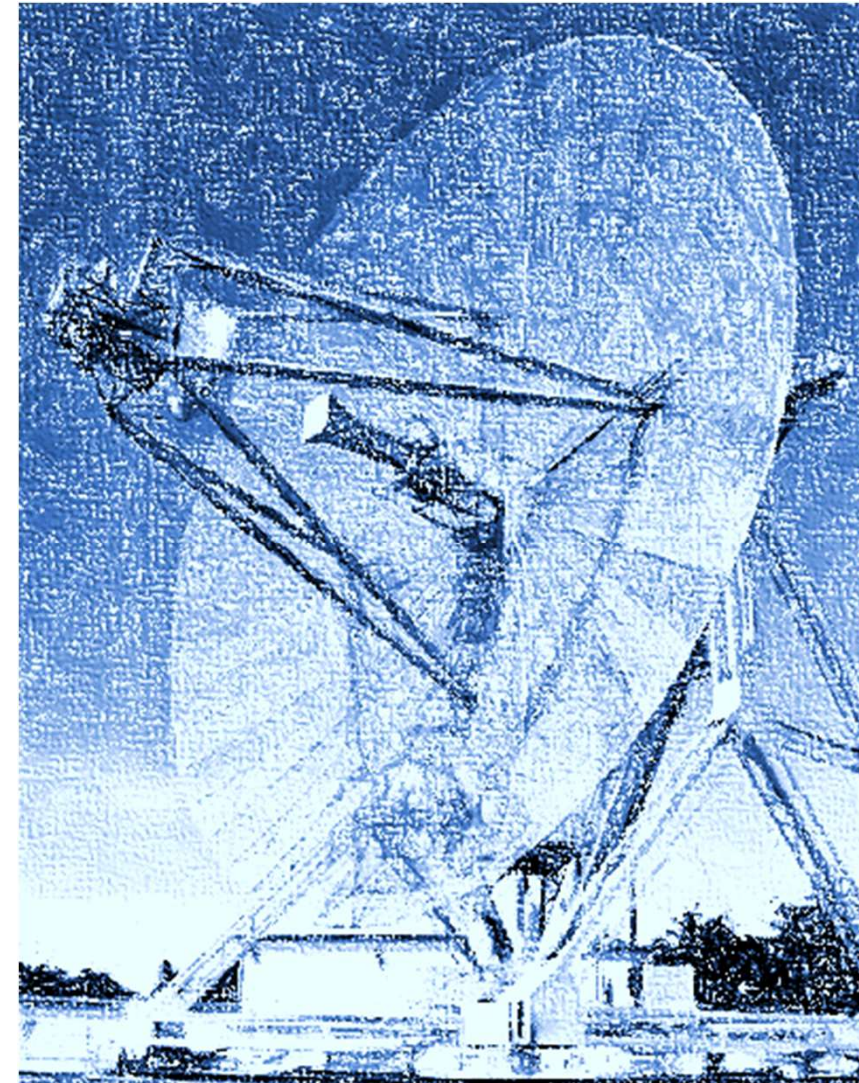




Cognitive Radars for ISAC

Maria Sabrina Greco

- Cognitive radars: simple concept and its foundations
- Applications
 - Beamforming in a Massive MIMO radar
 - Cognitive radar for ISAC
- Conclusions



Cognitive Radar: a simple concept and its foundations

IEEE Standard Radar Definition 686: A cognitive radar is a radar system that in some sense displays intelligence, adapting its operation and its processing in response to a changing environment and target scene. In comparison to adaptive radar, cognitive radar learns to adapt operating parameters as well as processing parameters and may do so over extended time periods.

The concept of **Cognitive Radar** has been introduced for the first time by Prof. Simon Haykin in 2006.

It has its foundations in some “older” idea:

- Sensor management paradigm
- Waveform diversity
- Knowledge based systems

Cognitive Radar: a simple concept and its foundations

4 basic processes – Fuster's paradigm

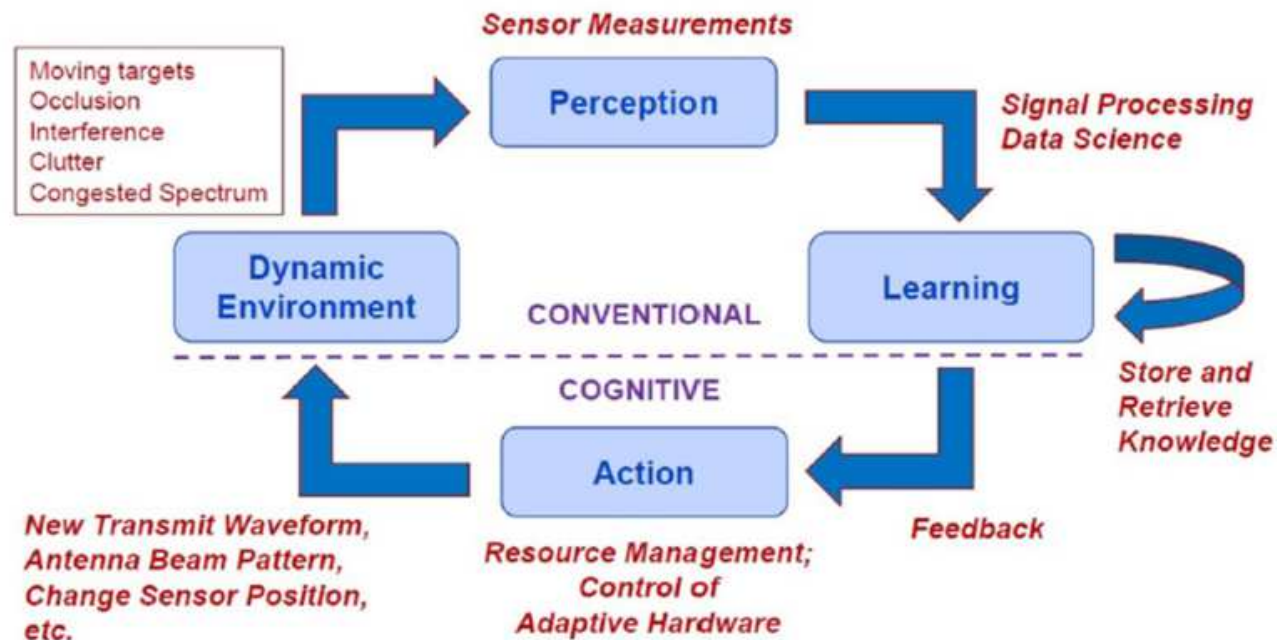
Bats, dolphins, human beings continuously learn and react to stimulations from the surrounding environment according to 4 basic processes:

- Perception-action cycle
- Memory
- Attention
- Intelligence

What are the equivalents in a cognitive radar?

Cognitive Radar: a simple concept and its foundations

The Perception-Action Cycle (PAC)



Block diagram of cognitive radar seen as a dynamic closed-loop feedback system

Cognitive Radar: a simple concept and its foundations

- **Memory** is the process through which information is registered, stored and retrieved. New perceptions determine new memories. Tasks such as target recognition and identification are strongly informed by memories.
- **Attention** requires processing the perceptions to extract information and to selectively concentrate on some aspect of information. It can require system actions for prioritizing the allocation of available resources (radar time, power, etc.).
- **Intelligence** is the most difficult to describe. We can say that it is the presence of a feedback at multiple levels that allows the systems to make intelligent decisions in face of inevitable uncertainties in the environment.

Cognitive Radar: a simple concept and its foundations

Which radar task can be made adaptive and cognitive?

- **Frequency management:** selection of the least disturbed frequency.
- **Clutter cancellation:** extensive use of geographical maps of the site and the operation environment, maps of fixed and moving targets.
- **Radiated waveform:** selection of LFM, non-LFM, hyperbolic frequency modulation, phase code, bandwidth, PRF, power.
- **Antenna beampattern:** selection of narrow, wide, weighted, unweighted beam, selection of different phased array antenna elements.

Cognitive radar approaches range from Bayesian formulations and information-driven objectives to data-driven strategies such as reinforcement learning for adaptive resource allocation.

Cognitive Radar: a simple concept and its foundations

Some enabling technologies

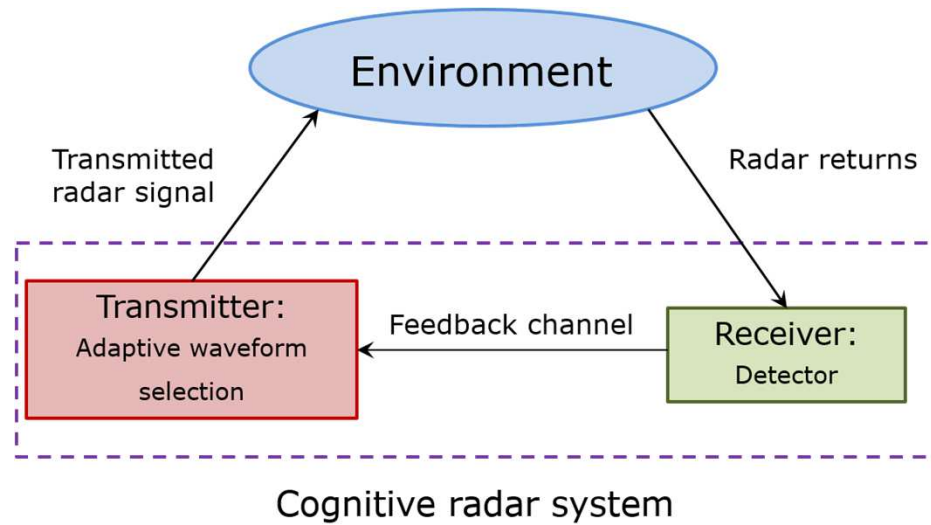
- **Multiband and multiantenna** to improve radar coverage, increase the radar functionalities, mitigate difficulties in detecting dim targets etc.
- **Adaptive digital waveform generator** for selecting the optimum waveform.
- **Photonics** to transfer large amount of data.
- **Active fully digital arrays** to select and form multiple beams.
- **MIMO systems** that provide many degrees of freedom (DoF).
- **Exploitation of new materials** (e.g. metamaterials), foldable-unfoldable structures to shape antennas.
- **Neuromorphic** chips and neuromorphic computing.
- **Adaptable RF components** (amplifiers, filters).

Cognitive Radar: a simple concept and its foundations

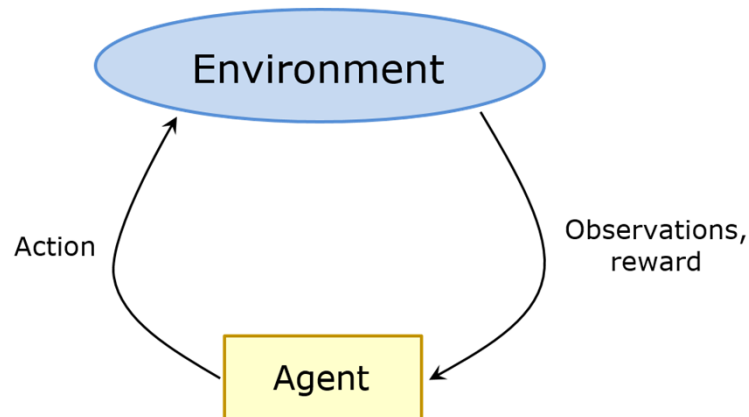
Category	Parameter	Description
Waveform	Peak power	Peak transmit power
	RF Frequency	Frequency of the RF carrier signal
	Pulse Repetition Frequency (PRF)	Repetition rate of pulses in a burst
	Pulse Width	Width of pulses in time
	Pulse Modulation	Specification of the modulation applied to each pulse
Time Management	Burst length	Number of pulses coherently integrated in a burst
	Number of bursts	Number of bursts non-coherently integrated into a dwell
	Dwell time	The time interval for all bursts that are jointly processed
	Revisit interval time	The time between repetitions of the task
Array Management	Beam steering	Electronic steering in angle applied to the radar beam
	Tapering	Amplitude weighting for each element in the array
	Subaperture management	Selection of a subset of array elements within the complete antenna aperture
Scheduling	Job execution time	The time at which the radar job is executed
Processing	Interference suppression	Specification of signal processing applied (e.g., adaptive nulling, STAP)
	Detection Threshold	Threshold for target presence declaration in each coherent processing interval
	Binary integration threshold	Required number of bursts with detections

Cognitive Radar: Reinforcement learning

Cognitive radar



Reinforcement learning (RL)



The agent learns how to make decisions to achieve a certain goal. This is done by trial and error interactions with the environment

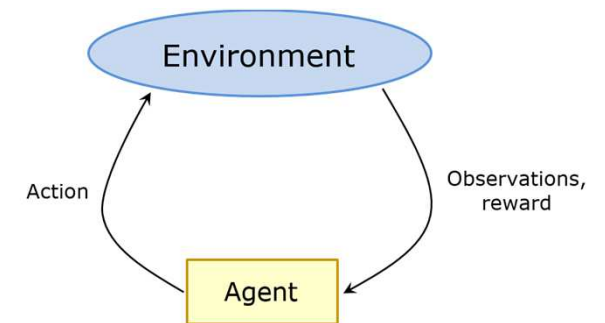
- Formally, the interactions with the environment in RL is described by Markov Decision Processes (MDP)

A Markov decision process (MDP) is defined by a tuple $\{S, A, P, r\}$, where S is a finite set of **states**, A is a finite set of **actions**, P is the transition probability from state s to $s' \in S$ after action $a \in A$ is performed, r is the immediate **reward** evaluated after a is executed.

- The actions are ruled by a **policy** $\pi: S \rightarrow A$, that is a function that maps a state $s \in S$ into an action $a \in A$. So, it defines which action has to be executed at each state.
- The reward is a scalar feedback signal that the agent always seeks to maximize.

Cognitive Radar: Reinforcement learning

- No supervised data, only a reward signal (i.e., feedback from the unknown environment)
- Agent learns through trial and error and improves its policy
- Reward indicates how well the agent is doing at step t
- Agent's actions change the environment, affecting subsequent data
- Agent's job is to maximize the cumulative reward



Example: make a humanoid robot walk

- positive reward for forward motion
- negative reward for falling down



Cognitive Radar: Beamforming for colocated Massive MIMO radars

$$\mathbf{y}_l^k = \alpha_l^k \mathbf{h}_l^k + \mathbf{c}_l^k.$$
$$\mathbf{h}(\theta) = (\mathbf{W}^T \mathbf{a}_T(\theta)) \otimes \mathbf{a}_R(\theta).$$

- \mathbf{y}_l^k : data vector for each angle bin l at time k
- α_l^k : signal parameter
- $\mathbf{a}_T(\theta)$: transmitter steering vector
- $\mathbf{a}_R(\theta)$: receiver steering vector
- θ : direction of arrival (DOA) of the target
- \mathbf{W} : complex beamforming matrix to synthesize correlated waveforms at different transmitters
- \mathbf{c}_l^k : complex unknown disturbance vector for each angle bin l at time k

Cognitive Radar: Beamforming for colocated Massive MIMO radars

- The statistical description of disturbance vector \mathbf{c}_l^k is usually unknown
- Its accurate modeling is a challenging task in practice
- A very weak statistical assumption on the disturbance is done

Assumption 1:

The disturbance is a realization of a discrete-time, circular, complex random process with a polynomial decay of its autocorrelation function.

- Assumption 1 is weak enough to include most practical disturbance models
- Hypothesis testing problem for each l out of L angle bins:

$$H_0 : \mathbf{y}_l^k = \mathbf{c}_l^k \quad k = 1, \dots, K$$

$$H_1 : \mathbf{y}_l^k = \alpha_l^k \mathbf{h}_l^k + \mathbf{c}_l^k \quad k = 1, \dots, K.$$

Cognitive Radar: Wald test-based target detection

- Wald type detector is proposed under the extremely general disturbance model

$$\Lambda_{l,\text{RW}}^k = \frac{2|(\mathbf{h}_l^k)^H \mathbf{y}_l^k|^2}{(\mathbf{h}_l^k)^H \hat{\mathbf{\Gamma}} \mathbf{h}_l^k},$$

where $\hat{\mathbf{\Gamma}}$ is the estimate of the unknown clutter covariance matrix $\mathbf{\Gamma}$

- $\Lambda_{l,\text{RW}}^k$ is asymptotically chi-squared distributed, as the number of virtual spatial channels N increases infinitely (i.e., Massive MIMO regime),

$$\Lambda_{l,\text{RW}}^k (\mathbf{y}_{l,g}^k | H_0) \underset{N_T N_R \rightarrow \infty}{\overset{d}{\sim}} \chi_2^2(0),$$

$$\Lambda_{l,\text{RW}}^k (\mathbf{y}_{l,g}^k | H_1) \underset{N_T N_R \rightarrow \infty}{\overset{d}{\sim}} \chi_2^2(\zeta),$$

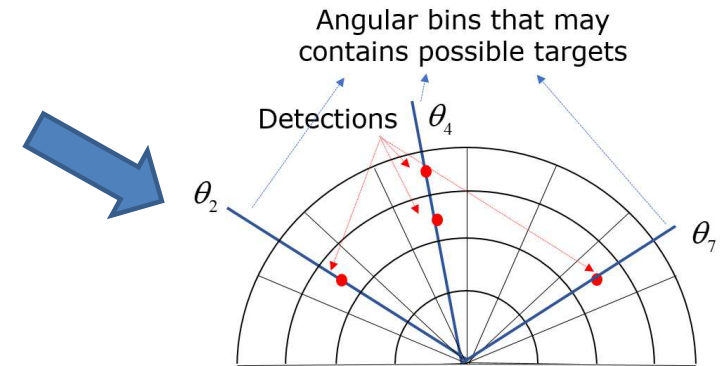
$$\zeta = 2|\alpha|^2 \frac{\|\mathbf{h}\|^4}{\mathbf{h}^H \mathbf{\Gamma} \mathbf{h}}.$$

Detector under H_1 depends on the beamforming matrix \mathbf{W}

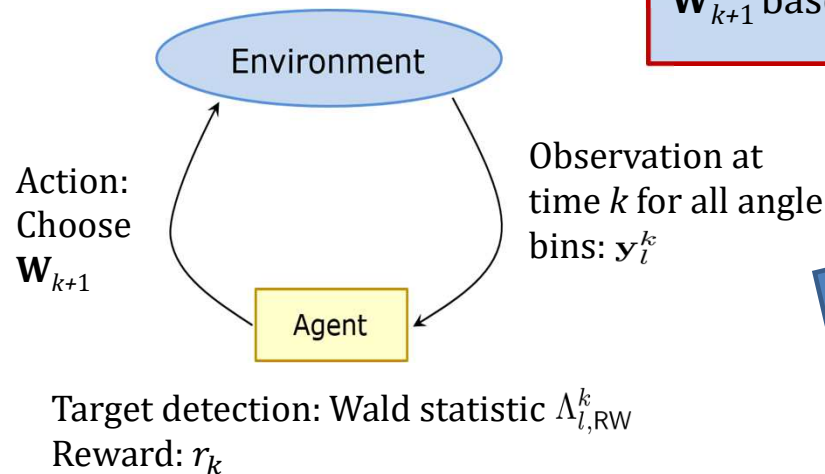
- $\Lambda_{l,\text{RW}}^k$ is asymptotically CFAR for every disturbance vector satisfying Assumption 1.
- $\Lambda_{l,\text{RW}}^k$ relies on a single snapshot

Cognitive Radar: Target state space and Actions

- The detections at the output of the Wald type test are used to define the **state space** at time step k . (The angular FoV is divided in L angle bins)
- In this example, the state is $s_k = 3$ and the angular bins that may contain targets are $\{\theta_2, \theta_4, \theta_7\}$.



Action: Given the state s_k at time k , choose the beamforming matrix \mathbf{W}_{k+1} based on the “immediate” reward r_k and on the past rewards.



The *best* matrix \mathbf{W}_{k+1} is the one that shapes the transmitted beam pattern by focusing the power towards the angular bins that contain potential targets.

Actions

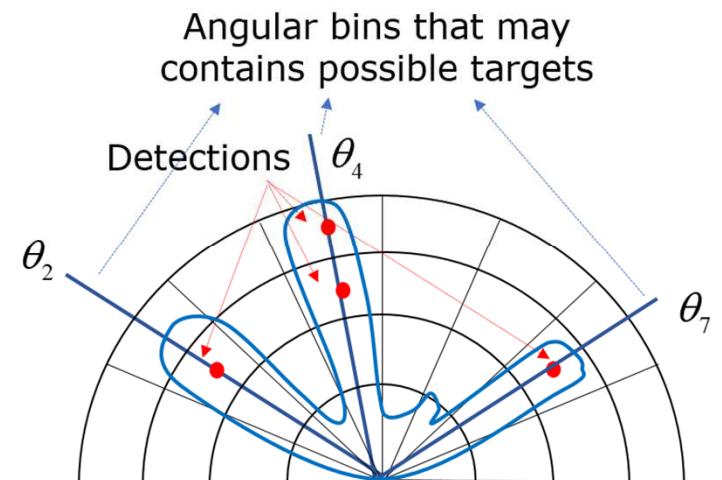
- Based on state s_k , the agent selects the corresponding i angle bins that most likely contain targets

$$\Theta = \{\theta_2, \theta_4, \theta_7\},$$

- Optimize the beamformer matrix \mathbf{W}_{k+1} to focus the beampattern towards the direction of those bins, solving the following optimization problem:

$$\begin{aligned} \max_{\mathbf{W}} \min_{j \in \mathcal{T}_i} \{ \mathbf{a}_T^T(\hat{\theta}_j) \mathbf{W} \mathbf{W}^H \mathbf{a}_R^*(\hat{\theta}_j) \} \\ \text{s.t. } \text{tr}(\mathbf{W} \mathbf{W}^H) = P_T, \end{aligned}$$

where $\mathcal{T}_i = \{1, \dots, i\}$ and $\hat{\theta}_j \in \Theta$



- The choice of a **good reward function** is a crucial aspect of any RL algorithm.
- A reasonable reward might be related to the probability of detection

$$r_{k+1} = \sum_{l=1}^{s_k} \hat{P}_{D_l}^k - \sum_{j=1}^{L-s_k} \hat{P}_{D_j}^k,$$

- The positive part is a summation of P_D over all s_k (i.e., the bins that most likely contain a target)
- The negative reward is summed over the bins that do not.
- Other rewards might be chosen i.e., capped reward (+1,-1), SINR,... etc.

$$\hat{P}_{D_l}^k = Q_1 \left(\sqrt{\hat{\zeta}_l^k}, \sqrt{\lambda} \right), \quad \hat{\zeta}_l^k = 2|\hat{\alpha}_l^k|^2 \frac{\|\mathbf{h}_l^k\|^4}{(\mathbf{h}_l^k)^H \hat{\Gamma}_l \mathbf{h}_l^k}, \quad \hat{\alpha}_l^k = \frac{(\mathbf{h}_l^k)^H \mathbf{y}_l^k}{\|\mathbf{h}_l^k\|^2}.$$

Cognitive Radar: SARSA algorithm and the function Q

- We used the **SARSA (state-action-reward-state-action)** algorithm to implement the RL.
- The best action at time step $k+1$ is chosen by maximizing a function of the immediate reward r_k and of a weighted sum of the past rewards (cumulative rewards).
- In RL, this function is called the *state-action value function Q*:

$$Q(s_k, a_k) \leftarrow Q(s_k, a_k) + \alpha (r_{k+1} + \gamma Q(s_{k+1}, a_{k+1}) - Q(s_k, a_k))$$

Learning rate

Discount factor

- The matrix $[Q]_{ij} = Q(s_i a_j)$ is not a priori known and has to be recursively estimated from the data:

$$Q_0, Q_1, \dots, Q_k, Q_{k+1}, \dots$$

SARSA (state-action-reward-state-action) learning-detection algorithm

1. Initialization:

Transmit orthonormal waveforms

Collect the data vectors \mathbf{y}_l^0 and through Wald-type detector obtain s_1 ,

Initial \mathbf{Q}_0 matrix (zeros): obtain a_1 .

2. Given the action a_k ,

Collect the data vectors \mathbf{y}_l^k ,

Obtain the new state through Wald type based detector: s_{k+1}

3. Evaluate the reward r_{k+1}

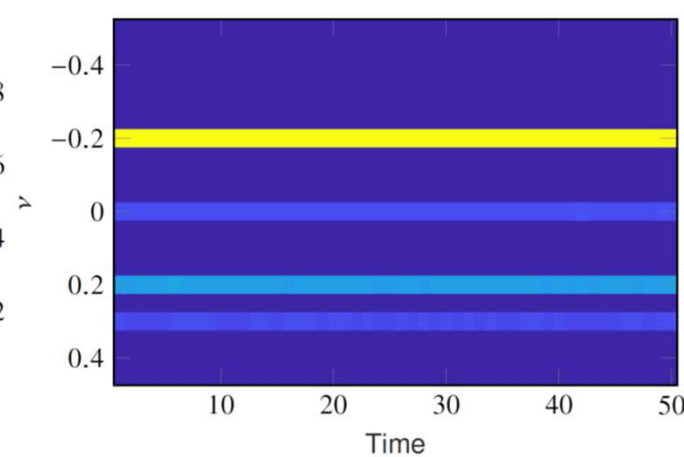
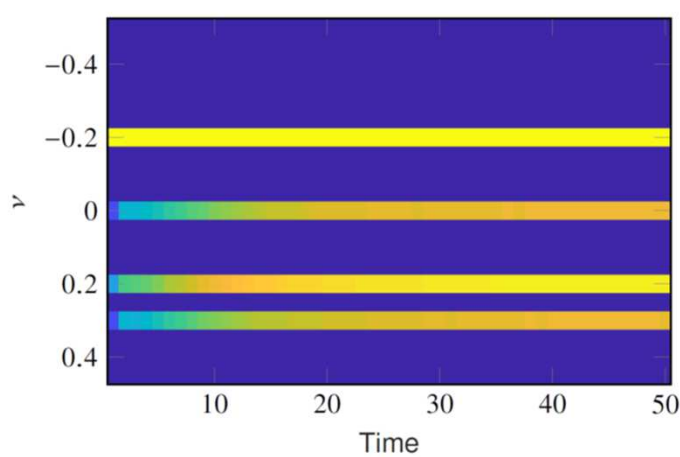
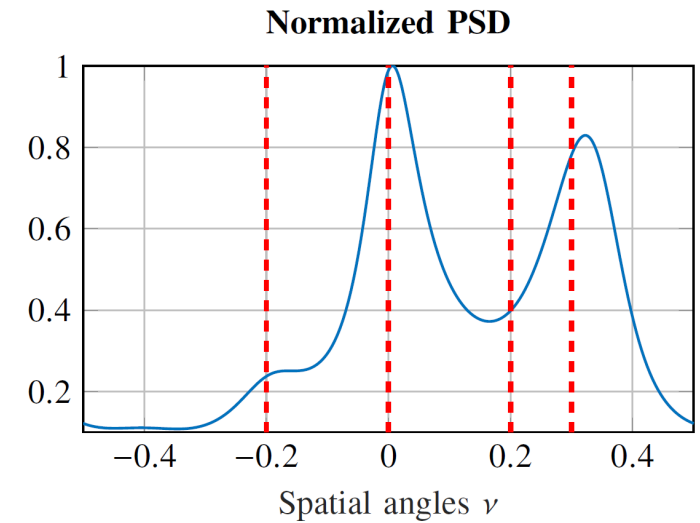
4. Choose a new action a_{k+1} using a ϵ -greedy algorithm:
$$a_{k+1} = \begin{cases} a_{\text{opt}} & \text{with prob. } 1 - \epsilon \\ a_{\text{rnd}} & \text{with prob. } \epsilon. \end{cases}$$

5. Update the \mathbf{Q} matrix

6. Repeat until observation time ends

Cognitive Radar: RL for static targets

- Four targets with different Signal to Noise ratio (SNR).
 - T1: -0.2, SNR = -5dB,
 - T2: 0, SNR = -8dB,
 - T3: 0.2, SNR = -10dB,
 - T4: 0.3, SNR = -9dB,
- The disturbance is modelled as a spatial AR(6)
- The innovations w_n are complex t-distributed (spiky clutter)



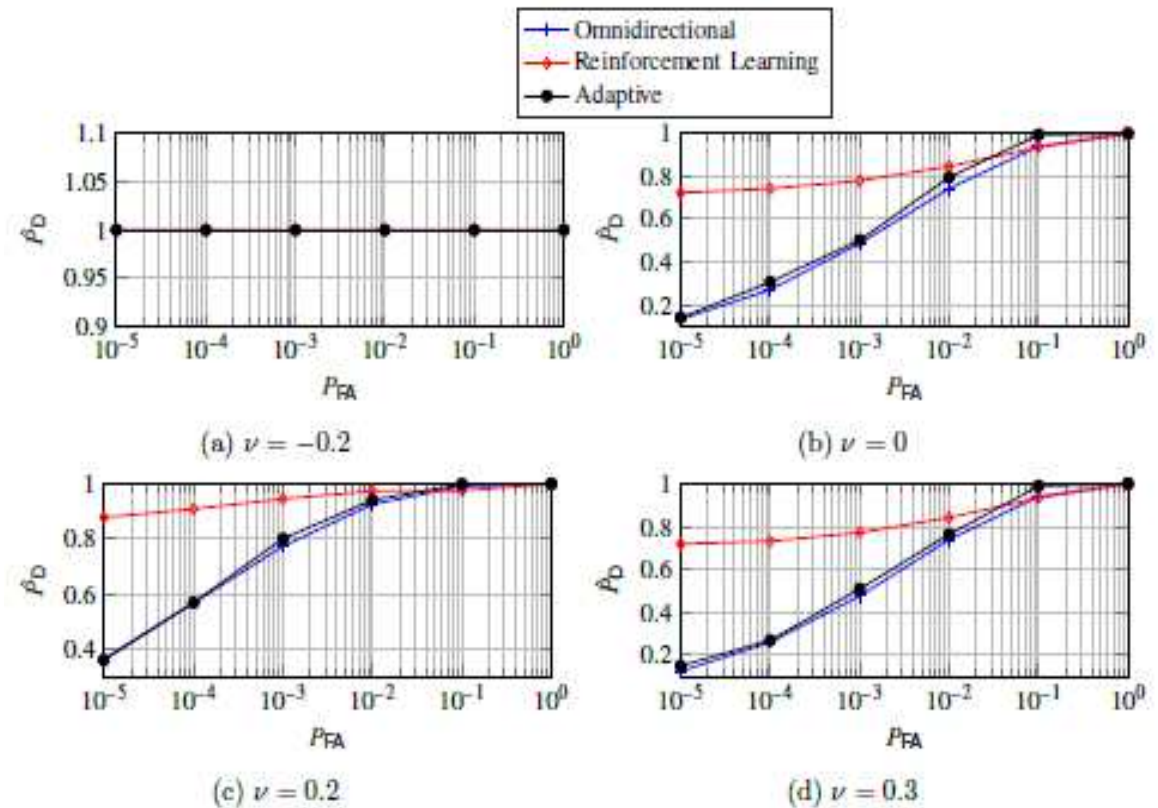
P_D for the proposed RL beamforming (left) vs omnidirectional (right), $P_{FA} = 10^{-4}$, $N = 10^4$.

Cognitive Radar: Static environment

Four targets with different Signal to Noise ratio (SNR), $N=10^4$

- T1 at -0.2, SNR = -5dB,
- T2 at 0, SNR = -8dB,
- T3 at 0.2, SNR = -10dB,
- T4 at 0.3, SNR = -9dB,

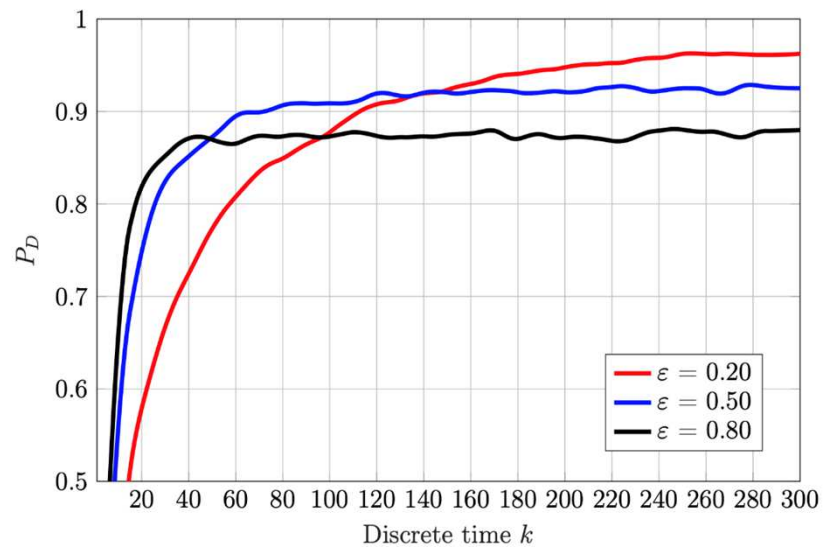
ROC using RL vs alternative approaches



ε parameter

The ε parameter balances the *exploration-exploitation* tradeoff in the ε -greedy policy

Target 2 – Scenario 1

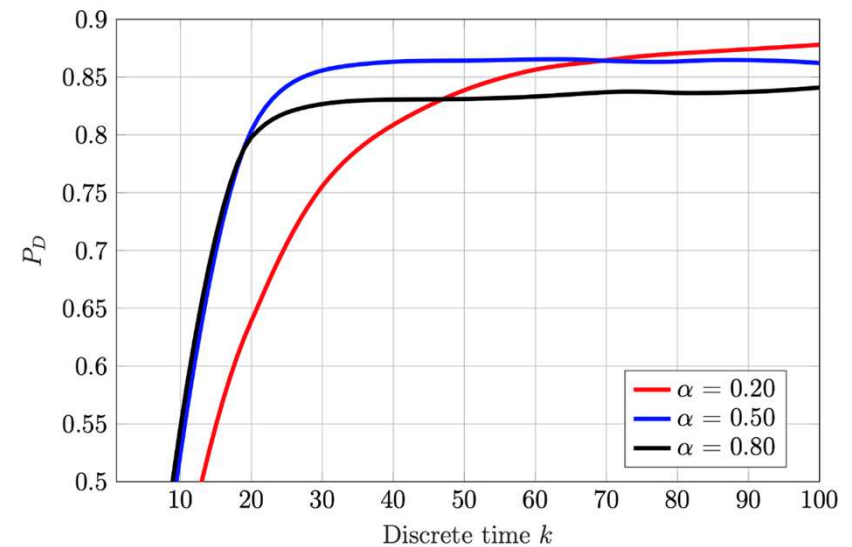


α parameter

The α parameter corresponds to the weight of the acquired information in the Q update formula

$$Q_{k+1}(s_k, a_k) = (1 - \alpha_k) Q_k(s_k, a_k) + \alpha_k (r_{k+1} + \gamma Q_k(s_{k+1}, a_{k+1})).$$

Target 1 – Scenario 2



- To combine the positive effects of low ε and α values in the steady-state phase and high values in the transitory phase, we introduce an adaptive algorithm.
- The initial x value is set to x_{max} and then its value is updated as

$$x_{k+1} = \begin{cases} \max\{c_1 \cdot x_k, x_{min}\}, & |r_k - r_{k-1}| < \eta_1 \\ \min\{c_2 \cdot x_k, x_{max}\}, & \eta_1 < |r_k - r_{k-1}| < \eta_2 \\ x_{max}, & |r_k - r_{k-1}| > \eta_2 \end{cases}$$

where $c_1 \in (0,1)$, $c_2 \in (1, +\infty)$ and x **corresponds to ε or α** .

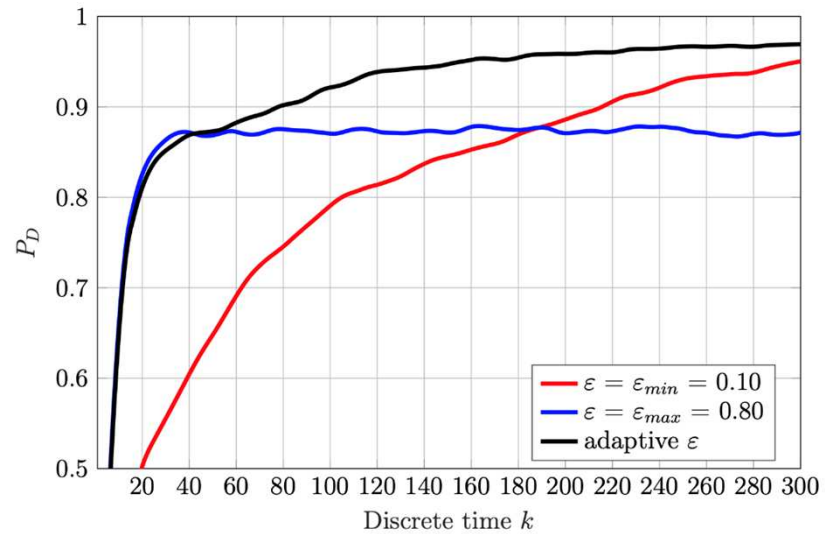
c_1 , c_2 , η_1 and η_2 change depending on which parameter (ε or α) is updated.

- The x parameter is not updated when the system is in exploration mode.
- The threshold values η_1 and η_2 depend on the choice of the *reward*.

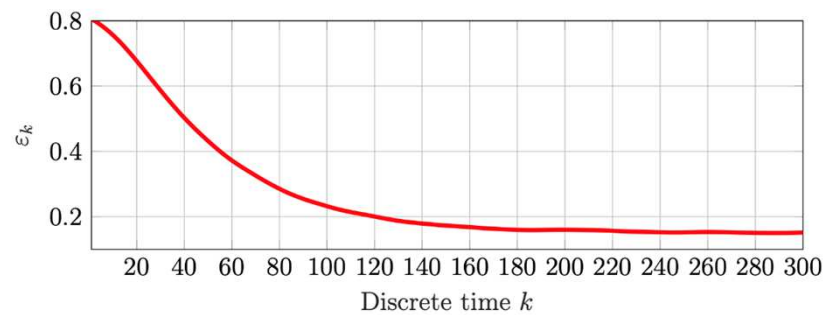
Adaptive ε and α algorithm - Performance

Adaptive ε

Target 2 – Scenario 1

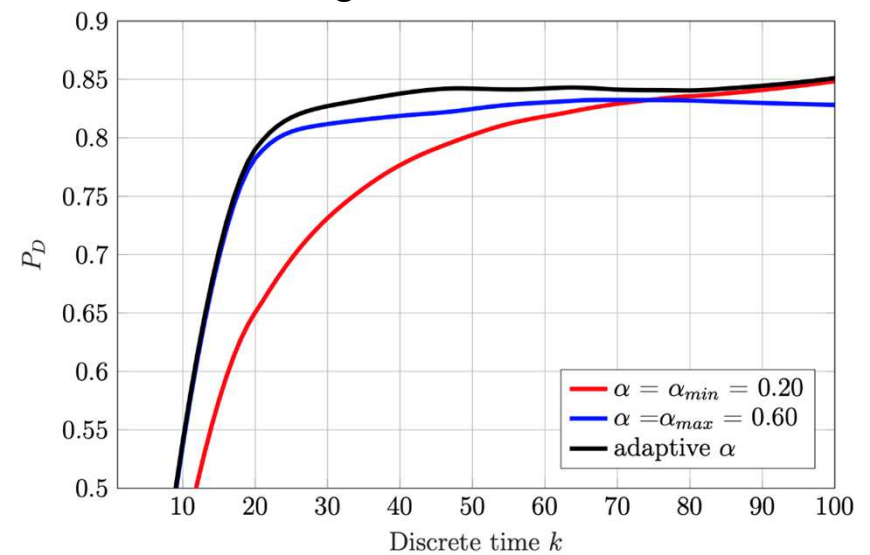


ε_k sequence

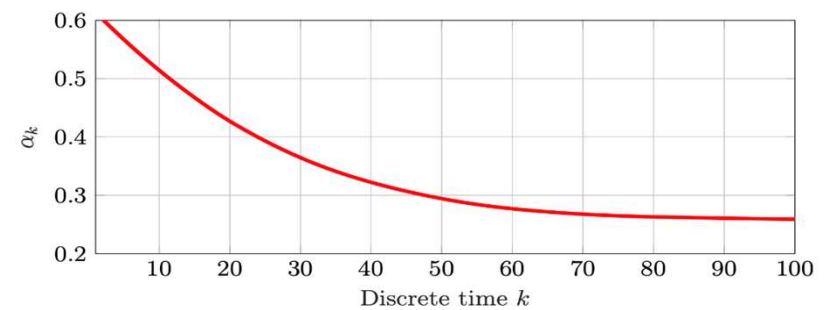


Adaptive α

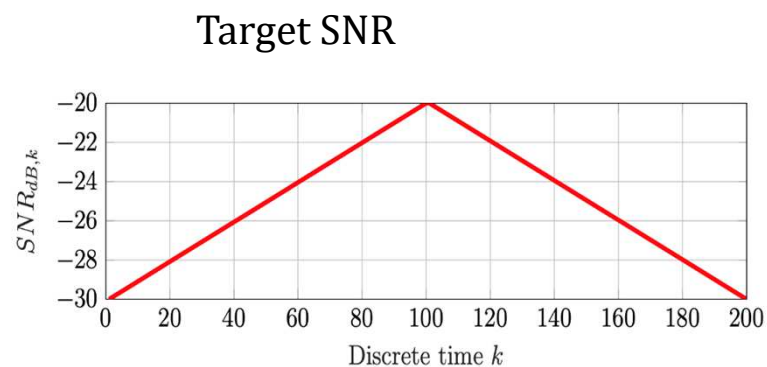
Target 1 – Scenario 2



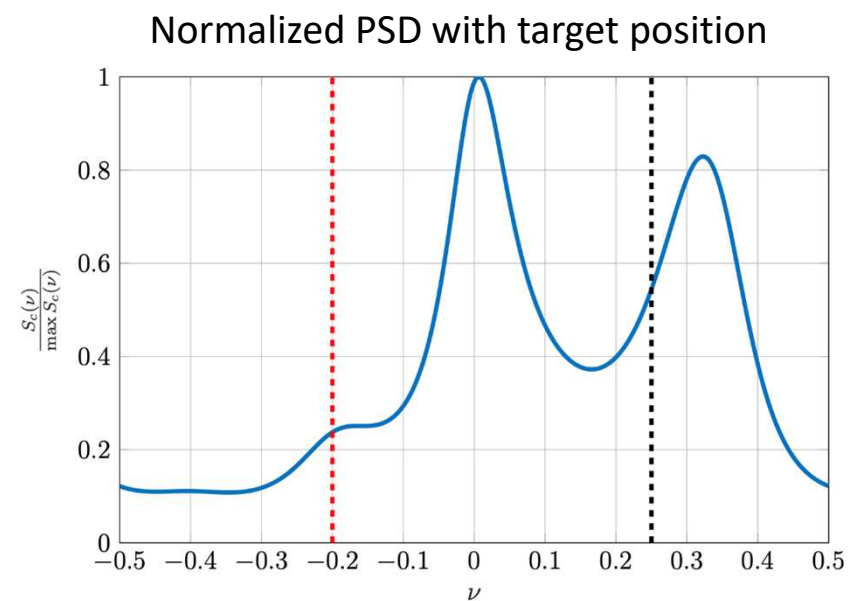
α_k sequence



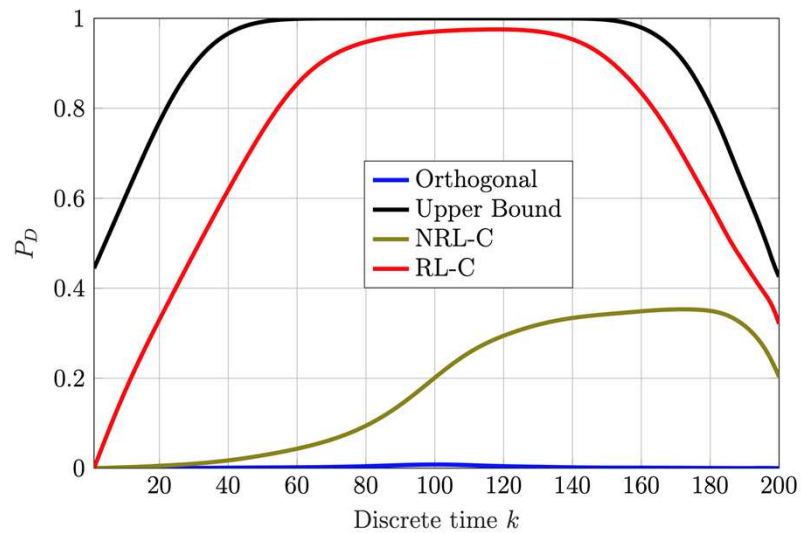
- In this scenario there are two targets with a **variable SNR** to simulate their movement.
- The noise process and target angular position are the same as in Scenario 1.



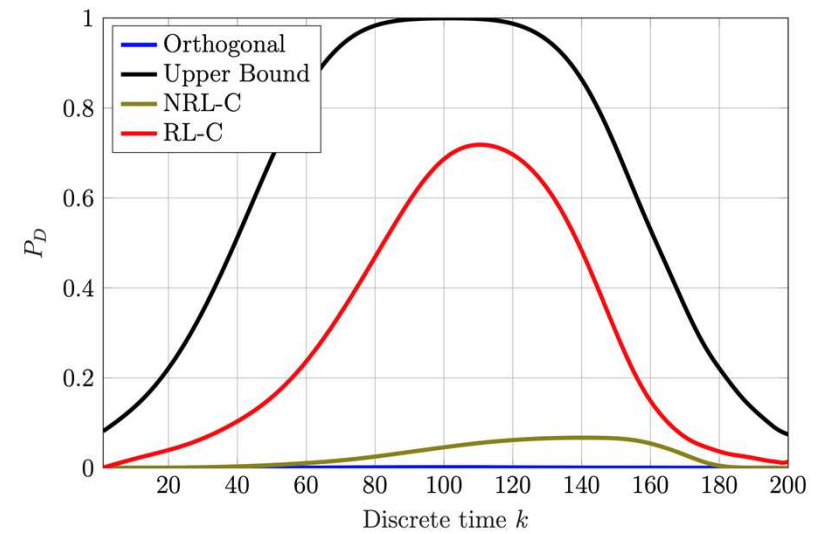
Time Interval	Target	Angular Bin	ν	SNR_{dB}
[1,200]	1	7	-0.20	see
	2	16	0.25	Figure A.6



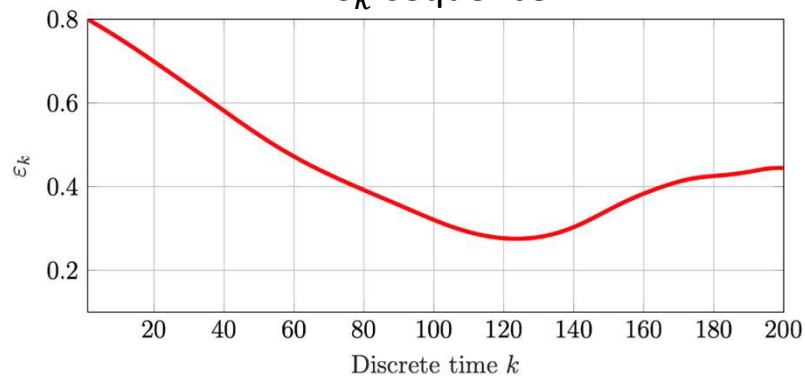
Target 1 – Scenario 3



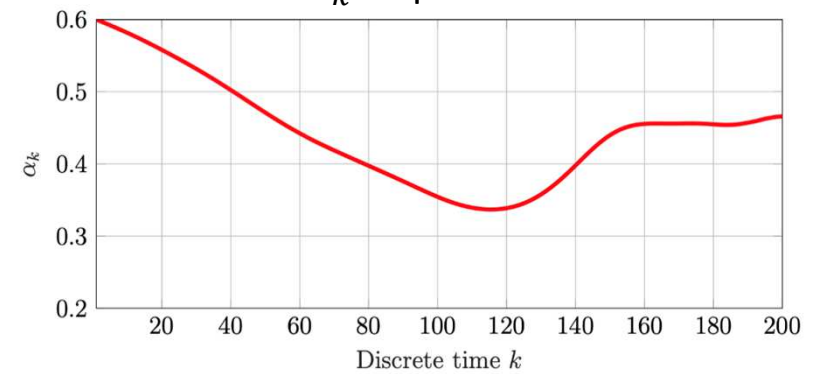
Target 2 – Scenario 3



ε_k sequence

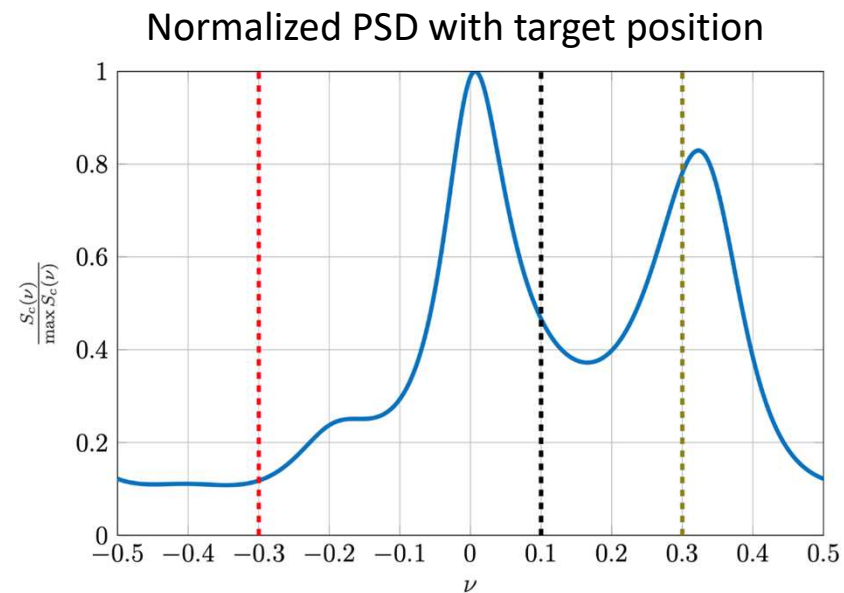


α_k sequence



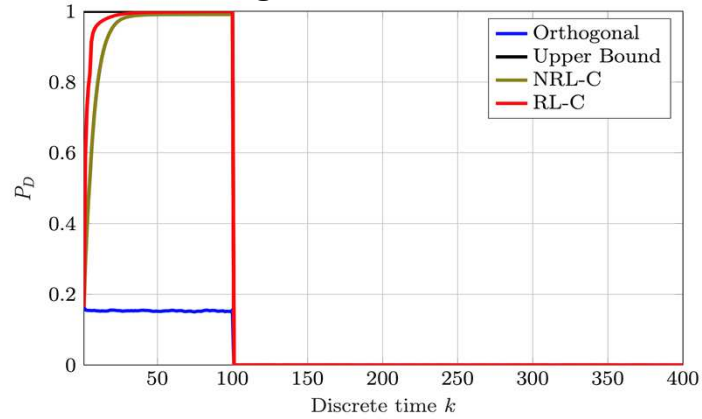
- The table describes a **non-stationary scenario** with 3 targets.
- **Target 1** is visible in [1,100].
Target 2 is visible in [1,300].
Target 3 is visible in [201,400].
- The noise process is the same as the previous simulations.

Time Interval	Target	Angular Bin	ν	SNR_{dB}
[1,100]	1	5	-0.30	-18
	2	13	0.10	-21
[101,200]	2	13	0.10	-21
[201,300]	2	13	0.10	-21
	3	17	0.30	-20
[301,400]	3	17	0.30	-20

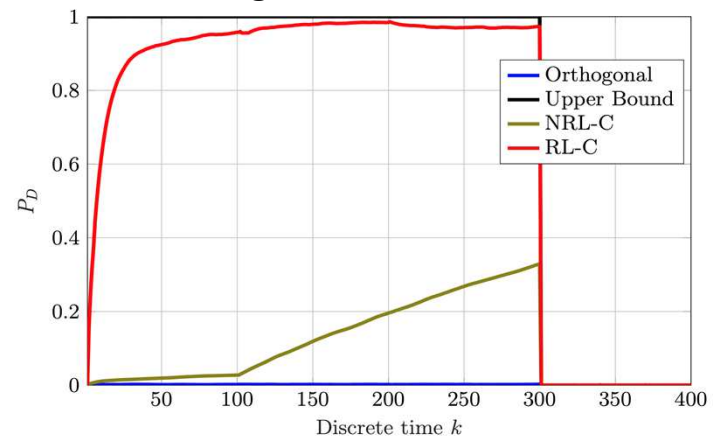


Performance scenario 4

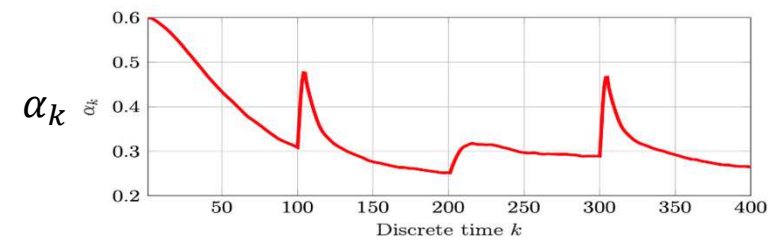
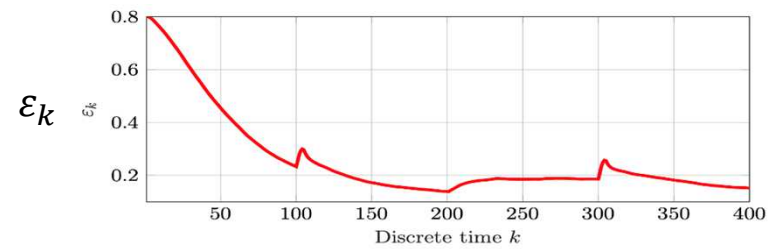
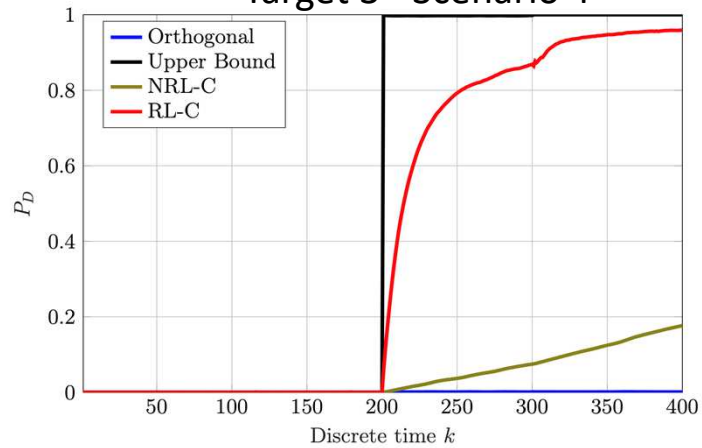
Target 1 - Scenario 4



Target 2 - Scenario 4



Target 3 - Scenario 4



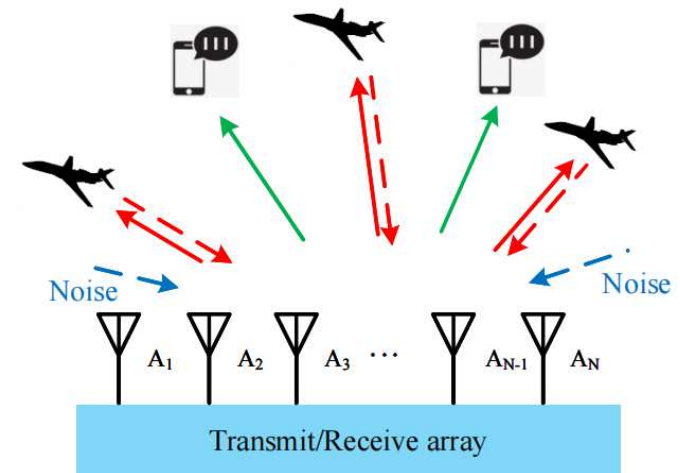
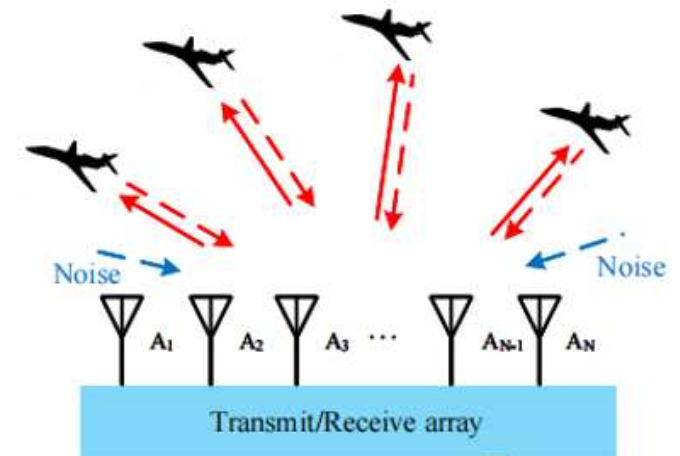
Integrated sensing and communications

- **Challenges of existing target detection:**

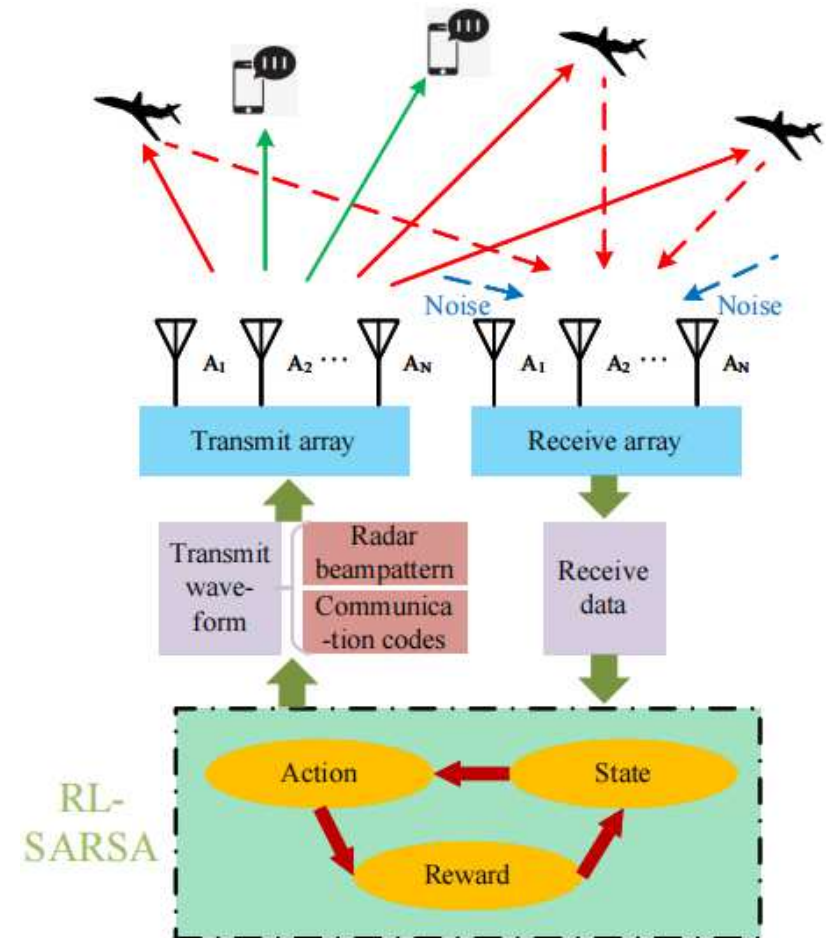
- Dynamic detection under non-stationary environment
- Increased detection of weak targets

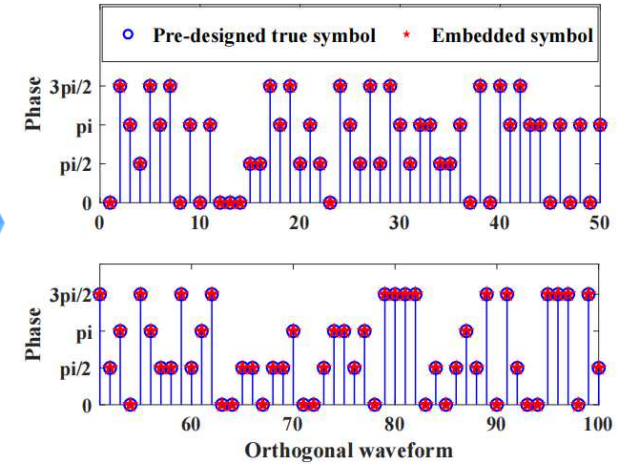
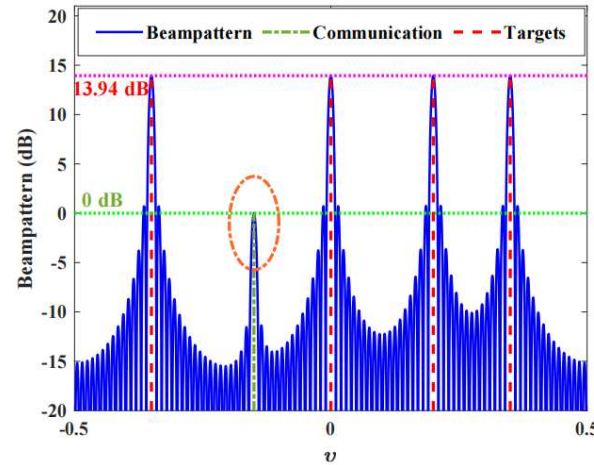
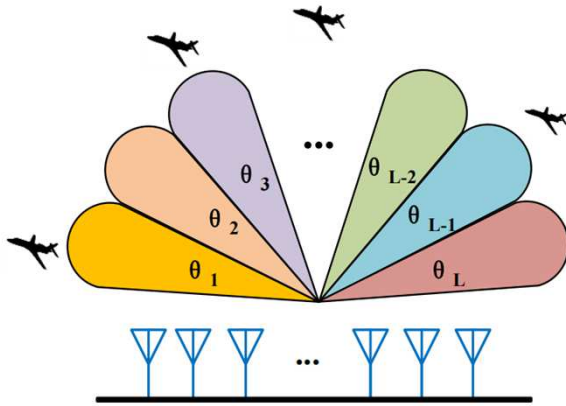
- **Exploring Massive MIMO resources:**

- Integrated mMIMO system to house both functions of radar and communication concurrently
- Alleviated spectral congestion



- **RL based multi-target detection**
 - Design a robust Wald-type estimator for mMIMO
 - Introduce RL into multi-target detection
 - Achieve dynamic detection under unknown environment
 - Enhance weak target detection performance
- **Realization of integrated communication**
 - Embed communication information into radar transmit waveform via complex beampattern modulation
 - Utilize two rotation transformation strategies to embed the communication codes





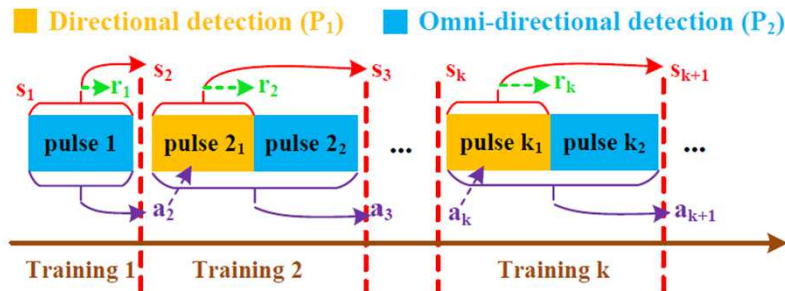
Divide the detection area into L discrete angular bins

Steer the beams to the angular bins that most likely contains a target while ensuring the communication power.

Embed communication codes

- The radar detection is improved by adding an omni-directional detection pulse into each training.
- The communication is integrated by a two-step joint waveform design utilizing rotation transformation.

- Improved SARSA**



The k th training is performed with two consecutive radar pulses, the first is directional, the second is omni-directional. In this way we increase the probability of detecting also very weak targets

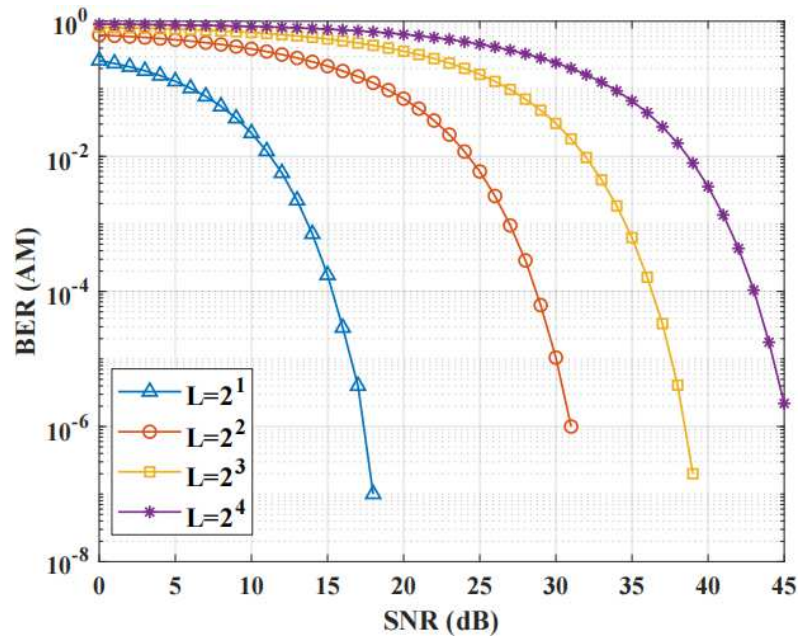
The new optimization problem is given by the problem P_1 and gives into account the beamforming and the constraints on the communication signals.

$\mathbf{g}_a \in R^{NT'}$ records the amplitude information of the NT' communication symbols

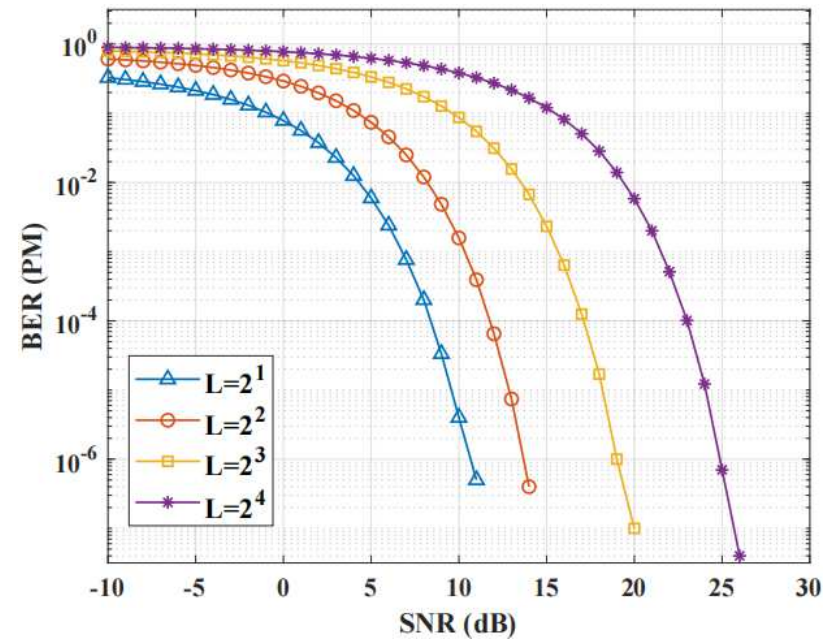
$\mathbf{g}_p \in C^{NT'}$ records the phase information of NT' communication symbols

$$\begin{aligned}
 (P_1) \quad & \max_{\mathbf{W}, \delta} \delta \\
 \text{s.t.} \quad & \mathbf{a}_T^T(\theta_i) \mathbf{W} \mathbf{W}^H \mathbf{a}_T^*(\theta_i) \geq \delta, \quad \forall \theta_i \in \Theta_k, \\
 & \|[\mathbf{W}]_{(i)}\|^2 = P_T, \quad 1 \leq i \leq N_T, \\
 & \begin{cases} |\mathbf{a}_T^T(\theta_c) \mathbf{W}| = \mathbf{g}_a^T, & \text{for AM} \\ \mathbf{a}_T^T(\theta_c) \mathbf{W} = (\mathbf{g}_a \odot \mathbf{g}_p)^T, & \text{for PM} \end{cases}
 \end{aligned}$$

BER performance



➤ AM mode



➤ PM mode

Future Directions and Challenges



Sensor collaboration and distributed cognition

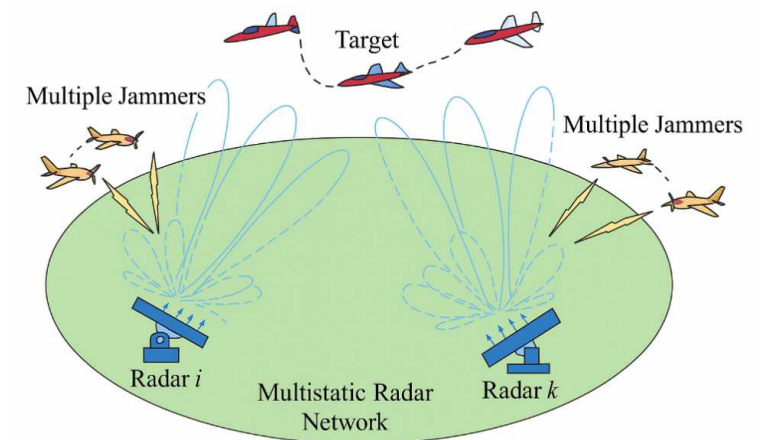
- **Distributed cognition** in radar systems extends the cognitive radar paradigm from a single adaptive sensor to a network of cooperating radar nodes.
- The nodes collectively perceive, learn, and act upon the environment. In this framework, perception, memory, learning, and decision-making processes are distributed across spatially separated agents and computational units.
- Through shared information, coordinated waveform design, and collaborative resource allocation, the radar network behaves as an intelligent collective rather than a set of independent sensors.
- Benefits:
 - Robustness to node failure
 - Better coverage
 - Reduced ambiguity
 - Improved detection probability
 - Resilience to jamming

Sensor collaboration and distributed cognition

- **Multi-Agent Reinforcement Learning** is an extension of RL that involves **multiple agents** interacting within a shared environment.
- Each agent learns to make decisions not only based on the environment's dynamics but also considering the actions and learning behaviors of other agents.
- Formally, a MARL problem can be represented as a **stochastic game** (also called a **Markov game**), defined by the tuple $(N, \mathbf{S}, \{\mathbf{A}_i\}_{i=1}^N, P, \{r_i\}_{i=1}^N)$, where:
 - N is the number of agents.
 - \mathbf{S} is the set of possible *states* of the environment.
 - \mathbf{A}_i is the set of *actions* available to agent i .
 - $P = P(s' | s, a_1, \dots, a_N)$ is the *transition probability function*, the probability of moving to state s' given the joint action of all agents.
 - $r_i(s, a_1, \dots, a_N)$ is the *reward function* for agent i .

Sensor collaboration and distributed cognition

- Each agent seeks to learn a **policy** $\pi_i(a_i|s)$ that maximizes its own expected cumulative reward, often while competing or cooperating with others. Similar learning approaches of RL can be applied to MARL.
- Depending on the setting, MARL can be:
 - **Cooperative**, where agents share a common goal.
 - **Competitive**, where agents have opposing objectives.
 - **Mixed**, where some cooperation and competition coexist.
- Applications are: EC and ECC, ISAC, target detection and tracking.



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Thanks for your attention

QUESTIONS?