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Enhanced knowledge-aided space–time adaptive processing exploiting inaccurate prior knowledge of the array manifold

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ABSTRACT

The accuracy of the prior knowledge of the clutter environments is critical to the clutter suppression performance of knowledge-aided space–time adaptive processing (KA-STAP) algorithms in airborne radar applications. In this paper, we propose an enhanced KA-STAP algorithm to estimate the clutter covariance matrix considering inaccurate prior knowledge of the array manifold for airborne radar systems. The core idea of this algorithm is to incorporate prior knowledge about the range of the measured platform velocity and the crab angle, and other radar parameters into the assumed clutter model to obtain increased robustness against inaccuracies of the data. It first over-samples the space–time subspace using prior knowledge about the range values of parameters and the inaccurate array manifold. By selecting the important clutter space–time steering vectors from the over-sampled candidates and computing the corresponding eigenvectors and eigenvalues of the assumed clutter model, we can obtain a more accurate clutter covariance matrix estimate than directly using the prior knowledge of the array manifold. Some extensions of the proposed algorithm with existing techniques are presented and a complexity analysis is conducted. Simulation results illustrate that the proposed algorithms can obtain good clutter suppression performance, even using just one snapshot, and outperform existing KA-STAP algorithms in presence of the errors in the prior knowledge of the array manifold.

1. Introduction

Space–time adaptive processing (STAP) is considered to be an efficient tool for detection of slow targets by airborne radar systems in strong clutter environments [1–4]. However, due to the large space–time degrees of freedom (DoFs), the full-rank STAP has a slow convergence and requires about twice of the DoFs of the independent and identically distributed (IID) training snapshots to yield an average performance loss of roughly 3 dB [1]. In real scenarios, it is hard to obtain so many IID training snapshots, especially in heterogeneous environments. Therefore, STAP techniques providing high performance in small training support situations have always been a hot topic in this area.

Reduced-dimension and reduced-rank methods have been considered to counteract the slow convergence of the full-rank STAP, such as the extended factored or the multibin element-space post-Doppler STAP method [2,3], the principal-components methods [5], the joint-domain localized (JDL) approach [6], the cross-spectral metric method [7], the multistage Winer filter method [8], the joint iterative optimization of adaptive filters [9] and the joint interpolation, decimation and filtering algorithms [10], etc. These methods can reduce the number of training snapshots to twice of the reduced-dimension, or twice of the clutter rank. The parametric adaptive matched filter (PAMF) based on a multichannel autoregressive model [11] provides another alternative solution to the slow convergence of the full-rank STAP. By exploiting the fact that space–time beamformers do not need all their DoFs to mitigate interference signals, sparse space–time beamformers are designed to improve the convergence for a generalized sidelobe canceler processor in [12] and a direct filter processor [13]. However, there is still need to improve the convergence or reduce the sample support when employing these approaches because the number of required snapshots is large relative to the non-stationarity assumption.

Recently developed knowledge-aided STAP (KA-STAP) incorporates prior knowledge, provided by digital elevation maps, land cover databases, road maps, Global Positioning System (GPS), previous scanning data and other known features, to compute the high-fidelity estimates of the clutter covariance matrix and exhibits good performance in heterogeneous environments [14–22,28,29, 23–26]. Among the developed KA-STAP algorithms, they can be

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categorized into two cases [14]: intelligent training and filter selection; and Bayesian filtering and data prewhitening. In this paper, we focus on the latter case. Colored loading implements the STAP filter in two steps: a prewhitening step using the prior matrix, followed by adaptive filtering [16,17]. Fully automatic methods for combining the matrix with prior knowledge and secondary data are considered in [18,19]. Furthermore, in [20], an automatic combination of the inverse of the matrix with prior knowledge and the inverse of the estimated covariance matrix from secondary data is developed. The authors in [21] introduced a knowledge-aided parametric covariance estimation (KAPE) scheme by blending both prior knowledge and data observations within a parameterized model to capture instantaneous characteristics of the cell under test (CUT). A low computation complexity approach that is similar to the KAPE is developed in [22]. A modified sample matrix inversion (SMI) through clutter covariance matrix estimated from least squares (LS) to overcome the range-dependent clutter nonstationarity in conformal array configurations is described in [23]. The convergence and the performance of KA-STAP algorithms are analyzed in [25] and [26]. In recently years, to reduce the requirements of the secondary data or the accurate prior knowledge of the clutter statistics, sparsity-based STAP algorithms are developed to compute the clutter covariance matrix by exploiting the sparsity of the clutter in the whole angle-Doppler plane [27–34]. These algorithms discretize the whole angle-Doppler into a large number of grid points and reconstruct the angle-Doppler profile or image using the sparse recovery methods. The corresponding recovered signal's dimension is very large (16 to 50 timing of the system DoFs), which leads to a high computational complexity.

Regardless of any KA-STAP method, the accuracy of prior knowledge will have a great impact on the STAP performance. In this paper, we focus on the mitigation of the impact of inaccurate prior knowledge and the development of a robust enhanced KA-STAP algorithm to estimate the clutter covariance matrix. The proposed method can be divided into three steps. First, it generates the candidates of the clutter space–time steering vectors using prior knowledge of the range of the measured platform velocity and the crab angle, and other radar parameters, unlike the approach in [21–24] which directly uses the array manifold. Then, the proposed method selects the important clutter space–time steering vectors and computes the corresponding eigenvectors and eigenvalues of the clutter subspace from the formulated candidates. Third, it estimates the clutter covariance matrix and computes the STAP filter. Furthermore, we detail several issues about using inaccurate prior knowledge of array manifold and also discuss some extensions of the proposed algorithm with the existing techniques. Compared with sparsity-based STAP, the proposed algorithm only over-samples the potential clutter Doppler and spatial frequencies using some prior knowledge, which significantly reduces the recovered signal's dimension. Additionally, the proposed algorithm can avoid the target signal cancelations because no desired target component corrupts the assumed model, which is also pointed out by [21]. Finally, simulation results demonstrate the effectiveness of our proposed algorithm.

The remaining paper is organized as follows. In Section 2, we introduce the signal model and the review of existing STAP using prior knowledge of array manifold. Then, in Section 3, we detail the proposed enhanced KA-STAP algorithm, discuss some extensions of the proposed algorithm with the existing techniques and also illustrate the implementations and complexity analysis. Simulated airborne radar data are used to evaluate the performance of the proposed algorithm in Section 4. Section 5 provides the summary and conclusions.

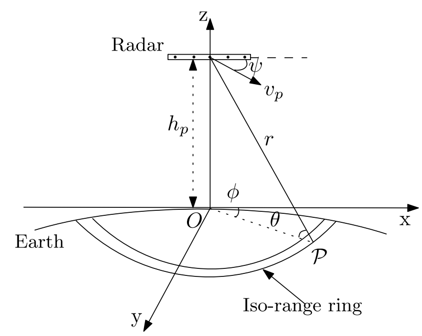

Fig. 1. Airborne radar geometry with a ULA antenna.

2. Background

2.1. Signal model and problem formulation

The system under consideration is a pulsed Doppler radar with a uniformly spaced linear array antenna (ULA) consisting of M elements on the airborne radar platform, as shown in Fig. 1. The platform is at an altitude h_p and moving with constant velocity v_p. The angle ψ refers to the crab angle between the platform velocity and the array. For a special scatterer point $\mathcal{P}$ (which can be the target or the discretized clutter patch) located at range r, the angle variables ϕ and θ refer to its azimuth and elevation. The radar transmits a coherent burst of pulses at a constant pulse repetition frequency (PRF) $f_r = 1/T_r$, where T_r is the pulse repetition interval. The transmitter carrier frequency is $f_c = c/\lambda_c$, where c is the propagation velocity and λ_c is the wavelength. The coherent processing interval (CPI) length is equal to NT_r. The received signal from an iso-range gate of interest can be presented by a space–time $NM \times 1$ data vector $\mathbf{x}$ (also called a snapshot vector).

A general model for the space–time clutter plus noise snapshot at the iso-range gate is given by [1]

$$\mathbf{x}_k = \sum_{i=1}^{N_a}\sum_{k=1}^{N_c} \sigma_{i,k}\mathbf{v}(\phi_{i,k}, \theta_{i,k}, f_{i,k}) + \mathbf{n}, \tag{1}$$

where $\mathbf{n}$ is the Gaussian white thermal noise vector, with the noise power σ_n^2 on each channel and pulse; N_a is the number of range ambiguities; N_c is the number of independent clutter patches over the iso-range gate; $\phi_{i,k}$ and $\theta_{i,k}$ is the azimuth and elevation to the ikth clutter patch; $f_{i,k}$ is the corresponding Doppler frequency; $\sigma_{i,k}$ is the complex amplitude for the ikth clutter patch with each element proportional to the square-root of the patch clutter–noise ratio (CNR); and $\mathbf{v}(\phi_{i,k}, \theta_{i,k}, f_{i,k})$ is the $NM \times 1$ space–time steering vector for the clutter patch with azimuth $\phi_{i,k}$, elevation $\theta_{i,k}$ and Doppler frequency $f_{i,k}$.

The space–time steering vector is given as the Kronecker product of the temporal and spatial steering vectors, denoted as $\mathbf{v}(\phi_{i,k}, \theta_{i,k}, f_{i,k}) = \mathbf{v}_t(f_{i,k}) \otimes \mathbf{v}_s(\phi_{i,k}, \theta_{i,k})$. For the ikth clutter patch, the corresponding temporal and spatial steering vectors are given by [1]

$$\mathbf{v}_t(f_{i,k}) = [1, \exp(j2\pi f_{i,k}T_r), \cdots, \exp(j2\pi(N-1)f_{i,k}T_r)]^T, \tag{2}$$

$$\begin{aligned}\mathbf{v}_s(\phi_{i,k}, \theta_{i,k}) \\ &= [1, \exp(\frac{j2\pi d}{\lambda_c}\cos\theta_{i,k}\sin\phi_{i,k}), \cdots, \\ &\quad \exp(\frac{j2\pi(M-1)d}{\lambda_c}\cos\theta_{i,k}\sin\phi_{i,k})]^T,\end{aligned} \tag{3}$$

where $[\cdot]^T$ denotes the transposition operation, d is the inter-sensor spacing of the ULA, and the Doppler frequency $f_{i,k}$ is