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Robust space time processing based on bi-iterative scheme of secondary data selection and PSWF method

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ABSTRACT

Prolate spheroidal wave function (PSWF) method could improve the target detection performance for space-time adaptive processing (STAP) in nonhomogeneous environment. However, it may be ineffective with system parameter error. In this paper, we correct the system parameter with clutter spectrum analysis. Since contaminated samples contained in the secondary data set have detrimental impact on this spectrum analysis, the traditional sample selection method of generalized inner production (GIP) is combined with PSWF method, and then a bi-iterative scheme is proposed. Firstly, the system parameter for PSWF is estimated via the analysis of spectrum image, which is constructed with the secondary data set. Then, the covariance matrix is derived by PSWF method with the estimated parameter. Thirdly, the GIP sample selection technique is implemented with the PSWF covariance matrix, and the secondary data set would be updated. Repeat these steps until a stable parameter is obtained. Several vital issues such as how to estimate the parameter with real data and why the precision of covariance matrix could be improved during the iteration are analyzed. In the end, the validity of the proposed algorithm is substantiated by practical and simulation results.

1. Introduction

Detecting moving targets embedded in the strong ground clutter echoes is a basic problem for air-to-ground geometry radar system, which has been studied for several decades. Space-Time Adaptive Processing (STAP) [1–3] and its extended algorithms have drawn a lot of attention for their effective ability to eliminate the adverse influence of clutter data. During the implementation, STAP requires an estimate of the clutter-plus-noise covariance matrix (which is named as the interference covariance matrix (ICM) in the rest of this paper for simplicity). Ordinarily, this matrix is estimated using the so-called secondary or training data, which are supposed to be independent and identically distributed (IID). Hence, sample selection algorithm (SDS) [4–8] is generally required to eliminate the nonhomogeneous samples (which are also called the contaminated samples) from the training data set. In nonhomogeneous environment [9,10], various terrain types would increase the difficulty in sample selection. On the other hand, the number of secondary samples influences the accuracy of covariance matrix directly. A well-known conclusion is that the average performance loss would be less than 3 dB [11] if the sample number is larger than twice the processing dimension. However, samples may be insufficient to estimate a precise ICM in nonhomogeneous environment.

Knowledge-Aided (KA) STAP [12–15], which is promoted by the Defense Advanced Research Projects Agency (DARPA), is a kind of effective algorithm to settle the above problem and has received substantive investigations over the past several decades. It uses the prior data to assist the estimation of ICM, which would improve the precision of the matrix remarkably. A typical algorithm of KA-STAP is to implement a convex combination of the prior ICM and the current one. However, inaccurate prior knowledge, which is possible in practice due to environmental changes or outdated information, can significantly degrade the performance.

The recently proposed PSWF-STAP method [16] constructs an assist ground stationary clutter subspace based on the system parameter. Therefore, the information outdate problem of the conventional KA-STAP algorithm would be relieved. In [8], a generalized inner production (GIP) algorithm [6,7] based on the estimated PSWF matrix is utilized to eliminate the outliers (moving target signal) from the training data set, which is robust in the nonhomogeneous environment. However, the system parameter error may also degrade its performance. As noticed by the authors themselves: "When this model is not valid, the performance of the

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algorithm will degrade." [16, p. 634]. Estimate the clutter subspace with a combination of both the assumed geometry and the received data is a feasible way to overcome this problem, which is the motivation of our work in this paper.

In PSWF-STAP algorithms, the construction of ICM is directly related to the ratio of temporal frequency to spatial frequency, which is conventionally calculated with system parameters. It is feasible to correct the value of this ratio with space-time spectrum analysis. However, this analysis algorithm also requires an estimated covariance matrix, and when contaminated samples are included in the secondary sample set, the precision of the estimated parameter is also not guaranteed. Therefore, the SDS processing should be carried out to exclude the contaminated samples. Generalized inner product (GIP) is a commonly used SDS technique to detect and eliminate the contaminated sample in nonhomogeneous environment. However, the performance of the GIP algorithm is strongly influenced by the accuracy of its initial covariance matrix. Therefore, the GIP method also requires a prior instruction to estimate an effective ICM.

Take the above discussions into consideration, a bi-iterative scheme of clutter-plus-noise covariance matrix estimation is proposed in this paper. Firstly, we estimate the parameter for PSWF method through the Capon (also named as MVDR) spectrum analysis [17] of the received secondary data other than using the system parameters directly, which would eliminate the adverse influence of the system parameter error. With a secondary sample set contaminated by the nonhomogeneous clutter, the initial estimated parameter would deviate from the true value. Then we employ the estimated parameter to estimate a PSWF clutter subspace and the subsequently ICM. Thirdly, use the PSWF covariance matrix for GIP sample selection and update the secondary sample set. Repeat these three steps until a stable parameter is obtained. With this iterative processing, the nonhomogeneous samples would be excluded from the sample set step by step, and a precise model for PSWF would be obtained.

The rest of this paper is organized as follows: in Section 2, signal model and the introduction of PSWF algorithm are given as the background knowledge. Then, the proposed recursive matrix estimate scheme with the combination of the PSWF and the GIP method is presented in Section 3. In Section 4, we provide the simulation results and the corresponding performance evaluation. Finally, we conclude this paper in Section 5.

2. Problem formulation

In this section, we firstly formulate the problem of STAP and then give reviews of the conventional PSWF, which will provide comprehensive background information for the following proposed method. We assume a uniform array with N channels sampling totally K pules in a coherent processing interval. The platform is moving with a constant velocity v_a and the angle of arrival is denoted by θ. Then, the sampled outputs may be represented as a $NK \times 1$ column vector $\mathbf{X}$. The symbols of other system parameters used in this paper include: d denotes the spacing of the uniform array, λ refers to the wavelength and f_{PRF} denotes the pulse repetition frequency.

In STAP, the optimal adaptive processing weight vector maximizes the output signal-to-clutter-plus-noise ratio (SCNR) and takes the form [1]:

$$\mathbf{w} = \rho \mathbf{R}^{-1}\mathbf{a}(f_s, f_t), \tag{1}$$

where ρ is an arbitrary non-zero scale, $\mathbf{R}$ denotes the interference space-time covariance matrix, $\mathbf{a}(f_s, f_t)$ is the steering vector of the target, f_s and f_t denote the spatial frequency and temporal frequency, respectively.

In side-looking STAP, the clutter rank is able to be evaluated according to Brennan rule [11] which leads to a low rank structure for the clutter. The Eigen-value Decomposition (EVD) of $\mathbf{R}$ takes the form:

$$\mathbf{R} = \sum_{m=1}^{M} (\lambda_m \mathbf{u}_m \mathbf{u}_m^H), \tag{2}$$

where λ_m and $\mathbf{u}_m$ are eigenvalues and the corresponding eigenvectors, respectively. The eigenvalues are supposed to be arranged with a descending order: $\lambda_1 > \lambda_2 \cdots > \lambda_r = \cdots = \lambda_M$. Notice that the clutter rank [2] $r = N + \alpha(K-1)$, where $\alpha = 2v_a/(f_{PRF} \times d))$ is an important parameter in the following estimation of PSWF.

The matrix $\mathbf{R}$ can be rewritten as:

$$\mathbf{R} = \mathbf{U}_c \mathbf{A}_c \mathbf{U}_c^H + \mathbf{V}_n \mathbf{B}_n \mathbf{V}_n^H, \tag{3}$$

where $\mathbf{U}_c = [\mathbf{u}_1, \mathbf{u}_2 \cdots \mathbf{u}_r]$ and $\mathbf{V}_n = [\mathbf{u}_{r+1}, \mathbf{u}_{r+2} \cdots \mathbf{u}_M]$, the diagonal matrix $\mathbf{A}_c = \mathrm{diag}\{\lambda_1, \lambda_2 \cdots \lambda_r\}$ and $\mathbf{B}_n = \mathrm{diag}\{\lambda_{r+1}, \lambda_{r+2} \cdots \lambda_M\}$. Symbol diag$\{\mathbf{x}\}$ denotes the a diagonal matrix with elements equal to $\mathbf{x}$. The space spanned by $\mathbf{U}_c$ is customarily named as the clutter subspace $\prod_c = \mathbf{U}_c \mathbf{U}_c^H$ while the space spanned by $\mathbf{V}_n$ is named as the noise subspace $\prod_n = \mathbf{V}_n \mathbf{V}_n^H$. Notice that the power of clutter is expressed by eigen-values and the inherent space-time spectrum structure is reflected by the subspace $\prod_c$.

Generally, the interference covariance matrix $\mathbf{R}$ is unknown and its estimation is required to perform the adaptive processing. Two different estimations are introduced here. First one is the commonly used sample covariance matrix (SCM), which requires the so-called secondary samples $\{\mathbf{X}_l\}_{l=1\cdots L}$. Those secondary samples are collected from L range bins and supposed to be target-free, independent and identically distributed (IID) as the observation under test. The SCM algorithm can be expressed as:

$$\mathbf{R}_e = \frac{1}{L} \sum_{l=1}^{L} (\mathbf{X}_l \cdot \mathbf{X}_l^H). \tag{4}$$

Without requirement of secondary samples, a prior ICM can be constructed based on the PSWF method with system parameters [16]. The calculation of the orthogonal signals is omitted in this paper and one can resort to [16] for a detailed introduction. Note that the estimated prior clutter subspace $\mathbf{U}_p$ by PSWF is primarily determined by the aforementioned parameter α. And the prior clutter subspace estimated by PSWF is denoted as:

$$\prod_p = \mathbf{U}_p \mathbf{U}_p^H. \tag{5}$$

With the orthogonal vector set $\mathbf{U}_p$, we can simplify the full rank weight $\mathbf{w} \propto \mathbf{R}_p^{-1}\mathbf{a}(f_s, f_t)$ deduced in [16], which can be denoted as:

$$\mathbf{R}_p = \mathbf{U}_p \mathbf{A}_p \mathbf{U}_p^H + \sigma_n^2 \mathbf{I}, \tag{6}$$

where identity matrix $\mathbf{I}$ denotes the theoretical noise covariance matrix, σ_n^2 is the noise power and $\mathbf{A}_p$ is the eigen-value diagonal matrix corresponding to $\mathbf{U}_p$. Then eigen-value matrix $\mathbf{A}_p$ could be estimated through:

$$\widehat{\mathbf{A}}_p = \mathbf{U}_p^H \mathbf{R}_e \mathbf{U}_p = \mathbf{U}_p^H \left\{ \frac{1}{L} \sum_{l=1}^{L} (\mathbf{X}_l \cdot \mathbf{X}_l^H) \right\} \mathbf{U}_p. \tag{7}$$

Substituting (7) into (6) we get the estimated interference covariance matrix based on the prior subspace $\mathbf{U}_p$ as well as the sample set $\{\mathbf{X}_l\}_{l=1,2\cdots L}$.

In paper [8], PSWF algorithm is combined with the GIP algorithm to eliminate the outliers. As the algorithm proposed in [16],