Adaptive Beamforming For Jamming Suppression In The Whole Range Domain

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***Abstract*—For the traditional early warning radar, only one weight vector is calculated in engineering application for adaptive spatial filtering in a pulse reputation interval (PRI). Therefore, if the training data do not contain the jamming, then the adaptive spatial filtering calculated cannot suppress the jamming. If the adaptive weights update in the whole range domain, the target signal may be contained in the training data, resulting in signal self-cancelling effect. In this paper, we propose a non-homogeneous detector (NHD) based method for updating the adaptive weights in the whole range domain when the training data is contaminated by target signal. The principle is given, and the effectiveness is verified by simulations.**

Keywords—adaptive beamforming, non-homogeneous detector, electronic jamming

I. Introduction

As the development of digital signal processing and adaptive array processing, adaptive jamming cancellation processing, such as sidelobe cancellation (SLC) and adaptive beamforming (ABF), have been widely used in early warning radars for suppressing sidelobe jamming. Both the ABF and SLC are designed to optimise some specific criteria such as minimum variance distortionless response (MVDR) and maximum signal-to-interference-plus-noise-ratio (SINR) [1]. The well-known MVDR beamformer has superior performance in interference-plus-noise suppression compared to data-independent beamformers so long as the statistical information of the interference and noise, which are free of the target signal, is known or can be estimated.

In adaptive radar applications, an estimate of the unknown interference covariance matrix is usually computed from the observed training data that contains only interference. This is called supervised training [2]. However, if there are steering vector errors, such as direction of arrival (DOA) error and array calibration errors, between the desired steering vector and the presumed one, and if the training data contain the target signal (this is possible when there are multiple closely-spaced targets in the received data cube or there are range-spread target), the performance of the standard SLC and ABF methods degrade dramatically [3-4]. This effect is called target signal cancellation, and it is more pronounced when the finite sample effects exist [5-7]. For this reason, in engineering application, the training data are generally collected from the long distance sample cells at the end of a PRI. This is because the target power from the long distance is very low, then the ABF still works well when the interference corrupted by target signal is observable.

Unfortunately, the most disadvantage of collecting training data from the long distance sample cells is that the electronic jamming may not exist in the long distance. In other words, if the electronic jammer does not transmit the jamming signal at the end of a PRI, the ABF computed from the long distance sample cells may not contain the statistical information of the interference, thus the ABF has no effect on the interference. Currently, the robust beamforming technique using some constraints, which can avoid the effect of the target signal cancellation when the sample data are corrupted by target signal, is developed for updating the weights in the whole range [8]. However, there are some disadvantages for the existing robust beamforming methods. Firstly, the performance of the existing robust beamforming methods degrade significantly when the input signal-to-noise-ratio (SNR) is high. Secondly, the constraint parameters in robust beamforming are generally decided by experience, and there is no robust algorithm to select the optimal parameters. Lastly the computational cost of robust beamforming is too huge, which is difficult for real-time implementation.

In this paper, based on the NHD [9-10], we propose a method to update the adaptive weights in the whole range domain. To cope with the complicated situation that the training data do not contain the jamming, the proposed method divides the whole range cells in a PRI into several range segments, a new adaptive weights is computed for each range segment. In additional, to alleviate the effect of the signal cancellation, the proposed method is based on the idea of eliminating the sample cells corrupted by target signal of each range segment, and then the remaining range cells without target signal can be used as the clear training data to form the adaptive weights robust to signal cancellation.

This paper is organized as follows. In Section II, we present some background about the ABF. The proposed method is given in Section III. Simulation results are presented in Section IV and conclusions are drawn in Section V.

II. Background

Consider a M -sensor uniform linear array (ULA) with an adjacent sensor spacing d . The received data at the nth snapshot can be expressed as

$$\mathbf{x}\left[n\right]=\sum_{p=1}^{P}\mathbf{a}\left(\theta_p\right)s_p\left[n\right]+\mathbf{n}\left[n\right] \tag{1}$$

where $s_p\left[n\right]$ is the pth interfering source, $\mathbf{a}(\theta_p)$ is the $M\times 1$ steering vector of the pth source, $\mathbf{n}\left[n\right]$ is the additive

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noise with a power $\sigma_n{}^2$, P is the number of impinging signals.

The MVDR beamformer is obtained by solving the following optimisation problem:

$$\min_{\mathbf{w}} \mathbf{w}^H \mathbf{R}_{xx} \mathbf{w} \text{ subject to } \mathbf{w}^H \hat{\mathbf{a}} = 1 \tag{2}$$

where $\mathbf{w}$ is the $M \times 1$ complex weight vector, $\mathbf{R}_{xx}$ is the interference and noise covariance matrix, and $\hat{\mathbf{a}}$ is the presumed steering vector of the look direction. The solution is given by [1]

$$\mathbf{w} = \frac{\mathbf{R}_{xx}^{-1} \hat{\mathbf{a}}}{\hat{\mathbf{a}}^H \mathbf{R}_{xx}^{-1} \hat{\mathbf{a}}} \tag{3}$$

In practice, $\mathbf{R}_{xx}$ is replaced by the sample covariance matrix

$$\widehat{\boldsymbol{R}}_{xx} = \sum_{n=1}^{L} \boldsymbol{x}[n] \boldsymbol{x}[n]^H \tag{4}$$

where L is the number of snapshots.

Ideally, training data only need to contain the interference and noise when estimating the sample covariance matrix. The smart jammer may transmit jamming within a limited distance, the traditional adaptive radars collected the training data from the long distance range cells at the end of a PRI cannot obtain the statistical information of the interference. The adaptive radars are able to update the estimate of the sample covariance matrix for each cell under test. However, if there are steering vector errors between the desired steering vector and the presumed one, and if the training data is contaminated by target signal, the weights computed by (3) will treat target signal in cell under test as jamming to suppress, that is signal cancellation. Moreover, this approach means that there are as many adaptive weights as there are range cells, which is far greater than the number of possible targets.

III. Proposed Method

In this section, we first present the principle of the NHD, and then, the proposed NHD based ABF method for early warning radar will be developed.

A. NHD

NHD propose test statistics, which are usually used to eliminate the outliers from the training samples set to overcome the non-homogeneity before applying the space-time adaptive processing algorithms [11]. Since the test statistics corresponding to training data with target signal have markedly different from that of the training data without target signal, it is easy to find the training cells contaminated by target signal, which can be deleted from the training data, then the remaining training data without target signal can be used to estimate the sample covariance matrix for calculating the weight vector.

The generalised inner products (GIP) algorithm [12] is a common NHD to detect the target signal in non-homogeneous sample environments [13]. The GIP statistics can be defined by

$$\eta = \mathbf{x}_n \mathbf{R}_{xx}^{-1} \mathbf{x}_n \tag{5}$$

where $\mathbf{x}_n$ is the range cell under test.

In the following, we will analysis two cases of GIP statistics. In the first case, it is assumed that the sample cell contains the interference, noise and target signal, $\mathbf{x}_n$ is then given by

$$\mathbf{x}_n = \mathbf{a} s[n] + \sum_{p=1}^{P} \mathbf{a}(\theta_p) s_p[n] + \mathbf{n}[n] \tag{6}$$

where $s[n]$ is the target signal and $\mathbf{a}$ is the steering vector.

Assume that all signals and noise are uncorrelated with each other. Then the interference and noise covariance matrix can be expressed as

$$\mathbf{R}_{xx} = \mathbf{U}_j \boldsymbol{\Lambda} \mathbf{U}_j{}^H + \sigma_n{}^2 \mathbf{U}_n \mathbf{U}_n{}^H \tag{7}$$

where $\boldsymbol{\Lambda} = diag\{\lambda_1, \cdots, \lambda_P\}$ consists of the P principal eigenvalues of $\mathbf{R}_{xx}$, $\mathbf{U}_j = [\mathbf{u}_1, \cdots \mathbf{u}_P]$ is the interference subspace, specified by the principal eigenvectors of $\mathbf{R}_{xx}$, and the remaining eigenvectors $\mathbf{U}_n = [\mathbf{u}_{P+1}, \cdots, \mathbf{u}_M]$ is the noise subspace.

Since the interference steering vector is orthogonal to the noise subspace, by ignoring the effect of noise of the sample cell in (6), the GIP statistics in (5) can then be written as

$$\begin{aligned} \eta_1 &= \mathbf{x}_n{}^H \mathbf{R}_{xx}^{-1} \mathbf{x}_n \\ &= \sum_{p=1}^{P} \frac{\left|\mathbf{u}_p^H \mathbf{a}\right|^2}{\lambda_p} s^*[n] s[n] + \frac{s^*[n] s[n] \left\|\mathbf{U}_n^H \mathbf{a}\right\|^2}{\sigma_n^2} \\ &\quad + \sum_{p=1}^{P} \frac{\left|\mathbf{u}_p^H \mathbf{a}(\theta_p)\right|^2}{\lambda_p} s_p^*[n] s_p[n] \end{aligned} \tag{8}$$

Additionally, in the second case, suppose that only interference and noise are contained in the sample cell, (5) can be rewritten as

$$\begin{aligned} \eta_2 &= \mathbf{x}_n{}^H \mathbf{R}_{xx}^{-1} \mathbf{x}_n \\ &= \sum_{p=1}^{P} \frac{\left|\mathbf{u}_p^H \mathbf{a}(\theta_p)\right|^2}{\lambda_p} s_p^*[n] s_p[n] \end{aligned} \tag{9}$$

Under condition of strong interference, we have $\lambda_p \gg {\sigma_n}^2$, then $\eta_1 \gg \eta_2$ is obtained. It can be clearly seen that the GIP statistics corresponding to sample cells corrupted by target signal have significantly different from that of the training sample cells without target signal. Therefore, the sample cells contaminated by target signal can be eliminated from the training data, and then the remaining sample cells without target signal will be used to estimate the sample covariance matrix for calculating the weight vector, which can avoid the effect of signal cancellation.

Actually, in the ideal case of exactly known $\mathbf{R}_{xx}$, the analysis mentioned above can be assured. However, the interference and noise covariance is estimated by the sample covariance matrix in practice. Therefore, it is assumed that only a small number of training data is contaminated by target signal, that is, the most of training data is clear. Under this condition, the statistical information of the target signal in the sample covariance matrix is negligible, and then the NHD can work well.

B. NHD based ABF for Radar

The basic idea of the NHD based ABF is to eliminate sample cells corrupted by target signal from the training data by using NHD before applying the ABF algorithms. For the early warming radars, the transmitted pulse width (PW) is very long to achieve enough power to obtain the long range detection performance. When the PW is long, both the noise jamming and repeater jamming can be considered as continuous wave, thereby simply obtaining the jamming samples for spatial filtering. Therefore, traditional early warming radars generally implement the ABF or SLC prior to pulse compression. However, at this time, due to long PW of early warning radars, many range cells may contain target signal, that is a large number of training data will be contaminated by target signal, resulting in failure of the NHD. In addition, if lots of training cells contaminated are deleted, the remaining training cells for estimating the covariance matrix are small, resulting in the degradation of the ABF. Obviously, target signal after pulse compression is sparse in range domain, which is able to cope with an adverse effect of applying the NHD prior to pulse compression. Therefore, in this paper we propose to select the training data and operate beamforming after pulse compression.

Consequently, the proposed NHD based ABF for radar is summarized as follows

- Divide the whole range cells in a PRI into several range segments after pulse compression.
- Use all sample cells of a range segment as training data for estimating a temporary sample covariance matrix.
- Calculate the GIP statistics of sample cells of a range segment using the corresponding temporary sample covariance matrix estimated in step 2.
- Eliminate the sample cells with large and abnormal GIP statistics from the training data, and then use the remaining sample cells to calculate a new sample covariance matrix for the range segment considered.
- Use the new sample covariance matrix to compute the adaptive weights, which is used for adaptive beamforming to all sample cells of a range segment considered.
- After beamforming, constant false alarm rate (CFAR) detector can be used to detect all potential targets.
- For the next range segment, repeat the above steps.

It should be noted that it is not possible to detect all potential targets using NHD. We only expect to find the sample cells contaminated by target signal with high SNR. Then after beamforming, the potential targets will be detected by using CFAR detector.

The proposed NHD based ABF method calculates a new weight vector for each range segment. That is to say, unlike the traditional adaptive radars, the weight vector of the proposed method is updating in the whole range domain. The proposed method also avoids the problem of signal cancellation. Moreover, the weight vector calculated by the training samples of a segment is used to suppress the jamming in this segment, which can avoid the adverse case that the training data do not contain the jamming.

IV. SIMULATIONS

In this section, simulations are performed to study the performance of the proposed NHD based ABF method. We consider a ULA with $M = 10$ sensors and half-wavelength spacing between adjacent sensors. One interfering signal with interference-to-noise ratio (INR) of 20 dB impinge on the array from the direction 40°. The target signal arrives from 0°, and the array is steered toward the direction of target. Take a range segment for example, it is assumed that this range segment considered contains 50 sample cells, each of which contains jamming signal. Two cases of sample data of the range segment will be considered. In the first case, the 10th, 25th and 40th sample cells of the range segment considered are corrupted by target signal of SNR=20dB. The second on is clear sample data without target signal.

A. Example 1

In the first example, the detection performance of target signal of NHD is considered. Fig. 1 shows the GIP statistics corresponding to two cases of training data mentioned above. We see clearly that the difference of the GIP statistics of two cases of training data is obvious. From the GIP statistics of training data with target signal, it is easy to detect the cells corrupted by target signal. Hence the cells contaminated by target signal can be eliminated from the training samples before estimating the covariance matrix for adaptive beamforming.

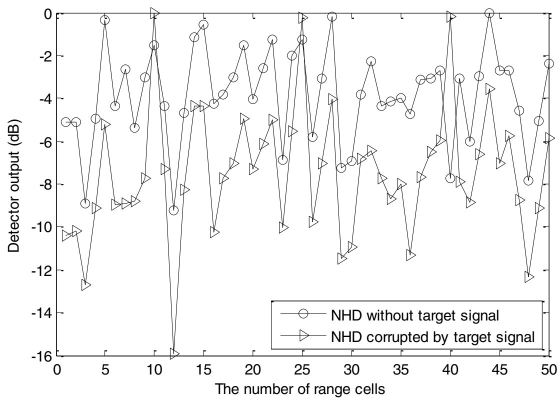

Fig. 1. GIP statistics corresponding to two cases of training data

B. Example 2

In the second example, we show the performance of the proposed ABF and the two cases of traditional ABF, which use the training data corrupted by target signal and clear training data respectively for estimating the covariance matrix.

Fig. 2 shows the resultant beampattern of the beamformers corresponding to proposed NHD based ABF, and the two cases of traditional ABF. It can be seen that both the proposed NHD based ABF and the traditional ABF without target signal can give satisfactory results. We also see clearly that the traditional ABF which uses training data corrupted by target signal fails to give a sensible result and suffers from signal cancellation severely.

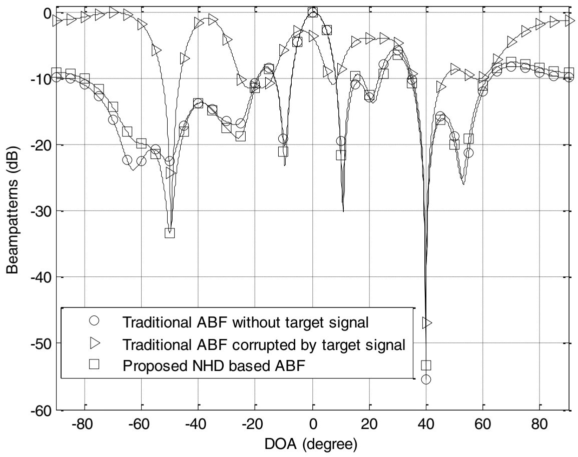

Fig. 2. Beampattern of the beamformers

Fig. 3 shows the output of the proposed NHD based ABF and the two cases of traditional ABF. It can be seen clearly that both the proposed NHD based ABF and the traditional ABF without target signal have similar performance, which perform much better than another traditional ABF. The output SINR of the traditional ABF corrupted by target signal degrades significantly, leading to the reduction of detection probability. The results shown in Fig. 3 clearly indicate that the robustness of the ABF, when updating the weights in the whole range domain, can be guaranteed by using the NHD for eliminating sample cells contaminated by target signal from the training data.

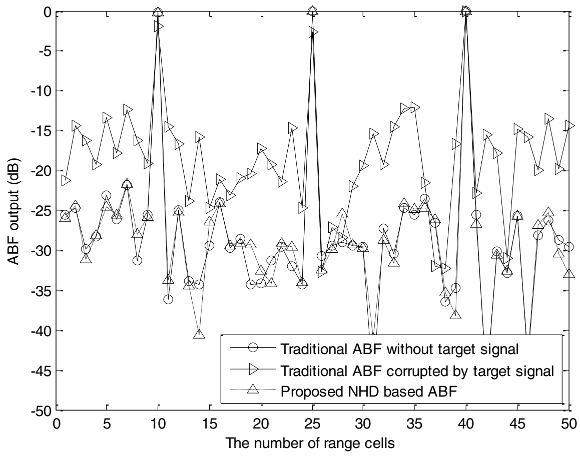

Fig. 3. Output of the beamformers

V. CONCLUSION

Based on the actual demand of electronic protection of early warning radar, an ABF method for updating the weights in the whole range domain, unlike the traditional ABF calculated the weights in the long distance, has been proposed. The whole range cells in a PRI are divided into several range segments, and each range segment has its own adaptive weights calculated using the sample cells in this range segment. To alleviate the effect of the signal cancellation, the proposed method is based on the NHD to eliminate the sample cells corrupted by target signal from the training data, and then the remaining sample cells are used to calculate the weight vector. Simulation results have been presented to demonstrate the effectiveness of the proposed method. In a follow-up study, the real data based analysis will be performed to further confirm the effectiveness and validity of the proposed method.

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