Digital Signal Processing 46 (2015) 41–48

Contents lists available at ScienceDirect

Digital Signal Processing

www.elsevier.com/locate/dsp

Adaptive array detection in noise and completely unknown jamming

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ARTICLE INFO

Article history:
Available online 4 August 2015

Keywords:
Array signal processing
Generalized likelihood ratio test
Signal detection
Unknown jamming
Wald test

ABSTRACT

The presence of jamming usually degrades the detection performance of a detector. Moreover, sufficient information about the jamming may be difficult to be obtained. To overcome the problem of adaptive array signal detection in noise and completely unknown jamming, we temporarily assume the jamming belongs to a subspace which is orthogonal to the signal steering vector in the stage of detector design. Consequently, by resorting to the criteria of generalized likelihood ratio test (GLRT) and Wald test, we propose two adaptive detectors, which can achieve signal detection and jamming suppression. It is shown, by Monte Carlo simulations, that the two proposed adaptive detectors have improved detection performance over existing ones.

1. Introduction

Detection of a multichannel signal in unknown disturbance is a hot topic in the field of array signal processing. The most pioneering and prominent detectors are Kelly's generalized likelihood ratio test (KGLRT) [1], adaptive matched filter (AMF) [2,3], and adaptive coherence estimator (ACE) [4]. Particularly, in [1] the signal has a known steering vector but with an unknown amplitude, and the noise is Gaussian distributed with an unknown covariance matrix. To estimate the covariance matrix, it is assumed that a set of independent and identically distributed (IID) training data is available. Consequently, the KGLRT is proposed according to the GLRT criterion. The AMF is designed for the same detection problem in [1], but it is obtained according to the two-step GLRT (2S-GLRT) criterion [2,3]. The KGLRT and AMF are both conceived for the homogeneous environment, where the training data and the test data share a common noise covariance matrix. In contrast, the ACE is devised in [4] based on the GLRT criterion for the partially homogeneous environment, where the test data and training data share the same noise covariance matrix only up to an unknown scaling factor. The KGLRT, AMF, and ACE are all for the point-like target detection, which is further investigated in [5–8] recently. Moreover, the problem of distributed target detection is dealt with in [9–13, and the references therein].

Note that all the cited references above do not take into account jamming. In practice, however, there usually exists intentional or unintentional jamming [14]. Suppression of deceptive jamming is considered in [15], where the jamming is rejected by multiple-input multiple-output (MIMO) radar with frequency diverse array (FDA). A mainlobe jamming suppression method is proposed in [16] based on eigen-projection and covariance matrix reconstruction. An intrusion detection system (IDS) framework for jamming detection and classification is proposed in [17] for wireless networks. The problem of detecting chaff centroid jamming is addressed in [18], and it is solved with the aid of the global positioning system (GPS) and inertial navigation system (INS). In [19] the jamming is deterministic and lies in a known subspace, many GLRT-based detectors are designed. For convenience, the jamming model in [19] is referred to as the subspace jamming, which is also considered in [20], but it is assumed to lie in both the test and training data, and a detector is proposed based on the method of sieves. The problem of signal detection in subspace jamming is further investigated in [21–24], where the potential target is spread in the range domain.

Remarkably, in most of the aforementioned references involved jamming it is assumed that some information about the jamming is known in advance. However, in practical applications it may be very difficult to obtain sufficient knowledge about the jamming. This brings a great challenge for signal detection. How to model the completely unknown jamming and devise effective detectors is

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http://dx.doi.org/10.1016/j.dsp.2015.07.006

the main motivation of this paper. Particularly, we focus on array signal detection of a point-like target in the presence of completely unknown jamming. An ad hoc model for the jamming is adopted at the stage of detector design. Precisely, we *temporarily* assume that it lies in a subspace orthogonal to the signal steering vector. Subsequently, we propose two adaptive detectors according to the GLRT and Wald test criteria. These two detectors admit certain intuitive physical interpretations, and they can achieve signal integration and jamming suppression simultaneously. For the performance evaluation, the cases of unknown (completely unknown or partially unknown) jamming and no jamming are all considered. It is shown that in the presence of unknown jamming, the two proposed detectors exhibit improved detection performance over the existing ones. Moreover, in the case of no jamming the proposed detector, derived according to the GLRT criterion, can still provide slightly better detection performance than the existing detectors in some situations.

The remainder of the paper is organized as follows. Section 2 formulates the problem to be solved. Section 3 gives the proposed detectors and shows some important properties of them. Numerical examples are provided in Section 4. Finally, Section 5 summarizes the paper.

2. Problem formulation

Suppose the data are received by an N-element uniform linear array (ULA). We want to discriminate between a binary hypothesis test, namely, hypothesis H_1 that a useful signal $\boldsymbol{s}_u$ exists in the data under test, which is denoted by an $N \times 1$ vector $\boldsymbol{x}$ and hypothesis H_0 that no useful signal exists in $\boldsymbol{x}$. The useful signal $\boldsymbol{s}_u$, if present, has the form $\boldsymbol{s}_u = a\boldsymbol{s}$, where a is the unknown nonzero signal amplitude and $\boldsymbol{s}$ is a known normalized signal steering vector. To sum up, the detection problem can be symbolically written as

$$\begin{cases} \mathrm{H}_0 : a = 0, \\ \mathrm{H}_1 : a \neq 0. \end{cases} \tag{1}$$

The normalized signal steering vector has the form

$$\boldsymbol{s} = \left[1, e^{j2\pi f_t}, \ldots, e^{j2\pi(N-1)f_t}\right]^T / \sqrt{N} \tag{2}$$

where $f_t = d\cos\theta_t/\lambda$, d is the interelement spacing, λ is the wavelength, θ_t is the angle of the target with respect to (w.r.t.) the array, and the symbol $(\cdot)^T$ is the transpose operation. To avoid grating lobe, d is set to be $d = \lambda/2$. Thus $f_t \in [-0.5, 0.5]$ and f_t is usually called the normalized spatial frequency.

Besides the possible signal, the test data $\boldsymbol{x}$ also contains disturbance $\boldsymbol{d}$, which consists of colored noise $\boldsymbol{n}$ (including clutter and white noise) and jamming $\boldsymbol{j}$. The noise $\boldsymbol{n}$ is modeled as a zero-mean complex circular Gaussian vector with an unknown covariance matrix $\boldsymbol{R}$, which is positive definite Hermitian. The jamming $\boldsymbol{j}$ is completely unknown. For the detector design, we temporarily assume that $\boldsymbol{j}$ is deterministic and lies in a subspace spanned by an $N \times (N-1)$ matrix $\boldsymbol{U}_\perp$, which is a semi-unitary matrix such that $\boldsymbol{U}_\perp^H \boldsymbol{s} = \boldsymbol{0}_{(N-1)\times 1}$ and $\boldsymbol{U}_\perp^H \boldsymbol{U}_\perp = \boldsymbol{I}_{N-1}$, with $(\cdot)^H$ being the conjugate transpose. Hence, $\boldsymbol{j}$ can be expressed as

$$\boldsymbol{j} = \boldsymbol{U}_\perp \boldsymbol{\alpha}, \tag{3}$$

where $\boldsymbol{\alpha}$ is an $(N-1) \times 1$ unknown coordinate vector. The rationale of such a model is explained below. Note that if we define

$$\boldsymbol{B} = [\boldsymbol{s}, \boldsymbol{U}_\perp], \tag{4}$$

which is an $N \times N$ unitary matrix, then $\boldsymbol{B}$ can be taken as a basis of the entire space $\mathbb{C}^{N\times N}$. Therefore, there exists an $N \times 1$ vector $\boldsymbol{b}$ such that

$$\boldsymbol{j} = \boldsymbol{B}\boldsymbol{b} = a_j \boldsymbol{s} + \boldsymbol{U}_\perp \boldsymbol{\alpha} \tag{5}$$

where $\boldsymbol{b} = [a_j, \boldsymbol{\alpha}^T]^T$ and a_j is a scalar. Equation (5) can be recast as $\boldsymbol{j} = \boldsymbol{j_s} + \boldsymbol{j}_\perp$, where $\boldsymbol{j_s} = a_j \boldsymbol{s}$ and $\boldsymbol{j}_\perp = \boldsymbol{U}_\perp \boldsymbol{\alpha}$. Note that the component $\boldsymbol{j_s}$ is the part of the jamming projected onto the signal subspace $\langle \boldsymbol{s} \rangle$, with $\langle \cdot \rangle$ standing for the subspace spanned by the matrix/vector argument. Moreover, we have $\boldsymbol{j_s} = \boldsymbol{P_s}\boldsymbol{j}$ for a given $\boldsymbol{j}$, where $\boldsymbol{P_s} = \boldsymbol{s}\boldsymbol{s}^H$ is the orthogonal projection matrix onto the signal subspace $\langle \boldsymbol{s} \rangle$. For ULAs, the signal steering vector is often Vandermonde [25], such as (2), and the array response drops off very quickly if the angle between the jamming and signal exceeds the beamwidth [26]. Therefore, $\boldsymbol{j_s}$ is usually small, especially for the jamming with low or moderate power. Hence, (5) can be approximated by (3).

As customary, we also assume that a set of IID training data, denoted by $\boldsymbol{x}_l$, $l = 1, 2, \ldots, L$, is available. $\boldsymbol{x}_l$ only contains noise $\boldsymbol{n}_l$, which shares the same statistical property with $\boldsymbol{n}$.

3. The proposed detectors

3.1. The Wald test approach

Let $\boldsymbol{\Theta}$ be a parameter vector, partitioned as

$$\boldsymbol{\Theta} = \left[\boldsymbol{\Theta}_r^T, \boldsymbol{\Theta}_s^T\right], \tag{6}$$

where $\boldsymbol{\Theta}_r = a$ and $\boldsymbol{\Theta}_s = [\boldsymbol{\alpha}^T, \mathrm{vec}^T(\boldsymbol{R})]^T$, with $\mathrm{vec}(\cdot)$ being the vectorization operation. Then the Wald test can be devised according to the formula [27]

$$t_{\text{Wald}} = (\hat{\boldsymbol{\Theta}}_{r_1} - \boldsymbol{\Theta}_{r_0})^H \left\{\left[\boldsymbol{I}^{-1}(\hat{\boldsymbol{\Theta}}_1)\right]_{\boldsymbol{\Theta}_r,\boldsymbol{\Theta}_r}\right\}^{-1} (\hat{\boldsymbol{\Theta}}_{r_1} - \boldsymbol{\Theta}_{r_0}), \tag{7}$$

where $\hat{\boldsymbol{\Theta}}_{r_1}$ is the maximum likelihood estimate (MLE) of $\boldsymbol{\Theta}_r$ under H_1, $\boldsymbol{\Theta}_{r_0}$ is the value of $\boldsymbol{\Theta}_r$ under H_0, $[\boldsymbol{I}^{-1}(\hat{\boldsymbol{\Theta}}_1)]_{\boldsymbol{\Theta}_r,\boldsymbol{\Theta}_r}$ is the $(\boldsymbol{\Theta}_r, \boldsymbol{\Theta}_r)$-part of $\boldsymbol{I}^{-1}(\boldsymbol{\Theta})$, evaluated at $\hat{\boldsymbol{\Theta}}_1$, namely, the MLE of $\boldsymbol{\Theta}$ under H_1, and

$$\boldsymbol{I}(\boldsymbol{\Theta}) = \mathrm{E}\left[\frac{\partial \ln f_1(\boldsymbol{x}, \boldsymbol{X}_L)}{\partial \boldsymbol{\Theta}^*} \frac{\partial \ln f_1(\boldsymbol{x}, \boldsymbol{X}_L)}{\partial \boldsymbol{\Theta}^T}\right] \tag{8}$$

is the Fisher information matrix (FIM) for $\boldsymbol{\Theta}$ [27]. The notations $\mathrm{E}[\cdot]$, $\partial(\cdot)$, $(\cdot)^*$, and $\ln(\cdot)$ stand for the statistical expectation, partial derivative, conjugate, and natural logarithm, respectively.

The joint PDF of $\boldsymbol{x}$ and $\boldsymbol{X}_L \triangleq [\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_L]$ for the problem in (1) under H_1 is

$$f_1(\boldsymbol{x}, \boldsymbol{X}_L) = c\det(\boldsymbol{R})^{-(L+1)} \exp\left[-\mathrm{tr}\left(\boldsymbol{R}^{-1}\boldsymbol{S}\right) - \boldsymbol{x}_1^H \boldsymbol{R}^{-1} \boldsymbol{x}_1\right], \tag{9}$$

where $c = \pi^{-N(L+1)}$, $\det(\cdot)$ denotes the determinant of a matrix, $\boldsymbol{x}_1 = \boldsymbol{x} - a\boldsymbol{s} - \boldsymbol{U}_\perp\boldsymbol{\alpha}$, and $\boldsymbol{S}$ is the sample covariance matrix (SCM) defined as

$$\boldsymbol{S} = \boldsymbol{X}_L \boldsymbol{X}_L^H. \tag{10}$$

Taking the logarithm of (9) and performing the derivative w.r.t. a and a^*, respectively, yield

$$\frac{\partial \ln f_1(\boldsymbol{x}, \boldsymbol{X}_L)}{\partial a} = \boldsymbol{x}_1^H \boldsymbol{R}^{-1} \boldsymbol{s}, \tag{11}$$

$$\frac{\partial \ln f_1(\boldsymbol{x}, \boldsymbol{X}_L)}{\partial a^*} = \boldsymbol{s}^H \boldsymbol{R}^{-1} \boldsymbol{x}_1. \tag{12}$$

Substituting (11) and (12) into (8) results in

$$\boldsymbol{I}_{\boldsymbol{\Theta}_r,\boldsymbol{\Theta}_r}(\boldsymbol{\Theta}) = \boldsymbol{s}^H \boldsymbol{R}^{-1} \mathrm{E}\left[\boldsymbol{x}_1 \boldsymbol{x}_1^H\right] \boldsymbol{R}^{-1} \boldsymbol{s} = \boldsymbol{s}^H \boldsymbol{R}^{-1} \boldsymbol{s}, \tag{13}$$

where we have used the fact that $\mathrm{E}[\boldsymbol{x}_1 \boldsymbol{x}_1^H] = \boldsymbol{R}$ under H_1. Taking the derivative of (11) w.r.t. $\boldsymbol{\alpha}^*$ or $\mathrm{vec}^T(\boldsymbol{R}^*)$ and performing the expectation operation yield the fact that $\boldsymbol{I}_{\boldsymbol{\Theta}_r,\boldsymbol{\Theta}_s}(\boldsymbol{\Theta})$ is a null vector. As a consequence, we have

$$\left\{\left[\boldsymbol{I}^{-1}(\boldsymbol{\Theta})\right]_{\boldsymbol{\Theta}_r,\boldsymbol{\Theta}_r}\right\}^{-1} = \left[\boldsymbol{I}_{\boldsymbol{\Theta}_r,\boldsymbol{\Theta}_r}(\boldsymbol{\Theta})\right] = \boldsymbol{s}^H \boldsymbol{R}^{-1} \boldsymbol{s}. \tag{14}$$