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A Massive MIMO Detection Strategy Towards Cognitive Radar

Fulvio Gini

Dipartimento di Ingegneria dell'Informazione
University of Pisa, Pisa, Italy
fulvio.gini@unipi.it

Motivations

- We know that **6G systems** will enable novel **sensing** applications within the smart cities paradigm, including, for example, intelligent vehicular networks, robot and drone tracking, enhanced emergency call localization, personal radar, and location-aware communications.
- A key feature enabled by **6G systems** is the integration of sensing and communication capabilities, known as **Integrated Sensing and Communication (ISAC)**.
- <u>6G systems provide the ideal framework to realize ISAC</u>. Thanks to the high frequencies and large bandwidths available in the millimeter-wave (mmWave) and sub-Terahertz (THz) bands, they can simultaneously: **(1)** Increase user data rates from the **communication perspective**, and **(2)** Improve range and Doppler resolution from the **sensing perspective**.
- **<u>Massive MIMO (MMIMO) systems</u>** will play a fundamental role, establishing a strong link between the ISAC objective and the Massive MIMO paradigm!

Motivations

- From a communication perspective, **Massive MIMO** systems offer significant advantages in terms of spectral efficiency, which increases monotonically with the number of antennas.
- Moreover, it has been shown that **Massive MIMO** systems can effectively mitigate spatial interference in wireless communications, even in the presence of imperfect channel state information (CSI).

> **Fundamental question: What are the potential benefits that the Massive MIMO paradigm can bring from the sensing perspective?**

- In this talk, we try to answer this question.
- We focus on the **radar target detection problem**.

[4] S. Fortunati, F. Lisi, A. M. I. Ahmed, A. Sezgin, M. S. Greco, and F. Gini, "Fundamental limits for ISAC - Asymptotics in **Massive MIMO Sensing** Systems", Chapter 5 of book *Integrated Sensing and Communications* (ISAC), Fan Liu, Christos Masouros, Yonina C. Eldar Editors, Springer, 2023.

Motivations

- The results described in this talk represents the first building block of a reinforcement learning-based dual-functional massive MIMO system for multi-target detection and communications.

Massive MIMO (MMIMO) radar

[1] S. Fortunati, L. Sanguinetti, F. Gini, M. S. Greco and B. Himed, "**Massive MIMO Radar** for Target Detection", *IEEE Trans. on Signal Processing*, vol. 68, pp. 859-871, January 2020.

RL-based cognitive MMIMO radar

[2] A. M. Ahmed, A. A. Ahmad, S. Fortunati, A. Sezgin, M. S. Greco and F. Gini, "A **Reinforcement Learning** Based Approach for Multitarget Detection in **Massive MIMO Radar**," *IEEE Trans. on Aerospace and Electronic Systems*, vol. 57, no. 5, pp. 2622-2636, Oct. 2021.

[3] F. Lisi, S. Fortunati, M. S. Greco, F. Gini, "Enhancement of a State-of-the-Art **RL-Based** Detection Algorithm for **Massive MIMO Radars**," *IEEE Trans. on Aerospace and Electronic Systems*, Vol. 50, No. 6, 2022.

[4] S. Fortunati, F. Lisi, A. M. I. Ahmed, A. Sezgin, M. S. Greco, and F. Gini, "Fundamental limits for ISAC - Asymptotics in **Massive MIMO Sensing** Systems", Chapter 5 of book *Integrated Sensing and Communications* (ISAC), Fan Liu, Christos Masouros, Yonina C. Eldar Editors, Springer, 2023.

[5] A. Umra, A. M. I. Ahmed, A. Sezgin, M. S. Greco, and F. Gini, "**Reinforcement learning** for intelligent radar target detection", Chapter 4 of book *Machine Learning for Radar Signal Processing,* IEEE-Wiley Press Book, 2026 (to be published).

[6] W. Zhai, X. Wang, M.S. Greco, F. Gini, "Weak Target Detection in **Massive MIMO Radar** via an Improved **Reinforcement Learning** Approach", *2022 IEEE International Conference on Acoustics, Speech and Signal Processing* (ICASSP), May 22-27, Singapore, 2022.

ISAC where the sensing is performed by a RL-based cognitive MMIMO radar

[7] W. Zhai, X. Wang, X. Cao, M. S. Greco, and F. Gini, "**Reinforcement Learning** based Dual-Functional **Massive MIMO** Systems for Multi-target Detection and Communications," *IEEE Transactions on Signal Processing*. Vol. 71, pp. 741-755, 2023.

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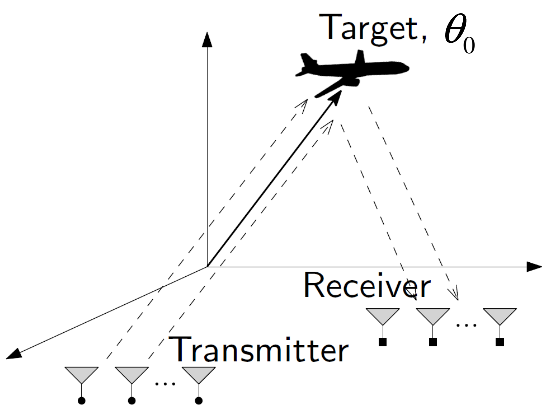
Signal model

- Consider a **colocated MIMO radar** system with *N* spatial DoF:
- N_T transmitting antennas
- N_R receiving antennas
- $N = N_T N_R$ virtual spatial channels



- The complex envelope signal at the receiving array generated by a point-like target with Direction of Arrival (DOA) θ_0 can be modelled as:

$$\mathbf{y}(t) = \alpha \mathbf{a}_R(\theta_0)\mathbf{a}_T^T(\theta_0)\mathbf{s}(t-\tau_0)e^{j2\pi f_D t} + \mathbf{d}(t), \qquad t \in [0,T]$$

$\mathbf{y}(t) \in \mathbb{C}^{N_R}$ receiving array output vector

$\mathbf{s}(t) \in \mathbb{C}^{N_T}$ transmitted signals vector

$\mathbf{d}(t) \in \mathbb{C}^{N_R}$ disturbance (clutter + white noise) vector at the receiver

Signal model

$$\mathbf{y}(t) = \alpha \mathbf{a}_R(\theta_0)\mathbf{a}_T^T(\theta_0)\mathbf{s}(t-\tau_0)e^{j2\pi f_D t} + \mathbf{d}(t), \qquad t \in [0, T]$$

$\alpha \in \mathbb{C}$ accounts for the two–way path loss and the target RCS

$\theta_0, \tau_0, f_D \in \mathbb{R}$ target DOA, Delay, and Doppler frequency

Uniform Linear Array (ULA)

$\mathbf{a}_R(\theta_0) = \begin{bmatrix} 1 & e^{j2\pi\nu} & \cdots & e^{j2\pi(N_R-1)\nu} \end{bmatrix}^T$ Receive steering vector

$\mathbf{a}_T(\theta_0) = \begin{bmatrix} 1 & e^{j2\pi\nu} & \cdots & e^{j2\pi(N_T-1)\nu} \end{bmatrix}^T$ Transmit steering vector

$\nu = \frac{d}{\lambda}\sin\theta_0$ target spatial frequency

$\frac{d}{\lambda} = \frac{1}{2}$ Standard ULA

Signal model

$$\mathbf{y}(t) = \alpha \mathbf{a}_R(\theta_0)\mathbf{a}_T^T(\theta_0)\mathbf{s}(t-\tau_0)e^{j2\pi f_D t} + \mathbf{d}(t), \qquad t \in [0,T]$$

- The transmitted signals vector can be expressed as:

$$\mathbf{s}(t) = \mathbf{W}\boldsymbol{\Phi}(t) \quad \in \mathbb{C}^{N_T}$$

$\mathbf{W} \in \mathbb{C}^{N_T \times N_T}$ weighting matrix (it shapes the transmit beampattern)

$\boldsymbol{\Phi}(t) \in \mathbb{C}^{N_T}$ vector of quasi–orthonormal transmitted waveforms

$$\int_0^T \Phi_i(t-\tau_0)\Phi_j^*(t-\tau)dt \cong \delta[i-j] \quad \forall \tau_0, \tau$$

[this stringent requirement will be removed later on].

Signal model

$$\mathbf{y}(t)=\alpha\mathbf{a}_R\left(\theta_0\right)\mathbf{a}_T^T\left(\theta_0\right)\mathbf{s}(t-\tau_0)e^{j2\pi f_D t}+\mathbf{d}(t), \qquad t\in[0,T]$$

- At the receiver the signal is processed: bank of Doppler matched filters (spaced in frequency by Δf) followed by sampling in fast-time with sampling interval Δt.
- The 2D range-Doppler samples are:

$$\begin{aligned}\mathbf{Y}(n,k)&=\int_0^T\mathbf{y}(t)\mathbf{\Phi}^H(t-n\Delta t)e^{-j2\pi k\Delta f t}dt\\&=\quad\cdots\\&=\alpha\mathbf{a}_R\left(\theta_0\right)\mathbf{a}_T^T\left(\theta_0\right)\mathbf{W}\mathbf{R}_{\Phi}(n,k)+\mathbf{D}(n,k)\end{aligned}$$

$$\mathbf{Y}(n,k)\in\mathbb{C}^{N_R\times N_T}, \quad n=1,\cdots,L_\tau, \quad k=1,\cdots,L_f$$

Signal model

$$\mathbf{Y}(n,k)=\alpha\mathbf{a}_R\left(\theta_0\right)\mathbf{a}_T^T\left(\theta_0\right)\mathbf{W}\mathbf{R}_\Phi(n,k)+\mathbf{D}(n,k)\quad\in\mathbb{C}^{N_R\times N_T}$$

- "Straddling loss" matrix:

$$\mathbf{R}_\Phi(n,k)=\int_0^T\mathbf{\Phi}(t-\tau_0)\mathbf{\Phi}^H(t-n\Delta t)e^{-j2\pi(k\Delta f-f_D)t}dt$$

- Disturbance matrix:

$$\mathbf{D}(n,k)=\int_0^T\mathbf{d}(t)\mathbf{\Phi}^H(t-n\Delta t)e^{-j2\pi k\Delta ft}dt$$

- The output matrix **Y**(*n*,*k*) can be expressed in vector notation:

$$\mathbf{y}(n,k)=vec\left(\mathbf{Y}(n,k)\right)=\alpha\mathbf{v}\left(n,k;\theta_0\right)+\mathbf{c}(n,k)\quad\in\mathbb{C}^N,\quad N=N_TN_R$$

Signal model

$$\mathbf{y}(n,k) = vec\left(\mathbf{Y}(n,k)\right) = \alpha\mathbf{v}\left(n,k;\theta_0\right) + \mathbf{c}(n,k) \quad \in \mathbb{C}^N, \quad N = N_T N_R$$

- where:

$$\mathbf{v}\left(n,k;\theta_0\right) = \left(\mathbf{R}_\Phi^T(n,k) \otimes \mathbf{I}_{N_R}\right)\left(\left(\mathbf{W}^T\mathbf{a}_T\left(\theta_0\right)\right) \otimes \mathbf{a}_R\left(\theta_0\right)\right)$$

$$\mathbf{c}(n,k) = vec\left(\mathbf{D}(n,k)\right)$$

- In radar terminology, the measurement vector **y**(*n,k*) is called *snapshot*.
- Usually, we transmit *K* pulses and we collect *K* snapshots for each range-Doppler resolution cell, i.e. each couple (*n,k*).
- If we assume that the disturbance **d**(*t*) is a zero mean w.s.s. process with covariance matrix:

$$E\left\{\mathbf{d}(t_1)\mathbf{d}^H(t_2)\right\} = \mathbf{\Sigma}(t_1 - t_2)$$

Signal model

$$\mathbf{y}(n,k) = vec\left(\mathbf{Y}(n,k)\right) = \alpha\mathbf{v}\left(n,k;\theta_0\right) + \mathbf{c}(n,k) \quad \in \mathbb{C}^N, \quad N = N_T N_R$$

Then:

$$\mathbf{m}(n,k) = E\left\{\mathbf{c}(n,k)\right\} = 0$$

$$\mathbf{\Gamma}(n,k) = E\left\{\mathbf{c}(n,k)\mathbf{c}^H(n,k)\right\}$$

$$= \int_0^T \int_0^T \left[\mathbf{\Phi}^*(t_1 - n\Delta t)\mathbf{\Phi}^T(t_2 - n\Delta t) \otimes \mathbf{\Sigma}(t_1 - t_2)\right] e^{-j2\pi k\Delta f(t_1 - t_2)} dt_1 dt_2$$

- If the disturbance samples are uncorrelated both in the temporal and spatial domains and the transmitted waveforms $\mathbf{\Phi}_i(t)$ are perfectly orthogonal:

$$E\left\{\mathbf{d}(t_1)\mathbf{d}^H(t_2)\right\} = \mathbf{\Sigma}(t_1 - t_2) = \sigma_d^2 \mathbf{I}_{N_R}\delta(t_1 - t_2) \quad \Rightarrow \quad \mathbf{\Gamma}(n,k) = \sigma_d^2 \mathbf{I}_N$$

- <u>This is a simple but rather unrealistic model!</u>

Signal model

- If we neglect the *straddling losses*, i.e. we assume that there exist n_0 and k_0 such that:

$$\tau_0 = n_0 \Delta t, \quad f_D = k_0 \Delta f$$

- the *snapshot* from the (n_0,k_0) range-Doppler resolution cell, where the target is present, becomes:

$$\mathbf{y}(n_0,k_0) = \alpha \mathbf{v}\left(n_0,k_0;\theta_0\right) + \mathbf{c}(n_0,k_0) \equiv \alpha \mathbf{v}\left(\theta_0\right) + \mathbf{c} \quad \in \mathbb{C}^N$$

- where:

$$\mathbf{v} = \mathbf{v}\left(n_0,k_0;\theta_0\right) = \mathbf{W}^T \mathbf{a}_T\left(\theta_0\right) \otimes \mathbf{a}_R\left(\theta_0\right) \quad \in \mathbb{C}^N$$

[the Range-Doppler indices (n,k) will be omitted from now on].

Signal model

- To conclude with the signal model, it is worth recalling that the **transmit beampattern** of a **MIMO radar** is given by:

$$b(\theta) = \mathbf{a}_T^T(\theta)\mathbf{R}_W\mathbf{a}_T^*(\theta)$$

where: $\mathbf{R}_W = \mathbf{W}\mathbf{W}^H$ and $\mathbf{W}$ is the weighting matrix

Total transmitted power: $P_T = Tr\{\mathbf{R}_W\}$

- By choosing the weighting matrix **W**, and consequently the matrix $\mathbf{R}_W$, we can shape the transmit beampattern.
- Thus, the choice of the transmitted waveforms plays a crucial role in the design of a MIMO radar.

Signal model

- The two extreme cases are the following:

$$\mathbf{W} = \sqrt{\frac{P_T}{N_T}}\mathbf{I}_{N_T} \quad \rightarrow \quad \text{orthogonal waveforms}$$

$$\left[rank\left(\mathbf{W}\right) = N_T \right]$$

$$\rightarrow \quad \text{omnidirection beampattern}$$

$$\mathbf{W} = \sqrt{\frac{P_T}{N_T}}\mathbf{a}_T^*\left(\theta\right)\mathbf{a}_T^T\left(\theta\right) \quad \rightarrow \quad P_T \text{ steered to direction } \theta$$

$$\left[rank\left(\mathbf{W}\right) = 1 \right]$$

Target detection problem

- The **target detection problem for a MIMO radar** can be cast as:

$$\begin{cases} H_0: & \mathbf{y} = \mathbf{c} \\ H_1: & \mathbf{y} = \alpha \mathbf{v}(\theta_0) + \mathbf{c} \end{cases}$$

- Most of the existing works rely on the following **simplifying assumptions**:

- **A.1.** Availability of a sufficiently large number *K* of *independent* and *identically distributed* (IID) measurement vectors (or *snapshots*).
- **A.2.** The disturbance vector **c** is assumed to be Gaussian distributed with diagonal (or block-diagonal) covariance matrix.
- **A.3.** The waveforms $\{\Phi(t)\}$ are assumed to be perfectly orthogonal.

<u>These three assumptions are rather unrealistic and generally violated in practice</u>!

Disturbance model assumptions

- For this reason, by exploiting the advantages resulting from a **massive** number of virtual antenna channels, we propose to overcome the previous simplified assumptions by considering a ***single-snapshot* scenario** (K=1) and by imposing only the following on disturbance **c**:

Assumption A1: The Autocorrelation Function (ACF) of $\{c[n]\}$ satisfies

$$R_c[m] = E\left\{c[n]c^*[n-m]\right\} = O\left(|m|^{-\gamma}\right)$$

$$\text{where } m \in \mathbb{Z}, \quad \gamma > \rho/(\rho-1), \quad \rho > 1$$

- **Assumption A1** (*polynomial decay of the ACF*) is weak enough to be satisfied for example by all the Gaussian and non-Gaussian **Autoregressive-Moving Average (ARMA)** processes of arbitrary order and by all the **compound-Gaussian** processes (typically used in radar to model non-Gaussian spiky clutter).

Disturbance model assumptions

- The second-order statistics of any discrete-time w.s.s. process with continuous Power Spectra Density (PSD) can be approximated well by an ARMA model.
- A stable ARMA(P,Q) process, with finite P and Q, satisfies Assumption A1, since its ACF decays exponentially.
- A subset of the general ARMA models are the autoregressive model of order P, AR(P).
- AR models share most of the properties of the ARMA models.

Goal: Find a robust decision statistic whose asymptotic distribution (as $N=N_T N_R \rightarrow \infty$) under H_0 does not depend on the unknown disturbance probability density function (pdf) $p_c(\mathbf{c})$.

Main result: A robust Wald-type detector

- Under Assumption 1, we derived a **Wald-type detector** that relies on an asymtotically normal and $\sqrt{N}$ -consistent estimator of the complex amplitude α obtained by the *Least Squares (LS)* method:

$$\hat{\alpha} = \frac{\mathbf{v}^H \mathbf{y}}{\mathbf{v}^H \mathbf{v}} \quad \rightarrow \quad \Lambda_{RW}(\mathbf{y}) = \frac{2\left|\mathbf{v}^H \mathbf{y}\right|^2}{\mathbf{v}^H \hat{\boldsymbol{\Gamma}} \mathbf{v}} \underset{H_0}{\overset{H_1}{\gtrless}} \lambda$$

- where $\hat{\boldsymbol{\Gamma}}$ is the following $\sqrt{N}$-consistent estimator of the disturbance covariance matrix (<u>obtained by a single-snapshot</u>):

$$\hat{\boldsymbol{\Gamma}}_{i,j} = \begin{cases} \hat{c}_i \hat{c}_j^*, & |i-j| \leq L \\ 0 & |i-j| > L \end{cases}$$

- $\hat{\mathbf{c}} = \mathbf{y} - \hat{\alpha}\mathbf{v}$, and L is the **truncation lag** that can grow with N, but more slowly than $N^{1/3}$.

Asymptotic performance

- Skipping all the details (that can be found in [1]), we proved that the derived **Wald-type detector** is **asymptotically** distributed as:

$$\Lambda_{RW}(\mathbf{y})\big|H_0 \overset{N\to\infty}{\sim} \chi_2^2(0)$$

$$\Lambda_{RW}(\mathbf{y})\big|H_1 \overset{N\to\infty}{\sim} \chi_2^2(\delta) \quad \text{where} \quad \delta \triangleq 2|\alpha|^2 \frac{\left|\mathbf{v}^H\mathbf{v}\right|^2}{\mathbf{v}^H\boldsymbol{\Gamma}\mathbf{v}}$$

- If $\mathbf{R}_\Phi(n,k)=\mathbf{I}_{N_T}$ and $\boldsymbol{\Sigma}(t_1-t_2)=\sigma_d^2\mathbf{I}_{N_R}\delta(t_1-t_2)$:

$$\delta=\frac{2|\alpha|^2}{\sigma_d^2}b(\theta_0)$$

$$b(\theta)=\mathbf{a}_T^T(\theta)\mathbf{W}\mathbf{W}^H\mathbf{a}_T^*(\theta)$$

is the transmitting beampattern.

Asymptotic performance

CFAR property and Receiver Operating Characteristic (ROC) curve

Under A1, the P_{FA} of $\Lambda_{RW}(\mathbf{y})$ is asymtptically given by:

$$P_{FA} = \Pr\left\{\Lambda_{RW}(\mathbf{y}) > \lambda \middle| H_0\right\} \overset{N\to\infty}{\to} e^{-\lambda/2} \quad \text{(CFARness)}$$

irrespective of the unknown disturbance pdf $p_c(\mathbf{c})$.

Moreover,

$$P_D = \Pr\left\{\Lambda_{RW}(\mathbf{y}) > \lambda \middle| H_1\right\} \overset{N\to\infty}{\to} Q_M\left(\sqrt{\delta}, \sqrt{\lambda}\right) = Q_M\left(\sqrt{\delta}, \sqrt{2\ln(1/P_{FA})}\right)$$

$Q_M(\cdot,\cdot)$ is the Marcum Q-function of order 1

Asymptotic performance

CFAR property and Receiver Operating Characteristic (ROC) curve

$$P_{FA} = e^{-\lambda/2} \quad \text{[CFAR property]}$$

$$P_D = Q_M\left(\sqrt{\delta}, \sqrt{2\ln(1/P_{FA})}\right)$$

- The minimum number $N=N_T N_R$ of virtual spatial DoFs needed to accurately approximate the asymptotic performance defines the **Massive MIMO regime for radar sensing**.

The Wald-type detector for MIMO radar

- The three biggest advantages of the proposed **robust Wald-type detector** for **Massive MIMO radar** are:

1. it needs only a *single-snapshot* to extract all the information required to discriminate between H_0 (target absence) and H_1 (target present);
2. it satisfies the closed form expression of P_{FA} and P_D previously reported under any disturbance scenario satisfying Assumption A1, i.e. it is *statistically robust*;
3. it satisfies the CFAR property in the *Massive MIMO regime*.

- The previous results about the Wald-type detector hold true **for any array geometry**.

Comparison with the Adaptive Matched Filter (AMF)*

$$\Lambda_{RW}(\mathbf{y}) = \frac{2\left|\mathbf{v}^H \mathbf{y}\right|^2}{\mathbf{v}^H \hat{\boldsymbol{\Gamma}} \mathbf{v}}, \qquad \Lambda_{AMF}(\mathbf{y}) = \frac{\left|\mathbf{v}^H \hat{\mathbf{R}}_c^{-1} \mathbf{y}\right|^2}{\mathbf{v}^H \hat{\mathbf{R}}_c^{-1} \mathbf{v}}$$

- **Multi-snapshots vs. Single-snapshot**:
  - The AMF requires a set of $K>N$ homogeneous secondary snapshots to get the full rank estimate of the disturbance covariance matrix $\mathbf{R}_c$.
  - The robust Wald-type detector relies on a single snapshot (K=1).

- **Gaussian-based vs. Robust:**
  - The AMF is a CFAR detector only if **c** and the set of secondary data used to estimate $\mathbf{R}_c$ are Gaussian distributed;
  - The robust Wald-type detector is asymptotically CFAR for every disturbance vector **c** satisfying Assumption A1.

* F. C. Robey, D. R. Fuhrmann, E. J. Kelly, and R. Nitzberg, "A CFAR adaptive matched filter detector," *IEEE Trans. on Aerospace and Electronic Systems*, vol. 28, no. 1, pp. 208-216, January 1992.

Numerical results

- We show here the numerical results for two different scenarios where the disturbance is spatially **correlated non-Gaussian** (spiky).

- Case 1: The disturbance is modelled as an AR(3) with

$$\bar{\rho} = [0.5e^{j2\pi 0}, 0.3e^{-j2\pi 0.1}, 0.4e^{j2\pi 0.01}]^T,$$

- Case 2: The disturbance is modelled as an AR(6) with

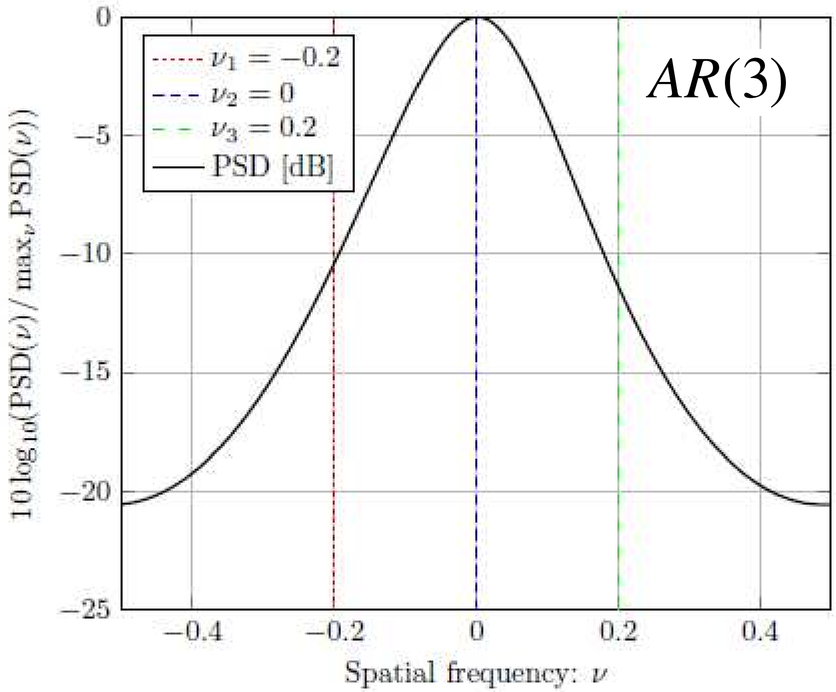
$$\bar{\rho} = [0.5e^{-j2\pi 0.4}, 0.6e^{-j2\pi 0.2}, 0.7e^{j2\pi 0}, 0.4e^{j2\pi 0.1}, 0.5e^{j2\pi 0.3}, 0.6e^{j2\pi 0.35}]^T,$$

- In both cases, the innovations $\{w_n, \forall n\}$ share a complex t-distribution:

$$p_w(w_n) = \frac{\lambda}{\pi\sigma_w^2}\left(\frac{\lambda}{\eta}\right)^{\lambda}\left(\frac{\lambda}{\eta} + \frac{|w_n|^2}{\sigma_w^2}\right)^{-(\lambda+1)}$$

$\lambda \in [1, +\infty)$ shape parameter, $\eta = \lambda / (\sigma_w^2(\lambda - 1))$ scale parameter

Spatial Power Spectral Density (PSD)



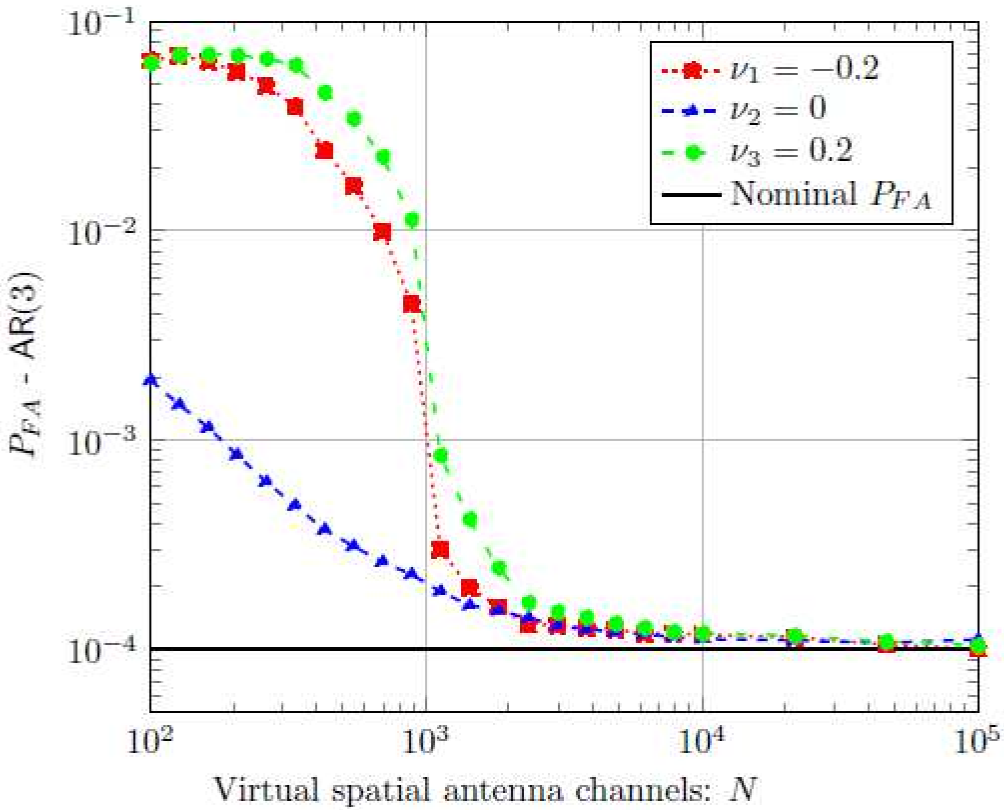
$$\lambda = 2$$
$$\sigma_w^2 = 1$$

- Virtual steering vectors: $[\mathbf{v}_i]_n = e^{j\pi(n-1)\sin(\phi_i)}$, $n = 1, \ldots, N$ and $\phi_i = \arcsin(\nu_i/2)$ where $\nu_1 = -0.2$, $\nu_2 = 0$ and $\nu_3 = 0.2$.

$$\mathbf{R}_\Phi(n,k) = \mathbf{I}_{N_T}, \quad \mathbf{W} = \mathbf{I}_{N_T}$$

3 targets from DOAs $\phi_i = \arcsin(\nu_i/2)$

Estimated and Theoretical P_{FA}: Case 1

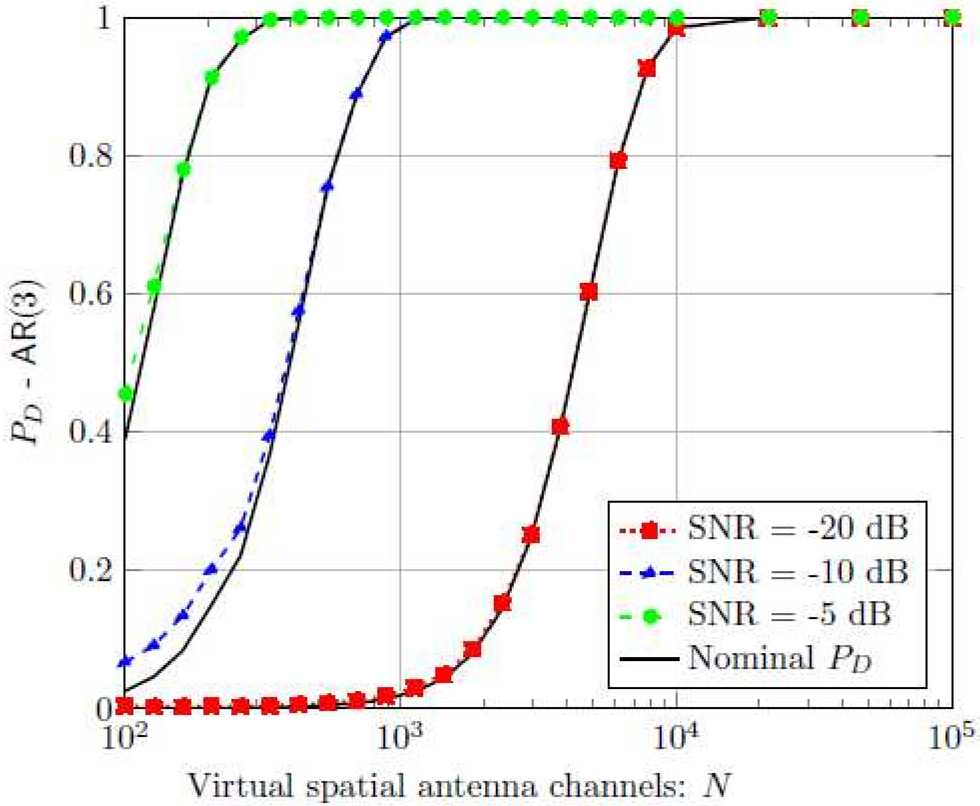


$\lambda = 2$

$\sigma_w^2 = 1$

- The estimated P_{FA} tends to the nominal value $\overline{P_{FA}} = 10^{-4}$,
- The massive MIMO regime is achieved for $N = N_T N_R \geq 10^4$

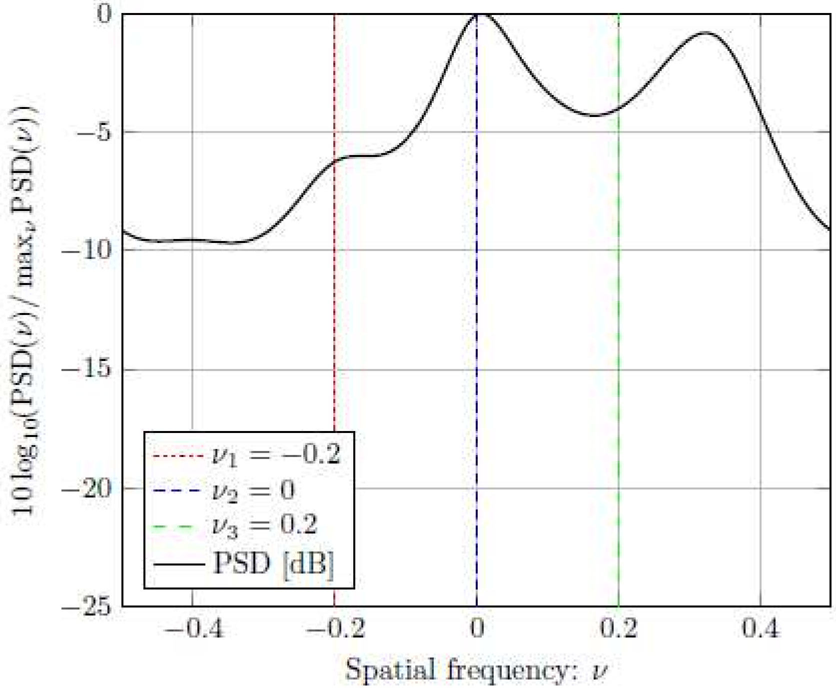
Estimated and Theoretical P_D: Case 1



$$\lambda = 2$$
$$\sigma_w^2 = 1$$

- The SNR is defined as $SNR = 10 Log_{10}\left(|\alpha|^2 / \sigma_d^2\right)$
- The estimated P_D is close to the asymptotic approximation.

Power Spectral Density (PSD) of the AR(6)



$\lambda = 2$

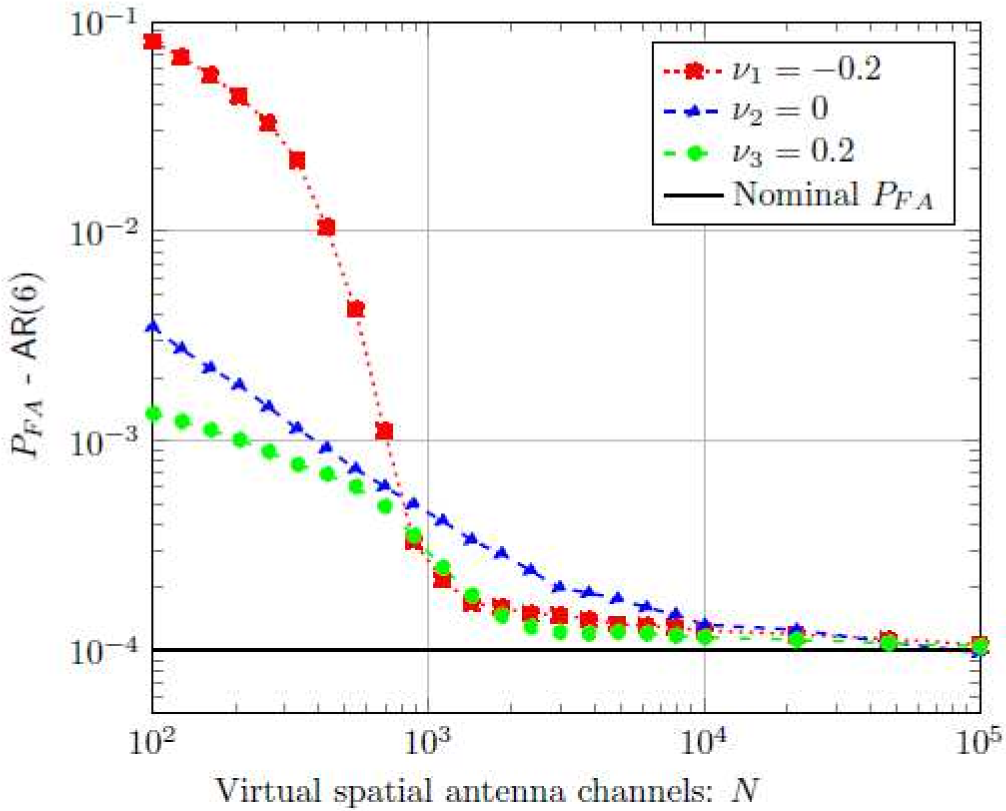
$\sigma_w^2 = 1$

- Virtual steering vectors: $[\mathbf{v}_i]_n = e^{j\pi(n-1)\sin(\phi_i)}$, $n = 1, \ldots, N$ and $\phi_i = \arcsin(\nu_i/2)$ where $\nu_1 = -0.2$, $\nu_2 = 0$ and $\nu_3 = 0.2$.

$\mathbf{R}_\Phi(n,k) = \mathbf{I}_{N_T}, \quad \mathbf{W} = \mathbf{I}_{N_T}$

3 targets from DOAs $\phi_i = \arcsin(\nu_i/2)$

Estimated and Theoretical P_{FA}: Case 2



$\lambda = 2$

$\sigma_w^2 = 1$

- The estimated P_{FA} tends to the nominal value $\overline{P_{FA}} = 10^{-4}$,
- The massive MIMO regime is achieved for $N = N_T N_R \geq 10^4$

On the P_D maximization

- The proposed **robust Wald-type (RW) test** has the **CFAR property** with respect to the unknown disturbance distribution.
- What about the **Probability of Detection** (P_D)? Can we maximize it somehow?
- From the previous results, we have that we can maximize P_D by choosing a suitable waveform matrix **W** according to the observed scenario:

$$P_D \overset{N\to\infty}{\cong} Q_M\left(\sqrt{\delta},\sqrt{\lambda}\right) \quad \text{where} \quad \delta = 2|\alpha|^2 \frac{\left|\mathbf{v}^H\mathbf{v}\right|^2}{\mathbf{v}^H\boldsymbol{\Gamma}\mathbf{v}}$$

$$\mathbf{v} = \left(\mathbf{R}_\Phi^T(n,k)\otimes\mathbf{I}_{N_R}\right)\left(\mathbf{W}^T\mathbf{a}_T(\theta_0)\otimes\mathbf{a}_R(\theta_0)\right)$$

- At each discrete-time k, after performing the detection in each angular bin, the radar system select the weighting matrix $\boldsymbol{W}_k$ to maximize the P_D, starting from some sort of knowledge of the environment.

Concluding remarks

- By exploiting the increased number $N=N_T N_R$ of spatial DoFs that a **colocated massive MIMO radar** can provide, a robust and CFAR Wald-type detector (RW) was derived.
- As $N \to \infty$ and if the disturbance ACF decays at least polynomially fast, the asymptotic distribution of the test statistic does not depend on the unknown disturbance pdf.
- This was the first attempt to apply the **massive MIMO paradigm** of communication systems to radar sensing.
- These results represent the first building block of a reinforcement learning-based dual-functional **massive MIMO** system for multi-target detection and communications.

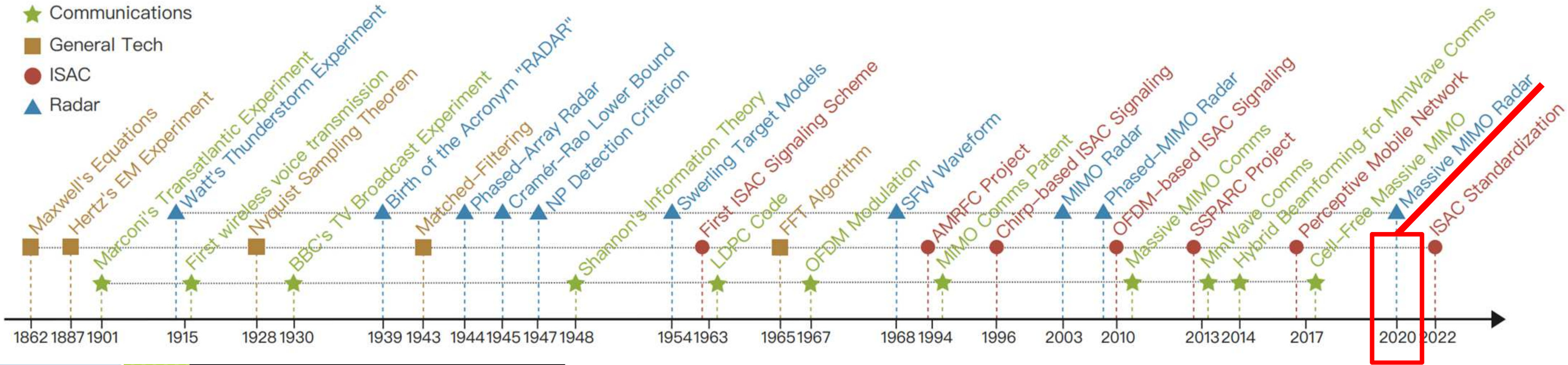
Concluding remarks

This talk is based on these two publications:

[1] S. Fortunati, L. Sanguinetti, F. Gini, M. S. Greco and B. Himed, "**Massive MIMO Radar** for Target Detection", *IEEE Trans. on Signal Processing*, vol. 68, pp. 859-871, January 2020.

[4] S. Fortunati, F. Lisi, A. M. I. Ahmed, A. Sezgin, M. S. Greco, and F. Gini, "Fundamental limits for ISAC - Asymptotics in **Massive MIMO Sensing** Systems", Chapter 5 of book *Integrated Sensing and Communications* (ISAC), Fan Liu, Christos Masouros, Yonina C. Eldar Editors, Springer, 2023.

In Fig. 1 the authors summarize **key milestones** achieved in **Radar & Communications (R&C)** history from a Signal Processing (SP) perspective, which are split into four categories with different markers, namely, the individual R&C technologies, general technologies that are useful for both, and ISAC technologies. **Paper [1] is cited within the "Radar" category**.



75TH ANNIVERSARY OF SIGNAL PROCESSING SOCIETY SPECIAL ISSUE

Fig. 1. The important milestones for R&C SP.

Fan Liu, Le Zheng, Yuanhao Cui, Christos Masouros, Athina P. Petropulu, Hugh Griffiths, and Yonina C. Eldar

Seventy Years of Radar and Communications

The road from separation to integration

IEEE Signal Processing Magazine, Vol. 40, No. 5, July 2023.

Concluding remarks

4.2.4. Integration into a Cognitive Radar Framework

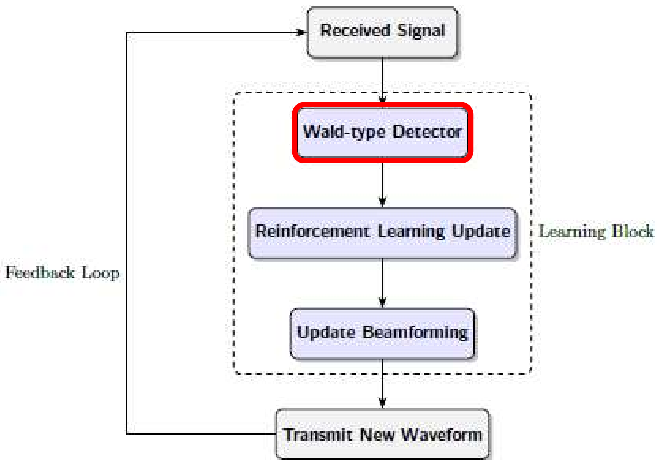


Figure 4.1: RL-Driven Adaptive Beamforming for Target Detection

- <u>**Subsequent work focused on**</u>:
  (i) the design of a reinforcement learning–based cognitive massive MIMO radar that continuously maximizes P_D in both static and dynamic environments; and
- **(ii)** the integration of this cognitive sensing strategy with communication functionality under an ISAC framework.

[5] A. Umra, A. M. I. Ahmed, A. Sezgin, M. S. Greco, and F. Gini, "**Reinforcement learning** for intelligent radar target detection", Chapter 4 of book *Machine Learning for Radar Signal Processing,* IEEE-Wiley Press Book, 2026 (to be published).

In the next talk **Prof. Maria S. Greco** will describe an **RL-based algorithm for waveform selection** that can be fruitfully combined with the results described in this talk, to develop <u>a fully adaptive and data-driven detection algorithm for **Massive MIMO radar** systems</u> that may achieve good performance without relying on any a priori knowledge of the environment.

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Massive MIMO radar

[1] S. Fortunati, L. Sanguinetti, F. Gini, M. S. Greco and B. Himed, "**Massive MIMO Radar** for Target Detection", *IEEE Trans. on Signal Processing*, vol. 68, pp. 859-871, January 2020.

Reinforcement Learning-based cognitive Massive MIMO radar

[2] A. M. Ahmed, A. A. Ahmad, S. Fortunati, A. Sezgin, M. S. Greco and F. Gini, "A **Reinforcement Learning** Based Approach for Multitarget Detection in **Massive MIMO Radar**," *IEEE Trans. on Aerospace and Electronic Systems*, vol. 57, no. 5, pp. 2622-2636, Oct. 2021.

[3] F. Lisi, S. Fortunati, M. S. Greco, F. Gini, "Enhancement of a State-of-the-Art **RL-Based** Detection Algorithm for **Massive MIMO Radars**," *IEEE Trans. on Aerospace and Electronic Systems*, Vol. 50, No. 6, 2022.

[4] S. Fortunati, F. Lisi, A. M. I. Ahmed, A. Sezgin, M. S. Greco, and F. Gini, "Fundamental limits for ISAC - Asymptotics in **Massive MIMO Sensing** Systems", Chapter 5 of book *Integrated Sensing and Communications* (ISAC), Fan Liu, Christos Masouros, Yonina C. Eldar Editors, Springer, 2023.

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ISAC/RL-based/ Cognitive Radar/ Massive MIMO radar

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ISAC/RL-based/
Cognitive Radar/
Massive MIMO radar

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[10] D. An, J. Liu, K. Zhong, J. Hu, H. Yao, H. Li, and F. Gini, "Per-User Dynamic Controllable Waveform Design for Dual Function Radar-Communication System," *IEEE Transactions on Aerospace and Electronic Systems*, Date of Publication: 28 October 2024.

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