

Off-grid Radar Target Detection with the Normalized Matched Filter: a Monopulse-Based Detection Scheme

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 - In real conditions, there is no reason to have $\theta = \theta_0$. We have mismatch : $\theta \neq \theta_0$, and **performance derived under on-grid model is not met.**
 - This motivates the search of a robust detection scheme.

- 1 Problem formulation
 - Model under study
 - GLRT
 - O -Grid

- 2 A monopulse-based solution
 - Definitions
 - The Procedure
 - Properties

- 3 Numerical Results
 - Detector Comparison
 - Simulation under white noise

- 4 Bibliography

The classical Radar detection problem is the following binary Hypothesis Test:

$$\begin{aligned} H_0 : r &= n \\ H_1 : r &= s(\cdot) + n \end{aligned} ; \text{ where}$$

- $r \in \mathbb{C}^N$ is the observation,
- $s(\cdot) \in \mathbb{C}^N$ is the signal echo reflected by a target with parameters (range, angle, Doppler...),
- $a \in \mathbb{C}$ is the complex amplitude of the received signal,
- $n \in \mathbb{C}^N$ is the additive noise vector, independent of the source signal.
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Here the signal $s(\theta)$ follows the general spectral analysis model (angle or Doppler shift in Radar):

$$s(\theta) = \frac{1}{\sqrt{N}} \begin{bmatrix} h \\ 1; e^{2i\theta} \\ \vdots \\ e^{2i(N-1)\theta} \end{bmatrix} \mathbf{i}^T ;$$

with $\theta = 1/N$: grid vectors are orthogonal.

The GLRT is:

$$T(r) = \frac{\max_{\theta_1} f_{H_1}(r)}{\max_{\theta_0} f_{H_0}(r)} \stackrel{?}{> \tau} :$$

where

- for $i \in \{0, 1\}$, f_{H_i} is the density function of r under H_i and θ_i are the unknown parameters under H_i ,
- guarantees a fixed Probability of False Alarm (PFA).

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$$t(r) = \frac{\max_{\theta_1} f_{H_1}(r; \theta_1)}{\max_{\theta_0} f_{H_0}(r; \theta_0)} : \quad ?$$

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- guarantees a fixed Probability of False Alarm (PFA).

When $\theta_1 = \theta_0 = \theta$ and $\theta_0 = \theta_1 = \theta$ with θ known, the GLRT is the following Normalized Matched Filter (NMF)

[Scharf and Lytle, 1971]:

$$t(r; \theta) = \frac{s(\theta)^H r}{s(\theta)^H s(\theta)} \frac{r^H r}{r^H r} \quad ? : \quad H_1$$

- Mismatch = $\theta - \theta_0$
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- Angle mismatch creates a degradation of the NMF response even without noise
- When θ uniformly distributed in a cell it can be shown $P_D \approx 1 - \frac{\theta^2}{\theta_0^2}$
[Rabaste et al., 2016]
- Even worse when $\theta \ll \theta_0$

- Extension of the GLRT to o-grid targets:

$$\text{GLRT}(r; \theta_0) = \max_{c \in [c_0 - 2; c_0 + 2]} t(r; c) \frac{H_1}{H_0} :$$

The best P_D , no closed form available, threshold unknown, precise approximation can be costly.

- Extension of the GLRT to σ -grid targets:

$$\text{GLRT}(r; \sigma) = \max_{c \in [\sigma^- = 2; \sigma^+ = 2]} t(r; c) \begin{matrix} H_1 \\ ? \\ H_0 \end{matrix} :$$

The best P_D , no closed form available, threshold unknown, precise approximation can be costly.

- Existing **sub-optimal cost-efficient** solutions include
 - Oversampling approximate GLRT, **threshold unknown**
 - Using DPSS subspace to approximate the cell structure, **analytical threshold** [Bosse and Rabaste, 2018]
 - Detection with bounded mismatch, **not yet suited to low PFA Radar context** [Besson, 2006]

- Extension of the GLRT to σ -grid targets:

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 - Detection with bounded mismatch, not yet suited to low PFA Radar context [Besson, 2006]
- These solutions do not correct the convergence issue for all and are not always near GLRT.

- Monopulse traditionally used to estimate target parameters from a single pulse [Mosca, 1969].
- The idea is to combine two tests in a function h that carries info about θ .
- Used with noise η can give an approximation $\hat{\theta}$

- Classically in monopulse, the function is:

$$h_{;0}(r) = \frac{t_{r;0-\frac{1}{2}} - t_{r;0+\frac{1}{2}}}{t_{r;0-\frac{1}{2}} + t_{r;0+\frac{1}{2}}}$$

- Classically in monopulse, the function is:

$$h_{;0}(r) = \frac{t_{r;0-\frac{\tau}{2}} - t_{r;0+\frac{\tau}{2}}}{t_{r;0-\frac{\tau}{2}} + t_{r;0+\frac{\tau}{2}}}$$

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- Classically in monopulse, the function is:

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- mismatch: $= -\tau$, noise-free function:

$$g_{;0}(\tau) = h_{;0}(s(0+\tau))$$

- Goal: compute $\hat{\tau}$ by inverting $g(\tau)$ thanks to h applied on noisy signal.

$$g(\cdot) = T \begin{matrix} h \\ 1 \\ \vdots \\ N-1 \\ i \end{matrix}$$

- $g(\cdot)$ needs to be invertible. This is not always the case.

Candidate $g(\cdot)$ functions for
 $N=10, \theta_0 = 0$.

$$(\cdot) = T \begin{matrix} h \\ 1 \\ \vdots \\ N-1 \\ i \end{matrix}$$

- $g ;_0$ needs to be invertible. This is not always the case.
- We use g_i in the following even with colored Gaussian noise. We note ig .

Candidate $g(\cdot)$ functions for $N=10, \theta_0 = 0$.

- The test procedure is the following, for every r of the grid:

The test procedure

- 1 compute $t_{l; 0 - \frac{r}{2}}$ and $t_{l; 0 + \frac{r}{2}}$;
- 2 compute $\hat{t} = g^{-1}(h_{l; 0}(r))$;
- 3 run the nal tests $t_{l; \hat{t} + 0} \begin{matrix} H_1 \\ ? \\ H_0 \end{matrix} g$.

- The test procedure is the following, for every r of the grid:

The test procedure

1 compute $t_{1-r; 0 - \frac{\alpha}{2}}$ and $t_{1-r; 0 + \frac{\alpha}{2}}$;

2 compute $\hat{\theta} = g^{-1}(h_{1-r; 0}(r))$;

3 run the usual tests $t_{1-r; \hat{\theta} + 0} \stackrel{H_1}{?} g$.

- the statistic of $t_{1-r; \hat{\theta} + 0}$ depends on the non-independent random variables and $\hat{\theta} = g^{-1}(h_{1-r; 0}(r))$ no closed form available for g
- g is approximated with Monte Carlo simulations

Let us describe some properties of this approach:

- Only $2N$ tests are run for the whole spectral space, and the rest of the computations are simply lookup table operations,
- When the SNR tends to infinity, $\hat{\theta} = \theta$ and the Probability of Detection (PD) tends to 1,
- When $\theta = 1$, $\hat{\theta}$ is an approximate MLE and our test is an approximate GLRT [Mosca, 1969],
- When $\theta \neq 1$, our test is still close to the GLRT in term of performance.

We compare our scheme to detectors of similar cost:

- An oversampled NMF with 2 tests per cell,
- A DPSS NSMF with subspaces of dimension 2

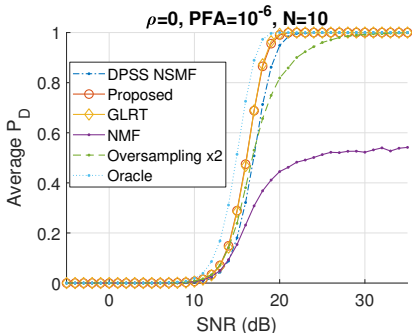
We compare our scheme to detectors of similar cost:

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We also compare it to :

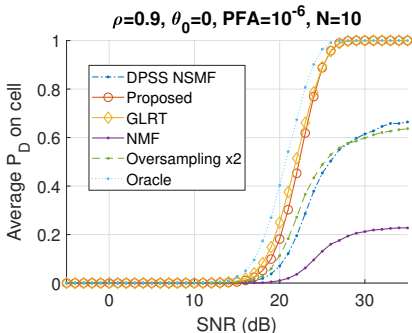
- The classical NMF
- An approximate GLRT using 50 tests per cell
- The Oracle detector, which knows where the target is and as such is the best detector possible

- Target parameter drawn at random uniformly.
- Our detector converges to 1 asymptotically and outperforms other detectors in the same computational range.



P_D of the detectors under white noise, for a P_{FA} of 10^{-6} , $N = 10$.

- Target parameter θ_0 drawn at random uniformly in $[\theta_0 - \sigma = 2; \theta_0 + \sigma = 2]$.
- In this cell, our detector stays close to the GLRT and does greatly better than the other detectors, which do not converge to 1.



P_D of the detectors with $\rho = 0.9$, $\theta_0 = 0$ for a P_{FA} of 10^{-6} , $N = 10$.

We introduced a new detector that approximates GLRT under white noise for θ -grid targets.

- simply based on the well-known monopulse procedure, classically used in array processing.

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We introduced a new detector that approximates GLRT under white noise for σ -grid targets.

- simply based on the well-known monopulse procedure, classically used in array processing.
- performance is close to GLRT while being cost-efficient
- Future works will investigate the performance of our detector under adaptive context, other noise models, and PFA-threshold relationship.

Thank You For Listening !

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