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A training samples selection method based on system identification for STAP

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ABSTRACT

In space-time adaptive processing (STAP), the selected training samples should have the same covariance matrix as the clutter of the cell under test (CUT). The traditional methods usually select samples whose waveforms are similar to that of the CUT. We notice that completely dissimilar waveforms may have the same covariance matrix. As a result, many valid samples are lost in traditional methods. So we propose a training samples selection method based on system identification. The proposed methods select samples with similar covariance matrices instead of similar waveforms. First, a samples selection model based on system identification is proposed. Then, the neural network is used to identify the clutter model of the CUT. Finally, samples are selected according to the output variance. Compared with the methods in [1, 2, 3, 4], the proposed method has the following advantages: (1) More than twice the valid training samples can be obtained; (2) The clutter suppression performance can be improved more than 2 dB for the measured data.

1. Introduction

Space-time adaptive processing plays an important role in ground clutter suppression of airborne radar, communication interference suppression [5–7] and weak target detection of sky-wave over-the-horizon radar [1,8,9].

In STAP, maximizing output signal-to-clutter-and-noise ratio (SCNR) is a key objective. The optimal weight vector of STAP is $\mathbf{w} = \mathbf{R}_{CUT}^{-1}\mathbf{s}/\left(\mathbf{s}^H\mathbf{R}_{CUT}^{-1}\mathbf{s}\right)$, where $\mathbf{s}$ is the space-time steering vector of the target, $\mathbf{R}_{CUT}$ denotes the clutter covariance matrix of the cell under test (CUT) [10]. However, $\mathbf{R}_{CUT}$ is unknown and needs to be estimated by the selected training samples in practical application.

To achieve an optimal performance, the selected training sample should meet the following conditions:

(1) $\mathbf{R}_{TS} = \mathbf{R}_{CUT}$, where $\mathbf{R}_{TS}$ denotes the covariance matrix of the training sample.
(2) The training samples should be sufficient, because the amount of training samples to achieve 3 dB optimal SCNR performance is approximately twice the dimensionality of STAP [11].

At present, training samples selection methods can be divided into three categories. The first is the power-selected training (PST) method [12]. It selects the samples with strong clutter power to deepen the clutter notch. The second category is the generalized inner product (GIP) method [13], which eliminates the samples through different clutter statistical characteristics from the CUT using generalized inner product. The third is based on the waveform similarity [1–4].

Among them, the method based on the waveform similarity [1–4] attracts wide attention. It usually chooses the samples whose waveforms are similar to the CUT in time or frequency domain. In [1], a method of training samples selection based on time-domain waveform similarity is proposed. It calculates the correlation coefficient between samples and the CUT in time domain, and those samples with the greater correlation coefficients are selected as the training samples. However, this method discards the dissimilar samples with the same covariance matrix as the CUT, which leads to the low utilization rate of samples. To solve this problem, a weighted method is suggested in [2]. However, this method discards the dissimilar samples with the same covariance matrix as the CUT, which leads to the low utilization rate of samples. To solve this problem, a weighted method is suggested in [3,4], the samples are selected according to the waveform similarity in frequency domain. This method chooses samples whose clutter spectrums are similar to that of the CUT.

We notice that the completely dissimilar signals can also have the same covariance matrix. The essence of the training samples selection problem is to find those samples with the same clutter covariance matrices as CUT rather than with the similar waveforms. Therefore, the traditional methods based on waveform sim-

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ilarity usually miss a large number of dissimilar samples with the same covariance matrix.

Based on the above considerations, a training samples selection method based on system identification is proposed. First, a samples selection model based on system identification is proposed. A neural network is further proposed to identify the clutter model of CUT, then the training samples are filtered by the identified clutter model. The samples with small output variance are selected as the training samples. Compared with the traditional methods based on waveform similarity in [1–4], the proposed method has the following advantages: (1) The obtained valid training samples in the proposed method is more than twice those in [1–4]; (2) The measured data demonstrates that the proposed method is 2 dB better than the methods in [1–4].

The remainder of this paper is organized as follows. Problem analysis is presented in Section 2. In Section 3, we derive our training samples selection method. Then the simulation analysis of the measured data is presented in Section 4. Finally, conclusions are drawn in Section 5.

2. Problem analysis

Consider a linear antenna array with N uniformly spaced elements, M pulses are transmitted in a coherent processing interval. The echo data $\mathbf{r}_k$ from the kth range cell is:

$$\mathbf{r}_k = \xi_k \mathbf{s}(\varphi, \omega) + \mathbf{c}_k + \mathbf{n}_k \tag{1}$$

where $\mathbf{r}_k$, $\mathbf{c}_k$, $\mathbf{n}_k$, $\mathbf{s}(\varphi,\ \omega) \in C^{MN}$, $\mathbf{c}_k$ and $\mathbf{n}_k$ are the clutter and the noise, respectively; ξ_k is the target signal amplitude, $\mathbf{s}(\varphi,\ \omega)$ is the space-time steering vector of the target, which can be given by:

$$\mathbf{s}(\varphi, \omega) = \mathbf{b}(\omega) \otimes \mathbf{a}(\varphi) \tag{2}$$

where $\otimes$ denotes the Kronecker product; $\mathbf{b}(\omega)$ is the temporal steering vector at normalized Doppler frequency ω, $\mathbf{b}(\omega) = \left[1 e^{j2\pi\omega} \cdots e^{j(M-1)2\pi\omega}\right]^T \in C^{M\times 1}$; and $\mathbf{a}(\varphi)$ denotes the angle steering vector at spatial frequency φ, $\mathbf{a}(\varphi) = \left[1 e^{j2\pi\varphi} \cdots e^{j(N-1)2\pi\varphi}\right]^T \in C^{N\times 1}$. Further, a detailed expression for $\mathbf{s}(\varphi,\ \omega)$ can be given by:

$$\mathbf{s}(\varphi, \omega) = \left[\left(1 e^{j2\pi\varphi} \cdots e^{j(N-1)2\pi\varphi}\right) e^{j2\pi\omega}\left(1 e^{j2\pi\varphi} \cdots e^{j(N-1)2\pi\varphi}\right) \cdots e^{j(M-1)2\pi\omega}\left(1 e^{j2\pi\varphi} \cdots e^{j(N-1)2\pi\varphi}\right)\right]^T \tag{3}$$

The clutter signal from the kth range is given by:

$$\mathbf{c}_k = \sum_{m=1}^{N_a}\sum_{n=1}^{N_c} \xi_{kmn} \mathbf{s}(\varphi_{kmn}, \omega_{kmn}) \tag{4}$$

where N_a denotes the number of ambiguous ranges, and N_c indicates the number of clutter patches, ξ_{kmn} is the complex amplitude and $\mathbf{s}(\varphi_{kmn},\ \omega_{kmn})$ denotes the corresponding space-time steering vector.

The formulation for the optimal weight vector of STAP is:

$$\min_{\{\mathbf{w}\}} \mathbf{w}^H \mathbf{R}_{CUT} \mathbf{w}, \quad st.\ \ \mathbf{w}^H \mathbf{s}(\varphi, \omega) = 1 \tag{5}$$

where $\mathbf{R}_{CUT}$ is the clutter covariance matrix in the cell under test $\mathbf{r}_{CUT}$, $\mathbf{w}$ is the MN-length weight vector and $(\cdot)^H$ is the conjugate transpose.

Therefore, the optimum weight $\mathbf{w}$ is:

$$\mathbf{w} = \frac{\mathbf{R}_{CUT}^{-1}\mathbf{s}(\varphi, \omega)}{\mathbf{s}(\varphi, \omega)^H \mathbf{R}_{CUT}^{-1}\mathbf{s}(\varphi, \omega)} \tag{6}$$

Since $\mathbf{R}_{CUT}$ is generally unknown, we have to estimate it by the selected training samples $\mathbf{r}_{TS_i}, i = 1, 2, \cdots, L$, where L is the number of the training samples. Let $\mathbf{R}_{TS_i}$ denote the clutter covariance matrix of $\mathbf{r}_{TS_i}$ and $\hat{\mathbf{R}}_{CUT}$ denote the estimate of $\mathbf{R}_{CUT}$, then we obtain:

$$\hat{\mathbf{R}}_{CUT} = \frac{1}{L}\sum_{i=1}^{L} \mathbf{R}_{TS_i} \tag{7}$$

In order to achieve an optimal performance, the ideal training samples should have the same clutter covariance matrix to the CUT, $\mathbf{R}_{TS_i} = \mathbf{R}_{CUT}$ and $L \geq 2NM$.

However, in practical application, the statistical characteristics of training samples always deviate from the CUT due to the presence of clutter discrete, terrain variations, and nonlinear array responses. These factors will lead to fewer valid samples and performance degradation of STAP. This paper introduces a novel training samples selection method to obtain more valid samples and improve the performance of STAP.

3. The proposed training samples selection method

In this section, it is proved that two different range cells with the same clutter covariance matrix may have completely dissimilar clutter waveforms. Meanwhile, we further analyze the shortcomings of traditional samples selection methods. Then a criterion of having the same clutter covariance matrix is presented. Finally our training samples selection method based on system identification is proposed.

3.1. Shortcomings of traditional methods

In order to estimate the clutter covariance matrix accurately, the ideal training sample should satisfy $\mathbf{R}_{TS_i} = \mathbf{R}_{CUT}$. The existing methods [1–4] select samples whose waveforms are similar to that of the CUT. However, same covariance matrices do not imply the waveforms are similar.

Proposition 1. *Two different range cells with the same clutter covariance matrix may have completely dissimilar clutter waveforms.*

Proof. Suppose there are two different range cells $\mathbf{r}_{k_1}$ and $\mathbf{r}_{k_2}$, their clutter signal are denoted as $\mathbf{x}$ and $\mathbf{y}$, respectively, $\mathbf{x} = (x_1, x_2, \cdots, x_l, \cdots, x_{MN})^T$ and $\mathbf{y} = (y_1, y_2, \cdots, y_l, \cdots, y_{MN})^T$, where $l = u \times N + v$, u and v are integers, $1 \leq v \leq N$, $0 \leq u \leq M-1$. x_l and y_l are the lth elements of vectors $\mathbf{x}$ and $\mathbf{y}$, which can be obtained from Eq. (4) as follows:

$$x_l = \sum_{m=1}^{N_a}\sum_{n=1}^{N_c} \xi_{k_1 mn} \exp\left(j2\pi\left(u\omega_{k_1 mn} + (v-1)\varphi_{k_1 mn}\right)\right)$$
$$y_l = \sum_{m=1}^{N_a}\sum_{n=1}^{N_c} \xi_{k_2 mn} \exp\left(j2\pi\left(u\omega_{k_2 mn} + (v-1)\varphi_{k_2 mn}\right)\right) \tag{8}$$

For short, the elements can be written as $x_l = |x_l|e^{j\theta_l}, y_l = |y_l|e^{j\beta_l}, l = 1, 2, \cdots, MN$. Let $\mathbf{R_{xx}} = E\{\mathbf{xx}^H\}$, $\mathbf{R_{yy}} = E\{\mathbf{yy}^H\}$ denote the covariance matrices of $\mathbf{x}$ and $\mathbf{y}$, respectively. □

We assume that $\mathbf{xx}^H = \mathbf{yy}^H$ can always be satisfied for any snapshots. Hence, we can get $\mathbf{R_{xx}} = \mathbf{R_{yy}}$. For simplicity, only the expression for $\mathbf{xx}^H$ is presented here:

$$\mathbf{xx}^H = \begin{pmatrix} |x_1|^2 & |x_1||x_2|e^{j(\theta_1-\theta_2)} & \cdots & |x_1||x_{MN}|e^{j(\theta_1-\theta_{MN})} \\ |x_2||x_1|e^{j(\theta_2-\theta_1)} & |x_2|^2 & \cdots & |x_2||x_{MN}|e^{j(\theta_2-\theta_{MN})} \\ \vdots & \vdots & \ddots & \vdots \\ |x_{MN}||x_1|e^{j(\theta_{MN}-\theta_1)} & |x_{MN}||x_2|e^{j(\theta_{MN}-\theta_2)} & \cdots & |x_{MN}|^2 \end{pmatrix} \tag{9}$$

Since $\mathbf{xx}^H = \mathbf{yy}^H$, the module and the angle of $\mathbf{x}$ and $\mathbf{y}$ satisfy the following relationship in Eqs. (10) and (11).

$$|y_1|^2 = |x_1|^2,\ |y_2|^2 = |x_2|^2, \cdots |y_{MN}|^2 = |x_{MN}|^2 \tag{10}$$