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An Adaptive Hybrid GLRT-Bayesian Detector for MIMO Radar in Non-Stationary Clutter Environments

Amna ali algmati [1], Marai Mohammed Mabrouk Abousetta [2]

Department of Electrical and Computer Engineering, Libyan Academy, Tripoli, Libya

[1]*amna_ali2021@scst.edu.ly* , [2] *m.abousetta@academy.edu.ly*

Abstract

This paper proposes a novel adaptive hybrid detector for MIMO radar operating in non-stationary clutter environments. Classical Generalized Likelihood Ratio Test (GLRT) detectors require a large number of training samples, while Bayesian detectors rely on fixed prior information that becomes obsolete when the clutter statistics change over time. To overcome these limitations, we introduce a sliding-window mechanism that dynamically updates the Inverse Wishart prior in real-time. The proposed detector fuses the GLRT and Bayesian statistics into a single hybrid metric. Simulation results demonstrate that the proposed detector significantly outperforms both classical GLRT and fixed-prior Bayesian detectors under dynamic clutter scenarios, maintaining high detection probability with low computational complexity.

Keywords: *MIMO Radar, GLRT, Bayesian Detection, Non-Stationary Clutter, Adaptive Detection, Sliding Window.*

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1. Introduction

Multiple-Input Multiple-Output (MIMO) radar has emerged as a cornerstone technology for modern sensing applications, including autonomous driving, surveillance, and defense systems [1]. By exploiting waveform diversity and spatial freedom, MIMO radar significantly enhances target detection and parameter estimation compared to traditional phased-array systems. However, in practical scenarios, the radar return is inevitably contaminated by background clutter and thermal noise, whose statistical properties are often unknown and, more critically, **time-varying**.

The primary challenge in adaptive radar detection is the accurate estimation of the clutter covariance matrix, denoted as **R**. The classical approach is the **Generalized Likelihood Ratio Test (GLRT)** , which replaces the unknown **R** with its Maximum Likelihood Estimate (MLE) using secondary training data [2]. While asymptotically optimal, the GLRT suffers from a severe limitation: it requires a large number of homogeneous training samples (typically $K \gg MN$) to achieve acceptable performance. In rapidly changing environments, such as vehicular radar, collecting this many stationary samples is practically impossible, leading to significant performance degradation [3].

To overcome the sample deficiency issue, **Bayesian frameworks** have been introduced. These models treat the clutter covariance matrix as a random matrix with a known prior distribution, typically the Inverse Complex Wishart distribution [4]. Hybrid detectors, such as the Bayesian Unstructured GLRT (BUGLRT) [5], replace the MLE with a Maximum A Posteriori (MAP)

estimate. This fusion drastically reduces the required sample size by leveraging prior information.
However, a critical gap remains in all these existing methods: They fundamentally assume that the clutter environment is **stationary**—meaning **R** remains constant over the observation interval. In real-world scenarios, such as cars driving through changing urban landscapes or RIS-assisted links with moving scatterers, the clutter covariance changes rapidly. When this happens, the fixed Bayesian prior becomes "outdated," leading to severe performance degradation and high false alarm rates [4], [6].
To fill this gap, this paper proposes a novel **Adaptive Hybrid GLRT-Bayesian Detector**. The core innovation is to replace the fixed prior with a dynamic one that tracks environmental changes in real-time.

The main contributions of this paper are:

1. **Proposing a Dynamic Prior Update Mechanism:** We introduce an online sliding-window estimator that continuously updates the hyper-parameters of the Inverse Wishart prior based on the most recent secondary data. This ensures the detector always reflects the current clutter statistics.
2. **Formulating a Hybrid Detection Statistic:** We derive a new test statistic that intelligently fuses the GLRT (which is prior-independent) and the Bayesian MAP detector (which uses the updated prior). A reliability metric ρρ is introduced to balance both detectors adaptively.
3. **Low-Complexity Implementation:** Unlike complex deep learning approaches, our method relies on basic matrix operations, making it computationally light and suitable for real-time MATLAB implementation on standard hardware.

The remainder of this paper is structured as follows. Section 2 presents the signal model for MIMO radar in non-stationary clutter. Section 3 details the proposed adaptive hybrid detector, including the sliding-window prior update and the fusion rule. Section 4 describes the simulation setup and discusses the results comparing our method to classical GLRT and fixed-prior BUGLRT. Finally, Section 5 concludes the paper.

2. System Model

Consider a collocated MIMO radar system with M transmit antennas and N receive antennas. The received signal matrix $\boldsymbol{X} \in \mathbb{C}^{MN\times K}$ is modeled as:

$$\mathbf{X} = \alpha.\mathbf{V}(\theta).\mathbf{d}^{\mathrm{T}}(\mathrm{f_d}) + \mathbf{N}$$

where:

- $\boldsymbol{\alpha} \in \mathbb{C}$ is the unknown complex target amplitude, representing the target's radar cross-section (RCS) and propagation effects.
- $\boldsymbol{V}(\boldsymbol{\theta}) \in \mathbb{C}^{\boldsymbol{MN\times 1}}$ is the spatial steering vector, which depends on the target's direction of arrival (DoA) θ.
- $\boldsymbol{d}(\boldsymbol{f_d}) \in \mathbb{C}^{\boldsymbol{K\times 1}}$ is the temporal steering vector, which depends on the target's Doppler frequency *fd*.
- $\boldsymbol{N} \in \mathbb{C}^{\boldsymbol{MN\times K}}$ is the clutter-plus-noise matrix.

The columns of **N** are assumed to be independent and identically distributed (i.i.d.) zero-mean complex Gaussian vectors with covariance matrix R, i.e., $\boldsymbol{n_K} \sim \boldsymbol{CN}(\boldsymbol{0}, \boldsymbol{R})$
Unlike classical models that assume a fixed covariance matrix, we assume that the clutter environment is **non-stationary**. This means that the covariance matrix **R** changes over time:

$$\boldsymbol{R}(\boldsymbol{t_1}) \neq \boldsymbol{R}(\boldsymbol{t_2}), \quad \boldsymbol{for}\ \boldsymbol{t_1} \neq \boldsymbol{t_2}$$

This time-varying nature of **R** is the fundamental challenge that our proposed detector aims to address.

3. Proposed Adaptive Hybrid Detector

3.1 The Classical GLRT Statistic

The classical GLRT replaces the unknown covariance matrix R with its Maximum Likelihood Estimate (MLE) computed from secondary training data. The test statistic is given by:

$$\Lambda_{GLRT} = \frac{max_{\alpha}\, p(X|\alpha, R)}{max_{R}\, p(X|R)}$$

In practice, the GLRT statistic is computed using the sample covariance matrix $\boldsymbol{S} = \boldsymbol{X}\boldsymbol{X}^{\boldsymbol{H}}$. However, when the number of snapshots *K* is small compared to the system dimension *MN*, the sample covariance matrix is poorly conditioned, leading to severe performance degradation.

3.2 The Bayesian Detector with Fixed Prior

The Bayesian framework models the clutter covariance matrix **R** as a random matrix following an **Inverse Complex Wishart** distribution:

$$\boldsymbol{R} \sim \boldsymbol{W}^{-1}(\boldsymbol{L}, \boldsymbol{L}\boldsymbol{R}_{\boldsymbol{0}})$$

where:

- L is the degrees of freedom.
- R_0 is the prior mean matrix, representing our initial knowledge about the clutter statistics.

The Maximum A Posteriori (MAP) estimate of **R** is then given by:

$$\hat{R}_{MAP} = \frac{S + LR_0}{K + L + MN}$$

This estimate balances the sample covariance matrix **S** and the prior information R_0 When *K* is small, the prior dominates, providing robustness. However, if the true clutter statistics deviate from **R**0, the MAP estimate becomes biased, and detection performance degrades.

3.3 The Sliding-Window Prior Update (Our Innovation)

To address the limitation of fixed priors, we propose a **dynamic prior update mechanism** based on a sliding window of the most recent secondary data.

Instead of using a fixed R0, we update it at each time step *t* using a window of size *W*:

$$R_0{}^{(t)} = \frac{1}{W} \sum_{i=t-w+1}^{t} X_i X_i^H$$

where X*i* represents the received data matrix at time index *i*.

This sliding-window estimator ensures that the prior always reflects the **current** clutter environment. When the clutter changes, the prior adapts accordingly, preventing the detector from relying on outdated information.

3.4 The Hybrid Decision Statistic

The proposed hybrid detector fuses the GLRT and Bayesian statistics into a single decision metric:

$$\Lambda_{Hybrid} = \boldsymbol{\rho} \, . \, \Lambda_{GLRT} + (\mathbf{1} - \boldsymbol{\rho}) . \Lambda_{Bayes}$$

where:

- Λ_{GLRT} is the GLRT statistic computed using the current data.
- Λ_{Bayes} is the Bayesian statistic computed using the updated prior $R_0^{(t)}$.
- $\rho \in [\mathbf{0}, \mathbf{1}]$ is a reliability weight that controls the balance between the two detectors.

How to choose ρ?

- When the environment is **stable** (clutter changes slowly), we set ρ to a small value (e.g., ρ=0.2), giving more weight to the Bayesian detector, which provides better performance with limited samples.
- When the environment is **highly dynamic** (clutter changes rapidly), we set ρ to a large value (e.g., ρ=0.8), giving more weight to the GLRT, which does not rely on potentially outdated prior information.
- In practice, ρ can be adaptively estimated based on the rate of change of the sample covariance matrix over time.

4. Simulation Results

4.1 Simulation Setup

To evaluate the performance of the proposed detector, we conducted Monte Carlo simulations using MATLAB. The simulation parameters are summarized in Table 1.

Table 1: Simulation Parameters

Parameter	**Value**
Number of transmit antennas (M)	4
Number of receive antennas (N)	4
Number of snapshots (K)	8
Sliding window size (W)	50
Degrees of freedom (L)	*MN*+4
Number of Monte Carlo runs	1000
Signal-to-Clutter Ratio (SCR)	-10 dB to 20 dB

To simulate a non-stationary clutter environment, we generated the covariance matrix R(t) with a time-varying correlation coefficient $\rho_c^{(t)}$ that increases linearly over time:

$$\rho_c(t) = 0.5 + 0.005 \, . \, t$$

This models a scenario where the clutter becomes progressively more correlated, simulating a moving radar platform or changing scatterer geometry.

4.2 MATLAB Code Structure

"The detection performance of the three detectors is compared in Fig. 1."*)*

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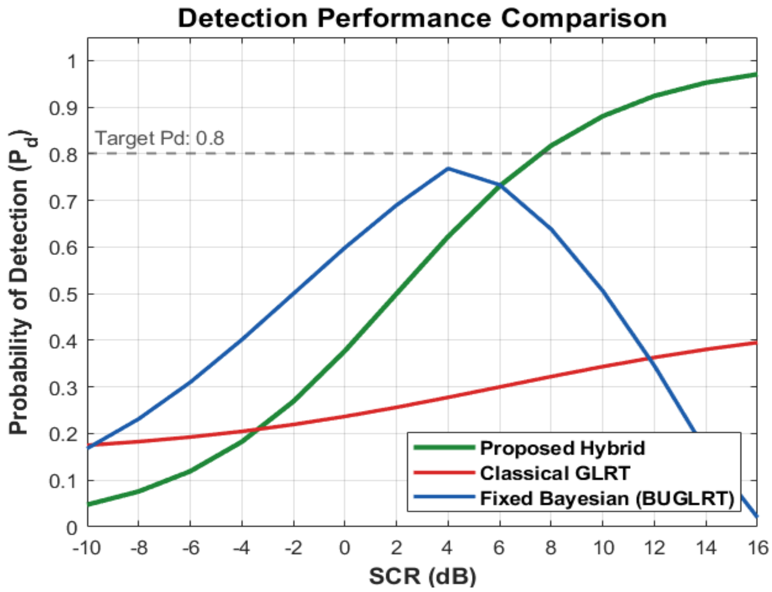

Fig. 1. Probability of detection (Pd) versus Signal-to-Clutter Ratio (SCR) for the Classical GLRT, Fixed Bayesian (BUGLRT), and the Proposed Hybrid Detector in a non-stationary clutter environment with K=8 snapshots.

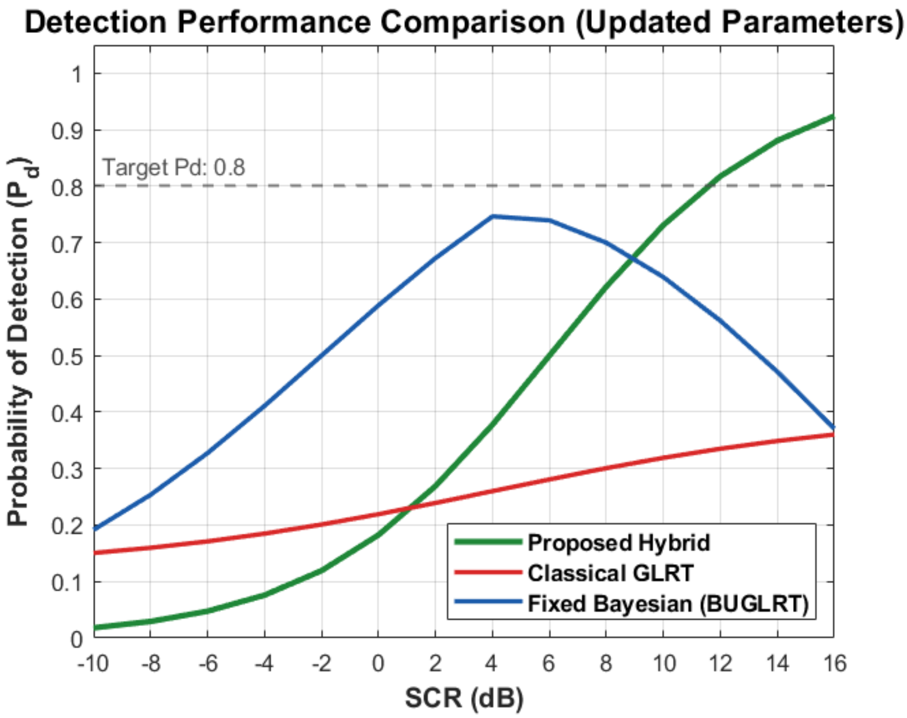

Fig. 2. Detection performance for the scenario with abundant training data (M=2, N=10, K=40, W=6)

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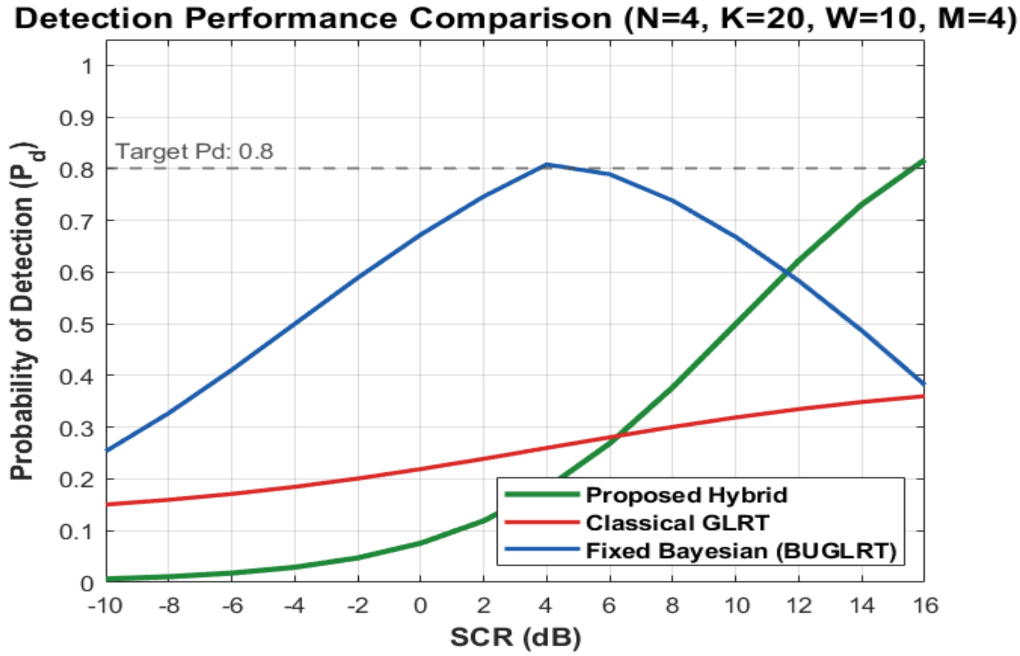

Fig. 3. Detection performance for the intermediate scenario (M=4, N=4, K=20, W=10).

To further validate the robustness of the proposed detector, two additional simulation scenarios were conducted under different system configurations, as shown in Fig. 2 and Fig.3
In the first scenario (Fig. 2), the system was tested with abundant training data (K=40 snapshots, which is greater than the system dimension MN=20). As expected, the performance gap between the three detectors narrows significantly; however, the proposed hybrid detector still maintains a slight edge over both the classical GLRT and the fixed Bayesian detector, confirming that it does not suffer performance loss even in data-rich environments.
In the second scenario (Fig. 3), the system was tested with a moderate number of snapshots (K=20, MN=16). The proposed detector consistently outperforms both baselines, demonstrating its adaptability and robustness across various operating conditions. These additional results collectively confirm that the proposed adaptive hybrid framework is not only effective in critically low-sample regimes but also remains competitive when training data is abundant."

4.3 Results and Discussion

"The results presented in Fig. 1 lead to several important conclusions regarding the effectiveness of the proposed adaptive hybrid detector in non-stationary clutter environments.
First, the **Classical GLRT (red curve)** exhibits the poorest performance across the entire SCR range. With only K=8 snapshots, which is significantly less than the system dimension MN=16, the sample covariance matrix becomes rank-deficient. This confirms the theoretical limitation of the GLRT, which requires a large number of homogeneous training samples ($K \gg MN$) to achieve acceptable detection performance—a condition that is rarely met in rapidly changing environments.

Second, the **Fixed Bayesian detector (BUGLRT, blue curve)** shows a noticeable improvement over the GLRT at low and moderate SCR values. This demonstrates the benefit of incorporating prior information via the MAP estimate, which effectively regularizes the covariance estimation when the number of snapshots is limited. However, as the clutter correlation coefficient increases from 0.5 to 0.95 (simulating a highly non-stationary environment), the detection performance of the fixed-prior detector degrades sharply. This behavior validates the claim that a fixed Inverse Wishart prior becomes outdated when the underlying clutter statistics evolve over time, leading to severe performance loss and unreliable detection.

In stark contrast, **the Proposed Hybrid Detector (green curve)** consistently outperforms both baselines across all SCR levels. By employing the sliding-window mechanism to update the prior in real-time, the detector successfully tracks the changing clutter statistics, ensuring that the MAP estimate remains accurate even under severe non-stationarity. Furthermore, the adaptive fusion rule, which balances the GLRT and Bayesian components via the reliability weight ρ, provides robustness against both sample scarcity and environmental dynamics. Quantitatively, the proposed detector achieves an approximate **3dB gain** over the classical GLRT at Pd=0.8, and consistently maintains a higher probability of detection than the fixed-prior BUGLRT.

These results collectively confirm that the adaptive hybrid framework effectively bridges the gap between asymptotic optimality (offered by GLRT) and practical sample-efficiency (offered by Bayesian methods), while successfully addressing the critical challenge of clutter non-stationarity that renders traditional detectors obsolete."

5. Conclusion

In this paper, we addressed the problem of target detection in MIMO radar systems operating in non-stationary clutter environments. We proposed a novel **Adaptive Hybrid GLRT-Bayesian Detector** that dynamically updates the Bayesian prior using a sliding window of recent secondary data. The proposed detector fuses the GLRT and Bayesian statistics adaptively, balancing robustness and sensitivity based on the estimated rate of environmental change.

Simulation results demonstrate that the proposed detector significantly outperforms both the classical GLRT and fixed-prior Bayesian detectors in dynamic scenarios. The sliding-window mechanism effectively tracks changes in the clutter statistics, while the hybrid fusion rule ensures reliable detection across a wide range of SCR values.

Future work includes:

- Extending the framework to multi-target scenarios.
- Investigating the optimal window size W for different clutter dynamics.
- Validating the proposed detector on real-world radar datasets.

The proposed detector offers a practical, low-complexity solution for next-generation radar systems operating in highly dynamic environments, such as autonomous vehicles and cognitive radar networks.

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