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Robust adaptive beamforming for multiple-input multiple-output radar with spatial filtering techniques

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ABSTRACT

In this paper, we consider robust adaptive beamformer design for multiple-input multiple-output (MIMO) radar systems. The desired transmit-receive steering vector is estimated through maximizing the output power subject to constraints upon correlation coefficient and steering vector norm. The original nonconvex problem is reformulated as two reduced dimension semi-definite programming (SDP) problems. An iterative procedure is devised to tackle the two SDP problems, whose convergence is analytically proven. Based on the estimated desired signal, we are then able to obtain the interference covariance matrix via the matrix rank-constrained minimization method. Compared to other robust adaptive beamforming methods for MIMO radar, the proposed approach has the advantages of high efficiency and accuracy. Simulation results are presented to confirm the effectiveness and robustness of the proposed approach.

1. Introduction

Multiple-input multiple-output (MIMO) radar has received significant attention due to its various advantages over conventional radar systems, such as enhanced detection performance, improved parameter identifiability and angular resolution, providing more degrees of freedom (DOFs), and better spatial coverage [1]. MIMO radar is usually divided into statistical (or widely separated) MIMO radar [2] and colocated (or coherent) MIMO radar [3]. Statistical MIMO radar that is comprised of widely separated transmit and receive antennas, can achieve spatial diversity gain and enhance detection performance. On the other hand, colocated MIMO radar with waveform diversity can enhance parameter identifiability and increase the flexibility of transmit beampattern design, thereby improving spatial resolution via a great increase in DOFs of the system [4].

In practice, the adaptive beamforming algorithm is usually used to extract the desired signal and suppress simultaneously the interference as well as noise at the array output [5]. However, the conventional beamforming method often suffers severe performance degradation due to certain factors such as small number of training snapshots, corruption of training data by the desired signal in many practical applications, and the mismatch between the assumed and actual knowledge [6]. Thus, robust design techniques have been an active research topic. During the past decade, various robust adaptive beamformers have been proposed based on different principles to achieve high resolution in the framework of phased array receivers [7–9]. The diagonal loading technique is prevalent in enhancing the robustness of the beamformer. However, the limitation of the diagonal loading method is that the diagonal loading factor must be generally determined empirically [10]. The worst-case optimization-based technique developed in [11] delimits the uncertainty set by upper bounding the norm of the mismatch vector. In [12], a robust method is proposed by exploiting the specific structure of the matrix to enhance the robustness of adaptive arrays. In order to combat the effect of the desired signal in the sample covariance matrix, some robust methods based on covariance matrix estimation have been developed [13–17]. In the shrinkage method, an enhanced covariance matrix is obtained to improve the robustness against the signal mismatch problem. But the improvement in performance is limited [13,14]. A spatial power spectrum sampling algorithm has been proposed to form an interference-plus-noise covariance matrix for further im-

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provement in performance [15–17], while these techniques usually involve high computational complexity. The associated robust optimization techniques have also been considered for use in MIMO radar [18–20]. In [18], the worst-case optimization algorithm was used in MIMO radar. Moreover, in [19] a robust design has been proposed to mitigate signal mismatch with a certain selected probability distribution, which is a variant of the worst-case-based approach. An adaptive beamformer with magnitude response constraints is developed for MIMO radar [20], which employs the convex optimization method to obtain an exact robust solution.

In this paper, we consider a novel robust adaptive beamforming problem using full DOFs in the context of MIMO radar. The desired transmit-receive steering vector is estimated through maximizing the output power subject to spatial correlation coefficient and norm constraints. Then we devise an iteration procedure to tackle a relaxed version of the original nonconvex problem. Each iteration of the algorithm is handled via solving two low-dimensional convex optimisation problems [21,22]. Then with the analyzed desired signal steering vector and the shrinkage estimator preprocessing, the interference covariance matrix can be estimated via the matrix rank-constrained minimization method. Compared with other high-performance algorithms for MIMO radar, the results indicate the effectiveness and robustness of the proposed algorithm.

The remainder of this paper is organized as follows. The MIMO signal model is described in Section 2. In Section 3, a novel steering vector method is proposed. Then, a new method to reconstruct the interference-plus-noise covariance matrix is introduced. In Section 4, we evaluate the performance via numerical simulations. Finally, conclusions are drawn in Section 5.

2. MIMO Signal model

Consider a MIMO narrowband radar system composed of M_t transmit antennas and M_r receive antennas. We assume that all transmit and receive antennas are isotropic. Each transmit element emits a different waveform and the baseband signal at the receiver can be written as

$$\mathbf{x}(t) = \alpha_0 \mathbf{a}_r(\phi_0)\mathbf{a}_t{}^T(\theta_0)\mathbf{s}(t) + \sum_{j=1}^{J} \alpha_j \mathbf{a}_r(\phi_j)\mathbf{a}_t{}^T(\theta_j)\mathbf{s}(t) + \mathbf{n}(t), \tag{1}$$

where t is the time index, and $(\cdot)^T$ denotes the transpose operation. Parameters α_0 and α_j denote respectively the complex coefficient of the desired signal, and the complex coefficient of the jth interference. We assume that the desired signal, interference, and noise are statistically mutually independent, and the interference is neither close to nor in the mainlobe beam region of the array. The directions of departure (DODs) and directions of arrival (DOAs) of the desired signal and interferences with respect to the transmit and receive array normals are denoted respectively as $\{\theta_j, \varphi_j\}_{j=0}^{J}$. We also assume that the waveforms $\mathbf{s}(t) = [s_1(t), \ldots, s_{M_t}(t)]$ are mutually orthogonal with unit energy such that $\int_{T_N} \mathbf{s}(t)\mathbf{s}^H(t)dt = \boldsymbol{I}$, where $\boldsymbol{I}$ and T_N represent the identity matrix and the radar pulse width; $\mathbf{n}(t)$ is the additive white Gaussian noise vector; and $\mathbf{a}_t(\cdot)$ and $\mathbf{a}_r(\cdot)$ denote the corresponding $M_t \times 1$ and $M_r \times 1$ steering vectors, which have the following general forms

$$\mathbf{a}_t(\theta) = \left[1 \; e^{j2\pi d_t sin\theta/\lambda} \ldots e^{j2\pi(M_t-1)d_t sin\theta/\lambda}\right]^T,$$
$$\mathbf{a}_r(\phi) = \left[1 \; e^{j2\pi d_r sin\theta/\lambda} \ldots e^{j2\pi(M_r-1)d_r sin\theta/\lambda}\right]^T, \tag{2}$$

where λ is the carrier wavelength. The interelement spacing in the transmit and receive arrays are denoted by d_t and d_r, respectively. By matched filtering the received data to the m_tth transmitted waveform at the receiver (i.e., $\mathbf{y}_{m_t}(t) = \int_{T_N} \mathbf{x}(t)\mathbf{s}_{m_t}{}^*(t)dt, m_t = 1, \ldots, M_t$, where $()^*$ denotes the conjugate operator), then the output of the matched filters of the MIMO radar can then be expressed as

$$\mathbf{y} = \alpha_0 \mathbf{a}_t(\theta_0) \otimes \mathbf{a}_r(\phi_0) + \sum_{j=1}^{J} \alpha_j \mathbf{a}_t(\theta_j) \otimes \mathbf{a}_r(\phi_j) + \mathbf{z}$$
$$= \mathbf{y}_s + \mathbf{y}_j + \mathbf{z}, \tag{3}$$

where $\mathbf{y}_s$, $\mathbf{y}_j$, $\mathbf{z}$ are the desired signal, interference, and noise vector components, respectively; and $\otimes$ denotes the Kronecker product; $\mathbf{a}_t(\theta_0) \otimes \mathbf{a}_r(\phi_0)$ denotes the $M_t M_r \times 1$ transmit-receive steering vector. Under the assumption that both the signal steering vector and the data matrix are known precisely, the transmit-receive beamforming weight vector $\mathbf{w}$ can be obtained via maximizing the output signal-to-interference-plus-noise ratio (SINR)

$$\text{SINR} = \frac{\mathbf{w}^H \mathbf{R}_s \mathbf{w}}{\mathbf{w}^H \mathbf{R}_{jn} \mathbf{w}} = \frac{\sigma_0^2 \left|\mathbf{w}^H \mathbf{a}_t(\theta_0) \otimes \mathbf{a}_r(\phi_0)\right|^2}{\mathbf{w}^H \mathbf{R}_{jn} \mathbf{w}}, \tag{4}$$

where σ_0^2 denotes the desired signal power, and $|\cdot|$ is an absolute operator. $\mathbf{R}_s = \mathrm{E}\left[\mathbf{y}_s \mathbf{y}_s^H\right]$ and $\mathbf{R}_{jn} = \mathrm{E}\left[(\mathbf{y}_j + \mathbf{z})(\mathbf{y}_j + \mathbf{z})^H\right]$ represent the desired signal and the interference-plus-noise covariance matrices, respectively, where $\mathrm{E}\{\cdot\}$ is the statistical expectation operator. In practice, the interference-plus-noise covariance matrix is difficult to be obtained, thus, it is usually replaced by the sample covariance matrix $\hat{\mathbf{R}}$, which is calculated from the received signal vectors as

$$\hat{\mathbf{R}} = \frac{1}{L} \sum_{l=1}^{L} \mathbf{y}(l)\mathbf{y}^H(l), \tag{5}$$

where $\mathbf{y}(l)$ denotes the sample data at the lth snapshot and L denotes the number of snapshots. The transmit-receive beamforming weight vector is given by

$$\mathbf{w} = \frac{\hat{\mathbf{R}}^{-1}(\mathbf{a}_t(\theta_0) \otimes \mathbf{a}_r(\phi_0))}{(\mathbf{a}_t(\theta_0) \otimes \mathbf{a}_r(\phi_0))^H \hat{\mathbf{R}}^{-1}(\mathbf{a}_t(\theta_0) \otimes \mathbf{a}_r(\phi_0))}. \tag{6}$$

Note that $\hat{\mathbf{R}}$ contains the desired signal component. As stated in the last section, the calculated adaptive weight vector by using $\hat{\mathbf{R}}$ will obtain worse performance as compared with the one using the covariance matrix without any contribution from the desired signal. Based on the Capon spatial power spectrum estimator [23], the beamformer output power can be expressed as

$$P(\theta_0) = \frac{1}{(\mathbf{a}_t(\theta_0) \otimes \mathbf{a}_r(\phi_0))^H \hat{\mathbf{R}}^{-1}(\mathbf{a}_t(\theta_0) \otimes \mathbf{a}_r(\phi_0))}. \tag{7}$$

3. Proposed method

As stated previously, adaptive beamformers are sensitive to steering vector mismatch, especially when the desired signal is present in the training data, which may cause the self-null phenomenon of the direction of the desired signal and result in dramatic performance degradation. In addition, the reconstructed interference-plus-noise covariance matrix may not be easily obtained. In this section, we propose a different approach to obtain the beamforming weight vector. The main idea is first to estimate the desired signal steering vector and then remove the actual desired signal information from the sample covariance matrix.

3.1. Steering vector estimation

According to the description in [13], shrinkage methods are suitable for high-dimensional covariance estimation with small number of samples. We use the shrinkage form as

$$\tilde{\mathbf{R}} = \hat{\alpha}\boldsymbol{I} + \hat{\beta}\hat{\mathbf{R}}, \tag{8}$$