ADAPTIVE RADAR DETECTION OF DISTRIBUTED TARGETS IN PARTIALLY-HOMOGENEOUS NOISE PLUS SUBSPACE INTERFERENCE

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ABSTRACT

This paper addresses adaptive radar detection of distributed targets embedded in noise plus interference assumed to belong to an either known or unknown subspace of the observables. We assume that a set of noise-only data is available (the so-called secondary data). Detection algorithms have been derived modeling noise vectors, corresponding to different range cells, as zero-mean, complex normal ones, sharing the same structure of the covariance matrix up to possibly different power levels between primary and secondary data. The common structure and the power levels are unknown at the receiver. The performance assessment confirms the effectiveness of the newly-proposed detection algorithms also in comparison to previously-proposed ones.

1. INTRODUCTION

Adaptive radar detection of targets embedded in Gaussian disturbance has received an increasing attention from the radar community in recent years, [1-4, and references therein]. Adaptive detection of distributed targets has been addressed in [1]; therein useful target echoes have been modeled as signals known up to multiplicative factors, possibly different from one range cell to another. Adaptive subspace detection of point-like targets has been addressed in [2]. Adaptive subspace detection of distributed targets in noise of unknown power plus deterministic interference, assumed to belong to an unknown subspace, has been considered in [3]. Finally, several detection algorithms for distributed targets are encompassed as special cases of the amazingly general framework and derivations in [4].

In the following we address adaptive detection of distributed targets, within a given set of range cells (the so-called primary data), in presence of complex normal noise, with unknown covariance matrix, plus subspace interference. A set of noise-only additional data (the so-called secondary data) is available. Primary and secondary data share the same covariance matrix up to possibly different power levels. Such model will be referred to in the following as partially-homogeneous environment and it subsumes as a special case the so-called homogeneous environment, namely the case that primary and secondary data vectors possess one and the same covariance matrix. Subspace interference is assumed to belong to an either known or unknown (but for its rank) subspace of the observables. The performance assessment, conducted by Monte Carlo simulation, confirms the effectiveness of the newly-proposed detection algorithms also in comparison to existing ones.

The paper is organized as follows. The next section is devoted to the problem formulation while the object of Section 3 is the design of detectors based upon the Generalized Likelihood Ratio Test (GLRT). Section 4 is devoted to the performance assessment and Section 5 contains some concluding remarks.

2. PROBLEM FORMULATION

Assume that an array of N_a antennas senses K_P range cells and that each antenna collects N_t samples from each of those cells. Denote by $\boldsymbol{r}_k$, $k \in \Omega_P \equiv \{1, \ldots, K_P\}$, the N-dimensional vector, with $N = N_a \times N_t$, containing returns from the k-th cell. Moreover, assume that the disturbance is the sum of colored noise and interference, denoted by $\boldsymbol{n}_k$ and $\boldsymbol{i}_k$, $k \in \Omega_P$, respectively, with $\boldsymbol{i}_k \in \mathbb{C}^{N\times 1}$ modeled as a deterministic signal; we want to decide between the H_0 hypothesis that the $\boldsymbol{r}_k$'s contain disturbance only and the H_1 hypothesis that they also contain useful target echoes $\boldsymbol{s}_k \in \mathbb{C}^{N\times 1}$, $k \in \Omega_P$.

Moreover, we suppose that the useful signal $\boldsymbol{s}_k$ and the interference $\boldsymbol{i}_k$, $k \in \Omega_P$, are linear combinations of r and q, $r, q \in \mathbb{N}$, $q + r \leqslant N$, linearly independent modes, respectively; otherwise stated, $\boldsymbol{s}_k$ and $\boldsymbol{i}_k$, $k \in \Omega_P$, are assumed to belong to the range spaces of the full-column-rank matrices $\boldsymbol{H} \in \mathbb{C}^{N\times r}$ and $\boldsymbol{J} \in \mathbb{C}^{N\times q}$, respectively. Thus, denoting by $\boldsymbol{p}_k \in \mathbb{C}^{r\times 1}$ and $\boldsymbol{q}_k \in \mathbb{C}^{q\times 1}$ the unknown signal and interference coordinates, we have that $\boldsymbol{s}_k = \boldsymbol{H}\boldsymbol{p}_k$ and $\boldsymbol{i}_k = \boldsymbol{J}\boldsymbol{q}_k$, $k \in \Omega_P$.

In the following we assume that $\boldsymbol{J}$ is either known or unknown. In fact, we first assume that $\boldsymbol{J}$ is known and that its range is linearly independent of the range of $\boldsymbol{H}$; secondly, we assume that $\boldsymbol{J}$ is unknown (but for its rank) and that, under the H_1 hypothesis, the ranges of $\boldsymbol{H}$ and $\boldsymbol{J}$ are linearly independent. The noise vectors $\boldsymbol{n}_k$'s, $k \in \Omega_P$, are modeled as N-dimensional complex normal random vectors, i.e., $\boldsymbol{n}_k \sim \mathcal{CN}_N(\boldsymbol{0}, \boldsymbol{M})$, $k \in \Omega_P$, with $\boldsymbol{M}$ being, in turn, a positive definite matrix; we assume that $\boldsymbol{M}$ is unknown. We also suppose that K_S secondary data, $\boldsymbol{r}_k = \boldsymbol{n}_k \sim \mathcal{CN}_N(\boldsymbol{0}, \nu\boldsymbol{M})$, $k \in \Omega_S \equiv \{K_P + 1, \ldots, K_P + K_S\}$, where $\nu > 0$ is an unknown parameter, namely data containing noise only, are available. Finally, we suppose that the $\boldsymbol{n}_k$'s, $k \in \Omega_P \cup \Omega_S$, are independent random vectors.

Summarizing, the detection problem to be solved can be formulated in terms of the following binary hypothesis test:

$$\begin{cases} H_0 : \begin{cases} \boldsymbol{r}_k = \boldsymbol{J}\boldsymbol{q}_k + \boldsymbol{n}_k, & k \in \Omega_P, \\ \boldsymbol{r}_k = \boldsymbol{n}_k, & k \in \Omega_S, \end{cases} \\ \\ H_1 : \begin{cases} \boldsymbol{r}_k = \boldsymbol{H}\boldsymbol{p}_k + \boldsymbol{J}\boldsymbol{q}_k + \boldsymbol{n}_k, & k \in \Omega_P, \\ \boldsymbol{r}_k = \boldsymbol{n}_k, & k \in \Omega_S, \end{cases} \end{cases} \tag{1}$$

where we suppose that $K_S \geqslant N$ and, as already stated, that $r+q \leqslant N$.

3. GLRT-BASED DETECTORS

3.1. GLRT for known J

Denote by $\boldsymbol{R} = [\boldsymbol{R}_P \boldsymbol{R}_S] \in \mathbb{C}^{N\times K}$ the overall data matrix, with $\boldsymbol{R}_P = [\boldsymbol{r}_1 \cdots \boldsymbol{r}_{K_P}] \in \mathbb{C}^{N\times K_P}$ the primary data matrix, $\boldsymbol{R}_S = [\boldsymbol{r}_{K_P+1} \cdots \boldsymbol{r}_{K_P+K_S}] \in \mathbb{C}^{N\times K_S}$ the secondary data matrix, and $K = K_P + K_S$. Moreover, let $\boldsymbol{Q} = [\boldsymbol{q}_1 \cdots \boldsymbol{q}_{K_P}] \in \mathbb{C}^{q\times K_P}$ and $\boldsymbol{P} = [\boldsymbol{p}_1 \cdots \boldsymbol{p}_{K_P}] \in \mathbb{C}^{r\times K_P}$.

The above hypothesis testing problem can be solved using the GLRT

$$\Lambda[\boldsymbol{R}] = \frac{\max\limits_{\nu,\boldsymbol{P},\boldsymbol{Q},\boldsymbol{M}} f_1(\boldsymbol{R};\boldsymbol{M},\boldsymbol{Q},\boldsymbol{P},\nu)}{\max\limits_{\nu,\boldsymbol{Q},\boldsymbol{M}} f_0(\boldsymbol{R};\boldsymbol{M},\boldsymbol{Q},\nu)} \underset{H_0}{\overset{H_1}{\gtrless}} T, \tag{2}$$

where $f_j(\boldsymbol{R};\cdot)$ is the probability density function (pdf) of $\boldsymbol{R}$ under the H_j hypothesis, $j=0,1$, and T the threshold value to be set in order to ensure the desired probability of false alarm (P_{fa}).

Let us firstly solve the optimization problem under the H_0 hypothesis; to this end, observe that

$$f_0(\boldsymbol{R};\boldsymbol{M},\boldsymbol{Q},\nu) = \left[\frac{1}{\pi^N \det(\boldsymbol{M})}\right]^K \left[\frac{1}{\nu}\right]^{NK_S} \times$$
$$\exp\left\{-\mathrm{tr}\left[\boldsymbol{M}^{-1}\left(\frac{1}{\nu}\boldsymbol{S} + (\boldsymbol{R}_P - \boldsymbol{J}\boldsymbol{Q})(\boldsymbol{R}_P - \boldsymbol{J}\boldsymbol{Q})^\dagger\right)\right]\right\},$$

where $\det(\cdot)$ and $\mathrm{tr}(\cdot)$ are the determinant and the trace of a square matrix, respectively, † denotes conjugate transpose, and $\boldsymbol{S} = \boldsymbol{R}_S\boldsymbol{R}_S^\dagger$. Maximizing over $\boldsymbol{M}$ and $\boldsymbol{Q}$, we get the following compressed likelihood function under H_0 [4]

$$f_0(\boldsymbol{R};\widehat{\boldsymbol{M}},\widehat{\boldsymbol{Q}},\nu) = \left[\frac{K}{e\pi}\right]^{NK} \left[\frac{1}{\nu}\right]^{K_P(K-N)} \frac{1}{\det^K[\boldsymbol{S}]} \times$$
$$\frac{1}{\det^K\left[\frac{1}{\nu}\boldsymbol{I}_{K_P} + \left(\boldsymbol{S}^{-1/2}\boldsymbol{R}_P\right)^\dagger\left(\boldsymbol{I}_N - \boldsymbol{P}_{\boldsymbol{J}_w}\right)\left(\boldsymbol{S}^{-1/2}\boldsymbol{R}_P\right)\right]}$$

where $\boldsymbol{I}_N - \boldsymbol{P}_{\boldsymbol{J}_w}$ denotes the projection matrix onto the orthogonal complement of the range of $\boldsymbol{J}_w = \boldsymbol{S}^{-1/2}\boldsymbol{J} \in \mathbb{C}^{N\times q}$. Similarly, the compressed likelihood under H_1 is given by

$$f_1(\boldsymbol{R};\widehat{\boldsymbol{M}},\widehat{\boldsymbol{Q}},\widehat{\boldsymbol{P}},\nu) = \left[\frac{K}{e\pi}\right]^{NK} \left[\frac{1}{\nu}\right]^{K_P(K-N)} \frac{1}{\det^K[\boldsymbol{S}]} \times$$
$$\frac{1}{\det^K\left[\frac{1}{\nu}\boldsymbol{I}_{K_P} + \left(\boldsymbol{S}^{-1/2}\boldsymbol{R}_P\right)^\dagger\left(\boldsymbol{I}_N - \boldsymbol{P}_{\boldsymbol{W}_w}\right)\left(\boldsymbol{S}^{-1/2}\boldsymbol{R}_P\right)\right]},$$

where $\boldsymbol{I}_N - \boldsymbol{P}_{\boldsymbol{W}_w}$ denotes the projection matrix onto the orthogonal complement of the range of $\boldsymbol{W}_w = \boldsymbol{S}^{-1/2}\boldsymbol{W} \in \mathbb{C}^{N\times(q+r)}$ with $\boldsymbol{W} = [\boldsymbol{H}\ \boldsymbol{J}] \in \mathbb{C}^{N\times(q+r)}$. In particular, if $q+r=N$ the compressed likelihood under the H_1 hypothesis is given by

$$f_1(\boldsymbol{R};\widehat{\boldsymbol{M}},\widehat{\boldsymbol{Q}},\widehat{\boldsymbol{P}},\nu) = \left[\frac{K}{e\pi}\right]^{NK} \nu^{NK_P} \frac{1}{\det^K[\boldsymbol{S}]}. \tag{3}$$

As a special case, plugging the compressed likelihoods for $\nu = 1$ into (2) yields the GLRT for homogeneous environment. However, in order to come up with the GLRT for partially-homogeneous environment, we need to maximize the compressed likelihoods with respect to $\nu > 0$. Note that, (3) diverges as ν tends to infinity and, hence, for $q+r=N$ the GLRT does not exist. Thus, we focus on the case $q+r<N$. To this end, denote by t_0 and t_1 the ranks of the matrices

$$\boldsymbol{A}_0 = \left(\boldsymbol{S}^{-1/2}\boldsymbol{R}_P\right)^\dagger\left(\boldsymbol{I}_N - \boldsymbol{P}_{\boldsymbol{J}_w}\right)\left(\boldsymbol{S}^{-1/2}\boldsymbol{R}_P\right)$$

and

$$\boldsymbol{A}_1 = \left(\boldsymbol{S}^{-1/2}\boldsymbol{R}_P\right)^\dagger\left(\boldsymbol{I}_N - \boldsymbol{P}_{\boldsymbol{W}_w}\right)\left(\boldsymbol{S}^{-1/2}\boldsymbol{R}_P\right),$$

respectively. It can be shown that, if $\frac{K_S}{K_P} > \frac{r+q}{N-r-q}$, the GLRT for partially-homogeneous environment can be re-cast as

$$\Lambda[\boldsymbol{R}] = \frac{\widehat{\nu}_0^{\frac{K_P(K-N)}{K}} \det\left[\frac{1}{\widehat{\nu}_0}\boldsymbol{I}_{K_P} + \boldsymbol{A}_0\right]}{\widehat{\nu}_1^{\frac{K_P(K-N)}{K}} \det\left[\frac{1}{\widehat{\nu}_1}\boldsymbol{I}_{K_P} + \boldsymbol{A}_1\right]} \underset{H_0}{\overset{H_1}{\gtrless}} T, \tag{4}$$

where $\widehat{\nu}_j, j=0,1$, is the unique positive solution of equation

$$\sum_{k=1}^{t_j} \frac{\lambda_{k,j}\nu}{\lambda_{k,j}\nu + 1} = \frac{K_P N}{K}, \quad j=0,1, \tag{5}$$

with $\lambda_{k,0}$, $k=1,\ldots,t_0$, and $\lambda_{k,1}$, $k=1,\ldots,t_1$, the nonzero eigenvalues of $\boldsymbol{A}_0$ and $\boldsymbol{A}_1$, respectively. The proof follows the lead of results in [1].

3.2. GLRT for unknown J

It is also possible to come up with the GLRT for unknown $\boldsymbol{J}$ (up to its rank) and the assumption that, under the H_1 hypothesis, the rank of $\boldsymbol{W} = [\boldsymbol{H}\boldsymbol{J}]$ is equal to $r+q$. We focus on $r+q<N$. For the case at hand, the GLRT is given by

$$\begin{aligned}\Lambda[\boldsymbol{R}] &= \frac{\max\limits_{\nu,\boldsymbol{J},\boldsymbol{P},\boldsymbol{Q},\boldsymbol{M}} f_1(\boldsymbol{R};\boldsymbol{M},\boldsymbol{Q},\boldsymbol{P},\boldsymbol{J},\nu)}{\max\limits_{\nu,\boldsymbol{J},\boldsymbol{Q},\boldsymbol{M}} f_0(\boldsymbol{R};\boldsymbol{M},\boldsymbol{Q},\boldsymbol{J},\nu)} \\ &= \frac{\min\limits_{\nu,\boldsymbol{J}} \nu^{\frac{K_P(K-N)}{K}} \det\left[\frac{1}{\nu}\boldsymbol{I}_{K_P} + \boldsymbol{A}_0\right]}{\min\limits_{\nu,\boldsymbol{J}} \nu^{\frac{K_P(K-N)}{K}} \det\left[\frac{1}{\nu}\boldsymbol{I}_{K_P} + \boldsymbol{A}_1\right]} \underset{H_0}{\overset{H_1}{\gtrless}} T.\end{aligned}$$

Denote by $m_0 = \min\{K_P, N\}$ and $m_1 = \min\{K_P, N-r\}$, the ranks of the matrices $\boldsymbol{S}^{-1/2}\boldsymbol{R}_P$ and $\boldsymbol{Z}^\dagger\boldsymbol{S}^{-1/2}\boldsymbol{R}_P$, respectively, where $\boldsymbol{Z}$ is such that $\boldsymbol{I}_N - \boldsymbol{P}_{\boldsymbol{H}_w} = \boldsymbol{Z}\boldsymbol{Z}^\dagger$ with $\boldsymbol{P}_{\boldsymbol{H}_w}$ the projection matrix on $\boldsymbol{H}_w = \boldsymbol{S}^{-1/2}\boldsymbol{H} \in \mathbb{C}^{N\times r}$. Then, it can be shown that the numerator and the denominator of previous equation, after minimization over $\boldsymbol{J}$, are given by

$$\begin{cases} \min\limits_{\nu} \nu^{m_0 - q - \frac{K_P N}{K}} \displaystyle\prod_{i=N-m_0+1}^{N-q} \left(\frac{1}{\nu} + \sigma_i^2\right), & \text{if } m_0 \geqslant q+1, \\ \min\limits_{\nu} \left(\dfrac{1}{\nu}\right)^{\frac{K_P N}{K}}, & \text{if } m_0 < q+1, \end{cases} \tag{6}$$

and

$$\begin{cases} \min\limits_{\nu} \nu^{m_1 - q - \frac{K_P N}{K}} \displaystyle\prod_{i=N-r-m_1+1}^{N-r-q} \left(\frac{1}{\nu} + \eta_i^2\right), & \text{if } m_1 \geqslant q+1, \\ \min\limits_{\nu} \left(\dfrac{1}{\nu}\right)^{\frac{K_P N}{K}}, & \text{if } m_1 < q+1, \end{cases} \tag{7}$$

respectively, where the σ_i's, $i = 1, \ldots, m_0$, and the η_i's, $i = 1, \ldots, m_1$, are the singular values of the matrices $\boldsymbol{S}^{-1/2}\boldsymbol{R}_P$ and $\boldsymbol{Z}^\dagger \boldsymbol{S}^{-1/2}\boldsymbol{R}_P$, respectively, arranged in increasing order. At this point, it is a simple matter to come up with the GLRT for unknown $\boldsymbol{J}$ and homogeneous environment ($\nu = 1$). We focus, instead, on the GLRT for partially-homogeneous environment. To this end, first note that the likelihood function under H_j diverges if $m_j < q+1$, $j = 0, 1$. Thus, we assume $m_0 \geqslant q+1$ and $m_1 \geqslant q+1$. The optimization problems (6) and (7) are similar to that considered for known $\boldsymbol{J}$. For instance, for $K_P \geqslant N$ the GLRT exists only if $\frac{K_S}{K_P} > \frac{r+q}{N-r-q}$ and is given by

$$\Lambda[\boldsymbol{R}] = \frac{\widehat{\nu}_0^{\left(N-q-\frac{K_P N}{K}\right)} \prod_{i=1}^{N-q} \left(\frac{1}{\widehat{\nu}_0} + \sigma_i^2\right)}{\widehat{\nu}_1^{\left(N-r-q-\frac{K_P N}{K}\right)} \prod_{i=1}^{N-r-q} \left(\frac{1}{\widehat{\nu}_1} + \eta_i^2\right)} \underset{H_0}{\overset{H_1}{\gtrless}} T. \tag{8}$$

As to $\widehat{\nu}_0$, it is the unique positive solution of equation

$$\sum_{i=N-m_0+1}^{N-q} \frac{\sigma_i^2 \nu}{\sigma_i^2 \nu + 1} = \frac{K_P N}{K}, \tag{9}$$

while $\widehat{\nu}_1$ is the unique positive solution of equation

$$\sum_{i=N-r-m_1+1}^{N-r-q} \frac{\eta_i^2 \nu}{\eta_i^2 \nu + 1} = \frac{K_P N}{K}. \tag{10}$$

Similarly, it is possible to come up with specific expressions of the GLRT for $N - r \leqslant K_P < N$ and $q + 1 \leqslant K_P < N - r$ omitted here for the lack of space.

As a final remark, note that equations (5), (9), and (10) can be solved by resorting to the Matlab function `roots` which evaluates the eigenvalues of a companion matrix of order $(t_j+1) \times (t_j+1)$ at most, $j = 0, 1$.

4. PERFORMANCE ASSESSMENT

In this section we carry out a performance assessment of the proposed algorithms by resorting to standard Monte Carlo simulation. In order to evaluate the thresholds necessary to ensure a preassigned value of P_{fa} and the Probabilities of Detection (P_d's) we resort to $100/P_{fa}$ and 10^4 independent trials, respectively. The performance analysis assumes $r = 1$, $q = 3$, $P_{fa} = 10^{-4}$, and steering vector $\boldsymbol{H} \equiv \boldsymbol{s} = (1/\sqrt{N})[1 \cdots 1]^T$. The p_k's are (complex numbers) with the same deterministic amplitude and independent and identically distributed (iid) phases uniform in $(0, 2\pi)$. As to the interference matrix $\boldsymbol{J}$, it is randomly generated[1] at each iteration of the Monte Carlo simulation. In addition, the interference coefficients $\boldsymbol{q}_k$, $k = 1, \ldots, K_P$, are iid complex normal random vectors (rv's) with zero mean and covariance matrix given by $\sigma_J^2 \boldsymbol{I}_q$. The noise vectors $\boldsymbol{n}_k$, $k = 1, \ldots, K$, are iid complex normal rv's with zero mean and exponentially-shaped autocorrelation with one-lag correlation coefficient $\rho = 0.95$ and mean square value σ_n^2. The signal-to-noise power ratio (SNR) is defined as $\text{SNR} = \boldsymbol{s}^\dagger \boldsymbol{M}^{-1} \boldsymbol{s} \sum_{k=1}^{K_P} |p_k|^2$ where $|\cdot|$ denotes the modulus of a complex number. Finally, the interference-to-noise power ratio (INR), defined as σ_J^2/σ_n^2, is set to INR $= 10$ dB. We analyze the performance of the GLRT-based detectors (4) and (8) also in comparison to ad hoc detectors relying on the two-step GLRT-based design procedure and to the one-step GLRT derived without taking into account the presence of the interference at the design stage [1]. For the sake of clarity, we recall here that the decision statistics of the ad hoc detectors for known and unknown $\boldsymbol{J}$ are given by [3]

$$\frac{\text{tr}\left\{(\boldsymbol{I}_N - \boldsymbol{P}_{\boldsymbol{J}_w})\,\boldsymbol{\Sigma}\,(\boldsymbol{I}_N - \boldsymbol{P}_{\boldsymbol{J}_w})\right\}}{\text{tr}\left\{(\boldsymbol{I}_N - \boldsymbol{P}_{\boldsymbol{W}_w})\,\boldsymbol{\Sigma}\,(\boldsymbol{I}_N - \boldsymbol{P}_{\boldsymbol{W}_w})\right\}}$$

and

$$\left(\sum_{i=q+1}^{m_0} \gamma_i\right) \Big/ \left(\sum_{i=q+1}^{m_0} \delta_i\right),$$

respectively. As to $\boldsymbol{\Sigma}$, it is given by $\boldsymbol{\Sigma} = \boldsymbol{S}^{-1/2}\boldsymbol{R}_P\boldsymbol{R}_P^\dagger\boldsymbol{S}^{-1/2}$, $m_0 = \min\{K_P, N\}$ is the rank of $\boldsymbol{\Sigma}$, while the γ_i's and the δ_i's, $i = 1, \ldots, N$, are the eigenvalues of $\boldsymbol{\Sigma}$ and $(\boldsymbol{I}_N - \boldsymbol{P}_{\boldsymbol{H}_w})\boldsymbol{\Sigma}(\boldsymbol{I}_N - \boldsymbol{P}_{\boldsymbol{H}_w})$, respectively, arranged in decreasing order.

Figure 1 refers to $N = 8$, $K_S = 16$, and $K_P = 8$ whereas Figure 2 assumes $N = 8$, $K_S = 32$, and $K_P = 8$. Figure 1 shows that the GLRT for known $\boldsymbol{J}$, given by (4), performs better than the corresponding ad hoc detector, but also that the GLRT for unknown $\boldsymbol{J}$, given by (8), experiences a small, although not negligible, loss with respect to the corresponding ad hoc detector. Moreover, comparison of Figures 1 and 2 shows that performances of corresponding one-step and two-step GLRT-based detectors are closer as K_S increases. Finally, all of the above detectors significantly outperform the GLRT designed without assuming the presence of subspace interference [1].

Figure 3, referring to $N = 16$, $K_S = 32$, and $K_P = 8$, highlights instead, as already pointed out in [3], that the two-step detector for unknown $\boldsymbol{J}$ is useless when $K_P < N$ and also that the one-step GLRT for known $\boldsymbol{J}$ outperforms the corresponding two-step GLRT for the considered design parameters. Figure 4, referring to $N = 16$, $K_S = 32$, and $K_P = 16$, confirms the superiority of plain GLRT's with respect to the ad hoc detectors for certain design parameters and that all of them outperform those designed without taking into account interference [1].

5. CONCLUSIONS

We have addressed adaptive radar detection of distributed targets in noise plus subspace interference. To this end, we resorted to the GLRT design procedure and assumed that a set of noise-only data is available. Noise returns from different range cells have been modeled as zero mean, complex normal, independent random vectors sharing the same covariance matrix up to possibly different power levels between primary and secondary data (partially-homogeneous environment). The covariance structure of noise returns is unknown at the receiver and so are the possibly different scaling factors. Interference is modeled in terms of deterministic signals which belong to an either known or unknown subspace of the observables. The performance assessment has shown that the newly-introduced (one-step) GLRT's can guarantee better performance than detectors relying on the two-step GLRT-based design procedure [3]. Moreover, the proposed GLRT's outperform those designed without taking into account interference [1].

[1] More precisely, the entries of $\boldsymbol{J}$ are iid random variables taking on values $\pm 1/\sqrt{N}$ with equal probability.

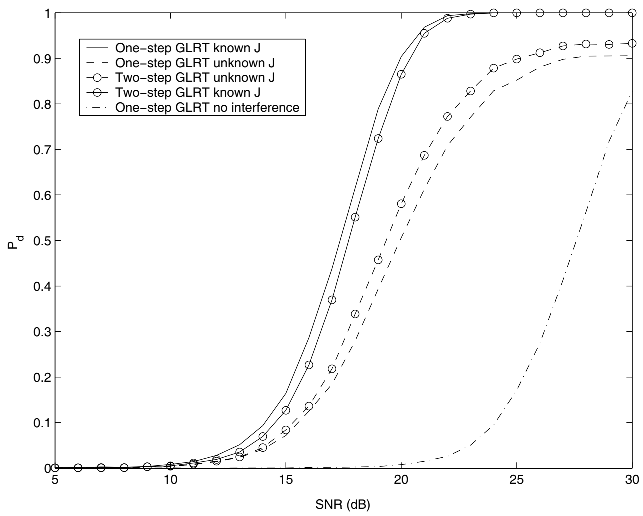

Fig. 1. P_d vs SNR: $N = 8$, $K_S = 16$, and $K_P = 8$.

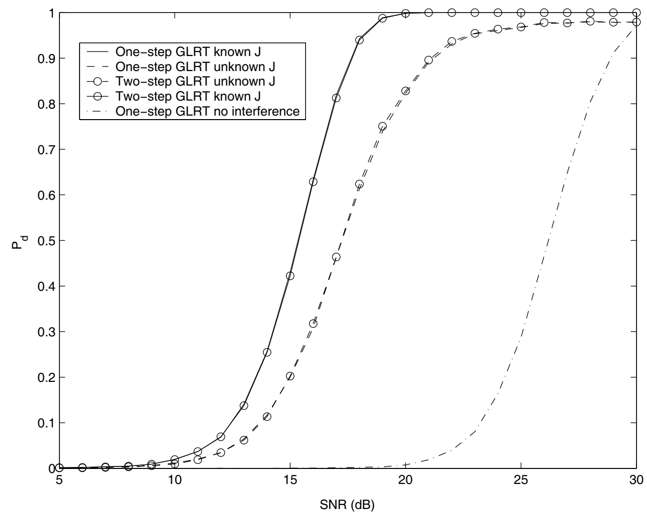

Fig. 2. P_d vs SNR: $N = 8$, $K_S = 32$, and $K_P = 8$.

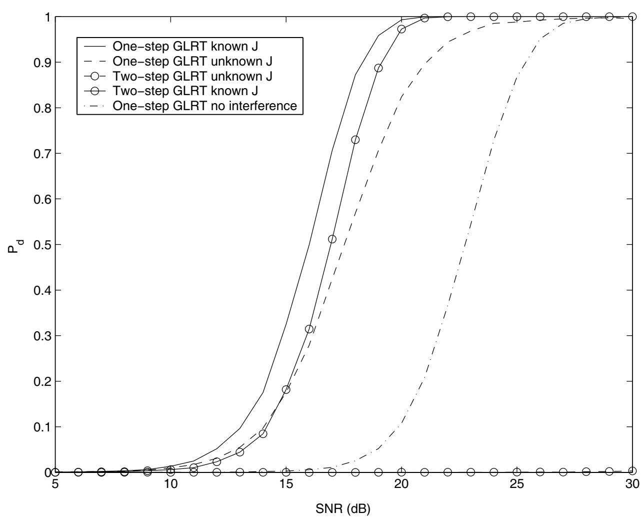

Fig. 3. P_d vs SNR: $N = 16$, $K_S = 32$, and $K_P = 8$.

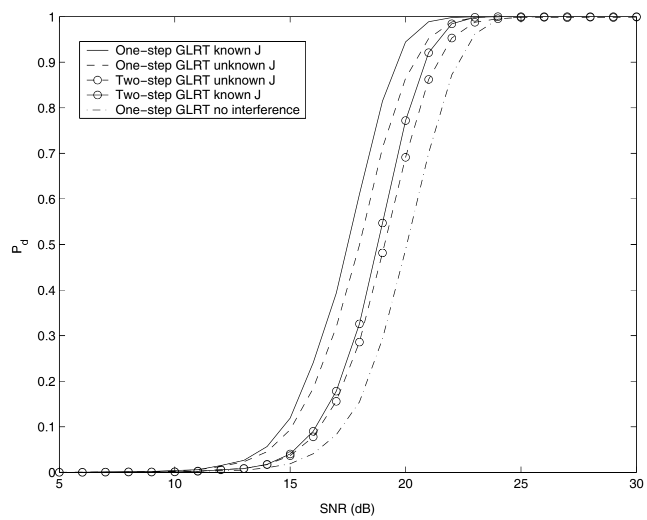

Fig. 4. P_d vs SNR: $N = 16$, $K_S = 32$, and $K_P = 16$.

6. REFERENCES

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