Smart Antenna Design For Real-Time Multi-Channel Power Spectral Density Estimation And Target Localization

Jun 27th, 2017

Jingyang Lu, Wenhao Xiong, Dan Shen, Genshe Chen
Intelligent Fusion Technology, Inc.

Erik Blasch, Khanh Pham
Air Force Research Laboratory

Outline

- ❖ Introduction
- ❖ System Model
- ❖ Petrels Algorithm
- ❖ Compressive Covariance Sensing
- ❖ Simulation Results
- ❖ Conclusion and Future Work

Cognitive Radio Network

- The definition of the Cognitive Network (CN) is proposed by Theo Kantor
- CN is defined as a network with a cognitive process that can learn from current network conditions making CN adapt to those conditions
- CN is aimed to provide highly reliable communication and increase the efficiency of radio spectrum utilization
- J. Mitola and G. Q. Maguire, "Cognitive radio: making software radios more personal," in IEEE Personal Communications, vol. 6, no. 4, pp. 13-18, Aug 1999
- S. Haykin, "Cognitive radio: brain-empowered wireless communications," in IEEE Journal on Selected Areas in Communications, vol. 23, no. 2, pp. 201-220, Feb. 2005

Cognitive Radio Network

The major advantage of a wireless mesh networks is the intrinsic redundancy and, consequently, reliability because a mesh network is able to reroute traffic through multiple paths to cope with link failures, interference, power failures or network device failures.

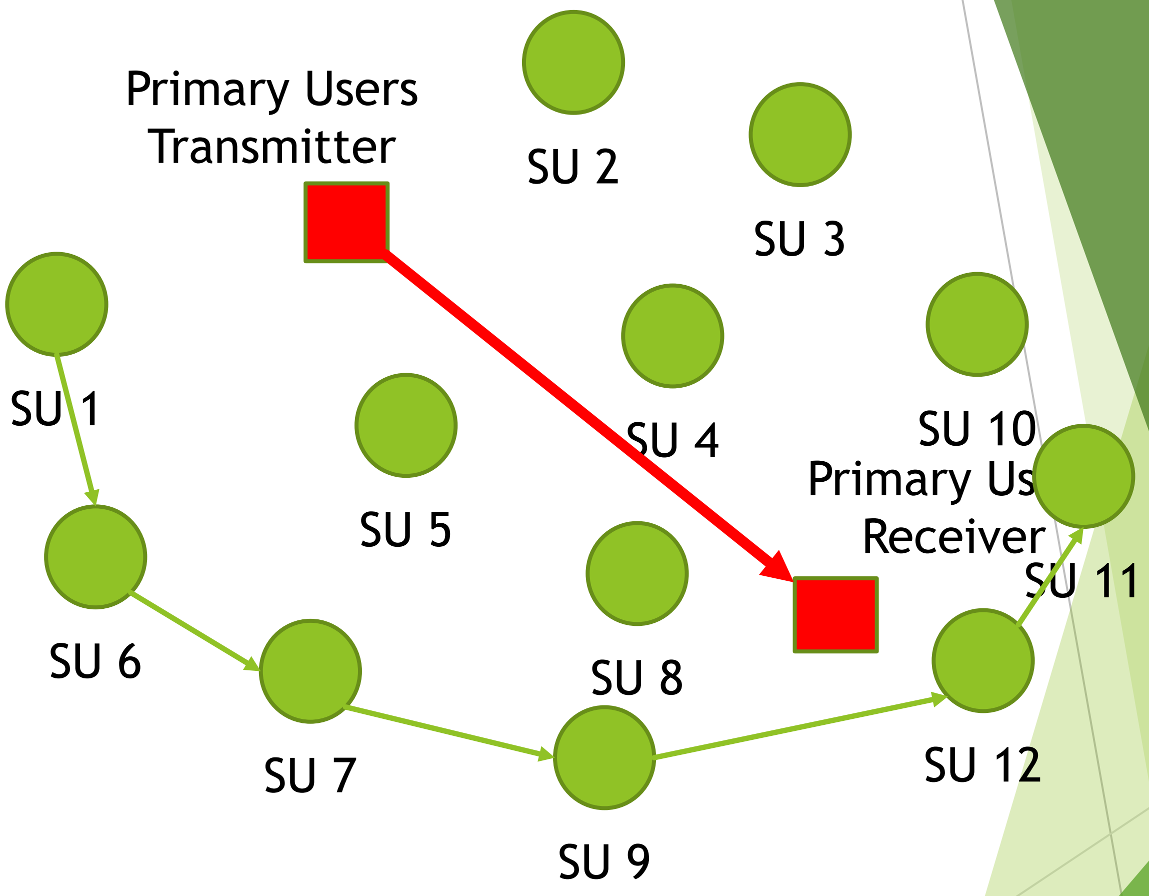


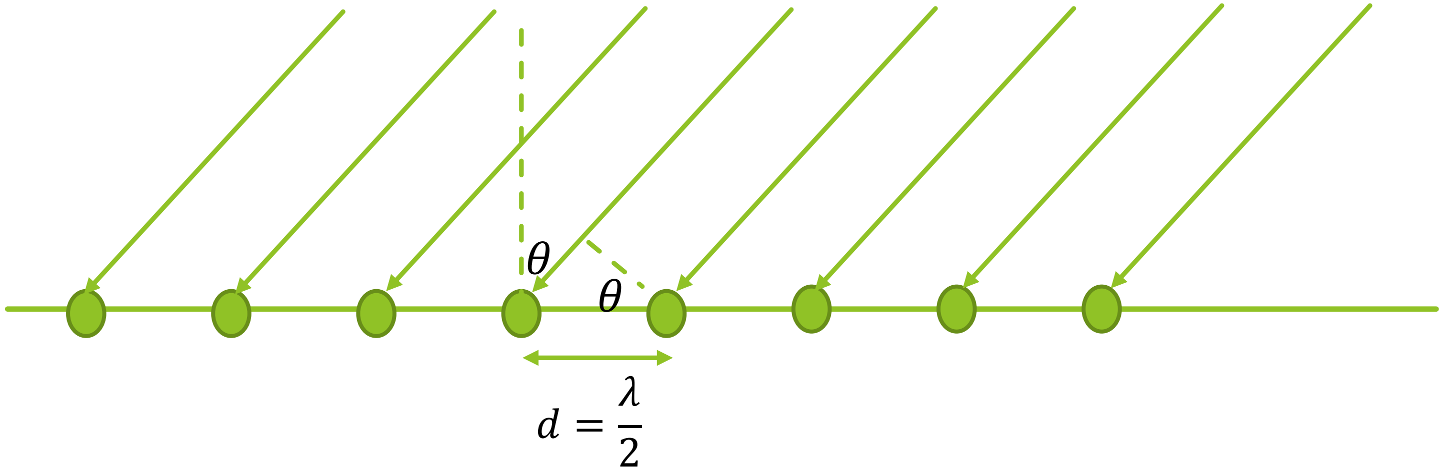
Figure 4: System Model

Objective: Provide highly reliable communication and increase the efficiency of radio spectrum utilization, achieve LPI/LPD

Outline

- ❖ Introduction
- ❖ System Model
- ❖ Petrels Algorithm
- ❖ Compressive Covariance Sensing
- ❖ Simulation Results
- ❖ Conclusion and Future Work

System Model



The position of each antenna is described as $P = \{mr|0 \le m \le N-1\}$
m:the index of each antenna, d :the distance between two adjacent antennas

$$\boldsymbol{x}_n = \boldsymbol{D}_n(\boldsymbol{\theta})\boldsymbol{s}_n + \boldsymbol{w}_n$$

$\{\boldsymbol{x}_n\}$ are the data stream observed at time $1,2,\dots,M$ with each $\boldsymbol{x}_n \in \boldsymbol{C}^N$, the columns of $\boldsymbol{D}_n \in \boldsymbol{C}^{N\times S}$ with $S \ll N$ span the S-dimensional measurement domain at time n.

$\boldsymbol{D}_n(\boldsymbol{\theta}) = [\boldsymbol{d}(\theta_n^1), \boldsymbol{d}(\theta_n^2), \dots, \boldsymbol{d}(\theta_n^S)]$, $\boldsymbol{d}(\theta_n^k)(k = 1,2,\dots,S)$

$\boldsymbol{d}(\theta_n^k) = \left[1, e^{-\frac{j2\pi d \sin(\theta_k)}{\lambda}}, \dots, e^{-\frac{j2\pi d(S-1)\sin(\theta_k)}{\lambda}}\right]^T$, $N\times1$ steering vector for the k_{th} source, $k = 1,2,\dots,S$.

Outline

- ❖ Introduction
- ❖ System Model
- ❖ Petrels Algorithm
- ❖ Compressive Covariance Sensing
- ❖ Simulation Results
- ❖ Conclusion and Future Work

Petrels Algorithms
(Parallel Subspace Estimation and Tracking by Recursive Least Squares)

$$f_n(\boldsymbol{D}) = \min_{\boldsymbol{\theta}} ||\boldsymbol{P}_n(\boldsymbol{x_n} - \boldsymbol{D\theta})||_2^2 + \delta\|\boldsymbol{\theta}\|_1$$

$$\widehat{\boldsymbol{D}} = arg\min_{\boldsymbol{D}} \sum_{t=1}^{N} \lambda^{N-t} f_t(\boldsymbol{D})$$

δ :the penalty coefficient in terms of signal sparsity.

$\boldsymbol{P}_n$: the observation selection matrix.

The $\boldsymbol{\theta}$ can be solved from by using the least squares method,

$$\widehat{\boldsymbol{\theta}} = \arg\min_{\boldsymbol{\theta}} ||\boldsymbol{P}_n(\boldsymbol{x_n} - \boldsymbol{D\theta})||_2^2 + \delta\|\boldsymbol{\theta}\|_1$$
$$= (\boldsymbol{D}^T\boldsymbol{P}_n\boldsymbol{D})^*\boldsymbol{D}^T\boldsymbol{P}_n\boldsymbol{x}_n$$

where $*$ denotes the pseudo inverse matrix.

$$\widehat{\boldsymbol{x}}_{\boldsymbol{n}} = \boldsymbol{D}\widehat{\boldsymbol{\theta}}$$

$$\widehat{\boldsymbol{D}} = arg\min_{\boldsymbol{D}} \sum_{t=1}^{N} \lambda^{N-t}(||\boldsymbol{P}_n(\boldsymbol{x}_n - \boldsymbol{D}\widehat{\boldsymbol{\theta}})||_2^2 + +\delta\|\boldsymbol{\theta}\|_1)$$

Input	A stream of vector x_n, observed patterns $\boldsymbol{P_n}$ and δ.
Initializatio n	An $M \times r$ random matrix $\boldsymbol{D}_0 = [\boldsymbol{d}_1^0, \boldsymbol{d}_2^0, \dots, \boldsymbol{d}_M^0]^T$ and $(\boldsymbol{R}_m^0)^* = \alpha I_r, \alpha > 0$ for all m=1,…,M
1:	For n = 1,2,..do
2:	$\hat{a}_n = (D_{n-1}^T P_n D_{n-1})^* D_{n-1}^T y_n$.
3:	If stream reconstruction is required $\hat{x}_n = D_{n-1}\,\hat{a}_n$.
4:	For m=1,…,M do
5:	$\beta_m^n = 1 + \delta^{-1} a_n^T (R_m^{n-1})^*\,\hat{a}_n$,
6:	$v_m^n = \delta^{-1} a_n^T (R_m^{n-1})^*\,\hat{a}_n$
7:	$(R_m^n)^* = \delta^{-1} a_n^T (R_m^{n-1})^* - p_{mn} (\beta_m^n)^{-1} v_m^n (v_m^n)^T$.
8:	$d_m^n = d_m^{n-1} + p_{mn}(x_{mn} - \hat{a}_n^T d_m^{n-1} (R_m^n)^*\,\hat{a}_n)$.
9:	End for
10:	End for

Outline

Compressive Covariance Sensing

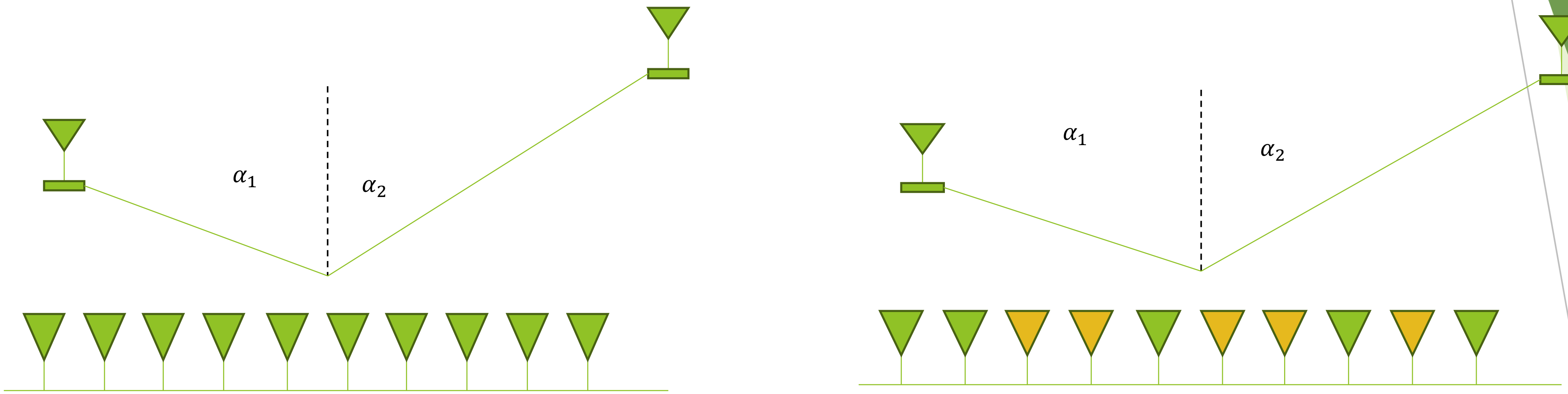


Figure: An uncompressed ULA with ten antennas receiving the signals from five sources in the far field (left). A compressed array with five antennas marked in yellow removed (right).

$$\hat{\Sigma}_{\boldsymbol{x}} = \frac{1}{N}\sum_{n=1}^{N} \boldsymbol{x}_n \boldsymbol{x}_n^H$$

$$\boldsymbol{\rho}[m-l] = \boldsymbol{E}(\boldsymbol{x}_n[m]\boldsymbol{x}_n^*[l])$$

$$\varphi := \{k_0, k_1, \dots, k_{K-1}\}$$

$$\boldsymbol{E}(\boldsymbol{y}_n[i]\boldsymbol{y}_n^*[j]) = \boldsymbol{E}\left(\boldsymbol{x}_n[k_i]\boldsymbol{x}_n^*[k_j]\right) = \boldsymbol{\rho}[k_i - k_j]$$

Compressive Covariance Sensing

Properties of CCS

1. Reduce the ***number of antennas***.
2. Allow the ***cost saving*** associated with the antennas: such as filter, mixers, ADCs.
3. "***Minimal Sparse Rulers*** **(MSR)**" is proposed to reduce the number of antennas required for $\boldsymbol{\Sigma}_x$ estimation.

Figure. A sparse ruler can be thought of as a ruler with a part of its marks erased, but the remaining marks allow all integer distances between zero and its length to be measure

Outline

- ❖ Introduction
- ❖ System Model
- ❖ Petrels Algorithm
- ❖ Compressive Covariance Sensing
- ❖ Simulation Results
- ❖ Conclusion and Future Work

Simulation Result

We simulated a target tracking application based on DOA where two platforms with $d/\lambda = 0.5$ and 10 antennas each are taking measurements of target with SNR= 15dB. The distance between two ULAs is set to be 10km (~6miles). The solution includes both least square algorithms using partial of observation (50%) and compressive covariance sensing (CCS). Figure on the right shows both algorithms can track the DOA with good performance

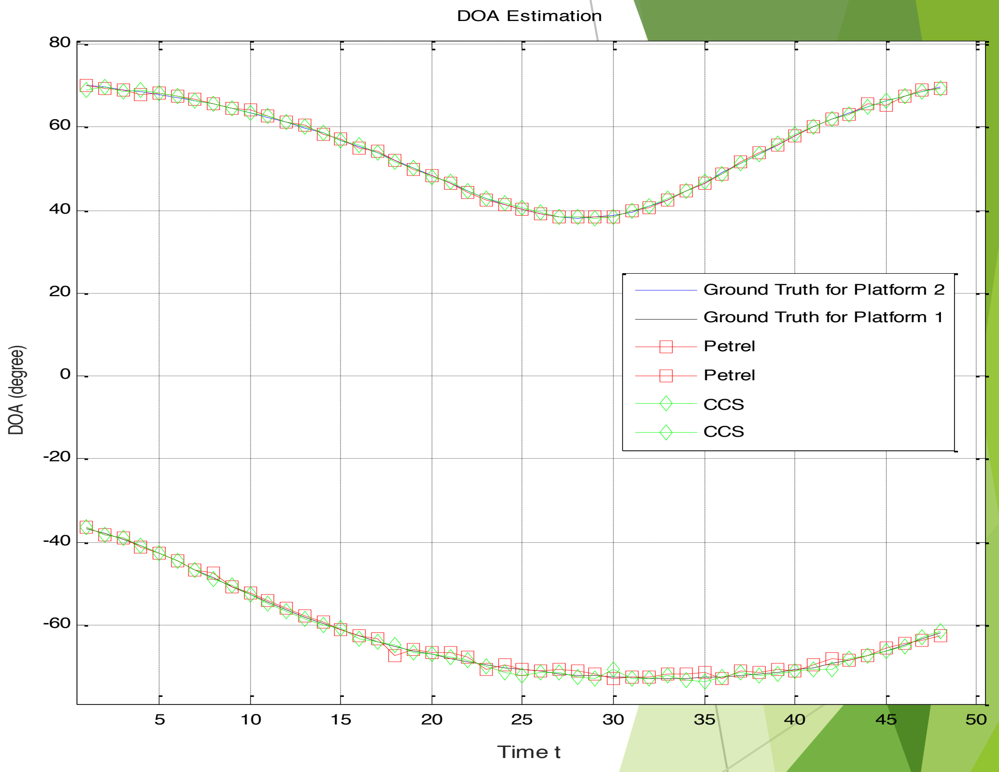
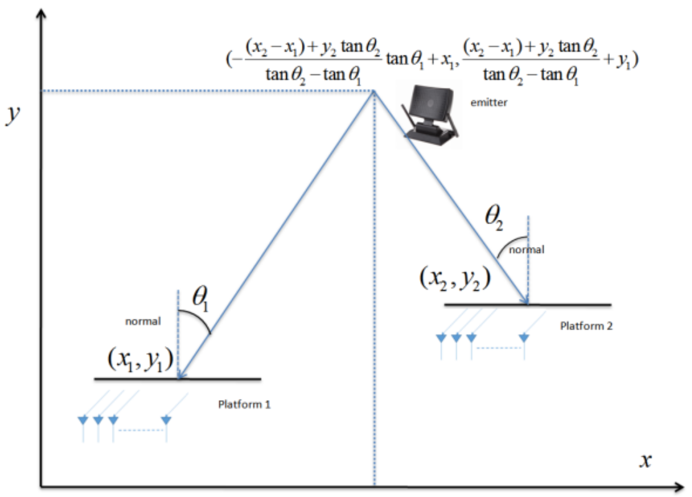
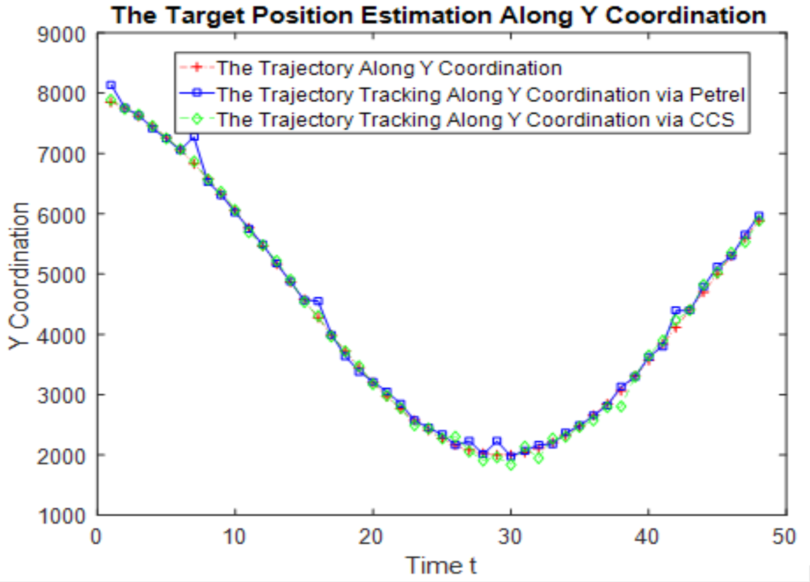


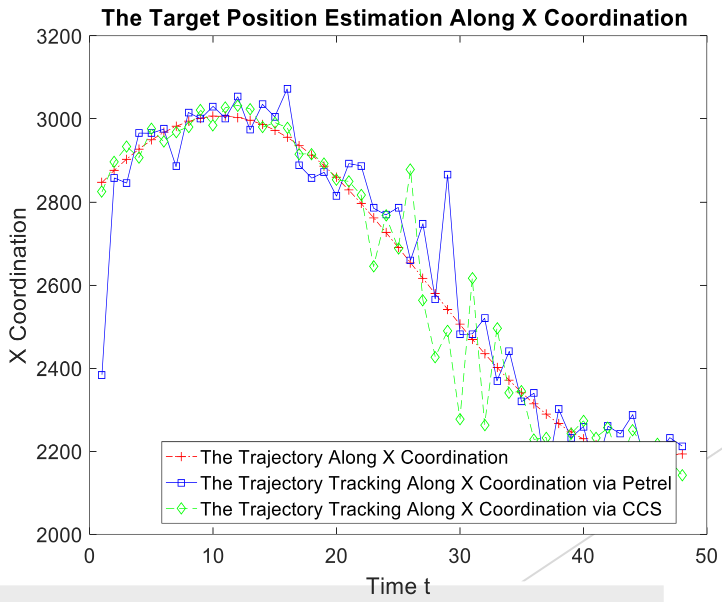
Figure: DOA Estimation Via least square and CCS based algorithms

Simulation Result

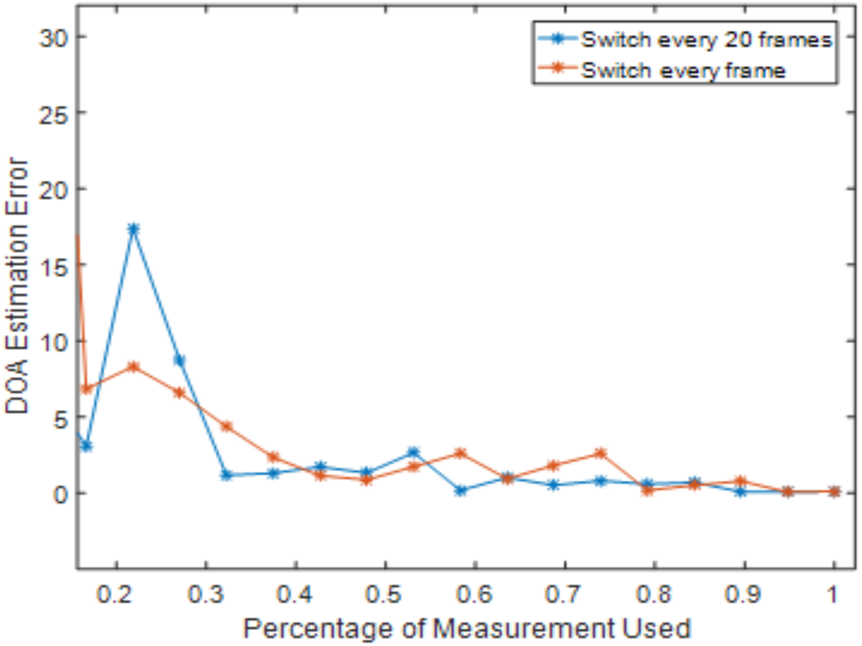


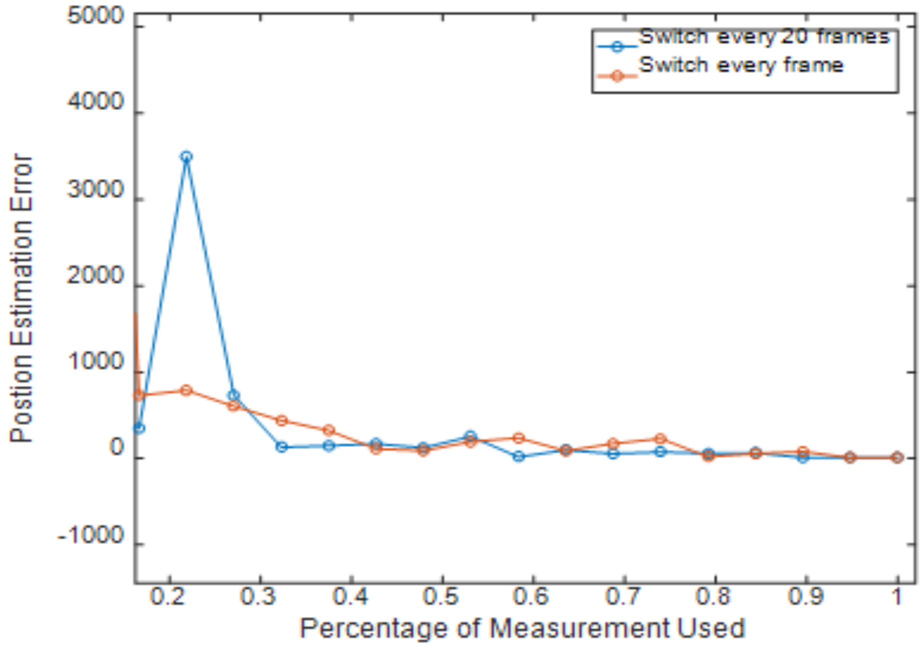
The Setup is save as the last one.





Simulation Result





- PETRELS algorithm, the system randomly selects partial observations to conduct the subspace estimation, which will increase the switching cost in the real application.
- In order to overcome switching cost, that system chooses the partial observation based on the predefined selection rules instead of randomly selecting.
- Figure above shows the system can still maintain a good performance when system switches every 20 data frames.

Outline

- ❖ Introduction
- ❖ System Model
- ❖ Petrels Algorithm
- ❖ Compressive Covariance Sensing
- ❖ Simulation Results
- ❖ Conclusion and Future Work

Conclusion

- An online subspace learning algorithm for direction of arrival (DOA) is proposed.
- Only partial observation of antennas is needed to estimate the subspace of the steering matrix.
- The rank of the subspace is not necessarily known at the beginning.
- CCS approach is also deployed in the DOA estimation.
- Future work will address the performance tradeoffs of spectral efficiency for the tracking and localization under the false information attack.

thank you!