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Knowledge Aided Covariance Matrix Estimation via Gaussian Kernel Function for Airborne SR-STAP

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ABSTRACT In practical airborne radar, the interference signals in training snapshots usually lead to inaccurate estimation of the clutter covariance matrix (CCM) in space-time adaptive processing (STAP), which seriously degrade radar performance and even occur target self-nulling phenomenon. To solve this problem, a knowledge-aided sparse recovery (SR) STAP algorithm based on Gaussian kernel function is developed. The proposed method distinguishes clutter components and interference signals in training snapshots by the priori knowledge that the clutter components are distributed along the clutter ridge, which dislodges interference signals from training snapshots by Gaussian kernel similar degree. Thus, the CCM is estimated by utilizing these snapshots. Finally, the proposed STAP weight vector is built, which is convenient for the subsequent signal processing. The experimental results were performed to verify the effectiveness and superiority of the proposed method. The test results also show that the proposed algorithm completely removes the interference signals, accurately estimates CCM, and improves the moving target detection performance in small-sample and non-homogeneous clutter environments.

INDEX TERMS Space-time adaptive processing, interference signals, clutter covariance matrix, Gaussian kernel similar degree.

I. INTRODUCTION

Space-time adaptive processing (STAP) can improve the ability of suppressing clutter and detecting targets in airborne radar [1]–[3]. Generally, we can compute the ideal weight vector and the optimal space-time adaptive filter output responses using the clutter covariance matrix (CCM) and target space-time steering vector. The CCM is estimated with its adjacent distance cell snapshots in practice [4]. In order to accurately estimate the CCM, the training snapshots need to satisfy the following conditions [5]: (i) if the output signal-to-interference plus-noise ratio (SINR) loss is < 3dB, the number of training snapshots should be at least than twice the system degrees of freedom. (ii) the training snapshots must be target-free and their clutter statistics characteristics are the same as those of the cell under test (CUT), namely, the independent and identically distributed (IID). In practice, radars usually work in heterogeneous environments [6], [7]. It is difficult to meet the above-mentioned conditions, especially in small-sample. Therefore, the estimated CCM is not correct, which results in the performance decline of clutter suppression and the target self-nulling effects [8].

With the rise and development of compressed sensing theory, sparse signal representation has become one of the most important research hotspots in signal processing field [9]–[11]. In recent years, STAP technology based on the sparsity of clutter power spectrum can obtain the high resolution clutter power spectrum estimation in a small number of training snapshots or single sample. Then, clutter suppression and moving target detection are realized by using the obtained

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space-time power spectrum. Several typical sparse recovery (SR) STAP algorithms have been applied in the heterogeneous environments, such as SR-STAP algorithm [12]–[14], direct data domain STAP algorithm and the improved algorithm [15]. These algorithms can reconstruct the training snapshots and CUT by sparse recovery. If the training snapshots contain the interference signals, the CCM estimated by these algorithms is inaccurate, even leading to the target self-nulling effect.

To solve the above problems, we need eliminate the interference signals of training snapshots. The usual methods are mainly focused on the research of Non-Homogeneity Detection (NHD) [16]–[18]. The generalized inner products (GIP) algorithm deletes the contaminated training snapshots by comparing the statistics with the designated threshold [16]. However, when there are many strong interference signals in the training snapshots set, GIP method can't completely eliminate the contaminated training snapshots. In [19], GIP non-uniform sample detection method based on knowledge-aided structure is proposed, which offline constructs the accurate CCM by using the prolate spheroidal wave functions (PSWF). A robust training snapshots selection algorithm based on the spectral similarity of the interference signals is proposed in [20], which selects the snapshots whose spectrums are similar to that of the CUT as the final training snapshots. However, in the situation of dense distribution of interference signals or the limited number of the training snapshots, the robustness of the above algorithms is poor. Moreover, these algorithms can degrade the performance of STAP owing to discard many contaminated snapshots in the heterogeneous environment.

In this paper, a knowledge-aided SR-STAP algorithm based on Gaussian kernel function is proposed for clutter suppression and moving target detection in small-snapshots and non-homogeneous clutter environments. The proposed algorithm uses the prior knowledge of clutter spectrum and Gaussian kernel similar degree to detect and eliminate the interference signals in the training snapshots, and accurately estimates the CCM. The simulated results show that the proposed method achieves a significant performance improvement for STAP in a small number of training snapshots.

The remainder of this paper is organized as follows. The STAP signal model is presented in section II. In Section III, the proposed STAP approach is presented, including Gaussian kernel similar degree and SR techniques. In section IV, simulation results and discussions verify the effectiveness of the proposed algorithm. Finally, section V draws the conclusions.

Notations: scalars, vectors and matrices are denoted by lowercase, bold lowercase and bold uppercase respectively. $(\cdot)^T$, $(\cdot)^H$ denote transpose and complex conjugate transpose operators respectively. $\otimes$, $E[\cdot]$ and $|\cdot|$ stand for the Kronecker product, the expected value and the absolute respectively. $\mathbf{I}_M$ is the $M \times M$ identity matrix, and $diag(\mathbf{a})$ denotes a diagonal matrix whose diagonal elements are equal to the column vector $\mathbf{a}$. $\max(\mathbf{a})$ denotes the maximum element of vector $\mathbf{a}$. $< \cdot >$ is the inner product.

II. SIGNAL MODEL

The system under consideration is a side-looking airborne phased array radar that consists of a uniform linear array (ULA). The radar contains N antenna sensors with inter-element spacing d and M transmitting pulses with pulse repetition interval (PRI) T_r in a coherent processing interval (CPI). Thus, ignoring the range ambiguity, the received space-time snapshots for a range bin are expressed as

$$\mathbf{x} = a_t\mathbf{v}(f_t, \varphi_t) + \mathbf{x}_u \tag{1}$$

where a_t denotes the unknown complex amplitude of the target. $\mathbf{v}(f_t, \varphi_t) = \mathbf{v}(f_t) \otimes \mathbf{v}(\varphi_t)$ is the corresponding space-time steering vector, where $\mathbf{v}(\varphi_t) = [1, e^{2\pi j\varphi_t}, \ldots, e^{2\pi j(N-1)\varphi_t}]^T$ is the spatial steering vector at the normalized spatial frequency and $\mathbf{v}(f_t) = [1, e^{2\pi jf_t}, \ldots, e^{2\pi j(M-1)f_t}]^T$ denotes the temporal steering vector at the normalized Doppler frequency. The normalized spatial and Doppler frequency can be, respectively, denoted by

$$\varphi_t = d\cos(\theta)/\lambda \tag{2}$$
$$f_t = 2vT_r\cos(\theta)/\lambda \tag{3}$$

where θ is the target directions, λ is the wavelength of radar, and v is the speed of the radar. The clutter plus noise data $\mathbf{x}_u$ can be expressed by

$$\mathbf{x}_u = \sum_{i=1}^{N_c} a_{c,i}\mathbf{v}(f_{c,i}, \varphi_{c,i}) + \mathbf{n} = \sum_{i=1}^{N_c} a_{c,i}\mathbf{v}(f_{c,i}) \otimes \mathbf{v}(\varphi_{c,i}) + \mathbf{n} \tag{4}$$

where N_c denotes the number of independent clutter patches in azimuth domain, $a_{c,i}$, $f_{c,i}$ and $\varphi_{c,i}$ are the random amplitude, the normalized Doppler and spatial frequency of the ith clutter patch respectively. $\mathbf{v}(f_{c,i}, \varphi_{c,i}) = \mathbf{v}(f_{c,i}) \otimes \mathbf{v}(\varphi_{c,i})$ is the space-time steering vector of the ith clutter patch. The corresponding spatial and temporal steering vector are, respectively, described by

$$\mathbf{v}(\varphi_{c,i}) = [1, e^{2\pi j\varphi_{c,i}}, \ldots, e^{2\pi j(N-1)\varphi_{c,i}}]^T \tag{5}$$
$$\mathbf{v}(f_{c,i}) = [1, e^{2\pi jf_{c,i}}, \ldots, e^{2\pi j(M-1)f_{c,i}}]^T \tag{6}$$

$\mathbf{n}$ is the Gaussian distribution noise vector and its power is σ_n^2. The normalized spatial and Doppler frequency of the ith clutter patch can be, respectively, denoted by

$$\varphi_{t,i} = d\cos(\theta_i)/\lambda \tag{7}$$
$$f_{c,i} = 2vT_r\cos(\theta_i)/\lambda \tag{8}$$

where θ_i is the spatial cone angle of the ith clutter patch. Assuming mutual independence of each clutter patch, the clutter plus noise covariance matrix (CNCM) is expressed as follows:

$$\begin{aligned}\mathbf{R}_u &= E\left[\mathbf{x}_u\mathbf{x}_u^H\right] \\ &= \sum_{i=1}^{N_c} E(|a_{c,i}|^2)\mathbf{v}(f_{c,i}, \varphi_{c,i})\mathbf{v}^H(f_{c,i}, \varphi_{c,i}) + \sigma_n^2\mathbf{I}_{NM} \\ &= \mathbf{VPV}^H + \sigma_n^2\mathbf{I}_{NM}\end{aligned} \tag{9}$$

where $\mathbf{V} = [\mathbf{v}(f_{c,1}, \varphi_{c,1}), \mathbf{v}(f_{c,2}, \varphi_{c,2}), \ldots, \mathbf{v}(f_{c,N_c}, \varphi_{c,N_c})]$ is the clutter space-time steering matrix, the clutter power matrix is $\mathbf{P} = diag([E(|a_{c,1}|^2), E(|a_{c,2}|^2), \ldots, E(|a_{c,N_c}|^2)]^T)$.

According to the minimum variance distortionless response criterion, the optimal STAP weight vectors can be respectively expressed as

$$\mathbf{w} = \frac{\mathbf{R}_u^{-1}\mathbf{v}_t}{\mathbf{v}_t^H \mathbf{R}_u^{-1}\mathbf{v}_t} \tag{10}$$

where $\mathbf{v}_t$ denotes the space-time steering vector of target. In practice, $\mathbf{R}_u$ is unknown. It is usually estimated from training snapshots which are assumed to be IID and target-free, which is given by

$$\tilde{\mathbf{R}}_u = \frac{1}{L}\sum_{l=1}^{L}\mathbf{x}(l)\mathbf{x}(l)^H \tag{11}$$

where $\mathbf{x}(l)$ denotes the lth target-free training snapshots and L is the number of training snapshots.

However, the training snapshots may contain the interference signals in practice, which degrade the STAP performance significantly. Particularly, if the interference signals have the same Dopple frequencies as the target, the target will be filtered out as clutter, which causes the target self-nulling effect. In general, the GIP approach can find and get rid of interference signals. However, the GIP approach can't completely remove them when the interference signals are distributed intensively. Particularly, when the training snapshots are few, the GIP approach can hardly work owe to throw away some contaminated snapshots. Actually, these renounced snapshots have also valuable clutter information.

III. THE PROPOSED ALGORITHM

We can eliminate the interference signals and preserve the clutter components in each snapshot to overcome the above problems. Hence, a robust knowledge-aided SR-STAP algorithm based on Gaussian kernel function will be described in detail.

A. GAUSSIAN KERNEL SIMILAR DEGREE

In this section, we give the concept of Gaussian kernel function. Suppose $\mathbb{X}$ is a non-empty subset in $\mathbb{R}^N$, and Φ is a nonlinear mapping from $\mathbb{X}$ to $\mathbb{H}$. $K(x, y)$ is defined as kernel function, which is defined as

$$K(x, y) = <\Phi(x), \Phi(y)> \quad \forall x, y \in \mathbb{X} \tag{12}$$

where $\mathbb{H}$ is a Hilbert space. The kernel function can change a non-linear problem into a linear one. Thus, the similarity can be calculated accurately by the kernel function [21]–[23].

Gaussian kernel function is one of the most popular kernel functions. Gaussian kernel function has better smoothing performance. In addition, it can approximate any nonlinear function and has fewer parameters. Therefore, Gaussian kernel is used to calculate the similar degree between x and y, which is given by

$$k(x, y) = \frac{1}{2\pi}\exp(-\frac{\|x-y\|^2}{2\sigma^2}) \tag{13}$$

where σ is density of kernel function and one adjustable parameter.

Making full use of all the information of each snapshot, the Gaussian kernel function can capture the nonlinear correlation between snapshots in the kernel function space and obtain better comparable results. The larger the similar degree of x and y is, the larger the kernel function value is, conversely smaller. Therefore, the similar degree between snapshots can be interpreted by the kernel function value, which is defined as the Gaussian kernel similar degree. Gaussian kernel similar degree discriminates and eliminates the interference signals to accurately estimate the CCM in this paper.

B. SR TECHNIQUE

Since the clutter focuses on the clutter ridge, the whole angle-Doppler plane is discretized into $N_s = \rho_s N$, $N_d = \rho_d M(\rho_s, \rho_d > 1)$ grids, where N_s and N_d are the number of angle and Doppler cells, respectively. Hence, the clutter plus noise data $\mathbf{x}_u$ in (4) can be rewritten as

$$\mathbf{x}_u = \sum_{i=1}^{N_sN_d} a_{c,i}\mathbf{v}(f_{c,i}, \varphi_{c,i}) + \mathbf{n} = \boldsymbol{\Phi}\mathbf{a} + \mathbf{n} \tag{14}$$

where $\boldsymbol{\Phi}$ and $\mathbf{a}$ are the $NM \times N_sN_d$ over-completed space-time steering dictionary and $N_sN_d \times 1$ angle-Doppler profile with nonzero elements representing the clutter spectrum, respectively, as given by

$$\boldsymbol{\Phi} = [\mathbf{v}(f_{c,1}, \varphi_{c,1}), \mathbf{v}(f_{c,2}, \varphi_{c,2}), \ldots, \mathbf{v}(f_{c,N_d}, \varphi_{c,N_s})]_{NM\times N_sN_d} \tag{15}$$

$$\mathbf{a} = [a_{c,1}, a_{c,2}, \ldots, a_{c,N_sN_d}]^T \tag{16}$$

Generally, the clutter spectrum is sparse, so several cells represent clutter components in the discretised angle-Doppler plane [24]. If $\boldsymbol{\Phi}$ is known, the sparse vector $\mathbf{a}$ can be formulated by the least absolute shrinkage and selection operator as shown by

$$\mathbf{a} = \arg\min_{\gamma} \|\mathbf{a}\|_1, \quad \text{subject to } \|\mathbf{x}_u - \boldsymbol{\Phi}\mathbf{a}\|_2 \le \varepsilon \tag{17}$$

where ε denotes the noise allowed error. If the training snapshots $\mathbf{x}_u$ contain the interference signals, the performance of SR-STAP algorithm will decline significantly, especially in the case of small samples. Moreover, when the interference signals are densely distributed in the training snapshots, SR-STAP algorithm can't work normally and even result in target self-nulling effect. According to the prior knowledge that all the clutter components distribute along clutter ridge in the angle-Doppler domain, we can distinguish the clutter components and the interference signals.

C. THE PROPOSED ALGORITHM

To address the problem, we use the clutter prior knowledge to select and eliminate the interference signals according to the Gaussian kernel similar degree. The number of training snapshots is L and $N_s = N_d$. $\mathbf{a}_l$ is the coefficient vector of the snapshot $\mathbf{x}(l)(l = 1, \ldots, L)$ obtained by (17). The whole procedure can be done as follows.

Step 1: We first array $\mathbf{a}_l$ in descending order by the absolute values of elements, and construct a new set Γ by the indices of elements.

Step 2: The Gaussian kernel similar degree k_{ji} between $\boldsymbol{\phi}(:, \Gamma(j))$ and $\boldsymbol{\varphi}_i$ is calculated as

$$k_{ji} = \exp(-\frac{\left\|\boldsymbol{\varphi}_i - \boldsymbol{\phi}(:, \Gamma(j))\right\|^2}{2\sigma^2}) \quad (i = 1, 2, \ldots, P) \tag{18}$$

where $\Gamma(j)$ denote the jth $(j = 1, 2, \ldots, N_sN_d)$ element of Γ, and $\boldsymbol{\varphi}_i(i = 1, 2, \ldots, P)$ is the space-time steering vector corresponding to the clutter ridge in angle-Doppler plane. All Gaussian kernel similar degrees form a set K_j, which is expressed as

$$K_j = [k_{j1}, k_{j2}, \ldots, k_{jP}] \tag{19}$$

Step 3: Then, if $\max(K_j) > \tau$ or $j = N_sN_d$, set

$$\Omega(z) = \Gamma(j) \tag{20}$$

continue to step 4; otherwise, set $j = j + 1$ and return to step 2, where τ denotes a threshold of Gaussian kernel similar degree.

Step 4: The jth iteration CCM estimation using the SR is given by [14].

$$\mathbf{R}_{l,j} = \sum_{z=1}^{Z} |\mathbf{a}(\Omega(z))|^2 (\boldsymbol{\Phi}\mathbf{e}_{\Omega(z)})(\boldsymbol{\Phi}\mathbf{e}_{\Omega(z)})^H \tag{21}$$

where $\mathbf{e}_{\Omega(z)} = [0_1, \cdots, 0_{\Omega_k(z)-1}, 1_{\Omega_k(z)}, 0_{\Omega_k(z)+1}, \cdots, 0_{N_sN_d}]^T$ and Z is the number of elements in set Ω.

Step 5: if $j = 1$, set $j = j+1$ and return to step 2; otherwise, calculate the error value between the CCM power values of two adjacent iterations, which is denoted by

$$\Delta_j = 10 * \log 10\left(\frac{\mathbf{x}^H \mathbf{R}_{l,j-1}^{-1}\mathbf{x}}{\mathbf{x}^H \mathbf{R}_{l,j}^{-1}\mathbf{x}}\right) \tag{22}$$

If $\Delta_j < \xi$ or $j = N_sN_d$, stop the iteration. Otherwise, set $j = j+ 1$, $z = z+ 1$ and return to step 2. ξ is error threshold. Then the CCM estimation is $\mathbf{R}_{l,O_l}$, where O_l denotes the last iterative time.

Step 6: When we obtain CCM of all training snapshots, the final available CCM is computed as

$$\mathbf{R}_{av} = \frac{1}{L}\sum_{i=1}^{L} \mathbf{R}_{i,O_i} \tag{23}$$

Step 7: The optimum filter weight corresponding to the $\mathbf{R}_{av}$ is yielded as

$$\mathbf{w} = \frac{\mathbf{R}_{av}^{-1}\mathbf{v}_t}{\mathbf{v}_t^H \mathbf{R}_{av}^{-1}\mathbf{v}_t} \tag{24}$$

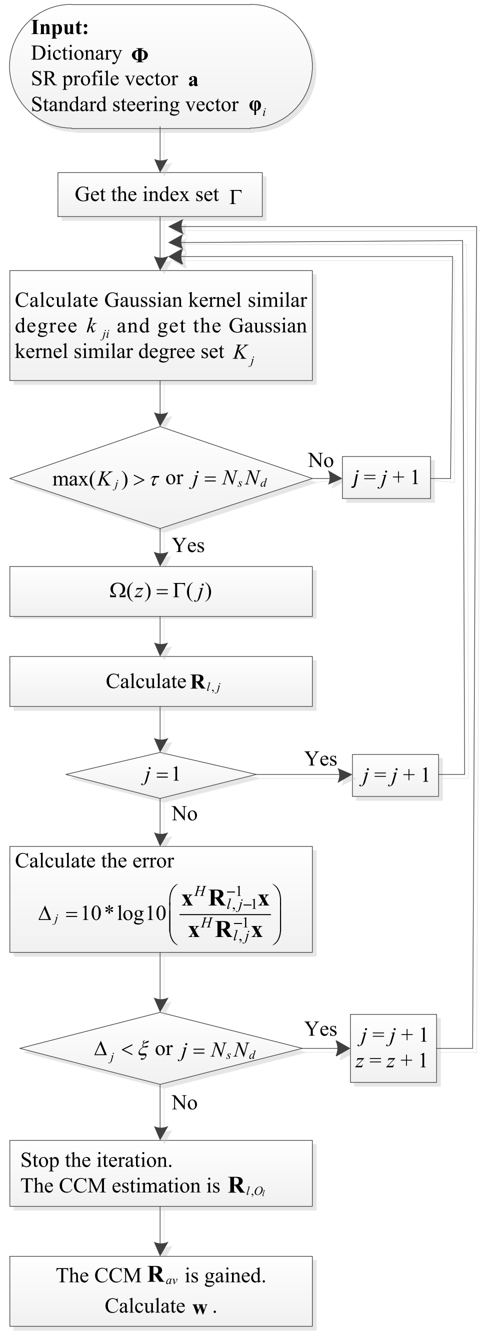
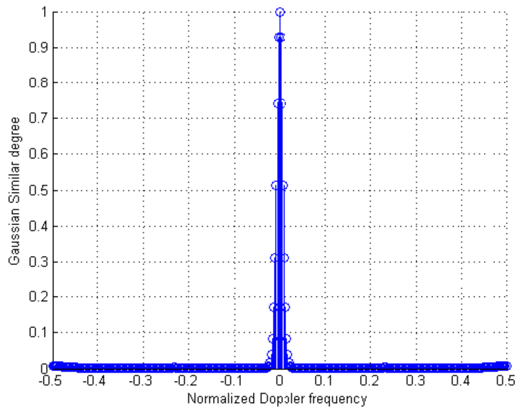
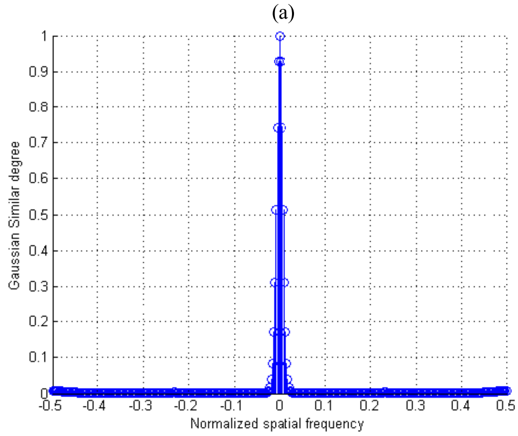


FIGURE 1. Float chart of the proposed algorithm.

The whole procedure can be summarized in Fig. 1. According to STAP theory, the clutter spectrum is distributed on the clutter ridge in the angle-Doppler plane, and the distribution of interference signals is quite different from that of clutter. This paper uses the prior knowledge to distinguish the clutter and interference signals by Gaussian kernel similar degree between the space-time steering vector of clutter ridge and that of the vector $\mathbf{a}_l$ SR coefficient, which is calculated by (18). Fig 2 shows the Gaussian kernel similar degrees among different space-time steering vectors. The steering vector whose normalized angle and Doppler frequency both



(a)



(b)

FIGURE 2. Gaussian kernel similar degree (a) Normalized Doppler frequency (b) Normalized spatial frequency.

are zero can be taken as the reference vector. The Gaussian kernel similar degrees between the reference vector and 361 steering vectors whose normalized angle is zero and normalized Doppler frequency distributes in $-0.5\sim0.5$ are given in Fig. 2(a). Fig. 2(b) shows the Gaussian kernel similar degrees between the reference vector and 361 steering vectors whose normalized Doppler frequency is zero and normalized angle distributes in $-0.5\sim0.5$. The results in the figure show that the Gaussian kernel similar degree between the reference vector and its adjacent vector decreases as the distance between them increases. Therefore, the interference signals can be discriminated by the Gaussian kernel similar degrees. Moreover, the performance of STAP is maintained by using clutter information of the contaminated snapshots. When the number of training snapshots is small and the distribution of interference signals is dense, the advantage of the proposed algorithm is particularly obvious. According to the simulation results, when the similar threshold set $\tau = 0.7$, the main clutter components can be selected and the ability to suppress interference signals is guaranteed.

Every iteration process will give a new clutter components set $\Omega(z)$ corresponding to the vector $\mathbf{a}_l$ SR coefficient and $\Omega(z) \supset \Omega(z-1)$, as is described in step 3. Thus, the CCM estimation is updated by the new set $\Omega(z)$. GIP algorithm mainly selects the training snapshots by calculating the value of $Q(l) = \mathbf{x}(l)^H \mathbf{R}_c^{-1} \mathbf{x}(l)$, where $\mathbf{x}(l)$ denotes the training snapshots and $\mathbf{R}_c$ is the CCM of CUT. Inspired by the GIP algorithm, the similar definition is defined to estimate the CCM accurately, which is defined by

$$Q_l(j) = \mathbf{x}^H \mathbf{R}_{l,j}^{-1} \mathbf{x} \tag{25}$$

where $\mathbf{x}$ denotes the CUT and $\mathbf{R}_{l,j}$ is the CCM obtained by the jth iteration of $\mathbf{x}(l)$. With the increase of iterations, the closer $\mathbf{R}_{l,j}$ is the CCM of CUT, the smaller the value of $Q_l(j)$ is. When the $Q_l(j)$ values of two adjacent iterations are almost equal, the iteration stops. In this case, $Q_l(j)$ should only have the target and noise components without clutter residuals and interference signals. After that, Δ_j between the two adjacent iteratives contains only the noise component by (22). Consequently, the error threshold ξ is set to the noise power, as is described in the step 5. When the CCMs of all training snapshots are obtained, and their mean is used as the final CCM of CUT. Finally, the optimal filter output response can be given by (24).

IV. RESULTS AND DISCUSSION

In this section, the theoretical derivation is verified by numerical experiments. To demonstrate the superior performance of our proposed method, some popular methods including SR-STAP [14] and GIP-STAP [16] are also employed as comparisons in the following experiments. The main parameters of the side-looking airborne radar system are listed in Table 1, and $\beta = 1$. We set $\rho_s = \rho_d = 6$, $\tau = 0.7$, and $\sigma^2 = 9$.

TABLE 1. Main parameters of STAP radar.

Symbol	Quantity	Value
N	the number of sensors	10
M	the number of pulses	10
λ	carrier wavelength	0.03 m
d	minimal inter-element distance	0.015 m
T_r	minimal PRI	0.25 ms
h	platform height	4000 m
CNR	clutter to noise ratio	40 dB
SNR	signal to noise ratio	10 dB
INR	interference to noise ratio	40 dB
σ_n^2	noise power	1 dB
	normalized spatial frequency of target	-0.3
	normalized Doppler frequency of target	0.1

A. BEAMPATTERNS IN ANGLE-DOPPLER

We use ten training snapshots to verify the performance advantages of the proposed algorithm in a small number of training snapshots. Five of them have dense interference signals whose range of the normalized Doppler frequency is 0.05-0.15. Beampatterns in angle-Doppler estimated by IJDL-STAP (the training snapshots of JDL-STAP have no

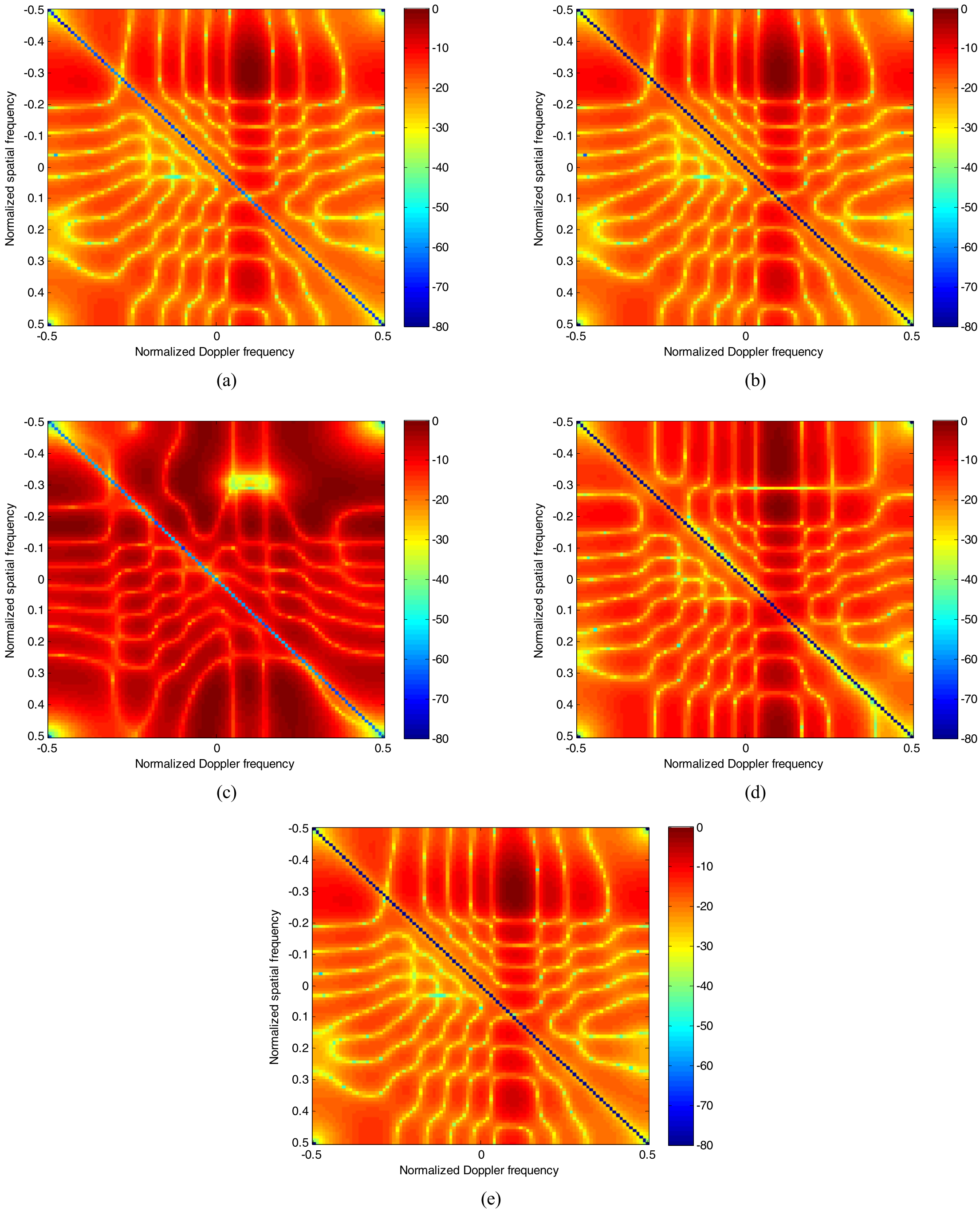


FIGURE 3. Beampatterns in angle-Doppler (a) IJDL-STAP (b) ISR-STAP (c) SR-STAP (d) GIP-STAP (e) Proposed approach.

interference signals), ISR-STAP (the training snapshots of SR-STAP have no interference signals), SR-STAP, GIP-STAP and Proposed approach are showed in Figs. 3(a)-(e). Because the normalized Doppler frequency of target signal is within those of the interference signals, it is found that he SR-STAP algorithm has no response peak value at the target position and the beampattern in angle-Doppler is seriously damaged, as shown in Fig. 3(c). However, the GIP-STAP algorithm can eliminate some training snapshots contained interference signals, but some residual training snapshots with interference signals form multiple response peaks to increase false alarm probability. Moreover, the clutter power of GIP-STAP is reduced compared with that of SR-STAP algorithm because some training snapshots are eliminated, as shown in Fig. 3(d). The proposed algorithm completely overcomes the influence of interference signals. Its performance is almost close to the ideal situation. This means that the proposed algorithm can extract useful clutter information

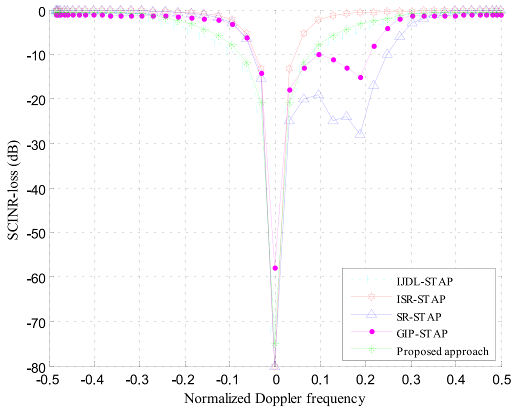


FIGURE 4. **SCINR loss.**

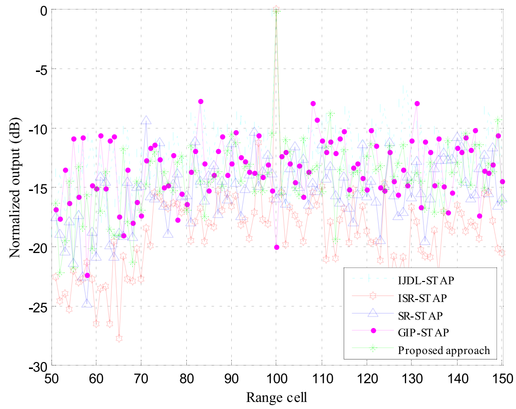


FIGURE 5. **Normalized stap filter outputs along range cell.**

from each training sample to estimate the clutter power spectrum as accurately as possible.

B. SCINR LOSS

Fig. 4 shows signal-to-clutter-plus-interference-and-noise power ratio (SCINR) loss of the tested approaches versus the normalized Doppler frequency curves. As shown in Fig. 4, the SR-STAP method can't work normally because of the CCM estimation error in the presence of interference signals. GIP-STAP has no big loss except the main clutter area, but its curve fluctuates greatly in the positions of interference signals Doppler frequencies. Moreover, GIP-STAP gets rid of some contaminated snapshots, which degrades the performance of target detection and clutter suppression. Since the proposed algorithm accurately estimates the CCM by using the clutter information in each training snapshots, the SCINR-loss curve is 12dB deeper than that of GIP-STAP in the main clutter region. Moreover, the SCINR loss curve of the proposed approach appears to be the optimal one except for the main clutter area. Hence, the proposed approach is better than other algorithms in clutter suppression and SCINR.

C. DETECTION ALONG RANGE CELLS

Next, we analyze the target detection along range cells by 100 Monte Carlo simulations. The same training snapshots from 100 range cells are processed by IJDL-STAP, ISR- STAP, SR-STAP, GIP-STAP and the proposed approach, respectively. Supposing that the target signal is located in the 100th range cell. Its normalized Doppler frequency is 0.1, and SNR is 10dB. The detection results along range cell is presented in Figs. 5. As shown in Fig. 5, IJDL-STAP, ISR-STAP and the proposed algorithm can effectively suppress the clutters and distinguish the target. However, the IJDL-STAP cannot use prior knowledge, its target detection results relatively poor. Since the Doppler frequency of the target signal is within that of interference signals, the normalized output power of SR-STAP and GIP-STAP in the 100th range cell is less than -10dB. It means that there's target self-nulling.

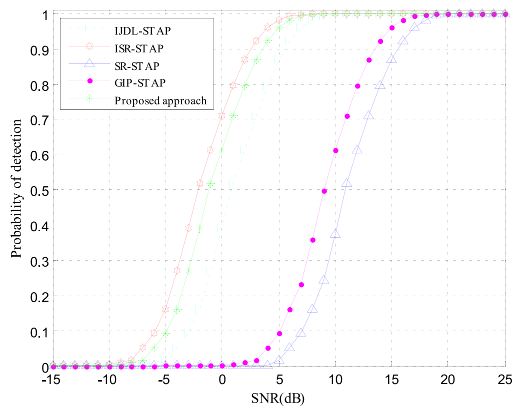


FIGURE 6. **Probability of detection.**

D. DPROBABILITY OF DETECTION

At last, Fig. 6 shows the probability of detection of IJDL-STAP, ISR-STAP, SR-STAP, GIP-STAP and the proposed algorithm respectively by 100 Monte Carlo simulations. In the simulations, we set the false alarm rate to 10^{-6}.The results shown in Fig. 6 again demonstrate that the performances of the proposed algorithm is best than that of the tested approaches when the probability of detection is fixed.

V. CONCLUSION

In the present study, a knowledge-aided SR-STAP approach based on Gaussian kernel similar degree was proposed. The algorithm can improve the detection performance and avoid target self-nulling phenomenon when the training snapshots are contaminated by interference signals in the airborne radar. The proposed algorithm decomposes the training snapshots by SR, selects the clutter components in the training snapshots by using the prior knowledge of clutter spectrum and Gaussian kernel similar degree. Finally, the CCM can be accurately estimated by making full use of the clutter information in each training snapshots. According to the simulation results, the proposed approach exhibits a better angle-Dopple beampattern, higher probability of detection, superior target detection output and SCINR loss compared with other methods in the presence of interference signals. Moreover, the advantages of the proposed approach are distinguished compared with other types approaches in a small number of training snapshots.

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