

Sub-Nyquist Collocated MIMO Radar in Time and Space

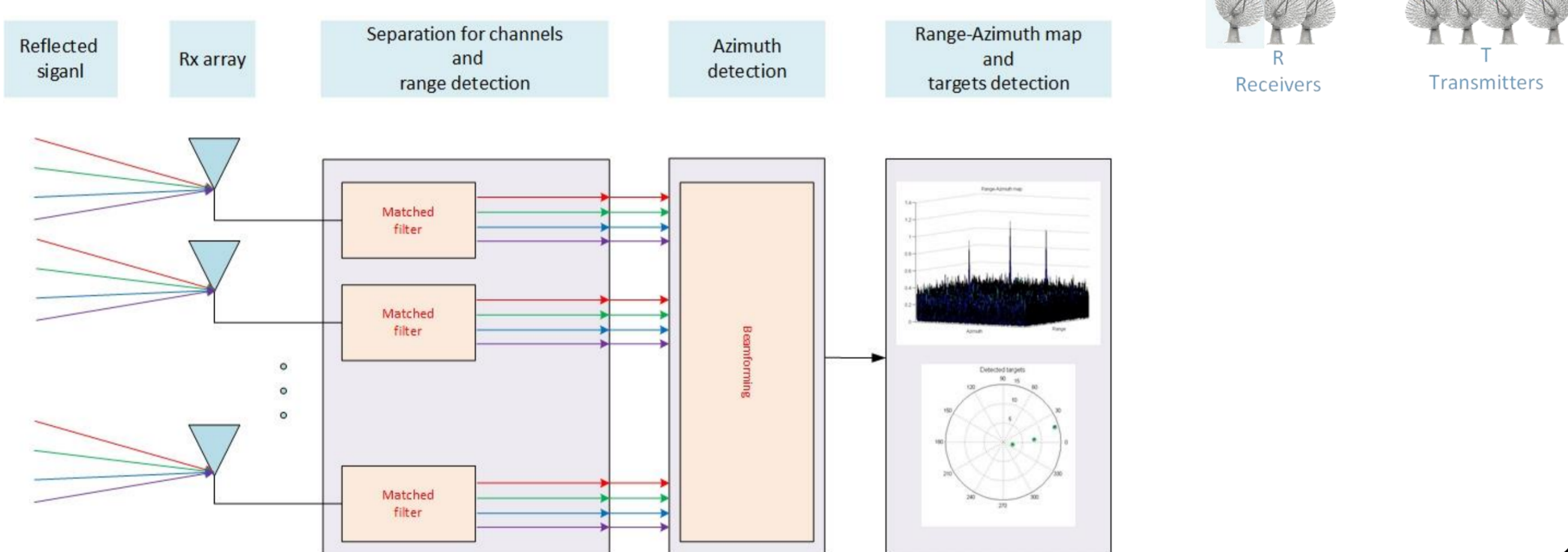
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Contributions

- Application of the sub-Nyquist framework to collocated MIMO radar in time and space while preserving the range-azimuth resolution
 - Low rate sampling and digital processing
 - Reduced number of antennas
- Recovery algorithm scaled with problem size by adapting the OMP algorithm to matrix form

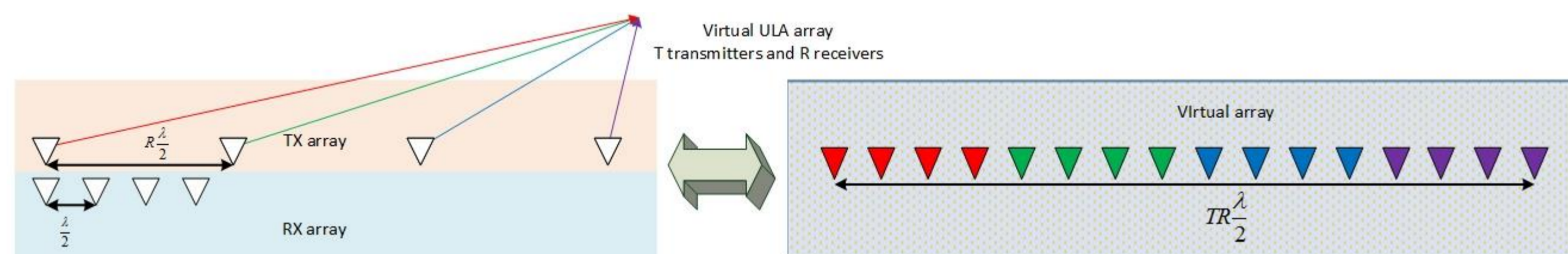
Collocated MIMO Radar

- MIMO combines multiple transmit and receiver antenna elements
- Each transmitting element radiates orthogonal waveforms
- Core idea:** achieving high spatial resolution by separation and coherent processing of the receivers' channels
- All space is uniformly lit - beamforming is done at the receiver
- Conventional processing for range-azimuth recovery:**



Resolution in Time and Space

- Classic approach adopts a virtual ULA structure



Resolution in the space domain

- Azimuth resolution: determined by virtual ULA's aperture
- Problem:** High resolution in the azimuth requires large number of elements

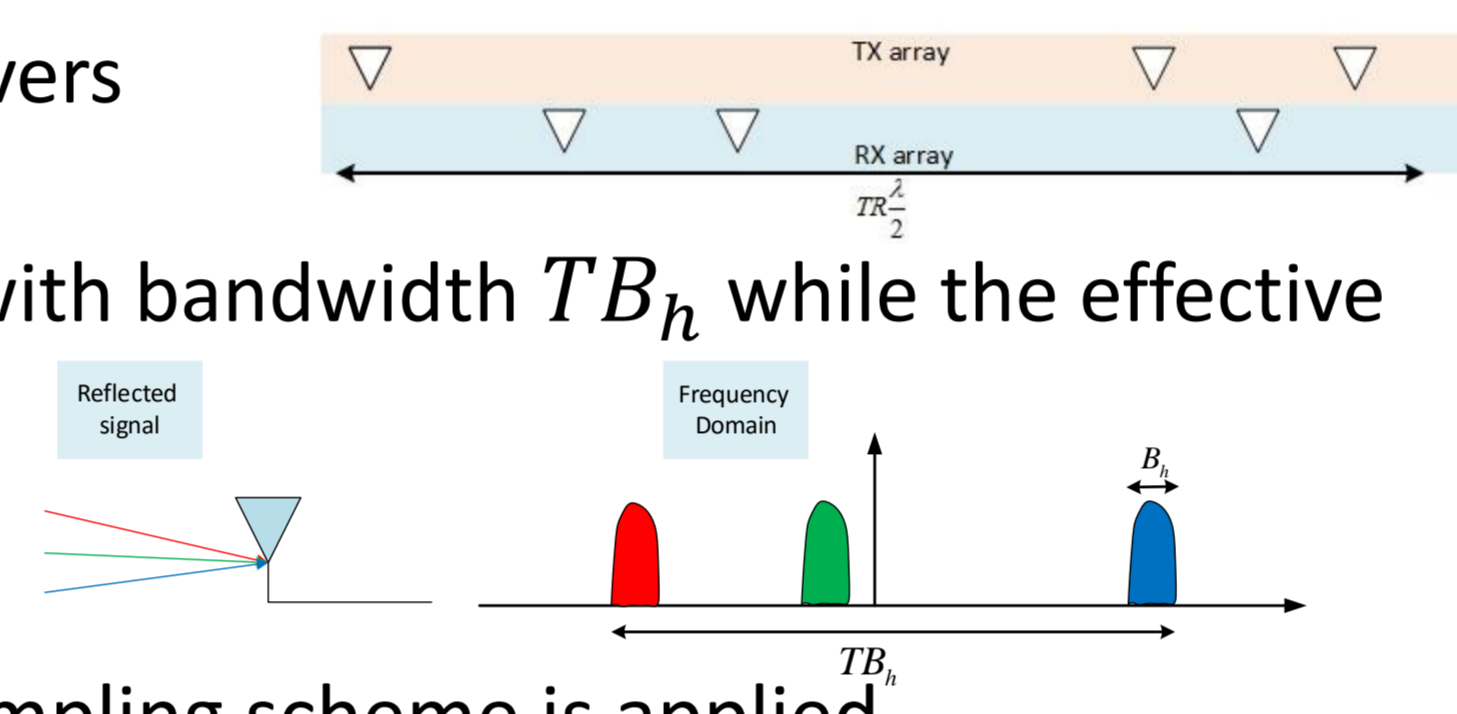
Resolution in the time domain

- Range resolution: determined by transmitted signal's bandwidth
- Problem:** High resolution in the range requires high sampling rate

Goal: break link between number of elements and spatial resolution and sampling rate and time resolution

Proposed Array Structure and Signal Model

- Frequency division approach
- Random array
- Sub-Nyquist in space**
 - Preserving azimuth resolution of T transmitters and R receivers while using $M < T$ transmitters and $Q < R$ receivers
 - Elements are randomly located with uniform distribution across the virtual ULA's aperture of T transmitters and R receivers
- Sub-Nyquist in time**
 - Preserving range resolution of signal with bandwidth $T B_h$ while the effective sampling rate is lower
 - The transmissions are performed over total bandwidth $T B_h$.
 - For each transmission, sub-Nyquist sampling scheme is applied



Xampling in Time and Space

- Received signal at the q th antenna after demodulation:

$$x_q(t) = \sum_{m=0}^{M-1} \sum_{l=1}^L h_m(t - \tau_l) e^{j2\pi f_{mq} \vartheta_l}$$

- Goal: estimate the targets range and azimuth τ_l, ϑ_l .

- Fourier coefficients of the channel between m th transmitter and q th receiver:

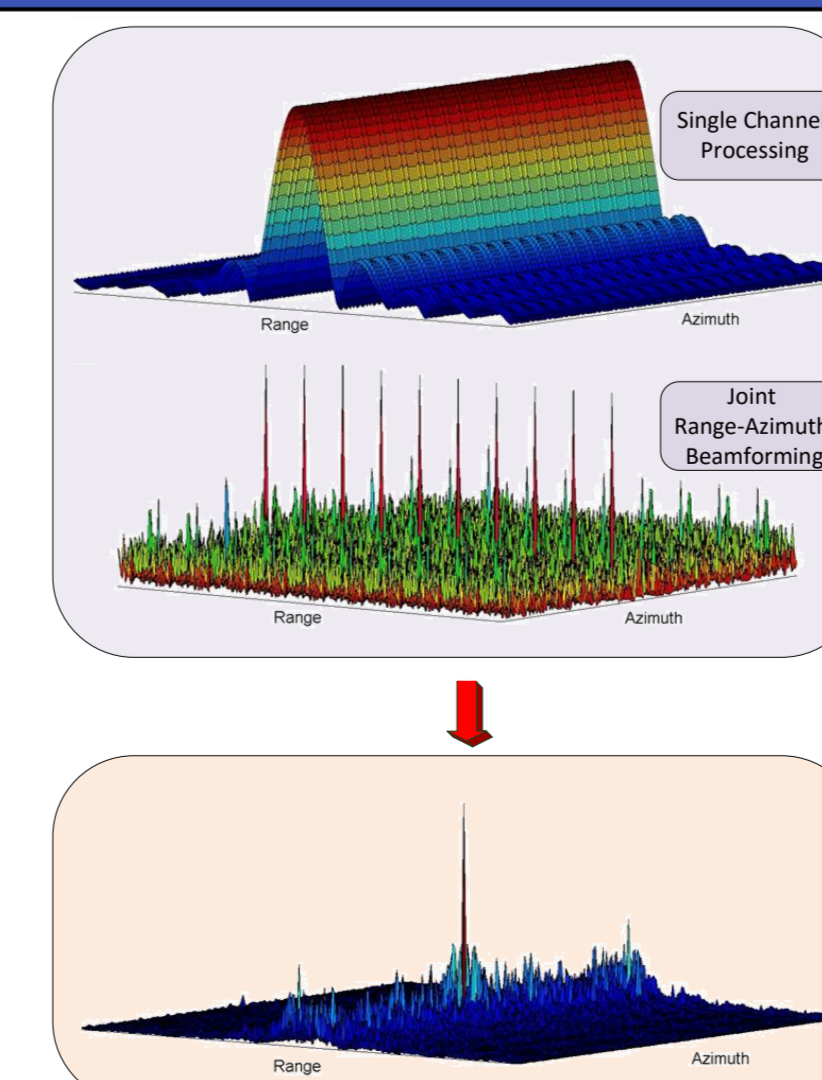
$$y_{m,q}[k] = \sum_{l=1}^L \alpha_l e^{j2\pi \beta_{mq} \vartheta_l} e^{-j\frac{2\pi}{\tau} k \tau_l} e^{-j2\pi f_m \tau_l}$$

- β_{mq} is governed by the elements location while f_m by the carriers frequencies
- Xampling: obtain set of Fourier coefficients from low rate samples

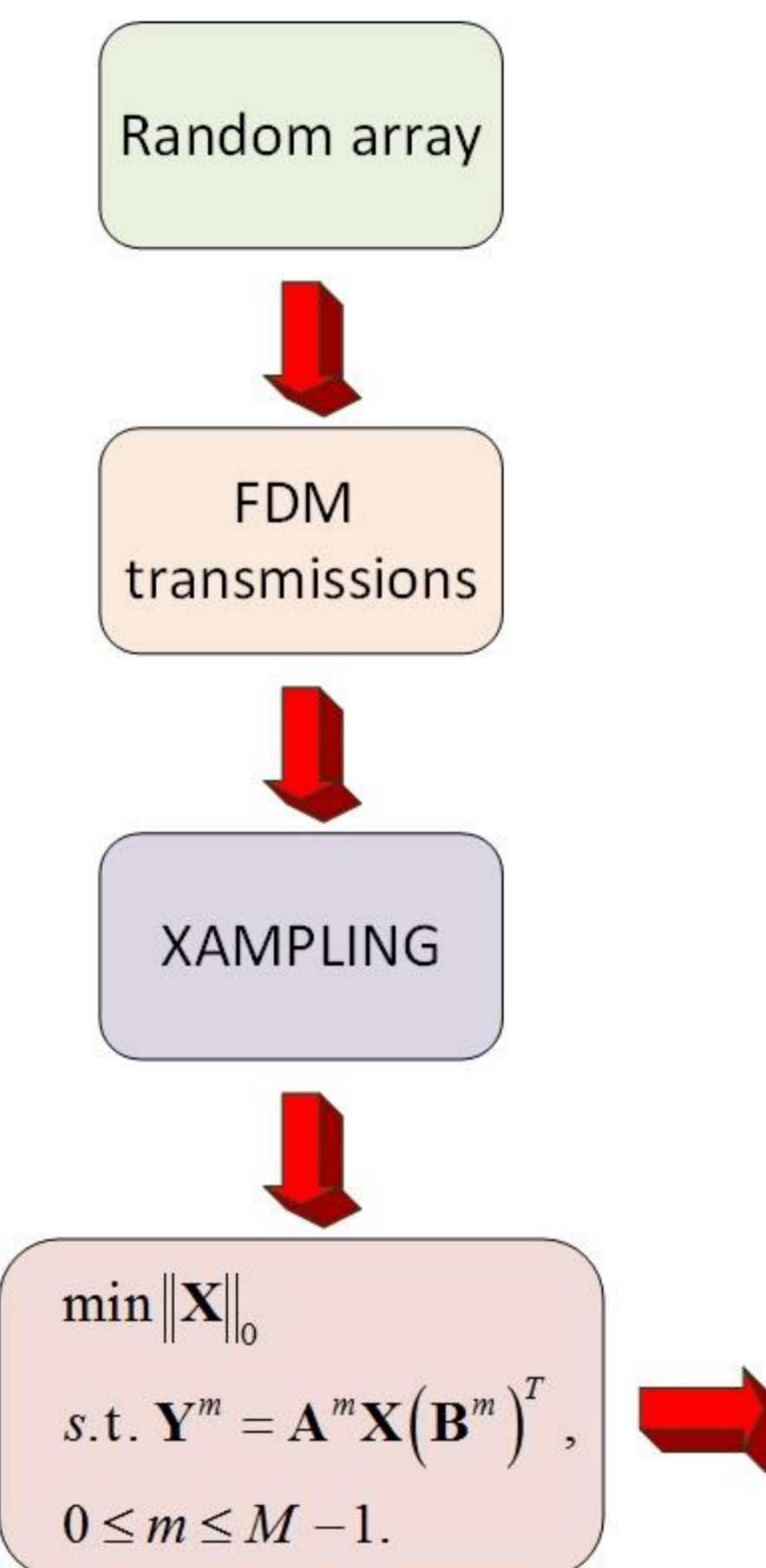
- Fourier coefficients for the m th transmission in matrix form $\mathbf{Y}^m = \mathbf{A}^m \mathbf{X} (\mathbf{B}^m)^T$
 - $\mathbf{A}^m, \mathbf{B}^m$: range-azimuth dictionaries
 - \mathbf{X} : sparse matrix whose elements are located at the targets' range-azimuth

Joint Range-Azimuth Detection

- Frequency diversity: channels are azimuth-dependent and range dependent
- Range-azimuth coupling resolved by using random array and joint range-azimuth detection
- By processing all channels together: achieve range resolution according to total bandwidth



Recovery algorithm via OMP Matrix Approach



Algorithm 1 OMP for simultaneous sparse matrix recovery
Input: observation matrices \mathbf{Y}^m , measurement matrices $\mathbf{A}^m, \mathbf{B}^m$ for all $0 \leq m \leq M-1$
Output: index set Λ containing the locations of the non zero indices of \mathbf{X} , estimate for sparse matrix $\hat{\mathbf{X}}$
 1: Initialization: residual $\mathbf{R}_0^m = \mathbf{Y}^m$, index set $\Lambda_0 = \emptyset, t = 0$
 2: Project residual onto measurement matrices:

$$\Psi = \mathbf{A}^m \mathbf{R} \mathbf{B}$$
 where $\mathbf{A} = [\mathbf{A}^{0T} \mathbf{A}^{1T} \dots \mathbf{A}^{(M-1)T}]^T$ and $\mathbf{B} = [\mathbf{B}^{0T} \mathbf{B}^{1T} \dots \mathbf{B}^{(M-1)T}]^T$ and $\mathbf{R} = \text{diag}(\{\mathbf{R}_t^0 \dots \mathbf{R}_t^{M-1}\})$ is block diagonal
 3: Find the two indices $\lambda_t = \{\lambda_t(1) \lambda_t(2)\}$ such that

$$[\lambda_t(1) \lambda_t(2)] = \arg \max_{i,j} |\Psi_{i,j}|$$

 4: Augment index set $\Lambda_t = \Lambda_t \cup \{\lambda_t\}$
 5: Find the new signal estimate

$$\alpha = [\alpha_1 \dots \alpha_t]^T = (\mathbf{D}_t^T \mathbf{D}_t)^{-1} \mathbf{D}_t^T \text{vec}(\mathbf{Y})$$

 6: Compute new residual

$$\mathbf{R}_t^m = \mathbf{Y}^m - \sum_{i=1}^t \alpha_i \mathbf{a}_{\Lambda_t(i,1)} (\mathbf{b}_{\Lambda_t(i,2)})^T$$

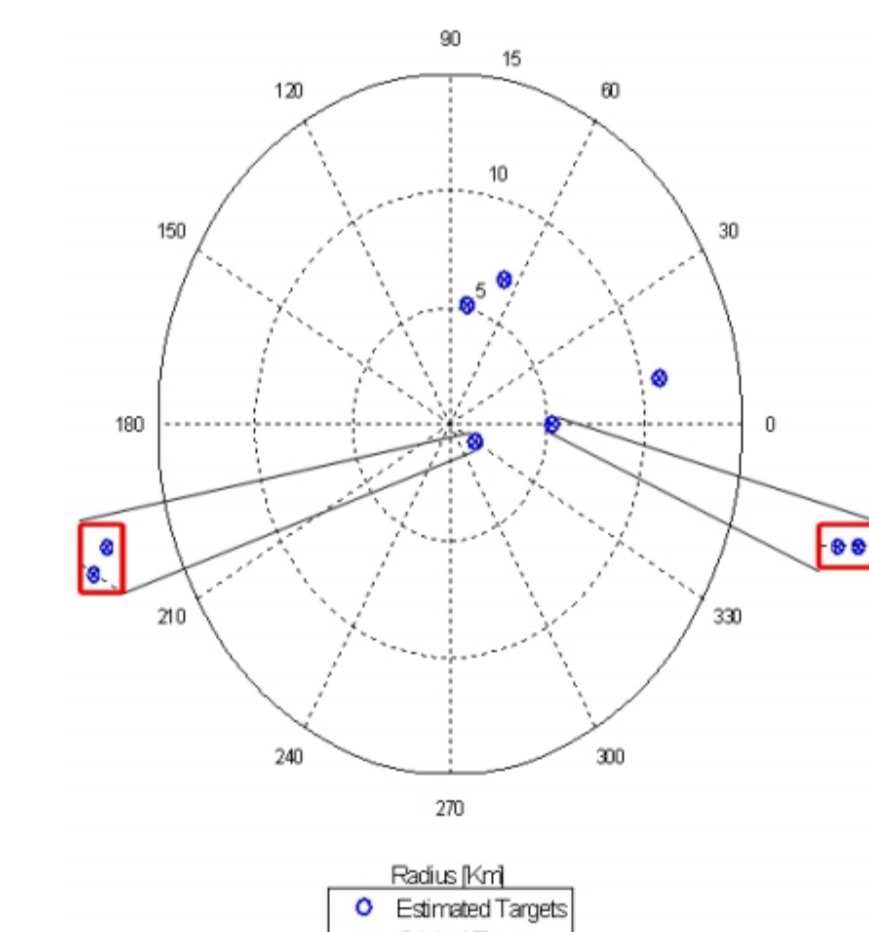
 7: Increment t and return to step 2 if $t \leq L$, otherwise stop
 8: Estimated support set $\hat{\Lambda} = \Lambda_L$
 9: Estimated matrix $\hat{\mathbf{X}}$: $(\Lambda_L(l,1), \Lambda_L(l,2))$ -th component of $\hat{\mathbf{X}}$ is given by α_l for $l = 1, \dots, L$ while rest of the elements are zero

Simulation results

Graph 1: Resolution in range and Azimuth

7 targets including couple of targets with close range and a couple with close azimuth

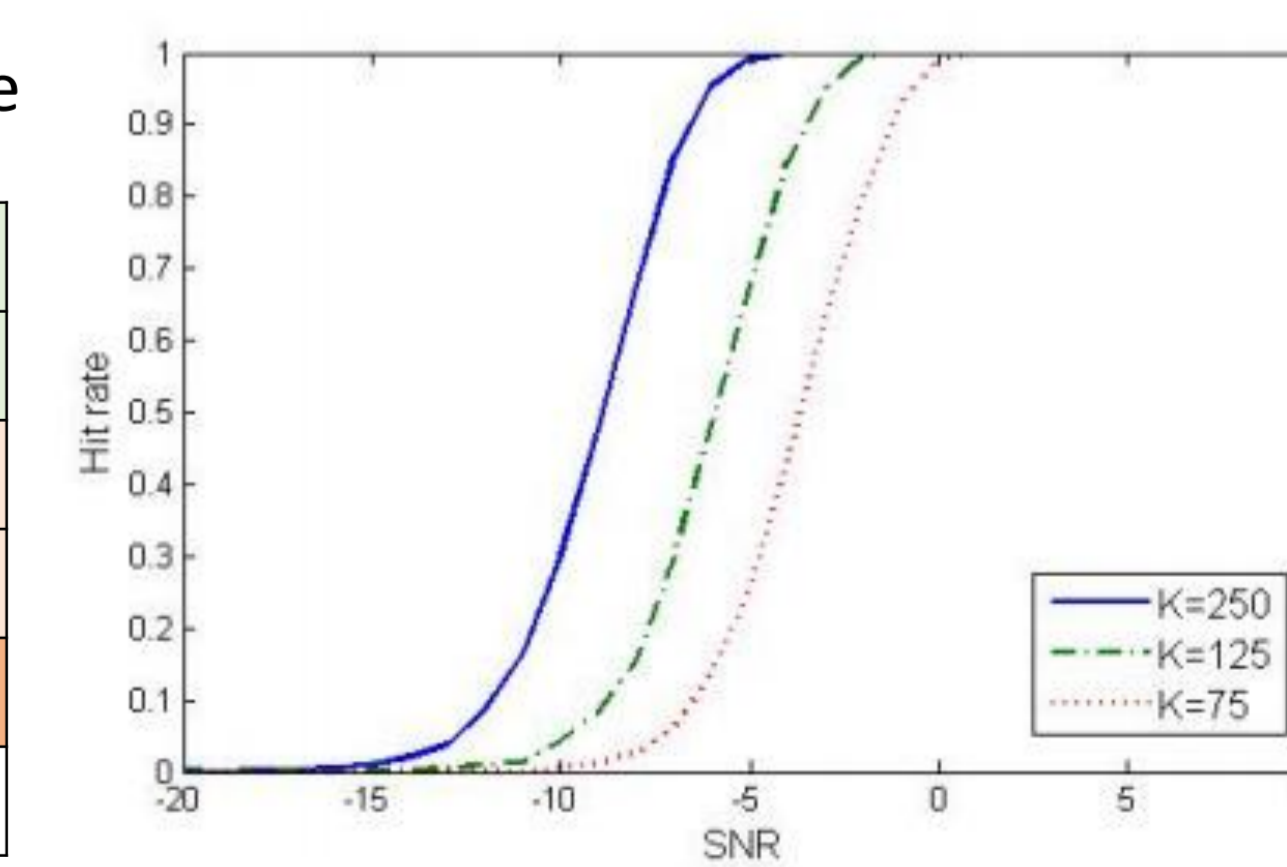
Spatial Reduction	T=20	M=10	50%
	R=20	Q=10	50%
Time Reduction	N=500	K=250	50%
Total samples reduction: 12.5%			



Graph 2: Hit rate vs SNR

10 targets range-azimuth recovery performance

Spatial Reduction	T=20	M=10	50%
	R=20	Q=10	50%
Time Reduction	N=500	K=250	50%
		K=125	25%
		K=75	15%
Total samples reduction: 3.75%			



References

- [1] M. Mishali and Y. C. Eldar, "From theory to practice: Sub-Nyquist sampling of sparse wideband analog signals", IEEE Journal of Selected Topics in Signal Processing, 2010.
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- [3] M. Rossi A.M. Haimovich and Y. C. Eldar, "Spatial compressive sensing for MIMO radar", Signal Processing IEEE Transactions on, 2014.