Journal of Systems Engineering and Electronics
Vol. 33, No. 5, October 2022, pp.1089 – 1094

Modified OMP method for multi-target parameter estimation in frequency-agile distributed MIMO radar

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Abstract: Introducing frequency agility into a distributed multiple-input multiple-output (MIMO) radar can significantly enhance its anti-jamming ability. However, it would cause the sidelobe pedestal problem in multi-target parameter estimation. Sparse recovery is an effective way to address this problem, but it cannot be directly utilized for multi-target parameter estimation in frequency-agile distributed MIMO radars due to spatial diversity. In this paper, we propose an algorithm for multi-target parameter estimation according to the signal model of frequency-agile distributed MIMO radars, by modifying the orthogonal matching pursuit (OMP) algorithm. The effectiveness of the proposed method is then verified by simulation results.

Keywords: distributed multiple-input multiple-output (MIMO) radar, multi-target parameter estimation, frequency agility, modified orthogonal matching pursuit (OMP) method.

DOI: 10.23919/JSEE.2022.000106

1. Introduction

Distributed multiple-input multiple-output (MIMO) radars have drawn increasing attention in recent years [1−3], since they can achieve improved radar target detection performance, especially for moving targets, via exploiting spatial diversity, and possess good anti-jamming abilities due to their widely separated antennas. It is well known that the radar cross section (RCS) of a target containing many scatters would be highly sensitive to the azimuth [4,5]. However, a distributed MIMO radar consists of several widely separated transmit/receive antennas, where each transmit-receive path pair provides an individual look at the target [6,7]. Thus the distributed MIMO radar can obtain different looks at the target. Although any individual look may contain a small amplitude target return, it is unlikely that all these looks have small amplitude target returns. Therefore, distributed MIMO radar can integrate these looks to exploit target RCS fluctuations and hence enjoy better target detection performance [8,9]. Furthermore, these looks at a moving target allow the distributed MIMO radar to observe it from different directions simultaneously, which may help the radar distinguish the moving target from the strong background clutter, especially when the radial velocity of the moving target is small [10]. Thus, distributed MIMO radars are suitable for detecting moving targets in clutter environments [11,12]. As for good anti-jamming ability, because the transmitters and receivers of a distributed MIMO radar are located at different positions [13,14], jammers cannot capture the spatial information of the receivers, which can prevent jammers from exactly imposing interference on the radar.

Frequency agility is an effective anti-jamming strategy for radars [15]. Frequency-agile radars refer to radars whose carrier frequencies vary in a random or pseudorandom manner from pulse to pulse [16]. Frequency-agile radars can enjoy good electronic counter-countermeasures (ECCM) performance. This is because the operating frequency band of a frequency-agile radar is difficult to track and predict, and hence jammers cannot exactly focus their energy on the radar's operating frequency band, which heavily impairs the effectiveness of the jammers. Although with good ECCM performance, when using the traditional matched filtering method for multi-target parameter estimation, frequency-agile radars may face the sidelobe pedestal problem that may cause weak targets to be submerged in the sidelobes of strong targets. To address this problem, by exploiting the sparsity of targets in the radar's observation area, sparse recovery methods are often employed for multi-target parameter estimation in frequency-agile radars [17,18]. As for the stability of these methods, it is proved that, as long as the number of targets satisfies a certain relationship, one can exactly recover the range-Doppler frequency parameters of the targets with a high probability [19]. Furthermore,

Manuscript received June 24, 2022.
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Wang et al. [20] introduced the block sparse recovery methods into the extended multi-target parameter estimation problem in frequency-agile radars and theoretically analyze the corresponding unique recovery condition.

In recent years, with the rapid development of electronic countermeasure techniques, more and more researchers have recognized the importance of a radar's ECCM capability, and how to improve a radar's anti-jamming ability has become a popular field of research [21−24]. As a matter of fact, the lack of the anti-jamming capability may heavily prohibit the practical applications of a radar system, because an ideal operating condition that does not contain any jamming signal cannot be always guaranteed in the real world. Introducing frequency agility into distributed MIMO radars can effectively enhance their anti-jamming abilities but can bring about the sidelobe pedestal problem in multi-target parameter estimation. To alleviate this problem, we try to achieve multi-target parameter estimation in frequency-agile distributed MIMO radar through the orthogonal matching pursuit (OMP) algorithm [25,26], a traditional sparse recovery method [27,28]. However, the OMP algorithm cannot be used directly, because it is not suitable for the signal model of frequency-agile distributed MIMO radars. Therefore, we modify the OMP algorithm according to the signal model and propose the modified OMP algorithm for multi-target parameter estimation in frequency-agile distributed MIMO radar. We also analyze the anti-jamming performance of a frequency-agile distributed MIMO radar. Finally, simulation results are given to demonstrate the effectiveness of the proposed algorithm.

2. Signal model

Assume that the frequency-agile distributed MIMO radar under consideration consists of M transmit antennas and N receive antennas, where all the transmitters and receivers are located at different positions in the x-y plane. Let (x_m^t, y_m^t) and (x_n^r, y_n^r) represent the locations of the m th transmitter and the n th receiver, respectively, where $m = 1,2,\cdots,M$ and $n = 1,2,\cdots,N$. As illustrated in Fig. 1, the frequency-agile distributed MIMO radar transmits a coherent burst of L pulses, and the carrier frequency corresponding to the lth pulse can be expressed as

$$f_l = f_0 + (r_l - 1)\Delta f,\ \ l = 1,2,\cdots,L \tag{1}$$

where f_0 denotes the initial frequency, Δf denotes the frequency step size, and r_l is a random integer between 1 and P, with P being the number of the available carrier frequencies.

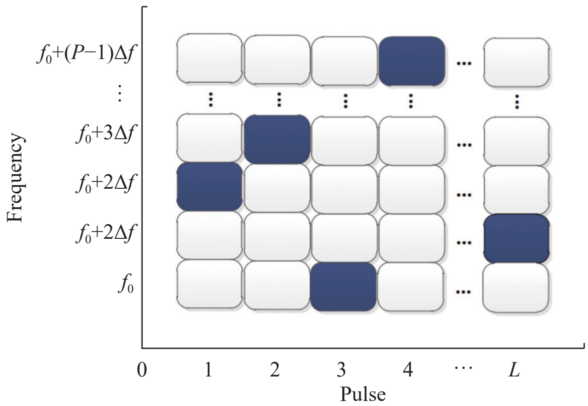


Fig. 1 An example of a frequency agile radar

Suppose that there are K moving targets in the given cell-under-test (CUT) whose location is denoted by (x,y) and that the K targets do not leave the CUT during the L consecutive pulse transmissions. The Euclidean distance between the CUT and the mth transmit antenna is

$$d_m^t = \sqrt{(x_m^t - x)^2 + (y_m^t - y)^2} \tag{2}$$

and the Euclidean distance between the CUT and the nth receive antenna is

$$d_n^r = \sqrt{(x_n^r - x)^2 + (y_n^r - y)^2}. \tag{3}$$

Thus, the baseband received signal of the nth receiver due to both the lth pulse transmission from the mth transmitter and reflections from the K targets can be expressed as

$$z_{mnl}(t) = \sum_{k=1}^{K} \beta_{mn}^k s_m\left(t - \frac{d_m^t + d_n^r}{\mathrm{c}}\right)\exp\left[\mathrm{j}2\pi f_{mnl}\left(v_x^k, v_y^k\right)t\right] + n_{mnl}(t) \tag{4}$$

where

$$f_{mnl}(v_x, v_y) = \frac{v_x(x_m^t - x) + v_y(y_m^t - y)}{\lambda_l d_m^t} + \frac{v_x(x_n^r - x) + v_y(y_n^r - y)}{\lambda_l d_n^r}, \tag{5}$$

$f_{mnl}\left(v_x^k, v_y^k\right)$ represents the Doppler frequency associated with the k th target and the transmit-receive path pair (m,n) during the lth pulse transmission, β_{mn}^k denotes the unknown reflection coefficient associated with the kth target and the transmit-receive path pair (m,n), $s_m(t)$ denotes the signal transmitted from the m th transmit antenna, c denotes the speed of light, and $n_{mnl}(t)$ denotes the clutter and noise corresponding to the transmit-receive path pair (m,n) during the lth pulse transmission. $\lambda_l = \mathrm{c}/f_l$ denotes the wavelength during the l th pulse transmission, and v_x^k and v_y^k represent the x-direction and y-direction components of the kth target's velocity, respectively. Here, the reflections of the K targets β_{mn}^k are assumed to be constant during the L consecutive pulse transmissions.

As illustrated in Fig. 1, a block represents the radar's operating frequency band in the given transmission pulse. The mth transmit antenna and the nth receive antenna are located at the azimuth angles θ_m^t and θ_n^r, respectively, when viewed from the CUT. Then, we have the following relationships:

$$\begin{cases} \cos\theta_m^t = \dfrac{x_m^t - x}{d_m^t} \\ \sin\theta_m^t = \dfrac{y_m^t - y}{d_m^t} \\ \cos\theta_n^r = \dfrac{x_n^r - x}{d_n^r} \\ \sin\theta_n^r = \dfrac{y_n^r - y}{d_n^r} \end{cases}. \tag{6}$$

Substituting (6) into (5) yields

$$f_{mnl}(v_x, v_y) = \frac{v_x}{\lambda_l}(\cos\theta_m^t + \cos\theta_n^r) + \frac{v_y}{\lambda_l}(\sin\theta_m^t + \sin\theta_n^r). \tag{7}$$

Usually, orthogonal waveforms are employed by distributed MIMO radars for transmission, i.e.,

$$\begin{cases} \displaystyle\int_{\mathcal{T}} s_m(t)\, s_m^*(t-\tau)\,\mathrm{d}t = \delta(\tau) \\ \displaystyle\int_{\mathcal{T}} s_m(t)\, s_{m'}^*(t-\tau)\,\mathrm{d}t = 0,\ m \neq m' \end{cases} \tag{8}$$

where $\delta(\cdot)$ denotes the Dirac delta function, $\mathcal{T}$ denotes the transmitted waveform's duration. Therefore, after pulse compression, the range-compressed signal of the CUT associated with the transmit-receive path pair (m,n) can be represented as a vector $\boldsymbol{z}_{mn} \in \mathbf{C}^{L\times 1}$ which can be expressed as follows:

$$\boldsymbol{z}_{mn} = \sum_{k=1}^{K} \beta_{mn}^k \boldsymbol{\omega}_{mn}\left(v_x^k, v_y^k\right) + \boldsymbol{n}_{mn} \tag{9}$$

where

$$\boldsymbol{\omega}_{mn}(v_x, v_y) = \begin{bmatrix} 1 \\ \exp[\mathrm{j}2\pi T_r f_{mn2}(v_x, v_y)] \\ \vdots \\ \exp[\mathrm{j}2\pi(L-1)T_r f_{mnL}(v_x, v_y)] \end{bmatrix}. \tag{10}$$

In (10), $\boldsymbol{\omega}_{mn}\left(v_x^k, v_y^k\right)$ denotes the temporal steering vector corresponding to both the kth target and the transmit-receive path pair (m,n). $\boldsymbol{n}_{mn} \in \mathbf{C}^{L\times 1}$ denotes the vector representing the clutter and the noise associated with the (m,n)th transmit-receive path. Usually, $\boldsymbol{n}_{mn}$ is assumed to be zero-mean complex Gaussian distributed, and its covariance matrix can be expressed as

$$\mathrm{E}\left[\boldsymbol{n}_{mn}\boldsymbol{n}_{mn}^{\mathrm{H}}\right] = \boldsymbol{R}_c. \tag{11}$$

In practice, $\boldsymbol{R}_c$ is often unknown and can be replaced by the sample covariance matrix of secondary data, maintaining the constant false alarm rate property [29]. Fig. 2 presents locations of the transmitter and the receiver.

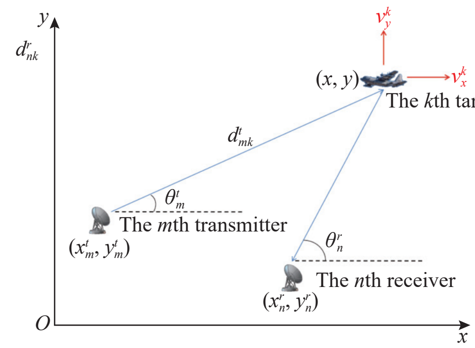


Fig. 2 Locations of transmitter and receiver with respect to target and its movement

3. Proposed method

Observing that the velocities of the K moving targets are sparse in the $v_x - v_y$ domain, we choose to estimate the velocities and reflections of the K targets via sparse recovery. To do this, we need to construct the dictionary at first. Let $\left\{\left(v_x^g, v_y^h\right)\right\}$ represent a two-dimensional grid in the $v_x - v_y$ plane, where g=1,2,$\cdots$,G and h=1,2,$\cdots$,H. According to the grid, we construct the dictionary $\boldsymbol{D}_{mn} \in \mathbf{C}^{L\times GH}$ corresponding to the transmit-receive path pair (m,n), where each column of $\boldsymbol{D}_{mn}$ is $\boldsymbol{\omega}_{mn}\left(v_x^g, v_y^h\right)$.

In what follows, we estimate the parameters of the K targets via sparse recovery. The OMP algorithm is a classical sparse recovery method with the advantage of easy implementation. In brief, it iteratively performs three steps: selecting atoms from the dictionary, estimating the corresponding weights of the selected atoms, and calculating the residual signal according to the selected atoms and their corresponding weights. Nevertheless, the OMP algorithm cannot be directly applied for multi-target parameter estimation in frequency-agile distributed MIMO radar, so we need to further modify the OMP algorithm according to the signal model in (9). There are mainly three modifications.

The first modification is the way to measure the correlation between the atoms in the dictionary and the residual signal, by which atom selection is realized. The OMP algorithm measures the correlation between the atom and the residual signal via coherent integration among all the elements, which, however, is not suitable for distributed MIMO radars. Actually, a distributed MIMO radar prefers coherent integration of the slow-time dimension and non-coherent integration among different transmit-receive paths [8,11,30]. Therefore, we select the atom that is most strongly correlated with the residual signal via

$$(g_t,h_t)=\arg\max_{(g,h)}\sum_{m=1}^{M}\sum_{n=1}^{N}\left|\boldsymbol{\omega}_{mn}^{\rm H}\left(v_x^g,v_y^h\right)\boldsymbol{R}_c^{-1}\boldsymbol{r}_{mn}\right|^2 \tag{12}$$

where $\boldsymbol{r}_{mn}$ denotes the residual signal corresponding to the (m,n)th transmit-receive path. Then, we add this atom into the collection of selected atoms, i.e.,

$$\boldsymbol{\Phi}_{t+1}=\left[\boldsymbol{\Phi}_t,\boldsymbol{\omega}_{mn}\left(v_x^{g_t},v_y^{h_t}\right)\right]. \tag{13}$$

The second modification is the way to calculate the weights of the selected atoms. The OMP algorithm obtains all the weights of the selected atoms in one step by using the least-squares approach. However, in our problem, the weights of the selected atoms should be estimated separately for each transmit-receive path, i.e.,

$$\hat{\boldsymbol{\beta}}_{mn}=\arg\min_{\boldsymbol{\beta}_{mn}}\|\boldsymbol{z}_{mn}-\boldsymbol{\Phi}_t\boldsymbol{\beta}_{mn}\|_{\boldsymbol{R}_c^{-1}}^2=$$
$$\arg\min_{\boldsymbol{\beta}_{mn}}(\boldsymbol{z}_{mn}-\boldsymbol{\Phi}_t\boldsymbol{\beta}_{mn})^{\rm H}\boldsymbol{R}_c^{-1}(\boldsymbol{z}_{mn}-\boldsymbol{\Phi}_t\boldsymbol{\beta}_{mn}). \tag{14}$$

It can be easily obtained that

$$\hat{\boldsymbol{\beta}}_{mn}^t=\left(\boldsymbol{\Phi}_t^{\rm H}\boldsymbol{R}_c^{-1}\boldsymbol{\Phi}_t\right)^{-1}\boldsymbol{\Phi}_t^{\rm H}\boldsymbol{R}_c^{-1}\boldsymbol{z}_{mn}. \tag{15}$$

The third modification is the calculation of the residual signal. The OMP algorithm gets the entire residual signal by subtracting the product of the selected atoms and their corresponding weights from the observed signal. Nevertheless, in our problem, since the weights of the selected atoms are estimated separately for each transmit-receive path, the residual signal should also be calculated separately for each transmit-receive path, i.e.,

$$\boldsymbol{r}_{mn}=\boldsymbol{z}_{mn}-\boldsymbol{\Phi}_t\hat{\boldsymbol{\beta}}_{mn}^t. \tag{16}$$

Since our proposed algorithm is obtained by modifying the OMP algorithm according to the signal model of frequency-agile distributed MIMO radars, we call it the modified OMP (MOMP) algorithm. The detailed description of the MOMP algorithm can be presented as the following steps.

(i) Initialize the residual signal $\boldsymbol{r}_{mn}=\boldsymbol{z}_{mn}$ (m=1,2,$\cdots$,M; n=1,2,$\cdots$,N), the index set $\varLambda_0=\varnothing$, the matrix collecting selected atoms $\boldsymbol{\Phi}_0$ is empty, and the iteration counter t=1.

(ii) Find the index (g_t,h_t) according to (12), and add (g_t,h_t) into the index set

$$\varLambda_t=\varLambda_{t-1}\bigcap\{(g_t,h_t)\}.$$

(iii) Augment the matrix of chosen atoms according to (13).

(iv) Estimate the weights of the selected atoms by (15).

(v) Calculate the residual signal via (16).

(vi) Increment t, and return to step (ii) if $t<K$.

(vii) The velocities and reflections of the K targets are estimated to be $\left\{\left(v_x^{g_t},v_y^{h_t}\right)\right\}$ (t=1,2,$\cdots$,K) and $\hat{\boldsymbol{\beta}}_{mn}^K$, respectively.

4. Anti-jamming performance analysis

The anti-jamming ability of a frequency agile distributed MIMO radar benefits from two aspects, i.e., its widely separated antennas and frequency agility. First of all, we consider the signal-to-interference-plus-noise ratio (SINR) gain obtained from the widely separated antennas. Assume that a jammer aims to impose interference on a frequency agile distributed MIMO radar. From the transmitted signal of the radar, the jammer cannot capture the spatial information of the radar's receivers, because the receivers and transmitters of the radar are located at different positions. Therefore, the jammer has to spread its energy over a much bigger spatial region to cover the radars receivers. Thus, the SINR of the radar echoes is improved, and the SINR gain is

$$G_{\rm DMIMO}=\frac{\varOmega_{\rm receivers}}{\varOmega_{\rm beam}} \tag{17}$$

where $\varOmega_{\rm receivers}$ and $\varOmega_{\rm beam}$ denote the operation region and beam width of the jammer, respectively. Then, we consider the SINR gain obtained from frequency agility. The jammer cannot predict the radars carrier frequency because of its random variation. As a result, the jammer fails to focus its energy exactly on the operating frequency band of the radar but is enforced to disperse its energy over a much wider frequency band to cover the randomly varying operation frequency band of the radar. Thus, the SINR gain benefited from frequency agility is

$$G_{\rm FA}=\frac{P\Delta f}{B} \tag{18}$$

where B denotes the radar's bandwidth. Finally, one can obtain the total SINR gain of the frequency agile distributed MIMO radar, i.e.,

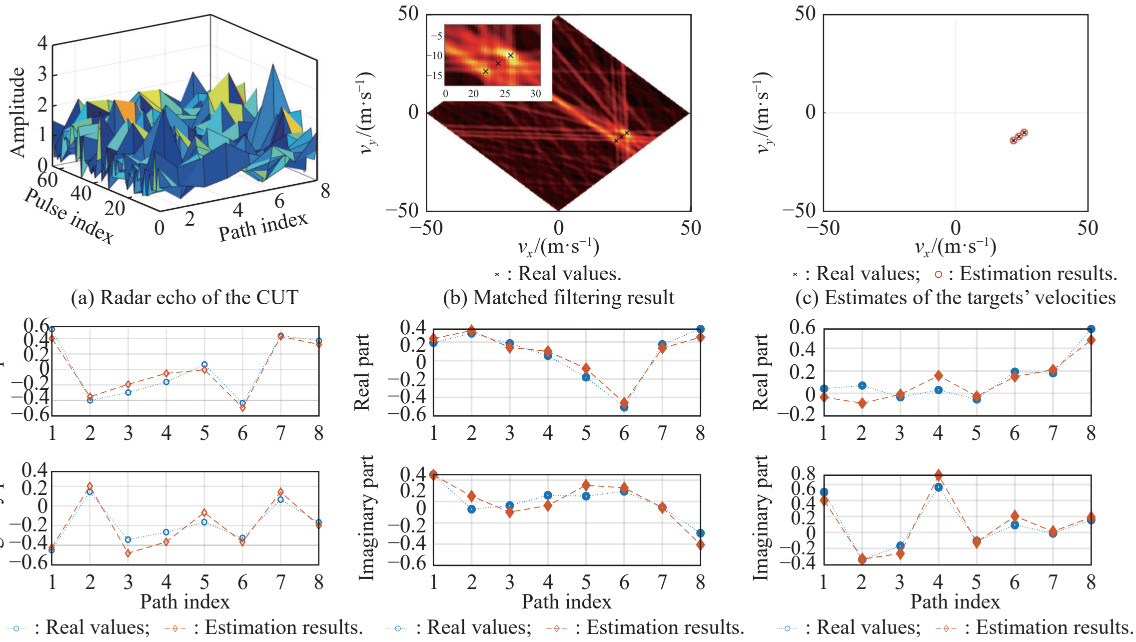
$$G_{\rm FA-DMIMO}=G_{\rm DMIMO}\cdot G_{\rm FA}.$$

5. Simulation results

In this section, we provide a numerical experiment to illustrate the effectiveness of the MOMP algorithm. A frequency-agile distributed MIMO radar used in the simulation consists of two transmitters and four receivers. When viewed from the CUT, the azimuth angles of transmitters are 5° and 85°, and the azimuth angles of receivers are 0°, 30°, 60°, and 90°. When viewed from the CUT, the azimuth angles of transmitters are 5° and 85°, and the azimuth angles of receivers are 0°, 30°, 60°, and 90°. The carrier frequency of the radar varies from 1 GHz to 1.5 GHz. The pulse repetition frequency and operating frequency bandwidth of the radar are 1 000 Hz and 5 MHz. The number of pulses is $L = 64$. Three targets exit in the CUT, and their parameters are listed in Table 1. Simulation results are given in Fig. 3. The radar echo of the CUT is shown in Fig. 3(a). The result obtained via the traditional matched filtering method is provided in Fig. 3(b), from which one cannot distinguish the three targets, i.e., the sidelobe pedestal problem. By contrast, the MOMP algorithm successfully distinguishes the three targets and accurately estimates their velocities, as shown in Fig. 3(c). In addition, the estimates of the three targets' reflections, which is obtained via the MOMP algorithm, are provided in Fig. 3(d)−Fig. 3(e). It can be observed that these estimates are in good agreement with real values, which illustrates the effectiveness of the MOMP algorithm for multi-target parameter estimation.

Table 1 Parameters of three targets in the CUT

Parameter	T1	T2	T3
$v_x/(\mathrm{m\cdot s^{-1}})$	26	24	22
$v_y/(\mathrm{m\cdot s^{-1}})$	−10	−12	−14
SINR/dB	−4	−4	−4



×: Real values.
×: Real values; ○: Estimation results.
○: Real values; ◇: Estimation results.

(a) Radar echo of the CUT
(b) Matched filtering result
(c) Estimates of the targets' velocities
(d) Estimates of the first target's reflections
(e) Estimates of the second target's reflections
(f) Estimates of the third target's reflections

Fig. 3 Parameter estimation of three targets in a frequency-agile distributed MIMO radar

6. Conclusions

In this paper, we propose a multi-target parameter estimation algorithm for frequency-agile distributed MIMO radars, via modifying the OMP method according to the corresponding signal model. Then, we describe how a frequency-agile distributed MIMO radar combats jamming and quantitatively analyze its anti-jamming performance in terms of SINR gain. Finally, simulations are provided to demonstrate that the proposed algorithm can distinguish multiple targets and exactly recover the velocities and reflections of these targets.

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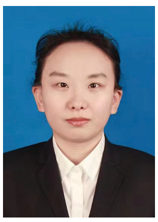

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