Clutter Mitigation for Joint RadCom Systems Based On Spatial Modulation

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Abstract—Joint radar and communication (RadCom) systems have been proposed to integrate radar and communication into one platform and achieve spectrum sharing in recent years. However, the joint RadCom systems cause the clutter modulation and the performance degradation of radar. Therefore, it’s very essential to improve the performance of radar when designing joint RadCom systems. This paper deals with the clutter mitigation for joint RadCom systems based on spatial modulation. The communication information embedding introduces variation of transmit beampatterns in a coherent processing interval (CPI) and causes the clutter modulation and spreading of the clutter spectrum. This paper proposes a reduced dimension spatial temporal adaptive processing (RD-STAP) method, i.e., we firstly perform time domain filtering and then perform spatial domain filtering on received data. As for time domain filtering, this paper mitigates the extended clutter by subspace projection (SP) and proposes a more effective eigen-decomposition algorithm based on Power method than singular value decomposition (SVD) to obtain clutter subspace basis vectors. And the matched filter is performed on the data after clutter mitigation to display the moving target. And receive beamforming is utilized for spatial domain filtering. Simulation results highlight the effectiveness of the proposed RD-STAP method and the eigen-decomposition algorithm.

Index Terms—Joint RadCom systems, Spatial modulation, Subspace projection, Clutter mitigation, Eigen-decomposition

I. INTRODUCTION

Joint RadCom systems, where the radar and communication systems utilize the same hardware platform and share the spectral resources, have been an effective way to achieve spectrum sharing [1]–[4]. As for the joint RadCom systems, where the radar is regarded as the primary function and the communication is regarded as secondary one, the main challenge is how to embed the communication symbols into the radar emission. Spatial modulation is widely utilized to embed communication symbols into the radar waveforms [5]–[10]. And the essence of spatial modulation is steer the mainlobe of the radar to the target of interest while designing the complex beampattern in the sidelobe to embed communication symbols. Therefore, joint RadCom systems inevitably introduce variations in radar beampatterns and cause clutter modulation problem and the spreading of the clutter spectrum.

In the literature, many clutter mitigation methods have been proposed. SP is usually utilized to mitigate the clutter [11]–[15], however, the basis vectors of clutter subspace are usually obtained by performing SVD on the covariance matrix, whose calculation complexity is very high. The Wiener filter, which can maximize the output signal to interference and noise ratio (SINR) [16]–[19], is widely utilized to mitigate the clutter in the literature. However, the computational complexity of matrix inversion is very high too. The authors in [20] make use of oblique projection (OP) to mitigate clutter, however, the desired signal subspace and clutter subspace should be known as prior information, which is usually not satisfied in practice. The authors in [21] analyzed the effect of spatial modulation on stationary clutter mitigation and proposed a calibrated matched filter based on SP. However, the ground reflection coefficients are assumed to be constant for each range cell and the Doppler frequency of the ground clutter is assumed as zero, which is usually not satisfied in practice. To the best of our knowledge, there is no existing work in the literature analyzing the effect of spatial modulation on clutter mitigation under more general clutter situation, which motivates our work.

In this paper, we assume the stationary clutter reflection coefficients obey the Gaussian distribution and analyze the effect of spatial modulation on stationary clutter mitigation for joint RadCom systems. We first design the beampatterns for joint RadCom systems based on spatial modulation under similarity constraint. After that, we analyze the slow-time signal model and the effect of spatial modulation. Finally, we propose a RD-STAP, i.e., we firstly perform time domain filtering and then perform spatial domain filtering on received data. As for time domain filtering, this paper mitigates the extended clutter by SP and proposes a more effective eigen-decomposition algorithm based on Power method than SVD to obtain clutter subspace basis vectors. And the matched filter is performed on the data after clutter mitigation to display the moving target. And receive beamforming is utilized for spatial domain filtering.

The reminder of this paper is organized as below. The spatial modulation based signaling strategy is described in Section II. The slow time signal model is presented in Section III. And the proposed RD-STAP and an effective eigen-decomposition method based on Power method are presented in Section IV. Simulation results are presented in Section V and conclusions are drawn in Section VI.

Notations: In this paper, the matrices and vectors are denoted by bold uppercase letters (i.e. A) and lowercase letters (i.e. a), respectively. The transpose and the conjugate operations are \( \cdot ^T \) and \( \cdot ^H \), respectively. \( \odot \) denotes the Hadamard element-wise product. \( \mathbb{C}^N \) denotes the set of \( N \)-dimensional vectors of complex numbers. \( \mathbf{I} \) denotes the identity matrix, whose dimension is determined by the context. \( \mathbb{E}\{\cdot\} \) denotes the mathematical expectation. \( | \cdot | \) denotes the module of a complex number, \( a^* \) denotes the conjugate of \( a \) and \( \|\mathbf{b}\| \)
denotes the Euclidean norm of the vector $b$. $\text{diag}\{b\}$ denotes the diagonal matrix whose $i$-th diagonal element is the $i$-th entry of $b$. $B^{-1}$ denotes the inverse matrix of the invertible matrix $B$. $CN(\alpha, \sigma^2)$ denotes a complex Gaussian distribution with mean $\alpha$ and variance $\sigma^2$. $\text{span}(A)$ denotes the subspace spanned by the column vectors of $A$. $j$ denotes the imaginary unit.

II. SPATIAL MODULATION BASED SIGNALLING STRATEGY

The phase modulation (PM) signalling strategy, which modulates the phase of the transmit beam patterns towards the communication direction, is the generalized mathematical formulation of existing spatial modulation techniques in joint RadCom systems.

Suppose a joint RadCom platform which is equipped with a $M$-element uniform linear array (ULA) with inter-element spacing of half wavelength. We assume that the same array is used for transmit and receive [22]. Suppose $L$ bits communication information are embedded in each pulse, the number of phase symbols is $K = 2^L$. In the previous literature, the similarity between different beampatterns is not considered. However, the similarity between different beampatterns is very essential to the performance of radar. As a consequence, we design the beamforming weight vectors under similarity constraint in this paper.

The first beamforming weight vector for the PM-based signalling strategy can be obtained by solving the following optimization problem:

$$
\begin{align*}
\min_{w_k} \quad & \max_{\theta} |w_k^H a(\theta)| \\
\text{subject to} \quad & w_k^H a_i = 1 \\
& w_k^H a_c = \Delta e^{j\phi_k}, \quad k = 1, \ldots, K
\end{align*}
$$

where $\Theta$ is the radar sidelobe region, $\Delta$ denotes the sidelobe level towards the communication direction, $a_i = [1, e^{-j2\pi \frac{d}{\lambda} \sin \theta_1}, e^{-j2\pi \frac{d}{\lambda} \sin \theta_2}, \ldots, e^{-j2\pi (M-1) \frac{d}{\lambda} \sin \theta_1}]^T$ and $a_c = [1, e^{-j2\pi \frac{d}{\lambda} \sin \theta_1}, e^{-j2\pi \frac{d}{\lambda} \sin \theta_2}, \ldots, e^{-j2\pi (M-1) \frac{d}{\lambda} \sin \theta_1}]^T$. $\phi_k$ denotes the steering vector of the target and communication receiver, $\theta_i$ and $\theta_c$ denotes the direction of the target and communication receiver, and $w_k$ is the $k$-th beamforming weight vector to form the beampattern whose phase towards the communication receiver located at $\phi_k$. Every phase $\phi_k$ is chosen from a predefined dictionary $\Omega = [\phi_1, \phi_2, \ldots, \phi_K]$ containing $K$ different phase symbols uniformly distributed in $[0, 2\pi]$, i.e., $\phi_k = \frac{(k-1)2\pi}{K}$.

As for the rest $K-1$ beampatterns, we aim to enforce the similarity constraint to control the similarity between the rest beampatterns with the first beampattern [23], which can be formulated as

$$
\|w_k - w_1\|^2 \leq \delta, \quad 2 \leq k \leq K
$$

where $0 \leq \delta$ denotes the similarity between two weight vectors. $\delta$ can achieve the tradeoff of the performance of radar and communication. The smaller $\delta$ is, the more identical between different radial waveforms are, which contributes to reduce clutter modulation and the spreading of the clutter spectrum. But the distance between different phase symbols in phase constellation becomes shorter, which increases the bit error rate (BER). As a consequence, $\delta$ should be carefully chosen to balance the performance of radar and communication.

The design for the rest $K-1$ beampatterns can be formulated as

$$
\begin{align*}
\min_{w_k} \quad & \max_{\theta} |w_k^H a(\theta)| \\
\text{subject to} \quad & w_k^H a_i = 1 \\
& w_k^H a_c = \Delta e^{j\phi_k}, \quad 2 \leq k \leq K
\end{align*}
$$

The optimization problem $P_1$ and $P_2$ are all convex, and can be solved by interior point method [24].

III. SLOW TIME SIGNAL MODEL

Consider the joint RadCom platform transmits a burst of $N$ slow-time pulses in a CPI. The transmit weight matrix $W = [w_1, w_2, \ldots, w_N] \in \mathbb{C}^{M \times N}$ modulate the radar pulses. Each column vector of $W$ is chosen from the $K$ vectors obtained by solving $P_1$ and $P_2$. The slow-time observation matrix $Y \in \mathbb{C}^{M \times N}$ in a CPI can be formulated as

$$
\begin{align*}
Y &= S + C + N \\
&= \alpha_t \tilde{d}_i(1)a_i, \tilde{d}_i(2)a_i, \ldots, \tilde{d}_i(N)a_i + C + N \\
&= [y_1, \ldots, y_M]^T
\end{align*}
$$

where $y_m \in \mathbb{C}^N$ denotes the data vector received by $m$-th antenna during the CPI, $\alpha_t$ denotes the complex scattering coefficient of the target of interest, $\lambda$ denotes the wavelength, $d$ denotes the array element spacing, $d_i = s \odot [1, e^{j2\pi \psi_1}, e^{j2\pi (2\psi_1)}, \ldots, e^{j2\pi (N-1)\psi_1}]^T$ denotes the temporal steering vector, $s = W^H a_i$, $\psi_t = f_{d/t}/T$ is the normalized target Doppler frequency with $f_{d/t}$ the actual target Doppler frequency and $T$ the pulse repetition interval (PRI). The $M \times N$-dimensional matrix $N$ denotes signal-independent noise samples, which is modeled as zero-mean random matrix with independent and identically distributed (IID) entries.

This paper considers the range unambiguous clutter situation, meaning that only clutter returns from a single range ring competes with potential targets in the cell under test (CUT). Specifically, the clutter matrix $C$ can be formulated as

$$
C = \sum_{i=1}^{N_c} \beta_i [\tilde{d}_i(1)a_i, \tilde{d}_i(2)a_i, \ldots, \tilde{d}_i(N)a_i],
$$

where $N_c$ denotes the number of discrete azimuth bins within the single range ring, $a_i = [1, e^{-j2\pi \frac{d}{\lambda} \sin \theta_1}, e^{-j2\pi \frac{d}{\lambda} \sin \theta_2}, \ldots, e^{-j2\pi (M-1) \frac{d}{\lambda} \sin \theta_1}]^T$, $\tilde{d}_i = b_i \odot d_i$ and the vector $b_i = W^H a_i$ denotes the variation of the temporal steering vector $d_i = [1, e^{j2\pi \psi_1}, e^{j2\pi (2\psi_1)}, \ldots, e^{j2\pi (N-1)\psi_1}]^T$ introduced by spatial modulation. What’s more, $\beta_i, \psi_t$ and $\psi_t$ indicate the complex scattering coefficient, the azimuth, and the normalized Doppler frequency of the scatter in the $i$-th azimuth bin, respectively. Without loss of generality, we assume that $\psi_t$ is uniformly distributed around a mean normalized Doppler frequency $\bar{\psi}_t$ in normalized Doppler interval $[\bar{\psi}_t - \epsilon_t/2, \bar{\psi}_t + \epsilon_t/2]$, where $\epsilon_t$ accounts for the uncertainty on the clutter Doppler, i.e., $\psi_t \sim U(\bar{\psi}_t - \epsilon_t/2, \bar{\psi}_t + \epsilon_t/2)$. 


When there is no information embedding in the radar pulses, the values of complex beampattern keep identical over \( N \) pulses and \( C \) can be rewritten as
\[
C = \sum_{i=1}^{N_c} \beta_i b_i [d_i(1) a_i, d_i(2) a_i, \ldots, d_i(N) a_i],
\]
where \( b_i = w_i^H a_i \).

When spatial modulation is utilized to embed communication symbols, the complex beampattern changes over different pulses disturbs the Doppler coherence of clutter returns, resulting in clutter modulation and the undesired spreading of the clutter spectrum. Traditional clutter mitigation methods, such as two-pulse canceler (TPC) [25], can’t mitigate the extended clutter effectively.

IV. CLUTTER MITIGATION BASED ON SUBSPACE PROJECTION

A. Covariance matrix of the clutter

We assume that reflection coefficients in different azimuth bins are IID with a distribution of \( CN(0, \sigma_c^2) \) where \( \sigma_c^2 \) denotes the power of the clutter and the clutter is assumed as stationary clutter, i.e., \( \psi_1 = \psi_2 = \cdots = \psi_N_c = 0 \). Without loss of generality, we assume that \( \epsilon_1 = \epsilon_2 = \cdots = \epsilon_{N_c} = \epsilon \). Consider the clutter and noise vector received by the \( m \)-th antenna during the CPI, we have that
\[
\tilde{y}_m = c_m + n_m,
\]
 where \( c_m \) and \( n_m \) is the \( m \)-th row of \( C \) and \( N \), respectively.

What’s more, we assume that \( \mathbb{E}[n_m] = 0 \) and \( \mathbb{E}[n_m n_m^H] = \sigma_n^2 I \), where \( \sigma_n^2 \) denotes the noise power. As a consequence, the covariance matrix of \( c_m \) can be formulated as [26]
\[
R_{(c,m)} = \mathbb{E}[c_m c_m^H] = \sum_{i=1}^{N_c} \mathbb{E}[|\beta_i|^2 a_i^H(m) (b_i \otimes d_i)] (b_i \otimes d_i)^H \]

where
\[
\mathbb{E}[|\beta_i|^2] = \sigma_c^2 (i = 1, \ldots, N_c) \quad \text{and} \quad \Phi \in \mathbb{C}^{N \times N} \quad \text{can be formulated as}
\]
\[
\Phi(l, m) = \mathbb{E}\{e^{2\pi i (l-m) / \psi} \}
= \int_{-\frac{\psi}{2}}^{\frac{\psi}{2}} e^{2\pi i (l-m) / \psi} \frac{1}{\epsilon} d\psi
= \begin{cases} 
1, & \text{if } l = m \\
\sin[\pi (l-m) / \psi] / \pi (l-m), & \text{otherwise}.
\end{cases}
\]

Therefore, the covariance matrix of \( \tilde{y}_m \) can be formulated as
\[
R_m = \mathbb{E}[\tilde{y}_m \tilde{y}_m^H] = \mathbb{E}\{ (c_m + n_m)(c_m + n_m)^H \}
= R_{(c,m)} + \sigma_n^2 I.
\]

As can be seen from Eq.(8) and Eq.(10), the covariance matrix of \( \tilde{y}_m \) is irrelevant with the antenna index \( m \). Therefore, we propose a RD-STAP, i.e., we firstly perform time domain filtering and then perform spatial domain filtering on received data. The framework of proposed RD-STAP is shown in Fig.1

In the following, we omit the subscript \( m \) of \( R_m \) and \( R_{(c,m)} \), i.e., \( R_m \) is replaced with \( R \) and \( R_{(c,m)} \) is replaced with \( R_c \).

1-th antenna

M-th antenna

Receive beamforming

\[
\mathbb{E}[|\beta_i|^2] = \sigma_c^2 (i = 1, \ldots, N_c) \quad \text{and} \quad \Phi \in \mathbb{C}^{N \times N} \quad \text{can be formulated as}
\]
\[
\Phi(l, m) = \mathbb{E}\{e^{2\pi i (l-m) / \psi} \}
= \int_{-\frac{\psi}{2}}^{\frac{\psi}{2}} e^{2\pi i (l-m) / \psi} \frac{1}{\epsilon} d\psi
= \begin{cases} 
1, & \text{if } l = m \\
\sin[\pi (l-m) / \psi] / \pi (l-m), & \text{otherwise}.
\end{cases}
\]

B. Subspace projection method

It is known that the clutter covariance matrix \( R_c \) can be eigen-decomposed by
\[
R_c = \sum_{i=1}^{r} \lambda_i u_i u_i^H = U_c \Delta_c U_c^H,
\]
where \( \Delta_c \) is the diagonal matrix \( \text{diag}(\lambda_1, \lambda_2, \cdots, \lambda_r) \) containing the eigenvalues of \( R_c \). \( U_c \) is the matrix composed of the corresponding eigenvectors, i.e., \( U_c = [u_1, u_2, \cdots, u_r] \). \( r \) denotes the rank of \( R_c \).

The clutter plus noise covariance matrix is formulated as
\[
R = R_c + \sigma_n^2 I.
\]

The eigen-decomposition of \( R \) is
\[
R = \sum_{i=1}^{r} \lambda_i u_i u_i^H + \sigma_n^2 \sum_{i=r+1}^{N} u_i u_i^H = U_c \Delta_c U_c^H + U_n \Delta_n U_n^H,
\]
where $\Delta_n = \text{diag}\{\lambda_{r+1}, \ldots, \lambda_N\}$, $\lambda_{r+1} = \cdots = \lambda_N = \sigma_n^2$ and $U_n$ is the matrix composed of the corresponding eigenvectors. The clutter subspace spanned by the eigenvectors can be denoted by

$$\text{span}(R_c) = \text{span}(U_c).$$

The clutter subspace contains almost all the information about the temporal steering vectors constructing the clutter data, the clutter components in the received signal can be rejected by projecting the received signal into the subspace orthogonal to the clutter subspace, i.e., noise subspace. The projection matrix can be formulated as

$$P = I - U_c(U_c^H U_c)^{-1} U_c^H.$$

The projected vector can be formulated as

$$\hat{y}_m = P^H y_m. \quad (15)$$

Considering the case where the Doppler frequency of the target of interest is unknown, the matched filter is performed on the projected vector $\hat{y}_m$ to display the moving target, which can be formulated as

$$g(\psi) = \hat{d}^H(\psi) \hat{y}_m = \hat{d}^H(\psi) P^H y_m = (P \hat{d}(\psi))^H y_m. \quad (17)$$

where $g(\psi)$ denotes the output of the matched filter corresponding to normalized Doppler frequency $\psi$, $\psi \in [-0.5, 0.5]$ denotes the normalized Doppler frequency of interest and $d(\psi) = s \circ \{1, e^{j2\pi\psi}, e^{j2(\pi/2)}, \ldots, e^{j2(N-1)\psi}\}^T$ denotes the weight vector of the calibrated matched filter matched to the normalized Doppler frequency $\psi$. The moving target can be detected by peak detection. As a result, the weight vector of Doppler filter bank is given by

$$w(\psi) = P \hat{d}(\psi). \quad (18)$$

where $w(\psi)$ is matched to the normalized Doppler frequency $\psi$.

The output SINR versus normalized Doppler frequency of interest can be formulated as

$$\text{SINR}(\psi) = \frac{|\alpha_k|^2 |w^H(\psi)d(\psi)|^2}{w^H(\psi) R w(\psi)}. \quad (19)$$

We apply the receive beamforming to the Doppler filter output of all $M$ antennas and obtain

$$\hat{P}(u, \psi) = a^H(u) \left( w^H(\psi)[y_1, \ldots, y_M] \right)^T, \quad (20)$$

where $\hat{P}(u, \psi)$ denotes the output versus electrical angle $u$ and normalized Doppler frequency $\psi$, and $a(u) = [1, e^{-j2\pi \frac{u}{2}}, e^{-j2\pi \frac{u}{4}} u, \ldots, e^{-j2\pi \frac{(M-1)u}{2}}]^T$ denotes the spatial steering vector.

The eigen-decomposition of $R$ is usually based on SVD [11]. However, it’s not necessary to calculate all eigenvalues and eigenvectors of $R$, since only clutter subspace is utilized to mitigate the clutter. What’s more, the dimension of the clutter subspace is smaller than that of the $R$ according to the Brennan’s rule [30], i.e., $r < N$. When the noise power $\sigma_n^2$ at the radar receiver is known as prior information, we propose an algorithm to obtain clutter subspace basis vectors based on Power method, which is more effective than SVD. Suppose that the eigenvalues of the $R$ are $\lambda_1, \lambda_2, \ldots, \lambda_N$, respectively.

And $\lambda_1 > \lambda_2 > \cdots > \lambda_r > \lambda_{r+1} = \lambda_{r+2} = \cdots = \lambda_N = \sigma_n^2 > 0$, which is always satisfied in practice, and the corresponding eigenvectors are $u_1, u_2, \ldots, u_N$, respectively. The clutter rank is defined as the number of the eigenvalues of $R$ that are bigger than noise power $\sigma_n^2$. This paper proposes an effective eigen-decomposition algorithm based on Power method to obtain the clutter subspace basis vectors, i.e., $r$ dominant eigenvectors of $R$.

The Power method is usually utilized to determine the dominant eigenvalue of a matrix—that is, the eigenvalue with the largest magnitude [31]. Besides, the eigenvector corresponds to the eigenvalue with the largest magnitude is calculated at the same time. Assume $\lambda_1$ is the eigenvalue with the largest magnitude of $R$ and $u_1$ is the corresponding eigenvector. In order to calculate the eigenvalue with the second largest magnitude of $R$ and the corresponding eigenvector, we perform Power method on the matrix $R - \lambda_1 u_1 u_1^H$. Repeat the above process until the basis vectors of clutter subspace are obtained. The detailed description of proposed eigen-decomposition method is shown in Algorithm 1.

**Algorithm 1 Proposed eigen-decomposition algorithm based on Power method**

**Input:** $N$, $R$, $\sigma^2$, $\ell$, $0 < v_0 \in \mathbb{C}^N$ ($v_0 \neq 0$), $\gamma = 10^{-3}$; $\lambda_1, \lambda_2, \ldots, \lambda_\ell$, $U_c = [u_1, u_2, \ldots, u_\ell]$, $\ell$;

1: for $i = 1$; $i <= N$; $i + +$ do
2: $\xi = 1$, $k = 1$;
3: while $\xi \geq \gamma$ do
4: $\eta_{k-1} = \|v_{k-1}\|_2$;
5: $y_{k-1} = v_{k-1}/\eta_{k-1}$;
6: $v_k = R y_{k-1}$;
7: $\theta_k = y_{k-1}^H v_k$;
8: if $k >= 2$ then
9: $\xi = |\theta_k|/|\theta_{k-1}|$;
10: end if
11: $k = k + 1$;
12: end while
13: $u_i = y_{k-1}$, $\lambda_i = \theta_k$;
14: if $\lambda_i <= \sigma^2$ then
15: Break;
16: end if
17: $R = R - \lambda_i u_i u_i^H$;
18: $\ell = \ell + 1$;
19: end for

$\lambda_1, \ldots, \lambda_\ell$ are the obtained eigenvalues of covariance matrix $R$, which satisfies $\lambda_1 > \lambda_2 > \cdots > \lambda_\ell > \sigma_n^2$, and $u_1, \ldots, u_\ell$ are the corresponding eigenvectors. In this paper, $u_1, \ldots, u_\ell$ are utilized to establish the clutter subspace, i.e., $U_c = [u_1, \ldots, u_\ell]$. The principle of Algorithm 1 is to calculate the $r$ dominant eigenvalues and corresponding eigenvectors of $R$ in turn based on Power method.

The computational complexity of minimum variance distortionless response (MVDR) beamformer with full Degrees of Freedom (DoF) is very high, since the computational complexity of inverse of the $NM \times NM$ dimensional covariance matrix is $O((MN)^3)$ [32]. The computational complexity of
performing SVD on $\mathbf{R}$ is $O(N^3)$. The computational complexity of performing proposed eigen-decomposition method on $\mathbf{R}$ is $O(N^2r)$ ($r < N$). It’s obvious that the less clutter rank $r$ is, the more effective the proposed method is, since the iteration number becomes less. As a result, the proposed eigen-decomposition method is more effective than SVD and the RD-STAP is more effective than MVDR beamformer with full DoF too.

V. SIMULATION RESULTS

In this section, simulation results are presented to illustrate the benefits of the proposed method. The dual-function platform is equipped with a 10-element ULA with an inter-element spacing of half-wavelength. The CPI consists of $N = 40$ pulses where the transmit weight vector for each pulse is randomly selected from the specially designed set. The sidelobe region of the radar is set as $\Theta = [-90^\circ, -10^\circ] \cup [10^\circ, 90^\circ]$. As for the parameters of the clutter, the clutter power is set as $\sigma_c^2 = 50$dB. We only consider the clutter located in $[-60^\circ, 60^\circ]$ where the clutter range ring is divided into 100 discrete clutter patches, i.e., $\bar{N}_c = 100$. The noise power is set as $\sigma_n^2 = 0$dB and the signal to noise ratio (SNR) is 5dB. The sidelobe level towards the communication direction is set as $\Delta = 10^{-2}$ and $\delta = 0.016$. What’s more, the normalized Doppler interval of the clutter is set as $\epsilon = 0.008$.

In the simulation, we assume the target, whose normalized Doppler frequency is 0.4, is located $0^\circ$. And the complex scattering coefficient of the target is set as $\alpha_t = 1$. A single communication receiver is located at $\theta_c = -50^\circ$. We assume that 2 bits of communication information are transmitted in every radar pulse, i.e., $K = 4$. For the PM based signalling strategy mentioned above, the phase symbols are $0$, $\pi/2$, $\pi$ and $3\pi/2$ radian, respectively, as shown in Fig. 2(a).

Fig. 2(b) shows the four transmit patterns with different phases and the four beampatterns are much similar, which contributes to decrease the range sidelobe modulation. At the same time, the phases of the four beampatterns towards the communication direction are equal to the predefined phase symbols.

As for the non spatial modulation and spatial modulation, the eigenvalues of covariance matrix $\mathbf{R}$ are shown in Fig. 3 and the corresponding clutter rank are 7 and 14, respectively. Therefore, spatial modulation causes the increase of the clutter rank.

We also adopt the Wiener filter proposed in [16], Doppler processing (DP), DP after two pulses canceler (DP-TPC) and SP based on SVD (SP-SVD) [11] to compare clutter mitigation performance. As for the non spatial modulation and spatial modulation, the output power versus normalized Doppler frequency at zero-azimuth based on these methods are shown in Fig. 4. As shown in the picture, the spatial modulation causes the spreading of the clutter spectrum and the TPC can’t mitigate the clutter and the target is masked by the extended clutter. What’s more, the Wiener filter bank can mitigate the clutter effectively and the target can be detected by peak detection. Besides, the performance of clutter mitigation based on SP is very close to the performance of Wiener filter bank. And the performance of the proposed method is better than SP-SVD.

Fig. 5 shows the output SINR versus normalized Doppler frequency for non spatial modulation and spatial modulation. As shown in the picture, the output SINR of matched filter is lowest. And the output SINR of proposed method is vary close to the Wiener filter and is bigger than the SP-SVD too.

Fig. 6 shows the angle-Doppler map using standard Doppler and receive matched filter and proposed RD-STAP when nonspatial modulation is utilized. As shown in the figure, the proposed clutter mitigation method can effectively mitigate the clutter.

Fig. 7 shows the angle-Doppler map using standard Doppler and receive matched filter and proposed RD-STAP when spatial modulation is utilized. Compare Fig. 6(a) and Fig. 7(a) the spatial modulation causes the spreading of the clutter spectrum and the target is masked by the extended clutter. What’s more, the proposed clutter mitigation method can mitigate the extended clutter.

We perform 3000 Monte Carlo simulations to calculate the average running time of eigen-decomposition based on proposed method and SVD on a PC (3.0GHz Intel(R) Core(TM) i7-9700 CPU, 8GB RAM). The average run time of the proposed algorithm and SVD algorithm are provided in Table I. It can be observed that the proposed algorithm is faster than the counterpart. This is due to the proposed algorithm only calculate a few eigenvalues and eigenvectors rather than all eigenvalues and corresponding eigenvectors.
Fig. 3. Eigenvalues of covariance matrix $\mathbf{R}$

(a) non spatial modulation

(b) spatial modulation

Fig. 4. Output power versus normalized Doppler frequency at zero-azimuth

VI. CONCLUSION

In this paper, we design the beampatterns for joint RadCom systems based on spatial modulation and analyse the effect of spatial modulation on clutter mitigation. The joint RadCom systems based on spatial modulation introduce variations in radar beampatterns and causes clutter modulation problem and the spreading of the clutter spectrum. We present analysis of the slow-time received signal model of spatial modulated shared waveforms and proposed an effective RD-STAP method, i.e., we firstly perform time domain filtering and then

| Algorithm         | SVD  | Proposed algorithm |
|-------------------|------|--------------------|
| Average computational time [ms] | 0.2192 | 0.199 |

Fig. 5. Output SINR versus Doppler frequency at zero-azimuth

(a) non spatial modulation

(b) spatial modulation

Fig. 6. Angle-Doppler map when nonspatial modulation is utilized

(a) Angle-Doppler map using standard Doppler and receive matched filter

(b) Angle-Doppler map using proposed RD-STAP
perform spatial domain filtering. As for time domain filtering, we propose an effective method based on SP to mitigate the extended clutter and an more effective eigen-decomposition algorithm based on Power method than SVD to obtain the basis vectors of the clutter subspace. After that, matched filter is performed on the data after clutter mitigation to display the moving target. And receive beamforming is utilized for spatial domain filtering. The computational complexity of the proposed RD-STAP is much lower than that of MVDR with full DoF. Simulation results validate that the proposed solutions are capable of mitigating the clutter effectively without affecting the dual functions of joint RadCom systems.

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