



# A PARAFAC-based technique for detection and localization of multiple targets in MIMO radar systems

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# Content of the talk

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**Context:** MIMO radar system.

**Problem:** Detection and localization of multiple targets present in the same range-bin.

**State of the art:** Radar-imaging localization methods (e.g. Capon, MUSIC)

**Limits:** Radar-imaging fails for closely spaced targets + sensitivity to Radar Cross Section (RCS) fluctuations

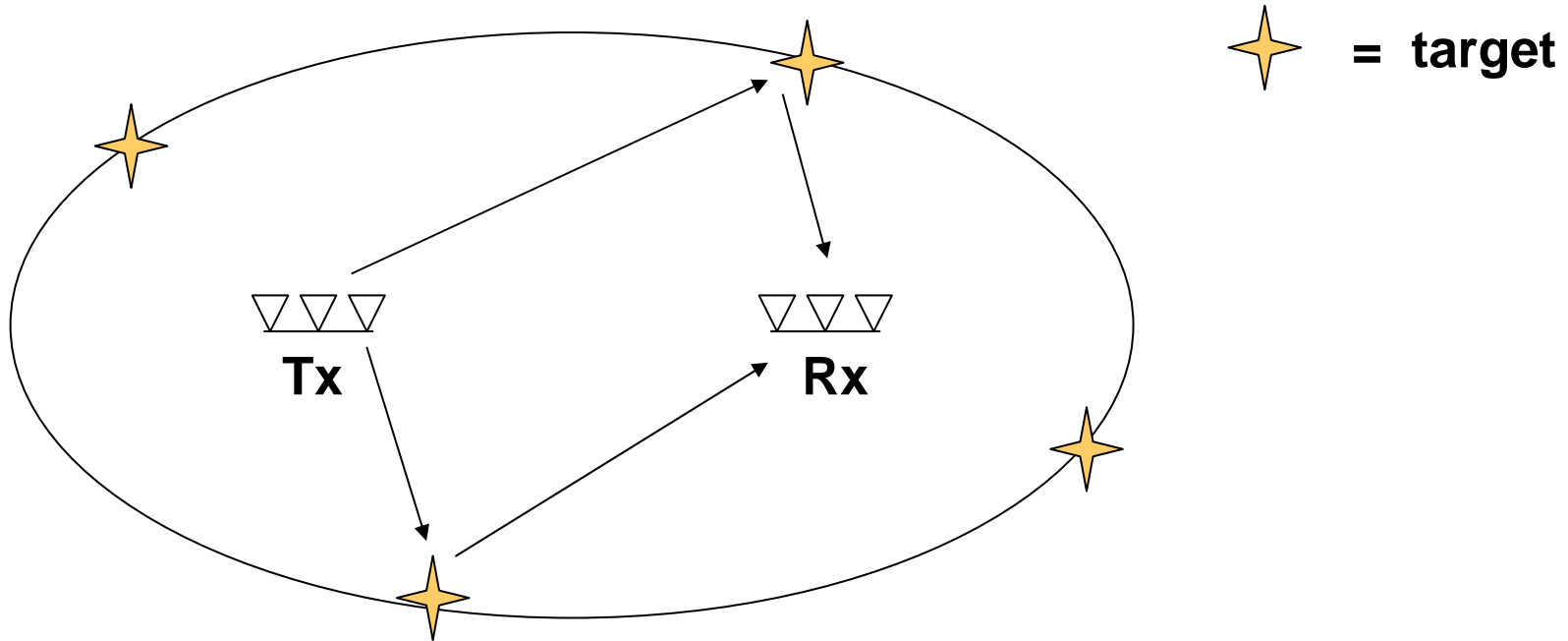
**Contribution:** Novel method, deterministic, exploits **multilinear** algebraic structure of received data  
→ **PARAFAC Decomposition of an observed tensor**

# Roadmap

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- I. **Introduction** (problem statement + data model)
- II. **State of the art** (Localization via Capon beamforming and MUSIC)
- III. **Localization via PARAFAC**
- IV. **Conclusion and perspectives**

# I. Introduction: problem statement



- K targets in the same range-bin
- Transmitter Tx and receiver Rx equipped with closely spaced antennas
- Target = a point source in the far field

**Problem : estimate the number of targets and their DODs and DOAS**

# I. Introduction: parameters

$M_t$  transmit colocated antennas

$M_r$  receive colocated antennas

$K$  targets in the range-bin of interest

$\mathbf{A}(\theta)=[\mathbf{a}(\theta_1), \dots, \mathbf{a}(\theta_K)]$  the  $M_t \times K$  transmit steering matrix

$\mathbf{B}(\alpha)=[\mathbf{b}(\alpha_1), \dots, \mathbf{b}(\alpha_K)]$  the  $M_r \times K$  receive steering matrix

$\mathbf{S}=[s_1(t); s_2(t); \dots; s_{M_t}(t)]$  is  $M_t \times L$ , holds  $M_t$  **mutually orthogonal** transmitted pulse waveforms, with

$L$  samples per pulse period

$Q$  consecutive pulses are transmitted

$\beta_{kq}$  RCS reflection coeff. of target  $k$  during pulse  $q$

# I. Introduction: data model

## Assumption : Swerling case II target model

« Receive and Transmit steering matrices  $\mathbf{B}(\alpha)$  and  $\mathbf{A}(\theta)$  constant over the duration of  $Q$  pulses while the target reflection coefficients  $\beta_{kq}$  are varying independently from pulse to pulse».

$$\mathbf{X}_q = \mathbf{B}(\alpha) \underbrace{\text{diag}([\beta_{1q}, \dots, \beta_{Kq}])}_{= \Sigma_q} \mathbf{A}^T(\theta) \mathbf{S} + \mathbf{W}_q, \quad q = 1, \dots, Q$$

↑  
 $M_r \times L$  received data

→ Times of arrival known (targets in the same range-bin).

→ Right multiply by  $(1/L)\mathbf{S}^H$  and simplify  $(1/L)\mathbf{S}\mathbf{S}^H = \mathbf{I}$

$$\mathbf{Y}_q = \mathbf{B}(\alpha) \Sigma_q \mathbf{A}^T(\theta) + \mathbf{Z}_q, \quad q = 1, \dots, Q$$

↑  
 $M_r \times M_t$  received data  
after matched filtering

## II. State of the art: single-pulse radar-imaging

Radar-imaging techniques working on per-pulse basis:

$$\mathbf{X}_q = \mathbf{B}(\alpha)\Sigma_q\mathbf{A}^T(\theta)\mathbf{S} + \mathbf{W}_q, \quad q = 1, \dots, Q$$

→ Beamforming techniques [Xu, Li & Stoica].

**Example: Capon Beamforming**. Suppose colocated arrays ( $\alpha=\theta$ ).

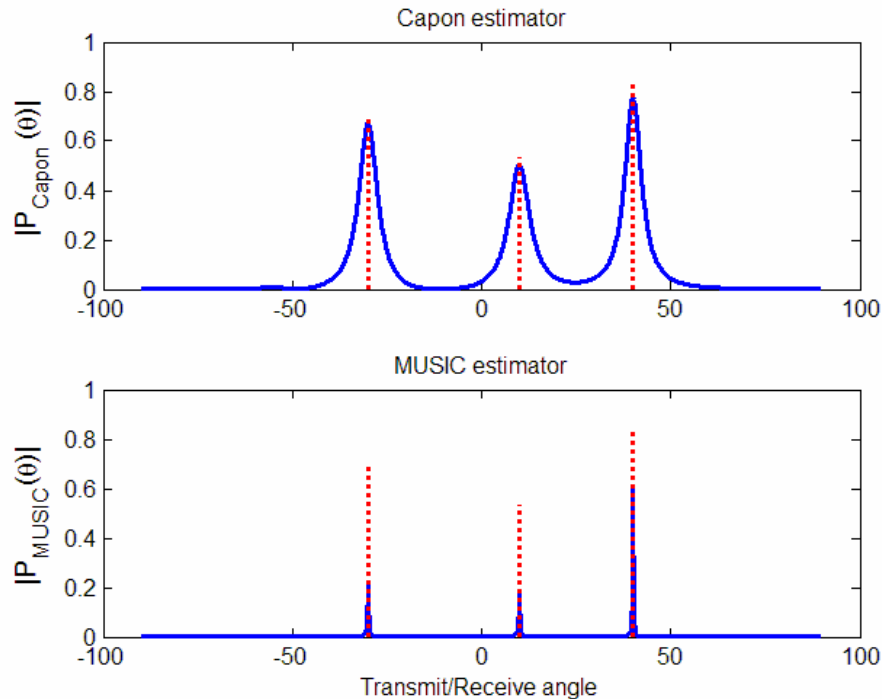
$$\hat{\beta}(\theta) = \frac{\mathbf{b}^H(\theta)\mathbf{R}_{XX}^{-1}\mathbf{X}_q\mathbf{S}^H\mathbf{a}^*(\theta)}{L[\mathbf{b}^H(\theta)\mathbf{R}_{XX}^{-1}\mathbf{b}(\theta)][\mathbf{a}^T(\theta)\mathbf{a}^*(\theta)]}, \quad \mathbf{R}_{XX} = \frac{1}{L}\mathbf{X}_q\mathbf{X}_q^H$$

→ **MUSIC estimator**.

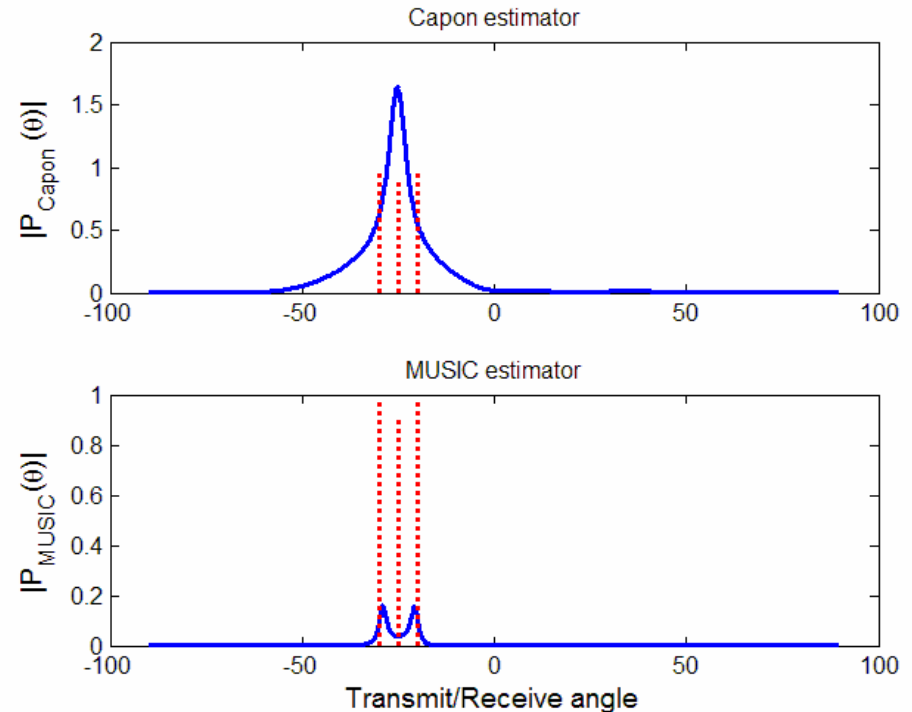
$$P_{MUSIC}(\theta) = \frac{1}{\mathbf{b}^H(\theta)\mathbf{E}_w\mathbf{E}_w^H\mathbf{b}(\theta)}, \quad \mathbf{E}_w = \text{noise eigenvectors of } \mathbf{R}_{XX}$$

## II. State of the art: single-pulse radar-imaging

Typical Capon and MUSIC spectra for a given pulse



**Widely spaced targets ( $-30^\circ, 10^\circ, 40^\circ$ )**



**Closely spaced targets ( $-30^\circ, -25^\circ, -20^\circ$ )**

❑ Problem 1: single lobe occurs for closely located targets

❑ Problem 2: update spectrum for each new pulse  $\rightarrow$  scintillation due to fading (fluctuations of RCS coeff. from pulse to pulse)



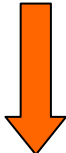
## II. State of the art: multiple-pulses radar-imaging

**Q** : Mitigate RCS fluctuations? → first need a multi-pulse data model

$$\boxed{\mathbf{Y}_q} = \boxed{\mathbf{B}(\alpha)} \quad \boxed{\cancel{\Sigma_q}} \quad \boxed{\mathbf{A}^T(\theta)} + \boxed{\mathbf{Z}_q}$$

 **vectorize**

$$\mathbf{y}_q = \underbrace{[\mathbf{a}(\theta_1) \otimes \mathbf{b}(\alpha_1), \dots, \mathbf{a}(\theta_K) \otimes \mathbf{b}(\alpha_K)]}_{= \mathbf{A}(\theta) \odot \mathbf{B}(\alpha)} \underbrace{[\beta_{q1}, \dots, \beta_{qK}]^T}_{= \mathbf{c}_q^T} + \mathbf{z}_q$$

 **Q pulses  
(concatenation)**

$$\mathbf{Y} = [\mathbf{A}(\theta) \odot \mathbf{B}(\alpha)] \mathbf{C}^T + \mathbf{Z}$$

## II. State of the art: multiple-pulses radar-imaging

Radar-imaging techniques working on a multi-pulse basis:

$$\mathbf{Y} = [\mathbf{A}(\theta) \odot \mathbf{B}(\alpha)] \mathbf{C}^T$$

□ Capon beamforming [Yan, Li, Liao]

$$P_{Capon}(\theta, \alpha) = \frac{1}{(\mathbf{a}(\theta) \otimes \mathbf{b}(\alpha))^H \mathbf{R}_{YY}^{-1} (\mathbf{a}(\theta) \otimes \mathbf{b}(\alpha))}$$

□ MUSIC

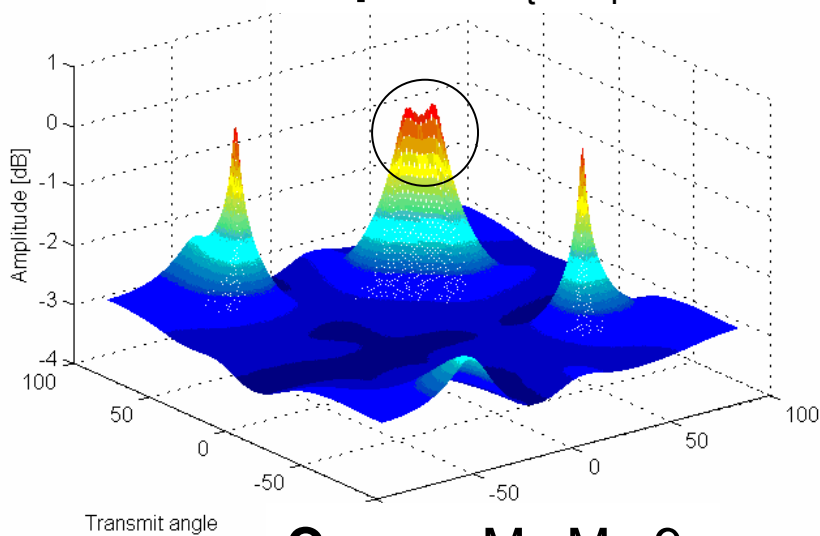
$$P_{MUSIC}(\theta, \alpha) = \frac{1}{(\mathbf{a}(\theta) \otimes \mathbf{b}(\alpha))^H \mathbf{E}_w \mathbf{E}_w^H (\mathbf{a}(\theta) \otimes \mathbf{b}(\alpha))}$$

$\mathbf{E}_w$  = noise eigenvectors of  $\mathbf{R}_{YY}$

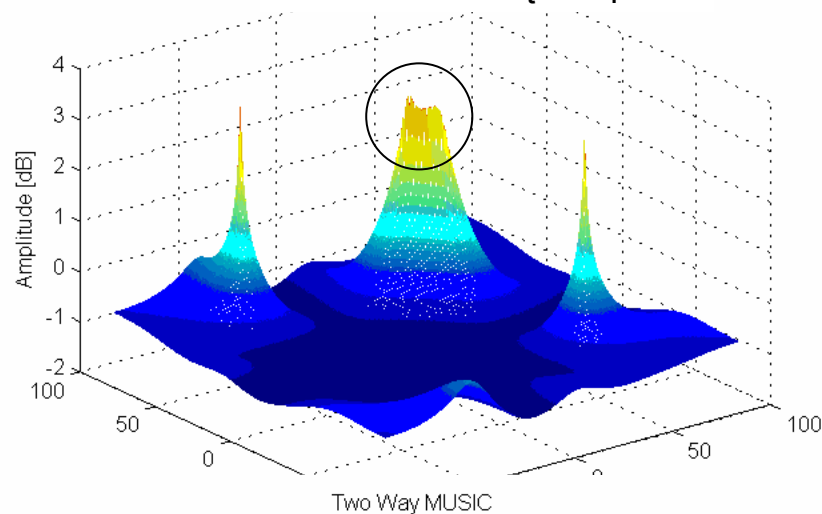
## II. State of the art: multiple-pulses radar-imaging

$$K = 5, \{\theta_k\} = \{40^\circ, 35^\circ, 30^\circ, -40^\circ, 65^\circ\}, \{\alpha_k\} = \{20^\circ, 25^\circ, 30^\circ, 50^\circ, -45^\circ\}$$

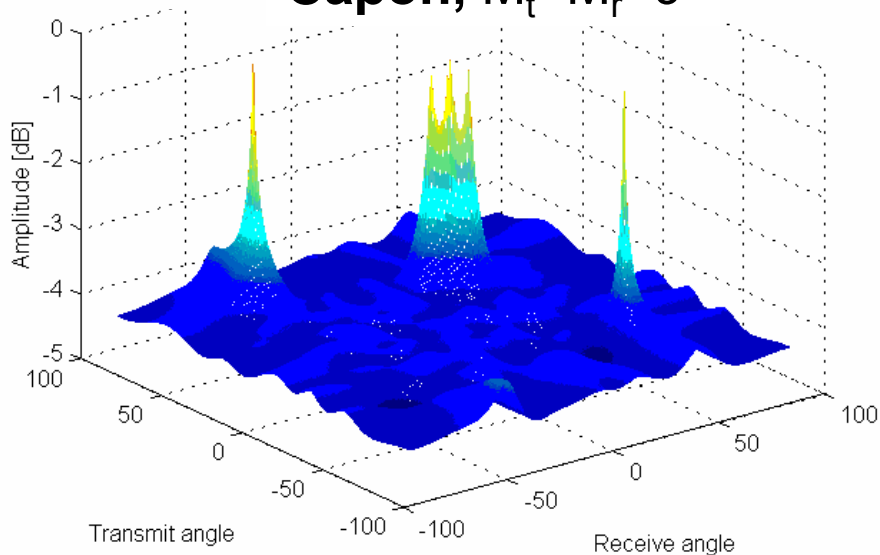
**Capon,  $M_t=M_r=4$**



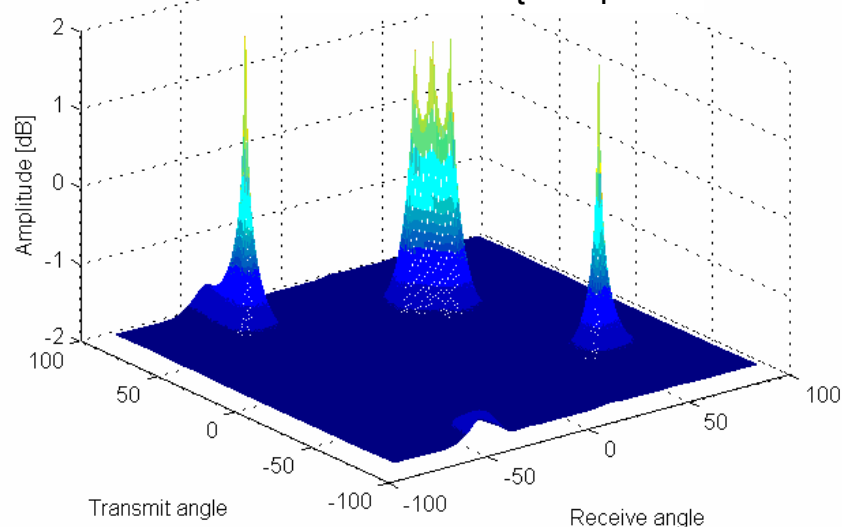
**MUSIC,  $M_t=M_r=4$**



**Capon,  $M_t=M_r=9$**



**MUSIC,  $M_t=M_r=9$**



# III. Localization via PARAFAC: overview

## Problems:

- ❑ Capon and MUSIC 2D-imaging work on multi-pulse basis **but** fail if no distinguishable lobe for each target (e.g. closely located targets)
- ❑ Capon and MUSIC spectra have to be computed for each pair of angles  
→ time consuming for dense angular grid

→ **Our contribution:** starting from the same data model,

$$\mathbf{Y} = [\mathbf{A}(\theta) \odot \mathbf{B}(\alpha)] \mathbf{C}^T$$

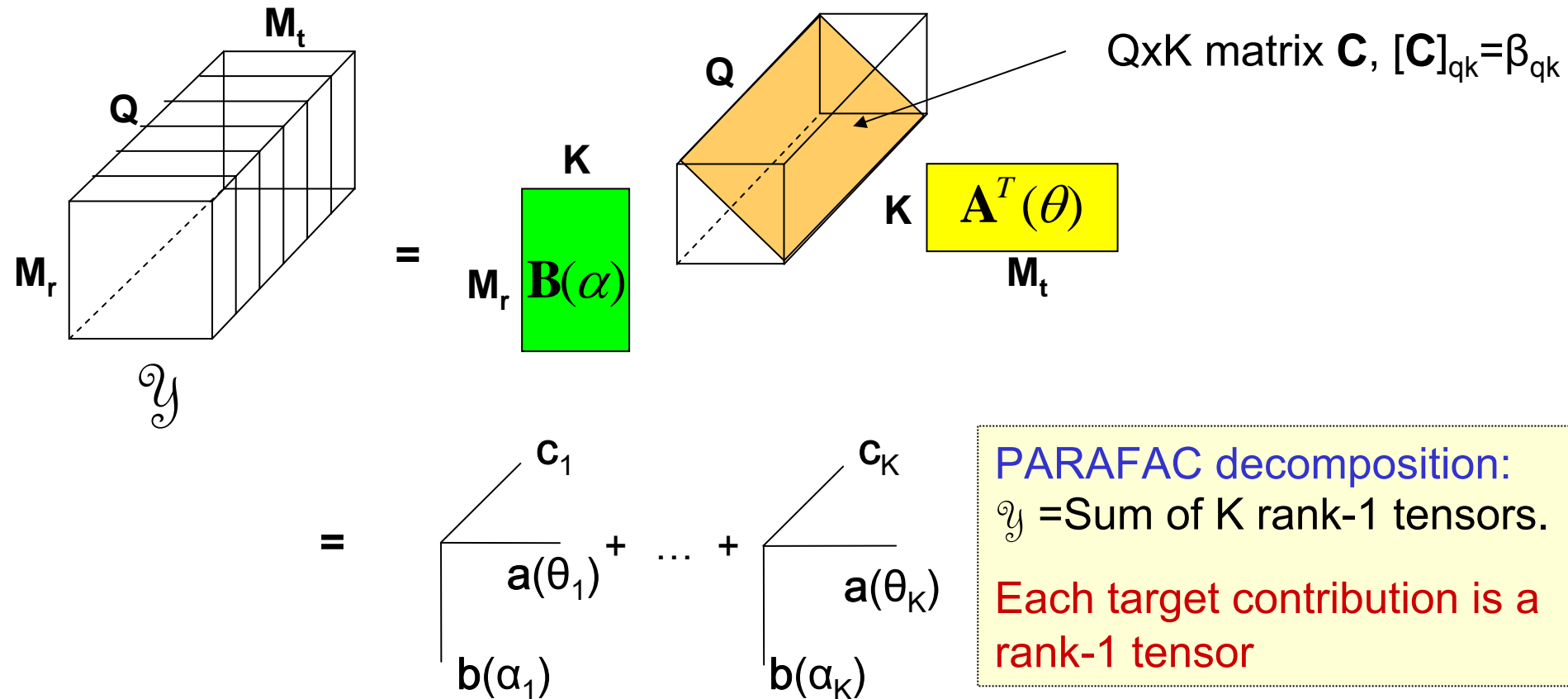
exploitation of the **algebraic structure of  $\mathbf{Y}$**  is sufficient for blind estimation of  $\mathbf{A}(\theta)$ ,  $\mathbf{B}(\alpha)$  and  $\mathbf{C}$ .

**Indeed  $\mathbf{Y}$  follows the well-known PARAFAC model.**

# III. Localization via PARAFAC: model

$$\mathbf{Y}_q = \mathbf{B}(\alpha) \Sigma_q \mathbf{A}^T(\theta) + \mathbf{Z}_q$$

$M_r \times M_t$  matrix observed  $Q$  times,  $q=1, \dots, Q$ .  $\mathbf{B}(\alpha)$  and  $\mathbf{A}(\theta)$  fixed over  $Q$  pulses.



# III. Localization via PARAFAC: summary

□ Given the  $(M_r \times M_t \times Q)$  tensor  $\mathcal{y}$ , compute its PARAFAC decomposition in  $K$  terms to estimate  $\mathbf{A}(\theta)$ ,  $\mathbf{B}(\alpha)$  and  $\mathbf{C}$ .

→ Several algorithms in the literature (e.g. Alternating Least Squares (ALS), ALS+Enhanced Line Search, Levenberg-Marquardt, Simultaneous Diagonalization, ...)

□ **Key point:** under some conditions (next slide), PARAFAC is unique up to trivial indeterminacies:

➤ Columns of  $\mathbf{A}(\theta)$ ,  $\mathbf{B}(\alpha)$  and  $\mathbf{C}$  arbitrarily permuted (same permutation)

➤ Columns of  $\mathbf{A}(\theta)$ ,  $\mathbf{B}(\alpha)$  and  $\mathbf{C}$  arbitrarily scaled (scaling factor removed by recovering the known array manifold structure on the steering matrices estimates, after which the DODs and DOAs are extracted).

# III. Localization via PARAFAC: uniqueness

□ **Condition 1:**  $\mathbf{A}(\theta)$  and  $\mathbf{B}(\alpha)$  full rank and  $\mathbf{C}$  full-column rank. If

$$K \geq 2 \text{ and } M_t(M_t - 1)M_r(M_r - 1) \geq 2K(K - 1)$$

then uniqueness is guaranteed a.s. [De Lathauwer].

□ **Condition 2:**  $\mathbf{A}(\theta)$  and  $\mathbf{B}(\alpha)$  are full rank Vandermonde matrices and  $\mathbf{C}$  full-column rank. If

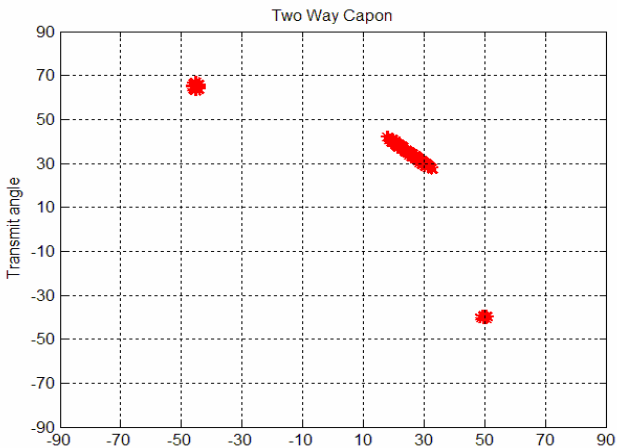
$$\max(M_t, M_r) \geq 3 \text{ and } M_t M_r - \min(M_t, M_r) \geq K$$

then uniqueness is guaranteed a.s. [Jiang, Sidiropoulos, Ten Berge].

$M_t=M_r$	3	4	5	6	7	8
$K_{\max}$ condition 1	4	9	14	21	30	40
$K_{\max}$ condition 2	6	12	20	30	42	56

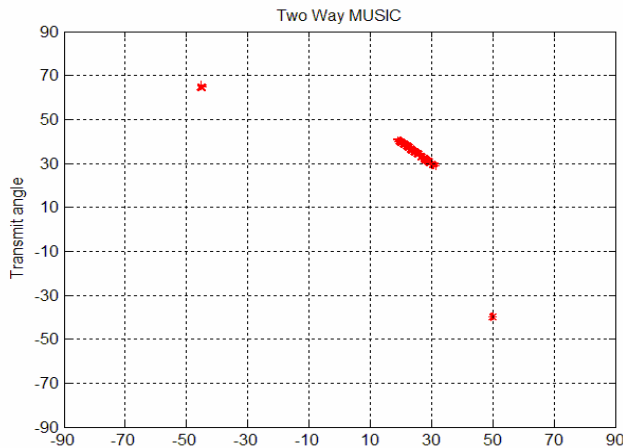
# III. Localization via PARAFAC: simulations

$$K = 5, \{\theta_k\} = \{40^\circ, 35^\circ, 30^\circ, -40^\circ, 65^\circ\}, \{\alpha_k\} = \{20^\circ, 25^\circ, 30^\circ, 50^\circ, -45^\circ\}$$



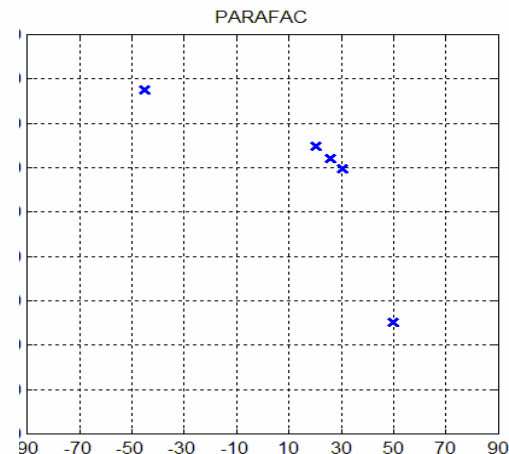
$$M_t=M_r=4$$

**CAPON**



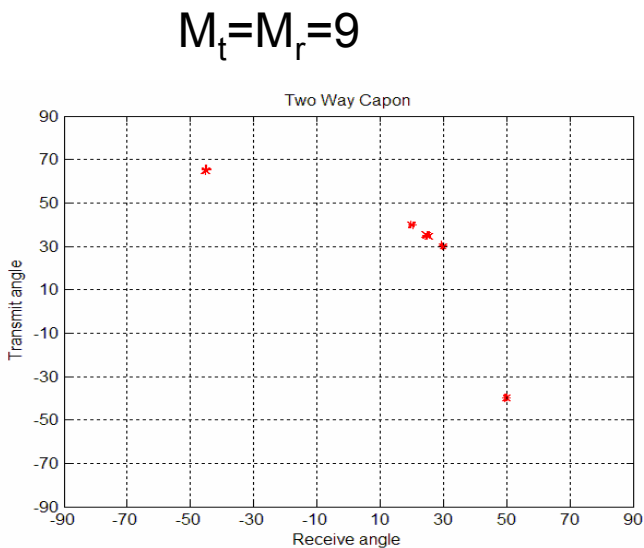
$$M_t=M_r=4$$

**MUSIC**

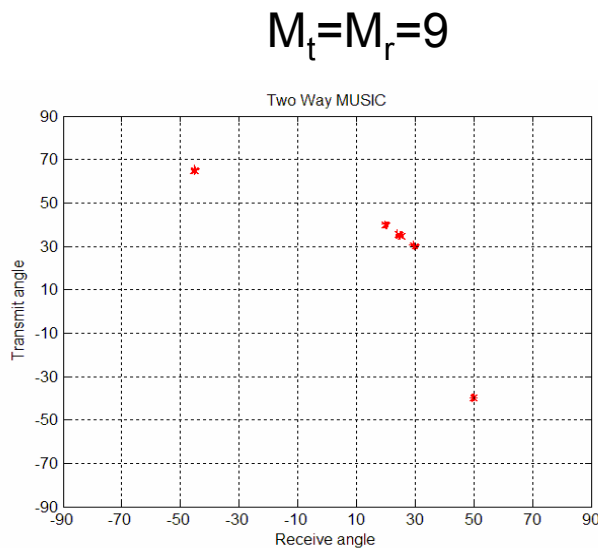


$$M_t=M_r=4$$

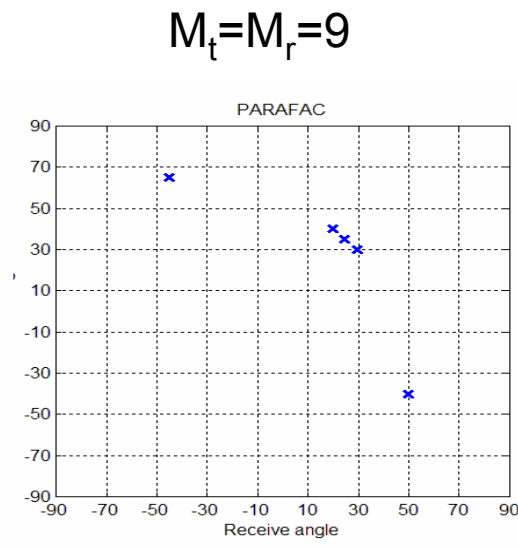
**PARAFAC**



$$M_t=M_r=9$$



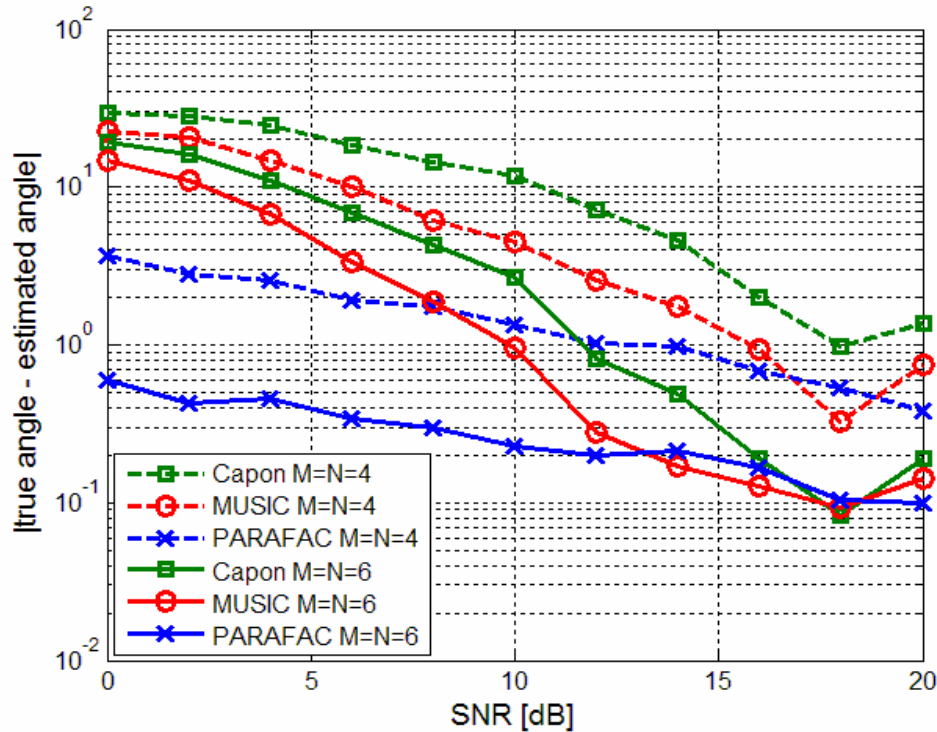
$$M_t=M_r=9$$



$$M_t=M_r=9$$



# III. Localization via PARAFAC: simulations



K=4 targets,

$M_t = M_r = 4$  and  $M_t = M_r = 6$ ,

100 Monte-Carlo runs

Angles randomly generated for each run (with minimum inter-target spacing of  $5^\circ$ )

# IV. Conclusion

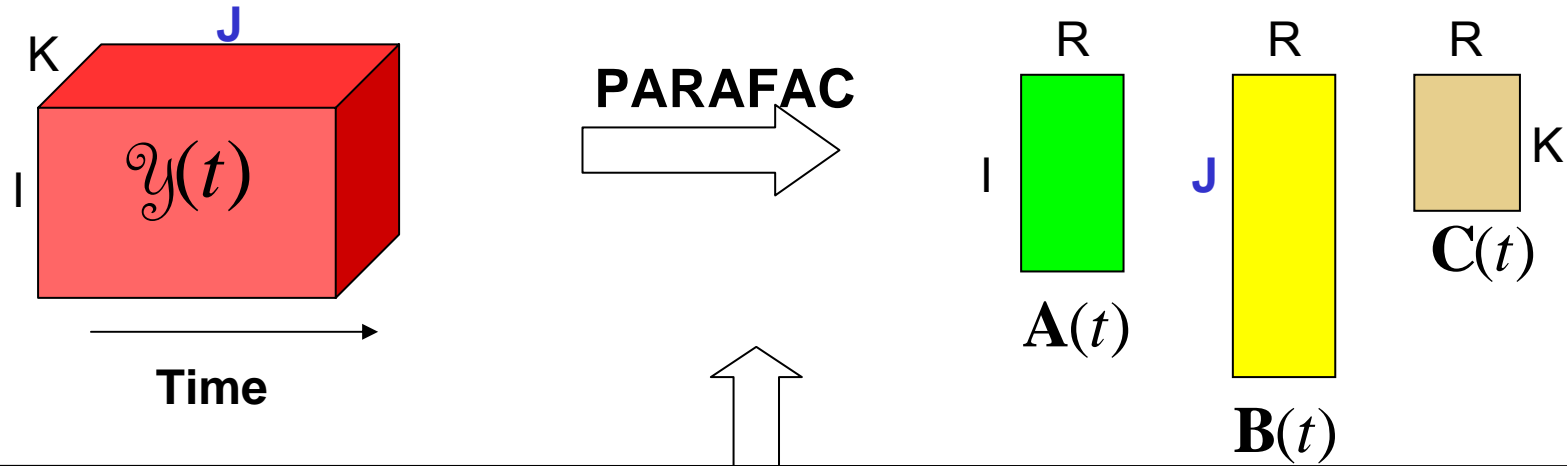
- PARAFAC = deterministic alternative to radar-imaging (Capon, MUSIC, etc)
  - Guaranteed identifiability
  - RCS fluctuations from pulse to pulse = time diversity  
= 1 dimension of the observed tensor
- PARAFAC outperforms MUSIC and Capon
  - Peak detection in radar-imaging fails for closely located targets
  - PARAFAC = estimation based on exploitation of strong algebraic structure of observed data.
- Extension (work in progress):

Generalization to the case of multiple sufficiently spaced transmit and receive sub-arrays.

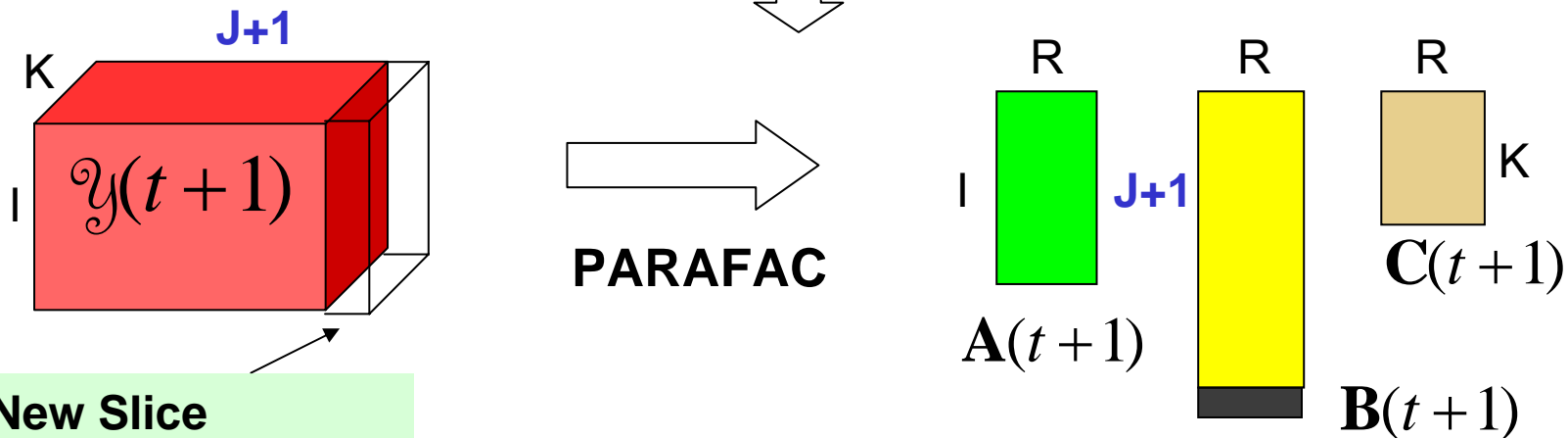
# Appendix: Target tracking via adaptive PARAFAC

« Adaptive algorithms to track the PARAFAC decomposition »

[Nion & Sidiropoulos 2009]



**LINK = adaptive algorithms to track the PARAFAC decomposition**



# Appendix: Target tracking via adaptive PARAFAC

5 moving targets. Estimated trajectories. Comparison between Batch PARAFAC (applied repeatedly) and PARAFAC-RLST (« Recursive Least Squares Tracking »)

