Source Localization and Tracking for Dynamic Radio Cartography using Directional Antennas

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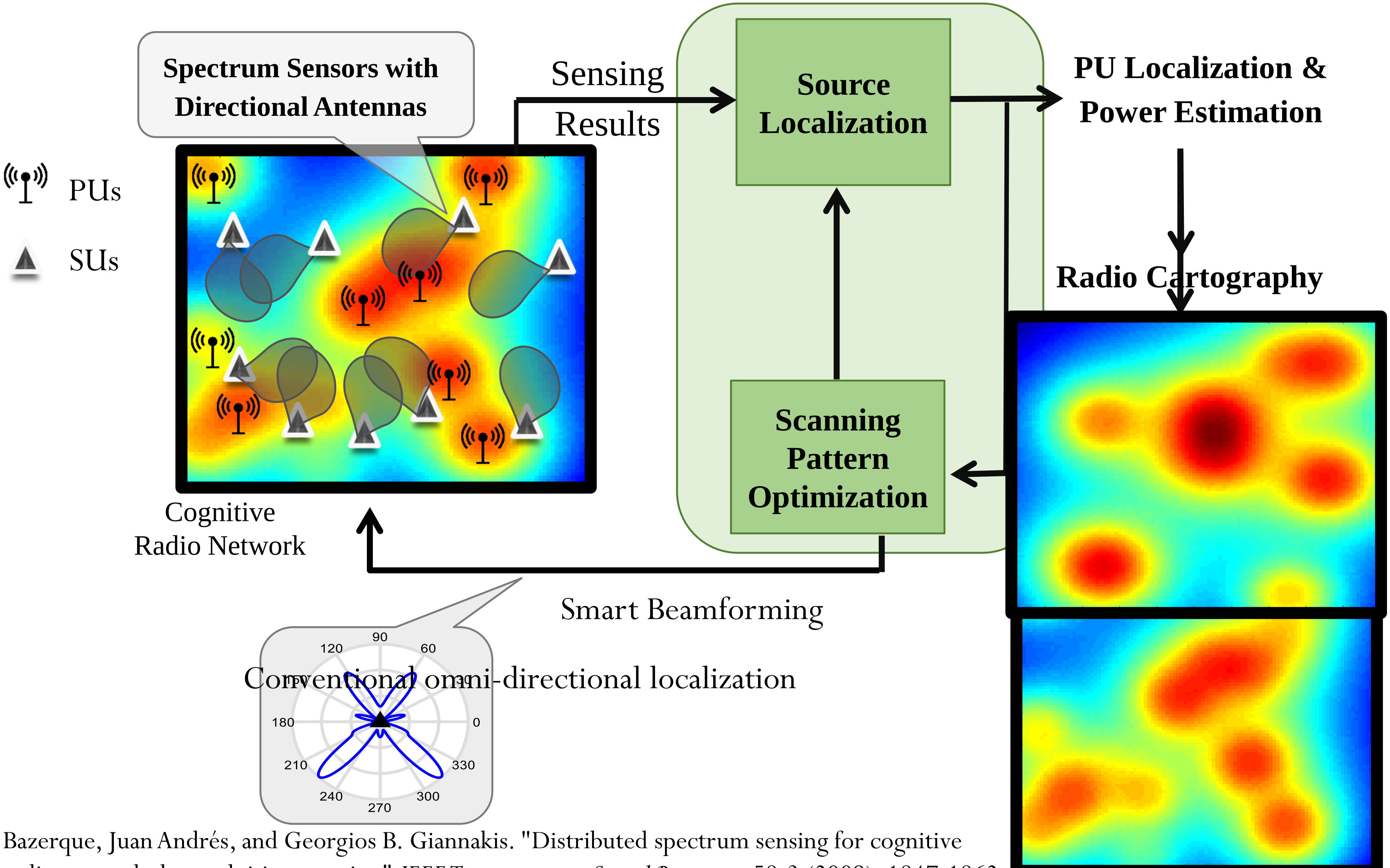
Overview



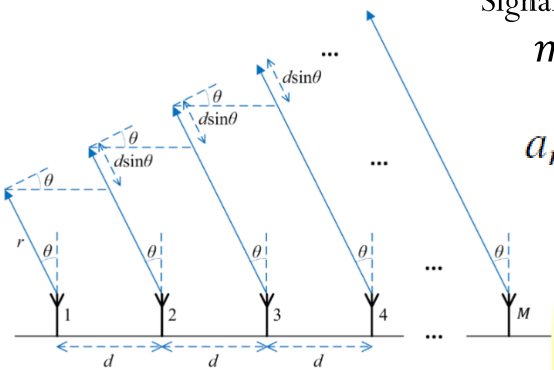
Bazerque, Juan Andrés, and Georgios B. Giannakis. "Distributed spectrum sensing for cognitive radio networks by exploiting sparsity." *IEEE Transactions on Signal Processing* 58.3 (2009): 1847-1862.

Outline

- Source Localization and Radio Cartography
- Impact of Directional Antennas on Spectrum Sensing
- Mathematical Formulation and Optimization
- Distributed Radio Cartography on Network's Edge
- Simulation Results for Radio Cartography

Problem Statement

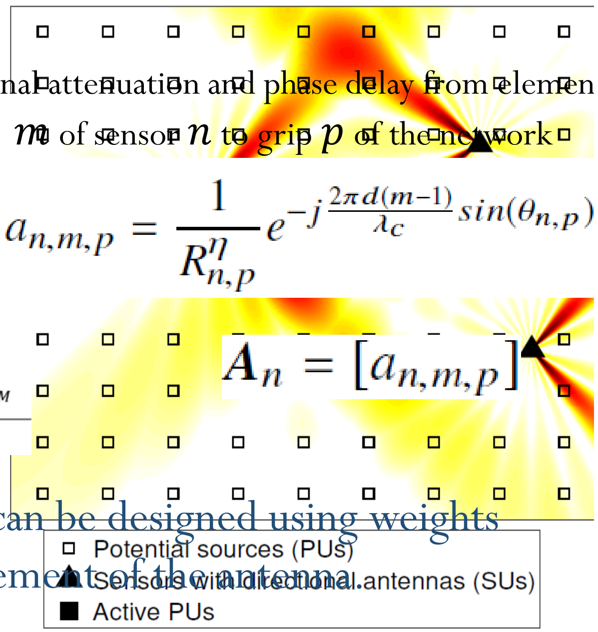
- The area is divided into P grid points (potential PU locations)
- Only few locations are active
- Each sensor is equipped with a Uniform Linear Antenna (ULA) with M elements

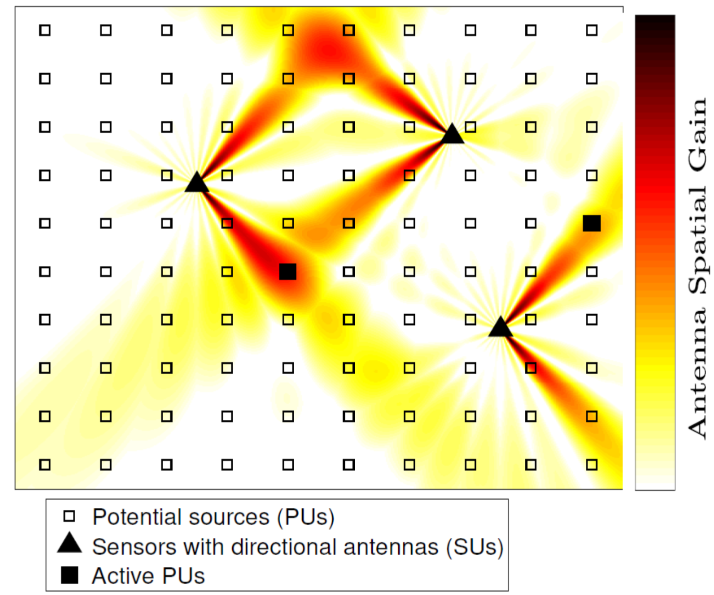


Signal attenuation and phase delay from element m of sensor n to grip p of the network

$$a_{n,m,p} = \frac{1}{R_{n,p}^{\eta}} e^{-j\frac{2\pi d(m-1)}{\lambda_c} sin(\theta_{n,p})}$$

$$A_n = [a_{n,m,p}]$$





Pattern of a ULA can be designed using weights on each element of the antenna.

The goal is to optimize antenna's patterns such that:

- **Previously detected sources are tracked accurately**
- **The whole area is covered to discover any upcoming sources**

Received Signal after Beamforming

- How is received signal related to Beamforming vectors?

signals from PUs:

$$\boldsymbol{s} = [s_1 \ \ldots \ s_P]^T$$

Beamforming vectors:

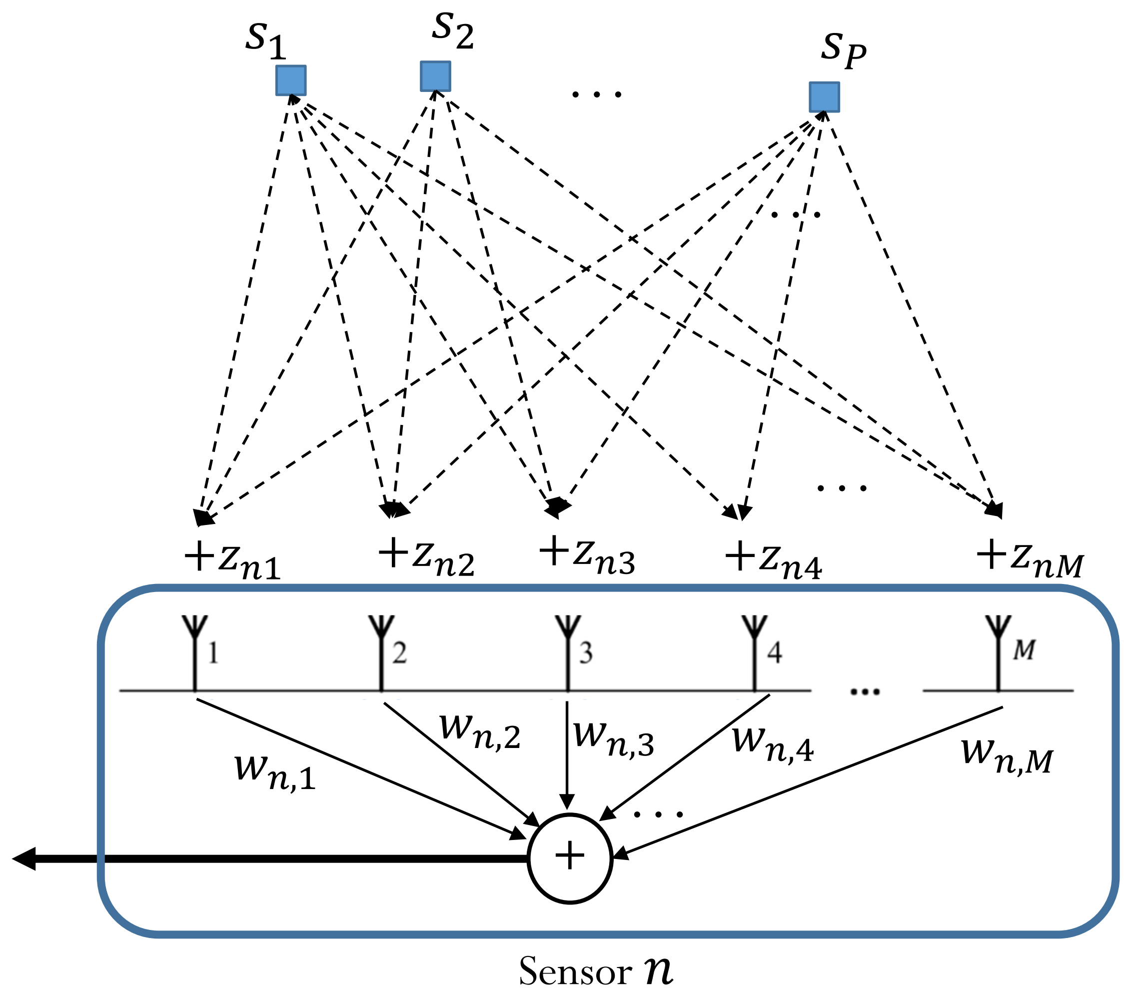
$$\boldsymbol{w}_n = [w_{n,1} \ \ldots \ w_{n,M}]^T$$

Receiver noise:

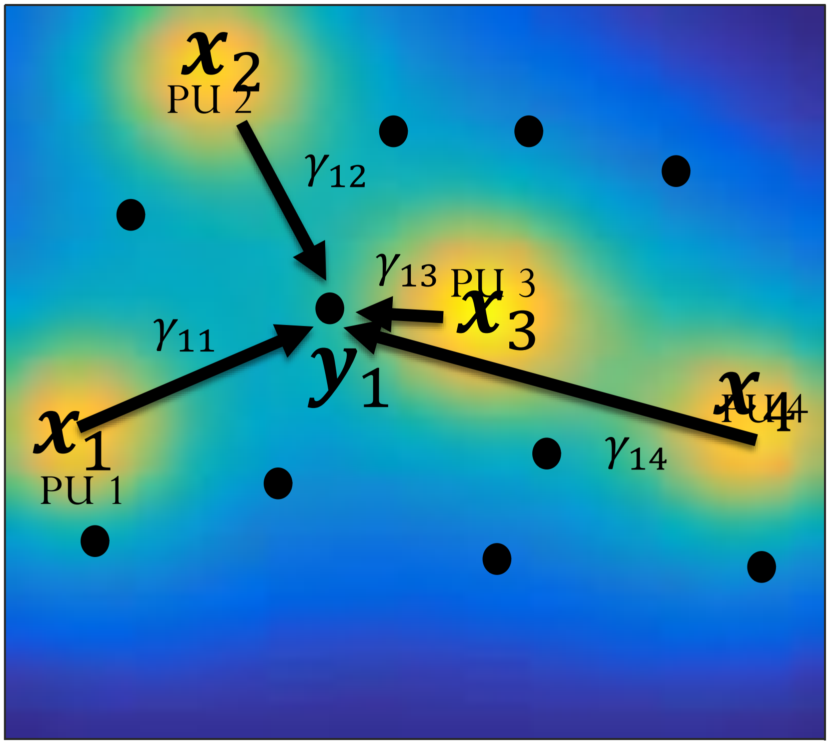
$$\boldsymbol{z}_n = [\mathrm{z}_{\mathrm{n1}} \ \ldots \ \mathrm{z}_{\mathrm{nM}}]$$

Received signal:

$$r_n = \boldsymbol{w}_n^H \boldsymbol{A}_n \boldsymbol{s} + \boldsymbol{w}_n^H \boldsymbol{z}_n$$



Sensing Received Signal Strength of Sources



$$y_n(t) = r_n^*(t) r_n(t) =$$

$$= \sum_{p=1}^{P} \underbrace{\boldsymbol{w}_n^H(t) \boldsymbol{A}_n \boldsymbol{C}_p \boldsymbol{A}_n^H \boldsymbol{w}_n(t)}_{=\gamma_{np}(t)} x_p(t)$$

$$+ \underbrace{\boldsymbol{w}_n^H(t) \boldsymbol{z}_n(t) \boldsymbol{z}_n^H(t) \boldsymbol{w}_n(t)}_{=v_n(t)} = \boldsymbol{\gamma}_n^T(t) \boldsymbol{x}(t) + v_n(t)$$

$$\boldsymbol{x}(t) = [x_1(t) \; x_2(t) \; \ldots \; x_P(t)]^T$$

is the propagation power vector

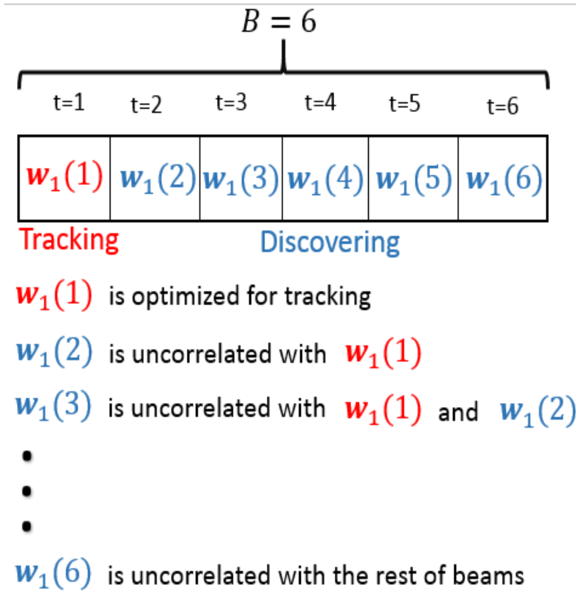
C_p is a $P \times P$ matrix

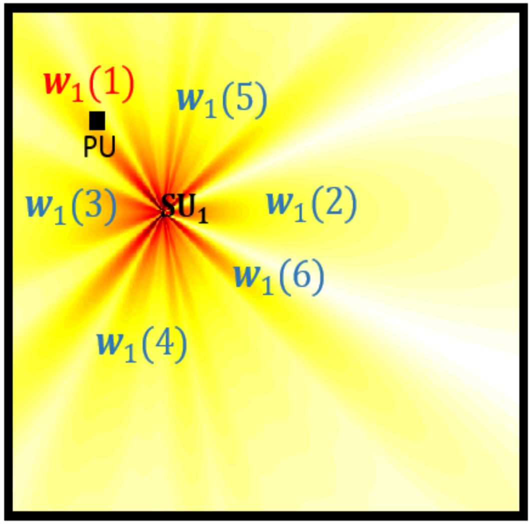
$$\boldsymbol{y}(t) = \boldsymbol{\Gamma} \boldsymbol{x}(t) + \boldsymbol{m}_v + \boldsymbol{\epsilon}(t)$$

$\boldsymbol{m}_v$ is a non-negative vector that indicates Expectation of RSS.

Beamforming Over a Dynamic Network

- A group of B time slots is considered as a time block
- In each time slot sensors scan the network with their specific beam patterns.
- In each time block one pattern is dedicated for tracking of previously detected sources.
- The rest of beam patterns are allocated for discovering any upcoming sources.





Problem Formulation

Joint localization and beamforming

$$< \hat{\boldsymbol{x}}(t), \hat{\boldsymbol{W}}(t) > = \underset{\boldsymbol{x},\boldsymbol{W}}{\operatorname{argmin}} \|\boldsymbol{y}(t) - \boldsymbol{\Gamma}(t)\boldsymbol{x} - \boldsymbol{m}_v\|_2^2$$

$$\text{s.t. } \boldsymbol{\Gamma}(t) = h(\boldsymbol{W}(t)), \quad \|\boldsymbol{x}\|_1 \leq C_0 \text{ and } \|\boldsymbol{w}_n\|_2^2 = C_1 \ \forall n$$

split

1

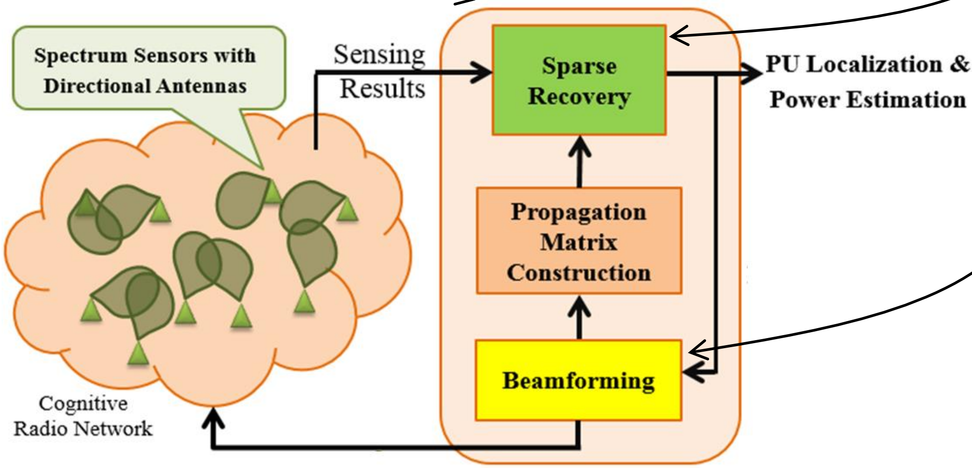
$$\hat{\boldsymbol{x}}(t) = \underset{\boldsymbol{x}}{\operatorname{argmin}} \|\boldsymbol{y}^B(t) - \boldsymbol{\Gamma}^B(t)\hat{\boldsymbol{x}} - \boldsymbol{m}_v^B\|_2^2 + \lambda\|\boldsymbol{x}\|_1$$

2

$$\hat{\boldsymbol{W}}(t+1) = \underset{\boldsymbol{W}}{\operatorname{argmin}} \|\boldsymbol{y}^B(t) - \boldsymbol{\Gamma}^B(t+1)\hat{\boldsymbol{x}}(t) - \boldsymbol{m}_v^B\|_2^2,$$

$$\text{s.t. } \boldsymbol{\Gamma}^B(t+1) = h(\boldsymbol{W}(t)).$$

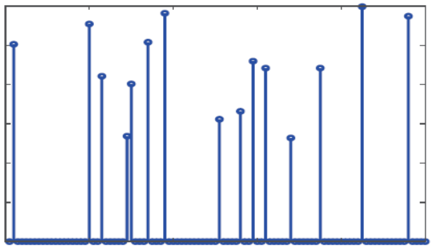
- Beamforming vectors of all sensors are collected in $\boldsymbol{W}(t)$
- The joint problem is split into two distinguished problems
- We will study each problem separately



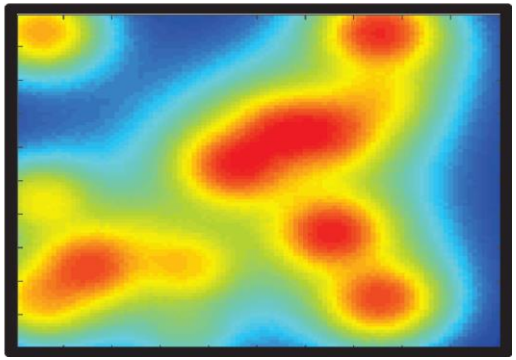
The first sub-problem: Localization

$$\hat{x}(t) = \underset{x}{\operatorname{argmin}} \| y^B(t) - \Gamma^B(t)\hat{x} - m_v^B \|_2^2 + \lambda \| x \|_1$$

- It is a well-known problem in statistics.
- There are several solvers including LASSO and Basis Pursuit.
- The output of this problem reveals the location and power of active PUs.



PU locations and their powers



The second sub-problem: beamforming

$$\hat{W}(t+1) = \underset{\boldsymbol{W}}{\operatorname{argmin}} \|\boldsymbol{y}^B(t) - \boldsymbol{\Gamma}^B(t+1)\hat{\boldsymbol{x}}(t) - \boldsymbol{m}_v^B\|_2^2,$$
$$\text{s.t. } \boldsymbol{\Gamma}^B(t+1) = h(\boldsymbol{W}(t)).$$

A known estimated $\hat{\boldsymbol{x}}$ **(tracking step)**	A general unknown $\boldsymbol{x}$ **(discovering step)**
$r_n(t) = w_n^H A_n \hat{x} + w_n^H z_n$ It is desired that w_n acts as a matched filter (matched to $\hat{\boldsymbol{x}}$) $w_n = A_n \hat{x}$	$\boldsymbol{\Gamma} = \underset{\boldsymbol{\Gamma}}{\operatorname{argmin}}\ \mathbb{E}_x \{\|\boldsymbol{y}(t) - \boldsymbol{m}_v^B - \boldsymbol{\Gamma}\boldsymbol{x}\|_2^2\}$ $\boldsymbol{\Gamma} = \underset{\boldsymbol{\Gamma}}{\operatorname{argmin}}\ \operatorname{trace}\left(\sum_n \gamma_n \gamma_n^T\right)^{-1}$

Joshi, Siddharth, and Stephen Boyd. "Sensor selection via convex optimization." *IEEE transactions on Signal Processing* 57.2 (2008): 451-462.

Algorithm

Algorithm Joint localization and beamforming (centralized)

Input: Location of SUs and RSS.

Output: $\boldsymbol{x}(t)$ (Location and powers of PUs for each t).

1: Random initialization of $\boldsymbol{w}_n(t)\ \forall n$.

2: Construct $\boldsymbol{\Gamma}$

for a new time slot t

3: Collect vector $\boldsymbol{y}^B$ from recent B time slots

4: Construct matrix $\boldsymbol{\Gamma}^B$ for recent B time slots

5: $\hat{x} \leftarrow$ Localization using Sparse Recovery

if t *mod* $B = 0$

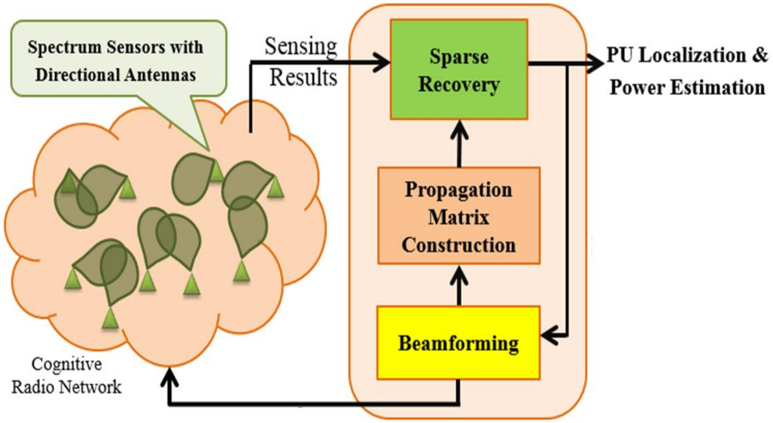
6: $\hat{w}_n(t+1) \leftarrow$ Update for Tracking

else

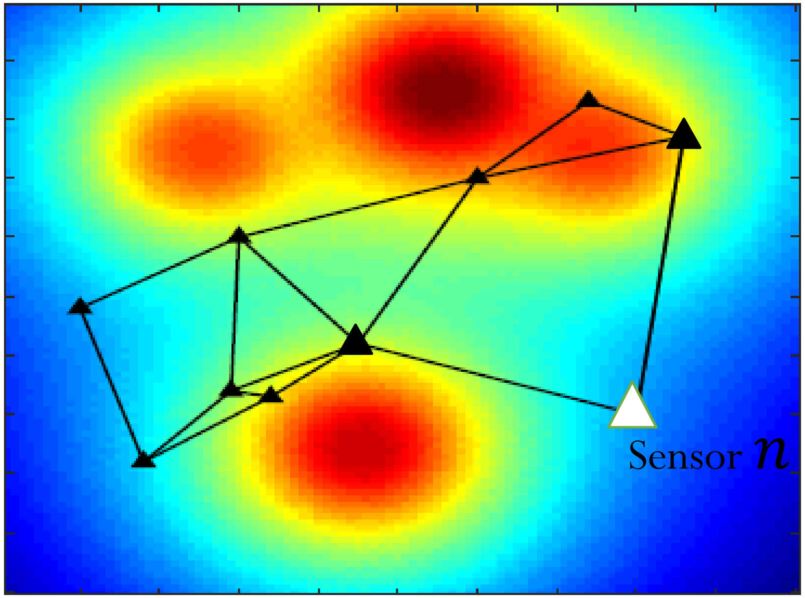
7: $\hat{w}_n(t+1) \leftarrow$ Update for Discovering

end

end



Distributed Localization and Beamforming

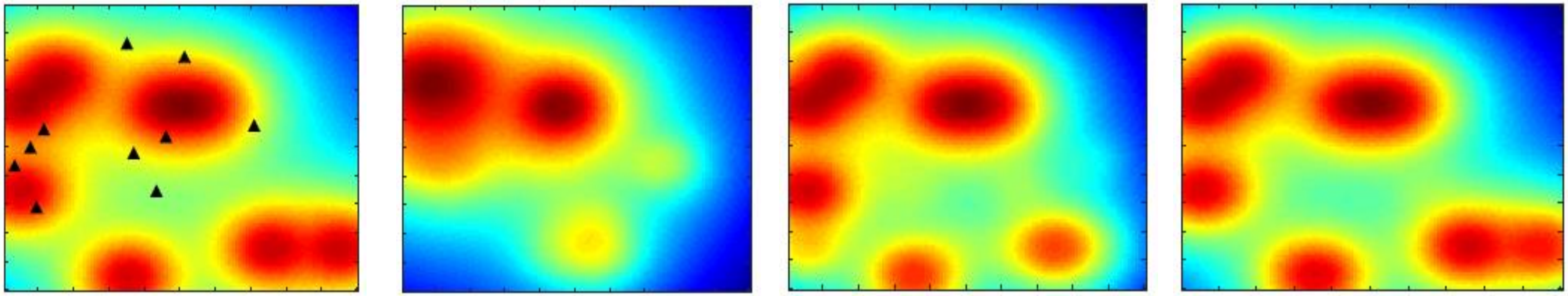


$$\hat{\boldsymbol{x}}^{(n)}(t) = \underset{\boldsymbol{x}}{\operatorname{argmin}} \|\boldsymbol{y}^{(n)}(t) - \boldsymbol{\Gamma}^{(n)}\boldsymbol{x} - \boldsymbol{m}_v\|_2^2 + \lambda\|\boldsymbol{x}\|_1 + \underbrace{\alpha \sum_{i \in \mathcal{N}_n} \|\hat{\boldsymbol{x}}^{(i)}(t-1) - \boldsymbol{x}\|_2^2}_{\text{Consensus term}}$$

- $y^{(n)}(t)$ is the collection measurements from sensor n and its neighbors.
- Neighborhood can be defined based on distance.
- $\hat{x}^{(n)}(t)$ is the estimated power spectrum at sensor n.
- Each node solves a specific optimization problem.
- Parameter α regularizes the problem to infuse information from neighbors

Experimental Results

Comparison of Estimated Power Map



Ground truth that synthesized data are generated accordingly.

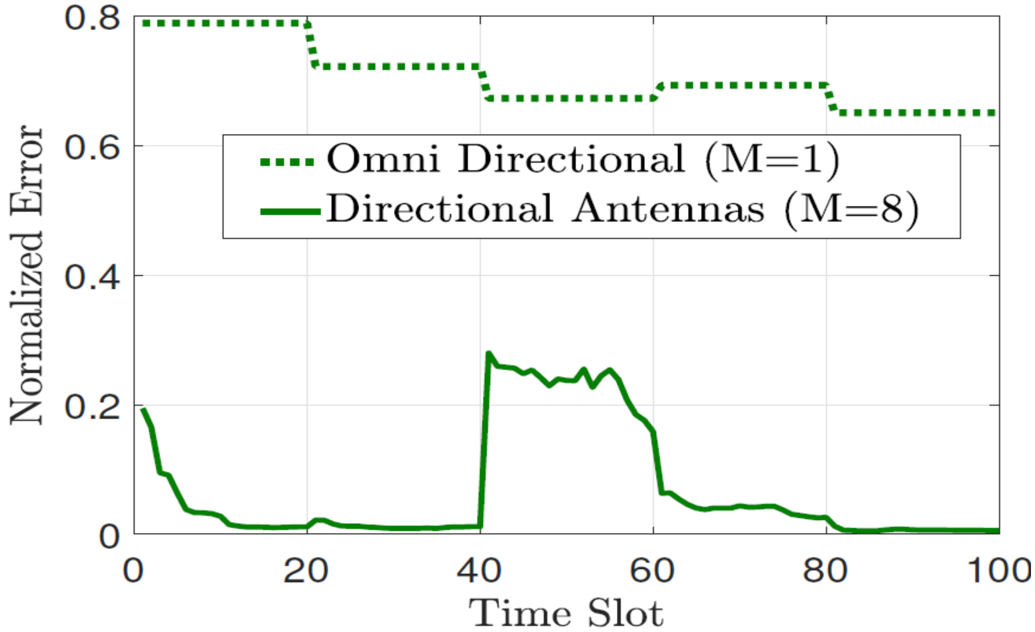
The estimated map using omni-directional SUs

The estimated map using directional antennas at SUs with randomly chosen initial patterns.

The estimated power map using the proposed algorithm after 20 time slots.

- There exist 10 SUs and 8 PUs.
- Omni-directional sensing recovers only a few true sources.
- Employing directional antennas even with random patterns provides a significant improvement in localization accuracy.
- Optimizing beams of directional antennas increases the localization accuracy.

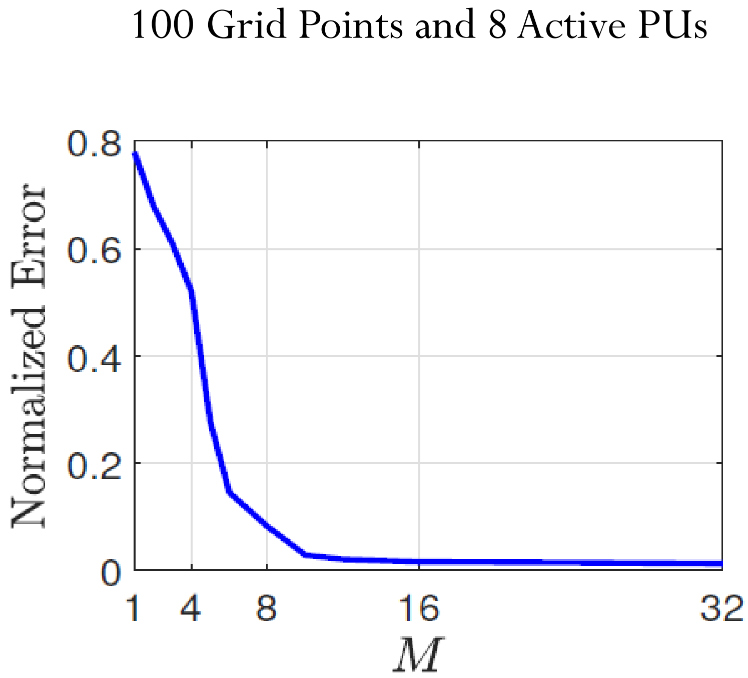
Numerical Comparison of Dynamic Localization



$$\text{normalized error}(t) = \frac{\|\boldsymbol{x}(t) - \hat{\boldsymbol{x}}(t)\|_2}{\|\boldsymbol{x}(t)\|_2}$$

- Each 20 time slots the locations of PUs are changed.
- Sequential sensing using omni-directional antennas provides redundant measurements.
- Directional antennas are able to provide uncorrelated measurements (innovative information) after each sensing to improve localization accuracy.

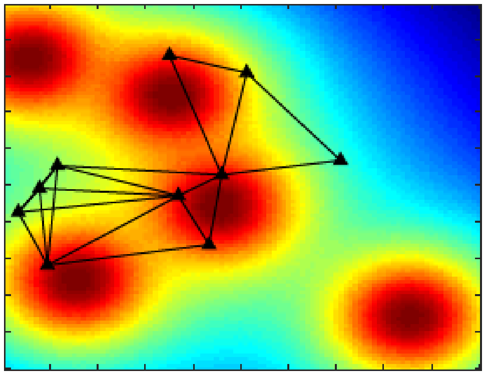
Impact of ULA Elements (M)

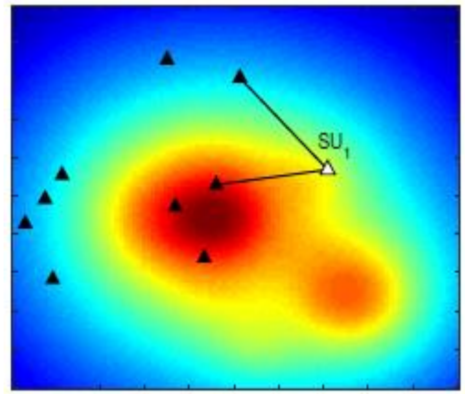
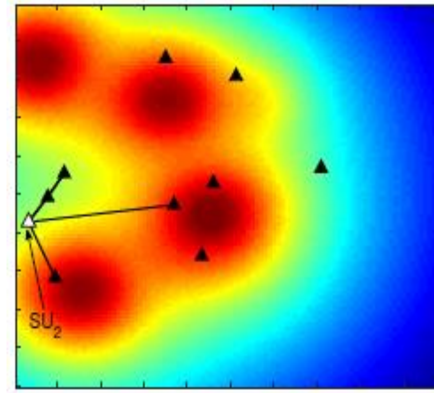
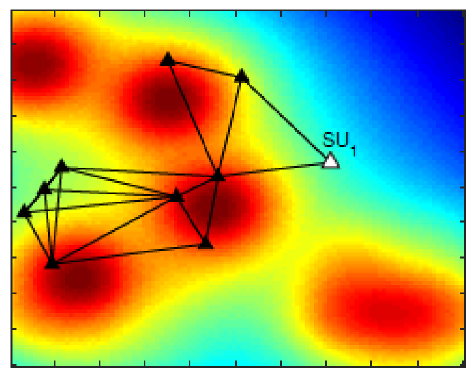
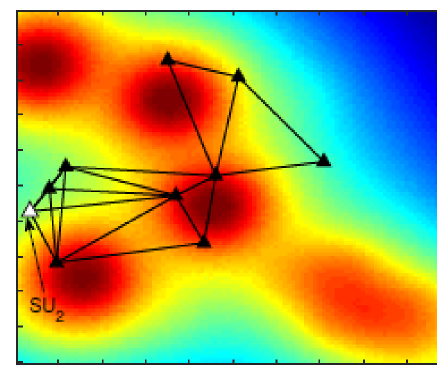


- As M increases, the localization accuracy improves.
- For a 10x10 grid with 8 PUs & 10 SUs, increasing M beyond 8 provides incremental accuracy improvement.

Distributed Localization and Beamforming

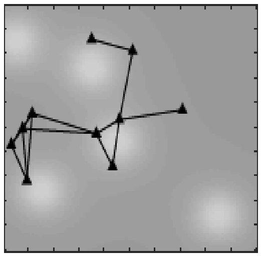
Ground Truth



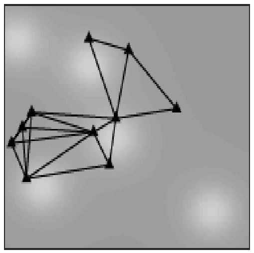
	Sensor 1	Sensor 2
t=1		
t=100		

- At the first time slot a rough power map is reconstructed.
- Each sensor only has access to its neighbors' measurements.
- As time goes on, the estimation of different sensors converge to each other.
- SU2 is connected to more sensors and its initial power map estimate is more accurate.

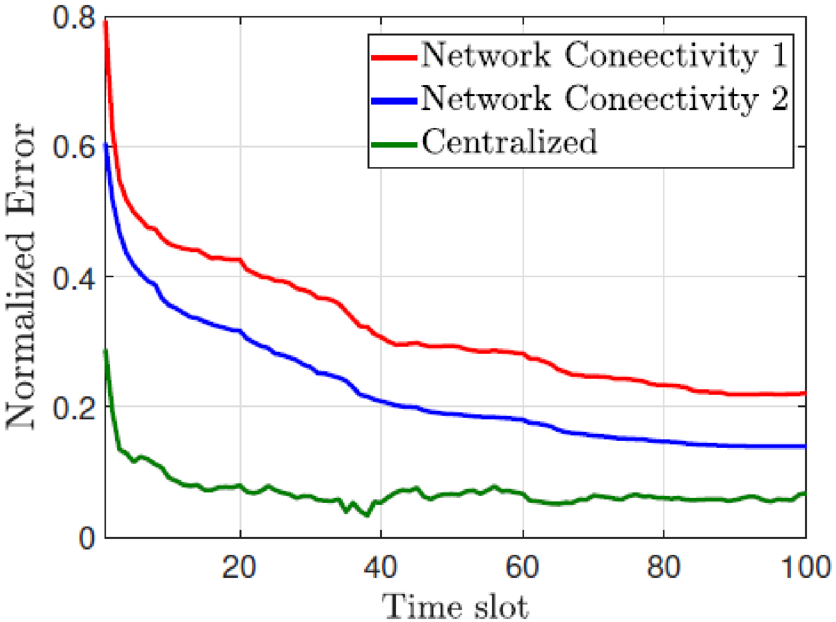
Impact of Graph Connectivity



Connectivity graph 1.



Connectivity graph 2.



(c) Normalized error for two connectivity graphs.

Range of connectivity is defined based on a threshold on distances of sensors.

α is assumed $1e-3$

As the neighborhood graph gets more connected, the algorithm reaches a more accurate consensus.

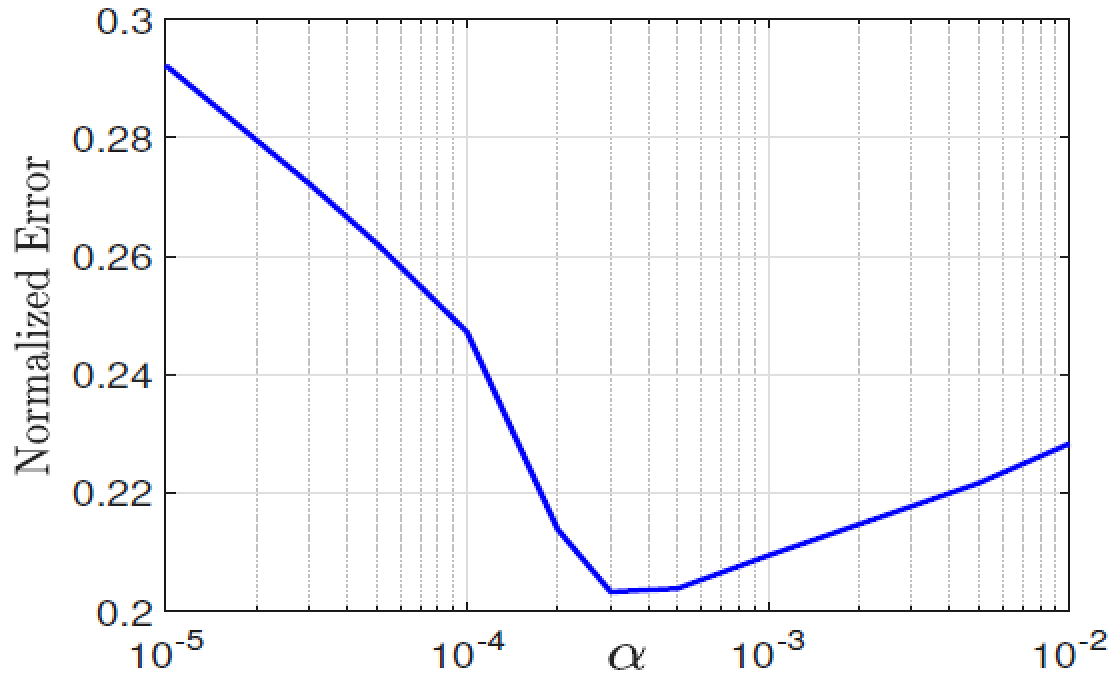
Impact of the Consensus Term

$$\hat{\boldsymbol{x}}^{(n)}(t) = \underset{\boldsymbol{x}}{\operatorname{argmin}} \|\boldsymbol{y}^{(n)}(t) - \boldsymbol{\Gamma}^{(n)}\boldsymbol{x} - \boldsymbol{m}_v\|_2^2 + \lambda\|\boldsymbol{x}\|_1 + \underbrace{\alpha \sum_{i \in \mathcal{N}_n} \|\hat{\boldsymbol{x}}^{(i)}(t-1) - \boldsymbol{x}\|_2^2}_{\text{Consensus Term}}$$

A small α implies nodes have less collaboration

A large α turns the problem to interpolation based on neighborhood

There is an optimal α



The impact of parameter α to reach consensus over time.

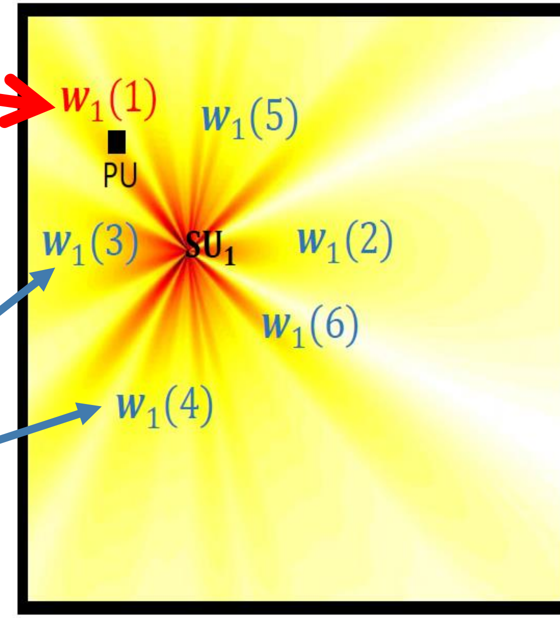
Conclusion

- To enable source localization and tracking for dynamic radio cartography, we formulated a joint localization and beamforming problem, using directional antennas at SUs.
- We split the problem into two sub-problems: localization and beamforming.
- Beamforming is performed in two steps of tracking and discovering.
- We considered both centralized and distributed localization and beamforming.
- Directional antennas enable us to (i) perform dynamic localization and tracking accurately, and (ii) provide a more accurate reconstruction of radio maps.

Thank you for your attention

Discovering Step

Tracking step



...

Update $\boldsymbol{w}(t+1)$ such that the volume of a polygonal whose vertices are rows of matrix Γ is maximized,

- Define $\boldsymbol{u}_n^T(t) = \boldsymbol{w}_n(t)^H \boldsymbol{A}_n$ for sensor n
- Collect all $\boldsymbol{u}_n(t)$ for B-1 time slots in rows of matrix $\boldsymbol{U}_B$

$$\boldsymbol{u}_n(t+1) = \underset{\boldsymbol{u}}{\operatorname{argmin}} \det(\boldsymbol{U}_B \boldsymbol{U}_B^T)^{-1} \quad \text{s.t. } \|\boldsymbol{u}\|_2^2 = 1$$

$$\tilde{\boldsymbol{w}}_n(t+1) = (\boldsymbol{A}_n \boldsymbol{A}_n^T)^{-1} \boldsymbol{A}_n \boldsymbol{u}_n(t+1),$$

Discovering step

$\boldsymbol{U}_B =$ [Known patterns from N sensors in B-1 time slots ; Unknown patterns for N sensors]

$NB \times P$