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Robust adaptive radar beamforming based on iterative training sample selection using kurtosis of generalized inner product statistics

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Abstract: In engineering application, there is only one adaptive weights estimated by most of traditional early warning radars for adaptive interference suppression in a pulse reputation interval (PRI). Therefore, if the training samples used to calculate the weight vector does not contain the jamming, then the jamming cannot be removed by adaptive spatial filtering. If the weight vector is constantly updated in the range dimension, the training data may contain target echo signals, resulting in signal cancellation effect. To cope with the situation that the training samples are contaminated by target signal, an iterative training sample selection method based on non-homogeneous detector (NHD) is proposed in this paper for updating the weight vector in entire range dimension. The principle is presented, and the validity is proven by simulation results.

Keywords: adaptive radar beamforming, training sample selection, non-homogeneous detector, electronic jamming, jamming suppression.

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1. Introduction

To suppress sidelobe interference, adaptive beamforming (ABF) and sidelobe cancellation (SLC), which are designed based on adaptive array specific criteria such as minimum variance distortionless response (MVDR) and maximum signal to interference plus noise ratio (SINR), have been highly applied in early warning radars [1]. Compared to conventional non-adaptive beamformers, the well-known MVDR beamformer has excellent suppression performance against interference plus noise as long as the covariance matrix of interference and noise is known.

In adaptive radar applications, the covariance matrix of interference and noise is usually estimated from the collected training samples containing only interference [2–4]. This is often referred to as supervised training [5]. However, if there are errors between the desired steering vector and the assumed steering vector, such as array gain-phase error and direction of arrival (DOA) error, and if the target signal is included in the training samples (this is possible when there are range-spread targets or multiple dense targets in the received data cube), the performance of the MVDR beamformer decreases significantly [6–11]. This effect is known as signal cancellation, which is more obvious when there are limited sample effects [12–16]. For this reason, in engineering application, training samples are usually collected from remote samples at the end of a pulse reputation interval (PRI). The reason is that the power of remote target echoes is very small, then the ABF still works normally when the interference observed is disrupted by target signal.

However, the biggest drawback of collecting training samples from remote samples is that there may not be jamming signal in the remote sample cells. That is to say, if the electronic jammer does not emit interference at the end of palse reputation interval (PRI), the ABF calculated using remote samples may not include the interference information. Therefore, the ABF can not suppress interference. Currently, some robust beamforming methods are developed to avoid the signal cancellation problem if the target signal is including in the training data [17]. However, the existing robust beamforming methods have some drawbacks. Firstly, when the input signal to noise ratio (SNR) is high, the performance of the existing robust beamforming methods is significantly reduced. Secondly, the constraint parameters are often selected empirically. Finally the computational complexity of robust ABF methods is too high to implement in real time.

Based on the non-homogeneous detector (NHD) [18–22], a method which can calculate the weight vector in the

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whole range domain is proposed in this paper. The entire range samples in the PRI are divided into multiple range segments, each range segment calculates a new weight vector separately. Moreover, to mitigate the impact of signal cancellation, an iterative training sample selection criterion is proposed to eliminate the range samples corrupted by target echo from training data of each range segment, therefore the remaining training samples can serve as clear training samples to compute robust weight vector.

This paper is organized as follows. In Section 2, some background on the ABF are introduced. The proposed method is presented in Section 3. Simulation results are shown in Section 4, and conclusions are presented in Section 5.

2. Background

Consider a M-sensor uniform linear array (ULA) with half-wavelength spacing between adjacent sensors. The data received at the nth snapshot can be represented as

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

where $s_p[n]$ is the pth jamming source, $\boldsymbol{n}[n]$ is the additive noise with a power $\sigma_n{}^2$, $\boldsymbol{a}(\theta_p)$ is the $M\times 1$ steering vector of the pth signal, and P is the number of jamming sources.

The well-known MVDR beamformer is the solution to the following constrained problem:

$$\min_{\boldsymbol{w}}\ \boldsymbol{w}^{\mathrm{H}}\boldsymbol{R}_{xx}\boldsymbol{w}$$
$$\text{s.t. } \boldsymbol{w}^{\mathrm{H}}\hat{\boldsymbol{a}}=1 \tag{2}$$

where $[\cdot]^{\mathrm{H}}$ denotes the Hermitian transpose, $\boldsymbol{w}$ is the $M\times 1$ adaptive weights, $\boldsymbol{R}_{xx}$ is the covariance matrix of interference plus noise, and $\hat{\boldsymbol{a}}$ is the presumed steering vector. The weight vector [1] is given by

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

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

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

where L is the number of training cells.

Theoretically, only interference and noise are needed to estimate covariance matrix. Advanced jammers can emit interference at a specified distance, the traditional adaptive radars collected the training sample cells from remote samples may not obtain the statistical information about interference. As shown in Fig. 1, where $\boldsymbol{w}$ represents the weight vector.

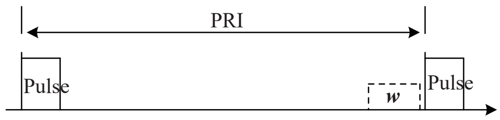

Fig. 1 Traditional SLC or ABF computing the weight vector using the long distance sample cells

The adaptive weights for each cell under test can be estimated. Nevertheless, if the training samples are corrupted by target signal and there are steering vector errors between the desired and assumed steering vectors simultaneously, MVDR beamformer suppresses the target signal as jamming, that is signal cancellation.

3. Proposed method

This section first presents the principle of the generalized inner product (GIP) based NHD, and then, the proposed robust ABF method based on iterative training sample selection will be developed for early warning radar.

3.1 GIP based NHD

To cope with the problem of non-homogeneity in the space-time adaptive processing (STAP), test statistics proposed by NHD are commonly used to identify the outliers in the training data [23–27]. The GIP algorithm is the most commonly used NHD for detecting outliers in a heterogeneous environment [28–31]. The GIP statistics are defined as

$$\eta=\boldsymbol{x}_t{}^{\mathrm{H}}\boldsymbol{R}_{xx}^{-1}\boldsymbol{x}_t \tag{5}$$

where $\boldsymbol{x}_t$ is the testing sample cell.

Here, two scenarios of GIP statistics will be analyzed. For the first scenario, the sample cell is assumed to contain the target signal, $\boldsymbol{x}_t$ is then given by

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

where $\boldsymbol{a}$ and $s[n]$ are the steering vector and the received target echo, respectively.

All received target signal, interference and noise are assumed not correlated with each other. The covariance matrix of interference plus noise can be represented as

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

where $\boldsymbol{\Lambda}=\mathrm{diag}\{\lambda_1,\lambda_2,\cdots,\lambda_P\}$ consists of the P largest eigenvalues of $\boldsymbol{R}_{xx}$, $\boldsymbol{U}_j=[\boldsymbol{u}_1,\boldsymbol{u}_2,\cdots,\boldsymbol{u}_P]$ is the interference subspace composed of the principal eigenvectors, and the remaining eigenvectors $\boldsymbol{U}_n=[\boldsymbol{u}_{P+1},\boldsymbol{u}_{P+2},\cdots,\boldsymbol{u}_M]$ is the noise subspace.

Due to orthogonality between the signal steering vector and the noise subspace, by ignoring the influence of noise in the received signal, the GIP statistics can be written as

$$\eta_1 = \boldsymbol{x}_t{}^{\mathrm{H}}\boldsymbol{R}_{xx}^{-1}\boldsymbol{x}_t = \sum_{p=1}^{P}\frac{\left|\boldsymbol{u}_p^{\mathrm{H}}\boldsymbol{a}\right|^2}{\lambda_p}s^*[n]\,s[n] + \frac{s^*[n]\,s[n]\left\|\boldsymbol{U}_n^{\mathrm{H}}\boldsymbol{a}\right\|^2}{\sigma_n^2} + \sum_{p=1}^{P}\frac{\left|\boldsymbol{u}_p^{\mathrm{H}}\boldsymbol{a}(\theta_p)\right|^2}{\lambda_p}s_p^*[n]\,s_p[n]. \tag{8}$$

In the second scenario, assume the sample cell only contains jamming and noise, (5) can be rewritten as

$$\eta_2 = \boldsymbol{x}_t{}^{\mathrm{H}}\boldsymbol{R}_{xx}^{-1}\boldsymbol{x}_t = \sum_{p=1}^{P}\frac{\left|\boldsymbol{u}_p^{\mathrm{H}}\boldsymbol{a}(\theta_p)\right|^2}{\lambda_p}s_p^*[n]\,s_p[n]. \tag{9}$$

If λ_p is greater than σ_n^2 in the case of strong jamming, we get $\eta_1 \geqslant \eta_2$. We clearly see that there is a significant difference in the GIP statistics of the range samples disrupted by the target echo compared to the range samples without the target echo. Thus, the contaminated samples can be removed, and then the remaining range samples without target echo are used to calculate the adaptive weights that is robust against signal cancellation.

In fact, the above analysis can be assured in the ideal case where $\boldsymbol{R}_{xx}$ is fully known. In practice, the sample covariance matrix is used. Thus, we presume that a small amount of range cells are disrupted by target echo, i.e., the majority of range cells do not contain target echo. In this case, the target statistics in the sample covariance matrix can be ignored, so that the GIP based NHD can work well.

3.2 Iterative training sample selection based on kurtosis of GIP statistics

In this section, a GIP based iterative method is proposed to iteratively eliminates contaminated range cells in the training range cells.

Let us define that

$$\boldsymbol{\eta}[n] = \boldsymbol{x}^{\mathrm{H}}[n]\boldsymbol{R}_{xx}^{-1}\boldsymbol{x}[n] \tag{10}$$

is the GIP statistics of the training sample cells $\boldsymbol{x}[n](n = 1,2,\cdots,N)$.

In [18], it has been proven that if the probability density function (PDF) of $\boldsymbol{x}[n]$ satisfies a Gaussian distribution, the PDF of GIP statistics in (10) will satisfy a Chi-squared distribution with the M complex degree of freedom .

In probability theory and statistics, the kurtosis of the Chi-squared distribution with M degrees of freedom has the following key property:

$$k = 3 + \frac{12}{M} \tag{11}$$

where k is the kurtosis of a distribution. As degree of freedom grows larger the graph of the Chi-square distribution becomes more like the graph of a normal distribution, and then, the kurtosis of the Chi-squared distribution approaches three.

Obviously, kurtosis can be used to measure how outlier-prone a distribution is. The kurtosis of the Chi-square distribution is $3 + \frac{12}{M}$. Distributions that are more outlier-prone than the Chi-square distribution have kurtosis greater than $3 + \frac{12}{M}$. Based on this key property of a Chi-square distribution, an iterative training sample selection method is proposed by eliminating the corrupted training cells iteratively. The basic concept of the proposed iterative training sample selection method is to compute the kurtosis of the GIP statistics in (10) firstly. If the kurtosis of the GIP statistics differs significantly from the theoretical kurtosis value of (11), then the training sample cell which has the maximum value of GIP statistics will be treated as corrupted sample cell and removed from the training cells resulting in a new training data that consists of the $N-1$ remaining sample cells. Otherwise, the existing training data will be retained for estimating the covariance matrix. The second iteration excises in similar fashion a sample cell from the remaining $N-1$ samples where the sample covariance matrix is calculated from these samples. This method is reiterated until the kurtosis of GIP statistics of the remaining samples approaches $3 + \frac{12}{M}$. We can see that there is a systematic way to determine the stop criterion of the proposed iterative selection method by using the key property which the GIP statistics obey the Chi-square distribution, the kurtosis of which is $3 + \frac{12}{M}$.

3.3 Description of the proposed adaptive radar beamforming

The basic concept of the proposed method is to identify contaminated sample cells in the training cells using the above GIP based iterative training selection method before calculating the adaptive weights of the ABF beamformers. The pulse width (PW) emitted by the early warning radars is very long, ranging from hundreds of microseconds to tens of milliseconds, in order to obtain sufficient power to achieve remote detection performance. Both the noise jamming and repeater jamming are usually regarded as continuous wave if the PW is long, thereby easily collecting interference signal for ABF. Thus traditional radars usually actualize the SLC or ABF before pulse compression. Due to long PW emitted by radars, many range samples may be corrupted by target echo, meaning that a large amount of training range samples will be contaminated, leading to NHD failure. Furthermore, if a large number of contaminated training range cells are removed, the remaining training range cells are insufficient to estimate a good sample covariance matrix, resulting in severe performance reduction of the ABF. After pulse compression, the target signal is clearly sparse in space and range domain, which can cope with the risk of applying the proposed GIP based method before pulse compression. Thus, after pulse compression, the proposed method then performs iterative training sample selection and ABF processing.

Accordingly, the proposed iterative training sample selection based ABF using GIP based NHD for early warning radar application is summarized as follows:

Step 1 After pulse compression, the entire received range samples of a PRI is divided into several range segments.

Step 2 Estimate a temporary interference plus noise covariance matrix by using all range samples within a range segment.

Step 3 Use the estimated temporary covariance matrix to caculate the GIP statistics of range samples.

Step 4 Use the method mentioned in Subsection 3.2 to remove the range samples with abnormal GIP statistics from training samples, and then compute a new interference plus noise covariance matrix using the remaining sample cells for the considered range segment.

Step 5 Calculate adaptive weights using the new interference plus noise covariance matrix for ABF in the considered range segment.

Step 6 After ABF, all potential targets can be detected using a constant false alarm rate (CFAR) detector.

Step 7 Repeat the above steps for the next range segment.

It should be noted that it is not possible to use GIP based NHD to identify all samples with targets. We only hope to identify range samples polluted by high power target echo. Then, after ABF, the CFAR detector will be utilized to detect the potential targets.

The proposed method calculates a new adaptive weights for each range segment. Fig. 2 shows the proposed ABF method based on the principle of segmentation processing. In other words, unlike the ABF of traditional radars, the adaptive weights of the proposed method are calculated multiple times over the entire PRI. This approach still works normally when there is a signal cancellation problem. In addition, the adaptive weight vector of a segment is calculated from the range samples within this segment in order to better suppress interference, avoiding the adverse situation where interference is not included in the training data.

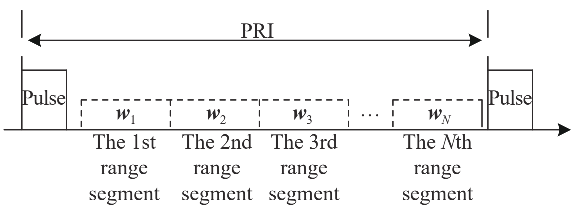

Fig. 2 Proposed segmentation processing based beamforming

4. Simulations

In this section, the performance of the proposed robust ABF method is studied by simulations. A ULA with $M = 10$ sensors and half-wavelength spacing between adjacent sensors is considered. An interference signal with interference to noise ratio (INR) of 40 dB incident on the array from the angle of -40°. The DOA of the target of interest is at 0°, and the array points toward the direction of target. Assume that the considered range segment has 100 sample cells, each containing interference. Two sample data scenarios will be considered for the range segment. In the first scenario, both the 10th and 40th samples of the considered range segment are disrupted by target echo. The second scenario is that there is clear sample data without target echo.

4.1 Effectiveness of GIP based NHD

In this example, the performance of GIP based NHD for contaminated samples detection is considered. The SNR of target signal for the 10th and 40th sample cells is 20 dB. The GIP statistics associated with two scenarios of training samples is shown in Fig. 3. We can clearly see that the difference in the GIP statistics between the two scenarios of range samples is significant. From the GIP statistics of corrupted training samples, range samples corrupted by target signal are easily detected. Therefore, prior to calculating adaptive weights for ABF, the samples corrupted by target echo can be removed from the training samples.

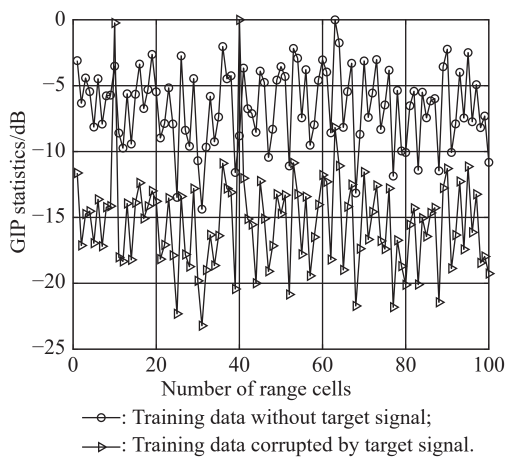

Fig. 3 GIP statistics corresponding to two sample scenarios

4.2 ABF performance

In the second simulation, we demonstrate the performance of the proposed robust ABF and the two scenarios of traditional ABF using the corrupted training samples and clear training samples to estimate the covariance matrix, respectively. The simulation parameters are the same as the first example.

Fig. 4 shows the resultant beampattern of the proposed robust ABF. It is obvious that both the proposed robust ABF and the traditional ABF with clear samples can achieve good performance. We also clearly see that the traditional ABF using corrupted samples cannot provide a reasonable results, and the sidelobe level is very high.

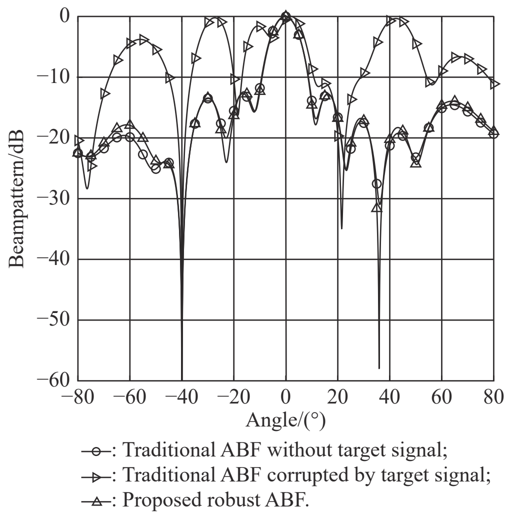

Fig. 4 Beampattern of the considered ABF

Fig. 5 shows the beamforming output. The target detection performance of the 10th range cell using cell average CFAR detector after ABF processing is shown in Fig. 6. It can be clearly seen that the proposed robust ABF has similar performance to the traditional target free ABF, and is much better than traditional ABF using corrupted samples. The output SINR of the traditional ABF using corrupted samples decreases severely, resulting in a decrease in detectability.

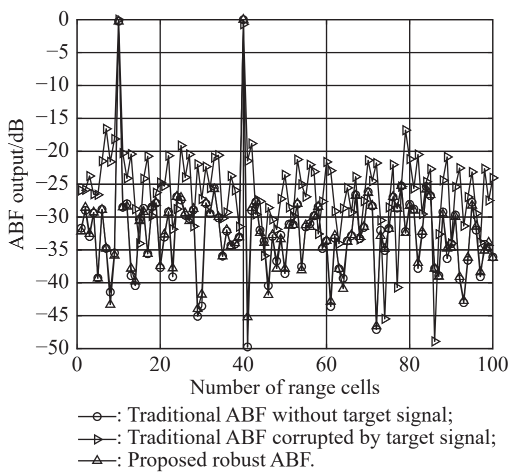

Fig. 5 Output of the beamformers

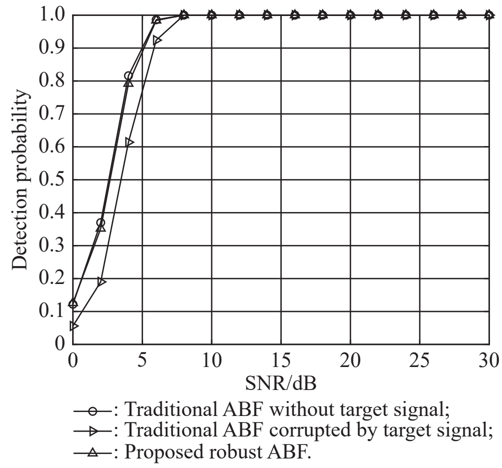

Fig. 6 Detection probability versus SNR

4.3 Effect of signals with high SNR on the detection performance of signals with low SNR

In the third example, we consider the effect of signals with high SNR on the detection performance of low SNR signals. We consider the 40th range cell contain a large target signal of SNR=30 dB. Fig. 7 shows the ABF output when the SNR of target signal of the 10th sample cell is 20 dB. The target detection performance of the 10th range cell using cell average CFAR detector after ABF processing is shown in Fig. 8. Obviously, for traditional ABF, the target signal with high SNR in the training range samples deteriorates severely the detection performance of the target signal with low SNR.

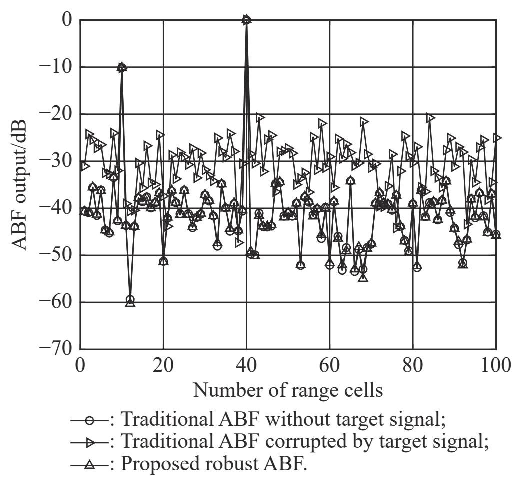

Fig. 7 Output of the beamformers of the third example

Like many existing radars, if the weight vector is computed using remote sample cells at the end of PRI, the SLC or ABF cannot adapt to the complex and changeable interference environment. If the weight vector is updating in the whole range without considering the case that the target signal contaminates training data, signal cancellation will reduce the target detection. However, the results shown in Fig. 7 and Fig. 8 clearly show that the robustness of the ABF can be guaranteed using the proposed GIP based method to remove corrupted range samples from training samples when calculating and updating adaptive weights in the entire range domain.

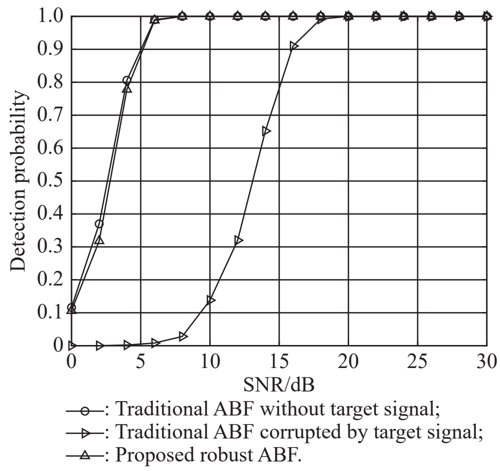

Fig. 8 Detection probability of the third example

5. Conclusions

Based on the practical need to improve interference suppression of early warning radar, a robust ABF method for calculating and updating the adaptive weights over the entire range domain has been proposed, which is different from traditional ABF calculating the weight vector at long distance. The range samples of a PRI are divided into multiple segments, each with its own weight vector, and the samples in that range segment are used for calculation. To mitigate the signal cancellation problem, the proposed method utilizes statistical properties of GIP kurtosis to identify the contaminated samples, and then calculates the weight vector using the remaining range samples. Simulation results demonstrate the validity of the proposed method. In future research, we will conduct analysis based on real data to further confirm the effectiveness of the proposed method.

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