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Airborne radar space time adaptive processing based on atomic norm minimization

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ABSTRACT

Existing sparse recovery based space-time adaptive processing (SR-STAP) methods discretize the angle-Doppler plane to generate the space-time steering dictionary, which will cause the off-grid problem, resulting in performance loss. This paper proposes an alternative processing model established in the continuous domain. Based on the positive semidefinite (PSD), block-Toeplitz, and low rank properties of the clutter covariance matrix (CCM), the subspace of clutter can be estimated by solving an atomic norm minimization problem. Then, the CCM is directly calculated by the Eigen-decomposition based process. If multiple independently and identically distributed (IID) training samples are available, the proposed method can be easily extended to the multiple measurement vector (MMV) model. With the joint sparsity and same subspace assumptions of different samples, MMV based atomic norm minimization STAP (ANM-STAP) method can further increase the estimation accuracy of the clutter subspace, and thus improve the clutter suppression performance. Simulation results demonstrate that, in comparison with typical SR-STAP methods, the proposed method can avoid the off-grid problem, achieve more accurate CCM estimation, and enjoy better clutter suppression performance with fewer training samples than the statistic STAP method.

1. Introduction

Space-time adaptive processing (STAP) is an effective signal processing technique to detect slowly moving targets in a strong clutter background for the airborne phased array radar system [1–3]. The performance of STAP depends on the estimation accuracy of clutter plus noise covariance matrix (CNCM). For classical statistical STAP methods, with the assumptions that the received signals of different range cells are independently and identically distributed (IID) and the training samples are target-free (i.e. no target is included, otherwise, the performance will be significantly degraded), the CNCM of the range cell under test (CUT) is usually estimated by the data of its adjacent range cells (i.e. the so-called training samples). However, the number of required IID training samples to obtain the suboptimal performance is so large that can hardly be obtained in the practical non-stationary and heterogeneous environments.

In order to reduce the number of training samples while suppress clutter and detect target effectively, many different types of STAP methods have been developed in the last few decades. Reduced-dimension and reduced-rank methods [4–9], such as joint-domain localization (JDL) method [4] and the multistage Wiener filter method [6], can reduce the number of required training samples to twice of the reduced dimension of the data and twice of the reduced clutter rank, respectively. Moreover, direct data domain (D3) STAP methods [10], which only use the data of the CUT, can bypass the problem of training sample support. However, the cost is the reduction of the system degree of freedom. Recently, knowledge-aided (KA) STAP methods [11–13] that employ both the prior knowledge and the data observations to capture the characteristics of clutter have gained increasing interests. Nevertheless, the accurate prior knowledge of the environment provided by road maps, optical or radar images and global positioning system is often difficult to obtain and exploit in practical applications.

Most recently, sparse representation/recovery (SR) based STAP (SR-STAP) methods have been extensively researched [14–20]. By exploiting the intrinsic sparsity of clutter and implementing advanced reconstruction algorithms, SR-STAP methods can achieve high-resolution clutter angle-Doppler profile and accurate CNCM estimation with a very small number of training samples (even with single training sample). Based on the sparse property of the clutter vector and along with the development of SR reconstruction algorithms, SR-STAP method has been modified and im-

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proved in different ways in recent years. For example, to improve the reconstruction accuracy of SR, multiple measurement vector (MMV) model and sparse Bayesian learning strategy have been applied in [20]. Besides, aiming to reduce the computational complexity of SR-STAP methods, several methods were put forward, including the fast-converged sparse Bayesian learning method in [21], spectrum-aided reduced-dimension SR method in [22], beam-space post-Doppler dimension reduced SR -STAP method in [23], etc. Furthermore, focusing on the problems caused by the array gain and phase errors, several methods have also been proposed to overcome the performance degradation [24,25]. By combining the strength of using prior knowledge, knowledge-aided sparse recovery (KA-SR) STAP method was also introduced in [26].

However, for most existing SR-STAP methods, the signal model is established by discretizing the angle-Doppler plane. In such case, since the supporting space-time vectors of the clutter subspace cannot be exactly presented by the defined space-time steering vectors, the off-grid/basis-mismatch problem occurs. According to Chae et al. [27], the off-grid problem will cause significant performance degradation. For problems caused by the discretization, a simple approach is to use multi-resolution refinement and decrease the grid size, which, however, will give rise to high coherence of the defined dictionary. Furthermore, reducing the grid size will increase the dimension of the dictionary and, therefore, increase the memory usage and the computational complexity of the reconstruction. To solve the off-grid problem of existing SR-STAP methods, a dictionary learning method and a parameter-searched orthogonal matching pursuit (OMP) algorithm have been proposed in [28] and [29], respectively. Although these methods can somehow eliminate the effect of off-grid problem and improve the estimation accuracy of the clutter angle-Doppler profile, the discretization is still necessary and the off-grid problem is unavoidable.

Corresponding to the sparsity of vectors used in conventional SR and compressive sensing (CS) techniques, another signal structure, i.e. the low-rankness of matrices, has been exploited with increasing attentions in recent years [30–32]. Low-rank matrix completion, representation, and decomposition were widely applied in the radar signal processing field, such as synthetic aperture radar (SAR) [33], inverse SAR (ISAR) [34], and through the wall radar (TWR) [35], etc. Inspired by these successful applications, in this work, the positive semidefinite (PSD), block-Toeplitz, and low rank properties of the clutter covariance matrix (CCM) is exploited and a novel STAP method with single and multiple training samples is correspondingly proposed. Different from the existing SR-STAP methods, in the proposed method, the CCM is directly estimated by solving an atomic norm minimization (ANM) problem and implementing the Eigen-decomposition process without discretizing the angle-Doppler plane and recovering the clutter angle-Doppler profile. Since the proposed estimation model is established in the continuous domain, the off-grid problem in most existing SR-STAP methods is avoided. Due to this property, with a small number of IID training samples, the proposed method can achieve more accurate estimation of the CCM and thus better clutter suppression performance than existing SR-STAP methods. Simulation results demonstrate the effectiveness of the proposed STAP method and its advantages over conventional classical statistical STAP and SR-STAP methods.

The rest of the paper is organized as follows. In Section 2, the signal model for airborne STAP radar is established, and the classical statistical STAP method is introduced. In Section 3, we briefly overview the SR-STAP method and discuss the off-grid problem and its effects. Our proposed ANM-STAP method with single of multiple training samples is presented in Section 4. Simulation results are given in Section 5 to validate the performance of the proposed method. Finally, Section 6 concludes the paper and presents some considerations of the future work.

2. Signal model

Consider a side-looking uniformly linear array (ULA) pulsed Doppler airborne radar system consisting of N elements with an interelement spacing d. The platform is flying with a constant moving velocity v. With the constant pulse repetition frequency (PRF) f_{prf}, a coherent burst of K pulses is transmitted in a coherent processing interval (CPI). Assume the clutter patches are evenly distributed in the azimuth angles within a single range cell and there are totally M clutter patches after discretizing the azimuth domain. Given the azimuth angle θ_{m}, the spatial frequency and normalized Doppler frequency of the mth clutter patch can be expressed as $f_m^s = d\sin\theta_m/\lambda$ and $f_m^t = \beta f_m^s$, where the superscript 's' denotes space, 't' denotes time, $\beta=2v/(df_{\mathrm{prf}})$ is the clutter ridge slope, and λ is the wavelength.

Ignoring the influence of range ambiguous clutter and jamming signals for simplicity, the received signal of the CUT collected over all pulse repetition periods and all array elements can be organized into a $NK\times 1$ vector $\boldsymbol{x}_0$, given by

$$\boldsymbol{x}_0 = \sum\nolimits_{m=1}^{M} \alpha_m \boldsymbol{s}_m^{t,s} + \alpha_T \boldsymbol{s}_T^{t,s} + \boldsymbol{n}_0 = \boldsymbol{x}_{C,0} + \boldsymbol{x}_{T,0} + \boldsymbol{x}_{N,0} \tag{1}$$

where $\boldsymbol{n}_0$ is the additive thermal noise vector, $x_{C,\,0}$ is the reflection coefficient of the mth clutter patch, clutter component, $x_{T,\,0}$ is the target component, $x_{N,\,0}$ is the noise component, $x_{N,\,0}$ is the noise component, α_m is the reflection coefficient of the mth clutter patch, and $\boldsymbol{s}_m^{t,s}$ denotes its space-time steering vector, which has the form of $\boldsymbol{s}_m^{t,s} = \boldsymbol{s}_m^t \otimes \boldsymbol{s}_m^s$, $\otimes$ denotes the Kronecker product, and

$$\begin{cases} \boldsymbol{s}_m^t = [1, \exp(j2\pi f_m^t), \ldots, \exp(j2\pi(K-1)f_m^t)]^T \\ \boldsymbol{s}_m^s = [1, \exp(j2\pi f_m^s), \ldots, \exp(j2\pi(N-1)f_m^s)]^T \end{cases} \tag{2}$$

are temporal and spatial steering vectors of the mth clutter patch, respectively. In (2), $j^2=-1$, and $(\cdot)^{\mathrm{T}}$ denotes the transpose operation. α_T is the complex amplitude of the target, and $\boldsymbol{s}_T^{t,s}$ is the space-time steering vector of the target determined by its azimuth angle and its relative velocity to the platform.

Assuming the clutter patches are mutually independent from each other, we can get the CCM $\boldsymbol{R}_C$ as

$$\begin{aligned} \boldsymbol{R}_C &= E[\boldsymbol{x}_{C,0}\boldsymbol{x}_{C,0}^H] = \sum\nolimits_{m=1}^{M} |\alpha_m|^2 \boldsymbol{s}_m^{t,s}(\boldsymbol{s}_m^{t,s})^H \\ &= \sum\nolimits_{m=1}^{M} |\alpha_m|^2 [\boldsymbol{s}_m^t(\boldsymbol{s}_m^t)^H] \otimes [\boldsymbol{s}_m^s(\boldsymbol{s}_m^s)^H] \end{aligned} \tag{3}$$

where $E[\cdot]$ denotes the expectation, and $(\cdot)^{\mathrm{H}}$ denotes the conjugate transpose operation.

Furthermore, the thermal noise component $\boldsymbol{x}_{N,0}$ is assumed to be a zero-mean complex Gaussian signal with covariance matrix $\boldsymbol{R}_N=\sigma^2\boldsymbol{I}_{NK}$ and uncorrelated with the clutter patches. Therefore, the clutter plus noise covariance matrix (CNCM) $\boldsymbol{R}_I$ of the CUT can be expressed as

$$\boldsymbol{R}_I = \boldsymbol{R}_C + \sigma^2 \boldsymbol{I}_{NK} \tag{4}$$

where σ^2 is noise power, $\boldsymbol{I}_{NK}$ denotes an $NK\times NK$ identity matrix. To suppress the clutter and noise components and detect the target, the optimal weighting vector $\boldsymbol{w}_0$ of the STAP processor is designed by maximizing the output signal-to-interference -plus-noise ratio (SINR), resulting in

$$\boldsymbol{w}_0 = \boldsymbol{R}_I^{-1}\boldsymbol{s}_T^{t,s} / [(\boldsymbol{s}_T^{t,s})^H \boldsymbol{R}_I^{-1} \boldsymbol{s}_T^{t,s}] \tag{5}$$

where $(\cdot)^{-1}$ denotes the matrix inverse operation.

In practice, the CNCM of the CUT is unknown in advance and must be estimated from the homogeneous training samples [1]. Assume the clutter of neighboring target-free range cells are independently and identically distributed (IID) with the clutter in the CUT, the CNCM of the CUT can be estimated by the classical statistical method via sample matrix inversion (SMI) approach, giving

$$\boldsymbol{R}_I = (1/L)\sum\nolimits_{l=1}^{L} \boldsymbol{x}_l \boldsymbol{x}_l^H \tag{6}$$