Sensor Signal Processing for Defence Conference

12th September 2023

Panel discussion:

The future of Defence Signal Processing: is it all just AI?

University of Strathclyde Engineering

A Novel Adaptive Architecture: Joint Multi-targets Detection and Clutter Classification

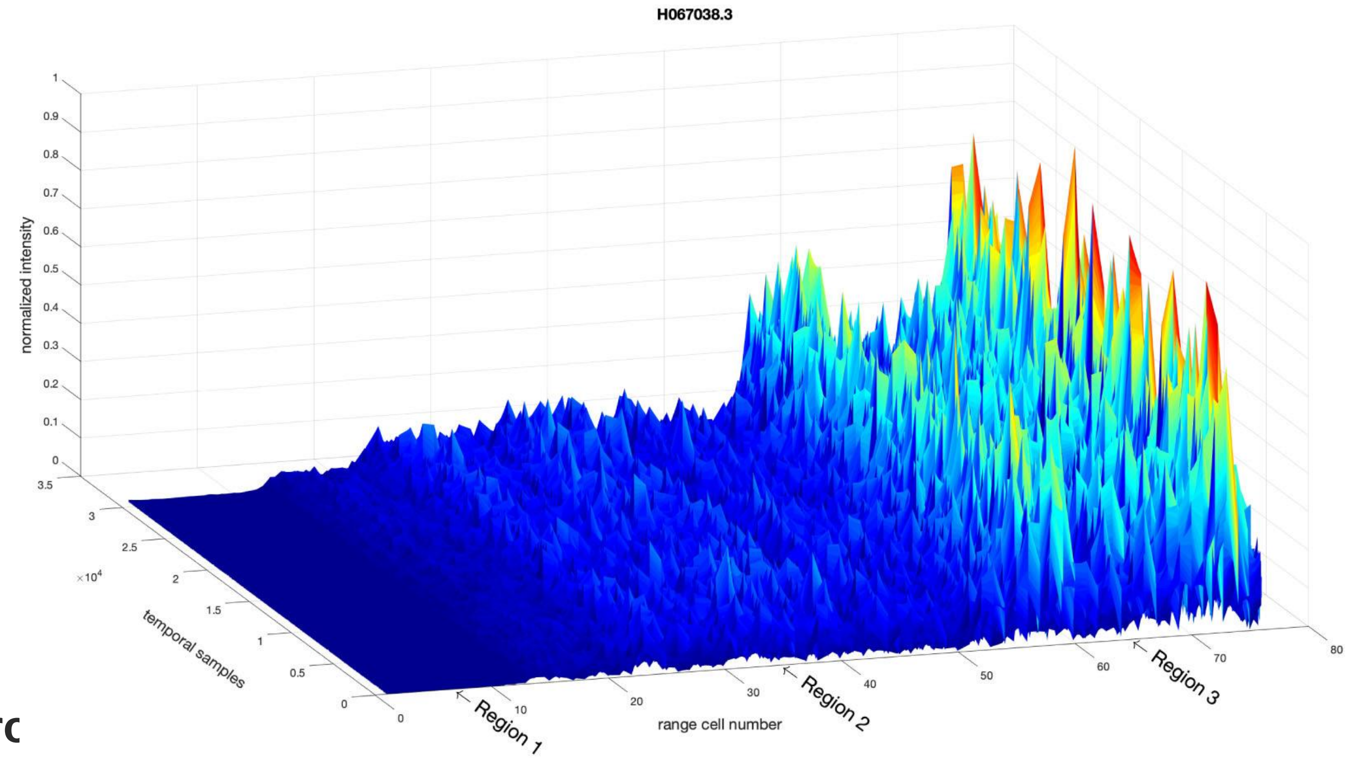
Linjie Yan[1], ***Carmine Clemente***[2], *Sudan Han*[3], *Chengpeng Hao*[1], *Danilo Orlando*[4], and *Giuseppe Ricci*[5]

1 Institute of Acoustics, Chinese Academy of Sciences, Beijing, China
2 Department of Electronic and Electrical Engineering, University of Strathclyde, G1 1XW Glasgow, U.K
3 National Innovation Institute of Defense Technology, Beijing, China
4 Universita' degli Studi "Niccolo' Cusano", Roma, Italy
5 Dipartimento di Ingegneria dell'Innovazione, Universita' del Salento, Lecce, Italy

Outline

Introduction

Adaptive radar detection embedded in Gaussian interference is a ubiquitous task, and it is still an attractive problem especially for complex operating scenarios.

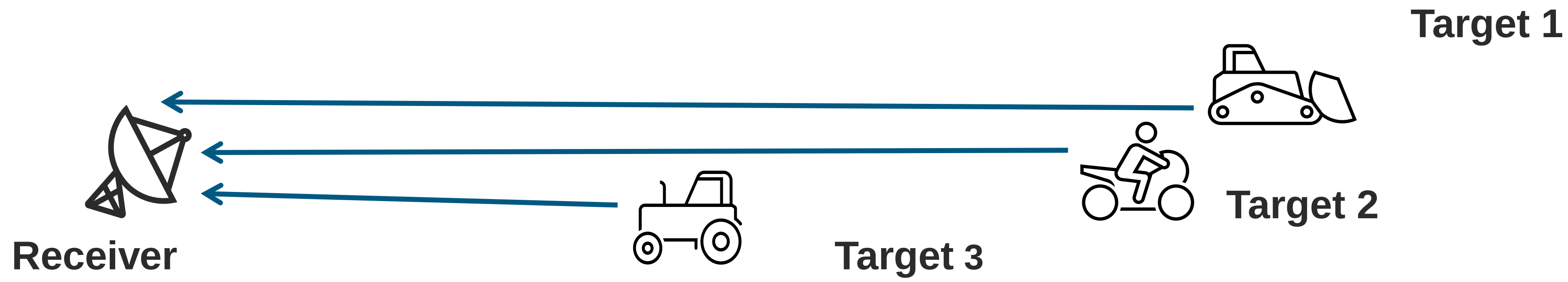


Heterogeneous envirc

The statistical properties of the interference vary over the range bins due to various types of terrain, clutter discretization, or outliers, which causes performance degradation due to a limited number of homogeneous training samples;

Introduction

- Another challenging scenario is the **target-rich environment;**
- In this case the structured echoes may contaminate training data;
- A consequence is the risk of incorporating target components into the covariance matrix estimate with a consequent reduction of the detector sensitivity.



Introduction

To overcome this drawback, a novel adaptive architecture is conceived to jointly face with the problem of **heterogeneous clutter echoes classification** and **multiple point-like targets detection** with lack of targets' information, including their **positions, number, and angles of arrival (AoA).**

Build **a model for a target-rich scenario** in heterogeneous clutter environment.

↓

Introduce **hidden random variables** for data classification.

↓

Estimate the unknown parameters by adopting the **Expectation-Maximization (EM)** together with a **grid search approach**.

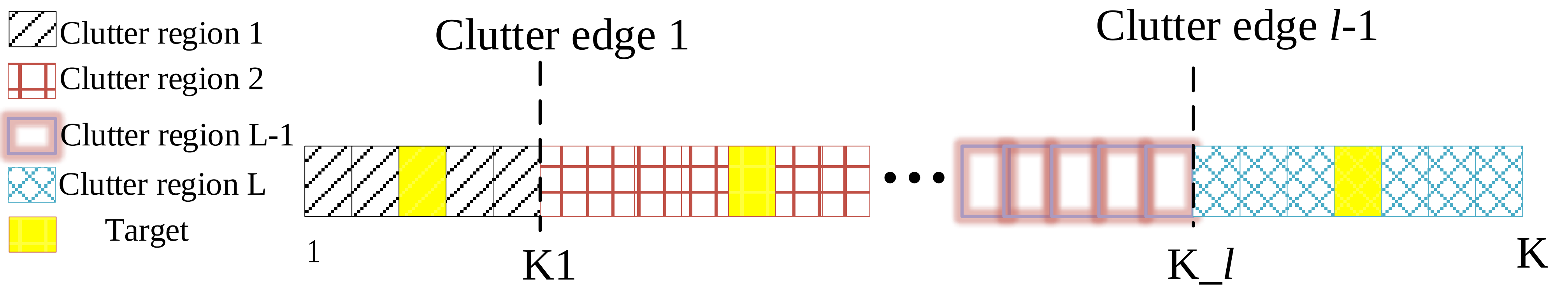
↓

Design a decision scheme based upon the **Likelihood Ratio Test**.

Problem Formulation

Scenario Description

Denote by $\boldsymbol{z}_1, \dots, \boldsymbol{z}_K$ the **N-dimensional vectors** representing the returns from K **range bins** of the region under surveillance, and $\boldsymbol{z}_k, k = 1, \dots, K$ are statistically independent.



Heterogeneous Clutter:

- ✓ All clutter returns from K range bins can ***be partitioned into L homogeneous subsets*** coming from the a priori information about the terrain types of the region;
- ✓ ***In each subset*** the clutter shares ***the same Gaussian statistical properties***.

Multiple deterministic targets: $\alpha_k \boldsymbol{v}(\theta_t), k \in \Omega_l^t$

- ✓ ***T targets are randomly present within the region of interest*** whose elements indexes in the lth clutter region is Ω_l^t;
- ✓ α_k is ***unknown deterministic factor*** accounting for target response, channel effects;
- ✓ $\boldsymbol{v}(\theta_t)$ denotes the spatial steering vector pointed along θ_t, which is the ***unknown AoA*** of each target;

Problem Formulation

Binary Hypothesis Test

The detection problem for the multiple deterministic targets can be formulated as a ***binary hypothesis test***

where $l = 1, \dots, L$:

$$\begin{cases} H_0: \boldsymbol{z}_k \sim \mathcal{CN}_N\,(\boldsymbol{0}, \boldsymbol{M}_l), k \in \Omega_l^c \\ H_1: \begin{cases} \boldsymbol{z}_k \sim \mathcal{CN}_N\,(\boldsymbol{0}, \boldsymbol{M}_l),\ k \in \Omega_l^c \backslash \Omega_l^t \\ \boldsymbol{z}_k \sim \mathcal{CN}_N\,(\,\alpha_k \boldsymbol{v}(\theta_t), \boldsymbol{M}_l),\ k \in \Omega_l^t \end{cases} \end{cases}$$

- where H_0 is the ***noise-only hypothesis***, H_1 denotes the ***signal-plus- interference hypothesis***;
- $\mathcal{CN}_N\,(\boldsymbol{0}, \boldsymbol{M}_l)$ denotes the ***N dimensional circular complex Gaussian distribution*** with mean $\boldsymbol{0}$ and unknown positive definite covariance matrix in the lth clutter region $\boldsymbol{M}_l$;
- $\Omega_l^c \backslash \Omega_l^t$ represents the index vector containing the homogeneous returns in the l th clutter region ***except for the targets components***;

The sets of ***unknown parameters*** associated with the distribution of $\boldsymbol{z}_k$:

$$\mathcal{P}_{0,k} = \{\Omega_l^c, \boldsymbol{M}_l : l = 1, \dots, L\}, \quad \textbf{under } \boldsymbol{H_0}$$

$$\mathcal{P}_{1,k} = \{\Omega_l^t, \Omega_l^c, \theta_t, \alpha_k, \boldsymbol{M}_l : l = 1, \dots, L\}, \quad \textbf{under } \boldsymbol{H_1}$$

Proposed Detection Architecture

We provide a solution to this problem by devising detection architectures capable of ***classifying the range bins*** according to their clutter properties and ***detecting possible multiple targets*** whose ***positions, number and AoA are unknown***.

Latent Variable Model

Introduce the hidden random variables accounting for different clutter types and the presence of a possible target.

Grid Search Method

Estimate AoA of multi-target

EM Algorithm

Estimate the unknown interference and multi-target parameters to obtain the AoA estimate.

Detector with Classification

- ✓ Separate the target response from the heterogeneous clutter.
- ✓ An adaptive LRT detector is built up based on the estimates.

A. Estimation Procedures for Deterministic Targets

B. Adaptive Detector with Classification Capabilities

Latent Variable Model

- We introduce a set of hidden K independent and identically distributed discrete random variables random variables $c_k, k = 1, \dots, K$;
- These variables account for the presence of a specific class of clutter and the presence of targets contaminating the k-th range bin.

The number of classes is therefore $L_c = L_s + L$ with $L_s = \ 0, 1$ controlling the presence of a possible target.

$$L_c = \begin{cases} L, & \text{under } H_0 \\ 2L, & \text{under } H_1 \end{cases}$$

where $L_c = L$ accounts for the ***number of clutter covariance classes***, whereas $L_c = 2L$ accounts for ***different clutter types and the presence of a possible target***.

EM Algorithm based on grid search

- The unknown interference and target parameters are estimated by a suitable modification of the EM algorithm in conjunction with a grid search approach to seek the most likely estimates of the AoAs.

- The EM algorithm is then applied to the overall data matrix $\boldsymbol{Z} = [\boldsymbol{z}_1, \ldots \boldsymbol{z}_K]$ under $H_i, i = 0{,}1$.

Algorithm 1: Estimation procedure based on EM and grid-search.

Input: L, $\boldsymbol{Z}$, $\theta_t, t = 1, \ldots, T$

Output: $\widehat{\Omega}_l^c$, $\widehat{\Omega}_l^t$, $l = 1, \ldots, L$, $\widehat{\mathcal{P}}'_{1,k}$, $k = 1, \ldots, K$

Latent Variable Model: introduce the hidden random variables $c_k, k = 1, \ldots, K$ accounting for different clutter types and the presence of a possible target;

for $\theta_t, t = 1, \ldots, T$ **do**

- **Parameters initialization:** $\widehat{\mathcal{P}}'^{(0)}_{1,k}$, $k = 1, \ldots, K$;
- **E-step**: compute the conditional expectation of $\boldsymbol{z}_k$ and obtain update rule of $q_k^{(h-1)}(Ls + l)$ at the $(h-1)$th iteration of EM;
- **M-step**: maximize the log-likelihood to get updates for $\widehat{\mathcal{P}}'^{(h)}_{1,k}$, $k = 1, \ldots, K$ with the inner cyclic iterations $m = m_{max}$;
- **if** $h = h_{max}$ *or convergence criterion is satisfied* **then**
  - set $t = t + 1$ and continue;
- **else**
  - set $h = h + 1$ and go to E-step;
- **end**

end

Estimate θ_t**:** $\widehat{\theta}_t = \max_{\theta_t \in \{\theta_1, \ldots, \theta_T\}} \mathcal{L}(\boldsymbol{Z}; \widehat{\mathcal{P}}_1^{(h_{max})})$.

…Full analytical derivations in the paper

Adaptive Detector with Classification Capabilities

The ***adaptive detector*** is based on the ***LRT*** where the unknown parameters are replaced by the previously-obtained estimates in the log-likelihood functions g_i

$$\prod_{k=1}^{K} \frac{g_0\left(\boldsymbol{z}_k; \hat{\mathcal{P}}'_{0,k}\right)}{g_1\left(\boldsymbol{z}_k; \hat{\mathcal{P}}'_{1,k}\right)} \gtrless \eta$$

where η is the ***detection threshold*** to be set according to the probability of false alarm.

For ***classification*** purposes, we separate the target response from the heterogeneous clutter by exploiting ***this formulation under*** H_1

$$\boldsymbol{z}_k = \begin{cases} \mathcal{CN}_N\left(\boldsymbol{0}, \widehat{\boldsymbol{M}}_{\hat{l}_k}{}^{(h_{max})}\right), & 1 \le \hat{l}_k \le L \\ \mathcal{CN}_N\left(\hat{\alpha}_k{}^{(h_{max})} \boldsymbol{v}(\hat{\theta}_t), \widehat{\boldsymbol{M}}_{\hat{l}_k - L}{}^{(h_{max})}\right), & L+1 \le \hat{l}_k \le 2L \end{cases}$$

with $\widehat{l_k} = \arg \max_{l=1,\dots,2L} q_k^{(h_{max})}(l)$, which reflects the information of the clutter regions and about the existence of a target.

Simulation Scenario

Using a Monte Carlo Analysis we have simulated a scenario using the following parameters:

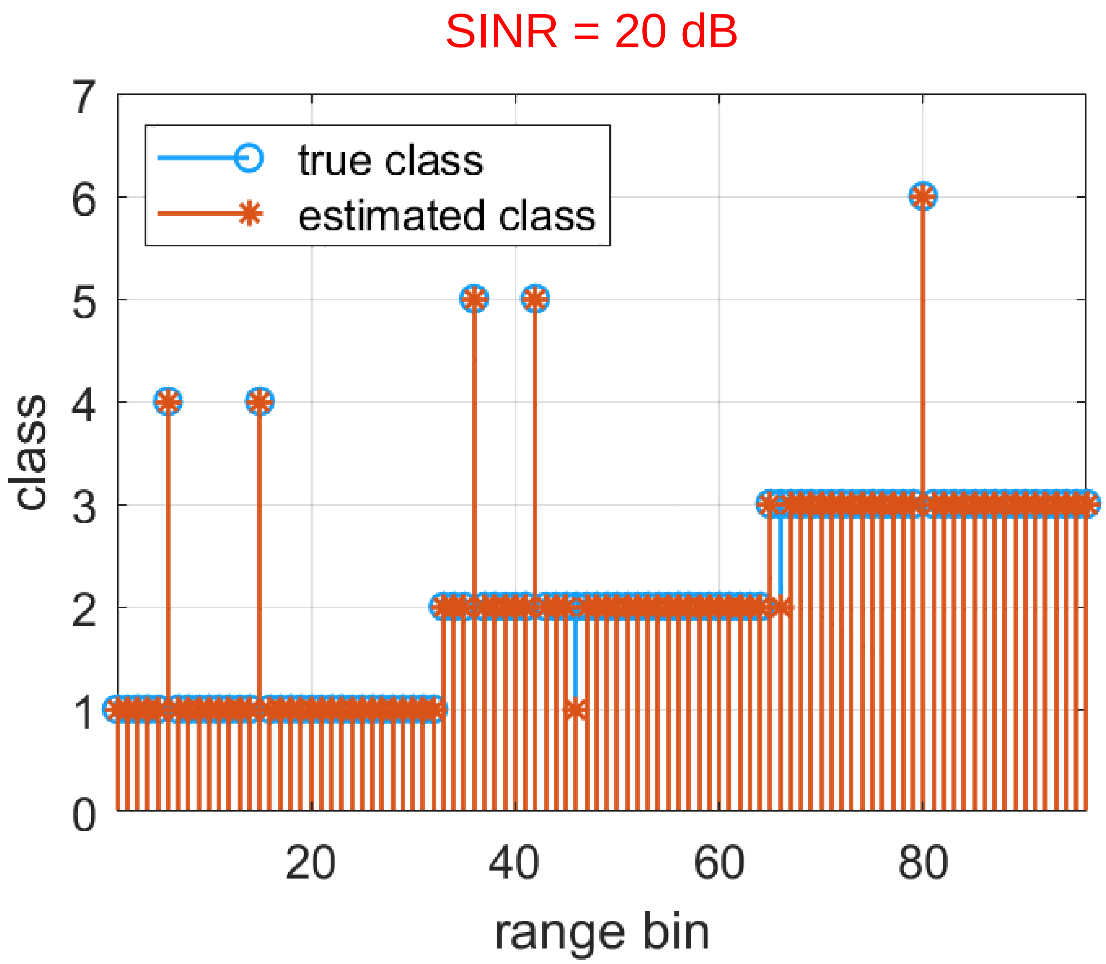
VARIABLES	PARAMETERS
Number of Channels - N	8
Number of Homogeneous Subset of Clutter-L	3
Generalised Information Criterion parameter - ρ	3
Maximum number of outer cyclic iterations - h_{max}	15
Maximum number of inner cyclic iterations - m_{max}	5
P_{fa}	10^{-3}
Angular Sectors	$-20°: 5°: 20°$

Classification Results

In the simulated scenario we have ***three clutter regions***, namely, $K_1 = K_2 = K_3 = 32$ range bins in each region comprise the scenario of interest.

Five targets appear at the 6th, 15th, 36th, 42th, and 80th range bin in the considered scenario. This operating scenario yields $L_c = 6$ considered classes.

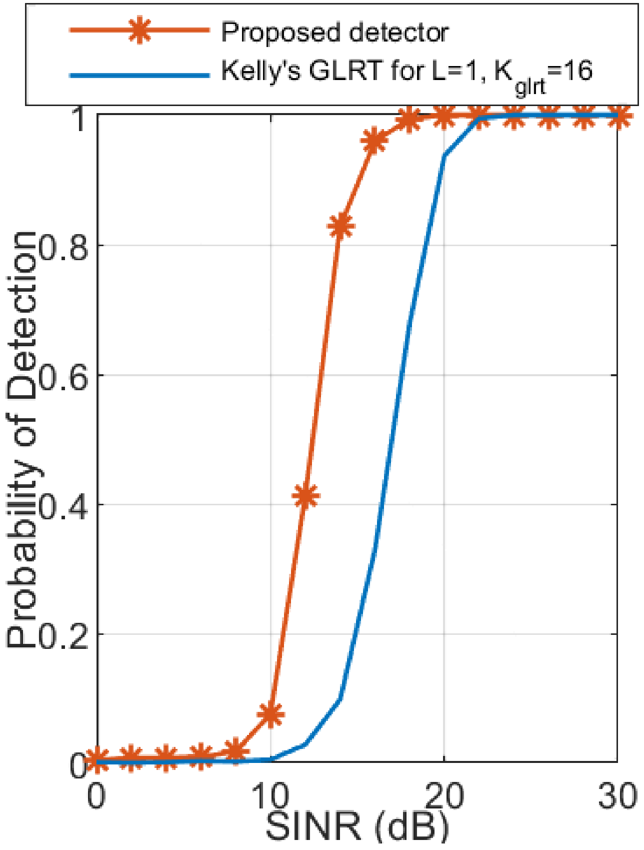
- ✓ **Classes 1-3:** the generic vector of the lth region ***does not contain any target component***;
- ✓ **Classes 4-6:** the generic vector of the lth region ***contains target components***.



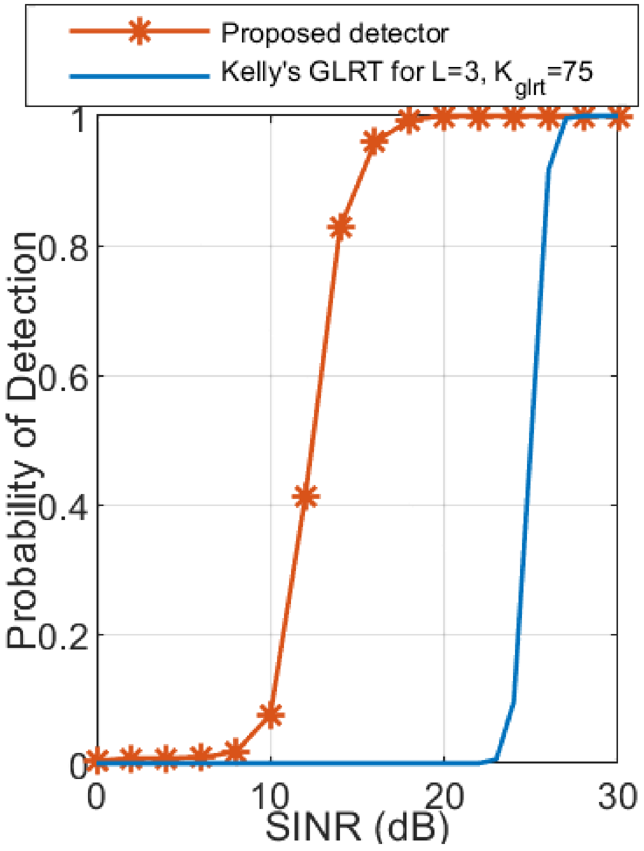
Detection Results

Comparision with ***Kelly's Generalized Likelihood Ratio Test*** in under multi-targets situation.

Case including one interfering target in the secondary data



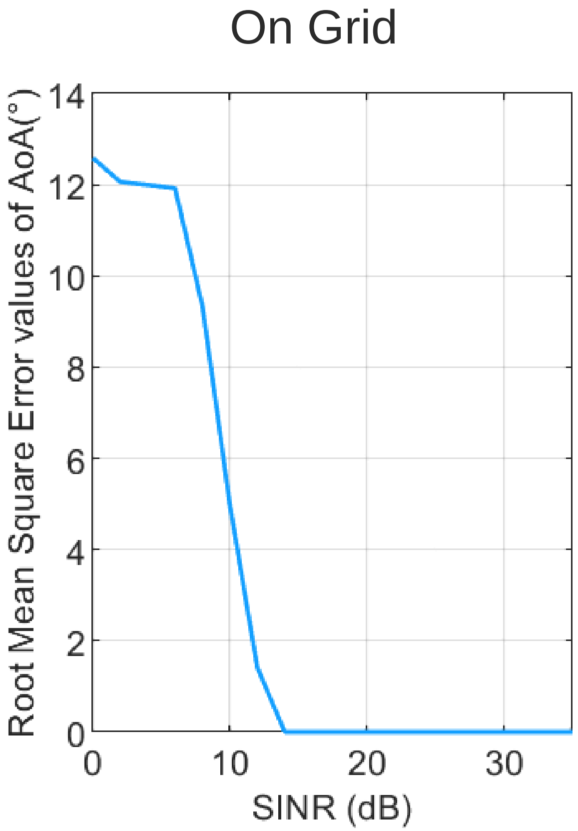
Case including multiple targets in the secondary data (jammers)

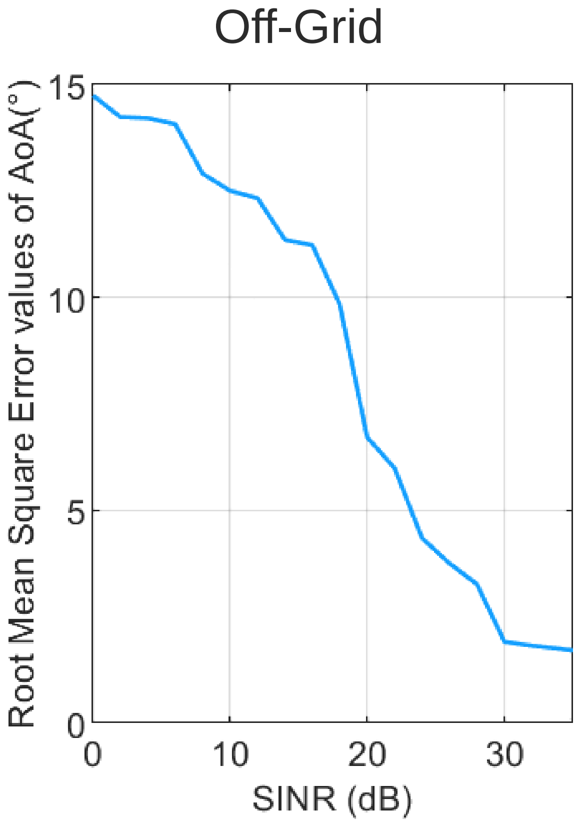


Kelly's GLRT does not account for secondary data contamination caused by the redundant targets leads to the performance degradation of this classical detector.

AoA estimation perfomance

In order to measure the error in ***target AoA estimation***, we estimate the ***Root Mean Square Error (RMSE) values*** with the true target AoA of $0°$ being ***on-grid*** and of $2°$ being ***off-grid***.





As expected in the off-grid case the RMSE converges to $2°$

AoA estimation perfomance

- We have addressed the problem of ***multiple point-like targets detection from an unknown AoA and in the presence of heterogeneous Gaussian clutter and the ubiquitous thermal noise***.
- At the design stage, we account for the heterogeneity of the operating scenario modeled as ***a variation of covariance matrices over the range cells***.
- Within this framework, ***the EM algorithm in conjunction with grid search*** technique are used to estimate the ***unknown distribution parameters***.
- An adaptive detector is also introduced resorting to the ***LRT criterion.***
- The algorithm is able to estimate the clutter region class, Detect the presence of a target and its position over range and AoA.
- The performance of the algorithm with respect to a conventional detector in presence of multiple targets, is verified based on simulated data.
- Possible future research can extend the proposed framework to the scenarios that considers ***the joint presence of point-like as well as range-spread targets and the testing on real recorded radar data.***

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