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2-D DOA Robust Estimation of Echo Signals Based on Multiple Satellites Passive Radar in the Presence of Alpha Stable Distribution Noise

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ABSTRACT In this paper, the low-performance problem of two-dimensional (2-D) direction of arrival (DOA) estimation with non-Gaussian noise in low signal-to-noise ratio is addressed. For echo signals of the multiple satellites' passive radar, a robust 2-D DOA estimation method based on improved zero-order statistics fractional low-order cyclic correlation (IZOS-FLOCC) under the alpha-stable distribution noise environment is proposed. First, we employ a uniform plane array to establish the model of received signals. Then, the IZOS-FLOCC of the echo signals is constructed based on the cyclostationarity. Finally, the IZOS-FLOCC of signals subspace is obtained by the optimization method. Moreover, we derive the Cramer–Rao low bound of the 2-D DOA estimation of echo signals based on multiple satellites' passive radar in the presence of alpha-stable distribution noise. The simulation results show that the proposed method can effectively estimate the 2-D DOA of echo signals based on multi-satellite radiation sources in the alpha-stable distribution noise environment and achieve better performance than the existing methods.

INDEX TERMS Direction of arrival (DOA), parameter estimation, alpha stable distribution noise, satellite, passive radar, Cramer-Rao low bound (CRLB).

I. INTRODUCTION

With the rapid advancement of science and technology, modern moving target positioning technology is increasingly developing toward high-tech, high-reliability and high-precision. Positioning technologies for these requirements are emerging in endlessly [1]. Passive positioning technologies have become powerful competitors of traditional active positioning technology. The traditional target positioning technology is generally an active positioning technology system. In such a system, the target location system does not emit the signal, and the target is located by using the transmitting signals of the non-cooperative radiation source. In other words, the echo signals of target are used to estimate positioning parameters, so that target positioning is achieved. Since the active positioning system needs to constantly emit the high-power electromagnetic waves, it is easily detected and attacked. This means that the active targeting positioning system does not have the characteristics of anti-electromagnetic interference and stealth. With the continuous development of stealth technology, signals source tracking technology and electromagnetic wave interference technology, the limitations of the traditional active positioning system are becoming more and more obvious. The passive positioning system can implement the process of target positioning without position information, which overcomes the shortcoming of active positioning system in a certain extent. In addition, there are many radiation sources available in passive positioning systems, such as the FM broadcast signals, GSM base station signals, satellite signals and so on [2].

As many satellites can be observed as passive radar at any time on earth, and many high-power satellite systems are gradually becoming more and more perfecting, which makes the target positioning system based on satellite passive radar has great potential and value. There are also great developments and opportunities in this area. Moreover, a receiver located on the ground often receive signals of multiple satellites at the same time in actual applications, so passive positioning system based on a conventional single radiation source is unfeasible [3]. If appropriate signal processing methods and multiple satellite signals are reasonably used, a passive positioning system based on multiple satellite passive radar can be constructed. At the same time, the advantage that a single radiation source-based positioning system does not have can also be obtained:

- Multiple external sources of radiation can ensure the targets are directed from different directions, which can improve the positioning performance of target.
- The reasonable data fusion of the target position information contained in the echo signals of multiple radiation sources can effectively improve the reliability and accuracy of the positioning system.
- The positioning capabilities of multiple external radiation sources can be complementary to improve the robustness of the positioning system.

Direction of arrival (DOA) estimation is a very important issue in the field of array signal processing [4], [5]. It is a technique that analyzes the target orientation based on the incident angle of the signal received by the array antenna. It is widely used in positioning, communication, and prediction. The accuracy of DOA estimation will directly affect the positioning accuracy of moving targets, so DOA estimation becomes one of the important links in the positioning of moving targets [6], [7]. However, the theoretical research of signal processing generally assume that the noise is Gaussian. Because the Gaussian distribution model is simpler than others and is convenient for theoretical analysis, algorithm research, and function implementation. DOA estimation in the Gaussian noise develop rapidly, and related technology research also tends to mature [8], [9]. As the electromagnetic propagation environment becomes more and more complicated, there is often a class of non-Gaussian noise with pulse characteristics in the actual signal transmission process, and it has larger amplitude data mutations relative to Gaussian noise, which is called alpha stable distribution noise. Alpha stable distribution noise has not second-order and above second-order statistics, so that the traditional DOA estimation algorithms under the Gaussian noise will no longer be suitable in this environment, and the DOA estimation in the presence of alpha stable distribution noise gradually becomes a research hot spot.

For the one-dimensional DOA estimation in non-Gaussian noise scenarios, some methods have been proposed. The generalized correlation entropy as the nonlinear transformation was adopted to achieve the DOA estimation under alpha stable distribution noise in [10]. Although this method overcome the disadvantage of relying on the noise feature index information when constructing fractional lower-order statistics, it ignored the time characteristics of the signals. Liu *et al.* [11] proposed an algorithm for DOA estimation by using ROOT-MUSIC. This algorithm was based on the polynomial, thus it avoided the spectrum peak search and provided higher resolution. It can be applied to DOA estimation under serious non-Gauss noise. However, this algorithm was only suitable for one dimension DOA estimation. Yin and Chen [12] effectively used the sparse model of the signal covariance matrix and proposed a new algorithm to estimate the DOA of the signals. The analytical solution of the regularization parameters was provided. The above methods only considered the one-dimensional DOA estimation. However, target positioning requires 2-D DOA information in non-Gaussian noise scenarios. In [13], a 2-D DOA estimation method for alpha-stable clutter was proposed by using the covariance matrix of signal sub-arrays. The feasibility of the algorithm was proved by data simulation experiments, and the estimation performance was degraded when the noise characteristics were strong. To the best of our knowledge, the above related works based on radar and other radiation sources are proposed in the non-Gaussian noise, and the 2-D DOA estimation based on satellite radiation sources has not been reported.

In this paper, a novel 2-D DOA estimation method based on cyclostationarity characteristics of the signal is proposed in alpha stable distributed noise environment. Firstly, the received signals of the uniform plane array antenna are modeled. And then, the echo signals are processed by improved zero-order statistics fractional low-order cyclic correlation (IZOS-FLOCC). Finally, the 2-D DOA estimation of the echo signals is obtained by using the optimization method and the improved MUSIC algorithm. The simulation results show that the proposed method can effectively estimate the 2-D DOA of echo signals in alpha stable distributed noise scenarios.

II. MODEL OF SYSTEM

The passive location system model based on multiple satellites for moving target is shown in Fig.1. The satellite signals can be transmitted to the signal processing module by the moving target reflection through the surveillance channel or reference channel. The reference channel mainly is received the satellite radiation signals. The surveillance channel mainly is received the weak echo signals, the direct path interference (DPI) and the multi path interference (MPI). The two channels both use array antenna. And the signal processing module is used to process and analysis the correlation between the reference channel and surveillance channel [14].

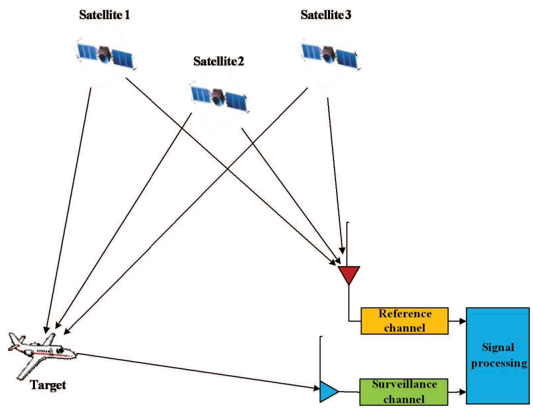

FIGURE 1. Passive location system model based on multiple satellites for moving target.

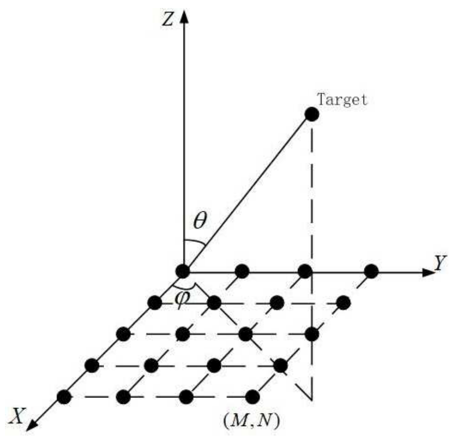

FIGURE 2. The structure model of uniform plane array antenna.

Usually, the DOA estimation algorithm is mostly based on the uniform linear array. However, the biggest disadvantage of the uniform linear array is that it only contains the 1-D angle information of the received signal, which is not suitable for the scene of azimuth angle and pitching angle joint estimation. The circular array can provide 2-D angle information of sources from 0 to 360 degrees, but the resolution of the circular array is low, resulting in a poor accuracy and high CRLB for DOA estimation. Since the uniform plane array has more array elements and the antenna gain is larger, it has higher estimation accuracy. Therefore, a uniform plane array as the receiving antenna for the two signal channels is used in this paper and its structure model is shown in Fig 2.

In Fig. 2, we assume that the number of array elements in the X and Y direction is M and N, respectively. The horizontal distance and vertical distance between each array element is $d = \lambda/2$, where λ is the wavelength of the signal incident on the array antenna. θ and φ represent the pitching angle and azimuth angle when the incident signal source to the antenna array. Assuming the coordinate origin is the reference point of the array, the X-axis and the Y-axis are the base lines, the signal steering vector of the k_{th} signal can be expressed as

$$\gamma = [\cos\varphi_k \sin\theta_k, \sin\varphi_k \sin\theta_k, \cos\theta_k], \tag{1}$$

where θ_k and φ_k represent the elevation angle and azimuth angle of the k-th signal. Therefore, the difference in the distance formed by the arrival of the signal at the (i_{th}, j_{th}) element can be expressed as

$$\beta_{ij} = 2\pi d(m\cos\varphi_k \sin\theta_k + n\sin\varphi_k \sin. \tag{2}$$

Because the distance between the array elements is d, (md, nd) is the position coordinate of the (i_{th}, j_{th}) array element on the antenna, where $m = 1, 2, \cdots, M$ and $n = 1, 2, \cdots, N$. The antenna element is in the plane of XOY, so the third item in (2) is zero and can be ignored. We assume

$$\begin{cases} u_k = 2\pi d\cos\varphi_k \sin\theta_k/\lambda \\ \upsilon_k = 2\pi d\sin\varphi_k \sin\theta_k/\lambda, \end{cases} \tag{3}$$

when the k-th signal reaches the antenna array, the steering vector formed in the X direction can be expressed as

$$A_X(\theta,\varphi) = [1, e^{ju_k}, e^{j2u_k}, \cdots, e^{j(M-1)u_k}]^T. \tag{4}$$

According to (3), the signal steering vector is extended to the K incident signal incident on the X direction of M array element. We can obtain

$$A_X(\theta,\varphi) = \begin{bmatrix} 1 & 1 & \cdots & 1 \\ e^{ju_1} & e^{ju_2} & \cdots & e^{ju_k} \\ \vdots & \ddots & \ddots & \vdots \\ e^{j(M-1)u_1} & e^{j(M-1)u_2} & \cdots & e^{j(M-1)u_k} \end{bmatrix}. \tag{5}$$

Similarly, the signal steering vector of K incident signal incident on the Y direction of N array element can be expressed as

$$A_Y(\theta,\varphi) = \begin{bmatrix} 1 & 1 & \cdots & 1 \\ e^{j\upsilon_1} & e^{j\upsilon_2} & \cdots & e^{j\upsilon_k} \\ \vdots & \vdots & \ddots & \vdots \\ e^{j(N-1)\upsilon_1} & e^{j(N-1)\upsilon_2} & \cdots & e^{j(N-1)\upsilon_k} \end{bmatrix}. \tag{6}$$

From (5) and (6), the signal steering vector of K incident signal incident on the uniform plane array can be expressed as

$$A(\theta,\varphi) = \begin{bmatrix} A_X dig_1(A_Y) \\ A_X dig_2(A_Y) \\ \vdots \\ A_X dig_N(A_Y) \end{bmatrix}, \tag{7}$$

where $dig_n(A_Y)$ is a diagonal matrix formed using each element of the n-th row of the matrix A_Y.

In this paper, we focus on the 2-D DOA estimation of the target echo signal, so we are interested in the surveillance channel signals. However, in the actual receiving process, the array antenna of the monitoring channel will not only receive the target echo signal, but also receive the DPI and

MPI with higher power as well as other interferences at the same time. Since the power of DPI, MPI, and other interferences are much greater than the echo signals, which will seriously affect the processing of echo signals. Therefore, these interference signals need to be suppressed firstly to estimate the DOA of echo signals according to [14].

From the above analysis, the surveillance channel signal after the suppression of DPI and MPI can be expressed as

$$X(t) = A(\theta, \varphi)S(t) + N(t), \tag{8}$$

where $A(\theta, \varphi)$ represents the steering matrix of multiple received echo signals, and A is the multiple echo signals received at the time t in the surveillance channel. $N(t)$ is the alpha stable distribution noise received at time t, which does not have a probability density function that can be expressed in a closed form [15]. It described by its characteristic function, which can be expressed as

$$\varphi(t)=\begin{cases}\exp\left\{j\mu t-\gamma|t|^{\alpha}\left[1+j\beta\cdot sgn(t)tan\left(\frac{\pi\alpha}{2}\right)\right]\right\}, & \alpha=1\\ \exp\left\{j\mu t-\gamma|t|^{\alpha}\left[1+\frac{\pi}{2}j\beta\cdot sgn(t)log\,|t|\right]\right\}, & \alpha\neq 1,\end{cases} \tag{9}$$

where α, β, γ and μ are characteristic exponent, dispersion coefficient, symmetrical parameters and positional parameters, respectively.

III. 2-D DOA ESTIMATION OF ECHO SIGNALS BASED ON MULTIPLE SATELLITES

Since the alpha stable distribution noise contains a lot of shock, it causes frequent mutations in the received signal, which will lead to frequent data abrupt changes in the received signals. There is no second-order and above second-order statistics for the alpha stable distribution noise, traditional DOA estimation method based on Gaussian noise is no longer applicable in this scenario. Therefore, it is necessary to construct new feature for 2-D DOA estimation of echo signals based on multi-satellite radiation sources under the alpha stable distributed nosie.

The traditional parameter estimation method based on fractional lower order statistics has been presented in alpha stable distribution noise. This is because the fractional lower order statistics can suppress alpha stable distribution noise. However, the method requires the prior knowledge such as the characteristic exponent α of the noise, so that the constructed fractional lower-order statistics satisfy $0 \le p < \alpha$, where p is the order of fractional lower-order statistics. Zero order statistics (ZOS) overcomes the limitations of traditional fractional lower-order statistics [16], [17]. That is, it does not require the α of the alpha stable distribution noise. Therefore, the statistics using the ZOS structured do not need to know the α of the noise distribution in advance and has great toughness. In addition, the existing DOA estimation methods using MUSIC algorithm are the most common [18]. The essence of MUSIC is decomposing the covariance matrix of the received signal to the signal subspace and the noise subspace, and using the orthogonality between the steering vector and the clutter subspace to achieve the purpose of DOA estimation. Therefore, based on the above analysis, we make full use of the cyclostationarity of signals and propose an improved DOA estimation method named IZOS-FLOCC. The fractional low order correlation (FLOCC) is used to initially suppress the alpha stable distribution noise firstly. Since the α of noise cannot be accurately known, the initial suppression cannot achieve the desired effect. Then, the improved zero order statistics (IZOS) is used to suppress the non-Gaussian noise again. Finally, 2-D DOA is estimated by the optimization MUSIC algorithm.

For the convenience of theoretical analysis, we rewrite (8) as follows

$$X = AS + N, \tag{10}$$

where X is the signal including noise received by the antenna array, and S is the multiple echo signals. A represents the steering matrix of S, and N is an additive alpha stable distribution noise. The FLOCC of X can be expressed as

$$R^{\varepsilon}_{X,p}(\varepsilon,\tau) = E\left[X(t+\frac{\tau}{2})\left[X^{H}(t-\frac{\tau}{2})\right]^{<p>}e^{-j2\pi\varepsilon t}\right], \tag{11}$$

where P is the order of the FLOCC, $(\cdot)^{<p>} = |\cdot|^{p-1}(\cdot)^{*}$, and ε is the cycle frequency. From (11), we can see that the original phase of the signal has been canceled when FLOCC that contains a conjugate operation by the signal. The signal does not contain the original phase information, so the subsequent nonlinear transformation will not change the signal original phase information.

If the matrix of FLOCC is directly decomposed into the noise subspace and the signal subspace, the 2D DOA of the signal is estimated by using the MUSIC algorithm based on the orthogonality between the steering vector and the noise subspace, the algorithm needs to obey the α information of the alpha stable distribution noise, because (11) is meaningful only when $0 \le p < \alpha$, and too large or too small will have a great influence on the parameter estimation results. Therefore, the next step is to find a nonlinear transformation, which is insensitive to α to deal with (11).

The ZOS of X can be expressed as

$$E(Y) = E\left[log\,|X|\right]. \tag{12}$$

According to (12), $Y = log\,|X|$ is a nonlinear transformation, and it does not need to know the α information of alpha stable distribution noise. All the fractional lower-order statistics of $Y = log\,|X|$ have limited ZOS. Therefore, DOA estimation can be performed on signals affected by alpha stable distribution noise by using ZOS as a nonlinear transformation. Inspired by ZOS, we propose IZOS transformation from (12) to deal with (11) as follows

$$S_{IZOS} = E\left[\log\left(R^{\varepsilon}_{X,p}\right)\right]. \tag{13}$$

If the signal subspace and the noise subspace are calculated by (11), there is the following cost between the statistics and the original statistics. The function described by the relationship

$$\min_{U_S} \left\| S_{IZOS} - \hat{S}_{IZOS} \right\|_F^2 \qquad s.t\ rank\ (S_{IZOS}) \leq K. \tag{14}$$

(14) can be solved by singular value decomposition (SVD) [19] of the matrix, which is specifically expressed as

$$SVD(S_{IZOS}) = U_S D_S V_S^H + U_n D_n V_n^H, \tag{15}$$

where $SVD(\cdot)$ denotes the SVD operator, D_S and D_n represent the diagonal matrix composed of K larger singular values and $MN - K$ smaller singular values after singular value decomposition of S_{IZOS}, respectively. U_S and V_S represent the left and right feature matrices of the diagonal matrix D_S, respectively. Similarly, U_n and V_n represent the left and right feature matrices of the diagonal matrix D_n. From (15), we can see that the optimal solution of (14) is

$$S_{IZOS} = U_S D_S V_S^H. \tag{16}$$

According to the related theory of the matrix, we can see that the linear matrix U_S is the signal subspace, and the estimate expression of DOA can be obtained as

$$SP(\theta, \varphi) = \frac{1}{A^H(\theta, \varphi)\left(I - U_S \langle U_S, U_S \rangle^{-1} U_S^H\right) A(\theta, \varphi)}. \tag{17}$$

If the signal subspace is obtained, the coordinates of the K largest peaks in the three-dimensional graph drawn by (17) can be found. The combination of K coordinates are the DOA of the estimated incident signals. For convenience, we rewrite the form of (16) as

$$S_{IZOS} = (U_S D_S)\, V_S^H = YZ, \tag{18}$$

where $Y = U_S$ and $Z = D_S V_S^H$. Then the cost function shown in (14) can be written as

$$J = \| S_{IZOS} - YZ \|_F^2. \tag{19}$$

In order to find the signal subspace, we need to take Y when the cost function shown in (19) is minimized. Substituting (13) into (19), we can obtain

$$\begin{aligned} J(Y, Z) &= \frac{1}{MNT} E\left[\left\| \log\left(R_{X,p}^{\varepsilon}\right) - YZ \right\|_F^2 \right] \\ &= \frac{1}{MNT} \sum_{m=1}^{MN} \sum_{t=1}^{T} E\left[\left| \log\left((R_{X,p}^{\varepsilon})_{mt}\right) - (YZ)_{mt} \right|^2 \right], \end{aligned} \tag{20}$$

where MN is the number of array elements in the antenna and T is the number of shots of the signal. $(R_{X,p}^{\varepsilon})_{mt}$ and $(YZ)_{mt}$ are the elements of m-th row and t-th column of matrix $R_{X,p}^{\varepsilon}$ and YZ, respectively. Let

$$\psi((R_{X,p}^{\varepsilon})_{mt} - (YZ)_{mt}) = E\left[\left| \log\left((R_{X,p}^{\varepsilon})_{mt}\right) - (YZ)_{mt} \right|^2 \right], \tag{21}$$

(20) can be rewritten as

$$J(Y, Z) = \frac{1}{MNT} \sum_{m=1}^{MN} \sum_{t=1}^{T} \psi\left((R_{X,p}^{\varepsilon})_{mt} - (YZ)_{mt}\right). \tag{22}$$

According to the optimization criterion, Y and Z can be estimated by minimizing (22). In this paper, the optimization algorithm is used to solve the unknown parameters in (22). We assume that the results of the n-th iteration can be written as $Y^{(n)}$ and $Z^{(n)}$, where $Y^{(0)}$ and $Z^{(0)}$ can be initialized into a random full rank and row full rank matrix, respectively. $(n + 1)$-th iteration results can be written as

$$Z^{(n+1)} = \arg\min_Z \left(J(Y^{(n)}, Z^{(n)}) \right), \tag{23}$$

and

$$Y^{(n+1)} = \arg\min_Y \left(J(Y^{(n)}, Z^{(n+1)}) \right). \tag{24}$$

If the above-mentioned iterative algorithm is adopted, the algorithm $J(Y, Z)$ is convergent, that is

$$J(Y^{(n)}, Z^{(n)}) > J(Y, Z^{(n+1)}) > J(Y^{(n+1)}, Z^{(n+1)}). \tag{25}$$

Substituting (22) into (23) and (24), we can obtain

$$\begin{aligned} Z^{(n+1)} &= \arg\min_Z \left(J_A(Y^{(n)}, Z^{(n)}) \right) \\ &= \arg\min_Z \frac{1}{MNT} \sum_{m=1}^{MN} \sum_{k=1}^{K} \psi((R_{X,p}^{\varepsilon})_{mt} \\ &\quad - (Y^{(n)} Z^{(n)})_{mt}) \\ &= \arg\min_Z \frac{1}{T} \sum_{k=1}^{K} \hat{\Psi}\left((R_{X,p}^{\varepsilon})_t - Y^{(n)} z_t \right), \end{aligned} \tag{26}$$

and

$$\begin{aligned} Y^{(n+1)} &= \arg\min_Y \left(J_A(Y^{(n)}, Z^{(n+1)}) \right) \\ &= \arg\min_Y \frac{1}{MNT} \sum_{m=1}^{MN} \sum_{k=1}^{K} \psi((R_{X,p}^{\varepsilon})_{mt} \\ &\quad - (Y^{(n)} Z^{(n+1)})_{mt}) \\ &= \arg\min_Y \frac{1}{MN} \sum_{m=1}^{MN} \hat{\Psi}(\left((R_{X,p}^{\varepsilon})_{(m)}\right)^T \\ &\quad - \left(Z^{(n+1)}\right)^T \left(y_{(m)}\right)^T), \end{aligned} \tag{27}$$

where $(R_{X,p}^{\varepsilon})_t$ and z_t represent the t-th columns of the matrices R_X^{ε} and Z, respectively. $(R_{X,p}^{\varepsilon})_{(m)}$ and $y_{(m)}$ represent the m-th row of $R_{X,p}^{\varepsilon}$ and Z. In summary, we can see that (26) and (27) have the same solution form, so we will solve (26) below, and the solution of (27) is same to (26). From the above analysis, we can see that the solution of (26) can be transformed into the following sub-problems

$$z_t^{(n+1)} = \arg\min_{z_t} \hat{\Psi}\left((R_{X,p}^{\varepsilon})_t - Y^{(n)} z_t \right), \tag{28}$$

where $z_t^{(n+1)}$ is the t-th column of $Z^{(n+1)}$, and the superscript and subscript are omitted for convenience of derivation. We define

$$f(z) = \hat{\Psi}\left((R^{\varepsilon}_{X,p}) - Yz\right). \tag{29}$$

According to the gradient descent method, the minimum value of $f(z)$ can be obtained by iterating the following

$$z^{(n+1)} = z^{(n)} + \mu^{(n)}\nabla f\left(z^{(n)}\right). \tag{30}$$

The best step can be given by

$$\mu^{(n)} = \arg\min_{\mu} \hat{\Psi}\left((R^{\varepsilon}_{X,p}) - Y\left(z^{(n)} + \mu^{(n)}\nabla f\left(z^{(n)}\right)\right)\right). \tag{31}$$

We iteratively solve (23) and (24) according to (25)-(31) until the relative error of two successive iterations is less than a very small constant ς. The signal subspace Y is substituted into (17). By searching the largest peak, the corresponding coordinate (θ, φ) is estimated by

$$\begin{aligned}\left(\hat{\theta}, \hat{\varphi}\right) &= \arg\max_{\theta,\varphi} SP(\theta, \varphi) \\ &= \arg\max_{\theta,\varphi} \frac{1}{A^H(\theta,\varphi)\left(I - Y\langle Y, Y\rangle^{-1}Y^H\right)A^H(\theta,\varphi)}.\end{aligned} \tag{32}$$

IV. THE CRLB OF 2-D DOA ESTIMATION IN ALPHA STABLE DISTRIBUTED NOISE

The alpha stable distribution noise has no specific probability density function. When $\alpha = 1$, which makes it subject to the Cauchy distribution noise [20], which exists the following form of probability density function

$$f(x) = \frac{1}{\pi}\frac{1}{\gamma^2 + (x-\delta)^2}. \tag{33}$$

Assuming that the signals and noise are independent of each other, the expression of the polar coordinate form of the probability density function of the multivariate Cauchy distribution is

$$f_{1,\gamma}(\rho) = \frac{\gamma}{2\pi(\rho^2+\gamma^2)^{3/2}}, \tag{34}$$

where ρ is the second-norm of multi-parameters. The joint probability density function of the sampled data can be expressed as

$$F(X) = \prod_{t=1}^{T}\prod_{l=1}^{L} f_{1,\gamma}\left(\left|x_l(t) - \sum_{k=1}^{K} a(\theta_k,\varphi_k)s_k(t)\right|\right), \tag{35}$$

or

$$F(X) = \prod_{t=1}^{T}\prod_{l=1}^{L}\frac{1}{2\pi}\frac{\gamma}{\left(\gamma^2 + \left|x_l(t) - \sum_{k=1}^{K} a_l(\theta_k,\varphi_k)s_k(t)\right|^2\right)^{3/2}}. \tag{36}$$

The logarithmic probability density function after ignoring the constant term can be expressed as

$$\begin{aligned}\Omega(X;\eta) = TL\log(\gamma) - \frac{3}{2}\sum_{t=1}^{T}\sum_{l=1}^{L}\log\Big(\gamma^2 + \Big|x_l(t) \\ - \sum\nolimits_{k=1}^{K} a_l(\theta_k,\varphi_k)s_k(t)\Big|^2\Big),\end{aligned} \tag{37}$$

where a_l is the l-th row of matrix A. We assume that the parameter to be estimated is $\eta = [s^T\ \ \theta^T\ \ \varphi^T]^T$, where

$$\begin{aligned}s = \big[&s_{1,\Re}(1), \cdots, s_{K,\Re}(1), s_{1,\Im}(1), \cdots, s_{K,\Im}(1), \\ &\cdots, s_{1,\Re}(T), \cdots, s_{K,\Re}(T), s_{1,\Im}(T), \cdots, s_{K,\Im}(T)\big]^T,\end{aligned} \tag{38}$$

and

$$\theta = [\theta_1, \theta_2, \cdots, \theta_K]^T, \tag{39}$$

and

$$\varphi = [\varphi_1, \varphi_2, \cdots, \varphi_K]^T, \tag{40}$$

where $s_{\Re}(t)$ and $s_{\Im}(t)$ represent the real and imaginary parts of signal $s(t)$, respectively. The Fisher Information Matrix (FIM) [21], [22] is defined as

$$J(\eta) = E\left\{\left(\frac{\partial\Omega(X;\eta)}{\partial\eta}\right)\left(\frac{\partial\Omega(X;\eta)}{\partial\eta}\right)^T\right\}. \tag{41}$$

In order to facilitate the derivation, the constant item is removed from (37) and rewritten as

$$\begin{aligned}\Omega(X;\eta) = -\frac{3}{2}\sum_{t=1}^{T}\sum_{l=1}^{L}\log\Big(\gamma^2 + \Big|x_l(t) \\ - \sum\nolimits_{k=1}^{K} a_l(\theta_k,\varphi_k)s_k(t)\Big|^2\Big).\end{aligned} \tag{42}$$

We give each element of (42) as following

$$\frac{\partial\Omega}{\partial\theta_i} = 3\sum_{t=1}^{T}\sum_{l=1}^{L}\frac{\Re\left(s_i^*(t)d_l^*(\theta_i)n_l(t)\right)}{\gamma^2 + |n_l(t)|^2}, \tag{43}$$

$$\frac{\partial\Omega}{\partial\varphi_i} = 3\sum_{t=1}^{T}\sum_{l=1}^{L}\frac{\Re\left(s_i^*(t)d_l^*(\varphi_i)n_l(t)\right)}{\gamma^2 + |n_l(t)|^2}, \tag{44}$$

$$\frac{\partial\Omega}{\partial s_{i,\Re}(t)} = 3\sum_{l=1}^{L}\frac{\Re\left(a_l^*(\theta_i,\varphi_i)n_l(t)\right)}{\gamma^2 + |n_l(t)|^2}, \tag{45}$$

and

$$\frac{\partial\Omega}{\partial s_{i,\Im}(t)} = 3\sum_{l=1}^{L}\frac{\Im\left(a_l^*(\theta_i,\varphi_i)n_l(t)\right)}{\gamma^2 + |n_l(t)|^2}, \tag{46}$$

where $d_l(\theta_i) = \frac{\partial a_l(\theta_i,\varphi_i)}{\partial\theta_i}$, $d_l(\varphi_i) = \frac{\partial a_l(\theta_i,\varphi_i)}{\partial\varphi_i}$, $\Re()$ and $\Im()$ indicate real and imaginary parts, respectively.

Assuming that the noise is a complex Cauchy noise with independent isomorphism of time and space, we have

$$E\left[\frac{\partial\Omega}{\partial\theta_i}\frac{\partial\Omega}{\partial\theta_j}\right] = 9E\left[\sum_{t=1}^{T}\sum_{l=1}^{L}\frac{\Re\left(s_i^*(t)d_l^*(\theta_i)n_l(t)\right)}{\gamma^2+|n_l(t)|^2}\times\frac{\Re\left(s_j^*(t)d_l^*(\theta_j)n_l(t)\right)}{\gamma^2+|n_l(t)|^2}\right]. \quad (47)$$

Let $n_l(t) = |n_l(t)|\,e^{j\xi_l(t)}$, $s_i(t) = |s_i(t)|\,e^{j\beta_i(t)}$, and $a_l(t) = |a_l(t)|\,e^{j\eta(\theta_i,\varphi_j)}$. (47) can be further written as

$$\begin{aligned}
&E\left[\frac{\partial\Omega}{\partial\theta_i}\frac{\partial\Omega}{\partial\theta_j}\right]\\
&= 9E\left\{\sum_{t=1}^{T}\sum_{l=1}^{L}\left|s_i(t)d_l(\theta_i)\right|\frac{|n_l(t)|}{\gamma^2+|n_l(t)|^2}\right.\\
&\quad\times\cos\left(-\beta_i(t)+\eta_l(\theta_i,\varphi_i)+\frac{\pi}{2}+\xi_l(t)\right)\\
&\quad\times\cos\left(-\beta_j(t)+\eta_l(\theta_j,\varphi_j)+\frac{\pi}{2}+\xi_l(t)\right)\\
&\quad\left.\times\left|s_j(t)d_l(\theta_j)\right|\frac{|n_l(t)|}{\gamma^2+|n_l(t)|^2}\right\}\\
&= 9\sum_{t=1}^{T}\sum_{l=1}^{L}\left|s_i(t)d_l(\theta_i)\right|\left|s_j(t)d_l(\theta_j)\right|\\
&\quad\times\frac{1}{2}\cos\left(\beta_i(t)-\beta_j(t)-\eta_l(\theta_i,\varphi_i)+\eta_l(\theta_j,\varphi_j)\right)\\
&\quad\times E\left[\frac{|n_l(t)|^2}{\left(\gamma^2+|n_l(t)|^2\right)^2}\right]\\
&= \frac{3}{5\gamma^2}\sum_{t=1}^{T}\sum_{l=1}^{L}\Re\left(s_i^*(t)d_l^*(\theta_i)s_j^*(t)d_l^*(\theta_j)\right).
\end{aligned} \quad (48)$$

(48) is written as a matrix

$$E\left[\left(\frac{\partial\Omega}{\partial\theta}\right)\left(\frac{\partial\Omega}{\partial\theta}\right)^T\right]=\frac{3}{5\gamma^2}\sum_{t=1}^{T}\Re\left(S^H(t)D_\theta^HD_\theta S(t)\right). \quad (49)$$

Similarly,

$$E\left[\left(\frac{\partial\Omega}{\partial\varphi}\right)\left(\frac{\partial\Omega}{\partial\varphi}\right)^T\right]=\frac{3}{5\gamma^2}\sum_{t=1}^{T}\Re\left(S^H(t)D_\varphi^HD_\varphi S(t)\right), \quad (50)$$

and

$$E\left[\left(\frac{\partial\Omega}{\partial\varphi}\right)\left(\frac{\partial\Omega}{\partial\varphi}\right)^T\right]=\frac{3}{5\gamma^2}\sum_{t=1}^{T}\Re\left(S^H(t)D_\varphi^HD_\varphi S(t)\right), \quad (51)$$

In addition,

$$\begin{aligned}
&E\left[\frac{\partial\Omega}{\partial s_{i,\Re}(t)}\frac{\partial\Omega}{\partial s_{j,\Re}(t')}\right]\\
&= 9E\left\{\sum_{w=1}^{L}\sum_{l=1}^{L}\frac{\Re\left\{a_w^*(\theta_i,\varphi_i)n_w(t)\right\}}{\gamma^2+|n_w(t)|^2}\frac{\Re\left\{a_l^*(\theta_j,\varphi_j)n_l(t')\right\}}{\gamma^2+|n_l(t')|^2}\right\}\\
&= 9E\left\{\sum_{w=1}^{L}\frac{\Re\left\{a_w^*(\theta_i,\varphi_i)n_w(t)\right\}}{\gamma^2+|n_w(t)|^2}\frac{\Re\left\{a_w^*(\theta_j,\varphi_j)n_w(t')\right\}}{\gamma^2+|n_w(t')|^2}\right\}+9E\\
&\quad\times\left\{\sum_{w=1}^{L}\sum_{l=1,l\neq w}^{L}\frac{\Re\left\{a_w^*(\theta_i,\varphi_i)n_w(t)\right\}}{\gamma^2+|n_w(t)|^2}\frac{\Re\left\{a_l^*(\theta_j,\varphi_j)n_l(t')\right\}}{\gamma^2+|n_l(t')|^2}\right\}\\
&= 9\sum_{w=1}^{L}E\left\{\frac{|a_w(\theta_i,\varphi_i)|\left|a_w(\theta_j,\varphi_j)\right||n_w(t)|^2}{\left(\gamma^2+|n_w(t)|^2\right)^2}\right\}\\
&\quad\times E\left\{\cos\left(\eta_w(\theta_i,\varphi_i)+\xi_w(t)\right)\cos\left(\eta_w(\theta_j,\varphi_j)+\xi_w(t)\right)\right\}\delta_{t,t'}\\
&\quad+9\sum_{w=1}^{L}\sum_{l=1,l\neq w}^{L}E\left\{\frac{|a_w(\theta_i,\varphi_i)|\,|n_w(t)|}{\gamma^2+|n_w(t)|^2}\right\}\\
&\quad\times E\left\{\cos\left(\eta_w(\theta_i,\varphi_i)+\xi_w(t)\right)\right\}\\
&\quad\times E\left\{\frac{\left|a_l(\theta_j,\varphi_j)\right||n_l(t)|}{\gamma^2+|n_l(t)|^2}\right\}\cdot E\left\{\cos\left(\eta_l(\theta_j,\varphi_j)+\xi_l(t')\right)\right\}\\
&= 9\cdot\frac{2}{15\gamma^2}\cdot\frac{1}{2}\sum_{w=1}^{L}|a_w(\theta_i,\varphi_i)|\left|a_w(\theta_j,\varphi_j)\right|\\
&\quad\times\cos\left(\eta_w(\theta_i,\varphi_i)-\eta_w(\theta_j,\varphi_j)\right)\delta_{t,t'}\\
&= \frac{3}{5\gamma^2}\sum_{w=1}^{L}\Re\left\{a_w(\theta_i,\varphi_i)a_w^*(\theta_j,\varphi_j)\right\}\delta_{t,t'}.
\end{aligned} \quad (52)$$

(50) is written as a matrix, we can obtain

$$E\left[\left(\frac{\partial\Omega}{\partial s_\Re(t)}\right)\left(\frac{\partial\Omega}{\partial s_\Re(t)}\right)^T\right]=\frac{3}{5\gamma^2}\Re\left(A^HA\right)\delta_{tt'}, \quad (53)$$

and

$$E\left[\left(\frac{\partial\Omega}{\partial s_\Im(t)}\right)\left(\frac{\partial\Omega}{\partial s_\Im(t)}\right)^T\right]=\frac{3}{5\gamma^2}\Im\left(A^HA\right)\delta_{tt'}. \quad (54)$$

So we can obtain

$$\begin{aligned}
&E\left(\frac{\partial\Omega}{\partial\theta_i}\frac{\partial\Omega}{\partial s_{j,\Re}(t)}\right)\\
&= 9E\left\{\sum_{t'=1}^{MN}\sum_{w=1}^{L}\sum_{l=1}^{L}\frac{\Re\left\{s_i^*(t')d_{w,\theta_i}^*(\theta_i,\varphi_i)n_w(t')\right\}}{\gamma^2+|n_w(t')|^2}\right.\\
&\quad\left.\times\frac{\Re\left\{a_l^*(\theta_j,\varphi_j)n_l(t)\right\}}{\gamma^2+|n_l(t)|^2}\right\}\\
&=9E\left\{\sum_{w=1}^{L}\frac{\Re\left\{s_i^*(t)d_{w,\theta_i}^*(\theta_i,\varphi_i)n_w(t)\right\}}{\gamma^2+|n_w(t)|^2}\frac{\Re\left\{a_w^*(\theta_j,\varphi_j)n_w(t)\right\}}{\gamma^2+|n_w(t)|^2}\right\}\\
&= 9\cdot\sum_{w=1}^{L}\left|s_i(t)\right|\left|d_{w,\theta_i}(\theta_i,\varphi_i)\right|\left|a_w(\theta_j,\varphi_j)\right|\\
&\quad\times E\left\{\frac{|n_w(t)|^2}{\left(\gamma^2+|n_w(t)|^2\right)^2}\right\}\\
&\quad\times E\left\{\cos\left(-\beta_i(t)+\eta_w(\theta_i,\varphi_i)+\frac{\pi}{2}+\xi_w(t)\right)\right.\\
&\quad\left.\times\cos\left(\eta_w(\theta_j,\varphi_j)+\xi_w(t)\right)\right\}
\end{aligned}$$

$$= 9 \cdot \sum_{w=1}^{L} \left|s_i(t)\right| \left|d_{w,\theta_i}(\theta_i, \varphi_i)\right| \left|a_w(\theta_j, \varphi_j)\right| \cdot \frac{2}{15\gamma^2} \cdot \frac{1}{2}$$
$$\times E\left\{\cos\left(-\beta_i(t)+\eta_w(\theta_i,\varphi_i)+\frac{\pi}{2}+\eta_w(\theta_j,\varphi_j)+2\xi_w(t)\right)\right.$$
$$\left.+\cos\left(-\beta_i(t)+\eta_w(\theta_i,\varphi_i)+\frac{\pi}{2}-\eta_w(\theta_j,\varphi_j)\right)\right\}$$
$$= \frac{3}{5\gamma^2}\sum_{w=1}^{L}\Re\left\{s_i^*(t)d_{w,\theta_i}^*(\theta_i,\varphi_i)a_w(\theta_j,\varphi_j)\right\}, \tag{55}$$

where $d_{w,\theta_i}(\theta_i, \varphi_i) = \partial a_w(\theta_i, \varphi_i)/\partial\theta_i$. (55) is written as a matrix,

$$E\left[\left(\frac{\partial\Omega}{\partial s_{\Re}(t)}\right)\left(\frac{\partial\Omega}{\partial\theta}\right)^T\right] = \frac{3}{5\gamma^2}\Re\left(A^H(t)D_\theta S(t)\right), \tag{56}$$

$$E\left[\left(\frac{\partial\Omega}{\partial s_{\Im}(t)}\right)\left(\frac{\partial\Omega}{\partial\theta}\right)^T\right] = \frac{3}{5\gamma^2}\Im\left(A^H(t)D_\theta S(t)\right), \tag{57}$$

$$E\left[\left(\frac{\partial\Omega}{\partial s_{\Re}(t)}\right)\left(\frac{\partial\Omega}{\partial\varphi}\right)^T\right] = \frac{3}{5\gamma^2}\Re\left(A^H(t)D_\varphi S(t)\right), \tag{58}$$

and

$$E\left[\left(\frac{\partial\Omega}{\partial s_{\Im}(t)}\right)\left(\frac{\partial\Omega}{\partial\varphi}\right)^T\right] = \frac{3}{5\gamma^2}\Im\left(A^H(t)D_\varphi S(t)\right). \tag{59}$$

Substituting the above formulas into the FIM matrix, we can obtain

$$J(\eta) = \begin{bmatrix} \aleph_{\Re} & -\aleph_{\Im} & \cdots & 0 & 0 & \Delta_{\Re}(1) \\ \aleph_{\Im} & \aleph_{\Re} & \cdots & 0 & 0 & \Delta_{\Im}(1) \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & \aleph_{\Re} & -\aleph_{\Im} & \Delta_{\Re}(T) \\ 0 & 0 & \cdots & \aleph_{\Im} & \aleph_{\Re} & \Delta_{\Im}(T) \\ \Delta_{\Re}^T(1) & \Delta_{\Im}^T(1) & \cdots & \Delta_{\Re}^T(T) & \Delta_{\Im}^T(T) & \Xi \end{bmatrix}, \tag{60}$$

where

$$\aleph = \frac{3}{5\gamma^2}\cdot A^H A, \tag{61}$$

$$\Delta = \frac{3}{5\gamma^2}\cdot\left[A^H D_\theta S(t), A^H D_\varphi S(t)\right], \tag{62}$$

$$D_\theta = \left[\frac{\partial a_1(\theta_1,\varphi_1)}{\partial\theta_1}, \frac{\partial a_2(\theta_2,\varphi_2)}{\partial\theta_2}, \cdots, \frac{\partial a_K(\theta_K,\varphi_K)}{\partial\theta_K}\right], \tag{63}$$

$$D_\varphi = \left[\frac{\partial a_1(\theta_1,\varphi_1)}{\partial\varphi_1}, \frac{\partial a_2(\theta_2,\varphi_2)}{\partial\varphi_2}, \cdots, \frac{\partial a_K(\theta_K,\varphi_K)}{\partial\varphi_K}\right], \tag{64}$$

and

$$\Xi = \frac{3}{5\gamma^2}\sum_{t=1}^{T}\Re\begin{bmatrix} S^H(t)D_\theta^H D_\theta S(t) & S^H(t)D_\theta^H D_\varphi S(t) \\ S^H(t)D_\varphi^H D_\theta S(t) & S^H(t)D_\varphi^H D_\varphi S(t)\end{bmatrix}, \tag{65}$$

where $\Re(\cdot)$ indicates the real part, $S(t) = diag\{s_1(t), s_2(t), \cdots, s_K(t)\}$. According to the properties of the matrix, the CRLB of the 2-D DOA estimation under alpha stable distributed noise can be expressed as

$$CRLB^{-1}(\theta,\varphi) = \Xi - \sum_{t=1}^{T}\Re\left[\Delta^H(t)\aleph^{-1}\Delta(t)\right]. \tag{66}$$

V. NUMERIC SIMULATION AND DISCUSSION

In this section, the effectiveness of the proposed method is evaluated through simulations. We consider three satellite signals as non-cooperative illuminators of opportunity signal include GPS, DVB-S, and INMARSAT. Without loss of generality, we assume that the carrier frequency is $f_G = 1.57GHz$, $f_G = 1.57GHz$ and $f_I = 4.2GHz$. The TDOA is $1\mu s$, $2\mu s$ and $3\mu s$, and FDOA are 100 Hz, 200Hz and 300Hz, respectively. The standard alpha stable distribution is used to model the non-Gaussian noise, and its parameter is set $\alpha = 1.5$ and $\gamma = 1$. Receiving antenna adopts 5×5 uniform area array. Distance between array elements is half the wavelength of the DVB-S satellite signal frequency. The DOA is set to $(40°, 60°)$. The number of snaps is 600. The fractional lower order cyclic correlation parameter $p = 1$. 1000 Monte-Carlo experiments are carried out under each experimental condition. The root-mean-square error (RMSE) of DOA estimates is adopted to evaluate the performance of the proposed method [23], which is expressed as follows

$$RMSE = \sqrt{\frac{1}{R}\sum_{r=1}^{R}\left(\hat{\rho}(r)-\rho\right)^2}, \tag{67}$$

where ρ is the theoretical value of the parameter to be estimated, $\hat{\rho}$ is the estimated value of the parameter, and R is the number of simulations.

The GSNR is defined as the ratio of the mean power of the signal and the average dispersion of the alpha stable noise [24], which can be expressed as

$$GSNR = 10\lg\left(\frac{1}{\gamma T}\sum_{t=1}^{T}|s(t)|^2\right). \tag{68}$$

In order to discuss the estimation performance of two-dimensional DOA under different generalized signal to noise ratios, simulations are performed under different GSNR and compared with [13] and the simulation results are shown in Fig. 3. From Fig.3, it can be seen that the proposed method can estimate the pitch angle and azimuth in the two-dimensional DOA estimation of echo signal under the alpha stable distributed noise, which indicates that the proposed estimation method can be estimated effectively for the DOA in this scene. Moreover, the proposed method has a lower RMSE than the [13] method under the same signal to noise ratio. This is because the proposed method takes into account the cyclostationarity of the signals, and the noise has no cyclic stability. Using the statistics constructed by IZOS to further suppress the non-Gauss noise, it can reduce the influence of the strong impulse characteristic of the noise to the parameter estimation, so the estimation

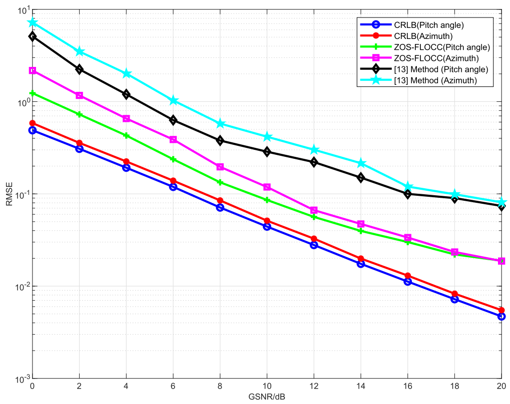

FIGURE 3. DOA estimation performance versus different GSNRs.

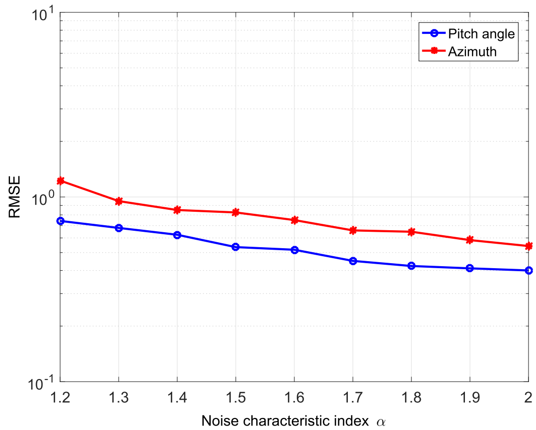

FIGURE 4. DOA estimation performance for different α.

performance of the proposed method is better than that of the [13]. In addition, it can be seen that the performance of DOA estimation is close to CRLB and then far away from CRLB with the increase of GSNR. The reason is that when the signal to noise ratio is low, the alpha stable distribution noise has a great influence on the signal, but the method can play the role of suppressing the noise, so the DOA estimation performance curve is gradually close to the CRLB. However, the influence of noise to the signal gradually decreases with the increase of signal to noise ratio, so the suppression of the noise is saturated gradually. The estimation performance of the algorithm to DOA also tends to be stable, while the CRLB still decreases at a fast speed, so the performance curve is gradually far away from the CRLB curve.

In order to discuss the influence of alpha stable distribution characteristic index α on the performance of DOA estimation when $GSNR = 4dB$, simulations are carried out under different GSNR, and the results are shown in Fig 4. From Fig.4, it can be seen that when GSNR is fixed, with the increase of α, the estimation of the pitch angle and azimuth angle decreases continuously, indicating that the estimation performance is gradually improved. However, the change of RMSE is slow, which shows that this method is not sensitive to the α value of the alpha stable distributed noise, so the proposed method has good properties and good robustness against the alpha stable distribution noise. This is because the α value determines the sharpness of the pulses in the noise, and IZOS has a good compression effect on the alpha stable distributed noise, so the proposed method has good adaptability to the alpha stable distributed noise with different characteristic exponents. In particular, when $\alpha = 2$ the DOA estimator also has a smaller RMSE, which shows that our method has better estimation performance in the case of Gauss distributed noise.

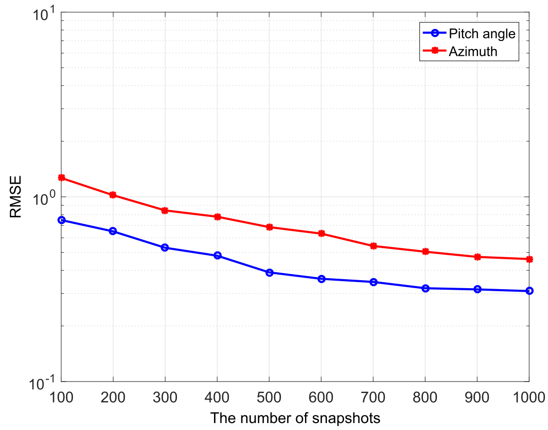

FIGURE 5. DOA estimation performance with the number of snapshots.

In order to discuss the effect of different snapshots on the performance of DOA estimation, simulations are carried out for different snapshots when $GSNR = 4dB$. The simulation results are shown in Fig.5. As we can see from Fig.5, with the increase of the number of signal snapshots, the RMSE of the pitch and azimuth estimates gradually decrease, but gradually tend to be stable. It shows that the accuracy of the two-dimensional DOA estimation in this scene increases with the increase of the number of snapshots. The reason is that the correlation between the two signals becomes stronger as the number of snapshots increases. Therefore, the DOA estimation performance can be improved by increasing the number of signal snapshots.

In order to discuss the influence of the number of elements on the DOA estimation results, the antenna is set to 4×4, 5×5 and 6×6, and the simulations are carried out under different GSNR. The simulation results are shown in Fig. 6. From Fig. 6, it can be seen that the RMSE of the DOA estimation is gradually reduced with the increase of the number of elements, which indicating that the estimation performance of the algorithm is also gradually improved. The antenna gain can be improved gradually as the number of antenna elements increases, and the performance of parameter estimation will become better, so we can see that the DOA estimation accuracy can be improved by increasing the antenna array element.

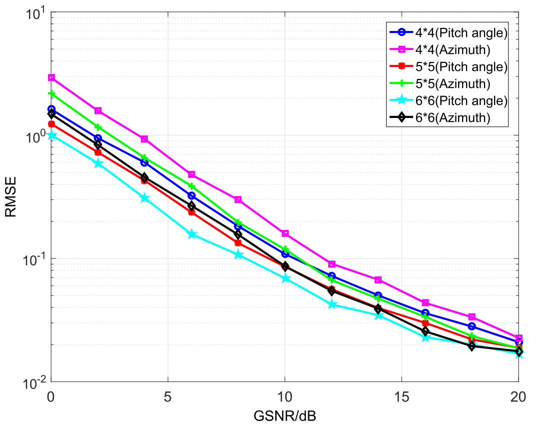

FIGURE 6. **DOA estimation performance with the number of elements.**

VI. CONCLUSION

In order to increase the accuracy of two-dimensional DOA estimation with the non-Gaussian noise in low SNR regions, a 2-D DOA estimation method based on IZOS-FLOCC is proposed. The received signal of the uniform array antenna is modeled firstly, and then the alpha stable distribution noise is suppressed by FLOCC and IZOS. Finally, the optimization method and the improved MUSIC algorithm are used to obtain the two-dimensional DOA estimation of the echo signals. The simulation results show that the proposed method can effectively estimate the two-dimensional DOA of the echo signals based on the multiple satellites passive radar in the alpha stable distribution noise, and its estimation performance is better than the subspace fitting method. In addition, the proposed method has good robustness to the alpha stable distribution noise with different characteristic exponents. Furthermore, the DOA estimation accuracy can be improved by increasing the number of snapshots or increasing the number of antenna elements.

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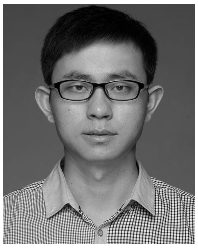

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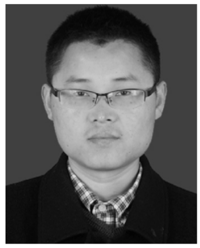

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