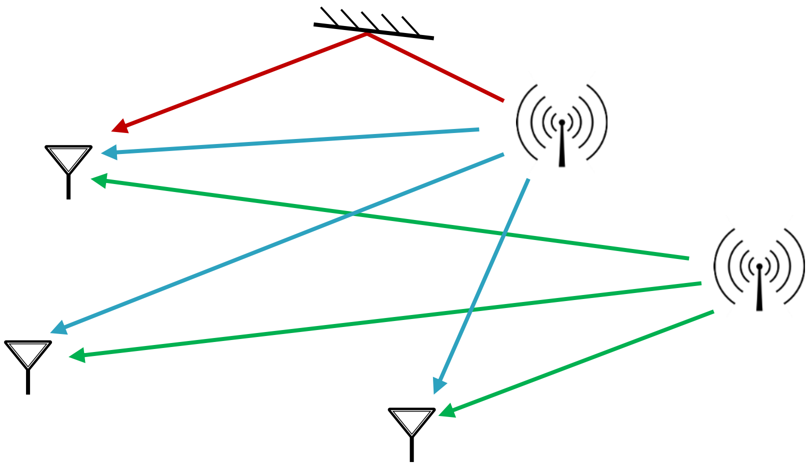
1. **Problem statement**
2. Proposed technique
3. Numerical examples
4. Summary and further work

Problem statement with no multipath

- Goal: estimate sources locations

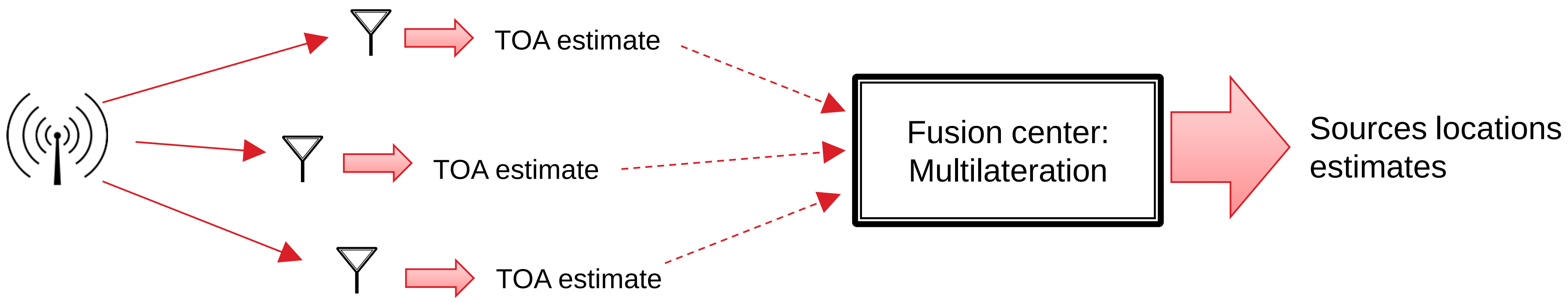
- Assumptions
  - Multiple sources
  - Known waveforms
  - Time of emission known
  - Widely space sensors
  - Invariant channel



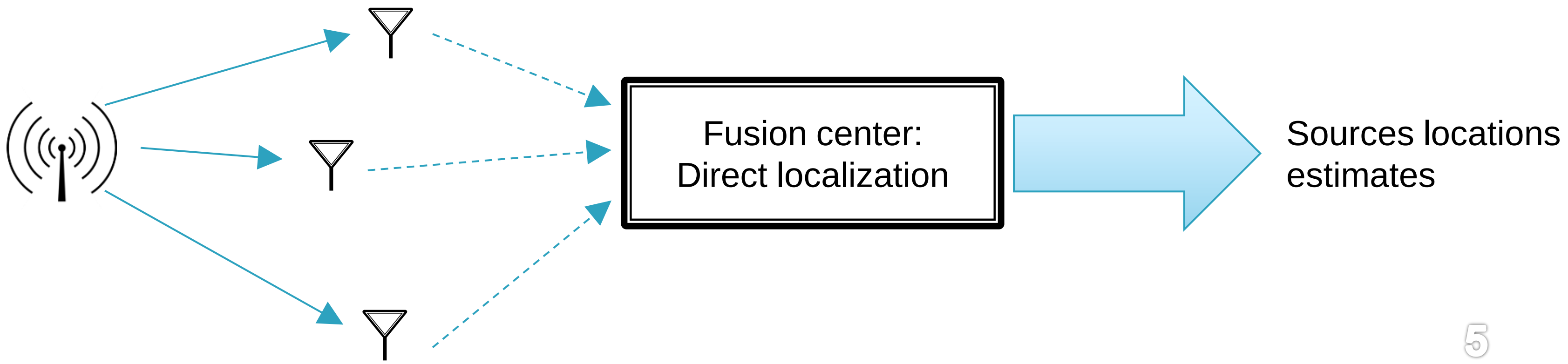
- Unknown parameters
  - Number of multipaths
  - Paths strengths
  - Sources locations

Direct localization: the concept

- Indirect localization:



- Direct localization:



Signal model with multipath

Noise-less signal received at l-th sensor:

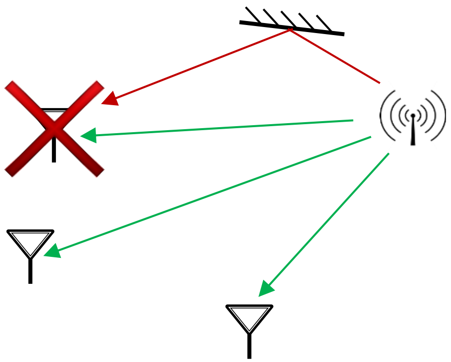
$$r_l(n) = \sum_{q=1}^{Q} b_{lq} s_q\left(n - \tau_l(\mathbf{p}_q)\right) + \sum_{q=1}^{Q} \sum_{m=1}^{M_{lq}} b_{lq}^{(m)} s_q\left(n - \tau_l\left(\mathbf{i}_{lq}^{(m)}\right)\right)$$

- Line-of-sight (LOS)
  - b_{lq} ➡ fading for LOS path
  - $s_q\left(n - \tau_l(\mathbf{p}_q)\right)$ ➡ LOS signal

- Non-line-of-sight (NLOS)
  - $b_{lq}^{(m)}$ ➡ fading for NLOS path
  - $s_q\left(n - \tau_l\left(\mathbf{i}_{lq}^{(m)}\right)\right)$ ➡ NLOS signal

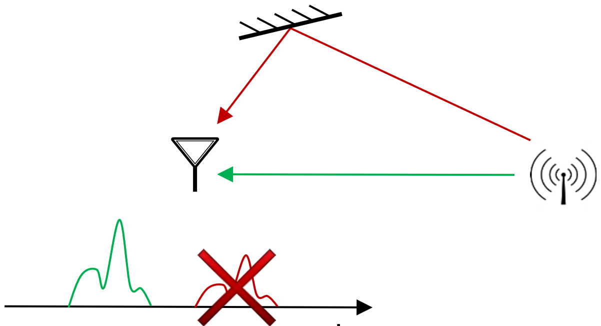
Reject sensors with strong NLOS

- Based on some kind of measure.



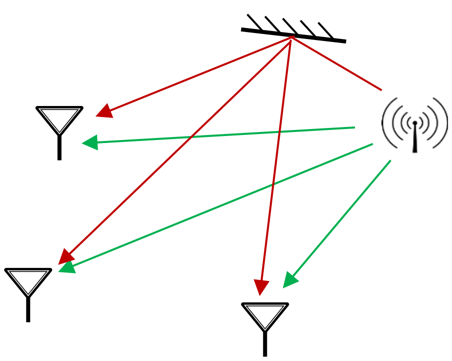
Select 1st arrival

- Problem if NLOS stations
- TOA estimation perturbed by closed arrivals



Single-bounce geometric model

- Assumes NLOS signals bounce only once
- Assumes known number of reflectors
- The location of the reflectors are estimated together with the locations of the sources.



Comparison direct and indirect

	Direct localization	Indirect techniques
Optimal ML estimation	ML on the sources position	ML on TOA's + And then ML on the sources locations
Performance at low SNR	Better	Worse
Data transmitted between nodes	Signals or a function of them	Intermediate parameters
Frequency-selective multipath	Our contribution	Some techniques exist for TOA

Very scarce!

- [Papakonstantinou-Slock,2008] proposed:
  - Using ML estimator assuming…
  - ✗ Known number of reflectors
  - ✗ Single-bounce multipath
  - ✗ No actual efficient implementation was given for finding ML solution

- [Wang-Ke-Liu,2013] proposed:
  - Sparsity-based technique
  - ✗ Frequency-selective channel learnt
    using a cooperative transmitter
    that sweeps through the area of interest.
  - After learning the channel direct localization can be applied easily.

High dimensional fitting problem

$$\min_{\substack{\mathbf{p}_1,\ldots,\mathbf{p}_Q \\ b_{11},\ldots,b_{LQ} \\ b_{11}^{1},\ldots,b_{LQ}^{(M_{LQ})} \\ \mathbf{i}_{11}^{1},\ldots,\mathbf{i}_{LQ}^{(M_{LQ})} \\ M_{11},\ldots,M_{LQ}}} \sum_{l,n} \left| r_l(n) - \sum_{q=1}^{Q} b_{lq} s_q\left(n - \tau_l(\mathbf{p}_q)\right) + \sum_{q=1}^{Q} \sum_{m=1}^{M_{lq}} b_{lq}^{(m)} s_q\left(n - \tau_l\left(\mathbf{i}_{lq}^{(m)}\right)\right) \right|^2$$

- Estimate sources locations
- Estimate nuisance parameters associated to LOS paths
- Estimate nuisance parameters associated to NLOS paths
- Estimate **hyperparameters** (complexity of signal model)

  ☞ ML estimation not suitable for hyperparameters

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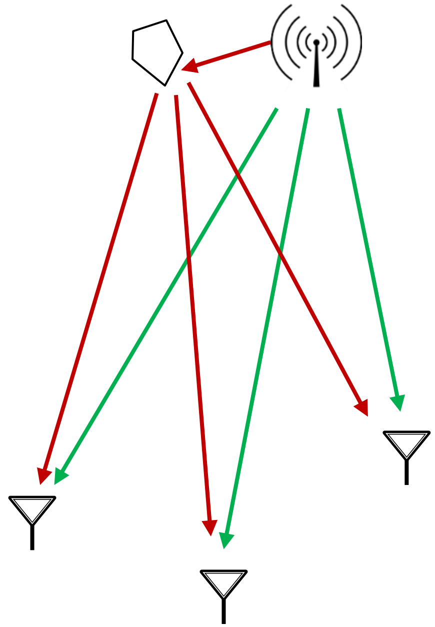
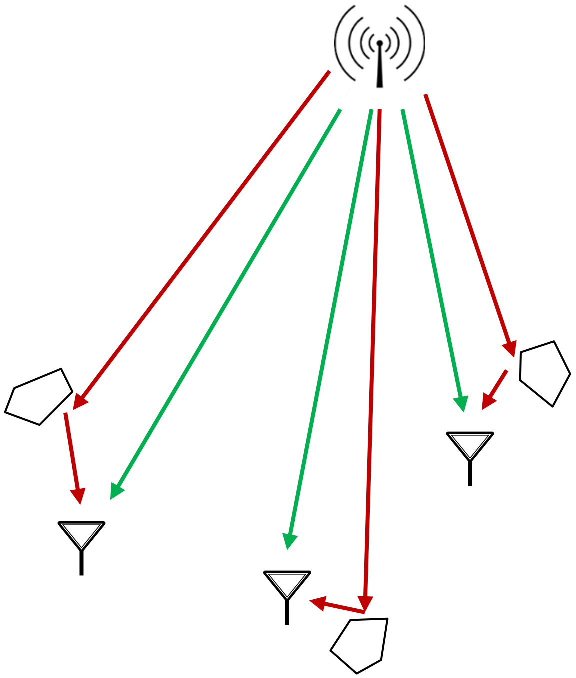
Originated close to the source



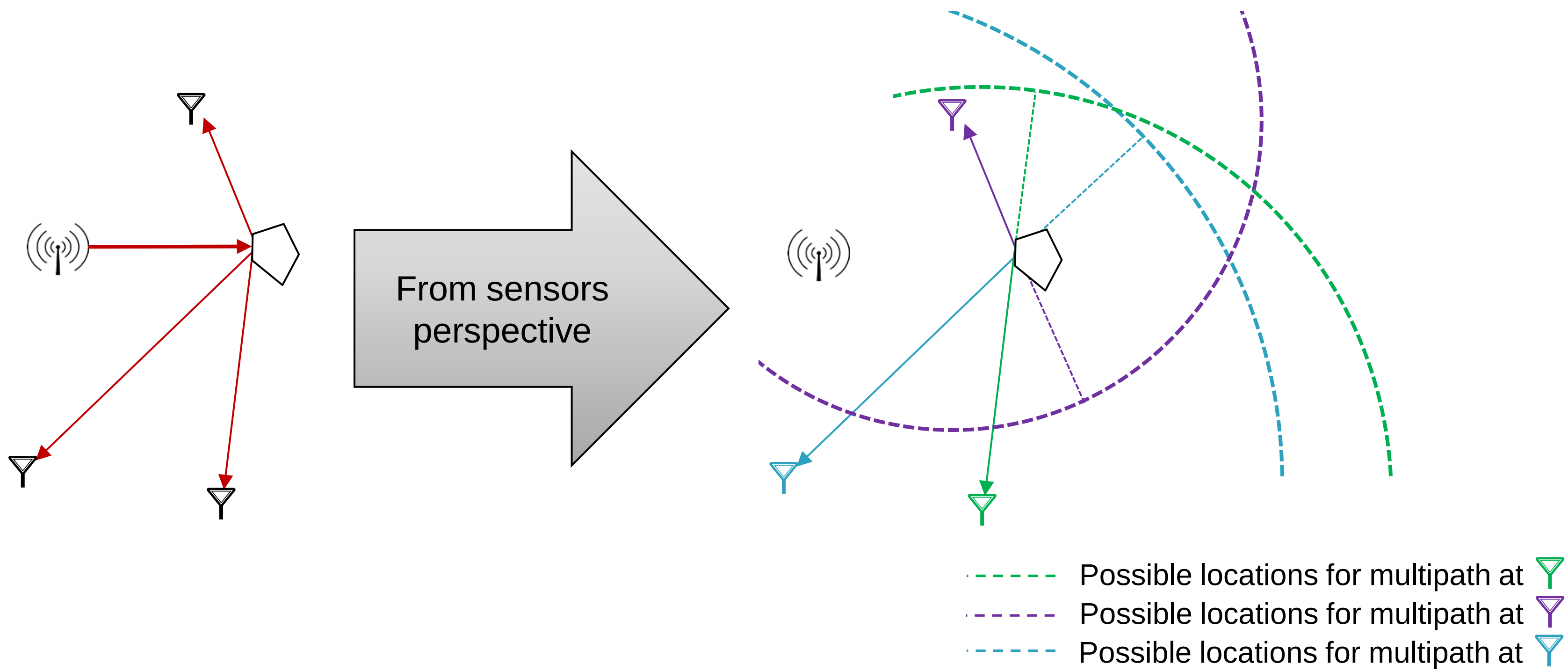
- Not independent multipaths
- Same reflector

Originated close to the sensors



- Independent multipaths

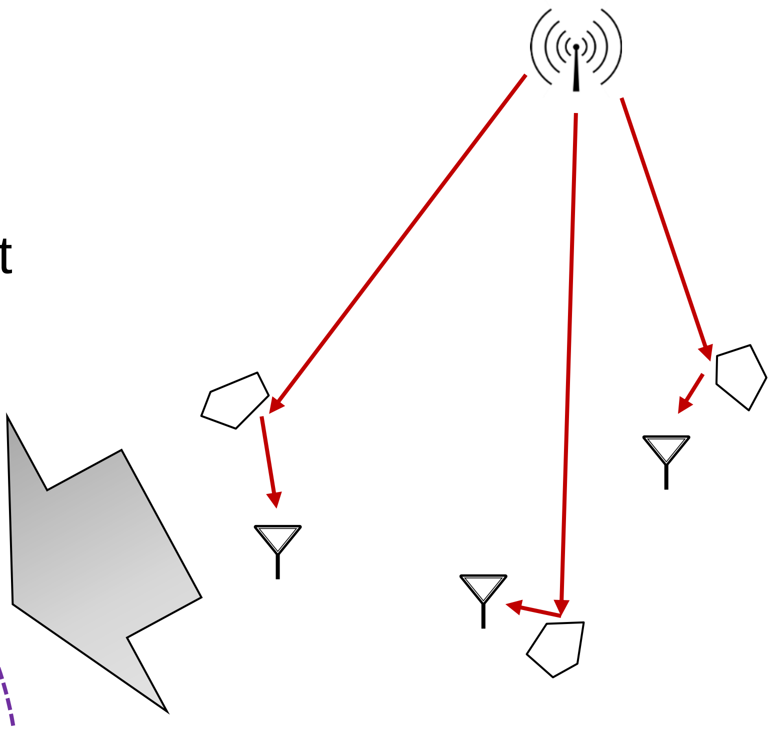
The NLOS circles do not intersect at a single location for the case of 3 or more sensors.

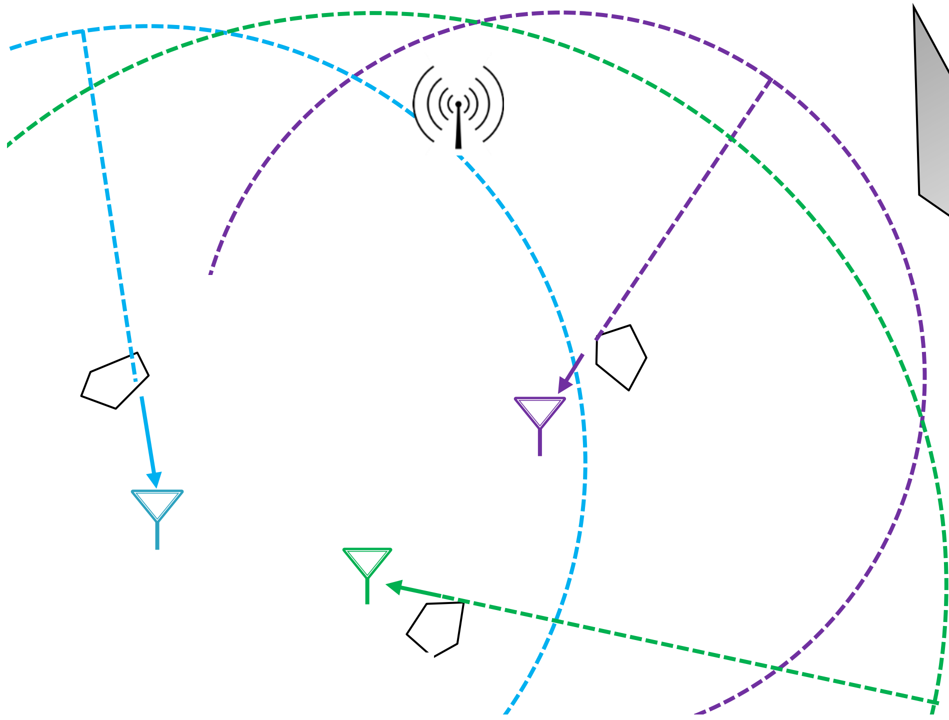


☞ We call **ghost location** any location inferred from NLOS paths.

Multipaths originated independently

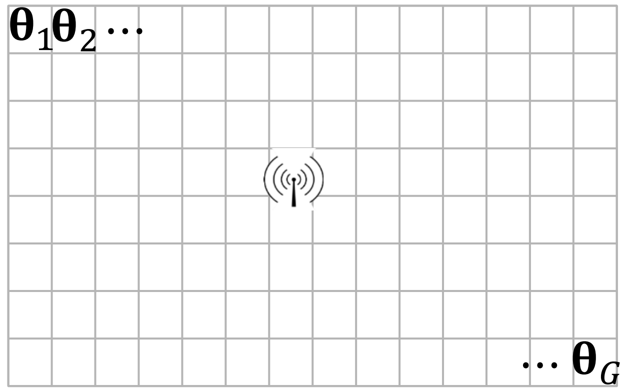
Probability of NLOS circles crossing at same location is very small





Sparse representation of the signal

1. Divide the area in G grid cells: $\boldsymbol{\theta}_1, \dots, \boldsymbol{\theta}_G$



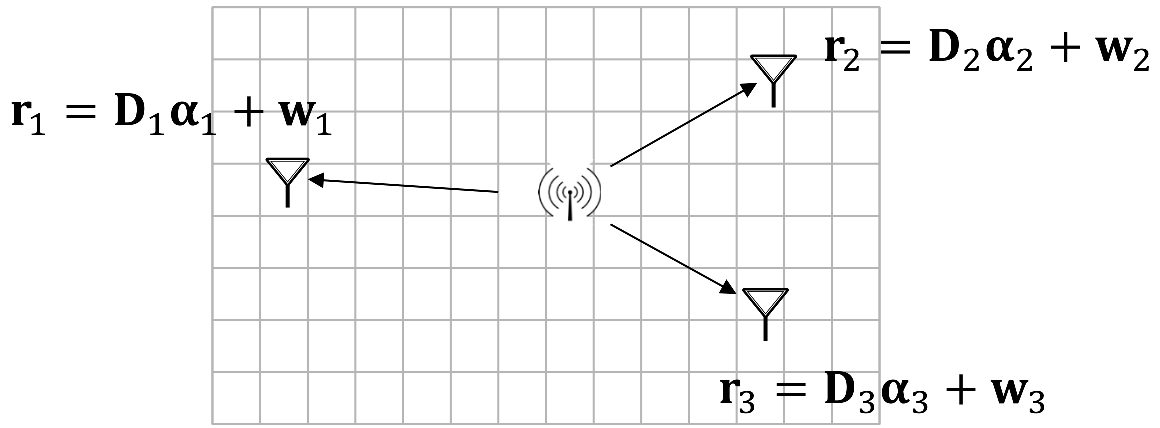
2. Stacking time samples for the l-th sensor (assuming 1 source):

$$\mathbf{r}_l = \left[\begin{array}{ccc|c|ccc} \mathbf{s}_1(\boldsymbol{\theta}_1) & \cdots & \mathbf{s}_1(\boldsymbol{\theta}_G) & \cdots & \mathbf{s}_Q(\boldsymbol{\theta}_1) & \cdots & \mathbf{s}_Q(\boldsymbol{\theta}_G) \end{array} \right] \boldsymbol{\alpha}_l + \mathbf{w}_l$$

- $\boldsymbol{\alpha}_l$ is a sparse vector with non-zeros on the indices corresponding to locations of sources or ghosts.

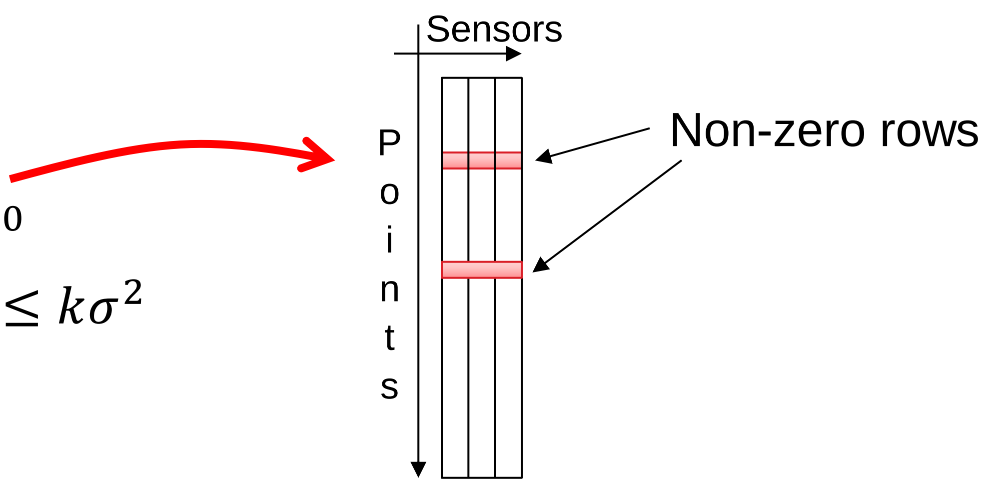
Sparse recovery problem

- Sparse assumption ➔ #ghosts + #sources ≪ # grid points



- Sparse recovery problem:

$$\begin{cases} \min\limits_{[\boldsymbol{\alpha}_1 \ldots, \boldsymbol{\alpha}_L]} & \|[\boldsymbol{\alpha}_1 \ldots, \boldsymbol{\alpha}_L]\|_0 \\ \text{subject to:} & \sum_{l=1}^{L} \|\mathbf{r}_l - \mathbf{D}_l\boldsymbol{\alpha}_l\|^2 \leq k\sigma^2 \end{cases}$$



- Provided we solved the sparse recovery problem and have a solution $[\boldsymbol{\alpha}_1 \ldots, \boldsymbol{\alpha}_L]$.

? How do we distinguish the entries corresponding to ghosts locations from the entry corresponding to the source?

- Example of a solution which happen to have 3 non-zero rows, and 3 columns because of the 3 sensors

$$[\boldsymbol{\alpha}_1, \boldsymbol{\alpha}_2, \boldsymbol{\alpha}_3] = \begin{bmatrix} \vdots & \vdots & \vdots \\ 2 & 0 & 5 \\ \vdots & \vdots & \vdots \\ 0 & 0 & 3 \\ \vdots & \vdots & \vdots \\ 4 & 9 & 7 \\ \vdots & \vdots & \vdots \end{bmatrix}$$

Which non-zero rows correspond to the source and which ones to ghosts?

Source ➔ illuminates three sensors or more

Ghosts ➔ illuminates two sensors at most

- The sparse recovery algorithm provides a solution without clean zeroes along the columns because of…
  - the noise
  - off-grid locations.
- Example of real numeric example with 3 sensors:

	⋮	
10.10	**4.76**	**3.19**
	⋮	
0.06	**5.73**	**1.71**
	⋮	
3.33	**2.31**	0.01
	⋮	

* These are the absolute values of the complex numbers.

- These zeroes are obvious.
- But with more noise they can be difficult to distinguish.

Solution?

~~Hard thresholding~~

Unsophisticated zero finder

- Very heuristic method.
- We simply multiply the absolute values of all entries in each row, i.e.:

⋮

10.10	**4.76**	**3.19**	= 153
	⋮		
0.06	**5.73**	**1.71**	= 0.59
	⋮		
3.33	**2.31**	0.01	= 0.08

⋮

→ Source location

- Possible problematic case → NLOS sensor

		⋮		
(Row of the source)	**10.10**	**4.76**	**3.19**	0.04
		⋮		
(Row of a ghost)	0.06	**5.73**	**1.71**	0.12
		⋮		

Algorithm

1. Set X=3
2. Set the threshold so that only 1 row has X non-zeroes.

	⋮		
10.10	4.76	3.19	0.04
	⋮		
0.06	5.73	1.71	0.12
	⋮		
3.33	2.31	0.01	0.07
	⋮		

3. Find the values for the elements in green squares that minimize the error $\sum_{l=1}^{L} ||\mathbf{r}_l - \mathbf{D}_l \boldsymbol{\alpha}_l||^2$ with the observations.
   1. If $\sum_{l=1}^{L} ||\mathbf{r}_l - \mathbf{D}_l \boldsymbol{\alpha}_l||^2 \leq k\sigma^2$

   ➔ Row with X values above the threshold corresponds to source

   2. Otherwise increment X and start again.

- ✓ By introducing the concept of ghost, our algorithm introduces a global way to distinguish NLOS from LOS, i.e. ghosts from sources.
- ✗ It doesn't utilize the fact that 2nd and later arrivals can only be due to NLOS paths.

- Removing 2nd and later arrivals from the signal:

Find non-zeroes

	Sensor 1	Sensor 2	Sensor 3
		⋮	
Location $\boldsymbol{\theta}_a$	10.10	4.76	3.19
		⋮	
Location $\boldsymbol{\theta}_b$	0.06	5.73	1.71
		⋮	
Location $\boldsymbol{\theta}_c$	3.33	2.31	0.01
		⋮	

Remove 2nd or later arrivals from the signal

Sensor 1	Sensor 2	Sensor 3
	⋮	
$\tau_1(\boldsymbol{\theta}_a)$	$\tau_2(\boldsymbol{\theta}_a)$	$\tau_3(\boldsymbol{\theta}_a)$
	⋮	
0.06	$\tau_2(\boldsymbol{\theta}_b)$	1.71
	⋮	
$\tau_1(\boldsymbol{\theta}_c)$	$\tau_2(\boldsymbol{\theta}_c)$	0.01
	⋮	

3 different flavors to our technique

Algorithm 1	Algorithm 2	Algorithm 3
1. Solve the sparse recovery problem 2. Find the source using the unsophisticated zero finder	1. Solve the sparse recovery problem 2. Find the source using variable thresholding	1. Solve the sparse recovery problem 2. Find non-zeroes using variable thresholding 3. Remove 2nd and later arrivals from the signal 4. Reapply steps 1 and 2

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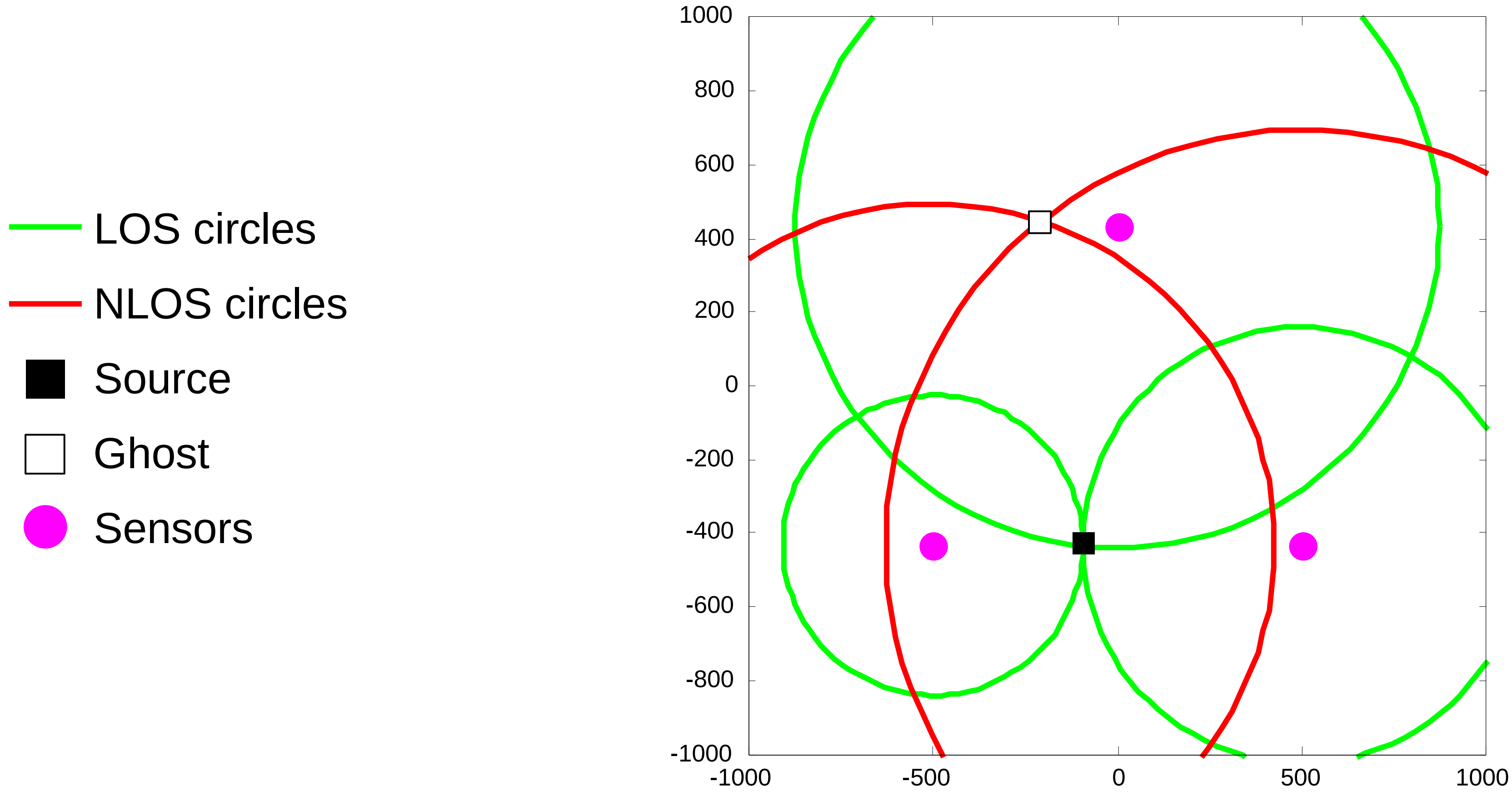
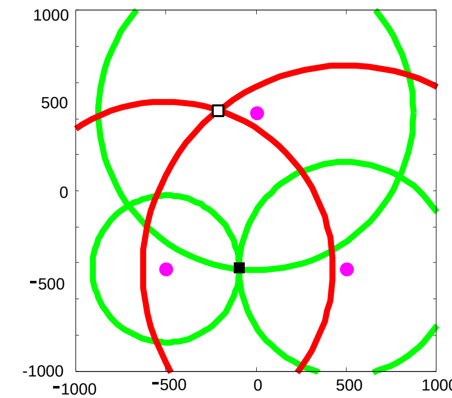
Simple scenario

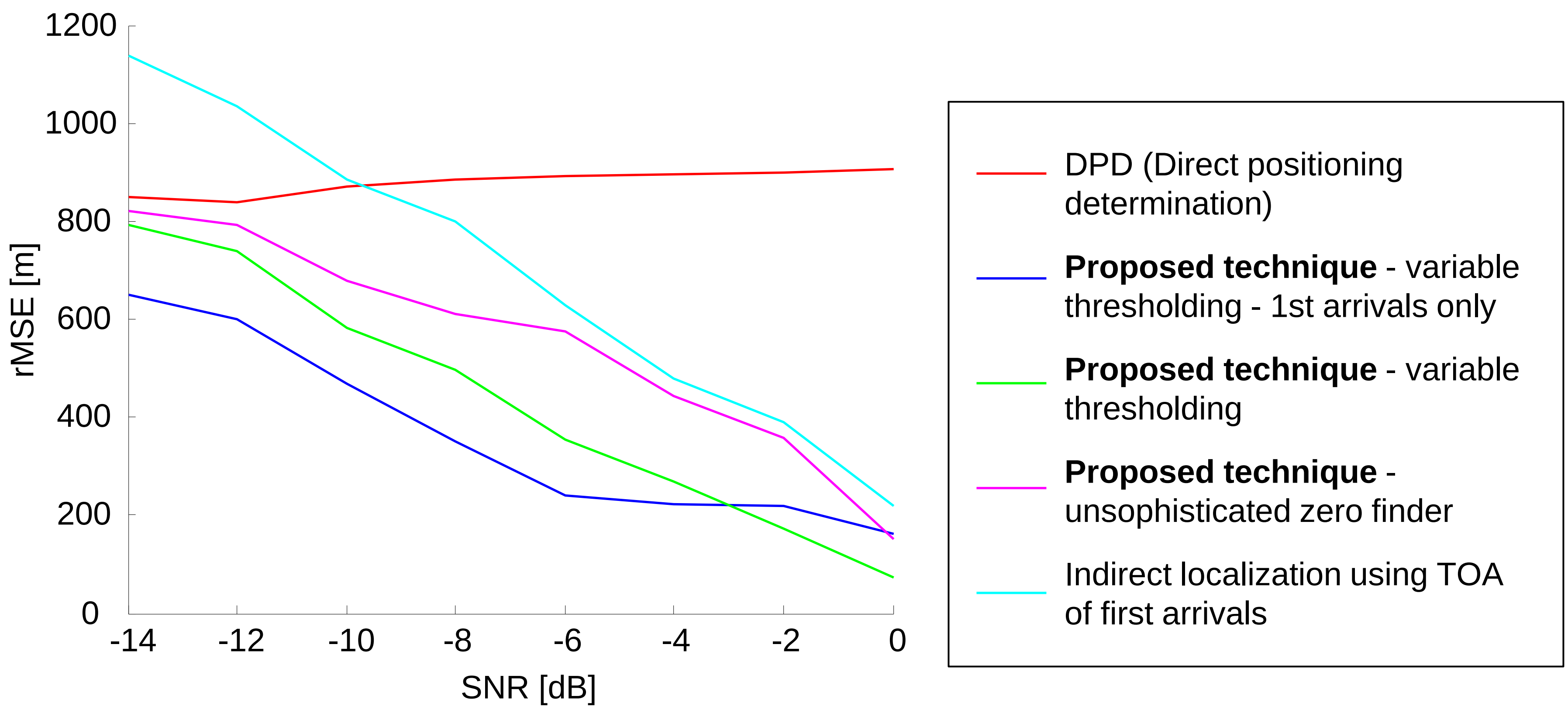
- 3 sensors with LOS paths with power 1
- 2 of these sensors have NLOS paths with power 3



Simple scenario: rMSE vs. SNR

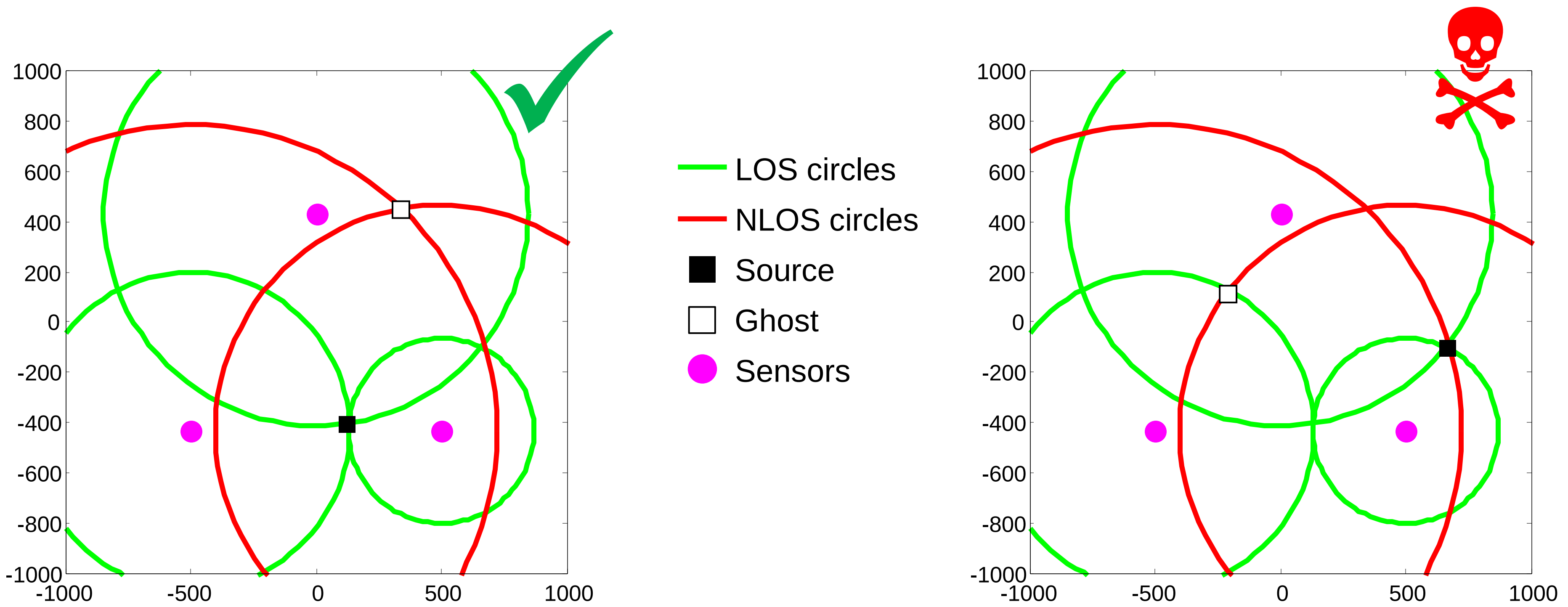
- 3 sensors with LOS paths with power 1
- 2 of these sensors have NLOS paths with power 3
- Bandwidth = 1MHz
- 100 samples per sensor
- Number of particles per point = 100





Problematic scenario

- 3 sensors with LOS paths with power 1
- 2 of these sensors have NLOS paths with power 3
- 1 NLOS circles happens to cross 2 LOS circles



Problematic scenario: rMSE vs. SNR

- 3 sensors with LOS paths with power 1
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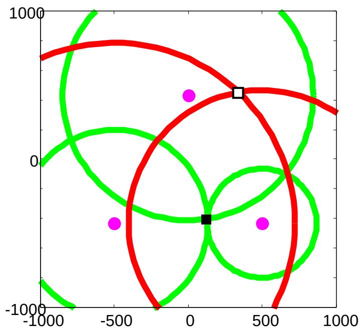
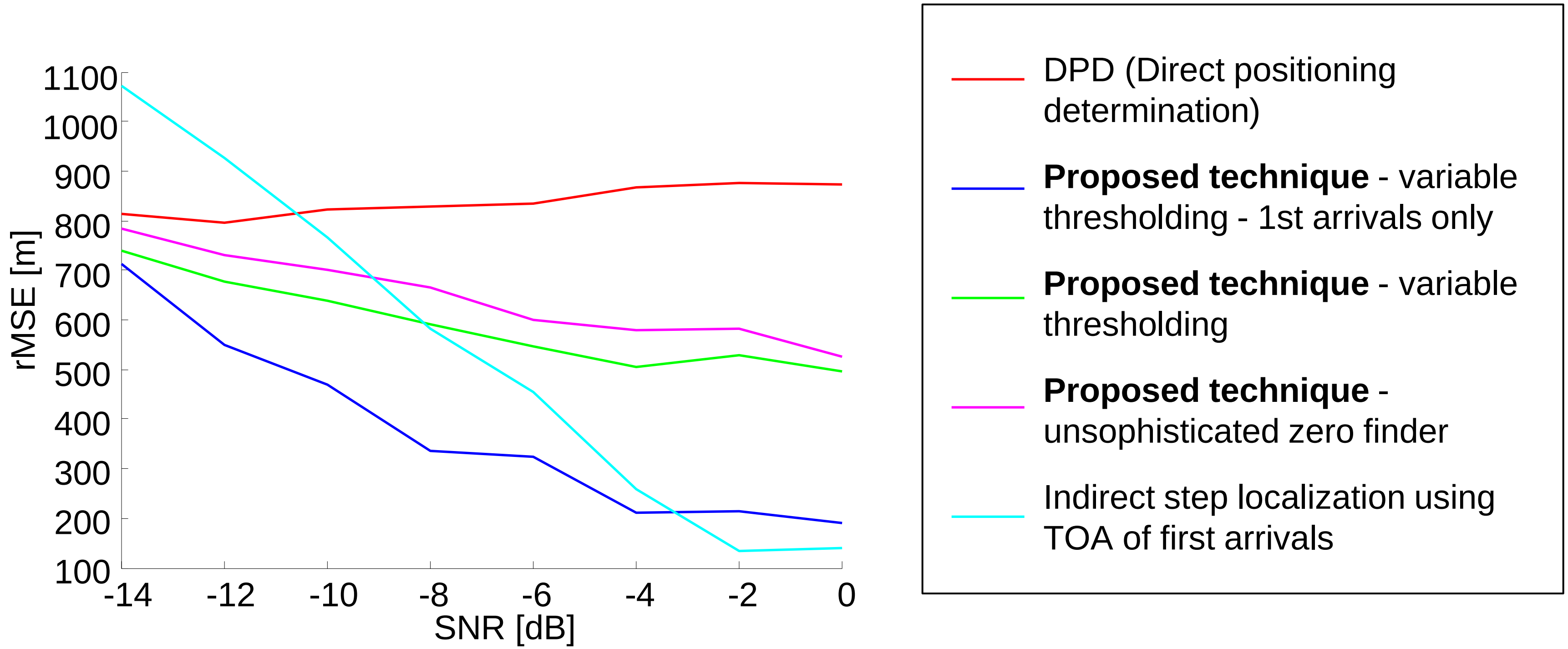
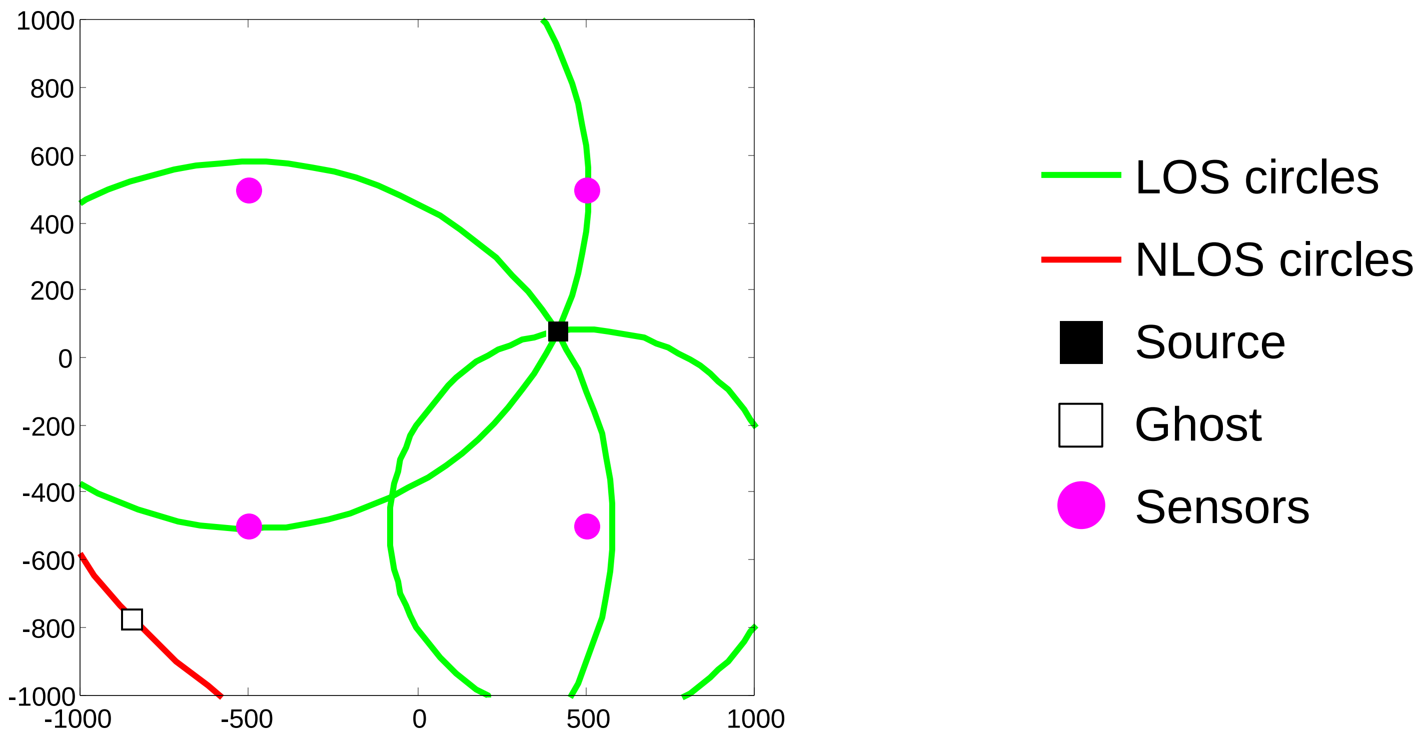
- ☠ 1 NLOS circles happens to cross 2 LOS circles
- Number of particles per point = 100
- 100 samples per sensor
- Bandwidth = 1MHz



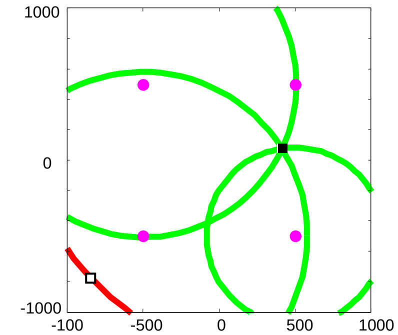


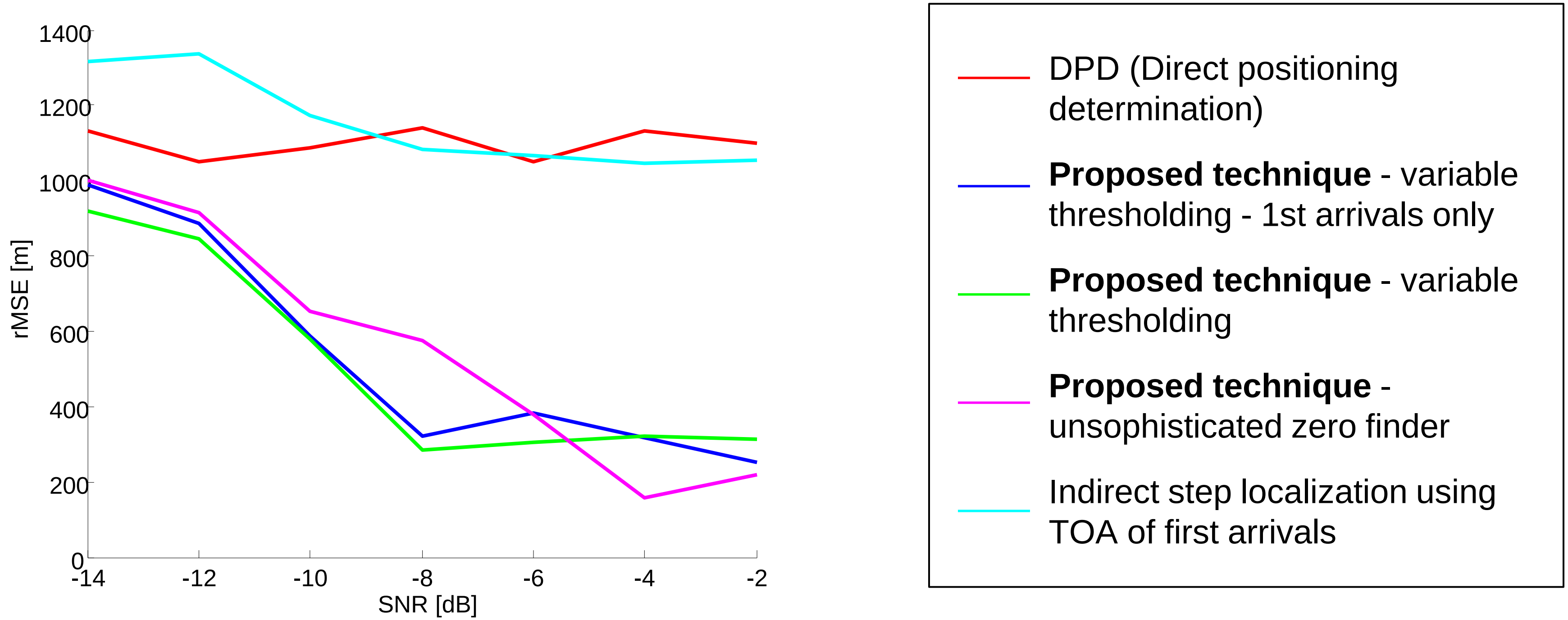
- 3 sensors with LOS paths with power 1
- 1 sensor receives only a NLOS path with power 3



Scenario with NLOS sensor

- 3 sensors with LOS paths with power 1
- 1 sensor receives only a NLOS path with power 3
- Bandwidth = 1MHz
- 100 samples per sensor
- Number of particles per point = 100





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Summary

- Contributions
  - First direct localization technique that deals with…
    - Flat multipath
    - Frequency-selective multipath
  - New approach to mitigating the multipath problem by using…
    - The ghost concept
    - Sparsity on the number of ghosts and sources

- Strengths:
  - Higher accuracy
  - Can deal with NLOS sensors

- Weaknesses
  - Large computational load
  - More data needs to be sent to the fusion center

Further work

- Further work done:
  - Ambiguity analysis: analyzing when the proposed technique fails
  - Extended the proposed technique to deal with stations with phased arrays → Angle + delay information
  - We show how to compress the received signals with negligible loss so that the sparse recovery problem running time remains constant with the number of acquired samples.

- Work in progress:
  - Expanding the ideas to the case of unknown signals

- Future work
  - Computing and plotting the CRLB

Thank you for your attention.

Please ask any questions.