IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received August 20, 2018, accepted September 26, 2018, date of publication October 1, 2018, date of current version October 25, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2873021

Sparsity-Based Non-Stationary Clutter Suppression Technique for Airborne Radar

KEQING DUAN[1], (Member, IEEE), HUADONG YUAN[1], HONG XU[2], WEIJIAN LIU[1], (Member, IEEE), AND YONGLIANG WANG[1]

[1]Wuhan Early Warning Academy, Wuhan 430019, China
[2]Electronic Engineering Department, Navy University of Engineering, Wuhan 430033, China

Corresponding author: Weijian Liu (liuvjian@163.com)

This work was supported by the National Natural Science Foundation of China under Grant 61871397, Grant 61501506, and Grant 61501505.

ABSTRACT Conventional space–time adaptive processing (STAP) technique can achieve perfect performance when applied to side-looking airborne radar (SLAR), where the clutter is relatively stationary, whereas it suffers significant degradation for non-SLAR due to severe range dependence, especially when range ambiguity is present. In theory, the range-dependent clutter is mainly located at the near range and can be eliminated via elevation non-adaptive or adaptive beamforming. However, the pure near-range clutter portion utilized for calculating elevation adaptive weights cannot be obtained due to range ambiguity in practice. In this paper, a novel method to adaptive extract the near-range clutter via sparsity-based technique is presented and the non-stationary clutter potion can be effectively eliminated by elevation adaptive beamforming. With this technique, the residual clutter becomes stationary, and thus, the corresponding STAP performance will be significantly improved.

INDEX TERMS Space-time adaptive processing (STAP), non-stationary clutter, sparse recovery (SR), clutter suppression, elevation adaptive beamforming.

I. INTRODUCTION

As is well known, clutter Doppler does not vary with range for side-looking airborne radar (SLAR) and therefore conventional space-time adaptive processing (STAP) technique can work well [1], [2]. However, the frequently encountered case in practice is non-SLAR, which can scan all the interesting directions. For non-SLAR, the Doppler of clutter echoes vary with range [3], and the independent and identical distributed (IID) condition of training samples cannot be satisfied. As a result, conventional STAP suffers dramatic performance degradation. Strictly speaking, the range-dependent clutter, i.e., non-stationary clutter, mainly locates at the near range, and hence the clutter at other ranges is approximately range-independent or stationary [3]. For low pulse-repetition frequency (LPRF) radar, the radar returns from near range can be directly rejected because the near-range targets are usually not interested ones. However, the airborne radar often works at medium PRF (MPRF) of high PRF (HPRF), so echoes from far range (nearly equivalent to the ambiguous range) fold over the near-range, i.e., unambiguous-range, returns, that is to say, range ambiguity often occurs. This effect may cause low Doppler targets to compete with near-range strong non-stationary clutter.

To solve the problem of clutter range dependence, many compensation algorithms have been proposed. Parametric methods such as the Doppler warping [4], angle Doppler compensation [5], and adaptive angle Doppler compensation [6] are only effective for range unambiguous case [2]. When there is range ambiguity, they cannot make the clutter across ambiguous ranges coincide simultaneously. Non-parametric methods such as the derivative-based updating [7], prediction of the inverse clutter covariance matrix (CCM) [8], and Taylor series expansion-based eigen-canceller [9] are applicable to range ambiguous cases. But their clutter suppression performance is sensitive to the accuracy of non-parametric models, which are unknown in practice.

In fact, the near-range clutter returns are mainly from the elevation sidelobe of array antenna [10]. Thus several elevation beamforming methods are proposed to mitigate the effect of non-stationary clutter. In principle, the three-dimensional (3D) STAP can effectively cancel the near-range clutter [10], [11]. Unfortunately, it is difficult to obtain

2169-3536 © 2018 IEEE. Translations and content mining are permitted for academic research only.
Personal use is also permitted, but republication/redistribution requires IEEE permission.
See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

enough IID training samples and requires huge computation load because of its large system degree of freedom (DOF). Subarray synthesis algorithm with non-adaptive pre-filtering in elevation also help to mitigate the effect of near-range clutter [12]. However, its performance depends on the accuracy of prior knowledge, such as elevation angle of the range cell under test (RCUT). Once the prior information is not given accurately, especially for non-flat terrain, it will lead to severe performance loss [12]. To overcome this problem, an adaptive pre-filtering in elevation for non-stationary clutter suppression is proposed in [13]. Nevertheless, its performance improvement is limited since only two system DOFs, i.e., sum and difference beams in elevation, are available for adaptive beamforming. Obviously, the non-stationary clutter exhibits a dependence on elevation angle-of-arrival, especially at near range, and the elevation elements on a planar array can be used to distinguish the echoes from different ranges.

As pointed out above, the near-range clutter mixed with the ambiguous far-range clutter at MPRF or HPRF mode for airborne radar. For adaptive pre-filter approaches, signal cancellation will be occurred if the training samples used for CCM estimation in elevation consists of the far-range clutter. Thus the key of elevation adaptive beamforming for non-stationary clutter suppression is to extract the pure near-clutter portion from the superposition of different ambiguous clutter. Furthermore, high convergence speed is also needed to avoid wider adaptive notch and potentially insufficient clutter suppression in elevation.

Fortunately, we found that the near-range clutter and other ambiguous clutter are from different and finite elevation angles, which means that the clutter spectrum in elevation spatial domain is sparse. Consequently, we can distinguish and abstract the near-clutter potion form clutter returns via classical sparse recovery (SR) technique [14]–[16]. On this basis, we further put forward a novel sparsity-based adaptive beamforming approach to mitigate the near-range clutter. After that, the residual clutter should be stationary and thus suboptimal performance of STAP can be obtained. Furthermore, to improve the convergence speed of above adaptive beamforming, pulses in a coherent processing interval (CPI) are all utilized as multiple measurement data to recover the location and power of near clutter sources and thus no training samples of adjacent range cells are needed. Compared with existing pre-filter algorithms [12], [13], the advantages of the proposed approach include: (i) independent on any prior knowledge and thus robust in practical clutter environment. (ii) sufficient elevation spatial DOFs are utilized and much deeper and narrower near-range clutter notch can be obtained. (iii) higher convergence speed for adaptive beamforming is achieved and wider adaptive notch is avoided.

The paper is organized as follows. In Section II, the characteristics of non-stationary clutter of non-SLAR are analyzed. Section III introduces the principle the proposed method in detail. Simulation results are shown in Section IV, and Section V summarizes the conclusion.

II. CHARACTERISTICS OF NON-STATIONARY CLUTTER

In this section, the range dependence of clutter for non-SLAR is discussed in detail. Consider a pulse Doppler airborne radar with a uniform planar array consisting of M and N elements in elevation and azimuth respectively, as shown in Fig. 1. The interval between two elements is equal to half wavelength. The x-axis is aligned with the normal of the array antenna, and the z-axis points vertically up. The counterclockwise angle between the flight direction and y-axis is θ_a; when $\theta_a = -90°$, the array antenna is a forward-looking array. The angles θ, φ and ψ denote the azimuth angle, elevation angle and cone angle, respectively. The platform is at altitude H and moving with constant velocity v. R_c denotes the slant range from the clutter patch to array antenna. Assume that a CPI contains K pulses.

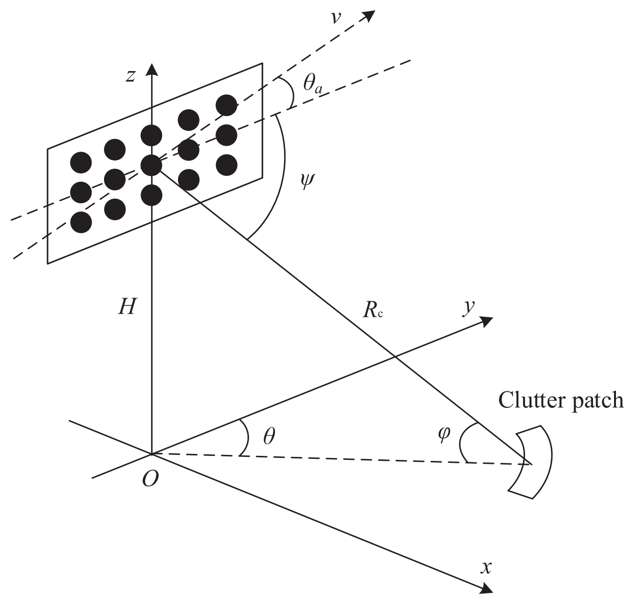


FIGURE 1. Airborne radar geometry with a uniform planar array.

According to Fig. 1, the relationship between the spatial frequency (i.e., cosine of cone angles) and clutter Doppler frequency can be described as the following well-known formula [3]

$$\begin{aligned} f_d &= \frac{2v}{\lambda}\cos(\theta+\theta_a)\cos\varphi \\ &= \frac{2v}{\lambda}\left(\cos\psi\cos\theta_a - \sin\theta_a\sqrt{1-\left(\frac{H}{R_c}\right)^2-\cos^2\psi}\right) \end{aligned} \tag{1}$$

where λ denotes radar wavelength. When $\theta_a \neq 0$, i.e., the array is mounted as a non-SLAR, the clutter Doppler varies with the slant range, and thus clutter is non-stationary. Obviously, it appears most severe especially for the forward-looking airborne radar (FLAR). Thus the FLAR is taken in this paper as a typical non-SLAR to discuss non-stationary clutter characteristics and evaluate the performance of

TABLE 1. Radar system parameters.

Symbol	Parameter	Value
λ	Wavelength	0.1m
d	Element spacing	0.05m
f_r	PRF	7500Hz
f_s	Sampling frequency	1MHz
v	Platform velocity	150m/s
H	Platform height	10000m
N	Element number of array in azimuth	8
K	Pulse number within one CPI	8
φ_t	Elevation angle of mainlobe	0^o
θ_a	Angle between the array axis and fly direction	-90^o
R_{max}	Maximum detection range	300km
CNR	Clutter-to-noise ratio	60dB

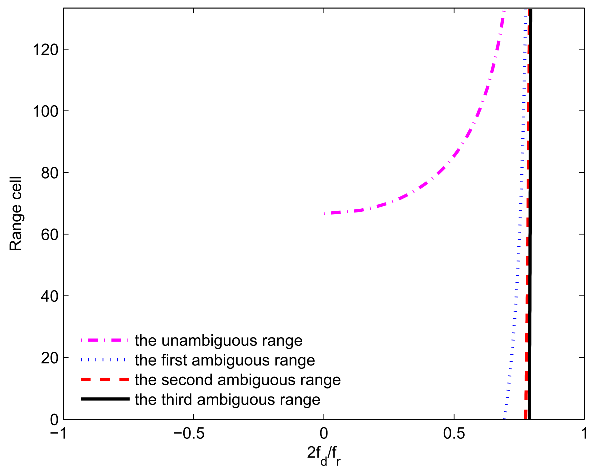


FIGURE 2. Range-Doppler trace for mainlobe clutter.

the proposed method. The system parameters are shown in Table 1.

The relationship between f_d of the mainlobe clutter and R_c, which is obtained by (1), is depicted in Fig. 2. For simplicity, only the first three ambiguous range are shown. The pink line in Fig. 2 describes the range-Doppler trace of mainlobe clutter corresponding to the unambiguous range which is dependent on PRF. The other lines denote the range-Doppler trace of mainlobe clutter related to each ambiguous range, respectively. Two points can be obtained from Fig. 2: (i) the range dependence of clutter mainly occurs at unambiguous range (i.e., the near-range region), and it decreases with range; (ii) the range dependence becomes very slight at ambiguous range, which means the clutter at other ranges (except for near range) is approximately stationary.

Since clutter returns of a certain range cell include clutter contribution, from near range and far range (due to range ambiguity), the clutter spectrum corresponding to the range cell should be a superposition of different clutter traces. On one hand, the IID training samples are not enough so that significant performance degradation will occurs. On the other hand, two clutter notch will be formed when conventional STAP is adopted; the first notch is the one due to primary clutter at near range; the second notch is due to multiple returns which come from farther distances. The extra clutter notch will bring up a lot of range blind zones [2], [3].

III. DESCRIPTION OF THE PROPOSED METHOD

A. REVIEW OF ELEVATION ADAPTIVE BEAMFORMING

Multiple clutter returns occur if there is range ambiguity. In this case the clutter echo of a certain range cell includes clutter contributions from other ranges. Thus, the clutter echo $\mathbf{x}_{se} \in \mathbb{C}^M$ for one column of array and one pulse corresponding to the RCUT can be denoted by [2]

$$\mathbf{x}_{se} = \sum_{p=0}^{P}\sum_{q=1}^{Q} \zeta_{p,q}\mathbf{s}_{se}\left(f_{se,p}\right) = \sum_{p=0}^{P} \mathbf{x}_{se,p} \tag{2}$$

where P denotes the maximum number of range ambiguities, Q denotes the number of clutter patches within an ambiguous range ring, ζ denotes the complex amplitude of the clutter patch, $f_{se,0} = \sin\varphi_0$ denotes the normalized elevation spatial frequency of the unambiguous clutter, $f_{se,p} = \sin\varphi_p$ $(p = 1, \cdots, P)$ denotes the normalized elevation spatial frequency of the pth ambiguous clutter, $\mathbf{x}_{se,0}$ denotes the unambiguous clutter data in $\mathbf{x}_{se}$, $\mathbf{x}_{se,p}$ $(p = 1, \cdots, P)$ denotes the pth ambiguous clutter data in $\mathbf{x}_{se}$, $\mathbf{s}_{se}$ denotes the elevation spatial steering vectors and is defined as follows

$$\mathbf{s}_{se}\left(f_{se,p}\right) = \left[1,\ \exp\left(j\pi f_{se,p}\right), \cdots, \exp\left(j\pi\,(M-1) f_{se,p}\right)\right]^{\mathrm{T}} \tag{3}$$

where $[\cdot]^{\mathrm{T}}$ denotes the operation of transposition.

Since the clutter contributions from different range can be assumed to be independent [2], the corresponding CCM of $\mathbf{x}_{se}$ can be written as

$$\mathbf{R}_{se} = E\left\{\mathbf{x}_{se}\mathbf{x}_{se}^{\mathrm{H}}\right\} = \sum_{p=0}^{P} E\left\{\mathbf{x}_{se,p}\mathbf{x}_{se,p}^{\mathrm{H}}\right\} = \sum_{p=0}^{P} \mathbf{R}_{se,p} \tag{4}$$

where $E[\cdot]$ denotes the operation of statistical expectation, $[\cdot]^{\mathrm{H}}$ denotes the operation of conjugate transposition, $\mathbf{R}_{se,0} = E\left\{\mathbf{x}_{se,0}\mathbf{x}_{se,0}^{\mathrm{H}}\right\}$ and $\mathbf{R}_{se,p} = E\left\{\mathbf{x}_{se,p}\mathbf{x}_{se,p}^{\mathrm{H}}\right\}$ $(p = 1, \cdots, P)$ denote the elevation CCM of unambiguous clutter and the pth range ambiguous clutter, respectively.

Obviously, if $\mathbf{R}_{se,0}$ is accurately known, we can design a weight vector $\mathbf{w}_{se}$ to cancel the near-range clutter

$$\hat{\mathbf{w}}_{se} = \arg\min_{\mathbf{w}_{se}} \mathbf{w}_{se}^{\mathrm{H}}\mathbf{R}_{se,0}\mathbf{w}_{se}, \quad \text{s.t. } \mathbf{w}_{se}^{\mathrm{H}}\mathbf{s}_{se}\left(f_{se,t}\right) = 1 \tag{5}$$

where $f_{se,t} = \sin\varphi_t$ denotes the normalized elevation spatial frequency corresponding to the direction of target. The weight vector is solved as

$$\hat{\mathbf{w}}_{se} = \frac{\mathbf{R}_{se,0}^{-1}\mathbf{s}_{se}\left(f_{se,t}\right)}{\mathbf{s}_{se}^{\mathrm{H}}\left(f_{se,t}\right)\mathbf{R}_{se,0}^{-1}\mathbf{s}_{se}\left(f_{se,t}\right)} \tag{6}$$

Then the output of adaptive beamforming for each column of array can be obtained through multiplying each column data $\mathbf{x}_{se}$ by the conjugate transposition of $\hat{\mathbf{w}}_{se}$.

Unfortunately, the near-range clutter is mixed with far-range clutter because of the range ambiguity, and $\mathbf{R}_{se,0}$ is difficult to be estimated by training samples. To solve this problem, in [13] the first received pulse is utilized, which is often discarded for coherently processing, to directly obtain the near-range clutter. However, most airborne radars work at multiple PRFs to solve the range ambiguity problem, thus the first received pulse of the current PRF is easily contaminated by the last received pulse of the front PRF.

B. EXTRACTION OF NEAR-RANGE CLUTTER VIA SR

As pointed out above, the primary and key problem to mitigate the non-stationary clutter is to extract the near-range clutter from the mixed clutter returns. Fortunately, the near-range clutter and other ambiguous clutter each individually enter into the received array antenna from a few different elevation angles, therefore the clutter spectrum in elevation spatial domain is very sparse. Recently, SR techniques have been successfully used to estimate the high-resolution spatial spectrum [17] or space-time clutter spectrum [18]–[26] with a very small number of training samples. In this paper, we exploit the sparsity of spectral distribution in elevation to estimate the location and power of the near-clutter. In other words, the near-clutter portion can be extracted via SR and then mitigated by adaptive beamforming in elevation spatial domain. The corresponding SR problem can be formulated as following optimization problem:

$$\hat{\mathbf{a}}_{\mathbf{se}} = \arg\min_{\mathbf{a}_{\mathbf{se}}} \|\mathbf{a}_{\mathbf{se}}\|_0, \quad \text{s.t. } \mathbf{x}_{se} = \Phi_{se}\mathbf{a}_{se} \tag{7}$$

where $\|\centerdot\|_0$ measures the number of nonzero elements in a vector, $\mathbf{a}_{se} = \left[a_{se,1}, a_{se,2}, \cdots, a_{se,M_s}\right]^{\mathrm{T}} \in \mathbb{R}^{M_s\times 1}$ are the sparse coefficients with non-zero elements representing the unambiguous clutter. $M_s = \rho_s M \quad (\rho_s > 1)$ is the number for discretizing the elevation spatial frequency f_{se}. ρ_s is the resolution scale along the elevation angle, and usually set to be 4, 5 or 6 as a rule-of-thumb [18]–[26]. $\Phi_{se} \in \mathbb{C}^{M\times M_s}$ is the overcomplete dictionary composed of elevation spatial steering vectors, given by $\Phi_{se} = \left[\mathbf{s}_{se}\left(f_{se,1}\right), \mathbf{s}_{se}\left(f_{se,2}\right), \cdots, \mathbf{s}_{se}\left(f_{se,M_s}\right)\right]$.

Equation (7) is just the canonical signal form of the SR problem, which can be interpreted as estimating a sparse vector $\mathbf{a}_{se}$ (i.e., as few non-zero elements as possible) from the single measurement data $\mathbf{x}_{se}$. Theoretically, once the elevation spatial frequency, f_{se}, is limited to the scope from -1 to $\sin\varphi_u$, the near-range clutter portion can be recovered accurately by solving (7) [14]–[16]. $\sin\varphi_u$ is the sine of elevation angle corresponding to the max unambiguous range R_u and can be calculated in advance by

$$\sin\varphi_u = -\frac{H}{R_u} = -\frac{2f_r H}{c} \tag{8}$$

where c denotes the speed of light. Consider only a few elevation elements are available in practice, we further reduce the scope of f_{se} to guarantee the accuracy of SR. In this paper, the scope of that is set to be 2α $(0 < \alpha < 0.5)$ which is dependent on the number of elevation elements. The set of α will be further discussed in Section IV. For the RCUT with the elevation angle φ_0, we set the scope of f_{se} in the following manner:

$$\begin{aligned}&\left[f_{se,min}, f_{se,max}\right]\\ &= \begin{cases}[-1, -1+2\alpha], & \sin\varphi_0 < -1+\alpha\\ [\sin\varphi_0-\alpha, \sin\varphi_0+\alpha], & -1+\alpha \le \sin\varphi_0 \le \sin\varphi_u-\alpha\\ [\sin\varphi_u - 2\alpha, \sin\varphi_u], & \sin\varphi_0 > \sin\varphi_u - \alpha\end{cases}\end{aligned} \tag{9}$$

If the noise is also considered, (7) can be formulated as the following optimization problem:

$$\hat{\mathbf{a}}_{se} = \arg\min_{\mathbf{a}_{se}} \|\mathbf{a}_{se}\|_0, \quad \text{s.t. } \|\mathbf{x}_{se} - \Phi_{se}\mathbf{a}_{se}\|_2^2 \le \varepsilon \tag{10}$$

where $\|\centerdot\|_2$ denotes the l_2 norm and ε is the noise error allowance.

From (2), we know that the different pulses in one CPI share the same clutter distribution characteristics. Thus all K coherent pulses for a certain range cell can be used as multiple measurements to improve the accuracy of SR in the presence of noise. Then (10) can be further formulated as a SR problem with multiple measurements data

$$\hat{\mathbf{A}}_{se} = \arg\min_{\mathbf{A}_{se}} \|\mathbf{A}_{se}\|_{2,0}, \quad \text{s.t. } \|\mathbf{X}_{se} - \Phi_{se}\mathbf{A}_{se}\|_F^2 \le \varepsilon \tag{11}$$

where $\|\cdot\|_{2,0}$ denotes a mixed norm defined as the number of non-zero elements of the vector formed by the l_2-norm of each row-vector, $\|\cdot\|_F$ denotes the Frobenius norm, $\mathbf{A}_{se} = \left[\mathbf{a}_{se}^{(1)}, \mathbf{a}_{se}^{(2)} \cdots, \mathbf{a}_{se}^{(K)}\right] \in \mathbb{R}^{M_s\times K}$ denotes an unknown clutter source matrix with each row representing a possible near-clutter clutter potion, $\mathbf{X}_{se} = \left[\mathbf{x}_{se}^{(1)}, \mathbf{x}_{se}^{(2)}, \cdots, \mathbf{x}_{se}^{(K)}\right] \in \mathbb{C}^{M\times K}$ denotes the measurements data of K pulses.

It is well known that the multiple sparse Bayesian learning (MSBL) algorithm is robust, sparse enough, parameter-blind and with no local minima in the presence of noise [16]. Furthermore, not only the location of clutter sources but also accurate clutter power can be recovered via the MSBL. Therefore, it is applied to solve the problem in (11). Here, we take the 100th range cell ($\sin\varphi_0 = -0.93$) as an example; the results of SR with M elevation elements is shown in Fig. 3. Moreover, the parameter α is set to be 0.1 here. As can be seen in Fig. 3, the location and power of near-range clutter sources are both effectively recovered even with two elevation elements and the accuracy increases with M.

Then $\mathbf{R}_{se,0}$ in (6) can be obtained as

$$\mathbf{R}_{se,0} = \sum_{i=1}^{M_s} \left|a_{se,i}\right|^2 \mathbf{s}_{se}\left(f_{se,i}\right)\mathbf{s}_{se}\left(f_{se,i}\right)^{\mathrm{H}} + \delta\mathbf{I} \tag{12}$$

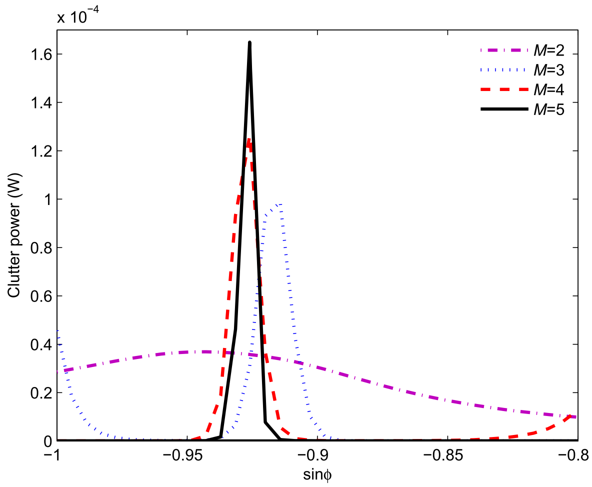


FIGURE 3. Clutter power versus normalized elevation spatial frequency.

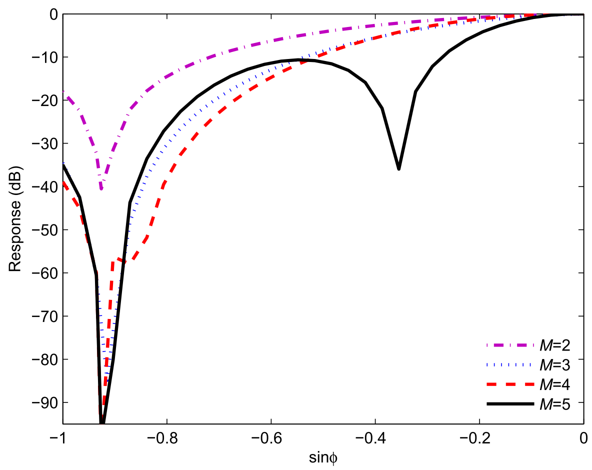


FIGURE 4. Frequency response with *M* elevation elements.

where δ is the energy of the artificial white noise, and $\mathbf{I}$ is an $M \times M$ identity matrix. Fig. 4 depicts the corresponding frequency response with M elevation elements. As can be seen in Fig. 4, the notches located at are all both formed and the depth of them also increases with M.

By the aforementioned processing, clutter non-stationarity mainly induced by the near-range echoes is greatly alleviated. Thus the residual clutter is approximately stationary and can be suppressed via existing azimuth-Doppler STAP methods. In brief, the novel method includes the sparsity-based elevation beamforming and the conventional STAP filter, and is denoted as SBEBF for simplicity. Notice that the interested targets cannot be eliminated by the proposed method, in which the echoes of targets are always received from the elevation mainlobe of array antenna.

IV. SIMULATION RESULTS

In this section, we evaluate the performance of the proposed SBEBF scheme with simulated data. The simulation parameters are in accordance with Table 1 and the 100th range cell is still taken as the RCUT. The parameter ρ_s is set to be 4. Here, all pre-filtering in elevation is cascaded by the diagonal loading sample matrix inversion (LSMI) method [27]. All presented results are averages over 100 independent Monte Carlo runs.

In the first experiment, the impact of both the value of parameter α and the number of elevation elements M to the performance of the SBEBF is investigated. The signal-to-clutter-noise ratio (SCNR) loss, which is defined by the ratio of the output SCNR to output signal-noise ratio (SNR) is used as a measure. The average SCNR loss is further defined as the mean of the SCNR loss for $f_d \in [(-1, 0.68) \cup (0.88, 1)]$. Fig. 5 shows the average SCNR loss of the SBEBF, where M is set to be 2, 3, 4 and 5, respectively and α varies from 0.05 to 0.4 with step size 0.05. The result in Fig. 5 indicates that: (i) the parameter α must be set to be relatively small to guarantee the SR performance when M is small; (ii) steady performance can be achieved with different α when M is bigger. In a word, the set of the scope of f_{se} for discretization is related with the number of elevation elements. With this fact in mind, we will use $M = 4$ and $\alpha = 0.1$ in the rest experiments.

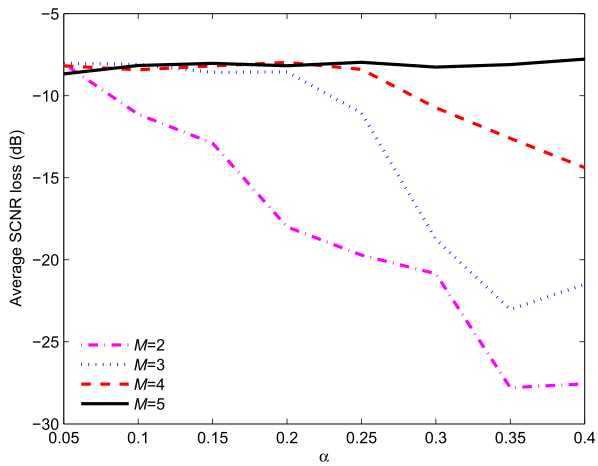


FIGURE 5. Average SCNR loss of SBEBF versus α.

In the second experiment, the performance of non-stationary clutter suppression at all range cells is examined. The residual clutter power in range-Doppler domain is compared between the conventional elevation beamforming (CEBF), in which the weight is equal to the space steering vector in elevation, and SBEBF in Fig. 6. As depicted in Fig. 6a, the range-dependent clutter is still severe after the CEBF and mainly located at the near range, which is in accordance with the theoretical analysis in Section 2. Obviously, the range-dependent clutter portion has been effectively eliminated via the SBEBF and the residual clutter is approximately stationary, as shown in Fig. 6b.

In the last experiment, we compare the SCNR loss of the SBEBF with the CEBF and existing elevation pre-filtering algorithms, such as the elevation spatial filtering (ESF) [12] and elevation adaptive digital beamforming (EADBF) in [13]. Since the earth surface is not truly spherical in real world

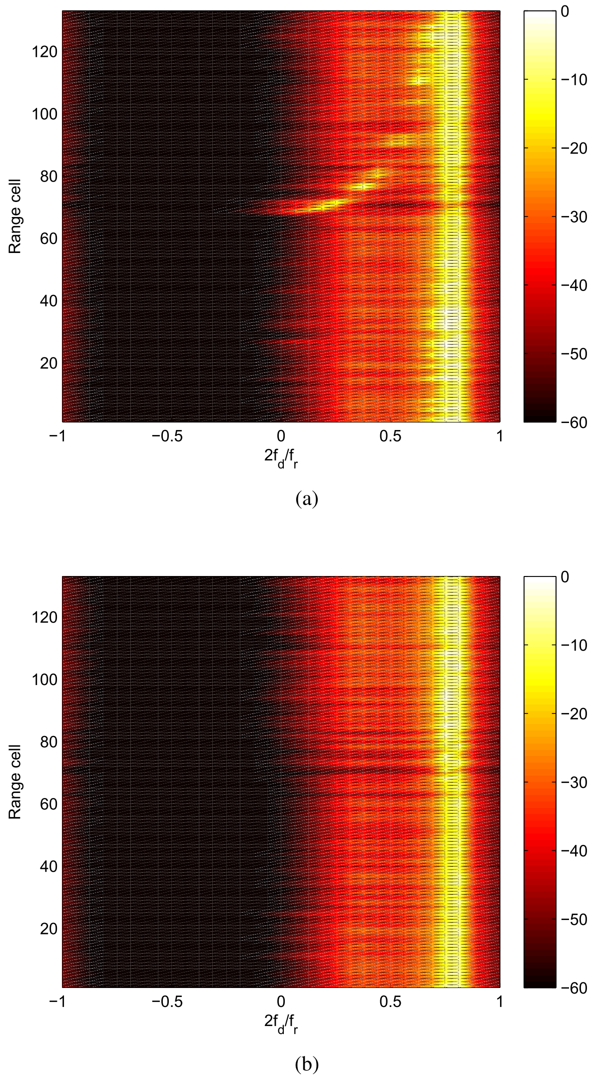


FIGURE 6. **Comparison of residual clutter power in range-Doppler domain. (a) CEBF. (b) SBEBF.**

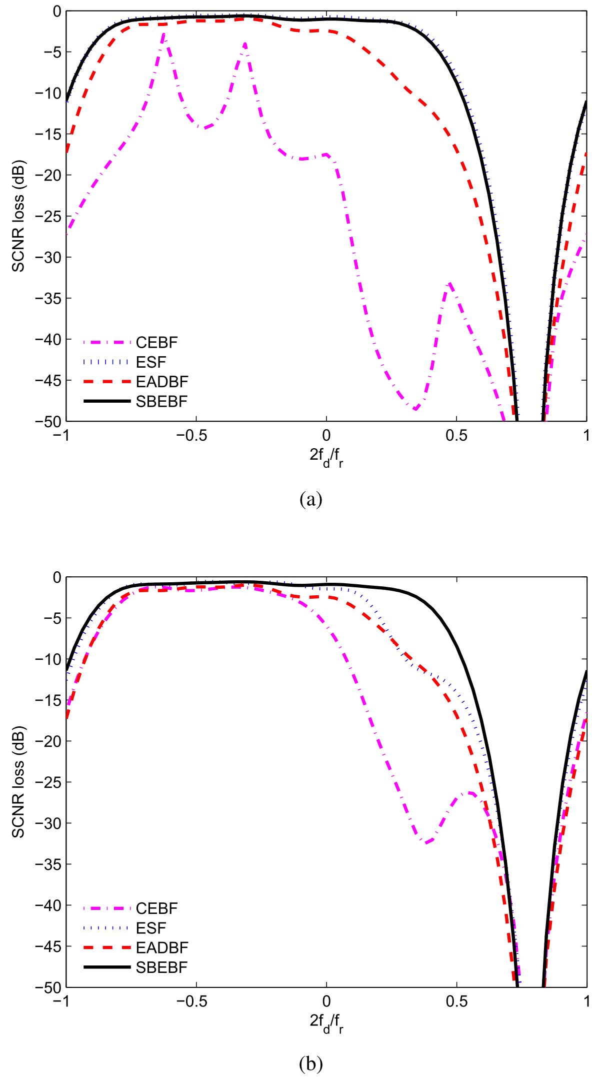


FIGURE 7. **SCNR loss comparison. (a) flat. (b) non-flat.**

applications due to terrain variations such as mountains, hills or basins, two simulated scenario includes flat and non-flat terrain are considered. The height of non-flat terrain is set to be 500m responding to hills compared with 0m for flat case, and thus φ_0 of the RCUT turns to be $-61.59°$ from $-67.82°$ and corresponding f_{se} increases about 0.05. The comparison of the SCNR loss of above mentioned algorithms is presented in Fig. 7. The results for flat terrain case is shown in Fig. 7a, the SCNR loss of the CEBF, which does not eliminate the non-stationary clutter via elevation beamforming, is most severe than other algorithms. Similarly, the SCNR loss of the SBEBF and ESF is approximately equal and both superior to the EADBF, in which only two elevation DOFs are available for adaptive beamforming. The comparison of performance for non-flat terrain case is depicted in Fig. 7b, where severely degradation occurs for the ESF. The reason is that the elevation beamforming of the ESF is non-adaptive with clutter data and thus is sensitive to the accuracy of φ_0. Obviously, the performance of proposed algorithm has not been affected by this error, in which the scope of f_{se} for SR is large enough and thus the bigger error for φ_0 is allowed. Similarly, the performance of the EADBF is still inferior to the SBEBF, and also not affected by the error of φ_0 because its adaptive beamforming is based on near-range clutter data.

V. CONCLUSIONS

In this paper, we have studied the problem of non-stationary clutter suppression in range ambiguous mode. Since the problem of range dependence is mostly related to near-range clutter induced from elevation sidelobe, the elevation adaptive beamforming technique can be utilized to eliminate the range-dependent clutter. However, the key of above technique is to obtain the near-clutter portion from the superposition of different ambiguous clutter. The main contribution of this paper is the presentation of a method for extracting the near clutter via SR technique, which is effective for non-stationary clutter suppression cascaded by existing azimuth-Doppler

STAP. Notice that the clutter data within different pulses are all utilized as multiple measurement vector to recover the near-range clutter sources, thus no training samples along range cells are needed. Furthermore, the novel method is not sensitive to the prior knowledge such as elevation angle of the RCUT because the near-clutter sources are adaptively recovered within a larger scope of elevation spatial frequency.

REFERENCES

[1] J. Ward, "Space-time adaptive processing for airborne radar," MIT Lincoln Lab., Lexington, MA, USA, Tech. Rep. 1015. Dec. 1994.

[2] R. Klemm, *Principles of Space-Time Adaptive Processing*, 3rd ed. London, U.K.: IET, 2006.

[3] Y.-L. Wang, Y. N. Peng, and Z. Bao, "Space-time adaptive processing for airborne radar with various array orientations," *IEE Proc.-Radar, Sonar Navigat.*, vol. 144, no. 6, pp. 330–340, Dec. 1997.

[4] O. Kreyenkamp and R. Klemm, "Doppler compensation in forward-looking STAP radar," *IEE Proc.-Radar, Sonar Navigat.*, vol. 148, no. 5, pp. 253–258, Oct. 2001.

[5] B. Himed, Y. Zhang, and A. Hajjari, "STAP with angle-Doppler compensation for bistatic airborne radars," in *Proc. IEEE Radar Conf.*, Long Beach, CA, USA, Apr. 2002, pp. 2750–2753.

[6] W. L. Melvin and M. E. Davis, "Adaptive cancellation method for geometry-induced nonstationary bistatic clutter environments," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 43, no. 2, pp. 651–672, Aug. 2007.

[7] M. Zatman, "Circular array STAP," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 36, no. 2, pp. 510–517, Apr. 2007.

[8] C.-H. Lim and B. Mulgrew, "Linear prediction of range-dependent inverse covariance matrix (PICM) sequences," *Signal Process.*, vol. 87, no. 6, pp. 1412–1420, Dec. 2007.

[9] S. Beau and S. Marcos, "Taylor series expansions for airborne radar space-time adaptive processing," *IET Radar, Sonar Navigat.*, vol. 5, no. 3, pp. 266–278, Mar. 2011.

[10] P. M. Corbell, J. J. Perez, and M. Rangaswamy, "Enhancing GMTI performance in non-stationary clutter using 3D STAP," in *Proc. IEEE Radar Conf.*, Boston, MA, USA, Apr. 2007, pp. 17–20.

[11] T. B. Hale, M. A. Temple, J. F. Raquet, M. E. Oxley, and M. C. Wicks, "Localised three-dimensional adaptive spatial-temporal processing for airborne radar," *IEE Proc.-Radar, Sonar Navigat.*, vol. 150, no. 1, pp. 18–22, Feb. 2003.

[12] X. Meng, T. Wang, J. Wu, and Z. Bao, "Short-range clutter suppression for airborne radar by utilizing prefiltering in elevation," *IEEE Geosci. Remote Sens. Lett.*, vol. 6, no. 2, pp. 268–272, Apr. 2009.

[13] M. Shen, X. Meng, and L. Zhang, "Efficient adaptive approach for airborne radar short-range clutter suppression," *IET Radar, Sonar Navigat.*, vol. 6, no. 9, pp. 900–904, Dec. 2012.

[14] S. F. Cotter, B. D. Rao, K. Engan, and K. Kreutz-Delgado, "Sparse solutions to linear inverse problems with multiple measurement vectors," *IEEE Trans. Signal Process.*, vol. 53, no. 7, pp. 2477–2488, Jul. 2005.

[15] M. E. Davies and Y. C. Eldar, "Rank awareness in joint sparse recovery," *IEEE Trans. Inf. Theory*, vol. 58, no. 2, pp. 1135–1146, Feb. 2012.

[16] D. P. Wipf and B. D. Rao, "An empirical Bayesian strategy for solving the simultaneous sparse approximation problem," *IEEE Trans. Signal Process.*, vol. 55, no. 7, pp. 3704–3716, Jul. 2012.

[17] D. Malioutov, M. Cetin, and A. S. Willsky, "A sparse signal reconstruction perspective for source localization with sensor arrays," *IEEE Trans. Signal Process.*, vol. 53, no. 8, pp. 3010–3022, Aug. 2005.

[18] I. W. Selesnick, S. U. Pillai, K. Y. Li, and B. Himed, "Angle-Doppler processing using sparse regularization," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process.*, Dallas, TX, USA, Mar. 2010, pp. 2750–2753.

[19] K. Sun, H. Meng, Y. Wang, and X. Wang, "Direct data domain STAP using sparse representation of clutter spectrum," *Signal Process.*, vol. 91, no. 9, pp. 2222–2236, Sep. 2011.

[20] Z. Yang, R. C. de Lamare, and W. Liu, "Sparsity-based STAP using alternating direction method with gain/phase errors," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 53, no. 6, pp. 2756–2768, Jun. 2017.

[21] X. Yang, Y. Sun, T. Zeng, T. Long, and T. K. Sarkar, "Fast STAP method based on PAST with sparse constraint for airborne phased array radar," *IEEE Trans. Signal Process.*, vol. 64, no. 17, pp. 4550–4561, Sep. 2016.

[22] Z. Wang, Y. Wang, K. Duan, and W. Xie, "Subspace-augmented clutter suppression technique for STAP radar," *IEEE Geosci. Remote Sens. Lett.*, vol. 13, no. 3, pp. 462–466, Mar. 2016.

[23] Z. Wang, W. Xie, K. Duan, and Y. Wang, "Clutter suppression algorithm based on fast converging sparse Bayesian learning for airborne radar," *Signal Process.*, vol. 130, no. 1, pp. 159–168, Jan. 2017.

[24] K. Duan, Z. Wang, W. Xie, H. Chen, and Y. Wang, "Sparsity-based STAP algorithm with multiple measurement vectors via sparse Bayesian learning strategy for airborne radar," *IET Signal Process.*, vol. 11, no. 5, pp. 544–553, Jan. 2017.

[25] K. Duan, W. Liu, G. Duan, and Y. Wang, "Off-grid effects mitigation exploiting knowledge of the clutter ridge for sparse recovery STAP," *IET Radar, Sonar Navigat.*, vol. 12, no. 5, pp. 557–564, Apr. 2018.

[26] Y. Guo, G. Liao, and W. Feng, "Sparse representation based algorithm for airborne radar in beam-space post-Doppler reduced-dimension space-time adaptive processing," *IEEE Access*, vol. 5, pp. 5896–5903, Apr. 2017.

[27] B. D. Carlson, "Covariance matrix estimation errors and diagonal loading in adaptive arrays," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 24, no. 4, pp. 397–401, Jul. 1998.

KEQING DUAN (M'15) was born in Hebei, China, in 1981. He received the B.S. and M.S. degrees from the Wuhan Early Warning Academy, Wuhan, in 2003, 2006, respectively, and the Ph.D. degree from the National University of Defense Technology, Changsha, China, in 2010, all in electrical engineering.

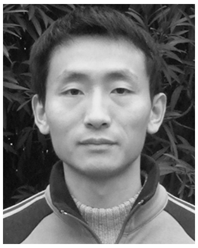
He is currently a Lecturer with the Key Laboratory of Radar Application Engineering, Wuhan Early Warning Academy. His research interests include space–time adaptive processing, radar signal processing, and sparse recovery technique.

HUADONG YUAN was born in Hubei, China, in 1985. He received the B.S. and M.S. degrees from the PLA University of Science and Technology, Nanjing, China, in 2007 and 2012, respectively.

He is currently pursuing the Ph.D. degree with the Wuhan Early Warning Academy, Wuhan, China. His current research interests include space–time adaptive processing, radar signal processing, multi-target tracking, and sparse recovery technique.

HONG XU was born in Sichuan, China, in 1991. He received the B.S. and M.S. degrees from the Wuhan Early Warning Academy, Wuhan, China, in 2013 and 2015, respectively.

He is currently pursuing the Ph.D. degree with the Department of Electrical Engineering, Naval University of Engineering, Wuhan. His current research interests include multi-target tracking, radar signal processing, and state estimation theory.



WEIJIAN LIU (M'14) was born in Shandong, China, in 1982. He received the B.S. degree in information engineering and the M.S. degree in signal and information processing from the Wuhan Radar Academy, Wuhan, China, in 2006 and 2009, respectively, and the Ph.D. degree in information and communication engineering from the National University of Defense Technology, Changsha, China, in 2014.

He is currently a Lecturer with the Key Laboratory of Radar Application Engineering, Wuhan Early Warning Academy. His current research interests include multichannel signal detection, and statistical and array signal processing.

YONGLIANG WANG was born in Zhejiang, China, in 1965. He received the Ph.D. degree in electrical engineering from Xidian University, Xi'an, China, in 1994.

From 1994 to 1996, he was a Post-Doctoral Fellow with the Department of Electronic Engineering, Tsinghua University, Beijing, China. He has been a Full Professor since 1996. He was the Director of the Key Research Laboratory, Wuhan Radar Academy, Wuhan, China, from 1997 to 2005. He was a recipient of the China Postdoctoral Award in 2001 and the Outstanding Young Teachers Award of the Ministry of Education, China, in 2001. He has authored or co-authored three books and more than 200 papers. His recent research interests include radar systems, space–time adaptive processing, and array signal processing.

Dr. Wang is a member of the Chinese Academy of Sciences and a fellow of the Chinese Institute of Electronics.