Design of robust radar detectors through random perturbation of the target signature

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Abstract—The paper addresses the problem of designing radar detectors more robust than Kelly’s detector to possible mismatches of the assumed target signature, but with no performance degradation under matched conditions. The idea is to model the received signal under the signal-plus-noise hypothesis by adding a random component, parameterized via a design covariance matrix, that makes the hypothesis more plausible in presence of mismatches. Moreover, an unknown power of such component, to be estimated from the observables, can lead to no performance loss. Derivation of the (one-step) GLRT is provided for two choices of the design matrix, obtaining detectors with different complexity and behavior. A third parametric detector is also obtained by an ad-hoc generalization of one of such GLRTs. The analysis shows that the proposed approach can cover a range of different robustness levels that is not achievable by state-of-the-art with the same performance of Kelly’s detector under matched conditions.

Index Terms—Radar, GLRT, robust detectors, mismatched signals

I. INTRODUCTION

The well-known problem of detecting the possible presence of a coherent return from a given cell under test (CUT) in range, doppler, and azimuth, is classically formulated as the following hypothesis testing problem:

$$\begin{align*}
H_0 & : \quad z = n \\
H_1 & : \quad z = \alpha v + n
\end{align*}$$

where $z \in \mathbb{C}^{N \times 1}$, $n \in \mathbb{C}^{N \times 1}$, and $v \in \mathbb{C}^{N \times 1}$ denote the received vector, the corresponding noise term, and the known space-time steering vector of the useful target echo.

In general $N$ is the number of processed samples from the CUT; it might be the number of antenna array elements times the number of pulses $[1]$, $[2]$. The noise term is commonly modeled according to the complex normal distribution with zero mean and unknown (Hermitian) positive definite matrix $C$, denoted by $CN_N(0,C)$. Modeling $\alpha \in \mathbb{C}$ as an unknown deterministic parameter returns a complex normal distribution for $z$ under both hypotheses; the non-zero mean of the received vector under $H_1$ makes it possible to discriminate between the two hypotheses

$$\begin{align*}
H_0 & : \quad z \sim CN_N(0,C) \\
H_1 & : \quad z \sim CN_N(\alpha v,C).
\end{align*}$$

In the pioneering paper by Kelly [3], the generalized likelihood ratio test (GLRT) is derived for $[1]$, assuming a set of $K \geq N$ independent and identically distributed training (or secondary) data $r_1, \ldots, r_K$, independent also of $z$, free of target echoes, and sharing with the CUT the statistical characteristics of the noise, is available. In [4] the performance of such a detector is assessed when the actual steering vector is not aligned with the nominal one. The analysis shows that it is a selective receiver, i.e., it may have excellent rejection capabilities of signals arriving from directions different from the nominal one. A selective detector is desirable for target localization. Instead, when a radar is working in searching mode, a certain level of robustness to mismatches is preferable. For this reason, many works have addressed the problem of enhancing either the selectivity or the robustness of GLRT-based detectors to mismatches. In particular, the adaptive matched filter (AMF) [5], which solves (1) following a two-step approach, is a prominent example of robust detector, while the adaptive coherence estimator (ACE, also known as adaptive normalized matched filter) [6] is another example of selective receiver. Other relevant examples of selective receivers are obtained by solving a modified hypothesis testing problem that assumes the presence of a (fictitious) coherent signal under the noise-only ($H_0$) hypothesis to make it more plausible in presence of signal mismatches [7], [8], [9]. A family of receivers, obtained by inserting a nonnegative parameter in the original Kelly’s detector, has been proposed in [10]: such a parameter, indicated as $\beta$ in the following, allows one to control the degree to which mismatched signals are rejected, so obtaining behaviors in between the AMF and Kelly’s detector. A different tunable receiver has been proposed in [11], which encompasses as special cases Kelly’s and W-ABORT detectors [9]. Although designed for enhanced selectivity, for values of its tunable parameter $\gamma$ smaller than $1/2$ it behaves as a robust detector, reaching the energy detector for $\gamma = 0$. Other approaches, as for instance those based on the cone idea, can guarantee an increased robustness at the price of a certain loss under matched conditions [12], [13]. A robust two-stage detector obtained by cascading a GLRT-based subspace detector and the Rao test has been proposed in [14]. Robust and selective detectors have also been used in the context of subspace detection [15], [16].

On the other hand, modeling $\alpha \in \mathbb{C}$ as a complex normal random variable with zero mean and variance $|\alpha|^2 = E[|\alpha|^2]$, returns a zero-mean complex normal distribution for $z$ under both hypotheses; hence

$$\begin{align*}
H_0 & : \quad z \sim CN_N(0,C) \\
H_1 & : \quad z \sim CN_N(0,C + |\alpha|^2 v v^\dagger)
\end{align*}$$

where $^\dagger$ is the Hermitian (i.e., conjugate transpose) operator.
This is a “second-order” approach to target modeling, i.e., the presence of a useful signal \( (H_1 \text{ hypothesis}) \) is modeled in terms of a modification of the noise covariance matrix, instead of appearing in the mean as conversely for the more classical problem \( 1 \). Interesting properties in terms of either rejection capabilities or robustness to mismatches on the nominal steering vector can be obtained by considering a random (instead of deterministic) target signal, depending on the way problem \( 2 \) is solved and possibly on the presence of a fictitious signal under \( H_0 \) \( 17, 18 \).

In this paper, we investigate the potential of a detector that solves the following new hypothesis testing problem

\[
\begin{cases}
H_0 : & z = n \\
H_1 : & z = \alpha v + \theta + n
\end{cases}
\] (3)

where \( \alpha \) is an unknown deterministic parameter and \( \theta \sim \mathcal{CN}_N(0, \nu \Sigma) \) represents a random component. The goal is to obtain a detector that exhibits the same probability of detection \( (P_d) \) of Kelly’s GLRT under matched conditions, but is more robust than the latter to mismatches between the nominal steering vector and the actual one. In the existing literature, the “win-win” situation in which robustness is achieved without any loss under matched conditions has been obtained so far through careful parameter setting of tunable receivers, notably the mentioned Kalson’s and KWA tunable receivers; here we propose a different approach which, remarkably, can cover levels of robustness that are not possible with such state-of-the-art receivers. The idea in \( 3 \) is in fact to add to the \( H_1 \) hypothesis a signal \( \theta \) that makes \( H_1 \) more plausible, hence hopefully the detector more robust to mismatches on the nominal steering vector \( v \). To this aim, a design matrix \( \Sigma \) is considered, multiplied by an unknown factor \( \nu \); in doing so, in case of matched signature no component will be likely found along \( \Sigma \) and the conventional case is recovered, i.e., the estimated value for \( \nu \) will be likely zero; conversely, if the mismatch causes some leakage of the signal that is captured by \( \Sigma \), the detector would tend to decide for \( H_1 \) more likely.

If we suppose that \( \theta \) is independent of \( n \), the resulting hypothesis testing problem turns out to be

\[
\begin{cases}
H_0 : & z \sim \mathcal{CN}_N(0, C) \\
H_1 : & z \sim \mathcal{CN}_N(\alpha v, C \nu \Sigma).
\end{cases}
\] (4)

In summary, the contribution of this paper is threefold:

- A new hypothesis test \( 4 \) for radar detection is introduced, which is a possible generalization of \( 1 \) and \( 2 \).
- The (one-step) GLRT is derived for such a test, for two choices of the design matrix \( \Sigma \). A third parametric detector is also obtained by an ad-hoc generalization of one of such GLRTs. Two-step GLRT-based detectors have been presented in our preliminary work \( 19 \). The detectors derived here have different complexity and behavior; importantly, they can guarantee negligible loss under matched conditions with respect to Kelly’s detector while providing diversified degrees of robustness depending on chosen parameters.
- A thorough analysis of the proposed detectors is performed, also deriving closed-form expressions for the \( P_{fa} \) for two of the detectors and showing that they have the desirable constant false alarm rate (CFAR) property.

The performance assessment reveals that the proposed approach can ensure different robustness levels, but always without any loss under matched conditions; this behavior is not achievable by state-of-the-art competitors, in particular Kalson’s and KWA tunable receivers.

The paper is organized as follows: Section II is devoted to the derivation of the GLRTs (with some proofs and lengthy manipulations in the Appendices). Section III addresses the analysis of the detectors. We conclude in Section IV.

II. GLRTs FOR POINT-LIKE TARGETS

In this section, we derive robust detectors employing the GLRT. To this end, we consider the following binary hypothesis testing problem

\[
\begin{cases}
H_0 : & z \sim \mathcal{CN}_N(0, C) \\
H_1 : & z \sim \mathcal{CN}_N(\alpha v, C + \nu \Sigma).
\end{cases}
\] (5)

where we recall that the training data \( r_k \) form a set of \( K \geq N \) independent (and identically distributed) vectors \( \nu \) independent also of \( z \), free of target echoes, and sharing with the CUT the statistical characteristics of the noise. The positive definite matrix \( C, \nu \geq 0 \), and \( \alpha \in \mathbb{C} \) are unknown quantities while \( v \in \mathbb{C}^{N \times 1} \) is a known vector. As to the (Hermitian) positive semidefinite matrix \( \Sigma \), it might be either known or unknown. In the former case, \( \Sigma \) reflects our knowledge about the random variations of the target steering vector around its nominal value \( v \). On the contrary, an unknown \( \Sigma \) implies that no specific knowledge is available. In such a case, obviously \( \Sigma \) cannot be estimated from a single snapshot (data from the CUT) and therefore one needs to make some further assumptions. The latter are mostly dictated by pragmatism so that the detection problem remains identifiable and mathematically tractable. Indeed, \( \Sigma \) should be viewed as a means to model the structure of the variations around \( v \) while \( v \) captures their amplitudes. In any case, one has to look at the ultimate performance for judging the goodness of each choice. In the sequel, we will assume that \( \Sigma \) is a known rank-one matrix, or that \( \Sigma = C \) (so that, although unknown, it does not introduce new unknowns in the problem).

A. Case 1: derivation of the GLRT for \( \Sigma = uu^\dagger \)

In this section, we address the case that \( \Sigma \) is a rank-one matrix. First we observe that the case \( \Sigma = vv^\dagger \), which enforces the target signature in both the mean and covariance,\( 4 \), returns Kelly’s detector, as discussed later in this section. We are instead more interested in a vector \( u \) aimed at making the \( H_1 \) hypothesis more plausible under mismatches. Intuitively, a design matrix \( \Sigma = vv_m v_m^\dagger \), where

\[1 \text{The condition } K \geq N \text{ ensures that the sample covariance matrix based on training data has full rank with probability one } \mathbb{P}.\]

\[2 \text{This choice amounts to assuming that } z = (\alpha + \epsilon)w + n \text{ where } \epsilon \text{ is a zero-mean complex normal variable with unknown power } \nu, \text{ independent of } n.\]
$v_m$ is a slightly mismatched steering vector, is a possible way to introduce some robustness without appreciable loss under matched conditions; nonetheless, other choices are possible, hence we provide a derivation for generic $\Sigma = uu^\dagger$.

The corresponding GLRT is given by

$$\Lambda(z, S) = \max_{C > 0} \max_{\nu \geq 0} \max_{\alpha \in \mathbb{C}} f_1(z, S|C, \nu, \alpha) \frac{H_1}{H_0} \quad \eta \quad (5)$$

where

$$f_1(z, S|C, \nu, \alpha) = \frac{1}{\pi^{N(K+1)/2} \det(C)} \frac{\det^{-K(C)}}{\det(\nu u u^\dagger + C)}$$

and

$$f_0(z, S|C) = \frac{1}{\pi^{N(K+1)/2} \det(C)} \frac{1}{\det(C)}$$

denote the probability density functions (PDFs) of $z, r_1, \ldots, r_K$ under $H_1$ and $H_0$, respectively, and let therein, in equation (39), $R = C, T_p = 1, T_1 = K$ (and, hence, $T_1 = K + 1$), $M = N, X = z - \alpha v, S_y = S, v = u, P = \nu$.

Proof: The result is a special case of the one derived in [18] letting therein, in equation (39), $R = C, T_p = 1, T_1 = K$ (and, hence, $T_1 = K + 1$), $M = N, X = z - \alpha v, S_y = S, v = u, P = \nu$.

In the following, we will denote by $l(b, \alpha)$ the partially-compressed likelihood under $H_1$, i.e.,

$$l(b, \alpha) = \left( \frac{K + 1}{\pi e} \frac{\det^{-K+1}(S)}{\det^{-K+1}(S)} \right) \left( \frac{1}{1 + (z - \alpha v)^\dagger S^{-1} (z - \alpha v)} \right)^{K+1} \left( \frac{1}{1 + (S + (1 + b) - 1) (z - \alpha v)^\dagger (z - \alpha v)} \right)^{K+1} \frac{u^\dagger (S + (1 + b) - 1) (z - \alpha v)^\dagger (z - \alpha v) - 1}{u^\dagger (S + (z - \alpha v) (z - \alpha v)\dagger - 1) (z - \alpha v) - 1} \right)^{K+1}.$$ (6)

As shown in Appendix A, it can also be re-written as

$$l(b, \alpha) = \left( \frac{K + 1}{\pi e} \frac{\det^{-K+1}(S)}{\det^{-K+1}(S)} \right) \left( \frac{1}{1 + b + ||\hat{z} - \alpha \hat{v}||^2} \right)^{K+1} \left( \frac{1}{1 + (S + (1 + b) - 1) ||\hat{z} - \alpha \hat{v}||^2} \right)^{K+1} \frac{u^\dagger (S + (1 + b) - 1) (\hat{z} - \alpha \hat{v}) - 1}{u^\dagger (S + (\hat{z} - \alpha \hat{v}) (\hat{z} - \alpha \hat{v})\dagger - 1) (\hat{z} - \alpha \hat{v}) - 1} \right)^{K+1}.$$ (7)

As to $\eta$, it is the detection threshold to be set according to the desired probability of false alarm ($P_{fa}$). Maximization over $C$ of the likelihood under $H_0$ can be performed as in [3]; in fact, the maximizer of the likelihood is given by

$$\hat{C}_0 = \frac{1}{K + 1} [zz^\dagger + S].$$ (8)

It follows that

$$f_0(z, S|\hat{C}_0) = \left( \frac{K + 1}{\pi e} \right)^{N(K+1)/2} \det (zz^\dagger + S)^{-K+1}.$$ (9)

Computation of the numerator of the GLRT and, in particular, maximization with respect to $C$ is less standard. However, it can be conducted exploiting the following result (a special case of the one in [18]).

Proposition 1: Assume that $u$ is a unit-norm vector (and that $K \geq N$). Then, for the likelihood under the $H_1$ hypothesis, given by equation (6), the following equality holds true

$$l_{\text{max}} = \max_{C > 0, \nu \geq 0, \alpha \in \mathbb{C}} f_1(z, S|C, \nu, \alpha)$$

$$= \left( \frac{K + 1}{\pi e} \right)^{N(K+1)/2} \max_{\nu \geq 0} \max_{\alpha \in \mathbb{C}} \frac{(1 + b)^{-1}}{\det^{-K+1}(S)}$$

$$= \left( \frac{K + 1}{\pi e} \right)^{N(K+1)/2} \max_{\nu \geq 0} \max_{\alpha \in \mathbb{C}} \frac{(1 + b)^{-1}}{\det^{-K+1}(S)}$$

$$= \left( \frac{K + 1}{\pi e} \right)^{N(K+1)/2} \max_{\nu \geq 0} \max_{\alpha \in \mathbb{C}} \frac{(1 + b)^{-1}}{\det^{-K+1}(S)}$$

$$= \left( \frac{K + 1}{\pi e} \right)^{N(K+1)/2} \max_{\nu \geq 0} \max_{\alpha \in \mathbb{C}} \frac{(1 + b)^{-1}}{\det^{-K+1}(S)}$$

$$= \left( \frac{K + 1}{\pi e} \right)^{N(K+1)/2} \max_{\nu \geq 0} \max_{\alpha \in \mathbb{C}} \frac{(1 + b)^{-1}}{\det^{-K+1}(S)}$$

where $b = \nu u^\dagger C^{-1} u$. 

Proof See Appendix A.

From the proposition above, $\alpha$ can be re-written as

$$\alpha(t) = t \alpha_1 + (1 - t) \alpha_2, \quad t \in [0, 1].$$

Accordingly, we have

$$|\alpha(t) - \alpha_1|^2 = |t \alpha_1 + (1 - t) \alpha_2 - \alpha_1|^2 = (1 - t)^2 |\alpha_2 - \alpha_1|^2,$$

$$|\alpha(t) - \alpha_2|^2 = |t \alpha_1 + (1 - t) \alpha_2 - \alpha_2|^2 = t^2 |\alpha_1 - \alpha_2|^2;$$
then, using equations (A.16), (A.19), and (A.20), together with the above two equations, yields

\[ l(b, \alpha(t)) = \left( \frac{K + 1}{\pi e} \right)^N \frac{1}{\det^K(S)} \]

\[ \times \ f_1(b, \frac{\|z - \alpha(t)\|}{\sqrt{2}}) \]

\[ \times \ l_2\left( b, \frac{\|\hat{P}_{\tilde{a}}(z - \alpha(t))\|}{\sqrt{2}} \right) \]

\[ = \left( \frac{K + 1}{\pi e} \right)^N \frac{1}{\det^K(S)} \]

\[ \times \ f_1\left( b, \frac{\|\hat{P}_{\tilde{a}}(z - \alpha(t))\|}{\sqrt{2}} \right) \]

\[ \times \ l_2\left( b, \frac{\|\hat{P}_{\tilde{a}}(z - \alpha(t))\|}{\sqrt{2}} \right) \]

with \( l_1(\cdot, \cdot) \) and \( l_2(\cdot, \cdot) \) given by equations (A.17) and (A.18), respectively. This reduces the complexity of the optimization over \( \alpha \), from a two-dimensional (complex-valued, i.e., real and imaginary parts) optimization to a simple linear (scalar) search in a finite interval. Summarizing, the GLRT can be written as

\[
\max_{b \geq 0} \max_{t \in [0, 1]} l(b, \alpha(t)) \quad \frac{H_1}{H_0} \geq \eta
\]

and also as

\[
\max_{b \geq 0} \max_{t \in [0, 1]} l_1\left( b, \frac{\|\hat{P}_{\tilde{a}}(z - \alpha(t))\|}{\sqrt{2}} \right) \quad \frac{H_1}{H_0} \geq \eta
\]

\[
\times \ l_2\left( b, \frac{\|\hat{P}_{\tilde{a}}(z - \alpha(t))\|}{\sqrt{2}} \right) \]

where \( R^2 = |\alpha_1 - \alpha_2|^2 \) (and \( l_1(\cdot, \cdot) \) and \( l_2(\cdot, \cdot) \) are given by equations (A.17) and (A.18), respectively). As a final comment, observe that it is reasonable to constrain \( b \) to belong to a finite interval, say \([0, b_{\text{max}}]\).

**B. Case 2: derivation of the GLRT for \( \Sigma = C \)**

In this case the matrix \( \Sigma \) is unknown (but equal to the covariance matrix of the noise). This is a convenient choice from a mathematical point of view, while it has no interpretation in terms of physical model of the signal — being \( C \) the covariance matrix of clutter plus noise, hence totally unrelated to mismatches on the steering vector. However, as mentioned, \( \Sigma \) is a design matrix with no other meaning of being the structure of a random term with power proportional to \( \nu \).

The corresponding GLRT is

\[
\Lambda(z, S) = \max_{C \geq 0} \max_{\nu \geq 0} f_1(z, S|C, \nu, \alpha) \quad \frac{H_1}{H_0} \geq \eta
\]

where

\[
f_1(z, S|C, \nu, \alpha) = \frac{1}{\pi^{N(K+1)}} \frac{1}{(1 + \nu)^N \det^{K+1}(C)} \]

\[
\times \ e^{-tr \left\{ C^{-1} \left[ \frac{1}{\pi e^2} (z - \alpha) (z - \alpha)^\dagger + S \right] \right\}}
\]

denotes the PDF of \( z, r_1, \ldots, r_K \) under \( H_1 \) while the denominator of the GLRT is given by equation (3). Again \( \eta \) is the detection threshold to be set according to the desired \( P_f \). We also recall that \( S \) is \( K \) times the sample covariance matrix computed on the secondary data.

Maximization over \( C \) of the likelihood under \( H_1 \) can be performed as in (3); in fact, we have that

\[
\tilde{C}_1(\nu, \alpha) = \frac{1}{K+1} \left[ \frac{1}{1 + \nu} (z - \alpha v) (z - \alpha v)^\dagger + S \right]
\]

Thus, the partially-compressed likelihood under \( H_1 \) becomes

\[
f_1(z, S|\tilde{C}_1(\nu, \alpha), \nu, \alpha) = \left( \frac{K + 1}{e \pi} \right)^{N(K+1)} \]

\[
\times \ \frac{1}{(1 + \nu)^N} \left[ \frac{1}{1 + \nu} \|z - \alpha \bar{v}\|^2 + S \right]^{-(K+1)}
\]

Plugging the above expressions into equation (2), after some algebra, yields

\[
\Lambda(z, S) = \frac{1}{\min_{\nu \geq 0, \alpha \in C} (1 + \nu)^N} \frac{1}{1 + \nu} \|z - \alpha \bar{v}\|^2
\]

where \( \tilde{z} = S^{-1/2} z, \quad \bar{v} = S^{-1/2} v, \) and \( \| \cdot \|^2 \) is the Euclidean norm of the vector argument. Moreover, minimization over \( \alpha \) leads to (20)

\[
\Lambda(z, S) = \frac{1}{\min_{\nu \geq 0} (1 + \nu)^N} \frac{1}{1 + \nu} \|P_{\bar{v}} \tilde{z}\|^2
\]

with \( P_{\bar{v}} \) the (orthogonal) projection matrix onto the orthogonal complement of the subspace spanned by the vector \( \bar{v} \).

Minimization of denominator with respect to \( \nu \) can be easily accomplished using the following proposition.

**Proposition 3:** The function

\[
f(\nu) = (1 + \nu)^{N(K+1)} \frac{1}{1 + \nu} \quad a > 0, K \geq N
\]

admits a unique minimum over \([0, +\infty]\) at

\[
\tilde{\nu} = \begin{cases} \frac{K+1}{N} - 1 a - 1, & (\frac{K+1}{N} - 1 a - 1 > 0) \\ 0, & \text{otherwise} \end{cases}
\]

given by

\[
f_{\text{min}} = \begin{cases} \frac{(K+1-N) a}{N} \pi^{N} \frac{K+1-N}{K+1-N}, & (K+1-N) a > 1 \\ 1 + a, & \text{otherwise} \end{cases}
\]

**Proof** See Appendix B.

Thus, it follows that the GLRT can be written as

\[
\Lambda_0(z, S) = \Lambda^{\tilde{\nu}}(z, S) \quad \frac{H_1}{H_0} \geq \eta
\]
Remarkably, in the appendix it is shown that the detector has the desirable CFAR property.

It is also important to stress that the derivation and, hence, the result is different from the detector proposed in [6]. More precisely, considering the derivation of the ACE as the GLRT to detect a possible coherent signal in presence of partially-homogeneous noise, given in [6], we highlight that therein the parameter \( \nu \) represents the possible mismatch between the power of the noise in the data under test and that of secondary data. Herein, instead, \( \nu \) enters the characterization of a possible random mismatch between the actual and the nominal useful signal. For this reason, we have \( 1 + \nu \) in place of \( \nu \) under \( H_1 \) (\( \nu C \) stands for the covariance matrix of the random term) and, in addition, \( \nu \) is not present under the \( H_0 \) hypothesis. This difference in the formulation of the hypothesis testing problem makes our detector more robust than Kelly’s detector [3] in presence of mismatched signals while it is well-known that the ACE is more selective than the latter (under the same operating conditions).

Notice also that, conditionally to
\[
\Lambda_0(z, S) = \begin{cases} \frac{\left(1 + \|z\|^2\right)\left(1 - \frac{1}{\zeta} \right)}{\left(1 - \frac{1}{\zeta} \right) \left(1 + \|z\|^2\right)}, & \|P_{\theta}^{\dagger} \hat{z}\|^2 > \frac{1}{\zeta - 1} \\ \frac{1}{\zeta - 1}, & \text{otherwise} \end{cases} \tag{14}
\]
\( \Lambda_0(z, S) \) is equivalent to Kelly’s statistics; it turns out that the robustness of the detector from use of \( \Lambda_0(z, S) \) under the condition complementary to (14). Thus, it seems possible to make the detector more robust by decreasing the probability to select “Kelly’s statistics”. In particular, we propose to replace \( \zeta \) in (14) with \( \zeta_c = \frac{K+1}{K+1+\epsilon}, \epsilon \geq 0 \). We also modify the decision statistic replacing \( \zeta \) with \( \zeta_c \). Accordingly, we consider the following parametric detector
\[
\Lambda_c(z, S) = \begin{cases} \frac{\left(1 + \|z\|^2\right)\left(1 - \frac{1}{\zeta_c} \right)}{\left(1 - \frac{1}{\zeta_c} \right) \left(1 + \|z\|^2\right)}, & \|P_{\theta}^{\dagger} \hat{z}\|^2 > \frac{1}{\zeta_c - 1} \\ \frac{1}{\zeta_c - 1}, & \text{otherwise} \end{cases} \tag{15}
\]
where
\[
\Lambda_c(z, S) = \begin{cases} \frac{\left(1 + \|z\|^2\right)\left(1 - \frac{1}{\zeta_c} \right)}{\left(1 - \frac{1}{\zeta_c} \right) \left(1 + \|z\|^2\right)}, & \|P_{\theta}^{\dagger} \hat{z}\|^2 > \frac{1}{\zeta_c - 1} \\ \frac{1}{\zeta_c - 1}, & \text{otherwise} \end{cases}
\]
\( \Lambda_c(z, S) \) is also shown that the performances in terms of \( P_f \) of detectors (13) and (15) depend only the SNR (equation (B.27)) and the cosine squared \( \cos^2 \theta \) (equation (B.28)) between the nominal steering vector and the actual one, which are the same performance parameters of Kelly’s, AMF, Kalson’s, and KWA detectors.

C. A note on ad hoc detectors for point-like targets

For the problem at hand, it is also possible to derive adaptive detectors resorting to the two-step GLRT-based design procedure: namely, first to derive the GLRT under the additional assumption that the matrix \( C \) is known, then to replace the unknown covariance matrix with an estimate obtained from secondary data. The derivation of the general case (i.e., not only a rank-one matrix) can be found in [19], where it is also shown that for \( \Sigma = C \) the detector has a closed-form expression. Therein, the reader can find a preliminary analysis of two-step detectors. In particular, it is shown that typically they are less powerful than the AMF (which has in turn a loss compared to Kelly’s detector) under matched conditions and more robust than the AMF under mismatched ones. Finally, in Appendix C we show that for \( \Sigma = \nu \nu^\dagger \) the two-step GLRT is equivalent to the AMF, whereas the proposed one-step GLRT for the same choice of \( \Sigma \) is equivalent to Kelly’s detector, as already discussed in Section II-A.

III. PERFORMANCE ANALYSIS

We assume a time steering vector, i.e., \( \nu = [1, e^{i2\pi f_d}, \ldots, e^{i2\pi (N-1)f_d}]^T \), with \( N = 16 \) and normalized Doppler frequency \( f_d = 0.08 \), a small value such that the target competes with low pass clutter. The target amplitude \( \alpha \) is generated deterministically according to the SNR defined in equation (B.27). To assess the robustness of the proposed detectors, we simulate a target with a mismatched steering vector, say \( p_t \), having normalized Doppler frequency \( f_d + \delta_f \) with \( \delta_f \in \{0.2/N, 0.4/N\} \). The values of \( \delta_f \) will affect the values of the cosine squared of the angle between the nominal steering vector and the mismatched one, denoted by \( \cos^2 \theta \) and given in equation (B.28), which is a standard way to quantify the mismatch in radar detection. Under matched conditions, of course, \( p = \nu \) and \( \cos^2 \theta = 0 \).

We model the noise component of \( z \) and the \( r_{k,s} \) as (independent) random vectors ruled by a zero-mean, complex Gaussian distribution. As to the covariance matrix, we adopt as \( C \) the sum of a Gaussian-shaped clutter covariance matrix and white (thermal) noise 10 dB weaker, i.e., \( C = R_c + \sigma_n^2 I_N \) with the \((m_1, m_2)\)th element of the matrix \( R_c \) given by \( R_c(m_1, m_2) \propto \exp(-2\pi^2 \sigma_c^2 (m_1 - m_2)^2) \) and \( \sigma_c \approx 0.073 \) (corresponding to a one-lag correlation coefficient of the clutter component equal to 0.97). In the following we assess the performance of the proposed (one-step) GLRTs, considering both \( \Sigma = \nu \nu^\dagger \) and \( \Sigma = C \), and the parametric detector (15). The former detector assumes \( v \) as an mismatched version of \( \nu \), in particular of \( 0.03/N \), and for the optimization with respect to \( b \) we adopt a logarithmic search in the span \([0, b_{\text{max}} = 10^3]\); as regards the parametric detector (15), we consider \( \epsilon = 0.1 \) and \( \epsilon = 0.2 \). It
will be apparent from the simulations below that such choices guarantee negligible loss with respect to Kelly’s detector under matched conditions.

A comparison is performed against the natural competitors for the problem at hand, that is the Kalson’s [10] and KWA [11] tunable receivers. Notice that for both such competitors, the level of robustness increases as the value of their tunable parameter decreases. For a fair comparison, only values that ensure practically the same performance of Kelly’s detector under matched conditions are considered, in particular $\beta = 0.5$ and $\beta = 0.8$ for Kalson’s detector and $\gamma = 0.45$ and $\gamma = 0.4$ for the KWA. For reference, the AMF [5], is also reported in all figures, because it is a well-known robust detector; however, it is worth remarking that it is not always a competitor, since it generally experiences a performance loss under matched conditions with respect to Kelly’s detector.

A first set of simulations (Figs. 1–9) refers to $P_{fa} = 10^{-4}$. We assess performance by Monte Carlo simulation with $10^3$ independent trials to set the thresholds and $10^3$ independent trials to compute the $P_d$ (the probabilities to decide for $H_1$ when a useful signal is present). Results under matched conditions are reported in Figs. 1–3 for different values of the number of secondary data, namely $K = 24, 32, 40$ respectively (i.e., besides the typical $K = 2N$, also $1.5N$ and $2.5N$ are considered). From such figures, it is apparent that the proposed detectors and the tunable competitors (Kalson’s and KWA) have essentially the same $P_d$ of Kelly’s detector, while as known the AMF exhibits a performance loss, which becomes negligible only when the number of secondary data is large enough. Notice that the KWA for $\gamma = 0.4$ and the parametric detector (15) for $\epsilon = 0.2$ start to experience some loss, especially for moderate SNR, hence smaller values of their respective parameters are not considered for a fair comparison.

Figs. 4–6 report the results under mismatch, in particular considering a cosine squared of the angle between the nominal steering vector and the mismatched one (given by equation (B.28)) equal to $\cos^2 \theta \approx 0.46$ (obtained for $\delta_f = 0.4/N = 0.025$). It emerges that the proposed approach yields a family of robust receivers, whose performance in terms of robustness to mismatches depends on the design matrix $\Sigma$ and number of secondary data $K$. The behavior of the GLRT for $\Sigma = C$ is very interesting, because it is (equivalent to Kelly’s detector under matched conditions and) more robust than Kalson’s and KWA receivers; the parametric detector (15) with both settings of $\epsilon$ is more robust than the GLRT for $\Sigma = C$ and can be even more robust than AMF, in particular
for $K = 32$, without the loss experienced by the latter under matched conditions. This “win-win” behavior is thus remarkably unique and not achievable with state-of-the-art receivers. Notice that the AMF can be considered a competitor only for $K = 40$ (where its performance loss under matched conditions compared to Kelly’s detector becomes very small), but Fig. 6 shows that the proposed detectors, in particular the GLRT for $\Sigma = C$ and the parametric detector (15) with both settings of $\epsilon$, are more robust than AMF; notice that this advantage comes at no increase in computational complexity.

The GLRT with $\Sigma = v_m v_m^\dagger$ needs higher values of $K$ to achieve almost the same robustness of the other proposed receivers (Fig. 6); otherwise, it progressively rejects the $H_1$ hypothesis: for $K = 32$ (Fig. 5) only for larger SNR, for $K = 24$ (Fig. 4) behaving as a selective receiver over the whole range of SNRs; also Kalson’s detector with $\beta = 0.8$ has this behavior, and they both approach the Kelly’s detector.

For a reduced value of the mismatch, the differences between the proposed detectors and the competitors reduce. Figs. 7–9 show the mismatched case with $\cos^2 \theta \approx 0.83$ (obtained for $\delta_f = 0.2/N = 0.0125$). We observe that the parametric
detector (15) still emerges as the most robust among the detectors that have negligible loss under matched conditions (compared to Kelly’s detector) hence excluding AMF for $K = 24, 32$; for $K = 40$, conversely, the detector (15) and AMF are almost equivalent.

A second set of simulations (Figs. 10-11) refers to $P_{fa} = 10^{-6}$ and focuses on the behavior of the proposed GLRT for $\Sigma = C$ and the parametric detector (15) in comparison to Kalson’s and KWA detectors; for reference, also the performance of Kelly’s detector and AMF are shown. Notice that, for such a small $P_{fa}$, Monte Carlo simulations are prohibitively long, hence we can compare only detectors for which a closed-form expression is available for the relationship between the threshold and the $P_{fa}$; for this reason we introduced the proposed GLRT with $\Sigma = \nu^b_m S^b_m$ cannot be included; besides, the detector with $\Sigma = C$ and the parametric detector (15) are simpler and show a more interesting behavior, hence are more appealing for applications. Again we resort to Monte Carlo simulation and to $10^3$ independent trials to estimate the $P_{fa}$. The values of the tunable parameters for the parametric detector and the competitors are chosen as before, because this guarantees no appreciable loss under matched conditions as shown in Fig. 10. In Fig. 11 we report the results under mismatched conditions for $\cos^2 \theta \approx 0.46$ and $K = 32$. Comparing the result with the corresponding Fig. 5 the better performance of the proposed receivers are even more evident. We see that they are more robust than Kalson’s and KWA detectors; in particular, the parametric detector with $\epsilon = 0.2$ is also more robust than the AMF for large SNR values while Kalson’s detector with $\beta = 0.8$ approaches the selective behavior of Kelly’s detector.

IV. CONCLUSION

We have proposed a novel family of robust radar receivers to detect the possible presence of a coherent return from a given cell under test mismatched with respect to the nominal steering vector. To this end, we have introduced a random component in addition to the deterministic useful signal; the random component has a given structure $\Sigma$, but its power $\nu$ is estimated from the data. This likely produces an estimate of $\nu$ close to zero under matched conditions, thus achieving no loss compared to Kelly’s detector (which is the benchmark for the considered problem). We have solved the hypothesis testing problem resorting to the GLRT approach and assuming for $\Sigma$ either a known rank-one matrix or the unknown covariance matrix of the noise. We have also introduced a parametric detector that naturally modifies the statistic of the latter GLRT and shares with it the CFAR property. The performance analysis has shown that proposed detectors are a viable means to deal with mismatched signals; in fact, compared to competitors that have negligible loss under matched conditions, the proposed approach guarantees an increased robustness.

APPENDIX A

DERIVATION OF EQUATION (9)

First observe that, by the matrix inversion lemma, we have

$$
\mathbf{u}^\dagger \left( \mathbf{S} + (1 + b)^{-1} (\mathbf{z} - \alpha \mathbf{v}) (\mathbf{z} - \alpha \mathbf{v})^\dagger \right)^{-1} \mathbf{u} \\
= \mathbf{u}^\dagger \mathbf{S}^{-1} \mathbf{u} - \frac{(1 + b)^{-1} |\mathbf{u}^\dagger \mathbf{S}^{-1} (\mathbf{z} - \alpha \mathbf{v})|^2}{1 + (1 + b)^{-1} (\mathbf{z} - \alpha \mathbf{v})^\dagger \mathbf{S}^{-1} (\mathbf{z} - \alpha \mathbf{v})}
$$

Thus, $l(b, \alpha)$ can be re-written as

$$
l(b, \alpha) = \left( \frac{K + 1}{\pi \epsilon} \right)^{N(K+1)} (1 + b)^{-1} \frac{1}{\det^{K+1}(\mathbf{S})} \\
\times \left[ \mathbf{\hat{u}}^\dagger \mathbf{\hat{u}} - (1 + b)^{-1} \mathbf{\hat{u}}^\dagger (\tilde{\mathbf{z}} - \alpha \tilde{\mathbf{v}}) (\tilde{\mathbf{z}} - \alpha \tilde{\mathbf{v}})^\dagger \right]^{K+1}
$$

where $\tilde{\mathbf{z}} = \mathbf{S}^{-1/2} \mathbf{z}$, $\tilde{\mathbf{v}} = \mathbf{S}^{-1/2} \mathbf{v}$, and $\mathbf{\hat{u}} = \mathbf{S}^{-1/2} \mathbf{u}$ are the whitened versions of $\mathbf{z}$, $\mathbf{v}$, and $\mathbf{u}$, respectively.
Notice also that
\[
\bar{u}^\dagger \bar{u} - (1 + b)^{-1} \frac{|\bar{u}^\dagger (\hat{z} - \alpha \hat{v})|^2}{1 + (1 + b)^{-1} |(\hat{z} - \alpha \hat{v})|^2 (\hat{z} - \alpha \hat{v})^\dagger (\hat{z} - \alpha \hat{v})} = \frac{\bar{u}^\dagger \bar{u} - \frac{|\bar{u}^\dagger (\hat{z} - \alpha \hat{v})|^2}{1 + (\hat{z} - \alpha \hat{v})^\dagger (\hat{z} - \alpha \hat{v})}}{1 + b + (\hat{z} - \alpha \hat{v})^\dagger (\hat{z} - \alpha \hat{v})}
\]
\[
= \frac{(1 + b)\bar{u}^\dagger \bar{u} + \bar{u}^\dagger \bar{u} |\hat{z} - \alpha \hat{v}|^2 - |\bar{u}^\dagger (\hat{z} - \alpha \hat{v})|^2}{1 + b + (\hat{z} - \alpha \hat{v})^\dagger (\hat{z} - \alpha \hat{v})}
\]

It turns out that \( l(b, \alpha) \) can be re-cast as
\[
l(b, \alpha) = \left( \frac{K + 1}{\pi e} \right)^{N(K + 1)} \frac{(1 + b)^{-1} \det K^{+1}(S)}{(1 + b + (\hat{z} - \alpha \hat{v})^\dagger (\hat{z} - \alpha \hat{v}))^{K + 1} \left[ (1 + b)^2 \left( \| \bar{u} \|^2 + \| \bar{u} \|^2 |\hat{z} - \alpha \hat{v}|^2 - |\bar{u}^\dagger (\hat{z} - \alpha \hat{v})|^2 \right) - \| \bar{u}^\dagger (\hat{z} - \alpha \hat{v})|^2 \right]^{K + 1} 1 + \left( \| P_{\theta}^\perp \hat{z} \|^2 \right)^{K + 1}}
\]

and letting \( |\bar{u}^\dagger (\hat{z} - \alpha \hat{v})|^2 = \| \bar{u} \|^2 |P_{\theta}^\perp (\hat{z} - \alpha \hat{v})|^2 \) it can be re-written in the form of equation (9).

**The GLRT with \( \Sigma = \omega \omega^\dagger \) is the Kelly’s detector**

If \( u = v \) and, hence, \( P_{\theta}^\perp \hat{z} = 0 \), the partially-compressed likelihood under \( H_1 \) of equation (9) becomes
\[
l(b, \alpha) = \left( \frac{K + 1}{\pi e} \right)^{N(K + 1)} \frac{(1 + b)^{-1} \det K^{+1}(S)}{(1 + b + (\hat{z} - \alpha \hat{v})^\dagger (\hat{z} - \alpha \hat{v}))^{K + 1} \left[ (1 + b)^2 \left( \| \bar{u} \|^2 + \| \bar{u} \|^2 |\hat{z} - \alpha \hat{v}|^2 - |\bar{u}^\dagger (\hat{z} - \alpha \hat{v})|^2 \right) - \| \bar{u}^\dagger (\hat{z} - \alpha \hat{v})|^2 \right]^{K + 1} 1 + \left( \| P_{\theta}^\perp \hat{z} \|^2 \right)^{K + 1}}
\]

and
\[
\max_{\alpha} l(b, \alpha) = \left( \frac{K + 1}{\pi e} \right)^{N(K + 1)} \frac{(1 + b)^{-1} \det K^{+1}(S)}{(1 + \| P_{\theta}^\perp \hat{z} \|^2)^{K + 1}}
\]

As a consequence, we also have that
\[
\max_{b \geq 0} \max_{\alpha} l(b, \alpha) = \left( \frac{K + 1}{\pi e} \right)^{N(K + 1)} \frac{1}{\det K^{+1}(S)} \left( 1 + \| P_{\theta}^\perp \hat{z} \|^2 \right)^{K + 1}
\]

and the GLRT, given by equation (5), can be written as
\[
\frac{1 + z^\dagger S^{-1}z}{1 + \left( P_{\theta}^\perp \hat{z} \right)^2} \quad 1 + z^\dagger S^{-1}z - \frac{|\hat{v}^\dagger S^{-1}z|^2}{\hat{v}^\dagger S^{-1}\hat{v}} \quad \frac{H_1}{H_0} \eta,
\]

with \( \eta \) a proper modification of the original threshold, that is equivalent to Kelly’s detector (we have also used equation 8 for the compressed likelihood under \( H_0 \)).

**Proof of Proposition 2**

First observe that \( l(b, \alpha) \) can be written as
\[
l(b, \alpha) = \left( \frac{K + 1}{\pi e} \right)^{N(K + 1)} \frac{1}{\det K^{+1}(S)} (A.16)
\]
\[
\times l_1 \left( b, |\hat{z} - \alpha \hat{v}|^2 \right) \times l_2 \left( b, \| P_{\theta}^\perp \hat{z} (\hat{z} - \alpha \hat{v}) \|^2 \right)
\]

with
\[
l_1(b, y_1) = \frac{(1 + b)^{-1}}{(1 + b + y_1)^{K + 1}} \quad (A.17)
\]

and
\[
l_2(b, y_2) = \left[ \frac{(1 + b) + y_2}{1 + y_2} \right]^{K + 1} \quad (A.18)
\]

In particular, \( l_1 \) is a strictly decreasing function of \( y_1 \) and \( l_2 \) is a strictly decreasing function of \( y_2 \). Moreover, \( l_1 \) attains its maximum at
\[
\alpha_1 = \arg \min_{\alpha} (\hat{z} - \alpha \hat{v})^\dagger (\hat{z} - \alpha \hat{v}) = (\hat{v}^\dagger \hat{v})^{-1} \hat{v}^\dagger \hat{z}
\]

and
\[
|\hat{z} - \alpha \hat{v}|^2 = |\hat{z} - (\alpha - \alpha_1) \hat{v} - \alpha_1 \hat{v}|^2 \quad (A.19)
\]
\[
\geq \hat{z}^\dagger P_{\theta}^\perp \hat{z}^\dagger \hat{v} + |\alpha - \alpha_1|^2 \hat{v}^\dagger \hat{v} \hat{z}^\dagger P_{\theta}^\perp \hat{z}
\]

where \( \hat{z} - \alpha_1 \hat{v} = P_{\theta}^\perp \hat{z} \). Thus, \( x \geq \hat{z}^\dagger P_{\theta}^\perp \hat{z} \), the equation
\[
(\hat{z} - \alpha \hat{v})^\dagger (\hat{z} - \alpha \hat{v}) = x
\]

is tantamount to
\[
|\alpha - \alpha_1|^2 \hat{v}^\dagger \hat{v} = x - \hat{z}^\dagger P_{\theta}^\perp \hat{z}
\]

and is a circle centered at \( \alpha_1 \) of proper radius. Similarly, \( l_2 \) attains its maximum at
\[
\alpha_2 = \arg \min_{\alpha} \| P_{\theta}^\perp \hat{z} (\hat{z} - \alpha \hat{v}) \|^2
\]

and
\[
\arg \min_{\alpha} \| P_{\theta}^\perp \hat{z} - \alpha P_{\theta}^\perp \hat{v} \|^2
\]

\[
= (\hat{v}^\dagger P_{\theta}^\perp \hat{v})^{-1} \hat{v}^\dagger P_{\theta}^\perp \hat{z}
\]
and
\[
\left\| P_{\hat{u}}^\perp (\hat{z} - \alpha \hat{v}) \right\|^2 = \left\| P_{\hat{u}}^\perp (\hat{z} - (\alpha - \alpha_2) \hat{v} - \alpha_2 \hat{v}) \right\|^2 \tag{A.20}
\]
\[
= \left\| P_{\hat{u}}^\perp \hat{z} - \alpha_2 P_{\hat{u}}^\perp \hat{v} - (\alpha - \alpha_2) P_{\hat{u}}^\perp \hat{v} \right\|^2 \\
= \left( I_N - P_{\hat{u}}^\perp \hat{v} \left( \hat{v}^\dagger P_{\hat{u}}^\perp \hat{v} \right)^{-1} \hat{v}^\dagger P_{\hat{u}}^\perp \right) \times P_{\hat{u}}^\perp \hat{z} - (\alpha - \alpha_2) P_{\hat{u}}^\perp \hat{v} \right\|^2 \\
= \left\| P_{\hat{u}}^\perp \big( P_{\hat{u}}^\perp P_{\hat{u}}^\perp \hat{z} - (\alpha - \alpha_2) P_{\hat{u}}^\perp \hat{v} \big) \right\|^2 \\
= \hat{z}^\dagger P_{\hat{u}}^\perp \big( \hat{z} - \hat{z}^\dagger P_{\hat{u}}^\perp \hat{v} \left( \hat{v}^\dagger P_{\hat{u}}^\perp \hat{v} \right)^{-1} \hat{v}^\dagger P_{\hat{u}}^\perp \hat{v} \big)^{-1} \times \hat{v}^\dagger P_{\hat{u}}^\perp \hat{v} + |\alpha - \alpha_2|^2 \hat{v}^\dagger P_{\hat{u}}^\perp \hat{v} \\
\geq \hat{z}^\dagger P_{\hat{u}}^\perp \big( \hat{z} - \hat{z}^\dagger P_{\hat{u}}^\perp \hat{v} \left( \hat{v}^\dagger P_{\hat{u}}^\perp \hat{v} \right)^{-1} \hat{v}^\dagger P_{\hat{u}}^\perp \hat{v} \big)^{-1} \times \hat{v}^\dagger P_{\hat{u}}^\perp \hat{v} - \alpha_2 \hat{v}^\dagger P_{\hat{u}}^\perp \hat{v}.
\]

Thus, \( \forall y \geq \hat{z}^\dagger P_{\hat{u}}^\perp \big( \hat{z} - \alpha \hat{v} \big) \right\|^2 = y \) is tantamount to
\[
|\alpha - \alpha_2|^2 \hat{v}^\dagger P_{\hat{u}}^\perp \hat{v} = y - \hat{z}^\dagger P_{\hat{u}}^\perp \hat{z} + \hat{z}^\dagger P_{\hat{u}}^\perp \hat{v} \left( \hat{v}^\dagger P_{\hat{u}}^\perp \hat{v} \right)^{-1} \hat{v}^\dagger P_{\hat{u}}^\perp \hat{z}
\]
and is a circle centered at \( \alpha_2 \) of proper radius.

Obviously, for \( \alpha_1 = \alpha_2 \) the maximum of \( l(b, \alpha) \), given \( b \), is attained at \( \alpha_1 \). Assuming instead \( \alpha_1 \neq \alpha_2 \), we can prove that the values of \( \alpha \) maximizing \( l(b, \alpha) \) belong to the segment whose endpoints are \( \alpha_1 \) and \( \alpha_2 \), indicated hereafter as \( S_{\alpha_1 \alpha_2} \).

To this end, we show that \( \forall \alpha \in C \setminus S_{\alpha_1 \alpha_2} \) there exists a point \( \bar{\pi} \in S_{\alpha_1 \alpha_2} \) such that
\[
l(b, \alpha) < l(b, \alpha_1). \tag{A.21}
\]
In fact, if \( \alpha \in C \) does not belong to the circle centered at \( \alpha_2 \) of radius \( |\alpha_1 - \alpha_2| \) as, for instance, \( \delta_1 \) in Figure 12, we can choose \( \bar{\pi} = \gamma \) that has a smaller distance from \( \alpha_2 \) than \( \delta_1 \), thus implying
\[
\left\| P_{\hat{u}}^\perp (\hat{z} - \delta_1 \hat{v}) \right\|^2 > \left\| P_{\hat{u}}^\perp (\hat{z} - \alpha_1 \hat{v}) \right\|^2,
\]
\[
\| \hat{z} - \delta_1 \hat{v} \|^2 > \| \hat{z} - \alpha_1 \hat{v} \|^2
\]
and, eventually
\[
l(b, \delta_1) < l(b, \alpha_1). \tag{A.22}
\]

If, instead, \( \alpha \in C \setminus S_{\alpha_1 \alpha_2} \) belongs to the circle centered at \( \alpha_2 \) of radius \( |\alpha_1 - \alpha_2| \) as, for instance, \( \delta_2 \) in Figure 12, we replace it with \( \gamma \), i.e., \( \bar{\pi} = \gamma \), that has the same distance of \( \delta_2 \) from \( \alpha_2 \) and a smaller distance from \( \alpha_1 \), thus implying
\[
\left\| P_{\hat{u}}^\perp (\hat{z} - \delta_2 \hat{v}) \right\|^2 = \left\| P_{\hat{u}}^\perp (\hat{z} - \gamma \hat{v}) \right\|^2,
\]
\[
\| \hat{z} - \delta_2 \hat{v} \|^2 > \| \hat{z} - \gamma \hat{v} \|^2
\]
and, eventually
\[
l(b, \delta_2) < l(b, \gamma). \tag{A.23}
\]

**Appendix B**

**Proof of Proposition**

The derivative of \( f(\nu) \) is given by
\[
\frac{d}{d\nu} f(\nu) = \frac{N}{K + 1} \left( 1 + \nu \right)^{\frac{N}{K + 1} - 1} \left( 1 + \frac{a}{1 + \nu} \right) - \left( 1 + \nu \right)^{\frac{N}{K + 1}} \frac{a}{(1 + \nu)^2}.
\]

Thus, \( \frac{d}{d\nu} f(\nu) < 0 \) if and only if \( \frac{N}{K + 1} (1 + \nu + a) - a < 0 \) or, equivalently, \( \nu < \left( \frac{K + 1}{N} - 1 \right) a - 1 \). It follows that the function \( f(\nu) \) attains its minimum over \((0, +\infty)\) at
\[
\hat{\nu} = \left( \frac{K + 1}{N} - 1 \right) a - 1
\]
if such a value is positive and at 0 otherwise.

**Characterization of detectors**

First we compute the \( P_{\alpha} \) of the parametric detector and, as a special case, that of the GLRT. To this end, let
\[
\hat{t}_K = \frac{t_K}{1 + t_K} = \frac{|z^\dagger S^{-1} v|^2}{v^\dagger S^{-1} \big( 1 + z^\dagger S^{-1} z \big)}, \tag{B.22}
\]
where \( t_K \) is Kelly’s statistic, namely
\[
t_K = \frac{|z^\dagger S^{-1} v|^2}{v^\dagger S^{-1} \big( 1 + z^\dagger S^{-1} z \big)} \tag{B.23}
\]
and
\[
b = \frac{1}{1 + z^\dagger S^{-1} \big( \frac{|z^\dagger S^{-1} v|^2}{v^\dagger S^{-1} v} \big) - \frac{|z^\dagger S^{-1} v|^2}{v^\dagger S^{-1} v}} \tag{B.24}
\]

It turns out that \( 1 + \| \hat{z} \|^2 = 1 + z^\dagger S^{-1} z = \left( 1 + \hat{t}_K \right) / b \) and
\[
\left\| P_{\hat{u}}^\perp \hat{z} \right\|^2 = z^\dagger S^{-1} \big( \frac{|z^\dagger S^{-1} v|^2}{v^\dagger S^{-1} v} \big) = \frac{1}{b} - 1 \text{ and, hence, the decision statistic of the parametric detector can be re-written as}
\]
\[
\Lambda_e(z, S) = \begin{cases} 
\frac{1 + \hat{t}_K (\frac{1}{b} - \frac{1}{\hat{t}_K})}{[\hat{t}_K (\frac{1}{b} - \frac{1}{\hat{t}_K})]^+}, & b < 1 - \frac{1}{\zeta} \\
1 + \hat{t}_K, & \text{otherwise.} \end{cases} \tag{B.25}
\]
Under the noise-only hypothesis the random variable (RV) \( \hat{i}_K \), given by equation (B.22), is distributed according to a complex central F-distribution with 1 and \( K - N + 1 \) degrees of freedom and it is independent of \( b \), given by equation (B.24), which, in turn, obeys a complex central beta distribution with \( K - N + 2 \) and \( N - 1 \) (complex) degrees of freedom \([8], [21], [22] \). In symbols, we write \( \hat{i}_K \sim \mathcal{CF}_{1,K-N+1} \) and \( b \sim \mathcal{CB}_{K-N+2,N-1} \). It is thus apparent that \( P_{fa} \) is independent of \( C \) and, hence, the detector possesses the CFAR property.

Moreover, we can compute \( P_{fa} \) as follows

\[
P_{fa} = \int_0^1 P[A(x, S) > \eta | b = x, H_0] f_b(x) \, dx
\]

where \( f_b(\cdot) \) denotes the PDF of the RV \( b \) \([22] \), i.e.,

\[
f_b(x) = \frac{1}{B(K + 2 - N, N - 1)} x^{K-N+1}(1-x)^{N-2}
\]

with \( 0 \leq x \leq 1 \), while

\[
p(x) = P[A(x, S) > \eta | b = x, H_0] = \begin{cases} 
1 - F_{\hat{i}_K}(y(x)), & 0 \leq x \leq 1 - \frac{1}{\zeta} \\
1 - F_{\hat{i}_K}(\eta - 1), & 1 - \frac{1}{\zeta} \leq x \leq 1
\end{cases}
\]

with \([22] \) formula (A.7)

\[
1 - F_{\hat{i}_K}(y) = \begin{cases} 
\frac{1}{1 + \frac{1}{y^{\zeta} - 1}}, & y \geq 0 \\
1, & y < 0
\end{cases}
\]

and

\[
y(x) = \eta x \left( \frac{\zeta - 1}{x} \right)^{1/\zeta} - \frac{\zeta}{\zeta - 1} - 1.
\]

To compute the \( P_{fa} \), we first observe that the derivative of the function \( y(x) \) is given by

\[
\frac{dy(x)}{dx} = \eta \left( \frac{\zeta - 1}{x} \right)^{-1} \left( \frac{\zeta x - 1 - x}{x} \right)
\]

and it is positive for \( 0 < x < 1 - \frac{1}{\zeta} \). Moreover, \( \lim_{x \to 0^+} y(x) = -1 \) and \( y(x - 1) = \eta - 1 \). It turns out that \( P_{fa} = 1 \) for \( \eta \leq 1 \). If, instead, \( \eta > 1 \), denoting by \( \mathcal{F}_\eta(\eta) \) that number in \( (0, 1 - \frac{1}{\zeta}) \) such that \( y(x) = 0 \), it follows that

\[
P_{fa} = \int_0^{\mathcal{F}_\eta(\eta)} f_b(x) \, dx + \int_1^{\mathcal{F}_\eta(\eta)} \frac{1}{\eta^{K+1-N}} \frac{1}{1 + y(x)} \, dx.
\]

Finally, the \( P_{fa} \) of detector \([13] \) is given by

\[
P_{fa} = \frac{1}{B(K + 2 - N, N - 1)} \left( \frac{K + 1 - N}{\zeta} + 1 \right) \frac{1}{\zeta} - B_{\mathcal{F}_\eta(\eta)} \left( \frac{K + 1 - N}{\zeta} + 1 \right) \frac{1}{\zeta}
\]

where \( B_{\zeta}(\cdot, \cdot) \) is the Eulerian beta function while

\[
B_{\eta}(\mu, \nu) = \int_0^1 t^{\nu-1}(1-t)^{\mu-1} \, dt
\]

is the incomplete beta function \([23] \).

As a special case, i.e., \( \epsilon = 0 \) and, hence, \( \zeta = \zeta \), we obtain the \( P_{fa} \) of the GLRT \([13] \).

On the other hand, if we suppose that under the \( H_1 \) hypothesis the actual useful signal is deterministic, but with a steering vector \( p \) different from the nominal one \( v \), i.e.,

\[
r = \alpha p + n, \quad n \sim \mathcal{CN}_N(0, C),
\]

\( \hat{i}_K \), given \( b \), is ruled by a complex noncentral F-distribution with 1 and \( K - N + 1 \) (complex) degrees of freedom and noncentrality parameter \( \delta \), with \([4], [22], [24] \)

\[
\sigma^2 = \text{SNR} \cdot b \cos^2 \theta,
\]

where

\[
\text{SNR} = |\alpha|^2 \|p\|^2 C^{-1} p
\]

and

\[
\cos^2 \theta = \frac{|p^\dagger C^{-1} p|}{(w^\dagger C^{-1} v)(w^\dagger C^{-1} p)}.
\]

In addition, the RV \( b \) obeys the complex noncentral beta distribution with \( K - N + 2 \) and \( N - 1 \) (complex) degrees of freedom and noncentrality parameter \( \delta_b \), with

\[
\delta_b^2 = \text{SNR} \cdot \sin^2 \theta.
\]

In symbols, we write \( \hat{i}_K \sim \mathcal{CF}_{1,K-N+1}(\delta) \) and \( b \sim \mathcal{CB}_{K-N+2,N-1}(\delta_b) \).

In the special case of perfect match between \( p \) and \( v \), then

\[
\delta^2 = |\alpha|^2 \|p\|^2 C^{-1} v \cdot b \text{ and } \delta_b^2 = 0 \quad \text{, i.e., } \quad b \sim \mathcal{CB}_{K-N+2,N-1}(\delta_b)
\]

and \( \hat{i}_K \sim \mathcal{CF}_{1,K-N+1}(\delta) \) given \( b \).

The above characterization highlights that performance of detectors \([13] \) and \([15] \) can be expressed in terms of \( P_{fa} \) vs SNR (equation \([B.27] \)) given \( \cos^2 \theta \) (equation \([B.28] \)) and \( P_{fa} \). In principle, such characterization could be exploited to compute \( P_{fa} \), paralleling the computation of \( P_{fa} \); however, analytical forms for \( P_{fa} \) are rather involved. As a matter of fact, we use Monte Carlo simulation to compute \( P_{fa} \) vs SNR, expressed by equation \([B.27] \), given \( \cos^2 \theta \) and \( P_{fa} \).
The corresponding GLRT is given by
\[ \Lambda(z, C) = \frac{\max_{\nu \geq 0} \max_{\alpha \in \mathbb{C}} f_1(z|\nu, \alpha)}{f_0(z)} \]
where
\[ f_1(z|\nu, \alpha) = \frac{1}{\pi^N} \frac{1}{(1 + \nu \nu^\dagger C^{-1} u) \det(C)} l(\nu, \alpha) \]
is the PDF of \( z \) under \( H_1 \) with
\[ l(\nu, \alpha) = e^{-\nu \nu^\dagger C^{-1} (z - \alpha v)^2} \]
while \( f_0(z) \), the PDF of \( z \) under \( H_0 \), is given by
\[ f_0(z) = \frac{1}{\pi^N \det(C)} e^{-z^\dagger C^{-1} z} \]

To maximize \( l(\nu, \alpha) \) with respect to \( \alpha \) we can re-write its exponent as
\[ -(z - \alpha v)^\dagger C^{-1} (z - \alpha v) + \nu \left( \frac{\nu^\dagger C^{-1} (z - \alpha v)^2}{1 + \nu \nu^\dagger C^{-1} u} \right) \]

where \( \tilde{z} = C^{-1/2} z, \tilde{v} = C^{-1/2} v, \) and \( \tilde{u} = C^{-1/2} u \). Using
\[ \|\tilde{z} - \alpha \tilde{v}\|^2 = \|P_{\tilde{u}} (\tilde{z} - \alpha \tilde{v})\|^2 + \|P_{\perp \tilde{u}} (\tilde{z} - \alpha \tilde{v})\|^2 \]
and
\[ \|\tilde{u}^\dagger (\tilde{z} - \alpha \tilde{v})\|^2 = \|\tilde{u}\|^2 \|P_{\tilde{u}} (\tilde{z} - \alpha \tilde{v})\|^2 \]
we obtain
\[ l(\nu, \alpha) = e^{-\frac{\|\tilde{u}\|^2 \|P_{\perp \tilde{u}} (\tilde{z} - \alpha \tilde{v})\|^2}{1 + \nu \|\tilde{u}\|^2}} \]

Now letting \( u = v \) and, hence, \( \tilde{u} = \tilde{v} \) we have an expression that can be easily maximized with respect to \( \alpha \) obtaining
\[ \max_{\alpha \in \mathbb{C}} l(\nu, \alpha) = e^{-\|P_{\perp \tilde{u}} \tilde{z}\|^2} \]
and hence
\[ \max_{\alpha \in \mathbb{C}} f_1(z|\nu, \alpha) = \frac{1}{\pi^N} \frac{1}{(1 + \nu \nu^\dagger C^{-1} v) \det(C)} e^{-\|P_{\perp \tilde{u}} \tilde{z}\|^2} \]

It follows that
\[ \max_{\nu \geq 0} \max_{\alpha \in \mathbb{C}} f_1(z|\nu, \alpha) = \frac{1}{\pi^N} \frac{1}{\det(C)} e^{-\|P_{\perp \tilde{u}} \tilde{z}\|^2} \]
and
\[ \Lambda(z, C) = e^{-\|P_{\perp \tilde{u}} \tilde{z}\|^2} \]

The corresponding adaptive detector, obtained by replacing \( C \) with the sample covariance matrix based on the secondary data, is obviously equivalent to the AMF.

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