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STAP-Based Airborne Radar System for Maneuvering Target Detection

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ABSTRACT With the rapid development of unmanned aerial vehicle (UAV), techniques are required for the detection and surveillance of such UAVs for both civil and military purposes. This paper addresses the maneuvering target detection with an airborne radar system based on a space–time adaptive processing (STAP) technique. A general signal model is established for the moving target, where the target is parameterized with angle, velocity, acceleration, and backscattering coefficient. A general adaptive matched filtering method is proposed involving multiple-dimensional search. An enhanced approach is devised by using a discrete searching technique within the acceleration dimension in order to reduce the computational complexity. The simulation examples are provided to demonstrate the effectiveness of the proposed method.

INDEX TERMS Airborne radar system, space-time adaptive processing, unmanned aerial vehicle, multiple-dimensional search, discrete searching technique, discrete step size.

I. INTRODUCTION

Airborne radar systems have great superiority in performing continuous surveillance of valuable moving target. It is known that airborne radar encounters serious ground/sea clutter whose Doppler spectrum spreads wildly. Space-time adaptive processing (STAP) technique plays an important role in suppressing the ground/sea clutter and interference by jointly exploiting degrees-of-freedom (DOFs) in both spatial and temporal domains [1], [2]. Recently development of unmanned aerial vehicle (UAV) technique boosts various applications, including both civil and military purposes. It is difficult to detect such UAVs in a complex electromagnetic environment even they have approached with quite short distances, which calls for enhanced signal processing techniques.

Conventional STAP methods involve huge DOFs in spatial and temporal domains, resulting in great amount of training samples for covariance matrix estimation. Generally, the covariance matrix of clutter and interference is usually estimated with the training data collected from ranges adjacent to the range under test. The amount of training data required for proper estimation of the covariance matrix is between 2 and 5 times the number of DOFs of the processor, provided that the training data satisfies the identical independent distribution (IID) condition [3]. This is a challenge for STAP with its DOFs equal to NK (N is element number, K is pulse number) [4]. To maintain the performance of STAP methods with limited sample supports, some suboptimal STAP approaches have been proposed [1], [5], [6]. In practice, the training support may follow different statistical distribution, which stimulates the research on sparse recovery based STAP approaches by exploiting the intrinsic sparse property of clutter echo [7]–[9]. Additionally, the performance degradation of STAP methods in practical applications may also attribute to the range dependence of clutter. To handle this problem, many clutter compensation techniques have been suggested [10]–[14]. It is noticed that, the aforementioned methods are mainly focus on suppressing clutter as much as possible, which is still a prospective topic due to various practical issues.

With the development of supper-high speed moving targets, efforts are paid to maximize output signal power by coherent accumulation of target. It is reported to use

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generalized constraints in adaptive beamforming to enhance detection performance of fast-moving target in [15], where the spatial-temporal defocusing of fast-moving target is addressed. The detection of fast-moving target has gained increasing interest in recent years with the development of super-high speed vehicles [16], [17]. The unmanned vehicle can reach a speed as high as 1000-2500 m/s [18]. In practice, the presumed parameters of moving target are usually mismatched with their true value, which will cause performance degradation of conventional STAP processors based on minimum variance distortionless response criterion. In [19], [20], a general magnitude and phase constrained STAP method is devised and the reference point of array is choosing as the first element for convenience. It shows the importance of reference point when design adaptive beamformers. In [21], [22], the robust adaptive beamforming techniques are proposed for multi-sensor array and STAP applications by using mainlobe control and steering vector constraints. Fast-moving UAVs usually move at high altitude and those slow-moving UAVs commonly appear at low altitude. It is reported that many kinds of UAVs fly at low altitude with small radar cross sector (RCS) and they are wildly used for civil and military purposes. They are not easy to be detected because their velocities are within the gap of synthetic aperture radar and STAP based radar [23]. Firstly, these UAVs are usually beyond the sight of most ground based radars. Secondly, serious performance loss occurs when performing coherent accumulation of such UAVs. There are some methods proposed for handling moving target refocusing in synthetic aperture radar [24]–[26], however, these methods are applicable for the relatively long coherent processing interval case and cannot be directly applied for the short coherent processing interval case. Since the UAVs show obvious non-linear phase variation over slow time due to its rotation wings, it is possible to classify the UAVs by their micro-Doppler properties [27], [28]. The micro-Doppler property can be extracted even in short coherent processing interval case, which indicates that high-order variation of phase history of moving target can be utilized to enhance the performance.

In this paper, the detection of maneuvering target is considered with STAP-based radar system. In this work, we present the phase history of moving target considering the acceleration and establish the general signal model. Such non-linear variation with respect to slow time will cause spectrum defocusing and result in performance degradation in STAP method. To alleviate this issue, a general adaptive matched filtering method is proposed in this paper, where the spatial and temporal steering vectors are extended to include spectrum defocusing case. It is pointed out that the spatial spectrum defocusing of target occurs in near-field situation and can be neglected in far-field situation [29]. Discrete searching technique is performed to obtain the estimates of velocity and acceleration. It is found that large step size can be used in the acceleration dimension, which requires slight increment of the computational complexity.

The remainder of this paper is organized as follows. Section II presents the signal model of the airborne array radar, where the maneuvering target signal is parameterized with angle, velocity, acceleration, as well as backscattering coefficient. A multiple-dimensional search method is proposed for extracting the parameters of the moving target in Section III. Simulation results and performance analysis are given in Section IV with conclusion remarks are drawn in Section V.

II. SIGNAL MODEL OF STAP-BASED RADAR WITH MANEUVERING TARGET

Without loss of generality, we consider a uniform linear array consisting of M elements and side-mounted on an airplane. The array elements are arranged along x-axis with inter-spacing d. All elements are assumed to be identical, omnidirectional, and isotropic. A total of K pulses are transmitted during the coherent processing interval. Within the processing interval, the initial velocity of the airplane is v_0 in the direction of x-axis denoted with $\mathbf{e}_v = (1, 0, 0)^{\mathrm{T}}$, thus the velocity of airplane can be expressed as $v_0\mathbf{e}_v$. The height of the airplane is H. Consider an arbitrary clutter patch on the ground and its direction vector is defined as $\mathbf{e}_i = (\cos(\varphi)\cos(\theta), \cos(\varphi)\sin(\theta), \sin(\varphi))^{\mathrm{T}}$ with φ and θ being the elevation and azimuth angles, respectively. The ground within an iso-range ring is divided into many independent clutter patches whose radar cross sectors are assumed to be Ryleigh distributed.

Suppose a maneuvering target with radial direction vector $\mathbf{e}_s = (\cos(\varphi_s)\cos(\theta_s), \cos(\varphi_s)\sin(\theta_s), \sin(\varphi_s))^{\mathrm{T}}$ corresponding to the radar platform. Note that the initial velocity of the moving target is $\mathrm{v_s}$ and its acceleration velocity is $\mathrm{a_s}$, both defined in the radial direction outwards the radar. Thus, the velocity of moving target can be written as $\mathbf{v}_s = (v_s + a_s t)\,\mathbf{e}_s$ in the three-dimensional coordinate system. For the m-th element and k-th pulse, the received echo of moving target is denoted as $x_{mk}(t - \tau_s(m,k))$, where $\tau_s(m,k) = \frac{R_s(m,k)}{c}$ is the time-delay and $R_s(m,k)$ is written as

$$\begin{aligned} R_s(m,k) &= 2R_0 - (m-1)\,d\cos(\varphi_s)\cos(\theta_s) \\ &\quad - 2\left(v_0 t_k \cos(\varphi_s)\cos(\theta_s) - \left(v_s t_k + \frac{1}{2}a_s t_k^2\right)\right) \end{aligned} \tag{1}$$

where R_0 is the slant range at zero-time instance, $t_k = (k-1)\,T$ is slow-time variable with T being the pulse repetitive interval, c is the light speed. Thus, the target signal is written as

$$\begin{aligned} x_{s,m,k} &= \sigma_s \exp(-j2\pi f_0 \tau_s(m,k)) \\ &= \sigma_s \exp\left(-j\frac{4\pi}{\lambda}R_0\right)\exp\left(j\frac{2\pi}{\lambda}(m-1)\,d\cos(\varphi_s)\cos(\theta_s)\right) \\ &\quad \times \exp\left(j\frac{4\pi}{\lambda}v_0 t_k\cos(\varphi_s)\cos(\theta_s) - j\frac{4\pi}{\lambda}\left(v_s t_k + \frac{1}{2}a_s t_k^2\right)\right) \end{aligned} \tag{2}$$

where σ_s is the equivalent coefficient of target signal, which incorporates transmit and receive beampatterns, transmit power, propagation loss, radar cross sector of target, range attenuation and so on, f_0 is the carrier frequency, and λ is the wavelength of the radar. It is known that the first exponential term is constant within the whole coherent processing interval, thus it can be merged into the coefficient. Thus, the target signal can be constructed as vector form

$$\begin{aligned}\mathbf{x}_s &= \left[x_{s,1,1}, x_{s,2,1}, \ldots, x_{s,M,K}\right]^T \\ &= \sigma_s \mathbf{a}\left(\varphi_s, \theta_s\right) \otimes \left[\mathbf{b}\left(\varphi_s, \theta_s, v_s\right) \odot \mathbf{c}\left(a_s\right)\right] \end{aligned} \tag{3}$$

where σ_s absorbs the constant exponential term, $\mathbf{a}(\varphi_s, \theta_s)$ is the spatial steering vector, $\mathbf{b}(\varphi_s, \theta_s, v_s)$ and $\mathbf{c}(a_s)$ are the linear and quadratic temporal steering vectors, respectively. They are written as

$$\mathbf{a}\left(\varphi_s, \theta_s\right) = \begin{bmatrix} 1 \\ \exp\left(j2\pi \frac{d}{\lambda} \cos\left(\varphi_s\right) \cos\left(\theta_s\right)\right) \\ \vdots \\ \exp\left(j2\pi \frac{d}{\lambda} (M-1) \cos\left(\varphi_s\right) \cos\left(\theta_s\right)\right) \end{bmatrix} \tag{4}$$

$$\mathbf{b}\left(\varphi_s, \theta_s, v_s\right) = \begin{bmatrix} 1 \\ \exp\left(j2\pi \left(\frac{2v_0 T}{\lambda} \cos\left(\varphi_s\right) \cos\left(\theta_s\right) - \frac{2v_s T}{\lambda}\right)\right) \\ \vdots \\ \exp\left(j2\pi \left(\frac{2v_0 T}{\lambda} \cos\left(\varphi_s\right) \cos\left(\theta_s\right) - \frac{2v_s T}{\lambda}\right) (K-1)\right) \end{bmatrix} \tag{5}$$

$$\begin{aligned}\mathbf{c}\left(a_s\right) &= \left[1, \exp\left(-j2\pi \frac{a_s T^2}{\lambda}\right), \right. \\ &\quad \left. \ldots, \exp\left(-j2\pi \frac{a_s T^2}{\lambda} (K-1)^2\right)\right]^T \end{aligned} \tag{6}$$

The acceleration of target causes non-linear phase history of the target over slow time. It results in spectrum defocusing in the temporal domain. Figure 1 shows the two-dimensional Fourier spectrum of moving target in spatial and temporal domains. It is seen that the spectrum defocusing phenomenon becomes obvious if the acceleration increases. The moving target splits into several parts due to large acceleration. It can be predicted that the output power of moving target will decrease if the acceleration is ignored when designing the processor.

For the clutter patch on the ground, the corresponding time delay is written as

$$\begin{aligned}\tau_i (m, k) = \frac{1}{c} &\left(2R_i - (m-1) d \cos\left(\varphi_i\right) \cos\left(\theta_i\right)\right. \\ &\left. - 2v_0 t_k \cos\left(\varphi_i\right) \cos\left(\theta_i\right)\right) \end{aligned} \tag{7}$$

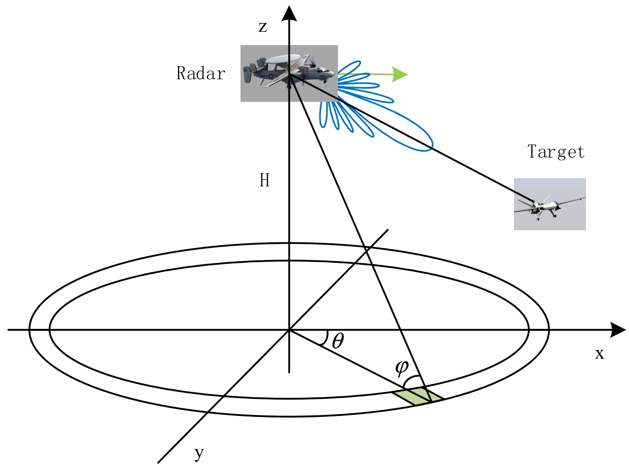


FIGURE 1. Geometry of ariborne radar and maneuvering target.

where R_{i} is the slant range at zero-time instance. Thus the contribution of such particular patch in the clutter echo corresponding to m-th element and k-th pulse can be written as

$$\begin{aligned} x_{i,m,k} &= \sigma_i \exp\left(-j2\pi f \tau_i (m,k)\right) = \sigma_i \exp\left(-j4\pi \frac{R_i}{\lambda}\right) \\ &\quad \times \exp\left(j\frac{2\pi}{\lambda} (m-1) d \cos\left(\varphi_i\right) \cos\left(\theta_i\right)\right) \\ &\quad \times \exp\left(j\frac{4\pi}{\lambda} v_0 t_k \cos\left(\varphi_i\right) \cos\left(\theta_i\right)\right) \end{aligned} \tag{8}$$

where σ_i is the complex-valued coefficient of clutter patch. The clutter echo consists of all contributions of the clutter patches within the range bin on the ground, including range ambiguity. Thus, the total clutter echo corresponding to the m-th element and k-th pulse can be written as

$$\begin{aligned} x_{c,m,k} &= \sum_{p=1}^{N_a} \sum_{i=1}^{N_c} x_{p,i,m,k} = \sum_{p=1}^{N_a} \sum_{i=1}^{N_c} \sigma_{p,i} \\ &\quad \times \exp\left(j\frac{2\pi}{\lambda} (m-1) d \cos\left(\varphi_{p,i}\right) \cos\left(\theta_{p,i}\right)\right) \\ &\quad \times \exp\left(j\frac{4\pi}{\lambda} v_0 t_k \cos\left(\varphi_{p,i}\right) \cos\left(\theta_{p,i}\right)\right) \end{aligned} \tag{9}$$

where N_a is the range ambiguity number and N_c is the patch number within each iso-range cell. The clutter echo can be constructed as

$$\begin{aligned}\mathbf{x}_c &= \left[x_{c,1,1}, x_{c,2,1}, \ldots, x_{c,M,K}\right]^T \\ &= \sum_{p=1}^{N_a} \sum_{i=1}^{N_c} \sigma_{p,i} \mathbf{a}\left(\varphi_{p,i}, \theta_{p,i}\right) \otimes \mathbf{b}\left(\varphi_{p,i}, \theta_{p,i}\right) \end{aligned} \tag{10}$$

where the temporal steering vector of clutter patch differs from that of moving target. As the phase history of an arbitrary patch remains linearly dependent on the slow-time, there is no quadratic temporal steering vector for the clutter echo. However, each clutter range cell incudes many clutter patches with different Doppler frequencies.

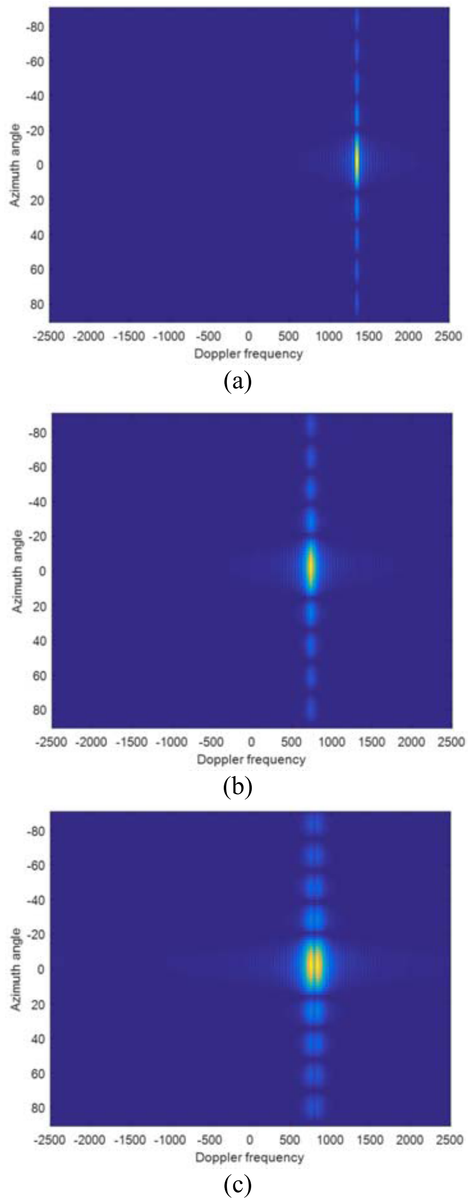


FIGURE 2. Spectrum spreading due to non-linear phase history. The acceleration is 0 in (a), 50m/s^2 in (b) and 100m/s^2 in (c). Other parameters can be found in Table 1.

III. THE PROPOSED GENERAL ADAPTIVE MATCHED FILTERING METHOD

It is known that the conventional method is capable of suppressing clutter and detect moving target. However, these methods suffer performance loss for the maneuvering target. In this section, a general adaptive matched filtering method is proposed for coherent accumulation of moving target as well as suppression of clutter.

Usually, the presumed spatial steering vector depends on the estimated angle of moving target. To include the general case, we introduce an additional spreading spatial steering vector to the conventional spatial steering vector. Thus, the presumed spatial steering vector is re-written as

$$\mathbf{p}_s = \mathbf{p}_{s0}(\varphi, \theta) \odot \mathbf{\Delta} \tag{11}$$

where $\mathbf{p}_{s0}(\varphi, \theta)$ is the same as conventional spatial steering vector and $\mathbf{\Delta}$ is a spreading spatial steering vector. The conventional spatial steering vector can be written as

$$\mathbf{p}_{s0}(\varphi, \theta) = \begin{bmatrix} 1 \\ \exp\left(j2\pi \frac{d}{\lambda} \cos(\varphi)\cos(\theta)\right) \\ \vdots \\ \exp\left(j2\pi \frac{d}{\lambda}(M-1)\cos(\varphi)\cos(\theta)\right) \end{bmatrix} \tag{12}$$

The spreading spatial steering vector is defined as

$$\mathbf{\Delta} = \left[\exp(j\varepsilon_1), \exp(j\varepsilon_2), \ldots, \exp(j\pi\varepsilon_M)\right]^T \tag{13}$$

where $\varepsilon_1 \cdots \varepsilon_M$ are defined as spreading factors in spatial domain. By adding the spreading spatial steering vector, the total steering vector in (11) will cover an angular region instead of an angular point. Thus it is valid for maneuvering target even with variation in angle within the coherent processing interval. This is reasonable when the geometry of radar and target cannot be invariant within the coherent processing interval, e.g., in near-field situation, the spreading spatial steering vector shows second-order phase variation with respect to element number. However, in far-field situation, the spreading spatial steering vector can be ignored.

Similarly, the presumed temporal steering vector is generalized to incorporate maneuvering target case. It consists of the conventional temporal steering vector and an additional spreading temporal steering vector, which is written as

$$\mathbf{p}_t = \mathbf{p}_{t0}(\varphi, \theta, v) \odot \mathbf{\Gamma} \tag{14}$$

where $\mathbf{p}_{t0}(\varphi, \theta, v)$ is the same as the conventional temporal steering vector and $\mathbf{\Gamma}$ is a spreading temporal steering vector. The conventional temporal steering vector can be written as

$$\mathbf{p}_{t0}(\varphi, \theta, v) = \begin{bmatrix} 1 \\ \exp\left(j2\pi\left(\frac{2v_0T}{\lambda}\cos(\varphi)\cos(\theta) - \frac{2vT}{\lambda}\right)\right) \\ \vdots \\ \exp\left(j2\pi\left(\frac{2v_0T}{\lambda}\cos(\varphi)\cos(\theta) - \frac{2vT}{\lambda}\right)(K-1)\right) \end{bmatrix} \tag{15}$$

The spreading temporal steering vector is defined as

$$\mathbf{\Gamma} = \left[\exp(j\delta_1), \exp(j\delta_2), \ldots, \exp(j\pi\delta_M)\right]^T \tag{16}$$

Considering the case of maneuvering target, we utilize the second-order spreading temporal steering vector in this paper, that is,

$$\mathbf{\Gamma}(\delta) = \left[1, \exp\left(-j2\pi\frac{\delta T^2}{\lambda}\right), \ldots, \exp\left(-j2\pi\frac{\delta T^2}{\lambda}(K-1)^2\right)\right]^T \tag{17}$$

The second-order spreading factor corresponds to previous analysis of moving target with acceleration. Similarly, the proposed temporal steering vector covers a region in Doppler domain instead of a particular Doppler frequency. Therefore, such temporal steering vector is valid for describing moving target with up to second-order motion parameters. The overall presumed steering vector can be constructed as

$$\mathbf{p} = \mathbf{p}_s \otimes \mathbf{p}_t = \mathbf{p}_0(\varphi, \theta, v) \odot [\boldsymbol{\Delta}(\varepsilon) \otimes \boldsymbol{\Gamma}(\delta)] \tag{18}$$

where $\mathbf{p}_0(\varphi, \theta, v) = \mathbf{p}_{s0}(\varphi, \theta) \otimes \mathbf{p}_{t0}(\varphi, \theta, v)$ is the conventional steering vector of target in the literature. Thus, the output of adaptive matched filtering processor can be calculated as

$$y = \mu \mathbf{p}^H \mathbf{R}^{-1} \mathbf{x}_s \tag{19}$$

where the superscript H is the conjugate transpose operator, $\mu = \frac{1}{\mathbf{p}^H \mathbf{R}^{-1} \mathbf{p}}$ is the normalized scale, and $\mathbf{R}$ is the clutter-plus-noise covariance matrix which is estimated with training data from adjacent range bins. The covariance matrix can be expressed by using eigenvalue decomposition, that is,

$$\mathbf{R} = \sum_{i=1}^{P} \gamma_i \alpha_i \alpha_i^H + \sigma_n^2 \mathbf{I}_{MK} \tag{20}$$

where γ_i and α_i are the i-th eigenvalue and corresponding eigenvector, respectively, P is the number of large eigenvalues of clutter-plus-noise covariance matrix and it usually indicates the subspace of clutter, σ_n^2 is the noise power, and $\mathbf{I}_{MK}$ is the identity matrix. Generally, the subspace of moving target differs from that of clutter, and the output of processor is written as

$$\begin{aligned} y &= \mu \frac{1}{\sigma_n^2} \mathbf{p}^H \left(\mathbf{I}_{MK} - \sum_{i=1}^{P} \frac{\gamma_i}{(\gamma_i + \sigma_n^2)} \alpha_i \alpha_i^H \right) \mathbf{x}_s \\ &= \mu \frac{1}{\sigma_n^2} \left(\mathbf{p}^H \mathbf{x}_s - \sum_{i=1}^{P} \frac{\gamma_i}{(\gamma_i + \sigma_n^2)} \mathbf{p}^H \alpha_i \alpha_i^H \mathbf{x}_s \right) \end{aligned} \tag{21}$$

Considering of the orthogonality between subspaces of target and clutter, it is written as

$$\begin{aligned} y \approx{}& \mu \frac{\sigma_s}{\sigma_n^2} [\mathbf{p}_{s0}(\varphi, \theta) \odot \boldsymbol{\Delta}(\varepsilon)]^H \mathbf{a}(\varphi_s, \theta_s) \\ &\otimes [\mathbf{p}_{t0}(\varphi, \theta, v) \odot \boldsymbol{\Gamma}(\delta)]^H [\mathbf{b}(\varphi_s, \theta_s, v_s) \odot \mathbf{c}(a_s)] \end{aligned} \tag{22}$$

For the far-field maneuvering target, the spreading in spatial domain is ignorable while the spreading in temporal domain is large enough to be considered. It is obtained that

$$\begin{aligned} y = {}& \mu \frac{\sigma_s}{\sigma_n^2} \exp\left(j(M-1)\pi \frac{d}{\lambda} \Phi \right) \frac{\sin\left(M\pi \frac{d}{\lambda} \Phi\right)}{\sin\left(\pi \frac{d}{\lambda} \Phi\right)} \\ & \times \sum_{k=1}^{K} \exp\left(j2\pi (\Psi_1 - \Psi_2)(k-1)\right) \\ & \times \exp\left(-j\pi \Psi_3 (k-1)^2\right) \end{aligned} \tag{23}$$

where $\Phi = \frac{d}{\lambda}[\cos(\varphi_s)\cos(\theta_s) - \cos(\varphi)\cos(\theta)]$, $\Psi_1 = \frac{2v_0 T}{\lambda}[\cos(\varphi_s)\cos(\theta_s) - \cos(\varphi)\cos(\theta)]$, $\Psi_2 = \frac{2(v_s - v)T}{\lambda}$, and $\Psi_3 = \frac{2(a_s - \delta)T^2}{\lambda}$ are auxiliary variables. In practice, the elevation angle can be taken as *a priori* knowledge, because the radar system always fixes the elevation angle and scans the azimuth space using beam scanning. Therefore, the azimuth angle of target is also *a priori* within a coherent processing interval. However, the estimation accuracy of elevation and azimuth angles depends on the beam width of the beampattern. Without losing of generality, the elevation angle of radar is assumed to be φ_0 and the azimuth angle is θ_0. It follows that the output of the STAP processor can be expressed as

$$y = \mathbf{w}^H(v, \delta)\, \mathbf{x} \tag{24}$$

where $\mathbf{w}(v, \delta) = \mathbf{R}^{-1}\mathbf{p}(\varphi = \varphi_0, \theta = \theta_0, v, \delta)$ is the adaptive weight vector, $\mathbf{x} = \mathbf{x}_s + \mathbf{x}_c + \mathbf{x}_n$ is the received echo of radar and $\mathbf{x}_n$ represents white Gaussian noise. By utilizing the output data, it is possible to estimate the velocity and acceleration of moving target by using maximum likelihood criterion, that is,

$$\{v, \delta\} = \max_{v,\delta} E\left\{ |y|^2 \right\} \tag{25}$$

In STAP method, the main objective is to discover whether a possible moving target exists with high efficiency. However, it is known that (24) involves two-dimensional search and increases the computational complexity. In the following, it shows that large step size can be used for discrete searching in the acceleration dimension. By doing so, it only has slight increment of computational complexity.

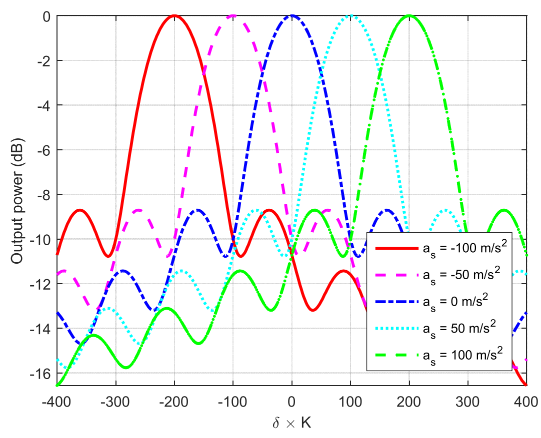


FIGURE 3. Output power with respect to searching step size referring to different accelerations.

To analyze the searching step size in acceleration dimension, we consider the performance loss due to mismatch of presumed steering vector of target and the true steering vector. Figure 3 provides the output power with respect to searching step size referring to different accelerations. It is seen that the small mismatch of the acceleration has slight influence on the output power. In other words, the coherence of target signal is very high even with a small acceleration. For example, for the moving target with zero acceleration, it results at most 3dB loss of output power if choosing the step size smaller than 50m/s^2. Due to practical constraints, the acceleration of

TABLE 1. System parameters.

Parameter	Value	Parameter	Value
Wavelength	0.02 m	Bandwidth	5 MHz
Pulse repetitive frequency	5 KHz	Range cell	30 m
Height of radar	1 km	Velocity of radar	100 m/s
Elevation of mainbeam	10 degrees	Azimuth of mainbeam	90 degrees
Element number	10	Pulse number	64
Element spacing	0.02 m	Signal-to-noise ratio (SNR)	15 dB
Elevation of target	8 degrees	Azimuth of target	92 degrees
Velocity of target	10 m/s	Acceleration of target	50 m/s^2
Clutter-to-noise ratio (CNR)	40 dB	Number of range bins	500

moving target can hardly reach 100m/s^2 for the low attitude UAVs. Thus, only limited tries are required for searching the acceleration of moving target in practice, which greatly reduces the computational complexity. It should be noted that the step size is also dependent on other radar parameters. Nevertheless, as the coherent processing interval is relatively small in STAP radar, the searching step size for the acceleration can always be very limited.

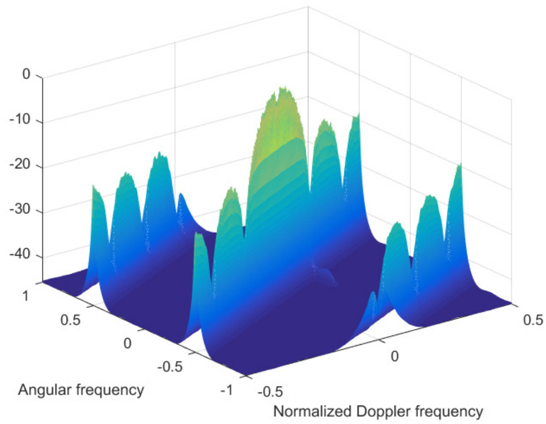
It is known that the azimuth angle is taken as beam pointing direction in STAP-based radar system and the moving target is testified in each Doppler cells. With analysis above, the testifying cells should be extended to Doppler-acceleration dimensions. Besides, the grid in Doppler dimension depends on the number of coherent pulse K while the grid in acceleration dimension is small and independent of coherent pulse K. Thus, the proposed general adaptive matched filtering method requires several times of computational burden larger than the conventional method.

IV. SIMULATION EXAMPLES

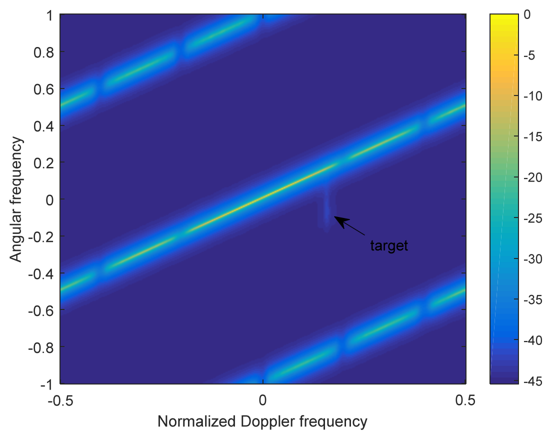
In this section, the characteristic of maneuvering target with airborne radar is studied and the proposed general adaptive matched filtering method is verified. The parameters are provided in the following table, which are used to regenerate the simulation results. Note that the velocity of airplane is along x-axis and the velocity of target is along radial direction outwards the radar.

A. SPECTRUM DISTRIBUTION AND SPACE-TIME RESPONSE ANALYSIS

As the array is side mounted on the airplane, the training data is approximate identical and independently distributed and the corresponding angular and Doppler frequencies of clutter are linearly correlated. Figure 4 shows the Capon spectrum of clutter and target. The clutter ridge is obviously seen and it represents the linear relationship. Besides, the beampattern of radar has influence on the power spectrum of clutter, which can be discovered from the simulation results. The slope of the clutter ridge depends on the parameters of radar.



(a)



(b)

FIGURE 4. Capon spectrum of target-plus-clutter-plus-noise. (a) Three-dimensional result and (b) two-dimensional view.

The moving target can also be observed though it is slightly spread in the spatial and temporal domains. Simulation results verify the effectiveness of the previous analysis. The distribution of clutter is well focused while that of target is defocused. This is caused by the second-order phase history of the maneuvering target.

In order to provide an intuitive understanding of the clutter suppression, Figure 5 shows the space-time adapted response for the presumed target. The adapted response forms a series of nulls along the clutter ridge, which realizes clutter suppression. The target is maximized with the mainbeam of the adapted response. It should be noted that the adapted response depends on the presumed steering vector and the target steering vector, which is written as

$$F(\theta, v, a) = \mathbf{p}^H(\theta_0, v_0, a_0)\,\mathbf{R}^{-1}\mathbf{s}(\theta, v, a) \tag{26}$$

where $\mathbf{p}(\theta_0, v_0, a_0)$ and $\mathbf{s}(\theta, v, a)$ are the presumed steering vector and true target steering vector, respectively. Given the presumed steering vector, the adaptive weight is constructed as $\mathbf{w} = \mu\mathbf{R}^{-1}\mathbf{p}(\theta_0, v_0, a_0) = \mu\mathbf{R}^{-1}\mathbf{s}(\theta_0, v_0, a_0)$. Thus, the adapted response can be rewritten as

$$F(\theta, v, a) = \mathbf{s}^H(\theta_0, v_0, a_0)\,\mathbf{R}^{-1}\mathbf{s}(\theta, v, a) \tag{27}$$

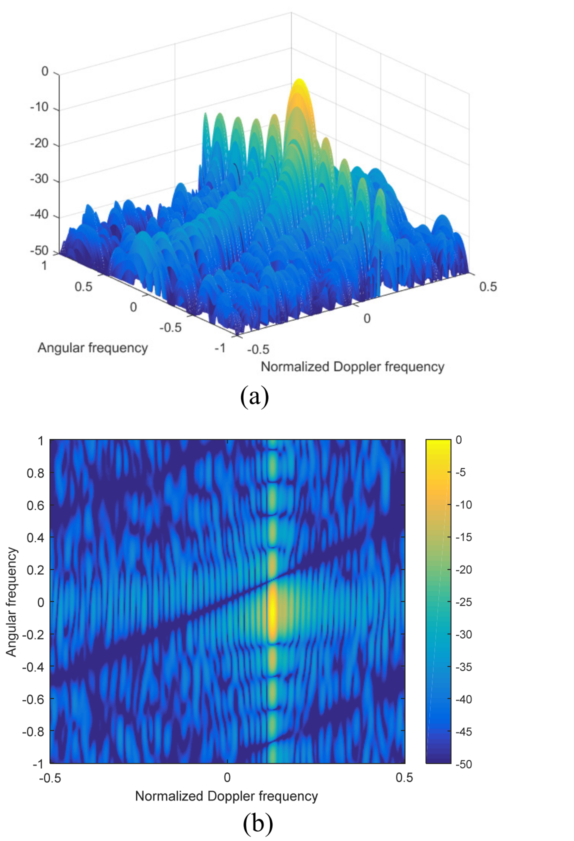


FIGURE 5. Space-time adaptive response. (a) Three-dimensional result and (b) two-dimensional view.

Because of the acceleration of target, it involves a three-dimensional response. In the simulation example, the response in angular and Doppler frequencies domains is calculated, where the acceleration of target is assumed to be zero. As shown in Figure 5, the mainbeam of adapted response is well maintained. However, though the adapted response is capable of suppressing the clutter, it is not necessary to maintain distortionless response of target due to the acceleration. Figure 6 shows the response in angular and Doppler frequencies domains, where the assumed acceleration is zero while the actual accelerations are 0m/s^2, 50m/s^2 and 150m/s^2, respectively. It is seen that the mainbeam of adapted response becomes distortion for large acceleration mismatch.

B. IMPROVEMENT FACTOR PERFORMANCE ANALYSIS

The improvement factor (IF) is commonly used as a criterion to evaluate the clutter suppression and target detection performance. Generally, the azimuth angle is taken as that of the mainbeam and the Doppler is to be determined. What is more in this paper, the acceleration is also to be determined. The IF is defined as

$$IF\,(v,a) = \frac{\frac{\mathbf{w}^H(v,a)\mathbf{R}_s\mathbf{w}(v,a)}{\mathbf{w}^H(v,a)\mathbf{R}_{c+n}\mathbf{w}(v,a)}}{\frac{\text{trace}\{\mathbf{R}_s\}}{\text{trace}\{\mathbf{R}_{c+n}\}}} \tag{28}$$

where $\mathbf{w}\,(v,a) = \mu\mathbf{R}^{-1}\mathbf{p}\,(\theta_0, v, a)$ is the adaptive weight vector with v being within unambiguous range and a being within limited region, e.g., [-200m/s^2, 200m/s^2], $\mathbf{R}_s$ is the covariance matrix of target signal, $\mathbf{R}_{c+n}$ is the covariance matrix of clutter-plus-noise, and trace{ } stands for the trace operator.

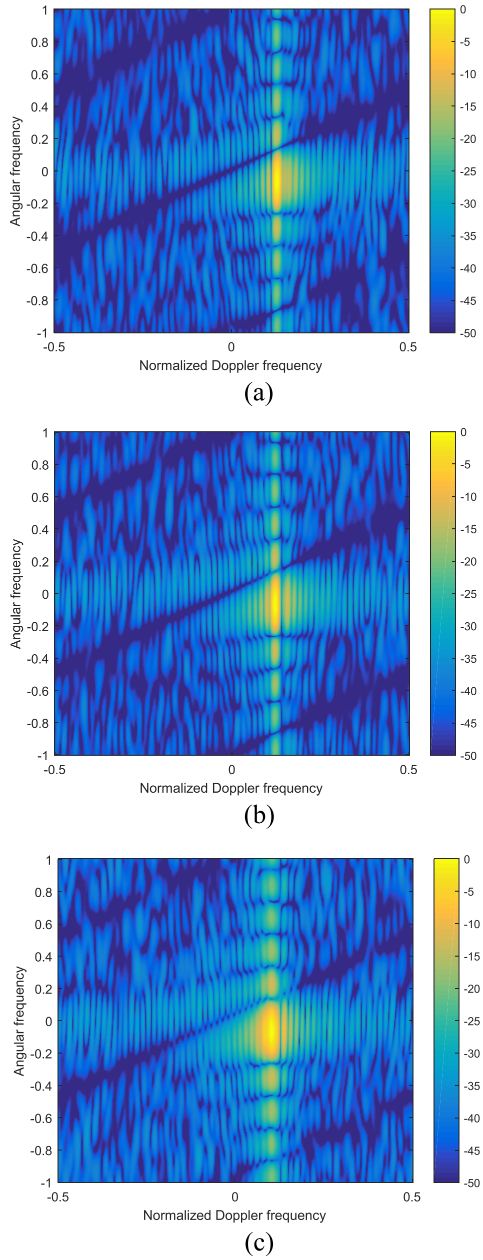
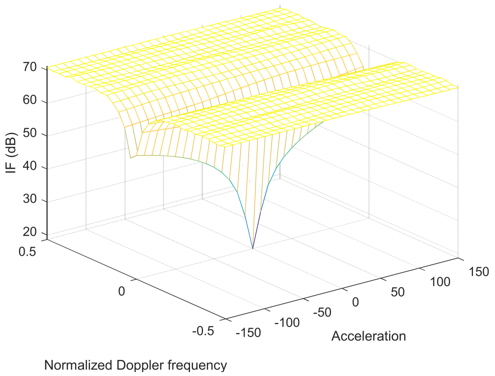
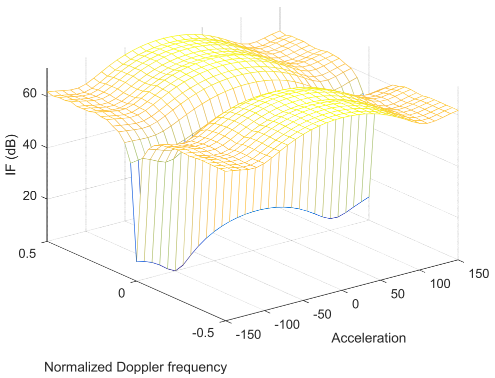


FIGURE 6. Space-time adaptive response for different accelerations. (a) 0m/s^2, (b) 50m/s^2, and (c)150m/s^2.

Figure 7 shows the IF performance with respect to normalized Doppler frequency and acceleration. In this simulation, Figure 7(a) shows the results of general adaptive matched filtering where the acceleration is included in the presumed steering vector. In contrast, Figure 7(a) shows the results of mismatched filtering where the acceleration is excluded in the presumed steering vector. It is seen that the performance of mismatched filtering method suffers serious performance degradation. To show the performance loss clearly, the IF



(a)



(b)

FIGURE 7. IF performance comparison. (a) Matched filtering and (b) mismatched filtering.

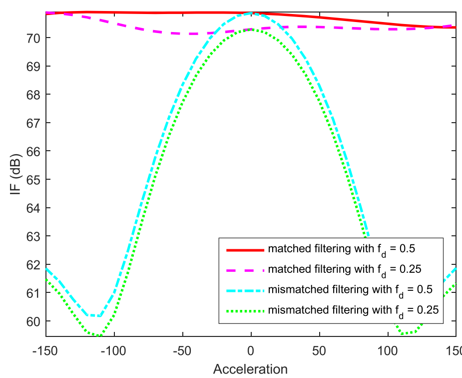


FIGURE 8. IF performance with respect to acceleration.

performance with respect to acceleration is presented in Figure 8. It is shown that the performance loss of mismatched method is about 10dB as the acceleration approaches 100m/s^2. In contrast, the proposed generalized adaptive matched filtering method maintains satisfactory performance of target detection. Moreover, we should also point out another interesting phenomenon that the performance improvement is enhanced even at zero Doppler frequency due to non-zero acceleration of the target. It is seen from Figure 9 that the performance improvement at zero Doppler frequency is enhanced for the target with large acceleration. This indicates that the subspace of moving target differs from that of clutter due to acceleration.

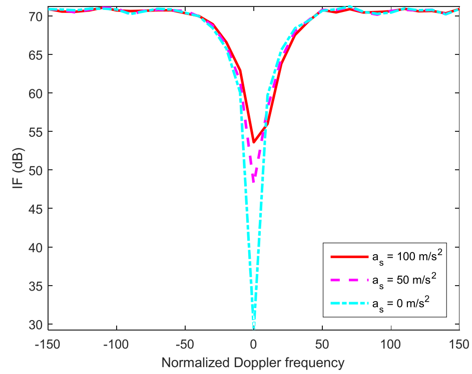


FIGURE 9. IF performance with respect to normalized Doppler frequency.

V. CONCLUSION

In this paper, the maneuvering target detection is studied with STAP based radar system. The influence of acceleration is analyzed and the target signal is modeled with its angle, velocity, acceleration as well as scattering coefficient. A general adaptive matched filtering method is proposed for the detection of moving target. The performance improvement over mismatched filtering method is studied with simulation examples. Simulation examples show that the performance improvement can reach 10 dB for large acceleration case. Furthermore, the discrete searching method along acceleration dimension is proposed. It is verified that the step size can be large and only limited trials is enough.

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