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Jian Li

University of Florida

Over a Century of Array Signal Processing

Watch on the IEEE Learning Network

Biography

Jian Li received the M.Sc. and Ph.D. degrees in electrical engineering from The Ohio State University, Columbus, in 1987 and 1991, respectively. She is currently a Professor in the Department of Electrical and Computer Engineering, University of Florida, Gainesville. Her current research interests include spectral estimation, statistical and array signal processing, and their applications to radar, sonar, and biomedical engineering. Dr. Li's publications include Robust Adaptive Beamforming (2005, Wiley), Spectral Analysis: the Missing Data Case (2005, Morgan & Claypool), MIMO Radar Signal Processing (2009, Wiley), and Waveform Design for Active Sensing Systems – A Computational Approach (2011, Cambridge University Press).

Dr. Li is a Fellow of IEEE and a Fellow of IET. She is a Fellow of the European Academy of Sciences (Brussels). She received the 1994 National Science Foundation Young Investigator Award and the 1996 Office of Naval Research Young Investigator Award. She was an Executive Committee Member of the 2002 International Conference on Acoustics, Speech, and Signal Processing, Orlando, Florida, May 2002. She was an Associate Editor of the IEEE Transactions on Signal Processing from 1999 to 2005, an Associate Editor of the IEEE Signal Processing Magazine from 2003 to 2005, and a member of the Editorial Board of Signal Processing, a publication of the European Association for Signal Processing (EURASIP), from 2005 to 2007. She was a member of the Editorial Board of the IEEE Signal Processing Magazine from 2010 to 2012. She is a co-author of the paper that has received the M. Barry Carlton Award for the best paper published in IEEE Transactions on Aerospace and Electronic Systems in 2005. She is also a co-author of a paper published in IEEE Transactions on Signal processing that has received the Best Paper Award in 2013 from the IEEE Signal Processing Society.

Over a Century of Array Signal Processing

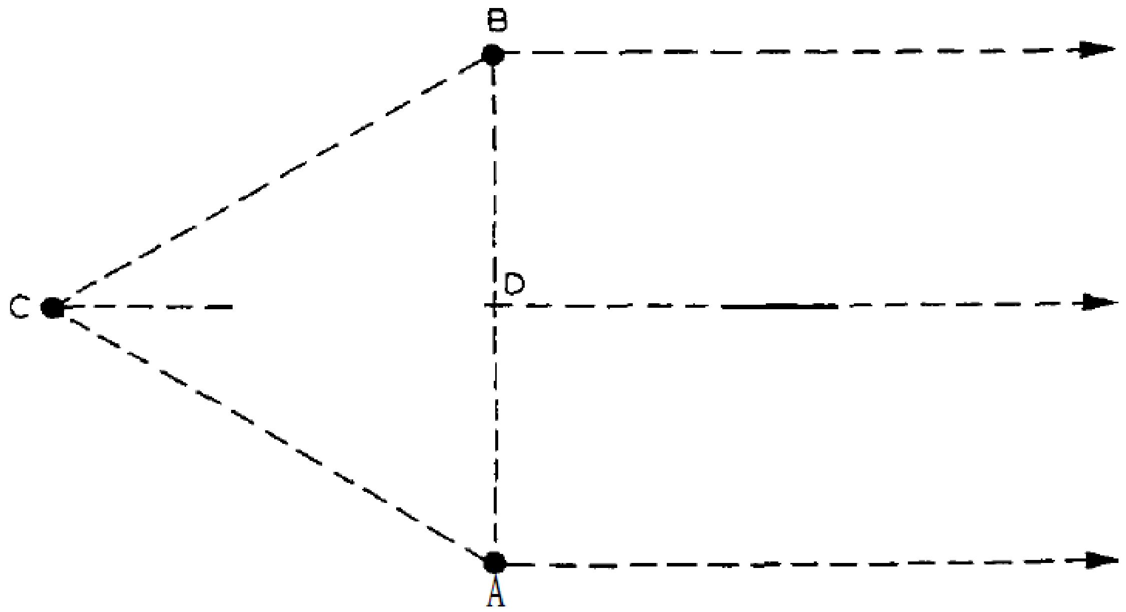
Since the introduction of phased array in 1905 by Karl Braun, a Nobel Laureate, array signal processing has advanced significantly over the past century. The era of adaptive array was started by Jack Capon, signified by his seminal paper in 1969. The Capon beamformer has better resolution and much better interference rejection capability than the data-independent beamformer by Karl Braun, provided that the array steering vector corresponding to the signal of interest (SOI) and the array covariance matrix is accurately known, and the SOI is uncorrelated to all other signals impinging on the array. However, whenever the knowledge of the SOI steering vector is imprecise, the number of data snapshots is scarce, or the SOI is correlated with a multipath, which are often the cases encountered in practice, the performance of the Capon beamformer may become worse than that of the data-independent beamformer. For over 50 years, making the Capon beamformer robust has attracted much interest and tens of thousands of papers on robust adaptive array processing have been published in the literature. To fundamentally overcome the limitations of the Capon family of beamformers, iterative approaches have been introduced in the recent literature. Most notably, the iterative adaptive approach (IAA) was published in 2010 and is shown to possess strong robustness, and can work well under single snapshot and arbitrary array scenarios. We will compare the nonparametric and user parameter free IAA algorithm with other well-known algorithms, including the data-independent beamformer, the Capon beamformer, the OMP algorithm introduced in the compressed sensing literature, as well as the parametric MUSIC and ESPRIT algorithms.

The Beginning：1905

Karl Ferdinand Braun

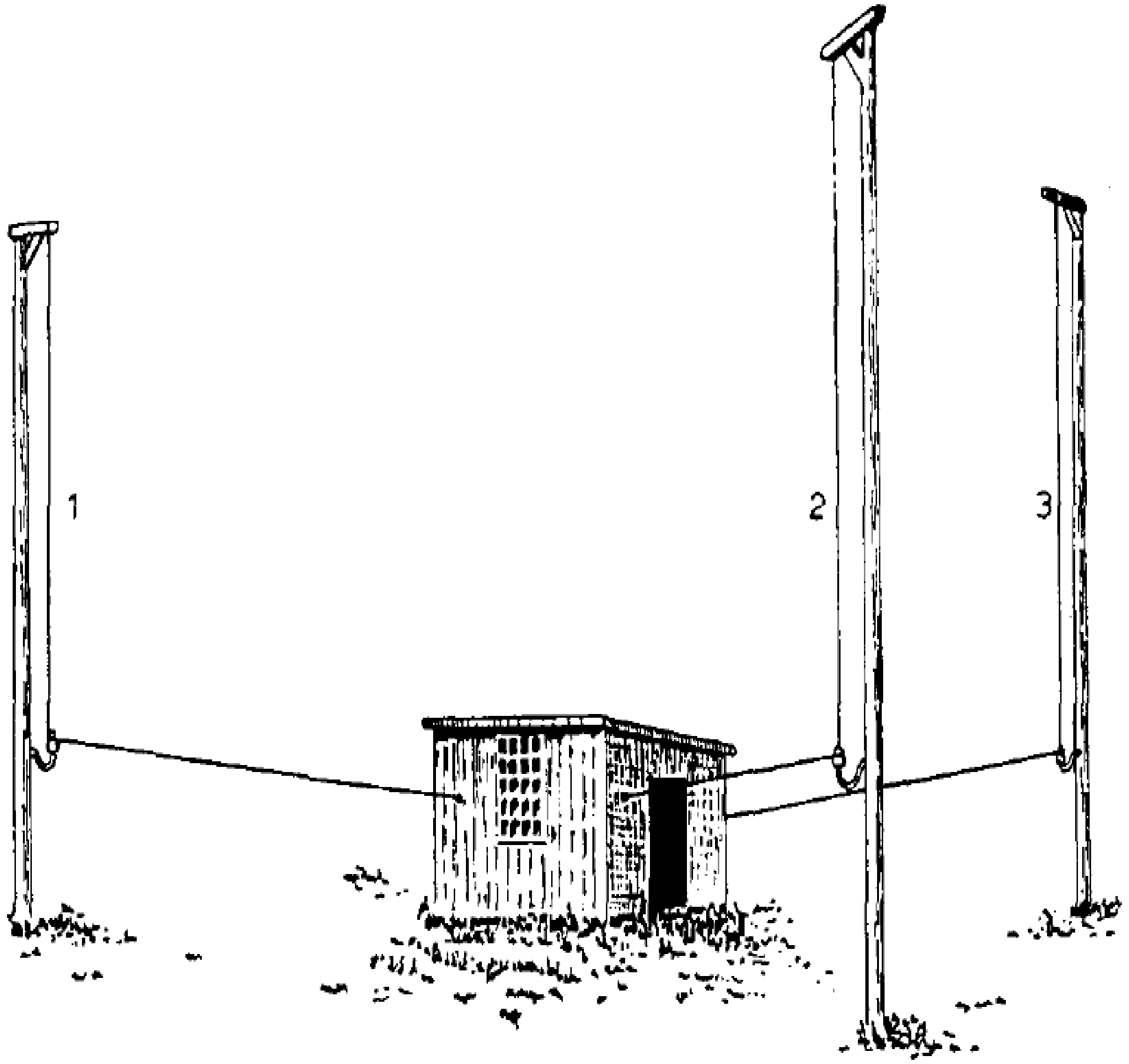
Received Nobel Prize in Physics in 1909.

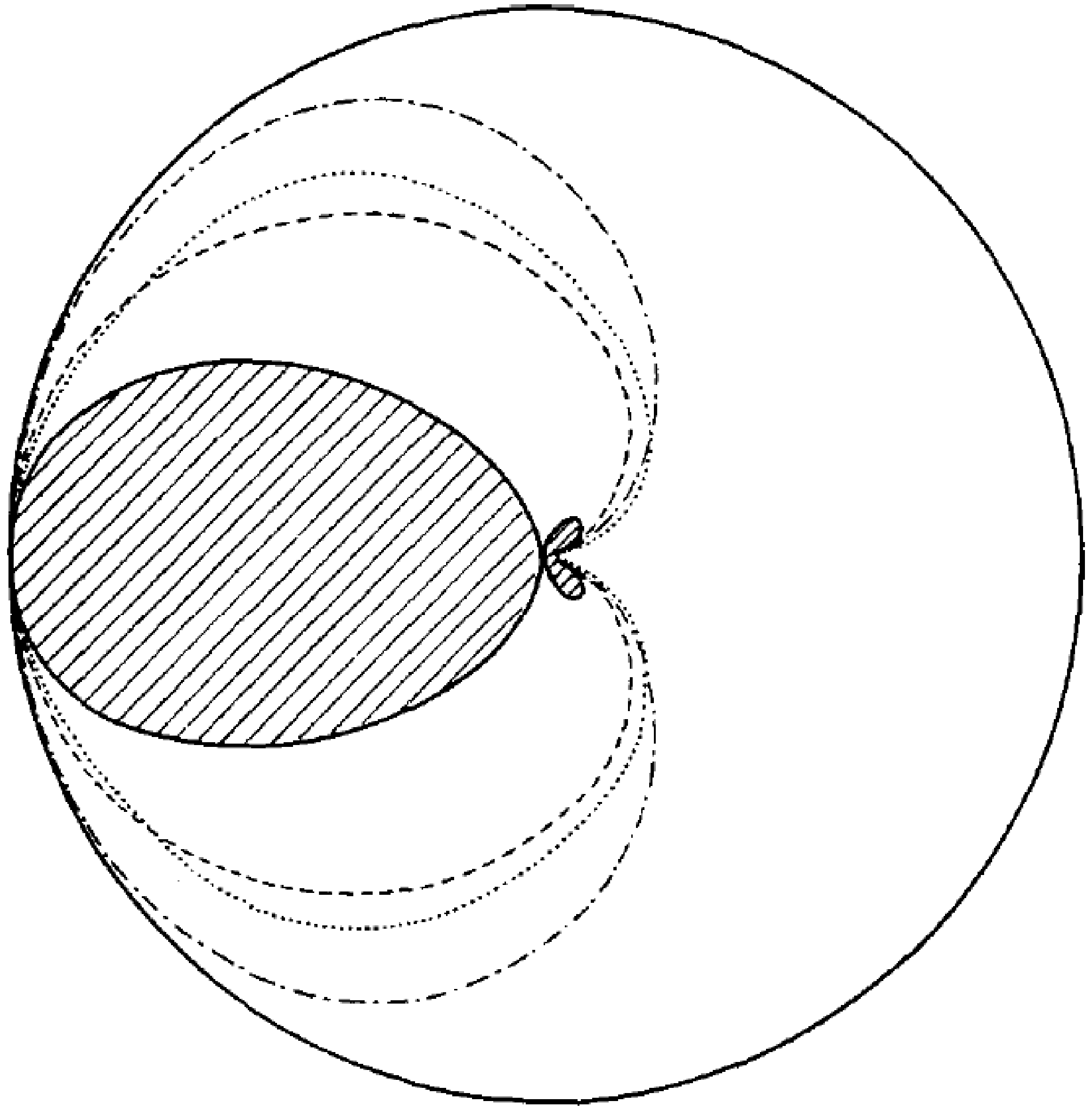
- **The Notion of Phased Array Was Introduced by Karl Braun (German) in 1905。**
- **During his lecture at accepting the Nobel Prize, he talked about how to arrange 3 antennas to transmit a signal coherently.**



K.F. Braun, Electrical oscillations and wireless telegraphy. Nobel Lecture, vol. 11, no. 1909, pp. 226-245, Dec. 1909.

Braun’s 1905 Experiment

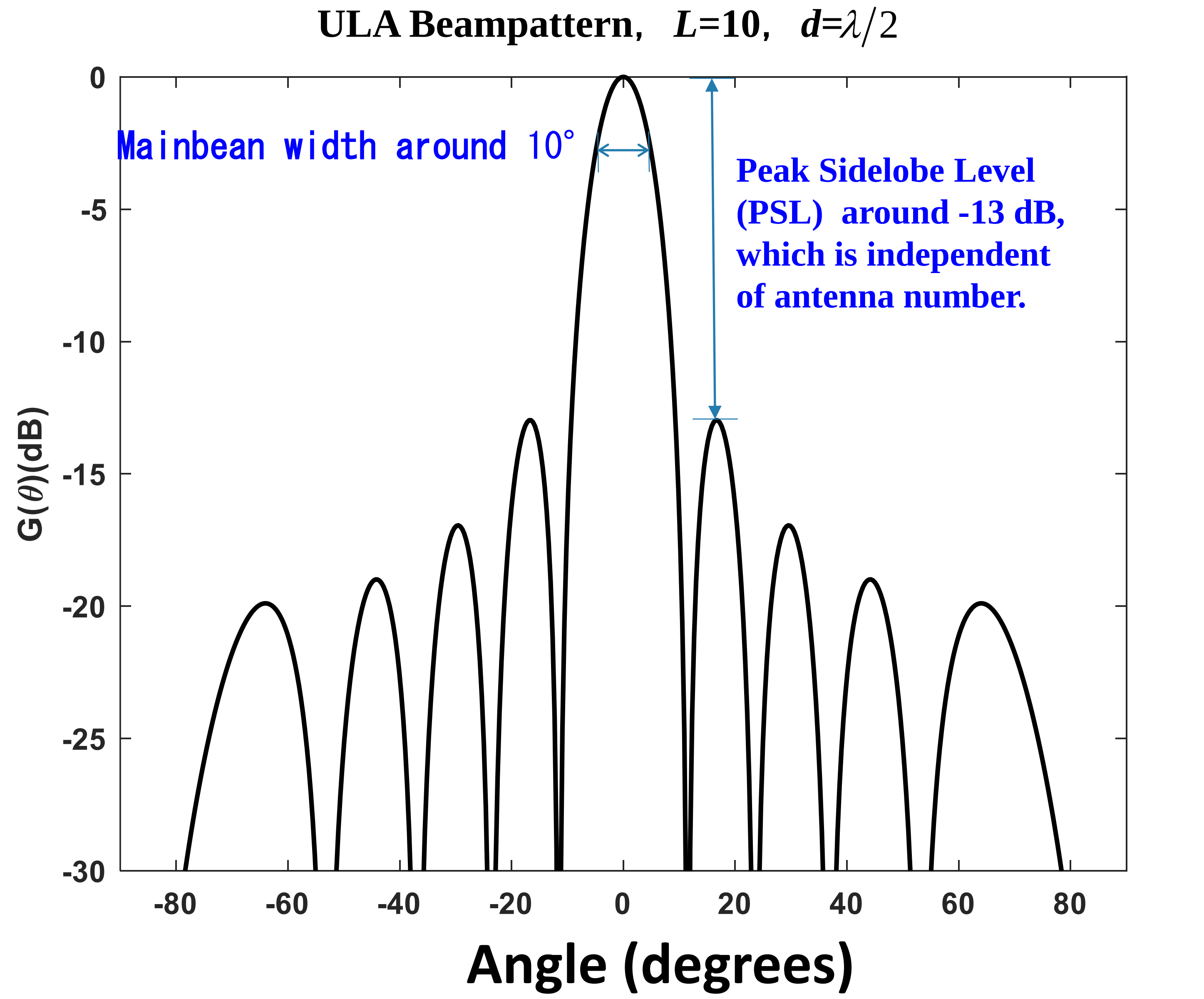




Array Beampattern

K.F. Braun, Electrical oscillations and wireless telegraphy. Nobel Lecture, vol. 11, no. 1909, pp. 226-245, Dec. 1909.

Merits and Limitations of Braun's Standard Beamformer



Array Beampattern: $G(\theta) = \left|\mathbf{a}^H(\theta)\mathbf{a}(0)\right|^2 / L^2$

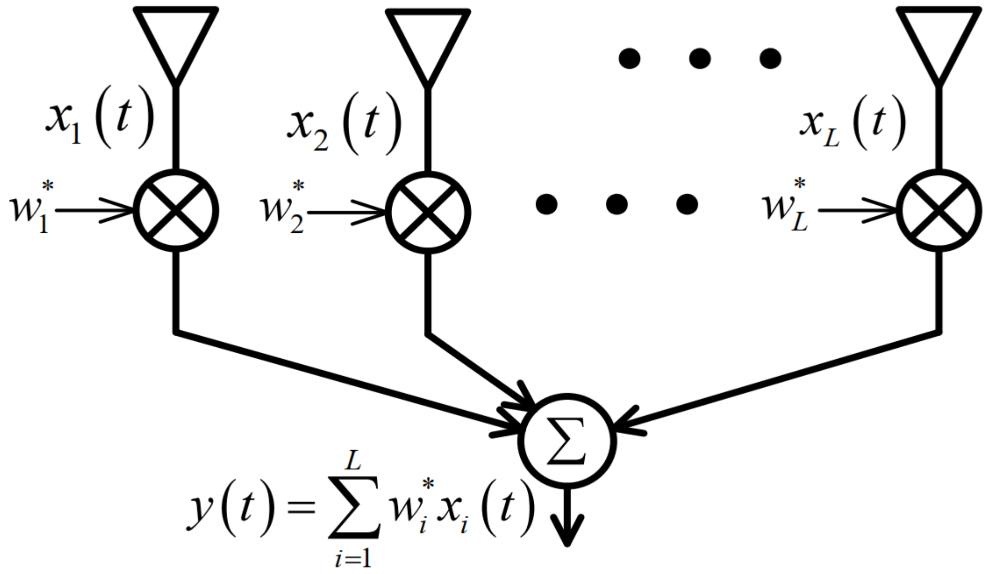
- For Narrowband Signals, Delays Cause Phase Changes – Hence the Name "Phased Array".
- In the Digital Era, the Standard Beamformer is also Called Digital Beamformer (DBF).

✓ **Robust**

× **Poor Resolution**

× **High Sidelobe Level**

× **Poor Interference Rejection Capability**



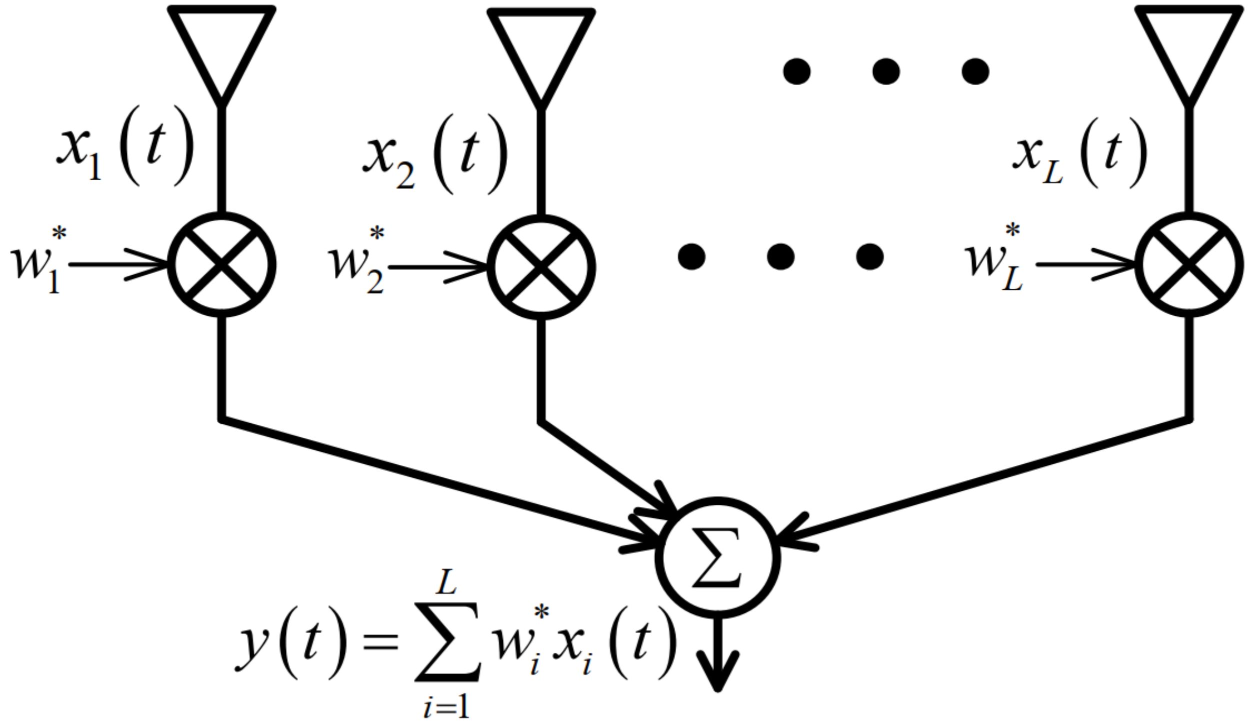
Array Weights are Data-Independent

The Era of Adaptive Array: 1969 -

Jack Capon

MIT Lincoln Lab

J. Capon, "High-resolution frequency-wavenumber spectrum analysis," in Proceedings of the IEEE, vol. 57, no. 8, pp. 1408-1418, Aug. 1969.



Array Weights are Data-Adaptive

- **In 1969, Capon Introduced the Minimum Power Distortionless Response (MPDR) Adaptive Beamformer.**
- **This started the Adaptive Array Signal Processing Research, which is still continuing.**

Capon Beamformer

- **Beamformer Weight Vector is Data-Dependent:**

$$\mathbf{w}^H = \left[w_1^*, \cdots, w_L^* \right]$$

- **The Goal is to Minimize the Array Output Power, Subject to the Constraint that the Signal-of-Interest is Passed Through Undistorted.**

$$\min_{\mathbf{w}} P(\mathbf{w}) = \mathbf{w}^H \mathbf{R} \mathbf{w}$$

$$\text{s.t. } \mathbf{w}^H \mathbf{a}(\theta) = 1$$

$$\boxed{\mathbf{R} = \mathrm{E}\left\{ \mathbf{x}(t) \mathbf{x}^H(t) \right\}}$$

- **Capon Weight**

$$\mathbf{w}_{\text{Capon}} = \frac{\mathbf{R}^{-1} \mathbf{a}(\theta)}{\mathbf{a}^H(\theta) \mathbf{R}^{-1} \mathbf{a}(\theta)}$$

- **Capon Beamformer Output Power**

$$\boxed{P_{\text{Capon}}(\theta) = \frac{1}{\mathbf{a}^H(\theta) \hat{\mathbf{R}}^{-1} \mathbf{a}(\theta)}}$$

Sample Covariance Matrix

$$\hat{\mathbf{R}} = \frac{1}{T} \sum_{t=1}^{T} \mathbf{x}(t) \mathbf{x}^H(t)$$

J. Capon, "High-resolution frequency-wavenumber spectrum analysis," in Proceedings of the IEEE, vol. 57, no. 8, pp. 1408-1418, Aug. 1969.

An Interesting Connection

- In 1955, Markowitz Introduced a Portfolio Management Theory to Reduce Risk for an Expected Return.
- It is Considered the First Revolution in Wall Street. The Theory is the Foundation to Modern-Day Investment Strategy.
- A Special Case of Markowitz's Work is Exactly the Capon Beamformer.

Harry Markowitz

Received Nobel Prize in Economics in 1990.

H. Markowitz, The Optimization of Quadratic Functions Subject to Linear Constraints. Santa Monica, CA: RAND Corporation, 1955.

Practical Challenges

Arthur B. Baggeroer

Member of U.S. Academy of Engineering

However, the Capon Adaptive Beamformer Is Too Sensitive To Be Used in Practice – Signal-of-Interest Can Get Suppressed!

1. **In Practice, Few Snapshots Available.**
2. **Presence of Array Steering Vector Errors (Caused by Calibration Errors, etc.).**
3. **Signals Correlated or Even Coherent.**
4. **Spatial Smoothing Not Possible for Sparse Arrays.**

In Practice, the Sample Covariance Matrix is Used to Replace the True Array Covariance.

$$\boxed{\hat{\mathbf{R}} = \frac{1}{T}\sum_{t=1}^{T}\mathbf{x}(t)\mathbf{x}^{H}(t) \rightarrow \mathbf{R}}$$

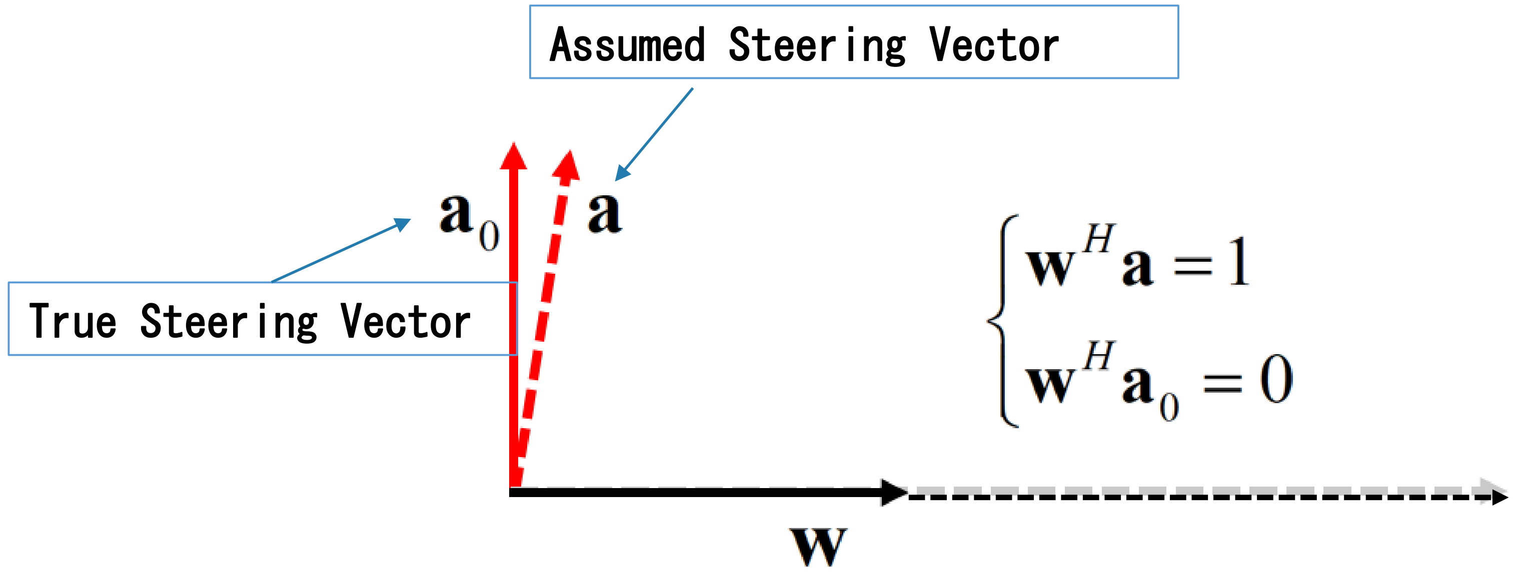
A. B. Baggeroer and H. Cox, "Passive sonar limits upon nulling multiple moving ships with large aperture arrays," *Conference Record of the Thirty-Third Asilomar Conference on Signals, Systems, and Computers (Cat. No.CH37020)*, 1999, pp. 103-108 vol.1.

Robust Capon Beamformer

Henry Cox

Member of U.S. Academy of Engineering

- **In 1973, Cox Studied Why the Capon Beamformer Fails to Work Properly in Practice.**
- **He Introduced the Notion of Norm Constrained Weight Vector.**



$$\begin{cases} \mathbf{w}^H \mathbf{a} = 1 \\ \mathbf{w}^H \mathbf{a}_0 = 0 \end{cases}$$

H. Cox, “Resolving power and sensitivity to mismatch of optimum array processors,” J. Acoustical Soc. Amer., vol. 54, pp. 771–785, 1973.

H. Cox, R. M. Zeskind, and M. M. Owen, “Robust adaptive beamforming,” in IEEE transactions on acoustics, speech, and signal processing, vol. 35, no. 10, pp. 1365– 1376, Oct. 1987.

Normed Constrained Weight Vector

- **Cox's Robust Capon Beamformer is Formulated As:**

$$\mathbf{w}_{\text{NCCB}} = \arg\min_{\mathbf{w}} \ \mathbf{w}^H \mathbf{R} \mathbf{w} \quad \text{s.t.} \quad \begin{cases} \mathbf{w}^H \mathbf{a} = 1 \\ \|\mathbf{w}\|^2 \le \delta \end{cases}$$

- **The Solution is Diagonal Loading on the Array Covariance Matrix**

$$\mathbf{w}_{\text{NCCB}} = \frac{(\mathbf{R} + \gamma \mathbf{I})^{-1} \mathbf{a}}{\mathbf{a}^H (\mathbf{R} + \gamma \mathbf{I})^{-1} \mathbf{a}}$$

γ Determined by Weight Vector Norm Constraint δ

H. Cox, "Resolving power and sensitivity to mismatch of optimum array processors," J. Acoustical Soc. Amer., vol. 54, pp. 771–785, 1973.

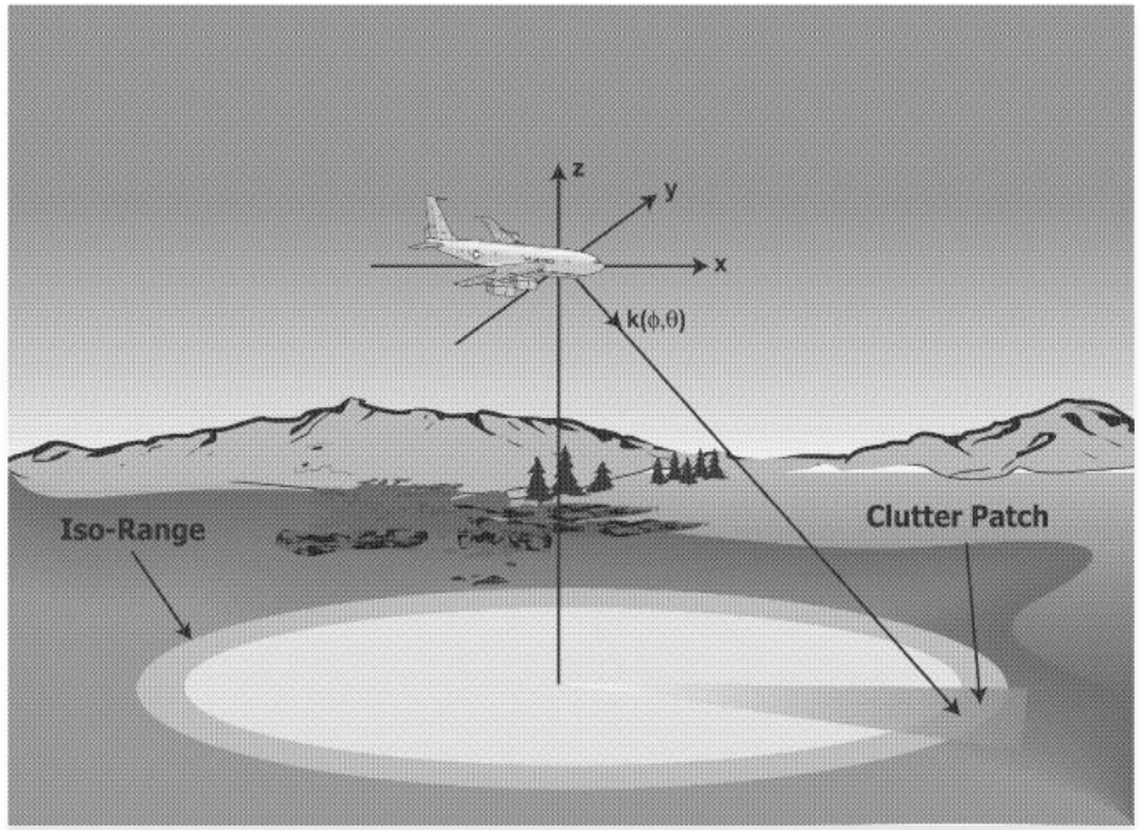
H. Cox, R. M. Zeskind, and M. M. Owen, "Robust adaptive beamforming," in IEEE transactions on acoustics, speech, and signal processing, vol. 35, no. 10, pp. 1365– 1376, Oct. 1987.

1. **Through constraining the norm of the weight vector, this robust adaptive beamformer is more robust than the original Capon beamformer.**
2. **It is widely used in practice.**
3. **It becomes DBF as $\gamma \to \infty$**
4. **In Practice, how to determine δ, a user parameter?**
5. **This robust adaptive beamformer still fails to work well when the desired signal is highly correlated or coherent with another signal (multipath, for example), few snapshots available, etc.**

Space-Time Adaptive Processing (STAP)

Irving S. Reed

Member of U.S. Academy of Engineering



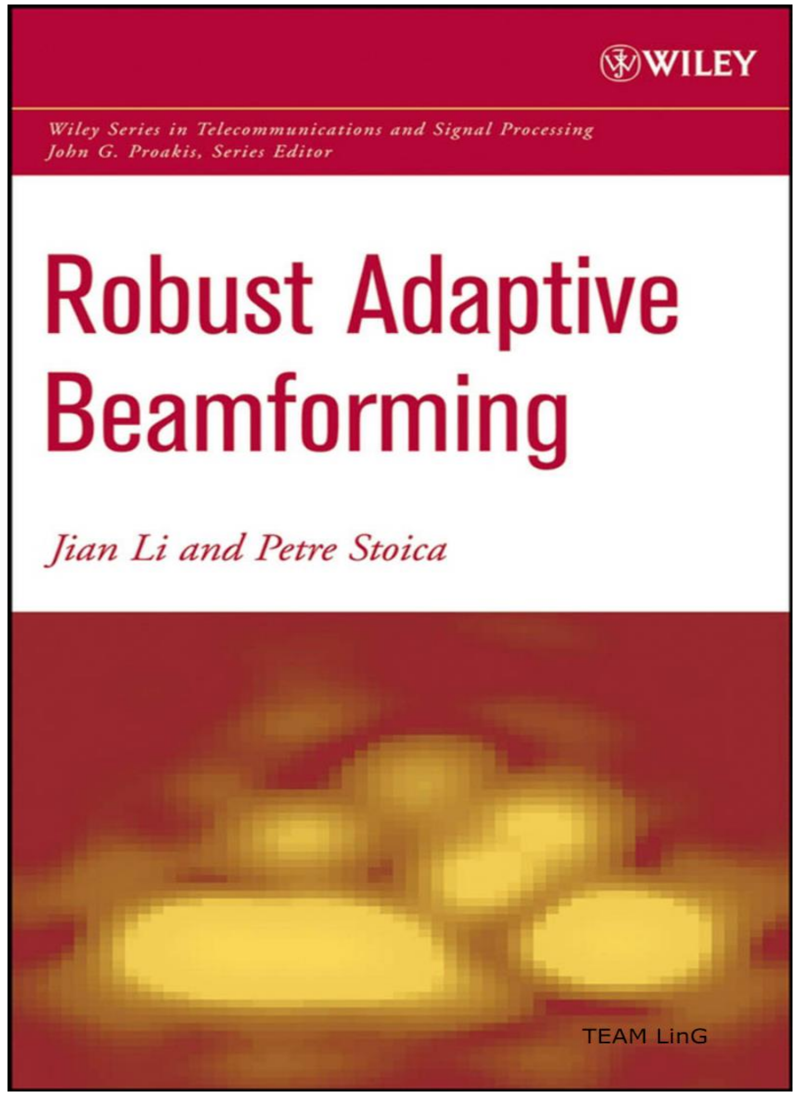
STAP for Wide Area Surveillance

In 1974, Reed et al. discovered that if the sample number is twice the data dimension, the SNR loss is 3 dB, when the sample noise-and-interference covariance matrix is used to replace the true one.

$$\hat{\mathbf{Q}} = \frac{1}{T}\sum_{t=1}^{T}\mathbf{x}(t)\mathbf{x}^{H}(t)$$

I. S. Reed, J. D. Mallett and L. E. Brennan, "Rapid Convergence Rate in Adaptive Arrays," in IEEE Transactions on Aerospace and Electronic Systems, vol. AES-10, no. 6, pp. 853-863, Nov. 1974.

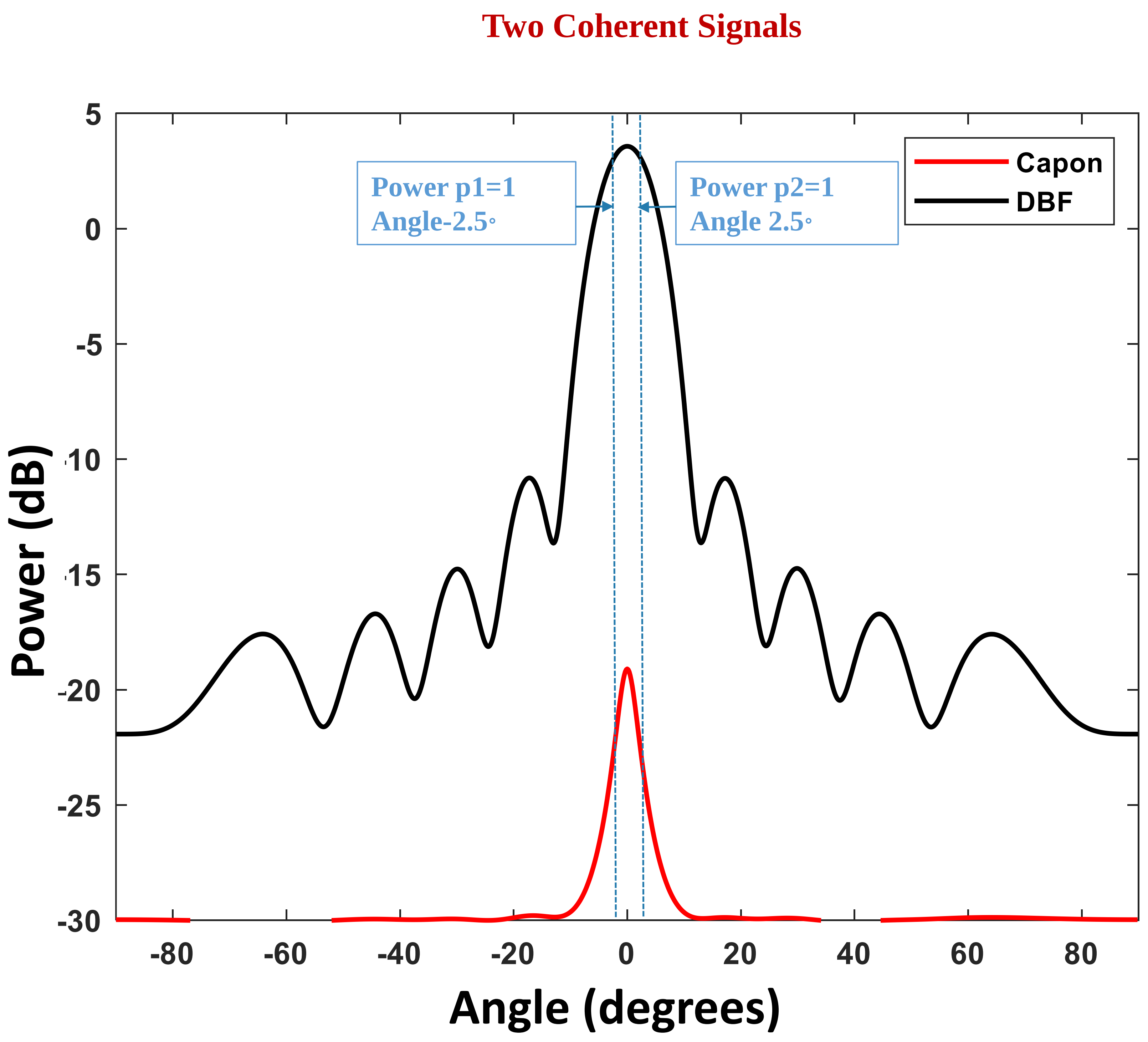
Over 50 Years of Robust Capon Beamformer Research



- Over the past 50 years, tens of thousands of papers have been published on making the Capon beamformer robust.
- New papers are still coming out every day.
- They are all limited to the Capon framework and hence suffer from the same problems:
  - They fail to work well when the desired signal is highly correlated or coherent with another signal (multipath, for example), few snapshots available, etc.
  - They all need user parameters that can be hard to choose in practical applications.

H. Cox, "Resolving power and sensitivity to mismatch of optimum array processors," J. Acoustical Soc. Amer., vol. 54, pp. 771–785, 1973.
H. Cox, R. M. Zeskind, and M. M. Owen, "Robust adaptive beamforming," in IEEE transactions on acoustics, speech, and signal processing, vol. 35, no. 10, pp. 1365– 1376, Oct. 1987.
J. Li, P. Stoica, and Z. Wang, "On robust Capon beamforming and diagonal loading," in IEEE Transactions on Signal Processing, vol. 51, no. 7, pp. 1702–1715, Jul. 2003.
J. Li, P. Stoica and Z. Wang, "Doubly constrained robust Capon beamformer," in IEEE Transactions on Signal Processing., vol. 52, no. 9, pp. 2407-2423, Sept. 2004.
J. Li, P. Stoica, Robust adaptive beamforming. John Wiley & Sons, 2005.

Limitations of Capon Family of Adaptive Arrays



- **Severe Degradations for Coherent (or Highly Correlated) Signals**

$$\mathbf{x}(t) = \mathbf{a}(\theta_1)s(t) + \mathbf{a}(\theta_2)s(t) + \mathbf{n}(t)$$
$$= \underline{\left(\mathbf{a}(\theta_1) + \mathbf{a}(\theta_2)\right)} s(t) + \mathbf{n}(t)$$

$$\boxed{\mathbf{a}(\theta_1) + \mathbf{a}(\theta_2) \neq \alpha \cdot \mathbf{a}(\theta), \ \forall \ \alpha, \theta}$$

Signals Suppressed as Interference

$$\boxed{\begin{aligned} &\min_{\mathbf{w}} P(\mathbf{w}) = \mathbf{w}^H \mathbf{R} \mathbf{w} \\ &\text{s.t.} \ \ \mathbf{w}^H \mathbf{a}(\theta) = 1 \end{aligned}}$$

- **Fails for sparse arrays with a single snapshot since spatial smoothing not possible.**

Iterative Adaptive Arrays: 2010 -

Jian Li

Member of European Academy of Sciences (Brussels)

- In 2010, Li et al. published the ***Iterative*** Adaptive Approach (IAA).
- IAA overcomes all of the limitations suffered by the Capon family of adaptive arrays.
- IAA retains the merits the Capon beamformer, including super resolution and excellent interference rejection capabilities.
- IAA has been used widely in practical applications.

T. Yardibi, J. Li, P. Stoica, M. Xue, and A.B. Baggeroer. "Source localization and sensing: A nonparametric iterative adaptive approach based on weighted least squares." *IEEE Transactions on Aerospace and Electronic Systems.*, vol. 46, no. 1, pp. 425-443, 2010.

W. Roberts, P. Stoica, J. Li, Tarik Yardibi, and Firooz A. Sadjadi. "Iterative adaptive approaches to MIMO radar imaging." *IEEE Journal of Selected Topics in Signal Processing*, vol. 4, no. 1, pp. 5-20, 2010.

J. Li, X. Zhu, P. Stoica and M. Rangaswamy, "High Resolution Angle-Doppler Imaging for MTI Radar," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 46, no. 3, pp. 1544-1556, 2010.

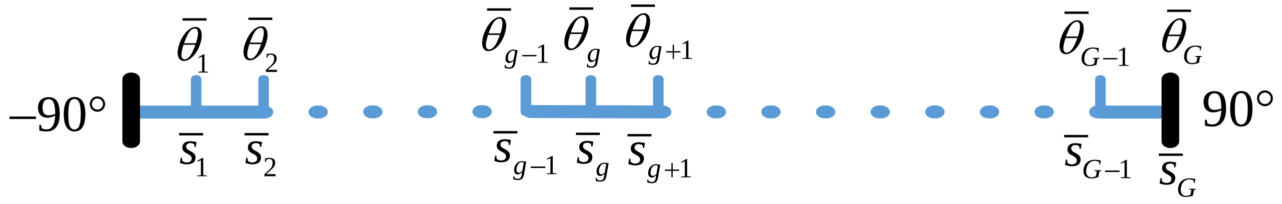
M. Xue, L. Xu and J. Li, "IAA Spectral Estimation: Fast Implementation Using the Gohberg–Semencul Factorization," *IEEE Transactions on Signal Processing*, vol. 59, no. 7, pp. 3251-3261, July 2011.

J. Karlsson, W. Rowe, L. Xu, G. Glentis and J. Li, "Fast missing-data IAA with application to notched spectrum SAR," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 50, no. 2, pp. 959-971, April 2014.

Iterative Adaptive Approach (IAA)

- Single Snapshot Example

Angle Grid $\bar{\boldsymbol{\theta}} = \left[\bar{\theta}_1, \cdots, \bar{\theta}_G\right]$



Grid size 5 to 10 times finer than Raleigh Resolution

Received Signal: $\mathbf{x} = \sum_g \mathbf{a}\left(\bar{\theta}_g\right)\bar{s}_g + \bar{\mathbf{n}} = \bar{\mathbf{A}}\left(\bar{\boldsymbol{\theta}}\right)\bar{\mathbf{s}} + \bar{\mathbf{n}}$

$$\bar{\mathbf{A}}\left(\bar{\boldsymbol{\theta}}\right) = \left[\mathbf{a}\left(\bar{\theta}_1\right), \cdots, \mathbf{a}\left(\bar{\theta}_G\right)\right] \quad \bar{\mathbf{s}} = \left[\bar{s}_1, \cdots, \bar{s}_G\right]^T$$

"Covariance Matrix": $\boxed{\tilde{\mathbf{R}} = \sum_g p_g \mathbf{a}\left(\bar{\theta}_g\right)\mathbf{a}^H\left(\bar{\theta}_g\right) = \bar{\mathbf{A}}\left(\boldsymbol{\theta}\right)\mathbf{P}\bar{\mathbf{A}}^H\left(\boldsymbol{\theta}\right)}$

$$\mathbf{P} = \mathrm{diag}\left\{p_1, \cdots, p_G\right\} \qquad p_g = \left|\bar{s}_g\right|^2$$

- Iteration initiated by DBF
- Usually converges in 10 iterations

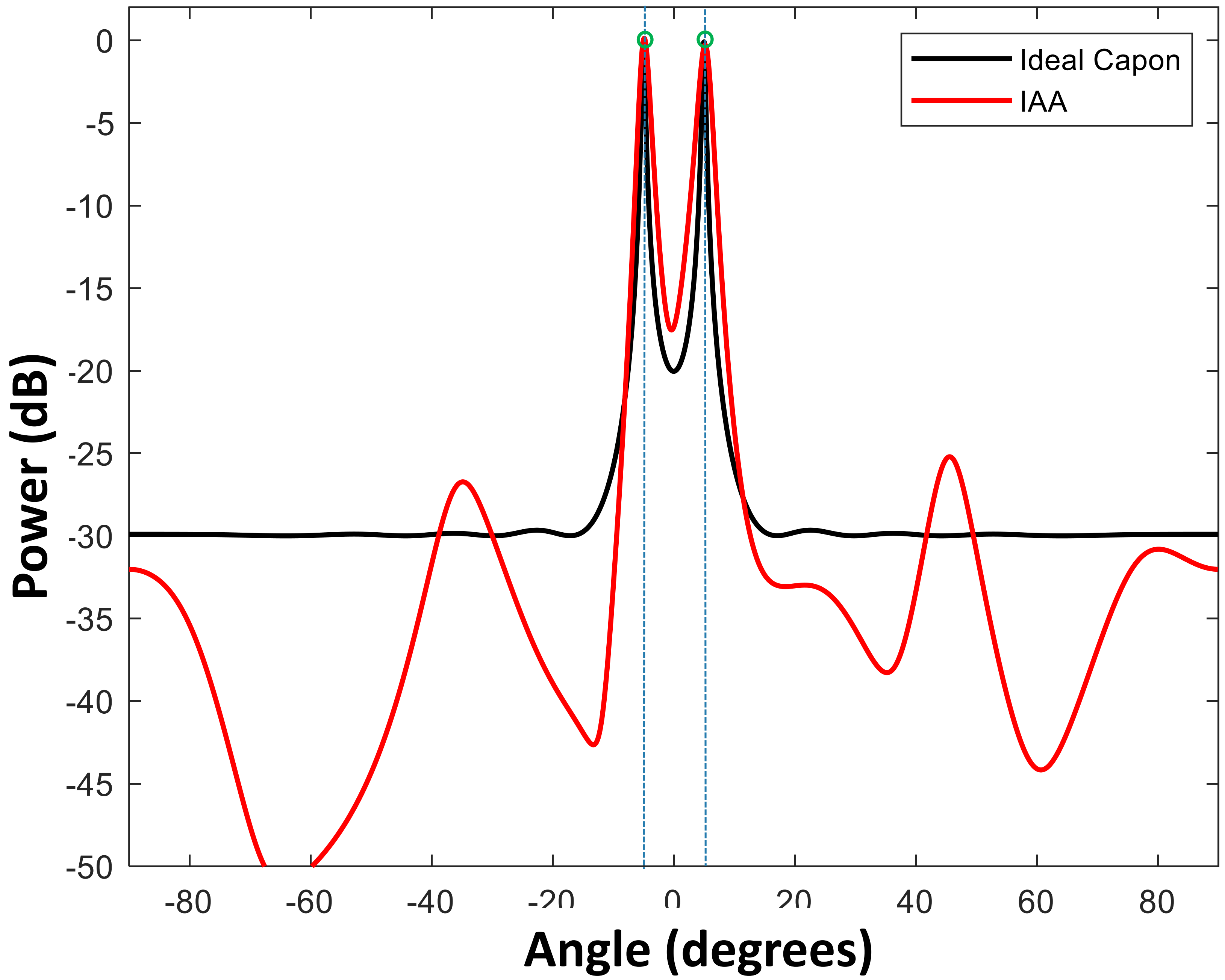
ith Iteration

$$\hat{\bar{s}}_g^{\,i-1} = \frac{\mathbf{a}^H\left(\bar{\theta}_g\right)\tilde{\mathbf{R}}^{i^{-1}}\mathbf{x}}{\mathbf{a}^H\left(\bar{\theta}_g\right)\tilde{\mathbf{R}}^{i^{-1}}\mathbf{a}\left(\bar{\theta}_g\right)}$$

$$\hat{p}_g^{\,i-1} = \left|\hat{\bar{s}}_g^{\,i-1}\right|^2 \Rightarrow \tilde{\mathbf{R}}^i = \bar{\mathbf{A}}\left(\boldsymbol{\theta}\right)\hat{\mathbf{P}}^{i-1}\bar{\mathbf{A}}^H\left(\boldsymbol{\theta}\right)$$

Single Snapshot IAA vs. Ideal Capon

ULA : L=10   SNR=20dB, Single Snapshot for IAA

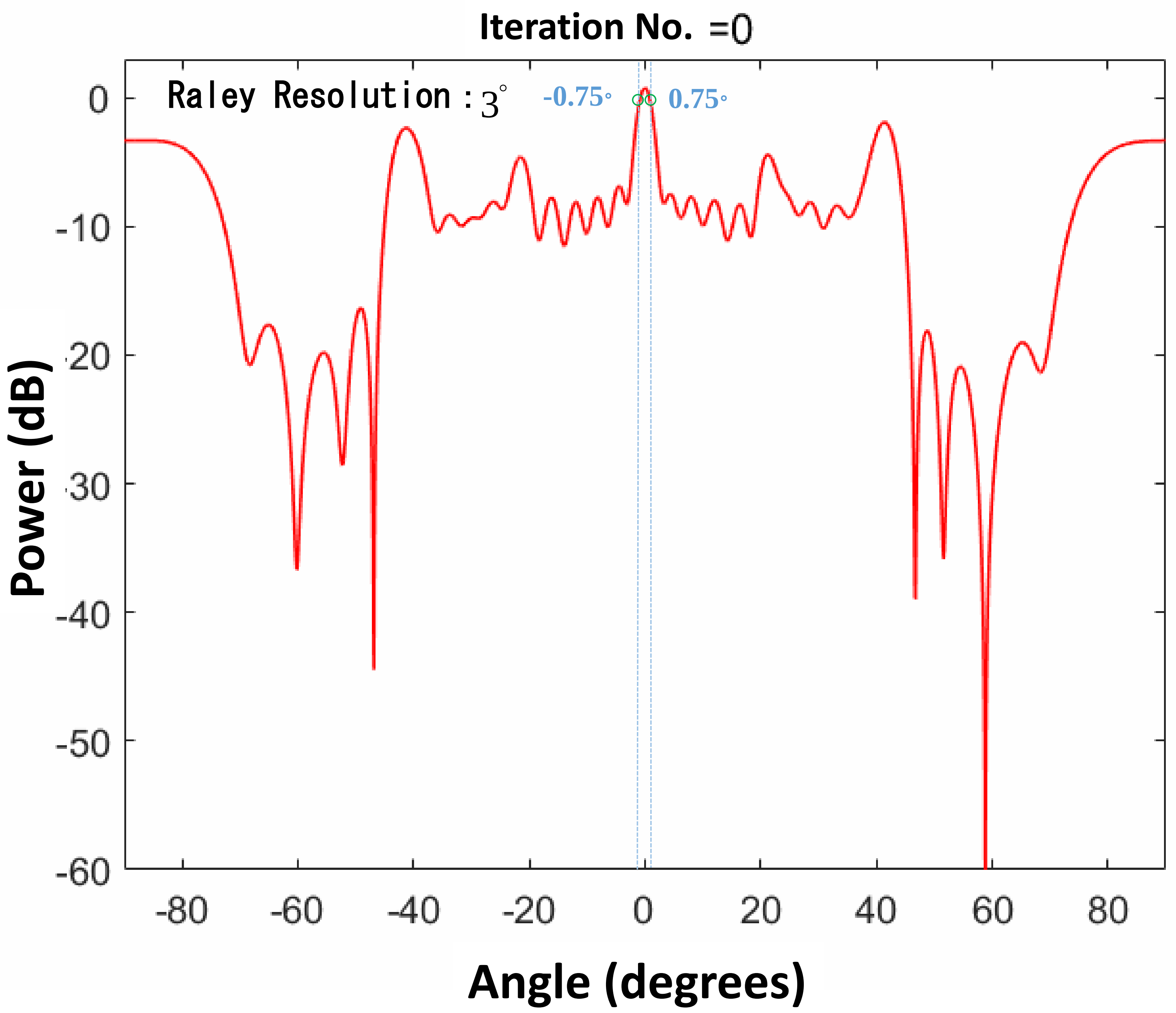


- **Ideal Capon:**
  - **Infinite Snapshot**
  - **Uncorrelated Signals**
  - **No Array Calibration Error**

✓**The Single Snapshot IAA Spatial Power Spectrum Is Similar to the Ideal Capon Spectrum.**

IAA Works When Capon Fails

Minimum Redundant Array：L=10 (17.5λ), SNR=20dB



- **Due to Sparse Array, DBF Sidelobe Level Very High.**
- **DBF Unable to Resolve the Two Signals**

✓**The Single Snapshot IAA Offers Super Resolution and Significantly Reduced Sidelobe Level.**

Weighted SPICE Framework

Petre Stoica

- International Member of the US Academy of Engineering
- Royal Swedish Academy of Engineering

- The Weighted SPICE Framework Includes IAA, SPICE, SLIM, LIKES, All of Which Are Iterative Adaptive Approaches.
- All of the Approaches Are Hyper-Parameter Free.
- IAA Is Most Likely the Most Robust In Practical Applications.

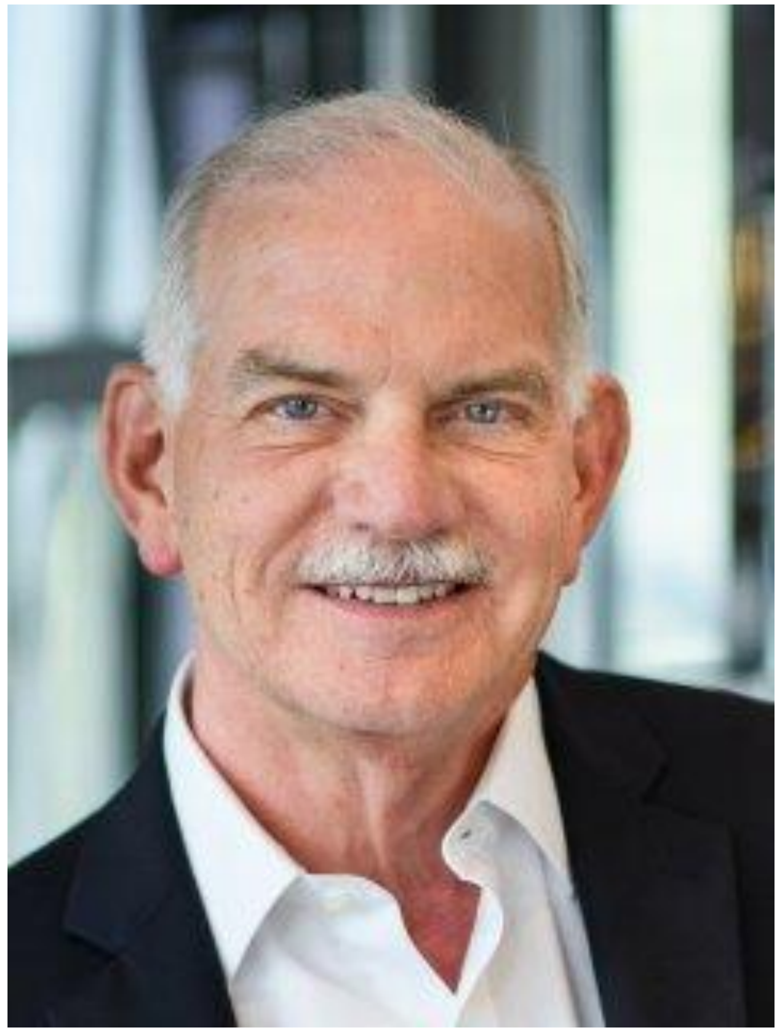
P. Stoica, P. Babu, and J. Li, "New method of sparse parameter estimation in separable models and its use for spectral analysis of irregularly sampled data," in IEEE Transactions on Signal Processing, vol. 59, no. 1, pp. 35–47, 2010.

X. Tan, W. Roberts, J. Li, and P. Stoica, "Sparse learning via iterative minimization with application to MIMO radar imaging," in IEEE Transactions on Signal Processing, vol. 59 no. 3, pp. 1088–1101, 2011.

P. Stoica and P. Babu, "SPICE and LIKES: Two hyperparameter-free methods for sparse-parameter estimation," in Signal Processing, vol. 92, no. 7, pp. 1580–1590, 2012.

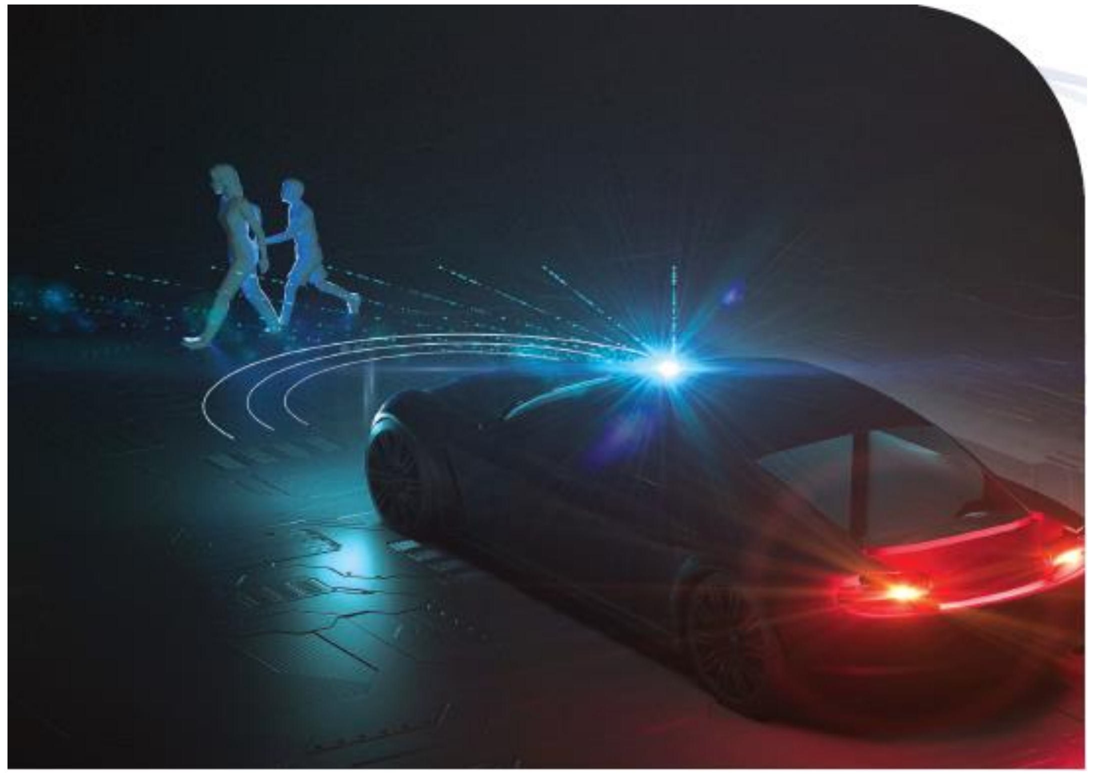
P. Stoica, D. Zachariah, and J. Li, "Weighted SPICE: A unifying approach for hyperparameter-free sparse estimation," in Digital Signal Processing, vol. 33, pp. 1–12, 2014.

IAA for Automotive Radar Angle Estimation



H. Vincent Poor

- Member of the US Academy of Engineering
- Member of the US Academy of Science



- This 2020 paper compared IAA with other algorithms for angle estimation in automotive radar.
- Attaining the desired 1 degree azimuth resolution a current challenge.

S. Sun, A.P. Petropulu and H.V. Poor, "MIMO Radar for Advanced Driver-Assistance Systems and Autonomous Driving: Advantages and Challenges," IEEE Signal Processing Magazine, vol. 37, no. 4, pp. 98-117, 2020

IAA vs. DBF

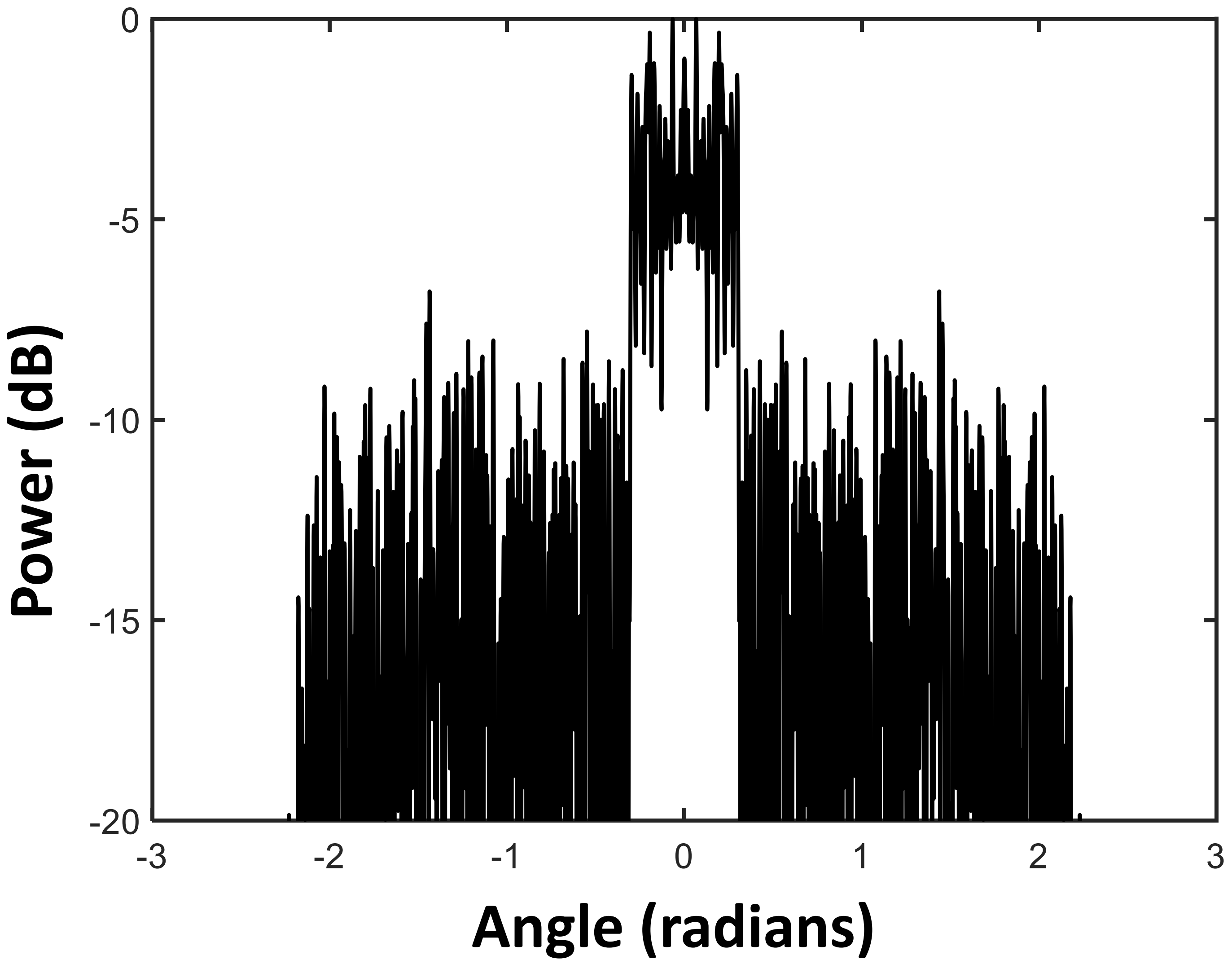
Table 1. The different DoA estimation algorithms in automotive radar scenarios.

Algorithm	Resolution	Snapshot	Array	Grid-Free	Rank Estimation	Robustness
DBF	Low	Single	ULA/SLA	No	No	Strong
MUSIC	High	Multiple	ULA	No	Yes	Medium
ESPRIT	High	Multiple	ULA	Yes	Yes	Medium
OMP	High	Single	ULA/SLA	No	No	Medium
IAA	High	Single	ULA/SLA	No	No	Strong

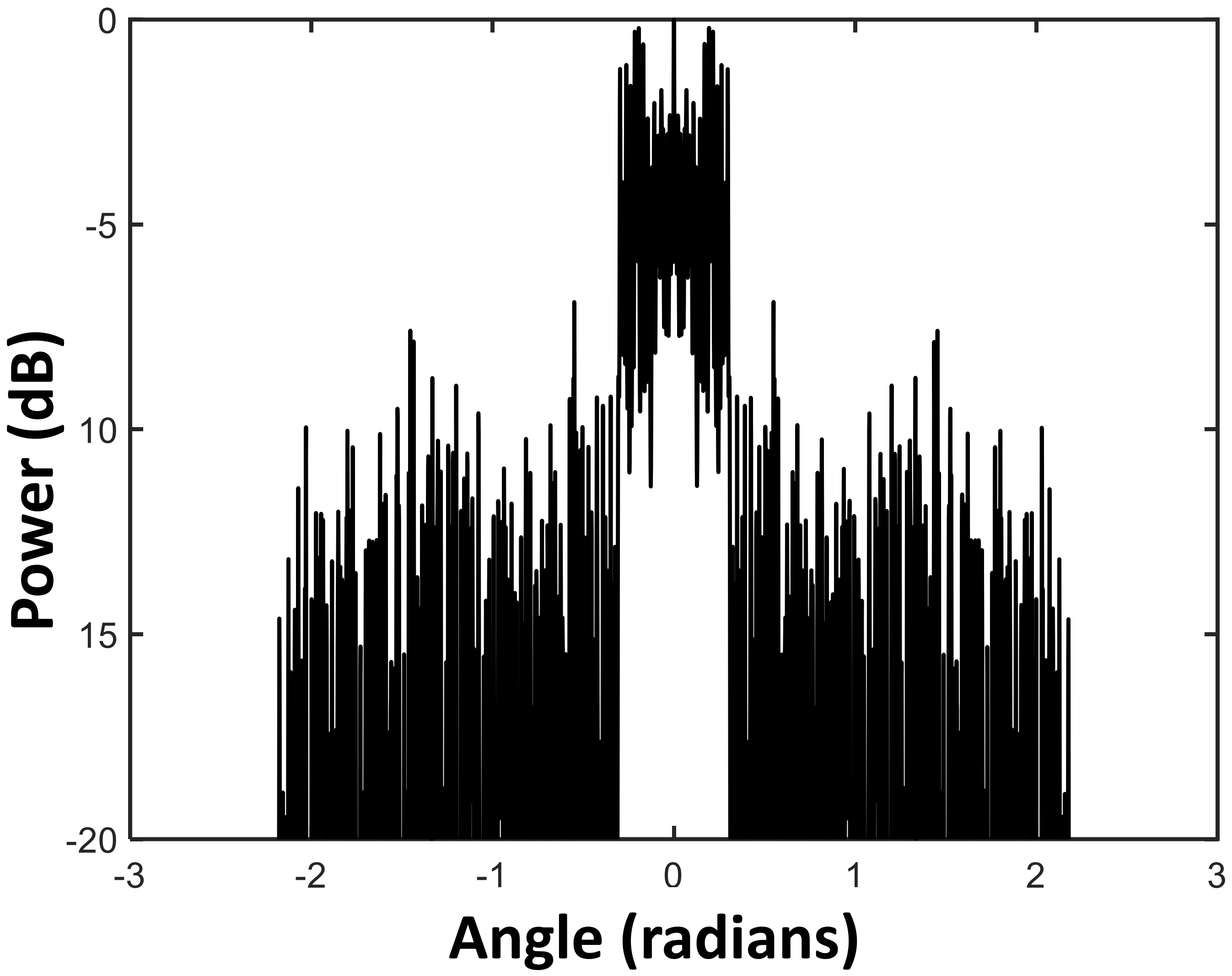
✓IAA Is the Only High Resolution Algorithm with Strong Robustness.

S. Sun, A.P. Petropulu and H.V. Poor, "MIMO Radar for Advanced Driver-Assistance Systems and Autonomous Driving: Advantages and Challenges," IEEE Signal Processing Magazine, vol. 37, no. 4, pp. 98-117, 2020

IAA vs. DBF (Distributed Source)



DBF



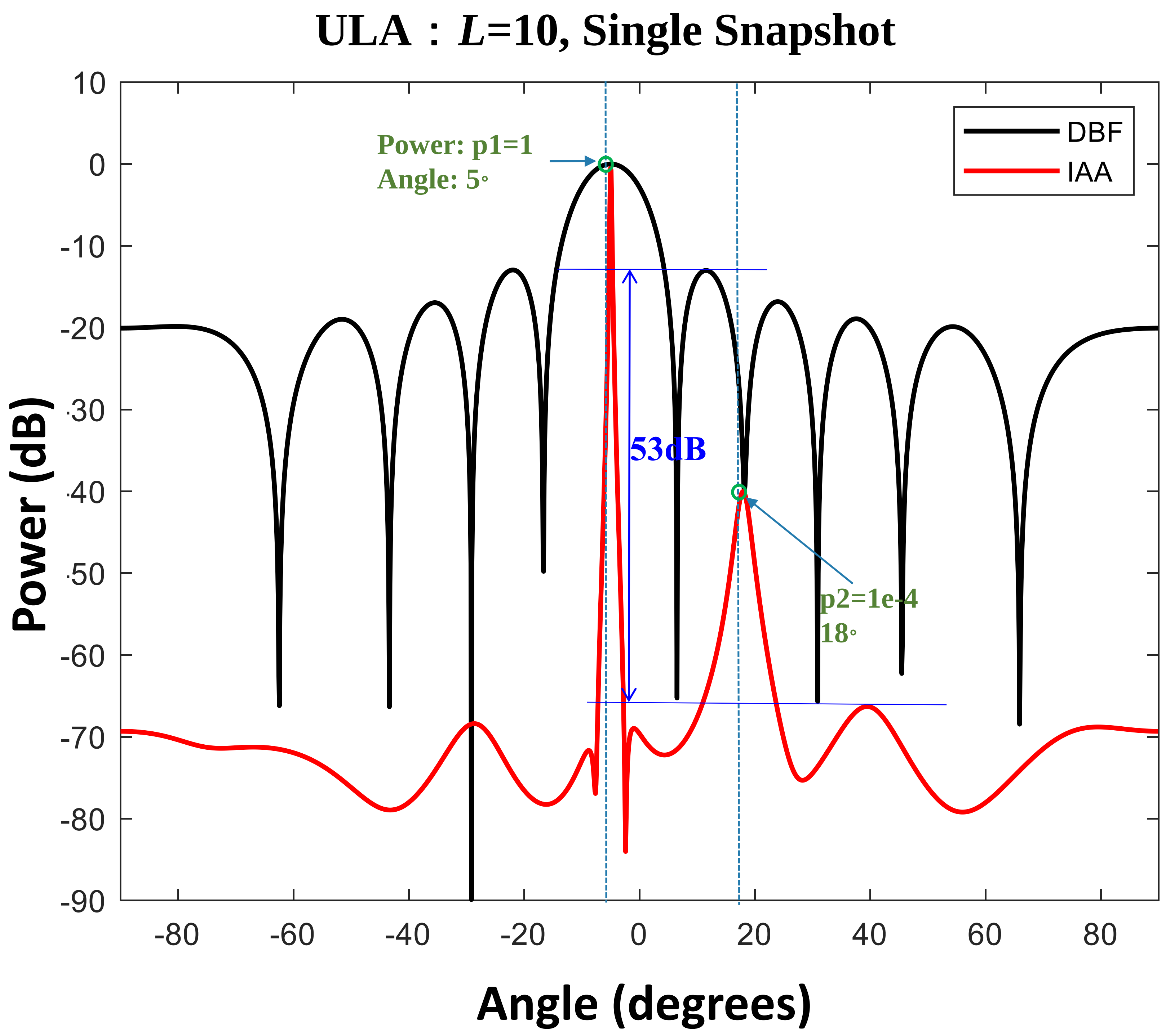
IAA

- **Sinc Signal (Pulsed Spectrum)**
- **Colored Noise**
- **SNR=1dB**

✓ **IAA and DBF Share Strong Robustness.**

IAA vs. DBF

	IAA	DBF
Sidelobe Level	Low	High
Weak Target Detection Capability	Strong	Weak
Interference Rejection Capability	Strong	Weak



✓ IAA Outperforms DBF Significantly
with Better Resolution and Much Lower Sidelobes
so that Weak Sources can be Revealed.

IAA vs. Parametric Algorithms

Table 1. The different DoA estimation algorithms in automotive radar scenarios.

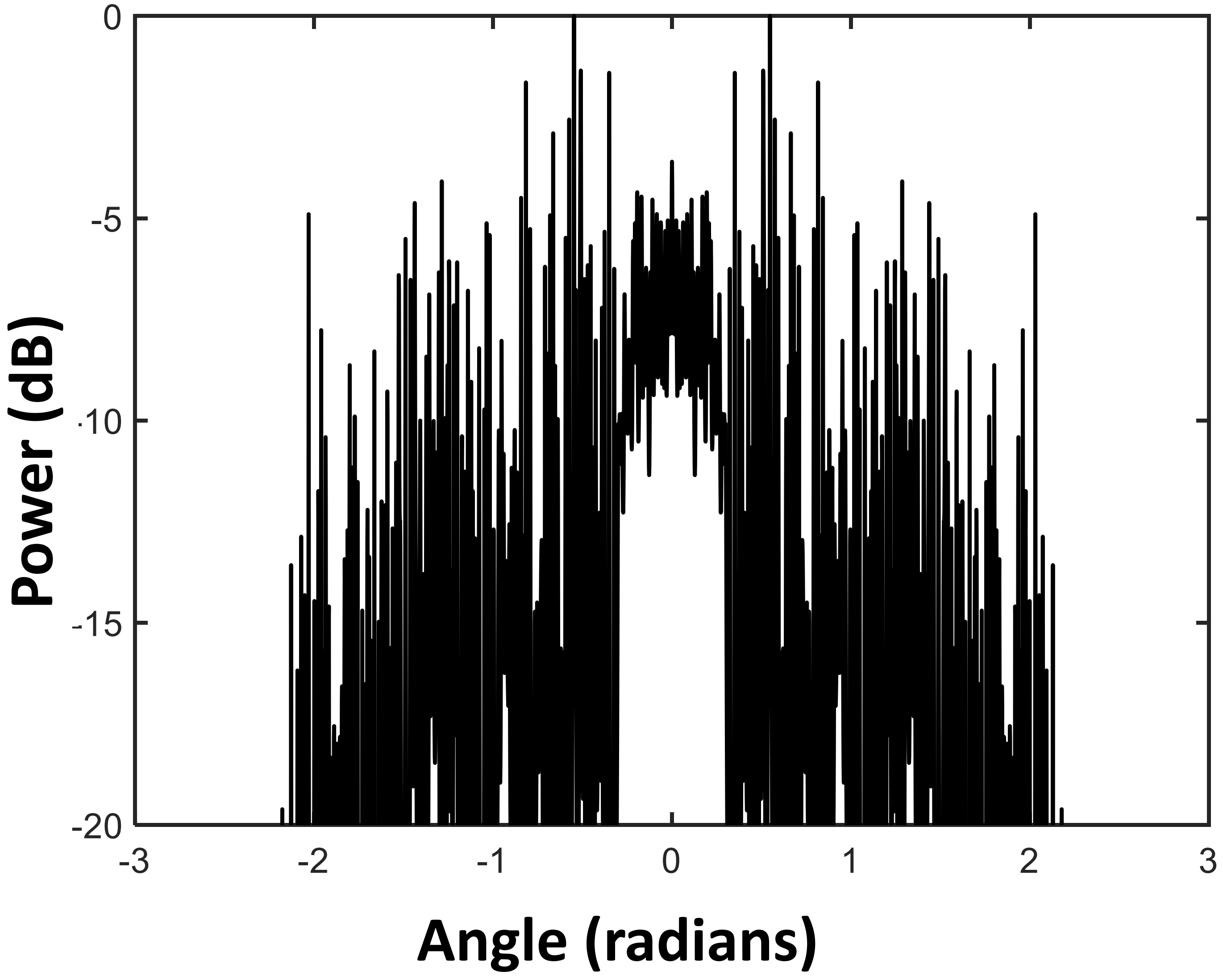
Algorithm	Resolution	Snapshot	Array	Grid-Free	Rank Estimation	Robustness
DBF	Low	Single	ULA/SLA	No	No	Strong
MUSIC	High	Multiple	ULA	No	Yes	Medium
ESPRIT	High	Multiple	ULA	Yes	Yes	Medium
OMP	High	Single	ULA/SLA	No	No	Medium
IAA	High	Single	ULA/SLA	No	No	Strong

- ✓ IAA Works for Single Snapshot and Sparse Arrays, but not MUSIC and ESPRIT.
- ✓ IAA Is User-Parameter Free – Easy to Use in Practice.

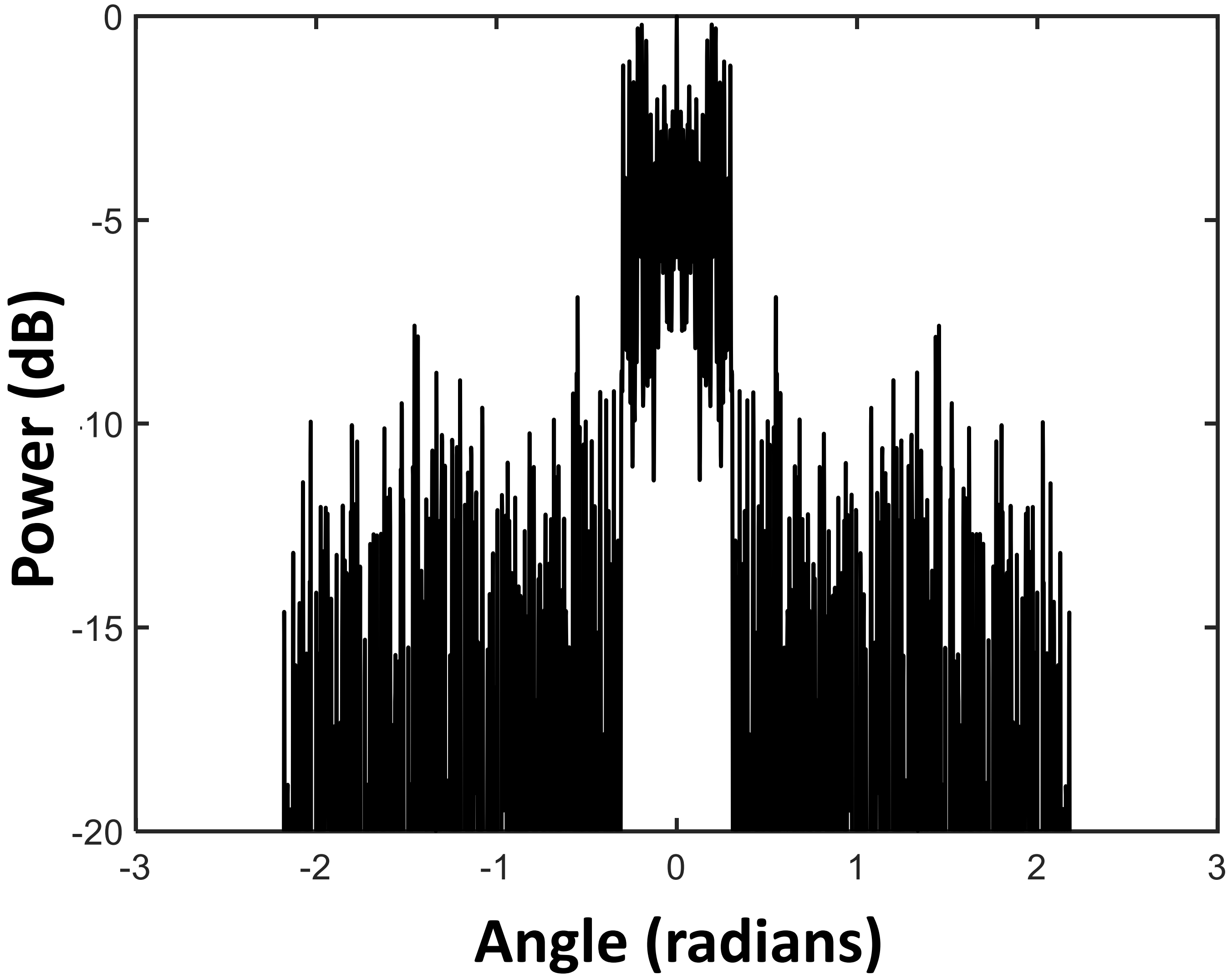
S. Sun, A.P. Petropulu and H.V. Poor, "MIMO Radar for Advanced Driver-Assistance Systems and Autonomous Driving: Advantages and Challenges," IEEE Signal Processing Magazine, vol. 37, no. 4, pp. 98-117, 2020

IAA vs. Parametric Algorithms

Sinc Signal, Colored Noise, SNR = 1dB



MUSIC



IAA

✓ **IAA More Robust and User-Parameter Free.**

IAA vs. Parametric Algorithms

	IAA	Parametric Methods
Signal Model	Not Needed	Needed
Noise Distribution	Not Needed	Needed

- ✓ IAA More Robust and Easier to Use in Practice.
- ✓ MUSIC and ESPRIT Are Not Applicable to Single-Snapshot and Sparse Array Scenarios.
- ✓ MUSIC and ESPRIT Need Parameters such as Subspace Dimensions and Noise Covariance Matrices.

IAA vs. Compressed Sensing Algorithms

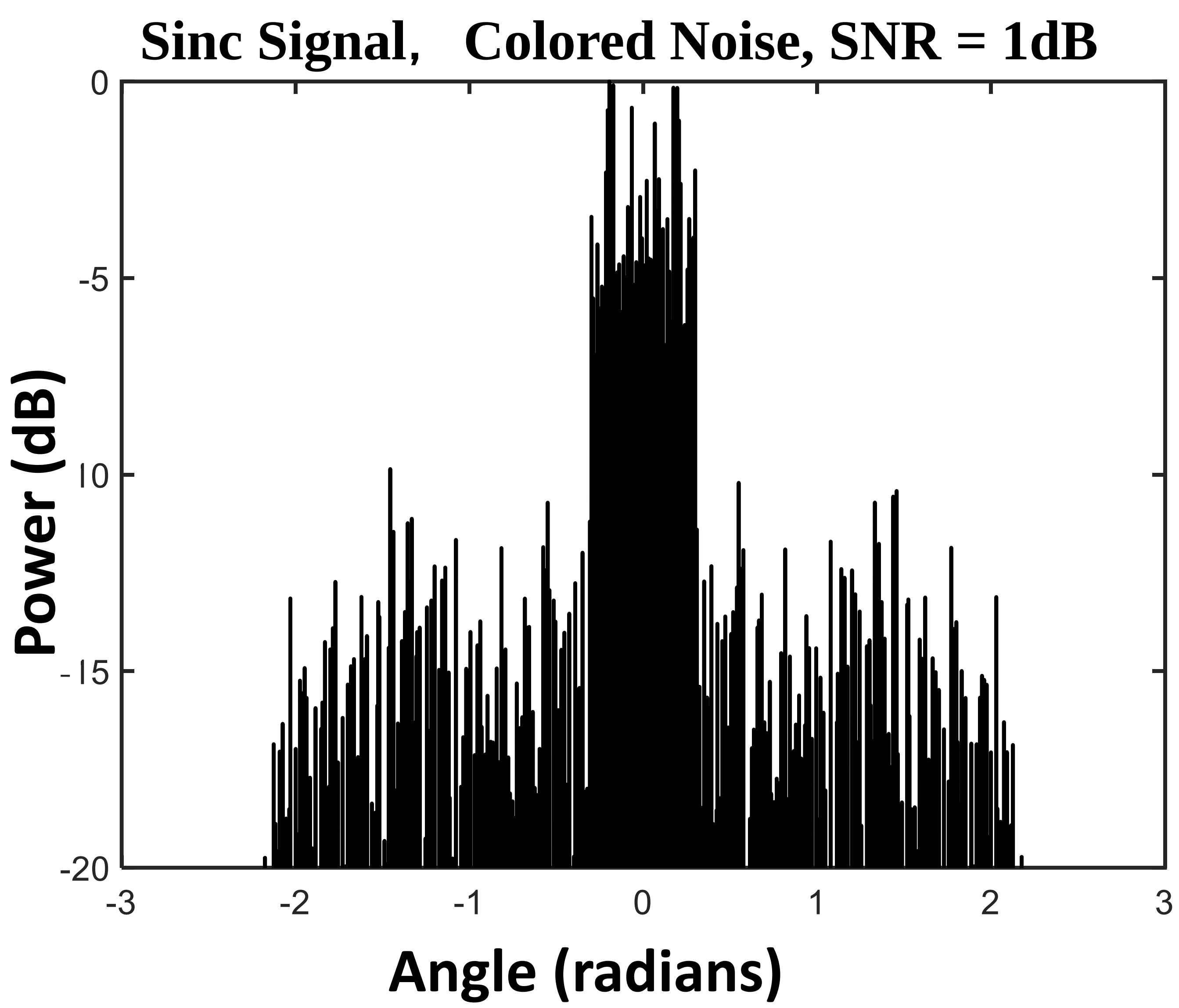
Table 1. The different DoA estimation algorithms in automotive radar scenarios.

Algorithm	Resolution	Snapshot	Array	Grid-Free	Rank Estimation	Robustness
DBF	Low	Single	ULA/SLA	No	No	Strong
MUSIC	High	Multiple	ULA	No	Yes	Medium
ESPRIT	High	Multiple	ULA	Yes	Yes	Medium
OMP	High	Single	ULA/SLA	No	No	Medium
IAA	High	Single	ULA/SLA	No	No	Strong

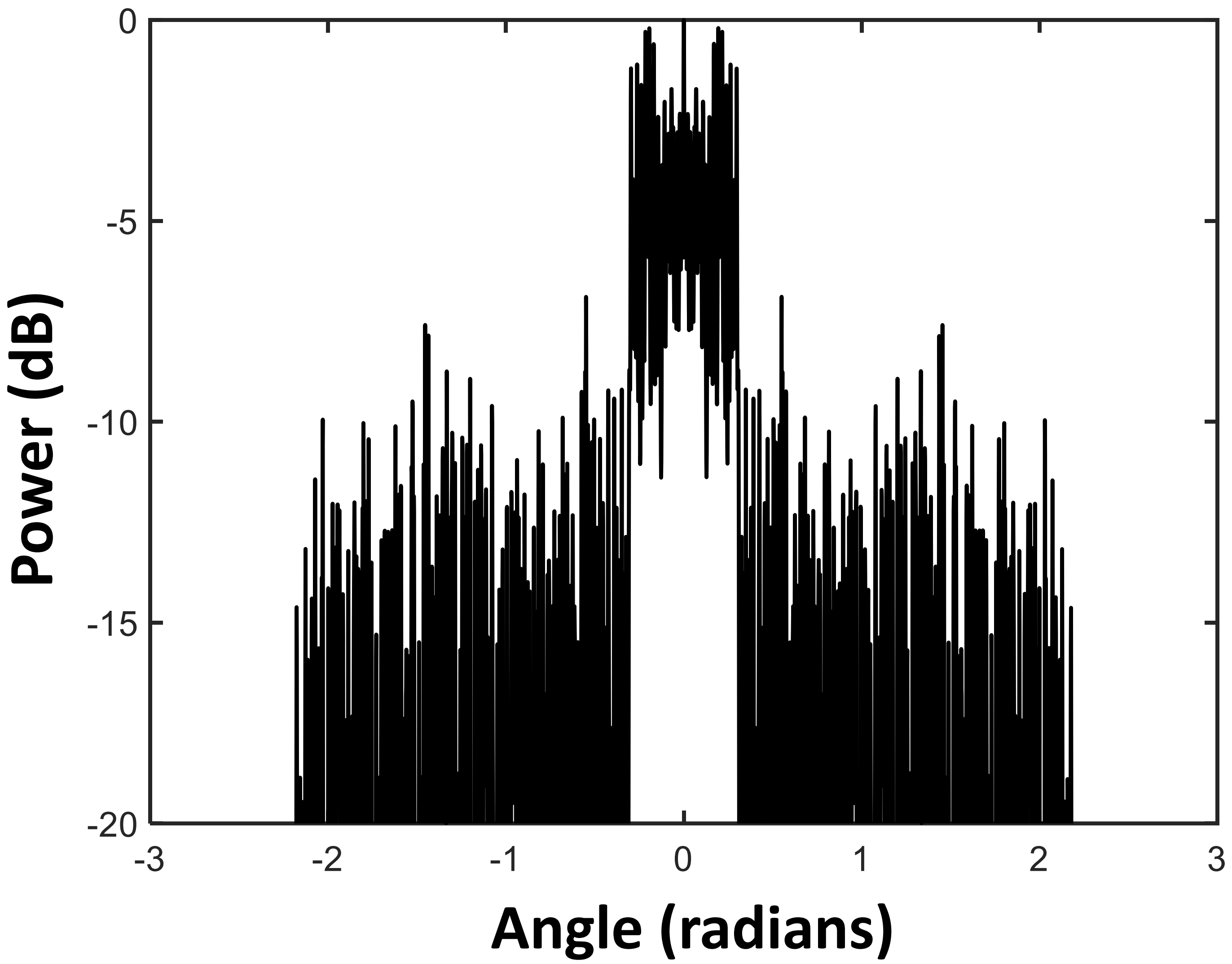
- ✓ **IAA Has Strong Robustness.**
- ✓ **IAA Is User-Parameter Free – Easy to Use in Practice.**
- ✓ **IAA Does Not Require Sparse Spectra.**
- ✓ **IAA Does Not Require Source Incident Angles on Grid.**

S. Sun, A.P. Petropulu and H.V. Poor, "MIMO Radar for Advanced Driver-Assistance Systems and Autonomous Driving: Advantages and Challenges," IEEE Signal Processing Magazine, vol. 37, no. 4, pp. 98-117, 2020

IAA vs. Compressed Sensing Algorithms



OMP



IAA

- ✓ IAA Has Strong Robustness.
- ✓ IAA Is User-Parameter Free – Easy to Use in Practice.
- ✓ IAA Does Not Require Sparse Spectra.
- ✓ IAA Does Not Require Source Incident Angles on Grid.

IAA vs. Compressed Sensing Algorithms

	IAA	Compressed Sensing Algorithms
User Parameter	Not Needed	Hard to Choose, Performance Sensitive to Choice
Sparsity	Not Needed	Needed

- ✓ IAA Has Strong Robustness.
- ✓ IAA Is User-Parameter Free – Easy to Use in Practice.
- ✓ IAA Does Not Require Sparse Spectra.
- ✓ IAA Does Not Require Source Incident Angles on Grid.

Intel Patent (Formerly Mobileye), Autonomous Driving

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(43) **Pub. Date: Apr. 30, 2020**

(54) **BEAMFORMING TECHNIQUES IMPLEMENTING THE ITERATIVE ADAPTIVE APPROACH (IAA)**

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G01S 7/03	(2006.01)

(52) **U.S. Cl.**

CPC ***H01Q 3/2694*** (2013.01); ***G01S 7/03*** (2013.01); ***H01Q 21/22*** (2013.01)

(57) **ABSTRACT**

Techniques are disclosed implementing two alternative approaches for adaptive beamforming for MIMO radar. The first of these includes a “reduced complexity” iterative adaptive approach (RC-IAA) algorithm, which uses two steps including a delay-and-sum beamforming step (DAS-BF) and an IAA step that is applied to the output generated by the DAS-BF step. A second technique is described that includes a “beam space” iterative adaptive approach (BS-IAA) algorithm, which uses three steps including a delay-and-sum beamforming step (DAS-BF), a region of interest (ROI) detection step that is applied to the output generated by the DAS-BF, and an IAA step that is applied to detected ROIs.

- 10 to 12 Automotive Radar per Vehicle (MIMO Radar is the Standard).
- 6-D Radar Imaging Possible.
- 1 Degree Spatial Resolution Desired but Challenging.
- Real-Time Implementation Challenging.

DARPA BLiP Program

Beyond Linear Processing (BLiP)

BAA: https://sam.gov/opp/818c44d90f884834bf01e2e1382956ac/view
Slides: https://www.darpa.mil/attachments/ProposersDayfinal%20releasedupdated20221110.pdf
FAQs: https://www.darpa.mil/attachments/20221109BLiPFAQ.pdf
Proposal deadline is December 21, 2022.

"BLiP is organized as an applied research program, intended to perform studies, design, development, and prototyping that will improve radar performance through the application of signal processing techniques that go beyond current linear processing methods. The BLiP program is directed toward general radar needs with a view to demonstrating feasibility and practicality of non-linear and iterative signal processing."

Thank You!