Ground Clutter Suppression Method for Three-Coordinate Air Search Radar Based on Adaptive Processing in Beam Domain

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Abstract. A novel ground clutter suppression method is proposed for the three-coordinate air search radar. According to the theory of statistical optimal beamforming, the optimal solution is given in the background of clutter and noise. The minimum variance distortionless response (MVDR) algorithm is used to process the received signals. When estimating the covariance matrix, in addition to the traditional selection of samples in the range domain, the samples in different scans can be selected based on cognition. In the case that the received data is the beam domain data and there is no information about the geometric configuration of the array, the beam domain response of the obvious target can be used as the target steering vector. Then the optimal weighted vector can be calculated to filter the received data. The processing results of the real data of the three-coordinate radar show the effectiveness of the proposed method in ground clutter suppression.

Keywords: Adaptive processing · MVDR · Clutter covariance matrix · Target steering vector

1 Introduction

The algorithm of clutter suppression in beam domain based on adaptive processing is adopted for various radar systems [1]. As the backbone radar in modern air defense system, three-coordinate radar can detect and track multiple targets in designated airspace, and measure the range, azimuth and altitude of targets at the same time [2, 3]. The ground clutter masks the low-altitude aircraft in the received signal of three-coordinate radar [4]. Therefore, by suppressing the clutter, the target detection capability of three-coordinate radar can be greatly improved [5].

Compared with the ground clutter, the target velocity is generally much larger, their Doppler difference can be used for clutter suppression [6]. Moving target indication (MTI) and moving target detection (MTD) are commonly used for ground clutter suppression. The MTI technology is equivalent to using a high-pass filter. By weighting and summing data of successive pulses, the ground clutter is mitigated. Thus the signal-to-clutter ratio and the probability of target detection can be improved [7, 8]. In the MTD technology, by covering the whole repetition frequency range through a set

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of band-pass filters, the target energy can be accumulated, while the clutter is suppressed [9, 10].

In the three-coordinate radar, the MTI and MTD technologies are generally used for clutter suppression, but spatial clutter suppression algorithms are rarely used. In this paper, we proposed a novel clutter suppression method in the spatial domain. Spatial adaptive processing is a practical signal processing technology, which has wide applications in interference suppression, clutter suppression and other fields [11, 12]. In this proposed method, the spatial covariance matrix of the clutter are first estimated. Then by using the minimum variance distortionless response (MVDR) algorithm, the optimal weighting vector is obtained. Since the array steering vector is unavailable in the beam domain data, the target steering vector in the beam domain is used to replace the conventional array steering vector [13, 14]. At last, by weighting the received signal in the beam domain using the obtained optimal weighting factor, the signal-to-clutter-plus-noise ratio (SCNR) of the received signal can be maximized. Thus the clutter is suppressed effectively.

2 Adaptive Processing Theory

2.1 Adaptive Processing in Array Element Domain

The received signal of a uniform linear array of M elements can be expressed as

$$\mathbf{x} = \mathbf{a}_0 s_0 + \mathbf{x}_{c+n} \tag{1}$$

where $\mathbf{a}_0 \in \mathbb{C}^{M\times 1}$ is the spatial steering vector of the target signal, $s_0 \in \mathbb{C}^{1\times 1}$ is the received target signal, and $\mathbf{x}_{c+n} \in \mathbb{C}^{M\times 1}$ is the sum vector of clutter and noise.

The target steering vector $\mathbf{a}_0 \in \mathbb{C}^{M\times 1}$ can be expressed as

$$\mathbf{a}_0(\theta) = \left[1, \exp\left(j2\pi\frac{d\sin(\theta)}{\lambda}\right), \cdots, \exp\left(j2\pi(M-1)\frac{d\sin(\theta)}{\lambda}\right)\right]^T \tag{2}$$

where d is the distance between array elements, λ is the wavelength, θ is the desired elevation angle of the target.

The received signal is filtered by a spatial weighted vector $\mathbf{w} = [w_1, w_2, \cdots, w_M]^T$, and the output $y \in \mathbb{C}^{1\times 1}$ is

$$y = \mathbf{w}^H \mathbf{x} \tag{3}$$

By using the well known MVDR algorithm, the optimal output signal to clutter and noise ratio (SCNR) can be achieved and the optimal solution $\mathbf{w}_{opt}$ is given as

$$\mathbf{w}_{opt} = \frac{\mathbf{R}_{c+n}^{-1}\mathbf{a}_0}{\mathbf{a}_0^H \mathbf{R}_{c+n}^{-1}\mathbf{a}_0} \tag{4}$$

The clutter covariance matrix $\mathbf{R}_{c+n} = E\{\mathbf{x}_{c+n}\mathbf{x}_{c+n}^H\} \in \mathbb{C}^{M\times M}$ has to be estimated from the clutter samples. The maximum likelihood estimation under the independent identically distributed Gaussian samples is

$$\hat{\mathbf{R}}_{c+n} = \frac{1}{K_\Gamma}\sum_{i\in\Gamma}\mathbf{x}_i\mathbf{x}_i^H \tag{5}$$

where $\mathbf{x}_i \in \mathbb{C}^{M\times 1}$ is the clutter sample, i is the index of range cell, Γ is the set of sample index, K_Γ is the number of samples Γ. The samples are selected in the range domain. The selected samples should have similar spatial distribution. In order to prevent the target from being eliminated, the clutter samples are selected by setting protection cells on the target.

2.2 Adaptive Processing in Beam Domain

The adaptive processing can also be processed in beam domain for dimension reduction. The array element domain signal is transformed to the beam domain by a linear transformation such as

$$\mathbf{z} = \mathbf{T}\,\mathbf{x} \tag{6}$$

where $\mathbf{z} \in \mathbb{C}^{N\times 1}$ is the beam domain signal, and $\mathbf{T} \in \mathbb{C}^{N\times M}$ is the transforming matrix used for conventional beamforming.

$$\mathbf{T} = [\mathbf{a}_0(\theta_1), \cdots, \mathbf{a}_0(\theta_N)]^T \tag{7}$$

where $\mathbf{a}_0(\theta_1), \cdots, \mathbf{a}_0(\theta_N)$ are the N beamforming vectors of interest, and $N < M$ is generally used for dimension reduction.

Then the filter output $\bar{y} \in \mathbb{C}^{1\times 1}$ is

$$\bar{y} = \overline{\mathbf{w}}^H\mathbf{z} \tag{8}$$

The optimal solution $\overline{\mathbf{w}}_{opt} = [w_1, w_2, \cdots, w_N]^T$ of the weighting vector can be obtained by

$$\overline{\mathbf{w}}_{opt} = \frac{\overline{\mathbf{R}}_{c+n}^{-1}\bar{\mathbf{a}}_0}{\bar{\mathbf{a}}_0^H\overline{\mathbf{R}}_{c+n}^{-1}\bar{\mathbf{a}}_0} \tag{9}$$

Accordingly, the estimated clutter covariance matrix $\overline{\mathbf{R}}_{c+n} = E\{\mathbf{z}_{c+n}\mathbf{z}_{c+n}^H\} \in \mathbb{C}^{N\times N}$ in the beam domain is

$$\hat{\overline{\mathbf{R}}}_{c+n} = \frac{1}{K_\Gamma}\sum_{i\in\Gamma}\mathbf{z}_i\mathbf{z}_i^H \tag{10}$$

where $\mathbf{z}_i \in \mathbb{C}^{M \times 1}$ is the clutter sample and i is the index of range cell. The method of selecting clutter samples is similar to the process of the array element domain, and then the clutter covariance matrix of the beam domain is calculated.

After the array element domain signal is linearly transformed into the beam domain, the steering vector $\overline{\mathbf{a}}_0 \in \mathbb{C}^{N \times 1}$ will also change accordingly.

$$\overline{\mathbf{a}}_0 = \mathbf{T}\mathbf{a}_0 \tag{11}$$

According to the array geometry and the beam direction information in the array element domain, the transformation matrix $\mathbf{T}$ for conventional beamforming is calculated. By substituting the above expressions, the clutter covariance matrix, target steering vector and spatial weighted vector in beam domain can be obtained, and then the beam domain signal can be filtered in linear spatial domain.

3 Implementation Methods of Adaptive Processing in Beam Domain

3.1 Adaptive Processing in the Same Scan

When the received data are beam domain data and lack of array geometry information, the transform matrix $\mathbf{T}$ is unknown. The clutter suppression can still be carried out directly in the beam domain data. In this case, the estimation of the clutter covariance matrix $\overline{\mathbf{R}}_{c+n}$ and the steering vector $\overline{\mathbf{a}}_0$ in the beam domain are necessary.

In this paper, the data of real target in the beam domain under the background of noise is considered as the steering vector in the beam domain. In a pulse, we first find the range cell where the maximum value of the target is located in the range-beam domain. Then the data of the beam domain of this range cell is extracted to form a vector. The target steering vector in the beam domain is obtained by normalizing the maximum value of the vector, as shown in Fig. 1. The coordinates of the maximum value are (1423, 6). The beam domain vector corresponding to the 1423 range cell is selected as the spatial target steering vector.

In order to suppress clutter, it is necessary to obtain the statistical characteristics of clutter spatial distribution. A certain amount of clutter samples with the same or similar spatial distribution are selected for covariance matrix estimation. In addition to the homogeneity of samples, it is also required that the samples should not contain the target signal component. The schematic diagram of clutter sample selection in the range domain is shown in Fig. 2. Several protection cells are set near the cell under test, and then enough cells are selected on both sides of the protection cells as clutter samples. Then the clutter covariance matrix in the beam domain can be calculated by using the selected samples.

Next, the clutter covariance matrix and the target steering vector are used to calculate the weighting vector of the beam domain, and the beam domain signal can be filtered in linear spatial domain. The flowchart of the proposed clutter suppression method in the one scan is shown in Fig. 3.

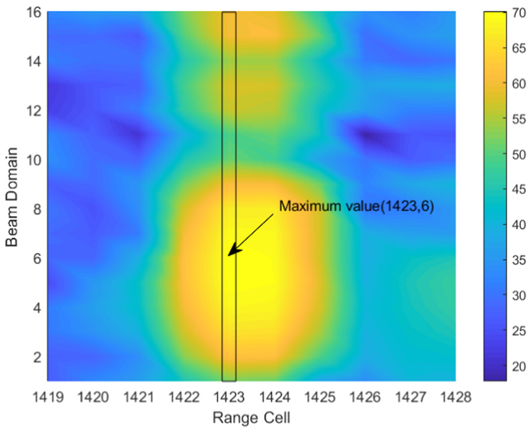

Fig. 1. Range-beam pattern of real target under noisy background

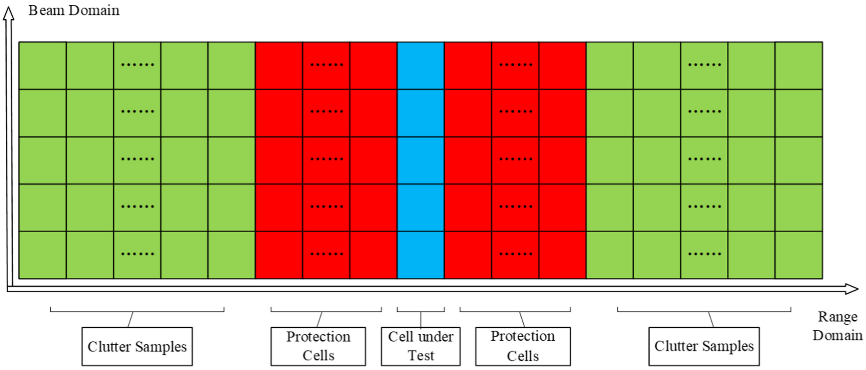

Fig. 2. Schematic diagram of clutter sample selection in the range domain

3.2 Adaptive Processing Based on Cognition

Generally speaking, modern radar systems mainly use the received data for processing, while ignoring external targets and environmental information. Therefore, the detection performance improvement faces a major bottleneck in the complex geographical and electromagnetic environment. To solve this problem, the concept of cognitive radar has been proposed in recent years. Cognitive radar has the ability of online perception and memory of environment and target information. Combined with the prior knowledge, it can optimize the transmitting and receiving processing mode in real time. By achieving the optimal match with the target and environment, target detection performance can be improved.

In the application of three-coordinate radar, we assume that the radar's location is stationary, and the received clutter is mainly ground clutter. The clutter information can be recorded and learned by multiple scans after the radar has been turned on. Such

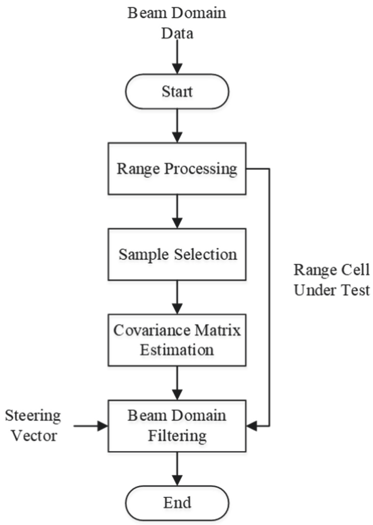

Fig. 3. Flowchart of proposed clutter suppression method in the one scan

information can then be used to assist in clutter suppression in the subsequent target detection. In the process of target detection, the information in clutter database can be updated periodically to adapt to the slow changing environment.

Specifically, for the beam domain adaptive filtering, we can use the multi-scans data of the same range cell under test as samples to estimate the clutter covariance matrix. When the adaptive filtering performance of different range cells is degraded due to the change of terrain, we can choose the historical data as samples for clutter suppression. The selection of clutter samples is shown in Fig. 4. According to the position of the cell under test, the data of the cell under test and its adjacent range cells in the previous scans are selected as the clutter samples. The target steering vector is the same as before, and the overall processing flow is shown in Fig. 5.

4 Experiments and Results

In this section, the real data are used to illustrate the performance of the proposed methods. The key parameters are as follows: the radar transmitted signal is LFM pulse signal, which is scanned mechanically at 360% in azimuth and electrically in elevation domain, and 16 beams are formed at 0–25%. After beamforming, the data format is beam-range-pulse, and then the beam domain adaptive processing is carried out by the proposed method.

Starting with the received beam domain signal, clutter samples are selected in the range domain of the same scan for covariance estimation. According to the beam domain information of the real target in the noise background, the steering vector is referenced, and then the adaptive filtering processing in the beam domain is completed. The results before and after clutter suppressing are shown in Fig. 6. The covariance

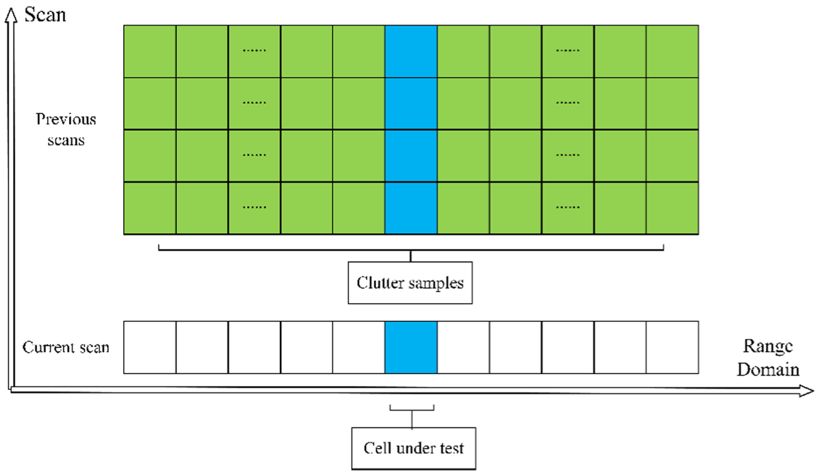

Fig. 4. Schematic diagram of clutter sample selection in previous scans

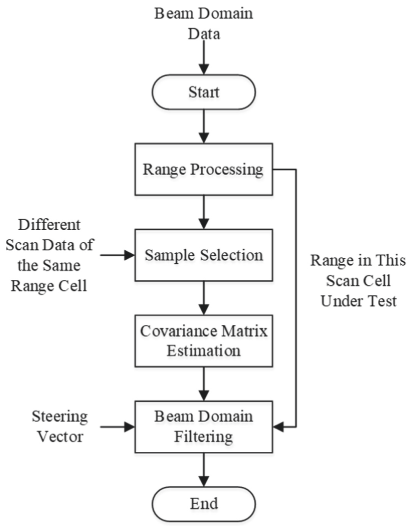

Fig. 5. Flowchart of proposed clutter suppression method based on cognition

matrix estimation is completed by range domain sampling based on cognition, and the results before and after clutter suppression are shown in Fig. 7.

It can be seen from Fig. 6 that the adaptive processing in beam domain by sampling in the range domain of the same scan can effectively suppress the clutter, and the SCNR improvement reaches 25.80 dB. It can also be seen from Fig. 7 that the adaptive processing in beam domain based on cognition has a limited suppression degree to clutter, and the improvement factor reaches 6.96 dB. The clutter suppression performance is obviously not as good as the former.

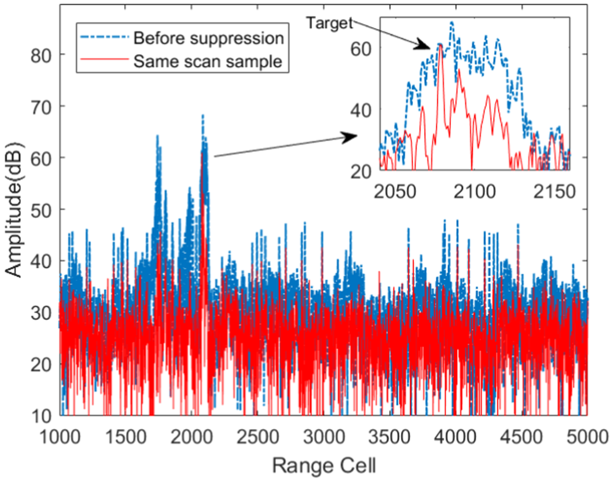

Fig. 6. Clutter suppression based on samples in the same scan

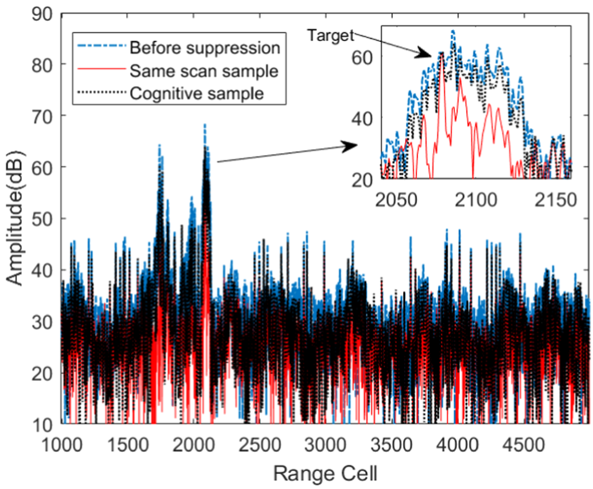

Fig. 7. Clutter suppression based on cognitive samples

Since the radar system may have certain errors when scanning in different directions, the azimuth of two adjacent scans is not completely aligned. This will increase the difference of data in different scans. In the ideal case of the system, the multiple measurement results of different static clutter in the same resolution cell should have good independent and identically distributed sample properties. In such ideal case, the suppression results should be much better. According to the simulated ideal cognitive data, the processing result is shown in Fig. 8.

It can be seen from Fig. 8 that the clutter suppression performance of adaptive processing in beam domain based on ideal cognitive data near target range cell is better

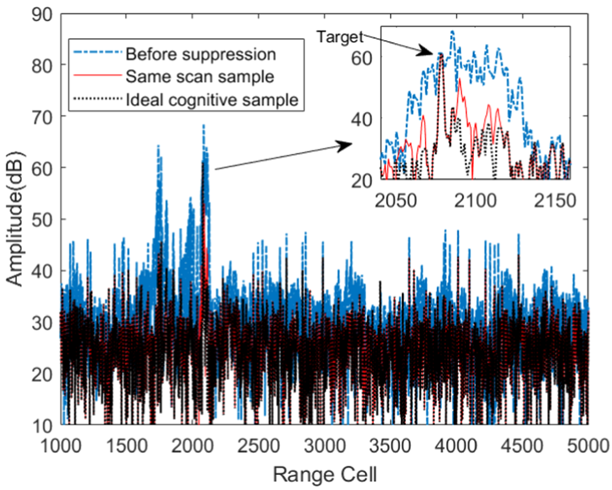

Fig. 8. Clutter suppression is based on ideal cognitive samples

than that of the sampling method in the range domain of the same scan. he suppression performance of other range cells is the same, and the calculated improvement factor is 27.08 dB.

5 Conclusion

In this paper, a spatial clutter suppression method based on adaptive processing is proposed for the three-coordinate radar system. The MVDR algorithm framework is adopted to clutter suppression in beam domain. When estimating the covariance matrix, in addition to the selection of samples in the range domain, we also proposed a method of selecting samples in different scans based on cognition. In the case that the received data is beam domain data, we proposed to use the beam domain response of the obvious target as the target steering vector. The performance of the methods on clutter suppression are verified by using the real data and the improvement factors are calculated. In addition, this method can be cascaded with the traditional slow-time domain clutter suppression algorithms to further improve the performance.

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